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Outperforming the market: a comparison of Star and NonStar analysts' investment strategies and recommendations

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We employ StarMine to investigate the impact of analyst recommendations on stock performance. We test whether star-ranked analysts generate abnormal returns and outperform non-stars in short and long portfolios. Utilizing buy-and-hold calendar-time portfolio methodology, we calculate portfolio alphas using various asset pricing models, including CPM, the Fama and French 3-factor model, and the Carhart 4-factor model. Results indicate that all analyst groups can generate abnormal returns exceeding the market average. Star-ranked analysts outperform non-stars in short portfolios by 0.5523% in monthly alpha, though no significant difference exists in long portfolio alphas. We also conduct regressor endogeneity tests and explore investor sentiment mechanisms by utilizing the GARCH model and frequency-domain causality analysis, with NASDAQ as a proxy for investor sentiment. These tests reveal that the momentum factor is exogenous, and investor sentiments have a statistically significant positive effect on stock return volatility, with changes occurring between 5 and 10 days. This research underscores the value of analyst insights for investors, validates StarMine's ranking effectiveness, and suggests market participants can benefit from incorporating analyst recommendations into their investment decisions. Our study makes a significant contribution to the existing literature by introducing a novel approach to understanding investor sentiment mechanisms through a causality model.

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Introduction

The efficient market hypothesis (EMH) by Fama (1965) states that if stock prices incorporate all available information in the market, it becomes challenging to leverage information for profit in such a highly efficient market (Li et al. 2017a). This process is explained by *random walk*, where changes in stock price are random. When new information arrives in the market, market participants are promptly informed and act upon the arrival of this new information. Several studies (De Bondt and Thaler, 1985; Brown et al. 1993) suggest that this new information could introduce uncertainty, leading to potential overreactions by investors who may sell or buy stocks in order to rebalance their investment portfolios. According to De Bondt and Thaler (1985) and Brown et al. (1993), this new information could lead to overreactions, prompting investors to sell or buy stocks to rebalance their investment portfolios. Thus, investors do react to the arrival of new information, which directly impacts the stock's performance. However, this explanation pertains to market reactions and does not directly challenge the EMH. The signaling theory suggests that analyst recommendations are useful in judging the underlying firm's value (Yasar et al. 2020). Any good news associated with the concerned firm may drive its stock prices. Similarly, bad news may drive its stock prices downward. It all suggests that analyst recommendations can influence stock performance due to information asymmetry and affect market efficiency.

The studies of Stickel (1995) and Womack (1996) argue that analysts' recommendations can potentially generate positive/negative market responses. Other studies also affirm that upside/downside changes in analysts' recommendations can be a source of positive or negative price drifts at the time of announcement (Barber et al. 2010; Vukovic et al. 2021 and 2020). With some evidence that analysts' recommendations do have some investment value, numerous studies have attempted to determine how the stock market responds to analysts with different attributes. Few studies examine the reputation of analysts and the success or failure of their stock-picking. (Emery and Li, 2009; Fang and Yasuda, 2009, 2014; Kucheev and Sorensson, 2019). The study of Li et al. (2017b) indicate that analysts can play a vital role in shaping the rival responses of target firms. Beside this, in some recent studies, authors utilize turnover rates to characterize the sentiment of investors (Liu et al. 2019).

The aim of this study is to explore whether the star status of an analyst can generate abnormal returns. Although there has been a large amount of research on the analysts' reputation (Fang and Yasuda, 2014; Kucheev and Sorensson, 2019; Su et al. 2019) and market reactions, many of the findings have been controversial. Moreover, to the best of the study's knowledge, the majority of scholars use Institutional Investor Magazine rankings data to determine the star status of an analyst. Analysts with "star" status have achieved a high level of success in providing valuable insights and generating excess returns through their stock recommendations.

The present study has the following characteristics: First, the study examines the NASDAQ market, where participants trade through a dealer as opposed to directly with one another (as in the case of an auction market, like the NYSE). It is a modified capitalization-weighted index, and this approach allows for more diversification. Second, the present study use StarMine analyst rankings, while most of the earlier studies analyze Institutional Investor Magazine analyst rankings. The Institutional Investor Magazine analyst rankings are determined by institutional investors' votes and input. StarMine analyst rankings, on the other hand, are based on a proprietary quantitative algorithm. As a result, StarMine analyst rankings are calculated using a more quantitative and data-driven approach. Third, unlike Kucheev and Sorensson (2019), the analysis does not divide the portfolios into two time periods depending on the year in which the analyst becomes a star and the year after their star status. Instead, it implies that experts who have been named stars in the past are more likely to make greater recommendations and are evaluated appropriately. Fourth, the study performs a further robustness test for analysis as follows: Star analysts are ranked first in StarMine's rankings are excluded from the initial sample of Star analysts. In light of this, we postulate two research questions:

RQ1: Can investors use analyst recommendations as an investment strategy to earn above-average returns? RQ2: Therefore, would analysts with a better reputation make more profitable recommendations than those with a lower reputation? The novelty of our study is in addition to the regressor endogeneity testing and the investor sentiment mechanism's employment with causality analysis. After portfolio construction, we calculate the risk-adjusted returns using multifactor asset pricing models with CAPM, Fama-French 3-factor, and Carhart 4-factor models. For testing the regressor endogeneity issue, we use the Durbin-Wu-Hausman specification test. Further, our study investigates the precise model through which star analysts' influence impacts fluctuations in stock prices. For this purpose, we employ the investor sentiment mechanism, where the NASDAQ Volatility Index (VXN) proxy is utilized as an exogenous regressor in the variance equation. Lastly, to examine the prevalence of the impact of investor sentiment on stock market volatility, we utilize the frequency-domain causality test.

Our study makes a significant contribution to the existing literature by introducing a novel approach to understanding investor sentiment mechanisms through a causality model. To the best of our knowledge, this is the first study that analyzes a proxy for investor sentiment and tests its statistically significant impact on stock price volatility. To achieve this, we employ the GARCH model and frequency-domain causality analysis, utilizing NASDAQ as a proxy for investor sentiment. In addition, our study addresses the issue of endogeneity, as examined by the robust Durbin-Wu-Hausman model. Furthermore, we contribute by providing unprecedented evidence regarding the influence of investor sentiment while distinguishing between temporary and permanent effects. Our findings reveal that investor sentiment is statistically significant and exerts a positive impact on stock return volatility. Notably, our study uncovers that stock market volatility induces changes in investor sentiment within a 5 to 10-day timeframe, with effects that are not of a permanent nature. This observation marks a valuable addition to the existing body of literature.

The remainder of the paper continues as follows: Section 2 analyzes and synthesizes available literature on analysts' recommendations and reputations; Section 3 covers the description of the dataset and the methodology; Section 4 discusses the key findings from the empirical results; and Section 5 concludes and offers suggestions for further research.

Literature background

Investment value of recommendations. Since Stickel (1995) and Womack (1996), the literature on the economic value of analyst opinions has significantly expanded (1996). According to Womack (1996), upgrades trigger a 30-day stock price drift, while price trends resulting from downgrades can persist for up to six months. Stickel (1995) investigates the relationship between analyst reputation and short-term price reactions based on nearly 17,000 recommendations from various analysts (proxied by their ranking in Institutional Investor Magazine's All America Research Team). The study reveals a positive relationship between analyst recommendations and short-term price reactions over a 12-year period.

However, subsequent studies have found that price reactions to analysts' recommendations are often short-lived and do not translate into profitable investment strategies (Jegadeesh and Kim, 2006; Leone and Wu, 2007; Barber et al. 2010; Loh and Stulz, 2011; Su et al. 2019). Leone and Wu (2007) report a positive relationship between analysts' recommendations and stock performance, especially for analysts with an AA status, indicating a persistent relationship. In contrast, Su et al. (2019) find that, assuming no transaction costs, upgrade recommendations fail to generate significant excess returns, while downgrade recommendations can result in large abnormal returns. Hobbs et al. (2021) analyze data from 1994 to 2015 to identify institutional investors managing more than $100 million who rarely rely on sell-side reports as an example of market participant behavior. Their study demonstrates that when institutional investors trade against recent analyst recommendation changes, they tend to incur losses.

Analysts' reputation and stock performance. Following Stickel's seminal work in 1995, there has been a substantial increase in scholarly investigations focusing on the relationship between analyst reputation and stock performance (Leone and Wu, 2007; Emery and Li, 2009; Loh and Stulz, 2011; Fang and Yasuda, 2014; Kucheev and Sorensson, 2019; Byun and Roland, 2020). Most studies initially examined the average price reactions, but recent research has shifted its attention to assessing the profitability by comparing the performance of star-rated and non-star-rated entities. Emery and Li (2009), for instance, compared the stock performance and determinants of rankings using a dataset of 20,239 recommendations issued by nearly 6000 analysts between 1993 and 2005. Their study contrasted Institutional Investor Magazine (II) and Wall Street Journal (WSJ) rankings, revealing that factors related to recognition play a significant role in determining rankings. Several studies argue that II rankings may be biased (Kessler, 2001; Kucheev and Sorensson, 2019).

Guo et al. (2020) contend that analyst recommendations often carry biases that create market friction. However, both Su et al. (2019) and Kucheev and Sorensson (2019) establish a well-established positive correlation between analyst reputation and their recommendation performance. Yet, some argue that an analyst's reputation might not solely stem from their skill but could be influenced by the brokerage house's reputation within which they work. Analysts often utilize in-house resources, influencing their recommendations. Fang and Yasuda (2014) even suggest that some top-ranked analysts in II may have achieved their status through fortunate circumstances. Kadan et al. (2020) lend credence to these perspectives by suggesting that analysts' stock selection proficiency and prediction accuracy depend on specific benchmarks. Fang and Yasuda (2014) categorized stock recommendations into reputation groups using the analyst's placement in the II All-America Research Team as a proxy, utilizing a substantial dataset spanning from 1993 to 2009.

To evaluate the comparative performance of star and non-star analysts, our study calculates risk-adjusted returns using various models, including the Capital Asset Pricing Model (CAPM) proposed by Sharpe (1964), the Fama-French 3-factor model introduced by Fama and French (1993), the Carhart 4-factor model developed by Carhart (1997), and a 5-factor model that includes a tech-sector index return. Barber et al. (2007) find that the performance of star analysts exhibits persistence, indicating that it's not solely due to chance but rather attributed to their enhanced access to firm management. Kucheev and Sorensson (2019) conduct a comparative analysis of different ranking systems, yielding the most significant average excess returns using a long-short portfolio strategy. Su et al. (2019) focus on the UK stock market and the reputation effect inside brokerage houses. Byun and Roland (2020) raise concerns about the suitability of forecast attributes and rankings data in previous investigations, suggesting that market participants assign greater significance to large organizations. This trend may contribute to the inconsistent findings observed in research projects employing II rankings. Kadan et al. (2020) confirm this by demonstrating that Fama-French factor alphas have statistical significance for small and low-coverage stocks but lack significance for large and high-coverage stocks.

Analysts' ranking systems. The measurement of analysts' reputation and its impact on stock performance has been a subject of extensive scholarly discourse. Within this literature, there has been considerable deliberation over the appropriate methods for measuring reputation and identifying the measurement types that yield the least biased outcomes. Table 1 illustrates the primary classifications of rankings in literature. Based on the evaluation methodology, it is possible to categorize each rating into two distinct types: objective rankings, such as StarMine and WSJ, and subjective rankings, exemplified by Institutional Investor Magazine. In summary, subjective rankings employ various evaluation methodologies and are grounded in survey outcomes. Two reputable and unbiased objective rankings are the "Best on the Street" published by the Wall Street Journal and "Top Stock Pickers" published by StarMine. The third objective ranking pertains to StarMine's "Top Earnings Estimators," which evaluates the precision and timeliness of analysts' earnings projections.

Rankings provided by Institutional Investor Magazine (II) are considered subjective, as they are susceptible to influences similar to "popularity contests" (Emery and Li, 2009). The evaluation process involves II distributing a survey to buy-side managers, soliciting their assessments of performance and several aspects related to sell-side analysts.

Kucheev and Sorensson (2019) argue that existing rankings inadequately assess portfolio profitability. They also provide evidence of significant alphas for the cluster of star analysts from II rankings, though with less informative relevance compared to rankings from StarMine and the Wall Street Journal. Byun and Roland (2020) conduct a critical examination of the subjectivity in rankings and raise concerns about market players' limited focus on major enterprises. The Wall Street Journal (WSJ) issues rankings known as "Best on the Street." This ranking system is typically determined by a cumulative score, derived from analysts' assessments over the previous year and computed as the total of one-day returns associated with their recommendations (Emery and Li, 2009). The ranking system has a short-term focus as it prioritizes analysts who offer recommendations on the same day as a substantial price fluctuation, while analysts who issue recommendations before or after the significant price change are penalized. These WSJ rankings may introduce substantial random influences in the selection process of prominent individuals. Emery and Li (2009) also document the significant underperformance of WSJ stars following their election, compared to those who were not designated as stars."

Thomson Reuters' StarMine rankings, which include "Top Stock Pickers" (TSP) and "Top Earnings Estimators" (TEE), have been issued annually since 1998. They are typically released in October each year, with exceptions in December 2009, May 2012, and August 2013. Despite their later introduction, StarMine rankings have gained significant influence in the sell-side research industry, serving as a crucial reference. Many Wall Street firms use these rankings to determine analyst compensation, as noted by Ertimur et al. (2011). Despite the relatively late introduction of

Table 1 Description of rankings.

Ranking name	Rating agency	Abbreviation used in this paper	Type of ranking	Measure	Measurement	Number of analysts per industry
"All-America Research Team"	Institutional Investor	II	Subjective / Qualitative	12 criteria (most important: industry knowledge and integrity; least important: stock picking, and accuracy of EPS)	Survey	3 + Runners-up
"Top Earnings Estimators"	StarMine	TEE	Objective / Quantitative	Accuracy and timing of earnings estimations	Calculation - EPS	3
"Top Stock Pickers"	StarMine	TSP	Objective / Quantitative	Excess returns on individual portfolios	Calculation - Recommendations	3
"Best on the Street"	The Wall Street Journal	WSJ	Objective / Quantitative	Total score for stock returns	Calculation - Recommendations	5 in 2003–2011, 3 in 2012, 2013

Table 1 shows the key differences between the measures. Rankings are divided into two groups (type of ranking) according to the ranking's evaluation approach. "All-America Research Team," issued by Institutional Investor Magazine, is in the subjective group due to its survey nature. "Top Earnings Estimators" and "Top Stock Pickers" by StarMine (Refinitiv) and "Best on the Street" by The Wall Street Journal are in the objective group. II rankings assess the analysts based on 12 various criteria, where stock-picking skills are not the foremost criterion. II chooses 3 analysts per industry and "runners-up"—those who will potentially be chosen as stars in future years. TEE and TSP have a substantial difference in measurement type. While TEE represents the accuracy and timing of EPS calculations, TSP is calculated based on the excess returns obtained by following the analysts' recommendations. Both the TSP and TEE choose three analysts per industry every year. Similar to TSP, WSJ rankings are also based on the recommendations and the total return of the recommended stock. For 2021, the WSJ did not publish the analysts' rankings. For more details, the study by Kucheev et al. (2017) may be referred to.

StarMine rankings, they hold a significant role in analysts' research, providing a vital and influential reference in the industry (Kim and Zapatero, 2023).

The determination of the TSP ranking is based on the abnormal returns generated by an unleveraged portfolio constructed according to analysts' recommendations. Calculating analysts' returns involves creating both long and short portfolios using a buy-and-hold approach, considering the market capitalization-weighted portfolio of all companies within a specific industry. Rebalancing occurs on a monthly basis and in response to an analyst's recommendation revision or the inclusion/exclusion of coverage.

The TEE ranking assesses how accurately each analyst predicts future earnings. As each analyst is evaluated relative to their peers, the TEE ranking can be seen as a relative accuracy measurement tool. This measure encompasses various factors, including the analyst's forecast error, the variance of the error, the analyst's error compared to other analysts' errors, the absolute earnings value of the firm, and the timing of measurements. The rankings are calculated on a daily basis, taking into account scores assigned to stocks, industries, and analysts. Unlike TSP and WSJ rankings, which give more weight to the investment value of analysts' recommendations, TEE rankings place greater emphasis on earnings forecasts (Kucheev and Sorensson, 2019).

Data and methods

Data and sample. We utilize multiple sources for data extraction. Stock recommendations are sourced from the Thomson Financials Institutional Brokers' Estimate System (I/B/E/S) Detailed Recommendations file. This system standardizes the diverse brokers' recommendation systems into a 5-point scale, where 1 corresponds to "strong buy," 2 to "buy," 3 to "hold," 4 to "sell," and 5 to "strong sell." Given the potential for different brokers to use varying measurement scales, standardization is of paramount importance. I/B/E/S Estimates, a component of the Institutional Brokers' Estimate System, has served as the industry standard for collecting and consolidating analyst forecasts of future earnings for publicly traded companies since its establishment in 1976. The dataset encompasses a vast geographical reach, including data from over 23,400 active companies across more than 90 countries, sourced from a network of 950+ firms and over 19,000 analysts, ranging from global to regional and local brokers. Notably, this data source stands out due to its extensive historical database, dating back to 1976 for North American data and 1987 for international data. It offers a range of data formats (Refinitiv, 2023). The daily holding period returns (HPR) for a stock, including dividends and other price adjustments like splits, are retrieved from the comparable Thomson Reuters' Refinitiv Eikon. In the realm of financial analysis, HPR refers to the overall return on an investment during the time it is held. It offers a comprehensive perspective on the performance of a stock, considering both capital appreciations, reflected in changes in the stock price, and income generated from dividends. Additionally, HPR accounts for various corporate actions, such as stock splits, which can impact the stock's price dynamics. The use of Thomson Reuters' Refinitiv Eikon dataset ensures the availability of accurate and reliable daily HPR data, providing a robust foundation for our empirical analysis. The value-weighted market return, book-to-market, size, and momentum factors are obtained from the Fama-French factors daily frequency database and used for regression analysis.[1]. The database is a reputable source that has gained widespread acceptance and is extensively used in finance research. Researchers depend on it for conducting robust risk-adjusted analyses, thanks to its consistency and transparency in financial research (see, for example, Hou et al. 2015; Jegadeesh and Titman, 1993; Carhart, 1997). Importantly, for each year of the analysis

Table 2 Recommendation sample described by year and number of analysts on coverage.

Year	Firms	Analysts	Stars (%)	Non-Stars (%)	Recommendation	Stars (%)	Non-Stars (%)
2010	88	424	3.1%	96.9%	816	2.6%	97.4%
2011	86	385	3.4%	96.6%	725	3.3%	96.7%
2012	93	373	1.6%	98.4%	656	1.7%	98.3%
2013	92	326	2.1%	97.9%	606	1.8%	98.2%
2014	92	307	2.9%	97.1%	502	2.6%	97.4%
2015	93	310	2.3%	97.7%	562	1.8%	98.2%
2016	96	296	3.4%	96.6%	601	1.7%	98.3%
2017	97	338	2.4%	97.6%	667	1.6%	98.4%
2018	94	213	1.4%	98.6%	406	1.0%	99.0%
2019	90	231	0.4%	99.6%	485	0.2%	99.8%
2020	98	246	1.6%	98.4%	561	0.7%	99.3%
Average	93	314	2%	98%	599	2%	98%

The table presents the number of firms, analysts, and recommendations included in the sample from 2010 to 2020 on a yearly basis. The left part of the table shows the number of analysts and the share (%) of Star and Non-Star analysts overall. The right part of the table indicates the overall number of recommendations and the share (%) of recommendations made by Star and Non-Star analysts. The number of recommendations does not include the reiterations but only the level changes.

(2010–2020), data on the analysts' ranks has been extracted by hand from StarMine.

StarMine's ranking data is integrated with the recommendation file using the analyst's name, the broker's affiliation, and the industry codes as reconciliation points. Ensuring each analyst is accurately linked to their recommendations requires meticulous work and double verification. As previously mentioned, StarMine annually releases a list of the top 1–3 analysts within each GICS industry, designating the top analyst as a "super-star" in their respective field (StarMine, 2020).

During data cleaning, it is important to note that the I/B/E/S recommendation file includes recommendations from anonymous analysts or those lacking relevant industry or brokerage house codes. Since these details are irrelevant to the study, they are excluded from the dataset before analysis (Kucheev and Sorensson, 2019). Additionally, stock recommendations tend to remain static and mature over time, diminishing their usefulness (Barber et al. 2010; Jagadeesh et al., 2014). Therefore, this research considers only shifts in recommendations, such as from "Buy" to "Sell" or "Sell" to "Buy," and initial recommendations (when the analyst starts covering), while disregarding subsequent occurrences of the same recommendation level. We combine data from two analyst rankings, TEE and TSP rankings, to create a single variable indicating an analyst's star status. This process begins by identifying the analysts who hold star status and those who do not. The primary objective of this combination is to expand the pool of star analysts. The underlying assumption is that both types of rankings offer insights into exceptionally skilled analysts. Therefore, our study categorizes a group of analysts into two distinct categories: "star" and "non-star." Table 2 presents the summary statistics for the recommendation sample. Each year, the dataset encompasses approximately 90 to 100 companies, which are constituents of the NASDAQ 100 index. We specifically concentrate on NASDAQ 100 companies for a specific reason: we intend to investigate the impact of excess returns within the highly dynamic tech sector. While many studies utilize the broader S&P index, we acknowledge that tech companies, characterized by their rapid responses to market shifts, provide a distinct environment for this analysis. This approach enables us to gain insights into the unique dynamics of the tech sector and their significance in the realm of financial research and investment strategies. The number of recommendations show the same trend as analysts, declining from 816 in 2010 to 561 in 2020. The number of recommendations issued by stars is at 2% on average, while non-stars issue almost 98% of all recommendations.

Table 3 presents the 5-level recommendations issued by different groups of analysts over the years from 2010 to 2020. Interestingly, in both analyst groups, the number of "hold" recommendations holds the majority, comprising approximately 41% of the total for both groups. On the other hand, "sell" and "strong sell" recommendations constitute the smallest portion of the sample. Among non-stars, the average percentage of "sell" recommendations is approximately 3.8%, while "strong sell" recommendations account for 1.3%. The Star analyst group has no observations for the "strong sell" level, but they have 3.7% for the "sell" level. However, it's worth noting a sharp declining trend in the "sell" level among Star analysts, which dropped to 0% after 2013.

The final dataset comprises a total of 6587 observations, encompassing changes in analyst recommendation levels and coverage initiations (initial recommendations) for 93 NASDAQ 100 index companies between 2010 and 2020. Table 4 categorizes the sample of recommendations into various transition categories, with the initial negative and first positive recommendations being the only pair present in the sample, indicating that no additional recommendation levels existed before 2010. These two sets of recommendations sum up to 4259 in total, with 1934 and 2325 recommendations, respectively. The trend in dynamics is negative, as evidenced by the declining number of total recommendations.

Portfolio Construction. Our study uses the portfolio construction method as described in Barber et al. (2006), and Fang and Yasuda (2014) based on analysts' recommendations (Strong Buy, Buy, Hold, Sell, Strong Sell)[2]. We construct calendar-time portfolios for each group of analysts in the year when the analyst was elected as a Star. The approach used in our portfolio construction differs slightly from that of Kucheev and Sorensson (2019) in that we do not partition the portfolios into two distinct time periods: one following the year in which the analyst achieved star status, and the year immediately after. Instead, it assumes that ever-elected Star analysts are prone to make better recommendations and are tested accordingly.

Crucially, there are no strict rules of portfolio formation, meaning that some studies construct three "long,", "hold," and "short" portfolios (Kucheev and Sorensson, 2019), while others build only "long" and "short" portfolios, including "hold" recommendations in the latter category (Barber et al. 2007; Fang and Yasuda, 2014; Su et al. 2019). Long and short portfolios within each analyst cohort indicate investing strategies in which

Table 3 Percentage of each recommendation level grouped by analyst Star status.

	Non-Star					*Star*				
Year	**Strong Buy**	**Buy**	**Hold**	**Sell**	**Strong Sell**	**Strong Buy**	**Buy**	**Hold**	**Sell**	**Strong Sell**
2010	22.5%	28.2%	41.3%	4.7%	3.4%	28.6%	9.5%	52.4%	9.5%	0%
2011	21.1%	33.7%	39.2%	4.7%	1.3%	12.5%	33.3%	41.7%	12.5%	0%
2012	12.4%	38.3%	43.7%	4.8%	0.8%	9.1%	27.3%	45.5%	18.2%	0%
2013	14.5%	35.8%	45.4%	3%	1.3%	9.1%	27.3%	63.6%	0%	0%
2014	19.2%	39.3%	38.2%	2.7%	0.6%	15.4%	23.1%	61.5%	0%	0%
2015	20.1%	34.2%	42.6%	2.2%	0.9%	20%	30%	50%	0%	0%
2016	14.2%	35.4%	44%	4.7%	1.7%	10%	20%	70%	0%	0%
2017	16.6%	43.4%	37.0%	2.4%	0.5%	27.3%	27.3%	45.5%	0%	0%
2018	23.9%	27.4%	44.3%	3%	1.5%	50%	25.0%	25%	0%	0%
2019	17.6%	40.1%	38.2%	2.9%	1.2%	100%	0%	0%	0%	0%
2020	13.6%	42.4%	36.4%	6.3%	1.3%	25%	75%	0%	0%	0%
Average	17.8%	36.2%	40.9%	3.8%	1.3%	27.9%	27.1%	41.4%	3.7%	0.0%

The table illustrates the number of recommendations (strong buy, buy, hold, sell, and strong sell) from 2010 to 2020 on a yearly basis. The percentage of each recommendation level is grouped according to the star status of an analyst, where the left side of the table represents the non-star analysts, and the right side of the table represents the star analysts. Obviously, star analysts make more positive recommendations and do not make any significantly negative recommendations (strong sells) compared to non-star analysts. A substantial part of the recommendations in both analyst groups account for hold recommendations (40% on average).

Table 4 The number of recommendation level changes (revisions).

Year	First negative	First positive	From negative to positive	From positive to negative
2010	340	350	61	65
2011	208	224	171	122
2012	190	215	116	135
2013	171	174	129	132
2014	127	179	112	84
2015	137	198	107	120
2016	188	179	117	117
2017	145	266	134	122
2018	116	124	85	81
2019	133	199	81	72
2020	179	217	96	69
Total	1934	2325	1209	1119

From negative to positive and *from positive to negative* are the recommendation revisions from the previous levels. In total, there are 6587 recommendations, revisions and coverage initiations observed in the sample. Coverage initiations have the largest part of the sample with 1934 negative and 2325 positive recommendations.

Table 5 The portfolio formation matrix.

Recommendations	Long Portfolio	Short Portfolio	Total
1 - Strong Buy	1169	-	1169
2 - Buy	2365	-	2365
3 - Hold	-	2708	2708
4 - Sell	-	256	256
5 - Strong Sell	-	89	89
Total	3534	3053	6587

The "Long" Portfolio comprises only positive recommendations ("Strong Buy" and "Buy"), while the "Short" Portfolio includes negative recommendations plus the neutral "Hold" recommendation.

analysts or investors take long (buy) positions in selected assets while concurrently adopting short (sell) holdings in other assets. These tactics are utilized with the purpose of potentially capitalizing on the relative performance of assets within each portfolio. For instance, within the context of each analyst cohort, a long portfolio may contain stocks that analysts approve as "buy" recommendations, predicting that these equities will appreciate in value. Conversely, a short portfolio may consist of companies marked as "sell" recommendations by analysts, with the idea that these securities will decline in value. The cumulative performance of these long and short positions influences the overall profitability of the portfolio. The portfolio formation matrix can be seen in Table 5, where the number of recommendations in each portfolio is normally balanced and excludes reiterations.

The methodology assumes that for each new recommendation, a hypothetical investor invests $1 at the end of the recommendation disclosure day into the matching portfolio. If the recommendation arrives on a weekend or holiday, the $1 is invested on the following working day. If the stock is recommended by more than one analyst, it will appear several times in the corresponding portfolio. If the recommendation is "Hold", "Sell", or "Strong Sell", the investor is assumed to shorten the stock by $1 and record the investment in the "Short" portfolio. In our study, each $1 invested is held for 30 days, assuming that a hypothetical investor is oriented toward short-term results. After 30 days from the recommendation date, each position is closed with a positive or negative return. As an additional test, Star analysts who are ranked as number one in *StarMine*'s rankings are detached from the initial sample of Star analysts.

Models. The next phase involves computing portfolio returns after the portfolios have been constructed. We employ equal monetary investment methodology which assumes that for each recommendation n, let $x_{n,t\text{-}1}$ be the compounded daily return of stock $i_{n,t}$ from the next day, when the recommendation is issued up to a future date $t-1$ (one day prior to date t), which can be described in the following equation (Barber et al. 2006; Fang and Yasuda, 2014; Kucheev and Sorensson, 2019):

$$x_{n,t-1} = R_{i_n,recdat_n+1} R_{i_n,recdat_n+2} * \ldots * R_{i_n,recdat_n t-1} \qquad (1)$$

where $R_{i_n,recdat_n t-1}$ is the total return of stock $i_{n,t}$ on calendar date *t-1*. Applying the Eq. (1) for all recommendations in the portfolio brings to the next step of daily portfolio return calculation. As such, the calendar date t gross return on a certain portfolio ρ, which contains recommendations from $n = 1$ to $N_{\rho t}$ will be defined as:

$$R_{\rho t} = \left(\sum_{i=1}^{N_{\rho t}} x_{n,t-1} * R_{i_n,t}\right) / \sum_{i=1}^{N_{\rho t}} x_{n,t-1} \tag{2}$$

where, $N_{\rho t}$ is defined as the total number of recommendations, which appear in the corresponding portfolio ρ on date t. Since the equal-weighted portfolio return calculation has met strong criticism for the possible bias (Dutta, 2015; Kothari et al. 2016), our study considers the value-weighted return of the portfolio (2) ρ on date t-1, denoting $x_{n,t-1}$ as a weight of each recommendation n in long or short portfolio. When applied, the equation above yields daily time series returns for each portfolio from 2010 to 2020.

The next step assumes calculation of the risk-adjusted returns using multifactor asset pricing models such as CAPM, Fama-French 3-factor model, and the Carhart 4-factor model. In our multifactor asset pricing models, we incorporate the following factors:

1. The portfolio returns.
2. The market return of firms traded on NASDAQ.
3. The risk-free rate of return is based on the 1-month treasury bill.
4. A size factor, calculated as the difference between the returns of value-weighted portfolios comprising small and large stocks (Sun et al. 2020).
5. A B/M (Book-to-Market) factor, computed as the difference between the returns of value-weighted portfolios containing high and low B/M stocks.
6. A momentum factor, determined as the average return of two high-return portfolios minus the average return of two low-return portfolios (Vukovic et al. 2023).

The following three equations represent these 3 asset pricing models, respectively:

$$R_{\rho t} - R_{ft} = \alpha_p + \beta_p\left(R_{m,t} - R_{f,t}\right) + \varepsilon_{p,t} \tag{3}$$

$$R_{\rho t} - R_{ft} = \alpha_p + \beta_p\left(R_{m,t} - R_{f,t}\right) + s_p SMB_t + h_p HML_t + \varepsilon_{p,t} \tag{4}$$

$$\begin{aligned} R_{\rho t} - R_{ft} = \alpha_p + \beta_p\left(R_{m,t} - R_{f,t}\right) + s_p SMB_t \\ + h_p HML_t + m_p MOM_t + \varepsilon_{p,t} \end{aligned} \tag{5}$$

Where $R_{\rho t}$ is the portfolio ρ return on a certain date t; $R_{m,t}$ is the market return of firms traded in NASDAQ; $R_{f,t}$ is the risk-free rate of return for the 1-month treasury bill; SMB_t is a size factor, HML_t is a B/M factor, MOM_t is a momentum factor. Initially, a basic CAPM model is used to evaluate the excess return against the market factor. Supplementary, three additional factors from the Fama-French 3 factor model are integrated to examine the persistence of excess return amid additional anomalies. Finally, the fourth momentum factor from the Carhart 4-factor model is introduced to determine if the excess return remains unaffected. This methodology aligns with common practices in recommendations research and aims to ensure the stability and reliability of the results. For detail on construction of the Fama French factors (SMB, HML, and MOM) following studies may be referred (Fama and French, 1993 & 2012; Balakrishnan and Maiti, 2017; Maiti and Balakrishnan, 2018 and 2020; Maiti, 2019). Average daily excess returns are multiplied by 21 working days to obtain an excess return monthly.

Endogeneity Issue. The assumptions of contemporaneous exogeneity, often assumed but seldom verified in financial panel data models, hold significant importance. When these assumptions are violated, it can result in inconsistent parameter estimates, unreliable standard errors, and hypothesis tests that lack validity. The Durbin-Wu-Hausman specification test used assess the endogeneity issue of the variable under investigation has a well-established in applied studies (Mulligan, 1996; Chen and Xia, 2020; Marques, 2022; Kouzez, 2023; Oloyede et al. 2021; Janot et al. 2016; Clemens et al. 2021; Thompson and Hay, 2015). It is known for its robustness (Chen and Xia, 2020) and is widely employed not only in social sciences (Marques, 2022; Kouzez, 2023; Oloyede et al. 2021) but also in natural sciences (Janot et al. 2016; Clemens et al. 2021; Thompson and Hay, 2015). Additionally, econometric software packages like EViews incorporate this method (EViews User Guide) for implementation, as it is pivotal for testing the endogeneity of equation regressors. Furthermore, it finds mention in widely used handbooks, such as the "Handbook of Financial Econometrics, Mathematics, Statistics, and Machine Learning" (Patrick, 2022a) and encyclopedias like the "Encyclopedia of Finance" (Patrick, 2022b).

The Durbin-Wu-Hausman specification test holds particular significance when dealing with panel data or constructing models with instrumental variables. The fundamental concept behind this test revolves around the evaluation of whether a specific independent variable within a regression model exhibits endogeneity, indicating a correlation with the error term. This test involves the computation of a test statistic, which is then contrasted with critical values from the chi-squared distribution to decide regarding the acceptance or rejection of the null hypothesis. We further employ the regressor endogeneity test. We employ the Durbin-Wu-Hausman specification test to examine the predictor variables in our model. The Durbin-Wu-Hausman specification test type tests can be employed to carry out least squares (Patrick, 2022a, 2022b). This test makes significant contributions to the advancement of specification tests that facilitate the comparison of parameter estimates obtained through diverse estimation methods. The test serves various objectives, including the selection between different model estimators (e.g., fixed effects versus random effects, Patrick, 2022b) and the assessment of alternative theoretical models (Chermak and Patrick, 2001, p. 78). The test is based on two estimators, providing:

$$x_t = X\beta + Z\Theta + u \tag{6}$$

$$X = G\Pi + v,\ Z = G\Delta + \eta \tag{7}$$

Where x_t is a vector of observations on a dependent variable, X is matrices of (possibly) endogenous explanatory variable for $x_t \in R^{n \cdot m_x}\left(m_y + m_x = m > 1\right)$, $G \in R^{n \cdot l}$ is a matrix of exogenous instruments, and u_t is the vector of structural disturbances for $u_t = (u_1, \ldots\ldots, u_n), \in R^n$, for the regressor z_t could be endogenous. If endogenous regressors are present, then the OLS estimators will supposedly fail this test. This is because it is assumed that the predictor factors and the error term are unrelated. All independent variables are assumed to be uncorrelated with the error term in OLS regression (Gujarati et al. 2012). The null hypothesis and alternative hypothesis of this test are follows:

$$H_0 : cov\left(x_t,\ u_t\right) = 0 \tag{8}$$

$$H_1 : cov\left(x_t,\ u_t\right) \neq 0 \tag{9}$$

The null hypothesis argues that the variable MOM_t, is exogenous. In the event that the null hypothesis is not rejected, it can be inferred that the ordinary least squares (OLS) estimators demonstrate consistency. Additionally, it may be inferred that the least squares estimator exhibits efficiency. The non-rejection of the null hypothesis implies that the primary variable may not exhibit significant endogeneity, and it could be more efficient to consider an alternative estimator like OLS.

The investor sentiment mechanism and causality analysis. Investor sentiment encompasses investors' collective outlook on the stock market, which can be shaped by a range of factors, including news, economic indicators, and market patterns. When investors grow more positive or negative in their market sentiment, it often leads to buying or selling of stocks. This, in turn, can result in short-term variations in stock prices and heightened market volatility. According to behavioral finance theory, investor sentiment significantly influences investment choices, asset valuations, and risk mitigation. Theoretical evidence supports the notion that investor sentiment can induce short-term fluctuations and even abrupt shifts in stock prices. Typically, sentiment affects companies characterized by youth, lack of profitability, high volatility, financial distress, growth orientation, small market capitalization, and non-payment of dividends. Positive (negative) shifts in sentiment result in decreases (increases) in return volatility and are linked to higher (lower) future excess returns. The impact of sentiments on stock returns is contingent on the prevailing market expectation. When the influence of sentiments on volatility is primarily unidirectional, it signifies that the price-pressure effect prevails in the market, benefiting noise traders during periods of elevated sentiment indices. Consequently, sentiment contributes to increased market volatility. Ultimately, heightened volatility in the stock market presents enhanced profit prospects for both long-term and short-term traders.

We conduct additional sentiment mechanism analysis for the following reasons. Firstly, heightened investor sentiment can significantly amplify stock market volatility. Furthermore, an upsurge in investor sentiment may induce selling pressure in the market, leading to reduced returns (Gao et al. 2022). Another factor to consider is that sentiment represents a systematic risk that is incorporated into pricing, resulting in contemporaneously positive correlations between shifts in sentiment and excess returns (Bouteska, 2020). Additionally, lower sentiment levels are associated with relatively higher subsequent returns, particularly in the case of smaller stocks, high volatility stocks, extreme growth stocks, and young stocks (Han, 2023). Lastly, the quest for information is positively linked to stock volatility and trading volume, as investors intensify their information searches to aid in decision-making and risk avoidance (Shu and Chang, 2015). Research on China's green stock markets has revealed that investor sentiment can significantly amplify stock volatility (Gao et al. 2022). Similarly, an examination of the impact of investor sentiment during the COVID-19 pandemic has shown that negative sentiment augments volatility, while positive sentiment diminishes it (Çevik et al. 2022). Furthermore, sentiment is considered a systematic risk that carries a price, with excess returns being simultaneously positively associated with shifts in sentiment (Lee et al. 2002). In emerging equity markets, it has been observed that an upsurge in investor sentiment can decrease returns, particularly influenced by the selling pressure prevailing in the market (Andleeb and Hassan, 2023). The objective of this approach is to capture, analyze, and understand the sentiment to inform stakeholders and improve decision-making processes within their domains (Song et al. 2022).

In the context of the Johannesburg stock exchange, research has indicated that when sentiment is low, subsequent returns tend to be relatively high for smaller stocks, high volatility stocks, extreme growth stocks, and young stocks (Muguto et al., 2022). Moreover, a study on investor sentiment during the COVID-19 pandemic has highlighted that investors intensify their information searches to aid their decision-making process in risk avoidance. This increased demand for information is positively linked to the volatility and trading volume of stocks (Jiang and Jin 2021). In summary, an elevation in investor sentiment can lead to a rise in stock market volatility. However, it is crucial to acknowledge that the relationship between investor sentiment and stock returns is intricate and can be influenced by a variety of factors, including the type of stock and prevailing market conditions.

To investigate the precise model through which the influence of star analysts impacts stock price fluctuations, we employ the investor sentiment mechanism. Our study assesses the effect of investor sentiment on stock market volatility by utilizing a GARCH (1, 1) model, wherein the investor sentiment proxy, represented by the VXN, is introduced as an exogenous regressor in the variance equation. The VXN index serves as a significant indicator of market expectations for short-term volatility, as evidenced by the pricing of options linked to the NASDAQ-100 Index. This metric quantifies the market's anticipation of short-term volatility within the pricing of NASDAQ-100 options with a 30-day timeframe. To this end, we estimate a GARCH (1, 1) model as follows:

$$\begin{aligned}\mathrm{GARCH} = {} & C(2) + C(3)\cdot RESID(-1)^2 + C(4)\cdot GARCH(-1)\\ & + C(5)\cdot NASDAQ\ VXN\end{aligned} \tag{10}$$

Moreover, to investigate the extent of the impact of investor sentiment on stock market volatility, we adopt the frequency-domain causality test, as proposed by Breitung and Candelon (2006). The main motivation for utilizing this test is its capability to offer a more comprehensive view of the magnitude and direction of causation across various frequencies, encompassing both short-term and long-term (permanent) effects.

The traditional Granger causality test, utilizing a vector autoregressive (VAR) framework (Granger, 1969), is able to produce a single statistic that summarizes predictability across all frequencies. However, this conventional approach does not account for the possibility that causal relationships might vary across different frequencies, as noted by Geweke (1982) and Hosoya (1991). To address this limitation, Breitung and Candelon (2006) introduce a frequency domain Granger causality test as an alternative method to more accurately assess short, medium, and long-term Granger causality. The aim of this test is to provide a more precise understanding of causal links between variables. In our study, we employ a bivariate vector autoregressive (VAR) model to encompass a co-integrated system and a higher dimensional system. This approach allows for the separation of short-term and long-term predictability.

We employ a test to determine the existence of Granger causality at any given frequency (ɘ). This test examines the null hypothesis proposed by Geweke (1982), for $\Lambda_{y\rightarrow x}$ (ɘ) = 0, where Y does not Granger cause X (Özer et al. 2020), and which can be expressed as:

$$H_0 : R(\text{ɘ})\beta = 0, \tag{11}$$

$$\text{with } \beta = (\beta_1, \ldots \beta_p) \text{ and } R(\text{ɘ}) = \begin{pmatrix} cos(\text{ɘ}), \cos(2\text{ɘ}), \ldots cos(p\text{ɘ}) \\ sin(\text{ɘ}), \sin(2\text{ɘ}), \ldots sin(p\text{ɘ}) \end{pmatrix} \tag{12}$$

When attempting to ascertain the results of the Breitung-Candelon (2006) Granger causality tests for the frequency (ɘ), it is necessary to compare the calculated test statistics value with the 5% chi-square significance value, considering 2 degrees of freedom.

Table 6 Performance of Long and Short Portfolios within each analyst group ((a) Panel 1. Long Portfolio, (b) Panel 2. Short Portfolio, and (c) Panel 3. Long-Short Portfolio).

(a) Panel 1. Long Portfolio

	Star (1)	Non-Star (2)	Star-1 (3)	Star vs non-Star (4)	Star-1 vs Star (5)	Star-1 vs non-Star (6)
CAPM alpha	0.0146*** (6.56)	0.0151*** (24.52)	0.0177*** (7.65)	−0.0005 (−0.22)	0.0030 (0.95)	0.0025 (1.06)
FF 3-factor alpha	0.0145*** (6.51)	0.0151*** (24.49)	0.0175*** (7.57)	−0.0006 (−0.24)	0.0030 (0.94)	0.0024 (1.03)
Carhart 4-factor alpha	0.0145*** (6.47)	0.0151*** (24.50)	0.0174*** (7.52)	−0.0006 (−0.27)	0.0029 (0.92)	0.0023 (0.98)

(b) Panel 2. Short Portfolio

	Star (1)	Non-Star (2)	Star-1 (3)	Star vs non-Star (4)	Star-1 vs Star (5)	Star-1 vs non-Star (6)
CAPM alpha	−0.0086*** (−4.82)	0.0178*** (15.40)	−0.0093** (−2.72)	−0.0265*** (−12.48)	−0.0007 (−0.19)	−0.0272*** (−7.57)
FF 3-factor alpha	−0.0086*** (−4.81)	0.0178*** (15.41)	−0.0091** (−2.67)	−0.0264*** (−12.46)	−0.0005 (−0.13)	−0.0270*** (−7.53)
Carhart 4-factor alpha	−0.0085*** (−4.74)	0.0178*** (15.40)	−0.0092** (−2.69)	−0.0263*** (−12.43)	−0.0007 (−0.19)	−0.0270*** (−7.59)

(c) Panel 3. Long-Short Portfolio

	Star (1)	Non-Star (2)	Star-1 (3)	Star vs non-Star (4)	Star-1 vs Star (5)	Star-1 vs non-Star (6)
CAPM alpha	0.0232*** (8.15)	−0.00270* (−2.06)	0.0270*** (6.57)	-	-	-
FF 3-factor alpha	0.0231*** (8.12)	−0.00274* (−2.10)	0.0267*** (6.51)	-	-	-
Carhart 4-factor alpha	0.0229*** (8.07)	−0.00273* (−2.09)	0.0266*** (6.53)	-	-	-

t statistics in parentheses: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
Note: Alphas are calculated for each group of analysts, i.e., stars and non-stars, as an intercept from the regression. As an additional test, the table includes alphas for the Star-1 category, those Star analysts who are ranked "number one". The right side of the table shows the difference in alphas between each group of analysts. The long-short portfolio suggests that stars, on average, have higher alphas compared to non-stars. "Number one"-ranked stars show overperformance in all portfolios.

Results and discussion

Factors' model results. Table 6A-C display risk-adjusted returns (alphas) calculated using CAPM (1965), Fama-French 3 factor model (1993), and Carhart 4 factor model (1997) for long and short portfolios within each analyst group. In addition to the overall sample of analysts categorized as Star and Non-Star, Table 6A-C encompasses a subset known as Star-1 analysts, who have achieved the top rating according to StarMine's rankings. The table has been divided into three distinct sections, denoted as Panel 1 (6 A), Panel 2 (6B), and Panel 3 (6 C). Panel 1 represents the long portfolio, Panel 2 represents the short portfolio, and Panel 3 displays the disparity between the long and short portfolios. The table categorizes analysts into three distinct groups, namely Stars, Non-Stars, and Star-1, and provides information about the alpha differentials associated with each group. In Table 6A-C, it is evident that the regression findings demonstrate highly significant alpha across all panels and analyst groups. The presence of substantial alphas implies that analysts' recommendations, in spite of categorization into Stars and Non-Stars, can yield abnormal returns, hence rejecting the efficient market hypothesis (EMH). These findings are in line with works of Womack (1996), Barber et al. (2001), and Fang and Yasuda (2014).

Table 6A, represents the average daily alphas for the long portfolio. In general, the results of the regressions show strongly significant excess returns for each group of analysts. Specifically, CAPM shows that Star analysts generate 0.0146% average daily (0.3066% monthly) excess returns. On first glance, non-stars outperform stars, with average 0.0151% daily (0.3171% monthly) abnormal returns. Coefficients are not significantly changed when different models are applied. As such, the Fama-French 3-factor model and the Carhart 4-factor model indicate approximately the same level of alphas as in CAPM. Looking at the right side of Table 6A, the results of the parametric test show insignificant alpha differentials across all the groups of analysts. Particularly, Kucheev and Sorensson (2019), report significant evidence that Stars can generate on average 0.35% monthly excess returns for Long Portfolio. These findings are approximately similar with the results obtained in our study. Despite the higher levels of alpha among non-stars and the inconsistency with most of the previous literature (e.g., Fang and Yasuda, 2014), it is hard to conclude that rankings are "popularity contests" (Emery and Li, 2009), since the result of parametric test shows insignificant difference between analyst groups. The reason for insignificant outperformance of Non-Stars in Long Portfolio might be due to increased attention on high weight firms that constitute the NASDAQ 100 index, as described in Byun and Roland (2020). Another explanation to the differences of reputation effect between the Short and Long Portfolios might be the "positivity bias" (Barber et al. 2001; Lötter and vd M Smit, 2018).

The short portfolio (Table 6B) is notably different from the long portfolio. Specifically, the results of three regression models suggest that stars have significantly higher excess returns compared to non-stars. As such, by shorting stocks in the short portfolio, star analysts generate average -0.0086% daily (0.1806% monthly) abnormal returns, while non-star analysts generate 0.0178% daily (0.3738% monthly) abnormal returns. It is vital to note that a short portfolio is considered profitable when the abnormal returns come with a negative sign, since shorting is done in the opposite direction. As a result, parametric test results indicate that star analysts significantly outperform non-stars by an average of −0.0265% daily (−0.5565% monthly). Coefficients and t-stats are unchanged when different regression models are applied. The statistically significant (at 1% level) monthly 0.5565% alpha differential is fully consistent with the results obtained by Fang and Yasuda (2014).

Table 6C represents the differences between long and short portfolios. Consistent with previous portfolio results, the excess returns in the long-short portfolio are approximately equal across all three models. Hence, focusing on the Carhart 4-factor alphas, stars generate on average 0.0229% daily (0.4809% monthly) abnormal returns. Calculations for alphas in the Stars group are statistically significant at the 1% level. The Non-Stars' long-short portfolio shows −0.00270% daily (−0.0567% monthly) abnormal returns, which are significant at the 10% level. While the abnormal returns generated by the long-short portfolio of stars match the results obtained by Kucheev and Sorensson (2019), non-stars are slightly different. More precisely, it finds that stars generate 0.53% monthly abnormal returns, while non-stars show 0.47% monthly alphas.

The study conducts a supplemental test to identify whether stars tend to underperform non-stars in long portfolios under any conditions. For these purposes, the study separates the "number one" ranked stars (Star-1) from the Stars group to construct the same models with alphas generated only by the current group of stars. Table 6A-C, Column 3, represents the alphas obtained from different asset pricing models for the Star-1 group. Along with alphas, columns 5–6 display alpha differentials between Star-1 vs. stars and Star-1 vs. non-stars, respectively. From the Carhart 4-factor alphas of the long portfolio, it can be seen that "number one" ranked stars generate on average 0.0174% daily (0.3717% monthly) excess returns, which are statistically significant at the 1% level. Despite the high levels of alpha generated in Long Portfolio, parametric test results for the differences between Stars-1 and other groups remain statistically insignificant. The short portfolio constructed on the recommendations of the Star-1 group shows the highest alphas (statistically significant at the 5% level) compared to other analyst groups. As such, the Star-1 group generates -0.0092% daily (0.1932% monthly) excess returns.

The difference between Star-1 and Star Short Portfolio is 0.0147% monthly, and it is statistically insignificant. However, the difference between the Star-1 and Non-Star Short Portfolios indicates highly statistically significant of 0.567% monthly abnormal returns. Analogously, in the long-short portfolio, the Star-1 group shows the highest and most statistically significant alphas in all three asset pricing models (e.g., 0.0266% daily and 0.5586% monthly alphas from the Carhart 4-factor model). The results obtained for "number one" ranked stars are in the line with similarly mentioned studies. For instance, Fang and Yasuda (2014) divided the *II* sample into top-rank AAs (like Star-1) and found that "number one" ranked stars generate statistically significant and high (2.91% monthly in the Long Portfolio) abnormal returns. However, the difference between Star-1 and non-Star groups is consistent only in the short portfolio, since the long portfolio differentials are not statistically significant in our study. The results of the long-short portfolio in the Star-1 subgroup of analysts are also somehow consistent with the results obtained by Kucheev and Sorensson (2019).

The seemingly equal performance of stars and non-stars in the long portfolio can be explained by the positive nature of "strong buy" and "buy" recommendations. It means that market participants prefer to obtain positive signals and act accordingly. On the other hand, it can be challenging for the analyst to provide negative recommendations (Emery and Li, 2009). Extended access allows the analysts to be aware of significant news and announcements much earlier than non-star analysts. It also allows them to process the non-publicly available information, while non-stars rely on the single piece of information that is publicly available. Moreover, the calculations of the non-star analysts might include only publicly available fundamental information, while the stars might gain superior fundamental knowledge. One possible explanation for the prevalence of more lucrative "sell" and "strong sell" recommendations among star analysts is their superior reputation and expertize in the field. Kadan et al. (2020) emphasize the significance of benchmarks as foundational elements for the recommendations. The authors underscore the criticality of understanding the source and characteristics of the information that support the analyst's findings.

Relative to the investigation by Kucheev and Sorensson (2019), our analysis does incorporate temporal considerations, such as monthly alpha generation. However, Kucheev and Sorensson (2019) delve into the seasonality of analyst optimism, uncovering a lack of significant relationship between seasonal target prices and market returns. They identify an optimism cycle that correlates with the rhythm of earnings disclosures rather than seasonal variations. Additionally, our findings suggest that analysts with a star ranking outperform the market, albeit predominantly in the short term. Kucheev and Sorensson (2019) propose that investors could gain from recognizing these cycles of optimism, hinting at potential market inefficiencies if such biases from analysts are predictable and correspond with the timing of corporate disclosures.

In concert with the conclusions drawn by Su et al. (2019), our study did not uncover a consistent benefit from analyst upgrades or downgrades when considering the market as a whole. This indicates that an analyst's reputation or brokerage rank is not invariably indicative of the value of their recommendations, particularly when transaction costs are considered. Our research delineates a clear demarcation between star analysts and their non-star counterparts in their capacity to secure abnormal returns, with this phenomenon being particularly pronounced in short-term portfolios. In alignment with Su et al. (2019), we also identify specific industry contexts—in this case, high-tech sectors—where analyst insights appear to offer genuine profit potential, thereby enhancing our nuanced comprehension of the contexts in which analyst recommendations may be of value.

Our findings corroborate the link between analyst rankings and investment performance, in accordance with Fang and Yasuda (2014), but the distinction is not significant within long-term portfolios—merely in short-term ones—implying a more subtle influence. On the matter of market efficiency, our results echo Fang and Yasuda's (2014) evidence that certain analysts deliver consistently valuable insights that lead to abnormal returns. We suggest, however, that such effects are more emphatically observed in short-term portfolios. Meanwhile, Fang and Yasuda (2014) explore the overarching capabilities of analysts with high reputations to excel over various investment timeframes.

Endogeneity test results. In assessing whether an endogeneity concern between the momentum factor and other included variables in our statistical model existed, we implemented the Durbin-Wu-Hausman assessment. The statistical outputs from this scrutiny are concisely summarized in the provided Table 7. The essence of this test is to compare the ordinary least squares (OLS) estimates with those procured through instrumental variable (IV) techniques, upholding the null hypothesis which posits that the suspected endogenous variables are actually exogenous.

The data reported in Table 7 reveal that the p-value linked to the J-statistic is quantified at 0.7537, which markedly exceeds the commonly accepted 5% significance benchmark. This significant statistic supports the maintenance of the null hypothesis, thereby substantiating the external position of the momentum variable within our specified econometric arrangement. The prominently high p-value suggests that the estimations employed are not contaminated by biases typically introduced by endogeneity, hence they are deemed both efficient in nature and consistent in their estimative capability—a vital prerequisite for authentic econometric analysis.

Table 7 The outcomes of the endogenous testing.

	Value	df	Probability
Difference in J-stats	0.0985	1	0.7536
	Value		
Restricted J-statistic	0.0985		
Unrestricted J-statistic	0		

The entry labeled 'Difference in J-stats' records a value of 0.0985 with a p-value that mirrors this at 0.7536, cementing the exogeneity stance for the momentum factor. Further substantiating this conclusion is the fact that the 'Restricted J-statistic' and 'Unrestricted J-statistic' mirror each other in value, fortifying the strength of the claim for exogeneity. This investigation not only bolsters the methodological foundation of our current analysis but also provides a template for the architectural design of future research models. By establishing the exogeneity of the momentum factor, the research empowers further scholarly pursuits to build upon econometric frameworks that assure structural integrity and methodological reliability.

The investor sentiment and causality results. Our study ventures to gauge the impact of investor mood on equity returns by using the Volatility Index (VXN) as a surrogate indicator of sentiment in the marketplace. The analytical findings, as outlined in Table 8, indicate that both the Autoregressive Conditional Heteroskedasticity (ARCH) and the Generalized ARCH (GARCH) coefficients are not only statistically notable and carry a positive sign, but they also collectively sum up to less than unity. This implies a clear and constructive relationship between investor sentiment levels and the oscillations in stock returns; a surge in sentiment leads to heightened volatility in the stock market, as depicted in Fig. 1.

In delving deeper into how frequently investor sentiment influences market volatility, our research incorporates the frequency-domain causality framework articulated by Breitung and Candelon (2006). This methodological approach sheds light on the causality's direction and magnitude across different time horizons. The insights from this methodology are visualized in Figs. 2 and 3, where the frequency parameter (ɵ) on the horizontal axis serves to determine the cycle's length in days through the equation:

$$T = 2\pi/ ɵ \tag{12}$$

The vertical axis in Figs. 2 and 3 illustrates the p-values of the calculated test statistics (F-statistics). Each test statistic and its associated p-values are obtained across the frequency range $0 < ɵ < \pi$. Also, by using the (ɵ), the study defines the long-run as $ɵ = 0.01$ and short-run as $ɵ = 2.5$.

According to Fig. 2, investor sentiments can contribute not only to the short run but also in the long run to stock (ɵ) (Özer et al. 2020). Interpreting the graphical analysis in Fig. 2 reveals that investor sentiment exerts influence not solely in immediate time frames but extends its reach into more extended periods as well. Conversely, Fig. 3 intimates that fluctuations in the stock market provoke shifts in investor sentiment predominantly within a window of 5 to 10 days, albeit these fluctuations do not have permanent effects.

The most profound contribution of our investigation lies in the finding that investor sentiment plays a pivotal role in the volatility of stock returns. This insight builds upon and extends the corpus of existing literature, providing fresh perspectives on the significance of market sentiment.

Table 8 The GARCH (1,1) estimates.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	−0.0049	0.0008	−6.017	1.770e-09
	Variance Equation			
C	−0.001388	0.000146	−9.490048	0.0000
RESID(−1)^2	0.381635	0.030422	12.54492	0.0000
GARCH(−1)	0.082328	0.024061	3.421677	0.0006
NASDAQ	0.000191	1.06e-05	18.12596	0.0000

Mechanism. The intricate relationship among the prognostications of renowned analysts, the inherent instability of the market, and the collective mood of investors intricately intertwines to mirror the multifaceted nature of financial markets and investor conduct. As demonstrated in Fig. 4, the counsel dispensed by preeminent analysts wields the potential to sway overall market sentiment and precipitate fluctuations in the short-term market climate. For example, an endorsement categorized as a "buy" or "strong buy" can foster a buoyant outlook on a firm's future, thereby elevating its stock value. Conversely, a directive to "sell" or "strong sell" can have an antithetical effect, leading to a dip in stock prices.

There are exceptional instances where the counsel from these esteemed analysts, coupled with prevailing market sentiment, can significantly intensify price dynamics and volatility within the marketplace—a phenomenon colloquially termed as "herding behavior." This observation confirms a cyclical interplay where top-tier analyst advice informs market sentiment, which in turn feeds back into market volatility. It is recognized that adverse sentiment amongst investors is a precursor to greater market turbulence when juxtaposed with optimistic sentiment. Therefore, the guidance from leading analysts, the fickleness of the market, and the sentiment among investors are dynamically linked. This triadic relationship forges cyclical interactions that can exacerbate the ebb and flow of market movements. Thus, a comprehensive grasp of these interrelations is imperative for investors who strive to base their financial decisions on deep market insight.

Figure 4 underscores this interconnectivity, highlighting the significant nexus between the insights of star analysts, market volatility, and investor sentiment.

Prior literature in the field has predominantly concentrated on isolated aspects of analyst influence, either focusing on the direct impact of recommendations on stock performance or on the behavioral response of the market to such recommendations. However, our study transcends the conventional analysis by illustrating the cyclical nature of the influence that star analysts exert on market sentiment and, concomitantly, how these sentiments synergistically amplify market volatility. The innovative proposition of our research is the identification of a dual feedback loop, which represents a significant departure from existing paradigms. It postulates that the recommendations from star analysts instigate shifts in market sentiment, which then precipitate short-term market volatility. In turn, this volatility influences subsequent market sentiment, establishing a dynamic and continuous loop of influence. This conceptual framework captures the nuanced reality that negative investor sentiments, often undervalued in existing literature, precipitate heightened market volatility when compared to positive sentiments.

Furthermore, by recognizing the herding behavior that occasionally amplifies the impact of analysts' recommendations, this study contributes to a refined understanding of market overreactions and corrections. The notion that these interactions can lead to feedback loops offers a new perspective on how market actors might exploit systematic patterns in market responses to strategic advantage.

Conclusion

The present study provides empirical evidence supporting the utility of analyst recommendations in the process of stock selection. The findings of the study offer empirical support for the notion that analysts with star rankings have the ability to generate superior alphas, hence surpassing the average performance of the market. The study also highlights the effectiveness of the ranking system used by StarMine in identifying the star analysts with superior stock-picking abilities. The signaling theory assumes that all the information on company's financial health is not available to all the investors at the same time Thus, the study findings indicate that signaling theory has existed in the financial market for a short period of time. However, it diminishes as analyst recommendations are incorporated into market prices, closing the information gap.

The present study's findings have many practical implications, notably highlighting the potential benefits for market participants who integrate analyst suggestions into their investing decision-making procedures. It also shows that market participants should conduct due diligence on analyst recommendations to generate higher returns. Then market participants can consider Star Analyst as a benchmark to compare their investment performance. The study findings indicate that there is no significant distinction in alphas between the star and non-star in the long portfolio. It supports EMH that all available information is quickly and accurately reflected in asset prices. The study results also indicate that information symmetry does play a role. However, by implementing the same investment strategy, star analysts cannot beat the market continuously due to increased market competition. Even though star analysts possess superior skills, the widespread accessibility of advanced technical tools for analysis diminishes the overall disparities in skill levels among analysts when it comes to making well-informed financial decisions. It is difficult to continuously beat the market with the same strategy according to EMH. The study results also indicate that information symmetry does play a role, and star analyst recommendations play a vital role in mitigating information asymmetry in financial markets.

The study's limitations are primarily associated with its data sources. The analysis of analyst rankings in this research was based on a specific set of data. As indicated in Section 2.3, broadening the variety of data sources could offer deeper and more generalizable insights. Including newer data and more companies in dataset, could thus enhance the study's current relevance and applicability (like NYSE or S&P market data).

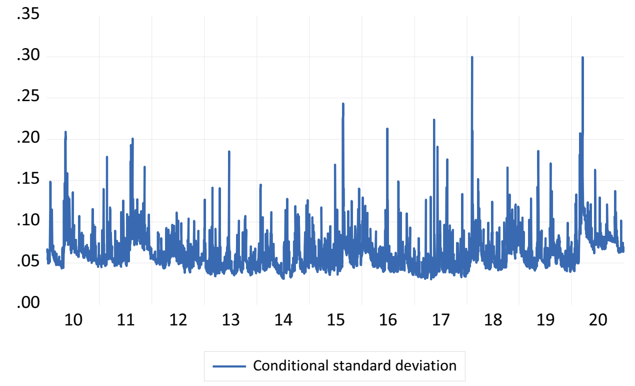

Fig. 1 Stock market volatility. This figure represents stock market volatility. The vertical axis represents conditional standard deviation for each observation. The horizontal axis represents the observations.

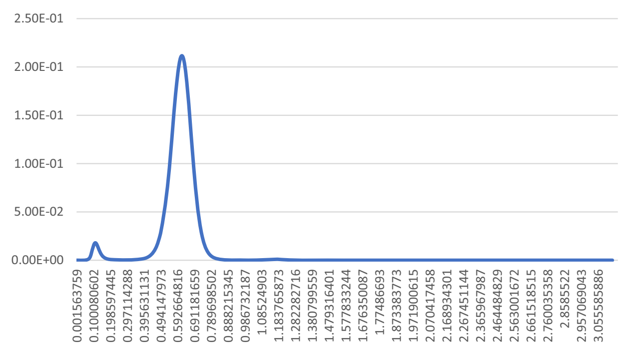

Fig. 2 Causality test analysis: Investor sentiment No Cause-Granger stock return volatility. This figure illustrates results of causality test analysis for investor sentiment no Cause-Granger stock return volatility. The horizontal axis represents the frequency parameter (ө). The vertical axis illustrates the p-values of the calculated F test statistics.

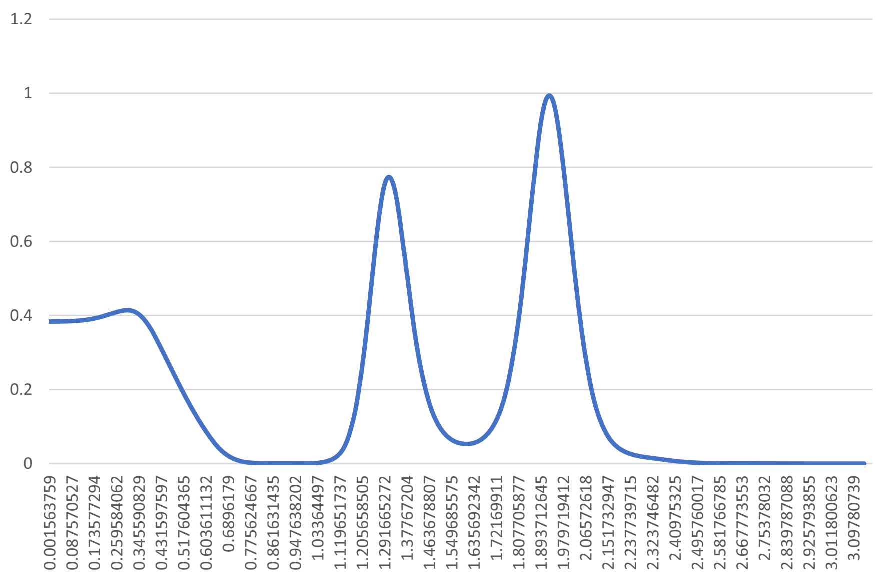

Fig. 3 Causality test analysis: stock return volatility No Cause-Granger Investor sentiment. This figure illustrates results of causality test analysis for stock return volatility no Cause-Granger Investor sentiment. The horizontal axis represents the frequency parameter (ө). The vertical axis illustrates the p-values of the calculated F test statistics.

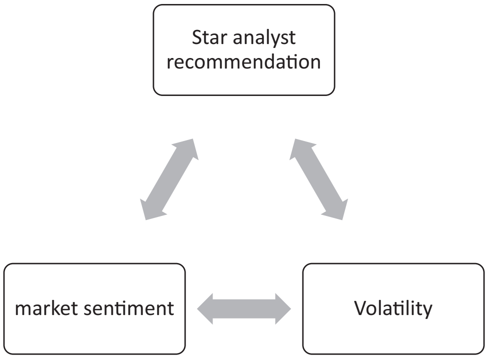

Fig. 4 The interconnectedness between star analyst recommendations, volatility, and market sentiment.

This research addresses the impact of information asymmetry in financial markets. Subsequent studies could delve deeper into this topic, specifically investigating the role of top-tier analysts in narrowing information disparities and how this affects overall market efficiency. Additionally, leveraging the foundational use of the GARCH model and frequency-domain causality analysis in this study, future research might probe further into the dynamics between investor sentiment and stock performance. This exploration could extend to analyzing the effects of various news types and economic indicators on investor actions and financial market results. Policymakers may consider different measures to enhance transparency, accuracy, and accountability in analyst recommendations to protect investors' interests.

Data availability

The datasets are available from the corresponding author on reasonable request.

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Notes

1 https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

2 Portfolio creation and evaluation include a variety of approaches and considerations. For instance, Vukovic et al. (2022a) note that some research suggests using an inflation allocation line. The neural network method is used to calculate and forecast portfolio returns in the study by Li et al. (2017b). The research of Vukovic et al. (2022b) then employs support vector machines, group techniques of data management, long short-term memory, and Markov switching autoregression for future value projections.

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Author contributions

Conceptualization, O.K., D.V., M.M; data curation, O.K., M. Ö and D.V.; formal analysis, D.V., O.K., M.M., and M.Ö.; investigation, O.K., M.Ö., D.V.; methodology, O.K., D.V., and M.Ö.; resources, O.K., M.R.; software, O.K, and M.Ö.; supervision, D.V. ; validation, D.V., O.K., M.R., and M.Ö.; visualization, O.K., M.Ö. and M.R.; writing-original draft, O.K., D.V.; writing-review and editing, O.K., D.V., M.M., and M.Ö., project administration, D.V.

Competing interests

The authors declare no competing interests.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Additional information

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