Quantitative Research on Main Street: Evidence from Seeking Alpha

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Abstract

We study the diffusion and consequences of quantitative research in retail markets using Seeking Alpha's 2019 rollout of Quant Ratings, a factor-based stock rating system. Quant Ratings predict returns and are increasingly incorporated into contributor-authored reports. Adoption is strongest among less quantitatively sophisticated contributors and is associated with significant improvements in recommendation informativeness without reducing firm-specific fundamental analysis. Retail order imbalances also become more aligned with Quant Ratings and more predictive of returns, particularly on report publication days. Overall, our findings show that standardized quantitative signals can improve contributor-authored retail research and help retail investors make more informed trading decisions.

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1. Introduction

Once confined to a handful of hedge funds, quantitative research, defined by its reliance on systematic, data-driven methods to predict future fundamentals and stock returns, has made significant inroads in the institutional asset management industry. A small but fast-growing literature explores how quant research shapes investor behavior, the role of traditional fundamental analysis, and market efficiency, and documents significant benefits including improved institutional investor trading performance (Cen et al., 2024; Sheng et al., 2026), higher quality of traditional analyst research (Birru et al., 2024; Chi, Hwang, and Zheng, 2025), and more efficient prices (Zhu, 2019; Coleman, Merkley, and Pacelli, 2022). Yet these benefits entail significant trade-offs: crowded institutional trades (Abis, 2022; Beggs and Hill-Kleepsie, 2025), lack of adaptability to accounting regime changes (Dyer, Guest, and Yu, 2025), and weakened incentives to conduct fundamental research, conjectured in Dugast and Foucault (2018) and Sloan (2019).

In this study, we examine the spread and consequences of retail-oriented quant research. Retail quant research is produced by well-established research firms such as Morningstar and Zacks, and more recently by retail-oriented platforms such as Seeking Alpha and TipRanks and is aimed at investors who would arguably benefit the most from the discipline imposed by systematic, data-driven methods. Retail investors have fewer resources and are more prone to behavioral biases than institutional investors, which helps explain why they trade against well-established return anomalies, hurting their performance and amplifying mispricing (McLean, Pontiff, and Reilly, 2025). Whether retail quant research meaningfully benefits individual investors is, however, an open question. Retail-oriented quant providers are unlikely to use novel datasets and statistical techniques, raising the possibility that any predictability they identify has already been arbitraged away by institutions. Even if retail quant research is informative, retail investors may be unwilling or unable to adopt it, as quantitative strategies are more abstract and less intuitive than narrative-driven fundamental analysis.[1]

We study the adoption and the consequences of retail-oriented quantitative research, using Seeking Alpha's 2019 rollout of Quant Ratings to contributors and premium subscribers as our empirical setting. This setting offers several advantages. First, subscriber-contributed equity research reports on SA are grounded in fundamental analysis, predictive of future returns (Chen et al., 2014) and widely read and used by retail investors (Farrell et al., 2022). This allows us to identify who receives quant research and when, and to study how its distribution affects both the production of retail fundamental research and the trading of retail investors. Second, Seeking Alpha's large and diverse contributor base enables us to test whether Quant Ratings primarily benefit already sophisticated contributors or instead democratize access to quantitative methods by helping less sophisticated contributors. Finally, the platform's design change offers clean identification. The rollout date is clearly defined, and archived pre-rollout Quant Ratings allow us to compare contributor behavior before and after the change in availability. In addition, the existence of stocks with equity research reports but no Quant Ratings provides a natural placebo test.

We first investigate whether Quant Ratings have investment value. Seeking Alpha's Quant Ratings are stock-level scores based on systematic factors such as valuation, profitability, growth, and momentum.[2] Analyzing a sample of more than 2,000 stocks over the period 2016 to 2022, we find that a strategy that buys stocks in the highest Quant Rating category and sells stocks in the lowest Quant Rating category earns an economically and statistically significant value-weighted CAPM alpha

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[1] Michael Nicks, CIO of the Pepperdine University endowment, acknowledged that it took the university years of self-education and dozens of meetings with quant managers before allocating just 10% of its portfolio to quantitative funds, illustrating how difficult it can be for even sophisticated investors to understand and trust quantitative strategies. See https://www.wsj.com/articles/the-quants-run-wall-street-now-1495389108.

[2] We confirm that SA's quant ratings strongly correlate with the Momentum, Value, Profit Growth, and Quality factor clusters of Jensen, Kelly, and Pedersen (2023).

of 1.92% per month and a six-factor alpha of 1.20% per month. Overall, these results indicate that Seeking Alpha's Quant Ratings possess meaningful investment value.

The 2019 rollout of Quant Ratings to contributors made a return-predictive quant signal available to a larger set of non-professional analysts and investors. We test for adoption along two margins: whether reports increasingly reference quantitative methods and whether contributor recommendations become more aligned with Quant Ratings. Analyzing nearly 100,000 subscriber-authored reports on stocks with Quant Ratings published between 2016 and 2022, we find that the percentage of reports referencing Quant Ratings increases from less than 1% in the pre-period to approximately 10% at the end of the post-period. More importantly, report recommendations are unrelated to Quant Ratings in the pre-period but become strongly and positively aligned with them in the post-period, even for reports that do not explicitly discuss the ratings, suggesting widespread contributor adoption.

We conduct a battery of tests to strengthen causal interpretation. First, we conduct a dynamic analysis that reveals no pre-trend in recommendation alignment prior to 2019. Second, we estimate Quant Ratings for both stocks covered and not covered by SA's quant model. The Estimated Quant Ratings closely approximate actual Quant Ratings for covered stocks and predict returns similarly for covered and uncovered stocks. We show that alignment with Estimated Quant Ratings increases only among covered stocks, suggesting that contributors respond to SA's platform-provided ratings rather than to quantitative information more broadly. Finally, an out-of-sample test exploiting the rollout of SA quant research on a different asset class (Exchange Traded Funds) and at a different time (2021) yields similar evidence of increased alignment between contributor recommendations and Quant Ratings.

Next, we examine whether adoption of quant research by contributors improves the informativeness of their recommendations without crowding out firm-specific fundamental analysis.

We decompose total informativeness, defined as post-recommendation buy-and-hold return, multiplied by the sign of the recommendation (Chen et al., 2014), into a *quant-style* component, which captures return performance attributable to recommending stocks based on their Quant Ratings, and a residual *quant-adjusted* component, which arguably reflects fundamental analysis. In baseline tests, we find no evidence of a change in overall informativeness after the rollout. However, reports explicitly referencing quantitative methods earn higher total returns and quant-style returns, with no decline in quant-adjusted returns. These findings are consistent with quant research adoption increasing the informativeness of contributor recommendations with no discernible negative effect on the collection and analysis of fundamental information.

To provide more direct evidence on the crowding out hypothesis, we examine whether quant research adoption reduces the depth of fundamental analysis in the report (as evaluated by ChatGPT), the length of the report, and its originality. Using the same research design, we find no evidence that quant research adoption reduces the quality of fundamental analysis. If anything, reports that explicitly reference Quant Ratings exhibit higher fundamental scores and become both longer and more distinctive from contemporaneous coverage. These findings further suggest that quant ratings complement rather than displace contributors' fundamental analysis and overall research effort.

A natural question is whether the distribution of quant research primarily benefits contributors who are already quantitatively sophisticated, thereby widening gaps in research capability, or instead benefits those least sophisticated. We construct three complementary measures of a contributor's quantitative sophistication: (i) a keyword-based measure of quant/finance background based on contributor biographies, (ii) an LLM-based assessment of quantitative expertise based on contributor biographies, and (iii) a behavior-based measure of sophistication based on the degree of alignment between a contributor's recommendations and Quant Ratings extracted from a random sample of pre-period reports.[3] We find that in the pre-period a recommendation's alignment with Quant Ratings is increasing in contributor sophistication, while the largest post-rollout increase in alignment occurs for recommendations issued by the least sophisticated contributors. Importantly, this convergence is accompanied by greater improvements in the informativeness of recommendations issued by less sophisticated contributors, consistent with quant research narrowing the gap in research capability.

Finally, we examine whether the benefits of Quant Research extend to retail investors. Specifically, we test whether daily retail order imbalances become more aligned with Quant Ratings and more predictive of future returns after the rollout. We expect these effects to be strongest on days when Seeking Alpha research reports are published because those reports may incorporate Quant Ratings and concentrate retail investor attention on the firm (Chen et al., 2014; Farrell et al., 2022), thereby increasing the likelihood that retail investors incorporate the quantitative signal into their trades. We find that in the pre-rollout period, retail investors trade against Quant Ratings on both report and non-report days. After the rollout, retail trading becomes more aligned with quantitative signals on report days but not on non-report days, indicating that reports serve as a key transmission channel. These results are robust to controlling for the report recommendation, indicating that the effect is not driven solely by retail investors mechanically following report recommendations. We also find modest improvements in retail trading informativeness, with the gains concentrated on report days. Together, these results suggest that SA's dissemination of Quant Ratings helps retail investors incorporate quantitative signals into their trading decisions and modestly improves trading quality.

Our study contributes to the literature in accounting and finance that studies quant research diffusion and its capital market consequences (e.g., Coleman, Merkley, and Pacelli, 2022; Birru et al., 2024; Dyer, Guest, and Yu, 2025). A central challenge in this literature is that quantitative research is

[3] We use a holdout sample to estimate the pre-period relationship between report recommendations and Quant Ratings.

typically proprietary, making it difficult to observe who receives quant signals and when, and to causally link quant signal acquisition to changes in investor behavior, especially in retail markets. By leveraging Seeking Alpha's 2019 Quant Ratings rollout, we provide novel evidence on the investment value of quantitative research and its effects on both non-professional research production and retail investor trading. This is important because retail investors have historically lacked access to quantitative research, and prior evidence on the informativeness and benefits of institutional quant research (e.g., Coleman, Merkley, and Pacelli, 2022; Birru et al., 2024) need not generalize to retail environments given substantial differences in resources, incentives, and sophistication.

Second, we address a central concern in this literature that the adoption of quantitative methods may crowd out firm-specific fundamental research (Sloan, 2019; Dugast and Foucault, 2018). Prior work documents net accuracy gains from adoption of quantitative methods by sell-side equity analysts (e.g., Chi, Hwang, and Zheng, 2025), but these gains may mask a decline in production of fundamental analysis. We test this concern directly and find no evidence that adoption of Quant Ratings reduces stock-specific analysis. Instead, our report-content evidence suggests that contributors, if anything, conduct more fundamental analysis following adoption.

Third, we shed light on who benefits from quant research diffusion in capital markets. We focus on the diffusion of a standardized, quant-based return predictor in a retail setting and show that the adoption gains are largest among less sophisticated contributors. In contrast, Sheng et al. (2026) focus on the diffusion of GenAI tools in professional asset management and find that performance gains disproportionally accrue to larger hedge funds. This contrast suggests that the distributional effects of quantitative innovation depend on both the market setting and the form of the technology itself: broadly accessible, standardized signals can narrow capability gaps, whereas more advanced tools may amplify existing advantages.

Finally, our study contributes to the emerging literature on social media platforms. In a recent review, Cookson, Mullins, and Niessner (2024) emphasize that platforms differ in design, audiences, and capital-market effects, and highlight Seeking Alpha's distinctive role as a source of contributor-authored fundamental research that distinctly affects capital markets (Chen et al., 2014; Drake et al., 2023; Farrell et al., 2022; Dim, 2025).[4] We show that the 2019 Quant Ratings rollout broadened this role. Seeking Alpha-produced quantitative research has significant investment value and shapes both contributor-authored research reports and retail investor trading. Our findings suggest that the rollout moved Seeking Alpha further away from a traditional financial media platform or a discussion-based finance forum and closer to the sell-side research model: it supplies paying users with fundamental research and proprietary quant research, just as sell-side research providers supply institutional clients with fundamental research and proprietary quant research and data (Birru et al., 2024; Chi, Hwang, and Zheng, 2025).

2. Institutional Setting, Data, and Descriptive Statistics

2.1 Seeking Alpha and Contributor-Authored Equity Research

Seeking Alpha (SA) is one of the largest investment-related social media websites, with approximately 17 million unique visitors each month and over 10 million registered users and 270,000 paid subscribers (as of 2021). In addition to providing market news and commentaries, financial information, and earnings call transcripts, the platform solicits, curates, and distributes contributor-authored equity research reports. Only contributors and paid subscribers (i.e., premium and pro-members) have full access to these reports.

[4] Platforms examined in prior literature include Twitter/X (Blankespoor, Miller, and White, 2014; Bartov, Faurel, and Mohanram, 2018; Campbell et al., 2023), StockTwits (Cookson and Niessner, 2020; Cookson, Engelberg, and Mullins, 2023), Estimize (Jame et al., 2016; Da and Huang, 2020; Jame, Markov, and Wolfe, 2022), The Motley Fool's CAPS platform (Avery, Chevalier, and Zeckhauser, 2016), and Wallstreetbets (Bradley et al., 2024). Cookson et al. (2024) complement these platform-specific studies by examining how investor-generated content varies across Twitter/X, StockTwits, and Seeking Alpha. Grennan and Michaely (2021) study FinTechs, a category that includes social-finance media platforms as well as online intermediaries and find that they can substitute for traditional financial analysis.

Contributor-authored reports resemble professional equity research in form and substance. They analyze financial statements and accounting performance, evaluate business models and competitive positioning, and include explicit stock recommendations (buy, hold, or sell) that reflect the contributor's assessment of expected return.[5] Prior studies find that these reports convey new information to the market (Chen et al., 2014; Dim, 2025), partially pre-empt information subsequently reflected in professional analyst reports (Drake et al., 2023), and inform retail investor trading (Farrell et al., 2022), suggesting they are a useful empirical proxy for high-quality retail-oriented fundamental analysis.

2.2 The 2019 Rollout of Quant Ratings

In December of 2018, Seeking Alpha acquired CressCap Investment Research, a quant research provider, and hired its founder/CEO Steven Cress to oversee the integration of its proprietary quantitative models into the platform. On June 3 of 2019, Seeking Alpha began to distribute Quant Recommendations, Quant Ratings, and Factor Grades to paid subscribers and contributors.

Quant Ratings reflect a quant model's predictions of sector-relative performance based on five factors (Valuation, Growth, Profitability, Momentum, and Earnings Revisions), as well as size and risk.[6] Precisely how factors are scored and mapped to Quant ratings is proprietary and not publicly disclosed. Quant Ratings are mapped to quant recommendations as follows: *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). Quant outputs are displayed prominently on stock pages and alongside research reports and are updated daily. See Appendix A for an example of quant research outputs for Tesla.

[5] SA's editorial guidelines emphasize that reports should offer "well-presented and informed opinions grounded in rigorous fundamental analysis." See https://about.seekingalpha.com/article-submission-guidelines.
[6] For additional information, see: https://seekingalpha.com/article/4263303-quant-ratings-and-factor-grades-faq.

An essential feature of the 2019 rollout is that it also made available Quant Ratings for the period 2015–2019. These pre-rollout Quant Ratings are dated and computed by the same proprietary model using information available as of their corresponding dates, creating a sharp, plausibly exogenous shift in contributor access to standardized quantitative signals.

2.3 Data and Sample Construction

We collect all Quant Ratings and Quant Recommendations and all contributor-authored research reports published from January 2015 through December 2022 on the platform.[7] For each report, we collect its ID, title, main text, date and time of publication, author, and ticker (or tickers), as well as the report recommendation: *Strong Sell*, *Sell*, *Hold*, *Buy*, or *Strong Buy*. Because *Strong Sell* and *Strong Buy* are infrequent, we pool them with Sell and Buy recommendations, respectively.

Following Chen et al. (2014), we consider only single-ticker reports. We further limit the sample to reports that explicitly mention the firm's ticker or name in the main text because Seeking Alpha retroactively changes tickers.[8] For example, reports written about LinkedIn prior to the Microsoft merger are assigned Microsoft's ticker. Finally, we require that research reports cover common stocks (CRSP share code 10 and 11) with available data in CRSP.

2.4 Descriptive Statistics

The sample period includes a pre-period (2016-2018), event year (2019), and a post-period (2020-2022). Table 1 provides year-by-year descriptive statistics. In an average year, there are approximately 4,200 common stocks with available CRSP returns; 2,750 of them have Quant Ratings and 2,510 of them have research reports. While Quant coverage steadily increases from 2,099 stocks

[7] 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.

[8] 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.

in 2016 to 3,543 in 2022, research report coverage exhibits no discernible time trend. The average number of research reports in a year is 19,219, and nearly 84% (16,121) of them cover stocks with Quant Ratings. Buy and Sell recommendations account for 54% and 9% of reports, respectively, while the remaining 37% of reports issue Hold recommendations.

Panel B of Table 1 reports the distribution of Quant Ratings and Quant Recommendations. The average Quant Rating is 2.95 with a standard deviation of 0.89. 64% of stocks are rated as *Hold*, while the remaining 36% of stocks are roughly evenly distributed across the other four categories (*Strong Sell*, *Sell, Buy,* and *Strong Buy*). The distribution of Quant Ratings and Quant Recommendations is stable over time, consistent with SA's claim that Quant Ratings are based on relative metrics.[9]

2.5 SA Quant Ratings and Academic Anomalies

In this section, we explore the extent to which Quant Ratings reflect firm characteristics that have been shown in the academic literature to predict stock returns. If Quant Ratings load very strongly on established return predictors, this would suggest that the platform packages well-documented cross-sectional signals into a standardized score for retail users. We follow Jensen, Kelly, and Pedersen (2023) [hereafter JKP] and construct 153 firm characteristics using market data from CRSP and accounting data from Compustat.[10] We retain the 118 characteristics predictive of stock returns in the JKP sample, and group them into 13 distinct factor clusters. We list the 118 firm characteristics and the corresponding factor cluster, in Table IA.1 of the Internet Appendix.

To construct 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

[9] Table IA.3 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%).

[10] 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.

quintiles where the long side corresponds to the side with the higher expected return in the original publication. For each stock-month, we define *Net Anomaly* as the number of times the stock appears in the long leg of an anomaly portfolio less the number of times it appears in the short leg.

We next estimate the following panel regression:

$$Quant\ Rating_{it} = \alpha + \beta_1 Net\ Anomaly_{it} + FE_{it} + \varepsilon_{it}, \qquad (1)$$

where *Quant Rating* is Seeking Alpha's *Quant Rating*, *Net Anomaly* is defined as above, and *FE* denotes sector × month fixed effects. We follow SA and define sectors using the GICS 11 sector classification. We standardize *Quant Rating* and *Net Anomaly* to have mean zero and unit variance, and we cluster standard errors by firm and month.

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,* and the estimate is highly significant (t-stat = 30.46). The model's within fixed effects R-squared is only 9%, indicating that most of the variation in *Quant Ratings* remains unexplained. Specification 2 reports the results from regressing *Quant Rating* on *Net Anomaly* scores computed for each factor cluster. We find significant differences in the relation between *Quant Ratings* and different anomaly clusters, resulting in a much higher within-fixed effects R-squared of 38%. Specifically, *Quant Ratings* are most strongly related to *Momentum, Value, Net Profit Growth, Low Risk,* and *Quality* factor clusters, consistent with SA's disclosure that its proprietary model incorporates *Momentum, Value and Profit Growth* factors, and negatively related to *Size* and *Reversal*. The negative loading on *Size* 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), likely reflects that the momentum strategies considered by SA do not follow the common academic convention of skipping the most recent one-month return.

3. The Investment Value of Quant Ratings

In this section, we examine whether SA's Quant Ratings are predictive of future returns. Quantitative signals are widely produced and traded upon by institutional investors, raising the possibility that retail-oriented quant research merely repackages information that has already been arbitraged away.

At the end of each month, from December 2015 through November 2022, we form five portfolios sorted by Quant Recommendation, along with a long-short portfolio that goes long *Strong Buy* stocks and short *Strong Sell* stocks. For each portfolio, we compute the average monthly return in the month following portfolios formation (i.e., January 2016 through December 2022), as well as alphas from the CAPM, Fama-French (1993) three-factor, Carhart (1997) four-factor, Fama-French (2015) five-factor, and five-factor-plus-momentum (six-factor) models.

Panels A and B of Table 3 report the equal-weighted and value-weighted portfolio returns. We find consistent evidence that average portfolio returns increase with the Quant 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, yielding an economically and statistically significant monthly hedge portfolio return of 2.15% per month. The six-factor alpha is lower at 1.52% but still statistically significant (t-stat of 3.5).[11] The long-short portfolio return remains highly significant for the value-weighted portfolios, indicating that predictability extends to larger and more liquid stocks.[12]

Figure 1 reports the value-weighted monthly CAPM alpha for each year in the sample. The estimates are positive in six of the seven years, and statistically significant in both the pre-event (2016-

[11] The decline is primarily due to the long-short portfolio's large loadings on value, momentum, and profitability factors (see Figure IA.1 of the Internet Appendix for factor loadings). While these factor loadings could capture either risk or mispricing, prior research suggests that mutual fund investors primarily 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 et al., 2021).

[12] While the reported alphas are economically large, Figure IA.2 shows that they are comparable in magnitude to those earned by the Net Anomaly strategy of Jensen, Kelly, and Pedersen (2023), which similarly aggregates information across a broad set of return predictors.

2018) and post-event (2020-2022) windows. The persistence of significant alphas in the post-period indicates that Quant Ratings retain investment value even after their introduction on SA.[13]

4. Quant Ratings and Their Impact on SA Contributor Research

Having established that SA's Quant Ratings have investment value, we next examine how they influence contributor research. We address two related questions: Do SA contributors incorporate Quant Ratings into their research reports and if yes, how does this affect report quality and informativeness?

4.1 Adoption of Quant Ratings by SA Contributors

We first explore whether contributor research reports discuss Quant Ratings. We identify reports that reference Quant Ratings adopting a dictionary-based and a ChatGPT-based approach. The dictionary-based measure, *Quant Report Text*, equals one if a report contains any of the following expressions: "quant," "factor grade," "value grade," "growth grade," "profitability grade," "momentum grade," or "revisions grade," including minor variants (e.g., "grade for value"). The ChatGPT-based measure, *Quant Report GPT*, equals one when ChatGPT determines that the report mentions Seeking Alpha Quant Ratings or Factor Grades, even briefly (see Appendix C for details). Appendix B provides excerpts from a bullish and a bearish Quant Report to illustrate how contributors incorporate Quant Ratings in their arguments.

Figures 2A and 2B plot the annual means of Quant *Report Text* and *Quant Report GPT*. The mean of *Quant Report Text* is essentially zero in the pre-rollout years (2016-2018); 1% in the year of rollout (2019); and steadily increases to about 4% in 2022. The ChatGPT measure shows a similar

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[13] One explanation for why the Quant Ratings continue to predict returns after the rollout is that their distribution is limited to roughly 70,000 premium subscribers. We note that momentum and quality, both reflected in the Quant Ratings, are widely traded through ETFs, yet they continue to generate economically large abnormal returns. This suggests that broad awareness and substantial capital allocated to these strategies do not necessarily eliminate their profitability.

time-series pattern, but with a much more pronounced increase in the post-period: 10% in 2022, consistent with contributors drawing on Quant Ratings without using the specific dictionary terms.

Our primary test of adoption examines whether Quant Ratings shape contributors' stated views about investment payoffs, as reflected in their recommendations. Specifically, we estimate the following panel regression:

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

where the dependent variable, *Report Rec*, equals one for SA reports making a buy recommendation, zero for hold recommendations, and negative one for sell recommendations, *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).[14] In our baseline specification, FE denotes date × sector fixed effects, where sectors correspond to the 11 GICS sectors. Standard errors are clustered by both firm and date.

Specification 1 of Table 4 reports the results. The coefficient on *Quant Rating* is insignificant, suggesting that in the pre-period, contributors' recommendations do not reflect the return-predictive signal embedded in Quant Ratings. In contrast, the coefficient on *Quant Rating* × *Post* is positive and significant, consistent with Quant Ratings shaping contributors' investment views in the post-period. Economically, a unit increase in the Quant Rating is associated with a 5.46 percentage point increase in *Report Rec*, which corresponds to an increase of roughly 13% relative to the mean of *Report Rec* (0.42).

In Table IA.4 of the Internet Appendix, we replace the *Quant Rating* variable with *Strong Buy, Buy, Sell, and Strong Sell* indicator variables (with *Hold* as the omitted category), and 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.[15] In Specifications 2 and 3, we augment the baseline

[14] We exclude the year of the rollout (2019) because the treatment varies within the year, making it difficult to classify observations as pre- and post-rollout. We include the rollout year in the event-time analysis reported in Figure 3.
[15] These findings, coupled with the fact that SA reports are far more likely to recommend a buy recommendation than a sell recommendation (see Table 1), suggest that stocks with favorable quantitative recommendations may experience an

model by including firm fixed effects and contributor fixed effects, respectively, and find similar results. These findings alleviate concerns that our results are driven by changes in the composition of Seeking Alpha contributors (e.g., the platform attracting more quantitatively sophisticated contributors) or shifts in the set of firms receiving contributor coverage.

Finally, we examine whether post-rollout recommendation alignment is stronger among reports that explicitly reference Quant Ratings. In Specification 4, we interact *Quant Rating* × *Post* with *Quant Report Text* and *No Quant Report Text*. In Specification 5, we conduct a parallel analysis using the ChatGPT-based classification variables, *Quant Report GPT* and *No Quant Report GPT*. We find consistent evidence that report recommendations tilt toward Quant Ratings in the post-period for both groups, but that the effect is significantly stronger among reports explicitly referencing Quant Ratings. For example, in Specification 4, the coefficient on *Quant Rating* × *Post* × *Quant Report Text* is 14.98, compared to 4.53 for *Quant Rating* × *Post* × *No Quant Report Text*. Overall, these findings suggest that contributors both explicitly reference and implicitly incorporate Quant Ratings into their investment recommendations following the rollout.

4.2 Strengthening Causal Inference

In this section, we conduct three additional tests to strengthen the case for changes in contributor research being driven by contributor adoption of Quant Ratings.

4.2.1 Event-Time Analysis

Our first analysis examines the alignment of SA report recommendations and quantitative ratings in event-time. Specifically, 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) and plot the respective coefficients in Figure 3. We find no evidence of a pre-trend. The

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.3 of the Internet Appendix).

coefficients on *Quant Rating* are statistically insignificant in all three years of the pre-period, and the point estimate is largest in the first year of the sample. In contrast, we find significant increases in each year of the post period. The largest estimate is in 2022, the year with the largest increase in the number of *Quant Reports* (see Figure 2). These results support the view that the increased alignment is driven by the Quant Rating adoption rather than time trends in contributor behavior.

4.2.2 Alignment Tests Using Estimated Quant Ratings

Contributors may become better at identifying the types of stocks favored by SA's quant model for reasons other than access to SA's Quant Ratings. For example, after 2019 they may rely more heavily on publicly available valuation, profitability, growth, momentum, or analyst-revision data used by SA's quant model, or acquire a similar quant signal outside the SA platform. To address this possibility, we reverse-engineer SA's *Quant Ratings* and construct *Estimated Quant Ratings* for both stocks with Quant Ratings and stocks without Quant Ratings. If the observed increase in alignment reflects a broader improvement in contributors' ability to identify stocks favored by SA's model, alignment should increase for both groups. If the effect instead reflects reliance on SA's Quant Ratings, the increase should be concentrated among stocks with official Quant Ratings.

Discussions with Seeking Alpha representatives suggest that stocks primarily lack official Quant Ratings for two reasons. First, some firms have insufficient historical return or accounting data to compute the predictors used by both SA's model and our estimated-rating model. Second, some firms lack the analyst forecast data incorporated into SA's Quant Ratings. We exclude firms with insufficient historical data, leaving firms without analyst coverage as the primary group of stocks without official Quant Ratings.

We estimate a random forest model with SA's Quant Ratings as the dependent variable and 59 predictor variables spanning valuation, growth, profitability, price momentum, and analyst forecast revisions (see Table IA.2 for additional details). We replace missing firm-level variables with industry-level medians and adopt an expanding window approach to predict Quant Ratings out-of-sample (e.g., we use 2015–2016 data to predict 2017 ratings, 2015-2017 data to predict 2018 ratings). The correlation between Estimated Quant Ratings and actual Quant Ratings is 0.70, suggesting that the model approximates SA's proprietary signal reasonably well.

Stocks without official Quant Ratings more often have missing firm-level information and therefore require greater use of industry medians when constructing Estimated Quant Ratings. This raises the concern that Estimated Quant Ratings in the sample of stocks without Quant Ratings may be less predictive of future returns and, therefore, contributor recommendations need not become more aligned with them after the rollout. To assess this concern, we form hedge portfolios on Estimated Quant Ratings separately for stocks with and without SA Quant Ratings. The resulting value-weighted CAPM alphas are similar across the two samples and comparable in magnitude to the alpha earned by portfolios formed on actual Quant Ratings (see Figure IA.4 of the Internet Appendix). Together, these findings suggest that the Estimated Quant Rating captures economically meaningful variation in expected returns in both covered and uncovered firms.

We estimate the following regression:

$$Report\ Rec_{it} = \alpha + \beta_1 Estimated\ Quant\ Rating_{it} \times Covered_{it} + \beta_2 Estimated\ Quant\ Rating_{it} \times Not\ Covered_{it} + \beta_3 Estimated\ Quant\ Rating_{it} \times Post_t \times Covered_{it} + \beta_4\ Estimated\ Quant\ Rating_{it} \times Post_t \times Not\ Covered_{it} + FE + \varepsilon_{it}, \tag{3}$$

where *Covered* and *Not Covered* indicate stocks with SA Quant Ratings and without SA Quant Ratings, respectively, *Estimated Quant Rating* denotes the random-forest prediction of SA's Quant Rating, and all other variables are defined as in Equation (2). Thus, β_3 and β_4 capture the change in the sensitivity of report recommendations to the *Estimated Quant Rating* for stocks with *Quant Ratings* and stocks without *Quant Ratings*.

Specification (1) of Table 5 reports our baseline model with date × sector fixed effects. We find that the coefficient on *Estimated Quant Rating* × *Post* × *Covered* is economically and statistically significant (4.39), whereas the coefficient on *Estimated Quant Rating* × *Post* × *Not Covered* is economically small and statistically indistinguishable from zero, alleviating the concern that the post-period increase in alignment reflects a general improvement in contributors' ability to identify stocks favored by SA's quant model. This contrasting pattern remains after including firm fixed effects (Specification 2) or contributor fixed effects (Specification 3), alleviating concerns that the results are driven by changes in the set of covered firms or shifts in contributor composition over time. Finally, firms with Quant Ratings have greater analyst coverage than firms without Quant Ratings because SA's quant model requires availability of firm-level analyst data. To ensure that the difference in analyst coverage does not confound our estimates, we limit the sample of firms with Quant Ratings to those followed by fewer than five, three, and one analyst (Specifications 4-6). Our results hold.[16]

4.2.3 The 2021 ETF Quant Rating Rollout

In this section, we examine how the March 2021 rollout of Quant Ratings for exchange-traded funds (ETFs) affects contributor-authored ETF research. This rollout occurred nearly two years after the introduction of Quant Ratings for individual equities and involved a completely different asset class and quantitative model.[17] As we show in Table IA.6 of the Internet Appendix, ETF Quant Ratings are predictive of ETF returns. Thus, documenting a similar post-rollout increase in alignment between contributor recommendations and ETF Quant Ratings provides additional evidence that a platform-provided quant signal can shape contributor research.

[16] If SA contributors were generally adopting more quantitative techniques, we would also expect them to incorporate signals beyond those in the SA quant model. We therefore compare signals positively correlated with SA Quant Ratings (e.g., momentum, value, profitability growth) to those negatively correlated (e.g., accruals, size, reversals). We confirm the results are significantly stronger for positively correlated signals (see Table IA.5), suggesting that contributors are primarily focused on SA Quant Ratings rather than broadly incorporating other quantitative measures in the post-event period.

[17] Information about how ETF Ratings are computed 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.

Our sample includes 8,428 single-ticker contributor-authored ETF reports with non-missing Quant Ratings from November of 2019 through December 2022. To more cleanly separate the pre- and post-rollout periods, we exclude reports written within two months of the March 2021 ETF Quant Rating rollout from the baseline tests. We define *Post ETF* as an indicator equal to one for reports published between June 2021 and December 2022, and zero for reports published between November 2019 and 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.

We report results in Table 6. The coefficients on *Quant Rating ETF* × *Post* are positive and significant in Specifications 1-3, ranging from 5.65 to 6.21 percentage points, consistent with report recommendations becoming more aligned with ETF Quant Ratings in the post-rollout period. In Specification 4, we include reports published within two months of the rollout and implement an event time analysis by interacting *Quant Rating ETF* with a series of four-month event-time indicators: three pre-event, one event, and three post-event. We find no evidence of pre-trends, and we observe an immediate and persistent increase in alignment in the post-period. Overall, these findings provide an out-of-sample validation of our main results and reinforce the interpretation that contributor research responds directly to the introduction of platform-provided quantitative signals.

4.3 Effects of Quant Ratings Adoption on Research Quality

In this section, we examine how Quant Ratings adoption affects recommendation informativeness and whether it weakens incentives to conduct independent, firm-specific, fundamental analysis. As emphasized by Dugast and Foucault (2018) and Sloan (2019), access to a common quant signal may crowd out independent information collection and analysis, resulting in research that is less original, less grounded in fundamental analysis, and potentially less informative. This concern is especially relevant in our setting because Chen and Hwang (2022) document a negative relation between a report's reliance on quantitative information and its informativeness. Quant Ratings may therefore improve research quality by giving contributors access to useful quantitative information, but they may also encourage reliance on standardized signals at the expense of independent analysis.

4.3.1 Recommendation Informativeness

Following Chen et al. (2014), we define recommendation informativeness (*Total Return*) as the buy-and-hold market-adjusted stock return (multiplied by -1 when the recommendation is a Sell), measured from day $t+1$ to day $t+63$, where day [t] is the day of the recommendation.[18] We drop Hold recommendations because their informativeness is not well defined, and we exclude day [t] from the return window to control for concurrent confounding events.

Conceptually, we view the informational value of a recommendation as having two components. The first is a common quant signal component, which reflects the value of picking stocks based on the Quant Rating. The second is a contributor-specific component, which reflects the value of independent information collection and analysis. To capture these components, we decompose *Total Return* into *Quant-Style Return* and *Quant-Adjusted Return* as follows. Each day, we sort stocks into 25 portfolios based on the Quant Rating (Quant Portfolio). A typical Quant Portfolio contains roughly 100 stocks, with a median spread of 0.06 between the maximum and minimum Quant Rating. We define *Quant-Style Return* as the average market-adjusted return across all stocks in the *Quant Portfolio*, and *Quant-Adjusted Return* as the difference between *Total Return* and the *Quant-Style Return*. We note that *Total Return*, *Quant-Style Return*, and *Quant-Adjusted Return* are noisy return-based proxies for recommendation informativeness and its underlying components.

We begin by estimating the baseline model:

$$Rec\ Informativeness_{it} = \alpha + \beta_1 Post_{\ t} + \varepsilon_{it}, \tag{4}$$

[18] Our main findings are robust to using both shorter and longer horizons (see Table IA.7 of the Internet Appendix).

where *Rec Informativeness* denotes either *Total Return, Quant-Style Return*, *Quant-Adjusted Return*, and *Post* equals to one for recommendations issued after the rollout and zero otherwise. Results, reported in Panel A of Table 7, show no statistically significant change in recommendation informativeness, or in either of its two components, following the rollout, suggesting Quant Ratings adoption is perhaps not sufficiently widespread to produce a detectable shift in recommendation informativeness in the full sample.

Next, we examine whether changes in recommendation informativeness are more pronounced when report content indicates contributor use of the Quant Ratings. Specifically, we augment Equation (4) by interacting *Post* with *Quant Report*, where *Quant Report* is measured using either the dictionary-based classification (*Quant Report Text*) or the ChatGPT-based classification (*Quant Report GPT*). Panels B and C report the corresponding results.

As expected, *Quant Report* recommendations generate significantly higher *Quant-Style Returns* in the post period: 1.64% in Panel B and 0.94% in Panel C. Importantly, these gains are not accompanied by lower *Quant-Adjusted Returns*, indicating that greater reliance on Quant Ratings does not displace firm-specific fundamental informativeness. The increase in *Total Returns* is positive but statistically insignificant in Panel B and marginally significant in Panel C ($p < 0.10$). In Table IA.7 of the Internet Appendix, we show that Panel C results are robust to alternative fixed-effects specifications (date, firm, contributor) and holding periods (one and six months).

Contributors may incorporate Quant Ratings into their recommendations without explicitly discussing them in the report. We therefore use the strength of the relationship between a report recommendation and a Quant Rating as an alternative measure of Quant Ratings use. Intuitively, a contributor who uses the quant signal in forming an investment opinion is more likely to issue Buy recommendations for stocks with relatively high Quant Ratings and Sell recommendations for stocks with relatively low Quant Ratings. To capture this relation, we compute a *Quant Alignment* score by multiplying a stock's Abnormal Quant Rating (defined as the stock's Quant Rating minus the cross-sectional mean Quant Rating) by 1 when the recommendation is Buy and -1 when the recommendation is Sell. We then augment Equation (4) by interacting *Quant Alignment* with *Pre* and *Post* indicator variables and report the results in Panel D of Table 7.

We find that *Quant Alignment* is associated with higher *Quant-Style Returns*, and this relation does not vary significantly across the pre- versus post- period. More interestingly, we find that the relations between *Quant Alignment* and *Quant-Adjusted Return* and *Total Return* are positive in the post-period, with the latter estimate being statistically significant. Taken together, these results suggest that Quant Ratings adoption improves recommendation informativeness without crowding out contributor-specific fundamental analysis.

4.3.2 Report Attributes

While the return-based tests in Table 7 yield no evidence of crowding out, *Quant-Adjusted Return* remains an indirect and noisy measure of the informational value of contributor research that quant research may diminish. To shed further light on the crowding out hypothesis, we examine whether research reports become less grounded in fundamental analysis, less original, or shorter.

Contributor research reports are generally grounded in traditional fundamental analysis, which predicts returns by collecting and interpreting hard and soft information about a company's strategy, financial reporting, industry conditions, and operating performance, heavily relying on analyst judgment. In contrast, Quant Ratings predict returns by applying statistical models to observable data. If contributors substitute toward this common quantitative signal, their reports may contain less firm-specific fundamental analysis.

We use ChatGPT to score each report on six fundamental analysis dimensions: strategy analysis, accounting analysis, estimation of fundamental value, industry analysis, firm-specific KPIs, and scrutiny of management. Each dimension is scored 0 if not mentioned, 1 for a brief mention, and

2 for a detailed discussion. Appendix C describes the rubric in greater detail. Our measure of depth of fundamental analysis, *Fundamental Score*, is the average of these six scores.

We first validate *Fundamental Score* by relating it to *Quant-Style Returns*, which captures the informational value of the quant signal, and *Quant-Adjusted Returns*, which captures the informational value of independent information collection and analysis. Our intuition is that reports rich in strategy, valuation, accounting, industry, and operating analysis should load more strongly on *Quant-Adjusted Return* than in *Quant-Style Returns,* because such analysis is more likely to uncover novel information distinct from the common quant signal rather than overlapping with it. In univariate regression analyses (untabulated for brevity), we find that a one-unit increase in *Fundamental Score* is associated with a 0.88% increase in *Quant-Adjusted Return* (t = 2.40) but is unrelated to *Quant-Style Return* (–0.12%, t = –0.78), validating *Fundamental Score* as a measure of fundamental analysis.

Traditional fundamental analysis tends to produce highly differentiated investment views because human judgment influences both what information is collected and how information is processed and integrated into an investment view. A common quant signal may both reduce incentives to gather information and anchor contributors to similar reasoning, resulting in more similar reports. To capture the extent to which contributors' views converge, we measure *Report Similarity* as the average cosine similarity between the text of a report and other reports written on the same stock in the prior 90 days.

If the adoption of a common quant signal leads to less information being collected and analyzed by contributors, then contributor reports will present and discuss less information, and become shorter. Our measure of report length is the natural log of total word count.

We estimate Equation (4) with *Fundamental Score, Report Length*, or *Report Similarity*, as the dependent variable and report our findings in Table 8. In Panel A, we find that contributor reports become more similar, consistent with the crowding out hypothesis, but also that their fundamental analysis scores and length increase, contradicting it. More importantly, when we focus on reports more likely to adopt Quant Ratings, and therefore more likely to exhibit any crowding out if it exists, we find no evidence to support the crowding out hypothesis (Panels B, C, and D). Relative to other reports, these reports become more grounded in fundamental analysis, more original, and longer following the rollout, suggesting contributors use Quant Ratings to complement rather than substitute for independent information gathering and analysis. These patterns are robust to the inclusion of alternative fixed effect structures (Table IA.8).

To conclude, neither our returns-based tests of changes in recommendation informativeness nor our tests of changes in report content yield evidence to support the crowding out hypothesis. If anything, adoption of quant ratings is associated with more informative recommendations, stronger fundamental analysis, greater effort, and more distinctive reports.

5. Quant Ratings Adoption and Consequences by Contributor Quantitative Sophistication

We next examine how the adoption and the consequences of Quant Research depend on a contributor's quantitative sophistication, which we broadly define as familiarity with data-driven, systematic investment approaches. This analysis speaks to the broader debate over whether quantitative research narrows or reinforces preexisting differences in research capabilities. More quantitatively sophisticated contributors may be less likely to adopt them because they already incorporate quant signals in their research and, therefore, have less reason to change their behavior, narrowing pre-existing differences in research capability. Alternatively, they may be more likely to adopt and benefit from Quant Ratings because they face lower costs of processing and integrating quant signals in their own research, magnifying pre-existing differences.

5.1 Measuring Quantitative Sophistication

We construct three measures of quantitative sophistication: two based on textual analysis of contributors' public profiles, and one based on contributors' pre-rollout stock selections.

The first measure, *Bio Words Sophistication,* is based on keywords that appear in contributor profiles and plausibly indicate a background in quantitative/institutional investing such as "Quant," "Long/Short," "Hedge Fund," and related expressions.[19] *Bio Words Sophistication* equals one if none of these terms appear, two if one term appears, and three if two or more terms appear in a profile.

The second measure, *Bio GPT Sophistication*, is based on ChatGPT's assessment of contributor quantitative sophistication. Specifically, we prompt ChatGPT to rate each contributor biography on a 1–10 scale based on the contributor's apparent experience with quantitative investing. *GPT Sophistication* equals one, two, or three when a contributor's score falls in the bottom tercile, middle, or top tercile of the sample distribution. Appendix E provides examples of contributor biographies and the corresponding *Bio Words Sophistication* score, *GPT Sophistication* score, and ChatGPT's score explanation.

Our third measure, *Quant Alignment Sophistication*, is based on how closely a contributor's recommendations align with the Quant Ratings prior to their rollout. To mitigate mechanical mean reversion arising from measurement error, we randomly divide pre-rollout recommendations into an estimation sample and a hold-out sample, requiring at least three observations in the estimation sample. This procedure ensures that contributor sophistication is estimated in a sample separate from the sample used to study the relation between contributor sophistication and Quant Ratings adoption. We compute a contributor's *Quant Alignment Sophistication* score in the estimation sample as follows: We first compute recommendation-level *Quant Alignment Scores* (defined in Section 4.3.1), aggregate them to the contributor level by averaging across recommendations issued by the same contributor, and then sort contributors into terciles: *Low, Medium,* and *High Quant Alignment Sophistication*.

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[19] The full list of words is: "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 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 (now called Investing Groups).

Finally, we construct a composite measure, *Quant Sophistication*, as the sum of *Bio Words Sophistication, GPT Sophistication, and Quant Alignment Sophistication,* and classify contributors into *Low, Medium, and High Sophistication* terciles.

5.2. Quant Ratings Adoption: The Role of Quantitative Sophistication

We first examine how discussions of Quant Ratings in contributor reports vary across contributors with different levels of Quantitative Sophistication. Figures 4A and 4B plot the frequency of *Quant Report Text* and *Quant Report GPT* for contributors in the Low, Medium, and High *Quantitative Sophistication* groups in the pre- period, the post-period, and the corresponding change. Both measures increase in the post-period in all groups, but the largest increase occurs in the Low Sophistication group. For example, *Quant Report Text* rises by 3.50 percentage points in the *Low Quantitative Sophistication* group compared to 1.35 in the *High* group. Untabulated tests confirm that the difference is highly significant.

Next, we examine how the increase in recommendation–Quant Rating alignment documented in Section 4.1 varies across contributors with different levels of quantitative sophistication. We re-estimate Equation (2) separately for contributors in the Low, Medium, and High Sophistication groups. Specifications 1–3 of Table 9 report the results for these groups, and Specification 4 tests whether the estimates for the Low and High groups differ from each other.[20] Panel A reports the results using the composite sophistication measure, while Panels B-D report results for the individual measures.

We find that the alignment between recommendations and Quant Ratings in the pre-period increases with contributor sophistication. For example, the coefficient on *Quant Rating* in Panel A rises

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[20] 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).

from −1.02% for the Low group to 4.09% for the High group, and the difference between the two estimates is statistically significant.

In contrast, the coefficient on *Quant Rating* × *Post* displays an opposite pattern. For example, in Panel A, it declines from 8.36% in the Low Sophistication group to -0.08% in the High Sophistication group, with the difference statistically significant. Thus, the post-rollout increase in recommendation–Quant Rating alignment documented in Section 4.2 is driven primarily by contributors with low quantitative sophistication. Taken together, the findings in Figure 4 and Table 9 suggest that the adoption of quant ratings following the rollout was strongest among less quantitatively sophisticated contributors.

5.3 Consequences of Quant Ratings Adoption: The Role of Quantitative Sophistication

We next examine whether the consequences of Quant Ratings adoption vary with contributor quantitative sophistication. The average improvement in recommendation informativeness documented in Section 4.3 may mask important differences across contributors. For example, less sophisticated contributors may experience larger gains from Quant Ratings because of their limited prior use of quantitative research, but they may also exhibit larger declines in firm-specific analysis, if they place greater weight on the quant signal. To explore this possibility, we estimate the following regression:

$$Rec\ Info_{it} = \alpha + \beta_1 Post_t + \beta_2 Low\ Soph_{it} + \beta_3 (Post_t \times Low\ Soph_{it}) + \varepsilon_{it}, \qquad (5)$$

where *Rec Info* and *Post* are defined as in Section 4.3.1. *Low Soph.* is equal to one for recommendations by contributors in the bottom tercile of a sophistication measure (as defined in Table 9), and zero if the contributor is in the top tercile. We exclude recommendations issued by contributors in the middle tercile, so that the estimates compare post-rollout changes between the least and most quantitatively sophisticated contributors.

Panel A of Table 10 reports results for the composite measure of quantitative sophistication. The post-rollout increases in recommendation informativeness and its components are larger for less sophisticated contributors than for more sophisticated contributors: 2.01% increase in *Total Return*, 0.59% increase in *Quant-Style Return*, and 1.43% increase in *Quant-Adjusted Return*. These findings indicate that less sophisticated contributors benefit more from the quant signal after the rollout, and that these gains extend to both Quant-style and Quant-adjusted informativeness. We find similar results in Panels B–D, which use individual sophistication measures, and in Table IA.9 of the Internet Appendix, where we consider alternative fixed effects and return holding periods.

In sum, we find the post-rollout increase in Quant Ratings adoption is concentrated among less quantitatively sophisticated contributors and accompanied by larger increases in recommendation informativeness for these contributors, consistent with the notion that Quant Ratings rollout narrows preexisting differences in research capabilities.

6. Quantitative Ratings and Their Impact on Retail Investor Trading

In our final section, we complement the contributor-focused analyses with tests of whether Quant Ratings similarly shape retail investor trading decisions. Identifying effects on retail trading is arguably more difficult because retail order flow reflects the actions of many investors with heterogeneous information sets, attention, and motives.

More broadly, whether Quant Ratings meaningfully affect retail trading depends on both investor exposure to the signal and investors' ability to interpret it. We suggest these conditions are best met on days contributor reports are published. Contributor reports attract retail investor attention and trading activity (Farrell et al., 2022), increasing the share of trading generated by Seeking Alpha users, some of whom have direct access to Quant Ratings. In addition, contributor reports may help investors interpret Quant Ratings by embedding them within a broader discussion of the firm.

Accordingly, any effects of the quant signal on retail trading are more likely to be observed on these days.

6.1 Retail Trading-Quant Rating Alignment

We examine whether daily retail trading becomes more aligned with Quant Ratings following the rollout by estimating the following panel regression:

$$Retail\ Imb_{it} = \alpha + \beta_1 Quant\ Rating_{it} + \beta_2(Quant\ Rating_{it} \times Post_t) + \beta_3 RDay_{it} + \quad (6)$$
$$+ + \beta_4(RDay_{it} \times Post_t) + \beta_5(Quant\ Rating_{it} \times RDay_{it}) + \beta_6(RDay_{it} \times$$
$$Quant\ Rating_{it} \times Post_t) + FE + \varepsilon_{it.}$$

Retail Imb is the difference between daily retail purchase volume and daily retail sell volume, scaled by total daily retail volume. Following Barber et al. (2024), we identify retail trades using TAQ exchange code "D" and classify them as buys (sells) when executed above (below) the quoted midpoint, excluding trades between 40%–60% of the NBBO.[21] *RDay* is equal to one on the day a contributor report is published; reports released after the market close are assigned to the following trading day, aligning the indicator with the first trading day on which investors can act on the information. *Quant Rating* and *Quant Rating* × *Post* are defined as in Equation (2), and FE denote date and firm fixed effects. The coefficients of interest are β_2, which captures the post-rollout change in retail trading-Quant Rating alignment on non-report days, and β_6, which captures the incremental change in alignment on report days.

Specification (1) of Table 11 reports the results from the estimation of Equation (6). We find that retail investors trade against the Quant Ratings in the pre-period ($\beta_1 < 0$ and $\beta_5 < 0$), consistent with prior evidence of retail trading against academic anomalies (McLean, Pontiff, and Reilly, 2025).

[21] Battalio et al. (2024) raise important concerns about the accuracy of TAQ-based measures of retail trading, highlighting the potential for both Type I and Type II classification errors. While this suggests caution is warranted, TAQ-based measures continue to be widely used in recent research, and several studies—including Farrell et al. (2022) and Green and Jame (2024)—document meaningful differences between retail and institutional trading using these measures. This evidence suggests that, despite limitations, the approach retains some utility for distinguishing between investor types in large-scale datasets.

In the post-period, retail trading becomes directionally more aligned with the Quant Ratings. Specifically, the coefficient on *Quant Rating* × *Post* is positive but insignificant (t stat of 1.37), whereas the coefficient on *Quant Rating* × *Rday* × *Post* is positive and highly significant (t stat of 4.24).[22]

One potential explanation for the documented increase in retail trading–Quant Rating alignment on contributor-report days is that contributor recommendations themselves become more aligned with Quant Ratings following the rollout (as shown in Section 4.1), and retail investors trade in the direction of contributor recommendations (Farrell et al., 2022). To explore this possibility, we control for the average report recommendation and find similar results (Specification 2). Thus, the report-day increase in alignment between retail order imbalances and Quant Ratings is consistent with retail investors' acquisition and use of Quant Ratings information beyond the information contained in report recommendations. Our results also remain when we exclude reports published within three days of earnings announcements (-1,1) and observations in the top 5% of the firm-level distribution of absolute returns or trading volume in the prior year to address concerns about attention-driven trading (Specification 3); and when we add firm × year fixed effects to control for changes in firm fundamentals and investor base over time (Specification 4).

In our final test, we augment Specification (4) by replacing the single indicator *RDay* with nine event-time indicators *RDay[k]*, with k ranging from -4 to 4, and plot the corresponding coefficients in Figure 5. We find that the shift toward greater alignment is concentrated on report publication day, consistent with the notion that contributor reports facilitate retail investors' exposure to and use of Quant Ratings.

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[22] We re-estimate Equation (6) replacing retail order imbalances with total order imbalance (from TAQ), which primarily reflects institutional trading, and find sharply different results (see Table IA.10). Specifically, total order imbalance is positively aligned with Quant Ratings in the pre-period, and this alignment does not increase on Seeking Alpha report days in the post-period. Since retail investors are the primary consumers of SA contributor-authored research and Quant Ratings, the contrasting findings reinforce the view that the post-rollout increase in alignment between retail order imbalance and Quant Ratings on report days reflects retail investor use of the Quant Ratings rather than a broader shift toward quantitative research in the market.

6.2. The Informativeness of Retail Investor Trading

We next examine whether the documented increase in alignment between retail order imbalance and Quant Ratings is accompanied by an increase in retail trade informativeness, defined as the ability to predict future returns. As in Section 4.3.1, we consider three return metrics: *Total Return* (buy-and-hold, market-adjusted return from day t+1 to day t+63, multiplied by −1 when retail order imbalance is negative), and its constituents, *Quant-Style* and *Quant-Adjusted Return*. We report the average retail trade informativeness in the pre-period, the post-period, and the difference between the two periods for both report days and non-report days. Based on our evidence that the increase in retail order imbalance-Quant Ratings alignment is concentrated on report days (Table 11 and Figure 5), we expect a larger increase in informativeness of retail trading on report days than on non-report days.

Panel A of Table 12 reports the results for report days. We find that *Total Informativeness* increases from 0.14% to 0.21%, but neither of these estimates nor their difference is statistically significant (Column 1). The decomposition reveals a statistically and economically significant increase in *Quant-Style Informativeness* from 0.03% to 0.15% (the latter statistically different from zero), and an insignificant decline in *Quant-Adjusted Informativeness* from 0.11% to 0.05% (neither statistically significant). We conclude that retail trading on report days becomes not only more aligned with Quant Ratings after their rollout (Table 11) but also more predictive of *Quant-Style* returns.

In Panel B, we find robust evidence that retail trading on non-report days predicts *Total Returns* and *Quant-Adjusted Returns* in both periods, and no evidence that it predicts *Quant-Style Returns* in either period, or that the predictive ability of retail order imbalance changes from the pre- to post-period. The fact that we can document an increase in *Quant-Style* informativeness only in the much smaller report day sample highlights the role of contributor-authored research reports in facilitating the diffusion and use of quant research in retail markets.

7. Conclusion

Using the 2019 rollout of Quant Ratings on Seeking Alpha as a setting, we present a consistent body of evidence that standardized quantitative signals can improve retail-oriented equity research and retail investor trading. First, Quant Ratings are predictive of future returns. Second, post-rollout, Seeking Alpha contributors reference the Quant Ratings more often in their research reports and issue recommendations that are more aligned with the Quant Ratings. Third, report recommendations that reference Quant Ratings become more informative about future returns, consistent with contributors adopting and benefiting from quant research. Fourth, we find no evidence of a decline in firm-specific analysis in the post-rollout period, alleviating concerns that diffusion of quantitative research may crowd out fundamental analysis. Fifth, both the Quant Ratings' adoption and the benefits from adoption are stronger among contributors with less prior quantitative experience, consistent with the ratings helping narrow differences in research capability. Finally, the Quant Ratings similarly affect retail trading: On report publication days, retail order imbalances become more aligned with Quant Ratings and better capture returns attributable to quantitative factors.

Broadly, our findings suggest that the benefits of quantitative research extend to retail markets. An important caveat is that Seeking Alpha serves a relatively sophisticated segment of retail investors and integrates Quant Ratings into a broader set of investment information services, including contributor-authored research reports, detailed financial information, earnings transcripts, news, and other analytical tools. Future research can examine whether quantitative signals have similar effects when offered by platforms or intermediaries that serve less engaged retail investors, or that provide such signals on a stand-alone basis.

Generative AI Disclosure Statement

During the preparation of this work the authors used ChatGPT to edit writing and improve readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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

Quant Rating ?

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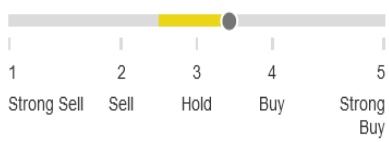


The overall quant rating is not an average of the factor grades listed. Instead, it gives greater weight to the metrics with the strongest predictive value.

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: Providing Rubric to Assess SA Reports' use of Quantitative and Fundamental Analysis

Prompt: *I am interested in the extent to which analysts conduct quantitative vs. fundamental analysis on Seeking Alpha. My plan is to attach reports and have you assessed each report on various dimensions. Below is a summary of the scoring I'd like you to use:*

Evaluate each Seeking Alpha article on one quantitative indicator and 6 fundamental (human judgment driven) dimensions. For every indicator assign 0, 1, or 2 points based only on text that is clearly present in the article.

- *0 = Not mentioned/No explicit or implicit reference to the indicator.*
- *1 = Brief Mention/ Indicator is cited or touched on but not developed in depth.*
- *2= Substantive use/ Indicator is an essential element of the report.*

Panel A: Construction of *Quant Report GPT*

Number	Indicator	What We Look For	Example
Q1	Quantitative Ratings	Direct use of Seeking Alpha Quant Ratings or Factor Grades	"Quant Valuation Grade is A-"; tables of grades.

Panel B: Construction of Fundamental Measures

Number	Indicator	What We Look For	Example
F1	Strategy Analysis	Discussion on business, competitive positioning, growth drivers, product roadmap.	"The company aims to double market share by 2027 via product-led expansion."
F2	Accounting Analysis	Deep dive into the financial statements and discussion on earnings quality, profit margins, cash-flow, leverage, working capital.	"Operating margin expanded 300 bps YoY; net debt/EBITDA is now below 1.5x."
F3	Estimation of Fundamental Value	DCFs, multiples comps, sum-of-parts, scenario tables.	"Our base-case DCF yields a $58 target; comps suggest a 10x EBITDA multiple is appropriate."
F4	Industry Analysis	A discussion on industry level factors and economic conditions that shape a company's profitability.	"With a $50B TAM and declining steel input costs, the setup looks favorable."
F5	Firm-Specific KPIs	References to operational metrics unique to the business (same-store sales, churn, leasing spreads, etc.).	"YoY; same-store sales rose 4.5%; churn improved 100 bps sequentially."
F6	Scrutiny of Management	Discussion on management guidance, management behavior, track record, and governance	"Heavy insider selling call into question long-term confidence"; "Aggressive M&A concerning given poor performance of past investments".

Appendix D: Variable Definitions

- *Quant Rating:* A proprietary stock-level quantitative rating constructed by Seeking Alpha. Ratings are publicly displayed beginning in June 2019; we collect backfilled ratings from January 2015 onward.
- *Post*: An indicator equal to one for the three-year period following the rollout of Quant Ratings (2020-2022) and zero for the three-year period prior to changes (2016-2018).
- *Quant Recommendation:* A categorical recommendation derived from the Quant Rating using Seeking Alpha's published mapping: Strong Sell (<1.5), Sell [1.5, 2.5), Hold [2.5, 3.5), Buy [3.5, 4.5), Strong Buy (≥4.5).
- *Report Rec:* Equals +1 for buy recommendations, 0 for hold recommendations, and −1 for sell recommendations.
- *Net Anomaly:* The number of anomaly portfolios (out of 118 significant predictors in Jensen, Kelly, and Pedersen (2023)) in which the stock appears in the long leg minus the number in which it appears in the short leg. The list of characteristics is provided in Table IA.1.
- *Net Factor Cluster:* The number of long minus short assignments for anomalies within a given factor cluster (13 clusters as defined in Jensen, Kelly, and Pedersen (2023); see Table IA.1).
- *Quant Report Text*: Indicator equal to one if the report text contains "quant," "factor grade," "value grade," "growth grade," "profitability grade," "momentum grade," "revisions grade," or close variants (e.g., "grade for value").
- *Quant Report GPT:* An indicator equal to one if ChatGPT classifies the report as mentioning Seeking Alpha Quant Ratings or Factor Grades, even briefly (see Appendix C).
- *Est. Quant Rating:* An estimated version of the Seeking Alpha Quant Rating constructed using 59 predictor variables (see Table IA.2). Missing values are imputed using industry medians. We estimate the model using a random forest with an expanding-window procedure (e.g., data through 2015 predict 2016, etc.), and all predictions are strictly out-of-sample.
- *Covered:* An indicator equal to one if the stock has an SA Quant Rating.
- *Not Covered:* An indicator equal to one if the stock lacks a Quant Rating due to insufficient sell-side analyst coverage.
- *Quant Rating ETF:* A proprietary quantitative rating for exchange traded funds (ETFs) constructed by Seeking Alpha. These ratings were disclosed on Seeking Alpha beginning in March of 2021. We collect backfilled quantitative ratings beginning in November 2019.
- *Post ETF:* An indicator equal to one for June 2021-December 2022 and zero for November 2019-December 2020. *Post ETF* is set missing for the 5 months [-2,2] centered around the introduction of ETF ratings (March 2021).
- *Rec Informativeness:* Recommendation informativeness, defined as the stock's buy-and-hold return from day t+1 to t+63 multiplied by the sign of the report recommendation (+1 for buy, −1 for sell), where Day *t* is the first trading day when an investor could trade based on the recommendation. We consider three return metrics:
    - *Total Return:* The market-adjusted stock return defined as stock return minus the value-weighted market return.
    - *Quant-Style Return*: For each firm-day, stocks are sorted into 25 portfolios by Quant Rating; this is the average market-adjusted return of the portfolio to which the stock belongs.
    - *Quant-Adjusted Return*: The difference between *Total Return* and *Quant-Style Return*.

- *Quant Alignment:* Report Recommendation × Abnormal Quant Rating, where Abnormal Quant Rating equals the stock's Quant Rating minus the cross-sectional mean Quant Rating on the same day.
- *Fundamental Score:* ChatGPT-based evaluation of report depth across six dimensions: strategy analysis, accounting analysis, valuation, industry analysis, firm-specific KPIs, and management scrutiny. Each dimension is scored 0 (not mentioned), 1 (brief), or 2 (detailed). See Appendix C for rubric details.
- *Report Length:* The natural log of the total word count in the report.
- *Report Similarity:* The average cosine similarity to all other reports on the same stock written within the prior 90 days.
- *Bio Words Sophistication:* We count the following words within each contributor's self-reported 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 Medium) if the bio contains one of the words, and 3 (or High) if the bio contains two or more of the words.
    - Appendix E provides an example of Bios with low and high *Bio Sophistication* scores.
- *Bio GPT Sophistication:* We tasked ChatGPT with rating contributor bios for quantitative skill using a scale ranging from 1 to 10. We set Bio *GPT Sophistication* to 1 (or Low) if the bio is ranked in the bottom tercile of the distribution, to 2 (or Medium) if the bio is ranked in the middle tercile of the distribution, and to 3 (or High) if the bio is ranked in the top tercile of the distribution.
    - Appendix E provides an example of Bios with low and high *GPT Sophistication* scores. The Appendix also provides ChatGPT's rationale for the ranking.
- *Quant Alignment Sophistication:* A contributor-level measure of pre-period recommendation alignment. For each recommendation, we define *Quant Alignment* as *Report Rec* × *Abnormal Quant Rating*, where *Abnormal Quant Rating* is the stock's Quant Rating minus the cross-sectional average Quant Rating on the same day. Using only pre-period observations (2016–2018), we randomly split each contributor's recommendations into an estimation and hold-out sample. We compute each contributor's average Quant Alignment in the estimation sample and sort contributors into terciles (Low, Medium, High).
- *Quant Sophistication (Composite): Bio Sophistication* + *GPT Sophistication* + *Quant Alignment Sophistication*.
    - We also split *Quant Sophistication* into low, medium, and high, based on tercile breakpoints.
- *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. (2024) algorithm.
- *RDay*: An indicator equal to one on days when contributor reports are published, and zero otherwise. Reports released after the market close are assigned to the following trading day.

Appendix E: Example of High versus Low Contributor Sophistication

High Quant Sophistication Bio:

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)
- ChatGPT 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.

Lower Quant Sophistication Bio:

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)
- ChatGPT 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.

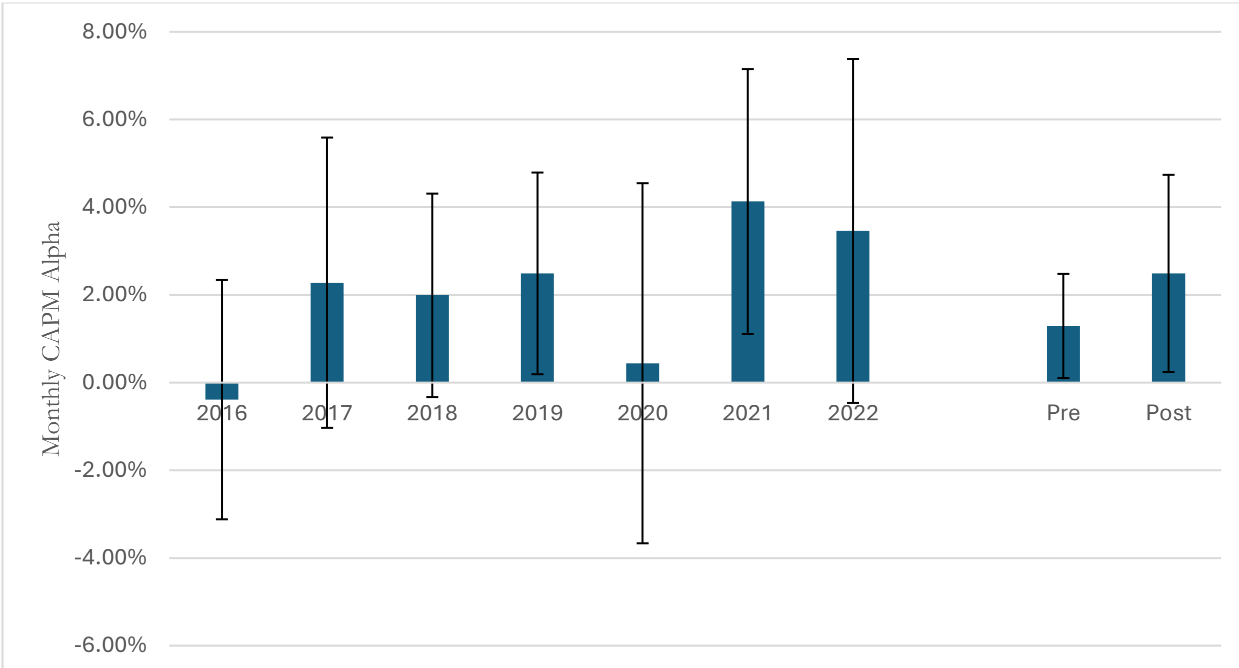


Figure 1: Returns to Long-Short Quant Recommendations Portfolios Over Time
This figure plots the value-weighted monthly CAPM alpha of the *Strong Buy* – *Strong Sell* portfolio (last column of Table 3), year by year and for the pre- (2016-2018) and post- (2020-2022) periods. Standard errors are computed from the time-series standard deviation, and the error bars report the 95% confidence intervals.

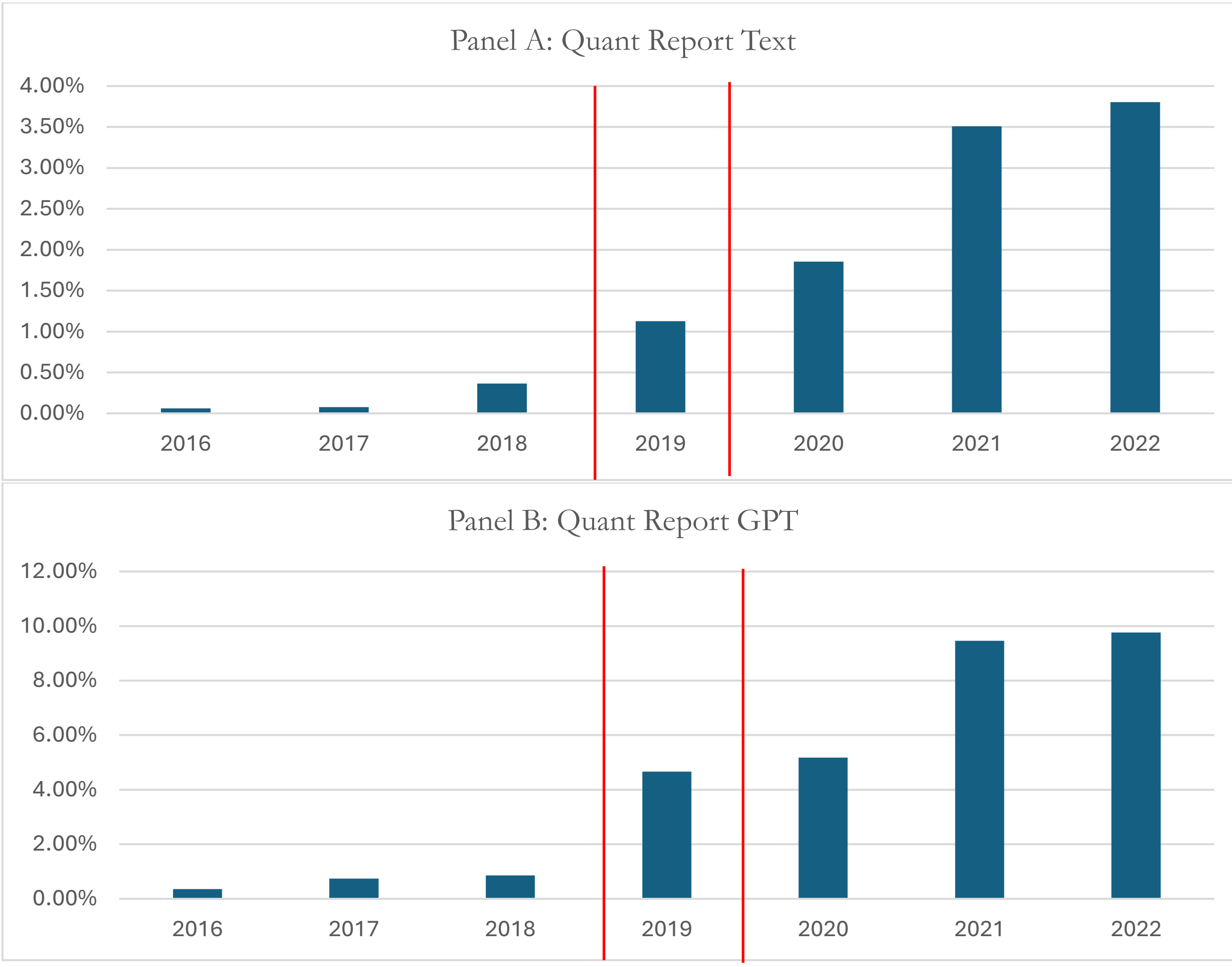


Figure 2: Frequency of *Quant Reports* by Year

Figure 2 plots the annual mean of the *Quant Report Text* and *Quant Report GPT* indicators in Panels A and B. *Quant Report Text* equals one if a report contains any of the following expressions (including minor variations): "quant," "factor grade," "value grade," "growth grade," "profitability grade," "momentum grade," or "revisions grade". *Quant Report GPT* equals one if ChatGPT classifies the report as making direct use of the SA Quant Ratings or factor grades. The red vertical line separates the pre-rollout period (2016–2018) from the post-rollout period (2020–2022).

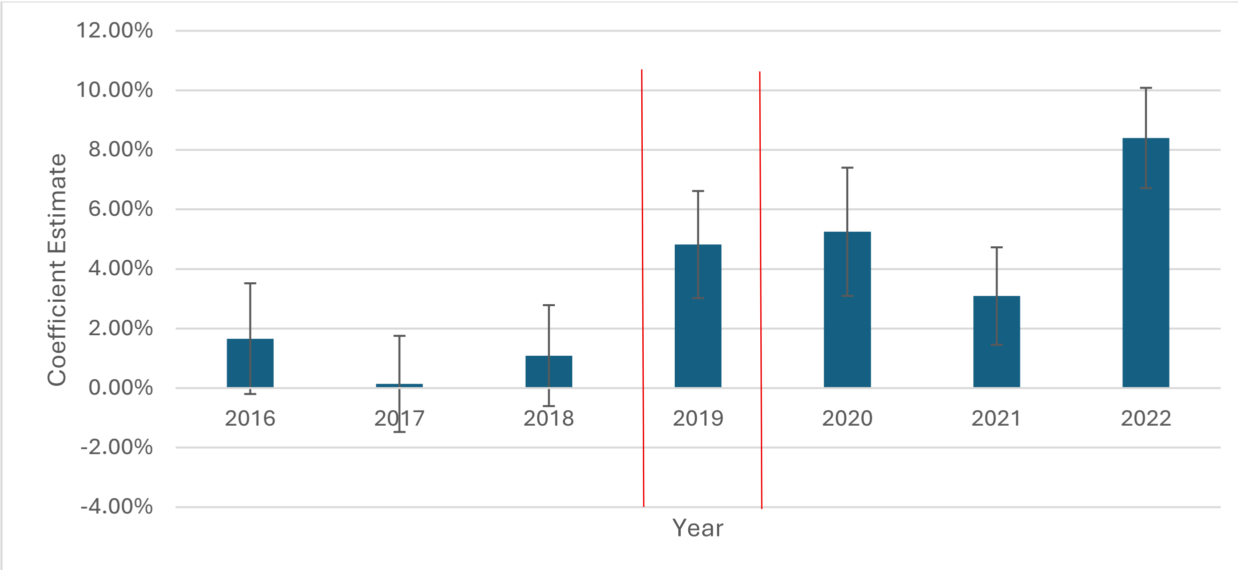
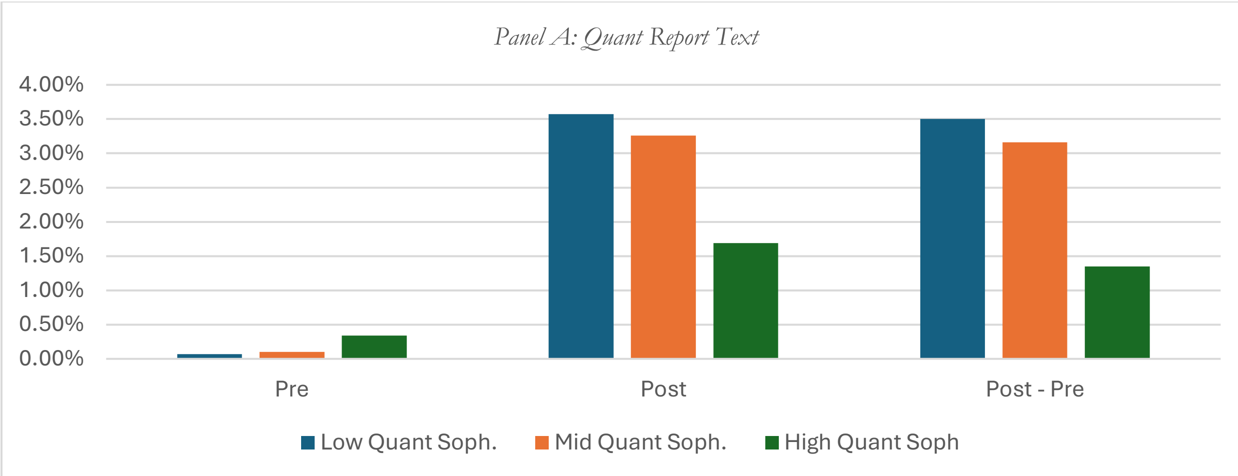


Figure 3: SA Report Recommendations and Quantitative Ratings by Year
This figure repeats the analysis in Specification 3 of Table 4 after replacing *Quant Rating* and *Quant Rating*× *Post* with *Quant Rating* interacted with indicators for each year of the sample (2016-2022). The figure plots the estimates 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 vertical line separates the pre-rollout period (2016–2018) from the post-rollout period (2020–2022).



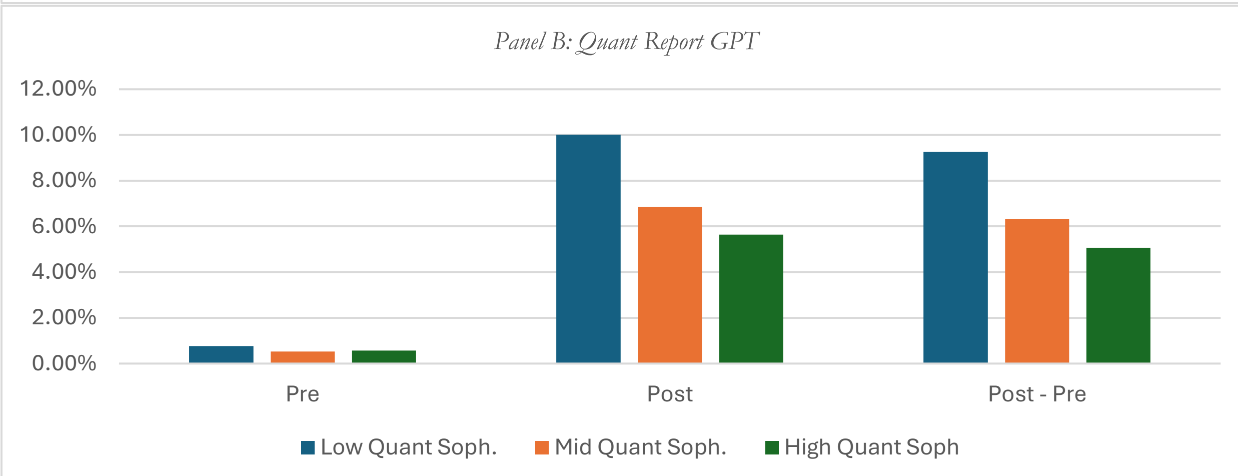


Figure 4: Frequency of *Quant Reports* by Contributor Quantitative Sophistication
This figure plots the percentage of reports classified as *Quant Report Text* (Panel A) and *Quant Report GPT* (Panel B) by *Contributor Quantitative Sophistication* in the pre-period (2016-2018) and post period (2020-2022). *Quant Report* is measured as either (i) *Quant Report Text* and *Quant Report GPT* are defined as in Figure 2. *Quantitative Sophistication* is the sum of three components: *Bio Words Sophistication* (the count of keywords in the author's bio associated with quantitative sophistication), *GPT Bio Sophistication* (ChatGPT's assessment of the bio's quantitative sophistication), and *Alignment Sophistication* (the average alignment between the recommendation and quant rating for a contributor across all reports in the pre-period estimation sample). Each sophistication measure is partitioned into three groups, where the lowest values are assigned a score of 1 and the highest values a score of 3. A contributor is classified as *Low Quantitative Sophistication* if their overall score is in the bottom tercile of the distribution, *High Quantitative Sophistication* if in the top tercile, and *Medium Quantitative Sophistication* otherwise.

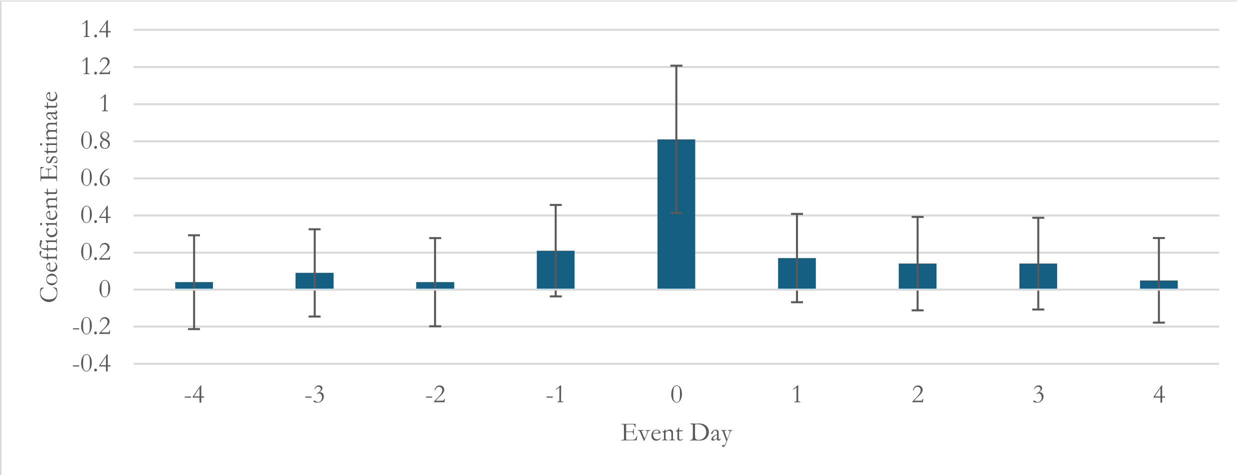


Figure 5: Retail Imbalances around SA Research Reports in Event Time

This figure plots retail imbalances in event-time in the days surrounding a research report. Specifically, we re-estimate Specification (4) of Table 11 after interacting *Quant Rating* × *Post* with nine indicators for coverage over the [–4,+4] window. For example, *Quant Rating* × *Post* × *Coverage*{*t–1*} captures the day before coverage, while *Quant Rating* × *Post* × *Coverage*{*t+1*} captures the day after. The estimates for each event day are reported as blue bars. Standard errors are clustered by firm and date, and the error bars report the 95% confidence intervals.

Table 1: Descriptive Statistics

This table reports summary statistics by year. Panel A reports the number of CRSP common stocks with share codes 10 or 11 (*CRSP Stocks*), the number of CRSP stocks with Quant Ratings on Seeking Alpha (*Stocks with Quant Ratings*), the number of CRSP stocks with at least one Seeking Alpha research report (*Stocks with Research Reports*), the total number of Seeking Alpha research reports on CRSP stocks (*Research Reports*), the number of Seeking Alpha research reports on stocks with Quant Ratings (*Reports on stocks with Quant Ratings*), and the percentage of report recommendations classified as buy and sell recommendations (*Pct. Buy* and *Pct. Sell*). We classify a report recommendation as buy if the author rating is "Buy" or "Strong Buy," and as sell if the author rating is "Sell" or "Strong Sell". Panel B reports summary statistics for the distribution of SA's Quant Ratings (ranging from 1 to 5). We present the mean and standard deviation of the Quant Ratings, along with the fraction of stocks rated as *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).

Panel A: Sample Size and Report Recommendations

Year	*CRSP Stocks*	*Stocks with Quant Ratings*	*Stocks with Research Reports*	*Research Reports*	*Reports on stocks with Quant Ratings*	*Pct. Buy*	*Pct. Sell*
2016	4,020	2,099	2,292	21,758	16,733	41.14%	7.38%
2017	3,943	2,244	2,169	21,395	17,274	41.35%	5.34%
2018	3,950	2,461	2,199	17,716	14,133	50.17%	5.07%
2019	3,952	2,968	2,229	16,080	13,349	61.02%	14.83%
2020	4,083	2,872	2,538	17,158	15,495	58.50%	11.63%
2021	4,774	3,061	3,047	17,885	14,704	64.00%	7.90%
2022	4,742	3,543	3,097	22,539	21,157	59.54%	8.63%
Average	4,209	2,750	2,510	19,219	16,121	53.67%	8.68%

Panel B: Distribution of Quant Ratings and Quant 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%	10.33%	9.20%
2017	2.92	0.88	7%	8%	64%	11.21%	9.68%
2018	2.93	0.88	8%	7%	65%	10.35%	9.59%
2019	2.92	0.89	7%	8%	63%	11.07%	9.95%
2020	2.96	0.87	7%	8%	65%	10.28%	8.77%
2021	2.99	0.91	9%	10%	62%	9.74%	9.23%
2022	2.96	0.92	9%	10%	61%	10.06%	10.01%
Average	2.95	0.89	8%	8%	64%	10.44%	9.49%

Table 2: Quant Ratings and Academic Anomalies

This table reports estimates from the following regression:

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

Quant Rating is the quantitative rating provided by Seeking Alpha, measured at the end of month *t*. In Specification 1, *Net Anomaly* is computed from the 118 return-predictive anomalies identified by Jensen, Kelly, and Pedersen (2023). It equals the number of anomalies for which a stock is assigned to the high-expected-return leg minus the number for which it is assigned to the low-expected-return leg. 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 Anomaly	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 Quant Recommendations

This table examines returns to portfolios sorted on SA Quant Recommendations, derived from the *Quant Ratings* as follows: Strong Sell if *Quant Rating* < 1.5, Sell if 1.5 ≤ *Quant Rating* < 2.5, Hold if 2.5 ≤ *Quant Rating* < 3.5, Buy if 3.5 ≤ *Quant Rating* < 4.5, and Strong Buy if *Quant Rating* ≥ 4.5. At the end of each month from December 2015 through November 2022, we assign stocks to these five portfolios based on their Quant Recommendation. We report average monthly returns in the month following portfolio formation, from 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 of monthly returns, 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: Quant Ratings and Report Recommendations

This table reports estimates from the following panel regression:

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

The dependent variable, *Report Rec*, 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 and 5 repeat the analysis in Specification 3 after partitioning *Quant Rating* × *Post* into *Quant Rating* × *Post* × *No Quant Report* and Quant *Rating* × *Post* × *Quant Report. Quant Report* is defined in two ways: (i) *Quant Report Text* (Specification 4), an indicator equal to one if a report contains any of the following expressions (including minor variations): "quant," "factor grade," "value grade," "growth grade," "profitability grade," "momentum grade," or "revisions grade"; and (ii) *Quant Report GPT* (Specification 5), an indicator equal to one if ChatGPT classifies the report as making direct use of the SA Quant Ratings or factor grades. *No Quant Report* equals one for all other reports. 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. Coefficients are multiplied by 100 for readability.

	[1]	[2]	[3]	[4]	[5]
Quant Rating	0.94	0.03	1.08	1.08	1.08
	(0.99)	(0.05)	(1.91)	(1.91)	(1.91)
Quant Rating × *Post*	5.46	4.16	4.94		
	(3.81)	(3.95)	(5.30)		
Quant Rating × *Post* × *No Quant Report Text*				4.53	
				(4.77)	
Quant Rating × *Post* × *Quant Report Text*				14.98	
				(8.53)	
Post × *Quant Report Text*				-3.38	
				(-1.67)	
Quant Rating × *Post* × *No Quant Report GPT*					4.56
					(5.90)
Quant Rating × *Post* × *Quant Report GPT*					8.64
					(5.88)
Post × *Quant Report GPT*					0.57
					(0.46)
Quant Rating × *Post (Quant Report – No Quant)*				10.45	4.08
				(5.93)	(3.43)
Observations	99,121	99,121	99,121	99,121	99,121
Sector × Date FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No	No
Contributor FE	No	No	Yes	Yes	Yes
Mean Dep Variable	0.42	0.42	0.42	0.42	0.42

Table 5: Estimated Quant Ratings and Report Recommendations: Covered vs. Not Covered Stocks

This table reports estimates from the following panel regression:

$$Report\ Rec_{it} = \alpha + \beta_1 Est.Quant\ Rating_{it} \times Covered_{it} + \beta_2 Est.Quant\ Rating_{it} \times Not\ Covered_{it} + \beta_3 Est.Quant\ Rating_{it} \times Post_t \times Covered_{it} + \beta_4\ Est.Quant\ Rating_{it} \times Post_t \times Not\ Covered_{it} + FE + \varepsilon_{it}.$$

Report Rec, *Post*, and *FE* are defined as in Table 4. *Est. Quant Rating* is an estimated Quant Rating, the construction of which is described in Appendix D. *Covered* is an indicator equal to one if the stock has a Quant Rating, while *Not Covered* equals one if the stock does not have a Quant Rating. Specifications 4-6 limit the sample of stocks with Quant Ratings to stocks with IBES analyst coverage of less than or equal to 5, 3, and 1 analyst, respectively. % *Not Covered* is the fraction of firms without a Quant Rating. Standard errors are clustered by firm and date, and t-statistics are reported in parentheses. Coefficients are multiplied by 100 for readability.

	[1]	[2]	[3]	[4]	[5]	[6]
Est. Quant Rating × *Covered*	1.38	0.12	1.29	-1.02	-0.62	2.89
	(0.98)	(0.17)	(1.82)	(-0.49)	(-0.29)	(1.18)
Est. Quant Rating × *Not Covered*	9.36	5.31	7.93	8.90	8.86	9.02
	(2.94)	(1.55)	(3.30)	(3.11)	(3.07)	(3.62)
Est. Quant Rating × *Covered* × *Post*	4.39	4.29	4.16	9.03	10.6	8.81
	(2.14)	(3.30)	(3.44)	(3.79)	(3.55)	(2.98)
Est. Quant Rating × *Not Covered* × *Post*	-1.17	-2.41	-0.40	-1.64	-1.55	-0.04
	(-0.28)	(-0.58)	(-0.12)	(-0.41)	(-0.39)	(-0.04)
Covered × *Post*	0.01	-5.69	0.26	-2.12	-0.52	3.22
	(0.35)	(-1.55)	(0.81)	(-0.50)	(-0.11)	(0.88)
Covered	0.03	13.86	1.92	10.56	9.57	8.6
	(0.66)	(4.76)	(0.78)	(3.28)	(2.49)	(3.14)
Covered Sample	All	All	All	IBES Coverage ≤5	IBES Coverage ≤3	IBES Coverage≤1
Sector × Date FE	Yes	Yes	Yes	No	No	No
Firm FE	No	Yes	No	No	No	No
Contributor FE	No	No	Yes	Yes	Yes	Yes
Observations	102,332	102,332	102,332	18,680	11,963	5,977
% Not Covered	4.04%	4.04%	4.04%	21.32%	32.40%	60.70%
Month FE	Absorb	Absorb	Absorb	Yes	Yes	Yes

Table 6: Quant Ratings and ETF Report Recommendations

This table reports estimates from the following panel regression:

$$Report\ Rec\ ETF_{it} = \alpha + \beta_1 Quant\ Rating\ ETF_{it} + \beta_2 Quant\ Rating\ ETF_{it} \times Post\ ETF_t + FE + \varepsilon_{it.}$$

Report Rec ETF equals 1, -1, or 0 when a research report on an exchange-traded fund (ETF) includes a buy, sell, or hold recommendation, respectively. *Quant Rating ETF* is the ETF's Quant Rating, and *Post* ETF is equal to one for reports published after the rollout of ETF Quant Ratings (June 2021 – December 2022) and zero for reports published 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. Specification 4 repeats the analysis in Specification 3 after including reports published during the rollout event months of January-May 2021 and 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 rollout of ETF Quant Ratings (i.e., June 2021 through December 2021). Standard errors are clustered by ETF and date, and t-statistics are reported in parentheses. Coefficients are multiplied by 100 for readability.

	[1]	[2]	[3]	[4]
Quant Rating ETF	4.08	3.30	4.34	
	(2.89)	(2.12)	(3.25)	
Quant Rating ETF × Post ETF	6.11	6.21	5.65	
	(2.96)	(3.35)	(3.03)	
Quant Rating ETF × [-16, -13]				4.71
				(1.63)
Quant Rating ETF × [-12, -8]				4.99
				(2.36)
Quant Rating ETF × [-7,-3]				3.03
				(1.50)
Quant Rating ETF × [-2,2]				3.37
				(1.41)
Quant Rating ETF × [3,9]				8.61
				(4.58)
Quant Rating ETF × [10,15]				12.46
				(7.44)
Quant Rating ETF × [16,21]				8.89
				(5.10)
Observations	7,442	7,442	7,442	8,428
Asset Class × Date FE	Yes	Yes	Yes	Yes
ETF FE	No	Yes	No	No
Contributor FE	No	No	Yes	Yes
Mean Dep Variable	0.29	0.29	0.29	0.29

Table 7: Quant Ratings and Recommendation Informativeness

Panel A reports estimates from the following panel regression:

$$Rec\ Informativeness_{it} = \alpha + \beta_1 Post_t + \varepsilon_{it}.$$

In Specification 1, *Rec Informativeness* is *Total Return*, defined as the buy-and-hold market-adjusted stock return from day t+1 to day t+63, multiplied by the report recommendation (equal to one for buy recommendations and negative one for sell recommendations). Reports recommending "hold" are excluded from the analysis. In Specifications 2 and 3, we decompose *Total Return* into two components: a component attributable to the average return of stocks with similar quantitative ratings (*Quant-Style Return*) and a residual component (*Quant-Adjusted Return*). Both measures are described in detail in Appendix D. Panels B and C include interactions between *Post* and *Quant Report Text* and *Quant Report GPT*, respectively. Both variables are defined as in Table 4. Panel D adds *Quant Alignment* × *Pre* and *Quant Alignment* × *Post*, where *Quant Alignment* is defined as *Abnormal Quant Rating* × *Sign*. *Abnormal Quant Rating* is the stock's Quant Rating minus the cross-sectional average Quant Rating on the same day, and *Sign* equals one for buy recommendations and negative one for sell recommendations. In Panels A–C, the sample consists of 57,767 report recommendations. In Panel D, which requires non-missing *Quant Alignment*, the sample consists of 57,002 report recommendations. Standard errors are clustered by firm and month, and t-statistics are reported in parentheses.

	Total Return	*Quant-Style Return*	*Quant-Adjusted Ret*
	[1]	[2]	[3]
Panel A: Baseline Test			
Post	-0.29%	0.01%	-0.30%
	(-0.49)	(0.05)	(-0.65)
Panel B: Quant Report Text			
Post	-0.30%	-0.04%	-1.18%
	(-0.47)	(-0.17)	(-1.24)
Post × *Quant Report Text*	0.49%	1.64%	-0.26%
	(0.53)	(4.85)	(-0.50)
Panel C: Quant Report GPT			
Post	-0.37%	-0.07%	-0.30%
	(-0.56)	(-0.29)	(-0.56)
Post × *Quant Report GPT*	0.93%	0.94%	-0.01%
	(1.85)	(4.40)	(-0.21)
Panel D: Quant Alignment			
Post	-0.55%	-0.04%	-0.50%
	(-0.97)	(-0.42)	(-0.94)
Quant Alignment × *Pre*	0.92%	1.52%	-0.60%
	(1.55)	(4.31)	(-1.30)
Quant Alignment × *Post*	2.17%	1.73%	0.44%
	(2.40)	(2.46)	(1.22)
Alignment (Post – Pre)	1.24%	0.21%	1.04%
	(1.11)	(0.26)	(1.60)

Table 8: Quant Ratings and Research Report Attributes

Table 8 parallels the recommendation informativeness tests of Table 7 by applying the same empirical structure to three text-based report attributes**:** *Fundamental Score,* based on ChatGPT's assessment of the depth of fundamental analysis in the report (see Appendix D); *Report Length*, defined as the natural log of the total word count in the report; and *Report Similarity*, defined as the average cosine similarity to all other reports on the same stock written in the prior 90 days. In Panels A–C, the sample consists of 98,208 report recommendations. In Panel D, which requires non-missing *Quant Alignment*, the sample consists of 85,328 report recommendations. Standard errors are clustered by firm and month, and t-statistics are reported in parentheses.

	Fundamental Score	*Report Length*	*Report Similarity*
	[1]	[2]	[3]
Panel A: Baseline Test			
Post	0.10	0.20	0.05
	(9.89)	(14.65)	(15.51)
Panel B: Quant Report Text			
Post	0.10	0.19	0.06
	(9.77)	(14.45)	(15.51)
Post × Quant Report Text	0.03	0.08	-0.01
	(3.38)	(5.25)	(-2.77)
Panel C: Quant Report GPT			
Post	0.10	0.19	0.06
	(9.82)	(14.45)	(15.60)
Post × Quant Report GPT	0.01	0.04	-0.01
	(1.22)	(3.54)	(-5.40)
Panel D: Quant Alignment			
Post	0.10	0.20	0.05
	(9.90)	(14.67)	(16.00)
Quant Alignment × Pre	-0.45	-0.02	-0.01
	(-0.92)	(-2.15)	(-5.14)
Quant Alignment × Post	0.94	-0.01	0.00
	(4.17)	(-1.55)	(-2.48)
Alignment (Post – Pre)	1.40	0.01	0.01
	(2.55)	(0.82)	(2.40)

Table 9: Contributor Quantitative Sophistication and Recommendation-Quant Rating Alignment

This table estimates Specification 1 of Table 4 separately for contributors classified into Low, Medium, and High *Quantitative Sophistication* terciles, and reports the corresponding coefficient estimates in Specifications 1-3. Specification 4 tests whether the estimates for the Low group differ significantly from those for the High group. In Panel A, contributors are classified using a Co*mposite Sophistication* measure, computed by summing three individual measures: (i) *Bio Words Sophistication*, defined as the number of keywords in the contributor's bio associated with quantitative or finance expertise; (ii) *Bio GPT Sophistication*, defined as ChatGPT's assessment of the quantitative sophistication of the author's bio; and (iii) *Quant Alignment* Sophistication, a revealed-behavior measure based on the relation between a contributor's recommendations and Quant Ratings estimated on a pre-period estimation sample (see Appendix D for details). Panels B–D classify contributors based on the individual measures. Panel D's sample includes observations from the post-period and from a pre-period holdout sample. Standard errors are clustered by firm and date, and t-statistics are reported in parentheses. Coefficients are multiplied by 100 for readability.

	Low	*Medium*	*High*	*Low - High*
	[1]	[2]	[3]	[4]
Panel A: Composite Sophistication				
Quant Rating	-1.02	2.34	4.09	-5.11
	(-1.69)	(2.70)	(4.74)	(-4.94)
Quant Rating × Post	8.36	7.71	-0.08	8.44
	(6.67)	(5.02)	(-0.05)	(4.63)
Obs.	30,281	21,048	25,326	55,607
Panel B: Bio Words Sophistication				
Quant Rating	1.14	-1.00	6.60	-5.46
	(2.15)	(-1.21)	(5.18)	(-4.06)
Quant Rating × Post	6.92	6.01	-1.23	8.15
	(6.17)	(4.58)	(-0.52)	(3.23)
Obs.	38,867	23,004	13,327	52,194
Panel C: Bio GPT Sophistication				
Quant Rating	-2.69	1.81%	1.11%	-3.80%
	(-2.47)	(2.75)	(1.41)	(-2.97)
Quant Rating × Post	12.73	4.57%	4.69%	8.03%
	(4.83)	(3.81)	(3.31)	(2.73)
Obs.	12,693	32,376	25,821	38,514
Panel D: Quant Alignment Sophistication				
Quant Rating	-5.25	2.87	6.14	-11.44
	(-4.20)	(2.27)	(4.78)	(-6.36)
Quant Rating × Post	9.88	1.15	2.31	7.56
	(5.73)	(0.63)	(1.31)	(3.12)
Obs.	16,560	16,445	16,480	33,040

Table 10: Contributor Quantitative Sophistication and Recommendation Informativeness

Table 10 extends the recommendation informativeness tests in Table 7 by examining whether the post-rollout changes in recommendation informativeness are larger for contributors in the bottom tercile of *Quantitative Sophistication* relative to contributors in the top tercile. Recommendations by contributors in the middle group are excluded. *Low Soph* is an indicator variable equal to one for recommendations by contributors in the bottom tercile. Panels A–D report results for the composite *Quantitative Sophistication* measure and its three components (see Appendix D for details). Standard errors are clustered by firm and month, and t-statistics are reported in parentheses.

	Total Return	*Quant-Style Returns*	*Quant-Adj Returns*
	[1]	[2]	[3]
Panel A: Composite Sophistication			
Post	0.94%	0.24%	0.70%
	(1.19)	(1.22)	(1.01)
Low Soph	-0.36%	-0.25%	-0.11%
	(-0.89)	(-2.74)	(-0.28)
Post × *Low Soph*	2.01%	0.59%	1.43%
	(2.54)	(2.63)	(2.08)
Obs.	31,266	31,266	31,266
Panel B: Bio Words Sophistication			
Post	0.74%	0.14%	0.60%
	(0.88)	(0.57)	(0.86)
Low Soph.	-0.32%	0.01%	-0.33%
	(-0.77)	(0.09)	(-0.86)
Post × *Low Soph*	1.59%	0.38%	1.21%
	(1.48)	(1.14)	(1.39)
Obs.	28,748	28,748	28,748
Panel C: Bio ChatGPT Sophistication			
Post	0.03%	0.21%	-0.18%
	(0.02)	(0.70)	(-0.15)
Low Soph.	0.47%	0.18%	0.29%
	(0.99)	(1.75)	(0.60)
Post × *Low Soph*	1.43%	0.59%	0.84%
	(1.27)	(2.62)	(0.78)
Obs.	21,631	21,631	21,631
Panel D: Quant Alignment Sophistication			
Post	1.15%	0.46%	0.69%
	(1.36)	(2.19)	(0.94)
Low Soph.	-1.19%	-1.09%	-0.11%
	(-2.40)	(-6.33)	(-0.21)
Post × *Low Soph*	2.24%	0.85%	1.38%
	(2.51)	(3.15)	(1.68)
Obs.	19,777	19,777	19,777

Table 11: Quant Ratings and Retail Order Imbalances

This table reports estimates from the following panel regression:

$$Retail\ Imb_{it} = \alpha + \beta_1 Quant\ Rating_{it} + \beta_2(Quant\ Rating_{it} \times Post_t) + \beta_3 RDay_{it} + \beta_4 RDay_{it} \times Post_t + \beta_5(RDay_{it} \times Quant\ Rating_{it}) + \beta_6(RDay_{it} \times Quant\ Rating_{it} \times Post_t) + FE + \varepsilon_{it}.$$

The dependent variable, *Retail Imb*, is the difference between daily retail purchase volume and retail sell volume, scaled by total retail volume. Retail trading is identified following Barber et al. (2024). *Quant Rating* and *Post* are defined as in Table 4. *FE* denotes firm and date fixed effects. *RDay* is equal to one on days when reports are published, and zero otherwise. Specification 2 augments the baseline by including the interaction terms *RDay* × *Report Rec* and *RDay* × *Report Rec* × *Post,* where *Report Rec* is the average of all recommendations issued on that day. Specification 3excludes reports published around attention-grabbing events, defined as those published in the three-day window around earnings announcements [−1,+1] or for firms in the 95th percentile of either absolute returns or trading volume (relative to their prior-year distributions). Specification 4 adds firm × year fixed effects. Standard errors are clustered by firm and date, and t-statistics are reported in parentheses.

	[1]	[2]	[3]	[4]
Quant Rating	-0.31	-0.31	-0.28	-0.61
	(-4.38)	(-4.38)	(-3.78)	(-6.38)
Quant Rating × *Post*	0.12	0.12	0.10	0.17
	(1.37)	(1.37)	(1.11)	(1.50)
RDay	3.13	2.76	3.62	2.86
	(5.99)	(5.35)	(6.26)	(5.33)
RDay× *Post*	-3.34	-3.21	-4.13	-2.92
	(-5.03)	(-4.53)	(-5.56)	(-4.25)
RDay × *Quant Rating*	-0.64	-0.64	-0.91	-0.73
	(-4.09)	(-4.13)	(-5.24)	(-4.62)
RDay × *Quant Rating* × *Post*	0.87	0.85	1.13	0.81
	(4.24)	(4.17)	(5.00)	(3.98)
RDay × *Report Rec*		0.99	1.04	0.77
		(6.17)	(5.53)	(4.07)
RDay × *Report Rec* × *Post*		-0.39	-0.35	-0.05
		(-1.79)	(-1.43)	(-0.21)
Date FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Firm × Year FE	No	No	No	Yes
Exclude Attention-Grabbing Events	No	No	Yes	Yes
Observations (Firm-Days)	3,600,095	3,600,095	3,188,018	3,188,018

Table 12: Quant Ratings and the Informativeness of Daily Retail Trading

This table examines the informativeness of daily retail trading in the pre- and post-period. Panel A focuses on days when research reports are published (149,522 firm-day observations). Panel B focuses on days when no research reports are published (3,456,132 firm-day observations). In Column 1, our measure of retail trading informativeness is *Total Return*, defined as the buy-and-hold, market-adjusted stock return from day t+1 to day t+63, multiplied by one (minus one) when retail order imbalance is positive (negative). Columns 2 and 3 decompose *Total Return* into a component attributable to the average return of stocks with similar Quant Ratings (*Quant-Style Return*) and a residual component (*Quant-Adjusted Return*). Both measures are described in detail in Appendix D. Standard errors are clustered by firm and month, and t-statistics are reported in parentheses.

	Total Return	*Quant-Style Returns*	*Quant-Adj Returns*
	[1]	[2]	[3]
Panel A: Days with Research Reports			
Pre	0.14%	0.03%	0.11%
	(1.05)	(0.99)	(0.87)
Post	0.21%	0.15%	0.05%
	(1.20)	(2.93)	(0.31)
Post - Pre	0.07	0.12	-0.06
	(0.29)	(2.14)	(-0.27)
Panel B: Days without Research Reports			
Pre	0.11%	0.02%	0.10%
	(3.42)	(1.66)	(3.95)
Post	0.16%	0.04%	0.12%
	(2.07)	(1.30)	(2.09)
Post - Pre	0.05	0.02	0.03
	(0.60)	(0.74)	(0.40)

Internet Appendix for:

Quantitative Research on Main Street: Evidence from Seeking Alpha

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

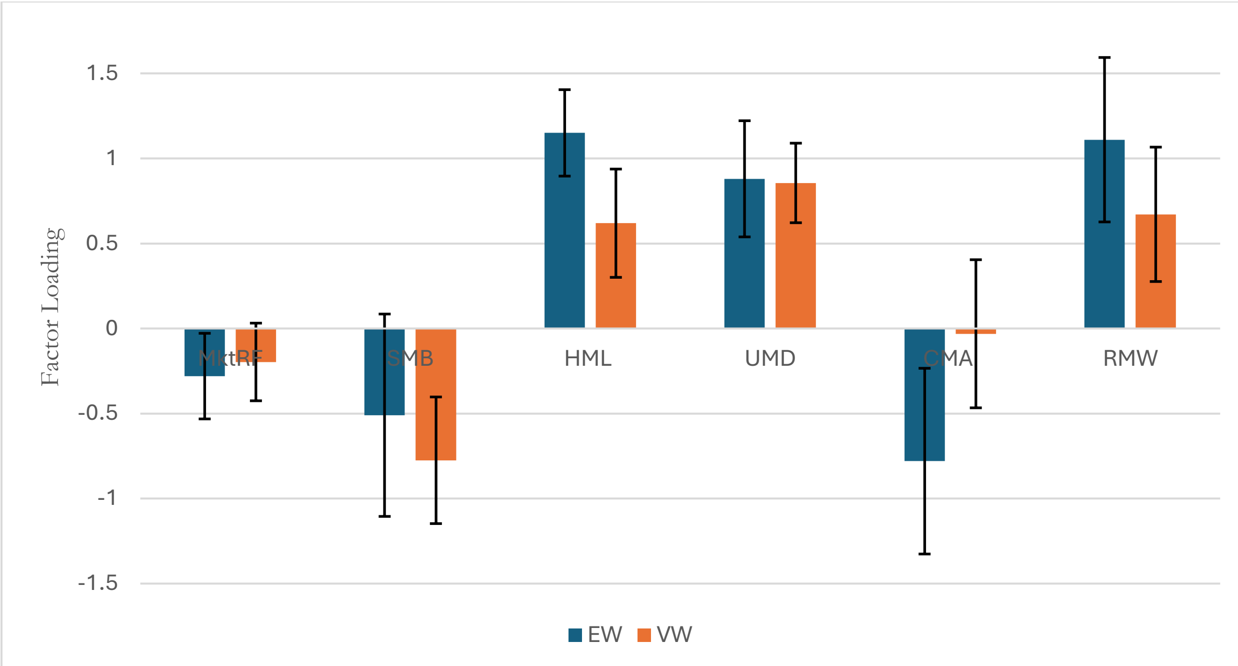


Figure IA.1: Factor Loadings of Long-Short Portfolio Sorted on SA Quant Recommendations

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 reported 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.

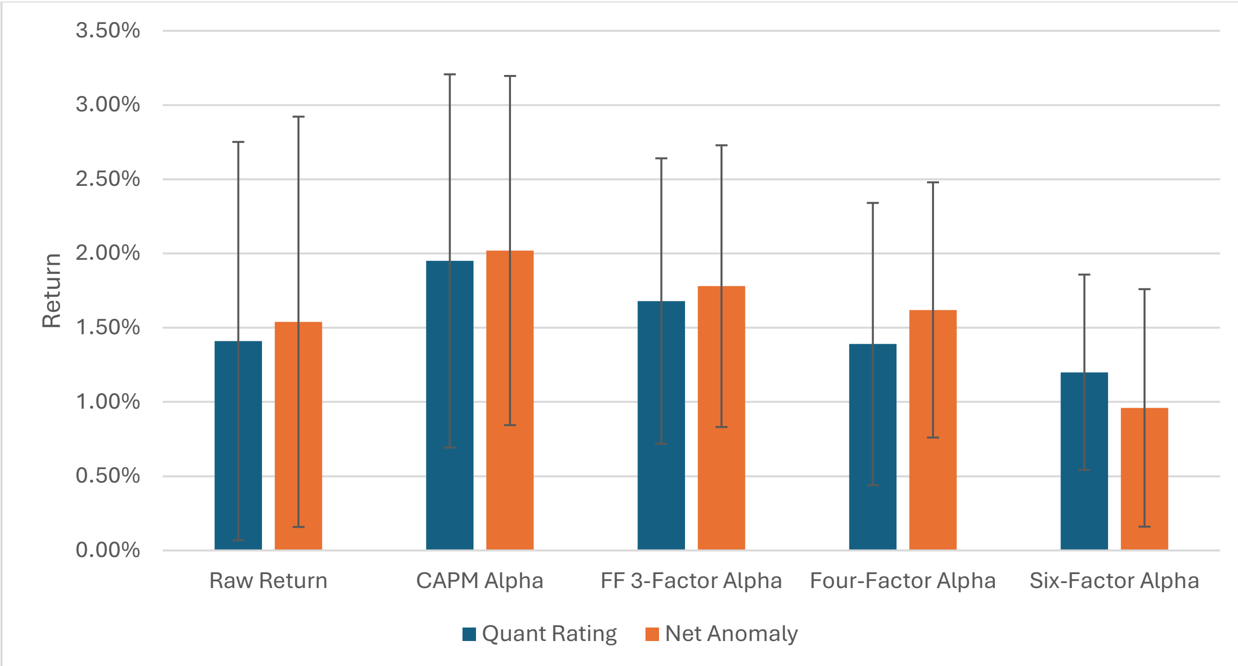


Figure IA.2: Return Predictability of SA Quant Recommendations versus Academic Anomalies
This figure reports the value-weighted returns to a strategy that buys stocks in the *Strong Buy* portfolio and shorts stocks in the *Strong Sell* portfolio. The blue bar reports the results based on sorting stocks 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), a composite measure developed by Jensen, Kelly, and Pedersen (2023) that aggregates many published academic anomalies. Portfolio breakpoints are chosen so that each portfolio contains the same proportion of stocks as the corresponding SA Quant Recommendation portfolio. 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 of monthly returns, and the error bars report the 95% confidence intervals.

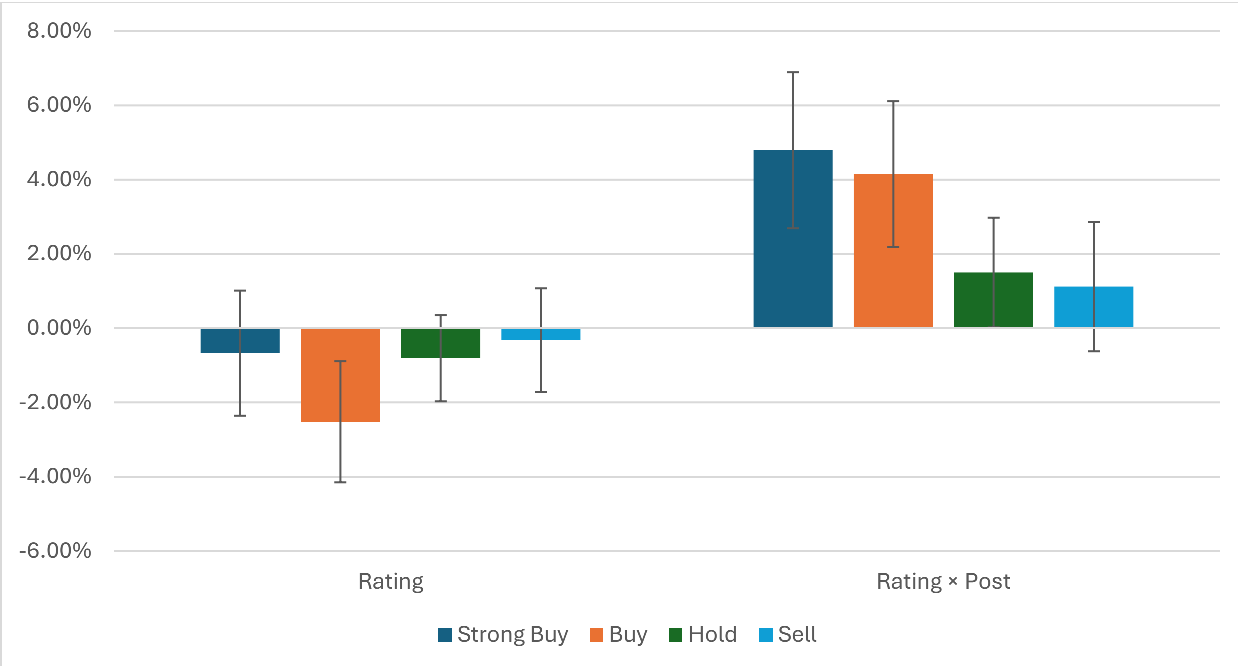


Figure IA.3: SA Coverage Decisions and Quant Recommendations

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 has 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-period (2020-2022) and zero for the pre-period (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.

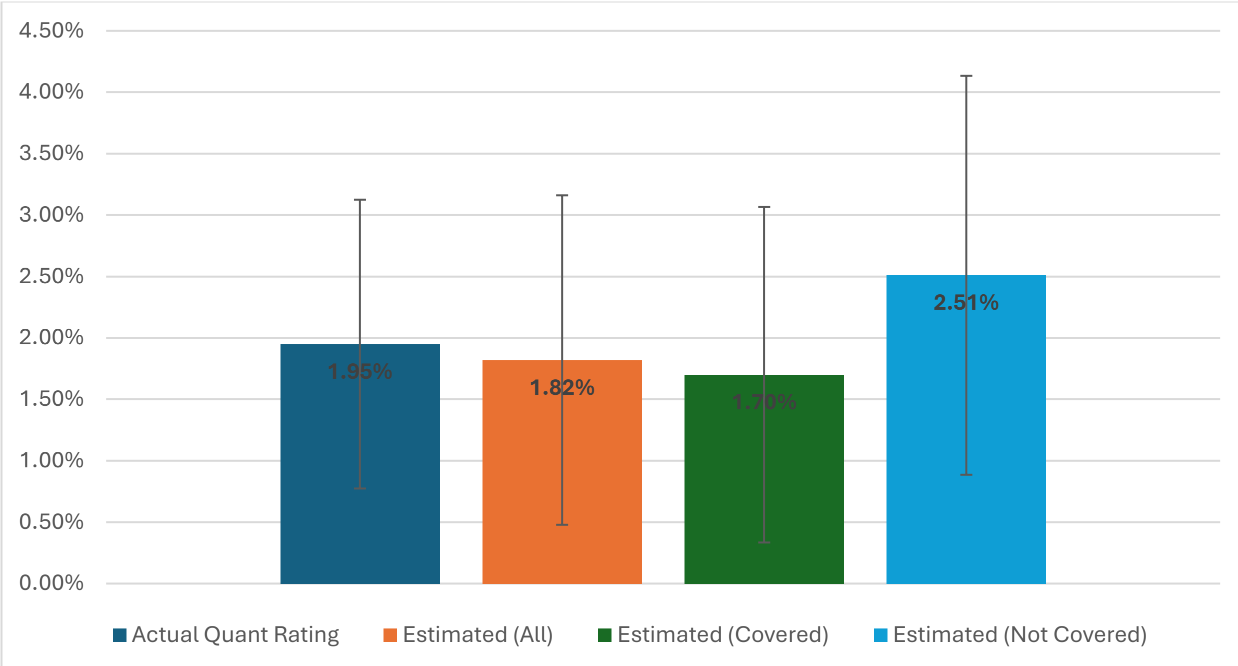


Figure IA.4. Return Predictability of Actual and Estimated Quant Ratings
This figure reports value-weighted CAPM alphas for long-short portfolios formed on actual and estimated Quant Ratings. "Actual Quant Rating" denotes portfolios formed using Seeking Alpha's official Quant Ratings. "Estimated" portfolios are formed using Quant Ratings predicted by the random forest model described in Appendix D. "Covered" and "Not covered" refer to firms with and without official Seeking Alpha Quant Ratings, respectively. Standard errors are computed from the time-series standard deviation of monthly returns, 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 each 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 positive 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: Variables Used to Construct Estimated Quant Rating

This table lists the predictor variables used to construct the Estimated Quant Rating, grouped by SA's Quant Factors.

Factor	Predictor Variable
Valuation	P/E Non-GAAP (TTM)
Valuation	P/E Non-GAAP (FWD)
Valuation	P/E GAAP (TTM)
Valuation	P/E GAAP (FWD)
Valuation	PEG GAAP (TTM)
Valuation	PEG Non-GAAP (FWD)
Valuation	EV / Sales (TTM)
Valuation	EV / Sales (FWD)
Valuation	EV / EBITDA (TTM)
Valuation	EV / EBITDA (FWD)
Valuation	EV / EBIT (TTM)
Valuation	EV / EBIT (FWD)
Valuation	Price / Sales (TTM)
Valuation	Price / Sales (FWD)
Valuation	Price / Book (TTM)
Valuation	Price / Book (FWD)
Valuation	Price / Cash Flow (TTM)
Valuation	Price / Cash Flow (FWD)
Valuation	Dividend Yield (TTM)
Growth	Revenue Growth (YoY)
Growth	Revenue Growth (FWD)
Growth	EBITDA Growth (YoY)
Growth	EBITDA Growth (FWD)
Growth	EBIT Growth (YoY)
Growth	EBIT Growth (FWD)
Growth	EPS Diluted Growth (YoY)
Growth	EPS Diluted Growth (FWD)
Growth	EPS GAAP Growth (YoY)
Growth	EPS GAAP Growth (FWD)
Growth	EPS FWD Long Term Growth (3-5Y CAGR)
Growth	Levered FCF Growth (YoY)
Growth	Free Cash Flow Per Share Growth Rate (FWD)
Growth	Operating Cash Flow Growth (YoY)
Growth	Operating Cash Flow Growth (FWD)
Growth	ROE Growth (YoY)
Growth	ROE Growth (FWD)
Growth	Working Capital Growth (YoY)
Growth	CAPEX Growth (YoY)
Growth	Dividend Per Share Growth (FWD)
Growth	1 Year Dividend Growth Rate (TTM)

Profitability	Gross Profit Margin (TTM)
Profitability	EBIT Margin (TTM)
Profitability	EBITDA Margin (TTM)
Profitability	Net Income Margin (TTM)
Profitability	Levered FCF Margin (TTM)
Profitability	Return on Common Equity (TTM)
Profitability	Return on Total Capital (TTM)
Profitability	Return on Total Assets (TTM)
Profitability	CAPEX / Sales (TTM)
Profitability	Asset Turnover Ratio (TTM)
Profitability	Cash From Operations (TTM)
Profitability	Cash Per Share (TTM)
Profitability	Net Income Per Employee (TTM)
Momentum	3M Price Performance
Momentum	6M Price Performance
Momentum	9M Price Performance
Momentum	1Y Price Performance
EPS Revision	FY1 Up Revisions (last 90 days)
EPS Revision	FY1 Down Revisions (last 90 days)

Table IA.3: 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.4: SA Report Recommendations and Quantitative Recommendations

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

	[1]	[2]	[3]
Strong Sell	1.69	2.05	2.26
	(0.83)	(1.24)	(1.41)
Sell	3.06	3.08	0.60
	(1.48)	(1.59)	(0.35)
Buy	8.00	1.23	4.73
	(2.64)	(0.72)	(3.17)
Strong Buy	3.86	2.08	3.68
	(1.75)	(1.35)	(2.89)
Strong Sell ×*Post*	-17.62	-12.17	-13.85
	(-6.01)	(-4.47)	(-5.47)
Sell ×*Post*	-8.33	-7.15	-7.65
	(-3.17)	(-3.18)	(-3.67)
Buy × *Post*	2.88	4.56	5.06
	(0.99)	(1.94)	(2.52)
Strong Buy × *Post*	5.84	2.35	5.54
	(2.31)	(1.09)	(2.92)
Observations	99,121	99,121	99,121
Sector × Date FE	Yes	Yes	Yes
Firm FE	No	Yes	No
Contributor FE	No	No	Yes
Mean Dep Variable	0.42	0.42	0.42

Table IA.5: SA Report Recommendations and Academic Anomalies

This table repeats 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	2.21	0.97	1.24
	(1.34)	(2.22)	(2.72)
Net Anomaly Negative	1.64	-0.29	-0.05
	(0.85)	(-0.56)	(-0.09)
Net Anomaly Positive × *Post*	1.38	2.04	2.31
	(0.88)	(3.28)	(3.77)
Net Anomaly Negative × *Post*	-2.31	-1.18	-0.40
	(-1.29)	(-1.96)	(-0.60)
(Positive - Negative) × *Post*	3.69	3.22	2.71
	(3.65)	(3.52)	(3.45)
Observations	95,133	95,133	95,133
Sector × Date FE	Yes	Yes	Yes
Firm FE	No	Yes	No
Contributor FE	No	No	Yes

Table IA.6: Returns to ETF Quant Ratings

At the end of each month, from November 2019 through August 2023, we sort exchange-traded funds (ETFs) into five based on their SA Quant 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 of monthly returns, 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.7: Quant Ratings and Recommendation Informativeness – Robustness

This table examines the sensitivity of the informativeness estimates of *Post* × *Quant Report GPT* from Panel C of Table 7. For reference, Row 1 reports the baseline estimates from Table 7. Rows 2-7 repeat the analysis after including different sets of fixed effects, and Rows 8 and 9 repeat the baselines analysis after changing the holding period from 63 days to either 21 days (Row 8) or 126 days (Row 9). Standard errors are clustered by firm and month, and t-statistics are reported in parentheses.

	Total Return	*Quant-Style Returns*	*Quant-Adj Returns*
	[1]	[2]	[3]
Panel A: Baseline Results			
1. Baseline (Table 7)	0.93%	0.94%	-0.01%
	(1.85)	(4.40)	(-0.21)
Panel B: Alternative Fixed Effects			
2. Time FE	0.20%	0.76%	-0.56%
	(0.38)	(3.47)	(-1.15)
3. Time × Sector FE	0.33%	0.83%	-0.50%
	(0.62)	(3.87)	(-0.99)
4. Author FE	0.96%	0.50%	0.46%
	(2.02)	(2.61)	(0.94)
5. Firm FE	0.69%	0.76%	-0.07%
	(1.41)	(3.31)	(-0.14)
6. Time × Sector & Author FE	0.77%	0.71%	0.06%
	(1.56)	(3.93)	(0.11)
7. Time × Sector & Firm FE	0.19%	0.62%	-0.43%
	(0.41)	(3.68)	(-0.90)
Panel C: Alternative Holding Periods			
8. 21-Day Holding Period	-0.14%	0.33%	-0.46%
	(-0.37)	(2.63)	(-1.43)
9. 126-Day Holding Period	1.84%	1.70%	0.14%
	(2.44)	(4.75)	(0.19)

Table IA.8: Quant Ratings and Research Report Attributes – Robustness

This table examines the sensitivity of the report attributes estimates of *Post* × *Quant Report GPT* from Panel C of Table 8 (with estimates multiplied by 100). For reference, Row 1 reports the baseline estimates from Table 8. Rows 2-7 repeat the analysis after including different sets of fixed effects. Standard errors are clustered by firm and month, and t-statistics are reported in parentheses.

	Fundamental Score	*Report Length*	*Report Similarity*
	[1]	[2]	[3]
Panel A: Baseline Results			
1. Baseline (Table 8)	0.85	3.63	-1.47
	(1.22)	(3.54)	(-5.40)
Panel B: Alternative Fixed Effects			
2. Time FE	0.89	3.19	-1.60
	(1.06)	(3.10)	(-6.00)
3. Time × Sector FE	1.29	3.28	-1.32
	(1.52)	(3.25)	(-5.23)
4. Author FE	2.94	3.16	-0.23
	(6.67)	(4.12)	(-1.03)
5. Firm FE	0.17	3.66	-0.57
	(0.20)	(3.19)	(-2.95)
6. Time × Sector & Author FE	2.74	2.93	-0.50
	(5.73)	(4.00)	(-2.82)
7. Time × Sector & Firm FE	0.61	3.30	-0.80
	(0.73)	(2.90)	(-4.17)

Table IA.9: Contributor Quantitative Sophistication and Recommendation Informativeness– Robustness

This table examines the sensitivity of the informativeness estimates of *Low Soph.* × *Post* from Panel A of Table 10. For reference, Row 1 reports the baseline estimates from Table 10. Rows 2-7 repeat the analysis after including different sets of fixed effects, and Rows 8 and 9 repeat the baseline analysis after changing the holding period from 63 days to either 21 days (Row 8) or 126 days (Row 9). Standard errors are clustered by firm and month, and t-statistics are reported in parentheses.

	Total Return	*Quant-Style Returns*	*Quant-Adj Returns*
	[1]	[2]	[3]
Panel A: Baseline Results			
1. Baseline (Table 10)	2.01%	0.59%	1.43%
	(2.54)	(2.63)	(2.08)
Panel B: Alternative Fixed Effects			
2. Time FE	1.76%	0.51%	1.25%
	(2.35)	(2.47)	(1.85)
3. Time × Sector FE	1.93%	0.58%	1.35%
	(2.20)	(2.89)	(1.70)
4. Author FE	1.91%	0.85%	1.06%
	(1.83)	(2.73)	(1.15)
5. Firm FE	2.38%	0.60%	1.78%
	(2.61)	(2.63)	(2.22)
6. Time × Sector & Author FE	2.61%	0.81%	1.80%
	(2.99)	(3.61)	(2.24)
7. Time × Sector & Firm FE	2.44%	0.67%	1.77%
	(2.55)	(3.43)	(2.02)
Panel C: Alternative Horizons			
8. 21-Day Holding Period	0.79%	0.28%	0.52%
	(1.88)	(2.70)	(1.34)
9. 126-Day Holding Period	1.53%	0.88%	0.64%
	(1.16)	(3.75)	(0.52)

Table IA.10: Quant Ratings and the Direction of Aggregate TAQ Trading

This table repeats the analysis in Table 11 after replacing retail order imbalances with *Aggregate TAQ Imb,* defined as the difference between total buy volume and total sell volume in TAQ, scaled by total trading volume. Trades are classified as buys or sells using the Lee and Ready (1991) algorithm. Standard errors are clustered by firm and date, and t-statistics are reported in parentheses.

	[1]	[2]	[3]	[4]
Quant Rating	0.26	0.26	0.26	0.17
	(6.72)	(6.72)	(6.48)	(3.15)
Quant Rating × *Post*	-0.13	-0.13	-0.13	-0.05
	(-2.67)	(-2.67)	(-2.64)	(-0.77)
RDay	1.67	1.53	1.19	1.03
	(6.15)	(5.71)	(4.01)	(3.66)
RDay × *Post*	-0.51	-0.46	-0.27	-0.35
	(-1.44)	(-1.29)	(-0.69)	(-0.97)
RDay × *Quant Rating*	-0.48	-0.48	-0.41	-0.3
	(-6.08)	(-6.10)	(-4.89)	(-3.62)
RDay × *Quant Rating* × *Post*	0.20	0.19	0.17	0.09
	(1.87)	(1.80)	(1.50)	(0.08)
RDay × *Rec.*		0.39	0.38	0.36
		(4.74)	(4.23)	(4.06)
RDay × *Post*		-0.16	-0.23	-0.21
		(-1.37)	(-1.80)	(-1.70)
Date FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Firm × Year FE	No	No	No	Yes
Exclude Attention-Grabbing Events	No	No	Yes	Yes
Observations (Firm-Days)	3,600,095	3,600,095	3,188,018	3,188,018