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DOES THE VALUE OF EQUITY RESEARCH DIFFER BETWEEN INDEPENDENT AND BROKERAGE ANALYSTS?

Sell-side equity research and stock returns in Finland

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ABSTRACT

Alatalo, Joona: Does the value of equity research differ between independent and brokerage analysts? Sell-side equity research and stock returns in Finland
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The purpose of this research is to examine whether investors are better served by following the recommendations of independent analysts compared to brokerage analysts during 2010–2018 in the Finnish stock market. This study contributes to the existing literature by examining the recommendation performance of purely independent equity research, which most past studies have been unable accomplish due to small sample sizes. Furthermore, the performance is compared to traditional brokerage research to examine whether the value of equity research differs between independent and brokerage analysts.

The data for this study extends from the year independent research begun in the Finnish market from February 2010 through May 2018. The data consists of stock recommendations for stock listed companies in OMX Helsinki. The final sample consists of 3438 recommendations issued by 24 research firms. The hypotheses are tested by examining the differences in average recommendation levels, announcement period returns, and long-term portfolio returns. Univariate analyses utilize two-sample *t*-test, two-sample Kolmogorov-Smirnov test and chi-squared test, whereas multivariate analyses are conducted with ordinary least squares (OLS) regression analysis.

The results show that brokerage analysts are relatively more optimistic than independent analysts. However, the market initially values the recommendation revisions from both analyst types equally. In contrast, independent analysts clearly outperform in the long-term by generating gross abnormal returns of approximately 10 % annualized, whereas brokerage analysts do not generate abnormal returns. The abnormal returns are robust to controlling for transaction costs and less frequent portfolio rebalancing. Moreover, the outperformance is more pronounced for stocks with greater information asymmetry. In addition, signs of the market learning to predict on-going research processes is documented, however, the tests do not control for other events taking place before the issuance of recommendations.

Keywords: independent equity research, analysts, conflict of interest, stock recommendations, abnormal returns

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Tämän tutkielman tarkoituksena on selvittää, onko sijoittajien hyödyllisempää seurata riippumattomien analyytikoiden suosituksia kuin pankkianalyytikoiden vuosina 2010–2018 Suomen osakemarkkinoilla. Tämä tutkimus edistää aiempaa kirjallisuutta tutkimalla riippumattoman osaketutkimuksen suositusmenestystä, jota aiempi kirjallisuus ei ole täysin pystynyt mittaamaan pienten otoskokojen takia. Tämän lisäksi suositusmenestystä verrataan perinteisiin pankkitoimijoihin, minkä avulla selvitetään, onko osaketutkimuksen arvossa eroja riippumattomien ja pankkianalyytikoiden välillä.

Tutkimusaineisto on kerätty vuodesta, jolloin riippumaton osaketutkimus alkoi Suomen osakemarkkinoilla alkaen helmikuusta 2010 ja päättyen toukokuuhun 2018. Aineisto koostuu osakesuosituksista listatuille yhtiöille OMX Helsinki markkinapaikalla. Lopullinen aineisto koostuu 3438 suosituksesta 24 osaketutkimuksen tarjoajalta. Hypoteesien testauksessa tutkitaan eroja suositustasoissa, julkaisuperiodin tuotoissa sekä pitkän aikavälin portfoliotuotoissa. Yhden muuttujan testeissä sovelletaan kahden otoksen *t*-testiä, kahden otoksen Kolmogorov-Smirnov -testiä sekä Khiin neliö -testiä ja monimuuttuja analyyseissä pienimmän neliösumman (OLS) regressioanalyysiä.

Tutkimustulokset osoittavat, että perinteiset pankkianalyytikot ovat suhteellisesti optimistisempia kuin riippumattomat analyytikot. Markkinat kuitenkin näkevät suositusmuutokset lyhyellä aikavälillä samanarvoisina. Sitä vastoin riippumattomat analyytikot menestyvät merkittävästi paremmin pitkällä aikavälillä tuottaen noin 10 % vuosittaista epänormaalia tuottoa, kun taas pankkianalyytikot eivät tuota epänormaaleja tuottoja. Epänormaalit tuotot ovat vankkoja ottaen huomioon transaktiokustannukset ja portfolioiden harvemman tasapainottamisen. Arvonluonnin osoitetaan myös painottuvan osakkeisiin, joilla on suurempi informaation epäsymmetria. Lisäksi tulokset osoittavat viitteitä siitä, että markkinat oppivat ennustamaan analyytikoiden tutkimusprosessia, vaikkakin testit eivät kontrolloi muiden tapahtumien mahdollista vaikutusta ennen suositusten julkaisemista.

Avainsanat: riippumaton osaketutkimus, analyytikot, intressiristiriita, osakesuositukset, epänormaalit tuotot

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1 INTRODUCTION

1.1 Background

Academic research on the capital markets acknowledges information as the main driver for changes in asset prices (Fama, 1970). The role of equity research is of interest to academics because of analysts' role as informational intermediaries in the markets. The value of equity research stems from the fact that there are costs to searching information (Admati & Pfleiderer, 1988). Investors can choose between incurring cognitive and opportunity costs of time, if they search information themselves, or monetary costs, if they outsource the information discovery to a third party, in this instance to equity analysts (Smith, Venkatraman & Dholakia, 1999). Consistent with this, various studies have documented value in analyst research as measured by the subsequent abnormal returns to analyst recommendations or research reports (Elton, Gruber & Grossman, 1986; Stickel, 1995; Womack, 1996). However, most studies do not account for transaction costs, which are found to have a diminishing effect on the abnormal returns (Barber et al., 2001).

The field of equity research became of increasing interest to practitioners and academics alike after the stock market bubble of 2000, and even more after the financial crisis of 2007. Many of the studies on equity research have questioned the impartiality of the research provided to investors when it is apparent that the goals of investors and analysts might not be aligned due to conflicts of interest. These conflicts have been acknowledged to stem from either investment banking services (Lin & McNichols, 1998; Michaely & Womack, 1999) or trading incentives (Hayes, 1998; Irvine, 2004; Jackson, 2005). An opposing hypothesis is also discussed: the superior information hypothesis states that other relationships with the research subject increase the information available to the analyst, which in turn leads to more accurate research. Various studies in the field have addressed this problem, but no clear consensus exists. This is at least partially explained by the three different definitions existing for independent research: (1) having no affiliation to the research subject (e.g. Michaely & Womack, 1999; Bradley, Jordan & Ritter, 2008), (2) having no investment banking business (e.g. Barber, Lehavy & Trueman, 2007;

Agrawal & Chen, 2008), or (3) having no other business apart from research services, in other words, purely independent (e.g. Cowen, Groysberg & Healy, 2007; Casey, 2013).

Although there is an extensive literature concerning equity research and its potential conflicts of interest, the area of purely independent research is still a scarcely studied area due to the small number of such research firms. Furthermore, recent regulatory changes, for example the MiFID II, increase the pressure on research departments to increase their independence by further separating the research departments from other parts of the firms. Consequently, the research departments need to come up with new business models to sustain their services. This change has been criticized by investment professionals (e.g. Financial Times, 2018), and said to lead to decreases in the amount and value of equity research. These concerns bring up the question whether investors are better served by research from purely independent research firms as opposed to traditional brokerage firms that are subject to potential conflicts of interest.

This paper extends the existing literature by investigating whether purely independent research provides more value to investors compared to traditional brokerage firm research. Furthermore, the effects of potential conflicts of interest in traditional brokerage research firms are analyzed and compared to independent research firms. Examination is done using data from the Finnish stock market from a recent time period from February 2010 through May 2018. Unlike some earlier studies that have had problems with having too few inputs from purely independent firms, the sample of this research does not share this problem, and there is a sufficient amount of independent recommendations to conduct reliable analyses and comparisons.

1.2 Research objective and questions

The purpose of this research is to investigate whether there is a difference in the value of equity research between purely independent and traditional brokerage analysts. The objective of the research comprises three research questions. The first question considers whether there is evidence of conflicts of interest existing for brokerage analysts due to the firms' other relationships with the research subjects. The second question aims to answer whether these potential conflicts of interest affect the value of equity research, as measured by the subsequent stock returns to recommendation revisions. To conclude, the third question is concerned with whether the characteristics of covered stocks differs between the analyst types, in other words, if value created by different analyst types stems from different type of stocks. Based on the review of prior literature and theory four hypotheses are formed. The relationship between the research questions and hypotheses is illustrated in Figure 1 below. The hypotheses of this study are as follows:

H1: *Brokerage analysts issue more optimistic recommendations and target prices than independent analysts.*

H2: *Independent analyst recommendations generate greater returns than brokerage analyst recommendations.*

H3: *Greater information asymmetry between investors and company management induces greater market reactions to recommendation revisions.*

H4: *The market learns to predict on-going brokerage research processes to a greater extent than independent research processes.*

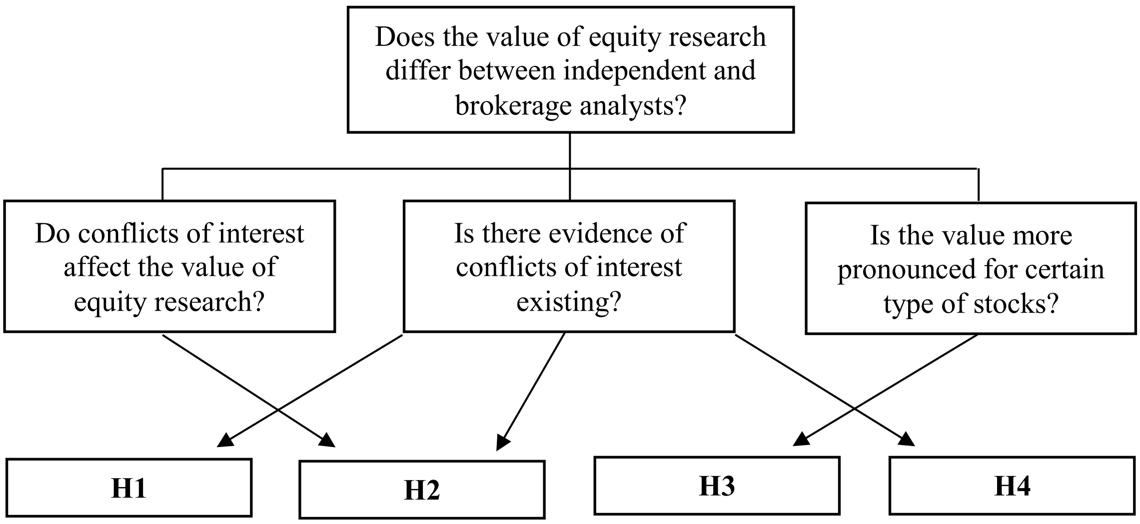

Figure 1. *Relationship between research questions and hypotheses*

1.3 Methodology and data

The approach to this research is quantitative. The research comprises three sets of tests to test the hypotheses. To measure the differences in relative optimism between independent analysts and brokerage and investment banks analysts, the average recommendations and target prices are compared, and the significance of possible differences is analyzed with a two-sample t-test.

Furthermore, to measure the information value of analyst research, two methods are applied. First, the market reaction around the announcement of a stock recommendations is analyzed by utilizing an event study method adopted from Bradley, Jordan and Ritter (2003; 2008). These announcement period returns are compared between the two analyst groups by utilizing two-sample t-test, two-sample Kolmogorov-Smirnov test and chi-squared test. In addition, regression analysis is utilized to control for target firm size, low analyst coverage and absolute recommendation levels.

Second, the long-term value of analyst research is analyzed by adopting a portfolio method from Barber, Lehavy and Trueman (2007). Portfolios are constructed by assuming a buy-and-hold investment strategy to analyst recommendations that are divided into buy and sell portfolios based on the level of the recommendation. Portfolios are rebalanced on a daily basis and reiterations of recommendations are excluded from the portfolios. Subsequently, daily returns are compounded to monthly returns, and abnormal returns are estimated with a regression analysis by using three different risk models: CAPM, 3-factor model and 4-factor model.

The research is conducted with a dataset of stock recommendations and target prices from the Finnish stock market from February 2010 through May 2018. Daily recommendations, target prices and stock price data are collected from the Thomson Reuters I/B/E/S database. The data is partly predisposed to a survivorship bias since recommendations for companies that an analyst firm has terminated coverage of are absent from the data. Furthermore, some research firms record their inputs anonymously due to which they are excluded from the data. The research data contains approximately 60 % of all the recommendations recorded in the database.

1.4 Structure of the research

The research is divided into five sections. In the following section the most important theories and prior literature around the subject are reviewed. The section starts by describing the role analysts have in the capital markets as information intermediaries and the value their research has for market participants. Then the quality of research is defined as the function of analysts' competence and independence and the most important factors documented to affect these are reviewed. Furthermore, the theories behind analyst conflicts of interest are presented and studies on independent equity research are reviewed in more detail. In addition, the regulatory environment concerning equity analysts is discussed. To finish, the second section summarizes the observations from prior literature and presents the hypotheses for this research.

Section three begins with describing the data sample collected for the analysis. Subsequently, the research design is presented along with the descriptions of the relevant models and statistical methods that are utilized. Moving over to section four, the results of the empirical analysis is presented consisting of descriptive statistics and analyses of recommendations, target prices, announcement period returns, and long-term portfolio returns. The section ends with a set of robustness checks to further validate the results.

The last section presents the most important findings of the study along with a discussion of their meaning and importance. The main contributions of the study are also presented. Moreover, the section contains evaluation of the reliability and limitations of the study before concluding with a discussion of some of the key themes emerging from the study that could be of interest for future research.

2 LITERATURE REVIEW AND HYPOTHESES

2.1 Role of equity research and investment value of analyst disclosures

2.1.1 Analysts role

In the capital markets new information is considered as the main driver for changes in asset prices (Fama, 1970). Although it is not clear whether all information is always and instantly incorporated into asset prices (see, e.g., Ball, 1978; Grossman & Stiglitz, 1980; Merton, 1980; Shleifer & Vishny, 1997; Barber et al., 2001), new information is still the factor on which changes in asset prices are based on. In order for investors to acquire new information, they will incur different kind of costs depending on how the information is acquired. If investor chooses to search, process and validate information himself, he incurs cognitive costs for the efforts he must engage in and also opportunity costs of time for the other activities he needs to abandon, whereas if the investor chooses to rely on a third party and buys information from them, he incurs monetary costs (Smith, Venkatraman & Dholakia, 1999). Consistently, Admati and Pfleiderer (1988) identify four information-related commodities in the capital markets: newsletters, security analysis, fund management and investment advisory services. In the case of equity research services are generally provided in the former two categories, especially in security analysis.

One of the objectives of equity research is to mitigate possible information asymmetries between company management and investors, which enables efficient allocation of resources, capital market development, increased market liquidity, decreased cost of capital, lower return volatility and higher analyst forecast accuracy (Kothari, Li & Short, 2009). Furthermore, analyst coverage helps to increase the recognition of stocks and the fundamental performance of companies (Li & Yue, 2015). In other words, analysts contribute to the available information in the markets and thus increase the market's efficiency (Lo, 2012) and reduce information asymmetry (D'Mello & Ferris, 2000).

Ramnath, Rock and Shane (2008) present a model of analysts reporting environment, which describes the most important inputs and outputs of analysts work, as well as key factors affecting their work. In the model, analysts collect information from five sources: (1) company earnings, (2) other information from SEC filings, (3) industry information, (4) macro-economic information, and (5) management communication and other information. Analysts then process and interpret the information to produce (1) descriptions of company prospects, (2) earnings forecasts, (3) price forecasts, and (4) recommendations, which combined ultimately lead to publishing a research report. (Ramnath, Rock & Shane, 2008.) The model provides insight into analysts' role in the capital markets, as well as to the nature of their work which can be summarized into two steps: (1) search and collect information from relevant available sources and (2) analyze, validate and interpret the available information.

Furthermore, Brown et al. (2015) find that when producing their outputs, analysts consider their private communication with company management even more useful than recent public disclosures by the company (see also Soltes, 2014). Even though companies are forbidden to disclose any material information in private discussions, communication with management provides analysts additional context to interpret publicly released information (Soltes, 2014). Moreover, the benefit goes both ways as private communication with analysts helps the companies itself prepare for public releases, for example, conference calls (Brown et al., 2018). In addition, analysts work as intermediaries in private conversations as they provide private management access to their institutional investor clients (Soltes, 2014; Brown et al., 2015).

In addition to working as intermediaries, analysts have an impact on other areas as well. Chen, Harford and Lin (2015) show that analysts have a monitoring role in corporate governance of companies. They find that less analyst coverage is associated with lower shareholder value, higher excess compensation of the CEO, higher probability of value-destroying acquisitions and higher probability of earnings management activities. Negative effects are also documented. He and Tian (2013) find that analyst coverage exerts pressure on company management to meet short-term targets, which hinders the company's performance in long-term innovation projects. In contrast, Guo, Pérez-Castrillo and Toldrà-Simats (2018) find that even though analyst pressure leads to decreases in internal research and development costs, it also leads to increased amount of venture capital investments and acquisition of other innovative firms, which in turn lead to more breakthrough innovations. In sum, these studies provide evidence of analysts monitoring role and its importance in decreasing agency costs between company management and owners.

2.1.2 Investment value of analyst coverage

As previously discussed, analysts' main role as intermediaries is to both provide and interpret information for investors (Schipper, 1991) which means that there are also two ways an analyst can provide value to investors: discover new information or interpret existing public information. Asquith, Mikhail and Au (2005) find that approximately half of analyst reports contain new information to the market. Furthermore, they find that the market tends to react to also those reports without new information, which is evidence that analysts merely interpreting information from other sources is valuable to investors (Asquith, Mikhail & Au, 2005). Moreover, Frankel, Kothari and Weber (2006) find that on average analyst reports are informative to the market. They also find that the ability to supply new information is a critical factor for an analyst when intending to follow a company. In essence, analysts become more informative when investors can derive more value from their reports.

Some slightly contradictory evidence is presented by Kothari, Li and Short (2009) who find that even though the market reacts to analyst reports, a heavy discount is applied, suggesting that the market either questions analysts' credibility or that the information provided is not valuable. Furthermore, Li and You (2015) find that analysts mainly create value by increasing the recognition of the stock and not by reducing information asymmetry, although their study is limited to coverage initiations and terminations and does not include on-going coverage. Difference of these results could stem from the fact that the recognition factor plays an important role when initiating the coverage of a stock, but the situation changes for on-going coverage and the information factor takes over.

Analyst reports are largely based on quantifiable measures, such as financial data, and hence the most important outputs are usually quantifiable also. Consistent with this Asquith, Mikhail and Au (2005) document significant market reactions to earnings forecast, recommendation and price target revisions, which all provide valuable information independently and in aggregate. However, qualitative components of the reports (analyst argumentation) are also found to provide valuable information (Asquith, Mikhail & Au, 2005). Furthermore, negative news is found to be more significant and the market generally applies a discount on positive news (Asquith, Mikhail & Au, 2005; Kothari, Li & Short, 2009).

Earnings forecasts

As analysts collect and interpret company specific and macroeconomic data, one of their most followed outputs is the prediction of future performance of the company, specifically the future earnings of the company. Earnings forecasts helps the investors to see how the business of the company is developing and they are also useful for the most common company valuation formulas. The value of analysts' earnings forecasts has been covered in a vast number of studies (Lys & Sohn, 1990; Abarbanell, 1991; Stickel, 1995; Francis & Soffer, 1997; Izkovic & Jegadeesh, 2004; Ciccone, 2005; Asquith, Mikhail & Au, 2005; Clement, Hales & Xue, 2011).

Lys and Sohn (1990) show that earnings forecasts revisions are informative to the market despite there being prior forecasts by other analysts, and that the forecasts explain roughly two thirds of the stock's performance prior to the forecast announcement. Furthermore, Clement, Hales and Xue (2011) show that the presence of other analyst forecasts allows the analyst to extract information from the other forecasts and issue relatively more accurate forecasts himself. Consistent with Lys and Sohn (1990), Abarbanell (1991) documents that analysts do not fully incorporate prior stock price development in their forecasts and discusses two possible explanations: (1) analyst inefficiency in interpreting publicly observable signals or (2) analysts having incentives to provide new forecasts only after collecting new private information independent of public price changes. The underlying assumption in these explanations is that the prior stock price performance is a reliable measure of future earnings, which means that stock prices always incorporate all available information. However, contradicting evidence on stock prices incorporating all available information has also been documented (see, e.g., Ball, 1978; Grossman & Stiglitz, 1980; Merton, 1987; Shleifer & Vishny, 1997; Barber et al., 2001).

Consistent with prior literature, Izkovic and Jegadeesh (2004) find that analyst earnings forecasts are informative, although their findings suggest that the value is greater when the forecasts are based on independently collected information rather than public information (e.g. company announcements). Moreover, Ciccone (2005) shows that the informativeness of analyst forecasts has increased over the years, and that greater value is provided when forecasting loss firm earnings rather than profit firm, because loss earnings seem to be more difficult to predict. Collectively these findings indicate that analysts in general have developed their expertise in forecasting and most value is provided when analysts seek for new information, especially on loss firms.

Earnings forecasts are not subordinate to recommendations or target prices nor vice versa as they all provide information independently and in aggregate (Asquith, Mikhail & Au, 2005). In fact, Francis and Soffer (1997) find that when a favorable recommendation is issued, investors pay increasingly more attention to earnings forecasts, which strengthen the already positive signal from the recommendation (see also Stickel, 1995). This finding suggests that investors tread with caution when it comes to favorable stock recommendations and make use of all the information before making any decisions based on the recommendation.

Stock recommendations and price targets

Stock recommendations are a clear signal for investors on which stocks analysts see the most potential in. Recommendations convey a clear course of action, whereas earnings forecasts and price targets are number estimates, and the interpretation whether they are potential or not is up to the user of the information (Elton, Gruber & Grossman, 1986). Nevertheless, all are informative and valuable to investors (Asquith, Mikhail & Au, 2005). Several studies have investigated the value of stock recommendations (Elton, Gruber & Grossman, 1986; Stickel, 1995; Womack, 1996; Francis & Soffer, 1997; Barber et al., 2001; Jegadeesh et al., 2004; Asquith, Mikhail & Au, 2005; Green, 2006; Jegadeesh & Kim, 2006; Barber, Lehavy & Trueman, 2010; Baker & Dumont, 2014; Altınkılıç, Hansen & Ye, 2016).

Elton, Gruber and Grossman (1986) are one of the first ones to study the value of analyst recommendations. They show that analyst recommendations earn excess returns up to three months after the recommendation is issued. Moreover, no differences in the performance between different analyst firms is identified. Stickel (1995) finds that analyst recommendations appear to have permanent informational effects, although the effect is small and other factors also seem to influence the subsequent abnormal returns. In contrast to Elton, Gruber and Grossman (1986), Stickel (1995) documents differences between analyst firms: recommendations by All-American analysts and analysts in larger firms have greater impact on stock prices, although this effect appears to be only temporary. Womack (1996) finds strong evidence that analyst recommendations influence stock prices and that the effect is not limited to the event period but instead a considerable post-recommendation drift is observed. Consistent with Stickel (1995), the effect appears to be significantly larger for smaller stocks (Womack, 1996). This finding indicates that there are fewer alternative information sources available for small stocks. Further analysis by Francis and Soffer (1997) shows that the informativeness of analyst recommendations stems from the revision of recommendation rather than from the absolute level of recommendation. However, a more recent study by Barber, Lehavy and Trueman (2010) evidences the opposite that both recommendation revisions and levels have value.

Extending on the characteristics of analyst recommendations, Jegadeesh et al. (2004) find that analysts tend to prefer growth and glamour stocks. Positive correlation with momentum indicators and negative correlation with contrarian indicators are documented. Furthermore, Jegadeesh et al. (2004) show that firms favored by analysts tend to outperform unfavored firms for which the researchers present two alternative explanations: (1) recommendations incorporate qualitative information about the firms that quantitative measures cannot control for, or (2) recommendation changes and subsequent marketing of these stocks itself causes the subsequent price drift.

Barber et al. (2001) test for the value of analyst recommendations in practice by forming two investment portfolios consisting of the most and least favorable consensus rating stocks. They find that the most (least) favorable consensus portfolio produces significant positive (negative) abnormal returns, evidencing that analyst recommendations have value. However, after controlling for transaction costs they find no statistically significant abnormal returns for either strategy. Moreover, Barber et al. (2001) argue that even though the average investor cannot constantly exploit these strategies due to transaction costs, those investors who are already determined to buy or sell a stock can because they will incur transaction costs nevertheless. Similar tests and findings of analyst recommendations having predictive power are reported in Green (2006), Jegadeesh and Kim (2006) and Barber, Lehavy and Trueman (2010). Furthermore, Jordan, Liu and Wu (2012) find that institutional investors follow the opinions of to their own analysts, which further strengthens the evidence of the value of analyst recommendations.

Some contradictory evidence is also documented. Baker and Dumont (2014) find an inconsistency by showing that analysts' hold recommendations consistently outperform buy recommendations, therefore suggesting that analyst recommendations do not have value and instead can actually be misleading. In a recent study, Altınkılıç, Hansen and Ye (2016) find that analyst recommendations are not informative anymore, and they argue that it is due to the increase of algorithmic trading which more efficiently corrects the pricing of assets. In other words, they posit that the average investor cannot reliably benefit from analyst recommendations anymore because algorithms instantly arbitrage these opportunities away.

In addition to recommendations and earnings forecasts, analysts issue target prices for the stocks they cover. Asquith, Mikhail and Au (2005) find that even if there already exists a recommendation, or earnings forecast, price targets still contain valuable information to the markets. Moreover, price target revision of an equal percentage to earnings forecast revision is actually found to exert larger stock price reactions.

2.2 Research quality and conflicts of interest

Even though some recent studies (e.g. Baker & Dumont, 2014; Altınkılıç, Hansen & Ye, 2016) have found some contradicting evidence, the overall consensus expects that equity research does have investment value as analysts search and process information on behalf of those investors utilizing the research. The value proposition lies in analysts' capability of discovering and sharing valuable insights into the target companies. However, the feasibility of the information is dependent on the analysts' priorities being aligned with the investors. Therefore, any conflicts of interest pose a threat for the quality and value of the information in practice.

In defining the quality of equity research, a viable concept from a related field of study is utilized. In audit literature, DeAngelo (1981) and Watts and Zimmerman (1981) posit that audit quality is dependent on two factors: auditor's independence and competence. DeAngelo (1981) argues that the value of audit is dependent on auditor discovering possible errors and subsequently disclosing the discovered errors. Similarly, Watts and Zimmerman (1981) present this paradigm of audit quality as a probability formula, where the probability of auditor reporting a breach is dependent on the probability of auditor actually discovering a breach and on the probability of the auditor then reporting the breach honestly. In other words, the analogy is that even if the auditor is independent from the audit subject, poor competence can still decrease the quality of the audit and, vice versa, high level of dependency to the audit subject can offset even a good level of competence.

The analogy is the same for the quality of equity research – the same two components together compose valuable equity research. The concept is not totally new for the field of equity research studies, although it has not been expressed as explicitly as in audit literature. Prior research (e.g. Lin & McNichols, 1998; Bradley, Jordan & Ritter, 2008; Kolasinski & Kothari, 2008) have measured analysts' independence by analyzing different type of research firms' average recommendations. Furthermore, analysts' competence has been measured by examining the short or long-term performance of their recommendations or target price estimates (e.g. Michaely & Womack, 1999; Barber, Lehavy & Trueman, 2007; Cliff, 2007) and the accuracy of their earnings forecasts (e.g. Cowen, Groysberg & Healy, 2007; Kolasinski & Kothari, 2008). Performance measures contain reinforcing information about analyst independence since for a conflicted analyst it is expected that their performance is inferior compared to non-conflicted analysts'. In conclusion, the audit quality concept works as a good framework for measuring equity research quality and the approach is applied in this study as the definition for analyst independence and the value of their research.

Figure 2 below illustrates the relation of these two factors. Shortfall in the independence factor increases the probability that a conflict of interest exists as denoted by the grey area. In this case the theoretical value of equity research is mitigated by the possible conflicts of interest. Furthermore, a shortfall in either factor is prone to decrease the value of the research and, vice versa, the value increases when either factor increases, in essence, when moving towards the top right corner in Figure 2. The primary objective in this study is to measure research firms' performance in relation to their independence to examine whether analysts have been able to provide value to investors with good quality research or not, and whether analyst independence has had a significant effect in the value provided. Independence factor is measured by examining recommendation and target price averages. Moreover, analysts' recommendation performance in both short and long-term is measured, which provides evidence on analysts' competence, and also strengthening evidence on their independence.

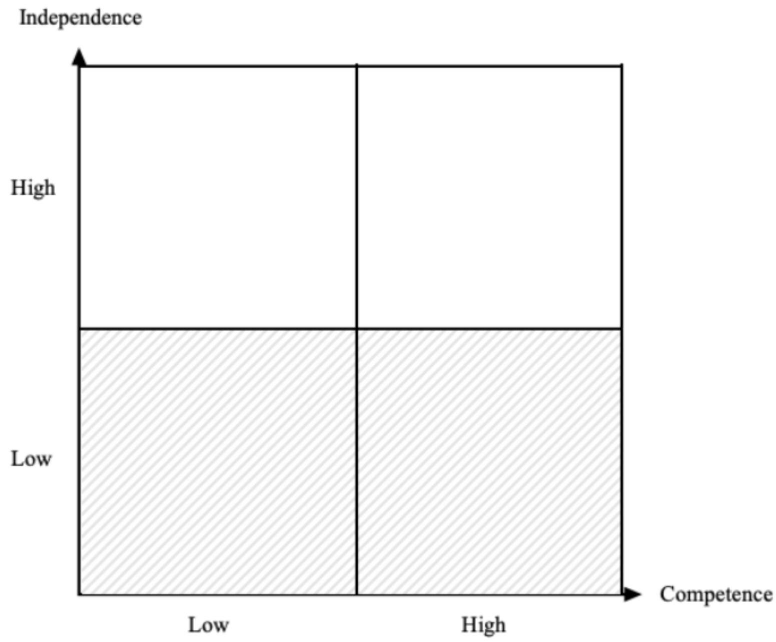

Figure 2. *Research quality framework*

In analyzing the value of equity research, especially from a retail investor's perspective, a third variable in addition to competence and independence must also be considered. As new information is the primary driver for changes in asset prices, new information including analyst research has the greatest value potential at the time of releasing the information after which it starts fading. This means that if the market learns of the new information before a public release, the value at the time of the public release decreases. In the case of equity research *analyst tipping* or *information leaking* has been suggested to happen when analyst firms have strong relationships with either large institutional traders (Irvine, Lipson, Puckett, 2007), short sellers (Christophe, Ferri & Hsieh, 2010) or options traders (Lung & Xu, 2014; Lin & Lu, 2015).

However, another alternative is that the market learns of the research process itself, in essence, the market learns when a research process in on-going and begins to predict its outcome. This could happen for a few reasons: (1) most analyst outputs are often disclosed immediately after a public release by the company (Soltes, 2014), (2) analysts often engage in private communication with company management during the process of writing a research report (Soltes, 2014; Brown et al., 2015), and (3) companies itself actively engage with the analysts to influence their reports (Brown et al., 2018). In conclusion, even though if the upcoming recommendation revision is fairly disclosed, the market (or some market participants) might learn of the on-going research process in advance and learning of the research process could then help the market predict the outcome of the upcoming revision.

2.2.1 Competence and behavioral biases

Competence

Systematic differences in analyst forecast accuracy are not generally found in early studies on analysts' performance (see a list of studies in Clement, 1999, p. 286). However, more recent studies have identified some systematic differences (Stickel, 1992; Sinha, Brown & Das, 1997; Mikhail, Walther & Willis, 1997, 2004; Clement, 1999; Mozes, 2003; Barber et al., 2006; Clement, Hales & Xue, 2011; Hilary & Hsu, 2013; Bradley, Gokkaya & Liu, 2016).

Stickel (1992) finds that the *Institutional Investor*'s list of *All-American Research Team*[1] analysts forecast earnings more accurately than other investors. Furthermore, All-Americans have a greater impact on stock prices, and a positive relation between analyst reputation and performance is found as well as with analyst pay and performance. In another study, Sinha, Brown & Das (1997) show that analysts with superior ex-ante performance remain superior ex-post the inspection period, suggesting that some analysts are able to consistently outperform other analysts. Similar findings are presented in Mikhail, Walther and Willis (1997; 2004). Clement (1999) builds on these papers and finds that analysts' experience and employer size increase the analysts' forecast accuracy and the number of firms and industries followed decreases it.

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[1] The Institutional Investor is an international publisher of premium journalism, newsletters and research in the field of finance. The All-American Research Team is an annual list of the best financial analysts in the US market as ranked by the Institutional Investor.

In contrast, Jacob, Lys and Neale (1999) find the opposite that analysts generally do not learn-by-doing, suggesting that experience is not related to forecast accuracy. They discuss that possible reason for this is because Mikhail, Walther and Willis (2004) include only analysts who survive for long periods, which means that underperforming analysts who have been replaced are not included in the sample, and because Clement (1999) does not control for all other analyst characteristics. In a more recent study Bradley, Gokkaya and Liu (2016) show that analysts' industry experience prior to working in equity research is positively related to forecast accuracy and to market reactions to forecast revisions.

Mozes (2003) takes an alternative approach and studies the speed at which analysts react to new public information by revising their forecasts and finds that forecast immediacy is negatively related to forecast accuracy. Mozes (2003) challenges the thinking of superior and inferior analysts with an alternative argument of two types of analysts: (1) analysts who emphasize usefulness (as measured by forecast immediacy) over forecast accuracy, in other words, provide analyses to the market quickly after new public information, and (2) analysts who emphasize forecast accuracy over usefulness, in other words, spend more time analyzing the new information. Moreover, Clement, Hales and Xue (2011) document that one source of analyst expertise is interpreting and supplementing information from other analysts to issue relatively more accurate forecasts than their peers, which is consistent with the forecast immediacy hypothesis of slower analysts being more accurate.

In conclusion, there may exist consistent differences between analysts' competence and emphasis, and investors ought to make sure to account for these in their decision making. Consistent analysts add more value (Hilary & Hsu, 2013) and it should be in investors' interest to look for these analysts. In addition, Barber et al. (2006) find that recommendation upgrades (downgrades) from analyst firms that issue the smallest percentage of buy recommendations significantly outperform (underperform) other analyst firms, evidencing that more conservative research firms provide more value with their recommendations.

Behavioral biases

Analysts face several behavioral biases which affect their ability to act rationally and produce value to investors. In certain situations analysts have been found to overreact (De

Bondt & Thaler, 1990) and, on the other hand, underreact (Abarbanell & Bernard, 1992). More specifically analysts tend to underreact to negative information and overreact to positive (Easterwood & Nutt, 1999). Furthermore, analysts have been documented to herd with other analysts when issuing either earnings forecasts (Trueman, 1994; Clement & Tse, 2005) or recommendations (Welch, 2000; Jegadeesh & Kim, 2010; Xue, 2017). For earnings forecasting, Clarke & Subramanian (2006) have document a U-shaped relation between analysts' employment risk and forecast boldness, which shows that analysts with very high or low employment risk are more likely to issue bold forecasts. In addition, Hilary and Hsu (2013) find that analysts consistently bias their forecasts downwards in order to be more consistent.

On a more practical level, Hirshleifer et al. (2019) document that analysts grow weary during the day and encounter decision fatigue, resulting in forecast accuracy declining over the course of the day. In addition, even weather conditions are documented to affect analyst activities. Presence of bad weather conditions at the time of an earnings announcement induces slower or lower probability of analyst responding to the announcement compared to analysts who experience pleasant weather conditions (Dehaan, Madsen & Piotroski, 2017). Taken together these behavioral biases evidence that analysts are "*decidedly human*" (De Bondt & Thaler, 1990, p. 57), and therefore irrational behavior can, and should, be expected from time to time.

2.2.2 Independence and conflicts of interest

In order for analyst research to be of high quality and valuable to investors the analyst must be independent, in essence, no conflicts should affect the analyst's view. Concerns of analyst conflicts voiced by the financial press (see, e.g., Lin & McNichols, 1998) led to various studies into brokerage[2] analysts' possible conflicts of interest. A conflict of interest as defined by Mehran and Stulz (2007, p. 268) is "-- *a situation in which a party to a transaction can potentially gain by taking actions that adversely affect its counter-*

[2] The term "*brokerage*" refers to all firms engaging in any sort of brokering activities, for example, investment banking or stock brokering.

party". In equity research the situation exists whenever an analyst is able to gain something by reporting biased research. Conflicts of interest in equity research have been documented to stem from either investment banking services or trading incentives (e.g. Lin & McNichols, 1998; Irvine, 2004; Brown et al., 2018).

Investment banking business

Investment banks provide services to other companies when they are faced with more complex financial transactions, for example, raising new capital, sale of securities, or mergers and acquisitions. A plethora of studies have examined if investment banking services induce conflicts of interest for the research analysts employed by the banks (Dugar & Nathan, 1995; Lin & McNichols, 1998; Carleton, Chen & Steiner, 1998; Michaely & Womack, 1999; Boni & Womack, 2002; Hong & Kubik, 2003; O'Brien, McNichols & Lin, 2005; Ljungqvist, Marston and Wilhelm, 2006; Barber, Lehavy & Trueman, 2007; Cliff, 2007; Chan, Karceski and Lakonishok, 2007; Ljunqvist et al., 2007; Agrawal & Chen, 2008; Corwin, Larocque & Stegemoller, 2017).

Dugar and Nathan (1995) find that investment banking ("IB") analysts are more optimistic than other analysts, although the subsequent stock returns do not differ between the groups. Similar findings are presented in Lin and McNichols (1998), who find that IB analysts issue on average more optimistic recommendations. Furthermore, no differences are identified in either earnings forecasts or post-recommendation returns. Consistently, Carleton, Chen and Steiner (1998) find that IB analysts issue more optimistic recommendations. However, in contrast to earlier studies their study also documents inferior performance by IB analyst recommendations compared to other analysts. Inferior performance by IB analyst recommendations is also documented by Barber, Lehavy and Trueman (2007), Cliff (2007) and Agrawal and Chen (2008). The inferior long-term performance indicates that IB analysts are not better stock pickers than independent even though they are found to be more optimistic.

Similarly, Michaely and Womack (1999) evidence that IB relationships result in biased recommendations and that their performance is inferior compared to other analysts. They discuss three possible explanations for this bias. The first explanation states that IB analysts could face a cognitive bias in that they genuinely believe that their IB clients are better firms than other firms they do not engage in business with. On the other hand, the second explanation states that the favorable recommendations itself cause the client firms to choose the investment bank over others (selection bias), resulting in the association between optimistic views and IB relationships. Furthermore, the third explanation is the intentional conflict of interest hypothesis that investment bankers pressure their analysts to issue more optimistic views to enhance client relationships.

Boni and Womack (2002) surveyed a group of buy-side investment professionals on analyst conflicts of interest. The survey shows that majority of the professionals believe that analysts buy recommendations rarely have value. In addition, when asked about analysts' motivation majority believes that analysts are mostly motivated by attracting and retaining IB clients and increasing IB sales. The finding suggests that these professionals not only acknowledge IB analysts' conflicts of interest, but also believe that they are a motivation for their actions. Moreover, over half of the professionals believe that independent analyst research is more valuable, and that the demand for independent research will increase in the future.

Further evidence on analysts' motivation to report biased recommendations is presented by Hong and Kubik (2003), who find that investment banks do not solely care for analysts' accuracy but also reward for their optimism. Similarly, Brown et al. (2018) find that analyst compensation is often dependent on generating other business for the firm. Other effects in addition to optimistic recommendations are also reported. O'Brien McNichols and Lakonishok (2005) find that investment banking relationships increase analysts' reluctance to disclose negative news. Furthermore, Chan, Karceski and Lakonishok (2007) show that analysts use earnings forecasts to win investment banking business, as well as that conflicts of interest are more pronounced for growth stocks and during economic boom periods.

Some contradictory findings also exist. Ljungqvist, Marston and Wilhelm (2006) do not find that greater optimism leads to more IB business, but instead has the opposite effect. The research argues this is due to a reputational effect, meaning that banks and analysts have an incentive to build their reputation, which prevents them from reporting biased research. Nevertheless, analysts with higher IB business potential still issued more optimistic recommendations. Similarly, Ljungqvist et al. (2007) find that even though IB analysts tend to be more optimistic, this effect is at least partially moderated by the reputational effect and the presence of institutional investors. However, for firms with large retail investor ownership and relationships with smaller investment banks, the conflicts still exist.

In conclusion, the evidence on investment banking relationships and analyst research is mostly in favor of the conflicts of interest hypothesis. Even after the regulators stepped in and sanctioned the ten largest investment banks in the US, conflicts of interest have prevailed in all other investment banks, which is evidence of the deep-reaching roots of the phenomenon (Corwin, Larocque & Stegemoller, 2017). Furthermore, the effects of these conflicts are more pronounced for retail investors who are unable to account for the possible biases unlike institutional investors who properly discount the opinions of conflicted analysts (Malmendier & Shanthikumar, 2007).

Trading incentives

Even if the research firm does not have investment banking business, it might still offer stock brokering services. Previous studies have acknowledged these services as another source for conflicts of interest (Hayes, 1998; Irvine, 2004; Jackson; 2005; Brown et al., 2018). Hayes (1998) develops a model where she examines the effect of trading incentives on analysts' production of information. She finds that these incentives lead analysts to produce information that maximizes the generated trading volume. Moreover, trading commissions can be maximized by issuing biased earnings forecasts, and the marginal return for the analyst is better when covering stocks that perform well, in other words positive views lead to higher trading volumes than pessimistic.

Irvine (2004) tests Hayes' model in practice and finds that, in contrast to Hayes' prediction, biasing earnings forecasts does not generate more trading. On the other hand, he does find that issuing buy recommendations generates significantly more trading commissions than other recommendations. Consistent with Hayes (1998), Irvine (2004) concludes that trading incentives can be a significant factor for inducing biased research. Consistent with Irvine (2004), Jackson (2005) finds that analyst optimism leads to increased trading volumes for the analyst's firm. However, he also finds that in doing so the analyst incurs a loss in reputation. Jackson (2005) argues that the only thing preventing an analyst from submitting to the trading incentives is increasing the importance of the reputational effect, which could be achieved by making analyst forecasting track record more transparent to investors. In doing so the expected reputational loss increases and the analyst will not give in to the incentives in the fear of major reputational loss. Furthermore, Brown et al. (2018) find that analyst compensation is often linked to their ability to generate trading commissions.

2.3 Regulatory environment concerning equity analysts

After the stock market bubble in the early 2000s, regulators begun to take more interest in the financial market regulations, and even more after the financial crisis in 2007. New regulations were introduced to prevent similar kind of market crashes from happening again. The most relevant regulatory changes concerning equity analysts have been the *Regulation Fair Disclosure* ("Reg FD") in 2000, *NASD rule 2711* and *NYSE rule 472* in 2002[3], the *Global Research Analyst Settlement* in 2003 and the *Markets in Financial Instruments Directive II* ("MiFID II") that was first introduced in 2007 and later amended in 2018. The former three are regulations introduced in the US and the latter one in the EU, although all of them have induced similar regulatory developments in other countries as well. In practice, the general principles and regulations that analysts follow are similar in all (western) markets, and new developments in one market are apt to cause similar changes in other markets as well.

Reg FD was a new rule enforced by the *Securities and Exchange Commission* ("SEC") in the US in 2000. The primary focus of the rule was to prevent companies from disclosing material information to selected parties, for example, in conference calls, meetings with institutional investors, or meetings with analysts, by making it mandatory to issue all material information fairly to all market participants at the same time (SEC, 2000). This change decreased the informational advantage analysts had over common investors since analysts were not be able to receive material information in private discussions anymore. This in turn should decrease the value of analyst research, since analysts have less new information to offer, or at least shift the focus of the value creation to interpreting

[3] These rules have been since superseded by *FINRA rule 2241* in 2015 which is primarily similar to the original rules.

public information rather than discovering new information. However, even after the Reg FD, analysts still engage in private communications with company management and analysts consider these discussions to provide more value than public disclosures alone (Soltes, 2014; Brown et al., 2015). On the other hand, Arand, Kerl and Walter (2015) show that the level of investor protection by regulators is positively associated with the informativeness of analyst research. This is consistent with Madura and Premti (2014) who find that the Reg FD decreased the magnitude of information leakages prior to recommendation revisions, and therefore common investors are able to derive more value from analyst research.

NASD rule 2711 and NYSE rule 472 directly governed the relationships between investment banking and research departments. The purpose of the rules was to prevent investment bankers from pressuring equity analysts to issue more favorable recommendations. The rules stated, for example, that a research analyst cannot be subject to supervision or control by an investment banker and that non-research personnel are not allowed to review or influence the formulation of research reports and recommendations (FINRA, 2019). Furthermore, following a series of investigations into investment bank conflicts of interest, a collection of regulators settled with ten of the largest investment banks in the US. The settlement which amounted up to 1,4 billion dollars in monetary terms also consisted of structural reforms for the organizations to further separate equity research and investment banking departments within the firms (SEC, 2003).

Following these regulatory reforms, Kadan et al. (2009) show that the regulations were successful at decreasing conflicts of interest and relative optimism by investment bank analysts. However, at the same time the overall informativeness of analyst recommendations has declined (Kadan et al., 2009). Similarly, Clarke et al. (2011) document that after the regulations affiliated analysts have issued fewer optimistic recommendations and that the overall market reaction to analyst recommendations has declined. Furthermore, Guan, Lu and Wong (2012) show that even though optimism has decreased, the accuracy of investment bank forecasts has also declined, and the performance of their recommendations has remained unchanged. This finding suggests that investors do not gain benefits even though investment bank optimism has decreased. In contrast, Lee, Strong and Zhu (2014) evidence that analyst forecast accuracy increased post-regulation, although consistent with Kadan et al. (2009) they find that the overall informativeness and stock price drift after recommendations has declined. In a more recent study, Corwin, Larocque and Stegemoller (2017) evidence that even though recommendation optimism decreased after the settlement in the sanctioned banks, it did not reduce optimism in non-sanctioned banks.

The introduction of MiFID II legislation in 2018 further separates the investment banking and equity research departments within banks. The revised legislation prevents banks from covering their research costs with other services of the firm, for example, with trading commissions or IB advisory revenues. Alternatively, the research services must be priced separately. This change has led to drops in the amount of research analysts, which some investment professionals believe weakens the quality of the research and decreases the available information in the markets, especially of small and medium sized companies (Financial Times, 2018; Bloomberg, 2019). This creates a pressure for brokerage firms to come up with new business models to sustain their research services or to refrain from offering research services altogether. However, it is still unknown what kind of effect MiFID II will have in overall once the industry conforms with the new regulation.

In conclusion, the regulatory changes have had positive effects on the capital markets as conflicts of interest have reduced and information has become more fairly available to all market participants. However, the effect on research analysts has not been as favorable. Recently many research firms have been cutting their research staff and decreasing stock coverage whilst having to look into developing new business models to sustain the services, for example, by charging the target companies for their coverage.

2.4 Independent equity research

There exist multiple definitions for independent equity firms which complicates the comparability of the results between the studies. Some researchers define independent research through affiliation to the research subject (e.g. Michaely & Womack, 1999), which means that if the firm providing the research does not have any other business with the research subject, the research firm is considered independent. However, this definition does not consider the characteristics of the research firms nor the possibility that recommendations are inflated to win more future business. Another group of researchers acknowledge these concerns to some extent and define independents as firms that do not engage in investment banking activities (e.g. Barber, Lehavy & Trueman, 2007). Problem with this definition is that firms with stock brokering services are categorized as independent research firms even though there is a possibility that trading incentives (e.g. Irvine, 2004) could still create a conflict of interest for the analysts. The last definition considers all these problems and defines (pure) independents as those firms that do not engage in any other business other than equity research (e.g. Cowen, Groysberg & Healy, 2006).

2.4.1 Division based on affiliation

Majority of prior literature have adopted the first definition for independent research (Lin & McNichols, 1998; Michaely & Womack, 1999; Bradley, Jordan & Ritter, 2003; Cliff, 2007; Bradley, Jordan & Ritter, 2008; Kolasinski & Kothari, 2008; Kadan et al., 2009). Lin and McNichols (1998) are amongst the first ones to compare the recommendation performance of affiliated and unaffiliated analysts. Scope of their study is twofold: to examine if affiliated analysts issue more favorable forecasts and recommendations, and how investors respond to recommendations by these two groups of analysts. Lin and McNichols (1998) show that even though affiliated analysts issue significantly more favorable recommendations, the post-announcement stock price performances do not generally differ between affiliated and unaffiliated. The research concludes that even though affiliated analysts are evidenced to issue more optimistic recommendations, their post-announcement returns underperform only in the announcement period, but no differences are identified in long-term returns.

Michaely and Womack (1999) also acknowledge that investment bank analysts might face an implicit pressure to issue positive recommendations for investment banking client in order to maintain good client relationships. The researchers are especially concerned about the trend of using analysts as part of the marketing and due diligence processes in investment banking assignments. By examining the immediate and long-run excess price reaction to affiliated and unaffiliated buy recommendations, the research documents a clear pattern between the two groups: unaffiliated analysts' recommendations outperform those of affiliated analysts in all examined time periods (Michaely & Womack, 1999). The effect is both economically and statistically significant after controlling for IPO and industry characteristics, which is in contrast to Lin and McNichols (1998) who do not find differences in post-announcement returns.

Bradley, Jordan & Ritter (2003) study IPO returns following the end of the quiet period and apply a number of tests to analyze the impact of analyst recommendations. First, they find that affiliated analysts issue more optimistic recommendations on average, although the difference to unaffiliated is very small and therefore not so aggravating evidence of conflicts of interest. Second, by studying the cumulative market adjusted returns ("CMAR") for a 5-day window around the end of the quiet period the research shows that firms with coverage initiated yield a significant abnormal return of 4.1 percent. However, the research does not find support to the conflict of interest hypothesis since after controlling for the number of coverage initiations, affiliation to the research subject does not have a significant effect on the return (Bradley, Jordan & Ritter, 2003). It is important to note that the study examines only initiations of analyst coverage and does not analyze the long-term returns nor the effect of subsequent analyst recommendation revisions.

Cliff (2007) argues that the existing literature on independent equity research has three important issues in measuring abnormal returns: (1) biased definition of the independent benchmark group, (2) use of arbitrary time periods, and (3) use of misspecified models. Due to these inadequacies, he augments the existing literature with a comprehensive comparison of independent and affiliated recommendations which accounts for these methodological problems. Cliff (2007) applies a portfolio method for detecting differences between recommendations by independent and affiliated analysts and analyzes the long-term performance of analyst recommendations. To account for possible use of a misspecified model, the abnormal returns are estimated by using CAPM, Fama and French's (1993) three-factor model and Carhart's (1997) four-factor model.

Cliff (2007) finds that even though the raw performance of the independent buy portfolio indicates that it outperforms the affiliated portfolio, the portfolio does not generate statistically significant abnormal returns. In overall, the performance of the independent portfolios is neutral. On the other hand, affiliated buy portfolio generates significant negative abnormal returns which supports the conflict of interest hypothesis. The affiliated outperform the independent only with the sell portfolio as the affiliated generate significant negative abnormal returns compared to the neutral performance of the independent portfolio. In conclusion, the findings are consistent with the conflict of interest hypothesis, documenting excessive optimism by the affiliated analysts buy recommendations. Even though the study supports the conflict of interest hypothesis, Cliff (2007) points out that by focusing solely on the period after the regulatory changes the affiliated recommendations seem to become more credible.

Bradley, Jordan and Ritter (2008) study analysts' behavior following IPOs and provide insight into analysts' conflict of interest. Consistent with Lin and McNichols (1998) and Bradley, Jordan and Ritter (2003), the study documents that affiliated analysts issue more optimistic recommendations than unaffiliated, although the difference is small. Furthermore, the research shows that the market reaction is greater for unaffiliated analysts during IPO quiet period and, conversely, greater for affiliated analysts in post-quiet period. The research argues that the market predicts initiations from affiliated analysts following an IPO and hence returns are low during IPO quiet period, but after the quiet period the recommendations become more unpredictable. Bradley, Jordan and Ritter (2008) conclude that after controlling for timing factors the market does not appear to discount recommendations from affiliated analysts. The finding is consistent with Lin and McNichols (1998) but in contrast to the findings of a similar study by Michaely and Womack (1999).

In relation to the finding, Bradley, Jordan and Ritter (2008) argue that unaffiliated analysts may actually be just as conflicted as affiliated analysts since it is in their interest to catch the attention of the company management to win more future business. On the other hand, they also point out that market practices have changed due to regulatory changes, and therefore the incentive to issue optimistic recommendations in hopes of winning future business has since decreased. Nevertheless, the argument is one of the first ones to address that the division based on only current affiliation to the research subject may not be a valid definition for independent research.

Kolasinski and Kothari (2008) study analysts' conflict of interest by comparing affiliated and unaffiliated analysts' behavior around merger and acquisition ("M&A") deals. First, the research finds that analysts affiliated with the acquirer company more likely to upgrade the acquirer's recommendation within 90 days of an all-cash M&A deal. Second, affiliation to the target company is found to increase the odds that an analyst will upgrade the acquirer's recommendation after the exchange ratio is fixed in a stock swap deal. Third, the research finds no evidence that affiliation around M&A deals affects analysts long or short-term growth or earnings forecasts. Kolasinski and Kothari (2008) conclude that M&A relationships have a significant impact on analysts' objectivity in regard to recommendations and hence supports the conflict of interest hypothesis.

Kadan et al. (2009) study the effect of the global research analyst settlement and related regulatory changes on analysts' recommendations and conflicts of interest. The research examines stock recommendations and subsequent stock price reactions before and after the regulatory changes. First, the research finds that recommendations have become more balanced as analysts issue less optimistic recommendations than before. Furthermore, optimistic recommendations have become more informative, whereas pessimistic ratings have become less informative. Second, the research shows that after the regulative changes, affiliated analysts are no longer more likely to issue more optimistic ratings than unaffiliated, although affiliated are still less likely to issue pessimistic ratings. In sum, Kadan et al. (2009) document weak evidence of potential conflicts of interest still existing. In addition, the research shows that following the regulative changes the overall informativeness of analyst recommendations has declined.

2.4.2 Division based on investment banking services

The second definition for independent research became more popular after researchers acknowledged that conflicts may originate from the pressure of trying to win future investment banking business for the bank (Bradley, Jordan & Ritter, 2008). More recent studies into analyst conflicts of interest have adopted this definition (Barber, Lehavy & Trueman, 2007; Agrawal & Chen, 2008; Clarke et al., 2011).

Barber, Lehavy and Trueman (2007) find that buy recommendations by independent research firms result in statistically significant higher abnormal returns compared to recommendations by investment banks. On the other hand, hold and sell recommendations by independent research firms underperform those of investment banks by a large and statistically significant amount. In conclusion, Barber, Lehavy and Trueman (2007) posit that investment bank analysts are more optimistic in issuing buy recommendations than independent analysts, although they also point out that the results might reflect hindsight bias due to the relatively narrow time period studied.

Agrawal and Chen (2008) argue that in order for stock research to impact investor behavior, the presumption that analysts respond to conflicts of interest by inflating their recommendations is not sufficient alone. In addition, investors should take analysts' recommendations at face value, since it is possible that investors understand and account for the possible conflicts of interest by discounting the analysts' opinions. In testing their hypotheses, Agrawal and Chen (2008) show that the levels of IB and trading commissions revenues are positively related to stock recommendations, indicating that greater conflicts of interest cause analysts to inflate their recommendations. Furthermore, greater percentage of investment banking or brokerage commissions revenues is found to be negatively correlated with announcement period returns. The finding suggests that investors generally understand the possibility of conflict of interest and rationally discount this from the opinions of the analysts. Other findings from the control variables show that the size of the analyst firm is positively (negatively) and the size of the company followed is negatively (positively) correlated with the market reaction to recommendation upgrades (downgrades). (Agrawal & Chen, 2008.)

In conclusion, the findings of Agrawal and Chen (2008) do suggest that analysts face conflicts of interest and generally respond by inflating recommendations. However, investors are not misled by this as they account for this effect by rationally discounting the opinions of potentially conflicted analysts. The rational discounting finding is partly consistent with Michaely and Womack (1999), who find that investors discount the opinions of affiliated analysts, but inconsistent with Bradley, Jordan and Ritter (2008), who find that investors generally do not discount the opinions of analysts.

Clarke et al. (2011) study the characteristics and market reaction to analyst recommendations before and after the global research analyst settlement and in addition examine the behavior of independent research firms following the settlement. Prior to regulatory changes the market reaction to recommendation upgrades is not significantly different between different analyst types. However, market reaction to affiliated analyst downgrades is significantly larger than to unaffiliated or independent analyst downgrades. After the regulatory changes the return on affiliated analyst upgrades is significantly increased and for downgrades the returns are significantly less negative for all analyst types, which suggests that post-regulation downgrades are not seen as informational as pre-regulation downgrades. In addition, Clarke et al. (2011) examine the market reaction to newly established independent analyst firm recommendations in the post-regulation period and the analysis shows that new independents' recommendation upgrades and downgrades are viewed as less informative than those of other analysts.

Clarke et al. (2011) conclude that even though a certain level of conflict of interest is theoretically expected from affiliated analysts, independent analysts' recommendations are still viewed as less informative in the post-regulation period. This finding is consistent with Kadan et al. (2009). However, the research heavily relies on the finding that newly established firms' recommendations result in lesser market reactions. This raises the question whether the lesser reactions are in fact due to inferior independent firm quality, or instead due to the fact that the market considers these new research firms as less credible until quality is proven with a good track record of recommendations.

2.4.3 Pure independent research

The last definition for independent research takes into account the possibility that trading incentives may induce conflicts of interest for the analysts. This definition has not been as popular due to the small amount of purely independent research firms, and studies using the definition often point out that the findings are not fully robust due to small sample sizes (e.g. Cowen, Groysberg & Healy, 2006). However, some studies have still adopted this definition (Carleton, Chen & Steiner, 1998; Clarke et al., 2004; Cowen, Groysberg & Healy, 2006; Jacob, Rock & Weber, 2008; Casey 2013; Liu & Peabody, 2015).

Carleton, Chen and Steiner (1998) division analyst firms to brokerage and independent firms on the basis if they operate on sell-side or buy-side[4]. Their study is one of the first ones to compare the research of sell-side banking firms with buy-side firms that are independent of other possibly conflicting services. The researchers expect that buy-side analysts do not feel the same pressure as banking analysts to inflate recommendations, since their sole motivation is to find the most profitable investment opportunities. The findings of Carleton, Chen and Steiner (1998) suggest that brokerage analysts face a conflict of interest due to which their recommendations are biased with excessive optimism as compared to those of independent non-brokerage analysts.

However, even though the division to sell-side and buy-side is valid for research, since buy-side analysts have no other interests other than to find the most profitable investment opportunities, it is challenging to adopt implications of the study into practice for common investors because buy-side recommendations are not generally made public as they occur. Instead, the recommendations are used to benefit the buy-side firm itself. For common investors to be able to benefit from independent research the firm providing the research should be willing to share its analyses to the public.

Cowen, Groysberg and Healy (2006) identify the need to study purely independent research firms to better understand if analyst optimism is driven by conflicts of interest. They are one of the first ones to study independent sell-side research firms separately. The empirical findings suggest that investment banks actually make less optimistic earnings forecasts than brokerage or independent firms. On the other hand, investment banks are shown to issue more optimistic recommendations, although the study only focuses on the amount of recommendations and does not evaluate their post-announcement performance. Furthermore, Cowen, Groysberg and Healy (2006) show that brokerage analysts are the most optimistic, indicating that trading incentives are the most important cause for conflicts of interest. The findings indicate that independent analysts are likely to have less conflicts of interest, although the tests conducted for independent analysts are not fully robust due to small sample size.

[4] Sell-side refers to firms that offer services to external parties (e.g. investment banks) when the external party is about to or considering executing some kind of transaction or investment, whereas buy-side refers to firms that are itself looking for potential investments (e.g. private equity firms).

Contradictory findings are presented in the working paper of Clarke et al. (2004). Unlike Cowen, Groysberg and Healy (2006), the study examines the immediate and one-year abnormal stock price reactions to recommendation revisions. The study finds that even though investment banks are shown to be more likely to issue buy recommendations, there is no significant difference in the post-announcement stock performance across any of the analyst types. In conclusion, Clarke et al. (2004) show that investment bank analysts are less optimistic than independent analysts.

Consistent with Clarke et al. (2004), Jacob, Rock and Weber (2008) find similar evidence that investment banks provide more accurate earnings forecasts than independent. However, the study only examines analysts' earnings forecasts and does not include examination of recommendations. Furthermore, Jacob, Rock and Weber (2008) suggest that the superiority of investment bank analysts is at least partially explained by three factors: (1) independent analysts' relatively higher optimism, (2) IB analysts' access to better resources, and (3) IB analysts' possible affiliation with the target providing them with informational advantage, namely the superior information hypothesis.

Casey (2013) also compares the performance of stock recommendation revisions by investment banks and pure independent research firms. Brokerage firms without IB business are excluded from the study altogether. Univariate analysis in the study indicates that investment bank analysts have significantly more experience, work at larger firms, provide more timely recommendations, and make more accurate forecasts. The latter is consistent with Jacob, Rock and Weber (2008) and Clarke et al. (2004). Even after controlling for analyst and firm specific characteristics, Casey (2013) finds that the initial market reaction to IB analysts' recommendations is greater than to those of independent analysts. Furthermore, examination of long-term performance further strengthens the evidence that IB analyst recommendations are more informative. Taken together the findings of the study suggest that independent analysts' recommendations are less informative than those of their investment banking counterparts', which is consistent with Clarke et al. (2004) and Jacob, Rock and Weber (2008).

In a more recent study Liu and Peabody (2015) apply a case study approach to evaluating the investment value of independent research by analyzing the equity recommendations from the independent research firm Morningstar. The study differs from most other studies in the field since it does not compare the performance of independent and brokerage analyst recommendations, but instead focuses on evaluating the value of Morningstar's research. First, the study shows that the distribution of different ratings is balanced and thus assumed not to be biased, which highlights the independence of Morningstar's analysts. Second, and quite surprisingly so, the results suggest that the absolute performance of lowest rating portfolio actually outperforms the highest rating portfolio. After controlling for risk and firm characteristics, the results remain the same with each increase in stock rating decreasing the annualized portfolio return by 1.45 % on average. The poor performance of Morningstar's independent analysts leads the researchers to conclude that independent recommendations might not provide value to investors, but instead could actually have the exactly opposite effect. (Liu & Peabody, 2015.)

2.5 Literature review summary

Synthesizing all the findings from the literature review, three key themes are identified. First, by examining analysts' role in the capital markets, different dimensions to analysts' role are identified. Most importantly analysts work as information intermediaries between companies and investors by providing new information and interpreting public information (Ramnath, Rock & Shane, 2008). Analysts' role as information intermediaries is found to provide value to investors (e.g. Womack, 1996). In addition, analysts have a monitoring role in companies' corporate governance (Chen, Harford and Lin, 2015) and a marketer role by increasing the recognition of individual stocks (Li & Yue, 2015), and investing in general. Most common analyst outputs include (1) company prospects descriptions, (2) earnings forecasts, (3) target prices and (4) recommendations, which together ultimately lead to publishing a research report (Ramnath, Rock & Shane, 2008). All of these content categories are found to provide value individually and in aggregate. In addition, analysts' qualitative supporting arguments are found to be as valuable as the more visible and straightforward numerical outputs (Asquith, Mikhail & Au, 2005).

Second, it is shown that the value of analyst research is a function of analyst's personal competence and independence from the research subject. Shortfall in either category increases the probability of biased, inaccurate research. Furthermore, systematic differences in analysts' competence are identified (e.g. Stickel, 1992; Clement, 1999). However, this could also be seen as analysts' choice between emphasizing accuracy or usefulness in their research (Mozes, 2003). Common denominator is that differences do exists, and investors should pay attention to these when utilizing analyst research. Furthermore, more consistent and conservative analyst firms are found to provide more value (Hilary & Hsu, 2013; Barber et al., 2006). Analysts' competence may also be deteriorated by behavioral biases such as over and underreacting (Easterwood & Nutt, 1999), or herding (Welch, 2000). Moreover, certain dependencies to the research subject are shown to expose the analyst to possible conflicts of interest in their research, which are shown to stem from brokerage services, more specifically from either investment banking services (e.g. Lin & McNichols, 1998) or trading incentives (e.g. Irvine, 2004).

Third, in studies comparing the performance of potentially conflicted and independent analysts three definitions for independent research firms are identified: (1) firm is unaffiliated with the research subject, but may still engage in investment banking or other brokerage services with other firms (e.g. Michaely & Womack, 1999), (2) firm does not engage in investment banking activities, but may still have stock brokering services (e.g. Barber, Lehavy & Trueman, 2007), and (3) firm is purely independent from any other services apart from equity research (e.g. Cowen, Groysberg & Healy, 2007). In essence, the aim of these studies have been to examine whether there is evidence of the conflict of interest hypothesis which predicts that non-independent analysts bias their research and are overly optimistic, or of the superior information hypothesis which in turn states that possible ties to the research subjects provides the analysts with an informational advantage, leading to more accurate research (Michaely & Womack, 1999).

Table 1 synthesizes the findings of the studies on the conflict of interest hypothesis. Majority of the studies find that conflicted analysts issue relatively more optimistic recommendations and earnings forecasts (e.g. Lin & McNichols, 1998; Carleton, Chen & Steiner, 1998; Bradley, Jordan & Ritter, 2003; Cliff 2007; Corwin, Larocque & Stegemoller, 2017). Evidence on announcement period returns is slightly more ambiguous. In some studies, the market is shown to discount the conflicted analysts' opinions (e.g. Dugar &

Nathan, 1995; Agrawal & Chen, 2008), whereas in others conflicted analysts generate larger returns (Bradley, Jordan & Ritter, 2008; Clarke et al., 2011), which in turn suggests that conflicted analysts would have superior information. However, long-term performance analyzes show that brokerage analysts either underperform (e.g. Michaely & Womack, 1999; Barber, Lehavy & Trueman, 2007; Cliff, 2007) or that no difference in performance exists (e.g. Dugar & Nathan, 1995; Lin & McNichols, 1998) compared to independent, whereas findings of long-term outperformance by brokerage analysts are scarce (e.g. Casey, 2013).

In conclusion, equity research is shown to have value and empirical evidence primarily supports this, although transaction costs usually diminish any abnormal returns. In addition, possible conflicts of interest are documented to affect the value. However, depending on the time period and method used the magnitude of the effect seems to vary considerably. For this reason, the aim of this study is to further extend the evidence on analyst conflicts of interest and independent equity research to investigate whether investors are better served by independent research instead of possibly conflicted brokerage research.

Table 1. Summary of the findings on independent equity research

Definition of independent research firm	View on conflict of interest hypothesis		
	In favor	Against	Mixed
No affiliation to research subject	Kolasinski & Kothari (2008) Cliff (2007) O'Brien, McNichols, & Lin (2006) Michaely & Womack (1999) Lin & McNichols (1998) Dugar & Nathan (1995)	Bradley, Jordan & Ritter (2008) Bradley, Jordan & Ritter (2003)	Kadan et al. (2009) Lin & McNichols (1998)
No investment banking services	Agrawal & Chen (2008) Barber, Lehavy & Trueman (2007)	Clarke et al. (2011)	
No investment banking or other brokerage services	Carleton, Chen & Steiner (1998)	Liu & Peabody (2015) Casey (2013) Jacob, Rock & Weber (2008) Clarke et al. (2004)	Cowen, Groysberg & Healy (2007)
No comparison involved	Brown et al. (2018) Corwin, Larocque & Stegemoller (2017) Chan, Karceski & Lakonishok (2007) Malmendier & Shanthikumar (2007) Jackson (2005) Irvine (2004) Hong & Kubik (2003)		Ljungqvist et al. (2007) Ljungqvist, Marston & Wilhelm (2006)

2.6 Hypotheses

Prior literature is primarily in favor of potentially conflicted brokerage analysts issuing relatively more optimistic recommendations (Michaely & Womack, 1997; Lin & McNichols, 1998; Barber, Lehavy & Trueman, 2007; Cliff, 2007). Trading incentives are also expected to influence analyst behavior, and create conflicts for the analysts (Hayes, 1998; Irvine, 2004; Jackson; 2005). Moreover, even though target price revisions are not widely covered in prior literature, they are expected to behave similarly to recommendations due to their immediate relation to the level of recommendation being issued. Therefore, the first hypothesis for this study is stated as:

> ***H1:*** *Brokerage analysts issue more optimistic recommendations and target prices than independent analysts.*

Previous studies in the field have documented value in analyst research as measured by post-recommendation stock returns (Womack, 1996; Barber et al., 2001). The value is attributed to analysts' role in providing the market with new information, interpreting public information or increasing the overall recognition of stocks (Asquith, Mikhail & Au, 2005; Frankel, Kothari & Weber, 2006; Li & You, 2015). As previously discussed, there are two competing hypotheses for analyst research: (1) the conflict of interest hypothesis, which states that potential conflicts arising from investment banking business or trading incentives cause analysts to bias their recommendations, and (2) the superior information hypothesis, which states that investment bank analysts have an informational advantage compared to their independent counterparts. Despite the slightly obscure consensus on the topic, majority of prior literature presented in Table 1 leans towards the conflict of interest hypothesis and therefore the second hypothesis of this study is stated as:

> ***H2:*** *Independent analyst recommendations generate greater returns than brokerage analyst recommendations.*

However, differences in the performance of different analyst types could also stem from differences in the characteristics of the covered companies. Greater information asymmetries are prone to induce greater market reactions to new pieces of information (e.g. Womack, 1996; Barber et al., 2001), in which case the value of analyst research is expected to be greater for stocks with greater informational asymmetries, which also contain more risk. Since the information available in the market about small stocks and stocks with low analyst coverage is relatively low compared to large and more popular stocks, firm size and coverage amount variables can proxy for information asymmetries (D'Mello & Ferris, 2000; Doukas, Kim & Pantzalis, 2005). Consequently, the third hypothesis of this study is stated as:

> ***H3:*** *Greater information asymmetry between investors and company management induces greater market reactions to recommendation revisions.*

Reputational effects are expected to control analyst conflicts of interests to some extent (Jackson, 2005; Ljunqvist et al., 2007), in essence, analysts refrain from reporting biased research to uphold their reputation. Even if an analyst refrains from reporting biased research to prevent reputational losses, a conflict may still originate if information of the upcoming revision leaks (Irvine, Lipson & Puckett, 2007; Christophe, Ferri & Hsieh, 2010). However, other alternative is that the market learns to expect and predict the on-going research processes for several reasons: most analyst reports take place after public company disclosures (Soltes, 2014), analysts discuss with companies prior to the reports (Brown et al., 2015), companies actively engage with the analysts in an attempt to convince analysts of the company prospects (Brown et al., 2018), and analysts sometimes publicly announce an upcoming report. Since leaking is a punishable offence and the financial markets are heavily regulated, learning from the research process itself is considered to be more plausible. Private interactions are expected to enhance the learning by the market, and because brokerage firms have more ties to the companies they are covering, it is expected that the market learns to predict the research conducted by brokerage analysts to a greater extent. This concludes the fourth and final hypothesis of this study, which is stated as:

> ***H4:*** *The market learns to predict on-going brokerage research processes to a greater extent than independent research processes.*

3 RESEARCH DATA AND METHODS

3.1 Data sample

Target market for this study is the Finnish stock market which is chosen due to the presence of an accredited purely independent equity research company, as well as due to the scarcity of prior research into analyst recommendations in the Finnish market. Time period for the study is chosen based on how long independent research has been provided in the Finnish market ranging from February 2010 to May 2018. The data sample consists of daily analyst recommendations and target prices.

The daily analyst recommendations and target prices are collected from the Thomson Reuters' I/B/E/S database. First, recommendation data has to be manually collected through Thomson Reuters Eikon software, which provides detailed historical data of those analysts that currently provide coverage on a specific company. Each data input contains the name of the analyst, name of the company, date, current recommendation, prior recommendation (if exists), target stock price (if issued) and current stock price. The data is provided in the software in a way that recommendations have to be collected separately for each company. Subsequently, these individual datasets are combined to form independent and brokerage datasets. Analyses on the data are conducted with Ox-Metrics and SPSS Statistics software.

Table 2 presents the number of recommendations and target prices in the sample. There are total of 24 research firms of which only one can be classified as purely independent. However, the difference in companies covered does not differ with the same magnitude. Moreover, the difference in the number of issued recommendations does not differ drastically, which allows for the examination of the differences between the groups. Nevertheless, the results from this examination should not be extrapolated too far, since it is possible that the independent side results are actually caused by firm specific characteristics rather being the effects of being independent research firm. Limitations of this study are further discussed in chapter 5.

Table 2. Sample recommendations and target prices

	Research firm type		
	Independent	Brokerage	Total
Research firms	1	23	24
Analysts	11	88	99
Companies covered	100	107	122
Recommendations	1125	2313	3438
Target prices	1108	2295	3403

3.2 Research design

This study contains three sets of analyses. First, differences in recommendation and target price averages between the analyst types are analyzed in a univariate analysis. Second, an event study approach is applied as initial announcement period returns to recommendation revisions are examined on a daily basis as well as on different event periods. Third, recommendation returns are analyzed in long-term by applying a portfolio method with a buy-and-hold investment strategy.

Differences in recommendations and target prices

Differences in the issued recommendations and target prices between the two analyst groups are analyzed to investigate whether one side is significantly more optimistic than the other. Analysis is done by comparing the average recommendation (on a scale from 1 to 5) and target price premiums (relative difference between the issued target price and the underlying stock price at the time of issuance) with a two-sample t-test. These analyses provide evidence for H1.

Announcement period returns

To analyze the announcement period returns an event study method similar to Bradley, Jordan & Ritter (2003; 2008) is utilized[5], where portfolio excess returns are cumulated over certain time periods to calculate cumulative market adjusted returns ("CMAR"), which are subsequently analyzed and compared between the different analyst types. The

[5] For other studies applying similar method see, e.g., Agrawal and Chen (2008) or Kolasinski and Kothari (2008).

event study method was originally made popular by Ball and Brown (1968), who studied the information content of accounting numbers in annual reports, and their effect to the stock prices of the companies. These short-term return analyses are conducted to provide evidence for H2, H3. Furthermore, the daily average returns prior to recommendation revisions are analyzed to provide evidence for H4.

Similar to Bradley, Jordan and Ritter (2008), analyst recommendations are divided into four types: (1) coverage initiations, (2) reiterations, (3) upgrades and (4) downgrades[6]. In the first set of analyzes all recommendation types are included, however, in further analyzes of recommendation returns only upgrades and downgrades are included due to the small number of initiations and reiterations in the sample. Recommendations are also grouped by analyst type: (1) independent and (2) brokerage analysts. Cumulative market-adjusted returns are calculated over four event periods surrounding the issuance of recommendation: 2-day, 5-day, 11-day and 21-day periods centered on the announcement date. Formula for calculating the CMAR over days t – n to t + m is adopted from Bradley, Jordan and Ritter (2008, p. 111) and it is stated as:

$$CMAR(t-n, t+m) = \sum_{t=t-n}^{t+m} \frac{1}{N_t} \sum_{i=1}^{N_t} (r_{it} - r_{mt}) \qquad (1)$$

where $t = 0$ is the recommendation date, N_t is the number of the sample returns on day t, r_{it} is the return on stock i on day t and r_{mt} is the market return on day t. To simplify, the average returns for each day surrounding the recommendation date are accumulated to calculate CMARs for (-10,+10), (-5,+5), (-2,+2) and (0,+2)-day periods.

Differences between the average CMARs of the two analyst groups are analyzed by comparing the average returns with a two-sample *t*-test as well as with a cross-sectional *regression analysis*. Furthermore, differences in daily returns surrounding the recommendation revisions are analyzed by comparing the average daily returns and the distributions of the returns with a two-sample *Kolmogorov-Smirnov* test and *chi-squared* test.

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[6] For the short-term analysis it is more informative to group the recommendations based on the revisions rather than grouping them by the level of the rating (e.g. Francis & Soffer, 1997) because, for example, an upgrade from strong sell to sell rating should be a slightly positive signal and if it was grouped with sell ratings the expectation would be that it is a negative signal.

Portfolio formation

For the long-term returns' analysis, a portfolio method similar to Barber, Lehavy & Trueman (2007) and Cliff (2007) is utilized. As described in previous section, the data sample is divided into two sets: (1) independent and (2) brokerage recommendations. The purpose of the long-term analysis is to evaluate the investment value of analyst recommendations from a retail investors' perspective and compare which type of analysts provide more value to the investor. These analyses provide further evidence for H2 and H3.

Independent and brokerage recommendation are further divided into two portfolios: "*buy*" and "*hold-sell*" (referred to simply as "*sell*") portfolios[7]. Recommendations were first divided into three portfolios with hold recommendations as a standalone portfolio, however, a two-portfolio approach as in Barber, Lehavy & Trueman (2007) was later chosen due to independent recommendations containing very few hold recommendations. Furthermore, combining holds with sells is justifiable as majority of investment professionals (Boni & Womack, 2002) and investors (Francis & Soffer, 1997) actually interpret hold recommendation as a sell sign.

When an analyst initiates or revises a recommendation for a stock the stock enters the respective portfolio with a one-euro weight at the close of trading on the day the recommendation is issued. This way the initial return from the recommendation revision is excluded from the portfolio returns, because as argued by Cliff (2007) most private investors do not have access, or do not continuously follow, real-time recommendation updates. Therefore, it is more likely that common investors will spot the recommendations with a delay and by that time professional and algorithmic traders have already taken advantage of the initial return. Conversely, when an analyst drops the coverage of a stock, or the recommendation is revised so that the stock enters the other portfolio, the stock will be removed from the respective portfolio at the close of trading. For example, when a sell recommendation is upgraded to buy recommendation the revision triggers a one-euro investment to the stock in the buy portfolio and the stock is removed from the sell portfolio. Both trades are done at the close of trading on the announcement date. A stock can enter the same portfolio multiple times only if multiple analysts have recommended

[7] I/B/E/S database divides recommendations into five rating categories: strong buy, buy, hold, sell and strong sell. In this study, the buy portfolio contains recommendations with strong buy or buy ratings and the sell portfolio recommendations of hold, sell or strong sell ratings.

the stock. A stock can also enter or exist in both portfolios at the same time due to the same reason.

Casey (2013) finds that the choice to include reiterations of recommendations in the portfolio approach can bias the investment bank portfolio performance since IB analysts generally issue more reiterations than independents. Therefore, recommendation reiterations are excluded from the portfolios. This means that a reiteration does not trigger a new investment in the portfolio and the original investment remains unmodified until the recommendation is upgraded or downgraded from the portfolio.

The daily return of a portfolio is the weighted return of its components and thus the daily return of a portfolio on day *t* can be expressed as (adopted from Barber, Lehavy & Trueman, 2007):

$$R_{pt} = \frac{\sum_{i=1}^{n_t} X_{it} R_{it}}{\sum_{i=1}^{n_t} X_{it}} \tag{2}$$

where R_{pt} is the portfolio return on day t, n is the number of recommendations in the portfolio, R_{it} is the adjusted return[8] on stock i on day t and X_{it} is the weight of stock i in the portfolio on day t. Weight of stock i equals 1 on day t, when recommendation was issued on day $t-1$ and after that the weight equals the compounded return on stock i from the close of trading on the day of the recommendation through day $t-1$.

Daily portfolio returns are compounded to monthly returns for further analysis. Whether recommendations have investment value is examined based on their ability to produce statistically significant abnormal returns in *regression analysis*. Cliff (2007) argues that past studies have had methodological problems concerning the risk models used to measure abnormal returns. To account for possible model misspecification, three different models are used to measure abnormal returns as in Cliff (2007): Capital Asset Pricing Model[9], Fama and French's (1993) 3-factor model and Carhart's (1997) 4-factor model[10].

[8] Returns are adjusted and include dividends as they are expected to be reinvested.

[9] The model was developed in Sharpe (1964) and Lintner (1965) and later presented in Sharpe (1970).

[10] The factors used in the two latter models are monthly European factors provided by Kenneth French (2018).

The risk-free rate used in the models is the one-month Euribor rate[11] and the market portfolio is the OMX Helsinki total return index ("OMXHGI"). Abnormal return is measured as the intercept from the estimations of the regression models.

3.3 Methods

Two-sample t-test

A two-sample t-test is a common test for statistical significance between two averages. The null hypothesis of the test is that the averages do not statistically significantly differ from one another. The formula for the two-sample t-test is stated as:

$$t = \frac{\bar{X} - \bar{Y}}{\sqrt{\frac{S_X^2}{n_X} + \frac{S_Y^2}{n_Y}}} \tag{3}$$

where $\bar{X}$ is the average of sample X, $\bar{Y}$ is the average of sample Y, S is the sample standard deviation, and n is the sample size.

Two-sample Kolmogorov-Smirnov test

A two-sample KS-test is used to compare the CMAR and daily return distributions of the different analyst type samples. The KS-statistic quantifies the maximum distance between the two samples' empirical distribution functions to determine whether these samples come from the same distribution. The null hypothesis of the test is that the two samples come from the same distribution, although the test does not state what that distribution is. Differences in the distributions are evidence of the market reacting differently to recommendations by different analyst types. The formula for the empirical distribution functions is stated as:

$$F_n(x) = \frac{1}{n}\sum_{i=1}^{n} I_{[-\infty,x]}(X_i) \tag{4}$$

[11] Monthly rate averages are retrieved from Bank of Finland (2018).

where I is the indicator function which is equal to 1 if X_i is less than or equal to x and zero otherwise. The KS-test statistic D is then calculated from the formula:

$$D_{n,m} = \sup_{x} \left| F_{1,n}(x) - F_{2,m}(x) \right| \tag{5}$$

where $F_{1,n}$ and $F_{2,m}$ are empirical distribution functions of the first and second sample, and the test statistic D is the maximum absolute difference between the empirical distribution functions as denoted by the supremum function.

Chi-squared test

A chi-squared test ("X^2-test") is a test of independence between two categorical variables. The test examines the association between two variables by determining whether the expected and observed frequencies of the variables have statistically significant differences. In this study, the chi-squared test is applied for a two-by-two classification, where the first variable is the analyst firm type (independent or brokerage) and the second variable is the daily distribution of market adjusted returns (positive or negative) prior to a recommendation revision. The test is applied to investigate whether there exists any association between the analyst types and the distribution of daily returns to positive and negative prior to a recommendation revision. Positive (negative) returns prior to a recommendation upgrade (downgrade) proxy for possible leaking of information. The formula for the chi-squared test is stated as:

$$X^2 = \sum_{i=1}^{r} \sum_{j=1}^{c} \frac{\left(O_{i,j} - E_{i,j}\right)^2}{E_{i,j}} \tag{6}$$

where r is the number of rows, c is the number of columns, O is the observed frequency and E is the expected frequency. Expected frequency for the cells is the row total times the column total divided by the grand total. The null hypothesis for the test is that the variables are statistically independent while the alternative hypothesis states that some association exists.

Linear regression analysis and related tests

The model used for the announcement period return cross-sectional regression analysis controls for firm size, low analyst coverage and absolute recommendation levels. Thus, the model used is stated as:

$$\begin{aligned} AR_{it} = \alpha_{it} + \beta_1 IND_{it} + \beta_2 SMALL_{it} + \beta_3 MEDIUM_{it} \\ + \beta_4 MAX1A_{it} + \beta_5 MAX2A_{it} + \beta_6 SBUY/SSELL_{it} \\ + \beta_7 BUY/SELL_{it} + \varepsilon_{it} \end{aligned} \tag{7}$$

where *AR* is the announcement period return, α is the intercept, *IND* is a dummy variable that equals one if the analyst is independent and zero otherwise, *SMALL* (*MEDIUM)* is a dummy variable that equals one if the firm is small-cap (medium-cap) stock and zero otherwise, *MAX1A* (*MAX2A)* is a dummy variable that equals one if a maximum of one (two) analyst is covering the stock and zero otherwise, *SBUY* and *BUY* (*SSELL* and *SELL*) are dummy variables that equal one if the recommendation is upgraded (downgraded) to strong buy or buy (strong sell or sell) rating, and ε is the error term.

In the time-series regression analysis of the long-term portfolio returns multiple risk models are employed. The first risk model used in this study is the *Capital Asset Pricing Model* ("CAPM"), which is a simple risk-return relation model used to calculate the required rates of returns for specified assets. The model takes into account the assets sensitivity to the systematic risk of the market and argues that an asset's required rate of return is dependent on how its risk compares to that of a market portfolio's. The formula for the model is as follows:

$$R_{pt} - R_{ft} = \alpha_p + \beta_p\left(R_{mt} - R_{ft}\right) + \varepsilon_{pt} \tag{8}$$

where R_{pt} is the portfolio return for month *t*, R_{ft} is the risk-free rate, α_p is the estimated abnormal return, β_p is the estimated market beta of the portfolio and R_{mt} is the return of the OMXHGI. Market beta essentially represents the systematic risk of the portfolio – any value above one indicates that the portfolio is riskier than the market and, vice versa, values below one indicate a less risky portfolio. The model is taught in almost all finance textbooks and it is widely used to estimate cost of equity capital and to measure abnormal performance of portfolios, however, it has not received much recognition in empirical testing because of its poor ability to explain stock returns (see, e.g., Blume & Friend, 1973), and since other factors in addition to the market factor have been found to affect the formulation of asset returns (Fama & French, 2004). Nevertheless, the model is included in the study, but the results are interpreted with caution.

Fama and French (1993) build on the CAPM model because US stock returns show only little relation to the market beta in CAPM empirical testing. They identify two new factors affecting the returns of common stocks: (1) Small Minus Big ("SMB") factor, which is the average return of three small-stock portfolios minus the average return of three big-stock portfolios, and (2) High Minus Low ("HML") factor, which is the average return of two high book-to-market stock portfolios minus the average return of two low book-to-market return portfolios. When we add these factors to the equation, the 3-factor model is stated as:

$$R_{pt} - R_{ft} = \alpha_p + \beta_p\left(R_{mt} - R_{ft}\right) + s_p SMB + h_p HML + \varepsilon_{pt} \tag{9}$$

where a positive coefficient for the SMB factor (s_p) indicates a tilt towards small-stocks in the portfolio and negative coefficient towards big-stocks, and a positive loading on HML (h_p) represents a tilt towards value stocks (high book-to-market) and negative loading towards growth stocks (low book-to-market) in the portfolio.

The last model used is the Carhart (1997) 4-factor model which introduces one more factor to the equation. It extends the model by controlling for stock return momentum. Adding the momentum factor the equation is stated as:

$$\begin{aligned} R_{pt} - R_{ft} = {} & \alpha_p + \beta_p\left(R_{mt} - R_{ft}\right) + s_p SMB + h_p HML + m_p MOM \\ & + \varepsilon_{pt} \end{aligned} \tag{10}$$

where MOM[12] is the monthly return premium on 12-month winner stocks minus 12-month loser stocks. (Carhart, 1997.) Positive loading on the momentum factor (m_p) indicates that the portfolio consists mainly of past winner stocks and negative loading that it consists of past loser stocks.

A set of tests are conducted to ensure reliable interpretation of the regression results. *Jargue and Bera* (1987) test ("JB-test") is utilized to test the goodness-of-fit of the sample and regression residual normal distributions. The test examines whether the sample skewness and kurtosis follow a normal distribution. The formula for the test statistic is stated as:

$$JB = \frac{n-k+1}{6} * \left(S^2 + \frac{1}{4}(C-3)^2\right) \tag{11}$$

where n is the number of observations, S is the sample skewness, C is the sample kurtosis and k is the number of independent variables. Null hypothesis of the test is that both skewness and excess kurtosis are zero, which means that the sample distribution matches a normal distribution.

Results from the sample normal distribution JB-tests are reported in Appendix 2. For the announcement period returns the null hypotheses are rejected for each sample (p-values 0,000) and for the portfolio returns it is rejected for the independent sell portfolio (p-value 0,05). However, even though the null hypothesis of the JB-test is rejected for some of the samples, the *central limit theorem* states that a sample distribution approximates to a normal distribution as the sample size increases. Usual threshold value for the theorem is a sample size greater than 30 (Holopainen & Pulkkinen, 2015). Therefore, approximate normality distributions are assumed for samples that do not pass the JB test because of large sample sizes.

White's (1980) test is used to test if the variance of the regression residual is constant. The test applies an auxiliary regression where it regresses the squared residuals from the original regression onto the original regressors, squared original regressors and their

[12] Other acronyms for the factor include "*UMD*" and "*WML*" (see, e.g., Cliff, 2007; Barber, Lehavy & Trueman, 2007).

cross-products. The null hypothesis of the test is that the residual is homoscedastic (has a constant variance). However, if the null hypothesis is rejected, the heteroskedasticity can be taken into account by using heteroskedasticity consistent standard errors. Consistently, the null hypothesis in the White's test is rejected for one regression model, the independent sell portfolio regression, and therefore heteroskedasticity consistent standard errors are calculated for this model.

Breusch-Godfrey test (Breusch, 1978; Godfrey, 1978) is used to test for the presence of serial correlation (autocorrelation) in the residual, which would cause incorrect conclusions from other tests and sub-optimal estimates of regression model parameters, if not taken into account. Null hypothesis of the test is that no autocorrelation exists. If the null hypothesis is rejected, autocorrelation of the residual can be taken into account by using autocorrelation consistent standard errors in the calculation of the regressor t statistics. However, no autocorrelation is detected as the null hypothesis holds for all of the regression models in this study.

4 EMPIRICAL RESULTS

4.1 Descriptive statistics

Table 3 reports the descriptive statistics for the sample recommendations and target price premiums divided into two groups based on analyst firm characteristics. Recommendation values range from 1 to 5[13], whereas target price premium is the relative difference between the issued target price and the underlying stock price on the date of the announcement. Average values indicate that brokerage analysts tend to be more optimistic in issuing both recommendations and target price premiums. The effect is greater for target price premium (10.2 % compared to 6.3 %), whereas the difference between average recommendation is not economically as large (2.65 compared to 2.87). Looking at the recommendation distribution in Panel B, a major difference is identified as the independent side almost never issue hold ratings, whereas it is the most common rating for the brokerage analysts. Moreover, the distribution shows that for independent optimistic recommendations form 54 % of all ratings compared to 47 % by brokerage firms. However, brokerage firms issue relatively less sell and strong sell ratings which causes their average recommendation to be more optimistic.

Table 3. Recommendation and target price premium descriptive statistics

	Independent		Brokerage	
	Ratings	Premiums	Ratings	Premiums
Panel A: Descriptive statistics				
n	1125	1105	2313	2295
Average	2.87	6.3 %	2.65	10.2 %
Min	1	-58.0 %	1	-61.1 %
1st Quartile	2	-1.2 %	2	-0.6 %
Median	2	5.6 %	3	8.1 %
3rd Quartile	4	11.8 %	3	16.1 %
Max	5	237.2 %	5	371.3 %
Std. Dev.	1.276	0.169	1.062	0.224

[13] Recommendation scale: 1 = strong buy, 2 = buy, 3 = hold, 4 = sell and 5 = strong sell.

Table 3 (*continued*)

Panel B: Recommendation distribution				
	Independent		Brokerage	
	n	%	n	%
Strong buy	148	13 %	339	15 %
Buy	457	41 %	738	32 %
Hold	13	1 %	744	32 %
Sell	409	36 %	388	17 %
Strong sell	98	9 %	104	4 %

Table 4 reports the monthly descriptive statistics for the different portfolios' returns and the four regressors. Return statistics are reported both as raw and market-adjusted. Average monthly return for the independent buy portfolio is 1.5 % (0.7 % market-adjusted), whereas it is 1.1 % (0.2 %) for the brokerage portfolio. Not controlling for risk, the raw return generated by following independent buy recommendations clearly outperforms the brokerage buy recommendations. Moreover, the average monthly returns for the sell portfolios are 0.5 % (-0.4 %) and 0.8 % (-0.1 %), respectively. Similar pattern is visible in the sell portfolio returns as the independent portfolio underperforms the brokerage portfolio, indicating that independent are also more accurate at picking loser stocks. Furthermore, it is useful to note that even though both portfolios generate negative market-adjusted returns, the raw returns for both sell portfolios are positive, indicating that short selling pessimistic analyst recommendations is not profitable. In addition, the maximum monthly returns for both independent and brokerage sell portfolios are actually higher than the maximum returns for the buy portfolios.

Moving on to the regressor descriptive statistics, the positive average monthly return for the *SMB* factor indicates that small stocks have outperformed big stocks during the examination period. On the other hand, the negative return for the *HML* factor indicates that low book-to-market stocks have outperformed more expensive stocks. Furthermore, the positive return for the *MOM* factor denotes the superior performance of stocks that have had good momentum 12 months prior.

Table 4. Portfolio return and regressor descriptive statistics

		Monthly data						
		Mean	Min	Q1	Median	Q3	Max	Std. Dev.
		Panel A: Independent portfolios						
Buy portfolio	Return	0.015	-0.118	-0.007	0.011	0.043	0.124	0.045
	Market-adjusted return	0.007	-0.053	-0.006	0.005	0.019	0.066	0.021
Sell portfolio	Return	0.005	-0.119	-0.023	0.005	0.026	0.131	0.044
	Market-adjusted return	-0.004	-0.049	-0.016	-0.006	0.007	0.073	0.021
		Panel B: Brokerage and investment bank portfolios						
Buy portfolio	Return	0.011	-0.123	-0.013	0.015	0.034	0.108	0.044
	Market-adjusted return	0.002	-0.045	-0.007	0.001	0.010	0.050	0.015
Sell portfolio	Return	0.008	-0.109	-0.023	0.011	0.032	0.111	0.044
	Market-adjusted return	-0.001	-0.026	-0.010	-0.001	0.006	0.036	0.012
		Panel C: Regressors						
	R_m–R_f	0.007	-0.116	-0.020	0.009	0.032	0.110	0.045
	SMB	0.002	-0.047	-0.008	0.001	0.014	0.038	0.016
	HML	-0.002	-0.045	-0.019	-0.003	0.012	0.064	0.024
	MOM	0.010	-0.091	-0.007	0.010	0.025	0.089	0.028

4.2 Recommendation and target price premium averages

Table 5 reports the averages for recommendations and target price premiums divided by recommendation type. Average recommendation differences are analyzed in Panel A using two-sample *t*-test. Looking at the full sample results, the average recommendation by independent (2.87) is more pessimistic than that of brokerage (2.65). The difference is also statistically significant (p-value 0.000). Same applies for coverage initiations where the average recommendation by independents is significantly (p-value 0.044) more pessimistic. Similarly, average independent ratings for reiterations and upgrades are slightly more pessimistic, however, these differences are not statistically significant. For downgrades the result is the same and the difference is significant (p-value 0.000). Collectively the results indicate that brokerage analysts issue relatively more optimistic recommendations, and that the difference is most pronounced for recommendation downgrades, hence providing support to H1.

Table 5. Univariate results for differences in recommendations and target prices

This table reports the recommendation and target price premium averages divided into four groups based on recommendation type: coverage initiations, reiterations, upgrades and downgrades. Full sample results for both research firm categories are also reported. N is the number of observations. Panel A reports the recommendation averages and Panel B the target price premiums averages. The null hypothesis of the difference *t*-tests is that the averages are equal.

Panel A: Recommendations

Recommendation type	Independent	Brokerage	Difference *p*-value
Full sample	2.87	2.65	**0.000**
n	1125	2313	
Initiations	2.79	2.45	**0.044**
n	101	122	
Reiterations	3.00	2.67	0.388
n	11	187	
Upgrades	2.08	2.03	0.309
n	507	1016	
Downgrades	3.67	3.30	**0.000**
n	506	988	

Table 5 (*continued*)

Panel B: Target price premiums			
Recommendation type	Independent	Brokerage	Difference *p*-value
Full sample	5.9 %	10.2 %	**0.000**
n	1108	2295	
Initiations	8.0 %	11.4 %	0.498
n	89	111	
Reiterations	9.8 %	17.0 %	0.355
n	11	186	
Upgrades	8.7 %	14.4 %	**0.000**
n	505	1014	
Downgrades	2.7 %	4.4 %	**0.080**
n	503	984	

Bolded values indicate significance at least at the 0.10 level.

Panel B shows the results for the differences in the average target price premiums. In the full sample, brokerage analysts on average issue target prices with a premium of 10.2 % compared to 5.9 % by independent analysts. The difference is both economically and statistically significant (p-value 0.000). Differences exist also for initiations and reiterations, although they are not statistically significant. Conversely, for recommendation upgrades the magnitude of the difference is large (8.7 % compared to 14.4 %) and significant (p-value 0.000). Furthermore, difference for downgrades is smaller in magnitude and only weakly significant (p-value 0.080), and therefore not so strong evidence. In sum, the evidence from target price premiums indicates that brokerage analysts are more optimistic than independent analysts. Therefore, the analysis of target prices provides support to H1.

In addition to average premiums, the percentage of achieved target prices is also calculated. In the sample, approximately 46 % (39 %) of independent (brokerage) target prices are achieved within the subsequent 12-month period, which further strengthens the evidence of brokerage analysts' relatively higher optimism.

The univariate analysis of recommendations and target price premiums comprises of three key findings. First, consistent with prior research (e.g. Lin & McNichols, 1998; Carleton, Chen & Steiner, 1998; Agrawal & Chen, 2008) brokerage analyst recommendations are on average more optimistic than those of independent. Moreover, the effect is most pronounced for recommendation downgrades. Second, similar pattern exists for target price premiums, although with the exception of the effect being most pronounced for recommendation upgrades. This is in contrast to Cowen, Groysberg and Healy (2006), who find that investment banks issue more pessimistic price targets. Third, of all issued target prices, 46 % of independent and 39 % of brokerage analysts' target prices are met within the subsequent 12-month period. Both values are slightly worse than the 54 % Asquith, Mikhail and Au (2005) find in their full analyst sample. In sum, the evidence indicates that potentially conflicted brokerage analysts are more reluctant to issue strong pessimistic recommendations and instead opt for more neutral downgrades and, in addition, issue more optimistic target prices for upgraded stocks. Collectively these findings primarily provide support H1 ("*Brokerage analysts issue more optimistic recommendations and target prices than independent analysts*").

4.3 Announcement period returns

Univariate analysis

Table 6 reports the cumulative market-adjusted announcement period returns associated with revisions of analyst recommendations. Returns are calculated over four different event periods: 3-day, 5-day, 11-day and 21-day windows centered on the announcement date. Moreover, returns are divided into different recommendation types. However, initiations and reiterations are omitted from further analyzes due to the small number of these recommendations. Differences in return averages and sample distributions are analyzed with two-sample *t*-test and KS-test, respectively. Full sample results show that, apart from the 3-day window, independent analysts induce more positive market reactions, indicating that the market discounts potentially conflicted brokerage analysts' opinions. However, none of the differences in the averages or distributions are statistically significant (p-values > 0.10). Similar pattern exists in recommendation type sub-samples: the market reaction is greater for independent recommendations compared to brokerage, although none of these differences are significant with the exception of the difference in average return for the 11-day window around recommendation upgrades (p-value 0.026). Collectively, the evidence implies that there are no significant differences between the announcement period returns for any of the recommendation types. The finding suggests that the market's reaction to analyst recommendations is on average the same for recommendations by any analyst type, in essence, the market does not discount for potential conflicts nor does it believe that some analysts have superior information. These results do not provide support to H2 ("*Independent analyst recommendations generate greater returns than brokerage analyst recommendations*").

Table 6. Univariate results for differences in cumulative market adjusted returns

This table reports the cumulative market-adjusted returns (CMAR) for four different time periods. Day 0 is the date when the recommendation is issued and days -10, -5, -2, +2, +5 and +10 are days relative to the issuance date. CMARs are reported for the full sample as well as for two sub-samples based on whether the recommendation is an upgrade or downgrade. Difference *p*-values represent the significance of the difference between the average CMARs from two-sample *t*-test. The null hypothesis of the difference *t*-test is that the averages are equal. KS *p*-value represents the significance of the difference between the distributions of the samples from the two sample Kolmogorov-Smirnov test. The null hypothesis of the KS-test is that the samples come from the same distribution.

Recommendation type	Event period	Independent	Brokerage	Diff. *p*-value	KS *p*-value
Full sample	(0,+2)	0.02 %	0.14 %	0.448	0.076
	(-2,+2)	0.23 %	0.06 %	0.482	0.827
	(-5,+5)	0.40 %	0.11 %	0.306	0.814
	(-10,+10)	0.36 %	-0.03 %	0.285	0.230
Upgrades	(0,+2)	1.40 %	1.40 %	0.984	0.110
	(-2,+2)	2.14 %	1.59 %	0.115	0.517
	(-5,+5)	2.43 %	1.50 %	**0.026**	0.298
	(-10,+10)	1.69 %	0.98 %	0.200	0.235
Downgrades	(0,+2)	-1.44 %	-1.20 %	0.291	0.342
	(-2,+2)	-1.82 %	-1.62 %	0.559	0.694
	(-5,+5)	-1.68 %	-1.35 %	0.437	0.870
	(-10,+10)	-1.12 %	-1.00 %	0.816	0.776

Bolded values indicate significance at least at the 0.10 level.

Figure 3 illustrates the 21-day window returns for recommendation upgrades and downgrades centered on the announcement of recommendations. Even though the analysis in Table 6 shows that the differences between the analyst types are not statistically significant, it is useful to examine the day-by-day formation of the cumulative returns. First, starting from day -10 relative to the announcement of recommendation revision, it is shown that the stock returns prior to the revision drift to the opposite direction, in essence, prior to upgrades the stock price drifts downwards and vice versa prior to downgrades. This is consistent with the notion that analysts follow the price levels of stocks to identify stocks that are currently underperforming (outperforming) but are believed to outperform (underperform) in the future, in other words, to identify future winners and losers. More interestingly, the figure shows that the drift actually reverses one day before (5 days before for independent upgrades) the actual announcement of the recommendation revision. This finding indicates that the market could learn of the on-going research process in advance and begin to predict its outcome.

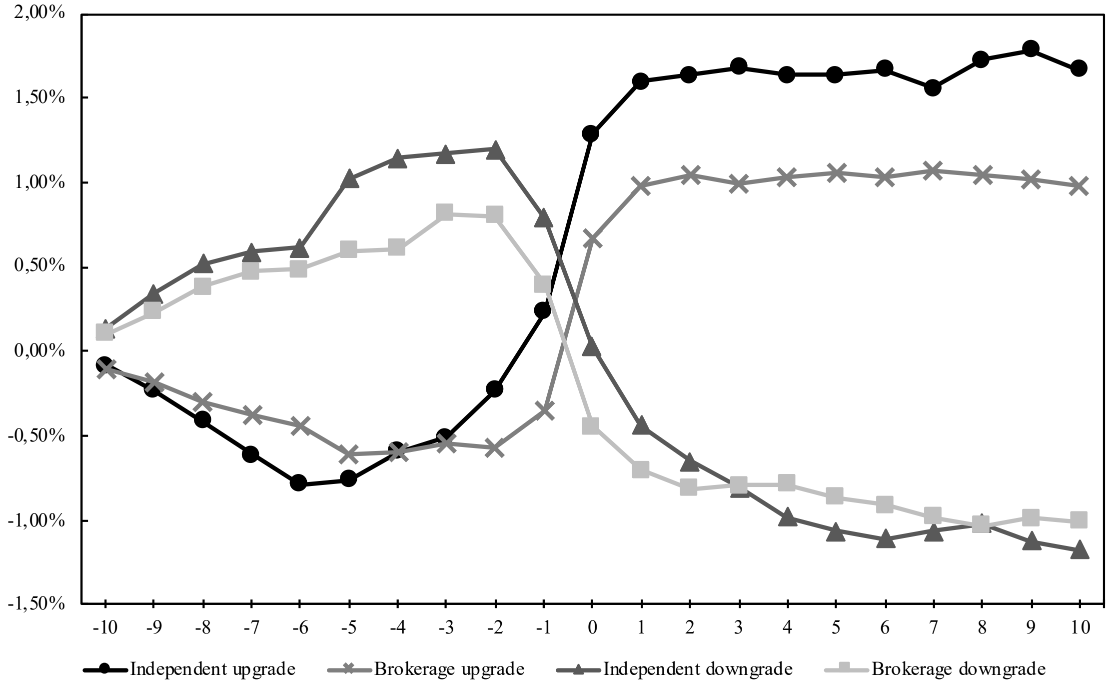

Figure 3. *Cumulative market adjusted returns for 21-day window*

Second, analysis of the announcement day 0 and the following days shows that the stock price reaction is most pronounced on the day of the announcement, as would be expected. The drift continues for one more day after the announcement after which it begins to fade. The fading takes longer for downgrades, whereas for upgrades the cumulative abnormal returns after day +1 are almost nonexistent. The finding is consistent with Altınkılıç. Hansen & Ye (2016), who argue that the post-revision drift is no longer significant due to high-frequency algorithmic trading, and that better availability of data in today's supercomputer era diminishes the informational role of analysts.

The daily accumulation of CMARs is further analyzed in Table 7, which reports the average daily market-adjusted returns ("MAR") from day -10 to the announcement day 0. First, looking at the average MARs in Panel A, the analysis shows that prior to recommendation upgrades independent (brokerage) MARs are negative until day -6 (-5) after which the MARs shift positive. Difference in the averages is significant on day -2 (p-value 0.030) and weakly significant on day -5 (0.075). Difference in the distributions is significant on day -6 (0.018), as well as weakly significant on days -3 and -2 (p-values 0.069 and 0.054, respectively). Moreover, the chi-squared test is significant on day -2 (0.035), suggesting that relatively greater amount of positive returns is associated with independent recommendations on this day. In sum, the analysis of upgrades suggests that the market could learn of the research processes as average MARs turn positive just before the revision. The evidence is stronger for independent and slightly more ambiguous for brokerage analysts. Evidence of the differences is not consistent as only day -2 returns evidence significant differences in all difference tests.

Table 7. Daily market-adjusted returns surrounding recommendation revisions

This table reports the average daily market-adjusted returns prior to the announcement of recommendation upgrades and downgrades. Daily returns are reported from day -10 through day 0 relative to the announcement date. *t*-tests are conducted both as one-sample and two sample tests. The null hypothesis in the one-sample test (column '*t*-stat') is that the daily average MAR equals zero. The null hypothesis in the difference *t*-test is that the independent and brokerage average MARs are equal. KS p-value represents the significance of the difference between the distributions of the independent and brokerage returns from the Kolmogorov-Smirnov test. The null hypothesis of the KS-test is that the samples come from the same distribution. The X^2-test is applied to investigate whether there exists any association between the analyst types and the distribution of daily market reactions (positive or negative) prior to the recommendation revision. The null hypothesis of the X^2-test is that no association exists between the analyst types and the distribution of positive and negative returns on the inspection day.

Panel A: Upgrades

Day	Independent	*t*-stat		Brokerage	*t*-stat		Diff. *p*-value	KS *p*-value	X^2 *p*-value
-10	-0.09 %	(-0.97)		-0.11 %	(-2.09)	**	0.832	0.120	0.683
-9	-0.14 %	(-1.58)		-0.08 %	(-1.81)	*	0.529	0.128	0.890
-8	-0.18 %	(-2.18)	**	-0.11 %	(-2.14)	**	0.470	0.253	0.879
-7	-0.20 %	(-2.00)	**	-0.08 %	(-1.68)	*	0.303	0.267	0.529
-6	-0.18 %	(-2.02)	**	-0.06 %	(-0.99)		0.254	**0.018**	0.833
-5	0.02 %	(0.26)		-0.17 %	(-3.24)	***	**0.075**	0.392	0.949
-4	0.17 %	(1.71)	*	0.01 %	(0.15)		0.174	0.165	0.609
-3	0.09 %	(0.88)		0.06 %	(1.07)		0.817	**0.069**	0.717
-2	0.28 %	(2.50)	**	-0.02 %	(-0.26)		**0.030**	**0.054**	**0.035**
-1	0.46 %	(2.81)	***	0.21 %	(1.66)	*	0.223	0.209	0.969
0	1.05 %	(7.24)	***	1.03 %	(12.16)	***	0.883	**0.001**	**0.000**

Table 7 (*continued*)

Day	Independent	*t*-stat		Brokerage	*t*-stat		Diff. *p*-value	KS *p*-value	X^2 *p*-value
Panel B: Downgrades									
-10	0.14 %	(1.65)	*	0.10 %	(2.00)	**	0.722	0.873	0.457
-9	0.21 %	(2.40)	**	0.13 %	(2.51)	**	0.458	0.700	0.212
-8	0.18 %	(1.99)	**	0.15 %	(2.55)	**	0.782	0.564	0.635
-7	0.07 %	(0.78)		0.09 %	(1.53)		0.837	0.918	0.581
-6	0.02 %	(0.25)		0.01 %	(0.15)		0.895	0.482	0.836
-5	0.41 %	(4.21)	***	0.11 %	(1.76)	*	**0.012**	**0.009**	0.201
-4	0.12 %	(1.15)		0.01 %	(0.21)		0.379	0.277	0.655
-3	0.02 %	(0.24)		0.20 %	(3.38)	***	0.133	0.105	0.772
-2	0.03 %	(0.24)		-0.01 %	(-0.14)		0.781	0.710	0.435
-1	-0.41 %	(-2.44)	**	-0.41 %	(-2.91)	***	0.992	0.218	0.168
0	-0.76 %	(-5.22)	***	-0.84 %	(-11.97)	***	0.640	0.038	**0.018**

*In one-sample tests statistical significance levels indicated with: * <0.10, ** <0.05 and *** <0.01.*
In difference tests bolded values indicate significance at least at the 0.10 level.

Moving over to Panel B, the results for independent and brokerage analysts are similar. The MARs are positive prior to the revision and turn negative one day before the downgrade. The negative returns on day -1 are statistically significant, as well as subsequent day returns. Furthermore, differences before the announcement are only significant on day -5 (p-value 0.012 for difference in the averages and 0.009 for difference in the distributions), which indicates that there are no consistent differences between the analyst types. In sum, the results from the downgrades sub-sample evidence that the market could learn of the research processes. Moreover, no differences are identified between the analyst types.

Collectively the analysis in Table 7 suggests that prior to a recommendation upgrade or downgrade the market appears to anticipate the revision, which suggests that the market learns of the on-going research processes and begins to predict their outcomes. Furthermore, the anticipation to independent revisions appears to be greater, however, differences between independent and brokerage analysts are primarily insignificant, suggesting that the effect of anticipation by the market is the same for both. Since no reliable differences are identified, and because the learning appears to be greater for independent research processes, the evidence does not provide support to H4 ("*The market learns to* *predict on-going brokerage research processes to a greater extent than independent research processes*").

However, two important limitations must be considered in interpreting these findings. First, the evidence of market learning could actually be evidence of self-selection bias, meaning that analysts often tend to upgrade (downgrade) recommendations only after some good (bad) news are reported about the company, in which case the good (bad) news itself would have caused the drift to turn positive (negative) just before a recommendation revision. For example, Soltes (2014) finds that 70 % of analyst reports are released immediately after a public company press release. The analysis presented does not control for these possible effects. Second, the findings assume that the recommendation revisions in the database are recorded on the correct dates, which cannot be confirmed.

Cross-sectional regressions

To further analyze the announcement period returns, a cross-sectional regression analysis is utilized. Results are presented in Table 8. These tests are conducted to build on the evidence from the univariate analysis in Table 6. Two different dependent variables are used: the 3-day and 5-day CMARs. The 11-day and 21-day CMARs are not included in this analysis due to the market reaction being most pronounced on the immediate days around the revision. In unreported tests it is found that the results from these regressions do not differ from those reported in Table 8. The regressions control for target company size (*SMALL* and *MEDIUM* variables), low analyst coverage amount (*MAX1A* and *MAX2A*) and absolute recommendation levels (*SBUY*, *BUY*, *SSELL* and *SELL*). More detailed variable descriptions are included in Table 8. Moreover, correlation matrix for the regressors is presented in Appendix 3. None of the correlations exceed the threshold of 80 % (see, e.g., Gujarati & Porter, 2009) and therefore it can be assumed that no multicollinearity exists between the variables.

First looking at the regressions of upgrades sub-sample, the coefficient for the *IND* dummy is negative (positive) in regression 1 (2), however, the coefficients are not statistically significant, indicating that the market reaction is the same for both type of analysts. Consistent with the analysis in Table 6, no significant differences are identified for market reactions to different type of analysts' upgrades. This finding does not provide support to H2.

Moreover, the company size coefficients are negative and positive in regression 1 and both negative in regression 2, but they are not statistically significant. Thus, for recommendation upgrades, there is no significant difference in announcement period returns for different size of companies. However, *MAX1A* coefficients are statistically significant (p-values <0.05) and positive in regressions 1 and 2, which indicates that companies with only one analyst covering them earn significantly higher announcement period returns than companies covered by more than one analyst. Moreover, the coefficients on *MAX2A* in both regressions indicate that increasing the number of analysts from one to two has a detrimental effect on the announcement period return, however, the coefficients are not statistically significant. In addition, *SBUY* and *BUY* variables show that the level of the recommendation is informative to the markets as indicated by the significant positive coefficients in regressions 1 and 2.

Moving over to the recommendation downgrades sub-sample, the *IND* coefficient is positive in both regressions 3 and 4, evidencing that the market reaction to independent downgrades is less pronounced than to brokerage downgrades. The effect is weakly significant (p-value 0.090) in regression 4. This evidence is in contrast to the evidence on upgrades and to the analysis on Table 6, where no differences in announcement period returns for different analyst types are identified. The finding that the market reaction to independent revisions is lesser is against H2, however, it is not statistically significant.

Furthermore, *SMALL* and *MEDIUM* variable coefficients are all negative and significant at the 0.01 level in both regressions 3 and 4. These variables evidence that the market reaction to analyst downgrades is more pronounced for small and medium sized stocks, and that the effect is both economically and statistically significant. Analyst coverage variables *MAX1A* and *MAX2A* indicate similar findings as in the upgrades sub-sample that the informational value of recommendation revision is more pronounced when only one analyst is covering the stock, however, the coefficients are primarily insignificant. Recommendation level variables *SSELL* and *SELL* are negative and significant in both regressions 3 and 4. The results are consistent with the buy sub-sample as recommendation levels are documented to contain value. Collectively, the firm size and coverage amount variables provide support to H3.

Table 8. Multivariate analysis of announcement period returns

This table reports the results of cross-sectional regressions of the announcement period returns. The dependent variable in regressions (1) and (3) is the 3-day cumulative market-adjusted return from day 0 to +2, and in regressions (2) and (4) the 5-day cumulative market-adjusted return from day -2 to +2. Regressions are run separately for upgrades and downgrades sub-samples. *IND* is a dummy variable that equals one if the analyst is independent, and zero otherwise. *SMALL* and *MEDIUM* are dummy variables that equal one if the target company is a Small Cap or Medium Cap stock, respectively, and zero otherwise. *MAX1A* and *MAX2A* are dummy variables that equal one if there is a maximum of one or two analysts covering the stock, respectively, and zero otherwise. *SBUY*, *BUY*, *SSELL* and *SELL* are dummy variables that equal one if the recommendation issued is a strong buy, buy, strong sell or sell rating, respectively, and zero otherwise. The *p*-values for the coefficients are presented in parentheses. The null hypothesis for these tests is a coefficient of zero.

	Upgrades				Downgrades			
	(1)		(2)		(3)		(4)	
Dep. Variable	(0,+2)		(-2,+2)		(0,+2)		(-2,+2)	
	Coeff.		Coeff.		Coeff.		Coeff.	
Intercept	0.009	***	0.012	***	-0.007	***	-0.007	***
	(0.000)		(0.002)		(0.000)		(0.006)	
IND	-0.001		0.004		0.004		0.007	*
	(0.655)		(0.332)		(0.114)		(0.090)	
SMALL	-0.006		-0.011		-0.020	***	-0.025	***
	(0.188)		(0.127)		(0.000)		(0.001)	
MEDIUM	0.001		-0.002		-0.012	***	-0.018	***
	(0.764)		(0.730)		(0.000)		(0.000)	
MAX1A	0.011	**	0.017	**	-0.006		-0.007	
	(0.013)		(0.014)		(0.129)		(0.290)	
MAX2A	0.001		0.005		0.007	**	0.008	
	(0.808)		(0.410)		(0.039)		(0.129)	
SBUY	0.009	***	0.006					
	(0.003)		(0.243)					
BUY	0.005	*	0.005					
	(0.069)		(0.245)					
SSELL					-0.008	**	-0.012	**
					(0.013)		(0.026)	
SELL					-0.004	*	-0.008	**
					(0.068)		(0.023)	
Model summary								
n	1516		1516		1488		1488	
p-value	0.019	**	0.071	*	0.000	***	0.000	***
Adj.R^2	0.0064		0.0040		0.0288		0.0192	

*Statistical significance levels indicated with: * <0.10. ** <0.05 and *** 0.01.*

Cross-sectional regressions provide two key findings. First, even though brokerage analysts were shown to issue more optimistic recommendations, the market reactions to recommendation revisions do not contain statistically significant differences between different type of analysts, meaning that the market equally values the initial information content of independent and brokerage analyst recommendations. This is consistent with the findings of Lin and McNichols (1998) and Bradley, Jordan and Ritter (2003), but in contrast to Michaely and Womack (1998) and Agrawal and Chen (2008), who find that the market discounts potentially conflicted analysts' views, or to Casey (2013), who finds the opposite that independent analysts generate smaller announcement period returns. Similar to Bradley, Jordan and Ritter (2003), the evidence supports neither the conflict of interest nor the superior information hypothesis, since the market values analyst recommendations equally.

Second, control variables for target company size, amount of analyst coverage, and recommendation levels provides further insight into analyst recommendation characteristics. Size of the target company does not have a significant effect on announcement period returns for upgrades, however, it does have a significant negative effect for downgrades, indicating that the market reaction to recommendation downgrades for small stocks is greater than for large stocks. This is consistent with, Womack (1996) and Barber et al. (2001), who find that analyst research is more informative for small stocks, since there is less information available in the market about these stocks. Low analyst coverage is also found to be associated with greater market reaction to both upgrades and downgrades. Stocks with only one analyst covering them have greater market reactions to recommendation revisions. Furthermore, increasing the number of analysts from one to two has a detrimental effect on the returns. This is consistent with Doukas, Kim and Pantzalis (2005) who show that stocks with low analyst coverage have greater informational asymmetries, which indicates that analyst research is more beneficial for these stocks. It is also consistent with Li and You (2015) who show that increasing investor recognition of a stock is associated with greater market reactions. In addition to recommendation revisions the recommendation levels itself are also found to be informative, which is consistent with Barber, Lehavy and Trueman (2010).

In conclusion, the analysis of announcement period returns suggests that no differences exist in the initial market reactions to recommendation revisions between independent and brokerage analysts, which does not provide support to H2 ("*Independent analyst recommendations generate greater returns than brokerage analyst recommendations*"). However, the evidence from the control variables for firm size and coverage amount (*SMALL*, *MEDIUM*, *MAX1A* and *MAX2A*), which proxy for greater information asymmetries, provide support to H3 ("*Greater information asymmetry between investors and company management induces greater market reactions to recommendation revisions*").

4.4 Portfolio performances

Table 9 reports the annual returns for each portfolio and the market index from 1st of February 2010 through 31st of May 2018 and the closing values of each portfolio indexed on 1st of February 2010. In addition, illustrative presentation of the indices is provided in Figure 4. Raw returns present the portfolio performances without controlling for risk or transaction costs. Performance of the independent buy portfolio clearly outperforms the brokerage buy portfolio and the market index by almost doubling the performance of the market. Brokerage buy portfolio also beats the market, but the difference is much smaller. Both sell portfolios underperform the market index, but again the difference to the market is greater for the independent portfolio. Not controlling for risk or transaction costs, the evidence indicates that analysts on average are able to identify both future winner and loser stocks, however, independent analysts significantly outperform brokerage analysts.

Furthermore, examining the yearly returns for brokerage portfolios shows that the sell portfolio actually outperformed the buy portfolio in four out of the eight years, whereas the independent sell portfolio outperformed independent buy portfolio only in 2010. Moreover, even though brokerage sell portfolio underperformed the market, the difference is marginal as Figure 4 illustrates. For both independent and brokerage the difference to the market index is more pronounced for buy portfolios, which indicates that analysts on average are better at identifying future winner stocks than loser stocks. However, the time examination period from 2010 through 2018 has been a continuous bull market for the Finnish stock market, which is the most likely explanation for the differences between buy and sell portfolios. Although, it is notable that utilizing a short selling strategy for analysts' pessimistic views would have been unprofitable as the sell portfolios' absolute performance is positive.

Table 9. Yearly portfolio and market returns and index closing values

This table reports the returns for the different portfolios and the OMXHGI index. The returns are yearly, except for years 2010 and 2018 where the returns are 11-month and 5-month returns, respectively. In addition, the index closing values of the portfolios and the market index on 31st of May 2018 are also reported.

	Independent		Brokerage		Index
Year	Buy	Sell	Buy	Sell	OMXHGI
2018	5.2 %	0.3 %	4.1 %	9.5 %	10.9 %
2017	21.8 %	4.4 %	11.7 %	10.5 %	10.7 %
2016	29.2 %	12.2 %	19.1 %	23.6 %	8.5 %
2015	42.9 %	14.8 %	23.2 %	11.6 %	14.9 %
2014	13.5 %	-0.9 %	6.7 %	6.9 %	10.7 %
2013	39.2 %	26.4 %	33.9 %	31.3 %	32.2 %
2012	12.4 %	11.3 %	16.9 %	13.6 %	14.1 %
2011	-20.0 %	-36.6 %	-26.9 %	-26.3 %	-27.0 %
2010	25.8 %	26.2 %	27.3 %	5.9 %	18.9 %
Index closing	422.6	150.5	265.1	207.7	218.3

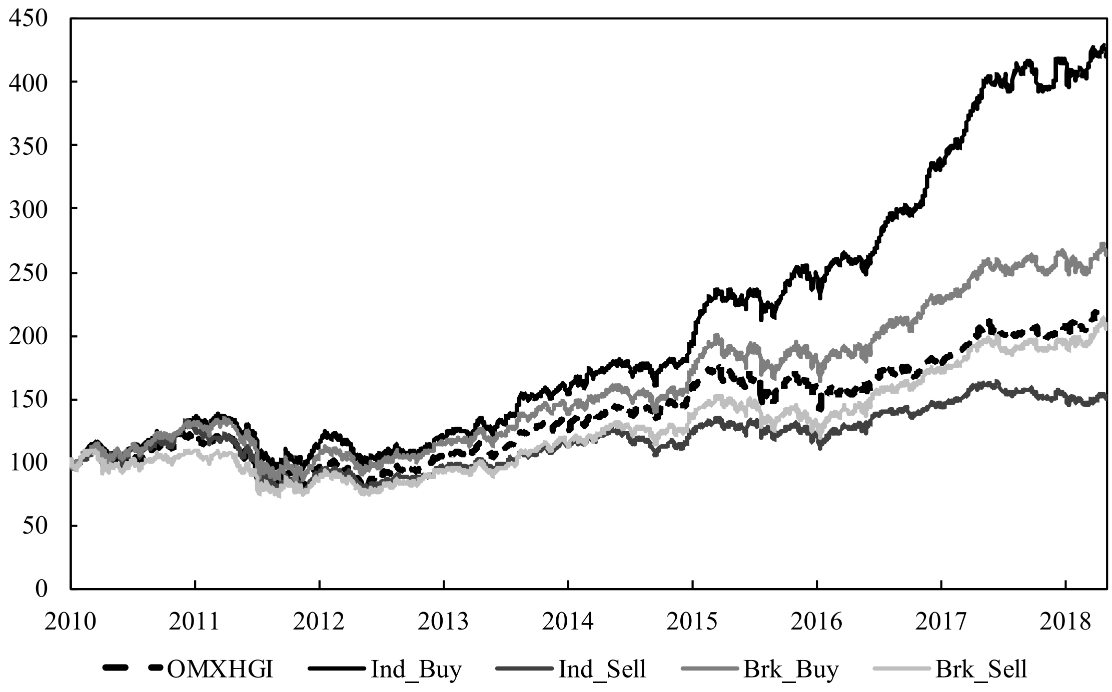

Figure 4. *Portfolio performance indices*

Table 10 reports the results of the time-series regressions of the monthly portfolio returns from February 2010 through May 2018. To control for possible model misspecification as in Cliff (2007), three different risk models are used: the CAPM, 3-factor model and 4-factor model. Correlation matrix for the regressors is presented in Appendix 4. None of the correlations exceed the threshold of 80 % and therefore it can be assumed that no multicollinearity exists.

First, analyzing the independent results shows that the buy portfolio has generated abnormal returns as measured by the alphas in the regressions. The annualized returns are roughly 9 % in the CAPM and 3-factor models and 10 % in the 4-factor model. These abnormal returns are significant at the 0.01 level in all three regressions. Moreover, the significant (0.01 level) positive loading on the *SMB* factor indicates that independent analysts tend to favor smaller stocks. As for the *HML* factor the loading is not reliably different from zero, indicating no tilt towards growth nor value stocks. Moreover, the significant (0.05 level) negative loading on the *MOM* factor indicates that most of the stocks in the portfolio tend to be past losers. Moving on to the independent sell portfolio, the alphas appear to be slightly negative, however, they are only weakly significant (0.10 level) in the FF and 4-factor models. The annualized abnormal return for the sell portfolio is approximately -5 %. Similar to the buy portfolio, the sell portfolio is also tilted towards small stocks as captured by the significant positive loading on the *SMB* factor. In addition, the portfolio loads positively at the 0.05 level on the *HML* factor, indicating a tilt towards value stocks. Moreover, the loading on the *MOM* factor is not reliably different from zero.

Second, looking at the brokerage portfolios the message is straightforward as all the alphas are insignificantly different from zero, indicating that neither portfolio is able to generate abnormal returns. Moreover, the *SMB* factor is significant and positive for the buy portfolio, indicating a tilt towards small stocks similar to the independent portfolios. Rest of the factors are not reliably different from zero, or one in the case of the market factor. Taken together the brokerage portfolio results indicate that the returns are mostly explained by the market return and that no positive or negative abnormal returns are generated.

Table 10. Portfolio performance regression results

This table reports the results of the time-series regressions of the four portfolios. The portfolio returns are monthly from February 2010 through May 2018. Regressions use portfolio returns in excess of the one-month risk-free rate, which is the one-month Euribor rate. The three models used are the CAPM, Fama-French (1993) 3-factor and Carhart (1997) 4-factor model. Excess return is the average portfolio return in excess of the one-month risk-free rate. Alpha coefficients are the estimates of the portfolio abnormal returns from the CAPM, 3-factor model (R_m–R_f, *SMB* and *HML*) and 4-factor model (adding *MOM*). The *p*-values for the alphas are presented in parentheses. In addition, factor loadings, sample sizes, model F-test *p*-values and adjusted R^2 are also reported for the 4-factor model. The null hypothesis for these tests is a coefficient of zero, except for the market factor where the null is one. The independent sell portfolio regression uses heteroskedasticity consistent standard errors for the calculation of the coefficient significances.

	Independent				Brokerage			
	Buy		Sell		Buy		Sell	
Excess return	0.014		0.003		0.009		0.007	
Alphas								
CAPM	0.007	***	-0.003		0.002		0.000	
	(0.001)		(0.139)		(0.161)		(0.701)	
3-factor	0.007	***	-0.004	*	0.002		0.000	
	(0.001)		(0.071)		(0.218)		(0.807)	
4-factor	0.008	***	-0.004	*	0.002		0.001	
	(0.000)		(0.080)		(0.174)		(0.685)	
Factor loadings								
R_m–R_f	0.903	**	0.897	*	0.962		0.962	
SMB	0.407	***	0.435	***	0.186	**	0.060	
HML	0.122		0.224	**	0.064		0.065	
MOM	-0.167	**	0.009		-0.035		-0.090	*
Model summary								
n	100		100		100		100	
p-value	0.000	***	0.000	***	0.000	***	0.000	***
Adj.R^2	0.8314		0.8159		0.9003		0.9302	

*Statistical significance levels indicated with: * <0.10, ** <0.05 and *** <0.01.*

Portfolio performance analysis shows that building a portfolio on independent analyst buy recommendations generates significant (0.01 level) positive abnormal returns after controlling for risk. The abnormal return documented is approximately 10 % annualized, which is consistent with the magnitude evidenced by Barber, Lehavy and Trueman (2007). Furthermore, the evidence shows a tilt towards small and past loser stocks. Similarly, the sell portfolio generates abnormal returns, although only weakly significant (0.10 level). In contrast, the brokerage portfolios do not generate any abnormal returns, and the returns are primarily associated with the market return. This finding is in contrast to Barber et al. (2001) who find that all analysts on average are able to generate abnormal returns before controlling for transaction costs.

In sum, independent analysts are found to outperform brokerage analysts in long-term performance after controlling for risk. This finding is consistent with Carleton, Chen and Steiner (1998), Michaely and Womack (1999), Cliff (2007) and Barber, Lehavy and Trueman (2007), who also document long-term outperformance by independent analysts.

The portfolio performance analysis provides further evidence on the hypotheses of this study. Independent analysts are able to generate value to investors, whereas brokerage analysts do not generate abnormal returns, which is evidence in favor of the conflict of interest hypothesis over the superior information hypothesis. The clear outperformance of the independent portfolios over brokerage portfolios provides support to H2 ("*Independent analyst recommendations generate greater returns than brokerage analyst recommendations*"). Furthermore, the positive and significant loadings on the *SMB* factor provide support to H3 ("*Greater information asymmetry between investors and company management induces greater market reactions to recommendation revisions*").

4.5 Robustness checks

The effect of paid research

The integrity of paid research has recently been questioned in the financial media as analysts might have incentives to issue more optimistic opinions to attract more research clients (HS, 2019). On the other hand, opposing argument states that independence is actually at the core of the business model, because if no trust exists between investors and paid coverage analysts, the value of the research decreases. Consequently, the coverage would become useless for the underlying companies, which would eventually lead to losing clients and breaking the business model. As most of the coverage by the independent firm in the sample is paid coverage, the next set of tests aim to investigate whether there is evidence of paid coverage resulting in biased research.

Table 11 reports the results of the univariate analysis of differences in recommendation, target price premium and announcement period return averages between paid and unpaid analyst research. First, Panel A compares the averages for recommendations and target price premiums. The differences in the averages indicate that paid independent recommendations are relatively more optimistic without controlling for any other factors. This finding indicates that independent in overall are more pessimistic than brokerage analysts because of pessimistic recommendations issued for unpaying companies, which offsets the optimistic recommendations issued for research clients. This finding partly challenges H1, however, the higher optimism of paid research could also stem from the fact that companies with good future prospects are more willing to pay for research services than companies that know they are going to underperform. Moreover, the evidence from the analysis of target price premiums is mixed, since paid coverage leads to optimism in target prices for downgraded stocks and, on the other hand, pessimism in upgraded stocks.

Table 11. Univariate analysis of paid and unpaid research differences

This table reports univariate analysis of differences in recommendations, target prices and CMARs between paid and unpaid coverage for recommendation upgrades and downgrades. Results are reported for both the full sample and for a sub-sample consisting of only independent observations. Set up of the analysis is similar to Tables 5 and 6.

Panel A: Recommendations and target price premiums						
	All research firms			Only independent		
Recommendation type	Paid research	Unpaid research	Diff. *p*-value	Paid research	Unpaid research	Diff. *p*-value
Upgrades						
Rating	1.95	2.07	**0.044**	1.95	2.24	**0.001**
n	278	1245		278	229	
Premium	8.9 %	13.3 %	**0.000**	8.9 %	8.4 %	0.684
n	276	1243		276	229	
Downgrades						
Rating	3.52	3.40	**0.092**	3.52	3.85	**0.000**
n	273	1221		273	233	
Premium	4.9 %	3.6 %	0.327	4.9 %	0.3 %	**0.002**
n	270	1217		270	233	
Panel B: Announcement period returns						
Upgrades						
CMAR (0,+2)	1.68 %	1.34 %	0.278	1.68 %	1.07 %	0.104
CMAR (-2,+2)	2.81 %	1.55 %	**0.006**	2.81 %	1.34 %	**0.008**
Downgrades						
CMAR (0,+2)	-2.09 %	-1.10 %	**0.001**	-2.09 %	-0.68 %	**0.000**
CMAR (-2,+2)	-2.64 %	-1.48 %	**0.008**	-2.64 %	-0.87 %	**0.002**

Bolded values indicate significance at least at the 0.10 level.

Moving over to Panel B, the announcement period returns evidence that the market reaction to paid coverage is significantly greater than for unpaid coverage. The finding shows that the market does not discount for paid coverage, indicating that the market does not consider there to exist any conflicts. This finding partly mitigates the previous finding that paid independent coverage is overly optimistic since the market does not consider there to exist conflicts of interest despite the higher optimism. This is consistent with the assumption that companies that know are going to perform well are more willing to pay for research services. To further validate this argument, the performances of paid and unpaid coverage companies are compared to test whether outperforming (underperforming) companies are more likely to buy (refrain from buying) research services. The analysis is done by reconstructing the independent buy portfolio and separating paid and unpaid coverage to their own portfolios. Table 12 below reports the regression results of the new portfolios.

Table 12. Portfolio regression results for paid and unpaid coverage

This table reports the results of the time-series regressions of the two new independent buy portfolios: paid coverage and unpaid coverage. The risk models are the same as in the regressions in Table 10. Abnormal return is measured as the alphas from these regressions. The null hypothesis for these tests is a coefficient of zero, except for the market factor where the null is one.

	Paid independent			Unpaid independent		
	Coeff.	*p*-value		Coeff.	*p*-value	
Excess return	0.017			0.009		
Alphas						
CAPM	0.011	(0.000)	***	0.001	(0.541)	
3-factor	0.010	(0.000)	***	0.001	(0.564)	
4-factor	0.012	(0.000)	***	0.003	(0.172)	
Factor loadings						
$R_m – R_f$	0.797	(0.000)	***	1.009	(0.864)	
SMB	0.591	(0.001)	***	0.167	(0.229)	
HML	0.175	(0.193)		0.022	(0.843)	
MOM	-0.148	(0.177)		-0.207	(0.021)	**
Model summary						
n	100			100		
p-value	0.000***			0.000***		
Adj.R^2	0.6644			0.8190		

*Statistical significance levels indicated with: * <0.10, ** <0.05 and *** <0.01.*

The results from Table 12 show that the paid coverage portfolio generates significant abnormal returns of approximately 15 % annualized, whereas the unpaid coverage portfolio does not generate any abnormal returns. However, the outperformance of the paid portfolio is at least partly explained by a strong tilt towards small stocks as evidenced by the positive and significant (p-value 0.001) loading on the *SMB* factor. In sum, the relatively higher optimism for paid coverage companies has not been misleading for investors, but instead led to higher abnormal returns, although at the expense of assuming more small firm risk. These findings further strengthen the evidence on H2 as well as on H3 since greater information asymmetry is evidenced to induce higher returns. Furthermore, the evidence validates the argument that companies that know they are going to outperform are more willing to pay for research services, which subsequently causes the higher optimism for paid coverage companies, and not possible conflicts arising from paid research. Hence, these tests validate the acceptance of H1 since paid research is not evidenced to cause conflicts.

The impact of transaction costs

As Barber et al. (2001) show, accounting for transaction costs will have a deteriorating effect on portfolio returns which can diminish the potential abnormal returns. In the second robustness test, the portfolios will be reconstructed to account for transaction costs. From a retail investor's perspective, average transaction cost per trade is estimated at 1 % of the trade value[14]. The cost is approximately in line with Barber et al. (2001), who estimate transaction costs at 1.31 % for their US based data. Because it was already shown that sell portfolios do not generate abnormal returns even before transaction costs, the impact of transaction costs is estimated only for the buy portfolios. Table 13 reports the results for the estimation of the abnormal returns in the time-series regressions after controlling for transaction costs.

Performance of both portfolios has naturally declined from the analysis of gross returns. Brokerage portfolio only barely outperforms the market index with a total return of 125 % compared to 122 % by the market, whereas the independent portfolio generates a total return of 251 %. Results from the regressions are identical in nature compared to the

[14] Approximation is a conservative estimate based on the transaction rates of five major stock brokerages in Finland at the time of writing.

analysis of gross returns. Even though the magnitude of abnormal returns has declined, the independent buy portfolio still generates abnormal returns of approximately 8 % annualized, whereas the brokerage portfolio does not generate any abnormal returns. In conclusion, the evidence on H2 is robust to controlling for transaction costs.

Table 13. Portfolio performance regression results after transaction costs

This table reports the results for the time-series regressions of the two buy portfolios after 1 % transaction costs. The setup and risk models are the same as in the regressions in Table 10, apart from the missing sell portfolios. Abnormal return is measured as the alphas from these regressions. The null hypothesis for these tests is a coefficient of zero, except for the market factor where the null is one.

	Independent			Brokerage		
	Coeff.	*p*-value		Coeff.	*p*-value	
Excess return	0.012			0.007		
Alphas						
CAPM	0.005	(0.013)	**	0.000	(0.758)	
3-factor	0.005	(0.017)	**	0.000	(0.895)	
4-factor	0.006	(0.003)	***	0.000	(0.781)	
Factor loadings						
$R_m – Rf$	0.903	(0.034)	**	0.962	(0.269)	
SMB	0.400	(0.001)	***	0.195	(0.035)	**
HML	0.128	(0.177)		0.073	(0.311)	
MOM	-0.161	(0.039)	**	-0.026	(0.659)	
Model summary						
n	100			100		
p-value	0.000***			0.000***		
Adj.R^2	0.8310			0.9001		

*Statistical significance levels indicated with: * <0.10, ** <0.05 and *** <0.01.*

The impact of less frequent portfolio balancing

All previous tests in this research assume that the portfolios are rebalanced daily, which requires effort and time from the investor, as well as induces more trading and subsequently more transaction costs. A more realistic scenario for the common investor is that the portfolio is balanced less frequently, and therefore the next test examines whether balancing the buy portfolios on weekly or monthly basis affects the abnormal returns generated by following analyst recommendations. Again, only buy portfolios are included in this test due to the sell portfolios not being able to generate significant abnormal returns even with daily balancing. Table 14 below reports the results of the portfolio regressions when the portfolios are balanced on a weekly and monthly basis. The results show that less frequent balancing reduces the abnormal returns, and the reduction is greater for the independent portfolio, whereas the brokerage portfolio average excess return is not materially affected. However, consistent with previous analyses, independent still outperform by generating significant abnormal returns, whereas brokerage portfolios do not generate significant abnormal returns. In sum, evidence on H2 is robust to less frequent portfolio rebalancing.

Table 14. Portfolio abnormal returns with weekly and monthly rebalancing

This table reports the results of the time-series regressions of the buy portfolios when the portfolios are rebalanced weekly and monthly. The setup and risk models are the same as in the regressions in Table 10, apart from the missing sell portfolios. Abnormal return is measured as the alphas from these regressions. The null hypothesis for these tests is a coefficient of zero, except for the market factor where the null is one.

	Independent				Brokerage			
	Weekly		Monthly		Weekly		Monthly	
Excess return	0.014		0.011		0.009		0.009	
Alphas								
CAPM	0.007	***	0.005	**	0.002		0.002	
	(0.001)		(0.019)		(0.203)		(0.274)	
3-factor	0.007	***	0.004	**	0.002		0.001	
	(0.001)		(0.021)		(0.266)		(0.331)	
4-factor	0.008	***	0.006	***	0.002		0.002	
	(0.000)		(0.004)		(0.219)		(0.278)	
Factor loadings								
$R_m – R_f$	0.903	**	0.880	***	0.964		0.963	
SMB	0.407	***	0.362	***	0.176	*	0.176	*
HML	0.122		0.138		0.063		0.081	
MOM	-0.167	**	-0.151	**	-0.033		-0.030	
Model summary								
n	100		100		100		100	
p-value	0.000	***	0.000	***	0.000	***	0.000	***
Adj.R^2	0.8314		0.8410		0.8985		0.9040	

*Statistical significance levels indicated with: * <0.10, ** <0.05 and *** <0.01.*

5 CONCLUSIONS

This research investigates the value of equity research from a retail investor's perspective by analyzing the information content and value of analysts' stock recommendations. The purpose of this research is to examine whether the value of equity research differs between purely independent and traditional brokerage analysts. Analysis is made by examining the average recommendation and target price levels, announcement period returns to recommendation revisions, and long-term portfolio returns. Tests are conducted with a dataset of Finnish sell-side equity analyst recommendations by 24 different analyst firms from February 2010 through May 2018.

In conclusion, the findings of this study evidence the following. First, brokerage analysts are shown to issue more optimistic recommendations and target prices. In the full sample, the average recommendation by independent analysts is 2.87 compared to 2.65 by brokerage analysts, and the difference is found to be statistically significant. Moreover, the difference in recommendation levels is most pronounced for recommendation downgrades sub-sample, where the average recommendation by independent analysts is 3.67 compared to 3.30 by brokerage analysts. This finding suggests that brokerage analysts are more reluctant to issue greater downgrades. Findings from target price premiums are similar in nature. In the full sample, brokerage analysts issued significantly higher target prices (premium of 10.2 % compared to 5.9 % by independent analysts). The difference is economically and statistically most significant for recommendation upgrades sub-sample (14.4 % compared to 8.7 % by independents). Collectively, these findings evidence greater optimism by brokerage analysts, which leads to accepting H1 of this study.

Second, no differences are found between the announcement period market reactions to recommendation revisions by different analyst types. Announcement period returns for independent recommendations appear to be relatively greater, however, the differences in the returns are not statistically significant, except for the 11-day window around recommendation upgrades, where the average CMAR of 2.43 % for independent recommendations is significantly different from brokerage CMAR of 1.50 %. Due to the differences being primarily insignificant, the findings suggest that the market values the initial information content of analyst recommendations equally and does not discount potentially conflicted analysts' views nor believes that they have superior information. The short-term returns analysis does not provide support to H2.

Third, in long-term portfolio performance independent recommendations are found to significantly outperform recommendations by brokerage analysts. The gross abnormal return from following independent buy recommendations with a buy-and-hold investment strategy is approximately 10 % annualized. In contrast to Barber et al. (2001), the abnormal performance is robust to controlling for transaction costs, which only decrease the abnormal return to approximately 8 % annualized. In addition, the abnormal returns are robust to balancing the portfolios less frequently than on a daily basis. Furthermore, independent sell portfolio underperforms that of brokerage, evidencing that independent analysts are also better at identifying underperforming stocks. However, neither sell portfolio is able to generate abnormal nor absolute negative returns, evidencing that short selling pessimistic analyst recommendations is not profitable. In sum, the statistical significance and magnitude of the difference between the buy portfolios leads to partly accepting H2.

Fourth, informational asymmetries as proxied by small firm size and low analyst coverage show that greater information asymmetry induces greater market reactions. More specifically, low analyst coverage is found to induce greater market reactions to recommendation upgrades, and small firm size to recommendation downgrades. The 5-day CMAR (-2,+2) to recommendation upgrades for firms with only one analyst covering them is 170 basis points greater than for firms with multiple analysts. Furthermore, the 5-day CMAR to recommendation downgrades for small-cap (medium-cap) firms is found to be -250 (-180) basis points more negative than for large-cap firms. Collectively, these findings evidence that greater information asymmetry induces greater market reactions, which leads to accepting H3.

Fifth, the returns prior to recommendation upgrades or downgrades suggest that the market could learn of on-going research processes and to predict their outcome, however, no reliable differences are identified between independent and brokerage firms. The negative drift before recommendation upgrades turns positive 5 days (4 days) prior to the revision for independent (brokerage) analysts. Moreover, for downgrades the positive drift turns negative one day prior to the recommendation revision for both analyst types. In sum, the evidence suggests that market learning is plausible for both analyst types and more pronounced before recommendation upgrades. Furthermore, the anticipation by the market appears to be greater for independent recommendations, although no significant consistent differences between the analyst types are identified. However, the tests do not control for other events taking place before the revisions and therefore the results could also be evidence of self-selection bias, meaning that analysts might tend to upgrade (downgrade) recommendations soon after some good (bad) news are reported about the company, in which case these good (bad) news itself would have caused the drift to shift. In addition, the findings assume that the recommendations in the database are recorded on the correct dates, which cannot be confirmed. Collectively, these findings do not provide support to H4, which leads to rejecting the hypothesis. To conclude, Table 15 summarizes the hypotheses of this study.

Table 15. Summary of the hypotheses

Hypothesis	Status	Comments
H1: Brokerage analysts issue more optimistic recommendations and target prices than independent analysts	Accepted	The difference is statistically significant for both, but economically more significant for target prices
H2: Independent analyst recommendations generate greater returns than brokerage analyst recommendations	Partly accepted	No differences are documented in announcement period returns, however, in long-term returns independent clearly outperform
H3: Greater information asymmetry between investors and company management induces greater market reactions to recommendation revisions	Accepted	Greater information asymmetries as proxied by small firm size and low analyst coverage are documented to induce greater market reactions
H4: The market learns to predict on-going brokerage research processes to a greater extent than independent research processes	Rejected	Market actually appears to anticipate independent recommendations to a greater extent, but no significant consistent differences are identified between the analyst types

There are two key contributions from this study. First, purely independent equity research is still a scarcely investigated field due to the small amount of purely independent firms. In addition, recent regulatory changes, for example MiFID 2, pressure traditional brokerage firm research to assume a more independent status as ties to other departments of the banks are being cut off and monitored more closely. The field calls for more research, and by examining a recent time period this study extends the existing literature and documents clear outperformance by independent analysts over brokerage analysts in long-term abnormal returns, which is robust to controlling transaction costs and less frequent portfolio rebalancing. This result indicates that the efforts of the regulators have had merit as independent research firms are capable of providing valuable research to investors despite having to come up with new business models to sustain the research business on its own.

Second, the independence of purely independent research firms has recently been questioned if the research firm is paid for its coverage by the target companies (HS, 2019). The results of this study indicate that the performance of paid coverage is not inferior, but instead superior to traditional research firms with unpaid coverage, as evidenced by the outperformance of the independent recommendations in this study. This indicates that the analysts have greater incentives to maintain the good quality of the research in order to attract more investor audience, and subsequently more research clients, in order to sustain the business model. The finding gives merit to the independent research firms charging for their coverage as well as to the brokerage firms which have chosen to shift towards charging for their research in order to increase the independence of their research units.

5.1 Reliability and limitations

For the interpretation of the results of this research, some important limitations must be considered. First, the chosen time period of this study takes place at the time of a long bull market as, apart from year 2011, the market index has increased each year with an average annual return of 10 %. Therefore, the findings of this study are largely confined to a market growth period and do not necessarily describe the situation in a bear market.

Second, even though the sample consisting of 24 individual research firms and 3438 recommendations is large enough for statistical testing, it does not fully represent the recommendations made in Finland during the time period due to some database restrictions. Out of the total recommendations in the database, approximately 60 % could be included in the sample. This notion further limits the generalizability of the results. Furthermore, the sample is predisposed to survivorship bias as recommendations are included in the sample only for those companies that the research firms are still covering. If a research firm dropped the coverage of a company during the time period, the recommendations issued before the termination are not accessible from the database. Moreover, some research firms choose to record their recommendations in the database anonymously and therefore these recommendations cannot be included in the sample.

Third, only one research firm in the sample qualifies as a purely independent research firm as other firms also engage in brokerage services (investment banking or stock brokering). Due to this reason the results of this study might be affected by certain company specific characteristics that are not accounted for. However, this is not because some pure research firms are absent from the data, but because no other pure independent research firms currently exist in the Finnish stock market.

5.2 Suggestions for future research

Couple interesting topics for future research emerge from this study. First, the role and value of equity research in today's supercomputer era is often questioned as vast information contents are available and accessible by almost everyone. Furthermore, regulatory pressures are causing traditional brokerage firms to cut down on their research staff, since the costs of the research can no more be included in the prices of other services (Financial Times, 2018). Research firms are under heavy pressure to shift towards new ways of doing business, whilst maintaining the integrity of their research. A new emerging business model in the industry is to charge the target companies for their coverage. At the same time, the research quality is questioned if the analyst firm receives their compensation from the target company (HS, 2019). Even though this study sheds light into the value of paid coverage, future studies need to address this issue in more detail to better understand what this shift means for the value of equity research.

Second, for the reason that this study does not control for firm specific factors of the independent company in the sample, future research could investigate further into what other factors affect the performance of equity research firms. For example, the vast digitalization efforts carried out by the independent company in the sample have strongly increased its presence in the market, specifically among retail investors. Whether this has increased the informativeness of the research or just increased the overall hype around the firm is yet to be answered. The effects of digital disruption and regulatory pressure are creating waves for the industry to shift towards new business and operating models and investors and academics alike ought to understand better what this means. In other words, what digitalization means for the equity research industry, and what are the effects of making equity research more easily accessible and more engaging to the common investors are important areas to investigate further.

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APPENDICES

Appendix 1: List of covered firms

Company	(1)	(2)	(3)	(4)		(1)	(2)	(3)	(4)
ADMICOM	Small	1	2	2.00	EVLI PANKKI	Medium	1	3	1.33
AHLSTRÖM-MUNKSJÖ	Large	3	18	2.44	EXEL COMPOSITES	Small	2	18	2.44
AKTIA	Medium	1	22	2.27	F-SECURE	Medium	2	32	2.47
ALMA MEDIA	Medium	2	31	2.94	FINNAIR	Large	3	42	2.69
ALTIA	Medium	1	1	3.00	FISKARS	Large	2	11	3.00
AMER SPORTS	Large	4	40	1.90	FONDIA	Small	1	3	3.67
APETIT	Small	1	19	3.37	FORTUM	Large	13	115	2.85
ASIAKASTIETO GROUP	Medium	1	6	2.17	GLASTON	Small	2	19	2.74
ASPO	Medium	3	24	2.46	GOFORE	Small	2	3	2.67
ASPOCOMP GROUP	Small	1	8	3.00	HEEROS	Small	1	3	3.67
ATRIA	Medium	1	32	2.44	HKSCAN	Medium	1	30	3.43
AVIDLY	Small	1	8	1.75	HUHTAMÄKI	Large	3	43	2.51
BASWARE	Medium	2	39	2.49	INNOFACTOR	Small	2	17	2.71
BITTIUM	Medium	2	34	2.94	INVESTORS HOUSE	Small	1	5	2.80
CAPMAN	Medium	3	29	2.48	KAMUX	Medium	3	4	1.75
CARGOTEC	Large	5	73	2.59	KEMIRA	Large	4	59	2.61
CAVERION	Medium	3	31	2.61	KESKO	Large	4	53	2.83
CITYCON	Large	6	40	2.50	KESLA	Small	1	9	2.44
CONSTI GROUP	Small	2	13	1.85	KONE	Large	8	59	3.10
CRAMO	Medium	3	40	2.40	KONECRANES	Large	6	52	2.58
DETECTION TECHNOLOGY	Small	2	8	2.63	KOTIPIZZA GROUP	Small	4	25	2.84
DIGIA	Small	2	30	1.83	LASSILA & TIKANOJA	Medium	2	26	2.50
DNA	Large	2	8	3.13	LEHTO GROUP	Medium	2	10	2.50
DOVRE GROUP	Small	1	1	5.00	MARIMEKKO	Small	3	29	3.45
EAB GROUP	Small	1	3	2.67	MARTELA	Small	1	22	2.14
EFECTE	Small	1	1	1.00	METSO	Large	6	64	2.55
EFORE	Small	1	9	3.67	METSÄ BOARD	Large	4	65	2.43
ELISA	Large	5	65	2.94	NEO INDUSTRIAL	Small	1	8	3.50
ENDOMINES	Small	1	5	3.20	NESTE	Large	7	104	2.74
EQ	Medium	2	14	2.71	NEXT GAMES	Small	2	5	2.20
ETTEPLAN	Medium	2	33	2.12	NIXU	Small	1	6	2.50

Appendix 1 (*continued*)

	(1)	(2)	(3)	(4)		(1)	(2)	(3)	(4)
NOKIA	Large	13	151	2.75	SILMÄASEMA	Small	1	3	1.33
NOKIAN RENKAAT	Large	6	66	2.73	SOLTEQ	Small	1	14	2.93
NORDEA BANK	Large	6	43	2.77	SRV	Medium	3	45	2.84
NURMINEN LOGISTICS	Small	1	2	4.50	SSAB	Large	6	50	3.12
OLVI	Medium	2	35	2.86	STOCKMANN	Medium	3	55	3.51
ORAVA	Small	1	19	3.11	STORA ENSO	Large	6	77	2.44
ORIOLA CORPORATION	Medium	3	45	2.71	SUOMEN HOIVATILAT	Medium	2	12	2.08
ORION	Large	5	48	3.52	SUOMINEN	Medium	2	23	2.96
OUTOKUMPU	Large	6	92	2.75	TAALERI	Medium	2	11	2.27
OUTOTEC	Medium	4	69	2.87	TALENOM	Small	2	9	1.78
PANOSTAJA	Small	1	11	2.91	TECHNOPOLIS	Medium	2	27	1.81
PIHLAJALINNA	Medium	4	14	1.64	TECNOTREE	Small	1	15	3.73
PIIPPO	Small	1	8	3.38	TELESTE	Small	2	34	2.53
PONSSE	Medium	2	29	2.90	TELIA	Large	8	60	2.73
PRIVANET GROUP	Small	1	7	3.14	TERVEYSTALO	Large	2	2	2.00
PÖYRY	Medium	2	25	3.56	TIETO	Large	5	50	2.98
QT GROUP	Small	1	2	1.50	TIKKURILA	Medium	4	51	2.92
RAISIO	Medium	2	24	2.21	TITANIUM	Small	1	5	2.60
RAMIRENT	Medium	3	54	2.81	TOKMANNI	Small	2	4	1.75
RAPALA VMC	Small	2	26	2.58	TOKMANNI GROUP	Medium	1	1	1.00
RAUTE	Small	1	20	3.20	UNITED BANKERS	Small	1	4	3.00
REMEDY	Small	1	1	1.00	UPM	Large	5	70	2.94
RESTAMAX	Small	1	10	1.80	UPONOR	Large	2	28	2.14
REVENIO GROUP	Medium	1	13	2.62	UUTECHNIC GROUP	Small	1	6	3.50
ROBIT	Small	1	3	2.33	VALMET	Large	5	39	2.74
ROVIO	Medium	2	3	2.00	VERKKO-KAUPPA	Small	2	15	2.27
SAMPO	Large	5	50	2.50	VINCIT	Small	1	4	4.00
SANOMA	Large	3	60	2.83	VÄISÄLÄ	Medium	2	28	3.14
SCANFIL	Medium	2	8	2.25	WÄRTSILÄ	Large	6	63	2.92
SIILI SOLUTIONS	Small	1	8	2.25	YIT	Large	4	56	2.59

(1) = Company size

(2) = Number of analysts covering the company

(3) = Number of recommendations

(4) = Average recommendation

Appendix 2: Sample normal distribution test results

Panel A: Announcement period returns				
	CMAR (0,+2)	CMAR (-2,+2)	CMAR (-5,+5)	CMAR (-10,+10)
Observations	3418	3406	3402	3393
Mean	0.001	0.001	0.002	0.001
Median	0.001	0.000	0.001	0.002
Standard deviation	0.041	0.064	0.078	0.097
Skewness	0.473	0.068	0.188	0.353
Excess Kurtosis	5.088	6.316	3.590	1.497
p-value	0.000**	0.000**	0.000**	0.000**
Panel B: Portfolio returns				
	Independent (Buy)	Independent (Sell)	Brokerage (Buy)	Brokerage (Sell)
Observations	100	100	100	100
Mean	0.014	0.003	0.009	0.007
Median	0.010	0.006	0.012	0.010
Standard deviation	0.046	0.045	0.045	0.045
Skewness	0.162	0.276	0.571	0.222
Excess Kurtosis	0.750	0.990	0.719	0.026
p-value	0.109	0.046*	0.060	0.602

*Normal distribution tests conducted with Jargue-Bera test. Null hypothesis states that sample distribution matches a normal distribution. Statistical significance levels indicated with: * <0.05 and ** <0.01.*

Appendix 3: Correlation matrix for cross-sectional regressions

	IND	*SMALL*	*MEDIUM*	*MAX1A*	*MAX2A*	*SBUY*	*BUY*	*SSELL*	*SELL*
IND		0.322**	0.005	0.282**	0.240**	-0.020	0.086**	0.084**	0.218**
		0.000	0.779	0.000	0.000	0.237	0.000	0.000	0.000
SMALL	0.322**		-0.269**	0.535**	0.530**	0.030	0.024	0.021	0.050**
	0.000		0.000	0.000	0.000	0.076	0.156	0.213	0.003
MEDIUM	0.005	-0.269**		0.003	0.333**	0.021	0.008	-0.010	0.027
	0.779	0.000		0.871	0.000	0.217	0.643	0.576	0.107
MAX1A	0.282**	0.535**	0.003		0.515**	0.002	0.016	0.032*	0.068**
	0.000	0.000	0.871		0.000	0.908	0.340	0.011	0.000
MAX2A	0.240**	0.530**	0.333**	0.515**		0.057**	0.040*	-0.019	0.038*
	0.000	0.000	0.000	0.000		0.001	0.020	0.268	0.027
SBUY	-0.020	0.030	0.021	0.002	0.057**		-0.297**	-0.101**	-0.223**
	0.237	0.076	0.217	0.908	0.001		0.000	0.000	0.000
BUY	0.086**	0.024	0.008	0.016	0.040*	-0.297**		-0.182**	-0.401**
	0.000	0.156	0.643	0.340	0.020	0.000		0.000	0.000
SSELL	0.084**	0.021	-0.010	0.043*	-0.019	-0.101**	-0.182**		-0.137**
	0.000	0.213	0.576	0.011	0.268	0.000	0.000		0.000
SELL	0.218**	0.050**	0.027	0.068**	0.038*	-0.223**	-0.401**	-0.137**	
	0.000	0.003	0.107	0.000	0.027	0.000	0.000	0.000	

*Statistical significance levels indicated with: * <0.05 and ** <0.01. Correlation coefficients presented above and p-values below.*
n = 3438. See Table 8 for variable descriptions. Pearson (Spearman) correlations presented above (below) the diagonal.

Appendix 4: Correlation matrix for time-series regressions

		R_m–R_f	*SMB*	*HML*	*MOM*
R_m–R_f	Correlation		-0.158	0.312**	-0.184
	Sig. (2-tailed)		0.117	0.002	0.067
SMB	Correlation	-0.112		-0.076	0.030
	Sig. (2-tailed)	0.266		0.451	0.769
HML	Correlation	0.295**	-0.020		-0.468**
	Sig. (2-tailed)	0.003	0.841		0.000
MOM	Correlation	-0.129	0.033	-0.467**	
	Sig. (2-tailed)	0.203	0.745	0.000	

*Statistical significance levels indicated with: * <0.05 and ** <0.01.*
n =100. Pearson (Spearman) correlations presented above (below) the diagonal.