Quantitative Analysis and the Value of Social Media Investment Research

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Abstract

We examine a platform design change on Seeking Alpha (SA) that reduced the cost of acquiring quantitative signals and educated investors on the benefits of quantitative investing. Following the change, SA report recommendations align more closely with quant ratings, particularly for reports mentioning quant-related terms and reports authored by less quantitatively savvy contributors. Furthermore, both types of reports become stronger predictors of returns. Retail trading also becomes more correlated with quant ratings following the release of SA reports. These findings suggest that the platform change improved the quality of contributor's investment recommendations and helped retail investors better incorporate quantitative signals.

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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 (ages 18-34), social media is the most popular source of investment research, surpassing conversations with friends and family, TV news, newspapers, and discussions with brokers or financial advisors.[1] The recent trading frenzies in Gamestop and other meme stocks, fueled by social media platforms, further highlight 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 an increased emphasis on quantitative research is one feature that can enhance 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

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

et al. 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] Social media platforms could potentially help investors correct these mistakes by educating them on the value of quantitative research, and by lowering the costs of obtaining 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 a platform design change on Seeking Alpha that reduced the cost of acquiring quantitative signals and educated investors about the advantages of quantitative investing. In June 2019, the SA product team announced the addition of quantitative ratings which would be accessible to all premium and pro subscribers on the website. The launch was accompanied by several educational initiatives (e.g., webinars) emphasizing the benefits of quantitative investing. In addition, SA 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 platform design changes. While the exact formula of the ratings is proprietary, SA states 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

[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.

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 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. This predictability remains significant in the post-disclosure period (2020–2022), indicating that quant ratings continue to be valuable even after their public release 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 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

[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.

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*. Additionally, we find no evidence that SA report recommendations were becoming 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 influence research production, we examine the introduction of quantitative ratings for exchange traded funds (ETFs), which are also predictive of future ETF returns. 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.

A potential concern is that SA contributors may naively follow ratings even when the ratings contain no useful information. To explore this possibility, we examine sell-side analyst consensus ratings, which were made available at the same time of stock quantitative ratings, but do not predict future stock returns. We find no evidence that contributor report ratings become more aligned with sell-side ratings following the design change. This result is consistent with contributors recognizing that quantitative ratings are more informative than sell-side analyst recommendations, possibly due to SA's educational programs that emphasize the advantages of quantitative investing.

One limitation of financial education programs is that the benefits may primarily accrue to the most sophisticated individuals, as less sophisticated individuals may be less attentive to new information sources or find the information too complex to incorporate (Fernandes, Lynch, and Netemeyer 2014). We use information from contributors' biographies to assess their quantitative sophistication. Before the platform design changes, 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 changes. Our findings suggest that SA's increased emphasis on quantitative research was particularly beneficial for less quantitatively sophisticated investors, who were likely less familiar with quantitative analysis.

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 stocks 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 observe a sharp increase in the correlation between retail imbalances and quantitative ratings on the day an SA report is released compared to the days immediately prior to the report release. This effect persists after controlling for both the report rating and the tone of the report, which is consistent with retail investors actively incorporating quant ratings into their investment decisions rather than merely passively following report recommendations.

Our study contributes 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 identify another important change to platform design, the increased emphasis of quantitative research on SA, 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 this 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 exploit 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 increased focus on quantitative research on the SA platform is another factor that helped a subset of market participants, SA contributors and retail investors, better incorporate quantitative signals.

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, the site attracts approximately 17 million unique visitors each month, boasts over 10 million registered users, and has more than 16,000 contributors who have published at least one report..[5] SA Reports are intended to provide new investment research, rather than to simply break news, and each report

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

undergoes significant editorial review. Prior work finds that SA reports contain value-relevant information that predict returns (Chen et al., 2014) and facilitate 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 white papers and webinars that discussed the advantages of quantitative investing.[6]

Appendix A provides an example of the quantitative metrics available for TSLA. 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 can also view the factor grades for the five primary factors incorporated 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 see how TLSA ranks on each metric relative to other firms in the same Global Industry Classification Standard (GICS) sector. For example, while TSLA received a relatively

[6] For example: https://seekingalpha.com/performance/quant and https://seekingalpha.com/article/4640675-webinar-replay-all-about-seeking-alphas-quant-stock-ratings.

low grade for Gross Profit Margin under the Profitability factor, it performed well on several other profitability-related 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 rating.[7] 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).[8] 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 SA.[9] We also obtain all research reports published on the SA website over the same window. For each report, we collect the following information: a report ID assigned by SA, report title, main text, date and time of the report publication, author name, the ticker (or tickers) assigned to each report, and the author's rating at publication. The author's rating at

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

[8] 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 access to additional features 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.

[9] 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.

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 *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.[10] 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, 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.

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

[10] This filter eliminates 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 repeat our main tests without this filter. We find very similar results.

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.[11]

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.[12] 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:

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

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

[11] Table IA.2 of the Internet Appendix also reports transition matrices for quant recommendations at a daily, monthly, and annual horizon. Ratings 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%).

[12] 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.

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.* 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 remains 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).[13]

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

[13] The magnitude of the return predictability is large, particularly when benchmarked to studies that focus on a single anomaly. As an alternative benchmark, we compute analogous return to a quant strategy using the *Net Anomaly* measure of Jensen, Kelly and Pedersen, 2023 (as describes in Section 2.3). The returns using this measure, reported in Figure IA.1 of the Internet Appendix, are very similar in economic magnitude.

alpha (1.20%) and the CAPM alpha (1.95%) suggests that passive factor loadings contributed roughly 0.75% to monthly returns.[14]

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 suggests that investors could potentially benefit from *Quant Ratings* even after they were made publicly available on the Seeking Alpha platform.[15]

4. Quant Ratings and SA Report Recommendations

In this section, we explore whether *SA* contributors incorporate quantitative analysis more into their research reports following the platform design changes.

4.1 The Frequency of "Quant" Reports

We begin by counting the number of SA reports that mention words commonly associated with SA's 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' as well as minor variations of each expression (e.g., "grade for value". Appendix B provides excerpts from a bullish and bearish *Quant Report.* While anecdotal, these excerpts indicate that SA quant ratings are directly incorporated in at least some SA reports.

[14] 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).

[15] This finding is perhaps surprising, as one might expect the dissemination of quantitative ratings to reduce or eliminate anomaly mispricing. One potential explanation is that Seeking Alpha's quant ratings are only accessible to a relatively small group (~70,000 premium subscribers). In contrast, anomaly strategies like momentum and quality are widely traded by ETFs with billions of dollars in assets under management (e.g., MTUM and QUAL). Further, despite their large-scale adoption, a strategy combining momentum and quality signals generate significant alpha (over 1% per month) during our post-sample period, suggesting that market inefficiencies may persist even with broad investor participation.

To provide more systematic evidence, Figure 3 plots the total number of *Quant Reports* over each year in the sample period. 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*. While the 3.15% estimate may seem modest in absolute terms, it represents a more than 20-fold increase relative to the pre-period. Further, the number of *Quant Reports* has been steadily increasing over time. This trend is consistent with more contributors recognizing the value of quantitative analysis, potentially as a result of SA's various educational initiatives (e.g., research reports, webinars, etc.) aimed at highlighting the benefits of quantitative research. This steady growth also 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 section.

4.2 The Alignment between Report Recommendations and Quant Ratings

Our second test examines whether SA report recommendations (i.e., Buy, Hold, or Sell) become more correlated with *Quant Ratings* after the platform design changes. 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. 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). 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).[17]

One potential alternative explanation for our findings is that the composition of stocks 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 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.

[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] These findings, coupled with the fact that SA reports are far more likely to recommend a buy recommendation then a sell recommendation (see Table 1), suggest that stocks with favorable quantitative recommendations may experience an increase in coverage relative to stocks with less favorable recommendations. Consistent with this prediction, we find that the coverage of stocks with *Strong Buy* ratings increase by five percentage points relative to stocks with *Strong Sell* ratings after the platform design change (see Figure IA.2 of the Internet Appendix).

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

We further investigate whether SA contributors rely specifically on SA Quant Ratings or incorporate a broader set of quantitative signals. Specifically, we compare how contributors incorporate quantitative signals that are positively correlated with SA Quant Ratings (e.g., momentum, value, and profitability growth) versus those that are negatively correlated (e.g., accruals, size, and reversals). To do so, we define *Net Anomaly Positive* as the sum of the *Net Anomaly* score across the six factor clusters that have a significant positive association with *Quant Rating* in Specification 2 of Table 2. Similarly, *Net Anomaly Negative* is defined the sum of *Net Anomaly* score across the six factor clusters with a significant negative association.

The correlation between *Quant Rating* and *Net Anomaly Positive* is 0.42, while the correlation between *Quant Rating* and *Net Anomaly Negative* is -0.09. Thus, if contributors are focusing primarily on SA Quant Ratings, we expect report ratings to become significantly more correlated with *Net Anomaly Positive* but not *Net Anomaly Negative*. Conversely, if users are becoming more quant-focused independent of SA Quant Ratings, we would expect report ratings to become more correlated with both *Net Anomaly Positive* and *Net Anomaly Negative*. To test this, we repeat Equation (2) by replacing *Quant Rating* with *Net Anomaly Positive* and *Net Anomaly Negative,* and we report the results in Table IA.4 of the Internet Appendix. Across all three specifications we find the coefficient on *Net Anomaly Positive* × *Post* is positive, the coefficient on *Net Anomaly Negative* × *Post* is negative, and the difference between the two estimates is significant at a 1% level. This finding suggests that SA contributors are primarily focused on SA Quant Ratings rather than more broadly incorporating various quantitative measures during the post-event period.

4.3 The Alignment between Report Recommendations and Quant Ratings – Quant versus Non-Quant Reports

We expect that the increased alignment between report recommendations and *Quant Ratings,* documented in the previous section, will 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 results for *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 the increased alignment between *Quant Ratings* and report recommendations holds 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 The Alignment between Report Recommendations and Quant Ratings - Exchange Traded Funds

To provide additional evidence that platform design changes can influence SA research production, in this section we examine the consequence of an alternative shock: 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. Much like stock quant ratings, ETF quant ratings are advertised on the platform as being significant predictors of future returns.[19] However, 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.[20] ETF Factor grades are based on the ETFs performance on various metrics relative to other ETFs in the same asset class.[21] Although SA introduced the quant ratings in March of 2021, they provided backfilled quant ratings beginning in

[19] We also independently confirm that ETF quant ratings predict future returns (see Table IA.5 of the Internet Appendix).
[20] 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
[21] 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.

November of 2019. Accordingly, our sample for this analysis includes 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. We find that *Quant Rating ETF × Post* is positive and significant, indicating that SA report ratings become 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.

Although there are no obvious pre-trends, the coefficients *Quant Rating ETF* in the pre-period are consistently positive. One possible explanation for this finding is that the platform design changes introduced in 2019 had spillover effects on ETF research. This would suggest that report ratings became more strongly correlated with ETF quant ratings following the initial platform redesign. Unfortunately, SA does not provide ETF ratings prior to 2019. Accordingly, we develop our measure of ETF quantitative ratings (*Estimated Rating ETF*), defined in greater detail in Appendix C. We find that the correlation between *Estimated Rating ETF* and SA's ETF quant ratings (when available) is 0.94, indicating that our estimated measure is a good proxy.

We then estimate the following regression:

$$Report\ Rating_{it} = \alpha + \beta_1 Est.Rating\ ETF_{it} \times PreStock_t + \beta_2 Est.Rating\ ETF_{it} \times PreETF_t + \beta_3 Est.Rating\ ETF_{it} + PostETF_t + FE + \varepsilon_{it,} \tag{3}$$

where *Pre Stock* is an indicator for the three year period prior to the introduction of quantitative ratings for stocks (2016-2018), *Pre ETF* is an indicator for the period after the introduction of stock quantitative ratings but before the introduction of ETF quantitative ratings (November 2019 – December 2020), and *Post ETF* is an indicator for the period after the introduction of ETF quantitative ratings (June 2021-December 2022), and FE denote asset class × date and firm fixed effects.

Specification 5 of Table 5 reports the estimates. The estimate on *Est Rating ETF* × *Pre Stock* is economically small and statistically insignificant, indicating that ETF report ratings were uncorrelated with ETF quantitative ratings prior to the platform design changes in 2019. In contrast, the estimate on *Est Rating ETF* × *Pre ETF* is positive, and it is also significantly greater than the estimate on *Est Rating ETF* × *Pre Stock*. This finding is consistent with the platform design changes influencing ETF research even prior to the availability of ETF quant ratings on the platform. In summary, the evidence from Table 5 indicates that both the reduced cost of accessing quantitative signals for ETFs (Specifications 1–4) and broader platform design changes emphasizing quantitative investing (Specification 5) contributed to contributors better aligning their ETF investment recommendations with quantitative signals.

4.5 The Alignment between Report Recommendations and Quant Ratings –The Role of Rating Informativeness

There are at least two reasons why SA report recommendations become more aligned with both stocks and ETFs quant ratings more following the platform design change. First, investors may naively follow ratings without considering the information content behind them. Second, users may recognize that quantitative ratings are informative, possibly due to Seeking Alpha's educational programs highlighting the benefits of quantitative investing.

To differentiate between these explanations, we analyze contributors' response to the introduction of Wall Street Ratings, which measures the consensus recommendations of sell-side analysts. Wall Street Ratings were launched concurrently with quantitative ratings. However, unlike quant ratings, SA's self-reported analysis indicates that Wall Street Ratings do not outperform the market.[22] Additionally, SA did not emphasize sell-side ratings in its educational programs.

Since we do not have access to the exact Wall Street ratings provided on the SA platform for the pre-period, we construct our own Wall Street Rating (*Estimated Wall Street Rating*), defined as the average sell-side analyst recommendation, collected from the IBES summary recommendation file in the month prior to the report rating.[23] The correlation between *Estimated Wall Street Rating* and SA's measure is 93%. We then estimate the following regression:

$$Report\ Rating_{it} = \alpha + \beta_1 Quant\ Rating_{it} + \beta_2 Quant\ Rating_{it} \times Post_t + \beta_3 Est.Wall\ Street\ Rating_{it} + \beta_4 Est.Wall\ Street\ Rating_{it} \times Post_t + FE + \varepsilon_{it,} \quad (4)$$

where *Report Rating*, *Quant Rating*, *Post*, and *FE* are defined in Equation 2.

Table 6 presents the results. We find that the coefficient on *Est. Wall Street Ratings* is positive, indicating that SA contributor ratings and sell-side analyst ratings are correlated. However, the coefficient on *Est. Wall Street Ratings × Post* is economically small and statistically insignificant. This

[22] See: https://about.seekingalpha.com/analyst-ratings. We also confirm that sell-side ratings do not earn significant positive abnormal returns in Table IA. 6 of the Internet Appendix.
[23] I/B/E/S assigns lower values to better recommendations (1= strong buy and 5 = strong sell). We reverse this pattern (1=strong sell and 5= strong sell) so that the IBES rating mirror the Wall Street Ratings on the SA platform.

finding is inconsistent with contributors paying more attention to wall street ratings after they become more readily available on the SA platform. Furthermore, the coefficient on *Quantrating* × *Post* is significantly greater than the coefficient on *Est. Wall Street Ratings* × *Post*. This finding supports the idea that contributors perceive quantitative ratings are more informative than wall street ratings, perhaps as a result of Seeking Alpha's educational initiatives.

4.6 The Alignment between Report Recommendations and Quant Ratings by Contributor Sophistication

We next examine whether our findings vary 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 correlate 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".[24] *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 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*

[24] 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).

Sophistication groups.[25] Specifications 1-3 of Table 7 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.[26] 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 sophistication issuing research report recommendations that are more aligned with quantitative ratings prior to the platform design changes.

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 platform changes 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

[25] 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.3 of the Internet Appendix, indicate that the estimates are qualitatively similar across all the sophistication measures.

[26] 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).

In this section, we investigate whether the platform design changes enhanced the value of SA research reports. We measure this improvement through two lenses: the correlation between report recommendations and future returns (Sections 5.1–5.3) and the extent to which the reports help retail investors integrate quantitative analysis into their trading decisions (Section 5.4).

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 platform design change. Taken together, these findings point to the possibility that SA report recommendations became more predictive of future returns (i.e., more informative) following the change. 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:

$$\begin{aligned} Ret_{it+1,t+x} = \; & \alpha + \beta_1 ReportRating \times Pre_t + \beta_2 ReportRating_{it} \times Post_t \times NonQuant_{it} \\ & + \beta_3 ReportRating_{it} \times Post_t \times Quant_{it} + \beta_4 Post_t \times Quant_{it} + FE + \varepsilon_{it.} \end{aligned} \tag{5}$$

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. *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 *Post* is an indicator for reports issued over the 2020-2022 period. *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.

Table 8 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.[27] 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

[27] 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.

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*. 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 9 repeat the analysis in Table 8 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 Table 8.

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 portfolio. 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.

In Table IA.7 of the Internet Appendix, we report that our central findings from Tables 8 and 9 are robust to the inclusion of various alternative fixed effects including, sector × month fixed effects (Row 2), firm fixed effects (Row 3), and firm × report rating fixed effects (row 4), contributor fixed effects (Row 5) or contributor × rating fixed effects (Row 6). The latter set of fixed effects are particularly useful for controlling differences in contributor skill. We also confirm that the main findings are robust to winsorizing returns at the 99th percentile (Row 7), which alleviates the concern that the results are driven by a small set of stocks that achieved extremely large returns, potentially for non-fundamental reasons (e.g., meme stocks).

5.3 Quant Ratings and the Informativeness of SA Research by Contribution Sophistication

The evidence from Section 4.6 indicates that the platform design changes 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:

$$\begin{aligned} Ret_{it+1,t+x} = \ & \alpha + \beta_1 ReportRat. + \beta_2 ReportRat._{it} \times Post_t \\ & + \beta_3 ReportRat._{it} \times QuantSoph_{it} \\ & + \beta_4 ReportRat._{it} \times Post_t \times QuantSoph_{it} + \ \beta_5 QuantSoph_{it} \\ & + \beta_6 QuantSoph_{it} \times Post + FE + \varepsilon_{it.} \end{aligned} \tag{5}$$

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 (5), and *QuantSoph* is the composite quantitative sophistication measure, standardized to have mean 0.[28]

[28] The results for the three individual sophistication measures, reported in Figure IA.4 of the Internet Appendix, are qualitatively similar.

Thus, our key estimate of interest is β_4 which measures how the change in report informativeness after the platform design changes 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.

5.4Do 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. While the platform design changes 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 estimate the following regression:

$$Retail\ Imb_{it+1} = \alpha + \beta_1 Quant\ Rating_{it} + \beta_2 Quant\ Rating_{it} \times Post_t + FE + \varepsilon_{it.} \quad (6)$$

Retail Imb is defined as the difference between retail purchase volume and retail sell volume, scaled by total retail volume, where retail trading is identified and signed using 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 execute between 40% and 60% of the National Best Bid or Offer.[29] Retail Imbalances are measured on the first trading day in which an investor could have traded on the report. *Quant Rating* and *Quant Rating* × *Post* are defined as in equation (2), and FE denote different sector × date and firm fixed effects. The sample is limited to firm-days with at least one SA research report.

Specification 1 of Table 11 reports the results. In the pre-period, we find that retail investors tend to trade in the opposite direction of quant ratings. Specifically, a one unit increase in quant ratings is associated with a -0.63% decline in retail imbalances. This finding is consistent with prior work that suggests that retail investors tend to trade against anomalies (McLean, Pontiff, and Reilly, 2022). In contrast, the estimate on *Quant Rating* × *Post* is positive and highly significant, indicating that retail imbalances become more aligned with quant ratings in the post-period. In terms of economic magnitude, this 0.91% estimate is roughly 5% of the standard deviation of retail imbalances.

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, Specification

[29] 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).

2 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. We find that removing firm-days with attention grabbing events leads to somewhat stronger results.

The positive estimate on *Quant Rating* × *Post* could be attributable to retail investors generally becoming more aware of quantitative analysis independent of the SA report. To better isolate the effects of the SA report, we decompose *Retail Imbalance* into two components: *Ave. Imbalance* and *Abn. Imbalance*. *Ave Imbalance* is the average retail imbalance for a firm during the month on days in which there are no SA reports released, and *Abn. Imbalance* is the difference between *Retail Imbalance* and *Ave Imbalance*. Specifications 3 and 4 report the results for *Ave Imbalance* and *Abn. Imbalance,* respectively. We find that the coefficient on *Quant Rating* × *Post* is significantly related to *Ave Imbalance*, which is consistent with retail trading generally becoming more aligned with quantitative ratings. However, the estimate on *Quant Rating* × *Post* is also significantly related to *Abn. Imbalance* and the point estimate is considerably larger *(0.96* vs 0.42). We also confirm that the two estimates are significantly different from each other (p <0.03).

We next examine *Abn. Imbalance* in event-time in the days surrounding the research report in Figure 5. Specifically, we repeat Specification 4 of Table 11, after measuring retail imbalance over the [-4,4] window, where *Abn. Imbalance (0)* measures retail imbalances on the first trading day in which an investor could have traded on the report, and *Abn. Imbalance* (*+1*) and *Abn. Imbalance (-1)* measure retail imbalance on the day after and the day before *Abn. Imbalance (0)*, respectively. We find that the significant increase is limited to the day of the report release, and perhaps the day after the report release ($p < 0.10$). 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.[30]

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 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 repeat the analysis in Specification 4 after controlling for the average report rating (i.e., *Report Rating*) across all reports for the firm on the day. Following Chen et al. (2024), we also include *NegSA*, defined as the average fraction of negative words across all articles published on SA about the firm on the day. Consistent with Farrell et al. (2022), we find that retail imbalances are significantly correlated with both *Report Ratings* and *NegSA*. However, the correlation between *Abn. Imbalance* and the two measures are relatively modest (ρ =2.17% and -1.51%, respectively), and the inclusion of these measures has virtually no impact on the coefficient on Quant *Rating* × *Post*. This finding is consistent with retail investors actively incorporating quant ratings into their trading decisions.

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 an increased emphasis on quantitative research can influence and enhance social media research. Our empirical strategy exploits a design

[30] 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.

change on the Seeking Alpha platform that both educated investors about the value of quantitative research and reduced the cost of collecting quantitative signals.

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. We next show that the platform design changes influence research production by SA contributors. Specifically, 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.

Our final sets of tests show that the incorporation of quant ratings by SA contributors enhances the value of SA research reports. Specifically, *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 contributors, consumers, and designers of Seeking Alpha. For contributors, while the percentage of *Quant Reports* is growing rapidly, it remains a relatively small fraction of total reports. Our findings suggests that contributors would benefit from more regularly incorporating quantitative research into their analysis. Similarly, consumers of SA research should prioritize reports that include some quantitative analysis. For SA's platform designers, enhancing the visibility and accessibility of quant ratings could further increase the informativeness of the site. For example, SA could prompt contributors to review quantitative ratings before submitting research or notify them when their recommendations conflict with these ratings.

More broadly, our findings suggest that modifications in platform design could improve financial literacy across social media sites, potentially benefiting even less sophisticated investors. However, we recognize that the benefits observed on Seeking Alpha may not apply to other social media platforms, especially those with very different organizational structures or audiences. Still, other platforms like TipRanks and Motley Fool have recently added their own version of quantitative ratings, signaling that quant research may be valuable for their users as well.[31] We leave it to future research to explore the effectiveness of quantitative ratings across various platforms and identify the circumstance under which quantitative analysis and other financial education initiatives are most beneficial for social media users.

[31] In September 2021, TipRanks developed "Smart Score" (https://www.tipranks.com/screener/top-smart-score-stocks), and more recently Motley Fool introduced "Q5Y" (https://www.fool.com/terms/q/q5y/),

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

Quant Rating

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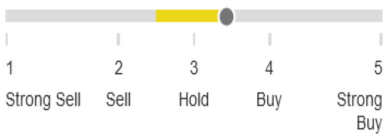

The overall quant rating is not an average of the factor grades listed. Instead, it gives greater weight to the metrics with the strongest predictive value.

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 platform design changes (2020-2022) and zero for the three-year period prior to changes (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', '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.
- *Estimated ETF Rating:* an ETF quant rating constructed based on the description provided by Seeking Alpha. The rating incorporates various variables, including:
    - 10 variables used to compute the Momentum grade
    - 2 variables for Expenses
    - 7 variables for Dividends
    - 8 variables for Risk
    - 3 variables for Liquidity

  Each variable is converted to a percentile ranking and any missing variable is assigned a ranking of 50%. We then regress *Quant Rating ETF* on the set of variables to obtain weights for each variable. *Estimated ETF Rating* is computed by applying these weights to the set of variables.

- *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).
- *Pre ETF:* an indicator equal to one the period after the introduction of stock quantitative ratings but before the introduction of ETF quantitative ratings (November 2019 – December 2020).
- *Pre Stock:* an indicator equal to one for the three year period prior to platform design changes (2016-2018).
- *Estimated Wall Street Rating:* the average sell-side analyst recommendation, collected from the IBES summary recommendation file. We multiple the IBES recommendation by negative 1 so that higher values correspond to more bullish recommendations.
- $Ret_{i,t+x}$: 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 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.
  - *Ave Imbalance* – the average retail imbalance for a firm during the month on days in which there are no SA reports released for the firm
  - *Abn Imbalance* – the difference between *Retail Imbalance* and *Ave 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)

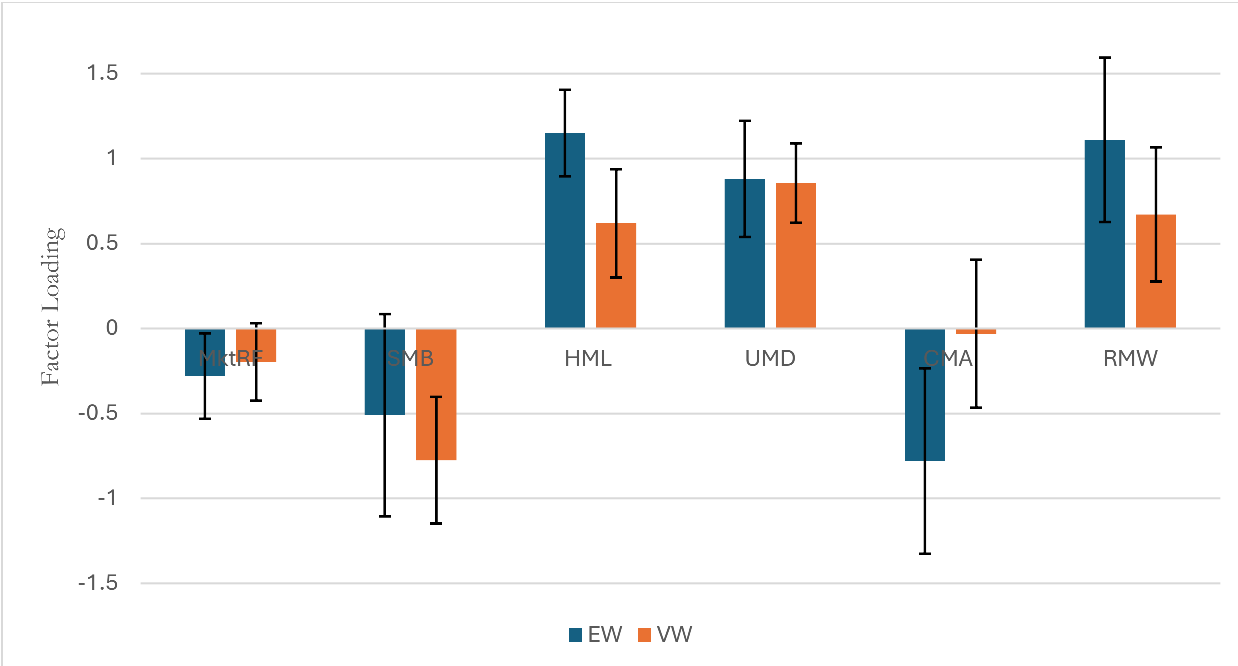

Figure 1: Factor Loading of Long-Short Portfolio Sorted on SA Quantitative Ratings

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.

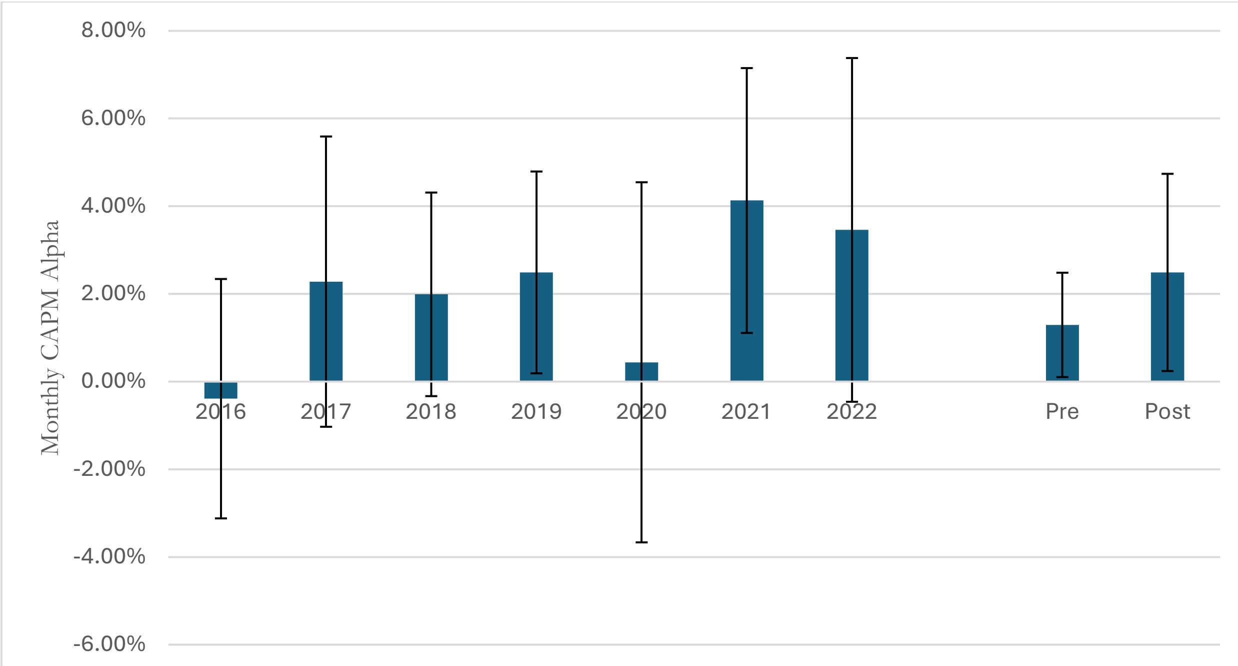

Figure 2: Returns to Long-Short Portfolios sorted on SA Quantitative Ratings by Year

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.

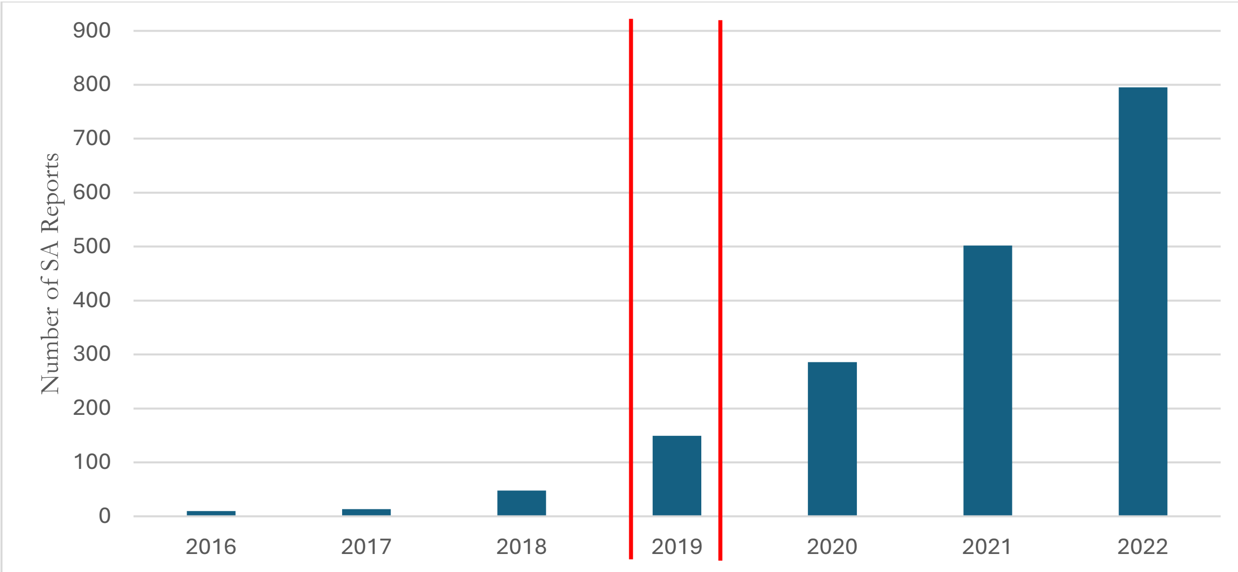

Figure 3: Frequency of *Quant Reports* by Year

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', 'revisions grade' or minor variants of each expression (e.g., 'grade for value'), The red lines separate the period prior to the platform design change (2016-2018) and the period after the design change (2020-2022).

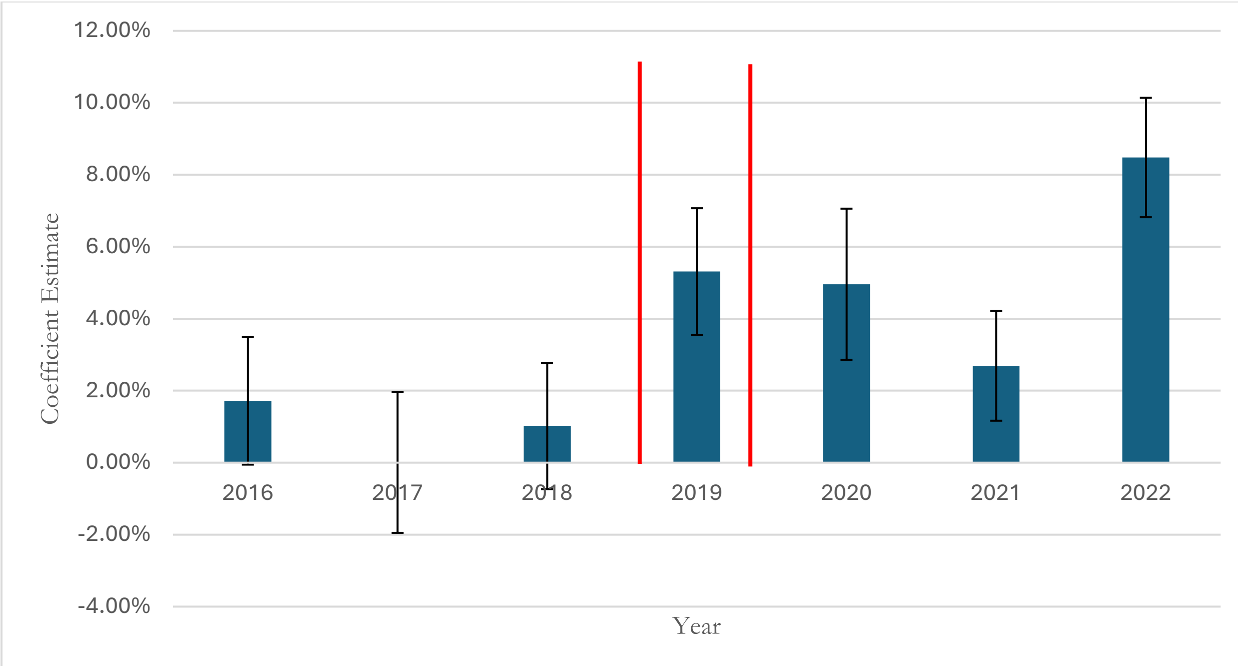

Figure 4: SA Report Recommendations and Quantitative Ratings by Year

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 *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 platform design change (2016-2018) and the period after the design change (2020-2022).

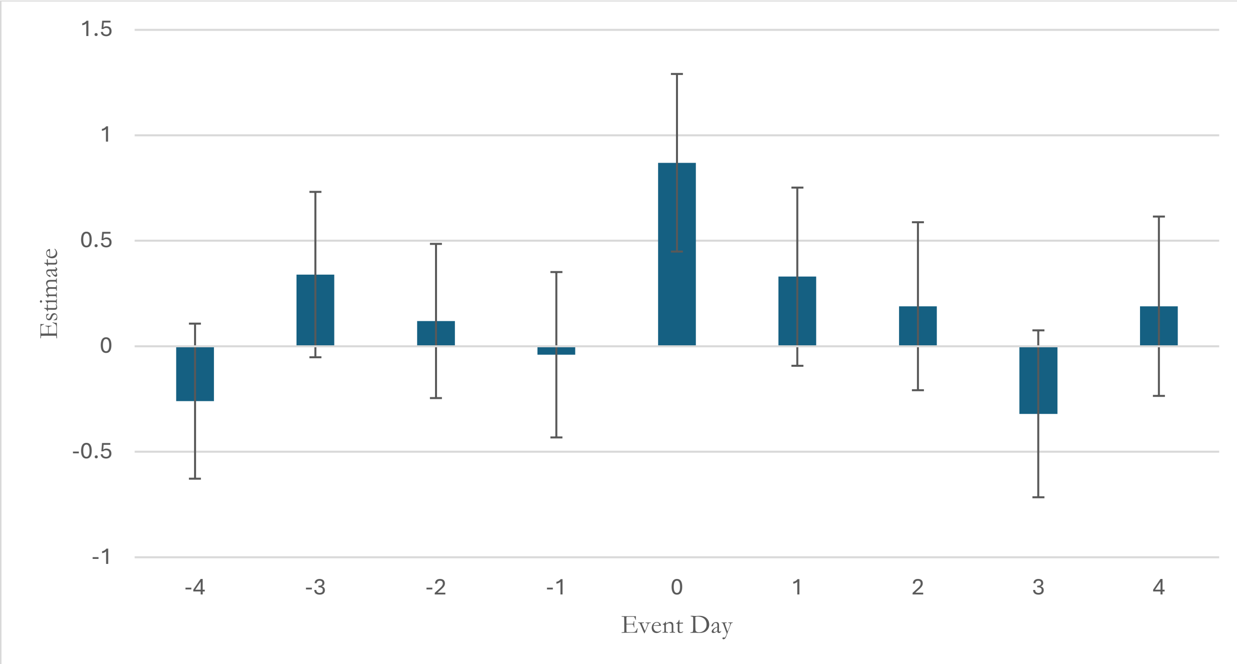

Figure 5: Retail Imbalances around SA Research Reports in Event Time

This figure plots the estimates on *Quant Rating* × *Post* from Specification 4 of Table 11 in event time around the release of SA research reports. Day 0 represents to the first day in which an investor could have traded on the report and thus matches to the results reported in Specification 4 of Table 11. Day +1 (Day -1) measure abnormal retail imbalances on the day after and the day before Day 0, and the other event days are defined analogously. The estimates for each event day are reported as blue bars and the 95% confidence intervals are 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 Recommendations

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 in the *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', '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 Report*				0.01%	-4.45%	-4.44%
				(0.47)	(-2.31)	(-2.36)
Quant Rating × *Post (Quant – No Quant)*				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:

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

Report Rating equals one for SA reports making a buy recommendation, negative one for reports making a sell recommendation, and zero for all other reports; *Quant Rating ETF* is SA's quantitative rating for exchange traded funds (ETFs), and *Post* ETF is an indicator equal to one if the report was written after 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). Specification 5 replaces *Quant Rating ETF* with an estimated ETF quant rating (*Est. Rating ETF*), expands the sample to 2016-2022, and adds three timing indicators: *Pre Stock*, an indicator for the three year period prior to the introduction of quantitative ratings for stocks (2016-2018), *Pre ETF,* an indicator for the period after the introduction of stock quantitative ratings but before the introduction of ETF quantitative ratings (November 2019 – December 2020), and *Post ETF,* an indicator for the period after the introduction of ETF quantitative ratings (June 2021-December 2022). The construction of *Est. Rating ETF* is described in Appendix C. Standard errors are clustered by firm and date, and t-statistics are reported in parentheses.

	[1]	[2]	[3]	[4]	[5]
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 ET × *[3,9]*				8.61%	
				(4.58)	
Quant Rating ETF × *[10,15]*				12.46%	
				(7.44)	
Quant Rating ETF × *[16,21]*				8.89%	
				(5.10)	
Est. Rating ETF × *Pre Stock*					0.54%
					(1.41)
Est. Rating ETF × *Pre ETF*					4.22%
					(3.18)
Est. Rating ETF × *Post ETF*					7.71%
					(6.46)
Est. Rating ETF × *(Pre ETF - Pre Stock)*					3.68%
					(2.34)
Observations	7,442	7,442	7,442	8,428	14,287
Asset Class × Date FE	Yes	Yes	Yes	Yes	Yes
Contributor FE	No	Yes	No	No	No
ETF FE	No	No	Yes	Yes	Yes
R-squared	56.22%	62.45%	63.79%	64.74%	70.92%
Mean Dep Variable	28.72%	28.72%	28.72%	28.72%	15.03%

Table 6: SA Report Sentiment and Wall Street Ratings

This table reports estimates from the following panel regression:

$$Report\ Rating_{it} = \alpha + \beta_1 Quant\ Rating_{it} + \beta_2 Quant\ Rating_{it} \times Post_t + \beta_3\ Est.Wall\ Street\ Rating_{it} + \beta_4 Est.Wall\ Street\ Rating_{it} \times Post_t + FE + \varepsilon_{it}.$$

Report Rating, *Quant Rating*, and *Post* are defined as in Table 4. *Est. Wall Street Rating* is defined as the average sell-side analyst recommendation taken from the IBES summary recommendation file, where strong sell = 1 and strong buy =5. All regressions include date × GICS sector fixed effects. Specifications 2 and 3 augment Specification 1 by including firm and contributor fixed effects, respectively. Below the regression estimates, we test whether the coefficient on *Quant Rating* × *Post* is significantly different from the coefficient on *Est. Wall Street Rating* × *Post*. Standard errors are clustered by firm and date, and t-statistics are reported in parentheses.

	[1]	[2]	[3]
Quant Rating	-0.48%	-0.23%	0.13%
	(-0.74)	(-0.35)	(0.23)
Quant Rating × *Post*	6.15%	3.82%	5.14%
	(5.30)	(3.83)	(5.51)
Est. Wall Street Rating	7.44%	5.00%	5.06%
	(3.82)	(6.37)	(8.54)
Est. Wall Street Rating × *Post*	-0.44%	1.48%	1.06%
	(-0.25)	(1.35)	(1.06)
(Quant – Est. Wall Street) × *Post*	6.59%	2.34%	4.08%
	(4.10)	(1.81)	(3.33)
Observations	92,032	92,032	92,032
Industry × Date FE	Yes	Yes	Yes
Contributor FE	No	No	Yes
Firm FE	No	Yes	No
Mean Dep Variable	42.41%	42.41%	42.41%
R-squared	18.86%	27.24%	37.40%

Table 7: 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 are 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 8: 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 9: SA Report Informativeness and Quant Reports - Return Decomposition

This table repeats the analysis in Table 8 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 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 9 and Appendix C). *Report Ratings* and *Post* are defined as in Table 8, and *QuantSoph* is the composite *Quantitative Sophistication* measure (as defined in Table 7), 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 Investor Imbalances around SA Reports

This table reports estimates from the following panel regression:

$$Retail\ Imb_{it+1} = \alpha + \beta_1 Quant\ Rating_{it} + \beta_2 Quant\ Rating_{it} \times Post_t + FE + \varepsilon_{it.}$$

Retail Imb. is defined as the difference between retail purchase volume and retail sell volume, scaled by total retail volume, where retail trading is identified and signed using the methodology of Barber et al. (2023). Retail imbalances are measured on the first trading day in which an investor could have traded on the report. *Quant Rating* and *Quant Rating* × *Post* are defined as in Table 4, and FE denotes sector × date and firm fixed effects. Specification 1 reports for the full sample of firm-days, and Specification 2 excludes 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. Specifications 3 and 4 decompose *Retail Imbalance* into *Ave Imbalance*, defined as the average retail imbalance for a firm during the month on days in which there are no SA reports released for the firm, and *Abn. Imbalance*, defined as the difference between *Retail Imbalance* and *Ave Imbalance*. *Specification 5* adds controls for two measures of the report sentiment, *Report Rating* (as defined in Table 4), and *NegSA*, defined as the average fraction of negative words across all articles published on SA about the firm on the day. Standard errors are clustered by firm and date, and t-statistics are reported in paratheses.

	[1]	[2]	[3]	[4]	[5]
Quant Rating	-0.63	-0.93	-0.29	-0.63	-0.66
	(-3.85)	(-4.95)	(-2.82)	(-3.89)	(-4.05)
Quant Rating × *Post*	0.91	1.37	0.41	0.96	0.94
	(4.40)	(5.68)	(3.29)	(4.41)	(4.38)
Report Rating					0.43
					(3.05)
Neg SA					-0.24
					(-2.13)
Sector × Date FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Exclude Attention Grabbing	No	Yes	Yes	Yes	Yes
Observations	82,029	68,546	68,546	68,546	68,546
Dep Variable	Retail Imb.	Retail Imb.	Ave Retail Imb.	Abn. Retail Imb.	Abn. Retail Imb.

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:

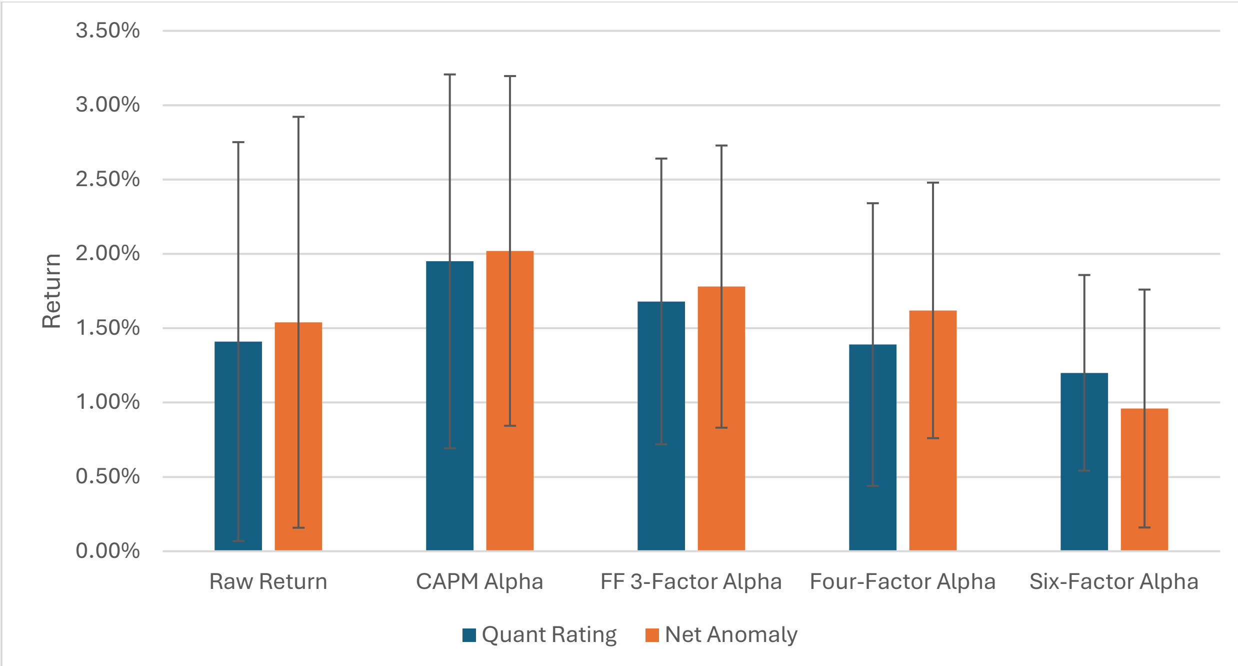

Figure IA.1: Returns Predictability of SA Quant Recommendations versus Academic Anomalies
This figure reports the value-weighted returns to a strategy that goes long stocks that in *Strong Buy* portfolio and short stocks in the *Strong Sell* portfolio. The blue bar reports the results based on sorting stocks into groups based on Seeking Alpha's 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.

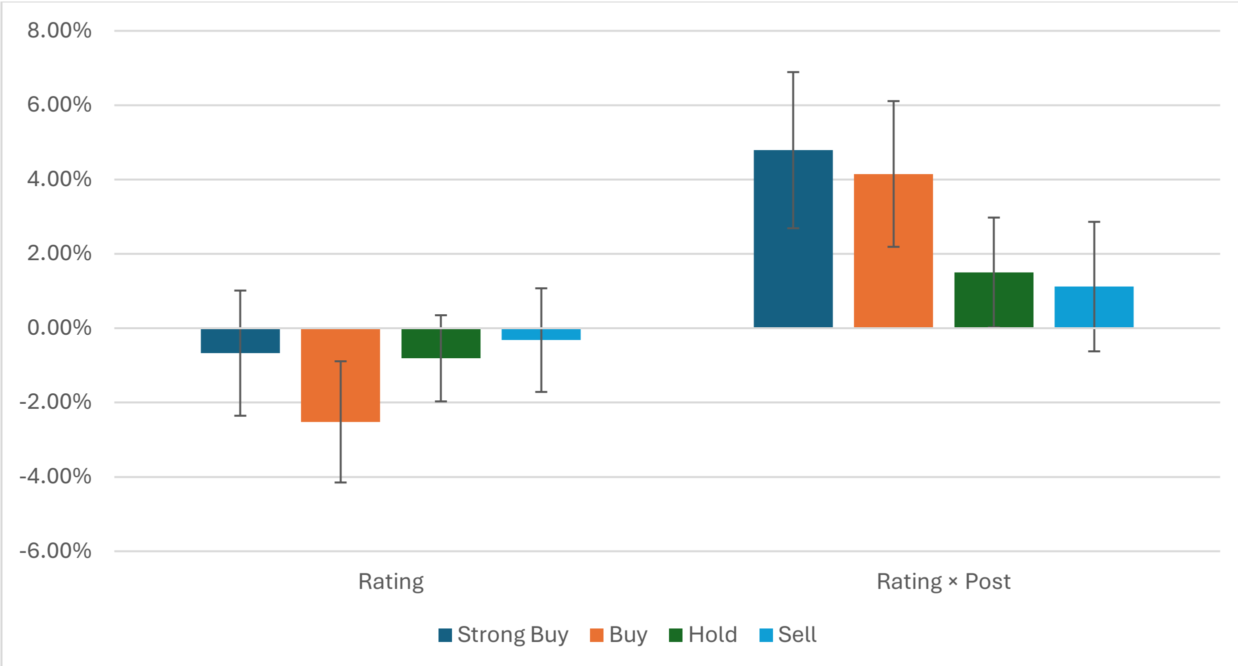

Figure IA.2: SA Coverage Decisions and Quantitative Ratings
This figure reports estimates from the following firm-month panel regression:

$$Coverage_{it} = \alpha + \beta_1 Quant\ Rec\ Ind_{it-1} + \beta_2 Quant\ Rec\ Ind_{it-1} \times Post_t + FE + \varepsilon_{it}.$$

The dependent variable, *Coverage*, equals one if the firm had at least one SA report during the month. *Quant Rec Ind.* is a vector of indicators for different quantitative recommendations: *Strong Buy, Buy*, *Hold,* and *Sell* (where *Strong Sell* is the omitted group), measured at the end of the previous month. *Post* is an indicator equal to one for the post-event window (2020-2022) and zero for the pre-event window (2016-2018), and FE denotes sector × month fixed effects and firm fixed effects. Standard errors are clustered by firm and month, and the error bars report 95% confidence intervals.

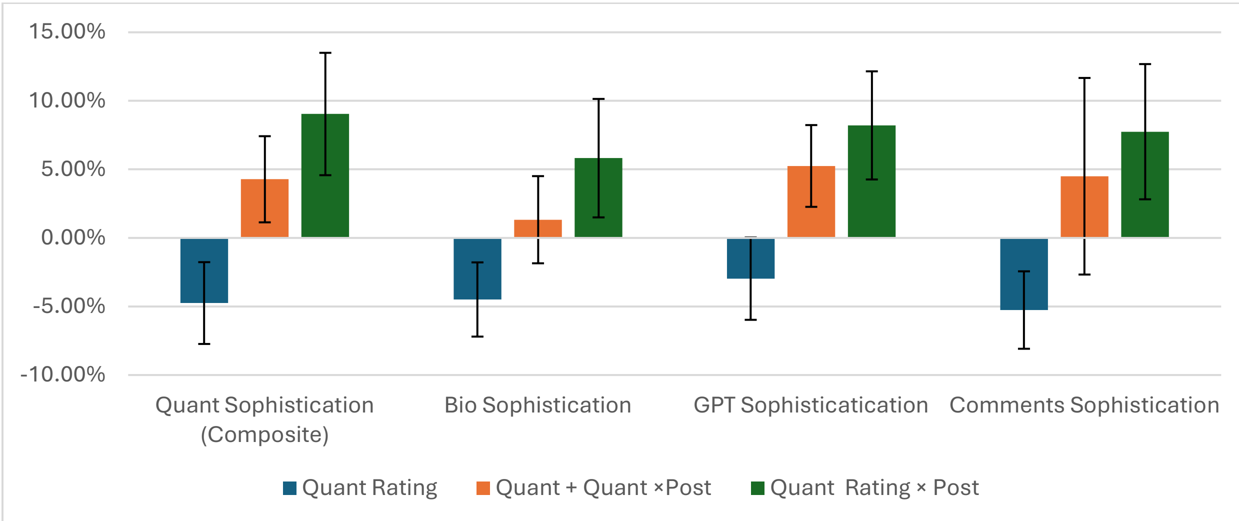

Figure IA.3: SA Report Sentiment and Quantitative Ratings by Quant Sophistication Measures
This figure reports the estimates from Specification 6 of Table 7 after replacing the composite *Quant Sophistication* measure with the three individual component measures: *Bio Sophistication, GPT Sophistication,* and *Comment Sophistication* (as defined in Table 7 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.

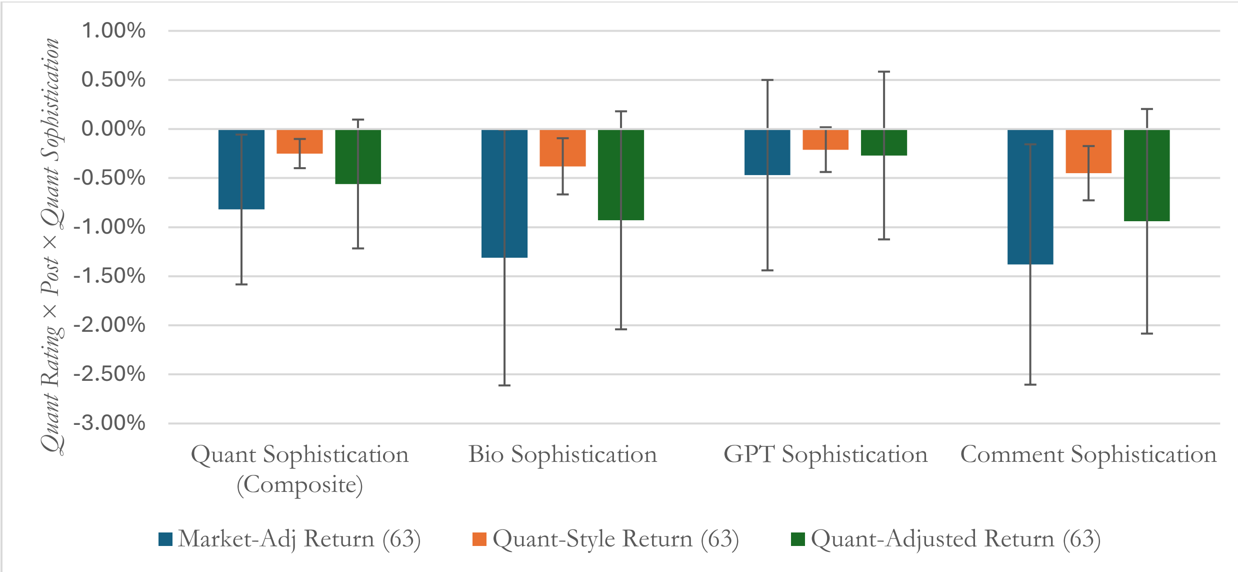

Figure IA.4: SA Report Informativeness by Quant Sophistication Measures

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 7 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 green bars. Standard errors are clustered by firm and month, 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
Sector × 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: SA Report Ratings and Academic Anomalies

This table repeats the analysis in Specifications 1-3 of Table 4 after replacing *Quant Rating* with *Net Anomaly Positive* and *Net Anomaly Negative*. *Net Anomaly Positive* is the sum of *Net Anomaly* across the six factor clusters that have a significant positive association with *Quant Rating* in Specification 2 of Table 2, and *Net Anomaly Negative* is the sum of *Net Anomaly* for the six factor clusters that have a significant negative association with *Quant Rating*. Below the regression estimates, we also test for whether the coefficients on *Net Anomaly Positive* × *Post* and *Net Anomaly Negative* × *Post* are significantly different from each other. Standard errors are clustered by firm and date, and t-statistics are reported in parentheses.

	[1]	[2]	[3]
Net Anomaly Positive	2.06%	0.87%	1.07%
	(1.21)	(1.91)	(2.17)
Net Anomaly Negative	1.76%	-0.16%	0.66%
	(0.88)	(-0.30)	(0.10)
Net Anomaly Positive × Post	1.46%	2.16%	2.41%
	(0.89)	(3.22)	(3.67)
Net Anomaly Negative × Post	-2.36%	-1.24%	-0.42%
	(-1.26)	(-1.82)	(-0.60)
(Positive - Negative) × Post	3.82%	3.40%	2.83%
	(3.51)	(3.38)	(3.41)
Observations	95,133	95,133	95,133
Sector × Date FE	Yes	Yes	Yes
Contributor FE	No	No	Yes
Firm FE	No	Yes	No

Table IA.5: Returns to ETF Quant Ratings

At the end of each month, from November 2019 through August 2023, we form five portfolios by sorting exchange traded funds (ETFs) based on their SA quantitative recommendation. This table reports the average monthly return to each portfolio in the month following portfolio formation. Panels A and B report the equal-weighted and value-weighted average portfolio returns, respectively. We report the style-adjusted return defined as the return on the ETF less the average return across ETFs in the same asset class and sub asset class (as reported by Seeking Alpha). We also report the 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). All alphas are style-adjusted. The last column reports the returns to a strategy that goes long ETFs in the *Strong Buy* portfolio and short ETFs in the *Strong Sell* portfolio. Standard errors are computed from the time-series standard deviation, and t-statistics are reported in parentheses.

Panel A: Equally Weighted Portfolios

	Strong Buy	Buy	Hold	Sell	Strong Sell	Strong Buy - Strong Sell
Style-Adj. Return	0.32%	0.07%	0.02%	-0.05%	-0.25%	0.57%
	(2.21)	(1.55)	(0.81)	(-1.87)	(-1.43)	(1.95)
CAPM Alpha	0.36%	0.09%	0.03%	-0.06%	-0.32%	0.67%
	(2.56)	(2.19)	(0.94)	(-2.64)	(-1.78)	(2.34)
FF 3-Factor Alpha	0.35%	0.08%	0.02%	-0.06%	-0.29%	0.64%
	(2.68)	(2.36)	(0.83)	(-2.83)	(-1.84)	(2.48)
Four-Factor Alpha	0.34%	0.08%	0.03%	-0.06%	-0.27%	0.61%
	(2.77)	(2.29)	(0.79)	(-2.82)	(-1.86)	(2.59)
Six-Factor Alpha	0.37%	0.08%	0.02%	-0.06%	-0.27%	0.65%
	(2.90)	(1.94)	(0.54)	(-2.50)	(-2.08)	(2.96)

Panel B: Value Weighted Portfolios

	Strong Buy	Buy	Hold	Sell	Strong Sell	Strong Buy - Strong Sell
Style-Adj. Return	0.55%	0.07%	0.05%	-0.04%	-0.32%	0.87%
	(1.50)	(1.37)	(0.24)	(-1.07)	(-1.69)	(2.06)
CAPM Alpha	0.62%	0.07%	0.06%	-0.05%	-0.38%	1.00%
	(1.70)	(1.35)	(0.32)	(-1.20)	(-2.24)	(2.51)
FF 3-Factor Alpha	0.57%	0.06%	0.04%	-0.05%	-0.36%	0.93%
	(1.67)	(1.54)	(0.21)	(-1.19)	(-2.20)	(2.56)
Four-Factor Alpha	0.57%	0.06%	0.05%	-0.05%	-0.34%	0.90%
	(1.63)	(1.45)	(0.30)	(-1.15)	(-2.39)	(2.56)
Six-Factor Alpha	0.57%	0.07%	0.03%	-0.05%	-0.27%	0.83%
	(1.52)	(1.47)	(0.21)	(-1.26)	(-2.08)	(2.19)

Table IA.6: Returns to Wall Street Ratings

At the end of each month, from December 2015 through November 2022, we form five portfolios by sorting stocks based on their *Est. Wall Street Rating*, defined as the average sell-side analyst recommendation, collected from the IBES summary recommendation file. Portfolio breakpoints are constructed to include the same percentage of stocks as the SA Quant Recommendations in Table 3. The 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 in the *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: Equally Weighted Portfolios

	Strong Buy	Buy	Hold	Sell	Strong Sell	Strong Buy - Strong Sell
Raw Return	0.68%	0.86%	0.86%	1.29%	1.36%	-0.68%
	(0.87)	(1.07)	(1.17)	(1.57)	(1.75)	(-1.58)
CAPM Alpha	-0.63%	-0.54%	-0.48%	-0.16%	0.11%	-0.74%
	(-1.42)	(-1.34)	(-1.52)	(-0.43)	(0.24)	(-1.70)
FF 3-Factor Alpha	-0.43%	-0.34%	-0.33%	-0.02%	0.30%	-0.73%
	(-1.64)	(-1.69)	(-2.38)	(-0.11)	(0.96)	(-1.82)
Four-Factor Alpha	-0.44%	-0.34%	-0.31%	0.05%	0.33%	-0.77%
	(-1.65)	(-1.62)	(-2.21)	(0.33)	(1.13)	(-1.96)
Six-Factor Alpha	-0.26%	-0.17%	-0.18%	-0.01%	0.27%	-0.53%
	(-1.08)	(-0.96)	(-1.52)	(-0.08)	(1.15)	(-1.58)

Panel B: Value Weighted Portfolios

	Strong Buy	Buy	Hold	Sell	Strong Sell	Strong Buy - Strong Sell
Raw Return	0.88%	1.20%	1.07%	0.95%	0.99%	-0.11%
	(1.30)	(2.01)	(2.02)	(1.65)	(1.80)	(-0.28)
CAPM Alpha	-0.36%	0.11%	-0.01%	-0.13%	-0.04%	-0.32%
	(-1.18)	(0.40)	(-0.15)	(-0.61)	(-0.19)	(-0.83)
FF 3-Factor Alpha	-0.30%	0.10%	-0.01%	-0.09%	-0.01%	-0.29%
	(-1.10)	(0.51)	(-0.31)	(-0.50)	(-0.03)	(-0.81)
Four-Factor Alpha	-0.29%	0.07%	-0.01%	-0.08%	-0.02%	-0.27%
	(-1.03)	(0.37)	(-0.12)	(-0.43)	(-0.14)	(-0.72)
Six-Factor Alpha	-0.13%	0.20%	-0.01%	-0.22%	-0.21%	0.08%
	(-0.48)	(1.15)	(-0.34)	(-1.40)	(-1.52)	(0.26)

Table IA.7: SA Report Informativeness and Quant Reports – Robustness

This table examines the sensitivity of the informativeness estimates from Tables 8 and 9. This analysis is limited to the 63-day return horizon. Specifications 1 and 4 reports *Market-Adjusted Returns* (as in Table 8), Specifications 2 and 5 report *Quant-Style Returns* (as in Specifications 3 of Table 9), and Specifications 3 and 6 report *Quant-Adjusted Returns* (as in Specifications 6 of Table 9). 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 8 and 9). In Row 2 we replace month fixed effects with sector × month fixed effects. In Rows 3-6 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 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. 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)