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The Value of Ranked Analysts' Recommendations

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Abstract

“**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.

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 investigation 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 in the past 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 follows four steps/parts that address two overarching **questions**: (1) Do star rankings capture any true skill, and, thus, can investors rely on the rankings? (Parts I and II) In other words, is there any investment value in recommendations from star analysts? (2) How do market conditions impact star analysts? (Parts III and IV)

First, the thesis examines the profitability persistence of the investment recommendations from analysts who are listed in the four different star rankings: *Institutional Investor* magazine, *StarMine's* “Top Earnings Estimators” and “Top Stock Pickers” and *The Wall Street Journal*, and shows the predictive power of each evaluation methodology. By investigating the precision of 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 more persistent skills of the

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.

Second, this thesis 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.

Third, this thesis 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 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.

Forth, this thesis analyzes 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. The study extends their research and documents how different ranking systems capture analysts' ability to handle changes in the economic environment. The results of this study show that market conditions impact analysts' 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.

Resumen

“**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.

Los analistas financieros desempeñan un papel clave en la recopilación, procesamiento y difusión de la información del mercado de valores. La selección de los mejores analistas, entre miles de ellos, es una tarea importante para los inversores, que determina la rentabilidad futura de sus inversiones. Amplia investigación se ha dedicado a encontrar los mejores analistas (analistas "estrella") en el mercado, basándose en diversos criterios para diferentes tipos de clientes. El estado del arte en este proceso se desarrolló en los llamados "Star Rankings", con las listas de los principales analistas que, en ejercicios anteriores, superaron a sus compañeros de profesión. ¿Cómo de útiles son las clasificaciones de analistas "estrella"? ¿Las recomendaciones de los analistas "estrella" tienen un mayor valor para la rentabilidad de las inversiones que las de los no "estrellas"? (*Es decir, las recomendaciones de analistas "estrella" aciertan con mejor precisión, tanto antes como después de ser seleccionados como "estrellas"*). O, ¿las clasificaciones de analistas "estrellas" simplemente representan rentabilidades pasadas, que tenderán a revertir a la media en el futuro? (*Es decir, en realidad las "estrellas" no son "estrellas" y desaparecen rápidamente del cielo*)

El **objetivo** de esta tesis doctoral es investigar empíricamente los resultados de las recomendaciones de los analistas "sell-side", centrándose en un grupo de analistas "estrella". Esta tesis se compone de cuatro partes que abordan dos **preguntas** generales: (1) ¿Las clasificaciones de los analistas "estrella" capturan habilidades reales y, por lo tanto, los inversores pueden confiar dichas clasificaciones? (Partes I y II) En otras palabras, ¿hay algún valor, desde el punto de vista de las rentabilidades de las inversiones, en las recomendaciones de los analistas "estrella"? (2) ¿Cómo afectan las condiciones del mercado a los analistas "estrella"? (Partes III y IV)

En **primer** lugar, la tesis examina la persistencia de las rentabilidades de las recomendaciones de inversión de los analistas que figuran en cuatro clasificaciones diferentes: la revista *Institutional Investor*, los "Top Earnings Estimators" y "Top Stock Pickers" de *StarMine* y el *The Wall Street Journal*, y muestra el poder predictivo de cada metodología de evaluación. Mediante la investigación de la precisión de las señales que utilizan las distintas metodologías para determinar quiénes son los analistas "estrella", el estudio distingue entre las metodologías de selección de "estrellas" que capturan la rentabilidad en la selección de acciones a corto plazo, y las metodologías que hacen hincapié en las habilidades más persistentes de los analistas. Como resultado, este estudio documenta que hay métodos de selección de analistas "estrella" que seleccionan sobre la base de habilidades de analista más duraderas y, por lo tanto, las rentabilidades de las recomendaciones de sus "estrellas" persisten, incluso después del anuncio de la clasificación. Los resultados indican que la elección de la clasificación ("ranking") de analistas que se utiliza tiene un impacto económico importante en las rentabilidades de las decisiones de inversión.

En **segundo** lugar, esta tesis investiga la estructura de las carteras construidas en base a las recomendaciones de los analistas "sell-side" y confirma que los rendimientos anormales se explican principalmente por la capacidad de selección de acciones ("stock picking") de los analistas, y sólo parcialmente por el efecto del exceso de peso en las acciones de pequeña capitalización. El estudio examina el número de acciones de las carteras, los pesos asignados a los deciles de diferentes importes de capitalizaciones bursátiles, los sectores en la "Clasificación Global Estándar de Sectores" ("Global Industry Classification Standard" ó "GICS"), y también realiza un análisis de atribución que identifica las fuentes del valor añadido en las rentabilidades.

En **tercer** lugar, esta tesis examina las diferencias en los patrones estacionales de las rentabilidades esperadas en los precios objetivos de los analistas "estrella" y no "estrella". Aunque los rendimientos del mercado en el período estudiado no poseen ninguno de los efectos estacionales investigados, los resultados muestran que ambos grupos de analistas, "estrellas" y no "estrellas", exhiben patrones estacionales, con precios más optimistas durante el verano, y con los analistas no "estrella" siendo más optimistas que los "estrella". Curiosamente, los resultados muestran que los analistas son muy optimistas en mayo, lo que está en contra del adagio "Vende en mayo y vete" ("Sell in May and go away"), pero en línea con la hipótesis de generar negocio: ya que, al enfrentarse los analistas "sell-side" a un conflicto de intereses, emiten recomendaciones y precios sesgados para generar negocio. El

análisis detallado revela que el ciclo optimista está relacionado con el calendario de anuncios de beneficios de las empresas, en lugar de con efectos específicos del mercado.

Por **último**, esta tesis analiza cómo un cambio en las condiciones económicas afecta a la competitividad de los analistas "sell-side". La atención se centra en los cambios provocados por la crisis financiera de 2007-2009, y el período de "incertidumbre" post-crisis de 2010-2013. El estudio sigue a Bagnoli et al. (2008), utilizando el cambio en la rotación de las clasificaciones ("rankings") como medida de la transformación en las ventajas competitivas de los analistas. El estudio extiende su investigación y documenta cómo diferentes sistemas de clasificación capturan la capacidad de un analista para tener en cuenta los cambios en el entorno económico. Los resultados de este estudio muestran que las condiciones del mercado afectan a los grupos de analistas de manera diferente, dependiendo de las ventajas competitivas del grupo.

Palabras clave: Alfa; Recomendaciones de los analistas; Inversor institucional; Analistas "sell-side"; Analistas estrella; StarMine; The Wall Street Journal.

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CHAPTER 1:

INTRODUCTION

1. Introduction

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 might 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).

In this thesis, the first two parts address both questions, while the second two parts extend our understating 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 two parts of the study discuss the origin of outperformance for star analysts and investigate the predictive power of different selection methodologies. The second two parts of the thesis address 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.

The first two parts in this thesis address this challenge attempting 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, the second two parts 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. This thesis extends this discussion and measures whether highly-reputed analysts consider seasonal anomalies when they issue their target prices depending on recommendation levels. This study documents an optimism cycle in expected returns and proposes an alternative explanation for observed within-a-year cyclical effects.

The last part of the thesis investigates 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 from 2007-2009 and the post-crisis "uncertainty" period of 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 of the study 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 focuses on the performance of star analysts and examines the research questions by using four different methodological perspectives, which are divided into four steps/parts for ease of comprehension (see Table 1).

Table 1. Thesis overview

Part	Focus	Analysis	Research Question	Time Frame *
I	Skill persistence	Returns-Based	RQ1	Year After and Year Before
II	Origin of stock-picking skills	Returns- and Holdings-Based	RQ2	Year After
III	Seasonality in recommendations	Seasonal Patterns	RQ3	Year After
IV	Competitiveness of stars	Turnover of stars	RQ4	Year After

*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.

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

The structure of this thesis is as follows. The introduction section is followed by five major 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 reports the results of conducted empirical study. The fifth section presents the discussions by synthesizing the findings of all four steps of this investigation, 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.

CHAPTER 2:

LITERATURE REVIEW

2. Literature review:

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 evidences 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 conveyed by 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 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.”¹

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

¹ From the article “Analyst Recommendations: Do Sell Ratings Exist? | Investopedia”, 2014

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 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).

On the other hand, 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 such star rankings? Can any star ranking guarantee an 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; Groyberg et al., 2008; Emery and Li, 2009; Fang and Yasuda, 2014). Table 2 summarizes the key results 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 have an influence on 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

Authors	Sample period	Main findings
Asquith et al. (2005)	1997-1999	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.
Bilinski et al. (2013)	2002-2009	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%.
Cliff and Denis (2004)	1993-2000	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.
Emery and Li (2009)	1993-2005	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".
Fang and Yasuda (2009)	1983-2002	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.
Fang and Yasuda (2014)	1994-2009	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.
Groysberg et al. (2008)	1988-1996	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.

Kerl and Ohlert (2015)	2005-2010	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.
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	I/I star 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

Analysts are rated as a "star" based on their quality of previous reports, accuracy of forecasts and returns generated for clients (Loh and Mian, 2006). This thesis covers four different rankings of sell-side analysts (see Table 3), which can be divided into two main groups according to the evaluation approach that they use (Kucheev et al., 2016): objective (*StarMine* and *The Wall Street Journal*) and subjective (*Institutional Investor*). Two objective rankings are based exclusively on the investment value of recommendations: "Best on the Street," issued by *The Wall Street Journal*, and "Top Stock Pickers," issued by Thomson Reuters' *StarMine*. A third objective ranking is "Top Earnings Estimators," issued by *StarMine*. It measures the

accuracy and timing of each analyst's earnings forecast. A subjective ranking that uses mixed evaluation methods is the survey-based "All-America Research Team" issued by *Institutional Investor* magazine. Below, a brief description is provided for each ranking's methodology.

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 asking 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 the 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 that 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 are 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.

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 each year (except of those lists announced in December 2009, May 2012, and August 2013). The STM-TSP ranking is based on the excess returns of a non-leveraged portfolio built on all of the recommendations of each analyst. The returns of each analyst are calculated 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, whenever the 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 against their peers. The measure accounts for several factors: the 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, from 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 since it does not consider the investment value of analysts’ recommendations, and, thus, STM-TEE does not measure the abnormal returns on portfolios.

Table 3. Description of rankings (Kucheev et al., 2016).

Ranking name	Rating agency	Abbreviation used in this thesis	Type of ranking	Measure	Measurement	Number of analysts per industry	Publication Month
"All-America Research Team"	Institutional Investor	I/I	Subjective / Qualitative	12 Criteria (most important: industry knowledge and integrity; least important: stock picking, and accuracy of EPS)	Survey	3 + Runners-up	October
"Top Earnings Estimators"	StarMine	STM-TEE	Objective / Quantitative	Accuracy and timing of earnings estimations	Calculation - EPS	3	October [†]
"Top Stock Pickers"	StarMine	STM-TSP	Objective / Quantitative	Excess returns on individual portfolios	Calculation - Recommendations	3	October [†]
"Best on the Street"	The Wall Street Journal	WSJ	Objective / Quantitative	Total score for stock returns	Calculation - Recommendations	5 in 2003-2011, 3 in 2012, 2013	May

[†]except of those lists of STM-TSP and STM-TEE that were announced in December 2009, May 2012, and August 2013.

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 earnings per share forecasts and target prices 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 target prices (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*.

Since 1993, *The Wall Street Journal* publishes 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 methodology 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 the 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.

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 seasonal/cyclical effects are reflected in analysts' recommendations. 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 Investors 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 downturn 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 case will change the economic conditions and affect investor sentiment that 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 for creating 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.

CHAPTER 3:

METHODOLOGY

3. Methodology

Depending on the purpose in each part of this thesis, I used four different methodological approaches, which are discussed below in this section. The first two parts 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 (part I) and a holdings-based analysis (part II). Part III employs a regression analysis with seasonal dummies to investigate the seasonal effects in recommendations and target prices. Part IV has a descriptive and comparative approach for identifying the changes in the turnover of analysts in different rankings.

3.1. Sample

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 because of the access to the lists of star analysts. The lists of analysts were collected in 2013 and 2014 when the earliest available year for StarMine and The Wall Street Journal lists was 2003. Thus, this research is based on the longest possible dataset, which includes the lists of stars from 2003-2013, and the market data from 2002-2014 (covers 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 (IBES) *Detail Recommendations File* 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 to “Buy”, 3 to “Hold”, 4 to “Sell” and 5 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 IBES 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 IBES.

The GICS Sector classification (Global Industry Classification Standard) is taken from the *Compustat* database and merged with the CRSP by company identification (CUSIP number). The earnings announcement days for parts I and III also come from the *Compustat* database.

The following filters are applied to the dataset. This study uses only recommendations for stocks classified as ordinary shares or American Depositary Receipts (CRSP Share Codes 10, 11, 12, 30, 31, and 32). To avoid the influence of “penny stocks” on the conclusions, recommendations for stocks with the price that is less than one dollar are excluded from the sample. Also, the recommendations from anonymous analysts or if the brokerage firm’s name or code is missing are excluded for the sample.

This study considers only recommendation changes and ignores re-iterations since previous research concluded that the changes carry more information than re-iterations (Boni and Womack 2006; Barber et al. 2010). The final recommendation sample consists of

three levels: “Long” (includes Strong Buy and Buy recommendations), “Hold”, and “Short” (includes Sell and Strong Sell recommendations). That is, if a particular analyst for a given company issues a Buy recommendation soon after Strong Buy, the second recommendation, that is Buy, is considered to be a re-iteration and thus it is omitted in the sample.

To deal with the overall rating distribution changes that occurred primarily because of the National Association of Securities Dealers (NASD) Rule 2711 in 2002, the approach similar to the one in Loh and Stulz (2011) was used. In response to NASD Rule 2711, many brokers changed from a five-point scale to a three-point scale for their recommendations (Kadan et al. 2009). By using the IBES Stopped Recommendations File, the dates when brokers stopped all previously issued recommendations are located, and then checked the following 60 days whether a broker resumed coverage but on a three-point scale by having a new ratings distribution of either [1, 3, 5] or [2, 3, 4]. If a broker stopped the recommendations in order to re-initiate them on a three-point scale, the recommendations are arranged in sequence before and after Rule 2711 as if there were no “Stop Recommendation” signal. Because this study considers only recommendation changes (not all recommendations), the subsequent recommendations after Rule 2711 that remain on one of the levels of Long, Hold, or Short as before Rule 2711 will be treated as re-iterations and, thus, ignored. At the same time, recommendations that were resumed on a different level (e.g. changed from Long to Hold or Short) are considered as recommendation changes and will affect the final constructed portfolios. As a result, the changes in brokers’ distribution ratings do not affect the results of the tests.

The final database contains 172,525 recommendation changes for 6443 companies listed on the NYSE, AMEX and NASDAQ markets that were announced between January 2002 and October 2014.

Table 4 displays the total number of analysts in the sample on an election-year basis. On average, approximately 13 percent of analysts in the sample are listed as “stars” every year. The table shows that for every one star analyst, there are approximately six non-star analysts in the sample. Additionally, 32 percent of analysts among the *Non-Stars* have been chosen as stars in some other year but not in the year under consideration. Out of 8459 analysts overall, 27 percent have been elected at least once as stars, with 7 percentage points (pp) for I/I, 11 pp – STM-TEE, 12 pp – STM-TSP, 15 pp – WSJ. For number-one ranked stars the figures are: 2.0 pp – I/I-1, 4.9 pp – STM-TEE-1, 5.4 pp – STM-TSP-1 and, for 4.4 pp – WSJ-1.

Table 4. Number of analysts and the percentage of each group represented in the sample on an election-year basis.

Election year	All analysts	Non-Stars ever elected as stars	Stars	Portion of analysts in entire groups of stars				Portion of analysts in Number-one ranked stars			
				I/I	STM-TEE	STM-TSP	WSJ	I/I-1	STM-TEE-1	STM-TSP-1	WSJ-1
2003	4118	30%	12%	6%	3%	3%	5%	1.3%	0.9%	1.0%	0.9%
2004	4001	30%	13%	6%	3%	3%	5%	1.4%	1.1%	1.0%	1.1%
2005	4038	31%	14%	6%	3%	3%	5%	1.4%	1.1%	1.0%	1.0%
2006	4168	32%	14%	6%	4%	4%	5%	1.3%	1.3%	1.3%	0.9%
2007	4208	32%	14%	5%	4%	3%	5%	1.3%	1.3%	1.3%	0.9%
2008	4160	32%	14%	5%	4%	4%	4%	1.3%	1.3%	1.4%	0.9%
2009	3920	35%	12%	3%	4%	4%	4%	1.0%	1.4%	1.4%	0.7%
2010	3827	34%	12%	1%	4%	4%	5%	1.5%	1.5%	1.4%	1.0%
2011	3976	34%	11%	1%	4%	4%	5%	1.3%	1.4%	1.4%	0.9%
2012	3932	31%	12%	4%	4%	4%	3%	0.9%	1.4%	1.3%	1.0%
2013	3882	29%	12%	4%	4%	4%	3%	1.4%	1.5%	1.5%	1.1%
Average	4021	32%	13%	4%	4%	4%	4%	1.3%	1.3%	1.3%	0.9%
Overall	8459	27%	27%	7%	11%	12%	15%	2.0%	4.9%	5.4%	4.4%

NOTE: Rankings by *Institutional Investor* (I/I), Thomson Reuters’ *StarMine* “Top Earnings Estimators” (STM-TEE) and “Top Stock Pickers” (STM-TSP), and *The Wall Street Journal* (WSJ).

Indexation by -1 indicates a group of number-one ranked analysts.

The average overlap among the ranking lists in each sample year is presented in Table 5. It shows the number of analysts listed by different rankings, the number of the same analysts in each pair of rankings, and the portion of the same analysts in each ranking list. Panel A presents these data for the entire groups of stars, while Panel B reports the results for the

Table 5. Average percentage of interdependence among rankings as the proportion of the same analysts in each ranking list.

Panel A. Entire groups of stars

Year	Proportion of the same analysts (# of the same analysts/# of Star analysts)											
	WSJ	STM-TSP	STM-TEE	I/I	STM-TSP	STM-TEE	I/I	WSJ	STM-TEE	I/I	WSJ	STM-TSP
	in I/I	in I/I	in I/I	in WSJ	in WSJ	in WSJ	in STM-TSP	in STM-TSP	in STM-TSP	in STM-TEE	in STM-TEE	in STM-TEE
2003	15%	11%	15%	19%	26%	12%	25%	45%	13%	37%	23%	14%
2004	9%	8%	12%	12%	28%	10%	18%	47%	11%	26%	17%	10%
2005	8%	8%	12%	12%	28%	9%	16%	40%	14%	23%	12%	14%
2006	8%	7%	16%	11%	32%	10%	11%	41%	23%	24%	12%	22%
2007	6%	9%	11%	7%	28%	12%	15%	37%	21%	16%	15%	19%
2008	6%	10%	11%	8%	26%	10%	15%	32%	22%	16%	11%	21%
2009	15%	17%	13%	10%	23%	14%	13%	27%	21%	9%	16%	19%
2010	12%	16%	11%	3%	25%	13%	6%	33%	18%	4%	16%	17%
2011	7%	6%	9%	2%	29%	11%	2%	38%	19%	3%	14%	19%
2012	4%	7%	10%	7%	25%	7%	8%	20%	22%	10%	5%	20%
2013	5%	12%	11%	6%	27%	9%	11%	20%	18%	9%	6%	17%
Avg.	9%	10%	12%	9%	27%	11%	13%	35%	18%	16%	13%	18%

Panel B. Number-one ranked Analysts

Year	Proportion of the same analysts											
	WSJ-1	STM-TSP-1	STM-TEE-1	I/I-1	STM-TSP-1	STM-TEE-1	I/I-1	WSJ-1	STM-TEE-1	I/I-1	WSJ-1	STM-TSP-1
	in I/I-1	in I/I-1	in I/I-1	in WSJ-1	in WSJ-1	in WSJ-1	in STM-TSP-1	in STM-TSP-1	in STM-TSP-1	in STM-TEE-1	in STM-TEE-1	in STM-TEE-1
2003	5%	2%	9%	7%	17%	0%	2%	17%	5%	13%	0%	5%
2004	2%	2%	7%	2%	14%	2%	2%	14%	2%	9%	2%	2%
2005	0%	5%	5%	0%	18%	5%	7%	16%	9%	6%	4%	8%
2006	2%	3%	5%	2%	22%	5%	3%	15%	17%	5%	4%	18%
2007	0%	4%	2%	0%	21%	0%	4%	14%	9%	2%	0%	9%
2008	0%	5%	5%	0%	15%	5%	5%	10%	10%	5%	4%	11%
2009	0%	5%	5%	0%	16%	5%	4%	11%	7%	4%	4%	7%
2010	2%	5%	4%	2%	14%	2%	5%	11%	7%	3%	2%	7%
2011	2%	2%	4%	2%	9%	5%	2%	7%	5%	4%	4%	5%
2012	0%	3%	5%	0%	13%	0%	2%	9%	13%	4%	0%	13%
2013	0%	0%	2%	0%	7%	0%	0%	5%	5%	2%	0%	5%
Avg.	1%	3%	5%	2%	15%	3%	3%	12%	8%	5%	2%	8%

NOTE: Panel A presents the data for entire groups of stars, while Panel B reports results for number-one ranked stars. The final line shows the average for each value. Comparisons are made on an election-year basis. Rankings by *Institutional Investor* (I/I), Thomson Reuters' *StarMine* "Top Earnings Estimators" (STM-TEE) and "Top Stock Pickers" (STM-TSP), and *The Wall Street Journal* (WSJ). Indexation by -1 indicates a group of number-one ranked analysts. The highest correlation is between WSJ and STM-TSP; the lowest is between WSJ and I/I. The number of star analysts in each industry varies in different rankings: for I/I it is 3 stars+ Runners-up, for STM-TEE and STM-TSP – 3 stars, and for WSJ – 5 stars.

number-one ranked stars. The table also presents the percentages of analysts who appear in another ranking. For example, the *Institutional Investor* ranking has, on average, 13 percent of analysts out of 191 unique names who were listed as “Top Stock Pickers” by *StarMine* in the same years. As can be observed, Top Stock Pickers and *The Wall Street Journal* exhibit the highest similarity in their published lists, while *Institutional Investor* and *The Wall Street Journal* have the lowest similarity. Such overlap is expected given the degree of similarities in the evaluation methods used. It also shows how different the lists of Star analysts are, which might explain the differences in the returns from their recommendations.

Table 6 shows the number of firms in the sample, which ranged from 3356 in 2010 to 3935 in 2006, and the percentage of firms covered by each group. On average per year, I/I, STM-TEE, and STM-TSP star analysts covered 22-23 percent, while WSJ covers 27 percent of the firms in the sample. Out of the total number of 6443 firms in the sample, I/I stars covered 36 percent of the firms, STM-TEE – 47 percent, STM-TSP – 50 percent, and WSJ – 58 percent. This difference suggests that these groups have different firm coverage and, thus, they issue recommendations for different universes of firms, which could be explained by the fact that the WSJ list has the highest turnover of names (see Table 22 and related discussion). Number-one ranked stars cover 10 percent of the firms, except WSJ-1, which covers 8 percent of the firms.

As can be seen in Table 7, the group of *Stars* issues on average 20 percent of all recommendations in the sample. Both WSJ and I/I stars issue more recommendations than STM-TEE and STM-TSP stars.

Table 6. Number of firms and percentage of firms in the sample covered by each group, calculated on an election-year basis.

Election year	Total number of firms	Stars	Portion of firms covered by entire groups of stars				Portion of firms covered by Number-one ranked stars			
			I/I	STM-TEE	STM-TSP	WSJ	I/I-1	STM-TEE-1	STM-TSP-1	WSJ-1
2003	3580	50%	31%	18%	19%	29%	12%	7%	7%	9%
2004	3660	50%	27%	17%	20%	29%	10%	8%	8%	9%
2005	3801	50%	27%	19%	19%	29%	9%	8%	8%	8%
2006	3935	48%	24%	22%	22%	26%	9%	9%	10%	7%
2007	3927	53%	24%	22%	22%	30%	9%	9%	10%	7%
2008	3752	51%	25%	25%	25%	27%	10%	13%	13%	8%
2009	3495	49%	18%	25%	25%	28%	9%	10%	11%	8%
2010	3356	52%	12%	27%	27%	29%	12%	12%	12%	8%
2011	3414	49%	12%	23%	22%	29%	12%	10%	9%	8%
2012	3390	49%	21%	25%	22%	20%	9%	11%	11%	9%
2013	3425	51%	24%	24%	25%	20%	10%	12%	12%	8%
Average	3612	50%	22%	22%	23%	27%	10%	10%	10%	8%
Overall	6443	71%	36%	47%	50%	58%	20%	29%	32%	30%

NOTE: Rankings by *Institutional Investor* (I/I), Thomson Reuters' *StarMine* "Top Earnings Estimators" (STM-TEE) and "Top Stock Pickers" (STM-TSP), and *The Wall Street Journal* (WSJ). Indexation by -1 indicates a group of number-one ranked analysts. Each group of star analysts covers approximately 50 percent of firms in the sample. Thus, the coverage universe differs for the various groups of stars.

The number of star analysts in each industry varies in different rankings: for I/I it is 3 stars+ Runners-up, for STM-TEE and STM-TSP – 3 stars, and for WSJ – 5 stars.

Table 7. Number of recommendations and the percentage of recommendations on an election-year basis by each ranking.

Election year	Entire sample	Stars	Entire groups of stars				Number-one ranked stars			
			I/I	STM-TEE	STM-TSP	WSJ	I/I-1	STM-TEE-1	STM-TSP-1	WSJ-1
2003	33,233	20%	10%	4%	5%	8%	2.0%	1.3%	1.3%	1.7%
2004	32,600	20%	9%	4%	5%	8%	1.9%	1.5%	1.6%	1.9%
2005	32,175	21%	9%	4%	5%	8%	1.5%	1.6%	1.5%	1.8%
2006	32,005	20%	8%	6%	6%	7%	1.7%	2.1%	2.2%	1.4%
2007	34,254	27%	8%	5%	10%	12%	1.8%	1.6%	2.0%	5.9%
2008	36,551	25%	7%	6%	7%	11%	1.8%	2.7%	2.9%	6.0%
2009	33,217	22%	5%	5%	10%	11%	1.5%	1.6%	2.1%	4.9%
2010	31,686	17%	2%	6%	6%	7%	2.1%	2.3%	2.3%	1.3%
2011	30,607	16%	2%	5%	4%	7%	2.0%	1.8%	1.6%	1.7%
2012	29,181	18%	6%	6%	5%	4%	1.6%	2.0%	2.3%	1.7%
2013	27,412	19%	6%	6%	6%	5%	1.8%	2.4%	2.2%	1.6%
Average	32,084	20%	6%	5%	6%	8%	1.8%	1.9%	2.0%	2.7%
Overall	291,731	19%	6%	6%	7%	9%	1.7%	2.1%	2.3%	2.7%

NOTE: Rankings by *Institutional Investor* (I/I), Thomson Reuters' *StarMine* "Top Earnings Estimators" (STM-TEE) and "Top Stock Pickers" (STM-TSP), and *The Wall Street Journal* (WSJ). Indexation by -1 indicates a group of number-one ranked analysts. The number of star analysts in each industry varies in different rankings: for I/I it is 3 stars+ Runners-up, for STM-TEE and STM-TSP – 3 stars, and for WSJ – 5 stars.

3.2. Building “paper” portfolios²

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, which “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 to measure profits on implementable investment strategies (Barber et al., 2001). The primary drawback of an event study with respect to measuring the performance of recommendations is the existence of confounding events, which makes 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 to isolate 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, they often coincide with each other. 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 occurring within the event window, making the findings from such 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 A “paper” portfolio refers to using calculated trading to backtest buying and selling securities without actual money being involved.

- (2) *Institutional Investor* (I/I), *StarMine* Top Earnings Estimators (STM-TEE) and Top Stock Pickers (STM-TSP), and *The Wall Street Journal* (WSJ);
- (3) Analysts ranked as number one (Top-Ranked): 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 Part I, these groups were compared 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 whole sample period for *Year Before* spans from January 2002 until December 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 that month. During the evaluation year, analysts are compared in a uniform way independently of the methodology 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 a 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 until 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 since that is the end of the last one-year period for the 2013 list of WSJ stars.

Because Parts II and III in the dissertation are not concerned with the performance persistence, these parts focus on comparing stars and non-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, re-iterations of recommendations are not included in

the portfolios. The same procedures are applied to a “Hold” (includes only Hold recommendations) and “Short” (includes Sell and Strong Sell recommendations) portfolios.

Table 8 reports the number of stocks held in the constructed portfolios that were built using the IBES recommendation sample according to the trading strategy described earlier in this section. For the Long portfolio, the average number of stocks is 585.81 for Stars and 1572.41 for Non-Stars. In the Hold portfolio, Stars have an average of 747.83 stocks, whereas Non-Stars have 1835.34 stocks. For the Short portfolio, the average number of stocks is 195.25 for Stars and 588.99 for Non-Stars. An analysis of the average number of stocks in the constructed portfolios shows that Non-Stars’ portfolios have approximately 2.7 times more stocks than Stars’ portfolios. This difference is expected, considering the difference in the number of recommendations by Stars and Non-Stars (see Table 7) because the group of Non-Stars is larger than the group of Stars (see Table 4).

Table 8. Descriptive statistics for the daily number of stocks in the constructed portfolios.

	Mean	Std.Dev.	Min	Max
Long Portfolios (Strong Buy, Buy)				
Stars	585.81	81.09	200	742
Non-Stars	1572.41	104.33	1312	1820
Hold Portfolios (Hold)				
Stars	747.83	91.45	331	927
Non-Stars	1835.34	97.32	1606	2094
Short Portfolios (Sell, Strong Sell)				
Stars	195.25	55.23	111	367
Non-Stars	588.99	87.95	393	907

NOTE: Star analysts are those listed in *The Wall Street Journal*, *Institutional Investor*, and Thomson Reuters’ *StarMine* “Top Stock Pickers” and “Top Earnings Estimators”. Analysts in the group of Non-Stars are those not listed in any of mentioned Star rankings during a particular evaluation year. Time period: from November 1, 2003 to May 31, 2014. The “Long” portfolio includes Strong Buy and Buy recommendations; the “Short” portfolio includes Sell and Strong Sell recommendations; the Hold portfolios include only Hold recommendations.

3.3. Portfolio returns

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

As a result of the portfolio strategy discussed in the previous section, the calendar day t gross return on portfolio ρ includes from $n=1$ to $N_{\rho t}$ recommendations and can be defined as:

$$R_{\rho t} = \frac{\sum_{n=1}^{N_{\rho t}} X_{n,t-1} R_{i_n,t}}{\sum_{n=1}^{N_{\rho t}} X_{n,t-1}}, \quad (1)$$

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:

$$X_{n,t-1} = R_{i_n, \text{recdat}_n+1} R_{i_n, \text{recdat}_n+2} \dots * R_{i_n, \text{recdat}_n t-1} \quad (2)$$

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 proposed by Carhart (1997):

$$R_{\rho\tau} - Rf_{\tau} = \alpha_{\rho} + \beta_{\rho}(Rm_{\tau} - Rf_{\tau}) + s_{\rho}SMB_{\tau} + h_{\rho}HML_{\tau} + m_{\rho}UMD_{\tau} + \varepsilon_{\rho\tau}, \quad (3)$$

where Rm_{τ} is a daily market return; Rf_{τ} is the risk-free rate of return; SMB_{τ} is a size factor, that is, the difference between the value-weighted portfolio returns of small and large stocks; HML_{τ} 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; UMD_{τ} is a

momentum factor, that is, the difference in the returns of stocks with a positive return momentum and those 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 better quality of analysts than a classical single-factor CAPM model (Lintner, 1965; Sharpe, 1964). The Carhart's four-factor model is used because earlier research shows this model has a superior prediction power over both CAPM and Fama-French (Fama and French, 1993) models (see e.g. Bello, 2008). Additional factors are not included, because they are not relevant for this investigation, such as the Tech-Sector ArcaEx Tech 100 Index (^PSE) (Fang and Yasuda, 2014), which is used as an extension to the four-factor model for the research covering the end of the 90th.

The alpha differentials (differences in alphas) are statistically tested 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 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 (*suest* and *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.

3.3.1 General assessment of the regression model

Goodness-of-fit. Most regressions of the Carhart 4-factor model in Parts 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 lower R^2 of approximately 46%.

Multicollinearity. By testing a variance inflation factor using a *vif* command after the regressions in Stata, four predictors in Carhart's model show very low collinearity. 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 finding (see, e.g., Bello, (2008)).

Heteroscedasticity tests show that it does not affect the conclusions of this study. 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 explain 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 Parts 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 those tabulated in Part I. Thus, the results of those tests lead to the conclusion that the heteroscedasticity is not a problem for the model and calculations.

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 for the analysis of 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 in this thesis, 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 (ε_{it}) from Equation 3.

Part II evaluates the sources of the portfolios' excess returns³ by using a performance *attribution analysis* for two dimensions following Brinson and Fachler (1985)—economic sectors (GICS Sectors), and for market-capitalization-weighted Size Deciles (CRSP Size Deciles)—according to the following equations:

³ Throughout this thesis, the following terminology is used 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.

$$\text{Allocation} = \frac{1}{T} \sum_j \sum_{\tau=1}^T \left[\left(w_{\rho j, \tau} - w_{mj, \tau} \right) \times \left(R_{mj, \tau} - R_{m, \tau} \right) \right] = \text{Static} + \text{Dynamic}, \quad (4)$$

$$\text{Static Added Value} = \sum_j \left[\frac{1}{T} \sum_{\tau=1}^T \left[w_{\rho j, \tau} - w_{mj, \tau} \right] \right] \times \left[\frac{1}{T} \sum_{\tau=1}^T \left[R_{mj, \tau} - R_{m, \tau} \right] \right], \quad (5)$$

$$\text{Dynamic Added Value} = \text{Allocation Effect} - \text{Static Added Value}, \quad (6)$$

$$\text{Selection} = \frac{1}{T} \sum_j \sum_{\tau=1}^T \left[\left(w_{mj, \tau} \right) \times \left(R_{\rho j, \tau} - R_{mj, \tau} \right) \right], \quad (7)$$

$$\text{Interaction} = \frac{1}{T} \sum_j \sum_{\tau=1}^T \left[\left(w_{\rho j, \tau} - w_{mj, \tau} \right) \times \left(R_{\rho j, \tau} - R_{mj, \tau} \right) \right], \quad (8)$$

where $w_{\rho j}$ and w_{mj} are the investment average daily proportions given to the j th market segment (GICS sector or CRSP size decile) for day τ in the constructed portfolio and the market portfolio, respectively,

$R_{\rho j}$ and R_{mj} are the investment daily returns of the j th market segment in the constructed portfolio and the market portfolio, respectively,

$R_{m, \tau}$ is the total return of the market portfolio at day τ , and

T is the number of days.

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), Part 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 our analysis helps us 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, we use the 10 sectors from the GICS of 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 (t), 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, $MS_{i,t}$, which is equal to the cumulative capitalization of all companies with greater capitalization plus half of its own capitalization. $MS_{i,t}$ 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

Part III of this thesis focuses on the seasonal patterns in analysts' recommendations and target prices. First, the seasonal effects in market returns are assessed. Second, Part III investigates whether there are seasonality patterns in the TP that are issued by stars and non-stars. Finally, the time-varying nature of TP are investigated on a more detailed level and discussed possible reasons for the observed patterns.

Part III uses a dataset of target prices with the following filters to the initial sample. The “penny stocks” are also omitted, that is, it considers only the target prices for companies that have a stock price of more than one dollar on the preceding trading day. The target price expected return, $TPER$, is defined similarly to Huang, Mian, and Sankaraguruswamy (2009) as $TP_t/P_{t-1}-1$, where TP_t is the analyst's target price with 12-month horizon issued on day t ; P_{t-1} is the share price on previous trading day before t . Because initial IBES sample of target prices contains outliers (probably due to coding errors in IBES), the 5% of observations are cut from both sides of the distribution⁴. As in Parts I and II, the recommendation dataset contains only recommendation changes (Boni and Womack, 2006). The $TPER$ and Recommendation Changes datasets are merged on analysts' identification number and announcement dates (variables `AMASKCD` and `ANNDATS` in IBES) omitting those observations that do not match.

The final database for Part III contains 67,973 target prices for 5142 companies listed on the NYSE, AMEX and NASDAQ markets that were announced between October 2003 and

⁴ Descriptive statistics for initial and our final sample is available upon request. The results of our study are qualitatively the same if the tests are repeated on the sample limited to $TPER$ of $(-1;1)$ and on the 1% cut of outliers.

November 2014. Table 9 reports the number of target prices conditional on recommendation categories. Non-Stars issued 3.6 times more target prices (53,239) than Stars (14,734). Both groups of Stars and Non-Stars have similar distributions of target prices among the recommendation categories, with 47 percent of target prices on the Buy level, 41 percent on Hold, and 12 percent on Sell (see Table 9). For both groups, the number of target prices was evenly distributed between the summer and winter seasons, having approximately 50% of target prices issued during the winter season.

Table 9. Number of target prices for each recommendation category for Stars (Panel A) and Non-Stars (Panel B) from November 2003 – November 2014.

Portfolio	Number of <i>TPERs</i> and % from All						Winter, % from Total
	Total (Winter + Summer)		Winter		Summer		
	No. <i>TPER</i>	% from All	No.	%	No.	%	
<i>Panel A. Stars</i>							
Buy	6866	47%	3439	46%	3427	47%	50%
Hold	6079	41%	3085	41%	2994	41%	50%
Sell	1789	12%	910	13%	879	12%	51%
All:	14,734	100%	7434	100%	7300	100%	50%
<i>Panel B. Non-Stars</i>							
Buy	25,035	47%	12,598	47%	12,437	47%	50%
Hold	22,010	41%	10,909	41%	11,101	42%	50%
Sell	6194	12%	3067	12%	3127	12%	50%
All:	53,239	100%	26,574	100%	26,665	100%	50%

NOTE: Target price expected return, *TPER*, is defined as $TP_t/P_{t-1}-1$, where TP_t is the analyst's target price with a 12-month horizon issued on day t ; P_{t-1} is the share price on the previous trading day before t . The Buy portfolio includes Strong Buy and Buy recommendations; Sell includes Strong Sell and Sell; Hold includes Holds. *Winter Season* is from November until April.

An OLS regression analysis with a seasonal dummy variables is used for capturing the differences among seasons (Bouman and Jacobsen, 2002):

$$R_{MKTt} = \mu + \gamma DS_t + \varepsilon_t, \quad (9)$$

where R_{MKT} is the return on the CRSP index (the daily and monthly raw returns and the log returns are tested); DS is a seasonal dummy that is equal to 1 for the 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. To study seasonal anomalies, such as the difference between *Summer* and *Winter*, coefficient μ will return a mean value during the summer, and γ will show the difference among seasons and the statistical significance of this difference.

Part 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_t 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 .

Two hypotheses are tested in Part III. The first hypothesis is whether the analysts' optimism that is reflected in $TPER$ is associated with 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 fourth 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 Part 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, this study follows Bagnoli et al. (2008) by using a turnover of rankings as a measure of the change in analysts' competitive advantages. Bagnoli et al. (2008) focus on the impact of Reg-FD on the turnover of analysts. This thesis extends their study and examines 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. This thesis 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 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.

CHAPTER 4:

RESULTS

4. Results

This chapter presents the results of the methodological approaches discussed in the previous chapter of this study. For the ease of comprehension, the results are divided into four parts, which follow a sequential order. First, the results of a returns-based analysis are discussed for testing the performance persistence of each group of stars and for comparing stars with their non-stars peers. Second, the results of the holdings-based analysis are discussed in the view of how the portfolios' structures can explain the performance. Third, the seasonal patterns are assessed in the investigated portfolios. Forth, the competitive advantages of different groups of star analysts are investigated under different market conditions.

4.1. Part I – Portfolio returns

Table 10 represents the average monthly excess returns (alphas) for groups of *Star* and *Non-Star* analysts during the year after rankings have been published (Panel A), during the evaluation year (Panel B) and as a comparison of the returns in the *Year After* with those of the *Year Before* (Panel C). The first three rows in each panel of the table show the returns of the Long, Hold and Short portfolios, while the third row (Long-Short) presents the total return on all of the recommendations for a particular group, which is the Long minus the Short portfolio returns.

As Panel A in Table 10 shows, the Long-Short portfolio of *Stars*, with monthly alphas of +0.53 percent, performed insignificantly different from the *Non-Stars*, with monthly alphas of +0.47 percent, leading to a statistically insignificant difference of 0.06 percentage points in abnormal returns for a Long-Short portfolio in the year after rankings were published. For alpha differentials among all portfolios in the *Year After*, only Long portfolio of *Stars* is statistically different from that of the *Non-Stars*. As can be expected, during the evaluation year (Panel B in Table 10), *Stars* had higher recommendation returns, of +1.08 percent, than

Table 10. Average monthly abnormal returns (alphas) for groups of Star and Non-Star analysts and differences in abnormal returns.

	Average monthly abnormal return (%)		Difference <i>Stars – Non-Stars</i>
	Overall groups		
Portfolio	<i>Stars</i>	<i>Non-Stars</i>	
<i>Panel A. Year After (November 2003 – May 2014)</i>			
Long: Strong Buy/Buy	0.33*** (4.09)	0.18* (1.75)	0.15** (2.03)
Hold	0.03 (0.45)	-0.07 (-0.73)	0.10 (1.57)
Short: Sell/ Strong Sell	-0.20 (-1.56)	-0.29** (-2.42)	0.09 (0.78)
Long-Short	0.53*** (4.56)	0.47*** (5.46)	0.06 (0.56)
<i>Panel B. Year Before (February 2002 – December 2012)</i>			
Long	0.62*** (7.28)	0.16 (1.46)	0.45*** (5.14)
Hold	0.01 (0.15)	-0.08 (-0.80)	0.10 (1.24)
Short	-0.46*** (-3.44)	-0.24 (-1.62)	-0.22* (-1.67)
Long-Short	1.08*** (9.00)	0.40*** (3.71)	0.68*** (5.30)
<i>Panel C. Difference Year After – Year Before (SUEST TEST)</i>			
Long	-0.29***	0.02	--
Hold	0.02	0.01	--
Short	0.26**	-0.05	--
Long-Short	-0.55***	0.07	--

t-statistics in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

NOTE: Rankings by *Institutional Investor* (I/I), Thomson Reuters' *StarMine* "Top Earnings Estimators" (STM-TEE) and "Top Stock Pickers" (STM-TSP), and *The Wall Street Journal* (WSJ). Portfolios are built according to recommendations: when a new recommendation is announced, \$1 is invested in the recommended stock by the end of the trading day (or on the next trading day if the recommendation is issued after the close of trading or is announced on a non-trading day), and the stock is held for one year or until the same analyst changes his or her recommendation or drops coverage, in which case the stock is withdrawn by the end of that trading day. All figures are obtained as intercepts from the regressions of the daily returns time series from two sample periods: the *Year Before* (February 2002 – December 2012) and the *Year After* (November 2003 – May 2014) on four standard risk factors (Carhart's four-factor model). The Long portfolio includes Buy and Strong Buy recommendations; Hold portfolio includes all Hold recommendations, while the Short portfolio includes Sell, and Strong Sell recommendations.

Non-Stars, with +0.40 percent. An analysis of the differences in returns from the *Year Before* to the *Year After*, as reported in Panel C, show that the *Stars* do not continue to perform on the same level, which is reflected as a significant difference in the returns on their Long, Short and Long-Short portfolios, while the group of *Non-Stars* had an insignificant difference in the returns on their Long, Short and Long-Short portfolios. Hence, it allows a conclusion that only Buy and Strong Buy recommendations of the group of *Stars* persistently outperform those of their Non-Star peers, although the *Stars* show a decrease in their performance in the *Year After*.

Table 11 shows the excess returns from recommendations issued by entire groups of stars: “I/I”, “STM-TEE”, “STM-TSP” and “WSJ” in the *Year After* (Panel A) and *Year Before* (Panel B) and the difference in returns between the *Year After* and *Year Before* (Panel C).

Long-Short portfolios from the groups of STM-TEE, STM-TSP and WSJ stars show positive and statistically significant alphas in both time periods, while I/I stars performed insignificantly different from the market in the *Year After*. Excess returns of the Long portfolios for all groups in the *Year Before* and *Year After* are statistically different from zero. Some Short portfolios are insignificantly different from zero (that of I/I, STM-TSP in the *Year After*, and I/I, STM-TEE in the *Year Before*).

As can be seen in Panel C of Table 11, Long, Short and Long-Short portfolios from WSJ and STM-TSP stars exhibit the greatest significant decrease in performance after election as a star, that is −1.48 percent for WSJ, and −1.37 percent for STM-TSP for their Long-Short portfolios. This decrease can be explained as the regression to the mean, which shows that it is very difficult to issue recommendations consistently generating portfolios with very high abnormal returns. At the same time, STM-TEE shows persistence because their Long-Short portfolio in the *Year Before* is insignificantly different to the *Year After* (albeit the group of

Table 11. Average monthly abnormal returns (alphas) for each group of star analysts.

Portfolio	Average monthly abnormal returns (%) entire groups of star analysts			
	I/I	STM-TEE	STM-TSP	WSJ
<i>Panel A. Year After (November 2003 – May 2014)</i>				
Long: Strong Buy/Buy	0.32*** (3.33)	0.32*** (3.09)	0.38*** (3.83)	0.23*** (2.18)
Hold	0.16* (1.70)	0.01 (0.10)	-0.02 (-0.24)	-0.02 (-0.21)
Short: Sell/ Strong Sell	0.18 (1.12)	-0.64*** (-3.44)	-0.16 (-0.79)	-0.40** (-2.02)
Long-Short	0.14 (0.96)	0.97*** (5.19)	0.54*** (2.69)	0.63*** (3.10)
<i>Panel B. Year Before (February 2002 – December 2012)</i>				
Long	0.39*** (3.70)	0.36*** (3.20)	0.90*** (8.13)	0.98*** (8.27)
Hold	0.05 (0.48)	0.05 (0.45)	0.05 (0.44)	0.01 (0.11)
Short	-0.01 (-0.07)	-0.24 (-1.08)	-1.02*** (-5.10)	-1.14*** (-5.66)
Long-Short	0.40** (2.37)	0.59*** (2.68)	1.91*** (9.58)	2.11*** (10.84)
<i>Panel C. Difference Year After – Year Before (SUEST TEST)</i>				
Long	-0.07	-0.04	-0.52***	-0.75***
Hold	0.11	-0.04	-0.07	-0.03
Short	0.19	-0.40*	0.86***	0.74***
Long-Short	-0.26*	0.38	-1.37***	-1.48***

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

NOTE: Rankings by *Institutional Investor* (I/I), Thomson Reuters' *StarMine* "Top Earnings Estimators" (STM-TEE) and "Top Stock Pickers" (STM-TSP), and *The Wall Street Journal* (WSJ). Portfolios are built according to recommendations: when a new recommendation is announced, \$1 is invested in the recommended stock by the end of the trading day (or on the next trading day if the recommendation is issued after the closing of trading or is announced on a non-trading day), and the stock is held for one year or until the same analyst changes his or her recommendation or drops coverage, in which case the stock is withdrawn by the end of that trading day. All figures are obtained as intercepts from the regressions of the daily returns time series on four standard risk factors (Carhart's four-factor model) and represented in monthly values from two sample periods: the *Year Before* (February 2002 – December 2012) and the *Year After* (November 2003 – May 2014). The Long portfolio includes Buy and Strong Buy recommendations; Hold portfolio includes all Hold recommendations; the Short portfolio includes Sell and Strong Sell recommendations.

STM-TEE has significantly different performance for their Short portfolio, as we can see in Panel C). For I/I stars, the drop is -0.26 percent.

Table 12 shows the average monthly excess returns for the top-ranked analysts (Number-one ranked analysts) for the *Year After* election (Panel A) and the *Year Before* (Panel B) and the difference between the *Year After* and the *Year Before* (Panel C). The Hold portfolios for all groups and all time periods perform insignificantly different from the market, having alphas insignificantly different from zero.

In the *Year After* election, the groups of STM-TEE-1 and I/I-1 stars show positive and statistically significant alphas for their Long-Short portfolios, while STM-TSP-1 and WSJ-1 stars performed on the market level, which is explained by relatively low and insignificant alphas for their Short portfolios. The highest return, and the only statistically significant one among the Short portfolios in the *Year After*, was generated by the STM-TEE-1 group, with -0.70 percent. Excess returns of Long portfolios for all groups in the *Year After* are positive and significantly different from zero. Panel C shows that Long, Short and Long-Short portfolios from STM-TSP-1 and WSJ-1 stars show a statistically significant decrease in performance from the *Year Before* to the *Year After*, while I/I-1 and STM-TEE-1 exhibit persistence from the *Year Before* to the *Year After*. Hence, comparing the returns in the *Year After* selection with the *Year Before* selection in Panel C of Table 12, the returns of STM-TSP-1 and WSJ-1 decrease, with a significant difference of -1.61 and -2.67 percent between alphas in the *Year After* and *Year Before*, respectively.

Table 13 and Table 14 report the alpha differentials obtained by comparing the abnormal returns between groups of stars in the *Year Before* and *Year After*. In both tables, results are reported for Long in Panel A, Short – Panel B, and Long-Short – Panel C. First, the discussion is provided of whether each particular group of stars outperformed the *Non- Stars*.

Table 12. Average monthly abnormal returns (alphas) for each group of Number-one ranked analysts.

Portfolio	Average monthly abnormal returns (%) number-one ranked star analysts			
	I/I-1	STM-TEE-1	STM-TSP-1	WSJ-1
<i>Panel A. Year After (November 2003 – May 2014)</i>				
Long: Strong Buy/Buy	0.44*** (3.26)	0.31** (2.20)	0.42*** (3.31)	0.38** (2.11)
Hold	0.09 (0.66)	-0.17 (-1.31)	0.02 (0.17)	-0.02 (-0.16)
Short: Sell/ Strong Sell	-0.27 (-1.14)	-0.70** (-2.44)	0.23 (0.59)	-0.20 (-0.46)
Long-Short	0.71*** (2.83)	1.01*** (3.34)	0.18 (0.46)	0.58 (1.26)
<i>Panel B. Year Before (February 2002 – December 2012)</i>				
Long	0.51*** (3.45)	0.31* (1.93)	0.93*** (5.83)	1.35*** (6.98)
Hold	0.12 (0.81)	0.19 (1.28)	-0.12 (-0.82)	0.02 (0.11)
Short	-0.35 (-1.34)	-0.28 (-0.84)	-0.85*** (-2.78)	-1.90*** (-4.96)
Long-Short	0.87*** (2.98)	0.58* (1.66)	1.79*** (5.34)	3.25*** (7.97)
<i>Panel C. Difference Year After – Year Before (SUEST TEST)</i>				
Long	-0.07	0.00	-0.51***	-0.97***
Hold	-0.03	-0.36**	0.14	-0.04
Short	0.08	-0.42	1.08**	1.70***
Long-Short	-0.16	0.43	-1.61***	-2.67***

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

NOTE: Rankings by *Institutional Investor* (I/I), Thomson Reuters' *StarMine* "Top Earnings Estimators" (STM-TEE) and "Top Stock Pickers" (STM-TSP), and *The Wall Street Journal* (WSJ). Indexation by -1 signifies a group of number-one ranked analysts. Portfolios are built according to recommendations: when a new recommendation is announced, \$1 is invested in the recommended stock by the end of the trading day (or on the next trading day if the recommendation is issued after the closing of trading or is announced on a non-trading day), and the stock is held for one year or until the same analyst changes his or her recommendation or drops coverage, in which case the stock is withdrawn by the end of that trading day. All figures are obtained as intercepts from the regressions of the daily returns time series on four standard risk factors (Carhart's four-factor model) and represented in monthly values from two sample periods: the *Year Before* (February 2002 – December 2012) and the *Year After* (November 2003 – May 2014). The Long portfolio includes Buy and Strong Buy recommendations; Hold portfolio includes all Hold recommendations; the Short portfolio includes Sell, and Strong Sell recommendations.

Then, the discussion of the differences in performance among all of the groups of star analysts is provided.

Table 13. Alpha differentials in the *Year Before* calculated as the difference in the excess return from the vertical group minus the excess return for a horizontal group of stars.

Alpha differentials (%) in the <i>Year Before</i> (February 2002 – December 2012) Groups of analysts								
	<i>Non-Stars</i>	I/I	STM-TEE	STM-TSP	WSJ	I/I-1	STM-TEE-1	STM-TSP-1
<i>Panel A. Long Portfolios: Strong Buy, Buy recommendations</i>								
I/I	0.23**							
STM-TEE	0.19	-0.03						
STM-TSP	0.73***	0.51***	0.54***					
WSJ	0.81***	0.58***	0.62***	0.08				
I/I-1	0.35**	0.12	0.15	-0.39***	-0.46***			
STM-TEE-1	0.14	-0.08	-0.05	-0.59***	-0.67***	-0.20		
STM-TSP-1	0.77***	0.54***	0.57***	0.03	0.04	0.42**	0.62***	
WSJ-1	1.19***	0.96***	0.99***	0.45***	0.38***	0.84***	1.04***	0.42**
<i>Panel B. Short Portfolios: Sell, Strong Sell recommendations</i>								
I/I	0.23							
STM-TEE	0.00	-0.22						
STM-TSP	-0.78***	-1.00***	-0.78***					
WSJ	-0.90***	-1.13***	-0.90***	-0.12				
I/I-1	-0.12	-0.34*	-0.12	0.66**	0.78***			
STM-TEE-1	-0.04	-0.26	-0.04	0.74**	0.86**	0.08		
STM-TSP-1	-0.62**	-0.84***	-0.62*	0.16	0.28	-0.50	-0.58	
WSJ-1	-1.66***	-1.88***	-1.66***	-0.88**	-0.76**	-1.54***	-1.62***	-1.04**
<i>Panel C. Long-Short Portfolios</i>								
I/I	0.00							
STM-TEE	0.19	0.19						
STM-TSP	1.51***	1.51***	1.32***					
WSJ	1.71***	1.71***	1.52***	0.20				
I/I-1	0.47	0.46**	0.27	-1.05***	-1.25***			
STM-TEE-1	0.18	0.18	-0.01	-1.33***	-1.53***	-0.28		
STM-TSP-1	1.38***	1.38***	1.19***	-0.13	-0.33	0.92**	1.20***	
WSJ-1	2.85***	2.84***	2.65***	1.33***	1.13***	2.38***	2.66***	1.46***

*** p<0.01. ** p<0.05. * p<0.1

NOTE: Rankings by *Institutional Investor* (I/I), Thomson Reuters' *StarMine* "Top Earnings Estimators" (STM-TEE) and "Top Stock Pickers" (STM-TSP), and *The Wall Street Journal* (WSJ). Indexation by -1 signifies a group of number-one ranked analysts. Excess returns were obtained from regressions for time series from a sample period of the *Year Before* (February 2002 – December 2012). Negative values are in red. Long portfolios (Panel A) include Strong Buy and Buy recommendations; Short portfolios (Panel B) include Sell and Strong Sell recommendations. Panel C shows the results for the Long-Short portfolios. Hold portfolios are not compared.

Comparing the returns of the Long portfolios of all of the groups of stars with those of *Non-Stars* in the *Year Before* (Panel A in Table 13), confirms that the groups of I/I, STM-TSP and WSJ stars and their number-one sub-groups significantly outperformed *Non-Stars*, while returns of the STM-TEE and number-one ranked STM-TEE-1 had insignificant differences with *Non-Stars*. Similar results were observed for the Short portfolios (Panel B in Table 13), where only STM-TSP and WSJ as well as their number-one sub-groups significantly outperformed *Non-Stars*. When the performance of the Long and Short portfolios are combined, that is the Long-Short portfolio (Panel C), it can be seen that STM-TSP and WSJ stars outperformed the *Non-Stars*. Such a finding is expected considering the similarity of the methods used by STM-TSP and WSJ rankings (recommendation-based) and our performance measures.

In line with the fact that STM-TSP and WSJ are based on the investment value of recommendations, and the methodologies of I/I and STM-TEE do not focus on the performance of the recommendations, it can be found that the Long, Short, Long-Short portfolios from the groups of STM-TSP and WSJ and their sub-groups of the number-one stars perform significantly better than both groups of I/I and STM-TEE and their number-one stars I/I-1 and STM-TEE-1 (Panel A, B and C in Table 13). Considering the returns for the Long and Short portfolios in the *Year Before*, the Long-Short portfolios represent similar patterns: stars ranked by the methodologies that take into account investment value of recommendations (STM-TSP and WSJ) outperformed those that do not use the recommendations in their selection methods (I/I and STM-TEE), with those differences being statistically significant. This result is expected given the evaluation methodologies applied to rank stars, since both STM-TSP and WSJ rankings are objectively measuring the investment value of the recommendations, whereas STM-TEE considers the accuracy and

timing of earnings forecasts, and the I/I ranking uses investment value as one of several attributes in its subjective methodology (survey) to select stars.

Comparing the returns of the Long portfolios in the *Year After* of all of the groups of stars with those of *Non-Stars* (first column in Panel A of Table 14), it can be found that only returns of I/I-1, STM-TSP and STM-TSP-1 stars significantly outperformed those of the group of *Non-Stars* at the 10 percent significance level, while entire groups of I/I, STM-TEE, and WSJ as well as number-one ranked stars from STM-TEE-1 and WSJ-1 did not significantly differ from *Non-Stars*. Analyzing Panel B of Table 14 for the Short portfolios in the *Year After*, it can be found that the differences between the excess returns of all of the groups of stars and those of *Non-Stars* were insignificant, except for I/I who underperformed, and STM-TEE who outperformed, the *Non-Stars*. This high performance of the Short portfolio for the STM-TEE and low performance for I/I was reflected in how the returns of these groups differ from the others. Hence, the differences in returns among most of the Short portfolios in the *Year After* are insignificant, except for I/I being significantly lower than some other groups of stars, and STM-TEE being significantly better than STM-TSP and their sub-group of STM-TSP-1. The results for the Long and Short portfolios explain why Long-Short portfolios of I/I underperformed *Non-Stars* and some of the groups of stars, while the STM-TEE and their number-one analysts performed significantly better than the *Non-Stars* and STM-TSP. This result can be interpreted as the reflection of the importance of making accurate earnings forecasts⁵ in order to predict a future price decrease, which facilitated the outperformance of the Short portfolios of the STM-TEE stars in order to outperform *Non-Stars* as well as STM-TSP stars.

⁵ As has been mentioned previously, earnings forecasts are important for valuation of stocks and thus for predicting future stock price (Ohlson 1995; Loh and Mian 2006).

Table 14. Alpha differentials in the *Year After* calculated as the difference in the excess return from the vertical group minus the excess return for a horizontal group of stars.

Alpha differentials (%) in the <i>Year After</i> (November 2003 – May 2014) Groups of analysts								
	<i>Non-Stars</i>	I/I	STM- TEE	STM- TSP	WSJ	I/I-1	STM- TEE-1	STM- TSP-1
<i>Panel A. Long Portfolios: Strong Buy, Buy recommendations</i>								
I/I	0.15							
STM-TEE	0.15	0.00						
STM-TSP	0.21*	0.06	0.06					
WSJ	0.05	-0.09	-0.09	-0.15				
I/I-1	0.26*	0.12	0.12	0.06	0.21			
STM-TEE-1	0.14	-0.01	-0.01	-0.07	0.08	-0.13		
STM-TSP-1	0.24*	0.09	0.09	0.03	0.19	-0.03	0.10	
WSJ-1	0.21	0.06	0.06	0.00	0.15	-0.06	0.07	-0.03
<i>Panel B. Short Portfolios: Sell, Strong Sell recommendations</i>								
I/I	0.47***							
STM-TEE	-0.35**	-0.82***						
STM-TSP	0.13	-0.34	0.48**					
WSJ	-0.11	-0.58***	0.24	-0.24				
I/I-1	0.02	-0.45**	0.37	-0.11	0.13			
STM-TEE-1	-0.41	-0.88***	-0.05	-0.53*	-0.29	-0.43		
STM-TSP-1	0.52	0.05	0.87**	0.39	0.63	0.50	0.93**	
WSJ-1	0.09	-0.38	0.44	-0.04	0.20	0.07	0.49	-0.43
<i>Panel C. Long-Short Portfolios</i>								
I/I	-0.32**							
STM-TEE	0.50***	0.82***						
STM-TSP	0.08	0.40*	-0.42*					
WSJ	0.16	0.49**	-0.34	0.09				
I/I-1	0.24	0.57***	-0.26	0.17	0.08			
STM-TEE-1	0.54*	0.86***	0.04	0.47	0.38	0.30		
STM-TSP-1	-0.28	0.04	-0.78*	-0.36	-0.44	-0.53	-0.82*	
WSJ-1	0.12	0.44	-0.38	0.04	-0.05	-0.13	-0.42	0.40

*** p<0.01. ** p<0.05. * p<0.1

NOTE: Rankings by *Institutional Investor* (I/I), Thomson Reuters' *StarMine* "Top Earnings Estimators" (STM-TEE) and "Top Stock Pickers" (STM-TSP), and *The Wall Street Journal* (WSJ). Indexation by -1 signifies a group of number-one ranked analysts. Excess returns were obtained from regressions for time series from a sample period of the *Year After* (November 2003 – May 2014). Negative values are in red. Long portfolios (Panel A) include Strong Buy and Buy recommendations; Short portfolios (Panel B) include Sell and Strong Sell recommendations. Panel C shows the results for the Long-Short portfolios. Hold portfolios are not compared.

By analyzing the persistence in the performance for the Long portfolios from the *Year Before* to the *Year After*, it can be concluded that the groups of I/I-1, STM-TSP and STM-TSP-1 performed significantly better than *Non-Stars* in both the *Year After* and *Year Before* (Panel A in Table 13 and Table 14), while the group of STM-TEE with their sub-group of number-one ranked STM-TEE-1 stars had insignificantly different returns from *Non-Stars* before and after rankings were announced. Additionally, it is important to mention that the difference in the returns of the Long portfolios in the *Year Before* (Panel A in Table 13) among the entire groups of star analysts shows that, while STM-TSP and WSJ stars and their sub-groups of number-one STM-TSP-1 and WSJ-1 stars significantly outperformed I/I, STM-TEE and their number-one sub-groups, the differences in returns among all of the groups in the *Year After* are insignificant (Panel A in Table 14). This result confirms the assumption that, in most cases, there is the regression to the mean, which explains why in the *Year Before* the differences in returns were mostly statistically significant while in the *Year After* all of the groups of stars perform insignificantly different from each other.

In summary, using the returns obtained by comparing the portfolio returns in the years after election, the conclusions are: Firstly, this study documents that only the Long portfolio of the group of *Stars* which has all unique names of ranked analysts from I/I, WSJ and *StarMine* rankings performs better than that of the *Non-Stars*. Note, though, that Short and Long-Short (Long minus Short) portfolios from both groups have statistically insignificant differences in returns. The finding that the group of *Stars* outperforms *Non-Stars* only for Buy and Strong Buy but not for Sell and Strong Sell recommendations is consistent with a hypothesis that reputation helps in mitigating conflicts of interest. According to Fang and Yasuda (2009), reputation effects from star rankings can improve the quality of analyst research and this improvement might happen more for favorable ratings like Buy and Strong Buy, which are more likely to be conflicted (Michaely and Womack 1999; Barber et al. 2006).

Considering that, in the year before election, *Stars* had significantly higher returns for their Long-Short portfolios and the differences between Long and Short portfolios were greater than in the year after, this study concludes that, on average, *Stars* are not able to repeat the observed high excess returns after they were selected as *Stars*. However, this result does not imply that all rankings' methodologies have the same low predictive power of the future returns.

Secondly, the investigated differences among subjective (I/I) and objective (*StarMine* and WSJ) rankings show that the returns of the recommendations from analysts ranked by the subjective ranking from the *Institutional Investor* had relatively low returns in the *Year Before* as well as in the year after election. Indeed, most of the portfolios from I/I stars underperformed the other groups of stars from objective rankings and even underperformed the Non-Star peers. Though this conclusion might be essential for the investors who are concerned about the investment value of recommendations, it is important to remember that the *Institutional Investor* ranking does not consider the recommendations as the primary evaluation criteria for selecting analysts. According to a list of attributes mentioned by the *Institutional Investor* magazine and to Table 1 in Bagnoli et al. (2008), stock selection is not the number one criteria institutions are looking for when ranking analysts. In fact, stock selection is typically not even among the top five attributes that institutional investors are looking for. Thus, the findings of this thesis do not contradict the intentions of the I/I ranking (that is, to evaluate subjectively the services provided by sell-side analysts).

Among the objective rankings, significant differences are found in their predictive power, which are discussed as the persistence of the performance from the *Year Before* to the *Year After* election. This study documents a significant decrease in performance from the *Year Before* to the *Year After* for the analysts who were ranked according to the investment value of the recommendations (STM-TSP and WSJ). This result might be explained by the low

predictive power of such recommendation-based election methods which lead to the regression to the mean, whereby the previous year's best performers should exhibit results that are closer to the average in subsequent years. However, the results of this study show significantly positive returns for the Long portfolios of the STM-TSP and STM-TSP-1 stars, which outperformed *Non-Stars* in the year after election, even though there is a decline in performance compared with the evaluation year. Overall, the results confirm the previous findings that reported low predictive power for the methods which focus solely on the past performance of the recommendations (Emery and Li 2009).

In contrast to the results for objective recommendation-based rankings, for STM-TEE ranking that is based on the accuracy and timing of earnings forecasts, the returns for Long-Short portfolios in the *Year After* differ insignificantly from those of the *Year Before*. More important is that this group outperforms *Non-Stars* and some other groups of stars (I/I and STM-TPS) in the year after election. The findings of this study document that this outperformance is explained by the high excess returns for the Short portfolio of STM-TEE, while their Long portfolio was insignificantly different from the *Non-Stars* as well as those of the other groups of stars. This conclusion emphasizes the importance of accurate earnings forecasts being used in the valuation models in order to predict future stock prices, especially the decrease in prices, which lead to the outperformance among Short portfolios.

Overall, this thesis concludes that the stock-picking skill is difficult to capture by focusing only on the performance of the recommendations over a one-year horizon. However, methodologies which consider other fundamental skills, such as earnings forecasts that are necessary for successful stock picks, gave much higher predictive power for the performance of future recommendations, even though the previous year returns by our evaluation methodology for those earnings-based stars were not as high as for the recommendation-based rankings.

4.1.1 Robustness tests

This study employs a method used by other researchers (Barber et al. 2007; Fang and Yasuda 2014) holding the stocks in the portfolio for one year or until the next recommendation change from the same analyst, whichever happens earlier. The baseline analysis considers all recommendation changes issued by all analysts listed in different rankings. This section discusses the results from imposing additional filters on the sample of recommendations and analysts. Also, it provides a discussion of alternative holding periods and construction of the Short portfolios.

First, an additional filter of the recommendations was applied excluding the recommendation changes which were issued on the same days as earnings announcement days in order to avoid contamination in measuring analyst stock-picking skill. While the previous study by Li et al. (2015) documents that the contemporaneous-with-news recommendation changes have higher market impact than the earnings announcements themselves since such recommendations help investors interpret the news, some of such recommendations might simply be piggybacking on the news without providing more value to investors. Excluding the recommendations that were issued on the same days as the earnings announcement dates obtained from the Compustat database (accounted for 3.4 percent of recommendations) shows that the main conclusions of this study remain the same, though the alphas were insignificantly decreased. Excluding the recommendations that were issued within a three-day window around earnings announcements (17.3 percent of recommendations) leads to slight changes in conclusions from the baseline analysis. Specifically, the Long portfolios of I/I in the *Year After* performed significantly better than the Non-Stars; also, the differences in returns for Long-Short portfolios among STM-TEE and STM-TSP became insignificant. However, the results of the comparison for the Long-

Short portfolios of each group of stars with the *Non-Stars* remain unaffected: STM-TEE outperformed, while I/I underperformed the group of *Non-Stars*.

Second, the calculations are repeated using two filters on the sample of analysts: (i) non-overlapping sample of stars; and (ii) in each industry, limit the number of stars to one, two, and three only (applies to I/I and WSJ, while *StarMine* lists remain unchanged). While the non-overlapping samples exclude those analysts who are performing well according to some or even all evaluation methods (subjective or objective), such a limitation might help to distil the differences between rankings' performance. By considering only three stars in each industry in I/I and WSJ lists, it tries to reduce the differences in the number of analysts in each group of stars and eliminate the influence of bottom-ranked analysts (runners-up) on our conclusions. In both cases, the focus is on the differences among groups of stars and found that, in the case of focusing on only three stars per industry, the main conclusions remain the same. After examining the results for non-overlapping samples, it was found that the highest change was for the groups of I/I and STM-TEE stars whose Long-Short portfolio returns were lower as compared to the baseline analysis. The decrease of the returns for some portfolios for non-overlapping groups of stars led to an insignificant difference in performance between groups of STM-TEE and I/I with STM-TSP stars. Since some star analysts appear in several rankings in a given year and the results are lower with non-overlapping samples of STM-TEE and I/I, this fact was interpreted as an indication that the best analysts are selected as stars in several rankings at the same time.

Third, some alternative portfolio constructs are used: (i) by taking the immediate year before rankings were announced instead of the previous calendar year; and (ii) by including Hold recommendations into Short portfolios, thus having only two portfolios to consider, namely Long and Short.

Taking an immediate year before the rankings' announcement uses the data that are more current and relevant. The fact that I/I and *StarMine* rankings are announced around October each year, and WSJ publishes its list of stars in May, potentially creates a bias, as information used for analysis is relatively stale for I/I and *StarMine* compared to WSJ. After repeating the calculations for a new time-frame of the *Year Before*, it was found that the excess returns for I/I changed insignificantly, while the returns for WSJ and STM-TSP decreased (especially for STM-TSP, since STM-TSP is published in October, the overlap of the immediate year before ranking is announced with the previous calendar year is lower than for WSJ, which is published in May). This decrease in the performance for recommendation-based rankings led to insignificant differences between the returns for Long-Short portfolios of STM-TSP and WSJ with those of the STM-TEE in the *Year Before*. Also, the difference among Long-Short portfolios for STM-TSP and I/I stars became insignificant. These results are in line with the main findings as they show that high excess returns were documented only during the same year as the evaluation year, while they regressed to the mean in subsequent time periods.

Alternative portfolio constructs were also tested by including Hold recommendations into the Short portfolio as in Barber et al. (2007) and in Fang and Yasuda (2014). Taking into account that analysts are reluctant to issue sell recommendations (Barber et al. 2007), investors might treat Hold ratings as a signal to sell, especially when this Hold is a downgrade from Buy or Strong Buy. While this might lead to a negative price reaction on some Hold recommendations, the upgrades from Sell/Strong Sell to Hold are expected to generate near market returns (Barber et al. 2010). By repeating all calculations, it was found that the alpha levels for Short portfolios that contain Hold/Sell/Strong Sell recommendations on a one-year horizon were close to zero for almost all portfolios⁶. That result is expected considering

⁶ Only the returns of the Short and Long-Short portfolios were affected in this robustness test, while the results for the Long portfolios remained unchanged.

that such Short portfolios had about 90 percent weight in Hold recommendations, and according to the results for “Long, Hold, Short” portfolio calculations, Hold portfolios have alphas insignificant from zero for all groups of analysts (except for the Hold portfolio of I/I stars, see Panel A in Table 11).

Additionally, all portfolios were reconstructed using shorter holding periods, such as 30 days as in (Fang and Yasuda 2014). It was found that the Short portfolios (Sell/Strong Sell recommendations) for some groups of stars had a very low number of stocks. Thus, Short portfolios of STM-TSP had only 9.1 stocks on average, STM-TEE had 7.5 stocks, and portfolios for the number-one ranked *StarMine* analysts had on average fewer than 5 stocks. Other time periods were tested within a horizon of one year (namely, 45, 60, 90, 180 days) and it was found that up to 180 days, the Short portfolios from the number-one ranked stars had a relatively low number of stocks (less than 10). Hence, those portfolios were highly undiversified and their excess returns were unreliable. Consequently, the main analysis was performed considering only a one-year horizon for the recommendations to be valid if they are unchanged. It was found that for short portfolios the number-one stars had on average 20 stocks and for the entire groups of stars the average number was more than 50 stocks during the investigated time period.

Finally, combinations of different restrictions were tested, such as a non-overlapping sample of only three stars in each industry, and excluding the recommendations on earnings announcement days. It was found that all possible filters affect the alpha levels, but do not influence our main conclusions on the differences between groups of *Stars* and *Non-Stars*, while the differences among Long-Short portfolios for the groups of stars become statistically insignificant. All the results of the robustness tests remain unpublished and are available upon request.

4.2. Part II – Portfolio structure

The returns-based analysis of the portfolios composed of recommendations by the groups of *Stars* and *Non-Stars* is conducted for the period from November 1, 2003, to May 30, 2014. The results are presented in Table 15. For reference purposes in the heading of Table 15 the corresponding figures are reported for the capitalization-weighted market returns (CRSP cap-weighted). Each panel of the table corresponds to Long, Hold, Short portfolio, respectively. The differences between the mean values for Stars and Non-Stars are presented in the third row of each panel of the table.

Consistent with the results reported in Table 10, for the Long portfolios, the monthly alphas are 0.33 percent for recommendations by *Stars* (significantly different from zero at the one percent level) and 0.18 percent for recommendations by *Non-Stars* (not significantly different from zero), and their difference of 0.15 percent is statistically significant at the five percent significance level. Market-adjusted returns for the Long portfolios are 0.46 percent for Stars and 0.34 percent for Non-Stars (both figures are statistically significant, whereas their difference is not significantly different from zero).

The Hold portfolios of the Stars and Non-Stars had market- and risk-adjusted returns and the difference between those returns among the groups is not significantly different from zero. Thus, as expected, the Hold portfolios perform at the same level as the market.

In examining the results for the Short portfolios, it can be observed that the monthly alpha is -0.20 percent for Stars (insignificant) and -0.29 percent for Non-Stars (significantly different from zero at the five percent level). Market-adjusted returns are -0.05 percent for Stars and -0.13 percent for Non-Stars. However, the differences between the market- and risk-adjusted returns for Stars and Non-Stars are insignificantly different from zero.

Table 15. Returns-based analysis of portfolios based on recommendations by Stars and Non-Stars (monthly values).

Portfolio	Raw Return, %	Total Risk (Std.Dev Raw Return)	Market-adjusted Return, %	Coefficient Estimates for the Four-Factor Model						Adjusted R ²	
				Alpha (intercept), %	$R_m - R_f$	<i>SMB</i>	<i>HML</i>	<i>UMD</i>	Idiosyncratic Risk		
<i>Panel A. Long</i>											
<i>Stars</i>	1.32*	30.96	0.46***	0.33***	1.08***	0.43***	0.07***	0.02**	4.13	98	
	(2.2)		(3.18)	(4.08)	(165.11)	(29.34)	(4.37)	(1.97)			
<i>Non-Stars</i>	1.20**	31.79	0.34**	0.18*	1.11***	0.46***	0.03**	0.03***	5.19	97	
	(1.95)		(2.12)	(1.74)	(142.08)	(24.71)	(1.84)	(3.40)			
Diff. <i>Stars-Non-Stars</i>	0.12*	-0.83	0.12	0.15**	-0.3***	-0.3***	0.4***	-0.2**	3.88	5	
	(1.56)			(2.02)	(-5.89)	(-2.38)	(3.07)	(-2.99)			
<i>Panel B. Hold</i>											
<i>Stars</i>	1.02**	31.36	0.16	0.03	1.04***	0.49***	0.11***	-0.12***	3.79	98	
	(1.67)		(0.95)	(0.45)	(187.21)	(39.38)	(8.59)	(-16.86)			
<i>Non-Stars</i>	0.94*	31.60	0.08	-0.04	1.05***	0.53***	0.12***	-0.10***	4.60	98	
	(1.54)		(0.48)	(-0.73)	(177.44)	(36.66)	(8.21)	(10.65)			
Diff. <i>Stars-Non-Stars</i>	0.07	-0.24	0.08	0.10	-0.01***	-0.03***	-0.01	-0.2***	3.24	4	
	(1.19)			(1.57)	(-3.32)	(-4.39)	(-1.12)	(-4.20)			
<i>Panel C. Short</i>											
<i>Stars</i>	0.81	33.74	-0.05	-0.20	1.06***	0.57***	0.23***	-0.19***	6.54	96	
	(1.24)		(-0.20)	(-1.55)	(120.79)	(32.80)	(11.85)	(-17.06)			
<i>Non-Stars</i>	0.73	33.01	-0.13	-0.29**	1.07***	0.52***	0.18***	-0.14***	6.18	97	
	(1.14)		(-0.62)	(-2.41)	(147.71)	(31.79)	(10.45)	(-13.56)			
Diff. <i>Stars-Non-Stars</i>	0.08	0.73	0.08	0.09	-0.01	0.05***	0.04***	-0.05***	6.11	4	
	(0.64)			(0.78)	(-1.25)	(3.30)	(2.68)	(-4.75)			

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

NOTE: Star analysts are those listed in *The Wall Street Journal*, *Institutional Investor*, and Thomson Reuters' *StarMine* "Top Stock Pickers" and "Top Earnings Estimators". Analysts in the group of Non-Stars are those who are not listed in any of the mentioned Star rankings during a particular evaluation year. Time period: from November 1, 2003 to May 30, 2014. The "Long" portfolio includes Strong Buy and Buy recommendations; the "Hold" portfolio includes only Hold recommendations; the "Short" portfolio includes Sell and Strong Sell recommendations. Market-adjusted returns are calculated by subtracting monthly CRSP cap-weighted returns from the monthly returns of the Long, Hold or Short portfolios. During investigated period, the average CRSP market return was 0.86% with standard deviation of 25.86. Abnormal returns (alphas) are obtained using the Carhart four-factor model. Idiosyncratic Risk is calculated as the standard deviation of the residuals from the regression analysis for the Carhart four-factor model.

The Long portfolio formed by recommendations from Stars has lower idiosyncratic and total risk than the portfolios formed by recommendations from Non-Stars. However, the Short portfolio of Stars has higher idiosyncratic risk than the portfolio of Non-Stars.

An analysis of market-adjusted and excess returns shows that only the Long portfolios for both Stars and Non-Stars outperform the market. Among the Short portfolios, only Non-Stars have beaten the market because their portfolio has a negative and statistically significant alpha. Additionally, Stars outperform Non-Stars on the Long portfolios because their returns are higher with lower total and idiosyncratic risk.

Table 15 also reports the estimated coefficients for the Carhart four-factor model. These coefficients show that both groups, Stars and Non-Stars, in all three portfolios prefer small value stocks with risk that is slightly higher than average market risk. Positive sign of momentum coefficient for Long portfolios and a negative for Hold and Short indicates that analysts downgrade their recommendations on stocks that have already performed poorly in the past. However, relatively small value of momentum factor for both groups' Long portfolios shows that the upgrade in recommendations is not necessary preceded by the positive and significant price momentum. Comparison of the coefficients between Stars and Non-Stars reveals that Stars prefer larger, value stocks with slightly less market risk.

4.2.1 Attribution analysis for GICS sectors and CRSP size deciles

Table 16 reports the results for the attribution analysis of the GICS sectors (Panel A) and CRSP size deciles (Panel B). The attribution analysis allows investigating the extent to which the excess returns are related to the analysts' selection or allocation effects. Each panel includes three parts for the Long, Hold, and Short portfolios. Within each part, the results are reported for Stars, Non-Stars and the difference between these groups. The results of the *t*-test show whether the Allocation, Selection or Interaction Effects are significantly different from zero.

Table 16. Attribution analysis for GICS sectors and CRSP size segments.

Panel A. Attribution analysis for GICS sectors, monthly values in %

	Allocation Effect	Dynamic Allocation	Static Allocation	Selection Effect	Interaction
Long Portfolios (Strong Buy, Buy)					
<i>Stars</i>	0.08**	0.05	0.03	0.33***	0.02
<i>Non-Stars</i>	0.04	0.02	0.02	0.30**	-0.05**
<i>Stars – Non-Stars</i>	0.04	0.03	0.01	0.03	0.07**
Hold Portfolios (Hold)					
<i>Stars</i>	0.05	0.03	0.02	0.08	-0.02
<i>Non-Stars</i>	0.04	0.03	0.01	0.00	-0.01
<i>Stars – Non-Stars</i>	0.01	-0.01	0.01	0.09	-0.01
Short Portfolios (Sell, Strong Sell)					
<i>Stars</i>	0.12**	0.09	0.03	-0.21	0.02
<i>Non-Stars</i>	0.05	0.04	0.01	-0.18	-0.01
<i>Stars – Non-Stars</i>	0.07*	0.05	0.02	-0.03	0.03

*** p<0.01, ** p<0.05, * p<0.1

Panel B. Attribution analysis for CRSP size deciles, monthly values in %

	Allocation Effect	Dynamic Allocation	Static Allocation	Selection Effect	Interaction
Long Portfolios (Strong Buy, Buy)					
<i>Stars</i>	0.16**	-0.01	0.17	0.17**	0.14**
<i>Non-Stars</i>	0.18**	0.01	0.17	0.07	0.10**
<i>Stars – Non-Stars</i>	-0.02	-0.01	0.00	0.09	0.04
Hold Portfolios (Hold)					
<i>Stars</i>	0.18**	0.00	0.18	-0.04	0.02
<i>Non-Stars</i>	0.18*	0.01	0.18	-0.03	-0.07
<i>Stars – Non-Stars</i>	-0.01	0.00	0.00	-0.01	0.10*
Short Portfolios (Sell, Strong Sell)					
<i>Stars</i>	0.14*	-0.05	0.19	0.06	-0.28**
<i>Non-Stars</i>	0.17*	-0.02	0.19	-0.11	-0.20**
<i>Stars – Non-Stars</i>	-0.03	-0.04	0.01	0.17	-0.08

*** p<0.01, ** p<0.05, * p<0.1

NOTE: Star analysts are those listed in *The Wall Street Journal*, *Institutional Investor*, and *StarMine* “Top Stock Pickers” and “Top Earnings Estimators”. Analysts in the group of *Non-Stars* are those who are not listed in any of the mentioned star rankings during a particular evaluation year. The time period:

from November 1, 2003 to May 30, 2014. The “Long” portfolio includes Strong Buy and Buy recommendations; the “Hold” portfolio includes only Hold recommendations; the “Short” portfolio includes Sell and Strong Sell recommendations. Ten main GICS sectors represent the sector classification. Attribution analysis for CRSP size was performed based on market-capitalization deciles. Monthly market-adjusted (MKT-adjusted) return is calculated as the raw portfolio’s return minus the market return. This MKT-adjusted return is equal to the Allocation plus Selection plus Interaction Effects. The differences in MKT-adjusted returns and Allocation plus Selection plus Interaction Effects are caused by rounding in the calculations.

For the Long portfolios, the Allocation Effects for the GICS sectors are small for both Stars and Non-Stars at 0.08 (significantly different from zero) and 0.04 percent (insignificant), respectively. The Dynamic and Static components in the Allocation Effects for both groups have equal contributions to the total Allocation Effect, with 0.05 percent for Dynamic for Stars and 0.02 for Non-Stars and 0.03 percent for Static of Stars and 0.02 for Non-Stars. The Selection Effect is 0.33 percent for Stars and 0.30 percent for Non-Stars, and both figures are statistically significant. The Interaction term shows the only statistically significant difference between the groups, whereas none of the other effects are different for Stars and Non-Stars.

For the Hold portfolios, the GICS attribution analysis shows relatively low and insignificant values (as expected) because the added value for the Hold portfolios is statistically insignificant (see Table 10 and Table 15).

For the Short portfolios, the Allocation Effect for the GICS sector for Non-Stars is only 0.05 percent (insignificant) compared with 0.12 percent (significant) for Stars, and the difference between the groups is 0.07 percent (significant). The Allocation Effect for the Short portfolios for both groups is explained primarily by the Dynamic component. The Selection Effect is low for both groups, -0.21 for Stars and -0.18 percent for Non-Stars (both values are insignificant).

For the CRSP size deciles in Panel B of Table 16, the Allocation Effect for all three portfolio types is very similar, at 0.16, 0.18, and 0.14 for the Long, Hold, and Short portfolios of Stars, respectively, and 0.18, 0.18, and 0.17 for Non-Stars, respectively (all values are statistically significant). These Allocation Effects are explained by the Static component, with the Dynamic allocation close to zero. For the Selection Effects, only the Long portfolio of Stars has a statistically significant Selection Effect of 0.17 percent. Thus, the outperformance

of the Long portfolios of Non-Stars is explained primarily by the Allocation Effects, whereas Stars have both allocation and selection skills.

To summarize the results of the attribution analysis, the Allocation Effect is relatively small for the GICS sectors and not as important as the Selection Effect, which is large for both the Long and Short portfolios. The difference in the Selection and Allocation Effects explains the outperformance of Stars compared with Non-Stars. It can be concluded that the overall excess returns are mostly explained by how well Star analysts select individual stocks within particular GICS sectors in combination with how those sectors are over- or underweighted in the portfolios constructed based on recommendations. This finding contributes to the study by Boni and Womack (2006), who conclude that analysts exhibit within-industry expertise by issuing recommendations that tend to outperform industry benchmarks. Kadan et al. (2012) also find that industry expertise is important for analysts. Another explanation for the significant Allocation Effect for *Stars* and the insignificant Allocation Effect for *Non-Stars* is that the Long and Short portfolios of *Stars* have substantially smaller numbers of stocks than those of the *Non-Stars*. Thus, high coverage by Non-Stars brings their Long and Short portfolios close to the market weights, whereas fewer stocks in the Stars' portfolios causes deviation from the market weights. The observed high deviation from the market weights in the Stars' portfolios also leads to the larger size of the Dynamic component relative to the Static component, while in the Non-Stars' portfolios, the Dynamic component is almost equal to the Static component.

Based on the CRSP size attribution analysis, it can be concluded that the Allocation Effect within size deciles is substantial and leads to the outperformance of both groups of analysts as compared to the overall market, although there is no difference in Allocation Effects among Stars and Non-Stars. At the same time, the Selection Effects for the size deciles are only significant for the Stars' Long portfolio. Such significant CRSP size

Allocation Effects for both groups reveal that analysts' portfolios gain sizable excess returns by overweighting particular size segments. Furthermore, the results of the analysis in this study does not provide any information about whether such a decision to allocate more wealth to profitable size segments is a conscious choice made by analysts or a methodological artifact that can be explained by the effect of overweighting (underweighting) small (large) stocks due to equal investment amounts of one dollar for each new recommendation.

4.2.2 Holdings-based analysis for GICS sectors

The results of a holdings-based analysis for the GICS sectors are reported in Table 17, where Panel A shows the Long, Panel B the Hold, and Panel C the Short portfolios. To illustrate further, Figure 1 reports the columns with the excess weights and excess returns for a Long portfolio. This analysis enables investigating the differences in weights and returns compared with the CRSP cap-weighted portfolio. The actual weights and returns are those assigned and obtained for a particular sector in the portfolio constructed based on the analysts' recommendations, whereas the market values are those obtained based on the CRSP cap-weighted portfolio calculations. The excess weights and returns are calculated as the difference between the actual and market values. Companies in IBES that were not matched with a GICS sector classification in the Compustat database but that had return time-series in CRSP are marked as "Unknown Sector" and represent 3.0 percent of the constructed (actual) portfolios.

The upper bar charts on Figure 1 present the difference in portfolio weights for the GICS sectors for the Long portfolios compared with the CRSP cap-weighted portfolio. These charts are built based on data from the columns showing the excess weights (columns 3 and 8) and excess returns (columns 6 and 10) from Table 17. Only the Long portfolio are illustrated because the patterns of over- and underweighting for the Long, Hold and Short

Table 17. Holdings-based analysis of monthly excess returns for GICS sectors.

Panel A. Long portfolios

GICS Sector	Stars						Non-Stars				Stars – Non-Stars	
	Investment Weights, %			Returns,%			Investment Weights, %		Returns, %		Difference Investment Weights, % (11)=(1)-(7)	Excess Returns, % (12)=(4)-(9)
	Actual	Market	Excess (3)= (1)-(2)	Actual	Market	Excess (6)= (4)-(5)	Actual	Excess (8)= (7)-(2)	Actual	Excess (10)= (9)-(5)		
(1)	(2)	(1)-(2)	(4)	(5)	(4)-(5)	(7)	(7)-(2)	(9)	(9)-(5)	(11)=(1)-(7)	(4)-(9)	
Energy	8.0	11.2	-3.3***	2.02	1.49	0.54**	10.2	-1.0***	1.88	0.40	-2.2***	0.14
Materials	8.4	4.9	3.5***	1.84	1.18	0.66***	7.1	2.2***	1.61	0.43*	1.3***	0.23
Industrials	15.0	9.5	5.5***	1.40	1.04	0.36*	10.5	1.1***	1.50	0.46***	4.5***	-0.10
Consum. Discr.	17.9	10.2	7.7***	1.40	1.03	0.37**	14.6	4.5***	1.08	0.04	3.3***	0.32***
Consum. Stap.	5.4	8.6	-3.2***	1.25	0.93	0.32*	2.9	-5.7***	1.40	0.47**	2.5***	-0.15
Health Care	10.0	10.7	-0.7***	1.41	0.96	0.46**	11.9	1.2***	1.38	0.43**	-1.9***	0.03
Financials	10.1	18.3	-8.2***	0.85	0.67	0.17	11.2	-7.1***	0.92	0.25	-1.1***	-0.07
Info.Tech.	16.4	15.3	1.1***	1.01	0.82	0.18	24.8	9.5***	0.95	0.13	-8.3***	0.05
Telecom. Serv.	2.0	3.1	-1.1***	1.47	1.03	0.45	2.1	-1.0***	1.42	0.40	-0.1***	0.05
Utilities	3.7	2.7	1.0***	1.29	0.92	0.37***	2.0	-0.7***	1.24	0.32***	1.7***	0.05
Unknown	3.0	5.6	-2.5***	0.74	0.65	0.09	2.7	-2.8***	0.87	0.22	0.3***	-0.13

*** p<0.01, ** p<0.05, * p<0.1

Panel B. Hold portfolios

GICS Sector	Stars				Non-Stars				Stars – Non-Stars	
	Investment Weights, %		Returns,%		Investment Weights, %		Returns, %		Difference Investment Weights, %	Excess Returns, %
	Actual	Excess	Actual	Excess	Actual	Excess	Actual	Excess		
Energy	6.9	-4.3 ^{***}	1.65	0.17	9.1	-2.1 ^{***}	1.66	0.18	-2.2 ^{***}	-0.01
Materials	8.2	3.3 ^{***}	1.22	0.04	6.2	1.3 ^{***}	1.40	0.22	2.0 ^{***}	-0.17
Industrials	14.0	4.5 ^{***}	1.09	0.05	9.8	0.3 ^{***}	1.17	0.13	4.2 ^{***}	-0.08
Consum. Discr.	18.4	8.2 ^{***}	0.99	-0.04	15.3	5.1 ^{***}	0.74	-0.29 [*]	3.1 ^{***}	0.25 ^{**}
Consum. Stap.	5.9	-2.7 ^{***}	1.22	0.29	2.9	-5.7 ^{***}	0.95	0.02	3.0 ^{***}	0.27 [*]
Health Care	9.7	-1.0 ^{***}	1.39	0.43 [*]	12.1	1.4 ^{***}	1.25	0.29	-2.4 ^{***}	0.14
Financials	11.6	-6.7 ^{***}	0.53	-0.14	13.7	-4.6 ^{***}	0.60	-0.07	-2.1 ^{***}	-0.07
Info.Tech.	15.6	0.3 ^{***}	0.82	-0.01	23.6	8.3 ^{***}	0.73	-0.09	-8.0 ^{***}	0.09
Telecom. Serv.	2.4	-0.8 ^{***}	0.97	-0.06	2.2	-1.0 ^{***}	1.01	-0.02	0.2 ^{***}	-0.04
Utilities	3.9	1.2 ^{***}	0.94	0.02	2.3	-0.4 ^{***}	0.79	-0.13	1.6 ^{***}	0.15
Unknown	3.4	-2.2 ^{***}	0.77	0.12	2.8	-2.7 ^{***}	0.29	-0.36	0.5 ^{***}	0.48

*** p<0.01, ** p<0.05, * p<0.1

Panel C. Short portfolios

GICS Sector	Stars				Non-Stars				Stars – Non-Stars	
	Investment Weights, %		Returns, %		Investment Weights, %		Returns, %		Difference Investment Weights, %	Excess Returns, %
	Actual	Excess	Actual	Excess	Actual	Excess	Actual	Excess		
Energy	7.8	-3.5***	1.10	-0.38	8.9	-2.4***	1.50	0.02	-1.1***	-0.40
Materials	8.5	3.7***	1.30	0.11	7.6	2.7***	1.08	-0.11	0.9***	0.22
Industrials	12.4	3.0***	0.87	-0.17	8.0	-1.4***	1.08	0.03	4.4***	-0.20
Consum. Discr.	19.8	9.6***	0.70	-0.33	14.8	4.6***	0.84	-0.19	5.0***	-0.15
Consum. Stap.	6.0	-2.6***	0.89	-0.04	3.3	-5.2***	1.22	0.29	2.6***	-0.34
Health Care	9.8	-0.9***	1.70	0.74**	11.4	0.7***	1.03	0.07	-1.6***	0.67**
Financials	12.1	-6.2***	0.38	-0.29	13.8	-4.5***	0.15	-0.53***	-1.7***	0.24
Info.Tech.	15.3	0.05	0.24	-0.59*	23.4	8.1***	0.55	-0.27	-8.0***	-0.32
Telecom. Serv.	2.6	-0.6***	1.70	0.68	3.2	0.1***	0.44	-0.58	-0.6***	1.26
Utilities	2.8	0.1	1.08	0.16	2.5	-0.2***	1.09	0.16	0.3***	-0.01
Unknown	3.2	-2.4***	-0.83	-1.48	3.1	-2.4***	-0.28	-0.92	0.1***	-0.55

*** p<0.01, ** p<0.05, * p<0.1

NOTE: Star analysts are those listed in *The Wall Street Journal*, *Institutional Investor*, and Thomson Reuters' *StarMine* "Top Stock Pickers" and "Top Earnings Estimators". Analysts in the group of Non-Stars are those who are not listed in any of the mentioned Star rankings during a particular evaluation year. Time period: from November 1, 2003 to May 30, 2014. The "Long" portfolio includes Strong Buy and Buy recommendations; the "Hold" portfolio includes only Hold recommendations; the "Short" portfolio includes Sell and Strong Sell recommendations. Ten main GICS sectors were used for the sector classification. Actual Returns and Weights are those for the constructed Long, Hold and Short portfolios. Excess Returns and Weights are the differences between the Actual and the corresponding market returns or weights, respectively.

portfolios are similar, except for the Industrials and Telecommunication Services sectors for Non-Stars: the Non-Stars' Short portfolio is underweighted in Industrials and overweighted in Telecommunication Services, whereas in the Non-Stars' Long and Hold portfolios, these sectors are overweighted and underweighted, respectively (see Panels B and C in Table 17).

In the Stars' Long, Hold and Short portfolios, the highest overweights are for Consumer Discretionary, Industrials and Materials, whereas for Non-Stars, the main overweights are in Information Technology, Consumer Discretionary and Materials. The most underweighted sectors for Stars and Non-Stars are Financials and Consumer Staples. The biggest difference in weights between Stars and Non-Stars is for the Information Technology sector, which is highly overweighted by Non-Stars, whereas it has almost the market weight for the Stars. Another difference between the Stars and Non-Stars is that the Utilities and Health Care sectors have opposite under- and overweight patterns for Stars and Non-Stars (Utilities is overweighted by Stars and underweighted by Non-Stars, while Health Care is underweighted by Stars and overweighted by Non-Stars). According to Table 17, all excess weights (columns 3 and 8) and the difference in weights between Stars and Non-Stars (column 11) are statistically significant at the one percent level.

The bottom bar charts in Figure 1 show the excess returns for the Long portfolios over the sectors' returns for the CRSP cap-weighted portfolios. The portfolios of Stars and Non-Stars outperform in all market sectors, although not all excess returns are significantly different from zero (see columns 6 and 10 in Panel A in Table 17). Both Stars and Non-Stars perform insignificantly different from the market in the Financials, Information Technology and Telecommunication Services sectors. Additionally, Non-Stars show insignificant outperformance (market performance) in the Energy and Consumer Discretionary sectors. Thus, Stars significantly outperform the market in more sectors (numerically) than do Non-

Stars. The only significant difference in returns between Stars and Non-Stars is observed for the Consumer Discretionary sector (see column 12 in Panel A in Table 17).

NOTE: Star analysts are those listed in The Wall Street Journal, Institutional Investor, and Thomson Reuters' StarMine "Top Stock Pickers" and "Top Earnings Estimators". Analysts in the group of Non-Stars are those who are not listed in any of the mentioned Star rankings during a particular evaluation year. Time period: from November 1, 2003 to May 30, 2014. The "Long" portfolio includes Strong Buy and Buy recommendations. The "Hold" and "Short" portfolios are not presented. Ten main GICS sectors are used for the sector classification.

Figure 1. Holdings-based analysis of monthly excess returns for GICS sectors.

In the Hold portfolios (Panel B in Table 17), Stars outperform the market only in the Health Care sector, whereas Non-Stars underperform in Consumer Discretionary. In all other sectors, the excess returns are insignificantly different from the market sector-specific

returns. With respect to the differences in returns between the groups, Stars significantly outperform Non-Stars (have higher returns) only in the Consumer Discretionary and Consumer Staples sectors.

The Short portfolio returns are presented in Panel C of Table 17. The excess returns are interpreted in the reverse manner: negative excess returns of portfolios show outperformance and positive excess returns correspond to underperformance. The reported excess returns for the sector-specific Short portfolios are not as high as for the Long portfolios. The sector-specific Short portfolios of Stars outperform the market in Information Technology and underperform in Health Care. The Short portfolios of Non-Stars outperform the market in Financials. The only sector in which Stars and Non-Stars have statistically significant differences in returns is Health Care, where Non-Stars outperform Stars by 0.67 percentage points.

4.2.3 Holdings-based analysis for CRSP size deciles

The results of a holdings-based analysis for CRSP size deciles are reported in Table 18, where Panel A shows the Long, Panel B the Hold, and Panel C the Short portfolios. The actual weights and returns are those assigned and estimated for a particular size decile in a portfolio constructed based on analysts' recommendations, whereas the market values are those obtained based on CRSP market capitalization-weighted portfolio calculations. Because cap-weighted deciles are used, the market weights for each size decile are roughly equal to 10 percent. The excess weights and excess returns are calculated as the difference between the actual and market values. For illustration, Figure 2 reports the excess weights (columns 3 and 6 from Panel A, Table 18) and excess returns (columns 6 and 10 from Panel A, Table 18). Only the results for the Long size-specific portfolios are illustrated because the patterns of over- and underweights for the Hold and Short portfolios are similar to that for the Long portfolio (see corresponding columns in Panels B and C of Table 18).

Table 18. Holdings-based analysis of monthly excess returns for CRSP size deciles.

Panel A. Long portfolios

Size Decile	Stars						Non-Stars				Stars – Non-Stars	
	Investment Weights, %			Returns, %			Investment Weights, %		Returns, %		Difference Investment Weights, % (11)=(1)-(7)	Excess Returns, % (12)=(4)-(9)
	Actual (1)	Market (2)	Excess (3)=(1)-(2)	Actual (4)	Market (5)	Excess (6)=(4)-(5)	Actual (7)	Excess (8)=(7)-(2)	Actual (9)	Excess (10)=(9)-(5)		
Largest	0.6	9.9	-9.4***	0.29	0.48	-0.19	0.6	-9.4***	0.73	0.25	0.0	-0.44
2	1.5	9.6	-8.1***	0.56	0.44	0.11	1.0	-8.6***	0.16	-0.28	0.4***	0.39*
3	2.1	10.0	-7.9***	0.85	0.81	0.04	1.8	-8.2***	0.97	0.16	0.3***	-0.12
4	3.5	9.8	-6.3***	0.70	0.68	0.02	2.6	-7.2***	0.58	-0.09	0.9***	0.11
5	5.2	9.6	-4.4***	0.95	0.88	0.07	4.2	-5.4***	1.04	0.16	1.0***	-0.08
6	7.5	9.9	-2.4***	1.12	0.97	0.16	5.8	-4.1***	0.91	-0.06	1.7***	0.22
7	9.8	9.7	0.04*	1.41	1.12	0.29**	8.4	-1.36*	1.17	0.05	1.4***	0.24*
8	13.5	9.6	3.8***	1.15	1.02	0.13	12.7	3.0***	1.06	0.04	0.8***	0.09
9	21.8	9.7	12.1***	1.29	1.08	0.21*	20.0	10.4***	1.16	0.08	1.7***	0.12
Smallest	34.6	12.0	22.6***	1.64	1.06	0.57***	42.8	30.8***	1.40	0.34***	-8.2***	0.23**

*** p<0.01, ** p<0.05, * p<0.1

Panel B. Hold portfolios

Size Decile	Stars				Non-Stars				Stars – Non-Stars	
	Investment Weights, %		Returns,%		Investment Weights, %		Returns, %		Difference Investment Weights, %	Excess Returns, %
	Actual	Excess	Actual	Excess	Actual	Excess	Actual	Excess		
Largest	0.6	-9.3***	0.14	-0.34	0.5	-9.5***	0.41	-0.07	0.2***	-0.26
2	0.9	-8.7***	0.37	-0.08	0.8	-8.9***	0.53	0.09	0.2***	-0.16
3	1.2	-8.8***	1.05	0.24	1.2	-8.8***	1.09	0.28	0.0***	-0.05
4	2.5	-7.3***	0.66	-0.02	2.1	-7.8***	0.57	-0.10	0.4***	0.09
5	4.0	-5.6***	0.80	-0.08	3.5	-6.1***	0.78	-0.10	0.5***	0.02
6	5.9	-4.0***	0.84	-0.12	4.9	-5.0***	0.91	-0.06	1.0***	-0.07
7	8.9	-0.8***	0.97	-0.16	7.5	-2.3***	1.01	-0.11	1.5***	-0.05
8	14.1	4.5***	1.08	0.06	12.1	2.5***	1.00	-0.02	2.0***	0.08
9	21.8	12.1***	1.09	0.01	19.4	9.7***	1.08	0.00	2.4***	0.01
Smallest	40.0	28.0***	1.04	-0.02	48.2	36.2***	0.88	-0.19	-8.2***	0.17*

*** p<0.01, ** p<0.05, * p<0.1

Panel C. Short portfolios

Size Decile	Stars				Non-Stars				Stars – Non-Stars	
	Investment Weights, %		Returns, %		Investment Weights, %		Returns, %		Difference Investment Weights, %	Excess Returns, %
	Actual	Excess	Actual	Excess	Actual	Excess	Actual	Excess		
Largest	0.6	-9.3 ^{***}	0.64	0.16	0.4	-9.6 ^{***}	0.27	-0.21	0.3 ^{***}	0.37
2	1.0	-8.7 ^{***}	0.85	0.40	0.6	-9.1 ^{***}	0.30	-0.14	0.4 ^{***}	0.55
3	1.1	-8.9 ^{***}	2.36	1.55 ^{**}	1.0	-9.1 ^{***}	1.16	0.35	0.2 ^{***}	1.20 [*]
4	1.8	-8.0 ^{***}	0.51	-0.17	1.7	-8.2 ^{***}	0.50	-0.18	0.2 ^{***}	0.01
5	3.1	-6.6 ^{***}	0.82	-0.06	3.2	-6.4 ^{***}	0.79	-0.08	-0.1 ^{***}	0.02
6	4.6	-5.4 ^{***}	1.09	0.13	4.5	-5.4 ^{***}	0.82	-0.14	0.1 ^{**}	0.27
7	9.0	-0.7 ^{***}	1.03	-0.09	7.6	-2.2 ^{***}	1.00	-0.12	1.5 ^{***}	0.03
8	14.6	5.0 ^{***}	1.09	0.07	12.0	2.4 ^{***}	0.99	-0.03	2.6 ^{***}	0.10
9	22.2	12.5 ^{***}	1.08	0.00	20.1	10.4 ^{***}	1.02	-0.06	2.1 ^{***}	0.06
Smallest	43.0	31.0 ^{***}	0.52	-0.55 ^{**}	49.2	37.1 ^{***}	0.51	-0.55 ^{***}	-6.1 ^{***}	0.00

*** p<0.01, ** p<0.05, * p<0.1

NOTE: Star analysts are those listed in *The Wall Street Journal*, *Institutional Investor*, and Thomson Reuters' *StarMine* "Top Stock Pickers" and "Top Earnings Estimators". Analysts in the group of Non-Stars are those who are not listed in any of the mentioned Star rankings during a particular evaluation year. Time period: from November 1, 2003 to May 30, 2014. The "Long" portfolio includes Strong Buy and Buy recommendations; the "Hold" portfolio includes only Hold recommendations; the "Short" portfolio includes Sell and Strong Sell recommendations. CRSP size classification is based on market-capitalization deciles. Actual Returns and Weights are those for the constructed Long, Hold and Short portfolios. Excess Returns and Weights are the differences between the Actual Returns and the corresponding market returns or weights, respectively.

The upper bar charts in Panel A in Figure 2 present the difference in portfolio weights for CRSP size deciles for the Long size-specific portfolios. For the Long, Hold and Short portfolios, Stars and Non-Stars significantly overweight small stocks and underweight the largest stocks, and the lowest three deciles are overweighted (excess weights are positive). The largest difference in weights is for small stocks in the first size decile, where the portfolio of Stars has 34.6 percent of their value and Non-Stars have 42.8 percent. The size decile with the largest stocks has only 0.6 percent in both the Stars and Non-Stars' portfolios.

The bottom bar charts in Panel A of Figure 2 show the excess returns for the portfolios with the market capitalization-weighted returns for size deciles. For the Long portfolios, Stars' size-specific portfolios outperform in almost all market deciles, except for the size decile with the largest stocks, in which the Stars portfolio underperforms. These excess returns for the largest size-specific portfolio of the group of Stars are statistically insignificant from the market returns. Also, the number of stocks was investigated. In the size-specific portfolios for the largest size decile constructed based on recommendations from Stars and Non-Stars, the averages were as low as 2.93 and 6.01 stocks, respectively. With such a low number of stocks in the largest size decile portfolios, one should not expect to observe any significant excess returns (due to increase in volatility of those portfolios). As seen in column 6 in Table 18, Stars outperform the market in the smallest two size deciles and in the seventh size decile (with an actual weight close to the weight of the market portfolio). However, Non-Stars outperform the market only in the smallest size decile (see column 10). With respect to the difference in returns between groups of Stars and Non-Stars, it was found that Stars significantly outperform Non-Stars in the smallest, seventh and second (next to largest) size deciles.

NOTE: Star analysts are those listed in *The Wall Street Journal*, *Institutional Investor*, and Thomson Reuters' *StarMine* "Top Stock Pickers" and "Top Earnings Estimators". Analysts in the group of Non-Stars are those who are not listed in any of the mentioned Star rankings during a particular evaluation year. Time period: from November 1, 2003 to May 30, 2014. The "Long" portfolio includes Strong Buy and Buy recommendations. The "Hold" and "Short" portfolios are not presented. CRSP size classification is based on market-capitalization deciles.

Figure 2. Holdings-based analysis of monthly excess returns for CRSP size deciles.

For the Hold size-specific portfolios, both groups have insignificant excess returns (see Panel B in Table 18). The difference in returns between Stars and Non-Stars is significant only for the smallest size decile, where the Hold size-specific portfolio of Stars outperforms that of Non-Stars by 0.17 percentage points.

In the Short size-specific portfolios (Panel C in Table 18), both groups outperform the market in the smallest size decile. In the other size deciles, Non-Stars perform insignificantly different from the market, whereas Stars underperform the market in the third size decile.

In summary, the results of the holdings-based analysis show that the portfolios for both groups of analysts have significantly different weights than the market capitalization-weighted portfolio. However, such differences in weights among the analysts' and market portfolios are difficult to interpret in a classical attribution analysis manner. Hence, these actual weights should not be attributed to analysts' allocation choices because analysts do not make any active allocation decisions. Analysts are typically industry experts who cover stocks within their sector. In addition, the sector weights in the constructed portfolios reflect how many analysts are covering a sector rather than analysts choosing to focus on that sector. Within a given sector, analysts perhaps can choose which stocks to cover, and that choice can – to some extent – explain the allocation effects among the size deciles. Furthermore, it may not be up to an analyst whether to cover a stock or not: it is likely a decision that is made by the investment banks who assign stocks to analysts for coverage. According to Table 17, the sector weights across the Long, Hold, and Short portfolios are fairly similar. This similarity in weights reflects that the weights in the studied portfolio methodology actually measure how much overall analyst attention/resources are focused on a particular sector versus others (which may be the banks' decisions more than the analysts' own). An additional point to consider is that the weights can be interpreted as an artifact of the way the portfolios are constructed (by investing one dollar in each recommendation). If the method

of portfolio construction is changed, for instance, by allocating more money to large revisions, then the weights will change and therefore the entire results should also change.

Stars and Non-Stars show persistently better performance in some market sectors. Stars outperform Non-Stars in all of the Long, Hold and Short portfolios, with significant differences only between the Long portfolios. At the same time, their outperformance against the market is primarily explained by holdings in the smallest market deciles. Considering that both groups significantly overweight the smallest three size deciles, it can be seen how the Allocation Effects reported in Panel B of Table 16 contribute to overall portfolio performance. Additionally, it is questionable whether such portfolios based on recommendations are attainable for large institutional investors because of the lack of liquidity and volume of the small stocks that represent the major portion of these portfolios. This question merits further investigation.

4.3. Part III – Seasonality

4.3.1 Seasonality in market returns in 2003-2014

Table 19 reports the results of regressing the daily and geometrically aggregated monthly CRSP returns on the seasonal dummy variables in order to measure seasonal effects based on the difference between summer and winter or between September and January and other months. The corresponding regressions from the equation 9 have all of the coefficients insignificant from zero. Thus, the results of the regression analysis show that there were no differences between summer and winter seasons during the investigated time period. Additionally, January and September had insignificantly different returns from the other months. These results are unexpected considering the extant literature, which reports seasonality effects for a number of financial markets. There are two possible explanations for the contradictory findings. First, the sample used in this study is more recent than most of the other papers, which usually consider the entire history of financial markets (e.g., Bouman

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and Jacobsen, 2002; Jacobsen and Marquering, 2008, 2009; Kelly and Meschke, 2010). In contrast, the sample period used in this study is only eleven years. According to statistical theory, by increasing the sample size, it is more likely that statistically significant differences between groups will be found. The t -statistic for the winter seasonal effects on logarithmic variables, which is close to the significance level, supports the hypothesis of a too-small sample size. Thus, extending the sample would likely result in finding significant seasonal effects for logged market returns. Second, the sample time period in this study is more recent relative to the extant literature, and it may be that seasonal effects are mitigated by market's awareness of these anomalies. The results of this study therefore call for further investigation of seasonality effects in financial markets in recent years in order to confirm their relevance for current markets.

To test the robustness of this investigation's findings, several additional untabulated tests were performed on the daily, monthly and quarterly returns in the CRSP market. First, the stationarity in market returns (daily, monthly and quarterly) was tested. The Dickey-Fuller (DF) test was used for the variable and the differenced variable, also performing DF test with a time trend. None of the tested variables had a time trend during the investigated time period. For all types of variables, it was found that the coefficient for the lagged variable in Dickey-Fuller tests are statistically significant. Thus, the null hypothesis of the Dickey-Fuller test was rejected, concluding the CRSP return data are stationary. Second, the regression tests were repeated using differenced, lagged, and seasonal differences accompanied by autocorrelation and partial autocorrelation functions in order to identify any seasonal patterns by autocorrelation. Once again, none of seasonal patterns under interest (winter, September, January effects) were identified in those tests. Only the quarterly time-series shows some (weak) seasonal correlation with a time lag of 5. All of the results and statistical tests remain untabulated but are available upon request.

Table 19. Seasonal effects in CRSP market returns from 2003-2014.

	R_{MKTt}		$\text{LN}(R_{MKTt})$	
	Daily	Monthly	Daily	Monthly
Dum.Winter	0.040 (0.95)	0.90 (1.19)	0.046 (0.97)	0.946 (1.23)
Dum.Jan	-0.058 (-0.66)	-1.159 (-0.84)	-0.056 (-0.63)	-1.164 (-0.83)
Dum.Sept	-0.002 (-0.03)	-0.032 (-0.02)	-0.035 (-0.04)	-0.097 (-0.07)

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

NOTE: Reported values correspond to the coefficients of the regression (9):

$R_{MKTt} = \mu + \gamma DS_t + \varepsilon_t$, where R_{MKTt} is the value-weighted return on the CRSP index (daily or geometrically compounded monthly values); DS is the seasonality dummy (winter dummy is equal to 1 for the November-April period or for the January or September months, and 0 otherwise). We regress raw returns (R_{MKTt}) as well as logarithmic returns on each seasonal dummy variable separately. All dummy variable coefficients are statistically insignificant, which shows that the seasonal effects of “Sell in May and go away”, January and September were not present during the investigated time period. The time period is from November 2003 to November 2014.

4.3.2 Seasonality in target prices

Table 20 reports the average target price expected return, (*TPER*), for Stars (Panel A) and Non-Stars (Panel B) in different seasons as well as the difference between Non-Stars and Stars (Panel C). The results show that both groups of analysts issue more optimistic *TPERs* in summer season than in winter. Non-Stars have 1.06 percent more optimistic *TPERs* than Stars unconditional on recommendation categories *TPER* (see figures for all recommendations in Panel A for Stars and Panel B for Non-Stars, and the difference between groups in Panel C). Conditional on recommendation categories, Non-Stars are more optimistic on Buy and Hold levels and less pessimistic in their Sell recommendations. For the within-group comparison between seasons, Stars (Panel A) and Non-Stars (Panel B) show similar patterns in the differences between summer and winter, with more optimistic *TPERs* in summer than in winter. For the group of Non-Stars, the differences between seasons are statistically significant on all recommendation levels. For the Stars, only the Buy and Hold

levels show a significant increase in optimism in summer, while their *TPERs* on the level of Sell recommendations are insignificantly different between seasons.

Table 20. Average target price expected return, *TPER*, conditional on the season for each recommendation category for Non-Stars and Stars.

Portfolio	Average <i>TPER</i> , %			Diff: Summer-Winter	
	Total	Winter	Summer	Diff.	<i>t</i> -stat
<i>Panel A. Stars</i>					
Buy	19.44	19.14	19.78	0.65*	(1.35)
Hold	4.62	4.49	4.75	0.26	(0.79)
Sell	-13.76	-14.13	-13.37	0.76	(1.24)
All:	9.3	8.98	9.62	0.64**	(1.95)
<i>Panel B. Non-Stars</i>					
Buy	20.51	19.94	21.09	1.15***	(4.67)
Hold	5.27	5.03	5.51	0.49***	(2.63)
Sell	-12.66	-13.44	-11.91	1.53***	(4.19)
All:	10.35	9.97	10.74	0.77***	(4.44)
<i>Panel C. Diff. Non-Stars – Stars</i>					
Buy	1.07*** (4.01)	0.08** (2.18)	1.33*** (3.51)	-	-
Hold	0.65*** (3.30)	0.53** (1.91)	0.86*** (2.74)	-	-
Sell	1.10*** (2.90)	0.70* (1.31)	1.47*** (2.74)	-	-
All:	1.06*** (5.66)	0.99*** (3.75)	1.12*** (4.24)	-	-

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

NOTE: Target price expected return, *TPER*, is defined as $TP_t/P_{t-1}-1$, where TP_t is the analyst's target price with a 12-month horizon issued on day t ; P_{t-1} is the share price on the previous trading day before t . The Buy portfolio includes Strong Buy and Buy recommendations; Sell includes Strong Sell and Sell; Hold includes Holds. *Winter Season* is from November until April.

4.3.3 Earnings announcements and optimism cycles in target prices

A plot of the average *TPER* throughout a calendar year in Figure 3 shows a clear time-varying dependence with three peaks in March, May and August. Both groups of Stars and Non-Stars show similar patterns, with Non-Stars having systematically more optimistic average *TPERs* in all months. The biggest difference between the groups is in January and October, while the smallest difference is in July and August.

NOTE: Target price expected return, $TPER$, is defined as $TP_t/P_{t-1}-1$, where TP_t is the analyst's target price with a 12-month horizon issued on day t ; P_{t-1} is the share price on the previous trading day before t . Market returns are value-weighted CRSP returns.

Figure 3. Average monthly $TPER$ (%) for Stars and Non-Stars and market returns.

Two hypotheses are tested in this study. First, whether analysts' optimism as reflected in $TPER$ is associated with current or expected market returns. For this hypothesis, CRSP monthly market returns are used as well as lagged values of those returns or lagged $TPER$. Table 21 reports the results of the regression analysis of $TPER$ on simultaneous as well as future and lagged returns investigating whether overall market conditions predict changes in analysts' optimism and reversed dependence of whether market returns can be predicted from changes in analysts' optimism. Almost all of the coefficients are statistically insignificant, which indicates that the target price expected returns are not correlated with market returns during the investigated time period. However, a model that considers differenced $TPER$ shows that a change in $TPER$ has some predictive power for current market returns. Because all of the regressions have a very low model fit (R^2), this study concludes that there is no correlation between market returns and the optimism of analysts for both the simultaneous and lagged variables.

Table 21. The dependence of the average monthly target price expected returns, $TPER$, on monthly market returns for the total sample of analysts (Non-Stars and Stars), monthly values.

Regressor	Dependent Variable					
	$TPER_m$	$TPER_m$	$TPER_m$	Diff. $TPER_m$	Diff. $TPER_m$	Diff. $TPER_m$
R_{MKTm}	-0.08 (-1.48)			-0.15*** (-3.33)		
$L.R_{MKTm}$		-0.09 (-1.52)			0.00 (0.05)	
$F.R_{MKTm}$			0.07 (1.28)			-0.00 (-0.04)
Constant	0.10*** (40.20)	0.10*** (40.01)	0.10*** (40.53)	0.00 (0.98)	0.00 (0.35)	0.00 (0.20)
Adj. R^2, %	0.9	0.9	0.5	7.2	0.8	0.8

t-statistics in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

NOTE: Target price expected return, $TPER$, is defined as $TP_t/P_{t-1}-1$, where TP_t is the analyst's target price with a 12-month horizon issued on day t ; P_{t-1} is the share price on the previous trading day before t . $aTPER$ is the average target price for all analysts in month m . Reported values correspond to the coefficients of the regression: $aTPER_m = \mu + \gamma R_{MKTm} + \varepsilon_t$, where R_{MKTm} is the geometrically compounded value-weighted return on the CRSP index on month m . L. and F. in front of the independent variables correspond to Lag and Lead operators, respectively. Diff. in front of the dependent variable $TPER_m$ corresponds to the difference operator. The time period is from November 2003 to November 2014. All regressions have very low model fit (R^2). Almost all coefficients were statistically insignificant, which shows that the target price expected returns are not correlated with market returns during the investigated time period. However, Model 4 shows that a change in $TPER$ has some predictive power for current market return.

The second hypothesis tests whether analysts' optimism is related to the calendar of companies' earnings announcements (EAs). Using the data from Compustat, this study calculates the fraction of EAs as the number of EAs issued by companies in a given month divided by the total number of EAs in that year. Plotting monthly $TPER$ and EAs on one graph reveals a correlation between $TPER$ and quarterly EAs (see Figure 4), with the strongest correlation between $TPER$ and the peaks in the number of fourth-quartile announcements for the previous calendar year in March and the first (in May) and second (in August) quartile EAs. The third quartile EAs correlate with the Stars' $TPER$ but not with the Non-Stars. By analyzing the time dependence on a more detailed level, it was found that the

optimism in analysts' *TPER* increases each time the number of quarterly reports is increasing; however, there is a strong decline in optimism in every one month before the majority of companies publish their EAs⁷. Thus, the analysts who issue reports one month before the majority of EAs are published do not have very optimistic forecasts. This result could be explained by the fact that most companies do not disclose much information one month before the date of their EAs. In contrast, the highest optimism is observed for *TPERs* that are issued in the same month when the majority of EAs are published. This explanation is similar and complementary to that by (Doeswijk, 2008), who investigates earnings forecasts and IPOs. Current study finds similar patterns reflected in target prices in more recent sample. One potential explanation for the observed optimism pattern is related to uncertainty about the market due to the number of new reports (new information), which may affect the optimism of analysts. During the periods with the highest number of issued company reports and in the amount of new information, analysts might have difficulty assessing the market and reaching consensus. Such uncertainty provides analysts an opportunity to deviate from the consensus by expressing overly optimistic views. Companies offer very little information in the period immediately before they announce their quarterly reports. During that period of high uncertainty about companies' reports, analysts might have a decrease in optimism that later increases as soon as the companies' reports are published.

Alternatively, the findings of optimism spikes that coincide with increases in the number of EAs can also be explained by the influence on the mood of analysts of the positive information that companies' EAs contain. Because EAs are one of the instruments used by companies to disseminate positive information, when the number of such reports increases

⁷ The findings are confirmed by regressing *TPER* and a log of *TPER* on the lagged percentage of earnings announcements (monthly number divided by the yearly total number of earnings announcements), having the regression coefficients to be positive and significant in both regressions. These results are available upon request.

in each quarter, analysts face a high inflow of positive information that in turn might create a positive bias in analysts' forecasts. An additional explanation for the observed positive bias could be attributed to analysts' overconfidence arising from new quantitative inputs, i.e., companies' quarterly earnings, for their valuation models. Such solid new data are easily justifiable, so analysts' confidence in their forecasts may increase, resulting in positive bias. Thus, analysts face two difficulties when the number of EAs peaks: first, an increased inflow of positive information, and second, overconfidence due to the new quantitative inputs in their valuation models. Both of these factors might lead to a quarterly cycle of optimism bias, which are reported in this study.

NOTE: Target price expected return, $TPER$, is defined as $TP_t/P_{t-1}-1$, where TP_t is the analyst's target price with a 12-month horizon issued on day t ; P_{t-1} is the share price on the previous trading day before t . The fraction of earnings announcements (EAs) is the number of EAs issued by companies in a given month divided by the total number of EAs in that year.

Figure 4. Average monthly $TPER$ (%) for Stars and Non-Stars and calendar of earnings announcements.

In summary, the results of this study show that analysts have a reversed pattern of optimism to the famous market adage “Sell in May and Go Away”, with more optimistic target price expected returns in summer than in winter. On average, Non-Stars are more optimistic than Stars, however Stars are more pessimistic in their recommendations to sell. This study did not find any significant correlation between target prices and market returns (both simultaneous and lagged values). Additionally, in contrast to the extant literature, this study did not find any seasonality in market returns over the investigated time period.

This study documents a pattern of optimism over the year, which is reflected in target prices, that has a strong correlation with the calendar of companies’ earnings announcements. Thus, optimism increases every quarter with the number of published quarterly reports and peaks in the month when the number of reports is highest before subsequently declining. Interestingly, the lowest optimism for analysts was reported for each one month preceding that with the highest number of earnings announcements. The results therefore reveal an optimism cycle exists but it is related to the activity of corporations rather than to changes of seasons.

4.4. Part IV – Change in competitiveness over time

Figure 5 reports the yearly number of industries and Figure 6 has the number of analysts for each ranking. On average, there are 56 industries and 147 analysts in I/I; 59 industries and 168 analysts in STM-TEE; 45 industries and 132 analysts in WSJ; and 57 industries and 158 analysts in STM-TSP. These figures were not uniform over the sample period for all rankings. For example, I/I ranked only 58 and 57 analysts in 2010 and 2011, since there were only the number one analysts in each industry in these years. Because of this reduced number of analysts in 2010 and 2011, two years were omitted when comparing pre-crisis turnover with the post-crisis uncertainty period.

NOTE: Star analysts are those listed in *The Wall Street Journal* (WSJ), *Institutional Investor* (I/I), and Thomson Reuters' *StarMine* "Top Stock Pickers" (STM-TSP) and "Top Earnings Estimators" (STM-TEE). Only the top three analysts are considered in the I/I and WSJ rankings to increase comparability with *StarMine* rankings.

Figure 5. Yearly number of industries in star rankings.

In 2012, the structure of industries represented in the I/I ranking changed with the lower number of industries represented (only 39), which affected the number of analysts ranked in that year (107). However, in 2013, I/I ranked 162 analysts in 56 industries, which was similar to the rankings in the pre-crisis period. The WSJ changed their industry structure in 2005 and reduced the number of industries from 48 in 2004 to 44 in 2005. The STM-TEE and STM-TSP rankings have very similar numbers of industries and analysts ranked. In both rankings, there were fewer analysts in 2003 and 2004, while beginning from the 2006, there were approximately 60 industries with 168 analysts in each ranking.

NOTE: Star analysts are those listed in *The Wall Street Journal* (WSJ), *Institutional Investor* (I/I), and Thomson Reuters' *StarMine* "Top Stock Pickers" (STM-TSP) and "Top Earnings Estimators" (STM-TEE). Only the top three analysts are considered in the I/I and WSJ rankings to increase comparability with *StarMine* rankings.

Figure 6. Yearly number of star analysts.

The turnover is calculated as the number of re-selected analysts divided by the total number of analysts in a given year. Table 22 reports raw turnover and adjusted figures accompanied with the results of the statistical tests. The adjustment is based on the number of industries in a given year that are similar to those of the preceding year. The adjustment of figures corresponds to the method of Bagnoli et al. (2008), which considers the change in the structure of industries as follows. If an industry was represented in the previous year but not in a given year, then the number of re-selected (not selected) analysts was increased (decreased) proportionally. Similarly, if an industry was not represented in a previous year but is listed in a given year, then the number of re-selected (not-selected) analysts was decreased (increased) proportionally. As in Bagnoli et al. (2008), the chi-squared test is used in this

Table 22. Turnover of names in star rankings as the percentage of re-selected analysts.

Group of stars	Raw / Adjusted for # Industries	Yearly percentage of re-selected analysts											Average	
		2002-2003	2003-2004	2004-2005	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2004-2008	2012-2013
I/I	Raw	72%	76%	79%	76%	72%	70%	73%	97%***	70%***	33%***	47%***	74%	40%***
	Adjusted	75%	77%	79%	76%	74%	71%	75%	97%***	73%***	54%***	47%**	75%	51%***
WSJ	Raw		8%	12%*	15%	14%	14%	15%	5%***	13%***	15%	9%**	13%	12%
	Adjusted		12%	35%***	19%***	14%	14%	21%**	5%***	13%***	17%	9%***	19%	13%**
STM-TSP	Raw	11%	9%	15%***	15%	15%	14%	17%	13%	20%***	18%	21%	14%	19%***
	Adjusted	53%	17%***	17%	18%	25%**	14%***	22%***	13%***	24%***	19%	21%	18%	20%
STM-TEE	Raw	23%	17%*	17%***	22%**	26%	26%	31%	29%	33%	34%	27%*	22%	30%***
	Adjusted	60%	22%***	17%**	25%***	30%*	26%	33%**	29%	36%**	34%	28%	24%	31%**

*** p<0.01, ** p<0.05, * p<0.1

NOTE: Star analysts are those listed in *The Wall Street Journal* (WSJ), *Institutional Investor* (I/I), and Thomson Reuters' *StarMine* "Top Stock Pickers" (STM-TSP) and "Top Earnings Estimators" (STM-TEE). Only the top three analysts are considered in the I/I and WSJ rankings to increase comparability with *StarMine* rankings. Each figure shows the percentage of analysts who were selected as stars in the previous year in a given ranking. Adjustment of figures corresponds to the method of Bagnoli et al. (2008) for considering the change in the structure of industries. If an industry was represented in the previous year but not in a given year, then the number of re-selected (not selected) analysts was increased (decreased) proportionally. Similarly, if an industry was not represented in a previous year but is listed in a given year, then the number of re-selected (not-elected) analysts was decreased (increased) proportionally. The last two columns on the right-hand side show the average figures for the 2004-2008 (pre-crisis) and 2012-2013 (post-crisis) periods. *P*-values of the chi-squared test on absolute figures (not on percentages) are reported as asterisks. The turnover in the first year (2002-2003 for I/I and *StarMine*, and 2003-2004 for WSJ) does not have the results of the chi-squared test because of the availability of the data for the previous years.

study for comparing year-to-year turnover and for comparing time of pre- and post-crisis periods. However, a direct number of analysts is taken for the chi-square tests in this analysis, while Bagnoli et al. (2008) apply the chi-square statistics to percentages of re-elected analysts. Obviously, their approach reduces the chi-square statistics by the total number of analysts in each pair of compared years (that is by 226, which was the average number of analysts). The discussion of whether the results and conclusions in their study would be affected by considering raw figures or applying the chi-square test to the number of analysts rather than percentages remains outside the scope of this thesis.

Furthermore, first, a year-to-year change in turnover is discussed for each ranking system (see yearly percentage of re-selected analysts in Table 22). Secondly, the pre-crisis period of a stable market is compared with the post-crisis uncertainty period (see two last columns on the right-hand side of Table 22). Thirdly, an analysis of the differences between high and low uncertainty periods of the excess returns on investment recommendations is conducted.

4.4.1 Survey-based ranking by Institutional Investor

An analysis of turnover of the I/I rankings appears in the first and second lines in Table 22 and are represented as a blue line in Figure 7, which shows the percentage of analysts re-selected each year (adjusted figures). The percentage of re-selected analysts in I/I ranking was, on average, as high as 74% during 2004-2008. This shows the majority of I/I star analysts were re-selected from one year to another. The changes in turnover from one year to another were insignificant during 2003-2009. Then, there is a drastic shift in turnover rate beginning from 2010, when the percentage of re-selected analysts increased to 97%. Such an extreme value in 2010 is explained by the fact that I/I in that year selected only number one stars in each industry, and those same stars had been selected in the previous 2009 ranking. Hence, the change in turnover in 2010 should not be attributed to a real increase in the

number of re-selected analysts, because the true figure would have been lower if I/I also issued rankings of the number two, three and runners-up analysts.

NOTE: Star analysts are those listed in *The Wall Street Journal* (WSJ), *Institutional Investor* (I/I), and Thomson Reuters' *StarMine* "Top Stock Pickers" (STM-TSP) and "Top Earnings Estimators" (STM-TEE). Only the top three analysts are considered in the I/I and WSJ rankings to increase comparability with *StarMine* rankings.

Figure 7. Yearly change in turnover of star analysts in each ranking.

After the crisis of 2008, the percentage of re-selected analysts drops significantly compared to the pre-crisis period (see the last two columns in Table 22). This increase in turnover after the crisis reflects how the change in overall market sentiment affected the way buy-side clients viewed the "helpfulness" of I/I star analysts. During pre-crisis period of "good" year of 2004-2007, investors were re-selecting the majority of stars in the I/I ranking. In contrast, after the crisis and during the period of market uncertainty, most probably because investors started to reconsider how they select analysts and which skills they most value in analysts. Also, the increase in turnover shows it is more difficult to maintain star status during crisis and market uncertainty periods.

4.4.2 Earnings-based ranking – “Top Earnings Estimators”

During the period under investigation, Top Earnings Estimators (STM-TEE) had a steady growth in the percentage of re-selected analysts (decrease in turnover), which could be explained by the fact that StarMine rankings gained popularity among brokerage houses as an external unbiased evaluation body. Some brokers began using StarMine rankings as performance measures, which might affect the allocation of resources among analysts in a brokerage firm. If so, because the popularity of StarMine has been increasing, STM-TEE star analysts in later years could have received access to better resources compared to other analysts within the firm, which helped them to be re-selected and maintain their star status. Also, these re-selected STM-TEE star analysts gain experience and knowledge of companies that they follow over time (corresponding to the experience curve), which improves analysts' ability to forecast the earnings of those particular companies and, in turn, increases their chances to be re-selected as stars.

Another explanation for the observed increase in the number of re-selected analysts is related to an improvement of StarMine's selection methodology. Although the year-to-year changes in turnover from 2007 to 2012 were not significant, the comparison of pre- to post-crisis periods reveals a significant decrease in turnover, which could be attributed to an improvement of the selection methodology used by StarMine, which relies on a proprietary metric called the Single-stock Estimate Score. This metric considers many factors; however, the details of the calculations are not disclosed to the general public.

4.4.3 Recommendation-based rankings – “Top Stock Pickers” and “The Wall Street Journal”

Both recommendations-based rankings, STM-TSP and WSJ, have differences between adjusted and raw figures when analyzing the changes over years. The WSJ ranking had insignificant shift in turnover from the pre- to post-crisis period, if raw figures are considered. However, when adjusted values are taken, the change from the pre- to post-crisis period is

significant. This change is related to the year 2005, when WSJ decreased the number of industries under consideration. Taking in account the methodology used in this study, a decrease in the number of industries for WSJ in 2005 leads to an increase in the number of re-selected analysts. Hence, the number of re-selected analysts in 2005 is an artifact of the methodology. If a real number of re-selected analysts is considered, as in raw values in Table 22, then the change in turnover from the pre- to post-crisis period for both raw and adjusted figures is insignificant. At the same time, the changes in year-to-year turnover for 2010 and 2011 are statistically significant for both, raw and adjusted figures. This shows that although the WSJ lists experience some changes during the crisis period, after the crisis, the turnover returns to the level of the pre-crisis years. This finding might be interpreted as if some analysts issue more-profitable recommendations during good years, while others are better in down-markets.

The turnover of StarMine's Top Stock Pickers (STM-TSP) has similar features as the WSJ rankings. STM-TSP had an insignificant change in turnover in the pre- to post-crisis period, as the last column of Table 22 shows. However, during the crisis years, there were some significant changes in turnover in 2010 and 2011. The only difference with WSJ is that STM-TSP has a statistically significant difference between pre- and post-crisis years for raw figures, which can also be related to the adjustment procedures that affect the year 2004 and, thus, in turn it may increase the percentage of re-selected analysts in the pre-crisis period.

4.4.4 Difference in profitability of recommendations in high and low uncertainty periods

Additionally, the time-varying behavior is analyzed for the profitability of investment recommendations issued by the four groups of star analysts. Time-series of portfolio returns for the period from November 2003 to November 2014 are taken from Part I of this study. These time-series returns were obtained by combining analysts' recommendations from the

IBES database into three dynamic portfolios (Long, Hold, and Short) under a buy-and-hold strategy, as discussed earlier in the methodology section.

The Carhart's four-factor model (Carhart, 1997) was used with an additional fifth dummy variable, DH , which is equal to 1 during months with a high uncertainty index (Equation 10). High uncertainty periods are those that have a policy uncertainty index higher than the average over the investigated period.

$$R_{\rho\tau} - Rf_{\tau} = \alpha_{\rho} + \gamma DH_{\tau} + \beta_{\rho}(Rm_{\tau} - Rf_{\tau}) + s_{\rho}SMB_{\tau} + h_{\rho}HML_{\tau} + m_{\rho}UMD_{\tau} + \varepsilon_{\rho\tau}. \quad (10)$$

where $R_{m\tau}$ is a monthly market return,

Rf_{τ} is the risk-free rate of return,

SMB_{τ} is a size factor, that is, the difference between the value-weighted portfolio returns of small and large stocks,

HML_{τ} 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_{τ} is a momentum factor, that is, the difference in the returns of stocks with a positive return momentum and those with a negative return momentum over months $\tau-12$ and $\tau-2$.

Using this model allows testing of the differences in profitability of analysts' recommendations between high and low uncertainty periods for each group of star analysts. An intercept and the coefficient DH in the model are interpreted as follows. Intercept α will return a mean value during the low uncertainty period, and DH will show the difference between low and high periods and the statistical significance of this difference. The results of this analysis are reported in Table 23.

Table 23. Difference in profitability of analysts' recommendations between high and low uncertainty periods (monthly values in percent).

Portfolio	I/I	STM-TEE	STM-TSP	WSJ
Long	-0.34* (-1.69)	-0.31 (-1.46)	-0.22 (-1.10)	-0.25 (-1.15)
Hold	-0.29 (-1.48)	-0.39** (-2.00)	-0.37* (-1.90)	-0.11 (-0.59)
Short	-0.45 (-1.36)	-0.12 (-0.32)	0.3 (0.73)	0.23 (0.55)
Long-Short	0.11 (0.37)	-0.19 (-0.50)	-0.53 (-1.28)	-0.48 (-1.13)

t-statistics in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

NOTE: Star analysts are those listed in *The Wall Street Journal* (WSJ), *Institutional Investor* (I/I), and Thomson Reuters' *StarMine* "Top Stock Pickers" (STM-TSP) and "Top Earnings Estimators" (STM-TEE). Reported values correspond to the coefficient DH from the regression on the Carhart four-factor model (Carhart, 1997) with an additional fifth dummy variable, DH , which is equal to 1 during high uncertainty months: $R_{pt} - R_{ft} = \alpha_p + \gamma DH_t + \dots + \varepsilon_{pt}$. High uncertainty periods are those that have a policy uncertainty index higher than the average over the investigated period. Time-series of portfolio returns are obtained from (Kucheev et al., 2016). Significant *t*-statistics are in bold. Time period is from November 2003 to November 2014.

Among Long portfolios, only I/I has a statistically significant coefficient of -0.34%, which shows that during high uncertainty periods, star analysts ranked by I/I subjective ranking have significantly less-profitable recommendations than during low uncertainty periods. Other groups of analysts have an insignificant difference in excess returns during high and low uncertainty periods. Among Hold portfolios, STM-TEE and STM-TSP have significant differences between high and low uncertainty periods, and other groups of stars show insignificant differences in performance. At the same time, Hold recommendations perform insignificantly differently from the market return (as shown in Part I). Also, Hold recommendations represent an analyst estimation for a given stock to perform on the level of the market (some brokers code this recommendation as "market perform"). Thus, this decrease in the performance of hold recommendations may simply reflect a change in the market performance from low to high uncertainty periods. Considering that the change in the performance of the Hold portfolios could just be explained by the change in overall

market performance, it is difficult to interpret this significant change in excess returns as a decrease in performance. Short portfolios with Sell and Strong Sell recommendations show insignificant differences between different periods for all groups of stars.

An analysis of the results shows that subjectively measured I/I rankings had the highest percentage of re-selected analysts (the lowest turnover) over the years, having on average 70% of analysts being re-selected from one year to another. In contrast, the objectively measured WSJ, STM-TEE, and STM-TSP had a significantly higher turnover of analysts, having, on average, only 20% of analysts being re-selected. At the same time, the change from the pre- to post-crisis period was statistically significant for I/I (decrease in the percentage of the re-selected analysts) and for STM-TEE (increase in the percentage of re-selected analysts) but was not significant for the recommendations-based WSJ and STM-TSP. The findings confirm that a change in the market conditions affects the turnover of subjective rankings (I/I) but not objective recommendation-based rankings (WSJ and STM-TSP).

The expected differences in turnover of analysts in different market conditions might be explained from two perspectives (hypotheses). First, investors could change their priorities and begin to value different skills, depending on the economic conditions. Second, analysts can possess a time-varying skill by being good stock-pickers only during either boom or bust market cycles.

For the first hypothesis, Bagnoli et al. (2008) discuss changing priorities. They find that the changes in priorities in 2000 and 2002 were not accompanied by significant changes in turnover in I/I rankings, as it was reflected by the reported (in their Table 1) rank of attributes that investors value for I/I rankings. Hence, the authors conclude that the changes in buy-side priorities that are not associated with Reg-FD do not drive the increase in turnover. However, the authors do not discuss how the change in market uncertainty could affect the priorities of the buy-side clients. For example, the change in the market uncertainty

index from Low in 2000 to High in 2001 could also reflect a shift in analysts' reputation, which was discussed in negative terms by the mass media in these years due to the number of conflicts that involved analysts. This negative reputation effect could also increase the turnover of analysts in the I/I ranking. An alternative explanation for changing buy-side priorities could be the recent finding of Loh and Stulz (2014) that investors value analysts' advice more in "bad" times, e.g., during the high uncertainty periods. It is reasonable to expect that investors should question more the quality of the advice they receive in bad times than they do in good times. Hence, investors might be pickier in bad times and look only for high value reports, while in good times, they might lower their quality selection criteria. As a result, the turnover in bad times should be higher than in good times.

For the second hypothesis, a previous study by Kacperczyk et al. (2014) confirms that the stock-picking skill has a time-varying nature dependent on the market conditions. By investigating the performance of fund managers, the authors found that managers, who outperform other funds and passive benchmarks, possess stock picking skill during booms and market timing skill in recessions. By extending this logic of the skills of managers to sell-side analysts, one can expect that sell-side analysts also have stock picking skill only during booms. However, market timing effects do not exist for analysts, because analysts cover a limited number of stocks, usually within one or several industries. Consequently, analysts could possess stock picking skills that are dependent on market conditions, which could be reflected in their recommendations outperformance only during periods of market booms. One argument against this hypothesis for the case of sell-side analysts is related to the nature of the performance measurements and to the difference in instruments available to fund managers and analysts. Analysts can issue sell recommendations during recessions, while fund managers have a limited set of instruments to use during negative market trends. Also, there is a liquidity constraint. While analysts can issue sell recommendations immediately and

this will be reflected in their recommendation-based performance measurements, fund managers usually cannot liquidate their holdings at once. An alternative interpretation of a time-varying hypothesis considers analysts to be either optimists or pessimists, tending to have upside or downside biases in their forecasts and recommendations. According to this hypothesis, when the market is booming, optimistic forecasters might have better performance than pessimistic forecasters. In contrast, during negative market trends, the pessimistic analysts should perform better than optimists. If such a optimistic/pessimistic distinction exists and some analysts are better in recessions while others are better in booms, it could be expected to observe a shift in turnover for objective rankings during changes from boom to recession and vice versa. However, the results reported in Table 22 do not represent any significant pattern of change in turnover when the market switches from High to Low uncertainty and vice versa, or when the crisis began in 2008 with an impact on lists of stars for 2007-2008. The results of analyzing the performance differences between High and Low uncertainty periods confirm the second hypothesis of the time-varying nature of analysts' skills for a group of I/I stars, because their Buy and Strong Buy recommendations have significantly lower excess returns during High uncertainty periods. Also, this time-varying performance of I/I stars might explain their significant change in turnover during high market uncertainty periods. Thus, investors might be able to recognize this effect and simply change their views on analysts, whom they previously voted to the I/I ranking because they considered them to be the best on the market.

In summary, the results of this study show that the subjectively measured I/I rankings undergo a significant increase in turnover during crisis and a post-crisis uncertainty period. Thus, the analysts' competitive advantages that were valid during the pre-crisis period became insufficient after the crisis. In contrast, the turnover of analysts in the objectively measured rankings by STM-TSP and WSJ, which are based on the profitability of analysts'

recommendations, had no clear pattern of changes. These results are interpreted as investors valuing different skills at different times, and this change in buy-side priorities impacts the list of analysts in I/I rankings. However, both the stock-picking skill and the skill to produce accurate earnings forecasts appear to be independent (or partially dependent) of market conditions. At the same time, these skills are difficult to maintain, as reflected in a relatively low percentage of re-selected analysts in all objectively measured rankings.

CHAPTER 5:

DISCUSSION

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? (Parts I and II) In other words, this thesis answers the question: Is there any investment value in the recommendations from star analysts?
- (2) How do market conditions affect star analysts? (Parts III and IV) In other words, how should investors change their view on analysts' rankings when market conditions change?

Parts I and II of this thesis discussed whether the investigated star rankings capture stock-picking skills and can thus aid investors in making profitable investment decisions. By investigating the precision of the signals that the various methodologies use in determining who the stars are, Part I distinguished between the star-selection methodologies that capture a short-term stock-picking profitability and those methodologies that emphasize more persistent skills of analysts. Next, Part II finds that the portfolio construction methodology that is used in Part I and in many other previous studies does not drive the conclusion that analysts possess significant stock-picking skills. Thus, the outperformance of some groups of star analysts can be explained by the differences in stock-picking skills of analysts, which were captured by the selection methods that are used by different star rankings.

In Part I, this study 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 is composed of 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 discussed in Part I confirm 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 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) 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 discussed in Part 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 Part I of this study 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 belief that the stock price will continue to rise 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 Part 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. Part III continues this discussion and analyzes whether star status helps to mitigate conflicts of interests that is measured by studying how optimistic target prices from star analysts are as compared to those from non-stars. Consistent with previous findings, the results of this study show that stars indeed issue less-biased forecasts that are reflected in less optimistic bullish recommendations and more pessimistic bearish ones. Simultaneously, in Part III it was shown that analysts are highly optimistic in May, which is against the 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 target prices.

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 persistency over time depending on market conditions. The results in Part 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 elect 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.

In summary, 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 and over time.

CHAPTER 6:

LIMITATIONS & FURTHER RESEARCH

6. Limitations and suggestions for further research

Although, this research is based on well-established methodologies and 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. This thesis has 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.

This thesis documents the existence of the seasonal patterns that are associated with the calendar of companies' earnings announcements. Using the First Call database, or any other alternative news database, will allow a more detailed analysis of the company-specific news (not limited to earnings announcement). Additionally, it would be interesting to investigate how company size is 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 various rankings, may perform better than those 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, JAE) 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. This thesis replicates and tests 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 amount 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 this study 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.

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