Shooting Stars:

The Value of Ranked Analysts’ Recommendations

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Abstract

Financial analysts play a key role in collecting, processing and disseminating information for the stock market. Selecting the best analysts among thousands of analysts is an important task for investors that determines future investment profitability. Extensive research has been dedicated to finding the best analysts of the market based on various criteria for different clienteles. The state of the art approach in this process has developed into so-called Star Rankings with lists of top analysts who have previously outperformed their peers. How useful are such star rankings? Do the recommendations of stars have higher investment value than the recommendations of non-stars (i.e., recommendations of Stars “shoot” more precisely before and after selection)? Or do star rankings simply represent the past performance that will regress to the mean in the future (i.e., in reality, Shooting Stars are not stars and quickly disappear from the sky)?

The aim of this Ph.D. thesis is to empirically investigate the performance of sell-side analysts’ recommendations by focusing on a group of star analysts. This thesis comprises four papers that address two overarching questions. (1) Do star rankings capture any true skill, and, thus, can investors rely on the rankings? (Papers I and II) (2) How do market conditions impact star analysts? (Papers III and IV)

Paper I examines the profitability persistence of the investment recommendations from analysts who are listed in the four different star rankings of Institutional Investor magazine, StarMine’s “Top Earnings Estimators”, “Top Stock Pickers” and The Wall Street Journal and shows the predictive power of each evaluation methodology. By investigating the precision of the signals that the various methodologies use in determining who the stars are, the study distinguishes between the star-selection methodologies that capture short-term stock-picking profitability and the methodologies that emphasize the more persistent skills of star analysts. As a result, this study documents that there are star-selection methods that select analysts based on more enduring analyst skills, and, thus, the performance of these methods’ stars persists even after ranking announcements. The results
indicate that the choice of analyst ranking is economically important in making investment decisions.

**Paper II** investigates the structure of the portfolios that are built on the recommendations of sell-side analysts and confirms that the abnormal returns are explained primarily by analysts’ stock-picking ability and only partially by the effect of over-weight in small-cap stocks. The study examines the number of stocks in the portfolios and the weights that are assigned to market-cap size deciles and GICS sectors and performs an attribution analysis that identifies the sources of overall value-added performance.

**Paper III** examines the differences in seasonal patterns in the expected returns on target prices between star and non-star analysts. Although the market returns in the sample period do not possess any of the investigated seasonal effects, the results show that both groups of analysts, stars and non-stars, exhibit seasonal patterns and issue more optimistic target prices during the summer, with non-stars being more optimistic than stars. Interestingly, the results show that analysts are highly optimistic in May, which contradicts the adage “Sell in May and go away” but is consistent with the notion of a trade-generating hypothesis: since analysts face a conflict of interests, they may issue biased recommendations and target prices to generate a trade. A detailed analysis reveals that the optimism cycle is related to the calendar of companies’ earnings announcements rather than the market-specific effects.

**Paper IV** discusses how a shift in economic conditions affects the competitiveness of sell-side analysts. The focus is on the changes that were triggered by the financial crisis of 2007-2009 and a post-crisis “uncertainty” period from 2010-2013. The study follows Bagnoli et al. (2008) in using a change in the turnover of rankings as a measure of a transformation in analysts’ competitive advantages. **Paper IV** extends their research and documents how different ranking systems capture analysts’ ability to handle changes in the economic environment. The results show that market conditions impact analyst groups differently, depending on the group’s competitive advantages.

**Keywords:** Alpha; analysts’ recommendations; Institutional Investor; sell-side analysts; star analysts; StarMine; The Wall Street Journal.
Sammanfattning

Aktieanalytiker spelar en nyckelroll genom att samlar, bearbeta och sprida information till aktiemarknaden. Att välja den bästa analytikern att arbeta med, bland tusentals analytiker, är en viktig uppgift för varje investerare. Det är ett val som har stor betydelse för möjligheten att nå en hög avkastning på investerarens portfölj. En omfattande forskning har ägnats åt att utifrån olika kriterier försöka hitta de bästa analytikerna på marknaden utifrån de behov som olika kategorier av investerare har. Detta har resulterat i utvecklandet av så kallade stjärnrankingar med listor över toppanalytiker som under föregående år överträffat sina kollegor. Hur användbar är sådan stjärnranking? Har rekommendationerna från stjärnor större ekonomiskt värde än rekommendationerna från de som inte är rankande som stjärnor, (dvs, är rekommendationerna från stjärnorna mera "träffsäkra" både före och efter valet)? Eller representerar årets stjärnranking helt enkelt tidigare prestationer som återgår till en medelmättig prestation året efter? (Det vill säga, är stjärnanalytiker stjärnor som faller som en stjärna på himlen och försvinner?)

Syftet med denna doktorsavhandling är att empiriskt undersöka det ekonomiska värdet av aktierekommendationer från analytikerna som arbetar på säljsidan. Undersökningen fokuserar på stjärnanalytiker som grupp. Denna avhandling består av fyra artiklar som försöker besvara två övergripande frågor. (1) Kan stjärnrankning identifiera äkta skicklighet, och kan därmed investerare förlita sig på denna ranking av analytiker vid valet av analytiker? (artikel I och II) (2) Hur påverkar olika marknadsförhållanden stjärnanalytiker? (artikel III och IV)

de metoder som identifierar analytiker som ger mera långsiktigt lönsamma rekommen
tationer. Studien dokumenterar att det finns metoder som kan identifiera vilka analytiker som har förmågan att ge långsiktigt lönsamma rekommendationer och därmed visat att deras skicklighet består även efter att de utsetts till stjärnanalytiker. Resultaten tyder på att valet av vilken ranking av analytiker som används av investerare vid valet av analytiker har ekonomisk betydelse och är därför en viktig del i investeringsprocessen.

I artikel II undersöks strukturen hos de portföljer som bygger på rekommendationerna från analytiker och bekräftar att överavkastningen förklaras främst av stjärnanalytikernas förmåga att välja rätt aktier och endast delvis genom att de har en övervikt av småbolagsaktier i portföljerna. I studien undersöks antalet aktier i portföljerna och vilken vikt som läggs på aktier i de tio olika storleksklasserna som de indelats i. Även fördelning på olika branscher undersöks. Skillnaden mellan stjärnornas och övriga analytikers portföljer undersöks med en metod som kallas ”Attribution Analysis” som identifierar källorna till det bättre resultat som stjärnanalytikernas portföljer uppvisar.

I artikel III undersöks skillnaderna i säsongsvariationer på den förväntade avkastningen på riktpriser utfärdade av stjärnanalytiker jämfört med övriga analytiker. Även om marknaden inte uppvisar någon av de undersökta säsongsvariationerna under den undersökta tidsperioden, visar resultaten att båda grupperna av analytiker, stjärnorna och övriga uppvisar säsongsmönster och utfärdar mera optimistiska riktpriser under sommaren, och där övriga analytiker är mer optimistiska än stjärnanalytiker. Ett mycket intressant resultat är att analytiker är mycket optimistiska i maj, vilket motsäger ordspråket ”Sälj i maj och lämna börsen”. Dock är resultatet i linje med hypotesen: De analytiker som arbetar på säljsidan har som främsta uppgift att generera aktieaffärer. Det blir då en intressekonflikt som får analytikerna att ge rekommendationer och utfärda riktpriser som är överoptimistiska. En detaljerad analys visar att denna optimism är kopplad till de fyra perioder under året när företagen publicerar sina delårsrapporter.

I artikel IV diskuteras hur en förändring i de ekonomiska förhållandena påverkar konkurrenskraften hos analytiker som arbetar på säljsidan. Studien fokuserar på de förändringar som utlöstes av finanskrisen 2007-2009 och den

**Nyckelord:** Alpha; Analytikernas rekommendationer; Institutional Investor; Analytiker på säljsidan; Stjärnanalytiker; Starmine; The Wall Street Journal.
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Yury Kucheev,
Stockholm, March 10, 2017
List of appended papers

This thesis is based on four papers that are enclosed at the end.

**Paper I**


**Paper II**


**Paper III**


**Paper IV**

Kucheev, Y.O. What trend is an analysts’ friend? How overall market conditions affect the competitiveness of financial analysts. *Working Paper*
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1. Introduction

“To shoot: to propel (as a ball or puck) toward a goal by striking or pushing with part of the body (as the hand or foot) or with an implement; also, to score by so doing <shoot the winning goal>; also, to begin to speak —usually used as an imperative <OK, shoot, what do you have to say>.”

“Shooting Star: a streak of light in the night sky that looks like a star falling but that is actually a piece of rock or metal (called a meteor) falling from outer space into the Earth’s atmosphere.”

Merriam Webster Online, Retrieved Nov. 2015.

Starting from the first half of the twentieth century (Graham and Dodd, 1934), an enormous amount of research has concentrated on the valuation methodologies to identify the most promising stocks and on how to combine these stocks into a portfolio with the maximal expected return for a given amount of risk (Markowitz, 1952). A majority of investors do not select stocks themselves but rather rely on the recommendations of financial analysts or they completely delegate the investment process to mutual fund managers or institutional investment managers, who also often use the advice of buy- or sell-side analysts (Brown et al., 2016). As a consequence, selecting the best financial analysts is one of the key processes in financial management that determines future investment profitability. Extensive research has been conducted on how to evaluate the performance of analysts, and the state of the art approach has developed into so-called Star Rankings. Star rankings provide investors with a list of analysts who according to various evaluation criteria, outperformed their peers in the past. The importance of star rankings is manifested in the establishment in 1998 and growth of StarMine’s rankings, which regularly updates and patents their innovative selection methods. Since then, StarMine is the main competitor of The Wall Street Journal and Institutional Investor’s rankings.

Typically, for these rankings, star sell-side analysts are identified as trusted and rated financial advisors to individual and institutional investors. An analyst is rated as a star according to his or her previous quality of reports, accuracy of forecasts and potential return that she or he may have generated for clients. There are star rankings that are based on periodic surveys with a focus on soft
skills, and there are rankings that use valuation models that are built on the financial output from analysts’ reports, e.g., recommendations or earnings forecasts. How useful these star rankings are for investors depends on two questions: first, whether the rankings’ method measures the true analyst skill and second, whether the star analysts’ performance persists over time.

There is a disagreement in academic studies on whether the accuracy of forecasts and the investment value of recommendations persist over time. Although some studies show that analysts exhibit a persistent ability to issue accurate forecasts (Bradshaw et al., 2012 and Bilinski et al., 2013) and, on average, the recommendations have significant investment value (Womack, 1996; Barber et al., 2001; Jegadeesh et al., 2004; Green, 2006), other researchers conclude that the past accuracy of earnings expectations and previous profitability of recommendations do not provide essential information for investment decisions (Stickel, 1995; Sorescu and Subrahmanyam, 2006; Hall and Tacon, 2010; Hess et al., 2012). Moreover, fewer studies have examined the relationship between analysts’ rankings and the profitability of their recommendations (Leone and Wu, 2007; Groysberg et al., 2008; Emery and Li, 2009; Fang and Yasuda, 2014).

Papers I and II address both questions, while Papers III and IV extend our understanding of how various market conditions, e.g., financial crisis or market seasonality, affect the work of analysts.

1.1. Research aim and questions

The purpose of this thesis is to conduct a comprehensive empirical investigation of star analysts’ performance that is measured by the investment value of their recommendations. The first part of the study discusses the origin of outperformance for star analysts and investigates the predictive power of different selection methodologies. The second part of the thesis addresses the question of how a time-varying nature of the stock market affects financial analysts.

As mentioned in the previous chapter, there is a disagreement in the extant literature on whether the investment value of star analysts’ recommendations
persists. If performance persists, then star rankings that are based on performance could provide a significant value for investors. However, a key question is whether performance persists and what explains an extraordinary performance, i.e., outperformance, for star analysts. Thus, it is necessary to investigate the nature of the outperformance for star analysts compared with non-stars. Typically, performance comprises two components, namely, skill and luck. Therefore, the performance of the star analysts after selection depends on the precision of signals that the various methodologies use in determining who the stars are. Methods that correlate more with stock-picking skill should have stronger predictive power than methods that are less attributed to skill. Previous studies by Emery and Li (2009) and Fang and Yasuda (2014) approached the problem of identifying a stock-picking skill by the two major rankings (Institutional Investor and The Wall Street Journal); however, these two studies report contradicting results. Consequently, the main challenge of a detailed analysis on how different star rankings can capture a true stock-picking skill requires further investigation.

Papers I and II in this thesis address this challenge and attempt to answer the following research questions.

- **RQ1**: Does an investor’s choice of a rating “agency” matter and how do the methodologies that are used by different star rankings predict the investment value of the recommendations?

- **RQ2**: To what extent can a holdings-based analysis explain the difference in performance between stars and non-stars?

After investigating the skill measurements and performance persistence of star analysts, Papers III and IV focus on how star analysts operate under different market conditions. By investigating the value of analysts’ recommendations under different market conditions, this thesis attempts to answer the following research questions.

- **RQ3**: Do analysts’ recommendations reflect the same seasonality patterns as the stock market?
RQ4: How persistent is the value of analysts’ recommendations under different market conditions?

Previous research documents significant seasonal patterns in aggregate market returns for many financial markets (see, e.g., Gultekin and Gultekin, 1983; Baker and Wurgler, 2006; Kelly and Meschke, 2010). Similar seasonal anomalies have been reported for sell-side analysts’ earnings forecasts, for the pricing of IPOs (Dolvin and Pyles, 2007 and Doeswijk, 2008), and for recommendation changes (Kliger and Kudryavtsev, 2014). A recent paper by Keloharju et al. (2016) documents the economic value of using seasonality in various investment strategies. Paper III extends this discussion and measures whether highly reputed analysts consider seasonal anomalies when they issue their target prices based on recommendation levels. This study documents an optimism cycle in expected returns and proposes an alternative explanation for observed within-a-year cyclical effects.

Paper IV discusses how a shift in economic conditions affects the competitiveness of sell-side analysts. This study examines the changes that were triggered by the financial crisis of 2007-2009 and the post-crisis “uncertainty” period from 2010-2013. By using a change in the turnover of rankings to measure the transformation in analysts’ competitive advantages, the study investigates how different ranking systems capture an analysts’ ability to handle changes in the economic environment. The results show how the market crisis of 2007-2009 and the post-crisis uncertainty period impacted various groups of star analysts, depending on the group’s competitive advantages.

1.2. Outline of the thesis

This thesis comprises a cover essay and four appended papers, one of which has been already published in an international journal. With the appended papers, the thesis focuses on star analysts and examines the research questions by using different perspectives (see Table 1).
Table 1. Overview of the papers

<table>
<thead>
<tr>
<th>Paper</th>
<th>Time Frame*</th>
<th>Research Question</th>
<th>Analysis</th>
<th>Focus</th>
</tr>
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<tbody>
<tr>
<td>I</td>
<td>Year After and Year Before</td>
<td>RQ1</td>
<td>Returns-Based</td>
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<tr>
<td>II</td>
<td>Year After</td>
<td>RQ2</td>
<td>Returns- and Holdings-Based</td>
<td>Origin of stock-picking skills</td>
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<tr>
<td>III</td>
<td>Year After</td>
<td>RQ3</td>
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<tr>
<td>IV</td>
<td>Year After</td>
<td>RQ4</td>
<td>Turnover of stars</td>
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</table>

*Time frame of Year After refers to the one year after a star list is announced. Year Before is the evaluation year, during which analysts were compared to be selected as stars.

Papers I and II use returns- and holdings-based analyses in addressing research questions RQ1 and RQ2 regarding whether the investigated methods of selecting star analysts capture stock-picking skills. Paper III answers research question RQ3 by investigating seasonal patterns in expected returns and proposes an alternative explanation for the observed seasonality in analysts’ expectations. Paper IV uses the turnover of names in star rankings to answer research question RQ4 concerning how changes in market conditions impact the competitiveness of sell-side analysts.

The structure of this cover essay is as follows. The introduction section is followed by five sections. The second section presents the empirical background on analysts’ recommendations, star rankings, and how market conditions affect analysts. The third section discusses the choice of methodological approaches that is used in this dissertation. The fourth section is dedicated to the summaries of the appended papers. The fifth section presents the discussions by synthesizing the findings of the appended papers, attempting to answer the research questions of this dissertation and explaining the theoretical and methodological contributions. The sixth section presents the limitations and suggests possible avenues of further research.
2. Analysts’ recommendations and star rankings

This section has several purposes. First, it presents the motivation behind the study of sell-side analysts and the investment value of their recommendations. Second, this section provides a brief description of the empirical evidence of the value of star rankings. Third, it attempts to clarify why it is important to consider changes in the market conditions when following analysts.

The efficient market hypothesis states that market prices reflect all available information (Fama, 1970). Furthermore, the hypothesis can be divided in three different forms. In the case of the weak form of informational efficiency, it is impossible to beat the market by using historical prices. A market is semi-strongly efficient if prices incorporate all public information. Furthermore, a market is strong-form efficient if prices reflect all available information, public or private. The semi-strong form of market efficiency states that investors should not be able to earn excess returns from trading on publicly available information, such as analysts’ recommendations. However, there could be profitable investment strategies that are based on the published recommendations of security analysts, which is supported by multiple studies that show that favorable (unfavorable) changes in individual analysts’ recommendations are accompanied by positive (negative) returns at the time of their announcements (Stickel, 1995; Womack, 1996; Barber et al., 2001; Boni and Womack, 2006; Barber et al., 2010; Loh, 2010).

Financial analysts, both sell-side and buy-side analysts, play a key role in collecting, processing and disseminating information for the stock market. Sell-side analysts work for investment banks, banks and brokerage firms. Buy-side analysts work for different types of investors, and institutional investors are the most important employers of buy-side analysts. In this thesis, I focus on sell-side analysts. As shown in this section, sell-side analysts are important for the capital market. Analysts generally specialize by industry, and in this way, they (most often, their employer) must decide what particular stocks to cover. Since analysts cannot cover too many firms, the majority of covered firms are large firms. In their work, analysts use information such as macroeconomic data, industry data, firm-specific operating and financial information, and security prices (Bradshaw, 2011). By using this information,
an analyst performs an analysis by considering a company’s historical financial performance, accounting policies, strategy, future prospects for sales and earnings growth. This information enters as an input for a valuation and arrives at a conclusion that is conveyed by a buy or sell recommendation and is normally supported by a formal report that contains the analysis. The recommendation is distributed through informal and formal channels to major clients, investors, company management and other market participants. By performing their analysis, sell-side analysts contribute to a better functioning capital market by reducing the information asymmetry through interpreting information from the company to the benefit of the different market participants, most notably, investors.

2.1. Role of analysts in the stock market

“…the rating [recommendation] gets the lion’s share of attention. It’s easy to understand why: ratings are the sexy sound bites that can be easily repeated in the financial media. Plus, most investors don’t have the time to sit down and read through a 20-page report.”

Investors, particularly money managers who must evaluate hundreds of companies when choosing which stocks to invest in, lack resources (especially time) for gathering and interpreting all the relevant information to make informed investment decisions. Brokerage analysts help them by processing and distributing the information about a particular company or industry (although there are analysts who cover multiple industries). Analysts are responsible for collecting and analyzing all new information on a company or industry that they cover to produce and spread earnings estimates and recommendations to buy-side customers (Michaely and Womack, 1999).

Practitioners and researchers in finance have long been interested in understanding how the activities of financial analysts affect the stock market (see, e.g., a literature review in Ramnath et al., 2008). Analysts’ duties are expected to contribute to market efficiency by reducing the information

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1 From the article “Analyst Recommendations: Do Sell Ratings Exist? | Investopedia”, 2014
asymmetry among external shareholders and corporate insiders. However, recent research calls into question whether analysts produce any new information or mainly serve other roles for their employers, such as marketing and trade-generating (Altinkılıç and Hansen, 2009 and Altinkılıç et al., 2013). A large number of academic studies is dedicated to the conflict of interests in equity research that arises because brokers spend billions of dollars each year on equity research with the goal of generating trading commissions and assisting corporate advisory services (Lin and McNichols, 1998; Irvine, 2000; Li et al., 2015). In the academic literature, there are two main arguments for viewing analysts as a marketing tool and, thus, for questioning the objectivity and value of analysts’ forecasts. First, many studies document systematic optimistic biases in analysts’ earnings forecasts (Lin and McNichols, 1998 and Bradshaw, 2004). Second, researchers argue that analyst recommendations and forecasts are usually issued immediately after company events so that they “piggyback” on the corporate news (Altinkılıç and Hansen, 2009). Therefore, observed price reactions should not be associated with the analysts’ recommendation changes but rather should be attributable to the company news that immediately preceded the revisions (Altinkılıç and Hansen, 2009).

In contrast, there are numerous studies that argue against the piggybacking hypothesis by documenting a significant value in analysts’ recommendations (Womack, 1996; Barber et al., 2001; Asquith et al., 2005; Boni and Womack, 2006; Li et al., 2015). These studies either report significant post-announcement drift or show that a portfolio that is built according to the analysts’ recommendations generates significant abnormal returns. A recent study by Li et al. (2015) investigates the link between corporate news and analysts’ recommendations and shows that only approximately 28% of all recommendations directionally confirm the preceding corporate events. The authors find that these “confirming revisions” facilitate the information discovery of corporate events and thus cannot be dismissed as piggybacking. They conclude that “…analysts are a significant source of new information beyond recent corporate news and they also help shape the market’s assessment of corporate disclosure” (Li et al., 2015, p. 822).
2.2. Star rankings

As the previous section concludes, analysts are very important for investors and money managers because they must evaluate hundreds of companies when choosing which stocks to invest in. Therefore, it is of great importance for investors and money managers to choose the right analysts to work with. Star rankings help investors to choose the best analysts by using a quantitative measurement of previous performance or by surveying investment fund managers and research directors. How useful are these star rankings? Can any star ranking guarantee the accuracy of future forecasts and profitability of recommendations or is it only a reflection of past performance? In answering these questions, it is necessary to investigate the link between past and future performance in terms of the persistency in issuing accurate forecasts and profitable recommendations.

The research has shown that analysts persistently issue accurate forecasts, which means that the analysts who performed well in the past will continue to perform well in the future (Mikhail et al., 2004; Leone and Wu, 2007; Fang and Yasuda, 2009; Bilinski et al., 2013; Kerl and Ohlert, 2015). These findings motivate the use of rankings of best performing analysts as a tool to enhance investment decisions. The relationship between analysts’ rankings and the profitability of their recommendations has been empirically investigated in the academic literature (Leone and Wu, 2007; Groysberg et al., 2008; Emery and Li, 2009; Fang and Yasuda, 2014). Table 2 summarizes the key findings that have been reported on the accuracy of forecasts and profitability of recommendations that were issued by star analysts. Although Emery and Li (2009) compared the profitability of the two prestigious star rankings by Institutional Investor and The Wall Street Journal with the profitability of non-stars and concluded that both rankings are primarily “popularity contests”, the academic research usually finds supportive evidence that star rankings provide value for investors. For example, Leone and Wu (2007) and Fang and Yasuda (2014) investigated the effect of analysts’ reputation on the profitability of their recommendations and found that star analysts have better stock-picking ability than their non-star peers. Many studies document that star analysts issue more accurate forecasts than non-stars issue (Cowen
et al., 2006; Fang and Yasuda, 2009; Kerl and Ohlert, 2015). In addition, Fang and Yasuda (2009) show that incentives for biased research are mitigated by the star reputation, which reduces the bias in forecasts.

Meanwhile, Mikhail et al. (2004) and Kerl and Ohlert (2015) provide evidence that market reaction does not differ for the reports of star and non-star analysts, as well as for non-star analysts who issue somewhat accurate forecasts. Obvious questions arise. How profitable is it to follow the recommendations of star analysts compared with other analysts? Why are the benefits of star rankings not utilized by market participants? Consequently, the research on the profitability of recommendations and accuracy of measurements has not only academic interest but also direct practical use and provides a general idea regarding the applicability of the reports from sell-side analysts. Considering the practical importance of forecasts, the literature has explicitly focused on the factors that impact the accuracy of earnings per share (EPS) estimates, target prices (TP) and the persistency of forecasts.

Table 2. Key references related to the importance of sell-side research and the persistency in issuing accurate forecasts

<table>
<thead>
<tr>
<th>Authors</th>
<th>Sample period</th>
<th>Main findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asquith et al. (2005)</td>
<td>1997-1999</td>
<td>EPS, TP and recommendation revisions are followed by a significant market reaction. Market reaction is stronger for (1) downgrades than for upgrades and (2) TP than for EPS. Justification is important. TP are achieved in 54.3% of the cases. No association was found between the valuation method and the market's reaction or TP accuracy.</td>
</tr>
<tr>
<td>Bilinski et al. (2013)</td>
<td>2002-2009</td>
<td>TP accuracy exceeds the accuracy of naive price forecasts. The previous accuracy of TP, forecasting experience, number of firms followed, country-specialization, and broker size predicts TP accuracy. The country’s institutional and regulatory settings impact the accuracy of TP. Analysts have differential and persistent skills to issue accurate TP. The mean absolute forecast error is 44.7%.</td>
</tr>
<tr>
<td>Cliff and Denis (2004)</td>
<td>1993-2000</td>
<td>Highly ranked analysts (by I/I ranking) are very important to both initial public offerings (IPO) and seasoned equity offerings (SEO). Issuing firms pay for analyst coverage through the underpricing of the offerings. Issuers deliberately underprice IPO to attract analyst attention and build the price momentum.</td>
</tr>
<tr>
<td>Author(s)</td>
<td>Years</td>
<td>Findings</td>
</tr>
<tr>
<td>------------------------</td>
<td>---------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Emery and Li (2009)</td>
<td>1993-2005</td>
<td>For The Wall Street Journal (WSJ) ranking, industry-adjusted investment recommendation performance is the only significant determinant to be re-elected as a star. After becoming stars, the recommendations of WSJ stars are significantly worse than non-stars; the recommendations and EPS from Institutional Investor (I/I) stars and the EPS forecasts from WSJ stars are not significantly different from the recommendations and EPS from non-stars. The authors conclude that these rankings are “popularity contests”.</td>
</tr>
<tr>
<td>Fang and Yasuda (2009)</td>
<td>1983-2002</td>
<td>Personal reputation (I/I stars) and bank reputation have a positive influence on the quality of forecasts. Conflicts of interest at top-tier banks have (1) a negative influence on non-star analysts compared with other analysts and (2) have a positive influence on the performance of I/I stars. Thus, personal reputation is an effective disciplinary device against conflicts of interests, while bank reputation alone is not.</td>
</tr>
<tr>
<td>Fang and Yasuda (2014)</td>
<td>1994-2009</td>
<td>The recommendations from the “All-America Research Team” star analysts significantly outperform the recommendations from non-stars before and after I/I election. Skill differences exist, because I/I election reflects institutional investors’ ability to evaluate and benefit from elected stars. The I/I election process picks up the otherwise unobserved characteristics that relate to analyst performance.</td>
</tr>
<tr>
<td>Groysberg et al. (2008)</td>
<td>1988-1996</td>
<td>If star analysts change employers, they tend to decline in star rankings. The decline is most pronounced for the analysts who moved to be solo or who moved to a firm with less resources. The analysts who moved with their teams and who moved to equivalent firms have no significant decline in performance. Firm-specific skills and a firm’s capabilities play an important role in the performance of star analysts.</td>
</tr>
<tr>
<td>Kerl and Ohlert (2015)</td>
<td>2005-2010</td>
<td>After analysts have received StarMine awards, they outperform non-stars in the accuracy of EPS but only in the short-run. The accuracy of TP is not different among stars and non-stars. The EPS accuracy of star analysts increases with the level of country- and company-specific corporate governance. Investors do not react differently to forecasts from stars compared with non-stars.</td>
</tr>
</tbody>
</table>
| Krigman et al. (2001)  | 1993-1995 | 30% of the companies that prepared SEO within three years from IPO changed the underwriter (not because of dissatisfaction with the IPO). IPOs that switched the underwriter were less underpriced than the IPOs that did not change. The reasons for changing the underwriter are firms hire underwriters with a better reputation and firms
buy additional and influential analyst coverage from the new lead underwriter. The results from a survey support the findings of the paper.

Leone and Wu (2007) 1991-2000 The outperformance of ranked analysts is found to be due to superior ability, and, therefore, the performance persists. Superior ability is attributed to innate talent, not to analysts’ experience. The I/I ranking is not a “popularity contest”. Instead, the ranking is a measure of analysts’ reputation. The buy-side clients value phone calls and written reports as much as stock picking and EPS. Younger analysts are more risk-averse, while ranked analysts deviate more from the consensus and take more risks.

Mikhail et al. (2004) 1985-1999 Analysts whose recommendations earned the most (least) excess returns in the past continue to outperform (underperform) in the future. The market recognizes these performance differences. A trading strategy that builds long and short portfolios on recommendations that are conditional on analysts’ prior performance is unprofitable. The average difference in the excess returns between top- and under-performers increases with the length of time over which prior performance is measured.

Stickel (1992) 1981-1985 “All-America Research Team” (I/I) analysts provide more accurate EPS forecasts and issue reports earlier and more often. I/I’s upward revisions impact prices more than the upward revisions from the other analysts. Downward revisions have no differences in the returns of I/I stars and non-stars.

2.2.1 How rankings select analysts

The ratings of sell-side analysts can be mainly divided into two groups according to the evaluation approach that they use. A quantitative approach uses a quantifiable output from analysts’ forecasts (such as earnings forecasts or recommendations); a qualitative approach surveys buy-side clients on their opinion regarding the best-performing analysts (Kucheev et al., 2016). This thesis covers four different rankings. Two rankings are based exclusively on the investment value of recommendations, namely, “Best on the Street”, which is issued by The Wall Street Journal (WSJ), and “Top Stock Pickers”, which is issued by Thomson Reuters’ StarMine (STM-TSP). One ranking is based on the accuracy and timing of earnings forecasts, namely, the “Top Earnings Estimator” that is issued by StarMine (STM-TEE); another survey-
based ranking, the “All-America Research Team”, is issued by *Institutional Investor* (I/I) magazine. Below, I provide a brief description of each ranking’s methodology.

Since 1993, *The Wall Street Journal* has published a list of “Best on the Street” analysts (before 2000, this ranking was named “All-Star Analysts”). This ranking is based on the score that an analyst obtained during the previous year based on the one-day returns of recommendations (if an investor invests one day before the recommendation is announced and realizes the return by the end of the recommendation day). This evaluation methodology is focused on a short-term price forecast, and it favors the analysts who issue a higher number of recommendations on the days when the price changes the most. Simultaneously, this evaluation penalizes the analysts who issue their recommendations before or after such sharp price changes. Moreover, investors must obtain the recommendation one day before it is announced to benefit from it, which could be the case for a limited number of investors with privileged access to analysts. In addition, WSJ’s evaluation method is blind for avoiding analysts who announced their recommendations on the same day but after a significant price change had already occurred (Yaros and Imielinski, 2013). All of these concerns may lead to a substantial random selection of analysts into a star ranking. Emery and Li (2009) found that after becoming stars, WSJ star analysts issue recommendations that underperformed the recommendations from the group of non-stars. The authors interpret this result as an effect of the regression to the mean because the short-term recommendation performance includes a substantial random component.

Thomson Reuters’ *StarMine* “Top Stock Pickers” (STM-TSP) and “Top Earnings Estimator” (STM-TEE), which both include three analysts per industry, have been issued annually since 1998. They are both issued around October every year (except for the lists that were announced in December 2009, May 2012, and August 2013). The STM-TSP ranking is based on the excess returns of a non-leveraged portfolio that is built on all of the recommendations of each analyst. The returns of each analyst are calculated by using the long and short buy-and-hold portfolio method relative to the market capitalization-weighted portfolio of all of the stocks in a given industry.
The portfolio is rebalanced each month and when an analyst changes rating, adds coverage or drops coverage. The STM-TEE ranking measures the accuracy of each analyst’s earnings forecasts, and it is a measure of relative accuracy, since the analysts are compared with their peers. The measure accounts for several factors, namely, an analyst’s forecast error, the variance of the analysts’ errors, the analyst’s error compared to other analysts, the timing of the estimates, and the absolute value of the actual earnings of the firm. This measure is computed daily and aggregated to provide scores on individual stocks, industries and the analyst overall (StarMine, 2015). Until 2012, STM-TEE’s evaluation was based on earnings forecasts from the previous calendar year. However, since 2012, STM-TEE uses the earnings from the immediate year before the announcement of the rankings lists. The STM-TEE ranking differs from the STM-TSP and WSJ rankings because it does not consider the investment value of analysts’ recommendations, and, thus, STM-TEE does not measure the abnormal returns on portfolios.

Although StarMine’s rankings appeared much later, they play an essential role in sell-side research by providing an “…influential and an important reference in the industry” (Kim and Zapatero, 2011). According to Beyer and Guttman (2011) and Ertimur et al. (2011), many Wall Street firms use StarMine rankings when defining payments to their analysts. Recent work by Kerl and Ohlert (2015) investigate the accuracy of EPS forecasts and the TP of StarMine analysts compared with their non-star peers one year after the analysts became stars. They find that analysts possess a persistent ability to issue accurate earnings forecasts, and after becoming stars, they continue to issue more accurate earnings forecasts than non-star analysts. Regarding the accuracy of TP, the authors cannot find any difference between the two groups of analysts. The insignificant difference in TP forecasts could, according to Kerl and Ohlert (2015), be due to the research methodology: star analysts with “Stock Picking Awards” and “Earnings Estimate Awards” are grouped together to compare their accuracy with the accuracy of non-stars without dividing the sample of StarMine’s stars into Top Stock Pickers and Top Earnings Estimators. However, according to the StarMine methodology for determining the “Stock Picking Awards”, analysts are not evaluated based on their EPS accuracy. Thus, it is possible that even in the year before they receive an award, this mixed group of stars does not outperform non-star
peers in terms of the accuracy of their forecasts. Furthermore, Kerl and Ohlert (2015) focus solely on the accuracy of EPS and TP and the factors that influence such accuracy and do not compare the performance of the recommendations that are issued by star analysts with the performance of non-stars.

To select the members of the “All-America Research Team” ranking, *Institutional Investor* (I/I) magazine sends a questionnaire to the buy-side investment managers and asks them to evaluate various attributes of sell-side analysts (Fang and Yasuda, 2014). This list of stars is published in the October issue of the magazine, and it is usually supplemented by the overall ranking of 12 attributes that investors found to be the most important. Industry knowledge and integrity are among the top-ranked attributes, while stock selection and earnings estimates are among the bottom-ranked attributes. This fact shows that the I/I ranking is not primarily focused on stock-picking ability but rather covers a wide range of attributes that are directly or indirectly related to the ability of an analyst to make profitable recommendations.

Previous research shows mixed results regarding the profitability of the recommendations that are issued by I/I stars. By measuring the investment value of recommendations from 1994-2009, Fang and Yasuda (2014) report that I/I stars outperformed the group of non-stars and have excess returns on their recommendations (Carhart 4-factor alphas) of 1.25% and -0.83% for the Buy and Sell portfolios of the I/I stars, and 1.09% and -0.71% for the Buy and Sell portfolios of non-stars. By using historical data from 1993-2005, Emery and Li (2009) investigated I/I and WSJ ratings. The authors identified the determinants of star status, and compared both rankings based on EPS accuracy and the industry-adjusted performance of investment recommendations in the year before and one year after analysts become stars. Emery and Li (2009) found that after becoming stars, the accuracy of star analysts’ EPS is not different from the EPS accuracy of non-star peers; the recommendations of I/I stars are not statistically better than the recommendations of non-stars, while the recommendations of WSJ stars are significantly worse. The authors concluded that both rankings are largely “popularity contests” and do not provide any significant investment value. In contrast, Leone and Wu (2007) investigated the investment value of I/I stars’ recommendations that were issued from 1991-2000 and found that star
analysts persistently issue profitable recommendations, and this outperformance is not because of luck but a superior ability to pick stocks.

2.3. How market conditions affect analysts

This thesis discusses how two types of market anomalies affect the work of sell-side analysts: first, how cyclical/seasonal effects are reflected in analysts’ recommendations and second, how financial crisis impacts the competitiveness of analysts. This section provides a brief overview of the literature on how these two anomalies may influence analysts’ recommendations.

Previous research documents significant seasonal patterns in the aggregate market returns of many financial markets (see, e.g., Kelly and Meschke, 2010). Similar seasonal anomalies were reported for sell-side analysts’ earnings forecasts for the pricing of IPOs (Dolvin and Pyles, 2007 and Doeswijk, 2008) and recommendation changes (Kliger and Kudryavtsev, 2014). However, it remains unclear whether highly reputed analysts consider seasonal anomalies when they issue their target prices and recommendations. If star analysts indeed outperform non-stars because stars possess better stock-picking ability, have access to greater resources, and hold a superior education, then the stars should be aware of seasonal patterns and could consider these anomalies when they issue their forecasts. Moreover, seasonal anomalies could be used strategically by analysts to time the market. For example, during low risk aversion periods, analysts could recommend young stocks, small stocks with high returns volatility, extreme growth stocks, etc. In contrast, in periods of high risk aversion, analysts could focus on large-cap stocks, low volatility stocks, and/or value stocks.

Previous research shows how “bad” market periods and economic uncertainty affect the decision-making processes of market participants. Some studies focus on how market conditions influence investors’ decisions (e.g., Karlsson et al., 2009 and Chiang and Zheng, 2010), whereas other studies discuss the performance of financial intermediators, such as fund managers and sell-side analysts, under different market conditions. During bad market conditions and periods of uncertainty, more new information is
produced that has more variation of outcomes across firms and over time. Therefore, the role of financial analysts in processing and disseminating the information of financial markets is more valuable in bad times (Loh and Stulz, 2014). This result means that the consumers of this information, buy-side clients, are supposed to examine analysts differently under different market conditions by paying more attention and being more selective during recessions and in contrast, less selective during “good” times. If such varying preferences exist, these effects will be reflected in how investors select analysts for star rankings that are based on the votes of buy-side clients. Such change in preferences will be reflected in the turnover of the names of star analysts from one year to the next.

Bagnoli et al. (2008) uses the turnover in star rankings to show the impact of Regulation Fair Disclosure (Reg-FD) on the sell-side analysts’ competitive advantage. The authors found that Institutional Investor magazine selects analysts according to investors’ votes based on overall helpfulness had a significant increase in turnover when Reg-FD was implemented in 2001. In contrast, The Wall Street Journal’s ranking, which is based on the profitability of analysts’ recommendations, did not have any significant change due to the Reg-FD. Although they indicate the fact that there are other factors that influence competitive advantages, such as unexpected downturns in the market, the main conclusion of the article of Bagnoli et al. (2008) is that the change in competitive advantages was caused primarily by the Reg-FD and not due to the overall market conditions. However, a downturn or a financial crisis in extreme cases will change the economic conditions and affect investor sentiment, which should be reflected in how investors select star analysts.

In summary, analysts play an important role of information intermediators in the market by helping investors to interpret information regarding particular companies and their stocks and on the entire market or specific industries. Considering that investors must choose a limited number of analysts to work with and that analysts face various conflicts of interest, it is important to investigate the factors that impact the performance of analysts. Previous research shows mixed results on the investment value of analysts’ recommendations. Although there are some contradicting conclusions in
recent articles, the main conclusion by the extant literature is that analysts do not simply piggyback on publicly available information but rather they help to assess corporate disclosures. It has been shown that analysts provide valuable recommendations that can potentially be used by investors to create a profitable portfolio of stocks.

In the investment management field, there is an ongoing debate on how past performance can help to predict the future. Multiple academic studies and practitioners have attempted to identify individual characteristics that can be used by investors to make better stock picks. The star rankings of analysts use various selection methodologies and support investors with a list of analysts, who performed better than others in a given year. The predictive power of different rankings is determined by the precision of signals that are captured by each ranking methodology and how these signals relate to the stock-picking skill. Although this question has high practical importance in selecting the best analysts on the market, it only has limited coverage in the related academic literature. Thus, it is interesting to investigate which ranking selection methodologies can help investors to select the best analysts. Simultaneously, it is interesting to discuss the academic question on how different signals correlate with the predictive power of profitable stock picks.

The previous research documents seasonal patterns not only on the aggregate market level but also in the analysts’ recommendations, in the pricing of IPOs, and in earnings forecasts. However, this seasonal anomaly has never been investigated from the point of view of how highly reputed analysts account for these anomalies compared to other analysts. Knowledge of this issue can reveal some strategies that star analysts use and explain why their recommendations are superior (if so). Another interesting question that relates to market anomalies is how do different market conditions impact the competitiveness of various star analysts? Both questions, seasonality and the impact of different market conditions on star analysts, can contribute to our knowledge of the time-varying analysts’ functions, which is important for investors to perceive analysts accordingly, depending on the seasonal effects and overall market conditions.
3. Methodology

Depending on the purpose in each individual paper, this study uses four different methodological approaches, which are discussed in detail in the papers and below in this section. The first two papers use a well-established recommendation-weighted portfolio strategy to test the profitability of recommendations (Barber et al., 2006) and is accompanied by a returns-based analysis (Paper I) and a holdings-based analysis (Paper II). Paper III employs a regression analysis with seasonal dummies to investigate the seasonal effects in recommendations and target prices. Paper IV has a descriptive and comparative approach for identifying the changes in the turnover of analysts in different rankings.

3.1. Data

This thesis is built on hand-collected lists of star analysts and on a dataset from the Wharton Research Data Services. This study covers the US stock markets (NYSE, AMEX and NASDAQ) from 2002-2014 and the lists of star analysts from Institutional Investor magazine, StarMine, and The Wall Street Journal. The choice of database is motivated by the richness of the database that allows performing comprehensive research. The widespread use of this dataset makes the results of this study comparable to the extant literature. The evaluation period is chosen because of data availability, particularly the lists of star analysts. The lists of analysts were collected in 2013 and 2014, when the earliest available date for StarMine and The Wall Street Journal lists was 2003. Thus, this research is based on the longest possible data set, which includes the lists of stars from 2003-2013, and the market data from 2002-2014, which includes one year before and one year after the star analysts’ data.

The following data sources are used in this thesis. The Thomson Financials Institutional Brokers’ Estimate System (I/B/E/S) Detail Recommendations File from the Wharton Research Data Services provides standardized stock recommendations for all of the various brokers’ scales by mapping all of the recommendations on a final scale from 1 to 5, where 1 corresponds to “Strong Buy”, 2 corresponds to “Buy”, 3 corresponds to “Hold”, 4
corresponds to “Sell” and 5 corresponds to “Strong Sell”. The Daily Stock File from the Center for Research in Security Prices (CRSP) provides daily holding period stock returns, which include dividends and price and cash adjustments. The Fama-French Factors – Daily Frequency database provides the daily returns for the factors of value-weighted market index, size, book-to-market ratio and momentum. The lists of star analysts were manually collected from Institutional Investor magazine (October 2003 – October 2013), StarMine (October 2003 – August 2013) and The Wall Street Journal (May 2003 – April 2013). The lists of stars are matched with I/B/E/S by analysts’ names and broker affiliations and then are double-checked for any possible inconsistencies (typos in names, analyst changes of broker in a given year, etc.). The sample does not include the analysts from some brokerage houses, notably Lehman Brothers and Merrill Lynch, because their recommendations are no longer available at I/B/E/S.

The sector classification of the Global Industry Classification Standard (GICS) is taken from the Compustat database and merged with the CRSP by company identification (CUSIP number). Additionally, the earnings announcement days for Papers I and III come from the Compustat database.

I use a similar approach as Loh and Stulz (2011) when addressing the overall rating distribution changes that occurred primarily because of the National Association of Securities Dealers Rule 2711 in 2002.

3.2. Building “paper” portfolios

Since the purpose of the study is to measure the value of analysts’ recommendations for investors, a calendar time investment strategy was chosen (Barber et al., 2006). Alternatively, an event-study approach could be used that “provides a perspective on the magnitude of mispricing that analysts are able to detect when they issue their recommendations” (Jegadeesh and Kim, 2006). However, an event-study approach does not allow the measurement of profits on implementable investment strategies (Barber et al.,

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2 A “paper” portfolio refers to using calculated trading to backtest buying and selling securities without actual money being involved.
The primary drawback of an event study with respect to measuring the performance of recommendations is the existence of confounding events, which make it difficult to disentangle the recommendation price effect from the price reactions to corporate news at the time of the event (Li et al., 2015). Another difficulty is isolating a price reaction to a particular recommendation because recommendations can be issued at any given point in time throughout the year at various frequencies for firms of various sizes and sector groups. Thus, recommendations often coincide with one another. For example, a new subsequent event, i.e., a new recommendation, can occur within a short period of time and interfere when testing the effects of a previous recommendation. This difficulty is a major drawback of the event-study methodology because the method is sensitive to other events that occur within the event window, which makes the findings from these studies dependent on the choice of the duration of the event window. In contrast, this study uses a portfolio approach that allows assessing the value of analysts’ recommendations from an investor’s perspective.

The entire sample of analysts is divided into the following groups:

1. **Stars and Non-Stars**;
2. **Institutional Investor (I/I), StarMine Top Earnings Estimators (STM-TEE) and Top Stock Pickers (STM-TSP), and The Wall Street Journal (WSJ)**; and
3. Analysts ranked as number one (Top-Ranked) in the I/I-1, STM-TEE-1, STM-TSP-1 and, WSJ-1.

When a particular analyst is rated as a star in two different industries, the analyst is included only once in a particular group of stars. However, the same analyst can appear in more than one ranking group.

In Paper I, these groups were compared by using two time frames.

1. **The Year Before** is the calendar year before a ranking is announced. For example, the WSJ list of stars is announced in May 2003. Thus, the previous calendar year, from January 2002 through December 2002, is the evaluation year for the WSJ ranking. As a result, the entire sample period for **Year Before** spans from January 2002 to December 2001.
2012. The first month of January 2002 is excluded from the regression analysis because some portfolios contained too few stocks and have extraordinary returns at the beginning of this month. During the evaluation year, analysts are compared in a uniformly way independently of the methodology that is used by a particular ranking by using the same portfolio approach for all groups.

2) The Year After is the one-year period that begins on the day that a particular ranking is announced and ends when the next year ranking list is announced (or twelve-month period for the last year 2013). For example, if the WSJ announcement is on May 12, 2003, the Year After begins on that day and ends on May 17, 2004 when the next ranking list was published. Although an entire sample period for Year After spans from May 2003 to October 2014, the groups are compared beginning one month after StarMine and I/I have published their lists, that is, from November 2003 (an incomplete month, October, is excluded from the regression analysis). The Year After period ends on May 2014 because this is the end of the last one-year period for the 2013 list of WSJ stars.

Papers II, III and IV focus on a comparison of stars with non-stars as well as various groups of stars only in the year after selection.

To measure the profitability of the recommendations, this research applies a well-established methodology by constructing dynamic portfolios (Barber et al., 2006 and Fang and Yasuda, 2014). Buy-and-hold “Long”, “Hold”, and “Short” portfolios are constructed for each sub-group of analysts in the year subsequent to the year in which the rankings were assigned (referred to as Year After) and for the year during which the analysts were evaluated (referred to as Year Before) (Barber et al., 2006 and Fang and Yasuda, 2014). For each new Strong Buy or Buy recommendation, $1 is invested at the end of the recommendation announcement day (or at the close of the next trading day, if the recommendation is issued after the closing of trading or on a non-trading day) into the “Long” portfolio. The transaction costs are not considered. The stock is held in the portfolio for the following calendar year if there are no recommendation revisions or recommendation changes by the
same analyst. If during the following year the analyst changes his or her recommendation level from Strong Buy or Buy to Hold or Sell or Strong Sell, then the stock is withdrawn from the “Long” portfolio and placed in either the “Hold” or the “Short” portfolio by the end of the trading day on which the new recommendation is issued (or at the close of the next trading day if the recommendation is issued after the closing of trading or on a non-trading day). If there is a recommendation revision, but the new recommendation is on the same level (that is, Buy or Strong Buy), then the stock is not kept in the same portfolio for an additional calendar year but only until the next recommendation change within one year from the initial recommendation. Thus, the re-iterations of recommendations are not included in the portfolios. The same procedures are applied to “Hold” (includes only Hold recommendations) and “Short” (includes Sell and Strong Sell recommendations) portfolios.

3.3. Portfolio returns

Portfolio holdings (Paper II) and returns (Paper I) were assessed by returns- and holdings-based analysis.

As a result of the portfolio strategy that is discussed in the previous section, the calendar day \( t \) gross return on portfolio \( \rho \) includes from \( n=1 \) to \( N_{pt} \) recommendations and could be defined as:

\[
R_{pt} = \frac{\sum_{n=1}^{N_{pt}} X_{n,t-1} R_{n,t}}{\sum_{n=1}^{N_{pt}} X_{n,t-1}},
\]

where \( X_{n,t-1} \) is the cumulative total gross return of stock \( i_n \) from the next trading day after a recommendation was added to the portfolio to day \( t-1 \), which is the previous trading day before \( t \), that is,

\[
X_{n,t-1} = R_{i_n, recdat_{n+1}} R_{i_n, recdat_{n+2}} \ldots R_{i_n, recdat_{t-1}}
\]
The daily excess returns for each group’s “Long”, “Hold” and “Short” portfolios are estimated as an intercept (alpha) that is calculated according to the four-factor model that is proposed by Carhart (1997):

$$R_{p,t} - R_{f,t} = \alpha_{\rho} + \beta_{\rho}(R_{m,t} - R_{f,t}) + s_{\rho}SMB_{t} + h_{\rho}HML_{t} + m_{\rho}UMD_{t} + \epsilon_{p,t}, \quad (3)$$

where $R_{m,t}$ is a daily market return, $R_{f,t}$ is the risk-free rate of return, $SMB_{t}$ is a size factor, that is, the difference between the value-weighted portfolio returns of small and large stocks, $HML_{t}$ is a book-to-market factor, that is, the difference between the value-weighted portfolio returns of high book-to-market and low book-to-market stocks, and $UMD_{t}$ is a momentum factor, that is, the difference in the returns of the stocks with a positive return momentum and the stocks with a negative return momentum over months $\tau-12$ and $\tau-2$.

The choice of a model to estimate the excess return of investigated portfolios over the market portfolio is grounded on the well-documented fact that multifactor regression-based models provide a better quality of analysts than a classical single-factor capital asset pricing model (CAPM) (Lintner, 1965; Sharpe, 1964). I use Carhart’s four-factor model because earlier research shows that this model has superior prediction power over both CAPM and Fama-French (Fama and French, 1993) models (see, e.g., Bello, 2008). In addition, I do not include any additional factors because they are not relevant to my investigation, such as the Tech-Sector ArcaEx Tech 100 Index ($^\text{PSE}$) (Fang and Yasuda, 2014), which is used as an extension to the four-factor model for the research that covers the end of the 90th.

The alpha differentials (differences in alphas) are statistically tested by using two approaches. The alphas for the groups in the same year, that is, Year After or Year Before, are compared by using the daily differences in gross returns, which are regressed on four factors according to Equation (3). An intercept from this regression returns the difference in alpha, and a $t$-test indicates whether this difference is statistically significant. To compare the excess returns between Year After with Year Before, the seemingly unrelated estimation is accompanied by a test for significant differences in the intercepts from various regressions ($\text{suest}$ and $\text{test}$ procedures in STATA).
All reported excess returns and alpha differentials are calculated daily, whereas the figures are reported in monthly values by multiplying the daily values with 21 trading days.

**General assessment of the regression model**

*Goodness-of-fit.* Most regressions of the Carhart 4-factor model in Papers I and II have an $R^2$ above 96%. The regressions on the difference of Long minus Short portfolios and on the difference between groups, which return alpha differentials, have a lower $R^2$ of approximately 46%.

*Multicollinearity.* Four predictors in Carhart’s model show very low collinearity according to the tests of a variance inflation factor by using a `vif` command after the regressions in Stata. The test shows the mean VIF of 1.32 and a tolerance ($1/\text{VIF}$) of 0.71 or higher for all four factors. These tolerance measures are significantly higher than a threshold of 0.1, which is used to check the degree of collinearity. This method allows the conclusion that none of the independent variables in the model can be considered as a linear combination of the other variables. The results in this study are consistent with previous findings (see, e.g., Bello, 2008).

*Heteroscedasticity* tests show that the conclusions of this study are not affected by heteroscedasticity. First, the heteroscedasticity tests were conducted in Stata, `hettest`, on the returns variable and on four predictors (first, by running `hettest` after the regression, second, by running `hettest` with a list of variables, i.e., `MKT`, `SMB`, `HML`, and `UMD`). The test after the regression fails to reject the null hypothesis of homoscedastic variance, while the second test with four predictors strongly rejects the null hypothesis and confirms heteroscedasticity. To investigate the severity of heteroscedasticity, a detailed Breusch Pagan test (BP test) is performed by first calculating the predicted value of the returns from the four-factor model. Then, the error terms (residuals) and their squared values are calculated. Next, the squared residuals on the four predictors from Carhart’s model are regressed, and whether any of the predictors explains the variation in residuals is investigated (BP test). An $F$-test with a $p$-value of 0.000 shows that there is heteroscedasticity; however, the $R^2$ of only 0.0134 reveals very small predictive power for the BP
test, because the variation in the four predictors explains less than 2% of the variation in the squared residuals, which allows a conclusion that the heteroscedasticity is very low. Finally, all calculations were repeated for Papers I and II by using $t$-statistics that were adjusted for heteroscedasticity and autocorrelation with White’s (1980) approach. All coefficients and their statistical significance from Robust Standard Errors regressions remain exactly the same as in the published paper. Thus, the results of the above specified tests lead to the conclusion that heteroscedasticity is not a problem for the model and does not impact the calculations of this study.

Serial correlation. The results of the analysis do not show any significant serial correlation in the returns on analysts’ portfolios. By using the daily time-series of returns, a serial correlation was tested by introducing the lagged variables, autocorrelograms were examined, and Dickey-Fuller tests (DF) were performed that test for the unit root (conducted on the return variables, with the time trend, and on differenced return variables). These tests show that both the lagged variable and trend coefficients were insignificant, and the DF test thus confirms a stationarity of the returns data. The momentum factor in the Carhart 4-factor model, $UMD$, should account for some serial correlation in the returns.

3.4. Portfolio structure

Two types of risk are measured, namely, *Total Risk* and *Idiosyncratic Risk*. A portfolio’s total risk is the standard deviation of the raw daily returns on the constructed portfolios. A portfolio’s idiosyncratic risk is the standard deviation of the return residuals ($\epsilon_{\rho\tau}$) from Equation 3.

Paper II evaluates the sources of the portfolios’ excess returns\(^3\) by using a performance *attribution analysis* for two dimensions following Brinson and Fachler (1985)—economic sectors (GICS Sectors), and for market-

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\(^3\) Throughout this thesis, I use the following terminology for returns. Market-adjusted returns refer to the entire portfolio returns minus the returns of the CRSP market, whereas excess returns are the segment-specific returns that relate to relevant segment benchmarks. The alphas that are obtained from the Carhart four-factor model are denoted as risk-adjusted or abnormal returns.
capitalization-weighted Size Deciles (CRSP Size Deciles)—according to Equations 4-8 in Paper II (see Paper II for a more detailed description).

The reported figures for the Allocation and Selection Effects are the average monthly values for each group’s portfolio. The Allocation Effect evaluates the decision to over- or underweight a particular market segment considering that segment’s return relative to the overall return of the benchmark. Good timing skills lead to allocating more money to segments that produce above-average returns. The Selection Effect measures the ability to construct specific market segment portfolios that beat the corresponding market segment benchmarks, which are weighted by the benchmark portfolio weights. In addition to traditional Brinson attribution analysis (Brinson and Fachler, 1985), Paper II follows Hsu et al. (2010) and divides the Allocation Effect into static and dynamic components. The static component measures the performance that is attributed to the persistent sector profile of the actual portfolio. The dynamic component measures the performance that is attributed to the timing ability. Distinguishing between static and dynamic effects in the analysis helps to disentangle whether the observed Allocation Effects are caused by constant portfolio weights or the dynamic timing of market segments.

For the market segmentation by sector classification, the ten GICS sectors are used: Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Telecommunication Services and Utilities. The GICS Sector Codes for each company are taken from Compustat and merged with CRSP based on company identification (i.e., a CUSIP number).

For market segmentation by Size Deciles, all of the companies in the CRSP are assigned to 10 size-specific capitalization-weighted (cap-weighted) portfolios based on their total company market capitalization that is calculated similarly to the calculation of the CRSP Cap-Based Indexes (CRSP, 2015). For each trading day \(\tau\), all of the companies are sorted from largest to smallest based on market capitalization and calculated as the total number of outstanding shares multiplied by the share’s price. Next, each company \(i\) is assigned a cumulative market capitalization score, \(MS_{i,\tau}\), which is equal to the
cumulative capitalization of all companies with greater capitalization plus half of its own capitalization. \( M_{i_1} \) is expressed as a percentage of the total CRSP market capitalization and is based on the midpoint of a company’s market capitalization, which assigns the company to the Size Decile portfolio in which the majority of its market capitalization lies. To allocate companies into the Size Deciles portfolios, capitalization-based breakpoints are set at 10 percent intervals (e.g., 10, 20, and 30). Finally, each company is assigned a size-specific cap-weighted portfolio number from 1 (largest) to 10 (smallest), which is later used in the performance attribution analysis.

3.5. Measuring seasonality effects

Paper III focuses on the seasonal patterns in analysts’ recommendations and target prices. First, Paper III assesses the seasonal effects in market returns. Second, it investigates whether there are seasonality patterns in the TP that are issued by stars and non-stars. Finally, Paper III investigates the time-varying nature of TP on a more detailed level and discusses possible reasons for the observed patterns.

OLS regression analysis with a seasonal dummy variable is used to capture the differences among seasons (Bouman and Jacobsen, 2002).

\[
R_{MKT_t} = \mu + \gamma DS_t + \epsilon_t, \tag{4}
\]

where \( R_{MKT_t} \) is the return on the CRSP index (the daily and monthly raw returns and the log returns are tested), \( DS \) is the seasonal dummy that is equal to 1 for a period from November to April and is zero otherwise or is equal to 1 for the month of January or September.

The coefficients in the model are interpreted as follows. For studying the seasonal anomalies, such as the difference between Summer and Winter, coefficient \( \mu \) will return a mean value during the summer, and \( \gamma \) will show the difference among seasons and the statistical significance of this difference.

Paper III investigates the seasonality in TP by using the TP expected return, \( TPER \), which is defined as \( TP_t / P_{t-1} - 1 \), where \( TP \) is the analyst’s target price.
with a 12-month horizon that is issued on day $t$, and $P_{t-1}$ is the share price on the previous trading day before $t$.

Paper III tested two hypotheses. The first hypothesis is whether the analysts’ optimism that is reflected in $TPER$ is associated with the current or expected market returns. For this hypothesis, the CRSP monthly market returns and lagged values of these returns or lagged $TPER$ are used. $TPER$ were regressed on the simultaneous, lagged and lead returns to investigate whether the overall market conditions predict the changes in analysts’ optimism and the reversed dependence of whether market returns can be predicted from the changes in analysts’ optimism. The second hypothesis tests whether analysts’ optimism relates to a calendar of companies’ earnings announcements (EA). By using the data from Compustat, a fraction of the EA is calculated as the number of EA that is issued by companies in a given month divided by the total number of EA in that year. Plotting the monthly $TPER$ and EA on one graph and regressing $TPER$ on the lagged percentage of EA reveals a correlation between $TPER$ and the quarterly EA. The strongest correlation occurs between $TPER$ and the peaks in the number of the forth quartile announcements for the previous calendar year in March and in the first (in May) and second (in August) quartile EA.

3.6. Change in competitive advantages

Based on the previous literature, two hypotheses are proposed in Paper IV on how market conditions, such as financial crisis or a several-year period of market uncertainty, affect the turnover of analysts in different ranking systems. This study addresses two research questions. First, in what way were different competitive advantages affected by the changes in overall market conditions? Second, what can explain these changes from the perspective of analysts and investors? Methodologically, Paper IV follows Bagnoli et al. (2008) by using a turnover of rankings as a measure of the change in analysts’ competitive advantages. However, although Bagnoli et al. (2008) focus on the impact of Reg-FD on the turnover of analysts, this research extends their study by examining how four different rankings capture analysts’ ability to handle the changes in the economic environment that were caused by the market crisis of 2007-2009 and what occurred with analysts’ competitive
advantages after this period. Paper IV uses both adjusted and unadjusted figures for the analysis, whereas Bagnoli et al. (2008) derived their conclusions from adjusted figures only.

Since various measures of competitiveness are reflected in different star ratings, i.e., “helpfulness” – in the I/I ranking, long- and short-term stock-picking and in STM-TSP and WSJ, the accuracy and timing of earnings estimates – in STM-TEE, a change in turnover should reflect a shift in these competitiveness characteristics of analysts. In addition, this change in turnover can be a reflection of investors’ preferences in the case of the survey-based Institutional Investor’s ranking.

The policy uncertainty index is downloaded from [www.policyuncertainty.com](http://www.policyuncertainty.com) and used as a measure of market uncertainty to compare the pre- to post-crisis periods. The webpage provides monthly values of the uncertainty index that are based on the frequency of news that mentions policy uncertainty. To identify periods with high and low uncertainty, the overall average index value is estimated from 1985-2013 (considering that the average value from 2003-2013 does not change the classification) by taking the mean of the monthly index values.
4. Short summary of papers

This chapter briefly presents the summaries of the four appended papers. The distribution of work among the authors for each paper is described in Table 3.

**Table 3. Authors’ contributions to each paper**

<table>
<thead>
<tr>
<th>Paper</th>
<th>Author(-s)</th>
<th>Authors’ contribution</th>
</tr>
</thead>
</table>
| I     | Kucheev Yury; Ruiz Felipe; Sörensson Tomas | **Idea:** All three co-authors contributed to developing the research idea.  
**Data:** Tomas provided the WRDS data. Felipe provided the lists of The Wall Street Journal stars. Yury hand-collected all the lists of stars and merged them with WRDS. Yury conducted all data management, programming, and statistics under the supervision of Tomas and Felipe.  
**Analysis:** The representation of the results, analysis and the discussion parts were developed with Tomas and Felipe.  
**Writing:** The article was mainly written by Yury and Tomas. |
| II    | Kucheev Yury & Sörensson Tomas | **Idea:** Both co-authors contributed to developing the research idea.  
**Data:** Tomas provided the WRDS data. Felipe provided the lists of The Wall Street Journal stars. Yury hand-collected all the lists of stars and merged them with WRDS. Yury conducted all data management, programming, and statistics under the supervision of Tomas.  
**Analysis:** The representation of the results, analysis and the discussion parts were developed by Yury under the supervision of Tomas.  
**Writing:** The article was written by Yury and Tomas. |
| III   | Kucheev Yury & Sörensson Tomas | **Idea:** Both co-authors contributed to developing the research idea.  
**Data:** Tomas provided the WRDS data. Felipe provided the lists of The Wall Street Journal stars. The lists of stars were hand-collected and merged with I/B/E/S by Yury. Also, Yury conducted all data management, programming, and statistics under the supervision of Tomas.  
**Analysis:** The representation of the results, analysis and the discussion parts were developed by Yury under the supervision of Tomas.  
**Writing:** The article was written by Yury and Tomas. |
| IV    | Kucheev Yury | As the sole author, Yury developed the research idea, performed the analysis, and wrote the paper. |
4.1. PI – Portfolio returns


This study analyzes whether investors can profit from the recommendations of ranked equity analysts. We examine whether an investor’s choice of a rating “agency” matters and how the methodologies that are used by different star rankings can predict the investment value of the recommendations. By investigating the precision of signals that the various methodologies use in determining who the stars are, we distinguish between the star-selection methodologies that capture a short-term stock-picking profitability and the methodologies that emphasize more persistent skills of analysts.

We use the data from the Thomson Financials Institutional Brokers’ Estimate System (I/B/E/S) Detail Recommendations File for the period of 2002-2013. We hand-collected the lists of star analysts from Institutional Investor magazine (October 2003 – October 2013), StarMine (October 2003 – August 2013), and The Wall Street Journal (May 2003 – April 2013). The lists of stars are matched with I/B/E/S by analysts’ names and broker affiliations. Our final database contains 172,525 recommendations for 6,443 companies that are listed on the NYSE, AMEX and NASDAQ markets that were announced between January 2002 and October 2014. The hand-collected database enables us to conduct original research by comparing the profitability of Institutional Investor’s rankings of analysts with the rankings of StarMine and The Wall Street Journal.

By using this database, we measure and compare the investment values of the portfolios that were formed by the recommendations of an entire group of star analysts (referred to as Stars), a group of non-star analysts (Non-Stars), and groups of stars as indicated by the different rankings (Institutional Investor magazine, StarMine’s “Top Earnings Estimators” and “Top Stock Pickers”, and The Wall Street Journal). We divide our sample into two time frames. The Year Before corresponds to the evaluation year, and the Year After corresponds to the one-year period after a particular star ranking is announced until the
next announcement date (and the twelve-month period for the year 2013 which was the last year for the rankings lists in our dataset).

Our results challenge the finding by Emery and Li (2009) that star rankings are largely “popularity contests”. In our study, we found that Buy and Strong Buy recommendations from the entire group of star analysts outperform these recommendations of non-stars in the year after selection, while stars Sell and Strong Sell recommendations performed similarly to non-stars.

After investigating the differences between subjective (I/I) and objective (StarMine and WSJ) rankings, we found that the returns of the recommendations from analysts ranked by the subjective ranking from I/I underperformed most of the other groups of stars and the group of non-stars. However, this finding does not contradict the intentions of the I/I ranking, whose methodology does not focus on the investment value of recommendations. Among the objective rankings, we found that the most persistent results were observed for the group of STM-TEE analysts, who were selected based on the accuracy and timing of the earnings forecasts. Their recommendations outperformed the groups of stars from STM-TSP, I/I and non-stars in the year after selection.

The choice of which analysts to work with has great importance for the long-term growth of an investor’s portfolio. Our results show that the stock-picking skill is difficult to capture by focusing only on the performance of the recommendations over a one-year horizon. In our study, we provided empirical evidence regarding which star rankings of sell-side analysts that a potential investor should have relied on, namely, the StarMine’s “Top Earnings Estimators”. We find it comforting that the estimation of future earnings is important for predicting portfolio returns, since the valuation models that are used to value stocks are built on a company’s future earnings. In conclusion, our results show that stock-picking ability reflects a set of skills that can be captured by using more fundamental evaluation methods such as the methods that consider earnings forecasts.
4.2. PII – Portfolio structure

Kucheev & Sörenssson. The origin of outperformance for stock recommendations by sell-side analysts.

An investment portfolio’s performance can be explained in terms of both selection (the outperformance in returns within a given sector) and allocation effects (the deviation in a portfolio’s sector weights relative to the market portfolio). This study measures whether the outperformance of the portfolios that were constructed by using sell-side analysts’ recommendations that have been previously reported in the academic literature is caused by the analysts’ selection skills or the portfolios’ allocation effects. Because analysts do not actually make any active asset allocation decisions, any significant portfolio’s allocation effects could be interpreted as an artifact of the portfolio’s construction approach. However, any significant portfolio’s selection effects will show that the analysts’ recommendations that went into a given portfolio outperformed the market.

Our study fills a gap between the earlier research that shows high abnormal returns for the dynamic portfolios that were constructed by using sell-side analysts’ recommendations (Barber et al., 2006, 2010; Fang and Yasuda, 2014) and the lack of detailed knowledge regarding the actual content of these portfolios. A holdings-based analysis allows us to compare the size and market sector weights in the dynamic portfolios of star and non-star analysts within the overall market structure.

First, we investigate how recommendation-based portfolio holdings differ from the market cap-weighted portfolio (the benchmark). We find that the portfolios that were constructed on sell-side analysts’ recommendations have significantly different market sector weights than a cap-weighted benchmark portfolio. We interpret that the extent to which the weights of the analysts’ portfolios deviate from the market portfolio reflects how much attention banks and analysts dedicate to certain sectors compared with other sectors. Our attribution analysis reveals that these differences in investment weights partially explain the observed outperformance. This finding emphasizes the importance of both a holdings-based analysis and a returns-based analysis.
Second, we apply a returns-based analysis and compare the performance of the constructed portfolios with the Center for Research in Security Prices’ (CRSP) market-cap-weighted portfolio (a portfolio of all assets that is traded on NYSE, AMEX and NASDAQ and whose returns’ time-series are included in the CRSP database). In this way, we also compare the portfolios that were constructed based on the recommendations of star and non-star analysts. An analysis of the market- and risk-adjusted returns (alphas) shows that Long portfolios (that include Strong Buy and Buy recommendations) that are based on both stars’ and non-stars’ recommendations outperformed the market during the study period. Stars had a monthly alpha of 0.34% for their Long portfolio, which outperformed the alpha of 0.20% for the non-stars’ Long portfolio (all of the values for and the difference between Long portfolios are statistically significant). The returns for Short (including Sell and Strong Sell recommendations) portfolios were significant for non-stars and insignificant for stars, whereas the difference between the Short portfolios of stars and non-stars was insignificant. The total and idiosyncratic risks for stars’ portfolios were lower than non-star’s portfolios.

Third, we implement a holdings-based analysis for the ten GICS Sectors (Global Industry Classification Standards). We find that the sector-specific returns for the Long portfolios of stars and non-stars were higher in all CRSP sectors (and significantly higher in seven (five) sectors for stars (non-stars)). An attribution analysis shows that the outperformance comes from the selection effect, which explains how well analysts select stocks within the GICS Sectors, whereas the allocation effect was trivial for non-stars and was significant (but small) for stars.

Fourth, we also implement a holdings-based analysis for CRSP market-cap Size Deciles and find that the constructed portfolios are heavily loaded with small stocks, which have approximately 40% invested in the smallest decile and approximately 80% invested in the three smallest deciles. Stars performed significantly better than non-stars in the smallest decile, whereas non-stars achieved higher returns in the largest decile (for the largest stocks, the differences from the market and among groups were insignificant). The excess returns were primarily attributed to allocation effects because a significant portion of the excess returns (approximately 0.17 percentage
points for both Long and Short portfolios of stars and non-stars) was caused by the allocation effect and may be explained by the fact that the constructed portfolios had more weight in small stocks, which leads to overall above-market performance.

Our results show that abnormal returns in the investigated portfolios are primarily driven by the analysts’ choice of small-cap stocks and by their ability to outperform sector-specific benchmarks. These results confirm that analysts possess substantial stock-picking skills. We show that the constructed portfolios for star compared with non-star analysts’ recommendations differ substantially regarding the weights and returns in different sectors and Size Deciles, which explains the difference in alphas. Finally, our paper provides a link between the alphas that were documented in several studies of recommendations (Barber et al., 2006, 2007; Fang and Yasuda, 2014; Kucheev et al., 2016 among others) that were issued by analysts and the content of the constructed portfolios. To our knowledge, this is the first study to conduct such an in-depth investigation of the portfolios that are used in the academic research, which show high abnormal returns given that we have shown the content of the constructed portfolios. We conclude that it is possible for investors to obtain returns close to these high abnormal returns by following the recommendations of sell-side analysts. However, large institutional investors may find it difficult to closely follow such portfolios because of the liquidity and supply of small stocks that dominate our recommendation-based portfolios.

We expect this study to be of interest to both academics and practitioners. From an academic perspective, our study contributes to a deeper understanding of how the abnormal returns of portfolios that are constructed based on analysts’ recommendations are obtained. From an investor’s perspective, our research strengthens our knowledge concerning analysts’ ratings, the investment value of their recommendations and the portfolio characteristics that will result from their advice. Finally, for sell-side analysts, our research provides decision support to make better recommendations in terms of understanding the importance of the choice of industry and the size of recommended firms.
4.3. PIII – Seasonality

Kucheev & Sörensson. *The seasonality in sell-side analysts’ recommendations.*

Previous research has shown significant seasonal patterns in aggregate market returns for many financial markets (see, e.g., Kelly and Meschke, 2010). Similar seasonal anomalies have been reported for sell-side analysts’ earnings forecasts, the pricing of IPOs (Dolvin and Pyles, 2007; Doeswijk, 2008), and recommendation changes (Kliger and Kudryavtsev, 2014). In this study, we measure whether highly reputed analysts consider seasonal anomalies when they issue target prices and recommendations. If one believes that star analysts indeed outperform non-stars because they possess better stock-picking ability, have access to greater resources, and possess better education, then one could assume that stars are better aware of seasonal patterns and could consider these anomalies when they issue their forecasts. Thus, seasonal anomalies could be used strategically by analysts to time the market.

The aim of this paper is to measure the difference in seasonal patterns for star and non-star analysts and discuss the potential source of such bias. By using the data from the US market for the period of 2003-2014 combined with the target prices and recommendations from sell-side analysts from the I/B/E/S database, we investigate the seasonality in analysts’ sentiment to discuss how the analysts’ optimism varies over time depending on various seasonal factors. We use TP because they are easier to interpret than IPOs or earnings forecasts in measuring analysts’ optimism. In addition, analysts issue target prices on a regular basis compared with rarer IPOs.

Our results show that both groups of analysts, stars and non-stars, issue more optimistic target prices in the summer season than in winter, although the CRSP market returns do not reflect any seasonal pattern during the investigated time period. These findings confirm that the analysts have higher expected returns during the summer and lower expected returns in the winter, independent of market returns. On a detailed level, non-stars are more optimistic than stars in their Buy and Hold recommendations but less pessimistic in their Sell recommendations. Our further investigation shows
that the optimism in TP relates to the calendar of companies’ earnings announcements rather than to the market returns of calendar seasons.

4.4. PIV – Change in competitiveness over time

Kucheev. *What trend is an analysts’ friend? How overall market conditions affect the competitiveness of financial analysts.*

This study investigates in what way a shift in overall market conditions affects the competitiveness of sell-side analysts. The extant literature studies how “bad” market periods and economic uncertainty affect the decision-making processes of market participants. Although some studies focus on how market conditions influence investors’ decisions, other studies examine the performance of financial intermediaries, such as fund managers and sell-side analysts, under different market conditions. During bad market conditions and periods of uncertainty, more new information is produced that has more variation of outcomes across firms and over time. Therefore, the role of financial analysts in processing and disseminating the information for financial markets is more valuable in “bad” times (Loh and Stulz, 2014). This finding means that the consumers of this information, buy-side clients, may look at analysts differently under different market conditions by paying more attention and being more selective during recessions and, in contrast, less selective during “good” times. If these varying preferences exist, this effect may be reflected in how investors select analysts for star rankings that are based on the votes of buy-side clients. Thus, the change in preferences should be reflected in the turnover of names of star analysts from one year to the next.

After reviewing the previous literature, I propose two hypotheses on how market conditions, such as a financial crisis or several-year period of market uncertainty, affect the turnover of analysts in different ranking systems. This study addresses two research questions. First, in what way were different competitive advantages affected by changes in the overall market conditions? Second, what explains these changes from the perspective of analysts and investors? Methodologically, I follow Bagnoli et al. (2008) and use a turnover of rankings to measure the change in analysts’ competitive advantages.
According to the authors, the star status represents the outcome of competition among analysts that is measured by the various performance criteria, depending on the ranking system. Therefore, the turnover of star analysts reflects the changes in the analysts’ ability to compete successfully.

Bagnoli et al. (2008) focus on how Reg-FD impacts the turnover of analysts, whereas I extend their study and examine how four different rankings capture analysts’ ability to handle changes in the economic environment that were caused by the market crisis of 2007-2009 and what occurred with analysts’ competitive advantages in the post-crisis period. Since different star rankings represent various measures of competitiveness, i.e., “helpfulness” – in the I/I ranking, long- and short-term stock-picking and in STM-TSP and WSJ, the accuracy and timing of earnings estimates – in STM-TEE, a change in turnover, i.e., a change in the number of re-selected analysts from one year to the next for a given ranking, should reflect a shift in these competitive characteristics of analysts. In addition, the shift in turnover may reflect investors’ preferences in the case of the Institutional Investor’s survey-based ranking.

An analysis of the turnover of analysts in the I/I ranking shows that before the crisis of 2008, the majority, approximately 75%, of stars is re-elected every year. After the crisis of 2008, the percentage of re-elected analysts dropped to 51%, which reflects a change in buy-side preferences. This change in preferences may be explained by the fact that the performance of investment recommendations that were issued by I/I stars significantly reduces during high uncertainty periods. Investors may recognize this decrease in the analysts’ performance and change their views on whom to vote for when they are asked to select stars for the I/I rankings.

The earnings-based STM-TEE ranking shows a steady decrease in turnover during the investigated time period; 24% of analysts were re-selected before the crisis, and 31% were selected after the crisis. One potential explanation for this increase of the number of re-selected analysts is that, over time, brokerage houses started to view StarMine rankings as an external valuation body for their analysts to compare their in-house analysts with their external peers. Because the popularity of StarMine was increasing, the analysts who
were selected as stars could have received better access to resources, which helped them to be re-selected again.

Both recommendation-based rankings, STM-TSP and WSJ, have significantly higher turnover than the previously discussed I/I and STM-TEE rankings; STM-TSP has only approximately 16% and WSJ has approximately 19% of stars being re-selected. Although there are some significant changes in turnover from one year to the next, I could not find any significant pattern that could explain how the crisis affected the turnover in these rankings. Moreover, the change in the performance of investment recommendations during high and low uncertainty periods was insignificant for all the objective rankings (STM-TEE, STM-TSP, and WSJ).

The results of this study show that the subjective I/I ranking had significant changes during the crisis and that turnover increased in the post-crisis period. Because “helpfulness” was the main criteria to select analysts for I/I, the change in turnover reflects either how investors changed their preferences of what they view as helpful or that the crisis affected the competitive advantages of analysts. An additional analysis of the returns for analysts’ recommendations, which shows that the performance of the investment recommendations that were issued by I/I stars significantly reduces during high uncertainty months, partially explains the increase in the turnover of analysts. In contrast, the objective rankings that are based on the profitability of analysts’ recommendations, namely, WSJ and STM-TSP, show no clear pattern in turnover changes from the pre- to the post-crisis period, although there were statistically significant changes in turnover for several year-to-year comparisons. Additionally, a relatively low percentage of re-selected analysts and unclear patterns of the impacts of market uncertainty on this skill reveals the random nature of this competitive advantage, which is difficult to maintain over years. I conclude that the stock-picking skill is independent of market conditions, while the “helpfulness” of I/I stars seems to be a temporary skill that works well only during “good” times. The analysis shows that for I/I stars, only a good trend is a “friend”.

The findings of this study are important to both investors and analysts. For an investor, the problem is to select analysts and what rankings to use
depending on different market conditions. If the competitive environment changes and analysts are required to develop and use different skills in various market conditions, then this fact poses an importance for buy-side clients to select other analysts when market conditions change. A problem for analysts is which skills to master to be selected in star rankings.
5. Discussion: Do Stars shine?

The previous research shows mixed results regarding the predictive power of analysts’ star rankings. This study was conducted to determine the value of star analysts’ recommendations by addressing two main questions. (1) Do star rankings capture any true skill, and, thus, can investors rely on the rankings? (Papers I and II) In other words, is there any investment value in the recommendations from star analysts? (2) How do market conditions affect star analysts? (Papers III and IV) In other words, how should investors change their view on analysts’ rankings when market conditions change?

Papers I and II discuss whether the investigated star rankings capture stock-picking skills and can thus aid investors in making profitable investment decisions. By investigating the precision of signals that the various methodologies use in determining who the stars are, Paper I distinguished between the star-selection methodologies that capture short-term stock-picking profitability and the methodologies that emphasize more persistent skills of analysts. Paper II finds that the portfolio construction methodology that is used in Paper I and in many other previous studies does not drive the conclusion that analysts possess significant stock-picking skills. These results can be explained by the differences in the selection methods that are used by different star rankings.

Paper I compared the performance of the rankings by The Wall Street Journal and StarMine that are explicitly based on analysts’ past performance, which is objectively measured, with the performance of the Institutional Investor rankings that are based on subjective survey assessments by analysts’ buy-side clients. The expected differences between objective and subjective rankings in predicting stock recommendation performance depend on the persistence of the outperformance of a small group of objectively ranked analysts. These objectively selected stars outperform other groups of analysts during each evaluation year. This outperformance comprises both stock-picking skill and luck. If outperformance is persistent, objective methods will have an edge over subjective methods. However, if outperformance is primarily due to luck and is not persistent, then subjective rankings may work better if the buy-side has insight on which analysts have better stock-picking skills amid the noise.
The results of Paper I show that objective rankings have higher predictive power in capturing stock-picking skill.

Another point to consider is that there are objective methods that do not explicitly consider recommendations, and, thus, they do not intend to assess stock-picking skills. Instead, these methods focus on other signals, such as the earnings forecasts that are considered by the StarMine’s “Top Earnings Estimators”. Whether these other methods have any relevance for identifying analysts whose recommendations outperform other analysts depends on how the measured signal is associated with the stock-picking skill. Clearly, some signals are more directly related to stock picks. To understand in what way particular signals relate to the value of recommendations, it is necessary to review what determines successful stock picks. James Valentine proposes a framework that discusses three areas (Valentine, 2011a) and mentions that issuing profitable recommendations requires having an edge over consensus thinking in at least one of the following areas: (1) financial forecast; (2) valuation methodology or multiples; and (3) the forecast of investors’ sentiment (if all fundamental valuations remain constant, often only the sentiment moves a stock price or even the entire market in the short term). The author states that a recommendation does not need to have all three elements, but if it has none “…it is probably of no value” (Valentine, 2011a, p. 11). Although the second and third areas are difficult to assess for external observers, such as investors, the first area, i.e., financial forecasts, can be easily assessed by evaluating the accuracy of forecasts, which is what the StarMine’s ranking “Top Earnings Estimators” assesses. The results in Paper I confirm that relying on methodology that evaluates the accuracy and timing of earnings forecasts provides higher predictive power for future profitable recommendations compared with methods that rely only on the past profitability of recommendations during the previous year.

Although the results in Paper I show that the “Top Earnings Estimators” had more profitable recommendations in the year after selection, this finding does not mean that superior financial forecasts by themselves guarantee the superiority of recommendations because the stock-picking skill should not be confused with valuation. In mid-1998, there were many analysts who could clearly show that technology stocks were overvalued; however, issuing bearish
recommendations would have been bad stock picks for another 18 months (Valentine, 2011b). Thus, an analyst could have superior financial forecasts and simultaneously consciously issue contradicting recommendations because he or she believes that the stock price is going to continue to rise or “to curry favor” for a given stock. The latter is known more as an optimistic bias that reflects an analyst’s sentiment about the stock. This thesis addresses the topic of analysts’ sentiment in Paper III.

Previous research has shown that analysts are positively biased and overoptimistic, since they issue more favorable recommendations, which is usually attributed to the conflict of interests that is well documented in the research on sell-side analysts (Hong et al., 2000; Hong and Kubik, 2003; Clement and Tse, 2005; Nolte et al., 2014). Fang and Yasuda (2009, 2014) document that star status helps in mitigating conflicts of interests, which is reflected in issuing less biased recommendations. This question is particularly relevant for recommendations compared with earnings forecasts because forecasts are easily quantifiable, while recommendations are analysts’ opinions. Therefore, analysts could be unbiased in their forecasts and simultaneously issue overoptimistic recommendations to “curry favor” (Bradley et al., 2008) with company management (Fang and Yasuda, 2014).

An additional point to consider concerns conflicts of interest, which analysts face if they want to be selected by the subjective rankings that could reduce the value for investors of the recommendations from I/I stars (Mola and Guidolin, 2009). Analysts may issue overoptimistic recommendations on a stock that a particular buy-side client is overweighting. Although this may lead to the poor performance of the analyst’s stock picks, it may help to buy some votes in the coming I/I poll. This reasoning is consistent with the previous findings by Mola and Guidolin (2009) who reported that I/I star analysts are more prone to issue too-optimistic ratings for the stocks that affiliated mutual funds hold. Paper III continues this discussion and analyzes whether star status helps to mitigate conflicts of interests that is measured by studying how optimistic TP from star analysts compare to non-stars. Consistent with previous findings, the results in Paper III show that stars indeed issue less-biased forecasts that are reflected in less optimistic bullish recommendations and more pessimistic bearish ones. Simultaneously, Paper III shows that
analysts are highly optimistic in May, which is against adage “Sell in May and go away” and may be a consequence of the conflict of interests (i.e., providing value for investors against generating trade for the firm). For maintaining stable market trade activity, analysts could issue overoptimistic recommendations to compensate for the negative market sentiment with overoptimistic expected returns on TP.

As discussed earlier in this section, star rankings evaluate different attributes when choosing analysts for their rankings: from qualitative measurements in survey-based I/I rankings to various types of quantitative criteria in WSJ and StarMine rankings. These criteria have different persistencies over time depending on market conditions. The results in Paper IV show that market conditions have a significant impact on the subjective rankings by I/I, which is explained by either a change in evaluation procedures or by the change in investors’ perspective on analysts. The results of this study show that the turnover of analysts in subjective I/I rankings is a “subject to change” under different market conditions most likely because investors’ preferences change under the influence of economic conditions (i.e., the impact availability of capital and overall investor sentiment). Moreover, if buy-side clients recognize that the performance of the investment recommendations that are issued by I/I stars is significantly lower during high uncertainty months, they may change their view on whom to vote for as stars in the next poll of I/I, which will lead to an increase in the turnover of I/I stars. Alternatively, investors may need different type of services in different economic conditions or they can value various skills in different times. In contrast to the subjective I/I ranking, objective rankings are rankings that apply objective criteria and base their selection on pure quantitative approaches, such as the accuracy of earnings forecasts or the profitability of recommendations. The turnover in objective rankings remains somewhat constant during various market times until the evaluation criteria are changed. In addition, the performance of investment recommendations does not differ in different uncertainty periods. These results suggest that the skills of stock picking and earnings forecasts are unrelated to market conditions and should persist over time.

The choice of which analysts to work with has great importance to the long-term growth of an investor’s portfolio. The results of this study show that
stars compared with non-star analysts possess stock-picking skills and this is why they issue more profitable recommendations. Moreover, the results show that stars are less-biased in their target prices. However, investors should be cautious when relying on star analysts because the value of analysts’ advice differs depending of the ranking’s selection methodology.
6. Limitations and suggestions for further research

Although this research is based on well-established methodologies and the considered various robustness tests, it has some limitations that leave room for further research on the value of sell-side analysts’ recommendations.

General issues. This study documents that the recommendations that are issued by star analysts are more profitable than the recommendations by non-stars. Papers I and II have taken a step in the direction of defining the origin of such outperformance and concluded that star analysts possess stock-picking skill. However, the source of this stock-picking skill remains uninvestigated (Fang and Yasuda, 2014, p. 236). More detailed analysis is needed to identify what factors explain the outperformance of star analysts (to address the causality problem). Possible directions in this research include, but are not limited to, the identification of the enduring skills that analysts possess (e.g., the skills that allow them to generate better forecasts, valuation models, and forecast market sentiment). Additionally, it is necessary to investigate whether star analysts’ recommendations have more influence on stock prices compared with the recommendations of non-stars, since the outperformance may partially be explained by the market attention on and over-reaction to stars.

Paper III documents the existence of the seasonal patterns that are associated with the calendar of companies’ earnings announcements. Using the First Call database will allow a more detailed analysis of the company-specific news (not limited to earnings announcements). Additionally, it would be interesting to investigate how company size and coverage by analysts are associated with analysts’ over-optimism.

This study answers the question of whether star analysts provide more value to investors compared with non-stars and whether potential investment strategies can be based on the recommendations from star analysts. The findings in this study provide a solid background for future research on various investment strategies that are based on the recommendations from star analysts.
Sampling. This study used a US sample of analysts and firms, which is the largest and most complete dataset. However, it would be interesting to replicate this study in an international context and focus on cross-country differences. Additionally, the current study is limited to four major rankings. Is there any difference between the investigated systems and other ranking systems (e.g., Zacks)? This question is particularly relevant in an international context because some markets have region-specific rankings.

This study neglects a question of “superstars”, e.g., the analysts who are ranked by several or even all rankings in the same year. It is reasonable to expect that superstars, especially the superstars who were selected by many rankings, may perform better than the stars who were selected only by one ranking. It would be interesting to investigate which combination of selection criteria provides the best outperformance.

Portfolio construction. After Barber et al. (2006) began to use a methodology to measure the investment value of sell-side analysts’ recommendation changes by constructing a “paper portfolio”, this method became the standard approach in the related academic literature. The first two papers in this thesis replicate and test this portfolio approach and conclude that this method is robust and allows the capturing of stock-picking skill. However, some assumptions and oversimplifications were made in this study. First, transaction costs were not considered. Second, this trading strategy assumes investing by the end of a given trading day. It would be interesting to investigate how the transaction costs and investing immediately after a recommendation announcement (intra-day trading) may affect the conclusions of this study. Third, this methodology considers investing equal amounts in each recommendation. What about over- and under-weighting strategies that invest different sums in stronger and weaker recommendations? Would these strategies change the performance and conclusions of this research?

Rankings. The results of Papers I and II raise the question of whether the current ranking selection methodologies are the best in identifying true skills. One possible improvement would be to consider several different criteria for
selection, such as the timing and accuracy of earnings forecasts and the profitability of recommendations.
References


