CHARLES UNIVERSITY

FACULTY OF SOCIAL SCIENCES

Institute of Economic Studies

Bachelor thesis

2018 **Pavel Hloušek**

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Bias and Accuracy in Equity Research: The Case of CFA Challenge

Bachelor thesis

Prague, 2018

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Academic Year: 2017/2018

Bibliographic note

Hloušek, Pavel. 2018. *Bias and Accuracy in Equity Research: The Case of CFA Challenge*. Bachelor thesis. Charles University, Faculty of Social Sciences, Institute of Economic Studies. Supervisor Jiří Novák M.Sc., Ph.D.

Abstract

This thesis analyses drivers of optimistic bias in equity research and substance of ability in explaining differences in accuracy among equity analysts. I have shown the existence of a relevant reason for optimistic bias in equity research, which is not related to conflict of interest - the usually referred driver of the bias. Then I have supported the stream of literature showing that analyst's ability is not a strong determinant of analyst's accuracy. A new perspective on the topics is offered by using a sample of equity reports from valuation competition CFA Research Challenge. Contribution of the thesis lies (i) in working with a sample of analysts who do not face the conflicts of interest proposed by the literature to be causing optimistic bias, which offers a unique opportunity to test whether such conflict-of-interest-free analysts issue biased recommendations and in (ii) using success in CFA Challenge as a new proxy for ability of equity analysts. The methods used are an analysis of bias and accuracy of target prices, hit-ratio of investment recommendations, and analysis of returns - estimated by CAPM, Fama French three-factor model and Carhart four-factor model.

Abstrakt

Tato práce analyzuje příčiny nadměrného optimismu v akciové analytice a význam dovedností při vysvětlování rozdílů v přesnosti mezi akciovými analytiky. Ukázal jsem přítomnost relevantního důvodu pro nadměrný optimismus v akciové analytice, který nesouvisí se střety zájmů - obvykle zmiňovaným důvodem pro nadměrný optimismus. Dále jsem podpořil proud literatury, který ukazuje, že dovednosti analytiků nejsou klíčový faktor přesnosti analytiků. Nová perspektiva na tyto témata je nabídnuta díky použití vzorku valuačních zpráv z valuační soutěže CFA Challenge. Přínos této práce spočívá (i) v práci se vzorkem analytiků, kteří nečelí žádnému střetu zájmů, zmiňovanému v literatuře jako způsobující nadměrný optimismus (ii) a v použití úspěchu v CFA Challenge jako nové proxy pro dovednosti v akciové analytice. Použité metody jsou analýza nadměrného optimismu a přesnosti cílových cen, hit-ratio investičních doporučení, a analýza výnosů - odhadnutých s pomocí CAPM, Fama French tří-faktorového modelu a Carhartova čtyř-faktorového modelu.

Keywords

CFA Challenge, asset pricing, equity research, equity analysts, optimistic bias

Klíčová slova

CFA Challenge, oceňování aktiv, kapitálové trhy, nadměrný optimismus

JEL Classification: G11, G12, G17

Range of thesis: 62 323 characters

Declaration of Authorship

1. The author hereby declares that he compiled this thesis independently, using only the listed resources and literature.

2. The author hereby declares that all the sources and literature used have been properly cited.

3. The author hereby declares that the thesis has not been used to obtain a different or the same degree.

Prague, 7 May 2018 Pavel Hloušek

Acknowledgements

I am especially grateful to my supervisor Jiří Novák M.Sc., Ph.D. for numerous comments, long discussions and his enthusiasm. Further gratitude goes to Karolína Chalupová, Robert Kaplan, Jan Habětínek and Andrey Britskyi for many valuable comments during seminars organized by Jiří Novák M.Sc., Ph.D. Last but not least, I am grateful to CFA Institute for providing me with the data.

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Notes: Please enter the information from the proposal to the Student Information System (SIS) and submit the proposal signed by yourself and by the supervisor to the Academic Director ("garant") of the undergraduate program.

Proposed Topic:

CFA Research Challenge: Investment Recommendations Back-Testing

Preliminary scope of work:

Research question and motivation

In 2016, hundreds of teams around the world participated in annual international corporate finance championship, CFA Research Challenge. After local round and regional final, the best teams have the opportunity to impress judges in global final. Quality of finalists' work, consisting of presentations and equity reports, is considered to be very high. Clearly, quality of analytical judgement is not the only criterion for choosing the winner. Other factors, such as presentation skills or graphical outline play their roles.

The main goal of this work is to evaluate whether teams are successful from the perspective of financial analysts' work, i.e. in giving their recommendations, and whether finalists are actually the most successful teams from this perspective. Moreover, some expected drivers of teams' success will be tested.

The hypotheses I will be testing are as follows.
H1: Recommendation "buy" or "sell" is a reliable predictor of future growth or decline.
H2: Recommendations of teams competing in global final are better than of those teams which were eliminated in regional level.
H3: Teams composed of both men and women provide more reliable recommendations.
H4: Reliability of finalists' recommendations is improving over the years.
H5: Valuations with lower terminal value relative to explicitly forecasted cash flows are more reliable.

Contribution

This thesis will be contributory in several ways. Firstly, it will provide feedback to the organizers whether the judgements of the winning teams fit reality the best. Secondly, it will show credibility of the competition as s professional experience. Thirdly, it will motivate teams competing in next years to focus more on the predictive capability of their work.

Methodology

I will be working with equity reports of the teams participating in the challenge, which I will use to obtain data regarding investment recommendations, valuation methodology, and information about teams. I will also need financial data, which I will obtain from Thomson Reuters platform. Expected amount of recommendations is in hundreds, therefore the data will be processed in Stata with the use of loops.

Return will be measured by several techniques, including both the very basic as well as the more advanced ones. Specifically, I will use:

- Simple stock return, net of risk-free rate

- The capital asset pricing model (CAPM)
- Fama-French three-factor model (3F model)
- Carhart four-factor model (4F model)
- Fama-French five-factor model (5F model)

Using the models stated above, I will calculate excess returns (alphas) for companies analysed by the competing teams to identify over and under-performing stocks. Alpha is the estimate of intercept in regression, i.e. the return a stock generated in excess over the market and other factors included in a model. If alpha is positive, stock generated excess return. I assume stocks with buy recommendation to generate excess returns, i.e. have positive alpha and vice versa. CAPM, 3F, 4F, 5F models are based on running a regression of company's stock returns on market returns and additional factors, which are specific for each model. Those returns are usually weekly or monthly and market is usually represented by appropriate stock index, e.g. S&P 500 for American-listed companies, EURO STOXX 50 for European stocks. I will be using monthly returns.

For CAPM model, the only factor used as an independent variable is the market return, net of risk-free rate. 3F model enriches CAPM by the effects of company size (SMB) and book-to-market (HML) ratio. SMB factor come into regression as additional variable representing difference between returns on diversified portfolio of the stocks with small and high market capitalization in the respective period. Similarly, HML represents difference between returns on diversified portfolio of the stocks with high and with low book-to-market ratio. SMB, HML effects are region-specific, as well as market returns are. Historical values for those factors are available at website of one of the authors of 3F model, Kenneth French. Definition of stocks with small or big and market capitalization or high and low book-to-market ratio is not strictly given, however, Kenneth French uses 10th and 90th percentile of the sample as a threshold for size and 30th and 70th percentile for book-to-market ratio. I will be using data from Kenneth French's web and therefore stick to this definition.

Carhart four-factor extends 3F model by a momentum factor, which is a tendency of rising prices to rise further and vice versa. Often, cumulative return for twelve months with a one-month lag is used. Historical values for momentum effect can be found on Kenneth French's web as well.

In contrast, 5F model introduced by Fama and French in 2015 does not include momentum factor. Instead it incorporates effect of profitability (RWA) and investment (CMA). The way those variables come into model is analogic to 3F model, RWA reflects the difference between returns on diversified portfolio of the stocks with robust and weak profitability, CMA reflects difference between returns on diversified portfolio of firms with low and high investment (conservative minus aggressive). Again, I will obtain data for RWA and CMA effects from Kenneth French's website.

I will now explain the application in testing my hypotheses. Using models described above, I will calculate alphas for each stock, i.e. each equity report providing an investment recommendation. In hypothesis H1, I expect stocks with a buy recommendation to have positive alphas and vice versa. I will test the hypothesis by running a regression of alphas on two binary variables; *buy recommendation* and *sell recommendation*.

In order to test hypotheses H2 to H5, I need to define *reliability* of the recommendations. I will measure it in two ways. Firstly, as a binary information, whether buy/sell recommendation corresponded to positive/negative alpha (not applicable for hold recommendation). Secondly, as a relative distance of the target price from the actual price twelve months after the team gave their presentation. Then, I will run regression of *reliability* on the respective team parameters.

Outline

1. Introduction
2. Literature review
3. Hypotheses
4. Data and methodology
5. Results and discussion
6. Conclusion
7. Bibliography

List of academic literature:

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Author **Supervisor**

Content

1. Introduction

Equity analysts also referred to as stock analysts, collect and evaluate information about companies, estimate their future financial performance, consider current market conditions, come up with a target price and finally issue an investment recommendation. Therefore, equity analysts play an important role in interpreting and disseminating information to investors (Fang and Yasuda 2014). Investors' decisions are influenced by analysts' recommendations (Frankel, Kothari, and Weber 2006), hence equity analysts affect stock prices.

If the recommendations are positively biased, following them by investors may lead to overpricing the stocks - buying them not for the belief that their true value is higher than the current market price but solely for the belief that someone will be willing to pay even more in the future - hence creating a stock price bubble (Harrison and Kreps 1978). Understanding determinants of optimistic bias in equity research is important to regulators of financial markets. Presence of conflicts of interest resulting from trade generating incentives has long been of interest of SEC[1]. In 2003, SEC took actions called Global Analyst Research Settlements against ten Wall Street firms and two analysts after their conflicts of interest have been discovered and investigated. The actions included penalties in the total value of $875 million, enforcement of physical separation of research and investment banking divisions, prohibition of paying bonuses to analysts based on investment banking revenues and other restrictions (SEC 2003). Conflicts of interest in equity research are currently a momentous topic in the European Union in the context of the new regulatory framework MiFID II (Chiarella et al. 2017).

Prior research has shown that analysts' recommendations[2] are too optimistic and has examined several reasons for the optimism. Most importantly, the reasons shown are due to various conflicts of interest analysts face. Other, behavioural, reasons for the optimism were proposed, but working with traditional data samples does not allow for examination of the alternative reasons since almost all equity analysts face some kind of conflict of interest (most commonly trade generation incentives). The first

[1] The U.S. Securities Exchange Commission.

[2] Talking about analysts' recommendations or analysts' forecasts being optimistically biased, I mean too high earnings forecasts, too high target prices and too optimistic investment recommendations, i.e., buy or even strong buy recommendation for a stock which will not have generated a positive return.

research question of this thesis is: *Is there a reason for optimistic bias in equity research beyond conflicts of interest?*

Moving from optimistic bias to drivers of differences in accuracy among analysts leads us to the second line of this study. There is a controversy in research on the extent to which analysts' skills influence their accuracy. Since skills and ability are problematic to measure, researchers are in search of reliable proxy. Often (Fang and Yasuda 2014; Emery and Li 2009; Leone and Wu 2007; Stickel 1992) *All-American Team Research Team* list issued by *Institutional Investor* is used as a sample of analysts with superb skills (AA analysts). Although Fang and Yasuda (2014) have shown that AA analysts are more accurate than non-AA, they admit that the difference may be to some extent driven by luck, analysts' influence on the market or better access to company management. If these factors are more important than skills, more influential analysts are followed by even more investment professionals, hence becoming even more influential and a large portion of equity research industry power is concentrated in hands of a few equity analysts, even though they are not better analysts. Indeed, Loh and Stulz (2011) show that AA analysts are more likely to influence the market.

Second commonly used proxy for ability in equity research is analyst's experience. Prior research suggests that experience is irrelevant for analysts' accuracy[3]. This controversy motivates the search for new proxies for ability in order to support one or the other line of research. Being able to identify more accurate analysts as well as the drivers of the differences in accuracy is important for investors, who prefer to make investment decisions based on accurate and rigorous information. But also for the researchers who use analysts' forecasts as a proxy for expectations of the capital market and for the whole market as the better access we have to accurate information, the closer we are to efficient markets (Fama 1970). Therefore, the second research question of this thesis is: *Are more skilled analysts more accurate?*

I am addressing the issue by using data from CFA Research Challenge, an annual global company valuation competition organized by CFA Institute. In this competition, teams have to analyse a company, prepare an equity report and give a presentation in front of judges. The competition starts with a local round in every

[3] A detailed discussion is provided in Literature Review.

involved country; continues with 3 regional rounds - Europe and Middle East Asia (EMEA), South, Central and North America (Americas) and Australia and the rest of Asia (Asia-Pacific). Then, in the global round, one winner is announced globally as well as one winner for in region. Equity reports from regional and global levels of the competition are used in this study as a sample of analysts' recommendations. In contrast with professional analysts, CFA Challenge participants do not face the conflicts of interest identified by prior research as causing optimistic bias[4]. That allows me to test the existence of further reasons for the bias. Moreover, I am using success in CFA Challenge as a proxy for ability. Comparing the accuracy of the regional winners (calling them *winners*; 3 in each season), I test whether reports of higher quality yield more accurate recommendations; hence, if more skilled analysts produce more accurate recommendations.

The remainder of the thesis is organized as follows. Section 2 introduces CFA Research Challenge; Section 3 reviews existing literature, formulates and motivates the hypotheses; Section 4 describes data and methodology; Section 5 presents results; and Section 6 concludes.

2. CFA Research Challenge

Let me give you an insight into rules and structure of CFA Research Challenge. Each team, consisting of three to five students, must be sponsored by a local university and only undergraduate and graduate students can participate. None individual can participate in more than one season. The research has to be conducted solely by the team members and based only on publicly available information plus two interactions with the subject company; one informational session (may include Q&A) and one follow-up communication. Teams are not allowed to contact the company in excess of the two interactions. Teams are allowed to conduct a survey but should avoid contacting anyone who is known to have ever been employed as an investment professional. Teams have the option to use for a faculty advisor and assigned industry mentor; both for a limited amount of time. The above-described restrictions should secure that the participants understand the company and the industry, but the analysis is conducted exclusively by the team. Each team prepares a written report of maximum

[4] Discussion of the conflicts of interest and explanation why CFA Challenge participants do not face them is provided in Literature Review.

10 A4 pages (plus maximum 20 pages Appendix) and a 10-minute presentation (plus 10 minutes for Q&A). The written reports may not be changed between the rounds, but the presentation can be adjusted based on the feedback received in the previous round(s) (CFA Institute 2017).

As only regional level and global level reports were examined, analysts in the sample should conduct equity research in such a quality[5] that the results are of informative value to traditional research focusing on professional analysts. Choice of success in CFA Challenge as a proxy for ability is motivated by the relevance of competition's criteria for company valuation skills. CFA Challenge presentation scoring sheet includes the following questions (CFA Institute 2017): (i) How thorough was their [financial] analysis of the industry, and competitors? (ii) Were the valuation methodologies appropriate and detailed? (iii) Was [the presentation] logical and did the facts support the recommendation? (iv) Were they able to answer the questions effectively and with confidence?

I argue that higher number of points received for the criteria above signify higher company valuation skills. Hence, if there is a difference in analysts' ability (in terms of aptitude or experience with analysing), higher accuracy for the winners should be observed.

3. Literature Review and Hypotheses Development

3.1 Earnings forecasts, target prices and investment recommendations

Equity analysts produce reports including forecasted future cash flows, based on them estimate future stock prices (so-called *target prices*) and finally, issuing investment recommendations. Researchers differ in which of the three metrics they use to their hypotheses regarding bias and accuracy in equity research. As Bradshaw (2011) argues, the majority of literature is concerned with earnings forecast accuracy and bias (Lang and Lundholm 1996; Hope 2003; Von Koch, Nilsson, and Collin 2015; Hovakimian and Saenyasiri 2014; Beckers, Michael Steliaros, and Alexander Thomson 2004). That might be surprising, considering that "target prices provide market participants with analysts' most concise and explicit statement on the magnitude

[5] CFA Challenge has 3 round - local, regional and global. I am using only reports of the teams which proceeded to regional round or above to secure a desired standard of analyses.

of the firm's expected value" (Brav and Lehavy 2003) and the observation that investment recommendations represent a crucial primary source of information for investors (Arun, Shankaran, and Jayadev 2016).

Bradshaw (2011) offers a reasoning for the disparity "whereas large samples of machine-readable earnings forecast data have been available since the early 1970s, ... for recommendations in 1992 and for target prices in 1996". Since the earnings forecast data are available much longer, the majority of papers as well as most methodological approaches are concerned with earnings forecasts. Another explanation might be the straightforwardness of evaluating earnings forecasts. Since there is no doubt about the meaning of earnings forecasts, they are only to be compared with actual earnings. Interpretation of and analysing target prices is much more puzzling. Without a doubt, they should be compared with observed market prices. But at what point in time should the market price be compared? Conventional research compares target prices with actual stock prices at the end of the forecast horizon; Bonini et al. (2010) argue "a target price is generally assumed to be a prediction that is realized within a specific period, not necessarily at the end of that period" and study target price bias around the day when the maximum/minimum price during the horizon is reached.

An investment recommendation is a summary of an equity report in one word and sends a positive, neutral or negative message to investors. The most common notation used to express analysts' opinions is "strong buy", "buy", "hold", "sell" and "strong sell". However, some analysts use terms as "overweight", "over-perform", "neutral" and others[6]. However, it is not usually problematic to understand the language of particular analysts, hence as we can see in the literature (Arun et al. 2016; Womack 1996), researchers usually translate recommendations to three-point scale: "buy", "hold" and "sell".

[6] Accumulate, outperformer, invest, underweight, underperformer, book profit (Arun et al. 2016).

To demonstrate the low amount of literature on target prices, I performed a simple test, inspired by (Bradshaw 2011). Below I report the number of results found on scholar.google.com with the respective words in the title.

earnings+forecast	831	results
analyst+earnings	457	results
analyst+target+price	17	results
target+price+forecast	5	results
analyst+earnings+target+price	1	result

Nonetheless, from the literature we know that analysts' earnings forecasts are an important input into valuation, hence for issuing target prices (Da et al. 2016). This work reacts to appeal of (Bradshaw 2011): "furthering our understanding of what analysts do and why they do it requires consideration of their portfolio of activities" and studies target prices and investment recommendations rather than earnings forecasts. Let me discuss what analysts want to communicate by their recommendations. Issuing a "buy" recommendation means that an analyst expects a particular stock to generate a superior return, usually, in the forthcoming 12 months (Bilinski, Lyssimachou, and Walker 2012). Issuing a "sell" recommendation then means the opposite; an analyst expects a particular stock to generate an inferior return.

3.2 On investment recommendation accuracy and bias

For the purpose of making the text of the thesis more understandable, let me define a ***stock that generated a superior return*** as a stock with positive alpha from asset pricing model and a ***stock that generated an inferior return*** correspondingly. Naturally, whether stocks generated a superior or inferior return is depending on the time horizon and asset pricing model chosen. We are using a time horizon of 300 trading days and daily return net of the risk-free rate, Capital Asset Pricing Model, Fama-French three-factor model and Carhart four-factor model. A stock either has generated a superior return (i.e., we observe positive alpha in applying an asset pricing model) or has not. I study whether stocks recommended by analysts to buy (sell) have (have not) generated superior returns[7]. Then let me define ***buy stocks*** as observations recommended to buy

[7] Observations with "hold" recommendation are excluded from this analysis as they are problematic to confront with realized returns. We could consider them as "correct" no matter what the actual returns are, but then, according to such an analysis, analysts who admit that they do not know which direction will the stock go would be considered as ultimately successful. Alternatively, we could choose an arbitrary value (e.g., 10%) and consider as correct the stocks that deviate in the range given by the value. Then stocks

and similarly ***sell stocks*** and ***hold stocks*** as observations recommended to sell and hold, respectively.

In order to robustly analyse investment recommendations, two approaches are used. First, I will use hit-ratio. Second, excess returns (i.e., alphas) conditional on investment recommendation will be analysed. Hit-ratio method (Arun et al. 2016) is mapping investment recommendations with a binary information whether a stock has or has not generated a superior return.

Observing returns on "buy stocks" and "sell stocks" allow us not only to find out what return we can generate by following the recommendations but also to test whether the returns of some specific stocks (in our case, those recommended by the winners of the competition) are significantly different. This approach is used, among others, by Fang and Yasuda (2014).

When evaluating analysts, we can examine two aspects: *accuracy* and *bias*. While the former is the absolute difference between predicted and observed quantity (in this work, mostly target price), the latter is concerned with optimism in analysts' predictions.

3.3 Optimistic bias in equity research

Issuing a "strong sell" recommendation is extremely rare and "sell" is still far less common than "buy" (Barber et al. 2006)[8]. There might be two effects causing this discrepancy: either there are more market-overperforming stocks than market-underperforming or analysts are too optimistic. The latter is called "the optimistic bias" phenomenon and is supported by extensive literature showing that analysts are too optimistic indeed in the United States (Cowen et al. 2006; Dreman and Berry 1995), in the United Kingdom (J. Capstaff et al. 2001; De Bondt and Forbes 1999), in Germany (Capstaff et al. 2001; Capstaff et al. 1998), in Belgium, France, Ireland, Netherlands, Spain, Switzerland (Capstaff et al. 2001). The phenomenon is called "the optimistic bias".

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with low volatility would be advantaged. Although their volatility could be taken into account, author of this work considers excluding "hold stocks" the most objective approach.

[8] The difference in frequency of buy and sell in even larger than between buy and strong buy or between sell and strong sell (Malmandier and Shanthikumar 2007).

With this literature support, a question arises: why are analysts too optimistic? Bradshaw (2011) reviews prior research by stating six reasons for the optimistic bias. Five of them represent various kinds of conflict of interest, the sixth one is analysts' behavioural bias; I expanded on it by adding informational asymmetry as the seventh reason. In the following paragraphs, let me thoroughly discuss the why CFA Challenge participants do not face any of the conflicts of interest, which will allow me to discriminate this group of reasons against the remaining two.

The first conflict of interest influences analysts who working within a firm also providing investment banking services. Sell-side analysts may then be motivated to issue recommendations which can potentially generate investment banking fees. This is, in particular, relevant, considering sell-side research is usually a cost, while investment banking is highly lucrative (Bradshaw 2011). As CFA Challenge participants are students, they are not connected to investment banking business. Moreover, the impact of their recommendations is assumed not to be high enough to influence an interest in acquiring a particular company, they do not face this conflict of interest. Therefore, analysts in this case do not face this first conflict of interest.

The second conflict of interest follows from the fact that analysts need information for their work. Hence they build relationships with management of the companies in order to secure a stream of information. To keep the relationship, issued recommendations should be in favour of the management. High stock price returns are favourable for the management since poor stock performance is associated with more probable top management change (Warner et al. 1988). Carrying out precise analysis and making management satisfied can be in contradiction, some speak about "analysts multi-tasking" (Francis and Philbrick 1993). Even though teams are allowed to contact the analysed companies to obtain additional data (as discussed in the Section on CFA Research Challenge), they have no motivation for being overly optimistic and for currying favour with management, because their ultimate goal is winning the competition. The probability of winning the competition is not affected by optimism in their reports, since, the analysed companies cannot influence the assessment. A game theorist would call the situation a non-repeated game.

The third conflict of interest concerns particularly brokerage house analysts' and results from incentives for trading; analysts working for brokerage houses are even more optimistic than those at investment banks (Cowen et al. 2006). Bradshaw (2011)

explains "it is easier to convince an investor to buy a stock that they do not own rather than convincing them to sell a stock they must already own". Although Bradshaw (2011) does not consider the possibility of short-selling, I argue that investors are more likely to follow a buy recommendation for psychological and economic reasons - short-selling is risky (Engelberg et al. 2018). Students have no trade generation incentives and it would be unreasonable to believe that brokerage firms compensate them for issuing positive recommendations.

The following three reasons are less common in the literature than those already mentioned, possibly due to the fact that their examination is more problematic. The fourth reason is keeping relationships with institutional investors, who, trade based on the recommendations. Selling acquired securities early after the opening of the position due a downgraded recommendation is viewed unfavourably (Bradshaw 2011). Students do not build relationships with institutional investors, hence do not face this conflict of interest.

The fifth reason is that companies with no prior analyst coverage hire analysts to produce a research on their own company. This conflict of interest is very narrow and certainly not the case of CFA Challenge, where companies to be analysed are designated by CFA Institute and students are not in any way motivated to work on a particular company rather than any other.

As each of the five previous reasons represent some kind of conflict of interest, we can, for the purpose of this study merge them together. The hypothesis that these reasons altogether are responsible for the optimistic bias in equity research will be for the purpose of this work called the ***conflict of interest hypothesis.***

The last reason for optimistic bias Bradshaw (2011) lists is "the behavioural bias inherent in the analysis of securities" and the development of an affinity to a firm causing analysts not to be able to see the company objectively. As the behavioural bias is individual and does not result from any externality, I expect students to face it as well as professional analysts do.

I extend the list of reasons for optimistic bias by information asymmetry present between company's management and the public (Healy and Palepu 2001). Analysts work with information provided by the companies they analyse. The companies are motivated to report and stress positive information while being careful with disclosing

the threats they face. This imbalance is also expected to influence the judgement of both professionals and students.

The last two reasons form a belief that optimistic bias is caused by the overly optimistic perception of the company and inability to reveal negative characteristics and potential risks of the companies. In this work, we will call this belief the ***pure optimism hypothesis***.

To summarize, there are conflicts of interests which are expected to be faced by professional analysts only and pure optimism which we expect to by faced by both professionals and students. Studying bias on professional analysts does not allow for differentiation between our two hypotheses. In the case of this study, by using the sample of non-professional analysts who do not face the conflicts of interest, which are commonly associated with optimistic bias, I am able to discriminate between the ***conflict of interest hypothesis*** and the ***pure optimism hypothesis***.

I am not aware of any paper working with a sample of analysts who do not face any conflict of interest, hence this work offers a unique opportunity to test the ***pure optimism hypothesis***. I hypothesize that whole optimistic bias cannot be explained by the ***conflict of interest hypothesis***, but that optimistic perception of companies biases the recommendations as well. Let me formulate a hypothesis stating that there is an optimistic bias in the sample.

Hypothesis 1: Target prices reported in CFA Challenge equity reports are significantly higher than later observed market prices.

3.4 What drives the differences in analysts' accuracy?

We know that there is a value in equity research (Womack 1996) and Sinha et al. (1997) provide results suggesting that there are differences among analysts. What researchers are not sure about, is whether the differences are caused by differences in company valuation abilities or by one of the alternative reasons: higher influence on the market or closer relationship with companies. Reacting to a traditional problem in, especially, social sciences research, unobservability of ability, researchers are in search of reliable proxy. Common proxies are experience and appearance on All-American Research Team list; the latter has been discussed in Introduction.

Clement (1999), Jacob et al. (1999), Mikhail et al. (1997) use experience as a proxy for ability in equity research context. Clement (1999) measures ability as experience and finds no significant effect of experience on accuracy, Jacob et al. (1999) and Mikhail et al. (1997) document positive effect only of firm-specific experience. Jacob et al. (1999) then find no effect after experience with specific companies is accounted for and Mikhail et al. (1997) do not address the issue of solely general experience (i.e., after the firm-specific experience is accounted for) due to a high correlation between the two variables. Using experience as a proxy for ability rely on assumptions that analysts' skills are increasing with experience[9].

All-American Research Team, annually-issued list of analysts identified as exceptional in a survey among institutional investors and money management firms in the U.S., Europe and Asia (Institutional Investor 2017) conducted by *Institutional Investor* magazine might be a good proxy for ability. Fang and Yasuda (2014) show that stocks recommended to buy issued by All-American analysts perform significantly better in 30 days after the issue day but do not perform better in the 11 months after. However, some say it is rather a proxy for reputation (Stickel 1992). Stickel (1992) uses an appearance on All-American Research Team list as a proxy for reputation and shows that All-American analysts provide more accurate forecasts, but also that they have a greater impact on stock prices. The accuracy of the forecast is important to the analysts themselves since analysts with lower accuracy are more likely to be replaced (Mikhail et al. 1999), although the effect of accuracy on the probability of keeping a job is lower than the effect of optimism (Hong and Kubik 2003).

Several factors other than ability have been shown to drive the differences in accuracy. Clement (1999) finds the number of companies an analyst follow is negatively associated with the accuracy of the analyst's forecasts. Another factor is the extent to which analysts influence the market; we know that recommendations issued by analysts influence the market.

In this part of the study, we are asking what drives the differences in accuracy among analysts. From what has been discussed above, we know that firm-specific

[9] This is related to general experience. To distinquish from firm-specific experience or, for example, industry experience, which is also documented to have a positive effect on accuracy (Mikhail et al. 1997). Similarly as with firm-specific experience, (Mikhail et al. 1997) where not able to distinguish between firm-specfic and industry experience.

experience increases accuracy and but we have no clear evidence that firm-non-specific and industry-non-specific experience increases accuracy. Literature suggests that All-American analysts are more accurate, but what is unclear is the extent to which analyst's ability is important for the probability of being selected to the All-American list. Let us call the belief that the differences in accuracy can be to some extent explained by differences in ability as ***ability hypothesis***. On the contrary, the belief that ability is irrelevant for accuracy in equity research will be called ***ability irrelevance hypothesis***. If the latter hypothesis holds, differences in accuracy are fully explained by the number of analysed companies, market influence and possibly also by other factors, which are still to be discovered. I argue that CFA Challenge participants do not have any market influence and they all have to analyse only one company hence the above-mentioned factors do not influence the probability of becoming a winner of CFA Challenge. That is why success in CFA Challenge is in this study used as a proxy for ability. Let me discuss the rationale more in detail.

CFA Research Challenge participants' recommendations do not affect the market for the following reasons. Firstly, they are made public no sooner than several months after the report was produced. Secondly, professional analysts' reports are perceived far more serious and making investment decision based on reports from students is not common.

In order to discriminate between ***ability hypothesis*** and ***ability irrelevance hypothesis***, the following three hypotheses were formulated. The hypotheses differ in how accuracy is measured.

The first way accuracy is measured is hit-ratio (Arun et al. 2016), method mapping investment recommendations with a binary information whether a stock has or has not generated a superior return. A buy recommendation is a hit if the stock has generated a superior return and a sell stock is a hit if the stock has not generated a superior return. A more skilled analyst should be able to forecast future course of a stock price with a higher probability of success than a less skilled analyst. That is the rationale behind the following hypothesis.

Hypothesis 2: The winning teams in CFA Challenge have higher hit-ratio.

A more skilled analyst should be more successful in identifying stocks that are going to generate very high returns and stocks that are going to generate very low

(even negative) returns. To test that, average returns on "buy stocks" and "sell stocks" were observed, which allows me not only to find out what return can be generated by following the recommendations but also to test whether the returns of some specific stocks (in our case, those recommended by the winners of the competition) are significantly different. This approach is used, among others, by Fang and Yasuda (2014)

Hypothesis 3: Stocks recommended to buy by the winning teams generate higher returns than the other buy stocks and stocks recommended to sell by the winning teams generate lower returns than the other sell stocks.

The previous two hypotheses were formed to test, in different ways, the accuracy of investment recommendations. The third employed approach is concerned with target price accuracy. I test whether target prices issued by winners are closer to later observed stock prices.

Hypothesis 4: Target prices reported in the winners' equity reports are closer to late observed market prices than target prices reported in equity reports of the other teams are.

4. Research Design

4.1 Data Sample

The data sample includes reports of all teams competing in CFA Research Challenge during years 2012-2016 which advanced to at least regional level. From written equity reports, I manually extracted relevant information: Date, Name of the company, Ticker, Investment Recommendation, Target Price and Actual Price. Financial and market data were obtained from Thomson Reuters Eikon, and factor data used to apply asset pricing models were downloaded from Kenneth French's website. I have been working with daily returns, although monthly returns are commonly used by practitioners or by researchers focusing on explaining the cross-section of expected returns (Fama and French 2014), due to a relatively short horizon of the analysis. Since investment horizon of analysts' recommendations is usually 12 months (Bilinski et al. 2012), using daily returns is not unusual in the field (see for example Fang

and Yasuda 2014). Moreover, daily return yield greater precision of estimates than weekly or monthly returns (Daves et al. 2000)[10].

I have calculated target price bias[11] 12 months since the issue date to identify outliers. I used 12 months as a time horizon for identifying outliers as it is the usual horizon in equity research (Bilinski et al. 2012). Then I have excluded 8 outliers, stocks with target price bias further than three standard deviations from the mean target price bias (i.e., with absolute z-score higher than three) because they did not correspond to the distribution of the rest of the sample and may be a result of an error.

The following table shows the number of reports (and recommendations) with respect to season and region.

Table 1 - Sample of Equity Reports

Year\ Region	Americas	Asia Pacific	EMEA	**Total**
2012	42	17	22	**81**
2013	44	19	26	**89**
2014	48	19	28	**95**
2015	51	21	28	**100**
2016	50	21	33	**104**
Total	**235**	**97**	**137**	**469**

Source: Author's analysis of CFA Challenge equity reports.

Investment recommendations were divided into three groups: "buy", "sell", "hold". It might be tempting to use "strong buy" and "strong sell" as well to have a smoother scale, but there are reasons for not doing so. First of all, those two recommendations, with "strong sell" in particular, are far less common than the three in the middle (Malmandier and Shanthikumar 2007). Second, interpretation of those two might be puzzling. While with "buy" an analyst says "I expect this stock to generate superior return", rules for issuing "strong sell" and "strong buy" are neither obvious nor unified. Investment banks and brokerage companies have their own internal rules

[10] Daves et al. (2000) study effect of return interval (daily, weekly, two-weakly and monthly) on precision of beta estimates and show that daily returns yield most precise estimates. I am not aware of any paper studying effect of return interval on precision of alphas.

[11] Formula for target price bias is given below.

(usually in terms of implied return cut-off) based on which they issue strong buy and strong sell recommendations.

Most researchers (among others Von Koch et al. 2015; Fang and Yasuda 2014; Brown and Ngo Higgins 2001; Lin and McNichols 1998) collect data from Institutional Brokers' Estimate System (I/B/E/S), a database operated by Thomson Reuters, offering earnings forecast and stock recommendation data for more than 22 000 companies worldwide ('I/B/E/S Estimates' n.d.).

4.2 How to measure bias and accuracy

4.2.1 Measuring bias

For measuring bias in target prices, i.e., testing **Hypothesis 1**, we stick to a formula used, among others, by Bonini et al. (2010) and simply compare the target price for a particular company with a stock market price of a particular company at a particular point in time.

$$Target\ Price\ Bias_{it} = \frac{Target\ Price_i}{Market\ Price_{it}} - 1$$

A particular investment recommendation (*i*), number of trading days since the issue date (t), price of the i stock t trading days since the issue date (Market $Price_{it}$).

Although most researchers agree on the basic structure of the formula (fraction of target price over market price), they differ in what is the right point in time. Asquith et al. (2005) use market price 12 months from the issue date, on the very end of the time horizon. However, as Bonini et al. (2010) argue, that target price is not a forecast of what should the stock price be at the end of the forecasting period, but rather a price which is expected to be observed at any time during the forecasting period. Bradshaw et al. (2013) take the critique into account and check whether the target price has been met at any point in time during the time horizon. However, investors are not able to identify when a stock is at its maximum or minimum and we do not have a reason to believe that investors exit from their positions right at the end of the forecasting horizon. That being said, we should not limit our attention to one point in time, but rather study what is happening over the whole forecasting horizon. If I, for example, find that the bias is increasing with the number of days since the issue date, the results will of interest to investors who then can adjust their return expectation based on the expected horizon of holding a stock. In other words, the longer they plan

to hold a stock, the more should they subtract from target price to get an unbiased expectation of the stock price. To observe how arget price bias evolves over time, market prices were centred for each stock around the issue date[12] and target price bias was calculated on each of the 300 subsequent trading days[13] (i.e., I have applied the target price bias formula 469*300 times). Then I take the average on each of the 300 trading days, calculate standard deviation on each of the 300 trading days and derive t-statistics on each of the 300 trading days. Further motivation for this approach is the desire for robust results. I am using trading days rather than calendar days because of the fact that trading days are not unified around the globe, hence matching trading days with calendar days would not be possible without adjustments.

To avoid confusion, let me stress that what I call 'target price bias' during the first days after the issue date is not what we understand as bias and what we focus on. To give an example, if a buy recommendation is issued, then naturally target price is immediately higher than market price - we certainly do not consider this as a bias. However, I use this approach since I consider relevant to show whether the market price is converging to target price or not.

4.2.2 Measuring accuracy

This subchapter aims at testing the remaining three hypotheses and is concerned with target price accuracy and investment recommendation accuracy. In this work, three approaches for measuring accuracy are applied; two are concerned with investment recommendations and one with target prices. To test **Hypothesis 2** so-called hit-ratio is used. This approach studies investment recommendation rather than target prices. I mark a stock recommendation as *a hit* either if a recommendation is to buy and the stock has over-performed the return given by a model or if a recommendation is to sell and the stock has underperformed the return given by a model, as is represented in the following simple table. Hold stocks are excluded from this analysis. Hit-ratio is then the share of hits in the sample.

[12] Issue date is the date on which particular report was issued. Issue date was obtained from equity reports and varies among countries (and among seasons, of course).

[13] Daily closing price is used to represent a market price on a particular day.

	$\alpha > 0$	$\alpha \leq 0$
Buy	1	0
Sell	0	1

α represents intercept from regression on daily stock returns.

For the robustness of the results, I employ four approaches to estimating alphas, namely, geometric average of daily stock return, Capital Asset Pricing Model, Fama French three-factor model and Carhart four-factor model. In the first approach, alpha is the calculated daily stock return. Next, I use the Capital Asset Pricing Model (Sharpe 1964; John Lintner 1965; Black 1972), incorporating the risk effect into return calculations in a way that it favours the stocks with lower volatility (risk). It is applied by running a regression of stock returns on market returns, both net of risk-free rate (Hope 2003).

The Capital Asset Pricing Model (CAPM) is estimated by the following equation (Sharpe 1964):

$$R_t^i = \alpha^i + \beta R_t^m + \varepsilon^i$$

Daily return on stock i during period t (R_t^i). represents intercept from regression (α^i), daily market return during period t (R_t^m).

Fama French three-factor model (Fama and French 1992) enriches CAPM by the effects of company size (SMB) and book-to-market (HML) ratio. SMB factor comes into regression as an additional variable representing the difference between returns on a diversified portfolio of the stocks with small and high market capitalization in the respective period. Similarly, HML represents difference between returns on a diversified portfolio of the stocks with high and with low book-to-market value ratio. SMB, HML effects are region-specific, as well as market returns are (Fama and French 1992). Definition of stocks with small or big and market capitalization or high and low book-to-market ratio is not strictly given, however, Kenneth French uses 10th and 90th percentile of the sample as a threshold for size and 30th and 70th percentile for the book-to-market ratio. I am using factor data from the website of one of the authors of the 3-Factor model, Kenneth French[14] and therefore stick to this definition.

[14] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/contact_Information.html

Fama French three-factor model is estimated by the following equation (Fama and French 1992):

$$R_t^i = \alpha^i + \beta_1 R_t^m + \beta_2 SMB + \beta_3 HML + \varepsilon^i$$

Daily return on stock i during period t (R_t^i). represents intercept from regression (α^i), daily market return during period t (R_t^m), size factor (SMB), book-to-market value factor (HML).

Carhart four-factor model (Carhart 1997) extends Fama French three-factor model by a momentum factor, which is a tendency of rising prices to rise further and vice versa (Carhart 1997). Often, cumulative return for twelve months with a one-month lag is used. Historical values for momentum effect can be found on Kenneth French's web as well.

Carhart four-factor model is estimated by the following equation (Carhart 1997):

$$R_t^i = \alpha^i + \beta_1 R_t^m + \beta_2 SMB + \beta_3 HML + \beta_4 MOM + \varepsilon^i$$

Daily return on stock i during period t (R_t^i). represents intercept from regression (α^i), daily market return during period t (R_t^m), size factor (SMB), book-to-market value factor (HML), market momentum factor (MOM).

Market momentum is not only one of the factors in Carhart four-factor model (Carhart 1997) but is also used as a control variable in the model below[15]. Let me explain why this is not duplicate. Momentum in the Carhart's asset pricing model is included because it is one of the most important factors in explaining the cross-section of expected returns (Harvey et al. 2016). Given the relevancy of momentum for explaining returns, Carhart's model is used in this study to estimate alphas (excess returns). On the contrary, momentum as a control variable in the model below is used, because market conditions are expected to influence the accuracy of target prices (Bonini et al. 2010). Specifically, analysts tend to overstate their predictions in upward markets (Bonini et al. 2010), hence negative sign is expected. That could be related to analysts' herding behaviour (Welch 2000).

[15] To avoid confusion, market momentum is marked MOM in Carhart's model and MM elsewhere.

The following model is employed to test whether being a winner has a significant impact on hit-ratio.

$$Hit_i = \gamma_0 + \gamma_1 W_i + \gamma_2 B_i + \gamma_3 W_i{*}B_i + MM_i + \epsilon_i$$

Dummy variable equal to 1 if stock i is a hit (Hit_i), dummy variable equal one if the stock is a buy stock (B), dummy variable equal one if the team which produced the report won is a winner (W_i), 6-months from the issue date market index momentum (MM_i).

Hypothesis 3 is assessed by using the alphas obtained with the approach described above and then is tested whether winners of the competition produce recommendations generating higher returns than less successful teams. Specifically, I test whether buy stocks recommended by the winners have higher alphas than the other buy stocks and whether sell stocks recommended by the winners have lower alphas then the other sell stocks. We are estimating the following equation separately for buy stocks and sell stocks.

$$\alpha_i = \gamma_0 + \gamma_1 W_i + \epsilon_i$$

α is taken from the previous approach, W is a dummy variable equal one if the team which produced the report won is a winning team.

The way **Hypothesis 4** is tested is fairly similar to how we are measuring target price bias. The difference is that only the absolute deviation of market price from target price is relevant to us, while we are not interested in the direction of the deviation. I then take the opposite number of the absolute deviation, so that the statistic is easily interpretable for us; the higher the statistic is the higher the precision.

$$Target\ Price\ Accuracy_{it} = -\left|\frac{Target\ Price_i}{Market\ Price_{it}} - 1\right|$$

A particular investment recommendation (i), number of trading days since the issue date (t), price of the i stock t trading days since the issue date (Market $Price_{it}$).

The debate on which point in time to use to measure the accuracy would go in a similar fashion as in the case of target price bias; I study the accuracy on 300 trading days consecutive after the issue date.

5. Results and Discussion

5.1 Descriptive Statistics

In Table 2, I report summary of data extracted data from the equity reports. Implied returns for buy/hold/sell have expected signs. The share of "buy" recommendations is 59% and buy-to-sell ratio is 2.86:1. This seems to be consistent with our ***conflict of interest hypothesis***, since the recommendations are less optimistic, compared to data in prior research. Womack (1996) finds the buy-to-sell ratio 7:1, Malmandier and Shanthikumar (2007) more than 12:1 and Arun et al. (2016) work with more than 75% of "buy" recommendations. However, as the process of assigning companies to analysts if very likely different in CFA Challenge and in the financial industry, we should not assume that the share of companies which indeed generate a superior return is the same. It might be the case that professional analysts are looking particularly for firms they expect to grow - that would explain higher buy-to-sell ratio for professional analysts. Therefore, we need to be careful with drawing any conclusions from those results as they might be easily misinterpreted.

Table 2 – Descriptive Statistics

Recommendation	Share on all recommendations	N	Average Implied Return	Median Implied Return
Buy	59.49%	279	25.19%	21.69%
Hold	19.83%	93	3.68%	4.10%
Sell	20.68%	97	-16.36%	-16.18%
Total	**100.00%**	**469**	**12.33%**	**14.73%**

Number of observations (*N*), average upside given by target price and market price on the issue day (*Average implied return*), median upside given by target price and market price on the issue day (*Median implied return*), stocks recommended to buy (*Buy*), stocks recommended to hold (*Hold*), stocks recommended to sell (*Sell*).

In Table 3 are reported daily alphas (i.e., daily excess returns) with respect to investment recommendation. Since I use dummy independent variables for "hold" and "sell", stocks recommended to buy are the base group. The key result to be read in Table 3 is that no matter which asset pricing model is used, buy stocks always have significantly positive alphas. Both hold stocks and sell stocks generate significantly lower returns.

Hold stocks alphas are significantly different from zero at 10% level only under CAPM, under the other three methods are not significantly different from zero. Under no asset pricing method are sell stocks alphas significantly different from zero[16].

Table 3 - Investment Recommendation and Daily Alphas

	Daily return	CAPM alpha	3F alpha	Carhart alpha
Constant	0.358***	0.484***	0.494***	0.503***
	(0.079)	(0.075)	(0.076)	(0.077)
Hold stock	-0.307*	-0.271*	-0.291*	-0.307**
	(0.158)	(0.150)	(0.151)	(0.153)
Sell stock	-0.395**	-0.342**	-0.356**	-0.354**
	(0.156)	(0.148)	(0.149)	(0.151)
Observations	469	469	469	469
R2	0.017	0.015	0.016	0.016
Adjusted R2	0.013	0.01	0.012	0.012
Residual Std. Error (df = 466)	1.321	1.254	1.267	1.281
F Statistic (df = 2; 466)	4.115**	3.474**	3.770**	3.811**

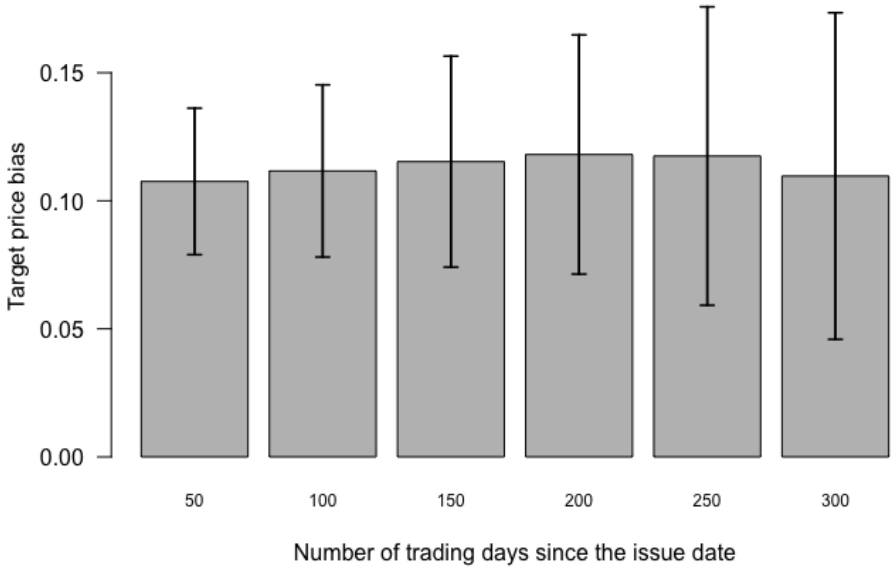
Daily excess return (i.e., net of risk-free rate) multiplied by 1000 (*Daily return*), daily alpha from CAPM multiplied by 1000 (*CAPM alpha*), daily alpha from Fama French three-factor model multiplied by 1000 (*3F aplha*), daily alpha from Carhart four-factor model multiplied by 1000 (*Carhart alpha*), stock recommended to sell (*Sell stock*), stock recommended to hold (*Hold stock*). ***, **, * indicate statistical significance at 1%, 5%, and 10% level respectively.

5.2 Is bias present?

In Figure 1 average target price bias is reported with its 99% confidence level on a selected number of days after the issue date. Bias is significantly positive 50, 100, 150, 200, 250 and 300 trading days after the issuance of target price. Further discussion on the bias follows.

[16] These results are not reported.

Figure 1 - Average target price bias on selected dates and its 99% confidence interval



Average of target price bias (calculated using the formula given in Methodology) of all stocks in the analysis on a given day (Target price bias), arrows show 99% confidence interval.

As described in Methodology, target price bias was calculated for each stock in each of the 300 trading days after the issue date (i.e., matrix 300 x number of stocks). We want to understand how the bias evolves over time; do market prices converge to target prices or is the bias increasing with the number of days from the issue date? That is what we see in Figure 2, which shows average bias and its significance. As explained in Methodology, I have centred the stock prices around their respective issue dates (day 0 in Figure 2 is the issue date for every stock) and calculated bias for each stock on each of the 300 trading days following the issue date. Average target price bias (the black, upper line in Figure 2) fluctuates between 0.10 and 0.14, which can be interpreted as a stable optimistic bias. In other words, stock prices do not get closer to the target prices as we move from the issue date towards the end of the investment time horizon and the bias remains positive over the whole studied period.

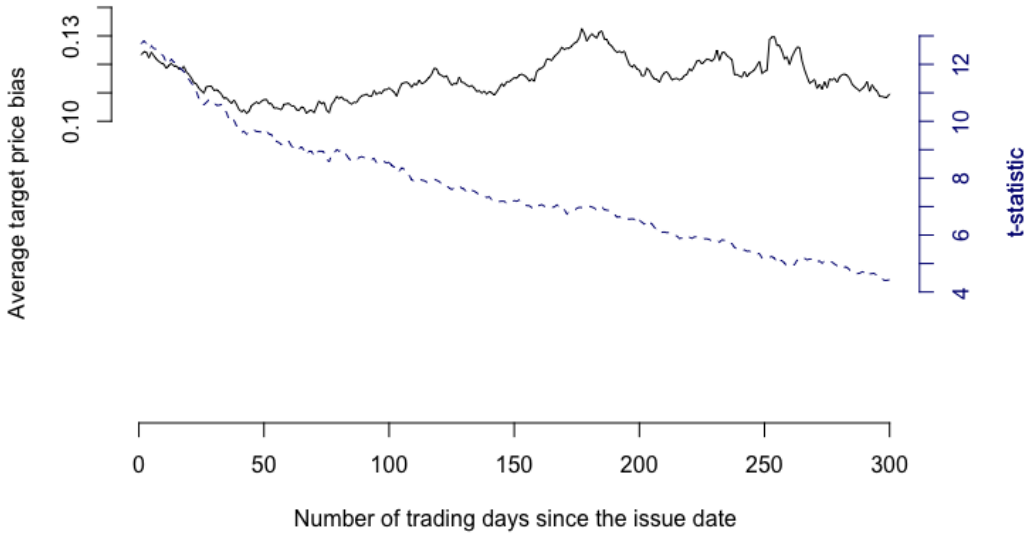
The variance of the bias is over the 300 trading days increasing; as a result, t-statistic (the lower, dashed blue line in Figure 2) is. The increasing variance of the bias

is not surprising, given the nature of stock price behaviour. New pieces of information are becoming public, the market reacts to those information and individual stocks are growing or falling. Having said that, we understand why variance of target price bias is increasing the further we get from the issue date. As a result, t-statistic decreases from 13 to 4.5 over the period we study.

However, the t-statistic is, over the whole period, large enough to say that target price bias is significantly positive even at 0.1% level on each of the 300 days following the issue date. This is a strong evidence in favour of the ***pure optimism hypothesis*** and thus in favour of **Hypothesis 1**. This result is important for investors and regulatory bodies of the financial industry because it shows that target prices are optimistically biased even in a conflict-of-interest-free sample of analysts.

Let me stress that target price bias which we observe in first days after the issue date is not what we understand as a bias. Target price bias is a deviation of market price from target price and that is naturally different from zero when the target price is issued. What is striking on the figure is that stock prices are not converging to target prices and that the bias is significant throughout the whole investment horizon.

Figure 2 - Average target price bias with respect to the number of days since the issue date



Average of target price bias (calculated using the formula given in Methodology) of all stocks in the analysis on a given day (*Average target price bias*), t-statistic of the null hypothesis that average target price bias is equal to zero on a given day (*t-statistic*).

5.3 Do winners have higher hit-ratio?

Let me remind that a stock recommendation as *a hit* either if a recommendation is to buy and the stock has over-performed the return given by a model or if a recommendation is to sell and the stock has underperformed the return given by a model. Hold stocks are excluded from the analysis as they send neither positive nor negative signal about the company in question. I have tested if the winners have higher hit-ratio, i.e., if they are more often correct about the future course of the stock price. Table 4 shows whether finalists and buy stocks have different hit-ratio from non-finalists and sell stocks.

For all asset pricing models used, buy stocks have higher hit-ratio. More importantly, although for CAPM, Fama French three-factor model and Carhart model hit-ratios are higher for both buy and sell stocks in case of winners, the differences are not significant. Market momentum has, as expected, negative sign. When drawing conclusions from the results, greater importance is given to CAPM,

Fama French and Carhart models, since daily return does not adjust returns for risk, which most investors want to do. The results are inconsistent with **Hypothesis 2**, hence consistent with ***ability irrelevance hypothesis***. This result corresponds to Clement (1999), who also found insignificantly higher accuracy for analysts with higher ability, which he surrogated by experience.

Table 4 – Finalists and Hit-ratio

	Daily return hit	**CAPM hit**	**3F hit**	**Carhart hit**
Winning team	-0.046	0.039	0.065	0.231
	(0.221)	(0.214)	(0.212)	(0.211)
Buy stock	0.203***	0.322***	0.347***	0.333***
	(0.058)	(0.056)	(0.055)	(0.055)
Winning team*Buy stock	0.053	-0.029	-0.013	-0.187
	(0.246)	(0.237)	(0.235)	(0.234)
Market momentum	-0.045	-0.061	-0.068	-0.047
	(0.044)	(0.043)	(0.042)	(0.042)
Constant	0.473***	0.398***	0.376***	0.398***
	(0.050)	(0.048)	(0.047)	(0.047)
Observations	376	376	376	376
R2	0.038	0.091	0.108	0.095
Adjusted R2	0.028	0.081	0.099	0.086
Residual Std. Error (df = 371)	0.479	0.462	0.458	0.457
F Statistic (df = 4; 371)	3.664***	9.280***	11.246***	9.776***

Hit-ratio where daily excess return (i.e., net of risk-free rate) is used as alpha (*Daily return hit*), hit-ratio where daily alpha from CAPM is used as alpha (*CAPM hit*), hit-ratio where daily alpha from Fama French three-factor model is used as alpha (*3F hit*), hit-ratio where daily alpha from Carhart four-factor model is used as alpha (*Carhart hit*), stock recommended to buy (*Buy stock*), market momentum over the previous 6 months (*Market momentum*), binary variable equal to 1 if the team is one of the winners. ***, **, * indicate statistical significance at 1%, 5%, and 10% level respectively.

5.4 Winners' recommendations and returns

In the following, I examine whether winners' stock recommendations generate higher returns than the other recommendations. To understand that this is not a duplicate of the preceding metric, consider the following case. Possibly, the winning teams are not more often correct, but they are more successful in identifying the stocks that are going to generate very high (or very low) returns. In that situation, Table 5 would show higher returns in case of buy recommendations (and lower returns in case of sell

recommendations) for winning teams. However, as can be seen in Table 5, the returns on the stock recommended by the winning teams do not yield significantly different results; therefore, the result is inconsistent with **Hypothesis 3**, hence consistent with ***ability irrelevance hypothesis*** and corresponding to Clement (1999).

Table 5 – Finalists and alphas

	Winners (1)	**Non-Winners** (2)	**Difference** (1) - (2)
Panel A: Buy recommendations			
Daily return	0.589	0.339	0.25 (0.232)
CAPM alpha	0.684	0.467	0.217 (0.228)
3F alpha	0.699	0.476	0.223 (0.229)
Carhart alpha	0.717	0.484	0.233 (0.232)
Panel B: Buy recommendations			
Daily return	-0.069	-0.034	-0.035 (0.596)
CAPM alpha	-0.023	0.151	-0.174 (0.52)
3F alpha	-0.058	0.148	-0.206 (0.527)
Carhart alpha	-0.103	0.162	-0.265 (0.521)

Daily excess return (i.e., net of risk-free rate) multiplied by 1000 (Daily return), daily alpha from CAPM multiplied by 1000 (CAPM alpha), daily alpha from Fama French three-factor model multiplied by 1000 (3F alpha), daily alpha from Carhart four-factor model multiplied by 1000 (Carhart alpha), "sell" investment recommendation (Sell stock), "hold" investment recommendation (Hold stock). ***, **, * indicate statistical significance at 1%, 5%, and 10% level respectively.

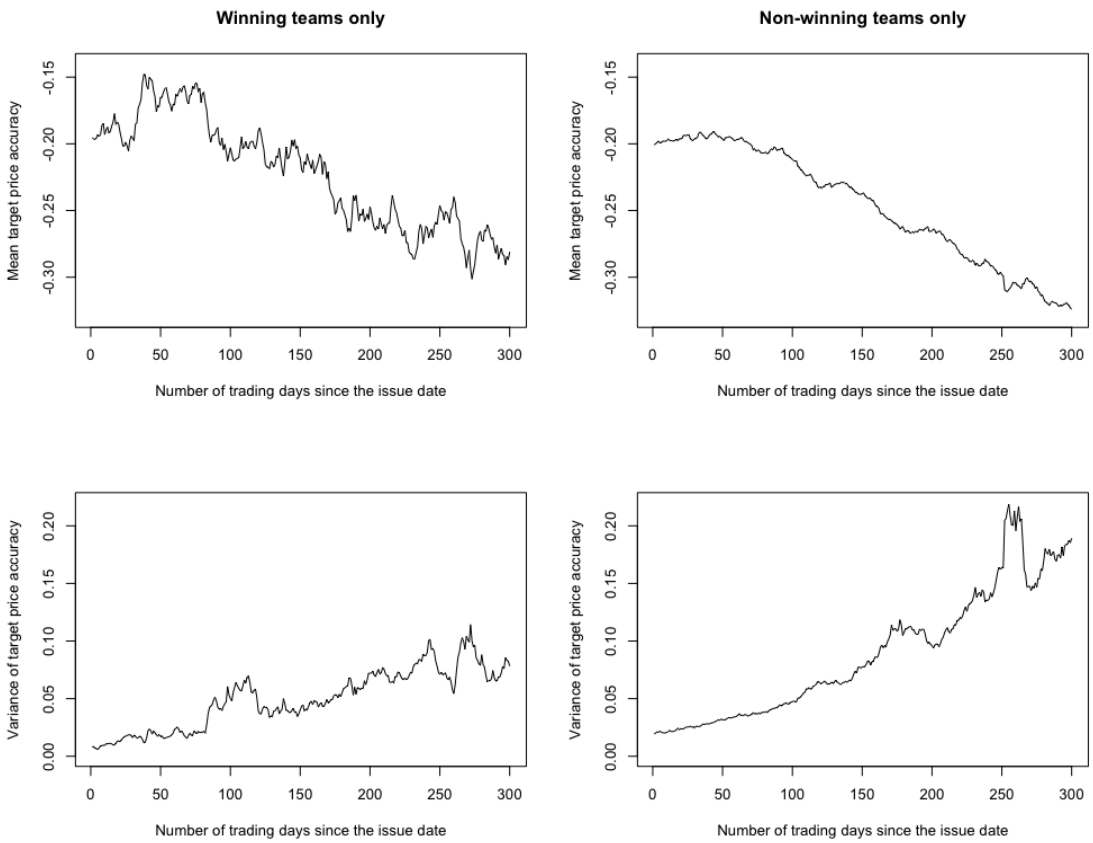
5.5 Do winners issue more accurate target prices?

The next question examined is whether higher target price accuracy is observed for the winning teams. Similarly, as for target price bias, I study the 300 trading days following the report issuance. I start by showing (Figure 3) how mean target price develops separately for the winning teams and non-winning teams and how the variance of target price bias in each of the groups evolves over the 300 trading days.

Both plots are smoother in case of non-winning teams, which is the result of having more observations for non-winning teams. For both groups, the mean target price accuracy is decreasing and its variance is increasing as we go further

from the issue date. In first 100 days, the winning teams are slightly more accurate but after that the groups get closer to each other and, at the very end of the observed period, winners become more accurate again. The variance of target price accuracy is increasing over time in both groups, similarly as in the case of target price bias.

Figure 3 - Target price accuracy (mean and variance), separately for winning and non-winning teams



Average of target price accuracy (calculated using the formula given in Methodology) of all stocks in the analysis, either belonging to group of winning or non-winning teams on a given day (*Mean target price accuracy*), variance of target price accuracy on a given day (calculated using the formula given in Methodology) of all stocks in the analysis, either belonging to group of winning or non-winning teams (*Variance of target price accuracy*).

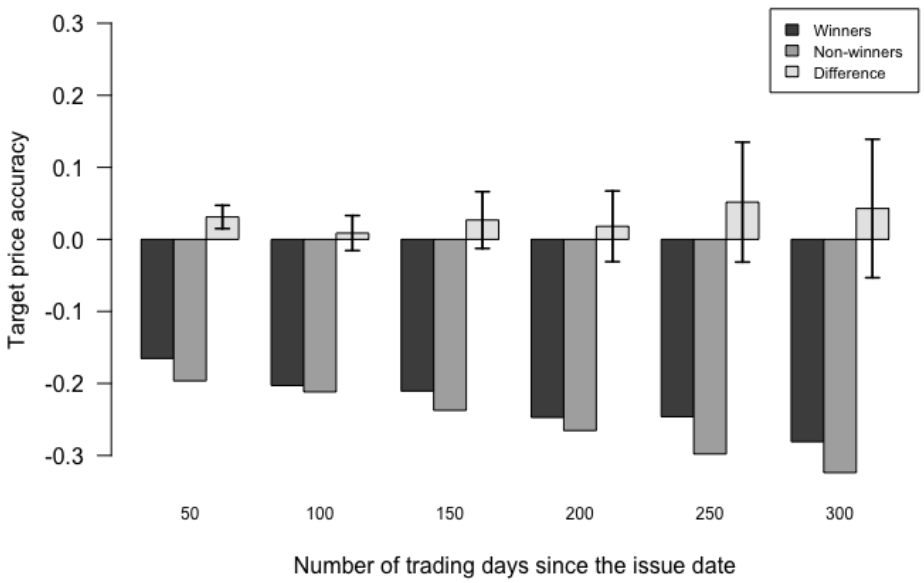
In Figure 4, target price accuracy separately for winners and non-winners on selected dates is reported, together with difference between the two and 95% confidence interval of the difference. 50 trading days after the target price issuance are winners significantly more accurate, but in drawing conclusion, more weight is given to observations later after the issue date. 50 trading days is still early

stage of investment time horizon, which is usually 12 months long. For the remaining selected dates, insignificantly higher accuracy for winners is observed.

I also report the difference between target price accuracy for the winning and non-winning teams and significance of the difference develop over 300 trading days since the issue date. The metric is highly volatile and no trend of accuracy is found as is illustrated in Appendix 1.

Although periods, where winning teams are significantly more accurate, can be found (please make a reference to Appendix 1), I do not consider the data to be showing convincing evidence of the higher accuracy of the winning teams. Being inconsistent with **Hypothesis 4**, we have another result consistent with ***ability irrelevance hypothesis*** and corresponding to Clement (1999).

Figure 4 - Target price accuracy on selected dates for winners and non-winners with 95% confidence interval of the difference



Mean target price accuracy of the winning teams minus mean target price accuracy of the non-winning teams (calculated using the formula given in Methodology) of all stocks in the analysis on a particular day (*Target price accuracy*), arrows show 95% confidence interval of the difference between mean target price accuracy for winners and non-winners.

All three approaches I have used to test whether differences in ability can explain differences in accuracy led to results consistent with ***ability irrelevance***

hypothesis, which leads me to conclude that ability is not a strong factor in explaining differences in accuracy. With that, I have contributed to the discussion on drivers of analysts' accuracy and supported the stream of literature using experience as a proxy for ability and showing that ability is not a strong predictor of analyst's accuracy, represented by Clement (1999) or Jacob et al. (1999). On the contrary, my results are in contradiction with Fang and Yasuda (2014), who use an appearance on All-American Research Team list as a proxy for ability and shows that All-American analysts are more accurate.

6. Conclusion

I have studied if there is a reason for optimistic bias in equity research even beyond conflicts of interest - the commonly referred reason for the bias and if analyst's ability is an important factor in explaining differences in accuracy among analysts. The former is important to investors and to regulators of the financial industry. The latter concerns investors, and researchers who use outcomes of equity reports as a proxy for capital market's expectation.

Prior literature identified several conflicts of interest faced by equity analysts. I have explained that CFA Challenge participants do not face any of the conflicts of interest and that allows me to test whether any other reason for optimistic bias in equity research exists and influences equity analysts'. I have shown that target prices in CFA Challenge are overly optimistic, even though the analysts do not face any of the conflicts of interests associated with the bias. That suggests the existence of a relevant reason for optimistic bias in equity research which is not related to conflict of interest - usually referred driver of the bias. In other words, my results suggest that optimistic bias cannot be fully explained by conflicts of interest.

The second part of the thesis is concerned with explaining differences in accuracy among analysts, specifically with ability as a factor explaining the differences. Given difficulties with measuring ability, there is a hunting for a reliable proxy. Prior research projects used analysts' experience or appearance on All-American Research Team list, identified in an annual survey among portfolio managers, as a proxy for ability. Prior research has not identified a significant increase in ability with non-firm-specific experience and has shown higher returns for All-American analysts. However, it is uncertain to what extent is the probability

of appearing on the list influenced by analyst's ability and how much by his or her relationships with institutional investors. This discrepancy motivates the search for another proxy for ability. I use success in CFA Challenge (being one of the three winners announced every season) as a proxy for ability. I have analysed returns of stocks recommended to buy/sell, hit-ratio of the recommendations and accuracy of target prices. All three approaches have shown higher accuracy for the winners, but the results are not statistically significant. Similarly as Clement (1999) who has also found insignificant higher accuracy for more skilled analysts while using their experience as a proxy for ability. These results are one piece of the puzzle and I consider the importance of ability for explaining differences in accuracy among analysts not fully understood yet. There is still a good deal of work to be done in the search for other proxies for ability or alternative ways of testing the effect of ability on accuracy in equity research.

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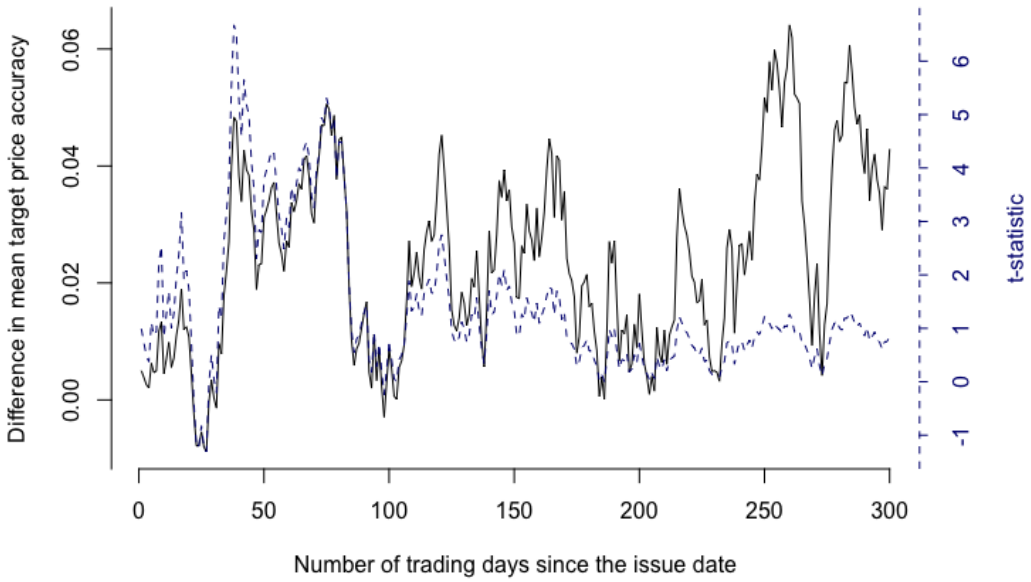
8. List of appendices

Appendix 1 - Figure 5 - Significance of the difference in target price accuracy between the winning and non-winning teams

9. Appendices

Appendix 1: Figure 5 -Significance of the difference in target price accuracy between the winning and non-winning teams



Mean target price accuracy of the winning teams minus mean target price accuracy of the non-winning teams (calculated using the formula given in Methodology) of all stocks in the analysis on a particular day (*Average target price bias*), t-statistic of null hypothesis that average target price bias is equal to zero (*t-statistic*).