Aalto University
School of Business

One man consensus
Can the only stock analyst covering a company move the markets?

Finance

Master's thesis

Atte Heikkilä

2016

Department of Finance
Aalto University
School of Business

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Spring 2016
Finance

Approved in the Department of Finance __ / __20__ and awarded the grade

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Abstract of master's thesis

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Title of thesis One man consensus – Can the only stock analyst covering a company move the markets?

Degree Master of Science in Economics and Business Administration

Degree programme Finance

Thesis advisor(s) Peter Nyberg

Year of approval 2016 **Number of pages** 87 **Language** English

BACKGROUND AND OBJECTIVES OF THE STUDY

The key objective of this study is to make sense of the information environment surrounding listed U.S. companies that have exactly one sell-side stock analyst covering them. Despite the large amount of stock analyst literature, this "One man consensus" setting has previously been left without academic attention. For small and illiquid listed companies that receive little attention from the investors, coverage from even one analyst might become decisively important, either in a good or bad way depending on their recommendation. Hence, this thesis studies the market reactions to the buy-hold-sell recommendation revisions issued by stock analysts who form the analyst consensus on their own.

DATA AND METHODOLOGY

The data set of this study covers all single analyst consensus recommendation revisions in the U.S. stock exchanges NYSE, NASDAQ and AMEX between 1994 and the end of 2014. Market reactions for these revisions are analyzed in an event study context for short-term event windows, as well as in an Ordinary Least Squares regression with and without fixed effects. A more novel influential recommendation method is also applied, based on both cumulative abnormal returns and abnormal turnover figures. A control sample of multiple-analyst consensus revisions for the same companies is introduced for comparative analysis. Both the One man consensus sample and the control sample are separately examined for upgrades and downgrades, and implications are thoroughly discussed.

EMPIRICAL FINDINGS

Results from the event study and the regression analysis show that on average, markets react to single analyst upgrades and downgrades in a statistical significant manner. However, the influential recommendation tests reveal that the proportion of visibly strong reactions remains small. One man consensus upgrades tend to induce stronger short-term reactions than the control sample upgrades, whereas negative reactions to downgrades are more muted than in the control sample. The tests control for firm quarterly earnings announcement events that might otherwise provoke incorrect conclusions about stock analysts' influence. Provided evidence suggests that in most cases, analyst coverage even from only one person improves the information environment for listed companies.

Keywords Stock analyst, equity analyst, recommendation, revision, market efficiency, incentives, Regulation Fair Disclosure

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Maisterintutkinnon tutkielman tiivistelmä

Tekijä Atte Heikkilä

Työn nimi One man consensus – Can the only stock analyst covering a company move the markets?

Tutkinto Kauppatieteiden maisteri

Koulutusohjelma Rahoitus

Työn ohjaaja(t) Peter Nyberg

Hyväksymisvuosi 2016 **Sivumäärä** 87 **Kieli** Englanti

TAUSTA JA TUTKIMUKSEN TAVOITTEET

Tutkimuksen keskeinen tavoite on selventää yhdysvaltalaisten, ainoastaan yhden osakeanalyytikon seuraamien pörssilistattujen yritysten informaatioympäristöä. Analyytikoiden toimintaa on tutkittu akateemisessa kirjallisuudessa runsaasti, mutta yhden analyytikon seuraamien yritysten tapaukset ovat toistaiseksi jääneet vaille huomiota. Pienille ja epälikvideille yrityksille, joista markkinat eivät ole kovinkaan kiinnostuneita, yhdenkin analyytikon seuranta voi olla ratkaisevaa, joko hyvässä tai huonossa mielessä. Tämä pro gradu -tutkielma kartoittaa osakemarkkinoiden reaktioita analyytikoiden ”osta-pidä-myy” -suositusmuutoksiin tilanteissa, joissa analyytikko muodostaa analyytikkokonsensuksen yksinään.

DATA JA METODOLOGIA

Tämän tutkimuksen aineisto muodostuu yhden analyytikon konsensuksen suositusmuutoksista vuosina 1994-2014 amerikkalaisissa pörsseissä NYSE, NASDAQ ja AMEX. Markkinoiden reagointia näihin muutoksiin tutkitaan tapahtuma-analyysilla (event study) lyhyellä aikavälillä, sekä pienimmän neliösumman regressiomenetelmällä (OLS) kiinteillä vaikutuksilla ja ilman. Analyysiin sovelletaan myös uudempaa vaikutusvaltaisten suositusten menetelmää, joka pohjautuu sekä kumulatiivisiin epänormaaleihin tuottoihin (CAR) että osakkeiden epänormaaliin vaihdantaan. Vertailuna hyödynnetään otosta, joka koostuu useamman analyytikon konsensuksen suositusmuutoksista. Yhden analyytikon pääaineistoa ja vertailuaineistoa tutkitaan molempia eriteltyinä suosituksen korotuksiin ja laskuihin, ja näistä juontuvia johtopäätöksiä pohditaan laajasti.

EMPIIRISET TULOKSET

Tapahtuma- ja regressioanalyysin tulosten perusteella voidaan sanoa, että markkinat reagoivat yhden analyytikon positiivisiin ja negatiivisiin suositusmuutoksiin tilastollisesti merkittävällä tavalla. Samalla vaikutusvaltaisten suositusten menetelmä osoittaa, että aidosti merkittävien reaktioiden suhteellinen määrä on pieni. Yhden analyytikon suositusten korotukset saavat pääsääntöisesti aikaan vahvempia reaktioita kuin korotukset vertailuaineistossa, kun taas suosituksen laskuissa negatiivinen markkinareaktio on vaimeampi kuin vertailuaineistossa. Empiirisessä testauksessa huomioidaan myös yritysten neljänneksittäiset tulosjulkistukset, jotka saattaisivat kontrolloimattomana tehdä empiiristen testien tuloksista epäselviä. Testattu aineisto viittaa siihen, että useimmissa tapauksissa yhdenkin analyytikon seuranta kohentaa yrityksen informaatioympäristöä.

Avainsanat Osakeanalyytikko, suositus, suositusmuutos, tehokkaat markkinat, insentiivit, Regulation Fair Disclosure

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1. Introduction

Many claim that a well-functioning financial market is based on swift transfer of information across the market and its participants – companies, investors, and the information intermediaries that act in between these two ends. One commonly quoted academic perception of this process is the Efficient Market Hypothesis (EMH), first introduced by Eugene Fama in 1970. This study will visit the EMH, a fundamental building block of modern financial theory, and point its focus towards stock analysts as information intermediaries. The aim of the thesis is to shed light on sell-side equity analysts who act as the only equity analysts covering a listed U.S. company at a given time, and more specifically, on the impact their recommendations have on companies' information environment. The subject enters a scantly studied area in the enormously studied stock analyst recommendation context. A state of exactly one analyst covering a company might perhaps not be optimal for that firm, but it is arguably better than not having any analyst coverage at all. The topic of the thesis will not be solely limited to efficient markets, as also other relevant angles, such as analyst incentives and effect of market regulation, are explored and discussed.

1.1 Setting of the study and key research area

The main stock exchanges of the United States, namely NYSE, NASDAQ and AMEX, contain several thousands of companies all across the nation, with a very varied sell-side stock analyst coverage. Many of the large and well-known companies, such as Apple, General Electric or Walmart, often have tens of analysts giving their recommendations of buying, holding or selling. In addition, these analysts provide estimates for key future financials for the companies, for instance about earnings-per-share (EPS) or revenue growth estimates. There are also hundreds of smaller companies that have just a handful of stock analysts following them, and plenty of those with no analyst coverage at all. The examined main sample of companies in the study consists of the firms with exactly one analyst covering them. As the amount of coverage and its influence on the company's stock price has been studied in many existing papers (see e.g. Irvine, 2003; Ertimur et al., 2011; Li & You, 2015), interest is not in the number of analyst per se. Instead, the theme of the study is to create a comparison of firms with just one analyst on one side, and firms with more analyst coverage on the other.

An average of sell-side analyst estimates forms the analyst consensus, which is often referred to by different stakeholders of a company, and most importantly, by investors. The aim of this paper is to explore the consequences of only one analyst forming the analyst consensus. By definition, consensus is not something one person can form by themselves. Nevertheless, in the financial discourse, when no more than one analyst covers a company, he or she effectively steers the whole analyst consensus for that firm. One of the main hypotheses in this study expects the stock market to react more pronouncedly to recommendation revisions in a "One man consensus" (hereon also OMC for short) situation, than when an analyst changes their recommendation among many other analysts who follow the same company.

An essential insight about stock analysts is that given the exactly same financial data, two stock analysts could have very different interpretations of a company's potential. One of the analysts might end up recommending buying the stock, while the other might recommend a sell. Recommendations are by no means an exact science, but rather, merely the opinion of an analyst, at one point in time. However, the market reaction to these fairly quantitative opinions can be qualitatively measured. In this study, reactions to recommendation changes will be measured in terms of short-term stock price reactions and changes in trading volume as a measure of investment activity. Due to their vast amount only in the United States, analysis about investors' response, single-analyst companies' characteristics, and the analysts themselves can prove rather interesting results with significant real-life implications.

Stock analysts are in many studies deemed valuable to the financial markets. For instance, Ivković & Jegadeesh (2004) suggest that the value provided by analysts could arise from the ability to collect and handle public information more efficiently and more independently than the market. This thesis will approach the discussion from a lone-covering stock analyst's angle: is the only analyst gathering information on a company well-received by the market? We know from existing research that companies gaining analyst coverage, having completely lacked it beforehand, usually experience positive short term stock returns due to increased investor attention and more news, and also due to the fact that initiation recommendations are around 90% of the time positive (Demiroglu & Ryngaert, 2010). However, if a single analyst following the company cannot induce any visible reactions from the market after the initial coverage announcement returns, their necessity could be questioned. On the other hand, if the analysts can indeed induce noticeable reactions, analyst incentives are to be discussed. An extensive review of relevant findings in the existing stock analyst literature will be presented in Section 2 of this paper.

Many investors perceive stock analysts as very important, if not the most important intermediaries of information outside the firm's own guidance and announcements. For numerous individual and institutional investors alike, analyst recommendations act as an essential guideline. For example, Chen and Cheng (2006) find that institutional investors increase holdings of firms with favorable recommendations, and for unfavorable recommendations vice versa. From the point of view of this study, an intuitive hypothesis would be that since the analyst view in general seems to usually have at least some kind of weight to investors, one person would relatively have even more influence when they form the whole analyst coverage on a company themselves. This thought is illustrated in the following scenario.

Imagine a company with an analyst coverage of 5 analysts, and let it be assumed that all of the 5 analysts receive the exact same share of the investor attention, i.e. 20% of total attention for each analyst. Now if there only were 2 analysts instead of 5, each analyst would receive 50% of the attention. Finally, if coverage is reduced by one more analyst, the single analyst would receive the undivided attention of the investors, or 100% of the attention. We know that in real-world financial markets, investors collect their information from a variety of sources besides analyst reports, making this thought experiment entirely theoretical. Even so, common sense would suggest that an audience listens more closely to one actor if he is alone on a stage, in comparison to when there are five actors presenting their thoughts at the same time.

1.2 Research questions and hypotheses

The aim of this study will boil down to a fairly simple question: when only one sell-side stock analyst forms the analyst consensus for an exchange-listed U.S. company, can the single analyst induce a more significant market reaction to their recommendation revisions than analysts in a more crowded consensus could? Companies with this kind of setting have widely been left outside the focus of academic research, despite the fact that they have formed a significant part of all exchange-listed companies throughout the years, both in the United States and in other countries. Companies like this tend to share a similar set of characteristics: they are often relatively small in size, and receive considerably less visibility in the news than their peers with a wider analyst coverage. According to previous academic research, analysts have an important role in the economy in disseminating information about companies to investors, especially about the small and opaque firms (see e.g. Stickel, 1995; Hong et al., 2000). Results in this paper will offer fresh input to that finding.

In the existing literature, it has generally been established that analyst coverage is beneficial for a company, especially when comparing a firm having no coverage and a firm having some coverage (e.g. Irvine, 2003; Crawford et al., 2012; Mola et al., 2013). In addition, for example Hobbs et al. (2012) claim that investors, institutional and individual alike, not only actively listen to stock analysts' opinions, but are often also better off by doing so. However, it is intriguing to see whether this matter is as straightforward with only one analyst. Can the one analyst induce movement in the market, or does the market ignore them? In the latter case, does it still hold that analyst coverage is beneficial to the company in these situations?

Hence, the core objective of this study is to make sense of the information environment surrounding companies that have exactly one stock analyst covering them. Most pressing research questions are the two following. Firstly, can the single analyst recommendation revisions provide information that the markets regard valuable? Secondly, is the informational environment different for sell-side stock analysts who are the sole analysts in an analyst consensus, than for other analysts? For both of the questions, quantifiable market reactions will be the key to explaining the information environment. To make sense of these questions on practical level, the following hypotheses are set:

H1: *Average market reactions to One man consensus analyst recommendation upgrades and downgrades revisions are different from zero in a statistically significant way.*

H2: *Market reactions to recommendation upgrades and downgrades by stock analysts in a One man consensus are visibly and statistically different from the market reactions, which are induced by analysts who share the consensus with others.*

Several kinds of tests are performed to solve the reliability of the hypotheses. The tests are conducted in the contexts of event study, regression analysis and searching for the proportion of the truly influential recommendation revisions.

Analyst tendency towards optimistic recommendations and the uneven division of buy and sell recommendations are well documented issues in the analyst literature (e.g. Barber et al., 2006). Consequently, an essential part of any paper studying analyst recommendation revisions is to separate recommendation upgrades and downgrades from each other and examine these two signals each on their own. Testing the reliability of H1 and H2 also entails that other likely influential factors are controlled for, such as the size of the company, the company's possible status as a growth firm, as well as other factors that might affect the magnitude of the market reaction.

Besides the outcome suggested by the two hypotheses, an equally possible finding for some of the tests is that single analyst recommendation revisions differ in no significant way from recommendation changes in multi-analyst consensus situations. Another imaginable outcome for the tests is that, simply put, a single analyst cannot really induce the markets to react in a noticeable way by revising their recommendation. However, particularly the latter kind of result would offer a fruitful basis for discussion in itself. The incentive for a brokerage house to have a well-paid stock analyst following a certain firm could then be questioned. Is there any point to have a sell-side equity analyst at all from a brokerage's, the covered company's, or the markets' point of view, if most of the time investors gain no new information from the analyst's recommendations?

1.3 Contribution to the existing literature

The contribution of this thesis to the existing vast number of finance and accounting academic studies on stock analysts is manifold. First and foremost, a key contribution is the examination itself of analyst recommendation changes when the analyst forms the analyst consensus on their own. Existing papers have studied the impact of the amount of covering analysts to some extent, but to the best of my knowledge, there has been no single paper published in major financial or accounting journals that would have studied the specific case of exactly one analyst making recommendation changes. One gap in the literature will thus be filled. As aforementioned on the previous pages, my hypothesis is that the influence of a stock analyst is likely to differ when they are the sole analyst covering a company, in comparison to when they are part of a more highly populated coverage group.

Secondly, I add to the analyst literature by examining the characteristics of the firms that at some point of their history have had only one stock analyst following them. The context of this thesis extends further than just the stock analysts, to the discussion of the informational environment of small and more illiquid companies. I examine the role of financial analysts who arguably have an important role in conveying information from companies to the investors – and especially so in the case of firms that arouse less public interest. Even small cap companies covered by stock analysts are seldom researched: for example, Guagliano et al. (2013) study analyst influence on small capitalization companies, but only in the Italian stock market.

Thirdly, my study adds to the previous studies on analysts with its extensive set of data. Observations used in my thesis span a time period of over 20 years, from the beginning of year 1994 until the end of year 2014, covering all recommendation changes for more than 1 700 exchange-listed companies in the United States. In other words, the base source of observations to the studied sample of companies is in principle all recommendations that are recorded by Thomson Reuters Institutional Brokers' Estimate System (IBES or I/B/E/S) during that time. Earlier history of recommendations is not explored, since for example Demiroglu & Ryngaert (2010) note that IBES recommendation data is scarce and incomplete before the end of 1993.

The most significant contribution of this study will hopefully lie in exploring the informational value that a single analyst can provide to the financial markets. Stock analyst recommendations' informational value to the markets has been a widely-researched topic for already several decades in the finance and accounting literature. However, academic research has so far found mixed results concerning the informational value of recommendation revisions, earnings and sales forecasts, coverage initiations and losses of coverage, in addition to recommendation levels themselves. Some studies go as far as to argue that analyst recommendations have practically no informational value to start with (e.g. Altınkılıç & Hansen, 2009). On the other hand, some studies assert that depending on different attributes of analysts or even on the market infrastructure, they do (e.g. Barber et al., 2006; Arand et al., 2009; Brown et al., 2009). This paper will continue the ongoing discussion in the single analyst scenario.

Some studies, notably the one by Jegadeesh & Kim (2010), have found that stronger market reactions can be induced by going against the existing analyst consensus, thus avoiding the herding effect of analyst recommendations. These contrarian recommendations are seen to have more informational value than just going along to the same direction as all of the other analysts. The setting is entirely different when there is only one analyst, as he or she cannot by definition go against the consensus. Since only one person forms the so-called consensus, the one analyst's recommendation changes will effectively move the entire analyst view about the company. On the pages that follow, I examine whether these changes in opinion have the power to induce market reactions in general, whether this happens after every revision and whether the market reactions are more powerful here than for firms with more analyst coverage.

In sum, this study will delve deep into the world of exchange-listed American companies that have previously received little academic interest, that is, the companies with a single stock analyst follower. As exhibited by the data, the status of being the only analyst interested in a listed company is no eternal bliss, as the interest of stock analysts and the brokerage houses employing them seems to be constantly in motion. Coverage initiations are issued and coverages are dropped in a fast pace, often leaving the time periods of being the sole analyst follower short. Consequently, also the amount of recommendation revisions by single analysts remains surprisingly low, given the enormous amount of recommendation changes in total during the studied time period. Finding a company that only one analyst is tracking raises questions already by its existence. What makes this company interesting enough for the one analyst to follow it, but on the flip side, what makes it uninteresting enough not to be followed by other analysts?

1.4 Scope of the study

To outline a meaningful area of research, the scope of the study needs to be clearly defined. To decide whether One man consensus recommendation changes markedly differ from other recommendation changes, a control sample is needed. Subsequently, a defining factor for the scope is the choice of a controlling sample for comparison. Instead of including all listed companies from the American stock markets, control observations are gathered from the same pool of observations as the main sample: companies that have had at least one single analyst consensus recommendation change in their history. Therefore, the control sample will record all recommendation revisions when analyst coverage has been larger than just one analyst. This limits the size of the control sample enormously and allows for more relevant comparison, since there is less variability in size, general investor interest and many other factors. The choice of the control sample is further motivated in Section 3, *Data*.

Main focus of the study is on the changes to recommendations, and because of that, recommendation levels as such are left outside the focal point of the study. For instance, longer-term stock price performance after setting one particular recommendation level is not studied in this paper. One point of view is that recommendation levels might not hold much information on their own (e.g. Jegadeesh & Kim, 2010). To address this view with an example, “hold” recommendations are fitting: what sort of signal to the markets is a hold recommendation in the first place, as a hold recommendation signals neither confidence nor mistrust in a stock? On the other hand, a revision from hold or to hold, either as an upgrade or downgrade, does at least intuitively contain some sort of a statement about the perceived potential of the stock going forward. Nonetheless, recommendation levels are not ignored completely, and their implications are also discussed especially in Section 5, *Empirical findings*.

Earnings forecasts are included as one control variable in regression analysis, yet their impact on the stock price is not studied as such in this thesis. There are some explanations for this limitation of the scope. Firstly, earnings forecasts are much more open to interpretations than simple buy or sell recommendations. A single earnings estimate does not clearly convey the opinion of an analyst on whether a stock should be bought or sold, even if the earnings estimate was somewhat higher or lower than a previous estimate by the same analyst. Secondly, Altınkılıç et al. (2013) argue in their paper that earnings forecasts on their own, in other words forecasts without an accompanying recommendation revisions, have very little informational value on average. Altınkılıç et al. (2013) also claim that a majority of earnings forecasts piggyback on recent news and events. Thirdly, Loh & Stulz (2011) note in their paper that only around 5% of earnings forecast revisions cause influential stock market returns – making it hard to distinguish whether the abnormal return was caused by this particular estimate or just by chance alone. Nonetheless, earnings forecasts are noted by Loh & Stulz (2011) to make recommendation changes more likely to be influential, when the recommendation change and forecast are announced at the same time. In this thesis, regression test control variables are created for earnings forecasts issued by analysts at the same time as recommendations.

To align the scope of the study, initiations of coverage are not regarded recommendation revisions. Even if the analyst had held coverage for a company previously, terminated it, and then newly initiated the coverage, I only include changes to currently outstanding recommendations. There is already a good amount of literature related to the market reactions of analyst coverage initiations (see e.g. Demiroglu & Ryngaert, 2010; Crawford et al., 2012) as these are often regarded as important informational events for any company. Instead, this thesis will solely focus on the changes to existing recommendations in stocks to observe the particular influence of the one analyst in a going concern setting.

Recommendation revision impact on peer companies, i.e. spillover effects of analyst recommendations onto other companies in the same industry, are not studied in this paper. As the companies in this study are likely to exhibit less investor attention than companies with more analyst coverage, and are often smaller in size as well, they are not expected to be "industry leader" companies by any definition. Despite not covering the effects on peers, categorizing companies into different industries could provide insights nonetheless. If notable differences between industries did exist, it would be interesting to see if some industries or sectors are more alert to analyst recommendation changes than others.

Herding among analysts is an often recurring topic in academic stock analyst literature (see e.g. Jegadeesh & Kim, 2010; Booth et al., 2014; Bradley et al., 2014). Herding, or in this case its absence, remains a relevant topic to discuss. The absence of herding effects might contain interesting implications for the analysts' behavior, as all of the consequences and drivers of herding are missing in One man consensus situations. These consequences are further explained in the literature review in Section 2. Analyst recommendation revisions in a multi-analyst consensus situation are examined in the control sample of this study, however, specific tests on herding are not included in this study due to the distinctive setting of the study.

1.5 Overview of the key results

Based on the sample of American publicly listed companies that have at some point had only one analyst covering them between 1994 and 2014, I discover that short-term cumulative abnormal returns (CARs) have been on significantly high levels following single analyst recommendation upgrades, and even more importantly, higher than when the same companies have had more analyst in their coverage. Based on the ordinary least squares regression analysis, I find a statistically significant correlation between being the only analyst and a higher CAR after upgrades, while controlling for other meaningful variables. In recommendation downgrades results are more mixed, but many of the test results suggest that the status of being the only analyst might lessen the short-term negative price impact following a recommendation downgrade, in comparison to multi-analyst situations for the same companies. Testing for the share of visibly influential recommendation revisions reveals that recommendations induce notably large price or trading volume reactions quite infrequently.

To control for the difference between an analyst's own contribution to reducing the informational asymmetries and contribution by a company's news announcements, I test whether omitting recommendation changes from the three-day period around a company earnings announcement date diminishes the significance of stock market reactions. I find that firstly, roughly 17% of the main sample single analyst consensus recommendation changes are timed inside a three-day range of an earnings announcement. This percentage is at least as high as found in several other studies (e.g. Loh, 2010; Loh & Stulz, 2011). I discover that this "piggybacking on earnings news", as named by Altınkılıç & Hansen (2009), can lure researchers to think an analyst has more impact on the market than they actually do.

1.6 Structure of the paper

This paper is organized in the following manner. The next Section 2, *Literature review*, provides a definition for sell-side stock analyst, presents their role in the financial markets and goes through a significant amount of relevant academic literature on stock analysts. Section 3, *Data*, introduces the processed set of data used in the study, in which observations colliding with earnings announcement information events have been removed. Section 4, *Methodology*, explains the multiple methods used in the study to discover the nature of One man consensus analyst recommendation changes, and of the market reactions following them. Section 5, *Empirical findings*, explains the results of the tests and suggests possible causes, whereas Section 6, *Discussion of the results*, goes through the implications of found results. Finally, Section 7, *Conclusion*, sums up the study and proposes avenues for future research on the subject.

2. Literature review

The literature review section summarizes the large amount of academic stock analyst literature by its relevant parts to this study. First, analysts are introduced as actors in the financial markets, and a summary of the market efficiency is provided. Secondly, studies discussing the value of analyst information and herding behavior are reviewed. Thirdly, literature concerning the regulatory environment for analysts is reviewed and finally, academic papers on analyst incentives and relationship with companies are covered.

2.1 Role of financial sell-side equity analysts in the financial markets

Stock analysts' relevance to the financial markets has been a topic of academicians' discussion and even a source of controversy already for several decades. In one of the most widely quoted studies on analyst recommendations, Womack (1996) claims that issuing buy or sell recommendations on stocks does indeed have a substantial influence on stock prices, not only immediately after the event but also in the subsequent months. The author also states that in his data, new added-to-sell recommendations happen much less frequently than added-to-buy recommendations, but the sells are markedly more predictive than buys. Furthermore, Womack (1996) notes that small-capitalization firms see significantly larger market reactions than larger-capitalization firms.

Two main categories of financial analysts include buy-side and sell-side analysts. This thesis only focuses on the sell-side analysts, in the same way as most of academic literature around financial analysts. Sell-side analysts, as characterized by Cheng et al. (2006), typically follow a group of companies in the same industry and in the same market (e.g. the U.S. stocks) and sell reports for their employer's, i.e. a brokerage firm's, clients. Hence the name "sell-side". Also the general investing public has access to their research on stock recommendations and forecasts, although usually the access needs to be paid for. On the other hand, buy-side analysts are employed by asset management companies such as mutual funds and they make internal recommendations and forecasts exclusively to money managers (Cheng et al. 2006). Based on the literature, it seems that the buy-side and sell-side analysts share many of the tasks that they perform: creating models to predict a company's earnings and other financial statement items, and producing reports on the future direction of the company based on those models in addition to other factors. That being said, Hobbs & Singh (2015) note that sell-side analysts tend to outperform buy-side analysts on a regular basis.

Sell-side analyst's job description almost always includes balancing on a fine line between two ends. On one hand, analysts are tasked with providing accurate, and if necessary, negative opinions about a company. On the other hand, maintaining relations with the company management remains crucial to gain meetings with the management and thus get access to valuable information. One could argue that stock analysts add the most value to the informational environment when they have changed their recommendation on a company after carefully gathering all necessary information available publicly and possibly privately, processing it and making their conclusions based on the information. If this change seems important enough to the market participants, the investors should react accordingly and the reaction should be seen in the company's stock moving, either in price or trading volumes. If no reaction in the stock can be observed, the implication might be that investors do not consider the analyst's change in opinion to be very relevant, for one reason or another. In today's world, it is no more very likely that investors have not had access to the information about a recommendation revision soon enough. For instance, the widely popular Bloomberg Terminal system is practically used by every major institutional investor in the world. Even for the investing public, analyst recommendations are often easily available through financial news and Internet sources.

A stock analyst generally serves both experienced investors such as institutions who might not have time to spare for analyzing individual companies, as well as other less-experienced investors, to whom analysts might act as an interpreter of one sort. One description of a good stock analyst in the financial press comes from the Finnish Kauppalehti newspaper[1]. A good analyst is characterized there as someone who can point out potential pitfalls in a company and who shortens the informational gap between two ends: the often optimistic business story laid out by company management on one side and hard reality on the other. Moreover, according to Jukka Oksaharju in the Kauppalehti news article, a skilled analyst is able to raise imminent risks about a company to public debate, something an ordinary investor might not notice otherwise.

[1] See http://www.kauppalehti.fi/uutiset/kotipizza-rajussa-nousussa---lahti-kuin-hauki-kaislikosta/8qufHizj (Kauppalehti.fi 22 December 2015, story in Finnish). Website visited on 13 January 2016.

2.2 *Efficient market hypothesis and stock analysts' stake in market efficiency*

Analysts' influence towards investors is deeply rooted in the theory of deliverance of relevant information into asset prices. The Efficient Market Hypothesis (EMH), a famous theory brought to public attention by Fama (1970), states that a market in which prices reflect all relevant information about an asset can be called an efficient market. The level of efficiency in a market is further divided by into three stages Fama (1970). In weak form efficiency, only historical information about an asset is reflected on the prices. The second level, semi-strong form, assumes that prices reflect all historical and current information that is explicitly publicly available. The most complete level of strong form market efficiency entails that also all private information, including information held by investors who have monopolistic access to relevant information, is reflected on asset prices.

Moreover, the market efficiency framework by Fama (1970) describes the environment where a stock analyst has to work in. If capital markets were strongly efficient at all times, it is unlikely that even a single analyst who has acquired relevant information from the company management could move the market in any direction with a recommendation change, as all possible relevant information would already be priced correctly. As we nevertheless sometimes witness major price swings right after analyst recommendation changes, it seems more plausible that it is rather the semi-strong or sometimes even weak form market efficiency that is at play.

The discussion on Efficient Market Hypothesis is carried on, among others, by Grossman & Stiglitz (1980) who argue that acquiring relevant information comes at a cost. According to their study, all relevant information cannot already be priced into assets, since otherwise those who perform the information acquisition, such as stock analysts, would not be compensated for their effort in acquiring information. Thus, according to Grossman & Stiglitz (1980), there exists a discrepancy between the market information efficiency and the incentives to acquire information. Differently put, information efficient markets are impossible according to Grossman & Stiglitz (1980).

Miwa & Ueda (2014) add to the discussion by studying the investors' slow reaction to analyst recommendation revisions. The authors find that recommendation changes contain earnings related information which is not explicitly disclosed in their earnings forecast revisions, and this results in frequent earnings forecast revisions after the recommendation change. However, Miwa & Ueda (2014) do not see this finding as direct violation of semi-strongly efficient capital markets. They claim instead that the slow price reaction to recommendation changes can possibly stem from a gradual flow of information to the markets due to the withheld earnings forecast information.

2.3 Herding and its effects

A constantly recurring topic in analyst research is the occurrence, causes and consequences of herding between analysts following the same stock. Herding here refers to the stock analysts' tendency to follow each other's opinions on stocks, as opposed to only basing their opinion on their own analysis. Several authors claim to have found evidence of analyst herding behavior. Results by Jegadeesh & Kim (2010) support the herding hypothesis, and the authors are able to show that analysts' recommendation behavior also exhibits non-information driven herding, i.e. moving towards the consensus even in the absence of relevant company information. Furthermore, the authors note that market reactions to analysts' recommendation revisions are stronger when the recommendation moves away from the consensus, rather than toward the consensus. According to the results, analysts are also reluctant to convey negative information. Their data shows stronger herding effects for downgrades than for upgrades, which signals that analysts are less eager to stand out from the analysts' crowd when they convey negative information. Yet, the market seems capable of anticipating analysts' tendency to herd, at least to some extent.

Regarding this thesis, it is apparent that analyst herding by its usual definition, meaning analysts herding on recommendations about a specific stock, naturally does not apply to companies with only one analyst following them. Nevertheless, the discussion remains relevant here as well: a stock analyst faces a rather different situation when they have to issue recommendations based only on their own facts and possibly intuition. Especially to a rookie analyst, the situation might seem troublesome when there is no reference point available. In usual multi-consensus situations, an opinion that wildly differs from the other analysts' consensus might trigger some kind of a sanity check for an analyst: are the numbers correct? Is there a side to the company that has not been considered in the analysis? Or, do I possess information that the other analysts are not aware of? In firms with a single analyst follower, the sanity checks need to stem from elsewhere.

2.4 *Do analysts produce valuable information?*

A large part of extant academic studies on sell-side stock analysts try to find out the actual influence of the analysts' recommendations and forecasts: do the analysts actually have any impact on how investors perceive the value of a company. Throughout the years, arguments have been laid both for and against the importance of what analysts say. The discussion started already decades ago. For example, Bjerring et al. (1983) study a Canadian brokerage house providing recommendations for U.S. and Canadian stocks, and the authors find that some financial analysts are able to make the markets more efficient by passing on information to the public. Consequently, an investor following the recommendations could have achieved significantly positive abnormal returns historically. Moving on from single recommendations to consensus recommendations by multiple analysts, Barber et al. (2001) explore a trading strategy based on buying companies with best consensus recommendations and selling short companies with the least favorable consensus recommendations. They conclude that this kind of trading strategy would have historically beaten the market, and in addition, it would have been more significant than size or book-to-market effects. Interestingly, the authors also note that this effect is more pronounced for small and medium size companies, where less public information is available. In fact, Barber et al. (2001) find no reliable difference in returns for most and least favorably recommended stocks for larger firms. These larger companies comprised around 70% of the total market capitalization at the time.

A recent example of the discussion that opposes the mainstream view on analysts has been started by Altınkılıç & Hansen (2009). The authors argue that analysts' opinions, exhibited, for example, by the changes in recommendations, rarely contain any information for the investors. The authors argue instead that recommendation revisions mostly cause insignificant price reactions on their own, due to analysts' tendency to piggyback on recent news events around the company, such as earnings announcements. Altınkılıç & Hansen (2009) state that the true motivation for revisions does not lie in transferring information, but in matters such as strategic career concerns for analysts. As continuation to this discussion, Yezegel (2015) does not completely oppose Altınkılıç & Hansen's (2009) point of view, but the author does maintain that stock analysts still do supply important information. According to Yezegel (2015), analysts revise their recommendations after earnings announcements primarily in three cases: when they detect mispricing, when they observe increases in information supply and when there is demand for advice from investors.

Bradley et al. (2014) take part in the discussion started by Altınkılıç et al. (2009) by examining recommendation revision time stamps. To begin with, the authors note that the times recorded in Thomson Reuters Institutional Brokers Estimate System often differ from the actual release times of the analyst recommendation revisions as hand-picked from other news sources. Bradly et al. (2014) also make an opposing statement in regard to the claims by Altınkılıç et al. (2009), as their results suggest that the uninformative results are due to wrongfully interpreting the time stamps. Bradley et al. (2014) hint that analyst revisions might have informational value also on corporate event days, beyond the reaction caused by, for example, an earnings announcement. They conclude by stating that analyst recommendation revisions remain a key information channel.

Liquidity and especially turnover, defined as shares traded divided by the total number of shares outstanding by e.g. Llorente et al. (2002), might have something to do with how fast information is reflected in the stock prices. Loh (2010) notes that a price drift is more pronounced for companies with lower turnover, in other words, companies with less trading activity might expect less drastic stock price reactions in the very next days following a recommendation revision. According to the author, the explanation for this lies in investor inattention.

In their widely quoted paper, Hong et al. (2000) discover that bad news about a company is likely to end up more slowly to the hand of hands of the investors than good news, in companies where analyst coverage is lower. The authors note that momentum strategies do seem to work well with companies that have lower analyst coverage. Hong et al. (2000) measure the coverage as residual analyst coverage, i.e. the firm size is controlled as size also strongly affects the profitability of momentum strategies. These results have interesting implications for my thesis, since the sample in this paper consists of firms with the lowest analyst coverage different from 0, and the companies are also likely to be small. Based on findings by Hong et al. (2000), one might possibly expect the stock price reactions in the few days' time window to be more muted from recommendation downgrades than from upgrades, since the authors' findings indicate that negative news would affect the price more slowly.

Jegadeesh et al. (2004) examine the characteristics of consensus analyst recommendation levels and changes to them. The findings of their study suggest that changes to the recommendation levels might contain more information than the mere absolute level of recommendation, and that the changes predict future returns. One of their interpretations is that recommendation changes capture qualitative aspects of a company's operations that are not visible in the quantitative signals. Their evidence is said to go hand in hand with the analysts' and many researchers' claim that analysts actually bring new information to the market. Alternative hypothesis by Jegadeesh et al. (2004) considers the possibility that analyst recommendations and changes might themselves cause a price drift through the publicity surrounding them. According to this latter hypothesis, analysts would not bring new information to the market.

Ivković and Jegadeesh (2004) study the timing of analysts' earnings forecasts and recommendation revisions. Firstly, the authors confirm that in their sample, stock prices reactions do follow on average the analysts' recommendation upgrades and downgrades, and the reactions seem to be more pronounced for small firms. They also conclude that recommendation changes produce more significant reactions than earnings forecast revisions. A reason for the outcome, the authors hypothesize, could be that analysts revise their earnings forecasts more easily and after smaller changes in company conditions, whereas for recommendation changes more important events must occur. The authors also note that their sample exhibits weaker market price responses to recommendation revisions in the period immediately after earnings announcements by the company.

A study by Derrien & Kecskés (2013) presents evidence that besides stock market effects, the degree of analyst coverage does have real effects on what a company is capable of doing, and not just on how the stock price moves. Using the argument by Kelly & Ljungqvist (2007) that a decrease in analyst coverage increases the information asymmetry as a foundation for their theory, Derrien & Kecskés (2013) argue that a decrease in coverage increases the cost of capital for companies. Consequently, the profitability of different projects decreases and so does the firm's amount of money available for investments. Moreover, a decrease in analyst coverage is likely to decrease the optimal amount of external financing, according to Derrien and Kecskés (2013). Their results are stronger for smaller firms and for firms with less analyst coverage. Based on these results, one might think that having even one analyst following a company and thus lessening the degree of information asymmetry is likely to be beneficial to the firm as compared to not having any, in terms of cost of financing. Future research could try to find out if a One man consensus of "sell" or "strong sell" can indeed lower the cost of capital.

Demiroglu and Ryngaert (2010) look at coverage initiation effects for companies that have previously lacked analyst coverage altogether. In their sample, coverage initiations often cause positive stock returns on average; however, the returns are strongly driven by positive recommendations and not only the initiation itself. In that study's sample, nearly 90% of initiation recommendations are buys or strong buys, which also implies that positive returns are not only due to initiating coverage, but starting to cover a company that is a good investment according to the broker firm and its analyst. Initiations with neutral “hold” recommendations have only a very small positive effect on the stock. The paper also concludes that coverage initiation causes greater increases in institutional stock holdings by institutions that had no prior positions in the stock. Furthermore, the authors hint that according to long-run return evidence in their sample, investors do not fully account for conflicts of interest in predictive content of investment bank-affiliated analyst initiations. This latest piece of evidence is not statistically conclusive however, as noted by the authors. On the same topic, an earlier study by Irvine (2003), looking at all initiations of coverage, notes that market responds generally positively to initiations of coverage, and that especially positive initiation recommendations tend to improve the liquidity of a company’s stock.

Loh & Stulz (2011) point out that analyst recommendation changes are sometimes linked to extremely large abnormal returns in stock prices, and some of these also capture the attention of the public as the press has a tendency to focus on them. However, their study shows that looking at individual recommendation revision events on their own and not as a part of a larger average, the significant majority of revisions end up having no visible impact on share price or trading volume at all. Recommendation change is by the authors defined influential in returns, if the abnormal return is in the same direction as the recommendation change and is statistically significant. According to the authors, many of the seemingly influential recommendation changes could be classified as plain noise in the return patterns, even if the stock price reaction was to the right direction. In terms of trading volume or more exactly stock turnover, a change is in the paper considered influential if it leads to an increase in volume at a statistically significant level. The authors note, using U.S. stock data, that only 12-13% of recommendation revisions in their sample are visibly influential, either in terms of price change (12% of recommendation changes) or turnover change (13% of recommendation changes). A surprising finding is that around a quarter of the analysts in their sample do not produce a single influential recommendation during their tenure.

Loh and Stulz (2011) also find that in general, growth firms, small firms, high institutional ownership firms as well as low analyst activity firms are more likely to be associated with influential recommendations than other types of firms. Thus, it could be expected that for many of the single analyst firms, several influential recommendations could be observed. After all, many of these firms are likely to be small growth firms, with little interest from individual investors and low news coverage. In turn, low analyst activity could partly stem from low analyst coverage. According to the authors, it is more difficult for an analyst to have an influential recommendation when more analysts follow a firm and when a company is larger.

2.5 Regulatory guidelines for analyst in the modern financial markets

Due to stock analysts' significant perceived influence on investor sentiment about companies, and especially the incentive problems linked to this influence, the activities of analysts have been carefully scrutinized and regulated through guidelines and laws since the beginning of the 21st century. Well known directives and regulations that are recognized by academicians and the public alike include the Regulation Fair Disclosure[2] (commonly Reg FD) in 2000 and the Sarbanes-Oxley Act[3] in 2002 in the United States. Another important regulation, Rule 2711[4], was issued by National Association of Securities Dealers (NASD) in 2002, directly affecting sell-side stock analysts' daily work. The impact of these regulations have gathered a lot of attention in recent academic research on stock analysts.

The Regulation Fair Disclosure effect is of interest for basically all studies on stock analysts after the turn of the millennium. Reg FD, issued in year 2000 in the United States, was primarily aimed to curtail the private interaction between company top management and stock analysts. Instead, an equal and even disclosure of information for all market participants was called for. Just based on statistical probabilities, one might expect that before Reg FD, the one analyst following a company could have been more likely to receive private information from management, in comparison to an "another brick in the wall" analyst within a larger coverage crowd. Gintschel & Markov (2003) show that after the implementation of Reg FD, price impact of financial analyst recommendations has dropped considerably in the United States, in other words, the regulation has at least to some extent succeeded in its purpose to curtail selective disclosure to certain analysts.

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[2] Description of Regulation Fair Disclosure from the Securities and Exchange Commission (SEC) website is found at https://www.sec.gov/rules/final/33-7881.htm. Website visited on 23 March 2016.
[3] Description of the U.S. Public Law from the SEC website is found at https://www.sec.gov/about/laws/soa2002.pdf. Website visited on 23 March 2016
[4] Description of the Rule 2711 from the FINRA website is found at https://www.finra.org/sites/default/files/RuleFiling/p000446.pdf. Website visited on 23 March 2016

Following the stock market crash in 2000-2001, new regulation 2711 in the American marketplaces by NASD were launched in 2002 to curb conflicts of interest by limiting relations between analyst research and investment banking departments at different brokerage houses. Moreover, NASD was concerned about general over-optimism of analysts, and ratings distributions that were strongly tilted towards the positive end of the 5-step rating spectrum from strong sell to strong buy. Kadan et al. (2009) note that at the time of the 2711 rule, a major migration happened for countless brokerage houses from a 5-tier recommendation system to a 3-tier system. Kadan et al. (2009) also argue that although this change might have seemed like a purely cosmetic change, it has in fact affected the informative content of recommendations. The authors claim that in a 3-tier scale system, the literal meaning more accurately reflects the original intention of the analyst, helping the conversion of information from an analyst to the public. Besides the NASD rule 2711 in 2002 and the Global Analyst Research Settlements in 2003, also the Sarbanes-Oxley Act (SOX), established as a United States federal law in 2002, had a chapter on securities analysts' conflicts of interest. The SOX act was thought to mainly address the corporate and accounting scandals caused by Enron and WorldCom to mention a few, but on the analyst side it did turn the NASD regulations into an actual law[5].

Due to the regulation changes, many of the brokerage houses move from a system of five rating levels to only three rating levels system (no strong buy or strong sell). Kadan et al. (2009) observe that affiliated analysts were indeed more likely to issue optimistic recommendations compared to unaffiliated analysts before the regulations. However, the authors note that in the post-regulation period, the informativeness of recommendations seems to have declined. Moreover, the Global Analyst Research Settlement between the Securities and Exchange Commission (SEC), NASD, NYSE and ten largest U.S. investment banks was announced in 2003 (SEC, 2003). The settlement aimed to curtail conflicts of interests between the same brokerage house's analyst section and investment banking departments. One measure was the establishment of firewalls, known as Chinese walls, meaning both physical and principled separation of the departments.

Altogether, it can be argued that despite the extra effort caused to the stock analysts in acquiring information, or possibly exactly because of it, financial markets and investors in the United States have benefitted from more rigorous regulatory environment around stock

[5] Description of the U.S. Public Law from the U.S. Government Publishing Office is found at https://www.gpo.gov/fdsys/pkg/PLAW-107publ204/html/PLAW-107publ204.htm. Website visited on 22 January 2016.

analysts. In general, a stable financial market infrastructure is considered essential not only for investor protection, but also for the efficiency of the markets. For instance, in a recent paper Arand et al. (2015) find that information value of analyst research has a tendency to increase as the level of regulatory investor protection increases.

2.6 Do analyst characteristics matter?

A generally accepted consensus in academic stock analyst research seems to be that individual analyst's characteristics do have some sort of significance on how their buy-sell recommendations are received by the investors. The indication here is that not all analysts can influence the opinions about a company in the same way – for example, so-called superstar analysts, who are celebrated in magazines such as the *Institutional Investor*, or analyst with longer career are sometimes expected to produce more reliable earnings forecasts as well as buy and sell recommendations on stocks (e.g. Ivković & Jegadeesh, 2004; Brown & Mohammad, 2010; Simon & Curtis, 2011). The accuracy of earnings forecasts by the analysts is also considered relevant to the reliability of recommendations by some. For instance, Loh & Mian (2006) argue that stock recommendations by more skillful earnings forecasters outperform the recommendations of worse forecasters. On the other hand, Park & Stice (2000) find evidence supporting the idea that while an analyst might be a skillful earnings forecaster in one company, their ability does not seem to spill over to other companies they follow.

Moreover, Loh & Mian (2006) look at relative accuracy and perform their tests with companies that have a minimum coverage of five analysts, to do a comparison on the accuracy of the analysts within the same company. This method has its own implications for my study as well, since accuracy is significantly more difficult to measure between single analysts following different companies. The varying nature of different companies is bound to pose problems: where one company might produce very easily-interpreted information, other companies are much more opaque. One could argue that, for example, it might be much more difficult to try to forecast earnings for a small, aggressively growing technology company than for a larger and more established industrial manufacturer for which the order book is publicly available.

2.7 Analyst incentives

Analysts' motivation and incentives to release certain kinds of recommendations is also a topic that has been under debate for decades. Researchers have tried to find links between analyst recommendations and the incentives that affect the decisions by analysts to promote certain companies and forecast negative outlooks for others. Stock analysts are commonly expected to be incentivized to issue recommendation upgrades instead of downgrades, as suggested by e.g. Ho & Harris (2000). Analyst incentives are also often hypothesized to be closely tied to the incentives of their employers, usually brokerage houses or other institutions (see e.g. Michaely & Womack, 1999). Recurring hypotheses include that stock analysts give favorable recommendations to firms that their brokerage house tries to gain investment banking fees from, such as underwriting fees or trading commissions. For example, Groysberg et al. (2011) find evidence consistent with stock analysts' compensation being linked to investment banking sales; however, only on the equity side and not the debt side. Yet, it seems that investment banks and brokerage firms associated with them are not solely to blame. A study by Jacob et al. (2008) argues that stock analysts working for investment banks actually make more accurate forecasts than other analysts. In addition to forecast accuracy, Jacob et al. (2008) find that investment bank analysts' forecasts also tend to be less optimistic than forecasts from non-investment bank analysts.

As evidenced by the existing literature on CEO actions and incentives, it is a fair assumption that stock analysts also think about their own personal future and career and not just that of their employer. Hong & Kubik (2003) note that brokerage houses do not solely care for accuracy, as in giving the correct recommendation to buy or sell the stock and forecasting correct financial figures, but they also reward optimistic analysts. The authors conclude that rewards for analysts have historically been less sensitive to accuracy and more sensitive to optimism, and that the findings suggest that analysts are rewarded for generally promoting stocks optimistically, not just for stocks underwritten by their employers. Analysts' optimistic recommendations have been discussed in various other studies as well. For instance, as mentioned earlier, Demiroglu & Ryngaert (2010) find that coverage initiations are almost always positive, meaning a buy or a strong buy recommendation, indicating that analysts mostly start covering stocks that they consider as good investments, at least initially.

Simon & Curtis (2011) examine the tendency of analysts to base their buy or sell recommendation on rigorous valuation models in comparison to vaguer growth-based heuristics. Not very surprisingly, the authors find that more accurate forecasters have lower correlation with growth-based heuristics. More accurate analysts using rigorous valuation models also appear to post most profitable stock recommendations. The implications for incentives in the study are that analysts' trade-generating incentives affect the way they use information in their valuation models, which in turn affects the recommendations they give out.

An earlier paper by Jackson (2005) studies the same topic and finds that both optimistic analysts and highly-reputed analysts generate more trade for their brokerage firms. According to Jackson (2005), this indicates that a stock analyst must choose between telling their honest opinion about a firm and generating increases in trading commissions. On the other hand, the author also observes that high reputation analysts generate more trading volume. One would think that this adds to the difficulty of choice made by the analyst, as reputation is most often achieved by making accurate, not overly positive, earnings forecasts.

2.8 Analyst relationships with senior management

Green et al. (2014) find that investor conferences lead to more informative and accurate analyst research, measured by immediate price impacts when the broker in question has a conference-hosting relation. It seems that, at least to some extent, the market takes into account that an analyst might gain some sort of insider knowledge benefit when they or the brokerage they work for have a closer personal relationship with company top management. Around the same subject, Cohen et al. (2010) note that also having attended the same university might create a link between a stock analyst and a company CEO, which in turn might be visible in stronger market reactions after an analyst with a relation to CEO makes a recommendation change. The results by Green et al. (2014) seem to hold also in the post-Regulation Fair Disclosure (issued in 2000) time period, but Cohen et al. (2010) note that a school-tie return premium drops from around 9% pre-Reg FD to nearly zero post-Reg FD. Cohen et al. (2010) do mention that in an environment with no regulations regarding disclosure, the school-tie premium seems to persist. The implication for the topic of this thesis is that if a stock analyst has somehow been able to build a personal relationship with the top management of the company they are following, this link could become even more significant when there are no other analysts covering the company.

In a recent paper, Soltes (2014) delves into the private interaction between stock analysts and the management of an unnamed, large-cap NYSE-traded company in the form of a case study. In the study, Soltes (2014) tries to examine and describe the nature of the communication methods and how information is exchanged between stock analysts and the top management of a large company. Although the author's data comes only from one particular firm, the evidence hints that private conversations and relation building with company top management might still be beneficial for stock analysts, even in the post-Regulation Fair Disclosure world. The author does note that collecting data on the private interaction is intensely challenging, mostly because much of the important exchange of information tends to happen very informally over the phone, between the analyst and the management. Nonetheless, the results by Soltes (2014) support the prediction which many market participants have for long shared, that is, the longer and more informally an analyst is able to interact with company managers, the easier it is for the analyst to produce new research reports on this company.

Some studies on stock analysts delve into frauds and their impact on analyst coverage. For instance, Young & Peng (2013) find that analysts are more likely to drop all coverage when an accounting fraud is reliably detected in a company, in comparison to just downgrading the stock they are covering. As such, the authors claim that analysts might have additional value to investors as a certain layer of investor protection. Lustgarten & Mande (1995) even suggest a relation between financial analysts' forecast revisions and company insider trading. However, they note that insider trading seems to constitute only a minor source of information for analysts.

A study by Bebchuk et al. (2011) tries to find out how the powerfulness of a company CEO affects the relationships of stock analysts and company management. The CEO Pay Slice (CPS) method is one way of measuring powerfulness. The CPS method uses the share of a chief executive officer's compensation out of the total compensation for the executive directors in the company as a proxy for how much influence and so-called power the CEO has. Jiraporn et al. (2014) find, using the CPS, that companies with powerful CEOs generally have less analyst coverage, most likely because powerful top managers have less of an incentive to conceal information and consequently, the CEOs' increased disclosure requires analyst coverage. Regarding One man consensus analyst coverage for companies, it could be insightful to see how the powerfulness of a CEO affects the results found in this paper. However, this topic is for now left for future research.

Using the literature presented in this section as groundwork for the empirical analysis, data selection is motivated next in Section 3, *Data*.

3. Data

This section goes through the origin, selection and filtering of relevant data, from stock market returns and volumes to analyst recommendation data and company financials. Selection of appropriate main and control samples is then motivated and lastly, possible limitations of the data are reviewed.

3.1 Analyst recommendation data

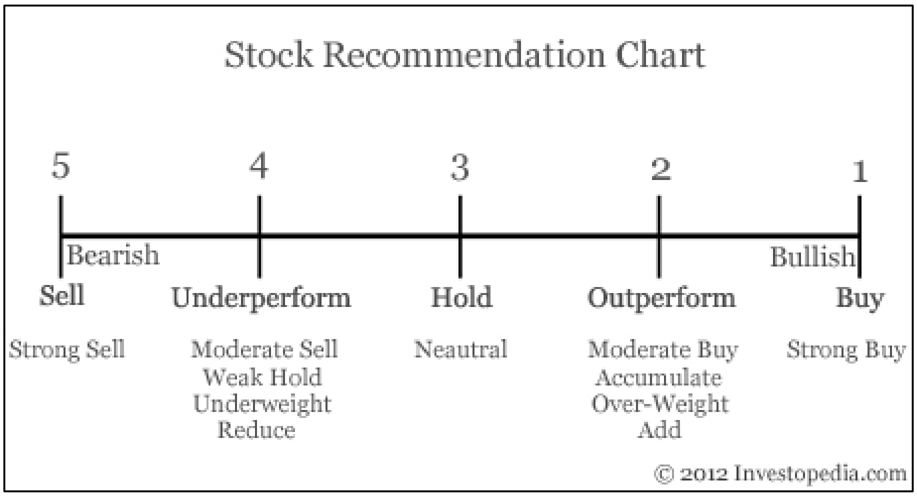
Following most studies on analyst recommendations, the sample of One man consensus and control sample analyst recommendations on U.S. exchange listed companies is collected from the IBES database. Reason for choosing United States as the source of data lies mainly in the availability of reliable data: among thousands of firms in the United States, the number of firms having only one analyst following them will remain sufficiently high to form a statistically relevant sample. Moreover, United States provides a consistent environment for conducting the study with over 20 years of historical analyst recommendation data. Despite the established analysts in most developed countries, Europe is a much more diversified area where legislations, securities markets and accounting practices vary from one country to another, however, in recent years less so due to the adoption of IFRS accounting. As in most of the U.S. analyst recommendation studies, the data in this paper starts from the beginning of 1994 and goes on uninterrupted until the most recent available months, in this case until the end of year 2014.

To collect a meaningful sample of observations, the data in this study will solely focus on recommendation revisions, in other words, changes to existing recommendations. Thus, reiterations of existing recommendations will be left out of the studied sample, although they often constitute a formidable part of recommendation issuance – two thirds of all recommendations in the study by Asquith et al. (2005), to mention one example. A key motivation for excluding reiterations comes from Asquith et al. (2005), who point out that market reactions to reiterations are generally small and statistically insignificant, and the mean abnormal price reaction to them in the U.S. market is 0.0%. Brown et al. (2009) confirm this finding in the Australian stock market, and note that after recommendation reiterations, stock market reaction is typically almost non-existent. As an example in my data, when an analyst confirms to IBES that a “buy” recommendation remains a “buy” for a given company, the recommendation change would get a value 0 and be then omitted from the data. After all, a recommendation reiteration is in essence neither a positive or negative statement, merely a confirmation that the earlier viewpoint by the analyst still stands.

Following the announcement of gradually closing down the Thomson Reuters First Call Historical Database, IBES remains arguably the most exhaustive analyst forecast and recommendation database globally. The exact time period for observing the analyst recommendations is set between January 1994 and December 2014. This data set, spanning 21 years, is practically as comprehensive of all One man consensus changes in the IBES data as is available and reliable. Noted by many analyst papers, for instance Loh & Mian (2006), analyst recommendation data is rather scarce before 1994, in comparison to analyst earnings estimate information starting in 1976 for American listed firms. Differing from data collection in some papers, my data does not incorporate any recommendations issued in 1993 into the data set to ensure the accuracy of the data.

Analyst rating scales used by brokerage firms are known to vary. Some brokers use a simpler, three step buy-hold-sell scale, whereas others utilize a five-step scale, with varying names. To make things more complicated, some brokerage houses do not use the neutral “hold” level at all. Figure 1 exhibits some of the most commonly used scale level names.

Figure 1 *Different names for analyst stock recommendation levels. Table downloaded from http://www.investopedia.com/articles/01/013101.asp. Website visited on 18 December 2015.*



To make recommendations from different brokerage houses commensurate, IBES records both the original number of the level and name of the level (e.g. 2 – Accumulate) as well as a recommendation level assigned by IBES (e.g. 2 – Buy). In the data of this study, only the recommendations based on the IBES scale are employed to achieve a uniform set of data. Numbers of recommendation levels are set as in the chart above – 5 for least recommended stocks i.e. strong sell, and 1 for strong buy. The sign of the change in recommendation changes is set conversely, but more intuitively: a plus for upgrades and a minus for downgrades. For example, an upgrade from underperform (4) to hold (3) is recorded as +1, whereas a downgrade from strong buy (1) to hold (3) is recorded as -2. As reiteration recommendations are excluded, in other words, there are no recommendation change events that would receive value 0.

3.2 Relevant stock exchange data, colliding earnings announcements and control variables

To ensure the availability and reliability of price and trading volume data for examining market reactions, I solely look at companies publicly traded in one of the three major exchanges in the United States, namely NYSE, NASDAQ and AMEX stock exchanges. As only common ordinary stocks are examined, all listed Real Estate Investment Trusts (REITs), mutual funds, Exchange-Traded Funds (ETFs), American Depositary Receipts (ADRs) and preferred shares are excluded from the data. The price and trading volume data is collected from the Center for Research in Security Prices (CRSP) database. An observation is only relevant to this study if its CRSP share code is either 10 or 11, which both indicate an ordinary common share with no special status found or necessary. ADRs, although representing the common shares of international companies listed in the U.S., must be excluded from the sample, since it is likely that many, if not all of these large international companies have analyst coverage in other countries. Consequently, even if this ADR firm had seemingly only one analyst in the United States according to the IBES, they would not in reality be the only analyst covering the stock globally. Daily prices, number of outstanding shares, comparison index returns and daily turnover amounts, defined as trading volume divided by the number of outstanding shares, are obtained from CRSP daily stock file.

Analysts sometimes publish their recommendation revisions and new earnings forecasts somewhat directly after company earnings announcement and other news events (e.g. Malmendier & Shanthikumar, 2006; Loh, 2010). An analyst might publish their recommendation revision based on the earnings announcement, and the stock price or trading volume movement might consequently be incorrectly attributed to the analyst's opinion change, when in fact the market reaction is primarily based on the company earnings announcement. For example, Malmendier & Shanthikumar (2006) as well as Loh & Stulz (2011) identify earnings announcement dates as the key company news events to be excluded from data when studying stock analysts, whereas Ivković & Jegadeesh (2004) study revision timing relative to earnings announcements. Thus, recommendation revisions that are published in a three-day window centered on the company announcement of quarterly or annual earnings are omitted from the data. Earnings announcement dates are obtained from the IBES database, from the U.S. actual earnings file.

Consequently, to only observe the "clean" market reactions to analyst recommendation revisions, I need to pick from the data recommendation revisions that are timed right next to company earnings announcement dates. These dates typically have even a large impact on the valuation of the company, following the study by Loh (2010), for example. Following recent papers on the subject in which the earnings announcement effects are taken into account, a relevant time window for excluding recommendation changes is considered (-1,1) around earnings announcements. This entails that if a recommendation change occurs one day before earnings announcement, on the announcement date or one day immediately after an announcement, the recommendation observation is excluded from the main sample and the control sample. The quarterly earnings announcement dates can often have both a significant price and volume impact, especially if the actual earnings come as a surprise relative to the analyst consensus expectation. In spite of this, in their recent study Li et al. (2015) find that only a minority, or 27.9%, of all recommendation revisions directionally confirm the information in the preceding corporate events. In other words, less than one third of recommendation revisions are "buy" or "strong buy" following positive news from the company, and "sell" or "strong sell" for negative news.

To control for other factors that typically affect the market reaction to analyst recommendation revisions, in the regression analysis part of this study, certain company financials and other relevant data are collected from IBES, CRSP and Compustat databases. These include concurring EPS forecast dates for the sample companies from the IBES unadjusted detail history file. Logarithms of market capitalizations, used as a proxy for size, are computed based on CRSP-reported outstanding number of shares and daily stock price. For logarithms of book-to-market ratios, book values are obtained from Compustat, and market values are as in the aforementioned market capitalizations. As a proxy for idiosyncratic volatility, volatility of abnormal returns is calculated based on the daily cumulative abnormal returns. Dummy variables for Regulation FD timing and skipping a recommendation level are included. A complete listing of control variables for regression analysis is presented in Table 1, and the method for measuring all of the control variables is further detailed in Section 4, *Methodology*.

Table 1 *Control variables for regression tests.*

Control variable	Explanation	Source of data
posit	Dummy for revision being an upgrade (value 1) or downgrade (value 0)	IBES
lnbm	Natural logarithm of book-to-market value	Compustat & CRSP
vola	Volatility of the daily abnormal returns	CRSP
lnmktcap	Natural logarithm of USD based market capitalization	CRSP
coneps	Dummy for whether a concurrent EPS forecast is issued (yes = value 1) by the analyst	IBES
regfd	Dummy for whether the recommendation happens before (value 0) or after (value 1) the Regulation Fair Disclosure rule implementation	IBES
skiprank	Dummy for whether the recommendation revision skips is greater in absolute terms than +1 or -1	IBES

3.3 Selecting the appropriate sample

Academic research on stock analysts has a tendency to examine analyst recommendation changes as a large aggregate of all possible companies listed on stock exchanges. Companies included in the samples often receive far less attention than the actual point of view of a given study, be it the accuracy of earnings predictions by the analysts, the degree of analyst independence or the herding of analysts to a certain direction, to mention a few examples. Nevertheless, usually nobody denies that the selection of the sample does have its role as well. Especially in this study, selecting the appropriate main sample and control sample must be well thought out, since the topic itself involves probing into the world of much more illiquid publicly listed companies that usually receive significantly less attention from market participants and more specifically, from only one analyst. We want to compare apples to apples: if we were to look at all possible recommendations aside from the One man consensus company changes, issues with comparability would be likely to arise from the sheer variability in firm characteristics. One example of this kind of test design is from Bushee & Miller (2012), who study Investor Relations efforts in small companies and effects to these small companies' liquidity, among other factors. The informational environments are likely to be largely different for companies with higher analyst coverages and thus, attention is this time only fixed at recommendation revisions in companies where One man consensus recommendation changes are also observed at some point in time. Consequently, the control sample for analysis is formed based on the same set of companies as the main sample of One man consensus changes.

A note here is that data used in this thesis differs markedly from the data used by many other studies on analysts, in terms of which analyst consensus observations are included. For example, a key characteristic in the data used by Loh & Stulz (2011) is that they have removed all of the observations for which fewer than three analysts have valid outstanding ratings, on the basis of ensuring that their sample focuses on firms that are of sufficient interest to investors. Same kind of principle is used in the earlier paper by Loh & Mian (2006), who remove observations with less than five outstanding analyst recommendations, because of their method of dividing analysts' EPS forecast accuracy ratings into five quintiles. On the other hand, the main sample of my thesis consists of the companies considered less interesting to investors, and these firms are also included in the control sample – hopefully adding something new to the existing literature in their own right.

As mentioned in Section 1, in many of the tests data is divided into two samples: main sample consisting of the single analyst recommendation change observations, and a control sample for comparison. The sample that is of most interest to us is obviously the sample containing recommendation changes given by analysts who are the only analyst following a company when issuing the recommendation. This sample is further on referred to as "One man consensus sample", "OMC sample" or "main sample". In addition, one control sample is examined as a benchmark for the One man consensus changes. This sample is hereon simply referred to as "Control sample". The Control sample consists of all recommendation changes in the same companies that have also had OMC revisions at some point. As a clear separation of the comparable samples is essential, none of the OMC changes are included in the Control sample. Thus, Control sample only contains recommendation revisions that have occurred when each analyst coverage has consisted of two or more analysts. Control sample also contains less companies than the OMC sample. This is because some of the companies have only had a maximum of one analyst covering at any point during their time on the exchange between 1994 and 2014. Section 5 *Empirical findings* explains the results of empirical tests for the different samples in detail.

Differing from the sample division explained the in the previous paragraph, in regression analysis tests the OMC revision events and events from Control sample are pooled together. OMC observations are then identified with *omc* dummy variable value 1, while recommendation revision events in which there are multiple analysts in the consensus get value 0. This whole pooled sample is then newly divided for regression tests. One sample contains only recommendation upgrade events with the number of covering analysts varying from one to many, and in turn, the second sample contains only downgrades. Third sample for regression tests is a combination of the preceding two, containing both upgrades and downgrades, and is referred to as the "Pooled" sample. Upgrades and downgrades are marked in the Pooled data set with a dummy variable *posit*, having value 1 if the recommendation change is an upgrade and 0 if it is a downgrade.

Amount-wise, the main OMC sample includes roughly 2 970 recommendation changes for around 1 750 companies with those observations excluded that are potential NASD changes, have per share price below 1 USD or are changes to the aforementioned stale recommendations. The Control sample contains roughly 12 100 observations for a little more than 1 150 companies. These approximately 1 150 companies are also included in the list for main sample companies, as the principle for deciding the samples instructs. The amounts reveal that the Control sample includes observations from roughly 66% of all the companies that are included in the OMC sample.

3.4 Processing the data and handling unclear observations

The identification of the main sample, i.e. the changes within a One man consensus are based on changes in the IBES summary file, which indicates the number of analysts forming the monthly consensus. The information from the summary file is then combined with the individual recommendation data from the IBES detail file, which documents every recommendation issued by stock analysts. IBES uses their own definition of deciding whether an analyst recommendation is still valid, in the sense that the analyst stands behind their opinion and that the investing public regards the opinion on the firm valid. In essence, the IBES definition dictates the “change to an outstanding recommendation” status of a recommendation change. Differently put, observations where it is not possible to confirm that an analyst changes an existing and outstanding recommendation of their own, the observation is excluded from the data. Examples are listed in the following chapters.

In general, all revisions where it cannot be exactly confirmed that a certain known analyst has changed their recommendation on a given company while working at the same brokerage firm, are removed from the data set. From the OMC sample and Control sample, dates with multiple analysts issuing recommendations are removed. As I am not looking at market reactions on a time stamp level inside one day, it would not be possible to attribute each reaction to a correct recommendation revision, if revisions from different analysts during the same day were not removed.

In the data, there are occurrences where it is unclear if an analyst has been the only analyst issuing recommendations at the time. For example, sometimes IBES summary data file claims the consensus has at a certain time consisted of only one analyst, but the IBES detail file shows that two different analysts have had outstanding recommendations. In these situations, both observations are removed from the data, since it would not be possible to define whether either of these two analysts has really been the only analyst. Processing further, some of the recorded recommendations at IBES are coded with a masked analyst code of “00000000”, indicating an unknown analyst. All observations with a masked analyst code are removed from the main sample and the Control sample. In addition, so-called stale recommendation revisions, i.e. revisions for recommendations that are older than one year measured by the IBES review date variable, are removed from the data. Linking the data from different sources, i.e. from IBES, CRSP and Compustat, give rise to some issues, such as incorrect linking of companies, or missing stock price or trading volume data. These observations with missing data points are excluded from the tested samples.

It is important to exclude also from the Control sample data the event windows where more than one analyst changes their recommendation. This follows the principle set earlier to identify the reaction caused by just one revising analyst and not multiple analysts. One justification for this is that analyst reports are never exactly the same: even if two analysts issued a downgrade of one recommendation level during the same day, they might have different information contents in their downgrade reports, and market reaction would be cumulated for both of these new batches of information. Fortunately, the amount of excludable observations remains absolutely and proportionally very low in the large data set.

In terms of data handling, noting the importance of the NASD 2711 rule and Reg FD, besides other changes in the regulation environment is crucial for this thesis. NASD, mentioned briefly in Section 2, was a self-regulatory authority until its 2007 merger with the NYSE regulation committee, to form the new Financial Industry Regulatory Authority (FINRA). Due to a NASD Rule 2711 issued in 2002 concerning research analysts, Kadan et al. (2009) note that many brokers changed their recommendation scales from a 5-tier scale (from "strong buy" to "strong sell") to a 3-tier scale (from "sell" to "buy" with only "hold" in between these ends). In the data of this study, the migration from one scale to another can be observed with a high number of recommendation level changes on September 9th 2002 and the days closely preceding it. Kadan et al. (2009) note that a grand majority of recommendation changes, recorded in IBES and dated close to September 9th 2002, were technical changes resulting from a migration to a different recommendation scale and not actual changes of analyst opinion about a company. Consequently, following the actions by Kadan et al. (2009) and Loh & Stulz (2011), all recommendation revisions observations dated between 2nd and 10th of September in 2002 are removed from the data. This action is done to ensure that only relevant recommendation changes are taken into account, meaning recommendation revisions based on analyst opinion change, and not those based on a technical tweak.

3.5 Possible limitations of the data

One possible limitation of this study has to do with the nature of IBES data. Despite IBES's status as probably the most comprehensive and most widely recognized stock analyst database globally, it is possible that not all of the outstanding recommendations are listed. This is because the submission of recommendations to IBES by analyst brokerage firms is voluntary, as noted by Wharton Research Data Services (WRDS)[6]. Furthermore, Ljungqvist et al. (2009) note that IBES database has a tendency to be modified every now and then. The authors conclude that between 2000 and 2007, cumulative abnormal returns calculated on the analyst recommendations have changed by significant figures from one year to another. According to IBES, these changes might happen for several reasons, for example when brokers change their rating scales, or because analysts are marked as anonymous for reliability reasons.

[6] Information from WRDS KnowledgeBase at https://wrds-web.wharton.upenn.edu/wrds/ (requires a login). Website visited on 25 November 2015.

Sometimes recommendations by certain brokers are plainly removed, such as when recommendations by Lehman Brothers timed around the financial crisis of 2008 and 2009 were omitted from IBES. WRDS[7] claims that other omissions might also happen due to legal and regulatory or reliability issues. However, despite these minor issues that basically all possible databases contain in one form or another, the IBES database is regarded as the number one reliable source for analyst forecast and recommendation data, and the information contained in the database can be considered accurate. To further support the recognition of IBES, another database recording analyst recommendations and at times utilized in the stock analyst academic literature, the Thomson Reuters First Call database, was announced in 2011 to merge with the IBES database. A migration from First Call to IBES was recommended by Thomson Reuters, the supplier of the IBES database.

[7] Information from WRDS KnowledgeBase at https://wrds-web.wharton.upenn.edu/wrds/ (requires a login). Website visited on 25 November 2015.

4. Methodology

This section describes the methods used in this study, from the principles of choosing the methods and formulas that are used for calculating different metrics. First, measuring cumulative abnormal returns, or CARs for short, in the framework of an event study is explained. Secondly, the methods for Ordinary Least Squares (OLS) regression analysis are reviewed. A third method used in this study, measuring the share of visibly influential recommendation revisions based on both stock price and trading volume impact, is clarified afterwards. Finally, the exclusion of tests regarding earnings-per-share (EPS) forecasts is motivated.

4.1 Selection of methods: event study and Ordinary Least Squares (OLS) regression

In principle, analyst recommendation changes are always unexpected to the investors at the time of their issuance. In addition, the degree to which stock analysts only work based on public information, versus the degree they work based on private information is usually unknown to investors. However, the market reactions to these more or less unexpected announcements can be measured in the context of an event study, which centers the event window on the trading date of the recommendation change. In this study, the market impact of an analyst's recommendation change is measured both in an immediate stock price return as well as turnover (daily trading volume divided by number of shares outstanding as defined by Llorente et al., 2002). The impacts are measured in short-term event windows around the announcement date of the change, which is set to occur on event window day 0. To discover the price impact of analyst recommendation revisions, cumulative abnormal returns are calculated to measure the influence of the recommendation revision.

Stock returns as well as turnover data are collected for each of the sample companies on a daily basis from CRSP. Benchmark index returns and other factors for calculating expected returns (Equation 2) in CAR formula (Equation 1) are likewise obtained from daily CRSP data. The abnormal price reactions are examined as such and within OLS regressions (Equation 3), as well as by following a method adjusted from Loh & Stulz (2011) of influential recommendation changes, described in detail in this section. Influential recommendation changes are studied firstly based on CARs (Equation 4) Turnover data is examined with the same influential recommendation change method (Equation 6).

The data from the main sample of this study reveals that One man consensus companies are by a majority small and somewhat illiquid companies. Consequently, high volatility and large daily swings in returns could be observed frequently, in comparison to firms that are traded in higher volumes and for which information flows arguably better to the hands of investors. Based on the potentially volatile returns of One man consensus companies, one might argue that even high abnormal returns after a recommendation change by the one analyst are simply explained with, for example, volatility or other prominent characteristics in the company's daily returns. This point of view would conclude that many of the seemingly high positive or negative abnormal returns are simply just "noise" in the usual return pattern.

In my thesis, these aforementioned concerns are mitigated by more than one method. Firstly, the method for calculating the expected return of a stock is chosen to reflect for the return pattern characteristics of the company. By definition, an abnormal return during one day is the actual return of a stock on that day, minus the expected return of the stock for that day. A general equally or value weighted stock exchange index is not used here, but rather daily expected returns for benchmark follow the Fama-French Three-Factor Model, as in the study by Fama & French (1993). Secondly, volatility of the abnormal daily returns as such is controlled in the regression tests with a volatility variable *vola*. Thirdly, to discover the shares of visibly influential recommendation revisions out of all recommendation changes, an adjusted methodology by Loh & Stulz (2011) is tested on the samples of this study. This less commonly used method is meant for identifying the specific influential changes, apart from the aggregated averages of CARs. The visibly influential change method requires for a truly influential change that it generates a significant cumulative abnormal return relative to the general volatility of the abnormal returns for the company. In addition, the market reactions need to end in the same signed direction as the recommendation revision suggests.

4.2 Methods for measuring cumulative abnormal returns

Firstly, cumulative abnormal returns are calculated to measure the core stock return-based market reaction to recommendation changes. Method for computing cumulative abnormal returns, for either (-1,1), (-2,2), (-5,5) or (-10,10) event time windows follows the equation:

$$CAR_i = R - E(R) = \prod_{t=0}^{i}(1 + R_{it}) - \prod_{t=0}^{i}(1 + R_{it}^{FF3FM}) \qquad (1)$$

Where R_{it} is the cumulated historical stock return including dividends on day t, and R_{it}^{FF3FM} is the cumulated return of a Fama-French Three-Factor Model expected return. In the event window, day 0 is set at the exact day of the recommendation change according to IBES data. The Fama-French Three-Factor Model based expected returns *E(R)* are more exactly determined according to the following equation:

$$E(R) = R_f + \alpha + \beta_1 * (R_m - R_f) + \beta_2 * SMB + \beta_3 * HML \qquad (2)$$

The parameters for deriving the expected return in each day of each event CAR are calculated with a (-50,-10) trading days' time period before the start of the actual event window. The expected return estimation window thus contains roughly two months of trading days and a gap of 10 trading days before the beginning of the actual event time window. The parameters include risk-free rate R_f, return of the market portfolio R_m, stock alpha, three betas and the factors for measuring size with small-minus-big market capitalization (SML) as well as value versus growth stock characteristic with high-minus-low book-to-market ratio (HML).

4.3 Ordinary Least Squares regression tests and used methods

To further study whether the One man consensus status of an analyst recommendation revision might impact the cumulative abnormal returns of a firm, an Ordinary Least Squares regression test is performed on the data set. For this experiment, a set of control variables is required. Observations that fill the One man consensus criteria are marked with a dummy variable *omc*. Company size is controlled on a daily level with a natural logarithm of market capitalization from CRSP, and the variable is named *lnmktcap*. Natural logarithm of book-to-market value (from Compustat, variable *lnbm*) is used as a proxy for whether the company is likely to be a growth firm, as opposite to a value firm. Natural logarithms are used to ensure comparability between large firm-specific differences in the values, both for market capitalizations and book-to-market values. The same goes for turnover figures later on, since regular trading volumes differ notably from one company to another. A Regulation Fair Disclosure dummy *regfd* is marked as 1 to all recommendation announcement days happening on or after 23 October 2000, the day Reg FD became effective, and 0 before that date.

For the OLS regressions, volatility in abnormal returns (variable *vola*) is used as a proxy for idiosyncratic volatility. Idiosyncratic volatility indicates the risk that does not correlate with market risk but instead, only has to do with the risk of the particular measured firm. In the portfolio management scene, the idiosyncratic risk can be diversified away with careful inspection of the companies and their volatility drivers that the portfolio manager plans to invest in. The dummy variable *coneps* gets value 1, if a concurrent earnings-per-share or EPS forecast by the stock analyst is issued on the same day that the recommendation revision is released by the same analyst. Dummy variable *skiprank* is marked as 1 in observations in which a recommendation change is anything else than +1 or -1. Hence the name of the variable, since the change "skips" one level of recommendations on the recommendation scale.

The OLS regression tests are performed using the following equation, in which the *omc* variable as well as every control variable receives their own coefficient, and β_0 represents the intercept:

$$\begin{aligned} CAR_i = \beta_0 + \beta_1 posit + \beta_2 omc + \beta_3 lnmktcap + \beta_4 lnbm + \beta_5 vola \\ + \beta_6 coneps + \beta_7 regfd + \beta_8 skiprank \end{aligned} \tag{3}$$

In tests where upgrades (recommendation change value sign +) and downgrades (sign -) are mixed in the same set of data, the dummy variable *posit* simply signifies whether the revision is an upgrade (*posit* gets value 1) or a downgrade (*posit* gets value 0).

4.4 Determining the visibly influential recommendations

For obtaining the share of the influential recommendations based on both event CARs and abnormal turnover, I use the following methods that closely follow those of Loh & Stulz (2011), with some differences. Firstly, to determine whether a recommendation revision has been visibly influential by its CAR, I determine for each observation whether the following is true:

$$/CAR_i/ > (1.96 * \sqrt{n} * \sigma_1) \tag{4}$$

Where n is the number of days in the event window, for instance 3 for (-1,1), and σ_1 is the volatility in daily abnormal stock returns for the past 60 trading days, with a 6-day gap from the beginning of the event window. If the formula above is true, and the sign of the CAR is positive when the recommendation revision is an upgrade, or the sign is negative when it is a downgrade, the recommendation is deemed visibly influential. The benchmark figure is multiplied with 1.96 in accordance with regular t-test significance statistics, with 1.96 acting as a proxy for the recommendation change being visibly influential with a 5% statistical significance rate. To perform a test with the same principle on turnover figures, abnormal turnover (*abnturn*) for one trading day is defined as

$$abnturn = \ln(\text{turnover in the day}) - \ln(\text{average turnover in the past 2 months of trading days}) \tag{5}$$

Where turnover is defined as trading volume divided by number of shares outstanding, and the average turnover has a gap of 6 days before the start of the event window. For a recommendation revision to be defined influential, the cumulative abnormal turnover in the event window, for instance in (-1,1), must satisfy the following condition:

$$abnturn > (1.96 * \sqrt{n} * \sigma_2) \tag{6}$$

Where n is the number of days in the event window, for instance 3, and σ_2 is the volatility in daily abnormal turnover in the past 2 months' trading days, again with a gap of 6 days before the event window. The methods used by Loh & Stulz (2011) are very similar to the Equations 4, 5 and 6 in this study. However, the event windows differ: Loh & Stulz (2011) use an event window of (0,1) for their influential recommendation revision tests, whereas this study looks primarily at the (-1,1) window. Note that differences arise in the value of *n*, which gets value 2 instead of 3 if a shorter (0,1) window is used. Furthermore, the exact number of days for which abnormal return volatility (σ_1 *and* σ_2) is calculated might differ from one paper to another, as well as the sample of companies studied itself.

4.5 Exclusion of earnings-per-share forecasts and analyst accuracy from the tests, and a note on sector classifications

This thesis will solely focus on stock analyst recommendations, namely the buy, sell or hold recommendations instead of earnings forecasts and other quantitative or qualitative opinions of the firm, such as sales growth estimates or industry forecasts. If investors would blindly obey the recommendations of a One man consensus analyst, a recommendation revision from hold to buy should cause a notable price increase due to increased amount of demand for the stock, as well as increased trading volumes due to exchanging of shares. Various studies examine earnings forecast revisions that are not accompanied by a buy-sell recommendation (e.g. Park & Stice, 2000; Altınkılıç & Hansen, 2013). Moreover, Loh & Stulz (2011) discover using their method that only around 5% of sole earnings forecast changes are deemed visibly influential.

A measure often linked with research on market reactions to analyst recommendations, namely the accuracy of an analyst's earnings or EPS predictions, is not used in this study, neither as a limiting or classifying factor in outlining the test samples nor as a control variable. Here a rather simple explanation exists, since in companies that have a sole one analyst follower, we cannot rank the one analyst to be a better or worse forecaster than others following the same company, as in firms with more coverage. In literature, the accuracy of an analyst is most commonly defined in relation to other analysts covering the same company and their forecasts. For example, the method of measuring forecast accuracy by both Park & Stice (2000) and Loh & Mian (2006) papers is based on ranking the analysts covering a company to five accuracy categories.

Moreover, it would not be very sensible to try to measure the accuracy of One man consensus analysts by comparing them to other analysts that follow other companies, since companies tend to vary a lot by how easy it is to forecast earnings for them. For an established company manufacturing consumer products, where demand does not fluctuate much, predicting earnings could be decidedly easier than for a small, high-growth IT solution services firm. Easiness here could be defined by how much the analyst consensus EPS forecast tends to miss the actual EPS in each quarter. A continued academic discussion revolves around whether analysts' forecasting ability is only firm-specific, which is what for instance Park & Stice (2000) argue. In contrast, Brown & Mohammad (2010) suggest that a general analyst ability in forecasting might be incrementally relevant to firm-specific ability. For the purposes of this thesis however, the general ability measure is excluded as research on the subject remains scarce.

Sector classifications and their CAR characteristics are also examined as a part of securing result robustness. Sector classifications for companies are obtained from IBES, which divides companies into 11 different sectors and a 12th category for miscellaneous or undesignated companies. The IBES sector classification is based in outline on the Standard & Poor's S&P500 classification system for U.S. companies. The IBES sectors are further detailed in Table 8 on page 70.

5. Empirical findings

This section explains the results of the tests described in the previous Section 4. Firstly, observations are made about the nature and outline of the data and results in general. Next, data and results are examined in terms of averages cumulative abnormal returns, and the profiles of CAR patterns are presented. In the following part, regression test results are described, followed by tests on the shares of visibly influential recommendations. Afterwards, some insights are presented on the predictive power of the One man consensus recommendation changes and the impact of regulation on stock analysts. Finally, robustness tests and sector CARs are presented.

5.1 Descriptive observations about the data

The general statistics about recommendation revision amounts, sorted by the magnitude of the recommendation change, are illustrated in Table 2.

Table 2 *Amounts (left table) and percentages (right table) of recommendation revisions in OMC sample and Control sample. The revisions span from the beginning of year 1994 to the end of year 2014. Included are companies listed on NYSE, NASDAQ and AMEX that have had One man consensus revisions during their history on the list, and thus belong in the OMC sample to start with. Revisions that collide with company earnings announcement days in a (-1,1) window around the EAD are excluded from this table and the tests.*

Magnitude of revision	**OMC sample**	**Control sample**	**Pooled**
- 4	18	42	60
- 3	27	77	104
- 2	645	2 539	3 184
- 1	1 023	4 179	5 202
+ 1	843	3 234	4 077
+ 2	397	1 966	2 363
+ 3	10	47	57
+ 4	5	28	33
All negative	1 713	6 837	8 550
All positive	1 255	5 275	6 530
Total	2 968	12 112	15 080

Magnitude of revision	**OMC sample**	**Control sample**	**Pooled**
- 4	0.6 %	0.3 %	0.4 %
- 3	0.9 %	0.6 %	0.7 %
- 2	21.7 %	21.0 %	21.1 %
- 1	34.5 %	34.5 %	34.5 %
+ 1	28.4 %	26.7 %	27.0 %
+ 2	13.4 %	16.2 %	15.7 %
+ 3	0.3 %	0.4 %	0.4 %
+ 4	0.2 %	0.2 %	0.2 %
All negative	57.7 %	56.4 %	56.7 %
All positive	42.3 %	43.6 %	43.3 %
Total	100.0 %	100.0 %	100.0 %

The first observation about the recommendations is that a majority, or some 57-58%, of recommendation revisions in all samples are downgrades, as illustrated by Table 2. The larger share of negative recommendation revisions could indicate several things. It could be possible that most coverage initiations are, knowingly or unknowingly, too optimistic throughout the sample. Excessive optimism would give rise to downgrades following the initial optimistic views, when analysts adjust their views on the company, possibly after becoming more informed about the nature of the company and getting to know its management on a deeper level. The finding about a larger number of downgrades than upgrades is in line with the findings by, for example, McNichols & O'Brien (1997), who also note that the frequency of downgrades is higher than that of upgrades.

The migration of many brokerages into a 3-point ratings system due to the NASD Rule 2711 in 2002 can be observed, in part, in the data by the small proportion of -4, -3, +3 and +4 recommendation change events in both the OMC and Control samples. In addition to the effects of the 2711 ruling, an important factor is also that huge upgrades and downgrades, up or down more than two levels, simply happen less frequently than smaller upgrades and downgrades, i.e. up or down one or two notches. A significant upgrade or downgrade outside a clear news event, such as the company declaring financial difficulty, would in a sense indicate that the analyst has radically changed their stance on a company, or perhaps updated their forecast model with whole new assumptions.

When recommendation revisions colliding with a (-1,1) time window centered on quarterly earnings announcement dates are excluded from the data, the One man consensus revisions amount to 2 968, as exhibited by Table 2. If the earnings announcement dates were not excluded, the One man consensus sample would contain 3 575 revisions, indicating that roughly 17%[8] of the recommendation revisions are excluded from further tests due to their date being very close to quarterly company earnings announcements. If the collision of analyst recommendation changes and earnings announcements were to happen randomly, one could expect that the probability of such incidence would be somewhere close to 4.76%[9]. However, as the percentage is notably higher, a conclusion is that many analysts deliberately time their issuance of recommendation changes close to earnings announcements, as found also by Loh (2010). One explanation for this would be that analysts adjust to the new information sent out by the firm, as suggested by Yezegel (2015), often meaning changing the parameters in analysts'

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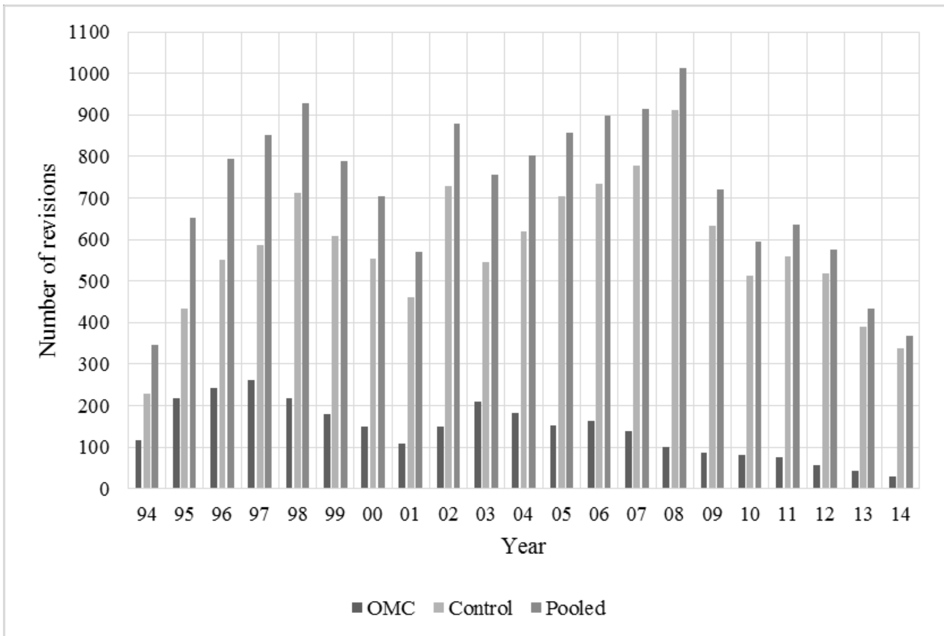
[8] (3575 – 2968) / 3575 = 0.16979… ≈ 17%

[9] (3 days' event window * 4 quarterly earnings announcements in a year) / 252 trading days in a year ≈ 4.7619%

estimation models, and thus sometimes adjusting their buy-sell recommendation at the same time. Nevertheless, to more accurately pinpoint a given analyst's contribution, and to dismiss the effect of analysts' piggybacking on company earnings announcement stock reactions, these kind of recommendation revisions are removed from the data.

Annual distribution of the revisions is presented in Figure 2. Exact amounts of the annual amounts are further disclosed in Appendix A.

Figure 2 *Annual distribution of recommendation revisions in OMC and Control samples, and these two combined (Pooled). Recommendation revisions are from the beginning of the year 1994 to the end of year 2014, in the American exchanges of NYSE, NASDAQ and AMEX.*



The general disbelief in the whole financial system during the crisis in 2008 and 2009 has likely left its mark on the number of analyst recommendations. For one, year 2008 has the highest number of revisions in total. Not surprisingly, most of the recommendation revisions during this time have been recommendation downgrades. Some cyclicality in the frequency of recommendation revisions can be noticed from Figure 2. For instance, after 2008 the annual number of revisions has been declining year by year. It is however possible that a part of this decline can be explained with technical reasons, as IBES has possibly not yet recorded all of the latest revisions in their systems.

Applying the filters described in the Section 3 of this thesis and removing all ADRs, ETFs, mutual funds and preferred stocks, as well as excluding from the data observation days with more than one analyst publishing a recommendation revision, leaves us with one or more recommendation revisions for 1 740 U.S. listed companies. All of these companies have had at least a single observation of a One man consensus recommendation change between the beginning of 1994 and the end of 2014.

On average, it also seems that higher analyst interest goes somewhat hand in hand with the size of the covered company. For the main OMC sample, the average market capitalization is roughly $231 million, while for the Control sample, average market cap is close to five times as high at $1.1 billion. Hence, many of the companies, at the time of their OMC revisions, are rather small on the U.S. listed company scale. For example, the SEC refers[10] to U.S. listed companies with a smaller than $300 million market cap as "micro cap". Nevertheless, even in the Control sample, the average firm would fall into the small cap company bucket by common definition. In terms of book value of equity, the average OMC sample company has an equity book value of merely $146 million, while the Control sample companies have on average $514 million. If book value of equity is used as a proxy for size, the average Control sample company would then be roughly 3.5 times bigger than an average OMC sample company.

The tenures of the analysts following smaller companies appear shorter than what one might expect: in the data set, it is rather uncommon to see the same analyst following a certain company for many years in a row, and it is even more uncommon for them to hold their status as the only analyst following a company for a long time. Altogether, a firm having only one analyst following them does not appear like a very permanent state throughout the sample. According to the data, analysts tend to hop in and out of the companies, and the number of analysts following a company varies significantly in time. Analyst interest around companies in general appears to follow somewhat cyclical trends. At times, there is more interest towards a company and multiple analyst flock to follow a company. At other times, the general interest seems to disappear when only one analyst, or no analysts at all continue covering the company.

The data also exhibits the fact that analysts do not seem to build their career around a single brokerage house. There are multiple instances where the brokerage house keeps on following a certain company, but the analyst changes. The change of the analyst might be

[10] See SEC Investor Publication at http://www.sec.gov/investor/pubs/microcapstock.htm. Website visited on 30 March 2016.

visible almost instantly when the new analyst issues their own recommendation, but sometimes there is a gap of several months or even years between the recommendations of the different analysts within the same broker. As the sample selection of this study goes, the recommendation of the new analyst in the same brokerage would not be considered as a relevant recommendation change. It is probably best not to assume that the brokerage house entirely dictates the opinions of their analysts, but instead, independence of each analyst's thought is considered a more plausible scenario.

If the actual recommendation levels instead of changes to levels are examined, the data hints that overall, the One man consensus analysts seem more optimistic than pessimistic about the companies they cover. Table 3 exhibits the probabilities of recommendation level to get revised into other levels.

Table 3 *Matrix of OMC sample recommendation changes. In Panel* **(1)***, row headers signal the former values before revision, and column headers mark the new values after revision in the sample of this study. For example, on the first row, a Strong sell is 8.6% of the time revised to Sell, 75.9% of the time to Hold, etc. The bottom row "All" exhibits the final recommendations in general. For instance, on bottom row, on average 3.3% of any existing recommendation is revised to Strong sell, etc. Panel* **(2)** *presents the proportions of recommendation levels before and after revision.*

(1)

		TO				
		Strong sell	Sell	Hold	Buy	Strong buy
	Strong sell		8.6 %	75.9 %	6.9 %	8.6 %
	Sell	8.8 %		75.2 %	11.2 %	4.8 %
FROM	Hold	6.0 %	12.0 %		45.8 %	36.2 %
	Buy	1.5 %	4.5 %	61.4 %		32.7 %
	Strong buy	2.0 %	1.5 %	61.6 %	34.9 %	
	All	3.3 %	5.8 %	43.0 %	25.5 %	22.4 %

(2)

	Before revision	After revision
Strong sell	2.0 %	3.3 %
Sell	4.2 %	5.8 %
Hold	31.5 %	43.0 %
Buy	32.4 %	25.5 %
Strong buy	29.9 %	22.4 %
All	100.0 %	100.0 %

Table 3 reveals that the "hold" recommendation level is favored by stock analysts – "hold" recommendation is where any recommendation is most likely to get revised into. In turn, if the existing recommendation is "hold", 82% of the time it gets upgraded, and only 18% of the time downgraded. From "buy" and "strong buy" recommendations, only 3.5%-6% of the revisions end up in a negative recommendation, whereas roughly 61.5% of both "buy" and "strong buy" end up in "hold". This finding indicates that many of the downgrades in the data cannot in fact be interpreted as clear shifts towards sell, but instead as the analysts becoming neutral about the stock. A positive tilt is apparent all along, as “strong sell” and “sell” recommendations combined form less than 10% of all recommendations both before and after revisions. The results for Control sample are very similar to the percentages in Table 3.

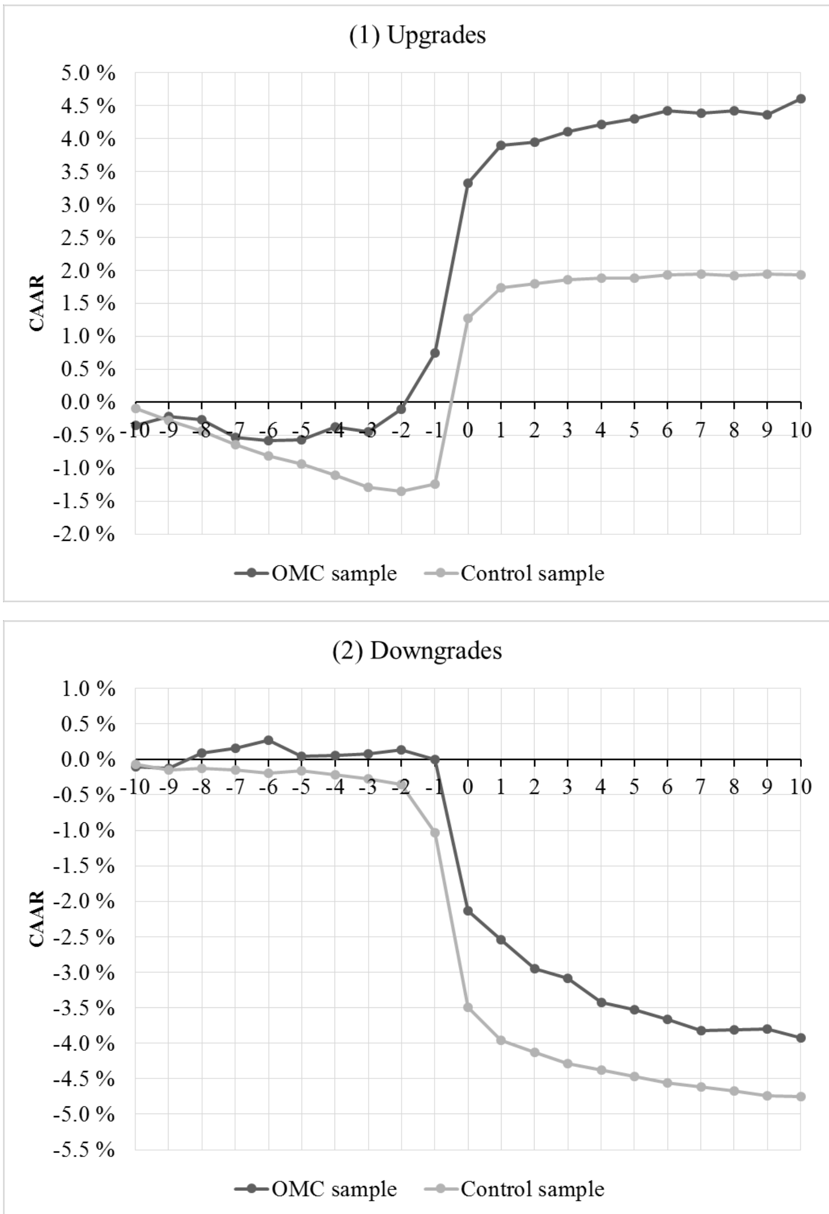
Upward-biased as the recommendations may seem, the statistics are not completely surprising in light of previous research. For instance, Barber et al. (2006) note that before the implementation of NASD 2711 Rule and especially before year 2000, the ratio of buy/sell recommendations was heavily tilted toward positive recommendations. Barber et al. (2006) report that the number of buy recommendations exceeded the number of sells by an enormous 35:1 ratio between 1996 and 2000. However, after the Rule 2711, the share of buys settled to around 45%, while sells still remained at 14% and holds at 41% of all recommendations, according to Barber et al. (2006).

Setting filters on the sample speaks on its own about the nature of the data: around 89% of upgrades are revisions to either buy or strong buy, whereas in comparison a minor 14% of downgrades actually end up in sell or strong sell recommendation. A grand majority of all downgrades end up in a “hold” recommendation, which might send a quite mixed signal to the markets. After all, a hold recommendation does not explicitly advise investors to sell their stock, but neither is it a statement of belief in the future of the stock. Sometimes analysts are even scolded in the financial press and by investors for setting hold recommendations, as a neutral recommendation can be seen as risk aversion on the analyst’s part, and even as worthless for the informational environment due to a hold recommendation’s low informational content. Consequently, some brokerages do not issue hold recommendations as part of their equity analyst services.

5.2 Cumulative abnormal returns on an average level

Profiles of the cumulative average abnormal returns (CAARs) in event time window (-10,10) for upgrades and downgrades, separately for the OMC sample and the Control sample, are illustrated in Figure 3.

Figure 3 *Upgrade and downgrade cumulative average abnormal returns for OMC sample and Control sample in (-10,10) event window. Dates relative to the observation are illustrated on the x-axis.*



The profiles of CARs illustrated in Figure 3 differ notably for the OMC sample and the Control sample. The One man consensus recommendation upgrades seem to cause an almost surprisingly large price hike in comparison to the other recommendation revisions. Tables are turned on the downgrade side, since the negative downgrade news about a company seem to have a larger impact on the companies when other analysts are also covering the firm. A curious note is that on the upgrade side, the abnormal returns for the OMC sample start cumulating rapidly already on day -1, before the actual recommendation change event on day 0. On the other hand, in the Control sample it seems that the market price starts to adjust to the new information only from day 0, presumably right after the markets receive the new information. Interestingly, there is no negative drift in downgrades on day -1 in the OMC sample, whereas a negative trajectory is already visible on day -1 in the Control sample.

In both upgrades and downgrades, market response beyond the immediate (-1,1) window seems slower in the OMC sample, since the abnormal returns seem to continue their upwards or downwards drift more pronouncedly after approximately day +1. Regarding the price drift, Savor (2012) studies stock returns after major price shocks and finds that price events accompanied with information are followed by a drift, but the drift exists only if the analyst recommendation change is of the same sign as the price drift (i.e. upgrades with upwards price hike and vice versa for downgrades). As one explaining factor for the shapes of the graphs, the drift of the abnormal returns could be attributed to the gradual incorporation of earnings-related information included in the recommendation revision, as suggested by Miwa & Ueda (2014). Figure 4 presents the CAR graphs in an even longer time window, from -20 days to +20 days around recommendation revisions, which further pronounces the slow price reaction in OMC revisions.

Figure 4 *Upgrade and downgrade cumulative average abnormal returns for OMC sample and Control sample in (-20,20) event window. Dates relative to the observation are illustrated on the x-axis.*

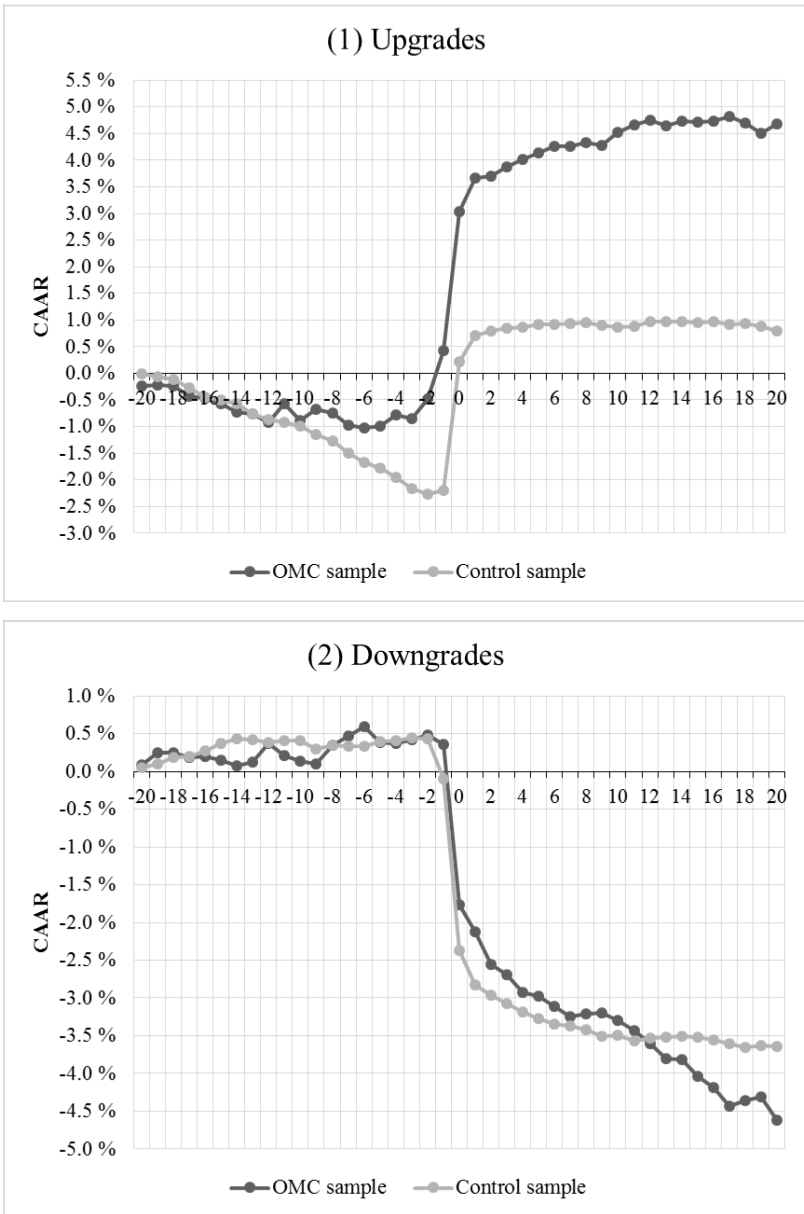


Figure 4 exhibits a few interesting aspects about the CAAR graphs, in comparison to Figure 3 graphs. For one, OMC downgrades show a continued negative price drift beyond the immediate short-term event windows. This drift seems to go on until at least +20 days after the downgrade, and it even seems to pass the milder drift from Control sample downgrades. In their paper, Hong et al. (2000) note that low-analyst coverage stocks seem to exhibit slower price reactions to negative news. Looking at Figure 4 downgrade graphs, the observation by Hong et al. (2000) appears to receive further confirmation.

Another noteworthy observation about both Figure 3 and Figure 4 upgrades is that firms in the Control sample appear to experience a prominent negative drift leading up to the upgrade event on day 0. The development of the CAAR here seems counterintuitive, as recommendation upgrades are by definition supposed to be mainly positive news event about a company. There is no apparent explanation for this noticeable negative drift right before the upgrade. As relevant information events are not examined in this study beyond just a few days around the revisions, it is possible that the negative drift could be driven by negative news events in the time period leading to the revision event. Yet, it would then be even more counterintuitive for one analyst out of a larger consensus to issue a recommendation upgrade after a negative news event. In addition, one could expect there to be positive news events in the Control sample, uncaptured by the earnings announcement date filter, which would at least partly offset the drift from negative events on an aggregate level. Since this thesis puts its main focus on the short-term market reactions after recommendation revisions, I encourage future studies to dive deeper into this curious longer-term phenomenon.

It seems that the magnitude of a recommendation change, for example whether the change is an upgrade of +1 recommendation level instead of a +3 upgrade, does not go hand in hand with the cumulative average abnormal returns. On the upgrade side, for example, nearly the opposite is true. As exhibited by the averages in Table 4, there does not seem to exist any clearly visible trend between the absolute strength of a recommendation change and the absolute CAR reaction.

Table 4 *Averages of cumulative abnormal returns in event window (-1,1), by the magnitude of recommendation change. "All negative" row shows recommendations of -4, -3, -2 and -1 combined and classified by sample, and "All positive" row in the same way for +1, +2, +3 and +4. Revisions colliding with earnings announcement dates, as stated by IBES and explained in Section 3, are excluded. The column "Pooled" refers here to OMC and Control samples combined.*

Magnitude of revision	**OMC sample**	**Control sample**	**Pooled**
- 4	7.55 %	-2.43 %	0.44 %
- 3	-0.99 %	-3.49 %	-2.85 %
- 2	-3.53 %	-3.82 %	-3.76 %
- 1	-2.50 %	-3.19 %	-3.05 %
+ 1	3.81 %	2.73 %	2.95 %
+ 2	4.76 %	3.39 %	3.61 %
+ 3	0.87 %	1.39 %	1.33 %
+ 4	0.24 %	2.67 %	2.36 %
All negative	-2.76 %	-3.42 %	-3.29 %
All positive	4.08 %	2.96 %	3.18 %

This result might stem from an argument that market perception is rather ignorant about the scale of the change. What matters more, is the overall direction of the change, be it positive or negative. Another explanation is related to the analyst rating scales that are utilized. One outcome of the aforementioned NASD 2711 Rule was that the absolute number of possible recommendation changes, i.e. 8 change possibilities from -4 steps to +4 steps, was replaced with only 4 change possibilities ranging from -2 to +2, thus further limiting the number of changes that skip one recommendation level. In Table 4, also some peculiar values are reported. For example, the table states that -4 recommendation changes from strong buy to strong sell in the OMC sample would induce a CAAR of +7.55%. This result seems to stem from only two statistical outlier observations (experiencing event CARs of over 40% each in the short-event windows), as the total number of -4 recommendation revisions in the OMC sample is only 18 from the beginning of 1994 until the end of 2014, as shown in Table 2.

Looking at the 3-day event window CAARs in (-1,1), centered around the IBES reported recommendation change announcement day, One man consensus upgrades and downgrades appear to differ from those of the Control sample, along the lines of the initial hypothesis H2. Table 5 presents the arithmetic averages CARs and two metrics of statistical significance.

Table 5 *Cumulative average abnormal returns for the OMC sample and Control sample in two event windows. Column t-stat refers to a cross-sectional t-statistic. Patell Z refers to a statistic calculated as in the study by Patell (1976). These statistics are used to define whether the CAARs are different from 0 in a statistically significant manner. The t-tests between samples (two bottom rows) measure whether CAARs between samples (separately for upgrade and downgrades) are statistically different from each other.*

	One man consensus sample						**Control sample**					
	Upgrades			**Downgrades**			**Upgrades**			**Downgrades**		
Event window	CAAR	t-stat	Patell Z	CAAR	t-stat	Patell Z	CAAR	t-stat	Patell Z	CAAR	t-stat	Patell Z
(-1,1)	4.08 %	12.61***	25.83	-2.76%	-7.91***	-15.90	2.96 %	25.30***	49.30	-3.42%	-23.44***	-57.80
(-2,2)	4.53 %	11.43***	21.92	-3.15%	-7.54***	-13.58	2.92 %	20.94***	39.06	-3.62%	-21.41***	-46.08
t-test between samples in (-1,1)	3.28 ***			1.80 *			3.28 ***			1.80 *		
t-test between samples in (-2,2)	3.83 ***			1.08			3.83 ***			1.08		

Statistical significances of t-values: * 10%, ** 5%, *** 1%.

Upgrades in the main sample of One man consensus recommendation changes induce an arithmetic average CAR of +4.08%, whereas the Control sample induces average CARs of +2.96%, in event window (-1,1). An extended event window of (-2,2) results in average CARs of +4.53% and +2.92%, in the same order. All samples of these CARs are cleaned of recommendation changes for stocks that have per share prices at or below 1.00 USD, to make sure the results are not driven by huge swings from returns in penny stocks. As expected, the absolute average CARs in upgrades events are diminished when recommendation changes dated in the 3-day window around a company earnings announcement day. If I was to include recommendation revisions that collide with earnings announcement dates, the average CAR for (-1,1) OMC upgrades would rise to +4.57%, and to +3.54% for the Control sample upgrades.

When attention is drawn to negative recommendation changes, i.e. downgrades, the overall average CARs become negative at -2.76% and -3.42% for One man consensus changes and the Control sample, respectively. Here it can be noted that the absolute abnormal price reaction in the main sample no longer exceeds the reactions in the Control sample. Again, if observations colliding with earnings announcement dates are not excluded from the sample, the negative average CAR drops to -3.51% for the OMC sample, and -4.25% for the Control sample in (-1,1) event window. If attention is set at results in (-2,2) for OMC and Control samples, the average CARs become -3.15% and -3.62%, respectively.

Based on results from existing literature, median CARs often differ considerably from arithmetic average CARs. Same principle applies to the results here, but nevertheless, upgrades (downgrades) still induce a notably positive (negative) median CAR in both the OMC sample and the Control sample. In event window (-1,1), median CARs for upgrades are +2.10% and +2.28% for main sample and control sample respectively, and for downgrades -1.86% and -2.30%, in the same order. These medians would seem to suggest that the CAAR of OMC sample upgrades is partly driven by large swings after some of the recommendation revisions in a short event window. Longer event windows seem to exhibit a slower abnormal price reaction mechanism for the One man consensus recommendation revisions. For instance, in a (-5,5) window, the upgrade medians for the OMC sample and Control sample become +2.48% and +2.10%, while downgrades induce reactions of -2.64% and -2.81%, in the same order.

The implications of the average CARs are intriguing, based on both the graphs in Figure 3 and 4 and the averages presented afterwards in Table 5. One could have expected that the abnormal returns swing more strongly for One man consensus companies both upwards and downwards after upgrades and downgrades than for companies in multiple analyst coverage situations. This assumption seems to only hold partly and specifically for recommendation upgrades, where the data suggests a stronger CAR upswing in all event windows. As a reference point, in their study of Italian small cap companies covered by stock analysts, Guagliano et al. (2013) find that after selecting out contaminating news events such as earnings announcements, only buy recommendations are found to convey information to financial markets in terms of a price reaction.

On the downgrade side however, it appears that the market reaction after OMC recommendation changes is more muted in all event windows, especially on the day of the recommendation and the days that follow immediately after. One explaining factor might lie behind where the recommendations are downgraded to, as evidenced by Table 3. Many of the seemingly negative downgrades are actually only downgrades from “strong buy” to “buy”, or from those two recommendations into “hold”. Thus, these downgrades send arguably a much less negative signal to the markets than a downgrade into “sell” or “strong sell” would.

McNichols & O’Brien (1997) hypothesize that stock analysts might sometimes delay the delivery of bad news on purpose, in this case recommendation downgrades. The authors claim that analysts are less likely to issue reports altogether when they possess unfavorable information. According to McNichols & O’Brien (1997), analysts might sometimes be prone to dropping all coverage instead of just issuing a downgrade, if an analyst views a company unfavorably. In the single analyst context, One man consensus analysts' reluctance to issue a downgrade could allow information to partly leak into the prices already before the announcement of the downgrade. This would in turn make the OMC downgrades exhibit a less negative short-term CAAR than the Control sample downgrades. However, the findings by McNichols & O'Brien (1997) do not seem to explicitly explain the milder negative market reactions to OMC analyst downgrades in my tests. In Figure 4, there is no visible negative drift between -20 and 0 days before the OMC downgrade, which could either indicate that the effect is not present, or that the leakage has already happened before the start of the (-20,20) event window.

Another possible explanation for smaller negative reactions comes from Hong et al. (2000). As explained in Section 2 and this section, Hong et al. (2000) note that less analyst coverage entails that negative news might diffuse more slowly across the investors. This effect of very small coverage would at least partly explain the smaller absolute CAARs immediately after recommendation downgrades by OMC analysts, as well as the longer-term negative price drift that follows, as illustrated in Figure 4.

5.3 Regression analysis of single analyst recommendation revisions

The entire sample of analyst recommendation revision observations, including both the One man consensus revisions as well as all of the Control sample revisions, is tested upon an ordinary least squares regression. This analysis is performed to examine whether a statistically significant correlation can be observed between individual cumulative abnormal returns, and whether the revising analyst has at the time of the event been alone in the analyst consensus for the company in question. Furthermore, the OLS regression tests might reveal also other aspects about the data and the effects of control variables. As described in Sections 3 and 4, *Data* and *Methodology,* a number of other potentially significant variables are included in the regression model, in search of the true contribution of the *omc* dummy variable. The tests are conducted both for the whole Pooled sample with OMC and Control observations, as well as for upgrades and downgrades separately.

The results of the OLS tests are presented for all regression samples in Table 6, for three different event time windows, that is, for (-1,1), (-2,2) and (-5,5).

Table 6 *Regression test results by event window, divided into upgrades, downgrades and these two as Pooled. Regression* **(1)** *presents results without fixed effects, whereas* **(2)** *and on the following page* **(3)** *are with fixed effects. Explanatory variables are detailed in Table 1. N indicates the number of observations. The dummy variable "posit" is omitted for tests that only contain upgrades or downgrades. Asterisks indicate the statistical significances of t-stats: * 10%, ** 5%, *** 1%.*

(1) OLS regression

	A. Pooled						**B. Upgrades**						**C. Downgrades**					
	(-1,1)		**(-2,2)**		**(-5,5)**		**(-1,1)**		**(-2,2)**		**(-5,5)**		**(-1,1)**		**(-2,2)**		**(-5,5)**	
Explanatory variable	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
posit	0.629	34.71***	0.065	30.76***	0.065	24.27***												
omc	0.013	5.29***	0.015	5.14***	0.016	4.23***	0.007	2.36**	0.011	2.96***	0.014	2.72***	0.018	4.76***	0.018	4.11***	0.016	3.07***
lnbm	-0.004	-3.51***	-0.006	-4.12***	-0.004	-2.12**	-0.000	-0.27	0.002	1.38	0.008	3.65***	-0.006	-3.4***	-0.011	-5.26***	-0.011	-4.58***
vola	-0.069	-1.36	-0.133	-2.23**	-0.120	-1.60	-0.368	5.63***	0.303	3.83***	0.250	2.35**	-0.330	-4.51***	-0.383	-4.51***	-0.310	-3.02***
lnmktcap	0.002	2.14**	0.002	1.67*	0.003	2.07**	-0.001	-1.22	-0.002	-1.31	-0.003	-1.69*	0.004	3.43***	0.004	2.94***	0.007	3.83***
coneps	-0.014	-7.48***	-0.160	-7.48***	-0.020	-7.18***	0.003	1.21	0.005	1.78*	0.014	3.68***	-0.026	-9.29***	-0.031	-9.67***	-0.042	-10.97***
regfd	0.007	3.34***	0.009	3.51***	0.011	3.47***	0.013	4.99***	0.012	3.93***	0.004	1.01	0.001	0.38	0.004	1.12	0.012	2.87***
skiprank	-0.002	-0.87	-0.000	-0.17	-0.003	-1.13	0.004	1.70*	0.002	0.63	-0.004	-0.97	-0.006	-2.16**	-0.002	-0.66	-0.002	-0.64
Constant	-0.057	-5.21***	-0.058	-4.47***	-0.071	-4.40***	0.023	1.71*	0.032	1.99**	0.054	2.44**	-0.073	-4.46***	-0.078	-4.13***	-0.116	-5.09***
N	14 197		14 197		14 197		6 158		6 158		6 158		8 039		8 039		8 039	

(2) Fixed company effects regression

	D. Pooled						**E. Upgrades**						**F. Downgrades**					
	(-1,1)		**(-2,2)**		**(-5,5)**		**(-1,1)**		**(-2,2)**		**(-5,5)**		**(-1,1)**		**(-2,2)**		**(-5,5)**	
Explanatory variable	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
posit	0.063	34.41***	0.066	30.97***	0.065	23.98***												
omc	0.010	3.32***	0.011	3.19***	0.012	2.56**	0.008	2.07**	0.014	2.78***	0.014	2.10**	0.010	2.03**	0.006	1.11	0.003	0.51
lnbm	-0.008	-4.14***	-0.010	-4.81***	-0.008	-3.07***	0.000	0.07	0.002	0.82	0.006	1.67*	-0.011	-4.04***	-0.016	-4.9***	-0.140	-3.75***
vola	0.174	2.59***	0.114	1.45	0.290	2.95***	0.296	3.29***	0.324	2.96***	0.205	1.38	0.026	0.26	-0.045	-0.39	0.368	2.7***
lnmktcap	0.006	3.06***	0.006	2.49**	0.005	1.66*	-0.003	-1.35	-0.006	-2.03**	-0.017	-4.23***	0.011	3.78***	0.014	4.17***	0.020	4.97***
coneps	-0.013	-6.79***	-0.016	-7.02***	-0.019	-6.66***	0.003	1.17	0.005	1.63	0.014	3.45***	-0.025	-8.06***	-0.031	-8.83***	-0.044	-10.53***
regfd	0.011	3.67***	0.016	4.43***	0.019	4.34***	0.014	3.76***	0.017	3.68***	0.017	2.70***	0.006	1.24	0.009	1.85*	0.015	2.5**
skiprank	-0.001	-0.36	0.001	0.48	-0.003	-0.89	0.007	2.53**	0.006	1.76*	-0.002	-0.45	-0.005	-1.53	0.000	0.05	-0.002	-0.55
Constant	-0.124	-5.13***	-0.126	-4.46***	-0.121	-3.42***	0.050	1.64	0.083	2.24**	0.229	4.51***	-0.178	-4.91***	-0.219	-5.3***	-0.309	-6.23***
N	14 197		14 197		14 197		6 158		6 158		6 158		8 039		8 039		8 039	

Table 6
Continued

(3) Fixed analyst effects regression

Explanatory variable	G. Pooled						H. Upgrades						I. Downgrades					
	(-1,1)		(-2,2)		(-5,5)		(-1,1)		(-2,2)		(-5,5)		(-1,1)		(-2,2)		(-5,5)	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
posit	0.061	32.33***	0.063	28.31***	0.063	22.27***												
omc	0.009	3.02***	0.009	2.58***	0.007	1.65*	0.012	3.01***	0.015	3.01***	0.015	2.26**	0.005	1.18	0.004	0.69	-0.004	-0.66
lnbm	-0.008	-5.05***	-0.011	-5.71***	-0.007	-2.91***	-0.001	-0.54	0.001	0.54	0.013	3.74***	-0.010	-4.05***	-0.016	-5.72***	-0.017	-4.91***
vola	0.111	1.66*	0.075	0.96	0.273	2.76***	0.318	3.49***	0.247	2.24**	0.207	1.36	-0.027	-0.28	-0.037	-0.33	0.335	2.42**
lnmktcap	0.002	1.44	0.002	1.38	0.005	2.68***	-0.006	-3.29***	-0.005	-2.31**	-0.001	-2.40**	0.007	3.52***	0.007	3.19***	0.012	4.45***
coneps	-0.015	-6.81***	-0.017	-6.78***	-0.022	-6.81***	0.000	0.02	0.002	0.58	0.008	1.72*	-0.028	-8.36***	-0.034	-8.55***	-0.045	-9.51***
regfd	0.011	2.93***	0.014	3.05***	0.015	2.51**	0.025	4.64***	0.025	3.94***	0.030	3.32***	0.003	0.49	0.005	0.80	0.007	0.94
skiprank	0.000	0.06	0.002	0.66	-0.001	-0.29	0.011	2.83***	0.015	3.27***	0.009	1.32	-0.006	-1.39	-0.003	-0.57	-0.005	-0.78
Constant	-0.069	-4.08***	-0.077	-3.84***	-0.121	-4.77***	0.072	3.14***	0.062	2.24**	0.093	2.44**	-0.116	-4.67***	-0.128	-4.4***	-0.202	-5.76***
N	14 197		14 197		14 197		6 158		6 158		6 158		8 039		8 039		8 039	

In short, the results of the OLS regression tests give at least some indication of a connection between individual event CARs and the *omc* dummy variable. In the tests for a Pooled sample that contains both upgrades and downgrades, *posit* dummy variable is added to control for whether the recommendation revision has been positive or negative. Throughout the pooled tests, the *posit* variable is found highly significant at 1% significance level and beyond, indicating that stock market reactions' directions appear to correlate very strongly with the direction of the recommendation change. In other words, positive changes on average do induce an upwards market price reaction and downgrades vice versa. Looking at the Pooled samples in different event windows, it seems apparent that *omc* variable has some importance, as the variable is statistically significant at 1% level in all but one of the event windows, in which upgrades and downgrades are combined into one data set. However, conclusions should not be drawn solely based on the pooled samples. Rather, upgrades and downgrades need to be examined separately to find out whether the *omc* variable and control variables act differently for positive or negative recommendation revisions.

A key finding about *omc*, the variable of our main interest, is that a statistically significant association between the *omc* variable and event CARs can be noticed in most of the OLS regression tests. In all of the non-fixed effects regression tests, the *omc* variable remains considerably statistically significant on at least 5% level, and often even on 1% level depending on the event time window. As mentioned in the previous chapter, in the pooled regressions, the coefficient for *omc* receives clearly statistically significant values throughout the tests. When upgrades and downgrades are examined separately, differences arise. On the upgrade side, the *omc* variable follows the story set by the event CARs, as the coefficient appears positively correlated with the positive average CAR reaction in a statistically significant manner. In downgrades however, the coefficients for *omc* are also positive, indicating that the status of a One man consensus analyst actually diminishes the negative abnormal return after a recommendation downgrade, on average. The regression tests with fixed company effects follow along the lines of these results, yet the statistical importance of the *omc* variable decreases and even disappears in some of the tests on the downgrade side.

Besides a regression that does not incorporate fixed effects (Panel 1 in Table 6) and a fixed company effects regression (Panel 2), a regression analysis is performed with fixed individual analyst effects (Panel 3). The results for the fixed analyst effect regression follow largely the results of Panel 2. For example, coefficients for *omc* variable remain positive and statistically significant for upgrades, yet for downgrades, the coefficients become statistically insignificant in all of the event windows.

Variables beside the *omc* have their own importance in the regression tests regarding their impact on recommendation event CARs. Following the findings of multiple other studies, e.g. Stickel (1995), variable *lnmktcap* as the indicator for natural log of market capitalization remains statistically significantly negative (positive) for upgrades (downgrades). This result implies that as expected, smaller firms experience greater swings in returns around recommendations than big firms. Also the growth or value company proxy *lnbm* reaches statistical significance in many of the tests. However, it seems that the status of a growth-company has most importance to downgrades. The *lnbm* variable associates negatively with event CAR in downgrades, implying that the more undervalued a stock is (undervalued referring to a value company instead of a growth company), the stronger negative abnormal market reaction a downgrade induces.

Regarding *coneps* variable, it seems that downgrades induce a stronger price drop when accompanied with an EPS estimate, reinforcing the negative message of a downgrade. Volatility in the daily abnormal returns, measured with variable *vola* acts as expected – the more volatile the stock is in general, the more positive (negative) is the abnormal market reaction after an upgrade (downgrade). On the other hand, the results on variable *skiprank* seem inconclusive. The dummy variable *skiprank* does not seem to affect CARs strongly in most of the tests, implying that the market does not place very much importance on whether the revisions move the recommendation only one step up or down, or many steps. This last result contradicts with the findings of Stickel (1995), who in his older sample of data finds that recommendation changes skipping recommendation levels induce larger absolute price reactions. The characteristics of the *regfd* variable will be discussed on their own later on in this section.

As mentioned on the previous page, a somewhat surprising aspect about these tests is that the *omc* variable acts quite differently for recommendation upgrades and downgrades. In upgrades, the coefficient for *omc* variable is all along positive, while in downgrades, the *omc* variable coefficient is rather counterintuitively also positive and statistically significant for many of the tests. The implied conclusion from these results is that the status of being the only analyst covering a company does make investors excited about upgrades, resulting in a price hike, while a downgrade from a One man consensus analyst makes the immediate drop in price actually less negative than when coming from other analysts. Nevertheless, this result holds with the downgrade graph presented in Figure 3, and the discussion thereafter.

5.4 Share of visibly influential recommendation changes based on CAR method and abnormal turnover method

First and foremost, it should be stated that the share of influential recommendations based on cumulative abnormal returns seems to hover around the same percentages as found by Loh & Stulz (2011), i.e. a little above 10% of all recommendation. As explained in Section 4, the influential recommendation method assigns a revision either influential or non-influential, depending on whether an observation CAR fulfills the set conditions. The exact figure of influential recommendations for One man consensus recommendation changes in a 3-day event window (-1,1) is 11.20% with earnings announcement dates included, and 9.23% when observations colliding with earnings announcement dates are excluded. For the Control sample, percentage of influential changes with EADs excluded is somewhat higher, 11.51%.

Altogether these figures seem even surprisingly low – roughly speaking, only one analyst recommendation revision in ten causes the markets to react into the same direction as the revision suggests, and with a magnitude that can be claimed to exceed the rough average volatility in the price of the stock. Regarding the results by Loh & Stulz (2011), one should note that the authors use a shorter and, some might argue, a more unconventional (0,1) event window than the tests in this study. In addition, the authors only use observations for companies that have at least three analysts forming the analyst coverage at the time of the recommendation revision. This entails that the setting for comparing results is not very accurate to begin with.

Comparing the percentages of influential recommendation changes based on the positivity or negativity of the original recommendation revision reveals some interesting aspects. For the OMC sample, as well as the Control sample, it is apparent that recommendation downgrades exhibit a significantly higher share of influential recommendation than upgrades. 14.22% of all downgrades in the OMC sample, earnings announcements excluded, are deemed visibly influential following the method described in Section 4 of this paper. In the Control sample, an even higher 17.84% of recommendations downgrades can be deemed visibly influential. This is in stark contrast with upgrades, where only 2.43% of OMC sample revisions are influential, whereas the same figure is 3.26% for the Control sample. This around 3% share of influential upgrades across both samples is almost miniscule, and it can probably be concluded that the share of influential recommendations is almost entirely driven by influential downgrades, rather than upgrades. As a note on comparability, dividing the visibly influential revision tests separately into upgrade and downgrade parts is something that Loh & Stulz (2011) did not perform. These results, as well as those obtained with the abnormal turnover method are further analyzed in the next Section 6, *Discussion of the results*.

If the influential status of recommendation revisions is measured in terms of daily turnover, turnover being daily trading volume divided by the number of shares outstanding, the results appear quite different from those attained with the visibly influential CAR method. For most parts, the consistent finding is that a noticeably larger part of recommendation revisions can be considered influential with the turnover method than with the CAR method. This time both upgrades and downgrades seem to encourage investors to start trading the stock, with 21.60% of all OMC revisions being visibly influential turnover-wise in event window (-1,1), earnings announcements excluded. In comparison, out of regular multi-analyst revisions in the Control sample, a considerable 27.50% are influential turnover-wise.

One explanation for larger percentages in the Control sample might lie in the following reasoning. When investors become interested in a stock, more analysts also start to flock to cover the company. Subsequently, when the general interest of the markets and analysts in a company is larger, investors might also monitor the stock more closely and more trading is bound to happen after news events, such as analyst recommendation revisions. Consistent with the pooled turnover results, One man consensus upgrades exhibit a smaller share of influential upgrades, with 19.13% in (-1,1), while the corresponding figure for observations with more coverage than one analyst in the Control sample is 25.64%. The corresponding figures for downgrades in the same order are 23.42% and 28.94%.

To sum up the tests regarding visibly influential recommendation revisions, a few clear patterns are apparent. Firstly, the choice of method does matter as a considerably smaller amount of CAR-based than turnover-based revisions appear visibly influential. Secondly, downgrades seem to muster a larger share of influential revisions than upgrades regardless of the used method. However, this result is much more apparent in the CAR-based tests. Thirdly, comparing the One man consensus sample with the Control sample, a consistent result is that a higher proportion of all recommendation revisions are influential when there are many analysts covering a company instead of just one, although the difference is not immensely large. However, as noted in the previous chapters, the absolute average CARs are in some cases higher in the OMC sample than in the Control sample. An intuitive conclusion based on these results would be that the single analysts can less often induce a clearly visible market reaction than other analysts, but when they do, the market reaction might be more pronounced.

5.5 Thoughts on target prices and analysts' ability to predict the future price of the company stock with their recommendation

The analysts' forecast and analysis horizons about their covered companies vary from one brokerage to another. For instance, a common time window for setting a so-called target price, or a prediction of the fair value of one publicly traded common share of the company, is 12 months. Another often used time frame is 6 months, but when the time horizon is not explicitly mentioned, it is usually considered to be 12 months instead of 6. Some brokerages also demand that their analysts explicitly mention the time frame on which their analysis about a company is based on. Bradshaw et al. (2013) note that most of the academic analyst literature tends to focus on buy-sell recommendations and earnings forecasts rather than target prices. In my mind, a possible reason for this could be that despite the more quantifiable aim that the target price offers for a reader of the analyst's report, the target price implicitly contains the same message as the buy or sell recommendation, when it is compared to the current market price of the stock. It might be that recommendations offer the most salient advice for an investor. The message of a buy recommendation – that the price is going to be higher in one year than it is today – might have more relevance to an investor than knowing whether the price of a stock is expected to be exactly 10 or 12 dollars higher, for example.

Going back to the idea of an analyst setting a 12-month time frame for their analysis and presumably for recommendations leads us to examine the accuracy of analysts' predictions. A scrutiny of the 12-month stock returns after analyst recommendation changes reveals that the One man consensus analysts are, on average, roughly as likely to correctly guess the direction of the stock price as to fail guessing the direction. On upgrade side, roughly 51% of the recommendation revisions are to the same direction as the revision indicates, that is, the return after 12 months is positive. On downgrade side, the same respective percentage of correct predictions hovers around 54%. Looking at both upgrades and downgrades, altogether close to half or 49% of the stocks have experienced a positive 12-month period following either a positive or a negative revision by a One man consensus analyst.

However, when the upgrade and downgrade samples are filtered with taking into account only revisions that make the outstanding recommendations either positive or negative, the percentages change. For instance, a recommendation upgrade from strong sell to sell or hold would be omitted from upgrades following this principle, as the outstanding recommendation would not become positive. After filtering, the percentage of upgrades that predict the stock price correctly becomes only marginally higher, ending up close to 51%. On the downgrade side and after the same kind of filtering to the opposite direction, the proportion of correct predictions drops to 48%. Skeptically put, the data suggests that analysts can predict the track of stock price as accurately as tossing a coin would. Having said that, it is important to realize that analyst recommendation revisions are not meant to predict stock prices in the same way as target prices are.

5.6 Impact of the Regulation Fair Disclosure

The implementation of Regulation Fair Disclosure and its effects on analysts' actions and influence have been discussed in various academic papers. For instance, Cornett et al. (2007) find that following to its original purpose, Reg FD has been successful in curbing the unfair disclosure to selected few analysts. Sun (2009) notes that the number of analysts following a firm has decreased after Reg FD for selective-disclosure firms. Sun (2009) also goes as far as to argue that the whole information environment has deteriorated after Reg FD for selective-disclosure companies. On the other hand, Eng et al. (2014) argue that on aggregate, the Reg FD has reduced information asymmetry and improved price efficiency.

The effect on One man consensus analyst recommendation changes is examined also in this study. Firstly, cross-sectional cumulative abnormal returns in the OMC sample and the Control sample are compared based on the Regulation Fair Disclosure (*regfd*) variable. Surprisingly enough, it seems that after the implementation of Reg FD and the increased scrutiny on stock analysts, CARs have risen in the main sample of One man consensus upgrades, while the negative reactions have been more muted for downgrades post-Reg FD. In the OMC sample (-1,1) upgrades for example, the difference between average CARs pre- and post-Reg FD is more than 2 percentage points, while in downgrades, market price reactions were a little more than 0.5 percentage points less negative, on average and post-Reg FD. In regression tests, the finding is that on upgrade side, *regfd* variable receives statistically significant positive values in correlation with CARs. In other words, average positive abnormal return reaction has become even more positive post-Reg FD. In downgrades, *regfd* is altogether statistically less significant, yet positive, which implies that adopting the Reg FD guidelines has diminished stronger negative reactions after recommendation downgrades.

There might be several explanations for these results. For example, it could be possible that before Regulation Fair Disclosure, the primary recipients of private information from firm management have in some cases not been stock analysts, but instead some other private parties. This hypothesis suggests that after the Reg FD rule, analysts have actually been in a more equal position to gather and process information, in comparison to other investors participating in the market. One explanation could also be that investors trust Reg FD to be successful in its main mission, i.e. in curtailing the non-allowed interaction between company management and certain analysts. Hence especially for single analyst coverage, an upgrade post-Reg FD might be more trustworthy in the eyes of the investors and induce a stronger positive reaction than pre-Reg FD.

Be that as it may, findings in this study are in contradiction with the findings of Cornett et al. (2007), who note that in their sample, market price impacts have diminished after Reg FD. On the other hand, my results are in line with those of Loh & Stulz (2011), who note that in their sample there are significantly more influential recommendations after the year 2000 implementation of Reg FD. One possible explanation for the grown amount, offered by the latter authors, is that the overall quality of analysts' work has been improved after a closer regulatory monitoring of analysts' behavior. Yet, some studies argue that Reg FD should not be viewed as a major change: for example, Ferreira & Smith (2006) claim that based on their results, investors have been responding to analysts' recommendations in the same way post-Reg FD as pre-Reg FD, and that practitioners should not change the way they view the whole analyst recommendation process.

5.7 Testing for the robustness of the results

Ensuring robustness in my thesis primarily relies on the trustworthiness of the following key pillars. Firstly, assurance is needed that event dates for the recommendation changes are correct, and that the value of the recommendation change is of the correct sign and magnitude. Secondly, stock returns, benchmark index data and turnover data should be readily available and reliable, so that the correct cumulative abnormal returns and abnormal turnovers can be calculated. Thirdly, it must be confirmed that the methods measure the factors that they are intended to measure. The next few chapters explain how robustness of my findings is tested and confirmed.

5.7.1 Reliability of the data

First part of testing the robustness, i.e. making sure that recommendation changes are correct, is most likely the trickiest one as I am relying only on the IBES database in collecting the analysts' recorded recommendations. Fortunately, IBES is regarded as a fairly trustworthy source of information regarding stock analysts, and in any case, the most extensive and most utilized one. Despite the issues brought up by Ljungqvist et al. (2009) regarding the changes to the data on an annual basis, it can be argued that changes to the database are meant to further enhance the comparability of analyst recommendations through time. Furthermore, regarding the nature of IBES data as well as the data from other data sources such as CRSP and Compustat, it does help that the samples in this study consist of thousands of observations and thus, a small number of mistakes can persist without materially affecting the quality of the results.

Both CRSP and Compustat data are most often considered to be very reliable for practically all companies covered. Most issues with these, in the framework of this study, have to do with linking the analyst recommendation data from IBES to the stock market returns and trading volumes from CRSP. The linking is executed relying on the historical Committee on Uniform Securities Identification Procedures (Cusip) identifiers for companies. One should note that the Cusip ID is the main identifier code for neither IBES nor CRSP databases, and thus some problems with linkages are bound to exist especially with a large data set. Nevertheless, the Cusip linkage provides stock return and turnover matches for the great majority of analyst recommendation events. Compustat needs to be separately linked to IBES, again using the Cusip identifiers and entailing the same potential problems as with CRSP.

5.7.2 Altering the expected returns formula

It is important to realize that the robustness of my results has very much to do with the accuracy and representativeness of the methods utilized in this study. The magnitude of results might change even materially depending on the used event window, e.g. between 3, 5 or 10 days' event windows. Even more variance might be added by the method of calculating and cumulating abnormal returns and whether the CAR formula includes an equally-weighted benchmark index, value-weighted benchmark index, or some other benchmark model for calculating expected returns. A few examples of other benchmark models are the Capital Asset Pricing Model (CAPM) model (Sharpe, 1964) or the Daniel-Grinblatt-Titman-Wermers (DGTW) model (Daniel et al., 1997). Furthermore, tweaking the method for determining influential recommendation revisions apart from non-influential revisions could change the outcome for the influential revisions tests. However, as Table 7 illustrates for CAARs, none of the key implications are materially affected by utilizing different benchmark indexes. Other minor changes, such as changing the estimation window for calculating the Fama-French Three-Factor Model expected returns, neither seem to affect the signs or significance values of the results presented in previous chapters.

***Table** 7 Cumulative average abnormal returns calculated using different methods for defining the expected returns. The expected returns E(R) in standard CAR formula are as according to Equation (1). CRSP value-weighted refers to CRSP index value-weighted market returns, while CAPM refers to Capital Asset Pricing Model expected return, calculated as in Equation 7 on page 68.*

Sample	**Expected return calculated as in**	**Upgrade CAAR**		**Downgrade CAAR**	
		(-1,1)	**(-2,2)**	**(-1,1)**	**(-2,2)**
OMC	CRSP value-weighted	4.15 %	4.72 %	-2.63 %	-2.87 %
	CAPM	3.95 %	4.40 %	-2.76 %	-3.14 %
Control	CRSP value-weighted	3.01 %	2.96 %	-3.30 %	-3.43 %
	CAPM	3.00 %	2.94 %	-3.40 %	-3.58 %

Table 7 illustrates that changing the way in which expected returns are calculated to extract average CAR figures does not materially affect the arithmetic averages from the tests that use the Fama-French Three-Factor Model calculated expected returns (see Table 4 for reference). Furthermore, another confirmation for the robustness of the results is that the share of visibly influential recommendation, using daily CARs calculated with the benchmarks in Table 7, is in comparison very close to the share calculated with the Fama-French Three-Factor Model. The exact formula for calculating expected returns according to the CAPM is as follows:

$$E(R) = R_f + \alpha + \beta * (R_m - R_f) \tag{7}$$

Where R_f refers to a risk-free rate, R_m refers to the market portfolio return and α and β to the alpha and beta of the stock in question, respectively.

5.7.3 Limiting the main sample further

Selecting an appropriate sample for the purposes of this study has been motivated in Section 3, *Data*. Nonetheless, an argument could be made that the OMC sample of recommendation revisions should only include observations that have a counterpart in the Control sample, as this might alter the results. Consequently, robustness is tested by observing the CARs of a modified OMC2 sample. This modified sample only includes OMC revisions for companies that have also had other revisions in multi-analyst coverage situations, in other words, for companies that are included in the original Control sample. It turns out that limiting the main sample further does somewhat affect the CARs, albeit not in a way that would change the implications of the results. The CARs after upgrades for the OMC2 sample in (-1,1) and (-2,2) windows become 4.38% and 5.17% respectively, while for the original OMC sample the same figures are 4.08% and 4.53%, as illustrated in Table 5. In downgrades, CARs for OMC2 are -3.00% and -3.35% in (-1,1) and (-2,2), while original OMC sample CARs are -2.76% and -3.15%. These numbers suggest that limiting the original OMC sample further does not materially affect the key findings of this study.

Furthermore, regression tests are also performed for a limited sample, in which only OMC2 observations are taken into account. The regression tests follow the same logic and utilize the same control variables as in regressions B and C (Panel 1) in Table 6. In principle, the original *omc* dummy is replaced with an *omc2* dummy with no other changes to the variables. However, as some of the original observations with *omc* value 1 are no longer included, the total sample size for upgrades and downgrades combined becomes roughly 860 observations smaller. Nonetheless, using a dummy variable *omc2* instead of the original *omc* yields highly similar results than those presented in Table 6. Coefficients of *omc2* are to the same direction as those of the original *omc* dummy, and statistical significances of the coefficients are very similar. In fact, none of the previously statistically significant coefficients become insignificant with the limited OMC2 sample. The implications of the original regression tests also hold for the coefficients of the control variables in the OMC2 sample test.

5.7.4 Testing for the importance of individual sectors

A possibility is that issuing One man consensus recommendation revisions in some sectors would drive the importance of being the one analyst more than in other sectors. Consequently, all recommendations were divided into 11 sectors and one miscellaneous group, and average CARs were examined. Table 8 on the next page presents the average CARs for each sector in three different event windows, for both upgrades and downgrades. Moreover, robustness of the overall results is checked by assigning separate dummy variables for each sector to see whether any sector exhibits a statistically significant correlation with the magnitude of event CAR.

Regarding Table 8, one should note that as the sample of data is divided into as many sectors as here, the number of individual observations falling into each sector might become unevenly small, as is illustrated by the N column. This might explain why, for example, the OMC downgrades in energy sector appear to show positive CARs. Furthermore, as it is sometimes difficult to assign companies into some particular sector, results might look different if, for instance, the U.S. Standard Industrial Classification (SIC) system were used instead of the IBES sector classifications. Hence, too many conclusions should not be drawn based on the cumulative average abnormal returns of each sector alone. In addition, in regression analysis in which each sector is assigned its own dummy variable, none of the sectors exhibit statistically significant t-statistics in OLS regression tests. At this point, although the tests for sectors are not entirely conclusive, the evidence hints that One man consensus recommendation changes in some particular industries or sectors are not likely to be the drivers of the results in this thesis as a whole.

Table 8 *Cumulative average abnormal returns for One man consensus sample revisions and Control sample revisions in different sectors between years 1994 and 2014. Sectors are assigned for companies based on IBES sector classifications, as explained in detail in Section 4.*

	A. OMC sample upgrades				B. OMC sample downgrades			
Sector	**(-1,1)**	**(-2,2)**	**(-5,5)**	**N**	**(-1,1)**	**(-2,2)**	**(-5,5)**	**N**
Finance	2.30 %	2.72 %	2.56 %	281	-1.43 %	-1.91 %	-1.37 %	351
Health care	6.12 %	7.20 %	6.50 %	147	-4.29 %	-4.19 %	-5.11 %	204
Consumer non-durables	4.37 %	3.58 %	0.51 %	89	-3.58 %	-3.75 %	-4.49 %	106
Consumer services	5.58 %	5.60 %	6.47 %	170	-4.22 %	-4.39 %	-5.29 %	272
Consumer durables	4.98 %	4.52 %	3.45 %	57	-4.28 %	-4.74 %	-4.20 %	88
Energy	3.41 %	4.88 %	3.88 %	69	1.17 %	1.80 %	2.20 %	65
Transportation	7.18 %	7.10 %	3.98 %	21	-1.52 %	-1.51 %	-3.13 %	31
Technology	4.28 %	5.54 %	6.70 %	159	-3.10 %	-4.46 %	-6.58 %	262
Basic industries	4.22 %	5.27 %	4.97 %	100	-2.84 %	-3.26 %	-4.03 %	109
Capital goods	3.54 %	3.47 %	4.54 %	130	-1.98 %	-2.24 %	-2.53 %	168
Public utilities	1.83 %	1.34 %	2.21 %	28	-0.39 %	-0.05 %	0.07 %	48

	C. Control sample upgrades				D. Control sample downgrades			
Sector	**(-1,1)**	**(-2,2)**	**(-5,5)**	**N**	**(-1,1)**	**(-2,2)**	**(-5,5)**	**N**
Finance	2.16 %	2.37 %	2.10 %	907	-1.71 %	-1.86 %	-1.35 %	1165
Health care	3.52 %	3.67 %	3.04 %	585	-5.48 %	-5.78 %	-5.96 %	811
Consumer non-durables	3.78 %	3.56 %	4.12 %	296	-4.41 %	-4.43 %	-5.28 %	377
Consumer services	2.75 %	2.59 %	2.22 %	773	-3.31 %	-3.58 %	-4.15 %	975
Consumer durables	3.09 %	3.46 %	2.40 %	274	-2.42 %	-3.03 %	-3.30 %	392
Energy	2.79 %	2.43 %	1.99 %	174	-2.58 %	-2.06 %	-2.49 %	235
Transportation	4.95 %	4.69 %	3.31 %	74	-2.67 %	-3.21 %	-4.18 %	97
Technology	3.25 %	3.01 %	2.07 %	908	-4.77 %	-5.00 %	-5.69 %	1171
Basic industries	3.05 %	2.90 %	1.03 %	513	-2.85 %	-3.17 %	-3.61 %	632
Capital goods	3.18 %	3.12 %	2.70 %	619	-3.14 %	-3.18 %	-3.04 %	803
Public utilities	1.24 %	1.15 %	0.70 %	152	-1.99 %	-1.99 %	-1.60 %	178

6. Discussion of the results

This section adds to the existing literature by discussing the results of this study in the context of efficient markets and stock analysts as a part of them. Firstly, key findings of the empirical results are summed up. Secondly, a question is posed whether it is better for a company to have only one analyst covering them, rather than no analysts at all. Thirdly, the small proportion of visibly influential revisions is discussed. The subsequent part presents thoughts about analysts' prediction skills and optimistic bias. Finally, this section takes a stand on the hypotheses set in Section 1.

6.1 Aim of the study and key results

The aim of this study is not to prove either the importance or the futility of One man consensus analyst recommendation changes. Instead, this thesis attempts to observe and interpret the nature of market reactions that follow recommendation revisions of analysts, who have at some point been the only analysts covering a listed U.S. company. Based on the results of this thesis, it cannot be outright concluded that being the sole analyst following a listed American company would allow moving the markets in any way the analyst wanted, at any time. Taking into account the extensive academic stock analyst literature and its findings, a clear-cut result in favor of total single analyst control over the market reaction would have been surprising to say the least. Nonetheless, this study does find some evidence that market reactions are different when only one analyst is covering a company, in contrast to when more than one analysts form the coverage.

For one, the different market reactions to upgrades and downgrades prove some interesting insights. Based on the empirical tests, averages of cumulative abnormal returns after upgrades are higher when issued by a One man consensus analyst in the tested event windows. Moreover, regression tests do show a positive, statistically significant connection between the abnormal return based market reaction and issuing an upgrade as the only stock analyst. This finding holds when control variables are added and colliding company earnings announcement dates are taken into account. When it comes to downgrades, market reactions differ from what one might intuitively expect. For the very least, based on test results, an argument can be made that being the only analyst and issuing a downgrade does not induce a stronger negative price reaction on average as by analysts in other situations. In fact, some of the regression results hint, although not with remarkable statistical significance, that being the single analyst correlates negatively with the magnitude of negative price reactions. Put differently, issuing a downgrade as one analyst out of a larger coverage would on average induce a stronger price drop than when a One man consensus analyst issues a downgrade.

Beyond examining CARs and performing OLS regressions, this study searches for the proportion of recommendation revision events that induce a large enough price or trading volume reaction for any investors to notice them. To state the most apparent result, not many revisions seem to move the market in a visibly large way when measured with abnormal returns, single analyst or otherwise. Only around one in ten recommendations can be considered visibly influential by their price reaction beyond the everyday volatility, and according to this measure, many of the market reactions to analyst revisions could be thought as non-abnormal “noise”. The turnover-based influential test method suggests a larger percentage, up to around one in four recommendations in certain tests. Here one must remember that both the OMC sample and Control samples observations consists of relatively small companies, for which regular daily trading activity might remain very low for days or even weeks. To sum up, visibly influential recommendations seem to be few and far between. That is particularly the case for significant market reactions after positive recommendation changes towards the buy end of the spectrum.

6.2 Beyond coverage initiations, is it better to have a single analyst covering a company than to have no analysts at all?

Suppose a company CEO had such a strong relationship with the only analyst covering their company that they could always persuade the analyst to relay exactly the message the CEO wanted to send. Would the CEO be able to move the markets to his or her favor? Based on the results presented in this thesis, maybe. The findings of this study suggest that analysts who follow a company by themselves do have at least some say on the market perception of the company. The evidence implies that especially after upgrades, the investors are sometimes bound to take a cue from what the analyst has suggested with a recommendation upgrade.

From the stock analyst’s point of view, ending up in a situation where he or she is the only analyst following a listed company could be rather pleasing, even desirable for an analyst.

It is likely that in such a situation, communication between the firm top management and the analyst is quite frequent, and almost certainly more frequent than when an analyst shares the coverage with one or more other analysts. In a situation where the analyst and the management are in very good terms, the analyst holds something close to exclusivity to both directions: he or she has a direct contact to the company management and he or she might also become the main deliverer of information to the markets. Regardless of the added disclosure and fairness requirements of the regulations, the results of this study hint that it might be wise for the company to cherish its relationship with the one analyst they might have. At times there might even be benefits for the company management that they did not expect: a skilled analyst could consult the company management on investor sentiment to different kinds of announcements, when their advice is asked for.

As is known from existing literature, e.g. Mola et al. (2013), most often it is better for companies to have at least one analyst following them rather than not to have it, to the extent that it might even benefit the company to pay for research. In fact, in 2006 the SEC in the United States endorsed small and illiquid companies to pay for analyst research (SEC, 2006). In its recommendation SEC noted that the lack of relevant information for different investors can lead to higher financing costs and even less efficient markets altogether if trading volumes are unhealthily low. According to Billings et al. (2014), paying for at least one analyst to cover a company also appears as beneficial to the company as having an analyst follow the company by their own choice. Billings et al. (2014) show data in support of the hypothesis that having some analyst coverage, paid for or otherwise, improves the flow of information from companies to the buy-and-hold investors. The authors also note that paid for analyst coverage does not lack in quality in comparison to non-paid for research, at least in terms of bias, accuracy or the ability to distinguish favorable future performance. In light of the evidence in this thesis, more support is discovered on the idea that recommendations coming from a One man consensus analyst do provide valuable information for investors on average, as for both upgrades and downgrades, the market reaction is statistically significant in majority of the tests.

Despite evidence suggesting that One man consensus analysts are able to provide value for the company they are following and for investors alike, the covered company does probably not perceive as favorably an analyst who consistently makes poor recommendations and forecasts on the firm’s performance. In a sense, the company management has an incentive on helping the analyst make accurate predictions of the firm’s near future. Analyst incentives, including their employer’s incentives as well as personal career concerns, are discussed almost always on some level in analyst research. However, incentives for company management to feed certain kind of information to stock analysts often receive considerably less attention. After all, investors are likely to perceive information from company management and stock analysts differently: it is no secret that company management sometimes issue overly optimistic forecasts on their company's performance, whereas stock analysts could be perceived as a more independent and more reliable source of information. Knowing the status of stock analysts could in some cases incentivize the management to firstly build a good relationship with the only analyst following their company and secondly, to try to control the message of the analyst in some ways.

Could a single analyst exploit their status as the deliverer of company-specific information in a mischievous way? Perhaps, but in general, blatant misleading of the stock markets by equity analysts does not seem very likely. For example, Agrawal & Chen (2008) find no evidence of analysts being able to systematically mislead investors with overly optimistic recommendations. Another relevant issue is asking whether the company management could take advantage of the one analyst's status for dishonest purposes. As pointed out by Simon & Curtis (2011), it is not the mere financials and valuation models based on them that guide analysts in making recommendations but instead, a vaguer sentiment about a firm's growth opportunities also plays part in more or less all of the analyst recommendations. Appealing to the sentimental part of an analyst's judgment is what company management could try to capitalize on, if the management wanted to implement their own ideas to the analyst's mouth. However, if and when career concerns matter to the single analyst, it is probably not wise to try to feed misleading information to the investors.

6.3 Do only a minority of revisions truly add value to the financial markets?

Regardless of whether analysts are thought to make a real impact in adding relevant information to the marketplace or not, many firms and other actors in the markets certainly seem to appreciate analysts' presence. For example, the aforementioned SEC encouraging small companies to pay for analyst coverage (SEC, 2006) and thus enhancing liquidity is a strong endorsement in itself. In addition to many studies confirming the value of increased analyst coverage (see e.g. Irvine, 2003; Billings et al., 2012; Mola et al., 2013), Bushee & Miller (2012) show that many companies proactively engage in increased Investors Relations (IR) activities to gain visibility among different kinds of investors and other actors in the market, such as stock analysts.

Despite the evidence presented in the regression tests, supporting the hypotheses that One man consensus analysts might have more say to the market perception about a company than do analysts sharing the consensus with others, the proportion of visibly influential recommendations appears to remain relatively low. Aggressive price reactions beyond the regular volatility do not appear to be caused by single analyst recommendation revisions more often than by other analysts. Changing the respective event time windows or basis for expected return in calculating CARs do not materially affect these findings. Indeed, all in all less than one fifth of both OMC sample and Control sample revisions induce a price reaction that is to the same direction as the revision suggests, and can be considered visibly influential beyond regular volatility of abnormal daily returns.

When measured with the abnormal turnover method instead of CARs, turnover measuring the percentage of traded amount of all outstanding shares, the percentages of influential recommendations are altogether higher. Evidently, the abnormal turnover method is not as straightforward as the CAR method. For instance, after an upgrade the turnover might seem influentially high, when in reality the stock price is falling after intense selling of the stock in the market. In this scenario the influential CAR method would determine the revision as non-influential, whereas the abnormal turnover method would deem the trading reaction influential, as one kind of false positive. Another explanation might simply lie in the turnover patterns of the companies in the sample. Most of the companies are small on the listed American companies' scale, and so infrequently traded that even a moderate rise in daily turnover might make an analyst recommendation seem influential. On the other hand, one could argue that even a small increase in daily turnover does increase market activity and thus, an analyst could be accredited for improving the informational environment, even if by a small degree.

An important factor to keep in mind is that, as noted by Asquith et al. (2005), an analyst can contribute to the financial markets beyond the actual recommendations of buying and selling of stocks, giving estimates about company earnings and other financials and setting target prices. Asquith et al. (2005) find that the textual content of an analyst's report does actually provide value for investors, especially when the analyst is issuing a downgrade. For some consumers of the analyst reports, the analysis might even have educational value, not only on the company but also on the industry or even on the whole economy. Institutional investors are known to be the primary consumers of stock analyst research reports. Among the countless opportunities of investing in stocks, reports with concise and apt analysis by stock analysts might stand out as almost an educational material about the company or the industry it represents. The same principle applies to the individual investors, who can at least partly enjoy the benefits of analyst coverage through the analysts' comments and interviews in the media.

Regarding the visibly influential recommendation revisions method, it could be argued that the whole course of measuring the percentage of influential recommendations is not the best way of deciding what recommendation is truly "influential", or valuable to the financial markets in the first place. One could argue that an analyst inducing even a small market reaction by their recommendation revision, measured by e.g. the abnormal return, is an influential contribution in itself. Even if the market reaction was not large enough to exceed the fairly artificially set threshold to determine the visibly influential status of an event, the investors might be better off having acquired the new information.

6.4 Analysts' prediction skills and tendency to retain non-negative recommendations

The previous Section 5 discussed the analyst recommendation changes' seemingly weak predictive power. Based on percentages of correct guesses with recommendation revisions, analysts correctly forecast stock returns half of the time – more or less as often as one would by randomly betting on a stock to rise or fall. Based on these results, One man consensus analysts do not appear as incomparable stock pickers, at least in the 12 months following the recommendation change. However, one should not jump to conclusions. It could be argued that the analyst offers the greatest contribution to the information environment surrounding a company right at the time of their recommendation change, and this would also be where market reacts the most. Moreover, Bradshaw et al. (2013) find that analysts' target price forecasting abilities are not particularly good in general, as a mere 38% of target price forecasts are met or beaten by the respective stock price at the end of a 12-month forecasting period. Thus, it cannot be directly concluded that One man consensus analysts should be unambiguously better or worse at predicting the stock price with their recommendation revisions than other analysts.

The data represents a common theme discussed in analyst literature, a bias towards the positive end of the recommendation scale. Especially in cases where the consensus is formed by only one analyst, it seems that the threshold to downgrade a stock to a "sell" or "strong sell" is even higher than expected. Here, both career concerns and the incentives of the brokerage might come to play. For example, Michaely & Womack (1999) straightforwardly state that recommendations by underwriter brokerage analysts show evidence of bias and that the market does not recognize the full extent of this bias. On the contrary, Agrawal & Chen (2008) assert that while some investors might act naively, on average the market is not fooled by optimism. It is undoubtedly a big leap for any analyst to issue negative statements about a company. Even more pronouncedly, being the only analyst and downgrading a stock to the sell category could even be disastrous to the stock price of a small and illiquid company. Womack (1996) notes that a wrongful sell call by an analyst might seriously hurt the existing relationship between company management and the analyst, making acquiring information and potential investment banking contracts more difficult to proceed with. Furthermore, investors are sure to remember the one analyst that they counted on and sold their stock, if afterwards the price went through the roof. Then again, this discontent is likely to also apply to upgrades when the stock price drops rapidly.

6.5 Discussion on hypotheses

Two hypotheses were presented in the introductory Section 1 of this paper. Hypothesis 1 set the expectation that average market reactions to One man consensus recommendation upgrades and downgrades would be statistically significant and different from 0. The empirical findings in Section 5 provide support for this first hypothesis. Evidence for the second hypothesis is however not as clear-cut. In Hypothesis 2, an assumption was made that the recommendation revisions issued by single analysts, i.e. analysts in a One man consensus situation, would be statistically differently received by investors than other revisions made for the same companies in multi-analyst consensus situations. As far as the results go, empirical evidence does provide support for Hypothesis 2, and especially so in the case of recommendation upgrades. The average market reaction, measured by abnormal returns, to OMC upgrades is not only statistically significantly positive and different from 0, but also statistically different from the Control sample upgrades. In downgrades, the average market reaction is negative and significantly different from zero, but it is much closer to the average of the Control sample downgrades. Regression analysis confirms the core results from abnormal returns, as the *omc* variable receives positive and statistically significant values for both upgrades and downgrades.

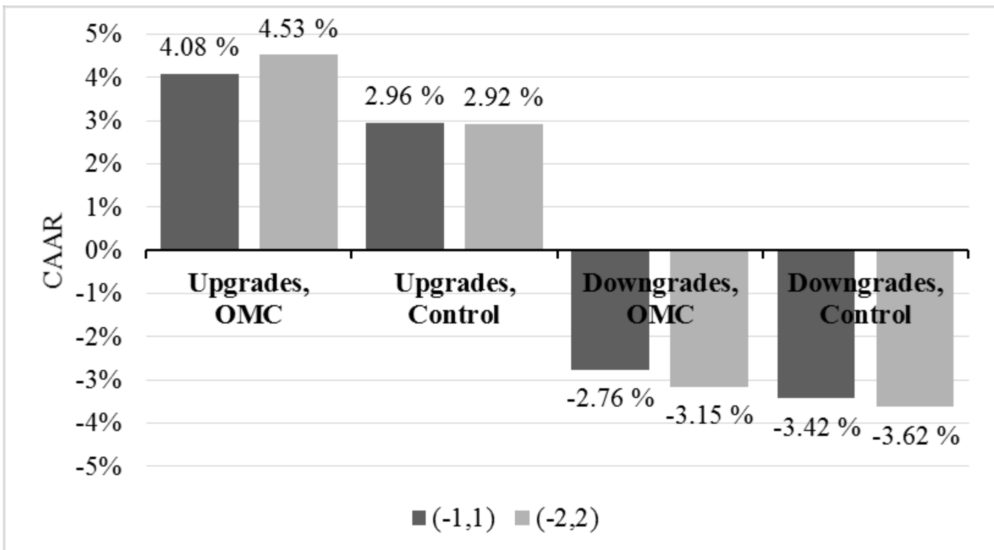
An important notion to keep in mind is that the discussion in this study has by many parts revolved around different averages. Implication here is that not every recommendation change is received with a major price swing or a trading volume spike. In reality, it is almost the opposite, which the tests on the proportion of visibly influential recommendation revisions display. However, the results do add material to the most profound questions in academic analyst literature. Can someone, in some way, become a stock analyst who can always transmit valued information to the financial markets and make the markets always react to this information? That question is still left to be solved in a definitive way. However, it seems that only a few analysts have so far been able to reach such level, even when they alone populate the whole analyst consensus for a company.

Next, the final Section 7, *Conclusion* sums up the key findings and implications of this thesis and suggests directions for further research on the subject.

7. Conclusion

This paper studies the information environment surrounding U.S. companies covered by exactly one stock analyst, through stock price and trading volume market reactions to recommendation revisions. A specific focus is on the non-reiteration recommendation revisions issued by analysts, i.e. upgrades and downgrades, as these signals are often quoted to transmit more information to the financial markets than mere recommendation levels or earnings forecasts without an accompanying recommendation revision (see e.g. Jegadeesh & Kim, 2006; Jegadeesh & Kim, 2010). A key finding is that on average, investors seem to respond to recommendation upgrades by single analysts more eagerly than to those by other analysts. On the other hand, recommendation downgrades by single analysts do not appear to stir as strong corresponding negative reaction as when coming from other analysts. To support this finding and to recapitulate the results found in Section 5, a compilation of key cumulative average abnormal returns is presented in Figure 5. This finding has some interesting implications for the curious, yet not entirely uncommon situations where analyst consensus for a listed U.S. company consists of exactly one single stock analyst. Furthermore, I discover that a noticeable positive bias is found in single analyst recommendations distribution, which in turn causes that many of the downgrades in the sample do not actually end up in "sell" or "strong sell" recommendation levels, but rather in "hold".

Figure 5 *Compilation of cumulative average abnormal returns of the One man consensus sample and the Control sample. Darker bars represent results in event window (-1,1), while light-colored bars represent results in event window (-2,2).*



Using a data set of all single analyst recommendation changes in the U.S. listed stocks over a time period of more than 20 years, cleared from revisions colliding with quarterly earnings announcement dates, the results in this study maintain that investors seem especially prone to reacting to recommendation upgrades of these analysts. Conversely, downgrades of the single analysts do not seem to create market hysteria. In fact, the market reacts to these downgrades more mutedly than when other analysts are present. Some drift after both upgrades and downgrades is also noticeable, possibly partly due to the findings of Gleason & Lee (2003) who note that price adjustment after analyst forecast revisions is slower for companies with smaller analyst coverage.

In a recent study, Li & You (2015) show three ways for stock analysts to create value: improving the fundamental performance of a company, reducing information asymmetry and increasing the investor recognition of the company. Despite the three possible channels, Li & You (2015) state that out of these options, only changes in investor recognition has robust explanatory power over initiation and termination period returns. Those results might very well hold on their own, but based on the findings in this study, it would be difficult to blatantly deny that a One man consensus situation did not have any impact on the information environment, due to the large average CARs and statistical significance of the *omc* variable.

This study presents some implications for research on analyst influence, as well as for the market perception of smaller, illiquid companies that do have the one analyst follower. The results imply that it does make sense for the one analyst to be aware of the "market pulse", in other words, it seems beneficial for the analyst to recognize what kind of market reactions can be plausibly expected after sending a signal to the markets. In addition to recommendation upgrades and downgrades, an EPS forecast revision or even a mere news comment might contain a lot of weight for the investors when coming from the only analyst. One could go as far as to say that a certain amount of cautiousness is called for from the analyst's end and also, from the brokerage firm's point of view. Secondly, it is probably still better to have analyst coverage than not to have any. Mola et al. (2013) note that, for instance, firms that lose all analyst coverage see their liquidity and institutional presence weakening and face a risk of having to delist. Based on the strong reactions found in this thesis that the recommendation revisions often induce, it seems that having even the one analyst covering the company might considerably improve the informational environment that the company acts in.

This thesis focuses on stock returns and trading volume based turnover as measures for market reaction to stock analyst recommendations. Other possible measures to examine market interest in a stock and liquidity could be to see if bid-ask spreads or institutional holdings vary after the single analyst recommendation revisions. These measures would perhaps not have been applicable to the short event periods applied in this thesis. Nevertheless, future research based on these indicators could go deeper into the issue. Another possible direction for research on single analyst consensus situations has to do with herding. It would be interesting to observe the second analyst that joins a One man consensus, and whether this later-joining analyst has any tendency to join the view of the previous sole analyst, or a tendency to set themselves clearly apart with a differing recommendation. If there did exist evidence for either of these behaviors, it could be further argued that the former One man consensus analyst has had an influence – if not on the market itself through prices and trading volumes, then on the behavior of other equity analysts. Yet, the findings of this study do answer one pressing question from Section 1: there is indeed a point in having a One man consensus analyst coverage for a company, not least from a market efficiency point of view.

Appendix A

Recommendation revision amounts in the United States stock markets, classified by the year of recommendation revision observation, and by the sample as defined in Section 3.

Year	OMC	Control	Pooled
1994	116	229	345
1995	219	433	652
1996	243	552	795
1997	263	588	851
1998	218	711	929
1999	181	609	790
2000	149	555	704
2001	108	462	570
2002	150	729	879
2003	210	547	757
2004	182	620	802
2005	153	703	856
2006	163	734	897
2007	138	777	915
2008	100	912	1012
2009	87	633	720
2010	82	512	594
2011	77	560	637
2012	57	518	575
2013	43	390	433
2014	29	338	367
Total	2 968	12 112	15 080

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