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Orifjon Kurbonov

Analyst recommendations and investment strategies in ADRs: star and non-star reputation

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Author: Orifjon Kurbonov
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ABSTRACT :
Sell-side analysts have become one of the key intermediaries in the capital markets linking investors and publicly traded corporations. The importance of sell-side analysts has developed since late 90th, when sell-side research market was valued in billion dollars. During this period media started to question the inner value of analysts reports and the content of the report, that is recommendations, earning estimates, and target price revisions. Specifically, they were blamed for receiving huge compensation for being lucky, because under efficient market hypothesis, it is impossible to generate access returns. Following the rising media concern, academic community started to study the nature of sell-side analysts and their reports. First, scholars were interested whether analyst recommendations, target price revisions are able to impact the stock prices, without mentioning the profitability pattern. Having proved that analyst recommendations are able to change stock prices, the next topic of interest was whether the stock reaction to analyst recommendation results in profitability, which is higher than the market return (e.g., S&P 500). In continuation, more and more studies appeared linking recommendation profitability with various analyst and brokerage house related attributes, such as reputation, size of the brokerage house etc. However, there is no strict conclusions on the analyst performance and recommendation profitability since scholars used different samples, methods, or rankings.

As a continuation of recent studies, this paper examines whether the analysts' recommendations can generate abnormal return and whether the analysts ranked as Stars in StarMine's "Top Stock Pickers" and "Top Earnings Estimators" rankings make more profitable recommendations in comparison to Non-Star group. Previously, only one paper compared 3 different rankings and concluded that rankings issues by Institutional Investor magazine - which are most often utilized in the literature - are subjective. Hence, this study is the second to utilize StarMine's objective ranking's hand-collected data. The sample of the research is narrowed to American Depositary Stock receipts to see whether recommendations differently touch the stocks of foreign companies. By applying buy-and-hold calendar-time-portfolios methodology with 30-day holding period, 2 portfolios (Long and Short) are formed for each Stars, Non-stars, and Star-1 groups resulting in 6 portfolios. The access returns of the portfolios are calculated using Fama-French 3/5/6 factor models with different risk factors. The results suggest that in the Long portfolio, Stars underperform Non-stars, while in the Short portfolio Stars and both Star-1 outperform Non-stars. The reason behind underperforming Stars in Long portfolio is mostly explained by risk-aversion of Stars in recommending risky stocks, while Non-stars "have nothing to lose" and take higher risk by recommending large number of ADRs. The same explains the outperformance of Stars in Short portfolio since Stars tend to conduct advanced research before shorting risky stocks.

KEYWORDS: analyst reputation, stock recommendations, sell-side analysts, ADR, cross-listing, StarMine

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Abbreviations

ADR	American Depositary Receipt
BNY	Bank of New York Mellon
NYSE	New York Stock Exchange
AMEX	American Stock Exchange
SEC	Securities Exchange Commission
I/B/E/S	Institutional Brokers' Estimate System
EMH	Efficient Market Hypothesis
TEE	Top Earnings Estimator
TSP	Top Stock Pickers
WSJ	Wall Street Journal
I/I	Institutional Investor Magazine
HPR	Holding Period Returns
GICS	The Global Industry Classification Standard
FF-***	Fama French Models

1 Introduction

Since the seminal work by Stickel (1995) and Womack (1996), much research has been done to analyze the existence of profitable investment strategies based on the published analyst recommendations and target price revisions (Barber et. al. 2001; Loh, 2010; Fang and Yasuda, 2014; Kucheev et al., 2019). Majority of the papers conclude that upside/downside changes in analyst recommendations can result in positive/negative abnormal returns at the time of recommendation announcement. Among initial conclusions, after the upside recommendation, stock prices are known to fluctuate for 1 month, while after the downside recommendation, prices are subject to change up to 6 months (Womack, 1996). The recommendation research has gone further since initial papers with a concentration on different analyst characteristics and attributes. As such, analyst affiliations with brokerage houses (Cliff, 2007), analyst reputation (Stickel, 1995; Fang and Yasuda, 2014; Kucheev, Ruiz and Sorensson, 2017, among others), factor of skill or luck, which then results in analyst's best performance (Leone and Wu, 2007; Emery and Li, 2009).

Although the topic is popular with existence of multiple subtopics, little is known about the reaction of cross listed stocks from analyst recommendations. Number of cross-listed stocks has been increasing over the past 20 years. In 2019, the number of American Depositary Receipt (ADR, hereafter) in the US stock market exceeded 3000 stocks (BNY Mellon, 2019). The main perspective of the paper is to detach ADRs from the whole sample of stocks to understand the reaction free of Ordinary Shares. The idea is to understand whether profitable investing strategies exist in ADRs in relation to analyst recommendations and whether the star status of the analyst accelerates profitability of the stock. Importance of this topic is twofold.

First, it will be possible to explore whether ADRs are profitable investments assuming a hypothetical investor listens to sell-side analysts. It is logical that investors would not form their portfolios based on ADRs only. However, results of this study will show if it is generally rational to include ADRs in the investment portfolio.

Secondly, if there is a reaction to analyst recommendations, then how it changes based on the reputation of the analyst, or the star status of the analyst. Analyst performance has been an interesting topic since a star status of the analyst supports them to earn huge compensations and encourages them to be promoted to higher levels (Emery and Li, 2009). The topic of whether analysts are actually skilled or lucky is also well-documented with several proofs. According to Crane and Crotty (2020), large fraction of 5500 equity analysts studied between 1993 and 2015 are skilled. Authors find that almost 97% of analyzed analysts have positive true abnormal returns, which is striking.

The research conclusions are not headed in one direction. For example, recent research by Altinkilic and Hansen (2009) and Altinkilic et al. (2013) argues that analyst recommendations are not well-informative compared to other information sources and “piggy-back” on other public information. To the author’s best knowledge this is one of rare scholars concluding against the analyst recommendations. Although there has been large amount of research on the analyst reputation (see, e.g., among latest Fang and Yasuda, 2009 and 2014 and Kucheev, Ruiz, and Sorensson, 2017; Su et al., 2020) and market reactions, almost all of them had seemingly controversial results. Moreover, to the best knowledge of the author, in order to consider the star status of an analyst, most of the scholars used rankings data from Institutional Investor Magazine, which is argued to be subjectively evaluated (Emery and Li, 2009). Only, Kucheev, Ruiz, and Sorensson (2017) in their paper examined the reputation effect from 3 different rankings – Institutional Investor Magazine, Wall-Street and StarMine.

The latter two ranking are believed to be more objective compared to data from Institutional Investor Magazine. The scarcity of studies with objective analyst rankings allows current study to be different from previous studies and continue testing the results obtained by previous scholars.

In respect to the study sample, majority of the papers have been using a mix of stocks, which are traded in NYSE/NASDAQ/AMEX stock exchanges with the central goal of testing the general reaction. ADRs, by their nature, are different from Ordinary Shares. In order to be traded in the US markets, foreign firms undergo strict audit and change their internal working principles in accordance with Securities and Exchange Commission (SEC) regulations. It is also proven that ADRs are more volatile compared to the most US stocks since they normally come from riskier, usually developing markets.

Consistent with the goals, this study utilizes analyst recommendations data from Thomson Financials Institutional Broker's Estimate System (I/B/E/S). Daily returns data is retrieved from Thomson Reuters Eikon Terminal. Analyst reputation data was collected manually from StarMine's[1] website. The list of ADRs is extracted from the whole sample of stocks, which are traded on NYSE/NASDAQ/AMEX stock exchanges. The time interval of the analysis is between 2010-2019 and covers almost 371 ADRs. For 371 ADRs there have been over 6359 recommendation changes in the period of 9 years. During the analysis, we identify that the overall number of recommendations has been increasing, while the number of downside recommendations has been rashly decreasing. We begin our research by fragmenting ADRs from the whole sample. Thereafter, recommendations are pulled for fragmented list of ADRs from the whole sample of recommendations, that have been issued from 2010 to 2019.

Reputations data is processed in a separate spreadsheet. More precisely, the data is collected manually for each evaluation year and combined with the whole recommendations data sheet with regards to the affiliation (brokerage house) of the analyst. In line with previous research, this paper applies well-tested methodology of buy-and-hold calendar-time portfolios. Current methodology has been documented and developed in previous papers (Barber et al., 2001; 2006; 2010). The methodology assumes that analysts are divided into two Star and Non-Star categories. Separate

[1] StarMine on their website states "StarMine is the world's largest and most trusted source of objective equity research performance ratings" (StarMine 2015).

portfolios are formed for each category of analysts – Long and Short portfolios with a holding period of one month. By default, I/B/E/S recommendations detailed data file divides the recommendations into five categories, which are illustrated in Figure 1.

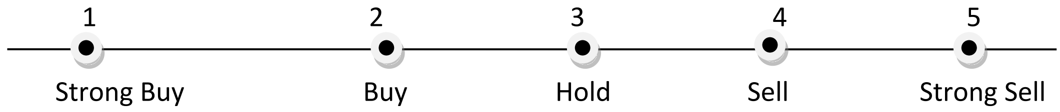

Figure 1. Categories of recommendations in I/B/E/S detailed file.

Strong Buy and Buy recommendations are placed into Long portfolio since they are meant to be positive, while Hold, Sell, and Strong Sell recommendations are meant to be negative and are placed into Short portfolio. Having formed portfolios for each category of analysts, $1 is invested into recommended stock at the end of the recommendation date. An investment is placed into corresponding portfolio, according to the scheme described above. A hypothetical investor holds the investment for 30 days and sells it with a positive or negative return.

2 Theoretical Background

Sell-side analysts propose their research through publishing reports. The analyst's report is a result of long-processed work of collection, evaluation, and dissemination of information related to fragmented number of firms and stocks. Analyst's report includes an earnings forecast, a stock recommendation, and target prices (Asquith, Mikhail, and Au, 2005). Recommendations, earnings forecasts, and target prices are the result of analyst's long-term assessment of firm's future success and fail over extensive time period. Assessment results are derived from fundamental research, financial models, and meetings with management. Additionally, most of the reports include short term trading ideas. Short term trade ideas are difficult to be researched since they are not gathered in a form of separate data, say in I/B/E/S, but they have to be extracted individually from analyst reports (Birru et al., 2022).

2.1 Market liquidity

Among the most important indicators to consider while choosing a stock market to outlay investments are price and volume. Together these indicators show the general trading activity on the specific market, and how market participants are generating excess returns. Institutional investors refer to the combination of price and volume as a "dollar volume liquidity", which is simply a share price multiplied by the daily trading volume. Higher dollar liquidity signals that market is large enough to make large trades without a serious impact on the market. High liquidity also tightens the bid-ask spread, which then minimizes the transaction costs. If the market liquidity is high, trading for retail investors becomes easier because it lowers the threshold for market entry. It is evident that if the market entry threshold is lower, the more retail investors bring their savings into the market. Eventually, it contributes to the market liquidity and trading becomes more transparent, leaving minimal space for arbitrage. Similarly, high liquidity helps to exit the market with minimal costs, in case of any negative sentiment.

During bad times, tough, liquid market might become non-liquid since everyone aims to sell. Overall, highly liquid stock markets are considered to be developed. The relationship between the market size and reaction severity is known to be negative (Murg and Zeitlberger, 2014). It means that traders and investors are able to generate excess returns only if the markets are highly liquid with a tight bid-ask spread.

2.2 Efficient Market Hypotheses

The efficient market hypothesis (EMH, hereafter) is a well-known theory, and it argues that the stock prices reflect all the information that is available, hence it is not possible to generate additional profits by trading stocks on different events or news. Specifically, current stock prices represent the fair value of the stock, which makes it impossible to find undervalued/overvalued stocks. According to the hypotheses, it is also impossible to gain higher profits than the market by selecting the stocks or entering the market in a specific time (Fama, 1991). Under the EMH world, it is also irrational to conduct any technical or fundamental analysis of the stocks. Despite being highly popular in modern finance literature, EMH is considered to be very controversial, and scholars tend to refute it in their papers.

It is not possible that all the markets are efficient. In real it is clear that some markets are less/more efficient. The inefficiency of the market might be driven by information asymmetries, the shortage of buyers or the sellers, high transaction costs, investor behavior and emotions etc. In fact, if the markets are fully inefficient, it leads to severe consequences as a market failure. Hence, all the markets are considered to be efficient with the exception of little inefficiency. Fama (1991) prosed three modifications of EMH:

1. Strong form of market efficiency argues that even the private information is reflected in stock prices, which leaves no space for any secret information e.g., earning

announcements before being presented to the public. Naturally, it is quite difficult to understand, especially nowadays.

2. Semi-strong form of market efficiency is slightly lighter than the strong form and it suggests that all the public information is reflected in the stock prices, leaving some space for private information to have probable impact on the stock prices. Additionally, under semi-strong form of market efficiency, technical analysis (analysis of stock price charts), or fundamental analysis do not work at all.

3. Weak form of market efficiency argues that past stock prices are reflected in the current price of the stocks, and one is unable to trade stocks based on historical prices. Technical analysis is also considered useless in this case. However, fundamental analysis can be used to correctly evaluate the condition of the company that issues the underlying stock.

The usability of the EMH has been widely questioned both in practical and theoretical grounds. If the severe form of EMH was true, then it would have destroyed the whole financial investments industry, including investment bankers, buy side analysts, sell side analysts and investors in general. A single example of the Warren Buffet can be an argument against the strongest forms of EMH. Warren Buffet, whose strategy is to focus on undervalued stocks, has made hundreds of million-dollar trades on the stocks over an extended period of time. Other than him, last 40 years the investing industry has skyrocketed, having portfolio managers that performed better than others, sell-side analysts that made highly-profitable recommendations. However, the proponents of EMH argue that the development of investing industry and examples of profitable strategies are mostly due to luck, but not due to the skill.

Fama (1991), when commenting the results of Stickel (1985), Lloyd-Davies and Canes (1978), argues that the sell-side analysts, who make price moving recommendations, have private information, which results is minor but statistically significant price changes once revealed to the public. These evidence follows the “noisy rational expectations” model of competitive equilibrium, proposed by Grossman and Stiglitz (1980). More precisely, Fama (1991) argues that since generating new information is tied up with costs, informed investors are paid for the expenses they make to check whether stocks reflect the private information. It makes the market “less than fully efficient”, which means there might be private information, which is not fully represented in the stock prices.

2.3 Analyst recommendations

Sell side analysts play crucial role in the capital markets by providing stock related research for brokerage clients that trade hundreds of millions of dollars based on the stock recommendations, earnings forecasts, and short-term trade ideas that are covered in the analysts’ reports. During mid-2000th, the role of stock analysts as investment advisors has been put under strong scrutiny. Specifically, finance media suggested that sell-side analysts are losing their objectivity towards the stock analysis to earn trust and respect from the clients of brokerage houses. In fact, the respect should have been earned by the investors, who follow the recommendations of the analysts. Specifically, the loss of objectivity was in issuing large numbers of positive recommendation of the covered stocks. Some of the investing media blamed analysts to be dishonest with complex conflict of interest, which makes the research worthless (Gimein, 2002). As discussed above, in a strong forms of market efficiency, analysts would not be able to add profitability since stock prices already would reflect the information that analysts base their conclusions on. The ability of the analysts to add value in the capital market could only be tested empirically (Jagadeesh and Kim, 2006). Prior literature also documents that sell-side analysts rarely issue negative (Sell or Strong Sell) recommendations. Some scholars report that during 1985-1999, less than 5% of all recommendation were negative, leaving 95% for positive recommendations (Jagadeesh et al., 2004).

Despite richness of the analyst topic, academic community and investment banks cannot reach one stable conclusion about the profitability and investment value of analyst recommendations and target prices. From one point of view, academic theory is still at odds whether recommendations worth considering, because results are multidirectional. At the same time, semi-strong form of market efficiency suggests that there can be no space to earn excess returns from implementing any investment strategies, such as analyst recommendations, but still large amount of banks and companies outlay huge financing for security analysis and sell-side analyst research, in particular.

2.4 Being a Star

Having found profitable investment strategies based on analyst recommendations, the literature separated the analysts in terms of their reputation. Specifically, analysts were then divided into Stars (highly reputable) and Non-stars (ordinary analysts). According to Emery and Li (2009), the star status can support an analyst earn fortune as an additional bonus/compensation. Scholars argue that being a star analyst of Institutional Investor rankings play of the 3 key roles in determining the analyst's compensation (Kessler, 2001; Stickel, 1992). The literature refers to the popular work of Rosen (1981), who identified the patterns of superstars in different industries. The compensation models of star-ranked sell side analysts are also best examined by the same paper. Specifically, Rosen (1981) identifies a phenomenon and calls it superstars, that are observed in music, film, and medical industries. Rosen (1981, 1992) claims that in a superstar model a tiny group of professionals earn the most, and the difference in compensation between different groups (stars vs non-stars) can be large.

The same arguments can be applied for the stock analysts for two main reasons. Firstly, people in the industry tend to think that analyst are not substitutable, meaning that not all analysts are able to make good recommendations as a certain small circle of analysts. Secondly, the talent is not measured correctly implying that a good performance of an analyst might be due to the compilation of knowledge and charisma at the same time. Thirdly, the product of sell-side analysts can be easily replicated by millions of other finance and non-finance specialists at a very low cost, but still people "listen to analysts". Finally, the information that is in control of an analyst is widely available for other people at very low costs. Evidently, the compensation model of analysts motivates them to become and keep being Stars.

During their journey of becoming stars, if analysts issue informative and less biased recommendations or earnings estimates, huge benefits were offered by the rankings such as partaking in the reduction of bias, which was estimated in $1.4 billion agreement between the regulators and brokerage houses to reduce the biased research (Smith, Craig, and Solomon, 2003). Investors are also left with huge benefits since they pay huge amounts of money for recommendations and target prices. Similarly, the academic community contributes a lot to identify less-biased analysts with better-performing recommendations and target price estimates.

3 Literature review

3.1 Retrospective literature of the topic

A survey conducted in 2014 by Greenwich Associates among buy-side investment banks conclude that institutional investors spent $11.55 billion on trading commissions and 59% of those commissions were paid for analyst research services. Moreover, recent research by Di Maggio, Egan, and Franzoni (2021) document that institutional investors are willing to pay about 40% higher trading commissions to get access to top analyst's research. Information comprehended by sell-side analysts is used to identify mispriced securities, while earnings forecast provides valuable information on future cashflows of the firm (Kothari, So, and Verdi, 2016). Womack (1996) suggests that there is a post recommendation stock price drift for upside recommendations, which is present up to 30 days. The price drift for downside recommendations may last almost 6 months. Having proven the effects of analyst reports, scholars were then interested in various analyst-specific attributes. One of them was an opinion that more reputable analysts are able to move the stock prices more intensely. This is also a central question in current research.

Stickel (1995) was among first-openers of the sell-side analyst topic in relation to the analyst's reputation. Using 17,000 recommendations from range of analysts over the 12-year period, the author analyzed the performance of security analysts on the Institutional Investor (II, hereafter) All-American Research Team relative to the performance of other analysts. The results of the research suggest that All-American analysts supply more accurate forecasts compared to other analysts. After the forecast of All-American analysts' stocks experience large upward move. In general, there is a positive relation between the reputation and performance of an analyst. Additionally, reputable analyst is better paid and promoted faster. Thereupon, a plethora of articles have been published in the search of profitable investment strategies in relation to analyst recommendations and target prices (see, e.g., Barber et al. 2001; Boni and

Womack 2006; Jegadeesh and Kim 2006; Leone and Wu, 2007; Barber et al. 2010; Loh, 2010; Loh and Stulz, 2011; among others). Leone and Wu (2007), using data from 1991 to 2000 also report a positive relationship between analyst reputation and stock performance. Specifically, authors conclude that All-American status of an analyst leads to better and persistent stock performance. Barber et al. (2001) in their initial research on the profitability pattern of the recommendations find out that buying/selling stocks with the most/least favorable consensus recommendations yield annual abnormal gross returns (including transaction costs) higher than 4%.

The conclusion holds provided the investor makes daily portfolio rebalancing with a fast reaction to consensus change. Those conclusions come against the well-known market efficiency theory since investors, not including transaction costs, are able to profitably utilize publicly available information on consensus recommendations. Results are also against popular view of Fama (1998) that reported consensus anomalies are due to random chance and are not stable since Barber et al. (2001) reports high t-statistics related to the portfolio returns. Additionally, authors conduct numbers of robustness tests, which result in the same conclusion. On the other hand, Altinkilic and Hansen (2009) and Altinkilic et al. (2010) protest to name analysts “prophets”. Instead, the results of analyzing intraday returns reveal that analyst announcements, on average, do not release new information. The reason behind popular conclusion of analyst informativeness is because forecasts are announced just after the significant news of the firm.

Overall, authors conclude that analysts “piggyback” on publicly available information and alter their thought according to the news. Contrary to this conclusion, analysts do not always rely on publicly available information. As such, as the reputation of the analyst rises, they are closer to the private information. It happens through attending manager meetings, calls. Additionally, analysts who are employed by (affiliated with) large brokerage houses have broader resources for analyzing the companies and publishing conclusions (Cliff, 2007).

In their seminal work, Birru et al. (2022), among first, analyze short-term trade ideas as a core component of analyst reports. The work is rare since short-term trade ideas are hard to be collected from a single source as, for example, analyst recommendations or target prices. By manually comprehending 4,543 short-term trade ideas issued between 2000 and 2015, authors find that both trading buys and trading sells generate significant abnormal price reactions. Economic magnitude of the generated reactions is comparable with stock recommendations and are three times larger than the target prices/earnings forecast revisions. These conclusions are contrary to the arguments of Altinkilic et al. (2010).

3.2 Analyst reputation and stock performance

Having numbers of conclusions on the stock price drifting effect of analyst reports, specifically recommendations, the reaction or absence of the reaction to analyst recommendations should be somehow explained. Hence, it is critical to analyze the attributes related to the analysts, such as the affiliation or the reputation. Barber, Lehavy, and Trueman (2007) and Cliff (2007), for instance, analyzed the performance of recommendations issued by independent analysts and affiliated analysts (employed by lead underwriters). Cliff (2007) finds that Buy and Hold recommendations made by independent analysts overperform the stocks recommended by affiliated analysts, however the affiliated analysts are better in recommending shorting opportunities.

The central question in this research refers to the reputation of the analyst and how it influences the performance of ADR stocks. Reputation of the analyst is measured according to the Star or Non-star status of the analyst. Star status refers to the highly reputable analyst, while Non-star status refers to the neutral analyst, who is not included in any analyst ratings. The Star status of the analyst is important in several contexts. First, looking at the Star status of the analyst, it is possible to measure profitability of the recommendations and make assumptions that their recommendations perform better than the recommendations of Non-star analysts. Second, the Star status is also highly important for the analysts. Once selected as a Star, it makes huge contributions to their career and wealth. The Star status results in huge numbers of extra bonuses and compensations measured in millions of dollars (Emery and Lee, 2009; Kucheev et al., 2017). Since the first paper by Stickel (1995), there has been written considerable number of papers analyzing analyst reputation (see, e.g. Leone and Wu, 2007; Emery and Li, 2009; Loh and Stulz, 2011; Fang and Yasuda, 2014; Kucheev et al., 2017). Of these papers, majority tested average stock price reaction to recommendation revision announcements in relation to the analyst reputation.

From discrepant papers studying different analyst rankings, Emery, and Li (2009), using a sample of 20,239 recommendations, issued by almost 6,000 analysts between 1993-2005, compared two rankings – Institutional Investor (II) and Wall Street Journal (WSJ). Findings indicate that factors with primary component of recognition are the main determinants of the rankings. Additionally, nor the II or WSJ Star analysts' recommendations do not significantly differ from that of Non-stars, meaning that analyst rankings are mostly "popularity contests". Despite large number of papers basing their research on II rankings, other scholars also concluded II to be biased (Kessler, 2001; Kucheev et al., 2017). This is because II rankings are not specialized for sell-side researchers, instead they are mostly for buy-side analysts and hedge funds.

Fang and Yasuda (2014) were one of the first to divide stock recommendations into several reputation groups, which are proxied by the analyst's position in II All-America Research Team. Using a large sample of data (392,711 recommendations) from 1993 to 2009, authors divided the stocks Long and Short portfolios. Following the methodology introduced by Barber et al., (2006; 2007), authors constructed calendar-time (dynamic) portfolios, that invest equal $1 to each new recommendation changes (upgrades or downgrades) issued by both Star and Non-star analysts. Hypothetical portfolios, which are aimed to follow the recommendations, are held for 30 days after investing. Portfolio returns are then accumulated by using the value-weighted intra-day return of the stocks. To see if Stars outperform Non-stars, authors calculate risk-adjusted returns for all portfolios using CAPM, Fama-French (FF, hereafter) 3-factor model, Carhart-4 factor model and 5-factor model, which adds a tech-sector index return to the original Carhar-4 factor model. Results suggest that recommendations issued by Stars perform better than those of Non-stars, having risk adjusted returns higher by 0.6% on a monthly basis in Stars group. Additionally, Star analysts' outperformance is persistent and is not due to luck but due to better access to the firm's management.

Of the most consequential results were then obtained by Kucheev et al. (2017). By processing a large sample of analyst recommendations data between 2003-2014, authors compared three rankings. namely, – II, WSJ's Best on the Street and StarMine's Top Stock Pickers and Top Earnings Estimators. Authors apply calendar-time portfolios methodology, as in the Barber et al. (2007), Fang and Yasuda (2014), which assumes that $1 is invested in each recommendation in the end of the recommendation date. In their model, $1 investment is held for 1 year if the analyst does not change their mind during the year. Similar to Fang and Yasuda (2014), authors find that Buy and Strong Buy recommendations, issued by Stars, significantly outperform Non-stars after a year of being elected as Star. On contrary, Sell and Strong Sell recommendations issued by both groups of analysts performed identically. Authors also argue that rankings composed by II are subjective since they are completed in a way of surveys. During the analysis, authors found that recommendations made by analysts ranked by II underperformed all of the stars and some of the non-stars. The best performer among the rankings was Starmine's Top Earnings Estimators. Su et al. (2020), focus on the UK market and analyze the reputation attribute among brokerage houses (BH), applying the same dynamic portfolios methodology. Using the data from 1995 until 2013 (58,647 stock recommendation revisions) and II All-Europe Research Team for BH rankings, they find BH reputation proxied by II has no significant impact on the stock performance, which supports the conclusion of Emery and Li (2009) about II rankings to be “popularity contests”. However, authors find significant and persistent performance of UK stocks, once the proxy is measured by the past year recommendation performance of the BH.

3.3 Introduction to ADRs

Despite a plethora of articles researching sell-side analyst performance, almost none of them study American Depositary Receipts. Samples of the studies are comprehended from NYSE/NASDAQ/AMEX stocks of both types – Ordinary shares and ADRs. ADR is a type of stock that represents foreign company’s shares that are traded in US dollars in the US stock exchanges. The underlying security is held by a US bank which purchases shares of the foreign company on a foreign exchange, i.e., holds on a custody. In general terms, ADRs allow US investors to take part in investing in overseas companies that are not available in other ways. It is also a good way to invest in emerging markets such as China and India.

For foreign companies, it is a way of attracting larger audience to their shares and raise capital, which they could not have accumulated in their home-countries due to limited audience or economic restrictions (Merton, 1987; Foerster and Karolyi, 1999; Lang et al., 2003). While the general description of ADRs is simple, there are different levels of them depending on the purpose, requirements, and outcomes. Level 1 ADR is the basic stock type that do not need to comply with SEC’s regulation nor US GAAP nor IFRS. Level 1 ADRs are traded in Over the Counter Market (OTC) and are not used to raise capital. Level 2 ADR is similar to Level 1, but they traded in major stock exchanges. They should also comply with SEC disclosure and use US GAAP or IFRS reporting standards. For Level 1 and Level 2 ADRs the foreign company is not obliged to make an IPO in the US stock market, rather shares are purchased in a foreign market by the US bank which then issues in US exchange in a fixed rate. Level 3 ADR obliges the foreign company to fully comply with SEC disclosure and establish an IPO. It gives a company space to raise substantial capital and fully take part in US trading activity.

3.4 Sell-side analyst rankings explained

Along with development of the sell-side research, there has always been a debate over the correct measurement of reputation, specifically, which ranking is the least biased. Majority of sell-side research use II ranking data as a proxy for analyst reputation. However, II rankings are blamed to be subjective. Moreover, relatively recently, there have appeared other rankings, which are argued to be objective. Table 1 represents the main types of rankings that have been popularized and used in previous literature. According to the evaluation approach each ranking can be divided into objective (StarMine and WSJ) and subjective (Institutional Investor Magazine).

Briefly, the subjective ranking applies various evaluation approaches and is based on survey results. Best on the Street, issued by the WSJ; “Top Stock Pickers” issued by StarMine, are considered two objective rankings. The third objective ranking is also issued by StarMine – “Top Earnings Estimator”, which measures the earnings forecast of analysts in terms of accuracy and timing.

Rankings offered by Institutional Investor magazine are criticized to be subjective and “popularity contests”, because in order to rank the analysts, II sends a survey to buy-side managers with request to evaluate the performance of sell-side analyst. Based on survey results, II derives 3 analysts in different industry categories, which are then referred as stars, and “runners-up” – those who are potential candidates to be elected as Stars in upcoming years. II publishes the rankings in October and includes 12 attributes, which are highlighted as the most important by investors. Interestingly, the stock picking ability and the correct earnings estimate are among the least important attributes, while the most crucial are the industry knowledge and trustworthiness. Hence, these attributes could be useful for certain clients, but it would be incorrect to measure portfolio profitability based on this survey answers (Kucheev et al., 2017). It might be the reason why previous papers had multidirectional findings. Fang and Yasuda (2014) used I/I rankings’ data and calculated portfolio returns through Carhart

4-factor model. Authors showed that II stars had monthly alphas of 1.25% for Buy portfolio and -0.83% monthly alphas for Sell portfolios compared to 1.09% and -0.71% alphas for Buy and Sell portfolios respectively in non-star group.

Kucheev et al. (2017)., also report significant alphas for Stars, derived from II rankings, although the significance is blurred compared to StarMine and WSJ rankings. Additionally, Su et al. (2020), using II rankings for UK stock market, reports significant effects of reputation on stock performance. On the other hand, Emery, and Li (2009), using the same data from II documents insignificant difference in performance of Stars from Non-stars.

“Best on the Street” rankings are issued by The Wall Street Journal (WSJ), where 5 analysts are ranked in each industry between 2003-2011 and 3 analysts per industry between 2012-2013. To the best knowledge of the author, WSJ rankings are not available for now. In general, the ranking is based on the aggregate score, which is obtained by the analyst in the last year and calculated as sum of 1 day returns of their recommendations (Emery and Li, 2009). The ranking is short-term oriented since it values the analysts, who issue recommendations on the day of a sharp price change, while the analysts who issue recommendations before or after the significant price change are “fined”. The most detrimental part of the ranking is the assumption that investors should have the recommendation a day before its announcement, which signals the privileged access to information. Yaros and Imielinski (2013) argues that WSJ rankings can generate significant random effects in the election of stars. Emery and Li (2009) as mentioned above, also documents significant underperformance of WSJ stars after being elected compared to non-stars.

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[2] Research Team"	Institutional Investor	I/I	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

Note: This table represents the four different analyst rankings, which, at least, once appeared in prior literature on the US stock market. Rankings are divided into 2 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); "Best on the Street" by *The Wall Street Journal* are in the objective group. Importantly, *II* rankings assess the analysts based on 12 various criteria, where stock picking skills is not the foremost criteria. *II* chooses 3 analyst per industry and "runners-up" – those who will potentially be chosen as stars in further 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 analyst recommendations. Both the *TSP* and *TEE* choose 3 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, *WSJ* does not publish the analyst rankings. Source: data are taken from Kucheev, Ruiz and Sorensson (2017).

Source: Kucheev, Ruiz, and Sorensson (2017)

Since 1998, much later than two previous rankings, Thomson Reuter' StarMine started to issue annual "Top Stock Pickers" (TSP) and "Top Earnings Estimator" (TEE) rankings, which select 3 analysts as Stars within each industry. Despite the late appearance of StarMine rankings, they have an important role in analyst research by providing powerful reference in the industry (Kim and Zapatero, 2011). The rankings are issued annually in October, as II rankings. The methodology of deriving the rankings is different from II's methodology. The calculation of TSP relies upon abnormal returns generated by non-leveraged portfolio, which is constructed from recommendations of analysts. Analyst returns are estimated by building long and short portfolios with buy-and-hold methodology in relation to the market capitalization-weighted portfolio of all existing stocks in a specific industry. Rebalancing takes place each month and/or when an analyst revises the recommendation or drops/adds coverage.

The TEE differs from TSP since it measures the accuracy of earnings forecast, issued by each analyst and it is a measurement tool of relative accuracy among all analysts because all analysts are evaluated in comparison to their peers. The calculation methodology factors in the analyst's forecast error, the variance of the error, the error of certain analyst compared to other analyst errors, the value of absolute earnings of the firm and the timing of the measurements. Scores on individual stocks, industries and analysts are aggregated by the daily measure of the rankings (StarMine, 2015). Importantly, from 2012 TEE uses earnings from the instant year before announcement of the rankings list, although before the evaluation was based on the forecast of earnings from the preceding year. As stated in Kucheev et al. (2017), TEE rankings are different from TSP and WSJ rankings, since it focuses on the earnings forecast, but avoids the investment value of analyst recommendations. Hence, TEE cannot be the right measure for portfolio abnormal returns. Yet, not wide range of papers have used the StarMine's rankings even though they are believed to be more consistent and reliable. Among few of them are Kerl and Ohler (2015), Kucheev et al (2017; 2019).

Previous literature on analysts' role in asset pricing is relatively rich and informative. Despite the semi-strong form of market efficiency, most of the scholars reported that analysts are able to influence the stock performance. Authors were able to document that analyst reputation plays a key role in making investment decisions, meaning they can generate higher excess returns. Importantly, authors centered the focus on general question by analyzing all the US stocks types in bulk. However, none of the papers divided stocks into ADRs and Ordinary Shares. Considering all the findings and gaps of previous literature, this study is aimed to continue investigating the sell-side research topic with a central focus on American Depositary Receipts and analyst reputation, which is proxied by unique hand-collected StarMine's rankings.

3.5 Statement of the Research Question

Although the topic of analyst research has been thoroughly studied, there are points that can be updated and developed. As such, scholars have repeatedly challenged the efficient market hypothesis by stating that stock prices are dependent on the components of analyst reports, e.g., recommendations, target price revisions, and earnings estimates (Kothari, So, and Verdi, 2016; Di Maggio, Egan, and Franzoni, 2021). All the analysis has been considering US shares in general, including Ordinary Shares and American Depositary Receipt stocks. There is no evidence how recommendations influence the American Depositary Receipt stocks, once considered separately. By their nature, ADRs are the imitation stocks which belong to foreign companies with several characteristics, nontypical to Ordinary Shares. For example, ADRs reflect the market situation of the country to which they belong and have different exposure to risk.

Additionally, when considering analyst attributes, most of the researchers used I/I All-American rankings data as a proxy to analyst reputation. Yet, I/I All American rankings are blamed to be subjective evaluation and are not able to reflect sell-side analysts' reputation (Kucheev et al., 2017). In this research, we use hand-collected StarMine's TSP and TEE rankings, which are based on calculations in contrast to surveys in I/I. Hence, the following research question is put forward:

RQ. Is it possible to set up profitable investment portfolios by following the recommendations of sell-side analysts from different reputation categories?

Over the past 20 years, access to information has become less costly and immediate. It also concerns most of the financial information. By using financial tools, investors are able to view analyst revisions and recommendations almost in live. Technologies also allow investors to create interactive portfolios of recommendations, which are initiated by their favorite analysts. Considering the background and goals of this research, following hypotheses are put forward:

H1. Portfolios comprised of analyst recommendations are able to generate abnormal returns in ADR context.

Coming from the first hypothesis, second hypothesis tests whether Star analysts issue more profitable recommendations compared to Non-stars.

H2. Portfolios comprised of recommendations of Star analysts are able to generate higher abnormal returns on average, compared to the portfolios of Non-stars in ADR context.

We will test these hypotheses by constructing a sample of recommendations made for ADR stocks and divide them into two analyst categories. For each analyst category, a hypothetical investor invests equal $1 amount at the end of the recommendation day. The investments are held for 30 days if the analyst has not changed their opinion for the recommendation. At the end of the time period, cumulative returns are calculated for the whole portfolio. The detailed description of sample and methodologies is presented in the following sections.

4 Methodology

4.1 Sample construction

Data for this research is obtained from several sources. First, the list of ADRs is extracted from the whole list of stocks traded in NYSE/NASDAQ stock exchanges. The recommendations data is collected from The Thomson Financials Institutional Brokers' Estimate System (I/B/E/S) Detailed Recommendations file. It provides a list of stock recommendations issued during specific period of time in a standardized way of 5 scales: 1 = "Strong Buy", 2 = "Buy", 3 = "Hold", 4 = "Sell", 5 = "Strong Sell". Since different analysts (brokerage houses) might have their own recommendation scales, the data in I/B/E/S allows to work with a single standardized scale for all the analyst recommendations. Returns data is obtained from the Refinitiv's Eikon terminal for the whole sample of NYSE/NASDAQ stocks. The returns data represent daily holding period returns (HPR) for an individual stock, which includes dividends and other price adjustments, such as splits. Fama-French Factors – Daily Frequency database is used to obtain value-weighted risk factors on market return, book-to-market, size, momentum, and investment factors. The data representing analysts' reputation was manually collected from the website of StarMine for each assessment year from 2010 to 2019. StarMine issues annual analyst rankings for each GICS industry, which includes 1 to 3 analyst per industry, where the 1st position is perceived as 'super-star' position (StarMine, 2020).

At first stages of data manipulation process, the I/B/E/S recommendation file was cleaned from redundant data. As such, the data file contained recommendations from anonymous analysts, analysts without any industry, affiliation, or brokerage house codes. The data is cleaned from this type of rows since they do not have any value for the research (Kucheev et al., 2017). As stated in previous research, stock recommendations, originally, are prone to become stale and unchanged, which makes them less informative over time (see e.g., Boni and Womack, 2006; Barber et al., 2010; Jagadeesh et al., 2014). In general, recommendations themselves are not so informative since they signal a level, not a level change. Hence, current study considers only the recommendation initiations and recommendation level changes, such as transitions from one level to another (e.g., from Buy to Sell; from Sell to Buy) and ignores the same level recommendation repetitions. The dataset for analyst reputation is derived from two rankings – TEE and TSP. They are merged and sorted in accordance with GICS industry groups to create a single variable, which indicates the Star or Non-Star status of an analyst. Data from various sources is then combined together. Specifically, the reputations dataset from StarMine's rankings is merged with recommendations data by matching the analyst names, the broker affiliations, industry codes, and brokerage house codes. The merging procedure was completed by hand and double-checked so that each analyst fits the exact recommendations they made.

Table 2 displays frequency statistics of the sample during the review period 2010-2019. The left part of the table summarizes main indicators as the number of ADRs and analysts. The table represents that the total number of ADRs during the review period equals 371. From 2010, the number of ADRs included in the sample shows a considerable increase, with 136 firms in 2010 and almost 202 firms in 2017. Total number of analysts issuing recommendations equals 1610 with an average number of 307. It can be clearly observed that the number of analysts fluctuates year over year and there is no strict trend. Last two columns of the left part of the table summarize the share of Star and Non-star analysts that made corresponding recommendations during the review period.

Out of total 1607 analysts, 3% is Stars and 97% are Non-stars. It is not surprising that Non-star analysts overweigh Stars significantly since the ranking requirements select only 3 analysts from each industry per year. It is also interesting to note that in 2014 the share of Star analysts picked up with 3,2% versus minimum 1% in 2014. The right side of the Table 2 shows the total number of recommendations made by each group of analysts on a yearly basis. The overall number of the recommendations in the sample is 6359. Similarly, the average number of recommendations in year over year is 636 with a fairly stable trend.

To sum up, in our sample 6359 analysts issued 6359 recommendations for 371 ADRs during 9-year period. Recommendations made by stars equal to 1,4%, while Non-stars issue the remaining 98% of the recommendations.

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

Year	Firms	Analysts	Stars (%)	Non-stars (%)	Rec-s	Stars (%)	Non-stars (%)
2010	136	322	1,6%	98,4%	620	1,3%	98,7%
2011	161	310	1,3%	99,0%	646	1,1%	98,9%
2012	158	291	2,7%	97,6%	613	3,1%	96,9%
2013	180	337	1,2%	98,8%	647	0,6%	99,4%
2014	191	344	3,2%	97,7%	710	2,1%	97,9%
2015	187	308	1,0%	99,0%	593	0,5%	99,5%
2016	163	262	2,7%	97,7%	522	2,1%	97,9%
2017	202	342	1,5%	99,1%	708	0,8%	99,2%
2018	201	304	1,6%	98,4%	670	0,7%	99,3%
2019	186	250	1,6%	98,4%	630	1,1%	98,9%
Average	177	307	1,8%	98,0%	636	1,4%	98,0%
Total	371	1610	3%	97%	6359	1,3%	98,7%

Note: The table presents the number of unique firms, analysts and recommendations included in the sample from 2010 to 2019 on a yearly basis. The left part of the table shows the number of unique firms and analysts and the share (%) of Star and Non-Star analysts in corresponding years. 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. On average, 98% of recommendations are made by Non-Stars, and only 2% - by Stars. Total number of unique analysts that appear in the sample is 371.

Table 3 shows the recommendation levels between two analyst reputation groups during the review period. Issuing negative recommendations is not favorable within the group of Stars since the only negative recommendation appears in 2010, while there is no indication of Sell recommendation from Stars in any years. To compare, Non-stars issued negative recommendations with more brevity, that is on average 6% Sell and 1% Strong Sell. Previous research indicates that analysts, once elected as Stars, try to hold the nomination in the next years and issuing negative recommendations is not largely supported by investors, which can result the future elections (Barber et al., 2007). Apart from negative recommendations, the distribution of positive and neutral recommendations in almost the same in both analyst groups. Exception might occur in Strong Buy with a prevalence of Stars, 23% on average compared to 16% by Non-stars. Important to mention that Hold recommendations comprise large portion of the sample 35% and 40% on average in Stars and Non-star groups respectively. However, Hold recommendations do not have significant economic impact when considered separately, hence it is rational to include them in the negative category (Fang and Yasuda, 2014).

The final dataset covers 6359 recommendations, issued by 1610 unique analyst during 2010-2019 time period. The total number of unique ADRs under review consists of 371 stocks. As previously mentioned, the literature stresses on the importance of analyzing recommendation level changes rather than recommendation level reiterations since reiterations are the repetition of the same previous recommendation.

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

	Star					*Non-star*				
Year	Strong Buy	Buy	Hold	Sell	Strong Sell	Strong Buy	Buy	Hold	Sell	Strong Sell
2010	13%	25%	50%	0%	13%	19%	32%	41%	8%	1%
2011	43%	29%	29%	0%	0%	13%	43%	36%	7%	1%
2012	5%	42%	53%	0%	0%	12%	32%	45%	9%	2%
2013	50%	25%	25%	0%	0%	14%	34%	42%	8%	2%
2014	27%	33%	40%	0%	0%	18%	40%	35%	5%	2%
2015	0%	67%	33%	0%	0%	14%	43%	37%	5%	1%
2016	9%	45%	45%	0%	0%	12%	38%	42%	6%	3%
2017	17%	67%	17%	0%	0%	23%	34%	38%	3%	1%
2018	40%	40%	20%	0%	0%	19%	36%	39%	5%	1%
2019	29%	29%	43%	0%	0%	18%	35%	42%	5%	1%
Average	23%	40%	35%	0%	1%	16%	37%	40%	6%	1%

Note: The table illustrates the number of recommendations (Strong Buy, Buy, Hold, Sell and Strong Sell) from 2010 to 2019 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 Star analysts, and the right side of table represents the Non-star analysts. Importantly, Star analysts make more positive recommendations and do not make any significantly negative recommendations compared to Non-Stars. A substantial part of the recommendations in both analyst groups comes to Buy recommendations (40% on average).

However, recently some scholars argued that reiterations actually have a confirmation effect to the original recommendation (Chen, Jung, and Ronen, 2017), which is the main concern for the future studies. In this study, we use only the recommendation level changes and initial announcements, as summarized in Table 4. Table shows that recommendation initiations comprise large portion of the recommendations, 41% and 48% First negative and First positive recommendations respectively. The recommendation level changes fluctuate around 5% for the whole sample of recommendations.

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

Year	First negative	First positive	From negative to positive	From positive to negative
2010	46%	46%	5%	3%
2011	39%	48%	8%	4%
2012	48%	38%	6%	8%
2013	48%	45%	4%	4%
2014	37%	56%	3%	4%
2015	38%	52%	5%	5%
2016	45%	45%	5%	5%
2017	38%	52%	5%	5%
2018	40%	50%	5%	5%
2019	37%	45%	7%	11%
Total, %	41%	48%	5%	5%
Total, N	2632	3048	335	344

Note: The table shows the percent of level changes and coverage initiations from 2010 to 2019 on a yearly basis, which are included in the sample. First negative and First positive are the categories to indicate the initiation of coverage by the analyst. From negative to positive and from positive to negative are the recommendation revisions from the previous levels. In total, 5680 recommendations refer to initiations, while 679 recommendations refer to level changes.

4.2 Portfolio construction

As an initial step towards calculating profitable analyst recommendations, it is necessary to group the recommendations according to different analyst attributes. In the case of this study, we group recommendations according to level of the recommendation and each analyst reputation groups. By doing so, we construct different buy-and-hold calendar-time portfolios. The calendar-time portfolios methodology was introduced by Barber et al. (2006) and has been used repeatedly by scholars in future studies. Similarly, this study constructs buy-and-hold calendar-time portfolios for each group of analyst reputation with a holding period of 30 days.

While there are various ways of modifying the portfolios, this study assumes that ever-elected Star analysts are prone to make more profitable recommendations compared to Non-star analysts. Hence, the recommendations of Star analyst, which are made before their election of stars are also included in the portfolios, e.g., if an analyst is elected as a start in October 2020, the portfolios might include recommendations of those analysts, which are made prior to October 2020. Additionally, there is no strict rule of forming portfolios in terms of different recommendation levels. Some of the authors (Kucheev et al., 2017) construct “Long”, “Hold”, “Short” portfolios for each level of the recommendations. However, others, (see e.g., Fang and Yasuda, 2014) include “Hold” recommendation into the "Short” portfolios, by arguing that “Hold” normally a negative signal.

Moreover, as a robustness test, authors detach “Hold” recommendations from “Short” portfolio and apply the same procedures again. As a result, “Hold” recommendations as a separate portfolio do not have a significant economic impact. For the purposes of this study, we construct 2 – “Long” and “Short” portfolios. “Long” portfolio comprises of “Strong Buy”, “Buy” recommendations, while “Short” portfolio consists of “Strong Sell”, “Sell”, and “Hold recommendations. Since most of the recommendations are just a reiteration, we exclude them from the portfolios, and include only the recommendation level changes and recommendation initiations. This way portfolios become more informative with a little level of noise. The portfolio formation matrix can be seen in Table 5, where recommendations on a 5-scale level are placed into corresponding Long or Short portfolios.

Next, we group portfolios in accordance with the analyst reputation – 2 “Long” portfolios separately for Stars and Non-stars, 2 “Short” portfolios separately for “Stars” and “Non-stars”. As a robustness check, we also include 2 portfolios for Number-1 ranked top Stars group within “Long” and “Short” portfolios. As a result, the there are 6 different portfolios for the empirical analysis. The graphical representation of the portfolios can be observed in Figure 2.

In general, methodology of calendar-time portfolios assumes that for each recommendation initiation or the level change, a hypothetical investor invest $1 at the end of the recommendation's disclosure day into the corresponding portfolio. If the recommendation is announced in holidays or weekends, the investment is made on the following working day. If the same stock is recommended by different analysts on the same day, then it will appear in the portfolio for several times.

The logic is quite consistent – if a new recommendation is "Strong Buy" or "Buy", it is placed to the "Long" portfolio, and if the recommendation is "Strong sell", "Sell" or "Hold", it is place in "Short" portfolio. The holding period of the investment is 30 days for the purposes of this research, meaning that a hypothetical investor is short-term oriented and trades actively. Moreover, recommendations tend to become stale and forgotten after the initial recommendation date, especially in the case of ADRs (Loh and Stulz, 2018). Subsequent to 30 days from the recommendation date, each position is closed with a positive or negative return. Gross returns are calculated for each date of the portfolio from 2010 to 2020 to comprise daily returns data table during the analysis period. Having collected gross daily returns for each portfolio, we calculate abnormal returns by applying additional empirical models, which will be discussed below.

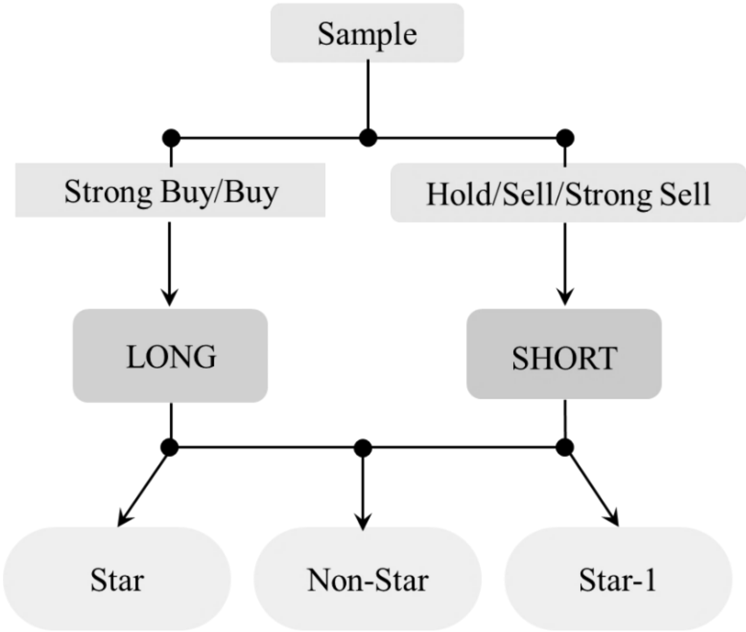

Figure 2. Construction of the portfolios.

Note: The figure illustrates the portfolio formation process. Long portfolio includes Strong Buy/Buy recommendations. Short portfolio includes Hold/Sell/Strong Sell recommendations. Having formed two portfolios, they are divided into 3 groups according to the reputation of an analyst.

Table 5. Portfolio formation matrix.

Recommendations	Long Portfolio	Short Portfolio	Total
1 - Strong Buy	1049	-	1049
2 - Buy	2334	-	2334
3 - Hold	-	2513	2513
4 - Sell	-	373	373
5 - Strong Sell	-	90	90
Total	3383	2976	6359

Note: The table displays the summary of how the recommendations are included in the Long and Short portfolios. As can be seen, the Long Portfolio comprises only positive recommendations (Strong Buy and Buy), while the Short Portfolio includes negative recommendations plus the neutral Hold recommendation. Motivation for the latter inclusion was obtained from the previous literature (Fang and Yasuda, 2014; Su et al., 2019), where authors claim that Hold recommendations are understood by market participants as a negative signal. Both portfolios are on balance with 3383 recommendations in the Long Portfolio and 2976 recommendations in Short Portfolio.

4.3 Analytic strategy

Having constructed portfolios, the next step towards answering the research question is to calculate corresponding daily returns of the portfolios. Firstly, by applying equal monetary investment methodology we calculate compounded daily returns for the $1 dollar investment from the day of investment until the end of the 30-day period. Technically, it assumes that for each recommendation *n*, we let $x_{n,t-1}$ to 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 is the last 30th day of the investment), as described in the following equation (Kucheev et al., 2017):

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

where $R_{i_n,recdat_n t-1}$ is the total return of stock $i_{n,t}$ on calendar date *t-1.* Applying the equation (1) for all the recommendations in the portfolio results in the holding period compounded returns for the recommended stocks. The sample calculation of compounded daily holding period returns is presented in the table of Appendix 1.

Secondly, it is the next step to calculate daily portfolio gross returns. Majority of the previous papers used equal portfolio returns calculation methodology and faced criticism for the possibility of bias (Dutta, 2015; Kothari, 2016). Hence, current study considers value-weighting methodology of the portfolio calculation. The calendar date *t* gross return of 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 the total number of recommendations represented in the portfolio ρ on date *t.*

The component of the equation (2) $x_{n,t-1}$ is a weight of each recommendation *n* in the portfolios. Equation (2), once applied to the whole portfolio, yields daily time-series returns, which are the final components of the portfolio calculation.

Since gross returns of the portfolios are not the correct representation of the profitability, we adjust the portfolio returns to R_{ft}, which captures 1 month T-bill returns. Daily abnormal returns of the portfolios are calculated as an intercept (alpha) by using 3 pricing factors, that is, Fama-French 3-factor model, Fama-French 5-factor model, and Fama-French 6-factor model. The latter model adds momentum factor to existing investment and profitability factors as described in the equation (5):

$$R_{\rho t} - R_{ft} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_{t+} h_p HML_t + \varepsilon_{p,t} \quad (3)$$

$$R_{\rho t} - R_{ft} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + r_p RMW_t + c_p CMA_t + \varepsilon_{p,t} \quad (4)$$

$$R_{\rho t} - R_{ft} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + r_p RMW_t + c_p CMA_t + m_p UMD_t + \varepsilon_{p,t} \quad (5)$$

where $R_{\rho t}$ is the portfolio ρ return on a certain date *t;* $R_{m,t}$ is the market return of all firms traded in NYSE, AMEX, and NASDAQ; $R_{f,t}$ is the risk-free rate of return for the 1-month treasury bill; SMB_t is a size factor, which is a difference between returns of value weighted portfolios consisting of small and large stocks; HML_t is a B/M factor, which is the difference between returns of the value weighted portfolios of high and low B/M stocks; RMW_t is a profitability factor and is defined as the difference between the stocks with robust and weak operating profitability; CMA_t is an investor factor, which defines the difference between conservative and aggressive stocks; UMD_t is a momentum factor, which is derived as an average return of two high return portfolios minus the average return of the two low return portfolios [3].

[3] For any further details, see French and French (2018). All returns for factors are obtained from the website of Kenneth French.

5 Results and Discussion

Table 6 shows the results of applying 3 different factor models to the daily portfolio returns, namely – Fama-French 3 factor model, 5-factor model, and 6-factor model. First, Panel 1 indicates the regression results for the Long portfolio, which includes Strong Buy and Buy recommendations. Similarly, Panel 2 displays the abnormal returns for Short portfolio, which includes Hold, Sell, and Strong Sell. First three columns indicate the reputational group of the analyst, while the last three columns show the net difference between abnormal returns of different analyst reputation groups.

Table 6. Performance of Long and Short Portfolios within each analyst group.

	Star (1)	Non-star (2)	Star-1 (3)	Star vs Non-Star (4)	Star-1 vs Star (5)	Star-1 vs Non-Star (6)
Panel 1. Long Portfolio						
FF 3-factor alpha	0.0170*** (11.94)	0.0341*** (28.65)	0,0037*** (7.79)	-0.0171*** (-9.14)	-0.0133 (-9.85)	-0.0304 (-23.57)
FF 5-factor alpha	0.0170*** (11.98)	0.0342*** (28.77)	0.0037*** (7.74)	-0.0172*** (-9.12)	-0.0134* (-9.80)	-0.0305** (-23.66)
FF 6-factor alpha	0.0172*** (12.10)	0.0345*** (29.04)	0.0036*** (7.61)	-0.0173*** (-9.07)	-0.0136* (-9.76)	-0.0309*** (-24.03)
Panel 2. Short Portfolio						
FF 3-factor alpha	-0.0058*** (-8.09)	0.0312*** (8.63)	-0.0019*** (-5.21)	-0.0370*** (-9.89)	0.00382 (6.08)	-0.0332*** (-8.91)
FF 5-factor alpha	-0.0058*** (-8.08)	0.0312*** (8.60)	-0.0019*** (-5.22)	-0.0370*** (-9.88)	0.00381 (6.07)	-0.0331*** (-8.90)
FF 6-factor alpha	-0.0057*** (-7.95)	0.0318*** (8.77)	-0.0019*** (-5.17)	-0.0375*** (-9.73)	0.00374 (6.02)	-0.0338*** (-8.80)

t statistics in parentheses
* p < 0.05, ** p < 0.01, *** p < 0.001

Note: This table displays the daily alphas, which are based on Fama-French 3-factor, 5-factor, and 6-factor models. The table is divided into two panels, where Panel 1 is for Long Portfolio, Panel 2 is Short Portfolio Each portfolio is constructed in a way that once a new recommendation is announced, $1 is invested in each recommended stock at the end of the trading day (or the next trading day if the announcement is on weekends/holidays) and held for 30 days. 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 Star-1 category, those Star analysts which are ranked “number one”. The right side of the table shows the difference of alphas between each group of analysts. All differences are tested using suest and lincomest commands in STATA software. In Long Portfolio, Stars significantly underperform Non-Stars by average -0.36% on a monthly basis. However, in Short Portfolio Stars significantly overperform Non-Stars on average by -0.77% on a monthly basis. “Number one” ranked Stars show underperformance in both of the portfolios.

Generally, the table shows that all generated abnormal returns in each analyst groups are highly significant. It suggests that the analysts are able to make profitable investment recommendations *ceteris paribus.* Existence of profitable investing opportunities stays against the well-known Efficient Market Hypothesis (EMH, hereafter), which argues the stock prices reflect all the events occurring around them immediately letting no room for excess returns. For research purposes, portfolio excess returns were tested using 3 different models, to catch for probable external effects, such as Market Return, or generated factors as Investment, Momentum etc. Interestingly, the models generate even higher abnormal returns once additional factors are added.

From Table 6, Panel 1, we can see that both Stars and Non-stars generate high daily abnormal returns, while the test group Star-1 has the least average daily abnormal returns. Looking at the FF-3 factor alphas, Stars generated 0.017% daily (0.357% monthly) abnormal returns compared to Non-stars – 0.034% daily (0.716% monthly). Results suggest that Non-stars are able to generate 2 times higher alphas in the ADR context. The Star-1 group, which represents Top-star analysts ranked number 1 shows the least favorable abnormal returns, which is 0.004% on a daily basis (0.084% monthly). The right side of the Table 6 shows the differences between alphas of Stars vs. Non-stars, Star-1 vs. Stars, Star-1 vs. Non-star tested by using parametric test (suest and lincomest commands) in STATA. From the table, the differences between the alphas of Stars and Non-stars are highly significant with a difference of -0.017% daily (-0.357% monthly) basis. Results of other factors models depict the same direction of alphas.

Panel 2 of Table 6 presents results of regressing the returns of the Short portfolio on series of pricing factors. We can see that all of the three pricing models yield almost the same results of excess returns. Looking at the alphas generated by Fama-French 3-factor model, it is clear that analyst recommendations can significantly move the stock prices. Contrary to the Long portfolio, Stars do outperform Non-stars in issuing negative recommendations. First model generates -0.0058% daily average abnormal returns, which is -0.122% on a monthly basis. On the other hand, Non-stars group of the Short portfolio generates highly negative abnormal returns on the level of 0.0312% on a daily basis and %0.6552 on a monthly basis. Important to mention that returns with a minus sign in the Short portfolio indicate that the portfolio is profitable since shorting trades are done in the opposite direction by selling the stocks. The third and the additional group in the Short portfolio is the Star-1 group, which indicates significant abnormal returns on the level of -0.00194% on a daily (-0.041%, monthly) basis. As for the parametric test results, the difference between Stars and Non-star group is significant and -0.78% on a monthly basis, which means that Star analysts are able to generate 0.78% higher monthly alphas in the Short group of the recommendations. Appendix B summarizes the regression results on a yearly basis to give a clearer understanding of the portfolio profitability.

In general, the regression results suggest that Hypothesis 1 is accepted i.e., analyst recommendations are able to move stock prices. This phenomenon has been repeatedly documented by previous research (Barber et al. 2006; Fang and Yasuda, 2014; Cheng, Jun, and Ronen, 2017; Birru, Gokkaya, and Stulz, 2022). Other than moving stock prices, the analyst recommendations are also able to generate abnormal returns, which will outperform the market return. On the other hand, the Hypothesis 2 is half-accepted since we do not document outperformance of Stars in the Long portfolio. Absence of outperformance is not due to insignificant parametric test results, but due to significant outperformance of Non-stars. Previously, scholars did not find any significant evidence that Stars outperform Non-stars in the Long portfolio due to the lack of significance in regression results (Emery and Li, 2006; Su, Zhang, and Joseph, 2020). In general, there might be several explanations towards the significant outperformance of low reputable analysts in the Long portfolio.

As stated by Barber et al., (2007) positive recommendations comprise large part of overall recommendations since negative recommendations are not favorable among investors. Here, the sample consists of ADRs, which are generally highly volatile stocks due to their exposure to high risk. The Star analysts, once elected as a Star, make high contributions to keep their status for the next year (Emery and Li, 2009; Loh and Stulz, 2018), which explains their risk-aversion. Shortly, one reason might be because recommending highly volatile stocks is popular among Stars. They might be involved in number of stable and high-value ADRs, such as Alibaba, or stocks from developed European countries. On the contrary, Non-stars might “have nothing to lose” and are brave to issue more recommendations even on small, highly volatile stocks that can generate large profits.

The results obtained from the Short portfolio are partly supporting the Hypothesis 2, as we observe a significant outperformance of Stars over Non-stars with circa 9.7% higher abnormal returns on a yearly basis. A theory that Star analyst outperform the Non-Stars in Short Portfolio is also documented by Su, Zhang and Joseph (2020), who researched the reputation of brokerage houses on the whole. Of more related literature, Kucheev, Ruiz and Sorensson (2017) conclude that only “Top Stock Pickers” analysts have significant abnormal returns in the Short Portfolio. The reason for inconsistency of the Short Portfolio with the latter paper might lie in joint nature of “Top Stock Pickers” and “Top Earnings Estimator” ranked analysts as used in this research. As explained below, issuing negative recommendations require high quality of knowledge. In positive recommendations, the analyst might issue trading Buy for several stocks, and some of the recommendations will work due to preferable market conditions. However, an analyst could not issue several sell recommendations and believe in the market conditions, since only severe times, like Covid-19 pandemic might crash the stocks in whole. Shortly, the outperformance of Stars in the Short portfolio might be resulted by scrupulous research of Star analysts, that issue Sell of Hold recommendations strictly for the less volatile ADRs that they cover. In the case of Non-stars, they might initiate coverage for various kinds of volatile stocks, which results in negative excess returns. Shorting highly volatile stocks might lead to severe consequences, especially in the case of small ADRs, most of which carry a risk of default or are highly responsive to news.

As introduced in Kucheev, Ruiz and Sorensson, 2017, this study detaches Star-1 group. In both of the portfolios, Star-1 group does not indicate any significant outperformance of Stars. Moreover, the Star-1 group generated lower abnormal returns in the Long portfolio compared to Non-stars. The reason behind severe underperformance of Star-1 group might be in data constraints, specifically, low data availability in this category of analysts.

Overall, obtained results partly contradict some of the existing literature and at the same time support the others. While there is no doubt that all the previous papers concluded that analysts’ recommendations have an economic value and are profitable (Barber et. al, 2001; Kucheev, Ruiz, and Sorensson, 2017; Birru, 2022), the part of the second hypothesis is multidirectional. Specifically, we find that being a Star does not pay out in higher profitability compared to the Non-stars in the Long portfolio. Emery and Li (2009), analyzing WSJ and I/I rankings, concluded that both rankings are “popularity contents” and Stars do not outperform the Non-stars. Su, Zhang, and Joseph (2020), analyzing British brokerage houses, also concluded that past performance as a proxy of reputation is not able to signal a higher profitability of the recommendations. In short, there might be several reasons why there is an inconsistency in the Long portfolio compared to other scholars (e.g., Fang and Yasuda, 2014). First, it is highly important to look at the rankings that are utilized in most of the studies. Fang and Yasuda (2014) and many more researchers used I/I rankings, where the subjectivity issue is a red flag. In technical terms, subjective rankings are highly probably to lean towards more positive recommendations. Hence, the number of star analysts in context of Buy and Strong Buy recommendations might be higher than in the objective rankings. Second, the underperformance of stars in the Long portfolio might be highly dependent on the sample, namely, ADRs and the sample size. As mentioned earlier, ADRs are by nature different from the Ordinary Shares and the response to ADR recommendations are different since the stocks are more volatile. Similarly, the audience of ADRs is much narrow as opposed to Ordinary Shares. Third, previous papers used large samples (e.g., 172,525 recommendations in Kucheev, Ruiz, and Sorensson, 2017; 392,711 recommendations in Fang and Yasuda, 2014), which might the one of the core reasons behind the differences in Long portfolio. Undoubtedly, analysts prefer making more positive recommendations, and the number of negative recommendations has been coming down since 2000th. It might the reason that recommendations of ADR sample (6359 companies) are not able to capture the true performance of stars in the Long portfolio. On the other hand, analyzing such a high number of recommendations for ADRs is merely possible since the number of ADRs that are available for analysis varies between only 500 companies. The same reason might lie in the underperformance of number-1 ranked stars in both of the portfolios. In this paper, they comprise minimal number of 4-5, which might undoubtedly impact the results. Finally, as already mentioned, the difference in the Long portfolio between this paper and some other papers is highly linked to the peculiarity of ADR firms, namely, exposure to higher risk and uncertainty, which stop Stars from covering more firms and give more frequent positive recommendations.

6 Conclusion

The aim of this study was to identify profitability pattern in analyst recommendations to conclude whether investors can form portfolios and generate abnormal returns based on these stock recommendations. Additionally, it was important to differentiate between different groups of analysts that issue recommendations – analyst elected as Stars (highly reputable) and Non-stars (ordinary). Analyst reputation have been one of the major topics in recent years since the Star status of an analyst helps to earn high salaries and bonuses along with opening gates to private information. Answering these questions would help to find possible investment strategies, which might be then applied by investors. Similarly important that the stock area was reduced to American Depositary Stock receipts to analyze the ADRs in a separate sample. ADRs are the main interest in this study because it there is no indication of papers on analyst recommendations analyzing only ADRs. However, by their nature ADR stocks are known to be more volatile and can generate extremely high returns and losses. Different analysts treat ADRs in a different way, e.g., Star analysts might be less involved in issuing recommendations for ADRs as a risk aversion towards their status, while Non-star will be less thoughtful and can cover wide range of highly risky stocks.

By constructing well-known buy-and-hold portfolios for each recommendation, we report regression results for Long and Short portfolios. Our results suggest that analysts indeed issue profitable recommendations i.e., buying, and short-selling stocks in accordance with analyst recommendation is expected to yield excess returns. From the perspective of positive recommendations, we identify that Star analysts significantly underperform Non-stars almost two times. For the investor it means that one can generate abnormal returns for the portfolios comprised of recommendations of Star analysts, but the profitability will be higher if the portfolios are formed from Non-star analyst recommendations. The opposite situation can be observed once looked at the Short portfolio. Specifically, in Stars tend to outperform Non-stars in downgrading or shorting ADRs. It may be explained by the fact that shorting stocks might require professionalism, since ADRs are by nature highly volatile and can lead to severe outcomes. The outperformance of Stars in Long portfolio has been documented by previous scholars (see, e.g., Mikhail et. al., 2004; Fang and Yasuda, 2014; Crane and Crotty, 2020), however little is known about underperformance of Stars.

The contribution of the current study largely leans towards using objective analyst rankings (StarMine) and limiting the observations sample to ADRs. Firstly, there little is known about the analyst literature, which applies hand-collected analyst rankings to form the portfolios. In this study, analyst rankings are derived by hand-collected *StarMine* database. On top of this, this is yet another confirmation that analysts play an important role in the formation of asset prices, and they are able to generate abnormal returns. More importantly, there is now evidence on how ADRs react to the analyst recommendations free of Ordinary Shares. Results of this paper can be implemented in real life trading by including recommended ADRs in investment portfolios according to nuances. Specifically, one could consider adding ADRs from the recommendation of Non-stars in their portfolio to maximize the profitability. At the same time, ADR recommendations from Stars can be added to the portfolio to maximize the returns. By adding both types of recommendations, and investor would properly distribute the investments and minimizes the risks related to American Depositary Receipts. Also, investors might want to consider that the underperformance of Star analysts in the Long portfolio might not be solely due to the lack of recommending ability, instead Stars could be less risky and recommend only stable and big ADRs. In short, more risk averse investors can consider listening to Non-stars in the Long portfolio.

Unarguably, this work can be improved by a) including wider time-frame; b) testing the affects of other rankings, such as TipRanks. Most importantly, the work can be enhanced by comparing the results with the Ordinary Shares sample. The comparison of the portfolio performance within a single study would contribute largely to the sell-side literature and in terms of ways of forming profitable portfolios.

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Appendices

Appendix 1. Calculation of the compounded daily holding period returns

	GOL.N	*ADR ticker*
$ USD	**23.07.2010**	*recommendation date*
23.07.2010	1	*$1 investment*
24.07.2010	1,023168909	
25.07.2010	1,046874616	
26.07.2010	1,053756918	
27.07.2010	1,046109916	
28.07.2010	1,013992506	
29.07.2010	1,046109916	
30.07.2010	1,079756726	
31.07.2010	1,114485743	
01.08.2010	1,150331776	
02.08.2010	1,19921273	
03.08.2010	1,119373839	
04.08.2010	1,128335347	
05.08.2010	1,10063614	
06.08.2010	1,130779395	
07.08.2010	1,161748186	daily holding period returns
08.08.2010	1,193565124	
09.08.2010	1,183246117	
10.08.2010	1,197004793	
11.08.2010	1,176366779	
12.08.2010	1,148849428	
13.08.2010	1,195284959	
14.08.2010	1,243597375	
15.08.2010	1,293862538	
16.08.2010	1,307825083	
17.08.2010	1,331095992	
18.08.2010	1,328303483	
19.08.2010	1,284554174	
20.08.2010	1,273384138	
21.08.2010	1,262311232	*compounded return t-1*
22.08.2010	0	

Appendix 2. Yearly abnormal returns of the portfolios

	Star	Non-star	Star-1	Star vs Non-Star	Star-1 vs Star	Star-1 vs Non-Star
Panel 1. Long Portfolio						
FF 3-factor alpha	4,28%	8,59%	0,93%	-4,31%	-3,35%	-7,66%
FF 5-factor alpha	4,28%	8,62%	0,93%	-4,33%	-3,38%	-7,69%
FF 6-factor alpha	4,33%	8,69%	0,91%	-4,36%	-3,43%	-7,79%
Panel 2, Short Portfolio						
FF 3-factor alpha	-1,46%	7,86%	-0,49%	-9,32%	0,96%	-8,37%
FF 5-factor alpha	-1,46%	7,86%	-0,48%	-9,32%	0,96%	-8,34%
FF 6-factor alpha	-1,44%	8,01%	-0,48%	-9,45%	0,94%	-8,52%

Note: This table displays the annual alphas, which are based on Fama-French 3-factor, 5-factor, and 6-factor models. The table is divided into two panels, where Panel 1 is for Long Portfolio, Panel 2 is Short Portfolio.