The drivers and profitability of sell-side analysts' recommendation revisions' tails

Daniel Vela Mata

Dissertation written under the supervision of Professor José Faias

Dissertation submitted in partial fulfilment of requirements for the International MSc in Finance, at the Universidade Católica Portuguesa, April 2024.

The drivers and profitability of sell-side analysts' recommendation revisions' tails

Daniel Vela Mata
Universidade Católica Portuguesa

Abstract

Faias (2017) develops a prediction exercise of influential recommendation revisions to construct a long-short strategy that earns significant alphas between 1999 and 2013. This work extends the results of that strategy until 2021 and adds new variables to the model, inspired by Loh and Stulz (2011) and Loh and Stulz (2018). I show that the equal-weighted long-short strategy exhibits abnormal returns, with a monthly return of 1.9% and a break-even round-trip transaction cost of 88.6 basis points, between 1999 and 2021. These results survive an extensive battery of robustness tests. Therefore, analyst recommendation revisions represent a valuable information vehicle for investors.

Keywords: influential recommendation revisions, prediction, investment strategy, market efficiency.

Abstrato

Faias (2017) desenvolve um exercício de previsão de revisões de recomendações influentes para construir uma estratégia "long-short" que gera alfas significativos entre 1999 e 2013. Este trabalho estende os resultados da estratégia até 2021 e acrescenta novas variáveis ao modelo, inspiradas em Loh e Stulz (2011) e Loh and Stulz (2018). Eu mostro que a estratégia "long-short" igualmente ponderada apresenta retornos anormais, com um retorno mensal de 1.9% e um limite de rentabilidade para custos totais de 88.6 pontos base, entre 1999 e 2021. Estes resultados sobrevivem a um extenso número de testes de robustez. Por conseguinte, as revisões de recomendações de analistas constituem um veículo de informação valioso para os investidores.

Palavras-chave: revisões de recomendações influentes, previsão, estratégia de investimento, eficiência de mercado.

Acknowledgements

I would like first and foremost to thank my supervisor, Professor José Faias, for his invaluable guidance throughout the process of writing my thesis and for all the support and dedication he has given me during my Masters journey.

My debt of gratitude extends to the institution, Universidade Católica Portuguesa, as well as to all the professors I have had the privilege of crossing paths with. This work is a testimony of all the knowledge, work, and commitment from the past five years of my life.

Finally, I would like to thank my mom, my girlfriend and her parents, for always being present throughout this process and for their unwavering support during the toughest moments of this journey.

Contents

I. Introduction

How valuable are sell-side analysts' opinions? This work builds on the most recent developments of literature on analysts' recommendations and their capacity to influence stock market valuations. Previous studies have addressed whether the average recommendation is influential (see Chen et al., 2005, and Altinkiliç and Hansen, 2009). Nonetheless, I focus on the determinants of influential recommendation revisions and revisit Loh and Stulz (2011) on the most important characteristics that determine whether a recommendation change is influential for investors' decisions. I follow Faias (2017) methodology to predict influential recommendation revisions using an endogenously defined threshold probability based on an *ex-ante* prediction exercise. Then, I examine the economic value of influential recommendation predictions using a self-financing investment strategy – Predicted Influential Recommendations Strategy (*PIRS*).

The contribution of this study to the existing literature is fourfold: first, I extend the sample used in Faias (2017) until the most recent available data, incorporating the years of the COVID-19 pandemic, and focusing solely on U.S. firms; second, I add different variables previously developed by preeminent authors, where the majority of variables is inspired or developed by Loh and Stulz (2011) and Loh and Stulz (2018), both to the model that predicts real influential recommendation revisions out-of-sample and to the analysis of recommendation characteristics that drive influential recommendation changes; third, I find that influential recommendation revisions' characteristics are dynamic and can have asymmetric roles for positive and negative recommendation revisions; finally, I show that a strategy exploiting the tails of price reactions to recommendation revisions remains profitable during the entire period, even after accounting for the investment lag experienced by investors when recommendations are issued during the market close.

Prior literature points to the analysts' information production role being significantly reduced by an improvement in overall market efficiency. Altinkiliç et al. (2016) analyze post-revision drifts following analysts' revisions of their stock recommendations and find that they are no longer able to provide information that is relevant in the long run for investors. This implies that, on average, the recommendation revisions' direction is no longer a good predictor of stock performance. This line of research has generated evidence that confirms the idea that market efficiency has improved over the last years, in line with the principle that market efficiency exists when economic agents are not able to profit from analysts' information, proposed by Jensen (1978). Additionally, these results corroborate the definition of market efficiency proposed by Fama (1970), which notes that markets are efficient if agents cannot reliably predict long-run common stock returns. Hayunga and Lung (2014) show that options investors anticipate the analyst's revisions until 3 days prior to the announcement. While Engelberg et al. (2020) suggest analyst recommendations may contribute to anomaly mispricing and market inefficiency. Choi and Lee (2022) contribute to the discussion on the role of security analysts as information intermediaries through a signal-to-noise volatility ratio to capture the efficiency contribution of analysts' recommendations. They show that revisions with a greater efficiency contribution generate significant impacts on prices, and, at the same time, they contribute for greater efficiency by inducing informed traders to active trading. Batten et al. (2022) find that analyst recommendations are not valuable by showing that a portfolio based on the recommendation level does not generate a significant performance in a recent ten-year period due to an optimism bias compared with the prior periods. They also provide evidence that despite the superior performance of a portfolio based on the changes of analyst recommendations, a portfolio strategy based on them generally performs worse and is less robust than a momentum strategy. These results hold even when restricting the analysis, to cases where analyst recommendation information works best.

This study focuses on reassessing the economic value of the tails of price reactions to analysts' recommendation revisions', i.e., influential recommendation revisions. Faias (2017) shows that a trading strategy based on the tails of recommendation revisions' price-reactions generates a monthly alpha of 2% between 1999 and 2013. Barber et al. (2010) show that both analysts' recommendation revisions and rating levels exhibit abnormal returns. Furthermore, a strategy conditional on the rating level and recommendation revisions outperforms both strategies solely based on the level and recommendation revisions, respectively.

Analyst-related characteristics have been associated with influential recommendation changes in previous literature. Bradley et al. (2014) and Loh and Stulz (2018) find that analysts' resources, proxied by the brokers' size, intensifies the stock price reactions in the same direction as the correspondent recommendation revisions. Cooper et al. (2001) show that leader analysts have a relatively higher impact on stock prices than follower ones, revealing that despite the analysts' tendency to herd, leader analysts are still the most impactful in the stock market. Additionally, they find that performance rankings based on the forecast timeliness are more informative than those based on abnormal trading volume and forecast accuracy. Diether et al. (2002) find that dispersion in analysts' earnings forecasts has a strong negative relation with future returns, with the effect being more pronounced in small stocks and stocks with a poor performance in the year before. Loh and Mian (2006) suggest that analysts who have issued more accurate earnings forecasts tend to issue more profitable recommendations. The average difference between the factor adjusted return of recommendation changes by analysts in the highest accuracy quintile relative to the ones by analysts in the lowest accuracy quintile was 1.27% by month. Clement (1999) shows that the analysts' forecast accuracy is positively related with the analysts' experience and the size of the employer, but negatively correlated with the number of industries and firms covered by the analyst. Frankel et al. (2006) analyze cross-sectional determinants of the informativeness of analyst research and find that informativeness is positively correlated with trading volume, volatility, and institutional ownership.

Other characteristics have been found to be relevant determinants on the influence of analyst recommendations. Jegadeesh and Kim (2010) find that the further away a recommendation change is from the consensus, the more influential it tends to be on stock prices, signaling the analysts tendency to herd on their recommendations. Irvine (2003) shows a distinctive positive reaction on prices surrounding an analyst's initiation of coverage relative to an analyst that already covered the stock. Pohl and Pursiainen (2023) show that stock index membership affects sell-side analysts' career outcomes and that they exhibit a strategic negative bias in their recommendations for firms just above the index cut-off around the time of determining the index weights. Boni and Womack (2006) show that the analysts' role as information intermediaries is more valuable if analyzed while controlling for the industry: an industry-based recommendation strategy improves the return-to-risk ratio and lowers the price momentum tilt compared to non-industry adjusted portfolios.

Regulatory events have also been shown to play a crucial role in the likelihood of influential recommendation revisions. Boni (2006) find that the Global Settlement Agreement, an inter-brokerage agreement tackling conflicts of interest between brokerage research and investment banking operations, led to a lower short-term reaction to analysts' recommendation changes in the 3-day window around the recommendation changes. Gintschel and Markov (2004) find evidence that following the Regulation Fair Disclosure, selective disclosure was curtailed, and the absolute price impact of analysts' output was reduced.

I attempt to identify the economic value of a portfolio based on predicted influential recommendation revisions using a long-short investment strategy. The construction of the portfolio is based on an out-of-sample prediction exercise of influential recommendation revisions, from which we buy (sell) stocks with positive (negative) recommendation changes. The model follows the methodology of Faias (2017), where the portfolio is rebalanced every day and holds each stock for a period of 21 trading days. Additionally, the first daily return of the recommendation is excluded, under the conception that investors are not able to act on the recommendations before they are made public. This strategy yields, on average, a return of 22.6% for the period between 1999 and 2021. For this same period, the strategy registers a significant alpha when conditioned for distinct factor models. It yields alphas of 23.3%, 23.8% and 22.1%, when conditioned for the Carhart (1997) four-factor model, Fama and French (2015) five-factor model and the Hou et al. (2021) q^5 model, respectively. This performance is extraordinarily high when compared with the *CRSP equal-weighted index* or with a portfolio strategy that trades on all recommendation changes based on their direction (*TRC*), which have an average return of 15.9% and 20.8%, respectively, during the same period. The *PIRS* performance exhibits a positive and significant skewness. The strategy performance is mostly concentrated around the first 4 days after the recommendations' announcement, as 61.4% of the total return is generated during this time. This suggests that the market takes time to incorporate the information from recommendation revisions. The strategy performance is mostly driven by the event reaction of the recommendations, but the drift still accounts for two-fifths of the total return in the first 21 trading days.

This strategy is consistent, as its performance is robust to different periods of time, holding periods and other confounding effects. It is robust to business cycles, as defined by the NBER, presenting an annualized alpha of 22.4% during contractions and 22.7% during expansions. The *PIRS* performance also holds when only large stocks are used, namely, S&P 500 index member stocks, yielding an annualized alpha of 14.4%. For comparison, the *TRC* strategy has an annualized alpha of 11.1% and an annualized average return of 10.9% with positive skewness when trading the S&P 500 index member stocks. I also analyze how the *PIRS* evolves over different periods of time. My results suggest that the best performance occurred in the interval between 1999 and 2013, with an annualized alpha of 26.5%, while the worst performance occurred between 2014 and 2021, with an annualized alpha of 18.8%.

I compute the turnover of the *PIRS* following Barber et al. (2001), and use it to compute the break-even transaction costs, i.e., the trading costs that would absorb the performance of the trading strategy. The break-even transaction costs are computed by dividing the annualized return or alpha by the annualized turnover of the strategy. Novy-Marx and Velikov (2014) provide evidence on the performance of numerous trading anomalies after accounting for transaction costs. Additionally, they estimate the round-trip transaction costs across market capitalization ranks, which I use as a benchmark to assess the ability of *PIRS* to withstand those costs. Other authors have put forward round-trip costs' estimations of the bid-ask spread of 1% for individual investors (Barber and Odean, 2000) and for mutual funds (Carhart, 1997). The *PIRS* performance remains positive after accounting for the benchmark round-trip costs for its average market capitalization, around \$8.1 billion. On average, the firms included in *PIRS* belong to the 68th percentile of the NYSE market capitalization as of the last June 30 prior to the recommendations' announcement date. The strategy would still be profitable for round-trip costs of 88.6 bps (basis points), generating a positive alpha for round-trip costs of 91.7 bps, whereas the *TRC* would still be profitable for transaction costs of 74.8 bps.[1]

The definition of influential recommendation revision used is unrelated to the reputation of the analyst in question, as it is based on the *ex-post* price reaction. However, it has been widely studied that firms value all-star research coverage (e.g., Dunbar, 2000, Krigman et al., 2001, Asquith et al., 2005, and Ljungqvist et al., 2009). Therefore, I analyze the relevance of the analyst's status for determining influential recommendation revisions and its impact on the strategy's performance. In my sample, I find that merely 12.7% of the influential revisions were issued by star analysts and only 21.1% of star analysts' recommendation revisions are influential. The *PIRS* performance using only star analysts' recommendation revisions is worse than the strategy without them, with an annualized alpha of 14.9% and 24.0%, respectively.

To assess the relevance of analysts' opinions and to capture the economic value generated by the *PIRS* solely based on these same recommendations, it is important to exclude recommendations that follow firm-specific events. As explained in Loh and Stulz (2011), and in Altinkiliç and Hansen (2009), this is the case of recommendations where it cannot be said that the traditional condition of event studies holds, i.e., events randomly impact the recommendations in question. Hence, I exclude recommendations with an earnings announcement, M&A deal, or security related events (e.g. cash dividends, capital adjustments, and other distributions made to shareholders of a security) within a 43 day window centered around the announcement date.[2] Additionally, for the same window, I also consider as events days with multiple analysts issuing a recommendation for the same stock to exclude situations where analysts piggyback one another on firm news (Bradley et al., 2008, and Loh and Stulz,

[1] I assume the factor model structure remains similar after incorporating transaction costs when analyzing the impact on the alpha of the strategy.

[2] Information on M&A announcements, earnings announcements and security related events was collected from Refinitiv Eikon©, *I/B/E/S* and *CRSP*, respectively.

2018).[3] Despite excluding, on average, 117 stocks from the portfolio, the *PIRS* performance remains unchanged, returning an alpha of 31.3%, revealing that the results are not driven by the effect of firm specific news.

I construct alternative strategies for the prediction of influential recommendation revisions. In the first alternative, I consider different sets of variables based on their marginal effects in-sample: either the top characteristics in each group of variables (recommendation, analyst, firm) or the top characteristics with highest marginal effect. Then I impose a new condition to the original model, where a recommendation is only influential if the values of its characteristics are greater than their historical means in the 5-year rolling window used for the *Probit* model. I have also modified this alternative strategy to include solely the selected variables in the *Probit* model and incorporated the additional condition that the values of the characteristics must be greater than their 5-year historical means in the definition of the threshold. These strategies perform better than *PIRS* when I condition the model for more than one characteristic. The second alternative uses a different method to compute the total error of the model, which changes the threshold value for which a recommendation revision is predicted as influential. This alternative underperforms *PIRS*. In the final alternative, I run a strategy based on *PIRS* conditioning for the direction of recommendation changes and the recommendation level as in Barber et al. (2010). The long leg uses upgrades of recommendations to recommendation levels of buy or strong buy, and the short leg uses downgrades towards recommendation levels of hold, underperform or sell. The performance is better than *PIRS*. All the described alternative strategies present, on average, larger idiosyncratic volatility than *PIRS* as they use fewer securities in each leg.

The remainder of this work is structured as follows. Section II presents the data and variables used. Section III describes the analysis on influential recommendation revisions characteristics, explains the model, and discusses the in-sample and out-of-sample results. Section IV details the investment strategy used to capture the economic value of the prediction exercise. Section V summarizes the robustness tests performed. Finally, section VI concludes. A glossary for all variables used and corresponding definitions is included at the end of the paper.

[3] Considering days with multiple recommendations for a stock as events within a 43- and 13-day window leads to all recommendations being excluded from the *PIRS*. Therefore, I only analyze the strategy excluding these events for a window of 21- and 6-days, before and after the recommendations' announcement date, respectively.

II. Data and Methodology

A. Data

The stock recommendation sample is retrieved from Thomson Financials' Institutional Brokers Estimate (*I/B/E/S*) U.S. Detail File. The sample is built from *I/B/E/S* ratings on U.S. firms, ranging from 1 (strong buy) to 5 (sell), issued by individual analysts from September 1993 to December 2021.[4] As in Loh and Stulz (2011), I use an inverted ratings scale, where a strong buy corresponds to 5. Additionally, I account for the change in the rating distribution caused by the National Association of Securities Dealers (NASD) Rule 2711 in 2002, which required brokerages to report the distribution of stock ratings across their coverage universe.[5] This analysis focuses on recommendation revisions, as prior research shows they contain more value than recommendations due to the market capacity to recognize the analysts' tendency to herd (Jegadeesh and Kim, 2010).

Recommendation changes are computed as the difference between an analyst's current rating and his prior outstanding rating. I exclude recommendations with no outstanding prior rating from the same analyst (i.e., analysts' initiations are disregarded). Analysts coded as anonymous by *I/B/E/S* are excluded since it is not possible to trace their recommendation revisions. Additionally, I exclude all securities that have fewer than five recommendations during the entire sample period or that have less than two years in the *CRSP* database. The criteria used for outstanding ratings follows the definition established by Loh and Stulz (2011): a rating is assumed to be outstanding if it is less than one year old and never more than two years old. In the cases where the rating is between one and two years old, it is considered outstanding only if there is an analyst forecast from the same analyst in the one-year window prior to the recommendation date (matching to the I/B/E/S Detail Earnings Forecast File). The changes in recommendations range from values between -4 and 4. The sample contains 8,693 unique firms and 9,812 unique analysts, and a total of 8,208 unique announcement dates. There are 235,171 recommendation changes, with 98.8% between -2 and +2. On average, in each month, there are 813 recommendation changes for a total of 490 unique companies. On average,

[4] Due to the limited access to the All-American annual polls of the *Institutional Investor* magazine, the period considered ends in 2021.

[5] This rule was approved on May 8, 2002, with an implementation period ending September 9, 2002. Many brokers reissued stock recommendations in the implementation period (Kadan et al., 2009). As a result, 2002 contains the greatest number of recommendations in I/B/E/S compared to any other sample year (Barber et al., 2006). To account for this structural break, I remove recommendation changes where the current recommendation is issued between May 8, 2002, and September 9, 2002 (inclusive) and the prior recommendation was issued before May 8, 2002. Such recommendation changes are likely to be motivated by the adherence to the NASD 2711 rule rather than by stock selection.

there are 8,109 recommendation revisions per year, with a maximum (minimum) of 13,216 (3,752) in 2008 (2021). The maximum (minimum) number of distinct analysts is 2,182 (1,145), observed in 2002 (1994). On the other hand, the maximum (minimum) number of different firms with a recommendation revision is observed in 2006 (2021), corresponding to 2,177 (1,288) firms. The year with the most (least) recommendation revisions of at least two categories as a percentage of the total number of recommendation revisions is 2007 (2000), with 36.7% (16.6%).

The data used for the computation of the different characteristics related to the recommendations and analysts was extracted from *I/B/E/S*, while the data used for the calculation of the variables related to the firm and security characteristics was extracted from *Compustat* and *CRSP*, respectively. Institutional ownership records were collected from *Thomson Reuters Stock Ownership* and the constituents of the S&P 500 and M&A Deals were collected from *Refinitiv Eikon*. The monthly factor returns of Hou et al. (2021) q^5 model were collected from the Hou-Xue-Zhang *q*-factors data library.[6] Finally, daily and monthly Fama-French (1993, 2015) and momentum factor returns were extracted from the Kenneth R. French – Data Library.[7]

B. Analyst Specific Variables

In this section I describe the main analyst variables used throughout the paper. The remaining variables and their construction are carefully explained in the Glossary – Variables Definition.

***Leader-follower ratio (LFR)*:** Introduced in Cooper, Day, and Lewis (2001) to capture the differential impact leader analysts have on stock prices. It is computed as the sum of the days elapsed between the current recommendation and the previous two recommendations from different analysts for the same stock, divided by the time elapsed between the current recommendation and the following two recommendations from different analysts for the same stock. The greater the value of the *LFR*, the more likely an analyst is followed by others.

[6] Available at https://global-q.org/index.html.
[7] Available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Broker size**:** Used by Loh and Stulz (2018) as a proxy for the resources available to analysts. I define it as the number of distinct analysts that issued a stock recommendation or earnings forecast for any horizon, during the previous 12 months, for a given broker.

Star analyst**:** A dummy variable equal to 1 if the analyst is ranked in the All-American (first, second, third, or runner-up teams) annual polls of the *Institutional Investor* magazine. The analysts' names in *I/B/E/S* are matched to the polls from *Institutional Investor* in the October issues since 1993, where the analyst keeps his status for a period of 12 months beginning in November. This variable captures the effect of the analysts' reputation on their influence in the stock market. Star analysts have already been widely addressed in prior literature (e.g., Dunbar, 2000, Krigman et al., 2001, Asquith et al., 2005, and Ljungqvist et al., 2009). Jin et al. (2023) find that star analyst's coverage decisions improve (worsens) following a drastic deterioration (improvement) in a firm's information environment. These results coincide with the idea that star analysts hold superior ability to identify mispriced stocks. Additionally, He et al. (2005) show that institutional investors, i.e., large traders, primarily pay attention to recommendations from star analysts instead of non-star analysts, while Bonner et al. (2007) find that earnings forecasts revisions by star analysts exhibit larger reactions by market participants.

Earnings forecast accuracy**:** Loh and Mian (2006) find that analysts who issue more accurate earnings forecast also issue more profitable stock recommendations, which implies they may have larger effects on stock prices. I compute the earnings forecast accuracy quintile of an analyst by sorting analysts for a given firm-year combination into quintiles, using the last available unrevised FY1 forecast of the analysts, following Loh and Stulz (2011). The analysts are assigned a forecast accuracy quintile (1 being the most accurate), based on the recommendations that the analyst issues during a 12-month window that overlaps three months into the next fiscal year, following Loh and Mian (2006). This way it is possible to apply the accuracy rank during the months when the fiscal year's actual earnings are announced.

Away from consensus**:** Jegadeesh and Kim (2010) show that stock price reactions are larger when further away a recommendation is from the consensus, which reveals the market capacity to identify analysts' tendency to herd. Thus, this dummy variable equals 1 if the new recommendation deviates from the consensus by two standard deviations of that consensus estimate. I define the consensus recommendation as the mean recommendation level that includes the most recent non-stale recommendations issued by all analysts covering the firm (Loh and Stulz, 2011).

***Concurrent earnings forecast*:** Kecskés et al. (2017) show that analysts' recommendations have a greater initial stock price reaction and a larger post-recommendation drift when they are accompanied by earnings forecast revisions. Therefore, I include a dummy variable that is equal to 1 when the analyst issued a FY1 forecast within a three-day window around the recommendation revision.

***Analyst experience*:** Mikhail et al. (1997) show that analysts improve their earnings forecast accuracy with experience. Following Loh and Stulz (2011), I consider analyst experience as the number of quarters an analyst appears on *I/B/E/S* since its first earnings forecast or stock recommendation. The earliest of the two dates is used when the analyst appears in the recommendations file and the earnings forecasts file. The two measures used, as proposed by the authors, are *absolute analyst experience*, represented by the total number of quarters an analyst appears in *I/B/E/S*, and *relative analyst experience*, defined as the number of quarters a particular analyst has covered a specific firm minus the average experience for all analysts covering that firm.

***Influential before*:** Loh and Stulz (2011) find that recommendation changes by analysts that have been influential previously with respect to any stock are more likely to be influential. This effect is stronger if the analyst has been influential before for the same stock. Thus, it is important to create two distinct dummy variables. The first equals 1 if the analyst has been influential with respect to any stock in the past, while the second equals 1 when the analyst has previously been influential with respect to the same stock.

C. Analysts' Influential Recommendation Revisions

I follow the methodology adopted by Faias (2017) to determine the effect of recommendation changes in stocks' returns. The return impact of a recommendation is measured by the cumulative buy-and-hold abnormal returns (*CAR*) for a two-day time window:

$$CAR_i = \prod_{t=0}^{1}(1 + R_{it}) - \prod_{t=0}^{1}\left(1 + R_{it}^{DGTW}\right) \tag{1}$$

where R_{it} is the raw return, measured by the ex-dividend returns from *CRSP*, of firm i on day t. $t = 0$ is the day of the recommendation announcement, except when the announcement occurs between 4:30 pm and 11:59 pm, in which case $t = 0$ is the following trading day. For recommendations whose announcement date is made during a non-trading day, the first trading day following the announcement is considered as $t = 0$.[8] The benchmark reference return used, R_{it}^{DGTW}, is the return on a benchmark portfolio of the same size, book-to-market and momentum characteristics similar to firm i, as defined by Daniel et al. (1997). Book-to-market (B/M) ratios are computed as in Fama and French (2006), while price momentum is computed every month based on the buy-and-hold return over the prior 12 months skipping the most recent month, following Loh and Stulz (2011). Firms are first sorted into quintiles each July based on their market cap on June 30 of each year using breakpoints determined from NYSE stocks. Then, they are sorted within each size quintile based on their B/M ratios. Lastly, firms within each size-B/M group are allocated into quintiles every month based on their price momentum. This means, size and B/M rankings are updated every 12 months, whereas momentum rankings are updated every month. The benchmark portfolios returns are then computed as in Loh and Stulz (2011) using the ex-dividend returns from *CRSP*, so that it is consistent with the computation of the raw returns for each firm.

Recommendation changes are considered influential when the *CAR* follows the same direction as the recommendation change and, simultaneously, the following inequality holds:

$$|CAR_i| > 1.96 \times \sqrt{2} \times \sigma_{\varepsilon_i} \tag{2}$$

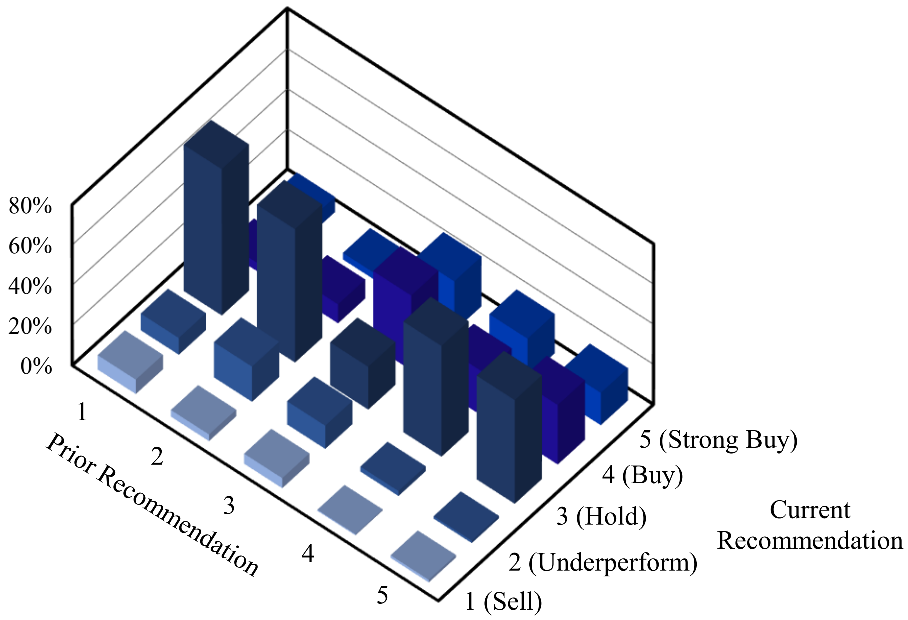
where σ_{ε_i} represents the *idiosyncratic volatility* of firm i, measured by the standard deviation of the residuals from a daily time-series regression of firm returns against the Fama and French (1993) three factors. The regressions are conducted for the period that starts three months before (t - 69) and ends six days before the recommendation announcement (t - 6). A recommendation is influential if its absolute *CAR* is greater than 1.96 times the standard deviation of the firm's prior three-month idiosyncratic volatility, multiplied by $\sqrt{2}$ since the *CAR* is calculated for a two-day window. I distinguish between positive and negative influential recommendation changes. A recommendation change is deemed positive if there is an upgrade and negative if there is not an upgrade (downgrade or reiteration).[9]

[8] As explained by Loh and Stulz (2011), most of the cumulative abnormal return in the period t = -5 and t = +5 around a recommendation lies in the window between t = 0 and t = 1.

[9] In Figure 1 and Table 1, reiterations are considered influential solely if they meet the condition in equation (2), that is, even if the *CAR* does not have a negative sign.

Figure 1 – Transition probabilities of influential recommendation changes

The top graph refers to the full sample and the bottom one to influential recommendation changes only. The sample of recommendation changes is from the I/B/E/S Detail U.S. File for the period from 1993 to 2021. A recommendation change is the difference between the analyst's current rating and his prior rating. Recommendation changes are deemed influential according to the criteria established in Section II.C.. Reiterations are deemed influential if the inequality in equation (2) holds, regardless of the direction of the recommendation change. Ratings are coded from 5 (strong buy) to 1 (sell), and the rating change level ranges from -4 to 4.



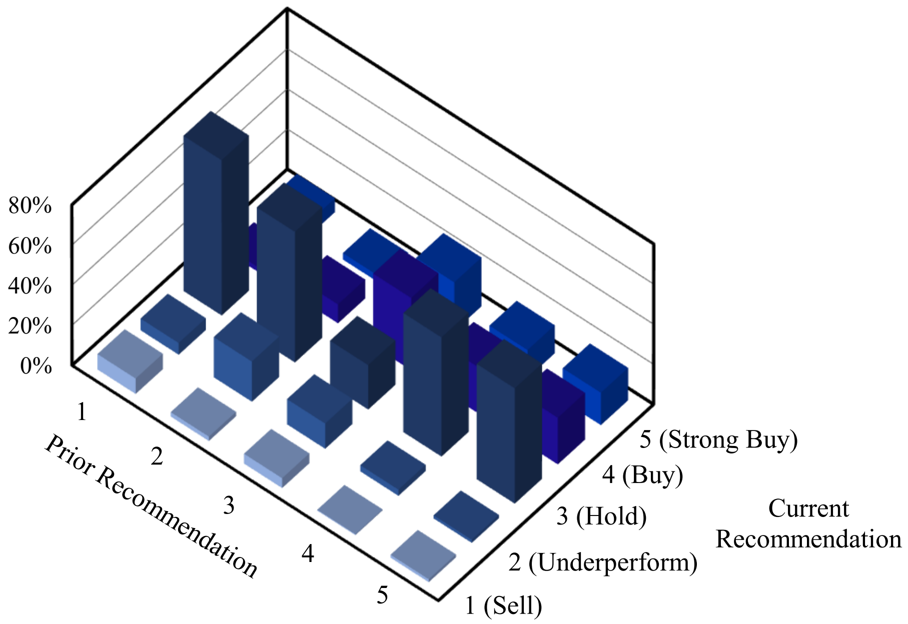


Table 1 – Descriptive statistics of *CAR*s

This table presents the descriptive statistics of the two-day (0,1) buy-and-hold *CAR*s (in percentage) for the full sample, the influential recommendation changes sample and the recommendation changes issued by the star analysts by each recommendation change level (from -4 to +4). The daily abnormal return is the raw return less the daily return of the corresponding DGTW portfolio. Each recommendation change is the difference between the analyst's current rating and prior rating. Recommendation changes are deemed influential according to the criteria established in Section II.C.. Reiterations are deemed influential if the inequality in equation (2) holds, regardless of the direction of the recommendation change. Ratings are coded from 5 (strong buy) to 1 (sell), and the rating change level ranges from -4 to 4. The KS test is the Kolmogorov-Smirnov D statistic testing for the normality of the sample distribution. The sample is from the I/B/E/S Detail U.S. File for the period from 1993 to 2021. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Filtered Samples	Mean	Mode	% *CAR* +	Skewness	Kurtosis	KS normal test	Percentiles					# Obs
							99%	75%	Median	25%	1%	
Recommendation Change = -4												
1) Full Sample	-5.523	-1.0	38.906	-0.78	11.68	0.181 ***	46.623	1.791	-1.498	-7.324	-88.663	658
2) Influential	-27.421	-10.0	0.000	-1.24	3.55	0.158 ***	-2.554	-8.879	-18.177	-39.226	-95.821	173
3) Star Analysts	-2.803	-1.0	33.333	-1.28	4.93	0.129	8.954	0.893	-1.193	-5.123	-20.307	42
Recommendation Change = -3												
1) Full Sample	-4.974	-0.5	34.686	-1.78	11.80	0.141 ***	25.330	1.445	-1.753	-7.013	-68.853	986
2) Influential	-21.863	-15.5	0.000	-1.54	4.96	0.155 ***	-2.253	-7.653	-15.466	-28.059	-89.607	257
3) Star Analysts	-7.140	-2.0	20.455	-2.50	12.27	0.220 ***	34.118	-0.194	-3.069	-7.583	-80.845	132
Recommendation Change = -2												
1) Full Sample	-3.722	-1.0	35.985	9.10	488.64	0.192 ***	27.394	1.389	-1.549	-5.924	-62.926	32,711
2) Influential	-17.983	-6.5	0.000	-1.95	6.81	0.175 ***	-2.428	-6.550	-11.518	-22.467	-82.109	8,496
3) Star Analysts	-3.858	-1.0	33.356	-2.96	19.23	0.164 ***	15.764	0.950	-1.612	-5.056	-57.689	3,004
Recommendation Change = -1												
1) Full Sample	-3.148	-0.5	36.847	7.33	346.47	0.186 ***	25.349	1.475	-1.399	-5.432	-55.624	66,154
2) Influential	-16.697	-4.5	0.000	-2.02	7.37	0.175 ***	-2.268	-6.150	-10.828	-20.936	-77.185	15,856
3) Star Analysts	-3.415	-0.5	33.989	-1.80	23.21	0.155 ***	17.250	0.970	-1.528	-5.190	-51.471	8,385
Recommendation Change = 0												
1) Full Sample	-0.096	0.0	49.638	111.27	18423.35	0.238 ***	23.466	2.679	-0.031	-2.705	-28.229	46,636
2) Influential	-0.343	5.0	49.671	58.93	4957.97	0.219 ***	38.279	7.818	-1.898	-8.115	-50.551	11,562
3) Influential with CAR>0	11.529	5.0	100.000	58.31	3868.19	0.308 ***	52.061	12.909	7.861	5.035	2.090	5,743
4) Influential with CAR<0	-12.060	-5.5	0.000	-2.70	12.37	0.185 ***	-2.045	-5.089	-8.067	-14.438	-62.080	5,819
5) Star Analysts	-0.157	0.0	48.386	0.53	24.09	0.126 ***	20.553	2.234	-0.134	-2.536	-21.774	8,242
Recommendation Change = 0 in Expansions												
1) Full Sample	-0.099	0.0	49.530	113.48	18168.85	0.255 ***	21.739	2.518	-0.041	-2.565	-27.221	41,399
2) Influential	-0.370	-4.0	49.189	58.38	4641.98	0.238 ***	39.010	7.190	-2.154	-7.712	-50.447	9,860
3) Star Analysts	-0.210	0.5	48.065	0.86	32.06	0.125 ***	16.592	2.073	-0.150	-2.394	-20.156	7,211
Recommendation Change = 0 in Contractions												
1) Full Sample	-0.075	0.0	50.487	-0.86	12.32	0.083 ***	30.130	4.703	0.066	-4.233	-33.574	5,237
2) Influential	-0.185	9.0	52.468	-0.61	5.38	0.049 ***	36.622	11.170	4.263	-10.862	-51.224	1,702
3) Star Analysts	0.209	0.0	50.630	-0.23	7.47	0.079 ***	28.310	4.734	0.097	-4.451	-31.161	1,031
Recommendation Change = +1												
1) Full Sample	2.261	0.5	60.925	18.86	1022.60	0.196 ***	37.810	4.674	1.148	-1.646	-23.490	58,408
2) Influential	13.657	4.5	100.000	17.34	562.31	0.234 ***	81.135	15.090	8.903	5.555	2.255	12,647
3) Star Analysts	2.668	1.5	64.168	38.89	2373.09	0.243 ***	33.884	4.528	1.319	-1.101	-17.025	7,351
Recommendation Change = +2												
1) Full Sample	2.488	1.0	62.156	12.91	435.42	0.190 ***	38.703	4.911	1.300	-1.512	-23.357	28,377
2) Influential	13.442	5.0	100.000	12.44	260.65	0.233 ***	80.622	14.766	8.777	5.601	2.259	6,669
3) Star Analysts	2.133	1.5	65.133	4.41	66.83	0.167 ***	32.128	4.072	1.336	-1.038	-16.012	2,782
Recommendation Change = +3												
1) Full Sample	1.554	-0.5	54.331	6.28	102.63	0.162 ***	33.573	4.072	0.629	-2.301	-23.110	762
2) Influential	13.151	4.0	100.000	7.00	66.55	0.235 ***	55.361	14.590	8.987	5.930	2.474	140
3) Star Analysts	1.886	4.0	60.656	0.51	7.23	0.131 **	26.923	4.149	1.496	-1.375	-21.628	122
Recommendation Change = +4												
1) Full Sample	2.228	1.0	60.334	2.26	19.69	0.150 ***	31.224	4.640	1.162	-1.679	-18.858	479
2) Influential	12.899	5.5	100.000	2.90	12.61	0.207 ***	68.857	15.427	8.643	5.666	2.879	89
3) Star Analysts	2.145	-1.0	62.264	1.90	7.07	0.200 **	20.299	3.253	0.944	-0.776	-4.792	53

In the full sample, 21.3% of the recommendations are influential as measured by abnormal returns. This value is consistent with Faias (2017), who finds that 19% of the recommendation changes are influential, and contrasts with Loh and Stulz (2011) where 12% of recommendation revisions are influential.[10] My results indicate that after the Regulation Fair Disclosure Act of 2000, implemented in August 2000, and the Global Analyst Settlement, published on 20 December 2002, recommendation changes exhibited a greater influence, with an increase in 10 and 8.7 percentage points, respectively, in the share of influential recommendation changes relative to the value prior to these events, 13.7% and 15.5%, respectively.

The transition probabilities of influential recommendation changes are plotted in Figure 1. The diagonal elements represent the reiterations of analyst recommendations. On average, analysts tend to be optimistic, i.e., prior hold ratings are more often upgraded, while non-hold ratings tend to be revised to hold ratings. Influential recommendation revisions have a larger share of recommendation revisions of at least two categories when compared to the full sample (31.6% vs 27.2%).

Table 1 presents the descriptive statistics of the *CAR*s in the sample across the recommendation change categories between -4 and +4. The results are displayed for the full sample of recommendation revisions, influential recommendation revisions and recommendation revisions issued by star analysts. All the positive (negative) rating changes categories have positive (negative) *CAR* means and medians. However, when considering periods of economic contractions, as defined by the NBER, reiterations have a consistent positive *CAR* median and, if issued by star analysts, a positive *CAR* mean. The 25th and 1st percentiles of *CAR*s from negative revisions exceed the ones of the 75th and 99th percentiles of positive revisions, respectively. Positive recommendation revisions have, on average, positive skewness, but negative recommendation revisions only exhibit consistent negative skewness for revisions of at least three categories and for reiterations during economic contractions. When considering solely the influential recommendation changes, the mean *CAR* of each recommendation revision level is further away from zero. Particularly, it is striking that the 1st (99th) percentile of all positive (negative) recommendation revisions is greater (lower) than zero, excluding reiterations. On the other hand, the distribution of star analysts'

[10] Loh and Stulz (2011) build different definitions of influential recommendation revisions with similar results to the one I opted to use. However, I consider this definition to be more conservative to guarantee a more robust *PIRS* performance.

recommendation revisions *CAR*s reveals that their recommendations are likely to induce a price-reaction that is not consistent with the direction of the recommendation revision. The 25th (75th) percentile of almost all positive (negative) recommendation revisions categories by star analysts is lower (greater) than zero.

III. Predicting Influential Recommendation Revisions

In this section, I assess the determinants of influential recommendation changes. I show how different recommendation, analyst and firm-related characteristics vary between influential recommendation changes compared to non-influential. I also examine the role that each characteristic plays in the likelihood of influential recommendation revisions.

A. In-sample Analysis of Influential Recommendation Revisions

I start by comparing the characteristics of influential with non-influential recommendation changes. Then, I decompose the role of each characteristic in the in-sample unconditional prediction of influential recommendation changes for the full sample of recommendation revisions and compare the results to the conditional prediction exercise for positive and negative recommendation revisions.

A.1. Summary Statistics of Influential Recommendation Revisions Characteristics

The descriptive statistics of the characteristics of unconditional influential and non-influential recommendation revisions are in Table 2.[11] On average, influential recommendation changes are conducted by analysts in higher *earnings forecast accuracy quintile*. This finding deviates from the results obtained by Loh and Mian (2006), who find that analysts who issue more accurate earnings forecasts generate higher annual returns with their stock recommendations. I observe that, on average, influential recommendation changes are further *away from consensus*, consistent with Jegadeesh and Kim (2010). In line with Mikhail et al.

[11] The table shows the same qualitative differences between influential and non-influential recommendation revisions for positive and negative influential recommendation revisions, except for the variables *star analyst* and *dispersion of FY1 forecast*, that refer only to negative recommendation revisions. These results are presented in the Appendix.

(1997), I find that analysts who issue influential recommendation revisions have more *experience* than other analysts, either *relative* or *absolute*. In contrast to Loh and Stulz (2011), I find that a similar share of influential recommendation revisions is issued by *star analysts* compared to non-influential recommendation revisions. *Broker size* is, on average, larger for influential recommendation changes compared to non-influential ones, which can reflect the influence on investors' perception of brokers' reputation or on their access to more resources (in line with Loh and Stulz, 2018). Consistently with Kecskés et al. (2017), I find that 50.5% of the of influential recommendation revisions are issued by analysts that issue earnings forecasts around the three-day window of the recommendation announcement, whereas only 42.2% do it for non-influential revisions. Therefore, on average, recommendations that have a *concurrent earnings forecast* generate larger price reactions. I find that only 30.8% of influential recommendation changes are issued by analysts who have previously been *influential for the same stock*, while 85.8% have been issued by analysts who have been *influential for any stock*. Non-influential recommendation changes have been issued by a lower percentage of previously influential analysts, 26.8% for the same stock and 80.4% for any stock, which is in line with the findings of Loh and Stulz (2011).

I find that, consistently with Loh and Stulz (2011), influential recommendation changes are, on average, issued by *leading* analysts. In contrast with these authors, I find that influential recommendation revisions have a lower *dispersion* in the last month before the recommendation announcement than non-influential recommendation revisions. I also find that, prior to a recommendation revision, the *idiosyncratic volatility*, *total volatility*, and *number of EPS forecasts* is lower for influential recommendation revisions, whereas the *daily turnover* is greater. The *consensus EPS forecast of FY1* adjusted by price is lower for influential recommendation revisions, which means that, on average, influential recommendation revisions tend to be more frequent on stocks with a higher price-to-earnings ratio consensus forecast. I show that influential recommendation changes are, on average, from stocks whose company is *smaller*, has a lower *book-to-market* ratio and a higher *institutional ownership* than non-influential revisions.

In line with Loh and Stulz (2011), I show the same results regarding the changes in the firm-environment around the recommendation dates. Influential recommendation revisions are more likely to be followed by an increase in the *number of EPS forecasts*, as well as in the stock's *idiosyncratic volatility*, *total volatility*, and *daily turnover*. I also show that an influential recommendation change is likely to be preceded by a decrease in the stock's price-to-earnings ratio *consensus forecast*, although this effect is lower for a non-influential recommendation change.

Table 2 – Comparison between analyst and firm characteristics for influential and non-influential recommendation changes

This table compares the average characteristics between two groups, influential and non-influential recommendation changes. Recommendation changes are deemed influential according to the criteria established in Section II.C.. Panel A presents analyst characteristics. Panel B presents firm characteristics. Panel C presents the changes in the firm environment around the recommendation announcement. The variables used are described in the Glossary – Variables Definition. *, **, *** denote the 10%, 5% and 1% significance levels, respectively.

Characteristics	Non-Influential	Influential	Difference	
Number of recommendation changes	185,025	50,146		
Share of total	78.68%	21.32%		
Panel A: Analyst characteristics				
Earnings forecast accuracy quintile	2.902	2.932	0.030	***
Star analyst	0.128	0.127	-0.002	
Away from consensus	0.108	0.140	0.033	***
Absolute analyst experience (# Qtrs)	29.421	31.220	1.800	***
Relative analyst experience (# Qtrs)	3.195	3.533	0.338	***
Concurrent earnings forecast	0.422	0.505	0.083	***
Influential before (any stock)	0.804	0.858	0.054	***
Influential before (same stock)	0.268	0.308	0.040	***
Broker size	110.886	120.495	9.609	***
Leader-follower ratio	2.891	5.173	2.281	***
Panel B: Firm characteristics prior to recommendation				
B/M ratio	0.607	0.563	-0.044	***
Size ($m)	10,762.6	9,741.0	-1,021.6	***
Institutional ownership (%)	0.643	0.680	0.037	***
Dispersion × 100	15.385	14.157	-1.227	***
Idiosyncratic volatility (%)	2.425	2.272	-0.154	***
Total volatility (%)	2.935	2.801	-0.134	***
Daily turnover	1.122	1.161	0.039	***
# of EPS forecasts	31.321	28.944	-2.376	***
Consensus FY1 forecast adjusted by price	0.033	0.032	-0.002	*
Consensus FY2 forecast adjusted by price	0.065	0.065	0.000	
Panel C: Change in firm environment around recommendation				
Δ Dispersion × 100 (-4M vs lastM)	0.298	0.160	-0.138	
Δ Idiosyncratic volatility (%) (-3m,+3m)	-0.096	0.338	0.434	***
Δ Total volatility (%) (-3m,+3m)	-0.112	0.372	0.484	***
Δ Daily turnover (-3m,+3m)	0.001	0.181	0.180	***
Δ # EPS forecasts (-3m,+3m)	-0.224	0.413	0.637	***
Δ in FY1 |Forecast revision| (-4M vs lastM)	0.023	0.021	-0.002	***
Δ in FY2 |Forecast revision| (-4M vs lastM)	0.019	0.018	-0.001	**

Table 3 – In-sample *Probit* models for influential recommendation changes

This table presents the in-sample *Probit* model estimates and t-statistics (in brackets below the coefficients) for the full sample and for positive and negative influential recommendation revisions. The binary dependent variable equals 1 if the recommendation is influential and zero otherwise. Recommendation changes are deemed influential according to the criteria established in Section II.C.. The marginal effect for continuous (dummy) explanatory variables represents the change in the predicted probability from an independent variable change of one standard deviation (from 0 to 1). The variables used are described in the Glossary – Variables Definition. *, **, *** denote the 10%, 5% and 1% significance levels, respectively.

	Full Sample		Positive Recommendation Changes		Negative Recommendation Changes	
Explanatory Variable	Coefficient	Marginal Effect (%)	Coefficient	Marginal Effect (%)	Coefficient	Marginal Effect (%)
Influential before (any stock)	0.128 ***	3.414	0.133 ***	3.661	0.123 ***	3.207
	(10.62)		(6.76)		(8.06)	
Influential before (same stock)	0.031 ***	0.870	0.038 ***	1.096	0.033 ***	0.907
	(3.74)		(2.88)		(3.08)	
Recommendation level	-0.028 ***	-0.770	0.028 ***	0.805	-0.004	-0.107
	(-5.89)		(3.09)		(-0.58)	
Absolute value of recommendation change	0.180 ***	5.244	0.000	-0.005	0.234 ***	6.715
	(33.07)		(-0.01)		(34)	
Star analyst	-0.025 **	-0.684	0.005	0.147	-0.030 **	-0.810
	(-2.3)		(0.29)		(-2.21)	
Upgrade dummy	0.030 ***	0.843				
	(3.12)					
Reg FD dummy	0.247 ***	6.530	0.211 ***	5.838	0.251 ***	6.461
	(16.87)		(8)		(14.12)	
Settlement dummy	0.047 ***	1.305	0.184 ***	5.169	0.017	0.456
	(3.4)		(7.17)		(1)	
Financial dummy	-0.060 ***	-1.647	-0.074 ***	-2.071	-0.052 ***	-1.393
	(-5.97)		(-4.53)		(-4.05)	
Past forecast accuracy quintile	-0.034 ***	-0.922	-0.038 ***	-1.076	-0.031 ***	-0.821
	(-6.08)		(-4.24)		(-4.36)	
Away from consensus	0.099 ***	2.816	0.092 ***	2.690	0.103 ***	2.864
	(9.01)		(5.26)		(6.85)	
Absolute analyst experience	0.000	0.000	-0.001 **	-0.020	0.000	0.009
	(-0.08)		(-2.05)		(1.23)	
Relative analyst experience	0.000	0.009	0.001 *	0.034	0.000	-0.010
	(0.77)		(1.71)		(-0.68)	
Concurrent earnings forecast	0.184 ***	5.113	0.073 ***	2.091	0.243 ***	6.607
	(25.53)		(6.27)		(26.37)	
Log(B/M)	-0.111 ***	-2.971	-0.087 ***	-2.430	-0.122 ***	-3.150
	(-25.95)		(-12.6)		(-22.14)	
Log(Size)	-0.069 ***	-1.833	-0.093 ***	-2.491	-0.055 ***	-1.420
	(-21.16)		(-17.48)		(-13.02)	
Price momentum	-0.004	-0.117	0.017	0.477	-0.019 **	-0.501
	(-0.69)		(1.56)		(-2.02)	
Log(Institutional ownership)	0.007 ***	0.183	0.011 ***	0.316	0.004 *	0.099
	(3.89)		(3.98)		(1.71)	
Short-term reversal	-0.282 ***	-7.658	-0.106 ***	-3.000	-0.365 ***	-9.607
	(-12.55)		(-2.82)		(-12.92)	
Log(Broker size)	0.074 ***	2.123	0.077 ***	2.278	0.072 ***	2.024
	(25.12)		(16.01)		(19.34)	

(continued)

Table 3

Continued

	Full Sample		Positive Recommendation Changes		Negative Recommendation Changes	
Explanatory Variable	Coefficient	Marginal Effect (%)	Coefficient	Marginal Effect (%)	Coefficient	Marginal Effect (%)
Past leader-follower ratio (LFR)	0.001 ***	0.038	0.002 ***	0.048	0.001 **	0.030
	(3.9)		(2.99)		(2.45)	
Dispersion	-0.035 ***	-0.977	0.023	0.650	-0.070 ***	-1.880
	(-3.01)		(1.25)		(-4.5)	
Consensus FY1 forecast adjusted by price	-0.026	-0.712	-0.153 ***	-4.332	0.024	0.660
	(-1.13)		(-3.86)		(0.88)	
Log(Idiosyncratic volatility)	-0.394 ***	-9.954	-0.454 ***	-11.699	-0.361 ***	-8.962
	(-17.21)		(-12.29)		(-12.35)	
Log(Total volatility)	0.132 ***	3.769	0.145 ***	4.260	0.118 ***	3.275
	(5.97)		(4.05)		(4.17)	
Log(Daily turnover)	0.066 ***	1.861	0.035 ***	1.012	0.082 ***	2.284
	(11.66)		(3.82)		(11.42)	
Log(# of EPS forecasts)	-0.096 ***	-2.564	-0.061 ***	-1.718	-0.113 ***	-2.935
	(-15.45)		(-6.05)		(-14.37)	
Pseudo R-squared	0.04523		0.04022		0.05396	
Observations	164,249		61,636		102,613	
Chi-squared test	7,692.42 ***		2,629.24 ***		5,647.21 ***	

A.2. Predicting influential recommendation revisions in-sample

To understand which characteristics are important to determine whether a recommendation change will turn out to be influential I use an unconditional *Probit* model, following Faias (2017). For the main analysis used in the out-of-sample prediction exercise, I run two separate *Probit* models to distinguish between positive and negative influential recommendation changes. The results for one single *Probit* model including the full sample have a lower accuracy in predicting influential recommendation revisions, since the model averages relevant differences between the distributions of the effects of characteristics across negative and positive recommendation revisions. As aforementioned, reiterations are considered as negative recommendation revisions for the main analysis of the results. The outcome variable for positive (negative) recommendation changes is the probability that the positive (negative) recommendation change is influential. These models are carried out using a kitchen-sink model, comprising all the variables that have been shown to predict recommendations in past literature. The two models use the same set of regressors, although the weights used are defined by the estimated coefficients (which may be significant or not). This method can capture the different role of each characteristic in explaining and predicting influential positive and negative recommendation revisions. Therefore, I endogenously capture the well-known asymmetric effect present in several financial stylized facts, one of which relates to the largest magnitude of drawdowns in stock prices following bad news (negative revisions) relative to the magnitude of the upward movements after good news (positive revisions).

The unconditional *Probit* model estimates for the full sample, as well as for positive and negative recommendation changes are presented in Table 3. The marginal effect for continuous (dummy) explanatory variables represents the change in the predicted probability from an independent variable change of one standard deviation (from 0 to 1). Hereinafter I discuss the main results for the full sample, and I outline the main differences between positive and negative revisions. Analysts that have previously been *influential regarding any stock* are more likely than others to produce influential recommendation revisions. The marginal effect is approximately 3.4%, which is relatively large given that the unconditional probability of a recommendation revision being influential is 21.3%. The same positive impact can be seen when the analyst has been *influential for the same stock*, even if it has a lower magnitude. This effect is slightly larger for positive recommendation revisions than for negative revisions. The *level* of a recommendation has a negative relation with the probability of issuing an influential recommendation change, i.e., all else equal, recommendation levels of strong buy and buy have a lower probability of being influential than sell or underperform recommendations. While this relation holds for negative revisions, the same cannot be said for positive revisions where the effect is positive and significant. In line with Asquith et al. (2005), I find that the *magnitude of a recommendation change* is relevant, as larger magnitudes withhold substantial new information. The absolute value of recommendation revisions has a great impact in the likelihood of a recommendation being influential, representing the second largest marginal effect value, around 5.2%. This means that upgrades (downgrades) of a four-point magnitude from sell (strong buy) to strong buy (sell) are more likely to be influential than lower magnitudes (the second chart in Figure 1 plots the transition probabilities of influential recommendation changes). However, this effect is notably asymmetric between positive and negative recommendation revisions. Whereas negative recommendation revisions have a strong and positive marginal effect, positive ones have a negative effect. Thus, all else equal, larger downgrades are more likely to be influential than upgrades of the same magnitude.

In contrast to Loh and Stulz (2011), I find that *star analysts* show a small negative effect in the predictability of influential recommendation revisions, with a marginal effect of -0.7%. The effect is positive and non-significant for positive recommendation revisions, while it is negative and significant for negative ones. The *broker size* where an analyst is employed increases the likelihood of a recommendation revision being influential by 2.1%, consistent with Loh and Stulz (2018). This effect is the same for positive and negative recommendation revisions. On the other hand, *leader* analysts are more likely to issue an influential recommendation change.[12] The effect is particularly weak, as in Loh and Stulz (2011), with a marginal effect value close to 0%. In consonance with Loh and Stulz (2011), I show that the *number of preceding earnings forecasts* decreases the probability that a recommendation change turns out to be influential. The effect is the same for positive and negative recommendation changes. In contrast with Loh and Stulz (2011), I find that the *dispersion* in analysts' earnings forecasts has a negative effect on the probability of analysts' recommendation revisions being influential, having a marginal effect value of -1.0%. The effect is similar across positive and negative recommendation revisions. The *upgrade* dummy reveals that positive recommendation changes are more likely to be influential. In agreement with the authors' findings, the *Reg FD dummy* presents a strong statistically significant effect in the predictability of influential recommendation revisions and constitutes the largest marginal effect.[13] The *settlement dummy* also presents a strong and positive effect on the likelihood of a recommendation change being influential, as shown by Loh and Stulz (2011).[14] While the effect of the latter is stronger for positive than for negative recommendation revisions, for the former it is weaker.

Past forecast accuracy decreases the probability of a recommendation revision being influential. According to Jegadeesh and Kim (2010), I show that recommendation revisions that are further *away from consensus* are more likely to be influential. The effect is larger for negative revisions compared to positive revisions, with marginal effect values of 2.9% and 2.7%, respectively. Contrarily to Mikhail et al. (1997), analysts' *experience* is not related to their influence. The third largest marginal effect of the model belongs to *concurrent earnings forecast*, with a value of 5.1%. This means that recommendation revisions which are issued with earnings forecasts are more likely to be influential. The effect is larger for negative than

[12] For the prediction exercise I use the average of the analyst's *LFR* from the prior 12 months, including only *LFR*s that consider recommendations issued prior to the current recommendation.
[13] *Reg FD* stands for Regulation Fair Disclosure, which was promulgated by the U.S. Securities and Exchange Commission (SEC) on August 10, 2000, and has become effective from October 23, 2000. This rule mandates that publicly traded companies must disclose material information to all investors at the same time. The indicator variable used in question takes a value of 1 from September 2000 onwards, as in Loh and Stulz (2011).
[14] *Settlement* stands for the Global Analyst Settlement, which was an enforcement agreement reached in the U.S. on April 28, 2003, between the SEC, the Financial Industry Regulatory Authority (NASD), the New York Stock Exchange (NYSE), and ten of the United States' largest investment firms, to establish independence between the investment banking and analysis departments of these ten firms. The corresponding indicator variable used takes a value of 1 from 2003 onwards, as in Loh and Stulz (2011).

for positive revisions. The results regarding firm characteristics show that recommendation changes on firms with lower *book-to-mark*et, lower *momentum*, lower *short-term reversal*, and lower *size*, have a higher likelihood of being influential. Influential recommendation revisions are more likely to be associated with stocks that present a greater *institutional ownership*, which is consistent with the finding of Ljungqvist et al. (2007), where analysts following firms with higher institutional ownership are quicker in reacting to bad news and issue more accurate earnings forecasts. On the other hand, the *FY1consensus forecast scaled by price* has a negative effect on the probability of a recommendation change being influential. However, this effect is positive for negative recommendation changes and negative for positive ones, with correspondent marginal effects values of 0.7% and -4.3%. Therefore, companies with a relatively higher price-to-earnings ratio are more likely to have an influential recommendation revision if it is a positive revision. In line with Loh and Stulz (2011) and Hsieh et al. (2023), stocks with higher average *daily turnover*, higher *total volatility* and lower *idiosyncratic volatility* are more likely to experience an influential recommendation revision.

This analysis shows that all characteristics are important in the prediction of influential recommendation changes, even if they differ in sign or economic magnitude. It is important to bear in mind that positive and negative recommendation revisions may be impacted differently by each variable and provide a distinct contribution, even if not statistically significant, to the prediction of influential recommendation changes from each side of the distribution of recommendation revisions.

B. Predicting Influential Recommendation Revisions Out-of-sample

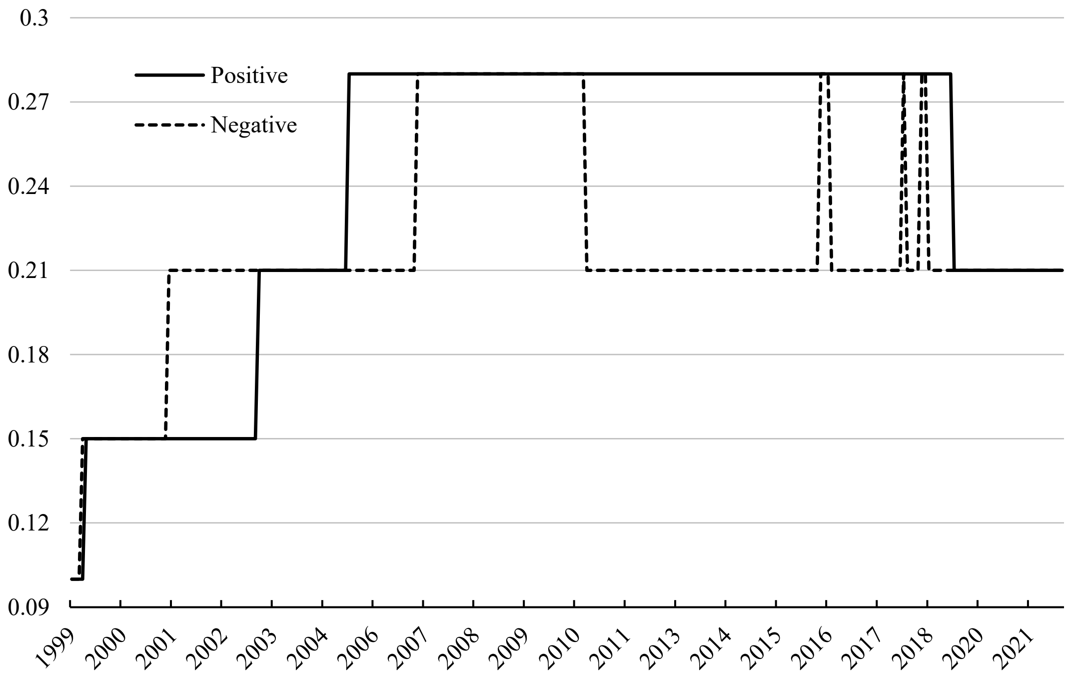
In this section, I first describe the methodology used in the prediction exercise of influential recommendation revisions out-of-sample. Then, I move on to the analysis of the time-varying importance of each characteristic to predict influential recommendation revisions, followed by the accuracy of the method used.

As aforementioned, it is not clear which variables should be used, either individually or as a subset, to identify which recommendation changes would be influential out-of-sample. I use the model proposed by Faias (2017), which endogenously establishes the weights applied to each variable and their relative importance in inferring which recommendation revisions are influential. I follow the same methodology explained in Section III.A.2. but adapt it for the out-of-sample prediction exercise. I use a rolling-window of the past five years, corresponding to

60 months of recommendation revisions, for the two in-sample *Probit* regressions in each month. The first two regressions cover the period between January 1994 and December 1998, with a total of 30,135 observations – 18,527 negative and 11,608 positive recommendation revisions. The model uses an average of 30,593 observations for each rolling window, which is large enough to ensure reasonable accuracy of the model. After running the rolling window in-sample models, I use the estimated weights of each characteristic to predict which recommendation revisions would be influential in the next month, beginning in January 1999. This prediction exercise is carried out for each month between January 1999 and December 2021, with an average of 482 recommendation revisions per month. By using a dynamic approach, the model can account for the changes in the marginal effects of the characteristics used to predict influential recommendation changes for each month. Therefore, *ex ante*, I would expect the role of each characteristic to change over time.

Figure 2 – Threshold value of *Probit* model for out-of-sample prediction

This figure plots the value of the endogenous threshold value of the *Probit* model used to differentiate influential from non-influential revisions out-of-sample, as described in Section III.B..



I use the predicted probability of the *Probit* model to distinguish between influential and non-influential recommendation revisions. I follow the criteria developed in Faias (2017) to define the threshold value, which is endogenously determined by the prediction model and thus overcomes the subjectiveness of an *ad-hoc* value. The methodology consists of using all observations from a rolling window of the previous 60 months (the same window used to estimate the *Probit* model) and selecting the threshold level that minimizes the measure of total error (*TE*), as defined below. For each month, using a grid between 0 and 100% with a length of 1%, I select the threshold value that minimizes the measure of total error, computed as:

$$TE = [\Pr(Predicted\ Non\ Infl|Infl)]^2 + [\Pr(Predicted\ Infl|Non\ Infl)]^2 \quad (3)$$

Or,

$$TE = \left(1 - \frac{\#Correctly\ Pred\ Infl}{\#Actual\ Infl}\right)^2 + \left(1 - \frac{\#Correctly\ Pred\ Non\ Infl}{\#Actual\ Non\ Infl}\right)^2 \quad (4)$$

By establishing the threshold value that minimizes this measure, the model can set endogenously the value that minimizes the joint in-sample relative error, and in turn minimizes the prediction error of the influential and non-influential recommendation changes. The threshold value is determined separately for positive and negative recommendation revisions.

In Figure 2, I present the two time-series of thresholds for positive and negative recommendation revisions. Both time-series present a similar pattern throughout the sample period, even though positive recommendation revisions generally have a greater threshold value. The values are mostly like those obtained by Faias (2017). The threshold value for positive (negative) recommendation revisions starts at 0.1 (0.1) and increases steadily until 2005 (2007) when it registers its maximum value of 0.28 (0.28). Following the Subprime Mortgage Crisis, the value remains the same (decreases to 0.21) for positive (negative) recommendation revisions. Between 2016 and 2018 the threshold value for negative recommendation revisions has bounced between 0.21 and 0.28. From the COVID-19 pandemic until the end of the sample, both threshold values are stable at 0.21. As noted by Faias (2017), these values are much different from 0.50, which means an *ad hoc* choice of 0.5 as the threshold would be a suboptimal choice.

Figure 3 reports the time-series evolution of the marginal effects of characteristics on influential recommendation revisions for positive (left panel) and negative (right panel) recommendation revisions. The higher the value of a variable in the plot, the more it contributes to the prediction of influential recommendation changes. It is important to note that the scale of the graphs is only different for the bottom graph. All these graphs can be helpful for an investor choice in the best path to define influential recommendation changes. An investor can just use the variables with the greater economic relevance or use a set of the most relevant, e.g., the top three. Hereinafter I present the results for the full sample and address the main findings and differences between the two *Probit* models, one for positive and the other for negative recommendation changes.

The *past forecast accuracy quintile* has a negative marginal effect most of the time. It is never a relevant variable for both positive and negative recommendation. *Influential before* and *influential before for the same company* have positive marginal effects throughout most of the period. *Influential before* is significant up until 2011 and between 2016 and 2019 for positive recommendation changes and is significant from 1999 onwards until 2012 for negative ones. *Influential before for the same company* is almost not significant throughout the sample, being only significant between 2003 and 2008 for both positive and negative recommendation revisions. *Concurrent earnings forecast* is significant throughout most of sample period as it stopped being significant for positive recommendation revisions after 2014 and exhibits a strong positive marginal effect. The maximum value of the marginal effects for positive and negative revisions happens around 2005, and it is one of two variables to rank first among all variables for both positive and negative recommendation revisions. This result suggests that analysts who consider the firm's future performance relative to its peers (by revising their recommendation on a firm), while also reconsidering their projections of the firm's future cash flows are systematically more influential (in line with Kecskés et al., 2017).[15] There is however a significant difference in the marginal effect value between positive and negative recommendation revisions, with the latter being larger. *Broker size* has a positive marginal effect throughout the entire sample period. There is a small difference between positive and negative recommendation revisions, with the former effect being consistently larger. Similarly, *leader* analysts also show a consistent positive marginal effect in the entire period, with the effect being greater for positive revisions in most of the time covered. The difference is striking in the periods between 2008 and 2015. The results obtained are in concordance with one of the hypotheses proposed by Loh and Stulz (2018) to explain analysts' greater impact in bad times: analysts' recommendations may be more impactful due to investors' propensity to overreact. This effect should be greater for *leader* analysts, which is in line with the evolution of the

[15] In the prediction exercise out-of-sample, *concurrent earnings forecast* only considers earnings forecasts issued in between t-3 and t, as opposed to t-3 to t+3, which is used in the *ex-post* analysis of influential recommendation changes.

marginal effect for positive recommendation revisions, which peaked in the years following the Subprime Mortgage Crisis. Regarding analysts' *experience*, the evolution of marginal effects exhibits a larger fluctuation, with the signals changing at different periods for positive and negative recommendation revisions. While the marginal effect for *absolute* and *relative experience* is more volatile for negative recommendation revisions, they are respectively consistently negative and positive, for positive recommendation revisions. The marginal effects of both variables are never significant.

Star analysts have a consistent positive marginal effect value for positive and negative recommendation revisions. This variable is negative (positive) from 2015 until 2021 (from 1999 until 2004 and from 2014 until 2021) for positive (negative) recommendation revisions. On the other hand, *away from consensus* has a clear distinct path for positive and negative recommendation revisions. Even if the values are always positive and significant across both positive and negative recommendation revisions, the variable always has a relatively higher relevance for the latter compared to the former. *Recommendation level* presents a similar pattern for both positive and negative recommendation revisions until 2014. The value is positive from 1999 until 2002 and negative until 2016 for positive recommendation revisions while it remains negative until 2021 for negative recommendation revisions. According to Stickel (1995), the larger the *absolute recommendation change* value, the greater the implied change in an analyst's conclusions concerning the prospects of a firm compared to the prior recommendation. *Absolute recommendation change* exhibits an instable pattern throughout time for positive recommendation revisions and a large consistent positive marginal effect during the entire period for negative recommendation revisions. It is always positive and ranked among the largest 6 marginal effects for positive recommendation revisions. The *financial dummy* has a negative marginal effect for both positive and negative recommendation revisions during most of the sample period. It reaches positive marginal effects in the period around the Subprime Mortgage Crisis, even if it is never ranked among the largest 6 marginal effects.

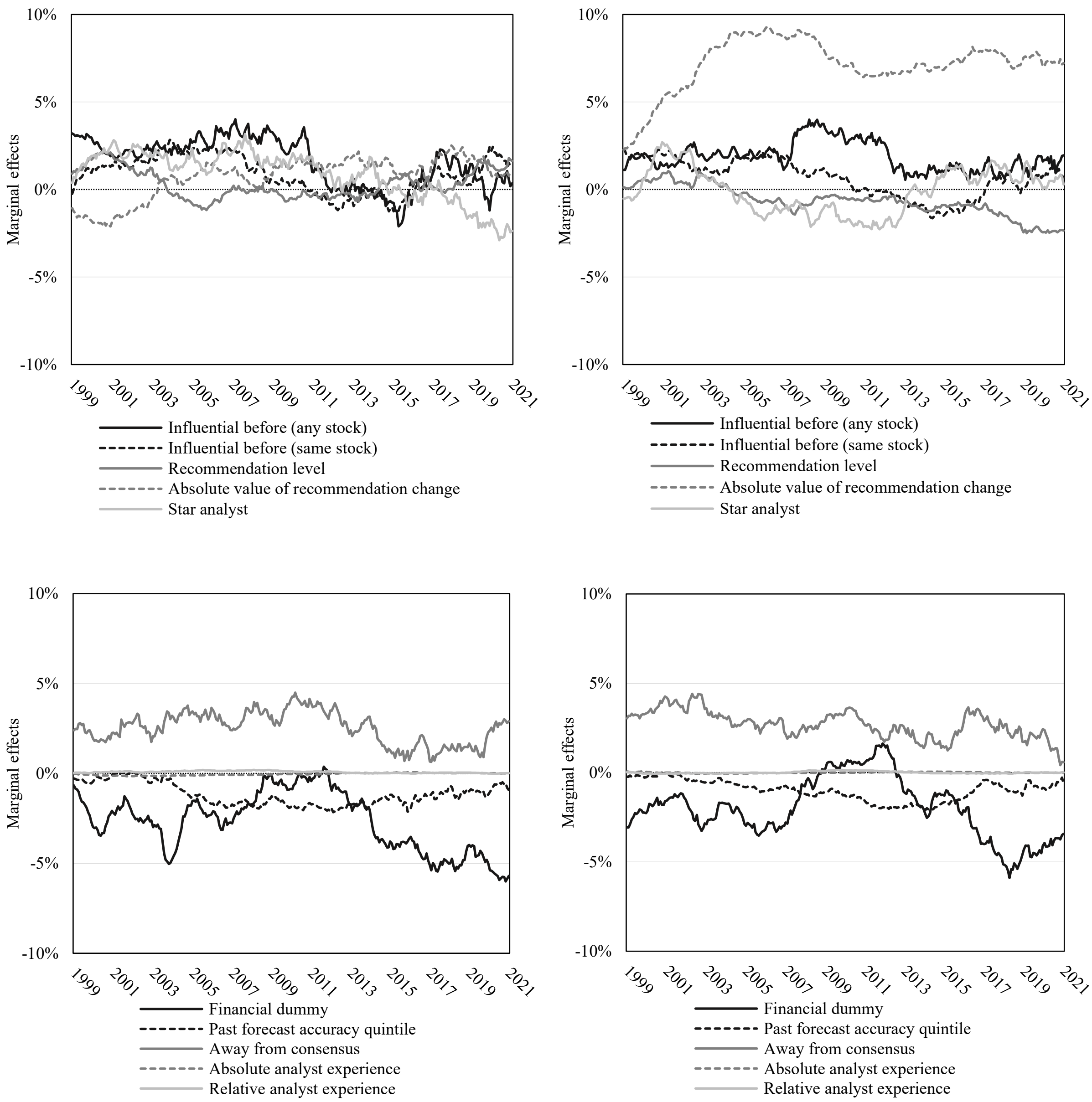
Dispersion has a positive marginal effect for positive during most of the period, whereas it is always negative for negative recommendation revisions. It is ranked as the largest marginal effect in 2015 for positive recommendation revisions. The *number of EPS forecasts* issued in the three months preceding a recommendation has a similar pattern for positive and negative recommendation revisions, reaching its largest value during the Subprime Mortgage Crisis. It is negative for the entire period for both positive and negative recommendation revisions. *Idiosyncratic volatility* is always negative for positive and negative recommendation revisions.

Total volatility is overall positive for positive and negative recommendation revisions, and it is only negative for negative recommendation revisions from 2018 until 2021. *Turnover* is mostly positive for both positive and negative recommendation revisions. While for negative recommendation revisions it only drops once to negative values in 2019, it has been varying around zero since 2012 for positive recommendation revisions. *Institutional ownership* almost always has a positive sign for both sides of the distribution of recommendation revisions. As suggested by Brown et al. (2014) and He et al. (2005), large traders are more inclined to follow sell-side analyst's opinions, especially due to fear of compromising their reputation, and are particularly interested in star analysts' advice. Lagging the *institutional ownership* by one additional quarter does not change economically the results (see Section V.E.). *Consensus FY1* has a consistently negative marginal effect for positive recommendation revisions. However, for negative ones it has a strong positive marginal effect between 1999 and 2008, remaining negative until 2015, and never recovering to previous levels. *Momentum* has an unsteady pattern throughout the entire sample for positive and negative recommendation revisions, while being mostly negative. After 2016 it becomes strong and positive for positive recommendation revisions. *Size* has a negative marginal effect during most of the period for both sides of the distribution of recommendation revisions. *Book-to-market* is always negative and has a very stable value throughout the period for positive and negative recommendation revisions with the value being relatively larger for the latter.

It is also relevant to outline the drastic difference in the importance of several variables between positive and negative recommendation changes. In Table 4 I present summary statistics of the different rank of each variable's marginal effect relative to the remaining variables for positive and negative recommendation revisions. The results show that the relevance of the characteristics for positive (negative) recommendation revisions fluctuates more (less) over time in the prediction of influential recommendation revisions. This table also summarizes the contrast between the role of each variable in the prediction of influential recommendation revisions for positive and negative recommendation revisions. *Consensus FY1* forecast, *dispersion* of FY1 consensus forecast, *short-term reversal* and *absolute recommendation change*, exhibit the larger differences in relative importance for the prediction of influential recommendation revisions between positive and negative recommendation revisions.

Figure 3 – Marginal effect of characteristics on influential recommendation changes

This figure plots the marginal effects of characteristics that explain influential recommendation changes, using a 5-year rolling window *Probit* model, estimated monthly starting in 1999. The binary dependent variable is 1 if the recommendation is influential and 0 otherwise. Panels on the left (right) hand side are for positive (negative) influential recommendation changes. The marginal effects for continuous (dummy) explanatory variables represent changes in the predicted probability when the independent variable changes by one standard deviation (from 0 to 1). Recommendation changes are deemed influential according to the criteria established in Section II.C.. The variables used are described in the Glossary – Variables Definition. Note that the scale of the bottom graphs differs in scale from the remainder graphs.



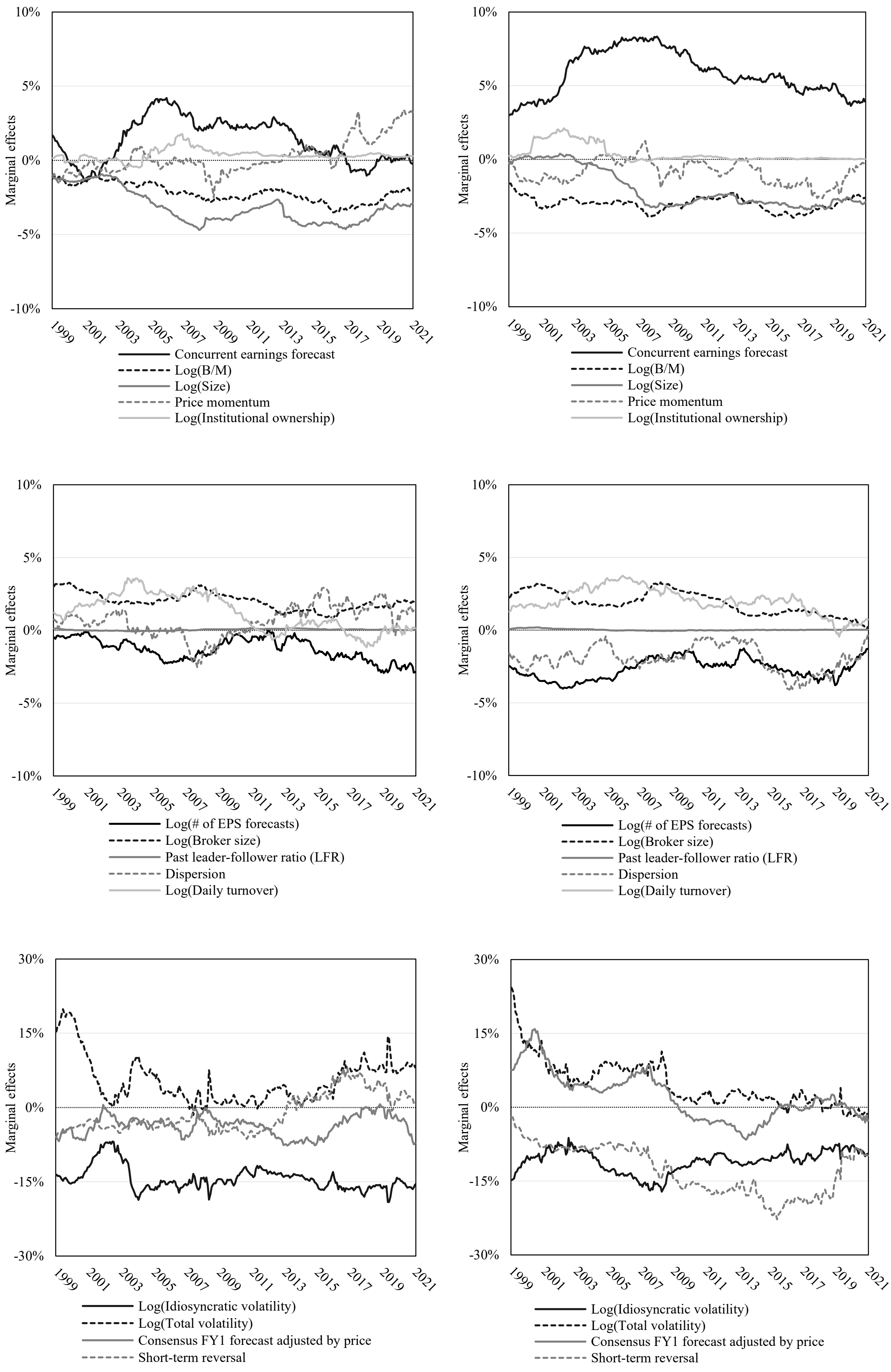

10%
5%
0%
-5%
-10%
Marginal effects
1999 2001 2003 2005 2007 2009 2011 2013 2015 2017 2019 2021
Concurrent earnings forecast
Log(B/M)
Log(Size)
Price momentum
Log(Institutional ownership)
Concurrent earnings forecast
Log(B/M)
Log(Size)
Price momentum
Log(Institutional ownership)
Log(# of EPS forecasts)
Log(Broker size)
Past leader-follower ratio (LFR)
Dispersion
Log(Daily turnover)
Log(# of EPS forecasts)
Log(Broker size)
Past leader-follower ratio (LFR)
Dispersion
Log(Daily turnover)
30%
15%
0%
-15%
-30%
Log(Idiosyncratic volatility)
Log(Total volatility)
Consensus FY1 forecast adjusted by price
Short-term reversal
Log(Idiosyncratic volatility)
Log(Total volatility)
Consensus FY1 forecast adjusted by price
Short-term reversal

Table 4 – Variables Rank Summary Statistics

This table reports summary statistics (average, median, mode, best, worst, and interquartile range) of the rank of each variable marginal effect across time. The variables used are described in the Glossary – Variables Definition.

Variables	Positive Recommendation Revisions						Negative Recommendation Revisions					
	Average	Median	Mode	Best	Worst	Interquartile Range	Average	Median	Mode	Best	Worst	Interquartile Range
Influential before (any stock)	7	5	3	1	19	7	6	7	7	3	11	3
Influential before (same stock)	10	8	6	3	18	5	10	9	8	4	17	5
Recommendation level	12	12	16	3	18	7	15	15	15	10	20	3
Absolute value of recommendation change	9	8	9	2	21	5	1	1	1	1	6	0
Star analyst	9	7	6	2	21	8	12	12	18	3	20	9
Financial dummy	20	21	21	9	23	4	17	19	22	7	23	6
Past forecast accuracy quintile	17	18	19	11	20	2	16	17	17	13	19	1
Away from consensus	3	3	1	1	9	2	5	4	3	3	8	2
Absolute analyst experience	14	14	14	10	16	1	12	12	12	8	16	3
Relative analyst experience	12	12	11	9	16	3	12	12	11	8	17	3
Concurrent earnings forecast	8	7	2	1	19	9	2	2	2	1	5	1
Log (B/M)	20	20	20	17	22	2	21	21	21	19	22	1
Log (Size)	21	22	22	17	23	1	19	20	21	12	22	4
Price momentum	12	14	17	2	20	7	15	16	18	8	19	3
Log (Institutional ownership)	10	10	10	7	17	2	10	10	10	8	14	2
Short-term reversal	15	22	23	1	23	20	24	24	24	21	24	1
Log(Broker size)	5	5	4	2	8	3	6	6	6	4	9	1
Past leader-follower ratio (LFR)	12	12	12	8	15	1	12	12	12	9	14	2
Dispersion	9	9	9	1	22	7	18	19	19	14	22	3
Consensus FY1 forecast adjusted by price	21	22	23	9	23	3	10	5	4	1	22	14
Log(Idiosyncratic volatility)	24	24	24	24	24	0	23	23	23	23	24	1
Log(Total volatility)	3	1	1	1	16	4	5	3	3	1	17	5
Log(Daily turnover)	9	7	5	1	19	7	6	6	5	3	15	2
Log(# of EPS forecasts)	18	18	18	12	21	2	20	19	19	16	22	3

Table 5 – Marginal Effects Correlation Matrix

The first (second) table corresponds to the correlation matrix of the time-series of marginal effects of the different variables for positive (negative) recommendation revisions. The variables used are described in the Glossary – Variables Definition.

	Inf before	Inf before same	Rec level	Abs Rec Chang	Star Analyst	Fin Dummy	Past Accuracy	Away from Cons	Abs Exper	Rel Exper	Concur EPS	Log B/M	Log Size	Mom	Log IO	ST Reversal	Log BS	Past LFR	Disper-sion	Consen-sus FY1	Log IVol	Log Tvol	Log Turnv	Log #EPS
Inf before	1.00																							
Inf before same	0.57	1.00																						
Rec level	-0.12	0.11	1.00																					
Abs Rec Chang	-0.37	-0.29	-0.65	1.00																				
Star Analyst	0.62	0.22	-0.21	-0.45	1.00																			
Fin Dummy	0.37	-0.27	-0.37	-0.16	0.62	1.00																		
Past Accuracy	0.21	0.41	0.71	-0.71	0.04	-0.32	1.00																	
Away from Cons	0.44	0.14	-0.49	-0.04	0.49	0.68	-0.25	1.00																
Abs Exper	-0.71	-0.66	-0.09	0.62	-0.74	-0.32	-0.46	-0.47	1.00															
Rel Exper	0.69	0.41	-0.46	-0.09	0.66	0.54	-0.19	0.61	-0.67	1.00														
Concur EPS	0.32	0.11	-0.79	0.32	0.37	0.54	-0.57	0.64	-0.19	0.62	1.00													
Log B/M	0.35	0.41	0.31	-0.70	0.42	0.26	0.61	0.33	-0.73	0.22	0.06	1.00												
Log Size	0.29	0.32	0.53	-0.78	0.28	0.14	0.78	0.12	-0.63	0.00	-0.25	0.88	1.00											
Mom	-0.48	0.09	0.15	0.45	-0.78	-0.76	0.02	-0.42	0.51	-0.52	-0.36	-0.32	-0.31	1.00										
Log IO	0.29	0.09	-0.37	0.30	0.17	0.26	-0.56	0.20	0.02	0.46	0.47	-0.25	-0.48	-0.07	1.00									
ST Reversal	-0.57	-0.16	0.10	0.45	-0.68	-0.77	-0.09	-0.71	0.71	-0.60	-0.47	-0.66	-0.53	0.72	-0.07	1.00								
Log BS	0.77	0.40	0.26	-0.63	0.49	0.39	0.35	0.40	-0.63	0.49	0.06	0.48	0.44	-0.45	0.17	-0.62	1.00							
Past LFR	-0.40	-0.85	-0.18	0.36	-0.24	0.31	-0.53	-0.02	0.70	-0.37	0.00	-0.48	-0.45	-0.02	0.13	0.15	-0.21	1.00						
Dispersion	-0.70	-0.42	0.34	0.14	-0.59	-0.53	0.19	-0.66	0.58	-0.81	-0.56	-0.24	0.01	0.44	-0.42	0.60	-0.63	0.23	1.00					
Consensus FY1	0.30	0.37	-0.03	0.10	-0.08	-0.17	0.15	0.03	-0.18	0.25	-0.19	-0.18	-0.03	0.14	-0.03	0.13	0.14	-0.35	-0.18	1.00				
Log IVol	0.07	-0.06	0.25	-0.47	0.41	0.40	0.32	0.21	-0.44	0.02	-0.20	0.50	0.56	-0.41	-0.20	-0.43	0.15	-0.08	-0.01	-0.02	1.00			
Log Tvol	0.11	0.16	0.56	-0.45	-0.26	-0.35	0.58	-0.36	0.02	-0.35	-0.42	0.27	0.47	0.14	-0.37	0.10	0.33	-0.12	0.26	-0.02	-0.32	1.00		
Log Turnv	0.66	0.65	-0.12	-0.44	0.69	0.28	0.23	0.43	-0.82	0.72	0.45	0.50	0.32	-0.52	0.08	-0.59	0.48	-0.65	-0.65	0.06	0.16	-0.17	1.00	
Log #EPS	0.11	-0.36	0.01	-0.42	0.57	0.62	0.11	0.35	-0.29	0.07	0.04	0.40	0.39	-0.62	-0.33	-0.57	0.27	0.27	-0.14	-0.39	0.47	0.01	0.12	1.00

	Inf before	Inf before same	Rec level	Abs Rec Chang	Star Analyst	Fin Dummy	Past Accuracy	Away from Cons	Abs Exper	Rel Exper	Concur EPS	Log B/M	Log Size	Mom	Log IO	ST Reversal	Log BS	Past LFR	Disper-sion	Consen-sus FY1	Log IVol	Log Tvol	Log Turnv	Log #EPS
Inf before	1.00																							
Inf before same	0.25	1.00																						
Rec level	0.19	0.41	1.00																					
Abs Rec Chang	0.20	-0.15	-0.39	1.00																				
Star Analyst	-0.56	0.05	0.08	-0.25	1.00																			
Fin Dummy	0.56	-0.20	0.40	-0.12	-0.52	1.00																		
Past Accuracy	-0.07	0.77	0.36	-0.27	0.54	-0.46	1.00																	
Away from Cons	0.19	0.45	0.75	-0.31	0.19	0.13	0.53	1.00																
Abs Exper	-0.36	-0.54	-0.13	-0.53	-0.06	0.25	-0.46	-0.27	1.00															
Rel Exper	0.72	-0.12	-0.11	0.12	-0.76	0.67	-0.44	-0.08	0.06	1.00														
Concur EPS	0.56	0.08	0.09	0.75	-0.57	0.31	-0.28	-0.03	-0.50	0.39	1.00													
Log B/M	0.03	0.31	0.23	-0.57	-0.27	0.12	0.09	0.09	0.12	0.15	-0.29	1.00												
Log Size	-0.03	0.65	0.78	-0.46	0.33	-0.04	0.64	0.61	-0.32	-0.42	-0.16	0.44	1.00											
Mom	0.29	0.26	0.10	0.23	-0.57	0.32	-0.14	-0.12	-0.17	0.35	0.51	0.30	0.06	1.00										
Log IO	0.04	0.42	0.69	-0.20	0.49	0.02	0.54	0.62	-0.49	-0.36	-0.07	0.11	0.81	-0.10	1.00									
ST Reversal	0.13	0.88	0.43	-0.26	0.08	-0.20	0.71	0.37	-0.44	-0.20	-0.02	0.51	0.77	0.36	0.48	1.00								
Log BS	0.63	0.50	0.71	-0.27	-0.20	0.57	0.27	0.65	-0.13	0.36	0.25	0.06	0.42	0.17	0.36	0.37	1.00							
Past LFR	-0.36	0.40	0.51	-0.73	0.67	-0.23	0.67	0.48	0.04	-0.60	-0.65	0.30	0.75	-0.33	0.61	0.49	0.21	1.00						
Dispersion	0.30	0.06	0.15	-0.04	-0.50	0.49	-0.31	-0.12	-0.07	0.47	0.21	0.60	0.17	0.63	0.10	0.23	0.11	-0.15	1.00					
Consensus FY1	0.08	0.80	0.54	-0.32	0.31	-0.22	0.77	0.53	-0.31	-0.37	-0.06	0.06	0.69	-0.04	0.45	0.73	0.58	0.63	-0.27	1.00				
Log IVol	-0.36	-0.25	-0.05	-0.23	0.58	-0.20	0.12	0.07	-0.03	-0.38	-0.54	0.07	0.17	-0.58	0.40	-0.18	-0.38	0.43	-0.13	-0.20	1.00			
Log Tvol	0.07	0.66	0.61	-0.48	-0.01	0.00	0.51	0.45	-0.01	-0.13	-0.06	0.37	0.67	0.26	0.30	0.71	0.57	0.47	0.08	0.75	-0.50	1.00		
Log Turnv	0.33	0.22	0.49	0.43	-0.38	0.29	-0.06	0.26	-0.33	0.05	0.78	-0.17	0.23	0.51	0.16	0.20	0.40	-0.27	0.13	0.23	-0.58	0.32	1.00	
Log #EPS	0.29	-0.32	-0.41	0.11	-0.58	0.42	-0.56	-0.49	0.41	0.66	0.20	0.07	-0.66	0.42	-0.69	-0.31	-0.03	-0.57	0.30	-0.47	-0.46	-0.23	-0.03	1.00

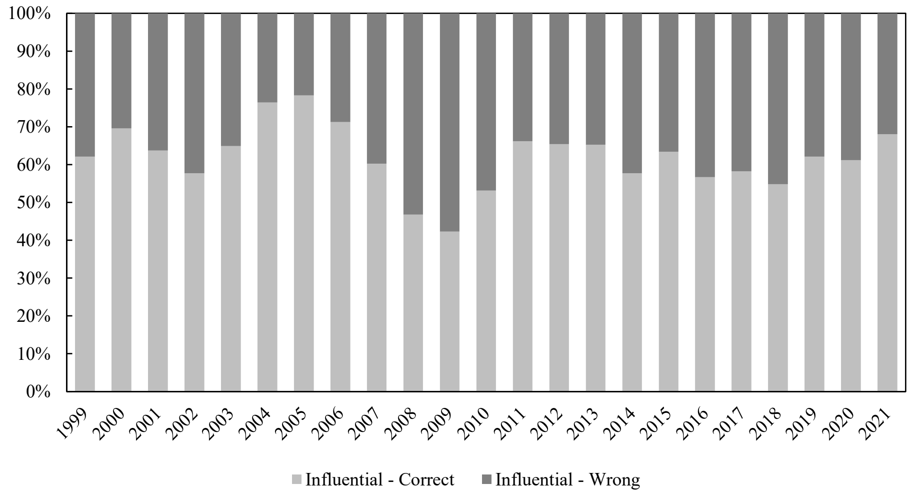
In Table 5, I present the correlation matrix for the time-series of marginal effects across variables for positive and negative recommendation revisions. These results show that, on average, the characteristics' contributions in predicting influential recommendation revisions are least likely to move in the same direction for positive recommendation revisions when compared to negative ones. This conclusion is particularly striking for the *recommendation level*, that is clearly negatively (positively) correlated, on average, with the remaining variables for positive (negative) recommendation revisions.

From the discussion above, it should be drawn that it is essential to use asymmetric modelling. This conclusion is supported by the differences in a variable's marginal effect over time across each side of the distribution of recommendation revisions, namely different signs or magnitudes, statistical significance, and relative relevance in the prediction of influential recommendation revisions.

The evolution of the average annual accuracy of the method applied between 1999 and 2021 (Figure 4) is measured by the proportion of correct forecasts relative to observed influential (top graph) and non-influential (bottom graph) revisions. The method accurately predicts, on average, 61.2% of the influential and non-influential recommendation changes, a minimum of 55.9% and a maximum of 61.2%, with a median of 59.5% and an interquartile range of 1.5%. If I consider them separately, a real influential (non-influential) recommendation change is, on average, correctly predicted 62.2% (55.5%) of the times, ranging from 42.3% to 78.3% (41.1% to 74.2%). I also separate this analysis between negative and positive recommendation changes (see results in the Appendix). The sample is compiled of 84,086 negative recommendation changes and 50,028 positive recommendation changes. On average, the method applied correctly predicts 56.8% of positive recommendation changes (59.6% for influential and 54.1% for non-influential) and correctly predicts 60.4% of negative recommendation changes (63.7% for influential and 57.0% for non-influential). Additionally, I show that the average accuracy of the model remains similar if I were to use a rolling-window of 3 or 10 years (Figure 5 and 6, respectively). The model using a rolling-window of 5 years combines a higher average and a more stable level of accuracy in predicting influential recommendation revisions and is thus more reliable than the other alternatives.

Figure 4 – Accuracy of out-of-sample forecasts

This figure plots the percentage of correct forecasts of influential (top graph) and non-influential (bottom graph) recommendation changes between 1999 and 2021. Recommendation changes are deemed influential according to the criteria established in Section II.C.. A recommendation change is forecasted to be influential based on the estimated value from a monthly 5-year rolling window *Probit* regression starting in 1994. This is explained in detail in Section III.B..



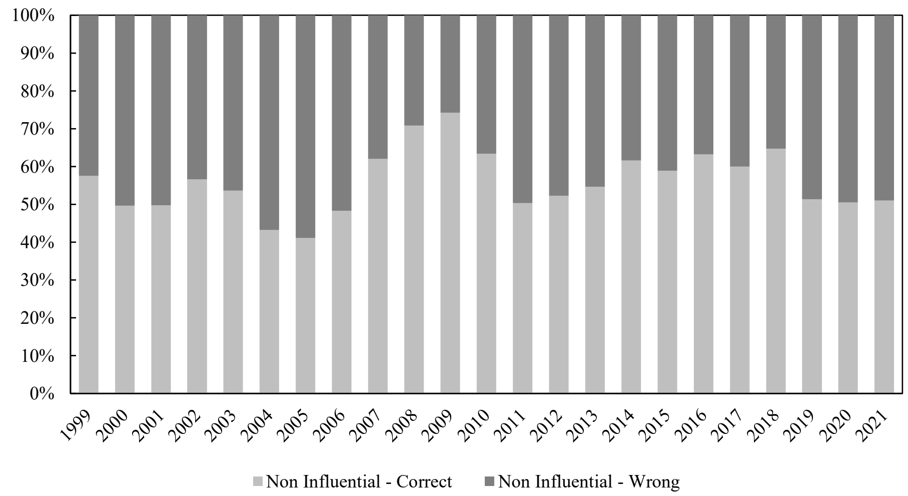
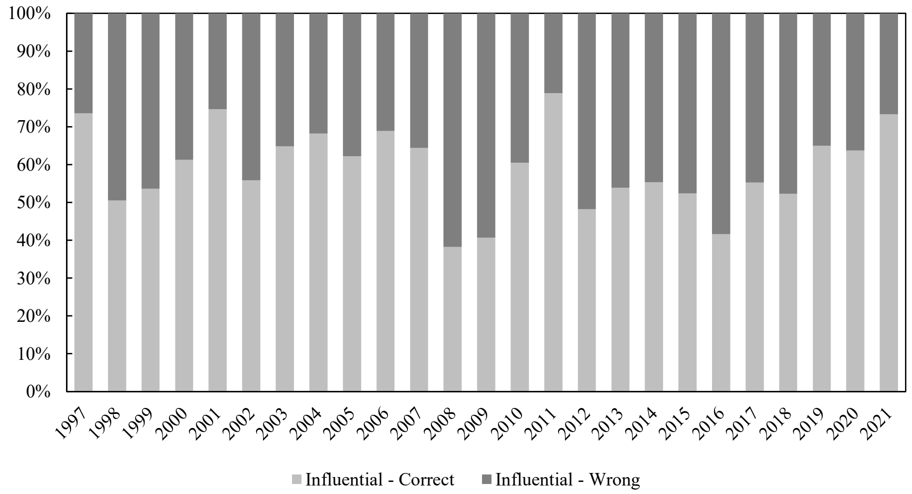


Figure 5 – Accuracy of out-of-sample forecasts 3 Years Rolling-Window

This figure plots the percentage of correct forecasts of influential (top graph) and non-influential (bottom graph) recommendation changes between 1997 and 2021. Recommendation changes are deemed influential according to the criteria established in Section II.C.. A recommendation change is forecasted to be influential based on the estimated value from a monthly 3-year rolling window *Probit* regression starting in 1994. This is explained in detail in Section III.B..



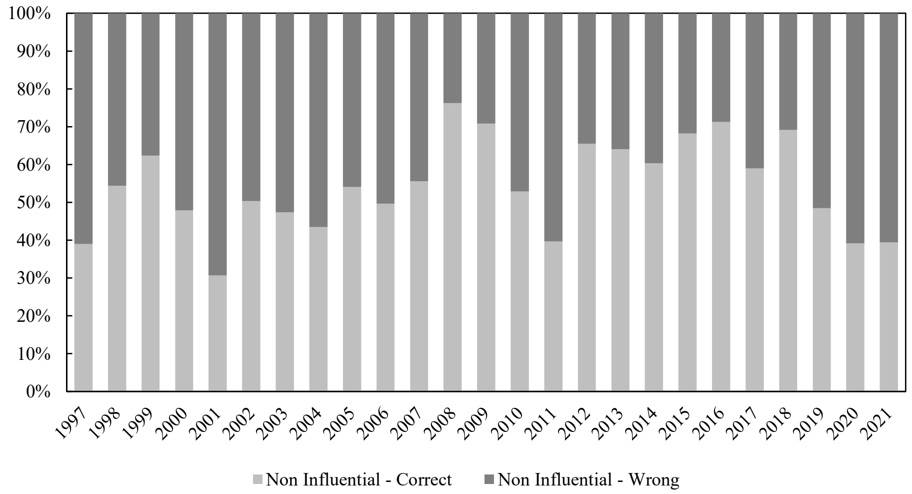
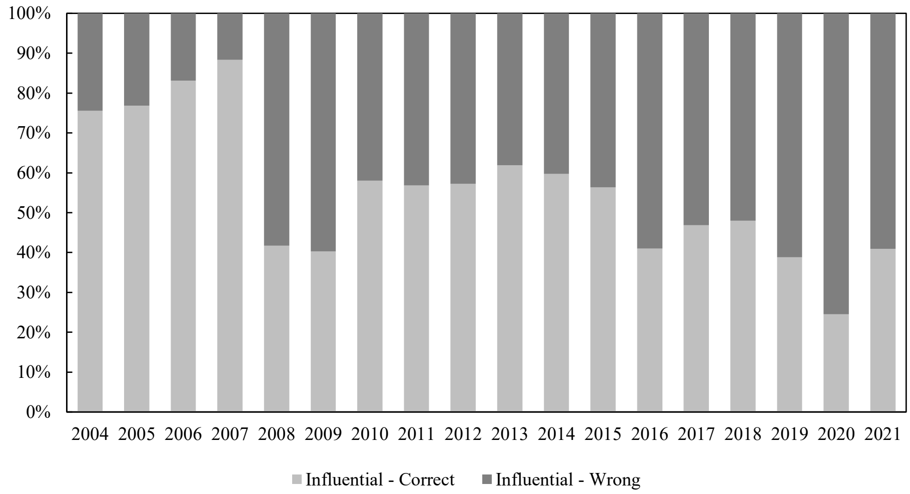
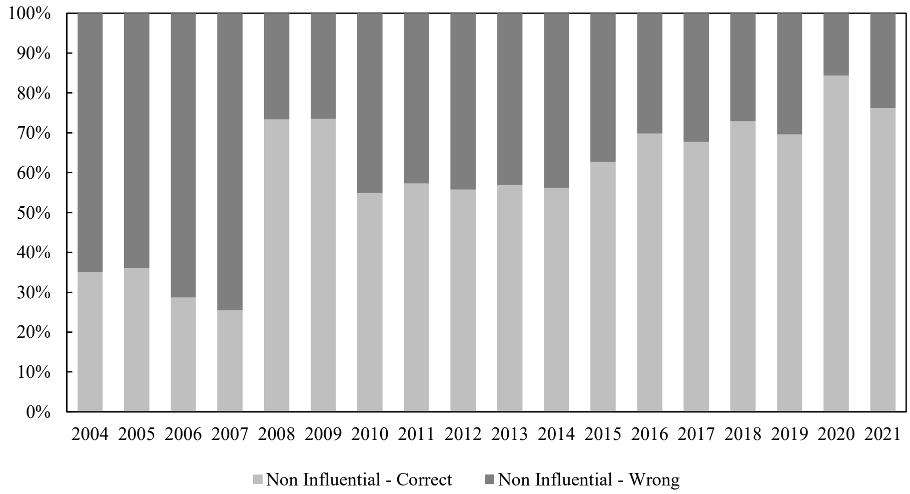


Figure 6 – Accuracy of out-of-sample forecasts 10 Years Rolling-Window

This figure plots the percentage of correct forecasts of influential (top graph) and non-influential (bottom graph) recommendation changes between 2004 and 2021. Recommendation changes are deemed influential according to the criteria established in Section II.C.. A recommendation change is forecasted to be influential based on the estimated value from a monthly 10-year rolling window *Probit* regression starting in 1994. This is explained in detail in Section III.B..





IV. Investment Strategy

There is an extensive body of literature that addresses the creation of investment strategies based on analysts' recommendations, with studies estimating it can generate significant alphas. Barber et al. (2001) show that an investment strategy based on the average recommendations of analysts, which is long (short) on buy (sell) recommendations, yields annualized returns of 18.8% (5.8%) between 1986 and 1996 in the U.S.. Green (2006) finds that placing long (short) positions following recommendation changes generates an average two-day return of 1.02% (1.50%) for upgrades (downgrades) after transaction costs. On the other hand, Batten et al. (2022) show that momentum-based portfolios perform better than investment strategies based on the recommendation level across all periods, size, and sectors, whereas it only underperforms a strategy based on recommendation changes in the utility sector.

To determine the economic value from analysts' recommendation revisions I follow the methodology proposed by Faias (2017). I construct calendar-time portfolios based on influential recommendation revisions and then examine their performance out-of-sample. To predict influential recommendation changes out-of-sample I use the methodology described in Section III.B.. In line with Boni and Womack (2006), positive and negative recommendation revisions, as defined in Section II.C., are included in the long and short portfolio, respectively. I disregard the level of recommendations since it is not included in the definition of positive and negative recommendation revisions in the prediction exercise. Therefore, I consider that no information about future returns is contained in recommendation levels (Jegadeesh and Kim, 2006). In this methodology, an investor takes the position in the same (next) trading day when the recommendation is issued if the market is open (closed) (Barber et al., 2007)[16]. This approach is considerably conservative since the return from the recommendation day is lost if it is issued before the market closing time, whereas if issued during the market close (including non-trading days), the first return is computed relative to the opening price of the next trading day. Thus, the underlying assumption is that the investor can only capture the return after day 1, or at the next market opening for the latter case. The position is held for a period of one month, i.e., 21 trading days. If there are multiple influential recommendation revisions for the same stock in the same day, we just take a position long or short of one unit. If during those 21 trading days there are more influential recommendation revisions for that stock with the same sign, instead of changing the position, I extend the position for the number of days elapsed since the last

[16] The market is considered closed if the announcement date corresponds to a non-trading day, or if the recommendation is announced during the period between 12:00 am and 7:59 am or 4:30 pm and 11:59 pm.

position was taken. If an influential recommendation revision with the opposite sign is issued for that stock during the holding period, the previous position is closed. This strategy is called Predicting Influential Recommendations Strategy (*PIRS*).

I exclude stocks when the price is below $5 on the recommendation announcement date (t=0), as D'Avolio (2002) shows that it is difficult to borrow stocks with prices below $5, making them unsuitable for short-selling. The stocks in the portfolios are equal-weighted, as in Faias (2017). However, Blume and Stambaugh (1983) show that equal-weighted returns are, on average, biased upwards because of the bid-ask bounce. In Section IV.D. I compute the strategy performance with value weighted portfolios as a robustness test. As markets are probably the most efficient for the largest firms, by attributing a higher weight to larger and more important firms, this approach may bias against obtaining abnormal returns, thus better capturing the economic significance of the strategy. Additionally, the portfolios are rebalanced daily and days without any stock investment are assumed to have no investment. It should be noted that each stock can meet the criteria for both the long and short portfolio. The performance is computed at the end of each month by aggregating the individual returns at a monthly frequency. I obtain three monthly returns time-series: purchasing positive recommendation revisions (long leg), selling negative recommendation revisions (short leg), and a zero-investment portfolio (long-short portfolio). The long-short return is computed as the difference in the returns of stocks in the long and the short legs. In this portfolio strategy I employ analysts' recommendation revisions as the basis for investment decisions as in Womack (1996).

A. Main Results

The results of the *PIRS* and respective benchmark strategies are presented in Table 6. The *PIRS*, composed solely of predicted influential recommendation changes, is presented in Panel A. The benchmark strategies used for comparison are comprised of a strategy that trades on all recommendation changes, *TRC* (Panel B); the *CRSP equal-weighted* (*CRSP EW*) *index* (Panel C); and a naïve equal-weighted portfolio of all stocks used in the *TRC* in each point in time (Panel D).[17]

[17] DeMiguel et al. (2009) show that different portfolio strategies are unable to outperform consistently the 1/N strategy out-of-sample.

Table 6 – *PIRS* and benchmarks results

This table reports summary statistics (monthly average number of firms in a portfolio, average market capitalization of the firms in each portfolio, annualized mean return, annualized standard deviation, skewness, kurtosis, annualized turnover and break-even round-trip costs). The break-even round-trip costs are computed by dividing the annualized mean return by the annualized turnover. For Panels A and B, three portfolios are formed: long-only, short-only, and long minus short. These strategies are implemented from 1999 to 2021. *, **, *** denote the 10%, 5% and 1% significance levels, respectively.

Portfolio	Mthly Avg # Firms	Avg Mkt Cap ($m)	Gross ann mean (%)	Ann Std Dev (%)	Skewness	Kurtosis	Ann Turnover (%)	Break-even ann mean (bps)
Panel A: *PIRS* (Predicting Influential Recommendations Strategy)								
Long	68	6,472	26.82 ***	18.50	-0.23	3.98 ***	1,386.72	193.4
Short	103	9,084	4.24	21.27	-0.29 **	4.51 ***	1,159.70	-
Long-Short	171	8,108	22.57 ***	9.09	0.38 **	4.31 ***	2,546.42	88.6
Panel B: *TRC* (Trading all recommendation changes)								
Long	235	10,745	24.55 ***	19.80	-0.19	3.96 ***	1,553.28	158.0
Short	402	11,316	3.77	20.65	-0.37 **	4.53 ***	1,224.95	-
Long-Short	637	11,187	20.78 ***	6.73	0.77 ***	6.89 ***	2,778.23	74.8
Panel C: *CRSP Equal Weighted Index*								
Long	-	-	15.89 ***	18.62	-0.06	4.55 ***	-	-
Panel D: Portfolio formed on the basis of naïve long-only strategy (1/N)								
Long	728	11,847	12.21 ***	20.19	-0.34 **	4.38 ***	434.43	281.1

Prior literature has proposed distinct factor models to shed light on common explanatory drivers of anomalies. Fama and French (1996) show that asset pricing anomalies are largely explained by a three-factor model, composed of market, size and value factors. However, subsequent literature has incorporated new factors that improve the explanatory power of these models. A variety of four-factor models has been shown to explain a large set of anomalies and generally outperform the three-factor model (Carhart, 1997, Hou et al., 2015, and Stambaugh and Yuan, 2017). However, new literature has shown these models could be improved by incorporating new factors or changing the model's construction (Fama and French, 2015, Barillas and Shanken, 2018, Fama and French, 2018, and Hou et al., 2019). Recently, Hou et al. (2021) show that the augmented q-factor model with an expected growth factor, the q^5 model, exhibits a strong explanatory power across 150 anomalies and largely outperforms the Fama-French six-factor model.

Table 7 – *PIRS* and Factor Decomposition

This table reports the results of different factor models regressions, namely the Carhart (1997) four-factor model, the Fama and French (2015) five-factor model, and the Hou et al. (2021) q^5 model, on the different strategies' performance. The correspondent annualized alphas, betas and adjusted R-squared are presented for each model. These strategies are implemented from 1999 to 2021. *, **, *** denote the 10%, 5% and 1% significance levels, respectively.

Coefficients	*PIRS*	*TRC*	*CRSP EW*	Naïve
		Panel A: Four-factor model		
Ann alpha (%)	23.35 ***	21.19 ***	6.74 ***	1.62 *
Mkt	-0.13 ***	-0.05 *	0.85 ***	1.05 ***
SMB	-0.10 **	-0.05	0.61 ***	0.49 ***
HML	0.09 **	0.06 *	0.04	0.09 ***
UMD	0.13 ***	0.03	-0.21 ***	-0.15 ***
Adjusted R^2	0.18	0.04	0.91	0.95
		Panel B: Five-factor model		
Ann alpha (%)	23.82 ***	21.48 ***	6.72 ***	1.74
Mkt	-0.18 ***	-0.07 **	0.90 ***	1.08 ***
SMB	-0.04	-0.03	0.51 ***	0.45 ***
HML	0.04	0.08	0.09 *	0.14 ***
RMW	0.07	0.02	-0.20 ***	-0.11 ***
CMA	-0.02	-0.06	-0.05	-0.15 ***
Adjusted R^2	0.13	0.03	0.88	0.94
		Panel C: q-factor extended model		
Ann alpha (%)	22.13 ***	20.07 ***	8.59 ***	3.70 ***
Mkt	-0.12 ***	-0.04	0.80 ***	1.01 ***
ME	-0.04	-0.04	0.39 ***	0.34 ***
IA	0.14 **	0.10 *	0.02	0.00
ROE	0.01	-0.11 **	-0.41 ***	-0.18 ***
EG	0.19 **	0.21 ***	-0.10 *	-0.24 ***
Adjusted R^2	0.15	0.06	0.91	0.94

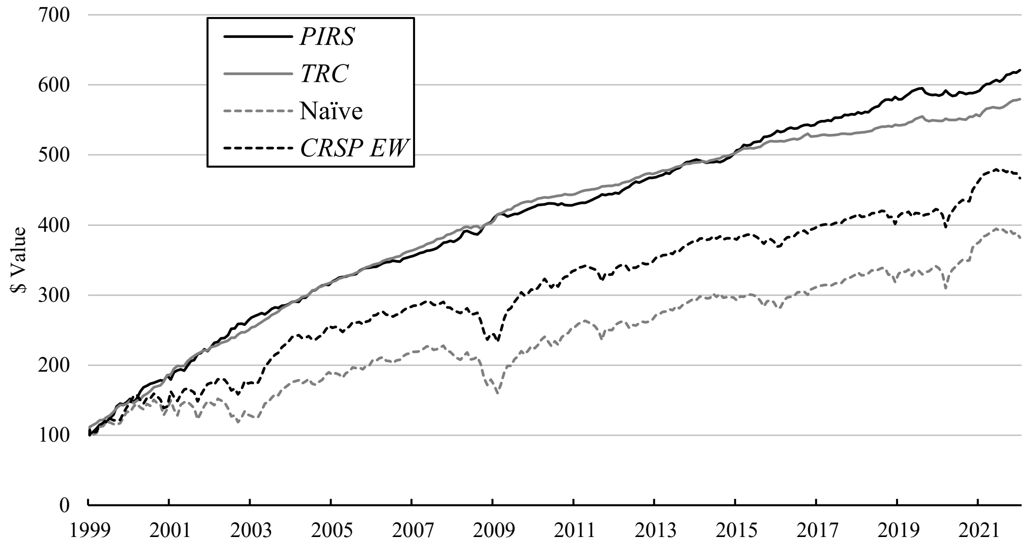
I apply a four-factor model (Carhart, 1997), five-factor model (Fama and French, 2015) and the q^5 model (Hou et al., 2021). The corresponding annualized alpha, betas and adjusted R-squared are presented in Table 7. The beta estimates of these factor models can shed light on the nature of firms composing each portfolio. The factor analysis reveals that the *PIRS* portfolio is tilted towards stocks that are contrarian to the market and have performed well, on average, in the recent past, of larger firms, with a high book-to-market ratio, a conservative investment approach and high profitability. Additionally, the firms have, on average, a high *ROE* and high expected growth.

The performance of the long-short portfolio shows that *PIRS* has an outstanding performance. The portfolio presents an average return of 22.6% with positive skewness. The *TRC* delivers an annualized return of 20.8%, while the *CRSP EW index* yields an annualized average of 15.9%, and the naïve portfolio delivers an annualized average of 12.2%. The *PIRS* outperforms all the remaining strategies, with an economically large difference. None of the factor models detailed above explain well the *PIRS* performance. The large outperformance of *PIRS* suggests that selecting predicted influential recommendation changes out of all the recommendation changes in the sample can be valuable for investors. Figure 7 shows the cumulative returns of all the above strategies starting in January 1999 with a basis of 100. Within this time span, *PIRS* outperforms the remainder strategies, achieving a final value that is 6.2 times its initial value, while the remainder strategies achieve final values that are at most 5.7 times their initial value (*TRC*). Another advantage of the method applied relates to the number of stocks used. On average, *PIRS* only uses 171 stocks, which compares to 637 stocks used in the *TRC* and 728 stocks used in the naïve portfolio. The same pattern occurs in the long and short portfolios. This evidence has implications for the transaction costs of each strategy, which I analyze further along.

The adjusted R-squared of *PIRS* is at most 0.18, with the Carhart four-factor model and *PIRS* returns are positively related to the value and momentum factors and negatively related to the size and market factor. From the remainder factor models is worth noting the positive load *PIRS* has on stocks with low investment and high expected growth as established in Hou et al. (2021) q^5 model. The adjusted R-squares for the long, short, and long-short strategies are of the same magnitude as previous literature (e.g., Loh and Mian, 2006, and Huang et al., 2009). The results show evidence that stock selection based on analyst's recommendation revisions has economic value from an investor perspective, with *PIRS* delivering an annualized alpha of 23.3% and the *TRC* of 21.2% for the Carhart four-factor model (in line with Boni and Womack, 2006). From here onwards, all alphas mentioned are obtained with the Carhart (1997) four-factor model.

Figure 7 – Cumulative returns

This figure plots the cumulative returns of four investment strategies, starting with a basis of 100. The four investment strategies are the *CRSP equal-weighted index*, the Naïve strategy, *TRC* and the *PIRS*, as described in Section IV.A.. These strategies are rebalanced daily during the period from 1999 to 2021.

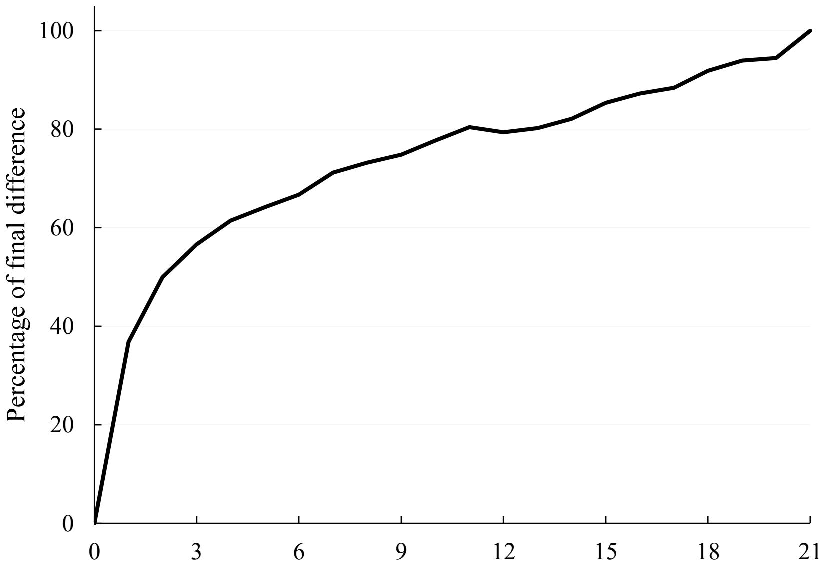


In Figure 8 I present the post-recommendation drift performance. It seems that, on average, the market incorporates the information quickly, as 56.6% of the total cumulative return is captured in the first three days. The post-drift value corresponds to two-fifths of the overall average price reaction in the period of 21 trading days after the recommendation revision is issued. In Figure 9 and 10, I also show that similar results can be found before and after 2013 (last year used in Faias, 2017), respectively. Therefore, it seems the market has not become faster in incorporating the information arising from forecasted influential recommendation revisions after 2013.

There is an asymmetric performance between the long and short legs of *PIRS*, with the former representing the major driver of the long-short performance. The average annualized return is 26.8% for the long leg and 4.2% for the short leg, but when I control for the Carhart risk factors, it becomes 17.5% and -5.8%, respectively. These results are consistent with established findings in the literature, that find negative and significant alphas for unfavorable recommendations – Womack (1996) shows that unfavorable recommendations have larger-magnitude reactions and stronger drifts when compared to favorable recommendations. If an investor is constrained to long positions, *PIRS* still outperforms the other strategies, as the *TRC* long leg delivers a significant annualized alpha of 14.3%. At the same time, the *CRSP EW index* yields an annualized alpha of 6.7% (Panel C), while the *TRC* is formed solely of stocks that produce an annualized alpha of 1.6% (Panel D). This in turn means a naïve portfolio comprising the stocks used in *TRC* fails to replicate the performance of the market using a smaller selection of firms with, on average, a larger size relative to those available in all the stock market.[18] Therefore, both *PIRS* and *TRC* may be more easily implemented since the transaction costs are reduced.

Figure 8 – Event reaction and pos-drift performance

This figure plots the average cumulative return of the long-short portfolio of *PIRS* during the next 21 trading days after trading a stock due to a forecasted influential recommendation revision, as described in Section IV.A..



[18] On average, the firms belong to the 70th percentile of the NYSE in terms of market capitalization as of the last available June 30 prior to the recommendations' announcement date.

Figure 9 – Event reaction and pos-drift performance before 2013

This figure plots the average cumulative return of the long-short portfolio of *PIRS* during the next 21 trading days after trading a stock due to a forecasted influential recommendation revision, as described in Section IV.A., between 1999 and 2013.

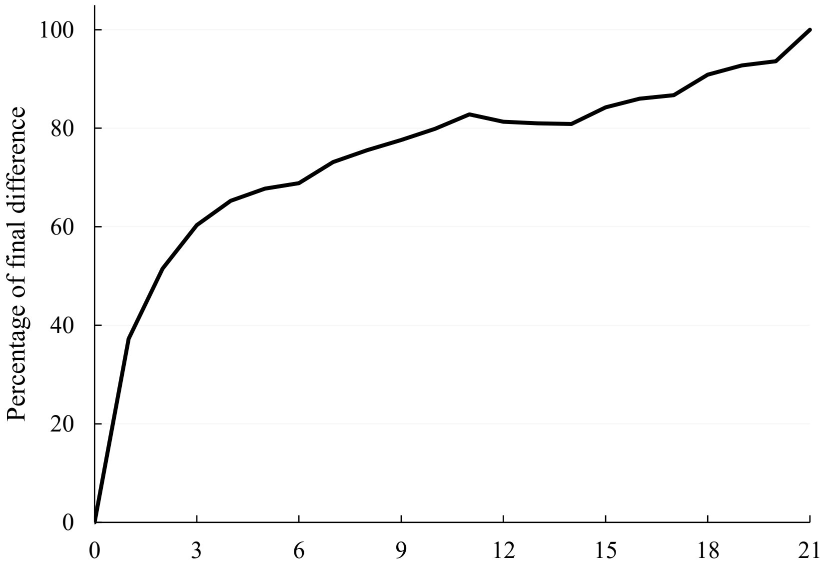
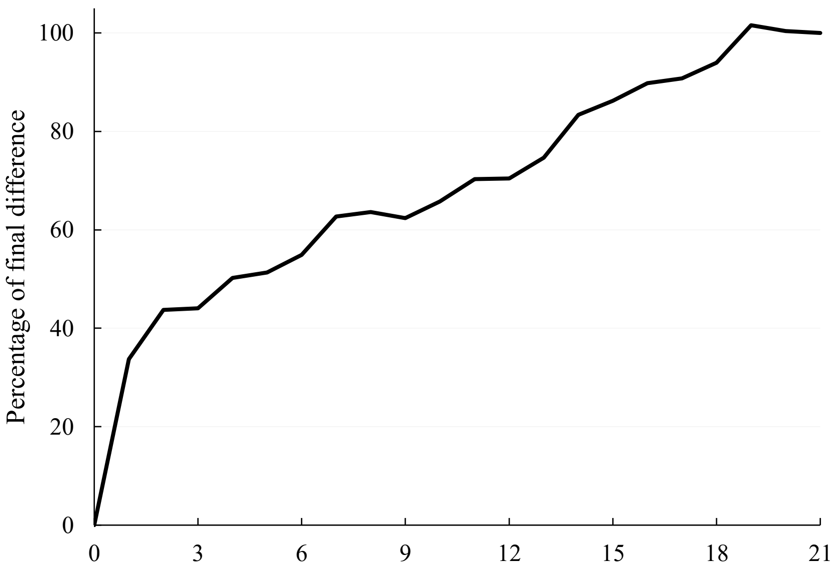


Figure 10 – Event reaction and pos-drift performance after 2014

This figure plots the average cumulative return of the long-short portfolio of *PIRS* during the next 21 trading days after trading a stock due to a forecasted influential recommendation revision, as described in Section IV.A., between 2014 and 2021.



B. Transaction Costs

Mikhail et al. (2004) show that a trading strategy which is long (short) in recommendation upgrades (downgrades) conditional on analysts' prior performance exhibits excess returns, which are nonetheless insufficient to cover transaction costs. Barber et al. (2001) corroborates this result, mostly due to excessive turnover of the strategies. However, Green (2006) finds that a strategy based on recommendation changes survives transaction costs. I follow Barber et al. (2001) in the estimation of annualized turnover, which will then be used to incorporate trading costs (i.e., bid-ask spread, brokerage commissions or trading impact).

Turnover is defined as the percentage of the portfolio's positions at the close of trading on t -1 that has been sold off at the close of trading on t. Turnover for firm i at time t is given by:

$$U_{it} = \sum_{i=1}^{n_{pt}} \max\{G_{it}\text{-}F_{it}, 0\} \tag{5}$$

The annual turnover is given by U_{it} times the number of trading days in a year. G_{it} represents the fraction of the portfolio's weights at the close of trading date t for each stock i in portfolio p, if there were no portfolio rebalancing, and is obtained by:

$$G_{it} = \frac{x_{it-1}(1+R_{it})}{\sum_{i=1}^{n_{pt-1}} x_{it-1}(1+R_{it})} \tag{6}$$

F_{it} is the real fraction used in the portfolio with daily rebalancing. The turnover of the long-short portfolio is at most as large as the sum of the turnover of each leg if there is no stock that meets the criteria for both legs at the same time.

The break-even transaction costs are obtained by multiplying the absolute value of the gross monthly return by 12 and dividing it by the annual turnover. Novy-Marx and Velikov (2014) estimate the round-trip transaction costs across market capitalization ranks, which I use as benchmark to assess whether the strategies survive transaction costs. The break-even transaction costs can be interpreted as the round-trip costs that would absorb the performance of the strategy. The higher the value the more likely a strategy remains profitable after being implemented in real-time.

The long and short *PIRS* portfolios exhibit turnovers of 1,387% and 1,160%, respectively, whereas the long-short *PIRS* portfolio exhibits a turnover of around 2,546% (Table 6). *TRC* has a similar turnover to that of *PIRS*, while the naïve long-only strategy (Panel D) exhibits a turnover of 434%. The average break-even transaction cost of the long-short *PIRS* portfolio is 88.6 bps whereas it is 74.8 bps for *TRC*. I find that the break-even transaction cost that would still generate a positive alpha for *PIRS* is 91.7 bps, whereas for *TRC* is 76.3 bps. These values assume that the factor model structure remains identical after incorporating transaction costs. The long leg of *PIRS* achieves a break-even transaction cost on the return of 193.4 bps and on alpha of 126.4 bps, which suggests that even after incorporating transaction costs, the long-short portfolio based on influential recommendation changes persists as an outstanding and valuable strategy. Overall, these values are consistently greater than the estimated round-trip transaction costs by Novy-Marx and Velikov (2014) for the average market capitalization of the stocks used in each strategy.

C. Corporate News Events

Altinkiliç and Hansen (2009) find that recommendation revisions do not produce, on average, statistically significant stock price reactions after excluding revisions where analysts piggyback on firms' news, such as earnings announcements. To assess whether the *PIRS* performance might be spurious and driven by company-specific events or news around the recommendation revisions dates of influential recommendation revisions, I exclude stocks that experience an event in the 43-day window around the recommendation revision date. Following Loh and Stulz (2018) and Faias (2017), I consider as events M&A deals announcements, earnings announcements, stock related events (e.g., liquidation, dividends, rights offer, etc.) and dates with multiple recommendation revisions on the same firm which are meant to proxy for dates with firm-specific news. After excluding all these events, except multiple recommendation revisions days, the number of stocks used in each portfolio is reduced substantially: the average number of stocks in the long-short portfolio is 54, less than a third of the original number.[19] Despite many events intersecting the sample of revisions, the results are very similar in terms of performance. Hence, these events have no direct impact on the strategy performance. There are no recommendation revisions that do not experience a multiple recommendation revision day in the span of the window considered, which may imply the existence of other firm-specific events that drive the *PIRS* performance. In Figure 11 and 12, I present a summary of the performance of the strategy when events are excluded for different windows.

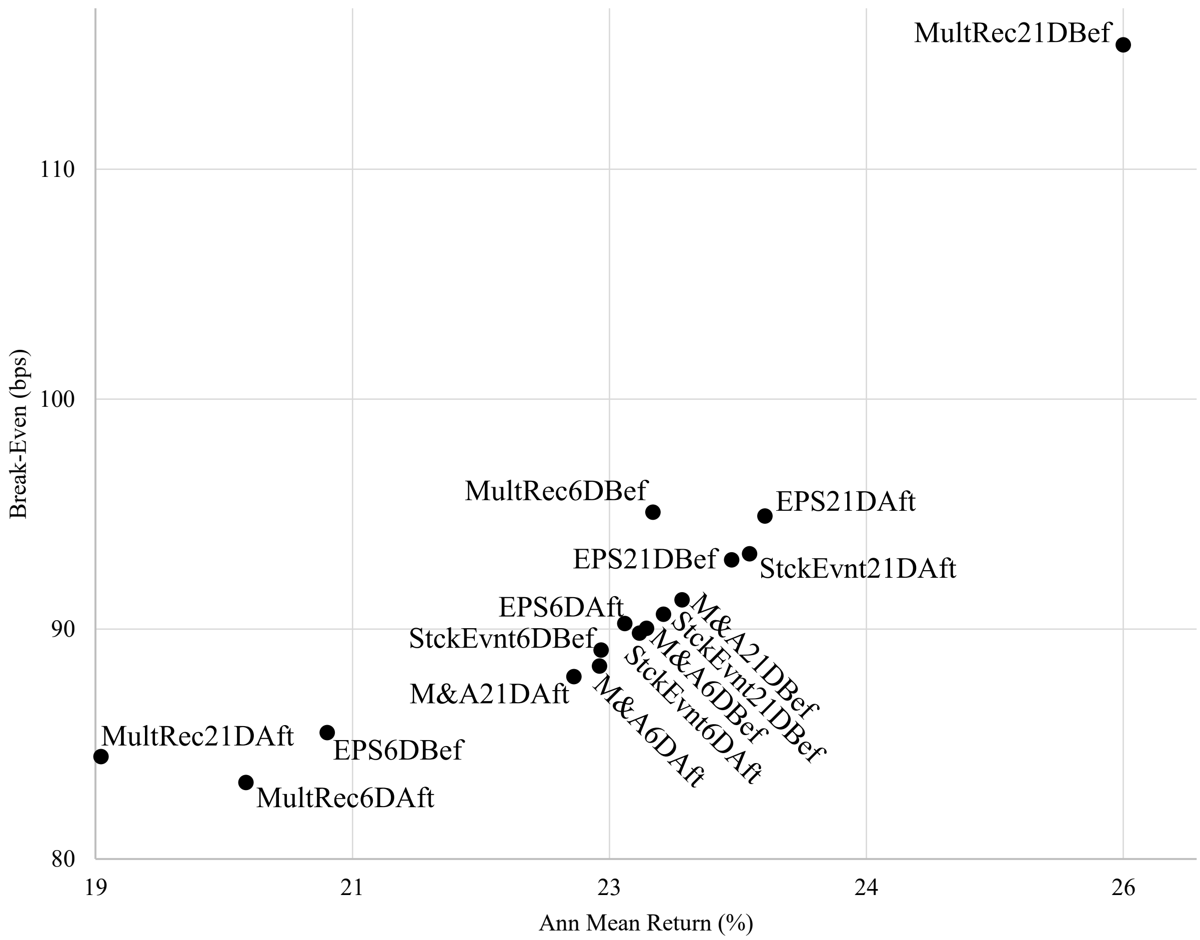
[19] Considering days with multiple recommendations for a stock as events within a 43- and 13-day window leads to all recommendations being excluded from the *PIRS*, which is why I include them here.

Figure 11 – Performance vs Break-Even Costs, Corporate News Events 43-Day and 13-Day Windows

This figure plots the annualized mean return and break-even transaction costs of *PIRS* excluding recommendations that suffer from events that coincide within a 43-day and a 13-day window centered around the recommendation announcement date. ExcAllEvnts disregards all recommendations with an earnings release, M&A deal announcement or stock events (e.g. cash dividends, liquidations and acquisitions or reorganizations) in a 43-day window centered around the recommendation announcement date. EPS43DW (EPS13DW) disregards all recommendations with an earnings release in a 43-day (13-day) window centered around the recommendation announcement date. M&A43DW (M&A13DW) disregards all recommendations with merger or acquisition deals announcements in a 43-day (13-day) window centered around the recommendation announcement date. StckEvnt43DW (StckEvnt13DW) disregards all recommendations with stock events in a 43-day (13-day) window centered around the recommendation announcement date.

Figure 12 – Performance vs Break-Even Costs, Corporate News Events 21-Day and 6-Day Windows

This figure plots the annualized mean return and break-even transaction costs of *PIRS* excluding recommendations that suffer from events that coincide within a 6-day and a 21-day window before and after the recommendation announcement date. EPS21DBef (EPS6DBef) disregards all recommendations with an earnings release in a 21-day (6-day) window before the recommendation announcement date. M&A21DBef (M&A6DBef) disregards all recommendations with merger or acquisition deals announcements in a 21-day (6-day) window before the recommendation announcement date. StckEvnt21DBef (StckEvnt6DBef) disregards all recommendations with stock events in a 21-day (6-day) window before the recommendation announcement date. MultRec21DBef (MultRec6DBef) disregards all recommendations with stock events in a 21-day (6-day) window before the recommendation announcement date. EPS21DAft (EPS6DAft), M&A21DAft (M&A6DAft), StckEvnt21DAft (StckEvnt6DAft) and MultRec21DAft (MultRec6DAft) represent the same strategies considering a 21-day (6-day) window after the recommendation announcement date.



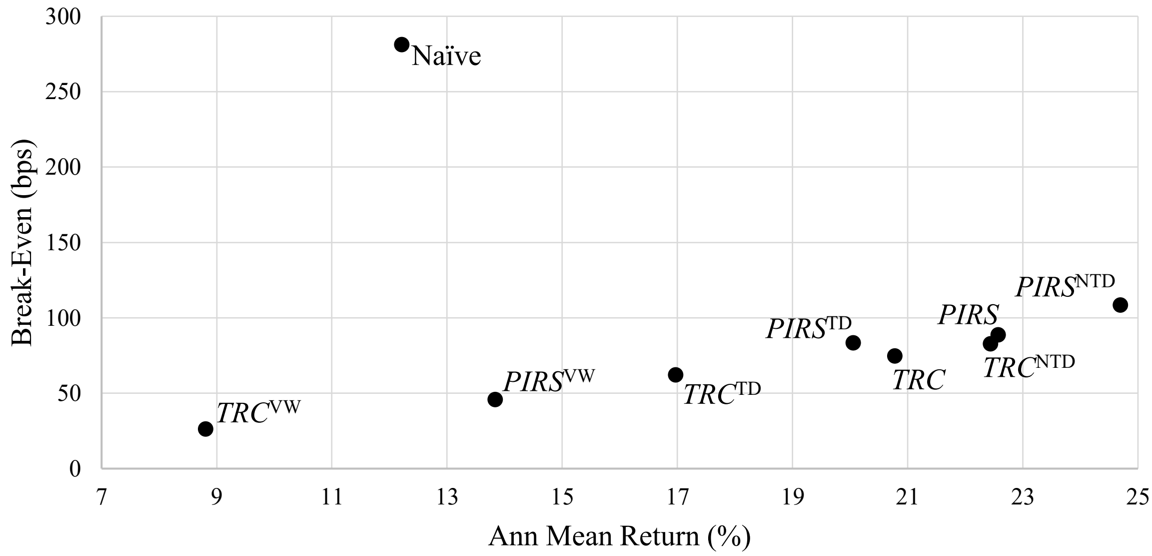
D. Investment Timing and Portfolio Weights

The timing of this strategy is a key determinant of its strong performance. Hence, I decompose the strategy between recommendations issued on trading days when the market is open, and recommendations issued when the market is closed (including non-trading days). The results obtained show that the strategy performance remains strong for both options, with annualized returns of 20.1% and 24.7%, respectively (Figure 13).

On the other hand, the strategy performance may be driven by the return bias created by using equal-weighted portfolios (Blume and Stambaugh, 1983). Therefore, I analyze whether the performance disappears with value-weighted portfolios. The results show that the strategy continues to show a robust performance, with an annualized return of 13.8% and a break-even round-trip cost of 45.8 bps (Figure 13).

Figure 13 – Performance vs Break-Even Costs, Investment Timing and Portfolio Weights

This figure plots the annualized mean return and break-even transaction costs of *PIRS*, *TRC* and Naïve strategies as described in Section IV.A.. The performance of *PIRS* (*TRC*) is also computed considering only recommendations announced during trading-days when the market was open, $PIRS^{TD}$ (TRC^{TD}), only recommendations announced during non-trading days or when the market was closed, $PIRS^{NTD}$(TRC^{NTD}), and with value-weighted instead of equal-weighted portfolios, $PIRS^{VW}$ (TRC^{VW}).



E. Alternative *PIRS* Modelling Strategies

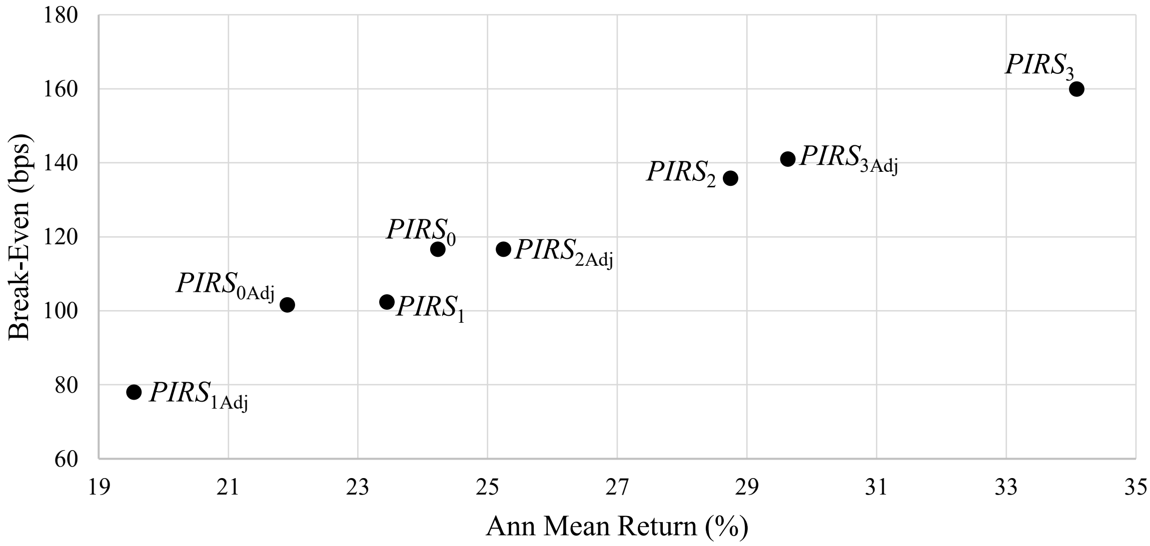
In this section I present alternative methodologies to predict influential recommendation changes to test if the main results are robust and conservative. The first part of the methodology is identical to the one described in Section III.A.2. and requires running the same *Probit* each month, for a rolling window of 5 years. Then for each month, the three characteristics (one recommendation characteristic, one analyst characteristic and one firm specific characteristic) with the largest marginal effects are considered. I impose a new condition to predict influential recommendation revisions to the original model: the values of the characteristics selected must be greater than their average of the last 5 years. This strategy is designated as $PIRS_0$. I find that its alpha is 24.7%, while it uses merely 36 stocks and presents a negative skewness.

I also run more strategies proposed in Faias (2017). They are constructed identically to $PIRS_0$ but use the characteristics with the greatest marginal effect from all characteristics at each point in time. Three strategies are constructed with the best, the top 2 and top 3 marginal effects, and are denominated, correspondingly, $PIRS_1$, $PIRS_2$ and $PIRS_3$. $PIRS_1$ holds, on average, a similar number of stocks to *PIRS*, around 120, while $PIRS_2$ has 74 stocks and $PIRS_3$ 37 stocks. The results show that more restrictions in the definition of predicted influential recommendation changes decrease the average number of assumed positions, while increasing the idiosyncratic volatility of these portfolios. An additional concern arises from the resulting unbalance in the number of stocks in each leg: the short portfolios have, on average, three times more stocks. The alphas of these strategies are 22.9%, 28.2% and 34.2%, for $PIRS_1$, $PIRS_2$ and $PIRS_3$, respectively. All these magnitudes are equivalent to those of *PIRS*, and they are achieved with a significant performance of the long portfolio, in some cases greater than *PIRS*. These three strategies exhibit positive and statistically significant skewness. Additionally, I reconstruct these strategies by imposing that the only variables used in the model for each month are the ones with the largest marginal effects for the last window. I label these strategies $PIRS_{0Adj}$, $PIRS_{1Adj}$, $PIRS_{2\text{Adj}}$ and $PIRS_{3\text{Adj}}$. Figure 14 presents a summary of the performance of these strategies.

For a more exhaustive analysis I construct a model that considers the full sample instead of running two separate models for positive and negative recommendation revisions, i.e., asymmetry is not considered. I also create a new strategy imposing a condition on the recommendation level, as in Barber et al. (2010). As in Faias (2017), I test the strategy performance when reiterations are included in the long leg or excluded from the portfolio. All these results reveal the strategy exhibits a robust performance and consistently contains economic value. The results of these strategies are summarized in Figure 15.

Figure 14 – Performance vs Break-Even Costs, Largest Marginal Effects

This figure plots the annualized mean return and break-even transaction costs of *PIRS* with alternative modelling strategies. The construction of these strategies is explained in Section IV.E..



V. Robustness Checks

In this section I briefly summarize different robustness tests I carried out to understand whether *PIRS* performs consistently. Figure 16 summarizes the performance of all robustness tests and respective strategies.

A. Market Conditions

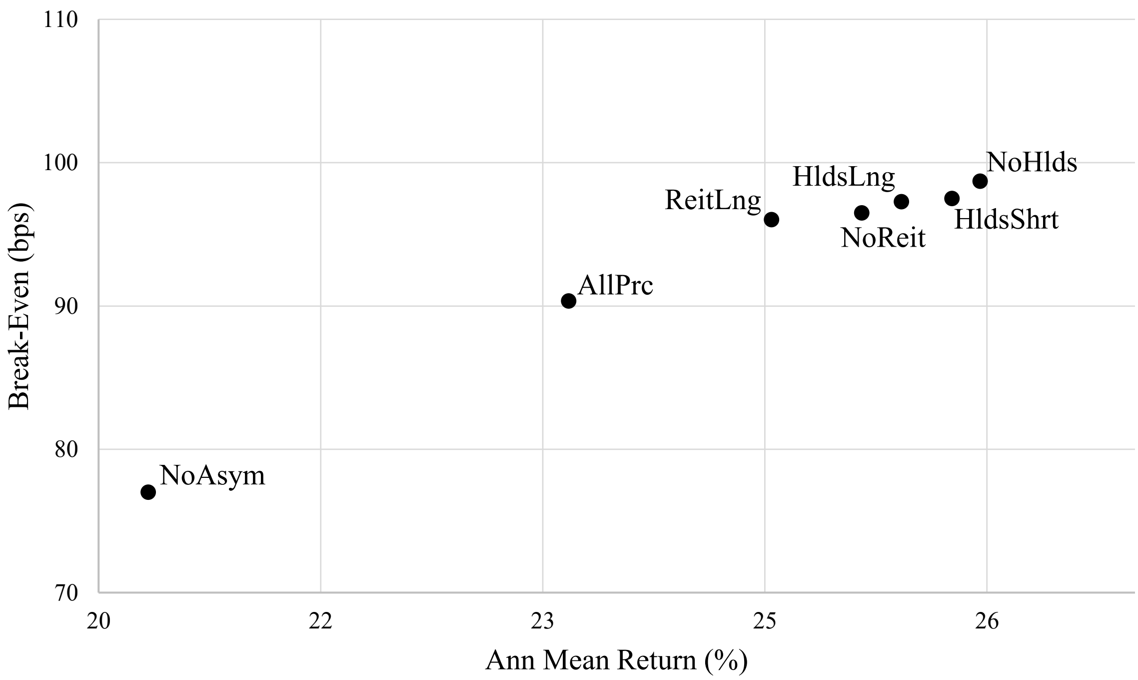
The *PIRS* performance could be driven by economic cycles, older performance, or other changes in market environment. I run the same analysis on *PIRS* for expansions and contractions, as defined by the NBER. During expansions the *PIRS* obtains an alpha of 22.7%, while during contractions the alpha is 22.4%. This strategy presents a higher alpha in expansions when compared to the *TRC* and the *CRSP EW index*, but it fails to outperform the *TRC* during contractions.

I analyze the strategy's performance in different time periods. First, I decompose the sample into the period used in Faias (2017), ending in 2013, and the subsequent period until 2021. In both periods the strategy delivers significant alphas, despite the lower performance registered in the second period. In the former period, *PIRS* and *TRC* deliver alphas of 26.5%

and 26.4%, respectively, while in the latter period they deliver alphas of 18.8% and 11.8%, respectively. These results constitute evidence that the strategy remained significant after 2013.

Figure 15 – Performance vs Break-Even Costs, Alternative *PIRS* Modelling and Construction Strategies

This figure plots the annualized mean return and break-even transaction costs of *PIRS* with different modelling and construction methodologies. AllPrc allows prices lower than 5$. NoAsym is formed with a *Probit* that uses the full sample, without capturing the asymmetric impact of positive and negative recommendation revisions. ReitLng (NoReit) uses reiterations as positive recommendation revisions (does not consider reiterations). Inspired in Barber et al. (2010), I consider an additional construction methodology for the *PIRS* that conditions for the recommendation level and for the recommendation revision category, where the long portfolio includes buy and strong buy recommendations, and the short portfolio includes sell and underperform. Three different strategies were considered based on hold recommendations allocation: not included, NoHlds; included in the long portfolio, HldsLng; included in the short portfolio, HldsShrt.



Previous literature has suggested that recommendation changes' informational value has decreased after the Regulation Fair Disclosure Act passed in August 2000 and after the Global Analyst Settlement published on 20 December 2002. To test these conclusions, I consider the periods from September 2000 until the end of 2021 and 2003 until the end of 2021. In both cases the *PIRS* and *TRC* strategy present significant alphas, with 21.5% and 20.0% in the former period, respectively, and 20.2% and 18.2%, respectively, in the latter period.

Additionally, I also assess the strategy capacity to survive major events, such as the Subprime Mortgage Crisis and the subsequent Sovereign Debt Crisis, as well as the COVID-19 pandemic. I consider the periods from 2009 to 2013, and from 2020 to 2021, respectively. The results during both periods are stronger than in other periods, with the *PIRS* and *TRC* registering alphas of 18.8% and 18.2%, respectively, in the former period and of 21.5% and 17.6%, respectively, in the latter period. These results are consistent with Loh and Stulz (2018), which show that during bad times analysts' recommendation revisions have a larger stock-price impact. These results are attributed to investors relying heavily on analysts and analysts working harder during bad times.

The results obtained suggest *PIRS* is robust in different market conditions, and it reveals a consistent positive skewness. Even during major crises, the strategy performance remains robust and statistically significant.

B. Holding Period

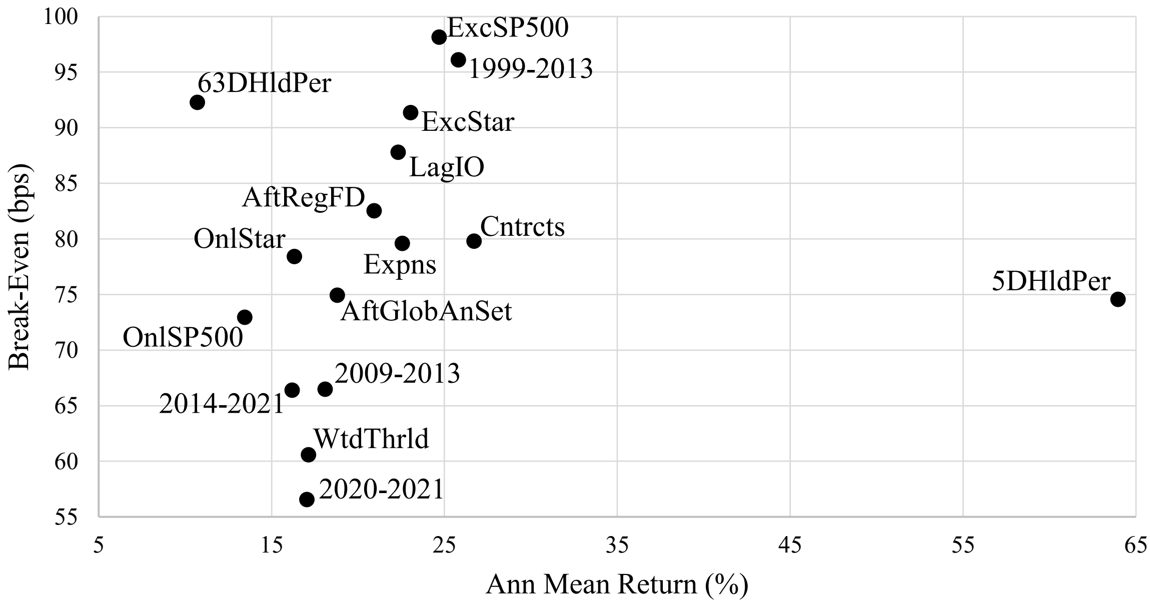
I define different holding periods, namely of one week (five trading days) and one quarter (sixty-three trading days), to test whether the *PIRS* performance may be driven by the holding period. Consistently with Stickel (1995), I observe a decrease in the annualized mean returns as the holding period increases. The annualized mean performance of *PIRS* and *TRC* for holding the stocks for a week is 65.4% and 53.1%, respectively, while it decreases to 10.5% and 12.5%, respectively, for a quarter. Nevertheless, *PIRS* remains attractive for each holding period and superior to the *TRC* performance. As most of the returns of the strategy are captured in the first few days, these results are not surprising.

C. S&P 500 Index Members

To assess if *PIRS* performance is driven by small stocks, I study the performance of a *PIRS* using solely the S&P 500 index members, and another excluding them from the baseline strategy. The S&P 500 index constitutes a proxy for the stocks with more visibility and for which it is more difficult to take advantage of any sources of public information. In many cases, the information about recommendations on these stocks is even broadcasted on specialized TV channels in real time. The *PIRS* performance remains strong in both alternatives. The long-short portfolios register an annualized alpha of 14.4% using solely the S&P 500 index members and 25.5% when they are excluded. For the long portfolios, it exhibits alphas of 14.1% using solely the S&P 500 index members and 18.4% when they are excluded.

Figure 16 – Performance vs Break-Even Costs, Robustness Checks

This figure plots the annualized mean return and break-even transaction costs of *PIRS* adaptations for robustness tests. LagIO considers lagged *institutional ownership* in the *Probit*. 5DHldPer (63DHldPer) differs from *PIRS* in Table 6 by considering a 5-Day (63-Day) holding period. WtdThrld considers a distinct method to compute the threshold value in the prediction exercise, as explained in Section V.F.. OnlStar (ExcStar) considers forecasted influential recommendation revisions from star analysts (non-star analysts). OnlSP500 (ExcSP500) considers forecasted influential recommendation revisions on members of the S&P 500 (non-members of the S&P 500). Expns (Cntrcts) considers forecasted influential recommendation revisions during expansions (contractions) as defined by the NBER. Other strategies consider different time periods: Faias (2017) period, 1999-2013; after Faias (2017) period, 2014-2021; during the Subprime Mortgage Crisis and the Sovereign Debt Crisis, 2009-2013; during the COVID-19 pandemic, 2020-2021; after the Regulation Fair Disclosure Act, AftRegFD; and, after the Global Analyst Settlement, AftGlobAnSet.



D. Star Analysts

Desai et al. (2000) and Fang and Yasuda (2013) show that star analysts' recommendations are significantly more profitable than recommendations of non-star analysts. To determine whether the performance of *PIRS* depends on the subset of analysts (in this case star analysts), I decompose the performance between star and non-star analysts. The performance of *PIRS* and *TRC* considering only star analyst has a lower performance by 6.3 and 5.8 percentage points, respectively, when compared to the original strategy. The average market capitalization of the firms included in the portfolio is much larger when only star analysts are included in the strategy. This result is expected as star analysts tend to cover more visible and larger stocks. Pohl and Pursiainen (2023) find that stocks with index memberships may cause their analysts to become star analysts, and that the careers implications of index memberships introduce significant bias to analysts' stock recommendations. When the strategies exclude recommendations from star analysts the performances of *PIRS* and *TRC* are similar to the ones from the original strategies. This result shows a low relative importance of star analysts in the strategy.

E. Institutional Ownership Timing

Institutional ownership is often not provided on a real-time basis, and it may take several months for firms to report updated information. Hence, *institutional ownership* percentage is a crucial firm-specific characteristic for predicting the influential recommendation changes. I assess the results using institutional ownership lagged two quarters, and the results remained similar.

F. Definition of *Probit* Threshold

I use an alternative measure to set the threshold value to distinguish between influential and non-influential recommendation revisions in the *Probit* models of Section III.B., following Faias (2017). In this measure, different weights are attributed to each component of the error term considering the performance of each group, influential vs non-influential. If the influential recommendation revisions perform better than non-influential ones, then this measure will be more conservative in determining which recommendation revisions are influential in detriment of non-influential recommendation revisions. The measure is given by:

$$RM = [\Pr(Predicted\ Non\ Infl|Infl)]^2 + \ \varphi[\Pr(Predicted\ Infl|Non\ Infl)]^2 \quad (7)$$

Or,

$$RM = \left(1 - \frac{\#Correctly\ Pred\ Infl}{\#Actual\ Infl}\right)^2 + \ \varphi\left(1 - \frac{\#Correctly\ Pred\ Non\ Infl}{\#Actual\ Non\ Infl}\right)^2 \quad (8)$$

where $\varphi = \frac{Non\ Infl\ Average\ 2\text{-}day\ CAR}{Infl\ Average\ 2\text{-}day\ CAR}$.

PIRS delivers an annualized alpha of 17.4% for the long-short and 13.5% for the long portfolio, meaning that there is a reduced incremental value on *PIRS*. Therefore, I opt to use the baseline method for conservative issues.

VI. Conclusion

This study contributes to the growing body of literature covering recommendation revisions and their subsequent stock price reactions by showing the economic value lying on the information and views of sell-side analysts. I re-examine the characteristics of influential and non-influential recommendation revisions, and I show their main dynamics across time. Additionally, I find evidence of the importance of asymmetric modelling to capture the differences between negative and positive recommendation revisions.

I develop an investment strategy reliant on a prediction exercise of influential recommendation revisions using relevant characteristics of recommendation revisions, as shown by Loh and Stulz (2011), Faias (2017) and Loh and Stulz (2018). I construct a long-short portfolio that buys positive and sells negative recommendation revisions that are predicted to be influential between 1999 and 2021. This portfolio yields an annualized alpha of 23.3%, using the Carhart factor model. This strategy clearly outperforms the *CRSP equal-weighted index* and a naïve portfolio. Its performance is not constrained by the timing of the investments, since the strategy yields a strong performance when it uses only recommendations issued during the market open or during the market close (including non-trading days). It presents a positive skewness, requires relatively fewer stocks for implementation, remains attractive for short-selling constrained investors and survives across business cycles.

After running numerous robustness checks, I conclude that this investment strategy is robust to high transaction costs, restrictions in the pool of available investments, such as excluding recommendations from star analysts, investing only in S&P 500 index members, or excluding recommendations with firm specific news or events around its announcement, and to different model and methodology specifications.

These findings suggest sell-side analysts recommendation revisions have economic value and provide evidence on the reality of capital market efficiency in its semi-strong form. These results may be attributed to a superior capacity for sell-side analysts to generate valuable information through their access to vast and more expensive resources that are more easily attainable through the economies of scale potentiated by brokers.

Future research may deepen the debate on the economic value of the tails of recommendation revisions' price-reactions. Among potential contributions, I propose studying strategies with real-time applications, new modelling techniques, the inclusion of other characteristics and extending the analysis to other datasets.

References

Altinkiliç, O., and Hansen, R. S., 2009, On the information role of stock recommendation revisions, *Journal of Accounting and Economics* 48, 17-36.

Altinkiliç, O., Hansen, R. S., and Ye, L., 2016, Can analysts pick stocks for the long run? *Journal of Financial Economics* 119 (2), 371-398.

Asquith, P., Au, A. S., and Mikhail, M. B., 2005, Information Content of Equity Analyst Reports, *Journal of Financial Economics* 75, 245-282.

Barber, B. M., and Odean, T., 2000, Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors, *Journal of Finance* 55, 773-806.

Barber, B. M., Lehavy, R., McNichols, M., and Trueman, B., 2001, Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns, *Journal of Finance* 56, 531-563.

Barber, B. M., Lehavy, R., McNichols, M., and Trueman, B., 2006, Buys, holds, and sells: The distribution of investment banks' stock ratings and the implications for the profitability of analysts' recommendations, *Journal of Accounting and Economics* 41, 87-117.

Barber, B. M., Lehavy, R., and Trueman, B., 2007, Comparing the Stock Recommendation Performance of Investment Banks and Independent Firms, *Journal of Financial Economics* 85, 490-517.

Barber, B. M., Lehavy, R., and Trueman, B., 2010, Ratings Changes, Ratings Levels, and the Predictive Value of Analysts' Recommendations, *Financial Management* 39, 533-553.

Barillas, F., and Shanken, J., 2018, Comparing asset pricing models, *Journal of Finance* 73, 715–754.

Batten, J. A., Ham, H., Lee, J., and Ryu, D., 2022, Are Analyst Recommendations Recommended?, Working Paper.

Blume, M. E., and Stambaugh, R. F., 1983, Biases in Computed Returns: An application to the Size Effect, *Journal Financial Economics* 12, 387-404.

Boni, L., 2006, Analyzing the analysts after the Global Settlement, in Y. Fuchita, Litan, R. E., ed.: Financial Gatekeepers: Can They Protect Investors?, *Brookings Institution Press and the Nomura Institute of Capital Markets Research*.

Boni, L., and Womack, K. L., 2006, Analysts, Industries, and Price Momentum, *Journal of Financial and Quantitative Analysis* 41, 85-109.

Bonner, S., Hugon, A., and Walther, B., 2007, Investor Reaction to Celebrity Analysts: The Case of Earnings Forecast Revisions, *Journal of Accounting Research* 45 (3), 481-513.

Bradley, D. J., Jordan, B. D, and Ritter, J. R., 2008, Analyst behavior following IPOs: The 'bubble period' evidence, *Review of Financial Studies* 21, 101-133.

Bradley, D., Liu, X., and Pantzalis, C., 2014, Bucking the Trend: The Informativeness of Analyst Contrarian Recommendations, *Financial Management* 43, 391-414.

Brown, N. C., Wei, K. D., and Wermers, R., 2014, Analyst Recommendations, Mutual Fund Herding and Overreaction in Stock Prices, *Journal of Finance* 60, 1-20.

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

Chen, Q., Francis, J., and Schipper, K., 2005, The applicability of the fraud on the market presumption to analysts' forecasts, Working paper.

Choi, Y., and Lee, S. S., 2022, On Efficiency Contribution of Analyst Recommendations to Financial Markets, Working Paper.

Clement, M. B., 1999, Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter?, *Journal of Accounting and Economics* 27 (3), 285-303.

Cooper, R. A., Day, T. E., and Lewis, C. M., 2001, Following the leader: A study of individual analysts' earnings forecasts, *Journal of Financial Economics* 61, 383-416.

Daniel, K., Grinblatt, M., Titman, S., and Wermers, R., 1997, Measuring Mutual Fund Performance with Characteristic-Based Benchmarks, *Journal of Finance* 52, 1035-1058.

D'Avolio, G., 2002, The Market for Borrowing Stock, *Journal of Financial Economics* 66, 271–306.

DeMiguel, V., Garlappi, L., and Uppal, R., 2009, Optimal Versus Naive Diversification: How Efficient is the 1/N Strategy?, *Review of Financial Studies* 22, 1915-1953.

Desai, H., Liang, B., and Singh, A. K., 2000, Do All-Stars Shine? Evaluation of Analyst Recommendations, *Financial Analysts Journal* 56, 20-29.

Diether, K. B., Malloy, C. J., and Scherbina, A., 2002, Differences of opinion and the cross-section of stock returns, *Journal of Finance* 57, 2113-2141.

Dunbar, C. G., 2000, Factors Affecting Investment Bank Initial Public Offering Market Share, *Journal of Financial Economics* 55, 3–41.

Engelberg, J., McLean, R. D., and Pontiff, J., 2020, Analysts and anomalies, *Journal of Accounting and Economics*, 69 (1), 101-249.

Faias, J., 2017, Does the market recognize which analyst reports are influential?, Working Paper.

Fama, E. F., 1970, Efficient capital markets: a review of theory and empirical work, *Journal of Finance* 25, 383-417.

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

Fama, E. F., and French, K. R., 1996, Multifactor explanation of asset pricing anomalies, *Journal of Finance* 51, 55–84.

Fama, E. F., and French, K. R., 2006, The value premium and the CAPM, *Journal of Finance* 61, 2163-2185.

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

Fama, E. F., and French, K. R., 2018, Choosing factors, *Journal of Financial Economics* 128 (2), 234–252.

Fang, L. H., and Yasuda, A., 2013, Are Stars' Opinions Worth More? The Relation between Analyst Reputation and Recommendation Values, *Journal of Financial Services Research* 46, 235-269.

Frankel, R., Kothari, S.P., and Weber, J., 2006, Determinants of the informativeness of analyst research, *Journal of Accounting and Economics* 41, 29-54.

Gintschel, A., and Markov, S., 2004, The effectiveness of Regulation FD, *Journal of Accounting and Economics* 37 (3), 293-314.

Green, T. C., 2006, The Value of Client Access to Analyst Recommendations, *Journal of Financial and Quantitative Analysis* 41, 1-24.

Hayunga, D. K, and Lung, P. P., 2014, Trading in the options market around financial analysts' consensus revisions, *Journal of Financial and Quantitative Analysis* 49, 725–747.

He, W., Mian, G. M., and Sankaraguruswamy, S., 2005, Who Follows the Prophets? Analysts' Stock Recommendations and the Trading Response of Large and Small Traders, Working Paper.

Hou, K., Xue, C., and Zhang, L., 2015, Digesting anomalies: An investment approach, *Review of Financial Studies* 28 (3), 650–705.

Hou, K., Mo, H., Xue, C., and Zhang, L., 2019, Which factors?, *Review of Finance* 23, 1–35.

Hou, K., Mo, H., Xue, C., and Zhang, L., 2021, An augmented Q-factor model with expected growth, *Review of Finance* 25, 1–41.

Hsieh, J., Ng, L., and Wang, Q., 2023, How informative are insider trades and analyst recommendations?, *Journal of Banking and Finance* 149, 106787.

Huang, J., Mian, G. M., and Sankaraguruswamy, S., 2009, The Value of Combining the Information Content of Analyst Recommendations and Target Prices, *Journal of Financial Markets* 12, 754-777.

Irvine, J. P., 2003, The incremental impact of analyst initiation of coverage, *Journal of Corporate Finance* 9 (4), 431-451.

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

Jegadeesh, N., and Kim, W., 2006, Value of Analyst Recommendations: International Evidence, *Journal of Financial Markets* 9 (3), 274-309.

Jegadeesh, N., and Kim, W., 2010, Do Analysts Herd? An Analysis of Recommendations and Market Reactions, *Review of Financial Studies* 23 (2), 901-937.

Jensen, M.C., 1978, Some anomalous evidence regarding market efficiency, *Journal of Financial Economics* 6, 95-101.

Jin, H., Mazouz, K., Wu, Y., and Xu, B., 2023, Can star analysts make superior coverage decisions in poor information environment?, *Journal of Banking and Finance* 146, 106650.

Kadan, O., Madureira, L., Wang, R., and Zach, T., 2009, Conflicts of interest and stock recommendations - The effects of the Global Settlement and related regulations, *Review* of *Financial Studies* 22 (2), 4189-4217.

Kecskés, A., Michaely, R., and Womack, K. L., 2017, Do earnings estimates add ′ value to sell-side analysts' investment recommendations? *Management Science* 63, 1855– 1871.

Krigman, L., Shaw, W. H., and Womack, K.L., 2001, Why Do Firms Switch Underwriters? *Journal of Financial Economics* 60, 245–284.

Ljungqvist, A., Marston, F., Starks, L. T., Wei, K. D., and Yan, H., 2007, Conflicts of Interest in Sell-side Research and the Moderating Role of Institutional Investors, *Journal of Financial Economics* 85, 420-456.

Ljungqvist, A., Malloy, C., and Marston, F., 2009, Rewriting History, *Journal of Finance* 64, 1935-1960.

Loh, R. K., and Mian, G. M., 2006, Do Accurate Earnings Forecasts Facilitate Superior Investment Recommendations?, *Journal of Financial Economics* 80, 455-483.

Loh, R. K., and Stulz, R. M., 2011, When Are Analyst Recommendation Changes Influential?, *Review of Financial Studies* 24, 593-627.

Loh, R. K., and Stulz, R. M., 2018, Is Sell-side Research More Valuable in Bad Times?, *Journal of Finance* 73 (3), 959–1013.

Mikhail, M. B., Walther, B. R., and Willis, R. H., 1997, Do security analysts improve their performance with experience?, *Journal of Accounting Research* 35, 131- 157.

Mikhail, M. B., Walther, B. R., and Willis, R. H., 2004, Do Security Analysts Exhibit Persistent Differences in Stock Picking Ability?, *Journal of Financial Economics* 74, 67-91.

Novy-Marx, R., and Velikov, M., 2014, A Taxonomy of Anomalies and Their Trading Costs, NBER Working Paper.

Pohl, S., and Pursiainen, V., 2023, The Role of Stock Indices in Analyst Career Outcomes and Stock Recommendations, University of St. Gallen, School of Finance Research Paper No. 4414198, *Swiss Finance Institute*, Research Paper No. 23-50.

Stambaugh, R. F., and Yuan, Y., 2017, Mispricing factors, *Review of Financial Studies* 30, 1270–1315.

Stickel, S. E., 1995, The Anatomy of the Performance of Buy and Sell Recommendations, *Financial Analyst Journal* 51, 25-39.

Womack, K. L, 1996, Do Brokerage Analysts' Recommendations Have Investment Value?, *Journal of Finance* 51, 137-167.

Glossary – Variables Definition

Variable	Definition
Analysts' Characteristics	
Leader-follower ratio (*LFR*)	Sum of the days elapsed between the current recommendation and the previous two recommendations from different analysts for the same stock, divided by the time elapsed between the current recommendation and the following two recommendations from different analysts. The greater the value of the *LFR*, the more likely an analyst is followed by others (see Cooper, Day, and Lewis, 2001).
Past *LFR*	Average of an analyst's *LFR*s for all stocks during the prior 12 months, excluding *LFR*s that use recommendations issued after the current recommendation (see Loh and Stulz, 2011).
Broker size	Number of distinct analysts that issued a stock recommendation, or that have issued earnings forecasts for any horizon, during the previous 12 months, for a given broker (see Bradley et al., 2014, and Loh and Stulz, 2018).
Star analyst	Dummy variable equal to 1 if the analyst is ranked in the All-American (first, second, third, or runner-up teams) annual polls in the *Institutional Investor* magazine as of the last October (see Faias, 2017).
Earnings forecast accuracy	Analysts are assigned quintiles based on their forecast accuracy for the previous fiscal year. Analysts are attributed their fiscal year quintile for a firm in the year before if the recommendation is issued between the end of the previous fiscal year and its earnings release date, or if they do not have an available quintile on that firm for the previous fiscal year. The quintile of an analyst is determined by sorting analysts for a given firm-year combination into quintiles, using the last available unrevised FY1 forecast of the analysts, following Loh and Stulz (2011). Only firm-years with at least five different analysts are considered. The analysts are assigned a forecast accuracy quintile (1 being the most accurate), based on the recommendations that the analyst issues during a 12-month window that overlaps three months into the next fiscal year. Analysts are

	attributed ranks based on the AFE (Absolute Forecast Error) for a given firm-year. The AFE of analyst i for firm j in fiscal year t is computed as: $$AFE_{ijt}= \lvert Actual_{ijt}\text{- } Forecast_{ijt}\rvert$$ The analyst with the lowest AFE gets a rank of 1. Analysts with the same AFE are assigned the same rank. Then, 0.25 is deducted from the rank and the resulting number is divided by the maximum rank in the firm-year to compute a percentile score for each analyst. Subtracting a number between 0 and 1 from the rank serves to equalize the observations allocated to the extreme quintiles. Finally, analysts are sorted into quintiles based on the following percentile score intervals: [0, 0.2],]0.2, 0.4],]0.4, 0.6],]0.6, 0.8], and]0.8, 1] (see Loh and Mian, 2006).
Past forecast accuracy quintile	Average quintile rank of an analyst based on the last unrevised FY1 earnings forecast for all the firms he covers in the previous fiscal year. Analysts are attributed their average quintile rank in the year before if they do not have an available average quintile rank for the previous fiscal year (see Loh and Stulz, 2011).
Concurrent earnings forecast	Dummy variable equal to 1 when the analyst issued a FY1 forecast within a three-day window around the recommendation revision (see Faias, 2017).
Analyst experience	*Absolute analyst experience*, represented by the total number of quarters an analyst appears in *I/B/E/S*, and *relative analyst experience*, defined as the number of quarters a particular analyst has covered that specific firm minus the average experience for all analysts covering the firm (see Loh and Stulz, 2011).
Influential before	*Influential before same stock*, dummy equal to 1 when the analyst has previously been influential with respect to the same stock. *Influential before any stock*, dummy equal to 1 if the analyst has been influential with respect to any stock in the past (see Faias, 2017).

Firms' Characteristics & Environment	
Financial dummy	Dummy variable equal to 1 if a firm is included at the moment of the recommendation in the sectors of Banking, Insurance or Other Financials, as defined in the Kenneth R. French data library, for the 17 Industry Portfolios.
B/M ratio	Book-to-market ratio at the end of the last December (see Fama and French, 2006).
Size	Market capitalization at the end of the previous month (see Loh and Stulz, 2011).
Price momentum	Last 12 months return, excluding the previous month (see Jegadeesh and Titman, 1993).
Institutional ownership	Percentage of shares owned by institutions as reported in Thomson 13f at the most recent quarter end (see Loh and Stulz, 2011).
# of earnings forecasts	Number of earnings forecasts with different horizons across all analysts for a given firm in the last three months ([-94, -4]).
Short-term reversal	Last month return (see Hsieh et al., 2023).
Daily turnover	Average daily percentage of shares traded of the total shares outstanding in the last three months ([-63,-2]) (see Loh and Stulz, 2011, and Hsieh et al., 2023).
Idiosyncratic volatility	Standard deviation of the residuals from a time-series regression on the prior three months ([-63,-2]) daily returns against the Fama-French three factor model (see Loh and Stulz, 2011, and Bradley et al., 2014).
Total volatility	Standard deviation of daily returns of the prior three months ([-63,-2]) (see Loh and Stulz, 2011, and Hsieh et al., 2023).
Dispersion	Standard deviation of the I/B/E/S FY1 forecasts divided by the absolute value of the mean forecast in the prior month (see Diether, Malloy, and Scherbina, 2002).
Δ Dispersion	Change in dispersion between the last month and three months before.
FY1 or FY2 adjusted consensus forecasts	Last month FY1 or FY2 consensus forecast scaled by price. The consensus forecast is defined as the average at the end of the month

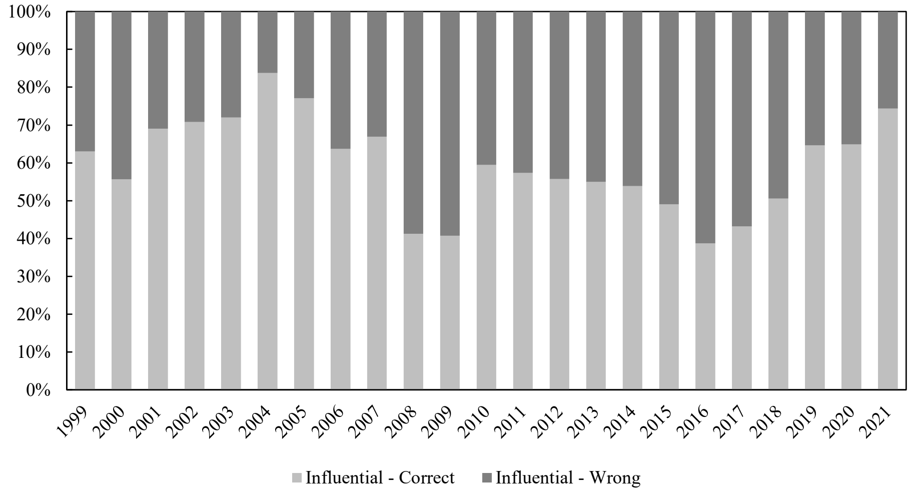
	of FY1 or FY2 forecasts outstanding as defined by Diether et al. (2002).
Δ in FY1 or FY2 |Forecast revision|	Absolute difference between the last month FY1 or FY2 consensus forecast and the correspondent four months before FY1 or FY2 consensus forecast.
Recommendations' Characteristics	
Recommendation change	Computed as the current rating minus the prior rating by the same analyst. The recommendations for which there is no outstanding prior rating from the same analyst (i.e., analyst initiations) are excluded. A rating is always assumed to be outstanding if it is less than one year old and never if it is more than two years old; if the rating is between one and two years old, it is considered outstanding only if there is an analyst forecast from the analyst in the one year window prior to the recommendation date (matching to the I/B/E/S Detail Earnings Forecast File) (see Loh and Stulz, 2011).
Recommendation level	*I/B/E/S* rating issued by an analyst, ranging from 1 (strong buy) to 5 (sell) (see Loh and Stulz, 2011).
Influential recommendation	Dummy variable equal to 1 if a recommendation revision is deemed influential. Recommendation changes are considered influential when simultaneously the *CAR* is in the same direction as the recommendation change and the following inequality holds: $$\|CAR_i\| > 1.96 \times \sqrt{2} \times \sigma_{\varepsilon_i}$$ where σ_{ε_i} represents the idiosyncratic volatility of firm i, which measured by the standard deviation of the residuals from a daily time-series regression of firm returns against market returns and the Fama and French (1993) three factors. The regressions are conducted for the period that starts three months before (t-69) and ends six days before the recommendation announcement (t-6). A recommendation is influential if its absolute *CAR* is greater than 1.96 times the standard deviation of the firm's prior three-month idiosyncratic volatility, multiplied by $\sqrt{2}$ since the *CAR* is calculated for a two-day window (see Faias, 2017).

	The *CAR* is computed as the cumulative buy-and-hold abnormal returns for a two-day time window: $$CAR_i = \prod_{t=0}^{1}(1 + R_{it}) - \prod_{t=0}^{1}\left(1 + R_{it}^{DGTW}\right)$$ where R_{it} is the raw return of firm i on day t. t = 0 is the day of the recommendation announcement, except when the announcement occurs between 4:30 pm and 11:59 pm, where t = 0 is the close of the following trading day. For recommendations whose announcement date is made during a non-trading day, the first trading day following the announcement is considered as t = 0. The benchmark reference return used, R_{it}^{DGTW}, is the return on a benchmark portfolio of the same size, book-to-market and momentum characteristics as firm i, as defined by Daniel et al. (1997).
Upgrade dummy	Dummy variable equal to 1 if a *recommendation change* is positive (see Faias, 2017).
Other Variables	
Settlement dummy	Dummy variable equal to 1 from 2003 onwards (see Loh and Stulz, 2011).
Reg FD dummy	Dummy variable equal to 1 from September 2000 onwards (see Loh and Stulz, 2011).

Appendix

Figure A1 – Accuracy of out-of-sample forecasts positive recommendation revisions

This figure plots the percentage of correct forecasts of influential (top graph) and non-influential (bottom graph) positive recommendation changes between 1999 and 2021. Recommendation changes are deemed influential according to the criteria established in Section II.C.. A recommendation change is forecasted to be influential based on the estimated value from a monthly 5-year rolling window *Probit* regression starting in 1994. This is explained in detail in Section III.B..



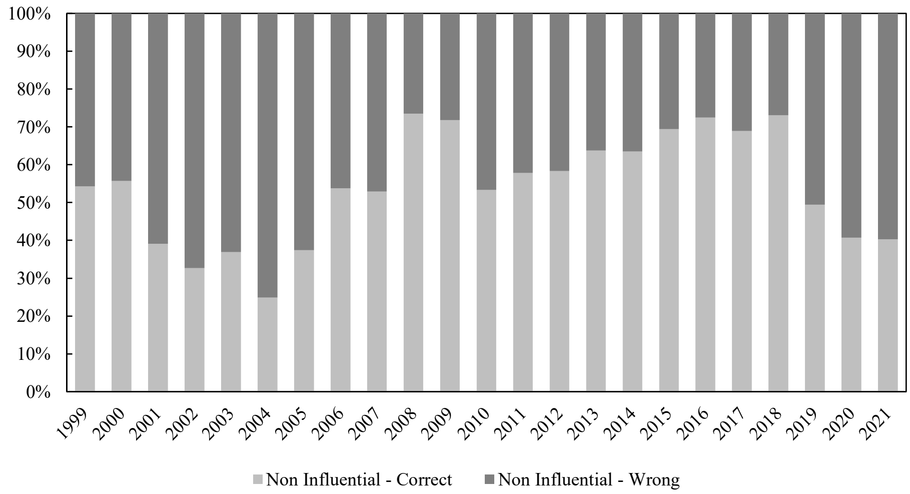
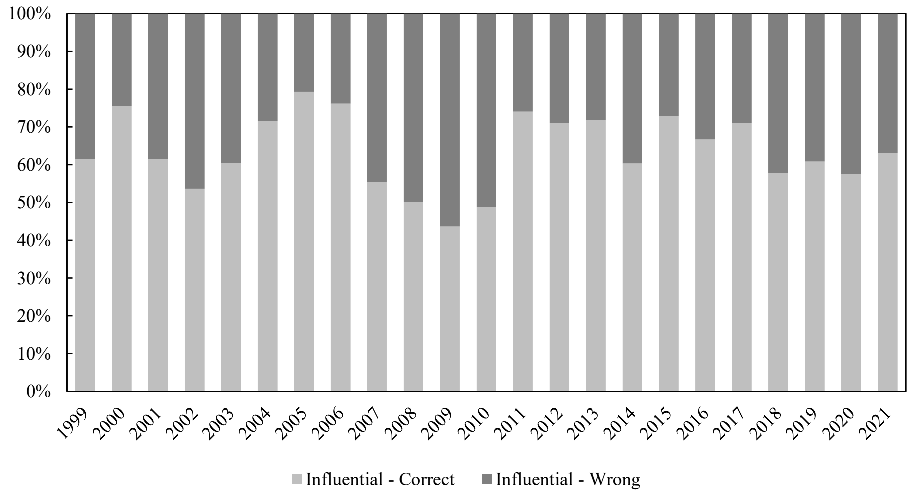


Figure A2 – Accuracy of out-of-sample forecasts negative recommendation revisions

This figure plots the percentage of correct forecasts of influential (top graph) and non-influential (bottom graph) negative recommendation changes between 1999 and 2021. Recommendation changes are deemed influential according to the criteria established in Section II.C.. A recommendation change is forecasted to be influential based on the estimated value from a monthly 5-year rolling window *Probit* regression starting in 1994. This is explained in detail in Section III.B..



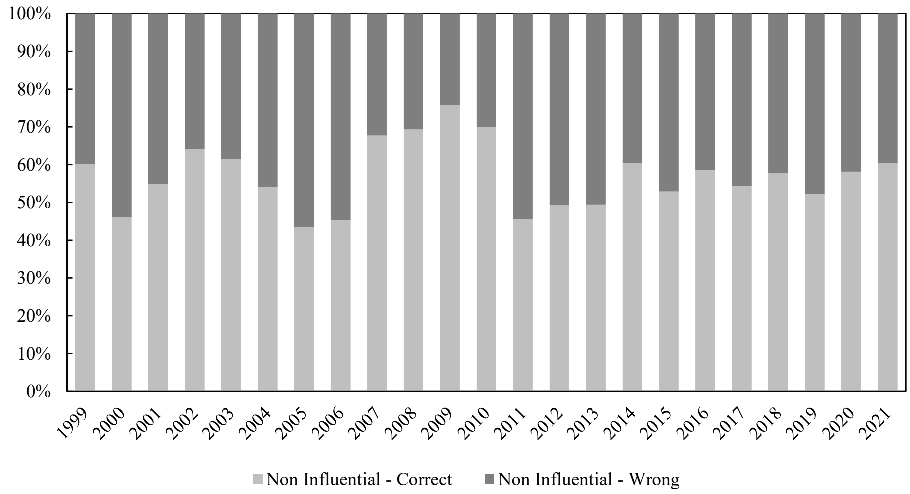


Table A1 – Comparison between analyst and firm characteristics for influential and non-influential recommendation changes

This table compares the average of each characteristic between two groups, influential and non-influential recommendation changes. Recommendation changes are deemed influential according to the criteria established in Section II.C.. The variables used are described in the Glossary – Variables Definition. *, **, *** denote the 10%, 5% and 1% significance levels, respectively.

	Positive Recommendation Changes			**Negative Recommendation Changes**		
Characteristics	Non-Influential	Influential	Difference	Non-Influential	Influential	Difference
Number of recommendation changes	68,481	19,545		116,544	30,601	
Share of total	77.80%	22.20%		79.20%	20.80%	
Panel A: Analyst characteristics						
Earnings forecast accuracy quintile	2.901	2.940	0.039 ***	2.903	2.926	0.023 *
Star analyst	0.116	0.120	0.004	0.136	0.131	-0.005 **
Away from consensus	0.123	0.154	0.031 ***	0.098	0.132	0.033 ***
Absolute analyst experience (# Qtrs)	29.649	31.921	2.272 ***	29.286	30.773	1.487 ***
Relative analyst experience (# Qtrs)	3.366	3.922	0.556 ***	3.094	3.284	0.190 ***
Concurrent earnings forecast	0.430	0.478	0.048 ***	0.417	0.521	0.104 ***
Influential before (any stock)	0.807	0.866	0.059 ***	0.804	0.853	0.049 ***
Influential before (same stock)	0.291	0.336	0.045 ***	0.254	0.290	0.035 ***
Broker size	100.065	113.365	13.299 ***	117.245	125.050	7.805 ***
Leader-follower ratio	2.618	3.827	1.209 ***	3.054	6.075	3.021 ***
Panel B: Firm characteristics prior to recommendation						
B/M ratio	0.617	0.597	-0.020 ***	0.601	0.541	-0.060 ***
Size ($m)	11,285.9	9,690.5	-1,595.5 ***	10,455.0	9,773.2	-681.8 ***
Institutional ownership (%)	0.647	0.690	0.043 ***	0.640	0.674	0.034 ***
Dispersion × 100	15.738	15.412	-0.326	15.177	13.357	-1.820 ***
Idiosyncratic volatility (%)	2.360	2.136	-0.224 ***	2.464	2.359	-0.105 ***
Total volatility (%)	2.863	2.649	-0.214 ***	2.977	2.898	-0.079 ***
Daily turnover	1.129	1.108	-0.022 **	1.117	1.195	0.078 ***
# of EPS forecasts	31.974	29.788	-2.186 ***	30.937	28.405	-2.531 ***
Consensus FY1 forecast adjusted by price	0.035	0.033	-0.002 *	0.033	0.031	-0.001
Consensus FY2 forecast adjusted by price	0.064	0.061	-0.004 ***	0.065	0.068	0.003 ***
Panel C: Change in firm environment around recommendation						
Δ Dispersion × 100 (-4M vs lastM)	0.243	0.012	-0.231	0.331	0.254	-0.076
Δ Idiosyncratic volatility (%) (-3m,+3m)	-0.085	0.117	0.202 ***	-0.102	0.480	0.582 ***
Δ Total volatility (%) (-3m,+3m)	-0.082	0.168	0.250 ***	-0.129	0.502	0.631 ***
Δ Daily turnover (-3m,+3m)	-0.003	0.111	0.114 ***	0.004	0.227	0.223 ***
Δ # EPS forecasts (-3m,+3m)	-0.004	0.180	0.184 **	-0.353	0.562	0.915 ***
Δ in FY1 |Forecast revision| (-4M vs lastM)	0.023	0.021	-0.002 ***	0.023	0.022	-0.002 ***
Δ in FY2 |Forecast revision| (-4M vs lastM)	0.018	0.016	-0.002 ***	0.019	0.019	0.000