Allow me to follow you:

How can the predictive value of security analyst recommendations best be employed as part of an investment strategy?

Mafalda Almeida e Brito
152418017

Dissertation written under the supervision of
Professor Dr. José Faias and Professor Dr. B. Burcin Yurtoglu

Dissertation submitted in partial fulfillment of requirements for the MSc in Finance,
at the Universidade Católica Portuguesa and for the MSc in Management,
at WHU – Otto Beisheim School of Management, September 2020.

Allow me to follow you:

How can the predictive value of security analyst recommendations best be employed as part of an investment strategy?

Mafalda Almeida e Brito
152418017

Abstract

This study investigates how to explore abnormal returns from an investment strategy that moves according to publicly available analyst recommendations relative to US companies. The portfolio that buys all the upgrades to Strong Buy and Buy and short sells all the downgrades to Strong Sell and Sell presents annualized abnormal returns of 65%, in the period from 1993 to 2019, compared against the five-factor model of Fama and French with momentum and short-term reversal. When calculating the transaction fee that leads to breakeven, the decade from 2010 to 2019 no longer holds significant abnormal returns if incurred in a one-way transaction fee higher than 0,04% of the trading value. This low breakeven fee compromises the profitability of the above investment strategy in current days. It is evidenced in this study that abnormal returns have a peak on the day when the recommendation is announced and that the day before also presents high abnormal returns. Strategies that constraints the stock selection on the level and change of the analyst recommendations bring slightly bigger abnormal returns. Results are higher for smaller firms and robust after testing for the firm's liquidity and for different time periods.

Keywords: Analyst, Recommendation, Abnormal, Returns, Investment, Strategy.

Permitam-me que vos siga:
Qual a melhor forma de utilizar o *predictive value* das recomendações dos analistas de ações como parte de uma estratégia de investimento?

Mafalda Almeida e Brito
152418017

Sumário

Este estudo investiga como explorar retornos anormais através de uma estratégia de investimento que se move de acordo com as recomendações de analistas disponíveis para o público e relativas a empresas americanas. A carteira que compra todas os *upgrades* para *Strong Buy* e *Buy* e vende *Short* todos os *downgrades* para *Strong Sell* e *Sell* apresenta retornos anormais anuais de 65%, no período de 1993 a 2019, em comparação com o modelo de cinco fatores de *Fama and French* com *momentum* e *short-term reversal*. Ao calcular os custos de transação que levam ao ponto de *breakeven*, a década de 2010 a 2019 já não tem retornos anormais significativos se forem incorridos custos de transação unidirecionais maiores que 0,04% do valor transacionado. Esta baixa taxa de *breakeven* compromete a rentabilidade das estratégias de investimento acima referidas, nos dias de hoje. É comprovado neste estudo que os retornos anormais têm um pico no dia em que a recomendação é anunciada, e que o dia anterior ao anúncio apresenta também retornos anormais elevados. As estratégias que restringem a seleção de ações ao nível e à mudança das recomendações dos analistas trazem retornos anormais ligeiramente maiores. Os resultados são mais elevados para as empresas mais pequenas e são robustos a testes do nível de liquidez das empresas e a diferentes períodos de tempo.

Palavras-chave: Analista, Recomendação, Anormais, Retornos, Investimento, Estratégia.

Acknowledgments

I am, first of all, sincerely grateful to Professor Dr. José Faias and Professor Dr. B. Burcin Yurtoglu, for becoming my supervisors. Their guidance and support were of great value since the beginning. I acknowledge FCT for all the support.

My gratitude is also extended to all my family and friends. Each person had a very distinct and important role in helping me to develop the necessary skills to write this dissertation. Some helped me with the analysis and the storyline, others with the writing and programming, and many with the strength to keep fighting. If I persisted, it was because of you; if I succeeded, it was with you!

Non Nobis,

Mafalda Almeida e Brito

Table of Contents

A. List of Tables

B. List of Figures

1. Introduction and Literature Review

This study explores how to profit from an investment strategy that moves according to publicly available analyst recommendations. This topic is relevant due to its controversial nature: market semi-strong efficiency implies that "investors should not be able to trade profitably on the basis of publicly available information, such as analyst recommendations" (Barber, Lehavy, McNichols, & Trueman, 2001, p. 531). However, there is an extensive academic literature studying potential market inefficiencies, and brokerage houses spend millions of dollars analyzing stocks and publicly making recommendations. Institutional investors also pay large amounts of money to get these forecasts and recommendations (Green, 2006).

The question that motivates this study then arises: why is the market attributing such high value to analysts' research, if not to capture higher stock returns? Apparently, analysts' daily work has the purpose of enhancing the returns of institutional and private investors that follow their recommendations. In general terms, equity research analysts' reports provide detailed evaluations of a firm's future performance (Asquith, Mikhail, & Au, 2005), and their value comes from the authors' analytical skills and ability to efficiently gather and process relevant data (Ivković & Jegadeesh, 2004). In most cases, reports include an earnings forecast, a price target, and a stock recommendation. These parameters are of great use to many market agents, such as brokers, investment advisors, analysts from other divisions, and individual investors. These agents usually make use of the recommendation consensus or individual recommendations from analysts with great reputation.

Academics have already spotted this rather intuitive and attractive possible source of abnormal returns. Stickel (1995) finds evidence for permanent and temporary price change triggered by brokerage house recommendations. The price change is influenced by many factors, namely the strength of the recommendation (e.g., Strong Buy is stronger than Buy), the magnitude of the change (e.g., double shifts have more impact than single shifts), the reputation of the analyst, the size of the brokerage house, the size of the recommended firm and contemporaneous earnings forecast revisions. Womack (1996) suggests that analysts have the ability of market timing and stock picking, considering that the large return at the time of the recommendations is, most of the time, independent from public news and releases. Following the author's logic, the excess stock return that follows the recommendation date is what justifies the millions of dollars annually spent by brokerage firms on the analysis of stock prices.

Besides the impact of recommendations, there is evidence for the short-term market reaction to target price announcements and the long-term co-movement of target prices and stock prices (Brav & Lehavy, 2003). There is also evidence for the impact of earnings forecast revisions, the effect of the announcement timing (Ivković & Jegadeesh, 2004), as well as the impact of reports' explicit content (Asquith et al., 2005). Although Loh and Stulz (2011) state that only 12% of the recommendations changes are influential, combining two or more of these factors helps distinguish the analysts with superior abilities to issue profitable stock recommendations (Loh & Mian, 2006). It also allows for outperforming strategies to be built (Huang, Mian, & Sankaraguruswamy, 2009). Although the reaction is higher in the U.S, Jegadeesh and Kim (2006) proved that stock prices also respond to recommendations revisions in the Group of Seven[1] industrialized countries, excluding Italy.

This study replicates the findings of Barber, Lehavy, and Trueman (2010). Instead of investing solely according to the level of the recommendation (e.g., buy when the recommendation is Buy) or strictly according to the change of the recommendation (e.g., buy when the recommendation is an upgrade), this work exploits higher abnormal returns by conditioning on both recommendation and level (e.g., buy when the recommendation is an upgrade to Buy). This study also includes the calculation of abnormal returns after deducting transaction costs, extending the work of Barber et al. (2010), which does not consider the impact of such expenses in abnormal returns.

The main findings of this work support the hypothesis that analysts are able to issue recommendations for stocks with temporary abnormal returns and that investors can profit from a strategy that follows these recommendations. Under the current analysis, the investment strategy that buys all stocks subject to upgrades to Strong Buy and Buy obtains an average annual return of 78% from 1993 to 2019. In particular, the average return of the first decade is identical to the average return of the whole period, which compares well to the findings of Barber et al. (2001). These authors earned an annualized mean return of 18,8% when buying the most favorable consensus recommendations, from 1985 to 1996. The investment strategy that buys all stocks subject to upgrades to Strong Buy and Buy and sells all downgrades to Sell or Strong Sell obtains an average abnormal return of 65%[2] in the period from 1993 to 2019.

[1] U.S., Britain, Canada, France, Germany, Italy, Japan.
[2] After controlling for the Fama-Franch five-factor model with momentum and short-term reversal.

This value is higher than the one achieved by Barber et al. (2010). These authors earned a 14% average annual abnormal return (5.5 basis points per day) when purchasing stocks subject to single upgrades to Buy and Strong Buy and short selling the stocks subject to single downgrades to Sell or Strong Sell, from 1986 to 2006.

The holding period of this study resembles the one used by Green (2006) and partially justifies why returns are higher than in the studies previously mentioned. Green (2006) studied the short-term profit from portfolios with two-day coverage, initiating the position very close to the announcement time. This author was able to obtain abnormal annual returns of around 90%, which are higher than the ones presented in the current analysis, as the coverage of this study starts later, at the market closure. To explore the effect of investing right at the announcement time, a subsection of this work reproduces the investment strategy of a one-day holding period to the nine days around the announcement day. In line with the findings of Green (2006), the announcement day is the day with higher returns, on average higher than 100%.

This study calculates the transaction fee that leads to the breakeven of each strategy and finds that the short portfolio is the one with the lowest breakeven fee. After including this fee, the investment strategy long and short curried out in this study produces 25% abnormal annual returns (10 basis points per day), which are similar to the abnormal returns of Green (2006), after transaction costs. The breakeven transaction fee was also calculated for each decade. The breakeven found for the last decade is, however, lower than the ones found in literature (one-way transaction fee of 0,04%). This low breakeven fee suggests that returns after transaction costs are no longer profitable in current days. On the other hand, the positive returns of the main investment strategy are robust when testing restrictions on firms' liquidity and, similarly to the findings of Barber et al. (2001), returns are larger for smaller market capitalization firms.

This dissertation is structured into six additional chapters. Chapter 2 describes the data used and how it was extracted and treated. Chapter 3 explains the methodology applied to build the first portfolio. Chapter 4 shows the results of the first portfolio and compares it with benchmarks. Chapter 5 starts by testing how returns change when including transaction costs, restricting on firms' liquidity, grouping companies by market capitalization, holding returns on different days around the recommendation day, and reproducing the portfolio in different periods. In the end of Chapter 5, additional portfolios are developed, corresponding to alternative investment strategies. Chapter 6 presents suggestions for further research and limitations of this study, and Chapter 7 concludes. The Appendices contains the list of the portfolios developed in this study and a description of how anomalies in the data were treated.

2. Data

2.1. Data extraction and treatment

Recommendations were extracted from Thomson Financial's Institutional Brokers' Estimate System (IBES) US Detail File. The extraction included all recommendations to US companies that were announced since September 1st, 1993 (first date available) up to the end of December 2019.

The data cleaned had in total 588 308 recommendations (76% of the initial extraction), after eliminating observations with **missing data** (3% of the initial extraction), eliminating all analysts with less than 5 recommendations (2% of the initial extraction), correcting **logical inconsistencies** (0,2% of the initial extraction), and by crossing over with the CRSP file (19% of the initial extraction was excluded when cleaning the CRSP database, as explained below).

Companies' returns were extracted from CRSP. The clean data had in total 34 548 454 returns (75% of initial extraction), after eliminating missing data (2% of initial extraction), excluding non-US common stocks (21% of initial extraction) and correcting logical inconsistencies (2% of initial extraction).

2.2.Explanation of concepts

Rating levels are classified on a numerical scale going from 1 to 5, respectively indicating: Strong Buy (1), Buy (2), Hold (3), Sell (4), and Strong Sell (5). **Rating changes** are related to an adjustment to the previous recommendation. A rating change happens when the same analyst provides a different recommendation from the one he/she previously issued, at a distinct point in time, for the same company. When the new recommendation is closer to Strong Buy than the previous one, there is an **upgrade**. On the other hand, if the new recommendation is closer to Strong Sell than the previous one, it is a **downgrade**. **Single rating changes** happen between two consecutive levels, for instance, from Strong Buy to Buy. **Double rating changes** occur between two levels with one level in between, for example, from Strong Buy to Hold. **Positive** recommendations refer to recommendations Strong Buy and Buy. **Negative** recommendations refer to recommendations Strong Sell and Sell. Hold recommendations are considered **neutral**.

Precedent recommendation refers to the previous recommendation issued by the same analyst for the same company. Specifically, if the analyst issues two consecutive recommendations for the same company, the first recommendation published is the precedent of the second. When an analyst issues a recommendation for a company for the first time, it is registered as an **Initiation**. It also automatically means that the recommendation has no precedent recommendation. **Reiterations** happen when an analyst issues a recommendation that is identical to the precedent recommendation, in other words, from Strong Buy to Strong Buy; from Buy to Buy; from Hold to Hold; from Sell to Sell; or from Strong Sell to Strong Sell.

2.3.Variables explanation[3]

The relevant variables concern the time, the identification of components and the dimensional values under study. The **recommendation announcement date** is the day when it was reported. Taking into consideration investors can have access to the recommendation on the announcement day by Thomson Reuters, the activation date and the revised date are not being accounted for. The **recommendation announcement time** contains the hour and minute when the recommendation was reported. This variable is important to see whether investors have access to the recommendation before or after the market closure (4 pm).

Relative to the identification of components, **CUSIP** is the code to identify the companies. Although CUSIP changes every time the name of the company changes, this is the company identification code used in the analysis due to its complementarity with other databases, for instance, CRSP[4]. The IBES Ticker is the identifier that allows the user to link companies over time regardless of changes in ownership. However, it is not used here because of its lack of complementarity with other databases. The **analyst masked code** refers to the code used to identify the analysts. It is appropriate to use this code because there are analysts that change the name but maintain the same masked code. The **share code** is the two-digit code describing the type of shares traded. It is only considered ordinary common shares, which have not been further defined (code 10) or which do not need to be further defined (code 11). The first two digits of the **standard industrial classification code** (SIC code) refer to a major group; the first three digits refer to an industry group; all four digits indicate an industry.

[3] Source: Thomson Financial's Institutional Brokers Estimate (IBES) US Detail File and CRSP
[4] For 28% of the data in CRSP, NCUSIP was used instead of CUSIP.

Relative to the dimensional variables, **price (P)** is the stock closing price on a specific trading day. **Share volume (V)** is the total number of shares of a stock sold on a trading day. **Holding period return** is the change in the total value of an investment in a common stock over some time interval per dollar of the initial investment. **Shares outstanding** are the number of publicly held shares, recorded in thousands.

2.4. Data Analysis and test for sufficient variation

Table 1 describes the yearly statistics of recommendations, analysts and companies. The data of each column in Table 1 is described below with more detail, as it offers a better insight into the phenomena under study.

Table 1: Yearly statistics of analyst recommendations data, 1993 to 2019

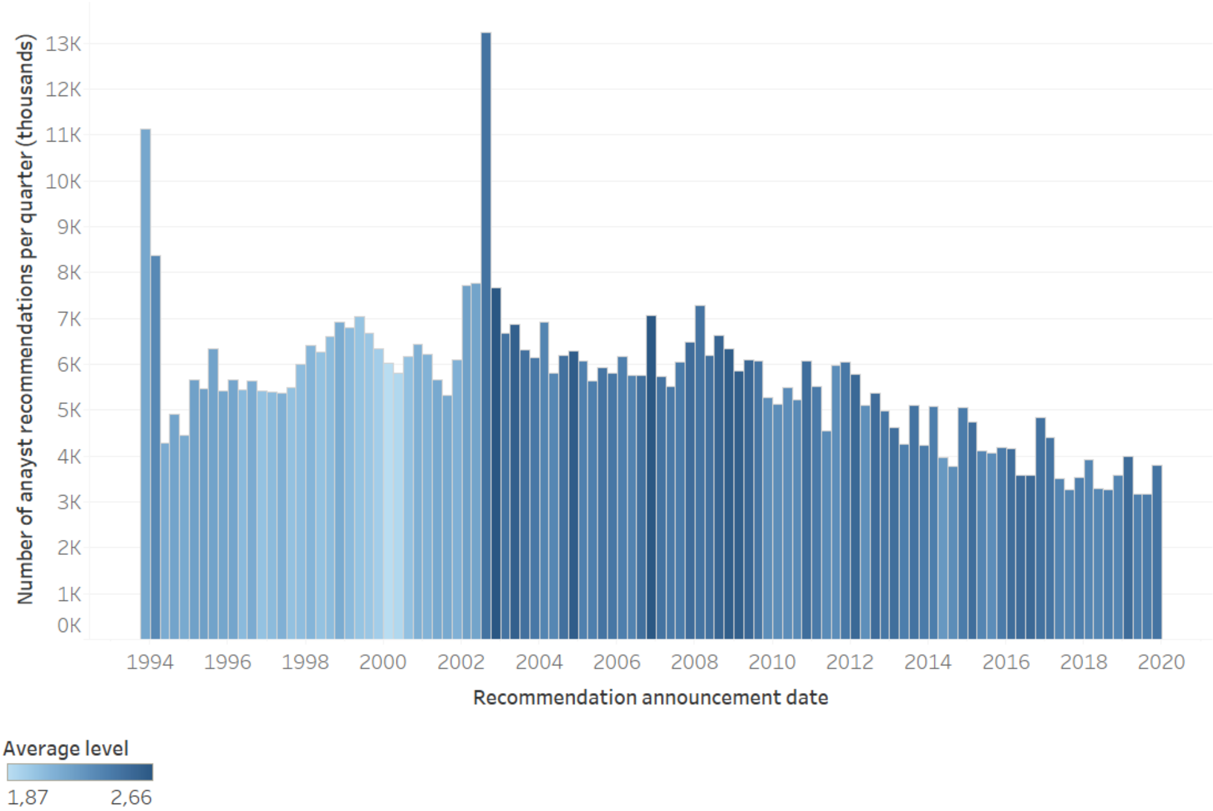
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year	# recommendations	Average recommendation level	# analysts	# companies	Average companies' Market Cap (000 000 USD)	Average analyst per company	Maximum analysts per company	Average companies per analyst
1993	11 142	2,18	1 097	3 025	3 374	3,55	21	9,79
1994	22 013	2,24	1 594	3 772	3 200	3,94	26	9,32
1995	22 932	2,21	1 768	3 963	3 770	3,81	24	8,53
1996	22 184	2,11	2 015	4 482	3 860	3,49	32	7,76
1997	22 259	2,07	2 316	4 740	4 501	3,48	27	7,12
1998	26 235	2,09	2 720	4 746	6 223	3,97	33	6,93
1999	26 863	2,02	2 908	4 522	8 217	4,38	29	6,81
2000	24 430	1,99	2 899	4 175	10 165	4,28	32	6,16
2001	23 306	2,14	2 741	3 507	8 709	4,67	40	5,97
2002	36 378	2,40	2 768	3 545	8 046	6,18	43	7,91
2003	26 013	2,51	2 531	3 288	8 035	5,42	37	7,04
2004	25 215	2,47	2 722	3 447	8 019	5,30	32	6,71
2005	23 446	2,44	2 774	3 524	7 782	4,86	30	6,17
2006	24 746	2,50	2 763	3 585	8 277	4,99	30	6,48
2007	23 805	2,48	2 725	3 578	9 115	4,78	28	6,28
2008	26 443	2,54	2 635	3 328	8 986	5,28	31	6,66
2009	23 307	2,50	2 494	2 970	7 372	5,61	36	6,68
2010	21 927	2,38	2 694	3 030	8 989	5,48	34	6,17
2011	22 117	2,39	2 760	3 018	9 902	5,45	39	5,96
2012	21 259	2,47	2 657	2 984	11 002	5,35	35	6,01
2013	18 221	2,47	2 462	2 886	13 180	5,04	30	5,91
2014	17 868	2,37	2 471	2 946	14 678	4,94	34	5,89
2015	17 114	2,42	2 393	2 976	14 429	4,75	28	5,91
2016	16 189	2,52	2 297	2 847	15 117	4,66	33	5,78
2017	14 706	2,42	2 137	2 805	18 505	4,42	37	5,80
2018	14 067	2,38	2 052	2 788	21 084	4,26	24	5,79
2019	14 123	2,47	1 974	2 791	21 597	4,24	34	6,00
Total	**588 308**	**2,34**	**10 561**	**14 807**	**9 266**	**4,69**	**43**	**6,72**

In total, there are 10 561 analysts who provide recommendations for 14 807 different companies. The median number of recommendations per analyst is 28, and the median number of recommendations per company is 14. Column 2 of Table 1 shows that there are approximately 22 259 recommendations issued per year[5] (median value). The year with more recommendations was 2002, with 36 378 recommendations. 1993 is the year with fewer recommendations since the database starts in the 4th quarter. From 2010 onwards, the number of recommendations decreases gradually, with numbers below the median. Overall, the analyst with more recommendations in total is called Judd M, and Intel is the company with more recommendations.

The average recommendation level 2,34 (column 3) is closer to a Buy (2), reflecting the expected bias towards positive recommendations. However, from the end of 2002 onwards, recommendations are less positive, on average. Figure 1 shows this trend by quarter: the y-axis reflects the number of recommendations, the x-axis indicates the quarter when the recommendation was announced, and the color of the bars represents the average recommendation level (the darker the color, the more negative the recommendation level). From the end of 2002 onwards, bars become darker, which might be related to the Regulation Fair Disclosure in 2000 (Loh & Stulz, 2011).

[5] Median number of recommendations per month: 1 808. November 1993, December 1993, and January 1994 have more recommendations than most other months. To avoid data inconsistencies (i.e. the increased number of recommendations in the first months available in IBES database might result from accumulated recommendations from the previous time that is not recorded), the year 1993 was excluded in one of the scenarios.

Figure 1: Average level of recommendations per quarter – bar plot from Tableau 2020.2



Going back to Table 1, column 4 shows that the number of analysts increased from 1993 to 1999, the year when it achieved its maximum (2 908 analysts). Until 2012, the value oscillated around the median (2 531 analysts). From 2013, the number decreased until 2019 (which has 1 974 analysts). The number of companies per year[6] (column 5) increased from 1993 until 1998 when it reached its maximum (4 746 companies). This number then decreased to levels around the median (3 328 companies per year). From 2012 onwards, the level of companies never surpassed 3 000 companies per year. 722 companies were recommended only once. These companies were not taken into consideration in the portfolios, as they have no precedent recommendation. The average market capitalization per year (column 6) increases over the period considered, with the natural exceptions associated with the crisis of 2001 and 2008. This trend is in line with the overall market evolution.

On average, each company is recommended by close to 5 analysts per year (column 7). 2002 is the year with the highest average number of analysts per company (close to 6). It was also the

[6] Looking at monthly data, September 2001 was a month with fewer companies compared to the neighborly months, suggesting an impact of the September 11th attacks in the US.

year that registered the company with more analysts per year (column 8): Oracle Corp recommended by 43 different analysts. On average, each analyst provides recommendations for approximately 7 companies per year (column 9). 1993 is the year with the highest average number of companies per analyst (close to 10 companies). The number decreased from 1994 to 2001when it reached its minimum (less than 6 companies). From 2003 onwards, analysts presented recommendations concerning, on average, between 6 and 7 companies per year.

2.5. Expectations about the data

There are two main expectations relating to the data that arise since recommendations come from analysts who respond to and are driven by incentives. Taking into consideration this behavioral bias, analysts may provide more positive recommendations to satisfy potential clients of their investment bank (Jegadeesh & Kim, 2006). A trend for the analyst to be cautious in incorporating negative information is also expected, meaning that changes to Hold are expected to be more common than changes from positive recommendations to negative recommendations directly.

2.6. Analyst recommendations matrix

Python (version 3.7.6) was used to efficiently identify the precedent recommendations, add the number of observations of each recommendation level from the large database, and build the tables presented in this section. Table 2 illustrates the number of recommendations for each rating level and rating change. The columns indicate the level of the recommendation, and the rows indicate the level of the precedent recommendation.

Table 2: Analyst recommendations matrix – Level & Change – 1993 to 2019

Number of analyst recommendations 1993-2019						
To:	**1 - STRONG BUY**	**2 - BUY**	**3 - HOLD**	**4 - SELL**	**5 - STRONG SELL**	**Total**
From:						
1 - STRONG BUY	15 834	27 280	47 062	1 035	1 066	92 277
%	*3%*	*5%*	*8%*	*0%*	*0%*	*16%*
2 - BUY	24 798	28 436	63 392	2 599	611	119 836
%	*4%*	*5%*	*11%*	*0%*	*0%*	*20%*
3 - HOLD	35 436	48 561	36 101	14 685	6 736	141 519
%	*6%*	*8%*	*6%*	*2%*	*1%*	*24%*
4 - SELL	663	1 884	12 786	3 840	695	19 868
%	*0%*	*0%*	*2%*	*1%*	*0%*	*3%*
5 - STRONG SELL	599	408	6 336	687	684	8 714
%	*0%*	*0%*	*1%*	*0%*	*0%*	*1%*
Initiation	56 663	69 841	70 720	6 146	2 724	206 094
%	*10%*	*12%*	*12%*	*1%*	*0%*	*35%*
Total	**133 993**	**176 410**	**236 397**	**28 992**	**12 516**	**588 308**
%	*23%*	*30%*	*40%*	*5%*	*2%*	*100%*

One can take the column 2-Buy from Table 2 as an example. In total, there are 176 410 Buy recommendations during the period considered. From those recommendations, 27 280 represent single downgrades, from Strong Buy to Buy. 28 436 recommendations are Reiterations, each having Buy as a precedent. 48 561 recommendations are single upgrades because they all have Hold as their precedent. 1 884 recommendations are double upgrades, from Sell to Buy. 408 are triple upgrades, having Strong Sell as their precedent. Finally, 69 841 recommendations were issued for the first by an analyst for that company. They are, therefore, Initiations.

Table 2 shows, as expected, that there are several more positive ratings than negative ratings, suggesting evidence for the behavioral bias to which analysts are exposed. Hold is the most common level and the jump to Hold is always the most common change, independent of the previous level.

Table 3 closer illustrates the recommendations' changes that occurred throughout the decades taken into consideration in this study.

Table 3: Analyst recommendations matrix per decade – Level & Change – 1993 to 2019

% of total per decade (Excluding Initiations and Reiterations)						
To:	**1 - STRONG BUY**	**2 - BUY**	**3 - HOLD**	**4 - SELL**	**5 - STRONG SELL**	**Total**
From:						
1 - STRONG BUY						
1993-1999	-	15%	15%	0%	0%	31%
2000-2009	-	9%	16%	0%	0%	26%
2010-2019	-	5%	17%	0%	0%	22%
2 - BUY						
1993-1999	15%	-	20%	1%	0%	36%
2000-2009	8%	-	21%	1%	0%	30%
2010-2019	3%	-	24%	1%	0%	28%
3 - HOLD						
1993-1999	10%	15%	-	2%	2%	29%
2000-2009	12%	15%	-	6%	3%	35%
2010-2019	13%	20%	-	6%	2%	41%
4 - SELL						
1993-1999	0%	1%	2%	-	0%	3%
2000-2009	0%	1%	5%	-	0%	6%
2010-2019	0%	1%	6%	-	0%	7%
5 - STRONG SELL						
1993-1999	0%	0%	1%	0%	-	2%
2000-2009	0%	0%	3%	0%	-	3%
2010-2019	0%	0%	2%	0%	-	2%
Total						
1993-1999	26%	32%	37%	3%	3%	100%
2000-2009	21%	24%	44%	7%	4%	100%
2010-2019	17%	25%	48%	8%	2%	100%

Table 3 shows that the trends found in Table 2 are verified in all decades. Moreover, when Hold is the precedent, there are more upgrades than reiterations or downgrades. The main difference between decades is that, with time, the number of changes to Buy and Strong Buy decreases while the number of shifts to Hold and Sell increases.

Table 4, below, shows that single upgrades and downgrades are more common than changes of higher order (double or higher changes). There are more downgrades than upgrades, although those downgrades happen within the positive side (form Strong Buy or Buy to Buy or Hold).

Table 4: Analyst recommendations matrix – Change – 1993 to 2019

	1992-2019		1992-1999		2000-2009		2010-2019	
	Total	%	Total	%	Total	%	Total	%
Upgrades	**132 158**	**22%**	**31 389**	**20%**	**59 358**	**23%**	**41 410**	**23%**
Single Upgrades	86 832	15%	22 315	15%	37 792	15%	26 724	15%
Double Upgrades	43 656	7%	8 492	6%	20 925	8%	14 239	8%
Other Upgrades	1 670	0%	582	0%	641	0%	447	0%
Downgrades	**165 161**	**28%**	**38 046**	**25%**	**76 499**	**30%**	**50 616**	**29%**
Single Downgrades	106 052	18%	25 462	17%	48 206	19%	32 384	18%
Double Downgrades	56 397	10%	11 695	8%	27 097	11%	17 605	10%
Other Downgrades	2 712	0%	889	1%	1 196	0%	627	0%
Initiation	**206 094**	**35%**	**67 464**	**44%**	**80 283**	**31%**	**58 348**	**33%**
Reiterations	**84 895**	**14%**	**16 729**	**11%**	**40 949**	**16%**	**27 217**	**15%**
Total	**588 308**	**100%**	**153 628**	**26%**	**257 089**	**44%**	**177 591**	**30%**

3. Methodology

3.1. Portfolio A

To determine how the predictive value of security analyst recommendations can best be employed as part of an investment strategy, this study constructs portfolios replicating the findings of Barber et al. (2010). The authors tested different investment strategies based on the change and level of analyst recommendations. They presented evidence that the highest average abnormal returns are the ones associated with upgrades to Strong Buy and Buy, and the lower ones are the downgrades to Sell or Strong Sell.

In the current study, Portfolio A explores the above findings within an investment strategy for Long-only investors, Short-only investors, and Long-Short investors. Firstly, in Portfolio A-Long, the investment strategy contains only long positions, i.e., only the returns from stocks subject to upgrades to Strong Buy and Buy were extracted. Secondly, in Portfolio A-Short, solely recommendations on a short position are invested in. This is done by extracting the returns from stocks subject to downgrades to Sell or Strong Sell. Thirdly, in Portfolio A-Long and Short, a combination of both the long and short positions is included in the investment strategy.

Note: Upgrades to Strong Buy are all the Strong Buy recommendations in which the precedent is either Strong Sell, Sell, Hold or Buy. Upgrades to Buy are all the Buy recommendations in which the precedent is either Strong Sell, Sell or Hold. Downgrades to Sell are all the Sell recommendations in which the precedent is either Strong Buy, Buy or Hold. Downgrades to

Strong Sell are all the Strong Sell recommendations in which the precedent is either Strong Buy, Buy, Hold or Sell.

3.1.1. Weights

Each stock is placed into the portfolio according to the following criteria. Every time a specific stock received an upgrade to Strong Buy or Buy, a weight of 1 was assigned. Every time a specific stock received a downgrade to Strong Sell or Sell a weight of -1 was assigned. Otherwise, a weight of 0 was considered.

Weights were assigned directly to the day following the recommendation announcement, as it will be explained in the Returns section below. The list of trading days is provided by the Kenneth R. French database[7], which allows one to include a list of trading days, even if no IBES recommendation was issued on that day. Announcements happening after the market closure (announcements occurring at 4 pm or later) are treated as if the announcement had been issued on the following day.

3.1.2. Returns

After allocating stocks into the respective portfolios, average daily returns were calculated. Each stock's daily return was fully captured on the day after the announcement. For simplification, it was assumed that, on the announcement day, the investor has free access to the information and can invest in the specific stock right before the market closes. The investor holds the investment for one day, divesting one day after the announcement, at the market closure. The analysis of Green (2006) showed that "most of the price response takes place by the time trading begins after the recommendation change". The author's trading period goes from the opening price after the recommendation change until the closing price on the following day. This justifies the one-day holding period established in the analysis carried out in this work, which includes only publicly available recommendations.

As mentioned before, all announcements happening after the market closure (announcements occurring at 4 pm or later) are treated as if the announcement had been issued on the following day[8]. Therefore, the return of these stocks will only be captured two days after the

---

[7] Kenneth R. French database: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[8] 16% of the recommendations are announced after 4:00 pm and considered as if announced on the following day. Investors need time from the moment the recommendation is announced until the trade is completed. In the interest

announcement. Since companies with prices below 5 USD are more difficult to trade, they were excluded when building the portfolio (D'avolio, 2002). They account for 6% of the total recommendations[9].

Assuming an equal dollar investment in each recommendation (Barber et al., 2010), daily returns on day $\boldsymbol{t}$ are estimated based on the following formula:

$$\boldsymbol{R_t} = \frac{\sum_{i=1}^{n_t^L} \boldsymbol{R_{it}^L} + \sum_{i=1}^{n_t^S} \boldsymbol{R_{it}^S}}{\boldsymbol{n_t^L} + \boldsymbol{n_t^S}} \tag{1}$$

where $\sum_{i=1}^{n_t^L} \boldsymbol{R_{it}^L}$ is the sum of daily raw returns from all stocks Long ($\boldsymbol{L}$), $\sum_{i=1}^{n_t^S} \boldsymbol{R_{it}^S}$ is the sum of daily raw returns from all stocks Short ($\boldsymbol{S}$), $\boldsymbol{n_t^L}$ is the total number of stocks Long and $\boldsymbol{n_t^S}$ is the total number of stocks Short.

3.1.3. Benchmarks

To analyze each portfolio's performance, this study uses three different benchmarks provided by the Kenneth R. French database: the Fama-French three-factor model (3FF), the Fama-French five-factor model (5FF), and Fama-French five-factor model with momentum and short-term reversal (5FF + Mom + STR), explained below. Daily returns of each benchmark portfolio are calculated to compare against the returns of the portfolios developed in this study. Their returns result from an equally weighted portfolio, rebalanced on a daily basis. The following formula below is used to estimate the daily returns $\mathbf{R}_t^{FF}$ of the portfolio composed by the Fama-French five-factor model with momentum and short-term reversal, on day $\boldsymbol{t}$:

$$\mathrm{R}_t^{FF} = \left(\boldsymbol{R_{mt}} - \boldsymbol{R_{ft}}\right) + \boldsymbol{SMB_t} + \boldsymbol{HML_t} + \boldsymbol{RMW_t} + \boldsymbol{CMA_t} + \boldsymbol{Mom_t} + \boldsymbol{STR_t} \tag{2}$$

where $\boldsymbol{R_{mt}} - \boldsymbol{R_{ft}}$ is the daily excess return on the market, $\boldsymbol{SMB_t}$ is the daily return on the portfolio of small-cap stocks minus large-cap stocks, $\boldsymbol{HML_t}$ is the daily return on the portfolio of high book-to-market stocks minus low book-to-market stocks, $\boldsymbol{RMW_t}$ is the daily return on

of simplification, this reaction time is ignored. Further analysis may consider taking into account reaction times of, for example, 1 hour, 30 minutes, or 15 minutes. In this database, 3% of the recommendations are announced between 3:00pm and 3:30pm; 3% of the recommendations are announced between 3:30pm and 4:00pm; and 4% of the recommendations are announced between 4:00pm and 4:30pm.

[9] The restriction on price higher or equal to 1 USD was also tested, which excluded 0,5% of the recommendation for companies with price under 1 USD. The results were similar to the results present in this approach.

the portfolio of robust operating profitability stocks minus weak operating profitability stocks, $\boldsymbol{CMA_t}$ is the daily return on the portfolio of conservative investment stocks minus aggressive investment stocks, $\boldsymbol{Mom_t}$ is the daily return on the portfolio built on the momentum factor and $\boldsymbol{STR_t}$ is the daily return on the portfolio built on the short-term reversal factor.

Daily returns of the benchmarks composed by the Fama-French three-factor model and the Fama-French five-factor model are estimated using the same formula, but excluding the factors $\boldsymbol{RMW_t}$, $\boldsymbol{CMA_t}$, $\boldsymbol{Mom_t}$, $\boldsymbol{STR_t}$, in the first portfolio and $\boldsymbol{Mom_t}$, $\boldsymbol{STR_t}$ in the second.

3.1.4. Performance Evaluation

This study employs a daily time-series regression for each portfolio, which allows the estimation of the average abnormal returns (alpha estimate) and, consequently, the analysis of each portfolio's profitability. This work used the models provided by the Kenneth R. French database to evaluate if returns reflect the predictive value of analyst recommendations or whether these returns result from other market factors (Barber et al., 2001).

To estimate average abnormal returns $\boldsymbol{\alpha_j}$, the daily returns of each portfolio $\boldsymbol{j}$ composed by the investment strategies in Portfolio A were, firstly, regressed against the three-factor model of Fama and French (3FF). The regression is the following:

$$\boldsymbol{R_t^j - R_{ft} = \alpha_j + \beta_j \left(R_{mt} - R_{ft}\right) + s_j\, SMB_t + h_j\, HML_t + \varepsilon_{jt}} \tag{3}$$

where $\boldsymbol{R_t^j - R_{ft}}$ is the difference between the average daily return of portfolio $\boldsymbol{j}$ and the risk-free rate, on day $\boldsymbol{t}$, $\boldsymbol{\varepsilon_{jt}}$ is the error term. The regression estimates the parameters $\boldsymbol{\alpha_j}$, $\boldsymbol{\beta_j}$, $\boldsymbol{s_j}$ and $\boldsymbol{h_j}$.

The five-factor model of Fama and French (5FF) were also used to calculate average abnormal returns. The regression is the following:

$$\begin{aligned}\boldsymbol{R_t^j - R_{ft} = {}} & \boldsymbol{\alpha_j + \beta_j \left(R_{mt} - R_{ft}\right) + s_j\, SMB_t + h_j\, HML_t + w_j\, RMW_t} \\ & \boldsymbol{+ c_j\, CMA_t + \varepsilon_{jt}}\end{aligned} \tag{4}$$

The regression estimates the parameters $\boldsymbol{\alpha_j}$, $\boldsymbol{\beta_j}$, $\boldsymbol{s_j}$, $\boldsymbol{h_j}$, $\boldsymbol{w_j}$ and $\boldsymbol{c_j}$.

Because analysts may be "over enamored with growth and glamour stocks" (Jegadeesh, Kim, Krische, & Lee, 2004, p. 1119) and "often piggyback on recent news, events, long-term momentum, and short-run contrarian return predictors" (Altınkılıç & Hansen, 2009, p. 17), it has been decided, as a third approach, to control for momentum and short-term reversal, in order to see if abnormal returns stay significant. momentum and short-term reversal were therefore added to the regression formula:

$$\begin{aligned} \boldsymbol{R_t^j - R_{ft}} &= \boldsymbol{\alpha_j + \beta_j(R_{mt} - R_{ft}) + s_j SMB_t + h_j HML_t + w_j RMW_t + c_j CMA_t} \\ &\quad \boldsymbol{+ m_j Mom_t + r_j STR_t + \varepsilon_{jt}} \end{aligned} \tag{5}$$

The regression estimates the parameters $\boldsymbol{\alpha_j}$, $\boldsymbol{\beta_j}$, $\boldsymbol{s_j}$, $\boldsymbol{h_j}$, $\boldsymbol{w_j}$, $\boldsymbol{c_j}$, $\boldsymbol{m_j}$ and $\boldsymbol{r_j}$.

4. Results

This section presents the results of the investment strategy implemented by Portfolio A.

4.1. Composition of Portfolio A-Long

Portfolio A-Long has 108 071 recommendations[10]. It invests long in approximately 7 100 companies from 1 000 different industries recommended by around 8 000 analysts. The mean market capitalization is approximately USD 11 100 million. On average, there are 16 long investments per day. Of the 6 631 days, there are around 1% which have no investment. For simplification, the cost of carrying related to the days with zero investment is not being considered. The Further Research Suggestions section will propose an alternative to deal with this expense. January 22nd, 2009 is the day in which the portfolio invests in the highest number of stocks: 200 stocks. September 10th, 2002 and January 25th, 2008 are the only two other days in which the portfolio invests in more than 150 stocks.

4.2. Composition of Portfolio A-Short

Portfolio A-Short has 24 225 recommendations[11]. It invests short in approximately 4 800 companies from 850 different industries recommended by around 5 000 analysts. The dispersion of companies' market capitalization is similar to Portfolio A-Long's. The mean market capitalization of approximately USD 9 400 million is USD 1 700 million lower than in

---

[10] Price restriction (higher or equal to 5 USD) excludes around 4 300 recommendations of 2 000 companies with mean Market Cap of USD 800 million (4% of the total number of recommendations assigned to Portfolio A-Long)
[11] Price restriction (higher or equal to 5 USD) excludes around 3 200 recommendations of around 1 500 companies with mean Market Cap of around USD 660 million. (8% of the total number of recommendations assigned to Portfolio A-Short)

Portfolio A-Long. There are more days with no investment than in the long strategy (of the 6631 days, 14% have no stocks Short). The average number of stocks short per day is 4. September 10th, 2002, with 220 stocks invested short, is the only day in which the portfolio invests in more than 150 stocks.

4.3. Returns of Portfolio A

Descriptive statistics of these portfolios are found in Table 5, together with the descriptive statistics of the returns of portfolios based on Fama-French factor models (three-factor model, five-factor model, and five-factor model with momentum and short-term reversal).

The portfolio composed by the Fama-French five-factor model with momentum and short-term reversal is the benchmark with the highest average returns (41% annually). Volatility is also the highest among the benchmarks (26% annually).

Compared to this benchmark, the average return of Portfolio A-Long is higher (78% annually), and volatility is lower (25% annually), suggesting the existence of abnormal returns. The average return of this portfolio exceeds the benchmarks average returns in all decades. The positive skewness (tail to the positive side) indicates that there are outliers that affect the results positively.

The average return of Portfolio A-Short (39% annually) is lower than the Fama-French five-factor model with momentum and short-term reversal, and the volatility is higher (36% annually). The average return of this portfolio exceeds, however, the average return of the other benchmarks. The negative skewness (tail to the negative side) indicates that outliers are affecting the results negatively. Kurtosis is higher than in the long strategy, indicating that tails (extreme returns) have more weight in this portfolio than in Portfolio A-Long.

Table 5: Summary statistics of returns of Portfolio A

Descriptive Statistic of returns	Average Return Annualized	Volatility Annualized	Max Daily	75%	Median Daily	25%	Min Daily	Skewness Daily	Kurtosis Daily
3FF									
1993-2019	**11%**	**22%**	**0,1134**	**0,0067**	**0,0008**	**-0,0055**	**-0,1399**	**-0,20**	**10,18**
1993-1999	8%	10%	0,0234	0,0038	0,0008	-0,0026	-0,0426	-1,00	5,55
2000-2009	14%	28%	0,1134	0,0085	0,0009	-0,0070	-0,1399	-0,15	8,63
2010-2019	10%	22%	0,0668	0,0084	0,0007	-0,0071	-0,1009	-0,22	3,49
5FF									
1993-2019	**18%**	**22%**	**0,1029**	**0,0072**	**0,0008**	**-0,0056**	**-0,1223**	**-0,11**	**6,79**
1993-1999	9%	10%	0,0565	0,0037	0,0005	-0,0030	-0,0352	0,23	5,54
2000-2009	30%	28%	0,1029	0,0096	0,0013	-0,0068	-0,1223	-0,16	5,37
2010-2019	12%	21%	0,0636	0,0081	0,0006	-0,0071	-0,0878	-0,11	2,61
5FF + Mom + STR									
1993-2019	**41%**	**26%**	**0,1586**	**0,0092**	**0,0020**	**-0,0059**	**-0,1340**	**-0,01**	**7,99**
1993-1999	57%	14%	0,0442	0,0070	0,0027	-0,0022	-0,0396	-0,13	2,61
2000-2009	48%	33%	0,1586	0,0115	0,0022	-0,0076	-0,1101	0,07	5,73
2010-2019	23%	25%	0,0981	0,0092	0,0012	-0,0074	-0,1340	-0,17	6,54
Portfolio A-Long									
1993-2019	**78%**	**25%**	**0,1231**	**0,0113**	**0,0027**	**-0,0053**	**-0,1056**	**0,32**	**4,77**
1993-1999	78%	21%	0,0715	0,0100	0,0026	-0,0039	-0,0781	-0,05	3,55
2000-2009	110%	30%	0,1231	0,0138	0,0040	-0,0057	-0,1056	0,41	4,44
2010-2019	45%	21%	0,0642	0,0098	0,0017	-0,0061	-0,0759	-0,03	1,99
Portfolio A-Short									
1993-2019	**39%**	**36%**	**0,1429**	**0,0071**	**0,0000**	**-0,0068**	**-0,2587**	**-0,98**	**15,39**
1993-1999	27%	36%	0,1173	0,0083	0,0000	-0,0047	-0,2058	-1,27	15,03
2000-2009	71%	42%	0,1429	0,0133	0,0000	-0,0069	-0,2587	-1,03	14,86
2010-2019	15%	30%	0,1200	0,0093	0,0000	-0,0077	-0,2080	-0,58	10,43
Portfolio A-Long and Short									
1993-2019	**72%**	**19%**	**0,0838**	**0,0087**	**0,0024**	**-0,0033**	**-0,1056**	**0,28**	**4,87**
1993-1999	74%	19%	0,0654	0,0091	0,0025	-0,0033	-0,0718	0,09	3,60
2000-2009	103%	22%	0,0838	0,0103	0,0036	-0,0033	-0,1056	0,29	5,12
2010-2019	39%	17%	0,0568	0,0071	0,0013	-0,0033	-0,0601	0,14	3,16

Portfolio A-Long and Short merges both long and short portfolios. As mentioned in the section Data, the data of this study has more upgrades to Strong Buy and Buy than downgrades to Strong Sell and Sell. This explains why the long portfolio has more recommendations than the short portfolio, and, consecutively, why it has a higher impact on Portfolio A-Long and Short. The average annual return of Portfolio A-Long and Short is 72%, which is higher than the average return of the Fama-French five-factor model with momentum and short-term reversal. Skewness and kurtosis are similar to Portfolio A-Long. Looking at each decade, average returns are higher from 2000 to 2009, when also most of the investments were made. The decade from

2010 to 2019 has the lowest average return. Even so, this value is higher than the average return of the benchmarks and returns are less volatile.

4.4. Abnormal returns of Portfolio A

Table 6 presents the Sharpe Ratios of the benchmarks. The portfolio composed by the Fama-French five-factor model with momentum and short-term reversal is the benchmark with the highest Sharpe Ration.

Table 6: Annualized Sharpe Ratios of Benchmarks

	Sharpe Ratio annualized		
	Fama-French 3-factor model	Fama-French 5-factor model	Fama-French 5-factor model + Mom + STR
1993-2019	**0,50**	**0,82**	**1,55**
1993-1999	0,85	0,88	4,06
2000-2009	0,50	1,07	1,47
2010-2019	0,48	0,58	0,92

Table 7 presents the Sharpe Ratios and abnormal returns of each regression. Although each regression has a different number of variables, the adjusted R-square was not included, since the R-squared is similar across the regressions, meaning that the adjustment will not add significant value. In the Portfolio A-Long, the higher average return and lower volatility contribute towards a higher annual Sharpe Ratio (3,02 compared to 1,55 Sharpe ratio of the Fama-French five-factor model with momentum and short-term reversal). The opposite happens in Portfolio A-Short. The lower average return and higher volatility contribute to a lower annual Sharpe Ratio (1,02). All strategies present positive alphas, significantly different from zero at a 99% confidence level, for the full period and all decades, with the single exception of the first decade of the short strategy, which is only significant at a 95% confidence level.

The results presented below provide evidence for the profitability of investment strategies that follow analyst recommendations and for the predictive value of the recommendation level and change, combined. Returns are positive after controlling for factors such as momentum and short-term reversal.

Table 7: Summary statistics of abnormal returns of Portfolio A

		Fama-French 3-factor model			Fama-French 5-factor model			Fama-French 5-factor model + Mom + STR		
Scenarios	Sharpe Ratio annualized	R-squared	alpha annualized		R-squared	alpha annualized		R-squared	alpha annualized	
Portfolio A-Long										
1993-2019	**3,02**	**64%**	**65%**	***	**64%**	**66%**	***	**64%**	**66%**	***
1993-1999	3,53	51%	62%	***	52%	63%	***	52%	60%	***
2000-2009	3,58	68%	107%	***	68%	108%	***	69%	107%	***
2010-2019	2,08	65%	32%	***	65%	32%	***	66%	32%	***
Portfolio A-Short										
1993-2019	**1,02**	**23%**	**46%**	***	**23%**	**45%**	***	**24%**	**45%**	***
1993-1999	0,63	4%	34%	**	4%	34%	**	4%	29%	**
2000-2009	1,64	32%	75%	***	32%	73%	***	32%	74%	***
2010-2019	0,50	27%	26%	***	27%	26%	***	28%	26%	***
Portfolio A-Long and Short										
1993-2019	**3,58**	**41%**	**66%**	***	**42%**	**67%**	***	**42%**	**65%**	***
1993-1999	3,73	47%	61%	***	48%	62%	***	48%	59%	***
2000-2009	4,54	39%	103%	***	40%	105%	***	40%	103%	***
2010-2019	2,33	50%	30%	***	50%	30%	***	51%	29%	***

5. Tests of robustness and complementary analysis

The positive returns presented in the previous section were obtained under specific scenarios that will be modified in the present section. These alternative scenarios include the presence of transaction costs, restrictions on firms' liquidity, different groups of companies, according to their market capitalization, different holding days and different time periods. At last, the criteria of buying and short selling the stocks will also be adjusted.

5.1. Transaction Costs

Considering that the investment in stocks was adjusted on a daily basis, it is of great importance to account for transaction costs.

Transactions costs are calculated as a transaction fee, which is a percentage of the daily trading value (Yu, Paul Chiou, Lee, & Lin, 2020) based on the following equation:

$$\boldsymbol{daily\ transaction\ costs} = \left(\mathbf{1} + (\mathbf{1} + \boldsymbol{r_t})\right) * \mathbf{transaction\ fee} \tag{6}$$

where $\boldsymbol{r_t}$ is the daily return of the portfolio on day $\boldsymbol{t}$, $\mathbf{1}$ accounts for the trading value invested in each day, $(\mathbf{1} + \boldsymbol{r_t})$ accounts for the trading value divested after a 1-day holding period, and the $\mathbf{transaction\ fee}$ is a percentage value.

Daily transaction costs are deducted from the initial daily returns to obtain net daily returns with transaction costs. According to Yu et al. (2020), the average transaction cost is 0,25% (25 bp) of the trading value, each way. Applying that fee, however, eliminates the cumulative return of Portfolio A.

Table 8 shows the sensitive analysis of cumulative returns of each Portfolio A to the transaction fee. The orange circle exposes the approximate breakeven fee of each portfolio. This fee must be around 0,08% to have cumulative returns higher than 1 in the Short strategy. The Portfolio A-Long and the Portfolio A-Long and Short have a transaction fee breakeven of around 0,15% and 0,14%, respectively.

Table 8: Sensitive analysis of cumulative returns to the transaction fee

Portfolio A-Long Sensitivity Analysis								
One-way transaction Fee	0,00%	0,05%	0,10%	0,15%	0,16%	0,20%	0,25%	0,30%
Cumulative Returns (USD)	374 027 530,93	538 218,71	769,43	1,09	0,29	0,00	0,00	0,00

Portfolio A-Short Sensitivity Analysis								
One-way transaction Fee	0,00%	0,02%	0,04%	0,07%	0,08%	0,10%	0,12%	0,14%
Cumulative Returns (USD)	5 763,43	592,17	60,79	2,00	0,64	0,07	0,01	0,00

Portfolio A-Long and Short Sensitivity Analysis								
One-way transaction Fee	0,00%	0,05%	0,10%	0,14%	0,15%	0,20%	0,25%	0,30%
Cumulative Returns (USD)	107 396 717,18	152 779,95	215,92	1,13	0,30	0,00	0,00	0,00

Table 9 shows the results of each portfolio per decade, assuming the lowest breakeven transaction fee 0,08%. In general terms, the breakeven fee of each portfolio is approximately half of its average return. Looking at the average return of each decade, one can see that each has a different breakeven point. The last decade is the one with a lower breakeven fee, which results even in negative alphas.

Table 9: Summary statistics of abnormal returns of Portfolio A with a constant or a decreasing transaction fee

		Fama-French 3-factor model			Fama-French 5-factor model			Fama-French 5-factor model + MOM + ST_REV		
	Sharpe Ratio annualized	R-squared	alpha annualized		R-squared	alpha annualized		R-squared	alpha annualized	
Panel A: Scenarios with transaction fee of 0,08%										
Portfolio A-Long										
1993-2019	**1,43**	**64%**	**26%**	*******	**64%**	**27%**	*******	**64%**	**26%**	*******
1993-1999	1,67	51%	24%	***	52%	24%	***	52%	22%	***
2000-2009	2,25	68%	67%	***	68%	68%	***	69%	67%	***
2010-2019	0,23	65%	-7%		65%	-7%		66%	-7%	
Portfolio A-Short										
1993-2019	**0,07**	**23%**	**12%**	*****	**23%**	**10%**	*****	**24%**	**10%**	*****
1993-1999	-0,21	4%	4%		4%	4%		4%	-1%	
2000-2009	0,79	32%	39%	***	32%	37%	***	32%	39%	***
2010-2019	-0,71	27%	-10%		27%	-10%		28%	-10%	
Portfolio A-Long and Short										
1993-2019	**1,54**	**41%**	**26%**	*******	**42%**	**27%**	*******	**42%**	**25%**	*******
1993-1999	3,73	47%	22%	***	48%	23%	***	48%	20%	***
2000-2009	2,72	39%	63%	***	40%	65%	***	40%	63%	***
2010-2019	-0,08	49%	-10%		50%	-9%		51%	-10%	
Panel B: Scenarios with transaction fee of 0,1% , 0,08% and 0,04%										
Portfolio A-Long										
1993-2019	**1,64**	**64%**	**31%**	*******	**64%**	**32%**	*******	**64%**	**31%**	*******
1993-1999	1,20	52%	14%	**	52%	15%	***	52%	12%	**
2000-2009	2,25	68%	67%	***	68%	68%	***	69%	67%	***
2010-2019	1,15	65%	12%	***	65%	13%	***	66%	12%	***
Portfolio A-Short										
1993-2019	**0,21**	**23%**	**17%**	*******	**23%**	**15%**	******	**24%**	**15%**	******
1993-1999	-0,42	4%	-4%		4%	-3%		4%	-9%	
2000-2009	0,79	32%	39%	***	32%	37%	***	32%	39%	***
2010-2019	-0,11	27%	8%		27%	8%		28%	8%	
Portfolio A-Long and Short										
1993-2019	**1,81**	**42%**	**32%**	*******	**42%**	**33%**	*******	**43%**	**31%**	*******
1993-1999	3,73	47%	13%	**	48%	14%	**	48%	10%	*
2000-2009	2,72	39%	63%	***	40%	65%	***	40%	63%	***
2010-2019	1,13	50%	10%	***	50%	10%	***	51%	10%	***

The assumption showed by Panel B of decreasing transaction costs over decades (0,10% in the first decade, 0,08% in the second decade, 0,04% in the last decade) makes the last decade abnormal returns significantly different from zero at a 99% confidence level for the Long and Short strategies. Decreasing transaction costs over decades is a realistic scenario, as confirmed by Altınkılıç, Hansen, and Ye (2016).

The strategy implemented with a single day holding period requires frequent transactions and high transaction costs. The previous section illustrated the existence of an investment strategy that generates economically significant positive abnormal returns. The current section confirms the expectation that transaction costs have a significant impact on the strategy developed in Portfolio A. Only investors with low transaction costs are able to benefit in a systematic way from those abnormal returns. Nevertheless, even for investors with higher transaction costs, if they are going to invest anyway and incur in transaction costs, they benefit from investing long in stocks that have just received an upgrade to a positive recommendation and investing short in stocks that just received a downgrade to a negative recommendation (Barber et al., 2001).

5.2. Restrictions on Liquidity

Restrictions on daily share volume (V) were added to control for companies with low liquidity. In this approach, the portfolio could only include stocks with a daily share volume higher or equal to 100 000[12] shares.

For Portfolio A-Long, the share volume restriction (share volume higher or equal to 100 000 shares) excludes 14 518 recommendations (13% of total recommendations) of 5 027 different companies with low mean market capitalization (only 5% of the mean market capitalization of the whole portfolio's sample). For Portfolio A-Short, the share volume restriction excludes 2 270 recommendations (9% of total observations) of 1 485 different companies with low mean market capitalization (only 7% of the mean market capitalization of the whole portfolio's sample). In Table 10, one can see this information in more detail.

[12] The restriction on share volume higher or equal to 10 000 shares was also tested, but results were similar to this approach. Of the companies with share price higher or equal to 5 USD, approximately 2% and 13% of the recommendations concerns companies with share volume lower than 10 000 shares and 100 000 shares, respectively.

Table 10: Summary statistics of analyst recommendations in terms of companies' share volume

	# observations	# different Analysts	# different Companies	# different Industries	Market capitalization (000 000 USD)			
Portfolio A-Long					**Mean**	**Max**	**Median**	**Min**
V < 100 000 shares	14 518	3 418	5 027	871	609	142 483	286	12
% of total	*13%*	*42%*	*55%*	*82%*	*5%*	*13%*	*13%*	*100%*
V >= 100 000 shares	93 553	7 914	7 121	986	12 756	1 136 676	2 837	18
% of total	*87%*	*95%*	*73%*	*91%*	*119%*	*100%*	*145%*	*761%*
Total	**108 071**	**8 228**	**9 068**	**1 060**	**11 124**	**1 136 676**	**2 119**	**12**
Portfolio A-Short								
V < 100 000 shares	2 270	1 031	1 485	478	694	119 820	282	13
% of total	*9%*	*22%*	*29%*	*56%*	*7%*	*10%*	*14%*	*100%*
V >= 100 000 shares	21 955	4 540	4 249	785	10 328	1 180 842	2 488	19
% of total	*91%*	*90%*	*72%*	*89%*	*123%*	*100%*	*151%*	*1 688%*
Total	**24 225**	**4 759**	**5 073**	**851**	**9 426**	**1 180 842**	**2 078**	**13**

Portfolio A-Long has, therefore, 93 553 recommendations, when the share volume restriction applies. The average number of stocks per day is 14. January 22nd, 2009 is still the day with the highest number of stocks invested (193 stocks). The same three top days in the scenario without restriction on share volume are the only days with more than 150 stocks invested in one day. Portfolio A-Short has 21 955 recommendations when the share volume restriction applies. Of the 6 631 days, the number of days with no stocks Short is more 4% than in the scenario without restriction on share volume. Nevertheless, the average number of stocks invested per day does not change. September 10th, 2002 is still the only day with more than 150 stocks invested in one day (184 stocks, less 40 stocks than in the scenario without restriction on share volume).

Looking at Tables 11, abnormal returns of all portfolios are still significant at a 99% Confidence Level, after testing the liquidity of firms. The restriction in share volume, apparently, does not affect Sharpe Ratio of Portfolio A-Long, but increases abnormal returns. On the other hand, the Sharpe Ratio and abnormal returns of Portfolio A-Short decrease after controlling for share volume. Portfolio A-Long and Short suffers a decrease in Sharpe Ratio and an increase in abnormal returns. With transaction costs[13], the Sharpe Ratio of Portfolio A-Long and Portfolio A-Long and Short increase together with abnormal returns. The abnormal returns of Portfolio

[13] Transaction fee of 0,08% was used, for being, approximately, the breakeven fee of the Short strategy, in the scenario without restriction on share volume.

A-Short become not significant at a 90% Confidence Level, and the Sharpe Ratio becomes negative.

Table 11: Summary statistics of abnormal returns of Portfolio A in terms of companies' share volume

1993-2019	Sharpe Ratio annualized	Fama-French 3-factor model R-squared	alpha annualized		Fama-French 5-factor model R-squared	alpha annualized		Fama-French 5-factor model + Mom + STR R-squared	alpha annualized	
Panel A: Scenarios without transaction costs										
Portfolio A-Long										
V > 0	3,02	64%	65%	***	64%	66%	***	64%	66%	***
V > 100 000	3,02	60%	73%	***	60%	74%	***	60%	73%	***
Portfolio A-Short										
V > 0	1,02	23%	46%	***	23%	45%	***	24%	45%	***
V > 100 000	0,80	22%	40%	***	22%	40%	***	23%	40%	***
Portfolio A-Long and Short										
V > 0	3,58	41%	66%	***	42%	67%	***	42%	65%	***
V > 100 000	3,46	38%	69%	***	39%	71%	***	39%	69%	***
Panel B: Scenarios with a transaction fee of 0,08%										
Portfolio A-Long										
V > 0	1,43	64%	26%	***	64%	27%	***	64%	26%	***
V > 100 000	1,54	60%	33%	***	60%	34%	***	60%	34%	***
Portfolio A-Short										
V > 0	0,07	23%	12%	*	23%	10%	*	24%	10%	*
V > 100 000	-0,10	22%	7%		22%	7%		23%	7%	
Portfolio A-Long and Short										
V > 0	1,54	41%	26%	***	42%	27%	***	42%	25%	***
V > 100 000	1,58	38%	30%	***	39%	31%	***	39%	29%	***

Table 12 shows this scenario's sensitivity analysis to the transaction fee. Except for the Short strategy, portfolios have a higher breakeven fee, as exposed by the orange circle.

Table 12: Sensitive analysis of cumulative returns to the transaction fee – after controlling for firms' liquidity

Portfolio A-Long Sensitivity Analysis								
One-way transaction Fee	0,00%	0,05%	0,10%	0,16%	0,17%	0,20%	0,25%	0,30%
Cumulative Returns (USD)	1 336 496 420,01	1 939 770,88	2 797,01	1,08	0,29	0,01	0,00	0,00

Portfolio A-Short Sensitivity Analysis								
One-way transaction Fee	0,00%	0,02%	0,04%	0,06%	0,07%	0,10%	0,12%	0,14%
Cumulative Returns (USD)	718,41	80,83	9,09	1,02	0,34	0,01	0,00	0,00

Portfolio A-Long and Short Sensitivity Analysis								
One-way transaction Fee	0,00%	0,05%	0,10%	0,14%	0,15%	0,20%	0,25%	0,30%
Cumulative Returns (USD)	247 512 664,03	354 711,98	505,02	2,65	0,71	0,00	0,00	0,00

Given the evolution of abnormal returns and Sharpe Ratio of Portfolio A-Long and Short, and the significance of all portfolios' abnormal returns, when not considering transaction costs, one may conclude that results are robust in terms of liquidity of the stocks selected.

5.3. Different companies' groups according to market capitalization

For the purpose of the data analysis exercise, the database used in this work was large, and portfolios hold many stocks in each strategy, for instance Portfolio A-Long invests in 7 thousand companies, with an average of 11 billion market capitalization. In practice, investors are subject to different preferences and restrictions when building their portfolios. To understand which companies were bringing higher abnormal returns in Portfolio A and to allow for variety in the size of future portfolios, the dataset was divided into 3 groups of companies according to their market capitalization (MC). As shown in Table 13, the companies with lower market capitalization (the first 3-quantile) were the ones bringing higher returns, both in the long and short strategies. The companies with higher market capitalization (the third 3-quantile) had lower abnormal returns and, inclusively, the abnormal returns of the short strategy were only significantly different from zero, at a 90% Confidence Level, when compared to the Fama-French five-factor model. When including a transaction fee of 0,08%[14] of the trading value, the short strategy results had negative returns only for the companies with higher market capitalization. These findings evidence that returns of smaller companies are more correlated with analysts' recommendations than returns of bigger companies. This shows that analyst recommendations have a higher impact on smaller companies, which can be partially explained by the higher inclination of Investors to follow analysts' opinion when the company is less prominent.

Table 13 shows the results of each strategy[15] for the 3-quantiles (Lower MC, Median MC and Higher MC), with and without a transaction fee of 0,08%.

[14] Transaction fee of 0,08% was used, for being, approximately, the breakeven fee of the Short strategy.
[15] The results were also calculated for each decade. In line with the returns of Portfolio A-Long and Short, the decade 2000-2009 is the one with higher returns on average, for both the short and long strategies and for all the 3-quantiles.

Table 13: Summary statistics of abnormal returns of Portfolio A in terms of companies' market capitalization

		Fama-French 3-factor model			Fama-French 5-factor model			Fama-French 5-factor model + MOM + ST_REV		
	Sharpe Ratio annualized	R-squared	alpha annualized		R-squared	alpha annualized		R-squared	alpha annualized	
Panel A: Scenarios without transaction costs										
Portfolio A-Long										
Lower MC	2,80	26%	98%	***	26%	99%	***	27%	97%	***
Median MC	2,23	42%	61%	***	42%	62%	***	42%	61%	***
Higher MC	1,93	49%	43%	***	49%	43%	***	49%	44%	***
Portfolio A-Short										
Lower MC	0,94	9%	45%	***	9%	45%	***	9%	45%	***
Median MC	0,91	16%	39%	***	16%	39%	***	16%	37%	***
Higher MC	0,01	21%	6%		21%	8%	*	22%	6%	
Portfolio A-Long and Short										
Lower MC	3,15	13%	105%	***	13%	107%	***	13%	104%	***
Median MC	2,41	22%	63%	***	22%	64%	***	23%	62%	***
Higher MC	1,88	29%	38%	***	29%	39%	***	30%	38%	***
Panel B: Scenarios with a transaction fee of 0,08%										
Portfolio A-Long										
Lower MC	1,87	26%	62%	***	26%	63%	***	27%	61%	***
Median MC	1,03	42%	23%	***	42%	24%	***	42%	23%	***
Higher MC	0,50	49%	4%		49%	4%		49%	5%	
Portfolio A-Short										
Lower MC	0,47	9%	26%	***	9%	25%	***	9%	25%	***
Median MC	0,23	16%	16%	**	16%	15%	**	16%	13%	**
Higher MC	-0,90	21%	-17%		21%	-16%		22%	-18%	
Portfolio A-Long and Short										
Lower MC	2,09	13%	68%	***	13%	70%	***	13%	67%	***
Median MC	1,00	22%	24%	***	22%	25%	***	23%	23%	***
Higher MC	0,12	29%	0%		29%	0%		30%	-1%	

5.4. Different holding days

To understand how returns change over the time around the recommendation, Portfolio A-Long and Short, with a holding period of one day, was implemented in each of the 9 days around the announcement day. The announcement day (day 0) is the day with the highest average abnormal returns[16]. This is aligned with Green (2006), who, as mentioned before, affirmed that "most of the price response takes place by the time trading begins after the recommendation change". Additionally, Table 14 shows that the day before the announcement day (day -1) has higher

[16] The announcement day is the day with the highest abnormal average returns also in every decade.

returns than the day that follows the announcement day (day 1). These results add on to the findings of Green (2006) by providing evidence to the value of information transmitted on the day before the announcement. Information gathered before that is still valuable on average. Nevertheless, it brings smaller abnormal returns than in the days after the announcement day. The same happens for scenarios with transaction fees of 0,08%[17] of the trading value.

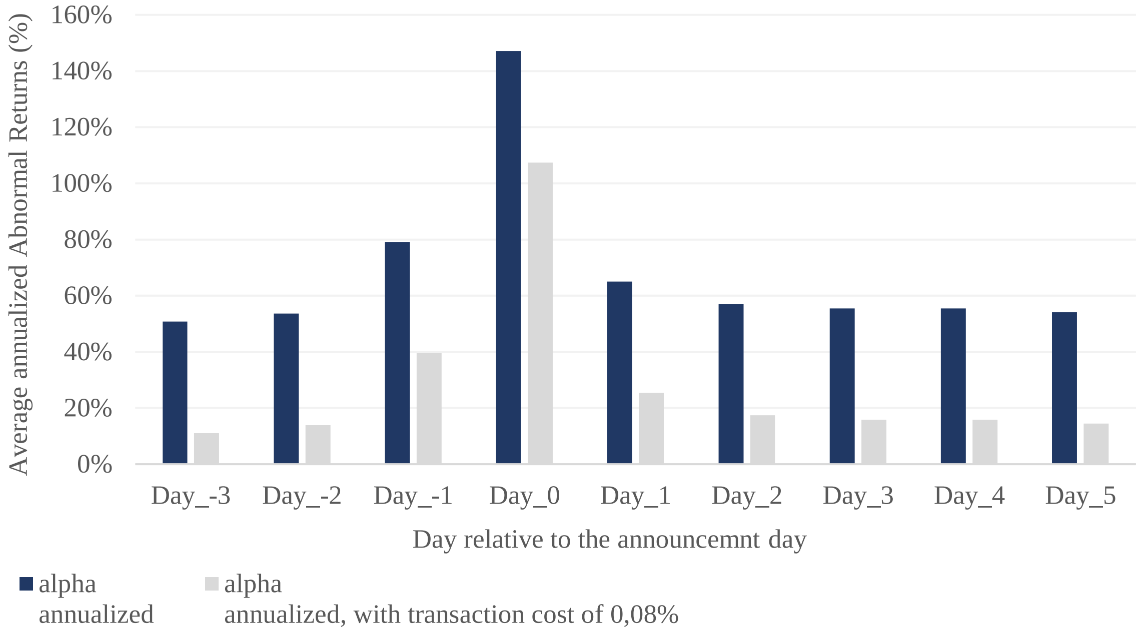
Table 14: Summary statistics of abnormal returns of Portfolio A, when transposed to the 9 days around the announcement day

1993-2019		Fama-French 3-factor model			Fama-French 5-factor model			Fama-French 5-factor model + MOM + ST_REV		
	Sharpe Ratio annualized	R-squared	alpha annualized		R-squared	alpha annualized		R-squared	alpha annualized	
Panel A: Scenarios without transaction costs										
Portfolio A-Long and Short										
Day_-3	2,90	43%	52%	***	44%	53%	***	44%	51%	***
Day_-2	2,94	40%	55%	***	41%	56%	***	41%	54%	***
Day_-1	3,99	38%	81%	***	38%	82%	***	39%	79%	***
Day_0	6,86	32%	149%	***	32%	150%	***	33%	147%	***
Day_1	3,58	41%	66%	***	42%	67%	***	42%	65%	***
Day_2	3,26	43%	58%	***	43%	59%	***	44%	57%	***
Day_3	3,19	43%	57%	***	44%	58%	***	45%	55%	***
Day_4	3,19	43%	57%	***	44%	58%	***	45%	55%	***
Day_5	3,14	43%	56%	***	44%	57%	***	44%	54%	***
Panel B: Scenarios with a transaction cost of 0,08%										
Portfolio A-Long and Short										
Day_-3	0,82	43%	12%	***	44%	14%	***	44%	11%	***
Day_-2	0,94	40%	15%	***	41%	16%	***	41%	14%	***
Day_-1	2,11	38%	41%	***	38%	42%	***	39%	39%	***
Day_0	5,08	32%	109%	***	32%	110%	***	33%	107%	***
Day_1	1,54	41%	26%	***	42%	27%	***	42%	25%	***
Day_2	1,16	43%	19%	***	43%	20%	***	44%	17%	***
Day_3	1,10	43%	18%	***	44%	19%	***	45%	16%	***
Day_4	1,10	43%	18%	***	44%	19%	***	45%	16%	***
Day_5	1,03	43%	16%	***	44%	17%	***	45%	14%	***

Figure 2 shows the evolution of annualized abnormal returns in the 9 days around the announcement day, compared to the Fama-French five-factor model with momentum and short-term reversal. The peak in Day 0 evidences the value of a strategy that follows analysts' recommendations.

[17] Transaction fee of 0,08% was used, for being, approximately, the breakeven fee of the Short strategy.

Figure 2: Average annualized abnormal returns of Portfolio A-Long and Short, when transposed to the 9 days around the announcement day



5.5. Different time periods

In the process of cleaning and understanding the data, some anomalies were detected: the first year with data available in the IBES has more recommendations per month than the other years; in October 2018, there was a restructuring of IBES variables[18]. Furthermore, according to Altınkılıç et al. (2016), average post-revision return drift was not significantly different from zero in the post-period from May 2003 to 2010[19].

In this section, the Portfolio A-Long and Short was replicated through different time periods to verify whether the data anomalies impact the results and whether the findings of Altınkılıç et al. (2016) are aligned with this study.

---

[18] "As of October 18, 2018, Thomson-Reuters changed the identifiers of a large number of brokers and analysts in I/B/E/S. It is likely that 13.8% of all broker IDs (ESTIMATOR) and 30.7% of all analyst IDs (ANALYS) have been reassigned. While the October 2018 change affected a large portion of the sample, WRDS has also become aware of a different issue wherein individual broker IDs (and all affected analysts) have been and will continue to be subject to reshuffle without warning. The safest course of action may be to treat each data vintage as an entirely separate sample. See this document for more detail. Additionally, UBS Equities was removed from I/B/E/S Detail History." (WRDS, 2020)

[19] These authors explained that some of the main factors responsible for lowering the post-revision return drift were the reduction of trading costs alongside with the increased use of supercomputers and algorithms that allow higher trading efficiency.

Looking at Table 15, abnormal returns with and without transaction costs[20] are robust after testing for different time periods. Abnormal returns are significant and even higher for the period May 2003 to 2010, contrasting with the findings of Altınkılıç et al. (2016).

Table 15: Summary statistics of abnormal returns of Portfolio A-Long and Short in different time periods

		Fama-French 3-factor model			Fama-French 5-factor model			Fama-French 5-factor model + Mom + STR		
	Sharpe Ratio annualized	R-squared	alpha annualized		R-squared	alpha annualized		R-squared	alpha annualized	
Panel A: Scenarios without transaction costs										
1993-2019	**3,58**	**41%**	**66%**	*******	**42%**	**67%**	*******	**42%**	**65%**	*******
1994-2019	3,59	42%	66%	***	42%	67%	***	43%	65%	***
1993-2018	3,66	38%	70%	***	38%	71%	***	39%	69%	***
2003-2010	4,88	41%	86%	***	41%	86%	***	43%	86%	***
Panel B: Scenarios with a transaction fee of 0,08%										
1993-2019	**1,54**	**41%**	**26%**	*******	**42%**	**27%**	*******	**42%**	**25%**	*******
1994-2019	1,53	42%	26%	***	42%	27%	***	43%	25%	***
1993-2018	1,64	41%	28%	***	42%	30%	***	42%	27%	***
2003-2010	2,71	41%	46%	***	41%	46%	***	43%	46%	***

5.6. Complementary Analysis

This section builds additional portfolios to explore how returns change relative to the stock selection criteria.

Recapitulating, the Portfolio A held a long position on all upgrades to Strong Buy and Buy and a short position on all downgrades to Sell or Strong Sell. However, Barber et al. (2010) demonstrate that single and double upgrades have higher predictive value than changes of higher order. Consequently, a second portfolio is built[21] – Portfolio B – with the following investment strategy: long position on all single and double upgrades to Strong Buy and Buy, and short position on all single downgrades to Sell or Strong Sell.

Expanding the later strategies, a third portfolio – Portfolio C – is built to captures only the recommendations where analysts maintain the direction of the recommendation, i.e., from neutral or positive to further positive recommendations or from neutral or negative to further

[20] Transaction fee of 0,08% was used, for being, approximately, the breakeven fee of the Short strategy.
[21] Weights and returns of all the additional portfolios are calculated following the same methodology as in Portfolio A.

negative. The Portfolio C-Long and Short is composed of a long position on upgrades from Hold or Buy and a short position on downgrades from Hold or Sell.

Because the long strategy of Portfolio A results in high abnormal returns, a fourth and fifth portfolio – Portfolio D-Strong Buy and Portfolio D-Buy – were built to solely capture the returns from upgrades to single recommendations levels. Portfolio D-Strong Buy is composed of a long position on all upgrades to Strong Buy and Portfolio D-Buy is composed of a long position on all upgrades to Buy.

Table 16 shows the abnormal returns of all alternative strategies, subdivided into the long position, short and long minus short (L&S). There are two shaded columns: the Sharpe Ratio column and the column with the annualized alpha of the Fama-French five-factor model with momentum and short-term reversal. This formatting helps distinguish which strategies held higher returns.

Table 16: Summary statistics of abnormal returns of Portfolio A, B, C and D without transaction costs

1993-2019		Fama-French 3-factor model			Fama-French 5-factor model			Fama-French 5-factor model + Mom + STR		
Scenarios	Sharpe Ratio annualized	R-squared	alpha annualized		R-squared	alpha annualized		R-squared	alpha annualized	
Long strategies										
Portfolio A-Long	3,02	64%	65%	***	64%	66%	***	64%	66%	***
Portfolio B-Long	3,03	63%	66%	***	63%	67%	***	64%	66%	***
Portfolio C-Long	3,01	63%	65%	***	63%	66%	***	63%	66%	***
Portfolio D-Str Buy	2,95	47%	75%	***	47%	76%	***	48%	75%	***
Portfolio D-Buy	2,27	47%	55%	***	48%	56%	***	48%	56%	***
Short strategies										
Portfolio A-Short	1,02	23%	46%	***	23%	45%	***	24%	45%	***
Portfolio B-Short	0,77	18%	35%	***	18%	35%	***	19%	34%	***
Portfolio C-Short	0,85	20%	40%	***	20%	39%	***	21%	39%	***
Long and Short strategies										
Portfolio A-L&S	3,58	41%	66%	***	42%	67%	***	42%	65%	***
Portfolio B- L&S	3,32	50%	66%	***	50%	67%	***	51%	66%	***
Portfolio C- L&S	3,48	44%	66%	***	44%	67%	***	45%	65%	***

All returns are significantly different from zero at a 99% Confidence Level. Furthermore, there are two main findings raised in Table 16. The first one is that the strategy investing long on all upgrades to Strong Buy – Portfolio D-Strong Buy – holds the highest abnormal returns from 1993 to 2019. The second finding is that, among the short strategies, the strategy that invests short in all downgrades to Strong Sell and Sell holds higher abnormal returns than strategies with more restrictive conditions. All the other returns are similar among the different portfolios. This similarity was expected since there are few changes of order higher than double changes. The total number of investments is similar in the three portfolios: around 100 000 stocks invested long and 20 000 stocks invested short.

One benefit of different stock selection criteria is the possibility of incurring in fewer trades, and, therefore, lower transaction costs. Table 17 confirms this hypothesis showing the results of the regressions after including transaction costs[22].

Table 17: Summary statistics of abnormal returns of Portfolio A, B, C and D with a transaction fee of 0,08%

1993-2019		Fama-French 3-factor model			Fama-French 5-factor model			Fama-French 5-factor model + Mom + STR		
Scenarios	Sharpe Ratio annualized	R-squared	alpha annualized		R-squared	alpha annualized		R-squared	alpha annualized	
Long strategies										
Portfolio A-Long	1,43	64%	26%	***	64%	27%	***	64%	26%	***
Portfolio B-Long	1,45	63%	26%	***	63%	27%	***	64%	26%	***
Portfolio C-Long	1,43	63%	26%	***	63%	27%	***	63%	26%	***
Portfolio D-Str Buy	1,60	47%	36%	***	47%	37%	***	48%	36%	***
Portfolio D-Buy	0,91	47%	16%	***	47%	17%	***	48%	17%	***
Short strategies										
Portfolio A-Short	0,07	23%	12%	*	23%	10%	*	24%	10%	*
Portfolio B-Short	0,00	18%	8%		18%	8%		19%	7%	
Portfolio C-Short	-0,01	20%	8%		20%	8%		21%	7%	
Long and Short strategies										
Portfolio A-L&S	1,54	41%	26%	***	42%	27%	***	42%	25%	***
Portfolio B- L&S	1,47	50%	27%	***	50%	28%	***	51%	26%	***
Portfolio C- L&S	1,51	44%	27%	***	44%	28%	***	45%	26%	***

In summary, Table 17 shows that, when including transaction costs, the two long and short strategies with more restrictions on the stock selection have slightly higher abnormal returns than Portfolio A. Reversely, the most wide-ranging short strategy is the only short strategy with significant alphas, at a 90% Confidence Level. Once more, upgrades to Strong Buy bring higher alphas than upgrades to Buy or any other long strategy. The effect of different stock selection would potentially be higher if restrictions on the rating level and change were sharper. Further

[22] Transaction fee of 0,08% was used, for being, approximately, the breakeven fee of the Short strategy.

research could, for instance, explore the abnormal returns of single upgrades to each positive level versus double upgrades and compare the results.

6. Further research suggestions and limitations

This study explores an investment strategy which relies solely on analyst recommendations. There are more aspects of the analyst report that can have an impact on the market reactions, for instance, the earnings forecast, the target price, the content of the report (Asquith et al., 2005), the accuracy of cash flow forecast (Pan, 2019) and the timing of announcement (Ivković & Jegadeesh, 2004; Rees, Sharp, & Wong, 2017). Another point that needs to be taken into consideration is that making the trade at the market closing does not allow investors to capture abnormal returns one encounters when transacting right after the recommendation announcement (Green, 2006). Moreover, instead of holding the stock for a single day, an alternative strategy could be to hold the stock for a longer period or until there is a recommendation change.

Equally weighted portfolios were built for the purpose of this analysis. This approach may be considered as a “naïve strategy”. Nevertheless, according to DeMiguel, Garlappi, and Uppal (2009), more “sophisticated models” do not consistently perform better than an equally-weighted (1/N) asset allocation. As mentioned in the Complementary Analysis section, exploring the abnormal returns of single upgrades to each positive level, or of other strategies restricting the stock selection, could generate lower transaction costs.

Further research could explore all the above elements to design a strategy that could potentially outperform the current one. It could also study whether analysts are either market predicters or influencers, once it is still undetermined the causal relation between analysts and market prices.

In practice, if someone wants to implement this strategy, this person could decide to use the consensus of analyst recommendations (for example, from the Recommendations Summary Statistics file from IBES), instead of using individual analyst recommendations. This information is easier to obtain and might provide a feeling of a safer choice, but it might miss the accuracy of individual analyst recommendations. Access to information may incur additional fees that are not being considered in the current study and investors may be restricted in the number of stocks to include in their portfolios. Moreover, daily rebalancing the portfolio may also be impractical for some investors[23].

The current strategy may also suffer from the following limitations, among others:

Ljungqvist, Malloy, and Marston (2009) demonstrate that historical contents of the IBES database suffer changes from year to year (in annual downloads from 2001 to 2007, between 1.6% and 21.7% matched observations suffered changes in the information from one year to the next). Besides, some analysts issue recommendations on a three-point scale – Buy, Hold, Sell – instead of a five-point scale (Barber et al., 2010). The lack of constancy and veracity of data may cause significant differences between the analysis presented in this work and a similar analysis carried out at a different point in time.

In the current analysis, on the days in which an investment is made, the full amount of cash was invested in an equally weighted portfolio. There are some days in which there was no investment (only 1% of the total number of days of each portfolio). When this happens, the cost of carrying was not considered. A possible alternative, which could be explored by further research, is to invest the full amount of cash in the money market, in all days with zero stocks invested.

7. Conclusion

This dissertation brings additional evidence to the impact of analyst recommendations. It replicates and updates part of the findings of Barber et al. (2010) in an investment strategy. It contributes with additional studies, including the calculation and deduction of transaction cost, which was not considered by Barber et al. (2010). To develop this study, a python code was created, which can easily be adapted to other investment strategies using the recommendations of analysts. This work also contributes towards a better understanding of the analysts' work, their recommendations, and their impact on companies subject to recommendations, from 1993 to 2019 in the US market.

Why is the market attributing such high value to analysts' research? Although it is still unknown whether analysts are either market predicters or influencers, the correlation between analysts' recommendations and market reaction is evident. Under the current analysis, the investment

[23] See Barber et al. (2001) for alternative portfolios that entail less frequent rebalancing.

strategy that buys all stocks subject to upgrades to Strong Buy and Buy obtains an average annual return of 78% from 1993 to 2019. The investment strategy that buys all stocks subject to upgrades to Strong Buy and Buy and sells all downgrades to Sell or Strong Sell obtains an average abnormal return of 65%[24] in the same period. These results exceed the returns obtained by similar stock selection strategies yielded by Barber et al. (2001) and by Barber et al. (2010). The one-day holding period of this study is motivated by the short-term portfolios with two-day coverage used by Green (2006). This holding period partially justifies why returns are higher than in the studies previously mentioned. To explore the effect of investing right at the announcement time, a subsection of this work reproduces the investment strategy of a one-day holding period to the nine days around the announcement day. In line with the findings of Green (2006), the announcement day is the day with higher returns, on average higher than 100%. The second day with higher abnormal returns is the day before the announcement day, which evidences that analysts report a trend that was already happening before the announcement day.

The short portfolio is the one with a lower breakeven fee. After including this fee, the investment strategy long and short carried out in this study produces 25% abnormal annual returns (10 basis points per day), which is similar to abnormal returns of Green (2006), after transaction costs. The breakeven found for the last decade is however lower than the ones found in literature (one-way transaction fee of 0,04%). The following question appears: Will this strategy be profitable in the future?

Finally, the positive returns of the main investment strategy are robust when testing restrictions on firms' liquidity and, similarly to the findings of Barber et al. (2001), returns are larger for smaller market capitalization firms.

[24] After controlling for the Fama-Franch five-factor model with momentum and short-term reversal.

References

Altınkılıç, O., & Hansen, R. S. (2009). On the information role of stock recommendation revisions. *Journal of Accounting and Economics, 48*(1), 17-36.

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

Asquith, P., Mikhail, M. B., & Au, A. S. (2005). Information content of equity analyst reports. *Journal of Financial Economics, 75*(2), 245-282.

Barber, B., Lehavy, R., McNichols, M., & Trueman, B. (2001). Can investors profit from the prophets? Security analyst recommendations and stock returns. *The Journal of Finance, 56*(2), 531-563.

Barber, B. M., Lehavy, R., & Trueman, B. (2010). Ratings changes, ratings levels, and the predictive value of analysts' recommendations. *Financial Management, 39*(2), 533-553.

Brav, A., & Lehavy, R. (2003). An empirical analysis of analysts' target prices: Short-term informativeness and long-term dynamics. *The Journal of Finance, 58*(5), 1933-1967.

D'avolio, G. (2002). The market for borrowing stock. *Journal of Financial Economics, 66*(2-3), 271-306.

DeMiguel, V., Garlappi, L., & Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *The Review of Financial Studies, 22*(5), 1915-1953.

Green, T. C. (2006). The value of client access to analyst recommendations. *Journal of Financial and Quantitative Analysis*, 1-24.

Huang, J., Mian, G. M., & Sankaraguruswamy, S. (2009). The value of combining the information content of analyst recommendations and target prices. *Journal of Financial Markets, 12*(4), 754-777.

Ivković, Z., & Jegadeesh, N. (2004). The timing and value of forecast and recommendation revisions. *Journal of Financial Economics, 73*(3), 433-463.

Jegadeesh, N., Kim, J., Krische, S. D., & Lee, C. M. (2004). Analyzing the analysts: When do recommendations add value? *The Journal of Finance, 59*(3), 1083-1124.

Jegadeesh, N., & Kim, W. (2006). Value of analyst recommendations: International evidence. *Journal of Financial Markets, 9*(3), 274-309.

Ljungqvist, A., Malloy, C., & Marston, F. (2009). Rewriting history. *The Journal of Finance, 64*(4), 1935-1960.

Loh, R. K., & Mian, G. M. (2006). Do accurate earnings forecasts facilitate superior investment recommendations? *Journal of Financial Economics, 80*(2), 455-483.

Loh, R. K., & Stulz, R. M. (2011). When are analyst recommendation changes influential? *The Review of Financial Studies, 24*(2), 593-627.

Pan, S. (2019). Analysts' Cash Flow Forecast Accuracy and Recommendation Profitability. *Journal of Accounting and Finance, 19*(5).

Rees, L., Sharp, N. Y., & Wong, P. A. (2017). Working on the weekend: Do analysts strategically time the release of their recommendation revisions? *Journal of Corporate Finance, 45*, 104-121.

Stickel, S. E. (1995). The anatomy of the performance of buy and sell recommendations. *Financial Analysts Journal, 51*(5), 25-39.

Womack, K. L. (1996). Do brokerage analysts' recommendations have investment value? *The Journal of Finance, 51*(1), 137-167.

Yu, J.-R., Paul Chiou, W.-J., Lee, W.-Y., & Lin, S.-J. (2020). Portfolio models with return forecasting and transaction costs. *International Review of Economics & Finance, 66*, 118-130. doi:https://doi.org/10.1016/j.iref.2019.11.002

Appendices

1. List of Portfolios

Portfolio A-Long: long position on all upgrades to Strong Buy and Buy.

Portfolio A-Short: short position on all downgrades to Sell or Strong Sell.

Portfolio A-Long and Short: long position on all upgrades to Strong Buy and Buy and short position on all downgrades to Sell or Strong Sell.

Portfolio B-Long: long position on all single and double upgrades to Strong Buy and Buy.

Portfolio B-Short: short position on all single downgrades to Sell or Strong Sell.

Portfolio B-Long and Short: long position on all single and double upgrades to Strong Buy and Buy and short position on all single downgrades to Sell or Strong Sell.

Portfolio C-Long: long position on upgrades from Hold or Buy (single and double upgrades to Strong Buy and single upgrades to Buy).

Portfolio C-Short: short position on downgrades from Hold or Sell.

Portfolio C-Long and Short: long position on upgrades from Hold or Buy and a short position on downgrades from Hold or Sell.

Portfolio D-Strong Buy: long position on all upgrades to Strong Buy.

Portfolio D-Buy: long position on all upgrades to Buy.

Portfolio D-Strong Buy and Buy: long position on all upgrades to Buy and Strong Buy.

2. Detection of logical inconsistencies and data anomalies

Some of the analysts with more recommendations are research groups. These are included in this analysis.

After analyzing the number of recommendations per day, recommendations of RESEARCH DEPT on the day 2004.08.05 were deleted. There were 537 recommendations announced on the same day by only this analyst, which was considered as a data mistake. In 2004, 2005 and 2006 the research department provided recommendations for around 200 companies each year[25]. The analysis was replicated, excluding this analyst and results were not changed.

There are 11 592 unique Analyst Names and 12 398 unique Analyst Masked Codes. Choosing the variable Analysts Masked Code to identify the analysts has three main advantages: it considers individual recommendations rather than group recommendations, it avoids spelling mistakes and accounts for different analysts with the same name.

CUSIP is used as the company identifier due to its compatibility with CRSP, even though there are around 200 companies identified by different CUSIPs over time. (e.g., FMSA holdings have different CUSIP; although Arconic split from Alcoa in 2016, they both have the same ticker (AA); the CUSIP of Alcoa has changed over time 5 times.)

After extracting the returns from CRSP, around 7 000 companies were not found in the database, including Google and Coca Cola. In these cases, the code NCUSIP of CRSP was used instead of CUSIP, to avoid missing relevant data.

September 8th, 2002, seems to have had a big effect on 2002 data, and so a second analysis excluding this day was performed, without changing the results. September 2002 is the month with more recommendations (5 280 recommendations). On September 8th, 2002, 1 916 recommendations were issued by several different analysts.

[25] From August 2004 to October 2006, this research department announced on average 24 recommendations per month. Around 63% of these recommendation were Hold, 26% strong Buy and 11% Strong Sell.