The Value of a Changed Opinion

Analyzing Stock Price Reactions to Analyst Recommendation Revisions

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Christoffer D. Brammer (102149)
Victor F. Näsström (125141)

Supervisor: Peter Feldhütter

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HANDELSHØJSKOLEN

Abstract

This thesis investigates the market reaction in stock prices to changes in analyst recommendations in Denmark and the United States. We examine a dataset of 102,417 analyst recommendation revisions for 1,403 stocks listed in Denmark and the United States for 2000 through 2019.

According to the market efficiency hypothesis, if analyst recommendations contain price-relevant information to the market, then prices should adjust immediately to incorporate the new information. We test whether there is any apparent drift or mean reversion after the announcement of recommendation revision as has been found around, e.g., earnings announcements and previous studies.

We find an immediate effect determined by both direction of change as well as the rating level of the recommendation revision. A positive (negative) recommendation revision, defined as an upgrade to "buy" (downgrade to "sell"), results in three-day buy-and-hold abnormal returns of 1.86% (-1.26%) in Denmark and 1.62% (-1.91%) in the US which are all significantly different from zero at the 1% significance level but is generally not significantly different between the two markets.

The results indicate an asymmetric reaction to positive and negative recommendation revisions in the U.S. market but not in Denmark, where upgrades to "buy" are associated with the most positive abnormal returns and a larger effect in absolute terms than downgrades to "sell."

We observe those recommendation revisions that skip rating level(s) experience higher abnormal returns than revisions that do not skip levels. We also show other significant determinants of the reaction to recommendation revisions such as market capitalization, trading volume, broker, year, the potential of the stock, and the distance of the recommendation from the consensus.

Furthermore, we find that stock prices do not respond immediately to recommendation revisions as abnormal returns are significant for the day following the announcement, and different forms of drifts and mean reversions are indicated depending on the type of recommendation change.

Lastly, we show that an investment strategy with long (short) positions in positive (negative) recommendation revisions and daily trading leads to significant abnormal returns before accounting for transaction costs.

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1 | Introduction

Background

To Zealand Pharma, a Danish life-science company, October 15th, 2019, was an extraordinary day. The market value of their equity increased by 18% – more than 1 billion DKK – in a single day. There did not seem to be any news relevant to the firm's profitability on that day. However, there was something else: Goldman Sachs reviewed their estimated firm value and upgraded their recommendation from a neutral "hold" rating to a bullish "buy" rating (Grønnemann, 2019). How can the opinion of a single analyst affect the price as much as it did? Perhaps this analyst knows something that the public does not. Perhaps the soaring stock price was not due to the recommendation change at all, but something else entirely.

Brokerage houses invest heavily in research departments attempting to uncover mispricing of stocks in the market and then publishing these findings (Barber et al., 2001; Womack, 1996). They frequently appear in financial news media, and there are several events like the one above, which indicate that investors take these recommendations into consideration. Another one of these events took place on the 15th of August 2007, as the Merrill Lynch analyst, Kenneth Bruce, downgraded his rating of Countrywide Financial (R. Loh & Stulz, 2009). This downgrade apparently led to a strong market reaction, resulting in the stock price diving down 13% on that day. Bruce argued that Countrywide could go bankrupt if liquidity worsened. Ironically, announcing this opinion could itself have caused it to go bankrupt. This market reaction shares similarities with a negative earnings surprise, where the prospects of a firm are suddenly less optimistic, and as a result, the expected return on the share price declines. However, as stated by one of the most influential researchers in the area, Womack (1996), analyst ratings are *opinions* and not *facts*. Whether this statement is correct or not is one of the things we want to explore in this thesis.

Analysts continuously form and update their expectations of future stock prices based on currently available information at any time and thus decide whether to upgrade, downgrade, or hold a given recommendation of a stock. If an analyst believes the future price of a stock to be higher (lower) than the current price, the analyst will choose to issue or change his/her recommendation to a buy (sell). On the contrary, he/she might choose to grant a "hold" recommendation, if his or her expectation of the future price does not differ materially from the current share price.

So does a recommendation change lead to a change in share price, on average? Unsurprisingly, the research on the topic is somewhat inconclusive. One of the central studies (Stickel, 1995) found that there were indeed abnormal profits to be made by listening to the analysts, as they seemed to have an impact on the stock price. The author found that upgrades and downgrades were associated with positive and negative excess returns, respectively. He also estimated these effects to be of roughly the same size in absolute terms. This was contested the following year by Womack (1996), who provided evidence that downgrades produced much larger abnormal returns than upgrades. He also found that downgrades continued to generate abnormal returns in at least six months following a recommendation change, while the mean post-event drift only lasted for around one month for upgrades.

Then, in 2001, another impactful paper was published (Barber et al., 2001). The authors attempted to estimate more realistic returns by constructing five portfolios based on consensus ratings with daily rebalancing. This meant that a single recommendation would not lead to a change in investment unless it led to the consensus rating of the given stock to cross the threshold into another portfolio. With this method, they found similar results to the previous literature, but upon including transaction costs estimated based on Keim and Madhavan (1998), they found no significant abnormal returns. Three of the four original researchers revisited the topic in a later paper (Barber et al., 2010) and found that upgrades had, in direct contrast to the evidence provided by Womack (1996), a greater impact on price than downgrades (in absolute terms). They also note that the direction and magnitude of the effects associated with recommendation changes were different, conditional on the level.

Jegadeesh & Kim (2006) took an international perspective, comparing the U.S. to the other G7 countries. They found the U.S. market to have the greatest price reactions associated with recommendation changes, although it was also present in five of the other six markets. Italy was the exception, as they found there to be no price reaction significantly different from zero. They concluded that although there was a significant effect in the U.S., the same could not be said for the rest of the world. In addition to estimating the initial price response, they found the same six markets to have excess returns significantly different from zero on the day following the recommendation change. Finally, they documented a post-event drift that lasted for two to six months, further supporting Womack’s (1996) findings. The presence of a delayed event response, they argued, was evidence of the market not being semi-strong form efficient.

Research Focus and Objectives

As seen above, all the studies are more than a decade old, and the data they study is even older than that. There have been far fewer peer-reviewed and well-known publications in the literature the last ten years, and so we set out to help fill that gap. In addition to investigating the U.S. market and comparing our results to the studies above, we also examine the much smaller and less studied Danish stock market.

This thesis examines the relationship between analyst recommendations and stock prices. More specifically, we investigate whether changes recommendations have an impact on stock prices. More than 1,400 stocks from the U.S. and Danish market have been analyses over the past 20 years to provide evidence of whether they are affected by recommendation changes or not. If these changes are associated with significant effects, can investors make abnormal returns by basing trading strategies on them?

The research question in this thesis is as follows:

How are stock prices affected by changes in analyst recommendations in Denmark and the United States?

To attempt to answer this question, we construct different groups of recommendation changes, depending on their initial and target rating. This is done to differentiate between positive and negative changes, amongst other attributes. We then estimate the returns excess of the expected returns of the given stock on the announcement day of the recommendation change. After estimating this same-day effect, we test if there are significant abnormal returns on the days surrounding the event. We estimate the cumulative abnormal return in the days following the recommendation change to attempt to answer whether investors can use recommendation changes to improve their profitability. A trading strategy based on the findings of this thesis is also tested to validate the conclusions in a practical setting on historical data. We also analyze other potential explanations for the price change by regressing abnormal returns on other variables.

Motivation and Relevance

We expect this thesis to be of use by both financial economists in academia and investors active in the stock markets of the United States and Denmark. In academics, this thesis is part of the discussion on market efficiency and the effect and information value of analysts' investment recommendations.

For practitioners, it can help to understand the impact of analysts' opinions and contribute to the decision making around investment decisions in terms of expected abnormal profits.

This thesis will be distinct from previous research in some important ways: We have a larger and most importantly, newer sample than most studies in the field. Additionally, we compare the Danish market, which has received very little attention in previous research. Most research has focused on the U.S. market, and central papers in the literature are primarily using data more than a decade old. We also include more types of recommendation changes, as we also consider new recommendations, where some of the older and central papers in the field, Stickel (1995) and Womack (1996), only analyze analyst recommendation revisions. Other central papers, such as Barber et al. (2001) and Jegadeesh et al. (2004), analyze changes to the consensus (average) recommendation level, where our focus is on the individual analyst's recommendation and the impact in the market when a single analyst changes his/her mind.

In opposition to much previous research, this thesis will not focus on the stock-picking capabilities of the individual analyst, but rather on the potential effect that the recommendation changes have on the market. As a continuation of this, we attempt to explain what the informational value of the analyst recommendations is. Fama (1970) argues that investors should not be able to generate abnormal from following analysts' recommendations as stock prices should already reflect all information publicly available, and prices should instantaneously adjust to include new information when it becomes available.

This is in high contrast with the presence of a financial industry with brokerage houses undertaking costly research activities. At the same time, investors should have an incentive in the form of high expected profits to pay the brokerage houses and analysts for these investment recommendations. The analysts might provide superior analyses to investors, or they might make private information accessible to the public by somehow having unique access to it. On the other hand, the content of their reports might not be very relevant at all. Perhaps investors simply believe that analysts represent some expected change in stock prices, and thus speculative investors trade on the recommendations in the hopes of attaining superior returns. As such, the thesis may be viewed as a contribution to the discussion on market efficiency.

Thesis Structure

The thesis is structured as follows. First, in section 2, we will review previous related literature to build the empirical background. In section 3, we will describe our methodology. Section 4 is a description of our data and the design of our analysis. Section 5 presents our analysis and findings in terms of both immediate effect, longer-term effect, and trading strategy. In section 6, we will attempt to give some perspective on the findings in this thesis and ideas for future research. We state our conclusion in the final section.

2 | Review of related literature

Initial research in the field

The seminal paper, “Can stock market forecasters forecast” (Cowles, 1933), attempted to estimate whether stock recommendations made by professional agencies had any investment value through superior stock-picking abilities. His sample consisted of a total of 7,500 recommendations made by 16 financial service providers and 20 fire insurance companies from the period 1928-1932. This was, to our knowledge, the first study in this field. Cowles found that investing based on their recommendations would yield negative, if any, abnormal profits. This might be a surprising result, as brokerage firms invest hundreds of millions of dollars annually in analyzing, producing, and publishing research and recommendations in order to promote the belief that some stocks are more attractive than others (Barber et al., 2001; Womack, 1996).

So why does the financial analyst industry produce these recommendations if they have no expected investment value above that of the market? One of the most frequently cited papers in the field (Womack, 1996) found that analysts did indeed have superior stock-picking, as well as market timing abilities. He found that new buy recommendations produced a short-lived mean post-event drift (+2.4%), while new sell recommendations produced a longer-lasting negative mean post-event drift (-9.1%).

Since then, the exact effect of analyst recommendation changes on stock prices has been an ongoing discussion, and there is probably no defining conclusion, as it may depend on the market, period of investigation, etc. The U.S. Securities and Exchange Commission simply states that “They exert considerable influence in today’s marketplace” (SEC, 2010). Most of the academic research in the field potential abnormal returns when adopting an investment strategy based on adhering to analyst recommendations and recommendation changes. There is mixed evidence regarding whether transaction costs remove these excess returns or not. The precise size and properties of this abnormal return vary greatly from study to study, as both the method and sample varies.

This section attempts to give an overview of the most central studies in the field. In order to adequately describe the differences of each paper, the first part of this section will describe (1) the three main sources of recommendations, (2) the essentials of the Efficient Market Hypothesis and how analyst recommendations might fit into this theory, (3) the most common recommendation types and (4) the different approaches to research design. Finally, these properties are used to categorize and compare the existing literature.

Table 1 below is an overview of the most central papers in the existing literature. We also gather information from other studies, but this table includes all studies with comparable methodology and samples that are used in this thesis.

Table 1 – Most relevant studies in the field

Year	Author(s)	Title	Period	Market(s)	Focus*
1995	Stickel	The Anatomy of the Performance of Buy and Sell Recommendations	1988 – 1991	US	Changes
1996	Womack	Do Brokerage Analysts' Recommendations Have Investment Value?	1989 – 1991	US	Changes
2001	Barber, Lehavy, McNichols & Trueman	Can Investors Profit from the Prophets? Security Analysts Recommendations and Stock Returns	1985 – 1996	US	Consensus level
2004	Jegadeesh, Kim, Krische & Lee	Analyzing the Analysts: When Do Recommendations Add Value?	1985 – 1998	US	Changes + Levels
2006	Jegadeesh & Kim	Value of analyst recommendations: International evidence	1993 – 2002	US, UK, Canada, France, Germany, Italy, Japan	Changes
2010	Barber, Lehavy & Trueman	Ratings Changes, Ratings Levels, and the Predictive Value of Analysts' Recommendations	1986 – 2006	US	Changes + Levels
2014	Soucek & Wasserek	Impact of Analys Recommendations on Stock Returns: Evidence from the German stock market	2000 – 2012	Germany	Changes
2016	Murg, Pachler & Zeitlberger	The impact of analyst recommendations on stock prices in Austria	2000 – 2014	Austria	Changes
2019a	Park &Park	Can investors profit from security analyst recommendations?	1994 – 2016	US	Consensus level
2019b	Park &Park	Is the Predictive Value of Analysts' Recommendations in Decline?	1994 – 2017	US	Changes + Levels

**The field "Focus" defines whether the paper investigates consensus or individual recommendation changes and the direction or rating levels of these.*

The three main producers of recommendations

Apart from acting as the intermediary between buyers and sellers of stocks, brokerage companies are also the main providers of stock price analyses to the investment community. They collect and analyze information and publish their research on specific firms and attempt to estimate the correct price of their shares. These analysts are referred to as “sell-side analysts” and are behind most of the publicly available stock recommendations. In contrast, “buy-side analysts” are mostly employed by institutional money managers in order to help them choose in which stocks to invest. The last category, “independent analysts,” are seldom involved in the actual purchase or sale of stocks but sell their reports to the ones who are. This study investigates recommendations made by all of the three groups.

The level of informational efficiency in the market

The following section assumes that the efficient market hypothesis (Fama, 1970) accurately describes price formation in the stock market, and that past prices cannot be exploited to predict future prices. This is not necessarily the true depiction of reality but making this assumption might lead to some interesting indications about the value of the content in analyst recommendations, and so analyst recommendations are frequently debated in the context of the efficient market hypothesis (Barber et al., 2001; Naeasimhan Jegadeesh et al., 2004; Panchenko, 2007; Womack, 1996).

Under the strong form of market efficiency, according to the hypothesis, investors cannot earn an above-market return on their portfolio by exploiting any information – public or private. The market quickly reacts to new firm-related events and incorporates all relevant information into the price immediately. As such, not even insider information may lead to an abnormal return. If an investment strategy based on the level of or changes in recommendations leads to an excess return, one can conclude that the market is not efficient in the strong form One could argue that in a market where investors know that a participant’s opinions influence the price, the analyst recommendation could be viewed as an “opinion” and thus a new event with information value on its own. However, as analysts are agents in the market themselves, this would contradict the strong form of efficiency. Whether or not the analyst recommendations are viewed as providing “new” information to the public is difficult to distinguish (Naeasimhan Jegadeesh et al., 2004; Womack, 1996). Opposite, if such a strategy does not earn excess returns, and analysts are known to have access to private information and conduct superior analyses, the strong form of market efficiency is implied by the theory. No immediate price reaction or excess returns will also support the notion that the market does not view analyst recommendations as “new” information in and of itself.

The semi-strong form of market efficiency is characterized by prices reflecting all publicly available information. If an investor can gain abnormal returns with the help of analyst recommendations, it either indicates that analysts can generate private information and make it publicly available, or the analyst recommendations are viewed as new, price-relevant information in and of themselves. It does not indicate that the analysts provide superior analysis of public information (fundamental analysis), as semi-strong form assumes this information to be already incorporated in the stock price. If an investor cannot gain excess returns with the strategy in a market with semi-strong form efficiency, it is implied that the recommendations provide no private or new information.

The final form of market efficiency, the weak form, is defined by prices only reflecting historical price information. This means that present prices do not incorporate all public and private information, as it indicates that investors may gain abnormal returns through analyst recommendations if the analysts have access to private information or are able to generate "new" information through superior fundamental analysis. This means that there exists asymmetric information, and that analyst recommendations counter this, thus leading to a price adjustment (Panchenko, 2007). If investors cannot consistently earn excess returns through analyst recommendations in a market that is known to be weak form-efficient, then the recommendations implicitly do not provide any new or private information to the public.

Another explanation for potential excess returns is research costs (Grossman & Stiglitz, 1980). Grossman & Stiglitz argue that perfectly informationally efficient markets as a theoretical concept is impossible in the real world. The analysts are undertaking costly analyses and must be compensated in order to continue doing so. This compensation stems from investors who believe that they can obtain excess returns by gaining valuable insights from the analysts. At least when there is potential price-relevant information to be uncovered through analysis. They call this an "equilibrium level of disequilibrium."

Different types of recommendations

A recommendation is a way for analysts to publish their opinion on the valuation of a particular stock and the current market price of that stock. The recommendation will usually include a rating together with a target price. The latter is the price that the analyst believes the stock to most likely have in the future (usually predicted to be 12 months into the future). The difference between this estimate and the actual price is thus the potential, according to the analyst. Logically, the sign and size of the potential are associated with the rating of the recommendation. The ratings are usually referred to on a five-level scale, ranging from very positive to very negative, where the label of the recommendation varies between brokers, terms like "strong buy" or "outperform" are used by most. Price effects associated with recommendations seem to be largest when the rating changes are to and from the extremes (1 and 5) (Womack, 1996).

As determinants of the stock prices develop over time, so does the analyst's opinion. Analysts form opinions when initiating coverage of a stock and issue a recommendation. These recommendations may be frequently revisited and changed, but sometimes analysts simply reiterate their past recommendation and signal that this is still their estimated target price and rating recommendation. Analysts can, at times, more or less explicitly, decide to end the coverage of a stock and no longer state their opinion of the particular stock. Thus, we can differentiate between four events: An entirely new recommendation, a recommendation revision, a reiteration of the previous rating, and termination of coverage by the analyst. When studying the effect of recommendation events, the literature tends to focus overwhelmingly on recommendation revisions (Naeasimhan Jegadeesh et al., 2004; Park & Park, 2019b). The central paper by Womack, (Womack, 1996), includes new ratings and assumes these to be a change from an initial "hold" rating, and thus includes them in his dataset of recommendation changes. The findings by Chen et al. (2017) indicate that reiterations, meaning no change in target price or rating, have what they refer to as a confirmation effect. They argue that reiterations reduce information uncertainty regarding the security, and find that reiterations have a price impact in the direction of the initial recommendation.

Research design variations

As previously introduced, the central question of this thesis is if – and if so, to which degree do – analyst recommendation changes affect stock prices. This question is related to multiple other perspectives in the study of the more general category of analyst recommendations. This section will attempt to categorize the different approaches in the literature.

The first distinction we see in the literature is whether individual recommendation changes or the consensus recommendation is studied. Even though every single recommendation, and the associated change thereof, influences the consensus, there is a distinction of whether researchers focus on the consensus and when this changes, as done by some studies (Barber et al., 2001; Naeasimhan Jegadeesh et al., 2004; Park & Park, 2019a; Stickel, 1995), or if researchers examine the individual recommendation issued or changed by an analyst as (Park & Park, 2019b; Womack, 1996). If studying the consensus, two recommendations for the same stock could be changed on the same day, and maybe offset each other, and then the consensus would not change, but a study of individual recommendation changes would recognize two change and examine a possible effect of this. Even if only a single recommendation is revised, it might not change the consensus and thus not trigger analysis in a consensus-oriented study, but with a focus on the individual change, the effect would be examined. Often, studies examining consensus form portfolios and measure investment returns over a longer period (Barber et al., 2001; Jegadeesh et al., 2004), whereas studies focused on individual recommendation changes are often formed as event studies.

Another distinction, regarding the event studies of the individual recommendation changes, is whether they look at the effect of the recommendation level of the revised recommendation or the direction of change from the old recommendation level. Some papers cluster their recommendation revisions and examine effects based on the rating of the new recommendation, where others study if the new recommendation is a more positive or negative recommendation than the previous (the direction of the change, i.e., upgrade or downgrade) (Park & Park, 2019a), and some papers combine the two signals and examine the effect based on both (Murg et al., 2016; Barber et al., 2010).

Next, there is a difference between the recommendation revision influencing the stock price, and the recommendation change having investment value. The first aspect is causality and correlation, and secondly, the timing and the ability to trade is essential. If recommendations are somehow correlated with returns that differ significantly from the expected market-adjusted return, it is not necessarily because of the recommendations themselves. The analysts might recognize price-relevant information about the firm before the rest of the market, which means that investors may be able to earn excess returns by adhering to the analysts. If the market views all or some specific types of analyst recommendation changes as new, price-relevant information in themselves, it implies that the recommendation has a direct causal effect on the stock price. This may also result in abnormal returns, although if such an effect is immediate, the investment value or trading possibility becomes non-existing, and it is not possible to trade in time to obtain the return. This implies that finding significant excess returns does not necessarily function as evidence towards the hypothesis that recommendation changes affect stock prices.

However, when determining if it is possible to construct a trading strategy resulting in above-market returns, the timing aspect must again be considered; is there an immediate or delayed reaction. In theory, if the market is efficient, a trading strategy based on immediate effects will not result in any abnormal returns, as the sellers will increase (decrease) their ask prices at the same time as buyers will increase (decrease) their bids. In practice, this "immediate effect" may not happen instantaneously. What is determined "immediate" is, therefore, relative to the context. In the context of trading strategies, whether a reaction is viewed as "immediate" or not can be determined by the possibility of trading on this market reaction. In other words, only the potential delayed effect facilitates a sound trading strategy.

The delayed effect, post-recommendation drift, may be similar to the post-earnings-announcement drift (PEAD) first described by Ball and Brown (Ball & Brown, 1968). This is where a stock's cumulative abnormal return tends to drift upwards (downwards) after a positive (negative) earnings surprise. The magnitude and duration of the post-recommendation drift may vary, but it has been documented in multiple studies (Barber et al., 2001; Murg et al., 2016; Stickel, 1995; Womack, 1996). The drift effect is in direct contrast to the efficient market hypothesis, as technical analysis of historical prices has been shown to have predictive value.

The last important distinction is if the effect is permanent or mean-reverting. Concluding that an effect is permanent is challenging, as one must define what constitutes a permanent effect, e.g., over what time horizon, the effect needs to be stable. Womack (1996) argues that the immediate effect appeared to be permanent, as he saw no quick mean-reversion in the stock price returns following a recommendation change.

Distribution of ratings

One commonly mentioned topic in the study of analyst recommendations is the fact that the distribution of ratings is strongly skewed towards positive recommendations (Barber et al., 2006). In the US, Barber et al. claim that the overwhelming majority of recommendations contain a positive rating ("buy" or "strong buy"). This skewness has led to allegations that analysts do not state their true beliefs, and that it is a result of the conflict of interest faced by analysts. It is argued that they are biased towards publishing positive reviews of their investment bank clients, as it might help to attract and retain more business in this area. The US has the lowest frequency of sell recommendations in all G7-countries, indicating that the conflict of interest is most substantial in this market (Narasimhan Jegadeesh & Kim, 2006).

Barber et al. (2006) describe the following development in the distribution: At the end of the first quarter of 1996, 60% of recommendations concluded a positive rating. 36% concluded a neutral ("hold"), and only 4% reported a negative ("sell" or "strong sell"). The following four years only exacerbated the situation further, and by the end of the second quarter of 2000, 74% of recommendations reported a positive rating. Neutral ratings accounted for 24% of the total, and only 2% reported a negative rating. However, this development reverted somewhat in the following three years, resulting in only 42% of recommendations reporting a positive rating by the end of the third quarter of 2003. At the same time, the number of neutral ratings increased to 42% of the total, and negative reviews jumped up to 17% of all ratings.

Barber et al. hypothesize that the development from 2000 to 2003 is partly due to the contemporaneous softening in economic conditions and the stock market decline during the so-called dot-com bubble. However, the authors also recognize that these two explanations might not explain the reversal completely and propose another potential explanation: NASD Rule 2711. The effect of this rule is another frequently studied subject in the field (Barber et al., 2006; R. Loh & Stulz, 2009; Park & Park, 2019b). NASD is an abbreviation for the National Association of Securities Dealers in the US. The rule required brokers to make their distribution of ratings public, and it was proposed on February 7, 2002. It also covered other areas related to the analysts' conflict of interest: The firms studied by the analysts were no longer allowed to review the research before publication, analysts were no longer allowed to receive compensation directly related to investment banking transactions, the firms were no longer allowed to explicitly provide goods or services to the analysts in return for favorable recommendations, and there were put restrictions on the personal trading in the firms that the analysts researched. The decision that the rule would be put in place was made public May 8 the same year.

Abnormal returns net of transaction costs

Much previous literature has found indications of abnormal returns from trading strategies based on analyst recommendations, but few have accounted for transaction costs (Barber et al., 2001). Any investment strategy will incur transaction costs in different forms, and the literature that attempts to account for these in investment strategies based on analyst recommendations suggests that the transaction costs incurred by primarily high turnover might surpass the potential abnormal return. In the central paper by Barber et al. (2001), the authors attempt to include these costs in the total return calculation and find that the profits net of costs are indistinguishable from zero. They estimate that a strategy based on consensus recommendations yield annual abnormal gross returns of more than 4%. This strategy entails buying (selling short) the stocks with the most (least) favorable consensus recommendations and daily rebalancing of the portfolio. However, these returns are diminished due to the costs of the frequent trades needed to attain this return.

The transaction cost estimates used by Barber et al. are calculated in another paper by Keim and Madhavan (1998). These calculations are based on both the explicit and implicit costs of trading. Explicit costs are easily measurable, as they are represented by specific accounting charges. They include the commissions paid to brokers and the taxes involved with the potential profits of the investment. The implicit costs are harder to measure, and as such, these estimates might vary considerably. These costs include the price impact of purchasing large amounts of stock and the potential opportunity costs of not trading on the new information in a timely manner. They conclude that dependent on firm size, trading costs average 0.727%, 1.94%, and 4.12% of the stock price for large, medium, and small market capitalization stocks, respectively. Barber et al. (2001) estimate that 70% of their trades would be large-cap stocks, resulting in a portfolio average round-trip trading cost of 1.31% of share value. The term “round-trip” simply means that this estimate includes the costs involved with both the purchase and the sale of the securities. The turnover of the portfolio, however, is above 400% annually, meaning that the annualized trading costs are at least four times as high as 1.31%. They define turnover as follows “Turnover or portfolio P during trading day T is defined as the percentage of the portfolio’s holdings as of the close of trading on date T-1 that has been sold off as of the close of trading on date T”. Comparing this to the gross annualized abnormal return of 4%, the net abnormal returns might even be negative. The authors also attempt to estimate the costs with monthly rebalancing of the portfolio, instead of daily, and this significantly decreases the turnover to below 300%. Unsurprisingly, the net abnormal returns are still indistinguishable from zero, as this delayed reaction to recommendation changes decreases the gross abnormal returns as well.

This is later contested by Park & Park (2019a) as they find a total 4.7-5.8% annualized abnormal return in the period 1994-2016 net of transaction costs with a portfolio following a similar strategy to Barber et al. (2001): Purchasing stocks with strong buy consensus recommendations and selling short their strong sell counterparts. They base their transaction costs on estimates calculated by Holden (2009) and Goyenko et al. (2009), which they deem to be more precise and realistic than those estimated by Keim and Madhavan (1998). These transaction cost estimates are based on effective spreads, as they argue that the trading volume varies over time, and this will have a major impact on total transaction costs. Barber et al. (2001) utilize a constant percentage estimate during the entire sample period, which results in only trading volume impacting the variation in transaction costs from day to day. They back up this claim by referring to Corwin and Schultz (2012) and Chen et al. (2017), who show that the performance of this measure is superior to the alternatives, especially from the late 1990s. Park & Park (2019a) compare the transaction cost estimates to ones calculated by Chang and Zhang (2014) and Fong et al. (2017), and they find that this choice does not alter the main result of the study.

The most obvious difference between the study of Barber et al. (2001) and Park & Park (2019a), besides their transaction cost estimates, is their sample period. Barber et al. (2001) investigate an earlier sample period, 1985-1996, so their data barely overlaps with the data of Park & Park (2019a). In addition to this, Barber et al. (2001) collect data from the Zacks database, and Park & Park (2019a) retrieves it from I/B/E/S. They explain that a reason that these two time periods may have very different abnormal returns net of transaction costs is that on April 9, 2001, the SEC ordered all stock exchanges in the U.S. to convert from fractional quotes of 1/16 to decimal quotes (additionally, these quotes were denoted in fractions of 1/8 until 1997) (Barber et al., 2006). Combined with the effective spread-based method of calculating transaction costs, this might be the most considerable explanation for the different results.

Estimation of “normal” return

Estimating the effect associated with a specific event entails that there is a normal state when this event does not take place. For stock prices, this could mean that an increase in price could be above the mean return. However, if the rest of the market makes similar moves, this might not be related to the research in the field of analyst recommendation uses several different measures to estimate this. The market model, CAPM, and factor models are most common. This section attempts to map the use of these methods and investigate their main differences. Below is an overview of the same papers as previously, this time specifying their method of estimating expected returns.

Table 2 – Expected return model used in other studies

Year	Author(s)	E(R) calculation method
1995	Stickel	Mean market adjusted
1996	Womack	Size-adjusted, industry-adjusted and Fama-French three-factor model
2001	Barber, Lehavy, McNichols & Trueman	Four-factor model after Carhart (1997)
2004	Jegadeesh, Kim, Krische & Lee	Four-factor model after Carhart (1997)
2006	Jegadeesh & Kim	Market model
2010	Barber, Lehavy and Trueman	Four-factor model after Carhart (1997)
2014	Soucek & Wasserek	CAPM
2016	Murg, Pachler & Zeitlberger	Market model and ARMA-market-GARCH
2019a	Park & Park	Four-factor model after Carhart (1997)
2019b	Park & Park	Four-factor model after Carhart (1997)
2019	Su et al.	CAPM

Main findings in the literature

One of the first central studies undertaken in the field (Stickel, 1995) finds that buy (positive) recommendations are associated with an average 1.16% abnormal return over an 11-day event window around the recommendation change and their sell (negative) counterparts are associated with an average -1.28% change. However, he notes that these figures are misleading, as they include confounding effects such as earnings forecast revision and earnings announcements. Keeping this in mind, the paper's definition of abnormal returns is excess market returns minus the expected market-adjusted return. The expected market-adjusted return is "the mean marked-adjusted return from the future benchmark period of Event Days +121 to +240". He argues that using a future period as a benchmark is more realistic than using past prices, as analysts might base some of their changes on historical prices.

The study also finds that recommendation changes to the extremes (strong buy and strong sell) have greater stock price impact than upgrades or downgrades to those in-between. He argues that this is an indication that analysts are able to detect to which degree a stock is over- or undervalued. This stronger effect seems to be a permanent information effect. Another related effect is what happens when a change in recommendation skips a rank (e.g., 3 to 5): As might be expected, this effect is stronger than single-rank changes. Contradictory to the previous effect however, these differences seem to be temporary only.

The following year, the well-known paper by Womack (1996), which was briefly mentioned at the beginning of this literature review, provided additional evidence of recommendation changes being associated with significant changes in stock prices. He notes that up until this point, Cowles' (1933) conclusion that most recommendations do not produce abnormal returns was the research consensus. Womack lists several previous studies that indicate that this conclusion is false, but note that these have all been subject to criticism regarding sample bias or imprecise data.

Womack uses three different methods to calculate excess returns. The first is a size-adjusted model. It is designed by subtracting the appropriate CRSP market capitalization decile returns from the sample firm's raw returns. The daily returns are compounded over a three-day buy-and-hold event window surrounding the recommendation change. Finally, the average of these percentages is calculated. The second model is similar to the first, but before size-adjusting the firms, they are categorized into their respective industries. The same compounded returns are then calculated, industry by industry, before they are averaged to a single figure. The third and last method used to calculate excess returns is based on the Fama and French three-factor model (Fama & French, 1993). Firm-specific factor coefficients are made by regressing firm returns on 1) value-weighted market returns, 2) returns measuring returns relative to market cap, and 3) returns to price-to-book ratio. These regressions are based on the previous five years of data. In order to calculate excess returns, the coefficients are then applied in the forecast period for the event month and the following 12 months.

Womack uses a more precise event window of three days instead of 11, and the findings are somewhat in line with those Stickel (1995). Within this event window, he finds that the average size-adjusted cumulative abnormal return is 2.98% for positive recommendation changes and -4.69% for negative ones. The industry-adjusted method yields similar figures of 2.84% and -4.99%, respectively. Finally, the Fama-French three-factor model generated estimates of 4.0% and -3.87%. Womack acknowledges that the event-period returns are not surprising or unprecedented, but that the magnitude of the recommendation change effect seems to be larger than other events. He argues that even though average returns from events such as dividend omission, mergers and take-overs might be larger, recommendation changes are frequent, repetitive events, which one would expect to have much less impact on stock prices.

Additionally, the findings indicate a drift in the months following the recommendation change. Womack estimates these delayed effects to be around 5% for positive recommendation changes and

-11% for negative recommendation changes. The positive price effect occurs predominantly in the first month following the event and is insignificantly different from zero after that. The much more persistent negative effect is significant for six months. Both changes appear permanent, as Womack finds no indications of mean-reversal. Related to our brief discussion of the post-event drift phenomenon in the "Research design variations" section, Womack goes on to argue that at first glance, this drift implicitly states that the market is not informationally efficient. He notes that this delayed market response has similar characteristics as the post-earnings announcement drift, but outlines one major difference between the two: "Post-recommendation drift begins after a simple, disseminated change of *opinion* by a market participant, while the cue for PEA drift is a quarterly earnings announcement, a new public *fact*." Whether analysts undertake superior fundamental analyses and/or have access to private information, or simply affect the price since their opinion is an inherent part of the price formation process, he refers to Grossman and Stiglitz' (1980) expanded view of the efficient market hypothesis for the following conclusion: As there are significant information search costs associated with analysts estimating firm value, there have to be abnormal returns to make up for them. What this informational value consists of is unclear, but he presents this explanation as to why brokers invest so heavily in issuing recommendations.

Another interesting finding is the asymmetric market reaction to new positive and negative recommendations. Womack finds that similar to changes in recommendations, new recommendations with a negative rating have a greater price impact than their positive counterparts. This might be associated with the skewed distribution of ratings: Womack finds that for every negative rating, there are seven positive ratings in the U.S. in the years 1989-1991. The time sample of this study predates that of Barber et al. (2006) and Jegadeesh & Kim (2006) described in the "Distribution of ratings" section above, but the distribution is similarly skewed towards optimistic recommendations. Given the greater effect associated with new negative recommendations, Womack concludes that they are more predictive than positive ones. He argues that this could be due to analysts recognizing that there are greater costs and risks associated with criticizing firms' share value. He refers to Pratt (1993), who he claims outlines a major cost associated with issuing negative recommendations: The potential cut off of information from firm management to analysts. The top management and investment contacts might be more willing to provide sensitive information if they expect a positive opinion in return. Incorrectly rating a stock "sell" is more visible and controversial than issuing a "buy" that turns out to be wrong, as there are generally more analysts being wrong about a given firm. Womack then states that these increased costs might explain the greater predictive ability of negative recommendations.

Other determinants of the stock price reaction to recommendation changes

The prior studies have found several other factors that indicate to impact the properties of the effect on analyst recommendations on stock prices.

Together with the rating, analysts publish a target price, of what they believe the stock price should be within a specific time horizon (usually 12 months, but sometimes 6 or 9 months). This target price, or more specifically its' relative distance to the current stock price, is found to affect the stock price reaction to a change in analyst recommendations (Narasimhan Jegadeesh & Kim, 2006; R. K. Loh, 2010; R. Loh & Stulz, 2009; Womack, 1996). Murg et al. (2016) note that this factor is not always significant but hypothesize that a higher "delta" (they define delta as the difference between current stock price and target price set by the analyst) indicates that the analyst is more optimistic than if the delta is lower. We call this variable "Potential," and it is defined as the difference between the target price and previous closing price, divided by the previous closing price for the given day.

Loh and Stulz (2009) and Loh (2010)found that more influential recommendation changes tended to, on average, have fewer analysts following the stock. They hypothesized that if a firm were already monitored by many analysts, a single analyst changing her or his mind would not have a large impact on the stock price, as the rating change would have little effect on the consensus recommendation. Opposite, a firm with a few recommendations covering their stock might be much more affected by a change in analyst opinion, as the consensus might drop or increase drastically after this single event.

Possibly related to the number recommendations, the effect of recommendation changes also seems to be affected by the size of the firms which the analysts are covering. Loh and Stulz (2009) found that more influential recommendations were more prevalent when analysts covered smaller firms. Through his decile grouping of recommendations by firm size, Womack (1996) found that firms in the smallest market-capitalization deciles reacted more to recommendation changes than larger firms. The reaction of recommendation changes to stock prices of mid-cap and large-cap stocks were not significantly different from each other, but significantly smaller than those of small-cap stocks. Stickel (1995) found similar results that the stock prices of smaller firms were generally more affected by recommendation changes. Stickel argued that these findings were consistent with the differences in firms' information environments: That smaller firms often received less information in the media and, in general, reported less information to the public. He argued that this made each piece of information be proportionally more important for the firm. Finally, he claimed that these differences seemed to be permanent information effects.

In their examination of influential recommendation changes, Loh and Stulz (2009) found that the firms they covered often had lower turnover than less influential recommendations. This could be interpreted as an indication that there was a negative relation between trading volume and the effect of an analyst recommendation change. Jegadeesh & Kim (2006) also investigated the relationship between recommendations and how much the stock was traded. However, they studied how recommendation revisions affected the volume on the announcement day. They found that stocks experienced an increase in volume on the day of the recommendation change and that this effect was largest in the United States out of all G7 countries. They argued that this was consistent with their findings that U.S. analysts added the most value. Other studies also argued that there could be significant abnormal value on the day of recommendation changes (Panchenko, 2007; Womack, 1996).

Loh (2010) argued that the prices of stocks with higher bid-ask spreads could take longer to adjust to price-relevant information due to illiquidity, potentially delaying the effect of events. This could be relevant in our case, as we also investigate to which degree the information content of recommendation changes is immediately incorporated into stock prices.

Studies examining the consensus rating of the stocks in relation to analyst recommendation changes found that changes further from consensus tended to have a greater effect on stock price (Jegadeesh & Kim, 2009; R. Loh & Stulz, 2009). This could possibly be due to the "herding effect" described by Jegadeesh & Kim (2009). Their findings indicate that analysts might be biased towards the consensus rating, and analysts changing their opinion to something opposite of the consensus would, therefore, be more visible to investors.

Loh (2006) discusses the possible inattention of investors and the underreaction to earnings announcements and recommendation revisions on Fridays due to investors possibly being less attentive to business news in the weekends. Dellavigna and Pollet (2009) provided evidence that this was indeed the case for earnings announcement surprises and other price-relevant news. This inattention led to a delayed price reaction. Kudryavtsev (2019) found that this same effect also applied to announcements of analyst recommendation changes.

Hypothesis Development

In this section, we will formulate the hypotheses set to form the basis of our thesis and structure our analysis. The development of these hypotheses will take the offset in the research question formulated earlier:

How are stock prices affected by changes in analyst recommendations in Denmark and the United States?

In order to answer this research question, we will form a set of hypotheses based on previous literature's findings and discussions. These hypotheses should then both help us with our research goal, but also aim to re-evaluate and further explore previous findings.

We will structure our analysis in two primary parts; a test of the effect of analyst recommendation changes and a more practical test of the findings in the form of an investment strategy based on the first part.

Previous literature presents several studies that conclude that analyst recommendations have a same-day reaction in share prices that is significantly different from zero (Womack, 1996) in the United States. The sample periods examined in most of the existing literature are from before the year 2000. The most recent study uses a sample period that ends in 2017, and they find the effect still to be present at that point (1996). We want to verify that this is correct and expand the sample to the end of 2019. Additionally, we want to investigate if this effect is present in the Danish stock market as well. We thus formulate the following main hypothesis 1:

(1) Stocks listed in Denmark and in the United States experience significant immediate price changes as a result of changes in analyst recommendations.

We divide the first main hypothesis into several sub-hypotheses to further specify the properties of this effect:

Barber et al. (2010) find that both the level of the recommendation (buy/hold/sell) and the direction (up-/downgrade) of the change is determining the reaction to the analyst recommendation change.

Murg et al. (2016) further argue that the direction of the change is more influential than the recommendation level itself. Thus, knowing the direction of a recommendation gives a better predictor of the stock price reaction than the recommendation level, as, e.g., a hold can both be upgrades and downgrades, and a strong sell recommendation can be upgraded to a sell, which is still a negative level but a positive direction. Our first sub-hypothesis is thus formulated as:

(1.a) The direction of the recommendation change affects the abnormal return more than the level of the recommendation change.

Park & Park (2019b) found that downgrades generally had a stronger impact on stock prices than upgrades in absolute terms. We thus want to test this asymmetry in reactions to recommendation changes for both Danish and U.S. stocks.

(1.b) Downgrades have a stronger absolute effect on stock prices than upgrades.

Examining the previous hypotheses further, we want to investigate if the most positive recommendations (defined as upgrades to buy) are also associated with the most positive abnormal returns and vice versa. Stickel (1995) found downgrades to “sell” to have a greater negative impact on stock prices than downgrades to “hold,” as well as upgrades to the most positive ratings as associated with the greatest positive impact on the stock price. In continuation, we thus hypothesize:

(1.c) Upgrades-to-buy have the most positive effect on stock prices, out of all upgrades, and downgrades-to-sell have the most negative effect.

Murg et al. (2016) and Stickel (1995) both found that the reaction to a recommendation that skipped a “rank” (i.e., had a greater magnitude of change in rating level) experienced a greater reaction in the stock price. We thus hypothesize that a change from “sell” to “buy” has a stronger reaction than a change from “hold” to “buy,” and thus we state:

(1.d) Recommendations changes that skip a level or more results in greater absolute abnormal returns than recommendation changes that do not skip a level.

Several studies have tested the effect of analyst recommendations in different markets around the world (Murg et al., 2016; Jegadeesh & Kim, 2006; Park & Park, 2019b). Jegadeesh & Kim (2006) find that the U.S. stocks experience the largest reaction to changes in analyst recommendation compared to markets of the G7 countries. We therefore hypothesize:

(1.e) U.S. stocks experience greater reactions to changes in analyst recommendations than Danish stocks.

Previous literature in the field has proposed several other explanatory variables for the reaction in stock price to analyst recommendation changes (Stickel, 1995; Womack, 1996; Jegadeesh et al., 2004; Jegadeesh & Kim 2009; Loh & Stulz 2009). We thus define our fifth sub-hypothesis as:

(1.f) The size of the abnormal return associated with a recommendation revision is dependent on other explanatory variables.

Some of these other explanatory variables include the new target price of the recommendation, number of analysts covering the stock, firm size, trading volume, bid-ask spread, consensus rating, whether the recommendation change was announced on a Friday and magnitude of the recommendation change. These variables were selected based on the prior studies described in the section "Other determinants of the stock price reaction to recommendation changes" above.

Several studies (Narasimhan Jegadeesh & Kim, 2006; Stickel, 1995; Womack, 1996) find that in addition to the immediate stock price reaction, the analyst recommendation changes still have a significant effect at least one month after the announcement of the change. Park & Park (2019a) find the effect of a negative recommendation change to still produce abnormal returns for six months. They also report that the immediate effect seems to be permanent, as there is no mean reversion. We want to verify those results in our U.S. sample and investigate if the results are similar for Danish stocks. We thus formulate our second main hypothesis:

(2) The immediate effect of an analyst recommendation change on stock price in Denmark and the United States is incomplete, and the full effect is incorporated into the stock price over several days.

Womack (1996) and Stickel (1995) found abnormal returns following recommendation changes. Their data sample predates ours, but Park & Park (2019a) also found abnormal returns associated with recommendation changes, and they used a sample that covers the first 17 years of our sample.

Barber et al. (2001) found the investment value of these effects to be indistinguishable from zero, so whether investors can profitably exploit recommendation changes remains uncertain.

Based on the findings from the previous hypotheses, we want to form a trading strategy and test if it is possible to generate positive abnormal returns by following a strategy based on analyst recommendation changes. Thus, our last hypothesis states:

(3) It is possible to construct a trading strategy based on changes in analyst recommendations that yields positive abnormal returns.

In summary, we formulate three main hypotheses from the outset of our research question with the purpose of first testing if stock prices immediately react to changes in analyst recommendation, next if prices have any form of longer-term reaction after an analyst recommendation change, and lastly if it is possible to exploit the information in analyst recommendation changes to generate a trading strategy yielding positive abnormal returns.

3 | Methodology

Research design

This thesis takes its offset in the positivist philosophy and uses a primarily deductive approach to form an explanatory study with hypothesis testing based on previous research and theories to detect any causal relationships within the area of analyst recommendations and their impact on stock prices. In this explanatory study, we observe a natural experiment in stock markets in the form of announcements of analyst recommendations, and we observe and analyze the reactions to this.

In our conclusion, we will take on the inductive approach and present our findings' relevance to the academic field and discuss potential further research.

The analysis in this thesis will exclusively be based on quantitative, secondary (raw) data. This data is primarily stock prices and other metrics on listed companies as well as coded representations of analyst recommendations. We will primarily take a cross-sectional approach to the analysis, but control for time-varying elements over the years, but a longitudinal focus of the development over time is not the focus of this thesis.

The central part of this thesis is formed around an event study. This will analyze the financial impact on the price of a stock when the event of an announcement of an analyst recommendation happens. The returns of a stock are analyzed in the time around the event with different time intervals to attempt to answer our research question and hypotheses of how markets react to analysts' recommendations.

In a second part, we will utilize the findings from the event study and those of previous research to further investigate what drives the reaction to analyst recommendation announcements. We will do this by applying a regression model to control for a number of factors, which we hypothesize to affect the market reaction to a recommendation change.

In the last analysis, we will test the findings from the previous by defining, testing, and discussing an investment strategy based on analyst recommendation changes under a number of assumptions and constraints.

Finally, we will discuss our findings, their coherence with previous literature, their implications for further research and practical use.

Methodology

The main part of this thesis follows a typical event study methodology as first introduced by Fama, Fisher, Jensen, and Roll (1969), refined by Brown & Warner (1980) and since extensively used in economics, accounting and finance for analysis of the impact of different types of events or shocks on stock prices and other measures or economic factors (Binder, 1998). Besides the event study, we will utilize regression models and test a trading strategy.

We utilize the R statistical language and environment with RStudio to model our data. Due to the size of our dataset as described later, we have deployed a cloud server in order to do computations.

Abnormal returns

The focus of the analysis is to which extend systemic abnormal returns are observable around analyst recommendation revision announcements. In order for a return to be considered "abnormal," we first need to specify a model to estimate "normal" returns. Abnormal returns are the difference between the actual *ex-post* return of a security on any particular day and the expected "normal" *ex-ante* return estimated for that day (Brown & Warner, 1980). Thus, the abnormal return can be denoted as:

$$AR_{i,t} = R_{i,t} - E(R_{i,t})$$

where $R_{i,t}$ denotes the discrete daily raw return (adjusted for stock splits and dividends) for stock *i* at time *t*, and $E(R_{i,t})$ denotes the expected normal rate of return of the same stock and time.

Normal returns

Previous literature suggests several models of estimating expected returns *ex-ante*. Models with adjustments for mean return, market, and risk have been utilized (Brown & Warner, 1980; Womack 1996). These models usually have the form of:

$$R_{i,t} = K_{i,t} + \epsilon_{i,t}$$

Where K is some form of expected return, and thus when reordered, ϵ becomes the abnormal return.

In order to estimate *ex-ante* the expected or normal return regardless of any recommendation change in this thesis, we choose to utilize a market and risk-adjusted model in the form of the theoretical framework of the Sharpe-Lintner Capital Asset Pricing Model (CAPM) (Brealey et al., 2015) as other previous studies have done (Souček & Wasserek, 2014; Su et al., 2019).

Thus, the expected return for stock *I* on day *t* is:

$$E(R_{i,t}) = R_{f,m,t} + \hat{\beta}_{i,t}(R_{m,t} - R_{f,m,t}),$$

where $R_{f,m,t}$ is the return on a risk-free asset in market *m* for day *t*, $\hat{\beta}_{i,t}$ is the estimated correlation between stock *I* and the market portfolio, and $R_{m,t}$ is the return on the market portfolio for day *t*.

As a proxy for the risk-free asset, we choose to use the 3-month US treasury bond in the US market, and for the Danish market, we use a 10-year treasury bond (*Danmarks Nationalbank*, 2019). Both are transformed into daily rates of return using an assumption of compounding over 365 days.

As the market portfolio, the S&P 500 index is chosen for the American stocks, and the OMX C20 index is used for the Danish stocks in our sample. Even though the OMX C20 index was replaced by the new C25 in 2017 as the benchmark index for the Danish stock market, we choose the older (and regrettably smaller) C20, as there is no data available for OMX C25 before 2017 (NASDAQ, 2020), and thus we choose to have consistent data throughout our 20-year period of investigation.

We estimate the market beta using an estimation period of 5 years prior to the event and calculate the correlation between the stock's monthly return and the market portfolio.

The definition of normal return is shown by several studies not to change the results in any significant way (Brown & Warner, 1980; Womack, 1996), though Binder (1998) argues that the Market Model approach results in biased estimates of abnormal returns. We, therefore, decide to investigate only the CAPM as our definition of expected return.

Cumulated returns (Buy-and-hold returns)

To cumulate returns over a period we use buy-and-hold abnormal returns (BHAR) defined as compounded daily returns using the product of the individual returns plus 1 in the period T. Thus, the BHAR is defined as:

$$BHAR_{i,t_1,t_2} = \prod_{t=t_1}^{t_2}(1 + AR_{i,t}) - 1$$

where $BHAR_{i,t_1,t_2}$ is the buy-and-hold abnormal return for stock I for the period from day t_1 to t_2, and $AR_{i,t}$ signifies the single day abnormal return for stock i on day t.

As described previously, several studies use a simple cumulative abnormal return (CAR)[1] as their measure of returns over a period. As widely discussed in the literature on the event study methodology, this can have an effect on the inference based on the results on long-term returns in excess of a few days. Barber & Lyon (1997) show that there can be significant measurement biases from using the simple arithmetic sum CAR as a measure of long-term return, and they argue that the BHAR measure using a geometric sum is more appealing on economic grounds as it takes into account compounding of the returns. Several studies in recent times also utilize the BHAR measure (R. Loh & Stulz, 2009; Park & Park, 2019b; Souček & Wasserek, 2014; Womack, 1996). One potential problem with the BHAR is that it tends to be right-skewed because of its lower bound, which potentially can lead to problems related to non-normality. Brown & Warner (1985) find that such issues with non-normality in returns are of little importance in large samples.

Significance Test of Differences

For the immediate market reaction, we estimate the abnormal return over an event window of the three days starting in day -1 through day 1: $BHAR_{i,-1,1}$.

Using a cross-sectional t-test under the null hypothesis that there are no abnormal returns during the event window, we test if there is evidence of any immediate market reaction in prices to new recommendations and changes in existing analyst recommendations. We thus test whether the average buy-and-hold abnormal return in the event period is different from zero, meaning that the event has no impact on abnormal returns under the null hypothesis.

We use the Welch alteration of the t-test, meaning we do not assume equal variance in the two samples (Stock & Watson, 2015).

[1] CAR is an arithmetic sum of returns over a period

We compute the mean of the buy-and-hold abnormal returns by:

$$\overline{BHAR_{t_1,t_2}} = \frac{1}{n}\sum_{i=1}^{n} BHAR_{i,t_1,t_2}$$

the t-statistic is then calculated as (Stock & Watson, 2015):

$$t_{BHAR} = \frac{\overline{BHAR_{t_1,t_2}}}{se(\overline{BHAR_{t_1,t_2}})}$$

where $\overline{BHAR_{t_1,t_2}}$ is the average buy-and-hold abnormal return in groups formed by different types of recommendation changes, and $se(BHAR_{t_1,t_2})$ denotes the standard error of the individual BHAR in these groups.

The t-test statistic is, under the null hypothesis, approximately t-distributed with a number of degrees of freedom specified by the Welch approximation (Stock & Watson, 2015). Depending on the significance level, there are certain critical values for the t-test statistic, for which the null hypothesis can be rejected. For sufficiently large degrees of freedom, the t distribution approximates the normal distribution, so with high degrees of freedom and a significance level of 5%, the critical value for the t statistic is 1.96. The general significance level in this thesis is 5% (95% confidence level) unless otherwise stated.

Even though the cross-sectional t-test assumes the abnormal returns to be normally distributed and independent and daily returns usually tend to be distributed with more fat tails, (Brown & Warner, 1985) show that t-statistics are not significantly affected as abnormal returns are close to normal with sufficiently large samples. Corrado (2011) summarizes that many studies have found no or minor issues with non-normality in daily stock return data from the New York Stock Exchange but states that there potentially could be issues about non-normality from other exchanges, including Nasdaq. Even though we have data from both NYSE, Nasdaq New York, and Nasdaq Copenhagen, we follow much previous research and utilize parametric tests, as potential non-normality and non-parametric tests are shown to be of little extra value (Corrado, 2011).

Cross-sectional Regression Model

In order to estimate the determinants of the immediate effect, and test other explanatory variables as suggested in hypothesis 1.f, we will carry out a cross-sectional regression. A multivariate ordinary least square (OLS) regression model will be proposed based on variables discussed or argued to be of importance by previous literature.

We will regress on both the three-day buy-and-hold abnormal return as a measure of the short-term effect as well as the day 0 abnormal return as a measure of the immediate market response. Thus, our regression model will look like:

$$BHAR_i \text{ } or \text{ } AR_i = \alpha + \beta_1 X_{1,i} + \cdots + \beta_k X_{k,i} + \varepsilon_i$$

Where $BHAR_i$ and AR_i is the three-day buy-hold abnormal return and day 0 abnormal return for stock *i* respectively, with the explanatory variables $X_{k,i}$ for each regressor *1 to k* for each stock *i*, β_k is the estimated coefficient for $X_{k,i}$, α is the constant, and ε_i is the error term.

The ordinary least square regression have assumptions of 1) exogeneity, which implies that the error term must have an expected value of 0, thus average 0 and not be correlated with the explanatory variables, 2) the errors must be independent and identically, normally distributed, 3) no extreme outliers, and 4) no collinearity between explanatory variables (Stock & Watson, 2015).

Furthermore, the OLS assumes normally distributed variables for and linear relationships between dependent and independent variables. These assumptions can be discussed with regard to our dataset. We will mitigate the linear relationship assumption by testing quadratic terms of some regressors. The normality of our return data as assumed to be of little issue as according to Brown & Warner (1985).

Trading strategy

Using the stock price data and recommendation changes from our sample of the years 2000 through 2019, we test will propose and test a trading strategy based on signals in the recommendations found in the first part of the analysis.

The specific strategy, conditions for actions, and assumptions for the test will be outlined in the analysis section.

Scope and delimitation

The thesis is delimited in certain ways due to focus, constraints, and obstacles faced in the process.

Our focus and research interest is that of the change in a single analyst recommendation and the contemporaneous market reaction in terms of the stock price.

Even though our interest is the immediate effect of the recommendation change announcement, the best measure of the "immediate" reaction available to us is daily returns. Though we have quite precise timestamps of recommendation announcements, the additional data collection, storage, and handling required by analyzing intra-day price changes in either hourly or even down to minutes changes is not feasible for this thesis.

We do not investigate analysts' other estimates and forecasts, such as earnings, profits, or other published estimates by analysts, as, e.g., Keckes, Michaely & Womack (2009) do. We also do not consider the accuracy or long-term predictable capabilities of analysts and their current, and former forecasts, as, e.g., Loh & Mian (2006) do.

We do not consider what leads to an analyst recommendation or revision thereof. We recognize that positive and negative earnings announcement surprises can both lead to contemporaneous stock price reactions, drifts in stock prices (Bernard & Thomas, 1989), and to new or changed analyst recommendations (Su et al., 2019). We want to control for this effect in order to disentangle the impact of the recommendation change. As discussed in the data section later, we have not been able to exactly control for earning announcements but have instead excluded recommendation revisions from days with much analyst activity, as a proxy for other confounding news leading analysts to revise their recommendations, such as earnings announcement surprises.

This thesis is focused on the Danish and U.S. stock market. This is to compare a large and thoroughly studied stock market with a smaller and less examined stock market. Our findings call for cautionary inference to other markets as there can be great differences among stock markets. Thus, our results might not be applicable to other markets.

4 | Data

Our sample consists of 1,403 stocks (1004 U.S. and 399 Danish) in the period from January 2000 through December 2019 (both included). In order to mitigate the risk of survivorship bias in our sample, we select "U.S." as all stocks that have been part of the S&P 500 index at any point within the 20-year period and "Danish" stocks are selected as all stocks that have been listed on the Danish stock exchange (OMX Copenhagen) in the 20-year period. These stocks are obtained from current listings as well as "leavers and joiners"-lists according to Refinitiv Eikon[2] and Nasdaq.

Analyst recommendations are downloaded from the Refinitiv I/B/E/S database. Other variables, such as stock (adjusted closing) prices, market cap, trading volume, etc. are downloaded from the Refinitiv Eikon database. Some control variables are calculated based on the downloaded variables. These calculations are presented when the variables are introduced in the analysis.

The I/B/E/S (Institutional Brokers Estimate System) database contains recommendations from brokerage houses and other analysts. The I/B/E/S also contains other estimates such as target prices, earnings, etc. The Refinitiv I/B/E/S provides us with the complete set of recommendations from 900 contributors (Refinitiv, 2020), where, e.g., Zacks Investment Research, which is frequently used by other researchers in the field, does only provide scholars with an incomplete subset of available recommendations (Barber et al., 2001). However, Refinitiv restricts the visibility of the names of some brokers issuing recommendations. Instead, they provide unique pseudonyms as broker identifiers, which stay constant for the specific broker over time. This is useful when we want to test if the strength of a recommendation change is affected by which broker issued the revision.

However, the I/B/E/S database is not without its flaws. Several studies (Acker & Duck, 2009; Ljungqvist et al., 2009) have found there to be incorrectly reported announcement dates for forecasts and recommendations up to 25% of the time. Ljungqvist et al. (2009) furthermore found several alterations to historical data in their "Rewriting History" paper, where they document different data entries between different downloads from the I/B/E/S database. The Wharton Research Data Services considers this to be of "non-trivial implications … [to event studies of] profitability of trading signals and consensus recommendation changes" (Glushkov, 2009), though they still consider the I/B/E/S as

[2] Refinitiv is the former Thomson Reuters

inferior to e.g. First Call due to its size of covered firms and contributors. Refinitiv considers data prior to 2008 as corrected for the issues discussed by Ljungqvist et al. (2009), but do actively change historical data as responses to brokers' requests for retrospective changes to their buy/hold/sell recommendations (Glushkov, 2009).

The issues of potentially erroneous announcement dates of recommendations in the I/B/E/S database we cannot do much about, other than assume that here many years after its publication, issues are less present. Jegadeesh & Kim (2006) found similar inconsistencies between I/B/E/S and Investex, but the issue was in almost all cases mitigated by expanding the event window from 1 to 3 days around the announcement date. We have not been able to find newer sources giving similar criticism to the I/B/E/S database.

The implementation of the NASD Rule 2711 in 2002 and knowing that Refinitiv allows for retrospective changes to historical recommendations make a case for worries of biased data from before 2002 if brokerage houses have asked Refinitiv to alter their historical recommendations as a result of the publication requirements of the NASD Rule 2711. We do not consider this as a great issue for our analysis, as it is a small part of our sample. Also, as can be seen below in Figure 1, there is a change in the structure of recommendations in the U.S. market is apparent around 2002, suggesting that our data from prior to the NASD Rule is not entirely biased at least.

The records for recommendations in the I/B/E/S database include identification of the brokerage house making the recommendation and the date and time of the announcement. The recommendation includes a standardized numerical rating between 1 and 5, with 1 being a “strong buy” recommendation going over 2 (“buy”), 3 (“hold”), 4 (“sell”), and 5 being a “strong sell” recommendation. This rating is standardized from whatever the individual security analyst chooses to name their rating, such as “market outperform” or “underweight”. The rating 0 also appears in the dataset and indicates the termination of coverage by the analyst. These 0-ratings are excluded from our analysis, and a possible next recommendation from the same analyst is treated as a new recommendation.

For recommendations where there is no previous recommendation for the ticker-broker pair, we consider it as the broker initiating coverage of the stock. Womack (1996) includes these new recommendations in his dataset and encodes it to be a change from a neutral “hold” (3) rating.

However, we choose to exclude these new recommendations from the revisions as done by Barber et al. (2001).

For this thesis, we downloaded the current recommendations for each stock (1,403 stocks) on each day (7,305 days), giving us a total of 32.7 million downloaded recommendations (4.1 million Danish and 28.6 million for U.S. stocks). Taking the distinct recommendations by the ticker-broker-announcement-date pair, we end up with 215,424 unique analyst recommendations.

For recommendations to be included in our sample of recommendation changes, they must follow these criteria:

1. The recommendation must have a rating between 1 and 5 as zeros are representations of dropped coverage of the stock by the broker.
2. The recommendation must have a previously known recommendation in order to be considered a change and for the magnitude of the change to be calculated. This means that we do not have recommendation changes from before January 2000, even though our downloaded data includes recommendations from before 2000, but with these, we do not know of the prior recommendation.
3. The recommendation must be different from the previous recommendation in terms of the standardized rating. Otherwise, it is regarded as a reiteration and excluded from our analysis.
4. Stock return (stock price) data must be available for all trading days in our event period.

There is the issue of recommendations changing when the stock market is closed. For recommendations issued or changed on non-trading days, such as weekends or holidays where the stock exchange is closed, as well as announcements after market close, we treat it as announced on the following trading day. This means that if a broker changes their recommendation Tuesday evening, the recommendation change date registered in our dataset is the next day, Wednesday. This is exactly what Park & Park (2019) do. This announcement day of a recommendation revision is in the following denoted as “Day 0”. Denmark and the United States have different time zones, and on some days, one market might be open and another closed (for differing reasons). All recommendation changes announced on these closing days have simply been moved to the nearest following trading day. Out of the 7,305 calendar days that exist in the period January 1, 2000 through December 32, 2019, the Danish market has 4,991 trading days, and the United States has 5,043.

As recommendations can sometimes follow or be triggered by unexpected figures in the earnings announcements, and such earnings announcement surprises are shown to be followed by a reaction and drift in the stock price (2006), we want to exclude recommendations issued on such basis. In other words, we seek to "clean out" the confounding effects that might be the cause of the effect on the stock price. In order to not only identify the largest earnings announcement surprises, but also find days with other, price-relevant events, we create a dummy variable "MultipleRecommendations" which takes the value of 1, when multiple recommendations change for the same stock on the same day, and 0 otherwise. Due to data access constraints of this thesis project, we were not able to obtain a list of earning announcements for our whole sample of stocks, but Womack (2006) finds the results to be consistent when excluding and including days with quarterly earnings announcements.

Eliminating the recommendations not satisfying the above criteria, we have a sample of 102,417 recommendations revisions for 1,153 stocks by 585 brokerage houses for the period January 2000 through December 2019. In the Danish stock market, our sample includes 8,117 recommendation changes, and for the U.S., this figure is 94,300. This is, to our knowledge, one of the largest and most recent samples in a study related to this field[3]. The most similar dataset in the existing literature is by Park & Park (2019) with their study of US stocks from 1997-2017.

In the following, we will provide an overview of our sample with some descriptive summary statistics.

Table 3 – Recommendation changes in sample

Market	Stocks	Brokers	Recommendation changes
US	968	509	94,300
DK	185	137	8,117
Total	1,153*	585**	102,417

** Companies that are listed in both Denmark and the United States and also are included in the S&P 500 have unique tickers. If the company is subject to a recommendation change, it only affects one of the tickers in the sample. This is done in order to avoid duplicate observations.*
*** Many of the brokers produce recommendations for both markets.*

Table 4 gives a complete overview of the level and directions of the recommendation changes. This is important when considering if the direction (upgrade/downgrade) or the level (buy/hold/sell) is

[3] E.g. Womack (1996) has 1,573 recommendations in his sample, Barber et al. (2001) uses more than 360,000 recommendations, but their sample period ends in 1996.

being examined. Both direction and level are pieces of information that together make up a recommendation change. The most obvious difference between DK and the U.S. is the much smaller sample size of the Danish market.

Table 4 - To-from recommendation change matrix – observations

US

From recommendation		To recommendation 1	2	3	4	5	Total
	1	-	5,913	13,056	317	278	19,564
	2	5,027	-	19,779	920	98	25,824
	3	12,170	18,740	-	6,229	2,171	39,310
	4	278	942	5,557	-	202	6,979
	5	240	76	2,077	230	-	2,623
	Total	17,715	25,671	40,469	7,696	2,749	94,300

DK

From recommendation		To recommendation 1	2	3	4	5	Total
	1	-	591	546	89	65	1,291
	2	574	-	1,251	495	92	2,412
	3	466	1175	-	613	266	2,520
	4	105	465	537	-	204	1,311
	5	80	92	233	178	-	583
	Total	1,225	2,323	2,567	1,375	627	8,117

Table 5 - To-from recommendation change matrix – percentages

US

From recommendation		To recommendation 1	2	3	4	5	Total
	1	-	6.3 %	13.8 %	0.3 %	0.3 %	20.7 %
	2	5.3 %	-	21.0 %	1.0 %	0.1 %	27.4 %
	3	12.9 %	19.9 %	-	6.6 %	2.3 %	41.7 %
	4	0.3 %	1.0 %	5.9 %	-	0.2 %	7.4 %
	5	0.3 %	0.1 %	2.2 %	0.2 %	-	2.8 %
	Total	18.8 %	27.2 %	42.9 %	8.2 %	2.9 %	100 %

DK

From recommendation		To recommendation 1	2	3	4	5	Total
	1	-	7.3 %	6.7 %	1.1 %	0.8 %	15.9 %
	2	7.1 %	-	15.4 %	6.1 %	1.1 %	29.7 %
	3	5.7 %	14.5 %	-	7.6 %	3.3 %	31.0 %
	4	1.3 %	5.7 %	6.6 %	-	2.5 %	16.2 %
	5	1.0 %	1.1 %	2.9 %	2.2 %	-	7.2 %
	Total	15.1 %	28.6 %	31.6 %	16.9 %	7.7 %	100.0 %

Table 5 is the same information, but this time in percentage terms, as to see where most of the changes are moving. The most noteworthy result here is possibly the high proportion of recommendation changes to 4 and 5 ("sell" and "strong sell", otherwise referred to as "negative") in Denmark compared to the United States.

Table 6 – Number of recommendation changes and yearly averages

	No. Recommendation Changes			Average rating*		
Year	**DK**	**US**	**Total**	**DK**	**US**	**Both**
2000	330	4,643	4,973	2.54	2.02	2.05
2001	251	5,021	5,272	2.55	2.15	2.17
2002	528	7,877	8,405	2.79	2.49	2.50
2003	470	5,619	6,089	2.80	2.60	2.62
2004	502	5,161	5,663	2.73	2.54	2.56
2005	500	4,836	5,336	2.79	2.45	2.49
2006	428	4,740	5,168	2.71	2.58	2.60
2007	549	4,802	5,351	2.74	2.50	2.52
2008	563	5,647	6,210	2.83	2.64	2.66
2009	471	5,452	5,923	2.90	2.58	2.60
2010	397	4,400	4,797	2.57	2.43	2.43
2011	362	5,182	5,544	2.65	2.47	2.48
2012	373	4,823	5,196	2.79	2.58	2.60
2013	316	4,136	4,452	2.82	2.54	2.56
2014	305	3,730	4,035	2.65	2.51	2.51
2015	344	3,842	4,186	2.69	2.55	2.56
2016	364	3,897	4,261	2.62	2.64	2.64
2017	362	3,529	3,891	3.00	2.53	2.57
2018	390	3,556	3,946	2.81	2.47	2.50
2019	312	3,407	3,719	2.83	2.60	2.62
Total	8,117	94,300	102,417	2.75	2.49	2.51

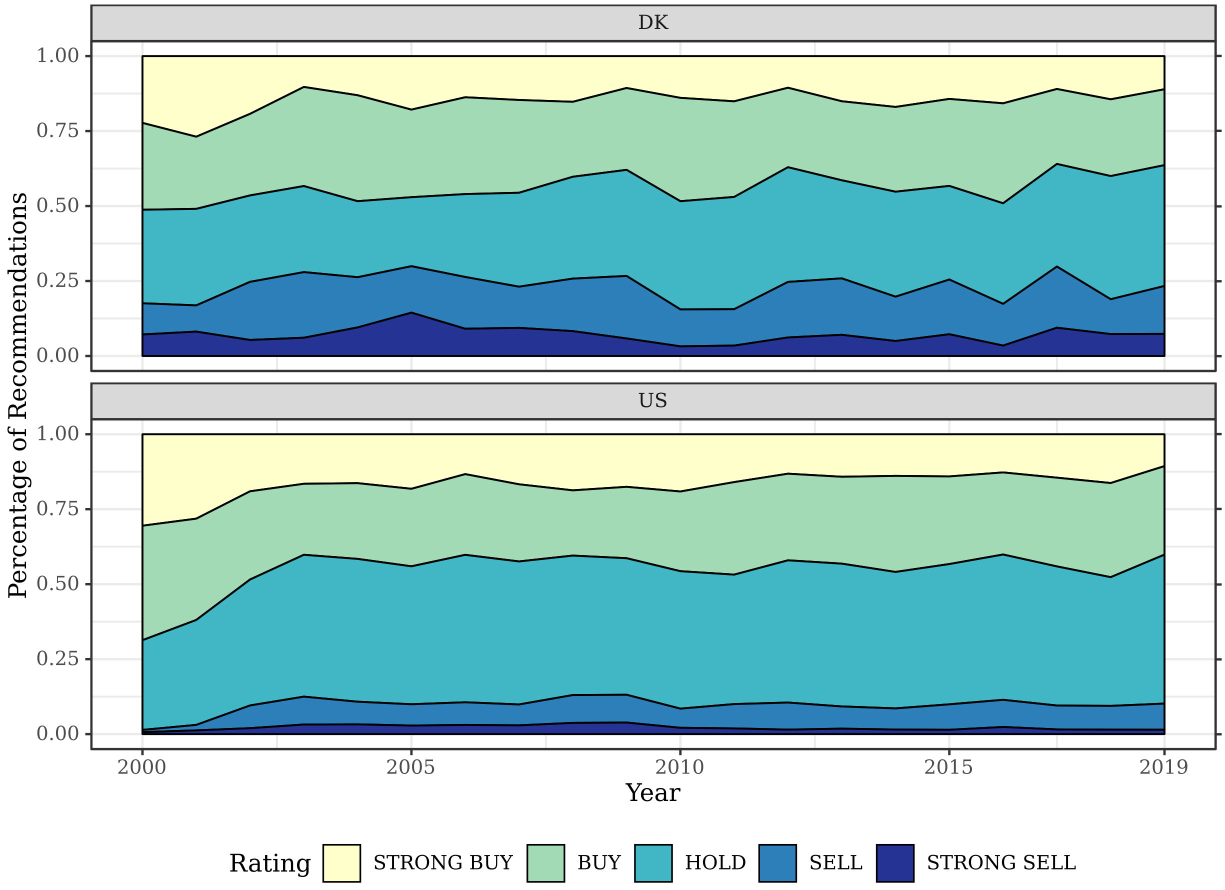
**It is important to note that this average differs from the "consensus" described in the literature in an important way: We exclude all recommendation changes announced contemporaneously with other at the same time. However, the United States is consistently closer to 1 (the most favorable rating) than Denmark.*

In Table 6 above, we see the development in the number of recommendation revisions per year and market as well as the average rating in our sample. The average number of recommendation revisions in Denmark is 411 per year and 4,784 per year in the United States. We see that, not surprisingly, Denmark has fewer recommendation revisions than the United States by approximately one order of magnitude, i.e., our Danish sample is around 1/10 of our U.S. sample. There seems to be a general negative trend in the number of recommendation revisions over time as the most recent seven years have fewer recommendation revisions than the mean of the entire period.

Another interesting point to notice is the spike of recommendation revisions in 2002. This can potentially be explained by the introduction and implementation of the NASD Rule 2711, which lead many analysts to revise their recommendations. The average rating will be described below.

In Figure 1, we see the distribution of the level of recommendation changes over the years in our sample period. Starting with the U.S. distribution of recommendations' ratings: As described in the literature review, there appears to be a strong positive skew in the distribution of ratings.

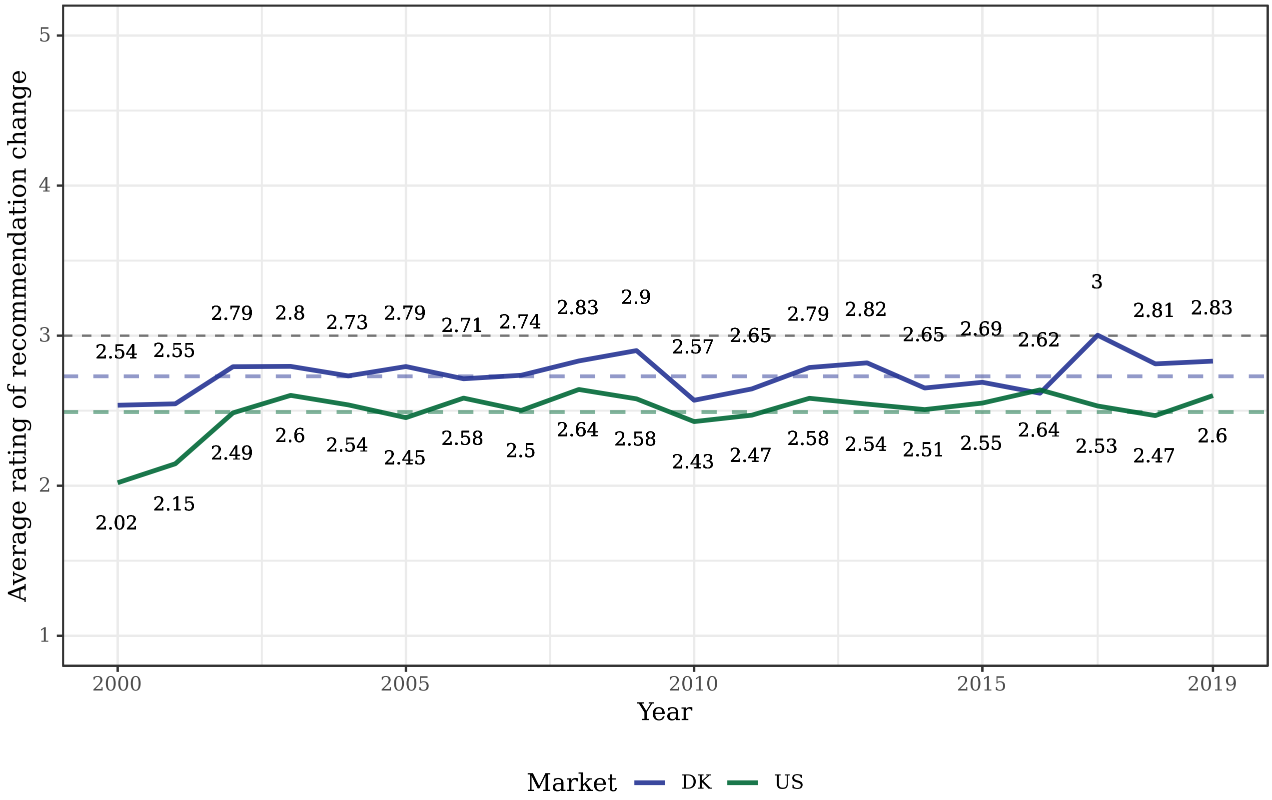
Figure 1 – Distribution of ratings published in recommendation changes by year and market



Upon first glance, one of the most immediate changes is from 2000 until around 2003, and Barber et al. (2006) explain that, possibly due to the NASD Rule 2711, the number of positive ratings decreased drastically from around the year 2000 to the end of their sample, the year 2003, so this data fits well with what they describe. Interestingly, 2003 also seems to be around the time where the "negative trend" stops. There definitely are changes present in the United States from each year to the next, but most seem roughly indifferent between 2003 and 2019. One thing worth noting is that "strong sell" appears to be somewhat shrinking from 2003 and over the rest of the period.

Positive recommendations accounted for approximately 41% of the total in 2019 in the United States, which is almost the exact same figure as 17 years prior. However, the number of neutral ratings accounted for 49%, and negative ratings only made up 10% of the total. A similar figure for positive ratings is found for the Danish stock market in 2019: 40%. The amount of neutral ratings, however, only amounts to 38% of the total, leaving a total 22% of recommendations in the Danish equities market to have negative analyst recommendation ratings. We will elaborate on the development leading up to 2019 in the analysis section, but the most important point worth noting here is the large difference in negative ratings in the two markets: Danish stocks get more than twice as many negative recommendations as U.S. stocks. This is well in line with the findings from the international study undertaken by Jegadeesh & Kim (2006), who conclude that the United States has the least negative/most optimistic recommendations.

Figure 2 – Average rating of recommendation changes by year and market

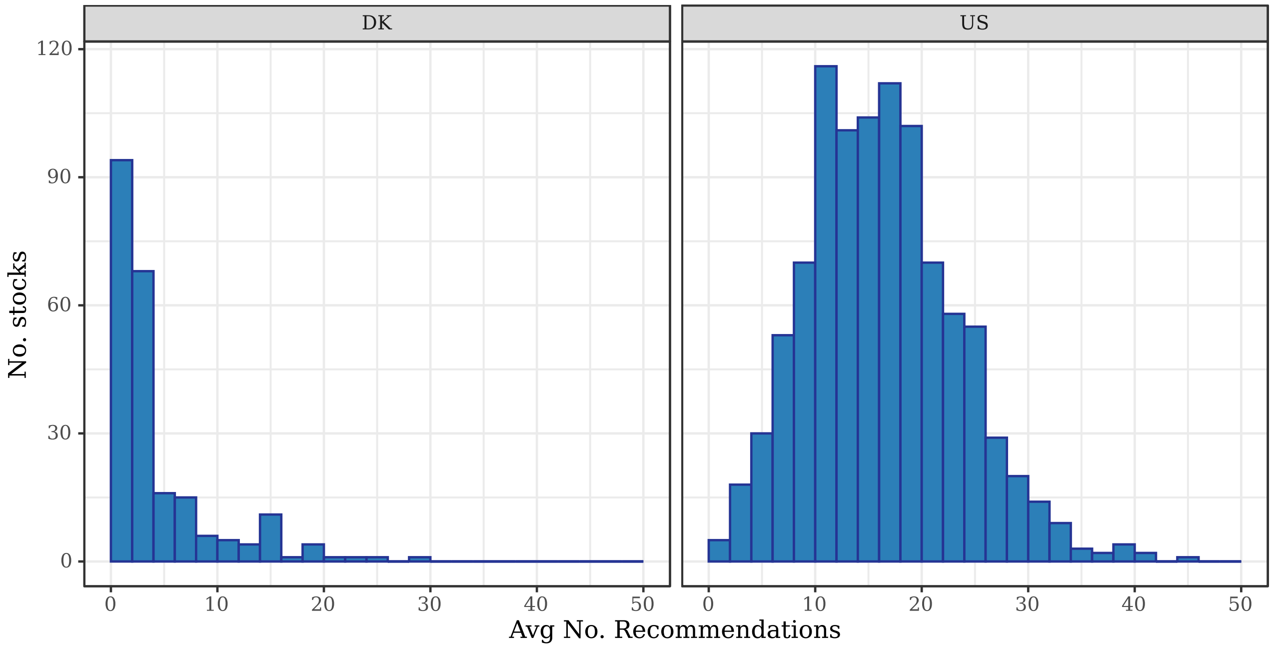


Average in Denmark is 2.72, and in the United States, it is 2.49 in the sample.

Figure 2 shows a tendency of the average rating of changed recommendations in Denmark to be "above" that of the US market. This means that the Danish stocks tend to get more negative recommendations, or at least that the average is closer to the theoretically "neutral" recommendation.

A t-test of the averages between the two markets gives a t statistic of 20.8, which under a null hypothesis of equal means in the two markets is approximately t-distributed with 12,243 degrees of freedom. This results in a p-value far below .001, and thus we reject the null hypothesis that the two markets have the same average rating for recommendation changes. Our data sample excludes recommendations revisions on days with multiple recommendations on the same day, but if we assume that our sample is representative of the population, then our findings indicate the tendency described in the previous figure: Recommendations of Danish stocks are less optimistic than U.S. stocks.

Figure 3 - Distribution of recommendations per stock in sample



In Figure 3 above, we see that not only is the sample for Danish stocks smaller than the U.S. sample; it is also differently distributed. We see that stocks are generally followed by more analysts and thus have more recommendations in the United States. This can probably be partly explained by the fact that we include all Danish stocks in the DK sample and thus stocks outside the main index, where the U.S. sample is defined by the highly followed S&P 500 index.

5 | Analysis

In this section, we will first utilize the event study method to test for any immediate and short-term effect on the stock price following an analyst recommendation change, and we will analyze the immediate effect further and attempt to decompose the reaction in order to determine what causes and influences the effect when we control for certain factors. Secondly, we will analyze if recommendation changes seem to have any longer-term effect on the stock return in the form of a drift or potential mean reversion. Lastly, we will propose a trading strategy based on the findings and test that different trading strategies to determine if it is possible to yield any abnormal returns by following signals from analyst recommendation changes under certain assumptions and constraints.

For simplicity, we have throughout the analysis grouped the recommendation ratings into three groups of levels (BUY, HOLD, SELL) instead of the five levels when considering strong buys and holds as well. Murg et at. (2016) do the same by arguing that the different recommendations within, e.g., the "buy" group are all recommendations to buy but can vary in their expression between analysts.

The immediate and short-term effect

For the immediate effect, we will analyze the abnormal return on the day of the recommendation change. We thus define an event window of a single day for the immediate effect. We again define the day of the recommendation announcement as Day 0, and thus the immediate effect is the abnormal return of a stock on day 0. If a recommendation change is announced after market close or on holiday, we treat it as announce on the following trading day.

The short-term effect we will analyze using an event window of 3 days, starting in day -1 and ending in day +1 after the recommendation announcement day. We cumulate the three days return using our buy-and-hold abnormal return, as defined in the methodology. We will primarily use and test this three-day BHAR as our measure of the short-term effect.

As described in the methodology, our abnormal return is the return (day t's adjusted closing price divided by day t-1's adjusted closing price minus 1) less an expected return estimated by the CAPM.

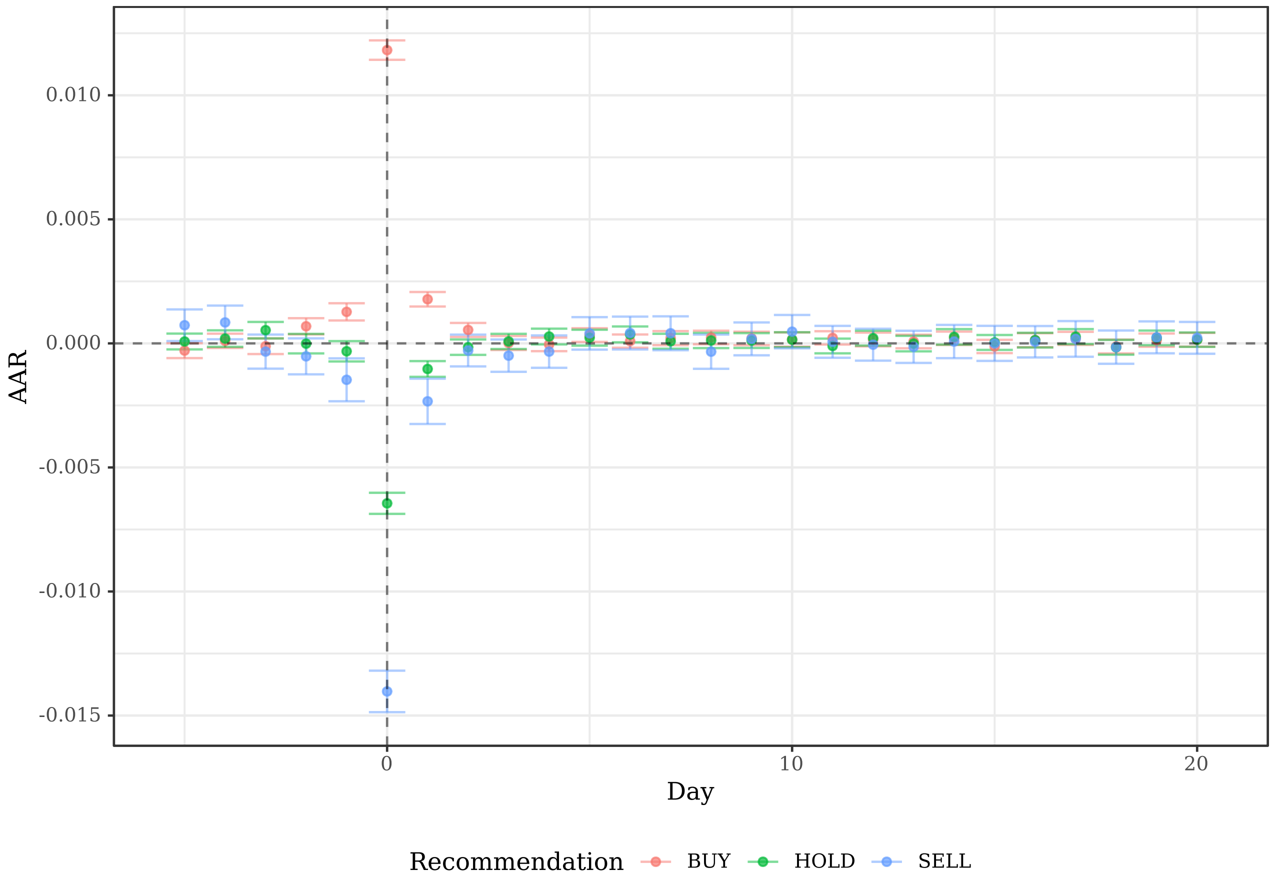
Following this, we will define any long-term effect or drift as the abnormal return after day 0, starting at day 1. This, we will analyze in a later section.

Impact of a change in rating level

First, we will analyze whether, as found by previous studies, a recommendation with a new rating level results in any abnormal returns in the immediate and short term. This will be our first step toward answering our hypothesis 1.a.

Figure 4 below presents the average abnormal return (AAR) per day from 5 trading days before to 21 trading days after a recommendation change. We see a significant AAR of 1.18% (-1.40%) on the day of the recommendation change when the new recommendation has a "buy" ("sell") rating.

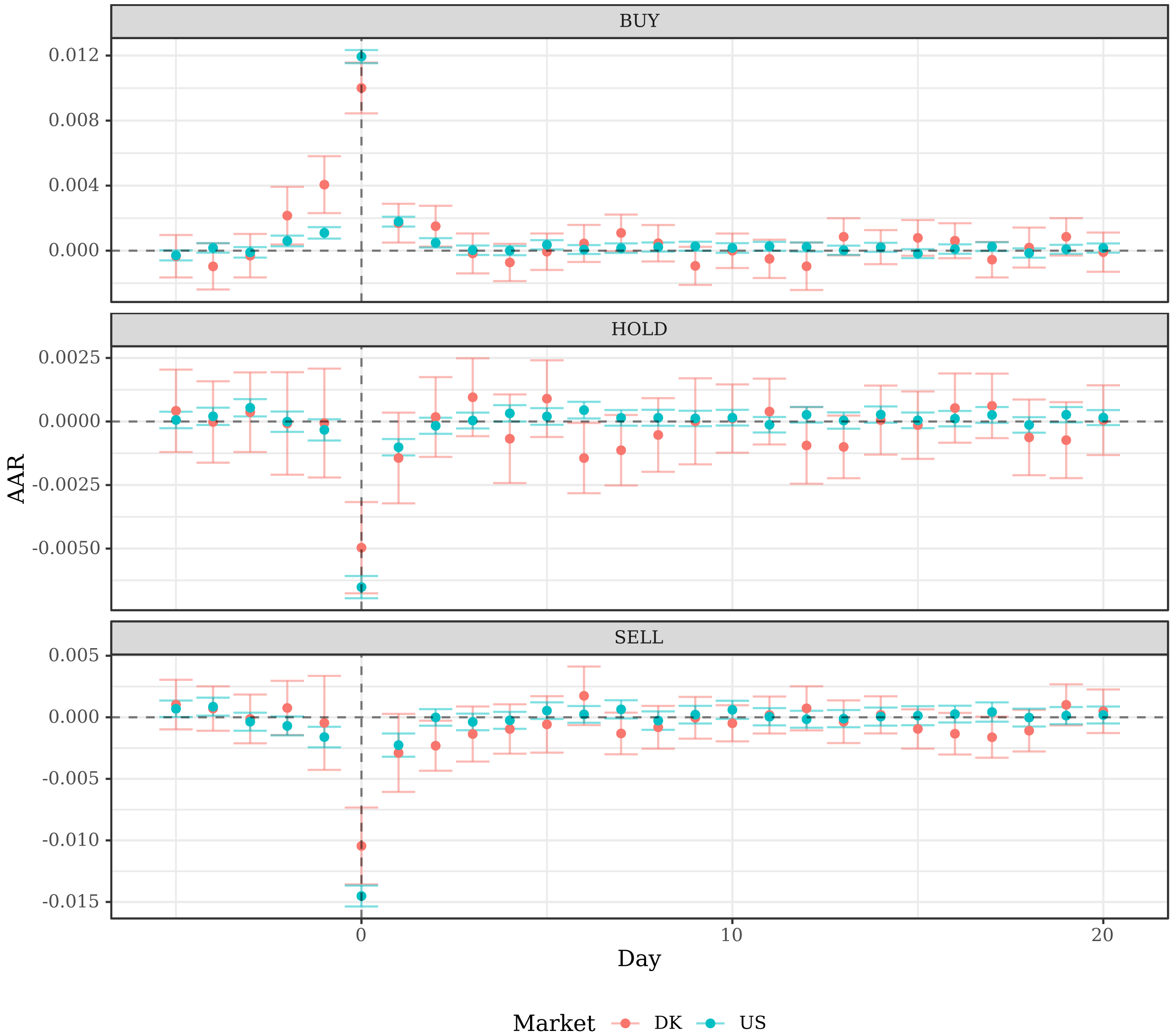
Figure 4 – AAR by Day and Recommendation Level with 95% confidence intervals



We also see an increase (decrease) both one and two days before and after the recommendation change, though it is much smaller and less significant. We also see that "hold" recommendations experience a significant negative abnormal return of .64% on day 0 and smaller negative returns day after the announcement.

The reaction before the announcement can have several explanations. One potential reason could be that some recommendation revisions follow other confounding news about the company that also led to a reaction in the stock price. Another explanation could be leakage to some market participants before recommendations are announced, i.e., insider information and trading. A third explanation could be errors with the encoded dates in the I/B/E/S database, so our model assigns the wrong relative date to the abnormal returns.

Figure 5 - AAR by Day, Recommendation and Market with 95% confidence intervals



The abnormal returns on day +1 can as well have several explanations. The most apparent is a delayed response to the recommendation revision announcement, possibly due to inattention or constraints of investors, as discussed by Loh (2010) and Kudryavtsev (2019). Another explanation could again be potentially erroneous data from the I/B/E/S database, in which case our model would attribute the return to the wrong day of some recommendation revisions and thus make the mean stand out from zero.

When we split the AAR graph in markets as done in Figure 5 above, we see the same pattern in both markets but a slightly higher (lower) abnormal return for day 0 in the US market for "buy" ("hold" and "sell") recommendations. We also see that the Day -1 and Day +1 ARs are significant for "buy" and "sell" recommendations in the US market, whereas they are only significantly different from zero for "buy" recommendations in Denmark. The significance is also generally higher for the US market, where we see a much lower standard error on the estimates. This is mainly due to the greater sample size of U.S. stocks.

We see significant negative reactions to "hold" recommendations in both markets. This can potentially be explained by investors tending to view hold recommendations as a negative signal rather than the "neutral" rating, which they, in theory, should be. This will be explored further when we investigate the level combined with the direction of change.

Table 7 – Test for difference in markets and asymmetry in the level of recommendation

				Difference in markets	
	All	**DK**	**US**	**t**	**df**
BUY	1.48%**	1.58%**	1.48%**	.63	1,318
HOLD	-.78%**	-.64%**	-.79%**	.97	958
SELL	-1.79%**	-1.22%**	-1.87%**	1.43	740
Asymmetry (BUY vs. SELL)					
t	3.63**	.78	5.44**		
df	7,991	874	7,976		

Test of three-day buy-and-hold abnormal return around the recommendation change announcement.
Welch t statistics are approx. t distributed with df degrees of freedom under the null hypothesis of no difference.
** is significant at 5%, ** is significant at 1%*

In Table 7, we test for a difference between the markets and asymmetry between buy and sell recommendations. Note that this test is based on the three-day BHAR around the event, and not on the day 0 AR. We are not able to reject the null hypothesis of equal mean abnormal return for the three groups of recommendations between the markets. Thus, our preliminary findings are that the two markets seem to react of equal proportions to changes in the recommendation rating level.

We are able to detect asymmetry in the reaction to “buy” and “sell” recommendations. We test if the absolute mean BHAR is equal under the Welch assumptions unequal variances. We find asymmetry for the collective sample, which seems to stem from the U.S. part, as the Danish findings are not significant, whereas the asymmetry is very significant in the United States. We thus conclude that the U.S. market reacts stronger to “sell” recommendations than “buy” recommendations in absolute terms. This is in line with the findings of Stickel (1995). This can be explained by the skewness in the distribution of rating levels in the recommendations, where many more positive recommendations are issued. Thus, investors might pay more attention to and value higher recommendation with a negative rating, as these are less frequent.

Impact of the direction of change

As stated in hypothesis 1.a, the abnormal return is also hypothesized to be affected by the direction of the change in recommendation, and not only what level the new recommendation is. In hypothesis 1.b, we furthermore hypothesize that recommendations to a lower rating (a downgrade) experience greater abnormal returns in absolute terms than upgrades. In Figure 6, we see the effect of upgrades and downgrades, respectively, in both markets as one.

Here we see close to the same picture as with the recommendation levels, with a very significant high absolute abnormal return on the recommendation announcement day and smaller significant returns on the days before and after. We do see lower volatility in the period before and after and generally lower standard errors than seen with the rating levels in Figure 4.

We see a slight tendency of an asymmetric response between up- and downgrades, as we saw with recommendation levels in the previous section. For recommendation upgrades, we see an average abnormal return of 1.23% on day 0, and for downgrades, we see a negative abnormal return of 1.14%. So, at first sight, hypothesis 1.b is not confirmed, but rather the opposite. We will test whether this asymmetry is significant below.

Figure 6 - AAR by Day and Direction of Change with 95% confidence intervals

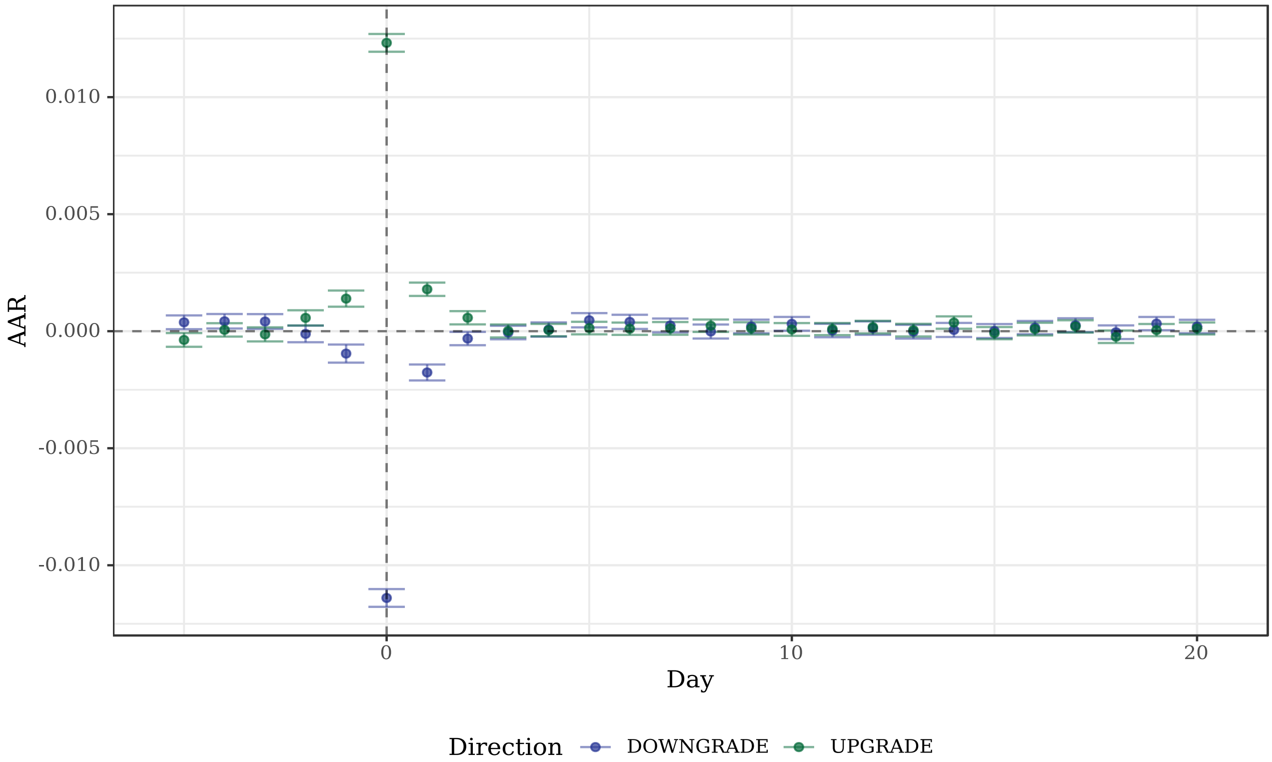
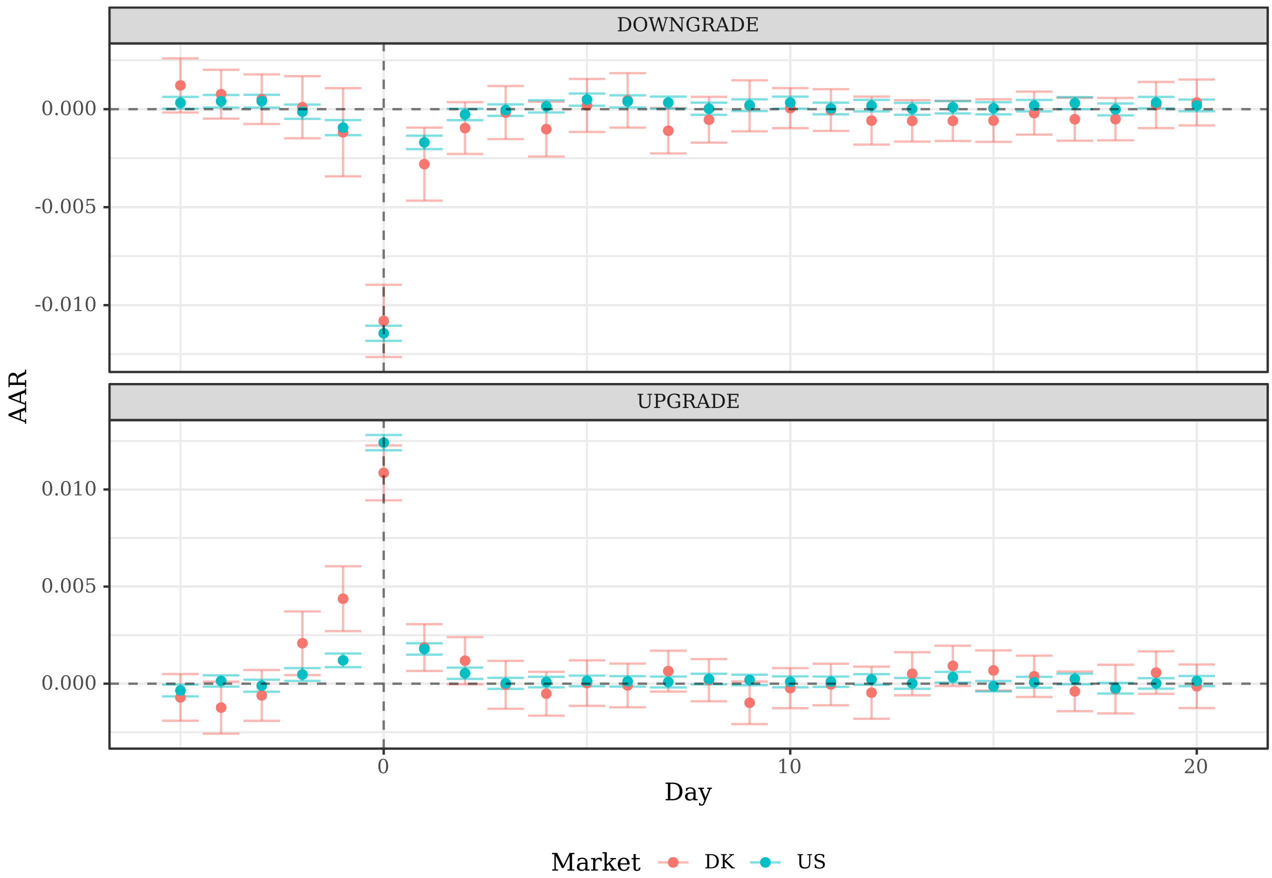


Figure 7 – AAR by Day, Direction of Change and Market with 95% confidence intervals



In Figure 7, we split the reaction between our two markets of investigation. We once again see an indication of a stronger reaction in the U.S. market. Overall, the patterns look the same as in Figure 6, only that day -1 in Denmark is quite high for upgrades at .44%.

In Table 8, we test for differences in the response between markets for the two groups of recommendation changes as well as for any asymmetric response to the two directions.

The asymmetric reaction to up- and downgrades, respectively, is not apparent as it was with regards to the recommendation rating levels in the previous section. Here we find a slightly stronger reaction to upgrades (1.23%) than downgrades (-1.14%), which is in contrast with the findings above as well as the findings of Stickel (1995) and Park & Park (2019) who found a greater reaction to negative recommendations. Investors apparently tend to react more strongly to negative recommendation levels but more strongly to the positive direction of change of the recommendations in our sample.

The asymmetry will be investigated further when we combine levels and direction of change, but for hypothesis 1.b, we can conclude that downgrades do not experience greater absolute abnormal returns than upgrades; instead, we see upgrades reacting stronger in the U.S. market, which is contradictory to what Park & Park (2019) found.

Table 8 – Test for difference in markets and asymmetry in the direction of recommendation change

				Difference in markets	
	All	**DK**	**US**	**t**	**df**
UPGRADES	1.55%**	1.71%**	1.54%**	1.33	1,622
DOWNGRADES	-1.42%**	-1.39%**	-1.42%**	.12	1,487
Asymmetry					
t	3.04**	1.17	2.81**		
df	47,104	2,164	44,609		

Test of three-day buy-and-hold abnormal return around the recommendation change announcement.
Welch t statistics are approx. t distributed with df degrees of freedom under the null hypothesis of no difference. For asymmetry, we test the absolute value of the mean abnormal return.
** is significant at 5%, ** is significant at 1%*

As with pure recommendation levels above, we also here do not find evidence of a difference in reaction between markets for the two groups of recommendation changes. We thus cannot conclude if one market reacts more to recommendations based on either the level or the direction of change in the recommendation revision.

The signal value of level versus direction

In this section, we take offset in our hypothesis 1.a, and we will investigate if there is a difference in the reaction to levels and direction of change, so if we can say that one is a better predictor of abnormal returns.

In Table 9, we see that there is no significant difference in the reaction to a positive level recommendation ("buy") and a positive direction of change ("upgrade"). For the negative revisions, we see that the level ("sell") causes a greater reaction than the signal of a downgrade.

Table 9 – Reaction to Level and Direction of Recommendation Revision in Total Sample

	Positive	Negative
Level	1.48%**	-1.79%**
Direction	1.55%**	-1.42%**
Difference		
t	1.51	4.41**
df	44,654	8,278

Test of three-day buy-and-hold abnormal return around the recommendation change announcement.
Welch t statistics are approx. t distributed with df degrees of freedom under the null hypothesis of no difference.
** is significant at 5%, ** is significant at 1%*

We will, in the following test, if this is also the case in each market individually.

Table 10 - Reaction to Level and Direction of Recommendation Revision by Market

DK	Positive	Negative
Level	1.58%**	-1.22%**
Direction	1.71%**	-1.39%**
Difference		
t	0.70	0.33
df	2,633	1,191

US	Positive	Negative
Level	1.48%**	-1.87%**
Direction	1.54%**	-1.42%**
Difference		
t	1.37	6.31**
df	41,011	7,885

Test of three-day buy-and-hold abnormal return around the recommendation change announcement.
Welch t statistics are approx. t distributed with df degrees of freedom under the null hypothesis of no difference.
** is significant at 5%, ** is significant at 1%*

In Denmark, we see no difference between the two signals of level and direction of change in recommendation revisions, and thus we cannot confirm our hypothesis 1.a that the signal of direction should have a greater impact than the level of the recommendation in Denmark. In fact, we cannot say that any of the signals should be a better predictor for abnormal returns than the other.

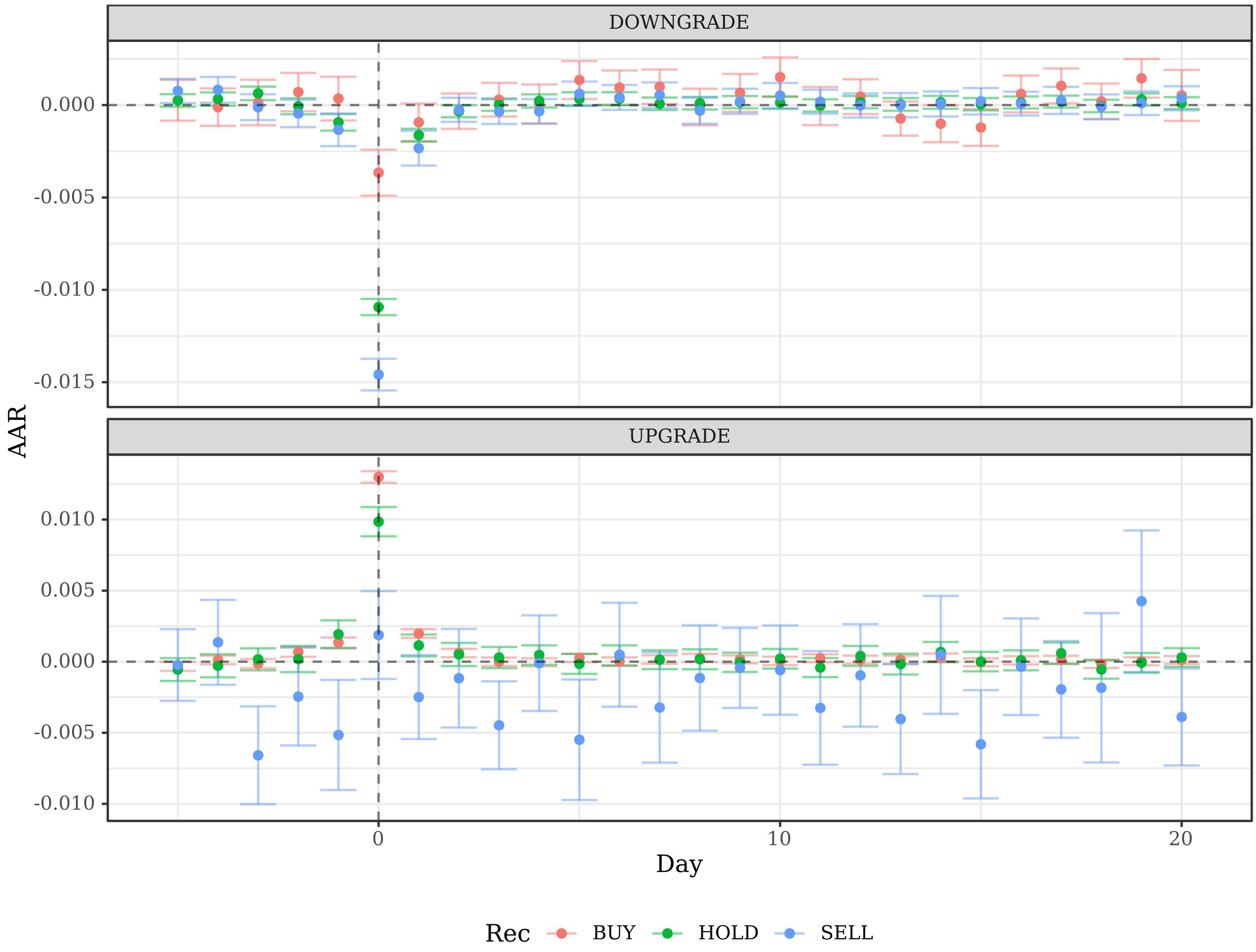
In the United States, we see the same as with the combined sample. The difference is only significant for the negative direction and level and in the opposite direction as hypothesized. We thus reject our hypothesis 1.a and conclude that the direction of a recommendation change does not cause a stronger reaction than the level. The opposite is indicated for the negative recommendation changes in the United States.

Impact of combined recommendation level and direction of change

The findings so far show a significant immediate effect of a recommendation change both when looking at the level or the direction of the change. With an offset in hypothesis 1.c, we want to examine if the combined signal of level and change, gives a better indication of the reaction.

In Figure 8, we combine the levels and directions in both markets. Generally, the same trend as earlier is apparent, with only upgrades to sell showing no significant day 0 abnormal return. Upgrades to sell is a "mixed" recommendation, with a positive signal in the direction, but still a negative level. It is also seen that the other "mixed" recommendation, downgrade to buy, has a smaller reaction than the other downgrades.

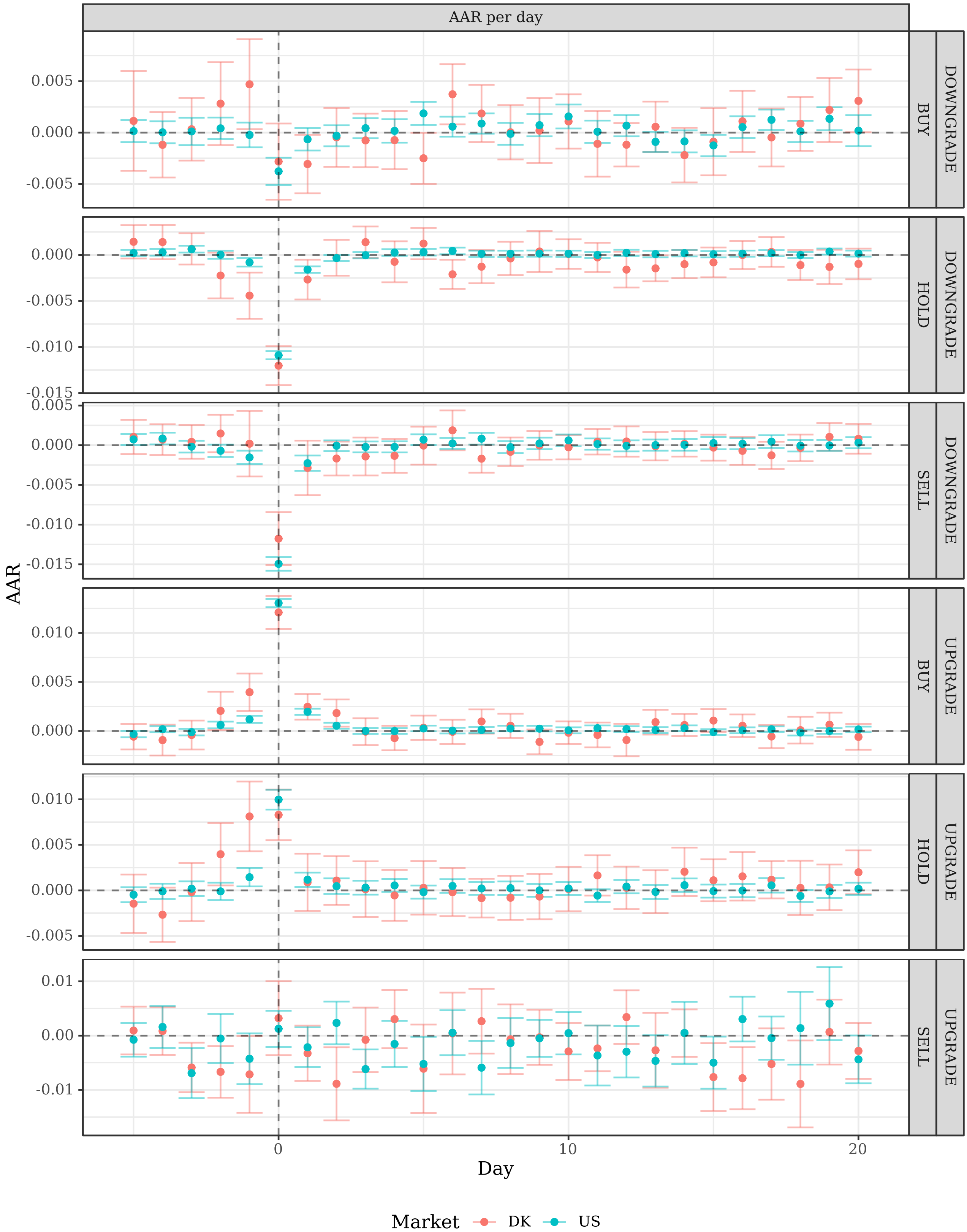
Figure 8 – AAR by Day, Direction, Level and Market with 95% confidence intervals



In Figure 9 below, we split the reactions by markets as well. Here, it is seen that day 0 abnormal returns are generally significant. For both markets, all but the "mixed" recommendations (upgrade to sell and downgrade to buy) are significant.

It is also seen that in several instances, there is a significant effect before the event day. This can possibly be explained by (1) recommendations being issued because of other events happening, or (2) some investors getting access to the information in the recommendation prior to the publication or in other ways anticipating it, or (3) misspecification of the announcement date in the I/B/E/S database as discussed previously.

Figure 9 - AAR by Market, Rating and Change Direction with 95% confidence intervals



The case for causality is difficult in the potential situations where recommendations might be seen as a reaction to other events, such as earnings announcements or external news about a company. We have attempted to control for this by excluding recommendations on days with multiple recommendation revisions for the same stock, and we will attempt to control further for this in later analysis, but the question of causality, we will primarily leave for future research.

In Figure 4, we saw a significant negative AR day 0 for hold recommendations. When we look at both recommendation level and the direction of the change, we see that the reaction in AR to a hold recommendation actually depends on whether it is a downgrade or an upgrade. The result of only looking at the level "hold" falsely concludes a negative reaction, which can be attributed to the aggregation of the two effects depicted in Figure 9, where the negative effect is of greater magnitude and with four times as many observations resulting in a biased and skewed average.

When aggregating the returns in the event window of day -1 through +1 as several other studies do (Womack, 1996; Loh & Stulz, 2009; Loh, 2010), we get the values as seen in Table 11. Here we see a significant effect of the event in most cases besides upgrades to sell in both markets and downgraded to buy in Denmark. All other effects are significant at the 1% level.

We also see that the difference between the two markets is only significant for downgrades to hold, so in regard to hypothesis 1.e, we find a stronger reaction to recommendation changes for Danish stocks. This is surprising, as some previous international literature finds that US stocks usually have a greater reaction than other markets (Jegadeesh, 2006). In response to our hypothesis 1.e, we cannot confirm a stronger reaction in the United States, but we find evidence of stronger reactions to a particular type of recommendation changes in Denmark.

The test statistic for testing the three-day buy-and-hold abnormal return of a group of recommendations is defined as:

$$t_d = \frac{BHAR_d}{\hat{\sigma}(BHAR_d)/\sqrt{n}}$$

Where t_d is the t-statistic for a given group of recommendation changes for day d, which follows a student-t distribution with n - 1 degrees of freedom. $BHAR_d$ is the average abnormal return for day d, $\hat{\sigma}(BHAR_d)$ denotes the standard deviation of $BHAR_d$, and n is the number of observations in the group.

Table 11 – Three-day BHAR by Direction, Recommendation Level and Market

Market	UPGRADES BUY	UPGRADES HOLD	UPGRADES SELL	DOWNGRADES BUY	DOWNGRADES HOLD	DOWNGRADES SELL
Both	1.63%	1.29%	-.59%	-.43%	-1.35%	-1.83%
	52.04**	15.39**	2.19*	4.35**	38.51**	22.62**
n	18,862	4,235	206	1,437	15,384	5,680
DK	1.86%	1.73%	-.76%	-.11%	-1.90%	-1.26%
	12.61**	6.03**	1.78*	.34	9.71**	2.56**
n	1,067	319	65	173	599	673
US	1.62%	1.26%	-.52%	-.47%	-1.33%	-1.91%
	50.49**	14.35**	1.51	4.60**	37.32**	28.86**
n	18,365	4,101	143	1,298	15,461	5,243
Difference between markets						
t	1.60	1.57	.44	1.03	2.85**	1.30
df	1,169	380	146	206	638	696

Abnormal return in event window of day -1 through day 1. The null hypothesis is 0 abnormal return on day 0.
The t-statistic below is student-t distributed with n – 1 degrees of freedom.
For the difference between markets, the t statistic is t distributed with degrees of freedom below as calculated using the Welch t-test method.
*Stars are marking the significance level. * is significant at 5%, ** is significant at 1%*

The asymmetry of positive and negative recommendation changes is visible between the upgrades to buy and the downgrades to sell, though apparently opposite in the two markets. To test if these means are significantly different, we will utilize the Welch two-sample t-test of the mean of the two groups' absolute abnormal return. The null hypothesis for the test is that the two groups have equal means.

First, we test if the combined sample of both markets experience asymmetry. The absolute means BHAR in the two groups are 1.63% and 1.83%, respectively. The test statistic is 2.35, which under the null is approximately t distributed with 7,760 degrees of freedom, resulting in a p-value of .019. We thus reject the null hypothesis at the 5% significance level and conclude that there is an asymmetry in reaction to upgrade to buy and downgrades to sell recommendations in the combined sample. At a significance level of 1%, we fail to reject the null hypothesis and cannot say that there is an asymmetry in response to positive and negative recommendation changes.

Next, we will test both markets individually. For Denmark, the absolute means of the BHAR of the two groups of recommendations are 1.86% and 1.26% for upgrades to buy and downgrades to sell, respectively. The test statistic is 1.16, which under the null is approximately t distributed with 794 degrees of freedom, resulting in a p-value of .247. We thus fail to reject the null hypothesis at the 5% significance level and thus cannot conclude any asymmetry in response to positive and negative recommendation changes for Danish stocks.

For the U.S. stocks, the two means are 1.62% and 1.91%. The test statistic is 3.96, which under the null is approximately t distributed with 7,869 degrees of freedom, resulting in a p-value of less than .001. We thus reject the null hypothesis at the 1% significance level and conclude that there is an asymmetric reaction to upgrade-to-buy and downgrade-to-sell recommendations in the United States.

With hypothesis 1.c, we wanted to examine if upgrades to buy recommendations revisions experience the greatest positive abnormal returns and downgrade to sell recommendation experience the greatest negative abnormal return. The findings so far indicate this, as for the combined sample, we do see this in Figure 11. To test this, we want to compare upgrades to buy with upgrades to hold, and downgrades to hold to downgrades to sell. We do not test with upgrades to sell, as this average is significantly negative. If the test for downgrades is not significant, we cannot conclude with regards to our hypothesis, and thus no further test regarding the downgrades to buy is necessary. The null hypothesis for the following test is that of no difference between the means.

For upgrades, the two means are 1.63% and 1.29%. The test statistic is 3.73, which under the null is approximately t distributed with 5,704 degrees of freedom, resulting in a p-value of less than .001. We thus reject the null hypothesis at the 1% significance level and conclude that for the total sample, upgrades to buy experience the greatest abnormal returns.

For downgrades, the absolute means of the BHAR of the two groups of recommendations are -1.83% and -1.35% for downgrades to sell and hold, respectively. The test statistic for the difference is 5.45, which under the null is t distributed with 8,235 degrees of freedom, resulting in a p-value of less than .001, we thus reject the null hypothesis at the 1% significance level and conclude that for the total sample, downgrades to sell experience the most negative abnormal returns.

We can thus accept our hypothesis 1.c in our total sample. In Table 12, we see that the U.S. market and the total sample confirm our hypothesis 1.c, but in Denmark, we cannot conclude the same.

Table 12 – T-test of difference in Change Direction per Market

	UPGRADE		Difference		DOWNGRADE		Difference	
Market	**BUY**	**HOLD**	**t**	**df**	**HOLD**	**SELL**	**t**	**df**
All	1.63%	1.29%	3.73**	5704	-1.35%	-1.83%	5.45**	8235
DK	1.86%	1.73%	.39	497	-1.90%	-1.26%	1.2	876
US	1.62%	1.26%	3.80**	5240	-1.33%	-1.91%	7.67**	8498

Abnormal return in event window of day -1 through day 1.
The test statistic is t distributed with degrees of freedom below as calculated using the Welch t-test method.
*Stars marking significance level. * is significant at 5%, ** is significant at 1%*

In hypothesis 1.e, we want to examine the difference in reaction between the two markets. In Table 11, we see the t-test for differences between the markets and can conclude that overall, there is no difference in the reaction among the two markets but for reactions to downgrades to hold, which are significantly different between the two markets.

Testing the magnitude of change

In the following, we test if the magnitude of the recommendation change affects the reaction to the recommendation according to our hypothesis 1.d. We group our total sample by changes of either one or more than one rating level. The recommendation changes of one level have a mean absolute abnormal return for the event window of 3.01%, and the changes of more than one level have a mean of 3.14%. We perform a test of the means of these two samples. The null hypothesis is no difference, which gives a test statistic of 3.44, which under the null hypothesis is approximately t distributed with 37,477 degrees of freedom. This results in a p-value of less than .001, which leads us to reject the null and conclude that the reaction to a recommendation changes by more than one level is greater than the reaction to a change of only one level.

For the collective sample, we thus accept our hypothesis 1.d and conclude that recommendation changes that skip a level (has a greater magnitude in the change) lead to greater reactions than recommendations that do not skip a rating level.

In the table below, we see that the magnitude does only seem to be significant for the reaction to downgrades to sell in the U.S. market and upgrades to hold in Denmark. It surprises that the difference in upgrades to buy, which have the possibility of great magnitude, is not significant.

Table 13 – T-test of difference in magnitude

	UPGRADES		DOWNGRADES	
Market	**BUY**	**HOLD**	**HOLD**	**SELL**
US	1.27	1.60	1.44	3.40**
	15,291	1,836	13,071	3,018
DK	.97	2.00*	1.26	1.30
	788	120	209	389

The null hypothesis is no difference in mean between magnitudes of change.
The t-statistic is student-t distributed. Degrees of freedom showed below the t statistic.
Upgrades to sell and downgrades to buy are excluded as no change of more than one is possible for these groups.
** is significant at 5%, ** is significant at 1%*

Other determinants of the effect

This part of the analysis will further examine the short-term effects found in Table 11 for other explanatory variables discussed in the literature. We do this to investigate if stock recommendation changes on firms with certain attributes are more or less affected than others. This might help us understand if some recommendation changes have a greater effect than others. First, we regress BHAR over both the short-term event window, defined as the 3-day buy-and-hold abnormal return, and over the immediate effect event window, defined as a one-day abnormal return. We run these regressions on the same variables as Table 11. Second, we run a similar regression of the short-term effect, but this time also including the other relevant variables described in the literature. Third, we use the same explanatory variables as the prior regression, but instead of using the 3-day BHAR as the dependent variable, we use the 1-day AR.

This split is made because the two approaches attempt to investigate different aspects of the recommendation change-effect on stock prices: The BHAR is used to measure, to a greater extent, the complete effect of changes in recommendations. In the literature, an event window of three days is more widely used (R. Loh & Stulz, 2009; Shah & Subayyal, 2012; Womack, 1996) than one of a single day (Jegadeesh & Kim, 2006) to capture the “immediate” effect. However, as illustrated clearly in the daily AAR-plots earlier in the analysis, the abnormal return on Day 0 is by far the most significant, although Day -1 and Day 1 also indicate significant abnormal returns. Therefore, in order to find a clearer indication of the immediate effect, we narrow the event window down to just one trading day and compare the results of the two regressions.

In these regression models, we include the recommendations previously excluded by our "multiple recommendations on same day" dummy, and we test of this dummy variable has a significant effect on the abnormal return in the event window. We thus include and test if stocks that are subject to several recommendation changes on the same day experience different abnormal returns than stocks that only receive one updated recommendation. As discussed in the methodology section, multiple recommendation changes on a single stock might be caused by earnings surprises, and findings from prior studies indicate that recommendation changes announced concurrently with earnings announcements are more influential (Su et al., 2019).

We will utilize a multivariate ordinary least square regression model to estimate the effect of the recommendation change and what determines the reaction when controlling for different factors.

Simple Regression Models

As found in the previous section, there seems to be a difference in response between markets, different recommendations changes, and different rating levels. Taking this as a starting point, our first regression model is:

$$BHAR_i \text{ or } AR_i = \alpha + \beta_R Rating + \beta_D Direction + \beta_M Market + \varepsilon_i$$

Where $\beta_R, \beta_D, \beta_M$ are the linear coefficient estimates for the rating level, the direction of the change, and the market, respectively. A constant, α, is included in order to control for any possible omitted variables.

We are also interested in the possible interaction between these variables to test if the effect of one variable depends on the level of another, e.g., if the effect of a downgrade depends on the market. In the previous sections, we saw indications that the reaction to upgrades and downgrades depended on market and level. We thus include interaction terms between the variables and run the model as specified by the equation:

$$\begin{aligned}
&BHAR_i \text{ or } AR_i = \alpha + \beta_R Rating + \beta_D Direction + \beta_M Market \\
&+\beta_{RD} Rating * Direction + \beta_{RM} Rating * Market \\
&+\beta_{RM} Direction * Market + \beta_{RDM} Rating * Direction * Market + \varepsilon_i
\end{aligned}$$

In Table 14, we see the results of the two regression models defined above. The results include several interesting findings.

Simple Regression Models Results

First, both regular R^2 and adjusted R^2 are very similar for the first simple model and the model with interaction terms. Thus, it does not seem that there are any significant interactions between the variables. In other words, they have a low correlation with each other.

Second, the term for the market is not significant in any of the models. This contrasts with our findings earlier in the analysis. This result is also unexpected when comparing it with those of the study undertaken by Jegadeesh & Kim (2006), which indicated that U.S. stocks reacted significantly more to analyst recommendation changes than any of the other six countries in the study. Even if the coefficients were significant, they still seem to have the opposite sign of what would be expected from the study and our own previous findings.

Third, the “upgrade” term is significant at the .1% level and has the highest absolute coefficient value across all the models. This is in line with the literature (Murg et al., 2016) and our findings from earlier in the analysis. The direction of a recommendation change is better at explaining abnormal returns than the new rating of the recommendation, which is what we hypothesized in hypothesis 1.a.

Fourth, the “hold” and “sell” terms are both significant in most cases. This is also expected from the literature (Murg et al. 2016), but their coefficients are clearly lower than the “upgrade” term.

Table 14 – Simple Regression Models

	BHAR		AR	
	(1)	(2)	(3)	(4)
RecHOLD	-0.005***	-0.017***	-0.004***	-0.008*
	(0.001)	(0.005)	(0.001)	(0.003)
RecSELL	-0.011***	-0.009	-0.007***	-0.009**
	(0.001)	(0.005)	(0.001)	(0.003)
DirectionUPGRADE	0.029***	0.024***	0.028***	0.017***
	(0.001)	(0.005)	(0.001)	(0.003)
MarketUS	-0.002	-0.004	-0.001	-0.003
	(0.001)	(0.005)	(0.001)	(0.003)
RecHOLD:DirectionUPGRADE		0.009		0.003
		(0.006)		(0.004)
RecSELL:DirectionUPGRADE		-0.012		0.002
		(0.009)		(0.006)
RecHOLD:MarketUS		0.009		-0.002
		(0.005)		(0.004)
RecSELL:MarketUS		-0.005		-0.003
		(0.005)		(0.004)
DirectionUPGRADE:MarketUS		0.001		0.006
		(0.005)		(0.003)
RecHOLD:DirectionUPGRADE:MarketUS		-0.005		0.005
		(0.007)		(0.004)
RecSELL:DirectionUPGRADE:MarketUS		0.004		-0.003
		(0.011)		(0.007)
Constant *(Rec = BUY, Direction = DOWNGRADE, Market = DK)*	-0.009*** (0.001)	-0.004 (0.005)	-0.011*** (0.001)	-0.004 (0.003)
Observations	43,291	43,291	60,348	60,348
R^2	0.093	0.094	0.112	0.114
Adjusted R^2	0.093	0.094	0.112	0.113
F Statistic	1,113.818*** (df = 4; 43286)	408.441*** (df = 11; 43279)	1,907.603*** (df = 4; 60343)	702.381*** (df = 11; 60336)
Note:				*p<0.05; **p<0.01; ***p<0.001

Short-term Regression Model

As discussed in the “Other determinants of the stock price reaction to recommendation changes” in the literature review, several other variables are proposed to influence the stock price reaction to an analyst recommendation change. In the following, we will briefly review the variables included in the next regression models and discuss their results.

We run regression models on groups of recommendations divided by recommendation level and direction of change. We thus estimate six different regressions and compare the results between the groups. These groups are the combinations of direction (upgrade/downgrade) and rating (buy/hold/sell).

Including the mentioned variables, three-day buy-and-hold abnormal return regression is defined as the following equation:

$$\begin{aligned} BHAR_i = \alpha &+ \beta_{MOVE} Movement_i + \beta_{POT} Potential_i + \beta_{POT2} Potential_i^2 + \beta_{NOREC} NoRecs_i \\ &+ \beta_{US} MarketUS_i + \beta_{VOL} \ln(Volume_i) + \beta_{MULTI} Multiple_i \\ &+ \beta_{MC} \ln(MarketCap_i) + \beta_{DIST} DistConsensus_i + \beta_{SPR} SpreadRel_i \\ &+ \beta_{FRI} Friday_i + \beta_{NORECDAY} NoRecsThisDay_i + \beta_{BR} Broker_i + \beta_{YR} Year_i + \varepsilon_i \end{aligned}$$

The betas β_x are the coefficient estimates for each of their respective variables. The variables are defined as follows (all referring to stock *i*):

“Movement” is a collection of three dummy variables, each representing the magnitude of the recommendation change (how many levels the rating changes).

We use the term potential as our variable measuring the relevant target price, and it is defined as the relative difference between the target price and the previous closing price. A quadratic term is included as we hypothesize that the effect of the target price on stock price is not linear.

“NoRecs” is the number of analysts currently covering the stock.

“MarketUS” is a dummy variable equal to 1 if the stock relevant stock is listed in the United States, 0 if it is listed in Denmark.

“Volume” is the trading volume of the stock on the given day. We also log-transform the trading volume for the same reasons as market cap.

“Multiple” is a dummy variable equal to 1 if there are more than one recommendation change on the stock on the given day, 0 otherwise.

“MarketCap” is the firm size measured in market capitalization on the given day. We log-transform the market cap to reduce the influence of very high values because of its right skewness and magnitude compared to the other variables.

“DistConsensus” is defined as the new rating of the recommendation that has changed minus the consensus of the stock.

The relative bid-ask spread, “SpreadRel”, is calculated as the spread between the latest bid and ask price of the day divided by the mid-price.

“Friday”, inspired by the literature to attempt to capture the “weekend inattention” hypothesized and indicated by prior studies. This is included in our model with a dummy variable taking the value of 1 if the recommendation change is announced on a Friday, and 0 otherwise.

Finally, we control for broker-specific effects by adding a fixed-effect term to the model. Also, we acknowledge that there are different states of the stock market in different years, and thus we control for yearly fixed effects.

In Table 15 below, we see the result of this regression model run on the six sub-samples grouped by recommendation level.

Starting with the first column, “Downgrade to buy”: This column consists of recommendation changes that have a change in rating from “strong buy” (value of 1 in I/B/E/S) to “buy” (value of 2 in I/B/E/S). As described in the methodology section, we combined these two sections in order to simplify the ratings to three levels instead of five.

The constant has a value of 6.5% and could if it was not insignificant, be interpreted as the effect BHAR of a recommendation change with the following traits: 1) Moves from strong buy to buy. 2) The target price is equal to the current closing price (this is unrealistic because an analyst probably would not recommend buying a stock that she or he expected to not increase in price). 3) There are no other analysts following the stock. 4) The market is Denmark. 5) The trading volume is zero (this is highly unrealistic, so we have to assume that there will be a certain trading volume that day, which is then further strengthening the negative effect of the recommendation change on the stock. 6) There are no other recommendation changes on this stock on this day. 7) The market cap of the firm is zero (this is impossible, and we do not have any observations with firm size equal to zero, so the interpretation of this variable has to be done in a similar way to that of volume). 8) The consensus rating of the stock is exactly 2 (buy), so there is zero distance to the consensus recommendation. 9) The relative spread is zero (also unrealistic, but we can imagine it to be very low). 10) It is a day other than Friday.

Short-term Regression Model Results

There are several interesting findings that relate to the literature discussed previously.

First, the adjusted R^2 for the different groups is ranging from 0.066 to 0.122, which means that adding these other variables does not explain more of the variation in BHAR for all of the groups, compared to the simple model previously described. However, many of the coefficients are significant, so that the variables might explain some of this variance still.

Second, the constants are significant for downgrades to hold and sell and upgrades to buy. Upon first glance, the downgrade-to-sell coefficient of -8.5% and the coefficient for upgrade-to-buy of 7.4% might seem to indicate that these two groups of recommendation changes have the strongest absolute effect on BHAR, compared to the other groups which all have smaller absolute coefficients. However, as explained above, these constants are by themselves not representative of the differences in means for the. We can thus not use these two figures to support or contradict hypothesis 1.b (upgrades to buy and downgrades to “sell” have the strongest absolute effects on stock prices).

Magnitude (how large the change in rating is) seems to only be significant for one group of recommendation changes: Upgrade to buy. A change in rating from hold to strong buy is associated with a .4% increase in BHAR, compared to an upgrade from hold to buy or buy to strong buy. This is consistent with the findings of Murg et al. (2016) and Stickel (1995) and our hypothesis 1.d. The largest positive change possible has a magnitude of four (strong sell to strong buy), and in this case, the coefficient is 1.1%, as would be expected. It is worth noting that “Movement3”, although not significant, indicates a tendency to have a coefficient of .6%, which is between the coefficients of the other two “Movement”-variables, as would be expected. Now, none of the other groups show significant differences associated with magnitude. We hypothesized that the effect of magnitude would be significant for both upgrades and downgrades, but these results indicate that only upgrades to buy are affected by the number of ratings skipped. We could interpret this as having something to do with the signal difference between upgrades and downgrades. Investors seem to care about "how positive" a positive change is, but less interested when it is a downgrade. In other words, they might interpret the signal value of a downgrade in a less nuanced way than an upgrade, possibly due to negative recommendation changes impacting the stock price more, as indicated by Park & Park (2019b). This could further be related to the majority of rating changes being positive, which would require investors to better distinguish the signal strength of the upgrade in order to differentiate between the different upgrades that are announced.

Potential, or the relative distance between the current price of a stock and the estimated target price, has the most prevalent effect when the recommendation change is a downgrade to hold. The coefficient for this group is -.9%. The only other group with a significant coefficient is upgrades to "buy", and this estimate is .2%. The coefficient of -.9% indicates that for a downgrade to hold, which may be expected to have a target price slightly above or around the current price (meaning that the value of "Potential" would be positive or close to zero), is associated with a negative effect on BHAR.

The quadratic term of potential is also significant for downgrades to hold, with a coefficient of -.7%. Interestingly, downgrades to sell, as the only other group with a significant coefficient to this variable, has a coefficient of 2.4%. The problem with interpreting the target price is that target prices are not necessarily corresponding directly to specific rating levels. How the analyst intended their target price to be interpreted by the investors and how the market interprets the target price is not set in stone. One might think that a "hold" recommendation is neutral and would be associated with a target price slightly above the current price, perhaps adjusted for risk or other factors. Nevertheless, as frequently discussed in this thesis, there is a skew of recommendations, and "hold" does not appear to be a neutral recommendation. Likewise, the way target prices are calculated and how they are intended to be understood could vary greatly from analyst to analyst. Jegadeesh & Kim (2006), Loh & Stulz (2009), Loh (2010), Womack (1996) and Murg et al. (2016) all discuss the impact of target price on the effect analyst recommendation changes have on stock prices, but our findings are unfortunately inconclusive, as the "Potential" term cannot be interpreted by itself.

The number of analysts following a stock was previously hypothesized to be negatively related to the absolute value of the effect of recommendation changes based on findings in the literature (Loh & Stulz, 2009; Loh, 2010). This seems to be exactly what our findings in this regression indicate as well. Downgrades to hold and sell have significant coefficients of .01% and .04%, respectively. This means that a negative effect of a recommendation change on BHAR will be “less negative,” the more analysts are following the stock. As long as the downgrade does have a negative effect, this reasoning makes sense. Upgrades to buy and hold have coefficients of -.04% and -.1%, which fits well with the result for downgrades.

The market is significant in this model for downgrades to hold (1.4%) and sell (1.4%) and upgrades to buy (-1.5%) and sell (5.8%). The two first three indicate stronger effects in Denmark. The last one is much larger and in the opposite direction. In other words, the last coefficient indicates that upgrades from strong sell to sell in the United States result in – everything else equal – a 5.8% greater BHAR. This should be taken with a grain of salt, though, as the sample size of this group is far smaller than any of the other. None of the simple regression models from the previous section indicated that the market was a significant variable. Our previous findings regarding hypothesis 1.e in the section “Impact of both recommendation level and direction of change” indicated that only downgrades to hold had significantly different effects on BHAR in the two markets. The findings by Jegadeesh & Kim (2006), which indicated that recommendation changes in the U.S. had a significantly greater effect on stock prices than other markets is not necessarily inconsistent with the findings of this regression. Their study did not compare Danish stocks to U.S. stocks, so it is certainly possible that the effect is larger in Denmark. However, it is unlikely, as stock prices in all of the other G7 countries reacted less to recommendation changes.

The volume appears to significantly impact the size of the impact of recommendation changes on stock prices in five out of the six groups. The coefficients are negative for all downgrades – indicating that higher trading volume on the day the recommendation change is announced is associated with stronger negative BHAR. Upgrades to buy and hold are also associated with stronger effects, the larger the trading volume. Loh and Stulz (2009) found a relationship between lower volume and higher abnormal returns as the result of recommendation changes, and Jegadeesh & Kim (2006) found there to be relatively higher trading volume on the announcement days of recommendation changes. Panchenko (2007) and Womack (1996) also found abnormal volumes on the announcement days. Our findings cannot support or contradict the findings in the latter three studies, as we do not estimate “normal” volume to compare with the volume of the trading day. However, our findings seem to contrast the results presented by Loh & Stulz (2009).

The dummy for multiple recommendations is significant for the same five groups. The coefficients span from 3.3% to 6.8%, in absolute terms between the five of them. By themselves, this would indicate that on days with more than one recommendation change on the given stock, abnormal return is lower in absolute terms than on days with just one recommendation change. This would contrast strongly to one of our main assumptions: That multiple recommendation changes often will come right after earnings surprises and other confounding effects. Fortunately, this is not the case, as this term has to be viewed in conjunction with the precise amount of recommendation changes on the given day. The coefficients for that variable are significant for all six groups and in opposite direction of the “multiple” term. The dummy, by definition, can only have the effect given by its’ coefficient. The impact of “No_Recs_This_Day” on BHAR, on the other hand, is the product of the amount and the respective coefficient. This means that the sum of these two effects is the resulting effect of multiple recommendation changes on the same day on the same stock.

The results regarding market capitalization of the firm covered by the recommendation change are in line with previous findings in the literature (Stickel, 1995; Womack, 1996; Loh & Stulz, 2009). Our results show that the larger a firm is, the smaller the effect of a recommendation change on BHAR. The coefficients are significant in all groups except upgrades to sell, which might be expected as an upgrade to sell is a mixed-signal: Positive incremental change due to the direction of the change, but still negative overall due to the negative level.

The distance-to-consensus variable is only significant for downgrades to hold and upgrades to hold. For the first group, a stock with a consensus recommendation more positive than hold will have a stronger negative effect. The opposite is true for the upgrade to hold. This is in line with the literature claiming that recommendations away from consensus have a greater effect (Jegadeesh & Kim, 2009; Loh & Stulz, 2009).

The relative spread variable is only statistically significant for downgrades to buy. The negative coefficient of -2.518 indicates that for a stock with larger relative spread, the downgrade will have a greater effect on BHAR. This group of recommendation changes is a mixed-signal, similar to the upgrade to buy, so there might be other factors not examined having an impact on this effect.

Lastly, whether the recommendation change was announced on a Friday does not have a significant effect on the change’s effect on BHAR. This means that we cannot support or contradict the findings of Dellavigna and Pollet (2009) and Kudryavtsev (2019).

Table 15 - Regression models three-day BHAR

BHAR	**DOWNGRADE to**			**UPGRADE to**		
	BUY	**HOLD**	**SELL**	**BUY**	**HOLD**	**SELL**
Movement2		-0.001	-0.004	0.004^{**}	0.001	
		(0.002)	(0.003)	(0.001)	(0.006)	
Movement3			-0.008	0.006		
			(0.005)	(0.003)		
Movement4			-0.008	0.011^{*}		
			(0.007)	(0.005)		
Potential	-0.002	-0.009^{***}	-0.006	0.002^{*}	-0.002	0.016
	(0.005)	(0.002)	(0.005)	(0.001)	(0.006)	(0.023)
Potential^2	0.00002	-0.007^{*}	0.024^{**}	-0.00004	0.017	-0.064
	(0.001)	(0.004)	(0.009)	(0.00004)	(0.009)	(0.040)
No_Recs	0.0001	0.0001^{*}	0.0004^{**}	-0.0004^{***}	-0.001^{***}	-0.0004
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.001)
MarketUS	0.007	0.014^{***}	0.014^{*}	-0.015^{***}	-0.009	0.058^{*}
	(0.011)	(0.004)	(0.006)	(0.003)	(0.007)	(0.027)
ln(Volume)	-0.004^{***}	-0.006^{***}	-0.007^{***}	0.007^{***}	0.009^{***}	-0.002
	(0.001)	(0.0004)	(0.001)	(0.0004)	(0.001)	(0.004)
Multiple	0.049^{***}	0.034^{***}	0.057^{***}	-0.033^{***}	-0.068^{***}	-0.096
	(0.010)	(0.003)	(0.009)	(0.005)	(0.014)	(0.054)
ln(Marketcap)	0.005^{***}	0.006^{***}	0.009^{***}	-0.006^{***}	-0.007^{***}	0.001
	(0.001)	(0.0004)	(0.001)	(0.0004)	(0.001)	(0.004)
Dist_Consensus	0.002	-0.006^{***}	-0.001	0.0002	0.007^{*}	0.010
	(0.004)	(0.001)	(0.002)	(0.001)	(0.003)	(0.011)
Spread_Rel	-2.518^{*}	-0.007	-0.002	0.011	0.019	-0.011
	(1.081)	(0.033)	(0.014)	(0.012)	(0.024)	(0.026)
Friday	0.003	-0.001	-0.004	-0.001	0.001	-0.011
	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)	(0.015)
No_Recs_This_Day	-0.028^{***}	-0.020^{***}	-0.032^{***}	0.021^{***}	0.041^{***}	0.050^{*}
	(0.003)	(0.001)	(0.004)	(0.002)	(0.006)	(0.024)
Constant	-0.065	-0.094^{***}	-0.085^{**}	0.074^{**}	0.031	-0.113
	(0.042)	(0.022)	(0.031)	(0.024)	(0.067)	(0.108)
Broker fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,356	14,758	5,206	18,061	3,751	159
R^2	0.213	0.089	0.122	0.092	0.141	0.433
Adjusted R^2	**0.122**	**0.066**	**0.072**	**0.072**	**0.074**	**0.057**
F Statistic	2.345^{***} (df = 140; 1215)	3.926^{***} (df = 359; 14398)	2.439^{***} (df = 280; 4925)	4.590^{***} (df = 388; 17672)	2.117^{***} (df = 269; 3481)	1.151 (df = 63; 95)

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Immediate Regression Model

Including the same variables as the previous model, we now shorten the event window to just one day. We refer to this as the "immediate effect". The one-day abnormal return regression is defined as the following equation:

$$
\begin{aligned}
AR_i = \alpha + \beta_{MOVE} Movement_i + \beta_{POT} Potential_i + \beta_{POT2} Potential_i^2 + \beta_{NOREC} NoRecs_i \\
+ \beta_{US} MarketUS_i + \beta_{VOL} \ln(Volume_i) + \beta_{MULTI} Multiple_i \\
+ \beta_{MC} \ln(MarketCap_i) + \beta_{DIST} DistConsensus_i + \beta_{SPR} SpreadRel_i \\
+ \beta_{FRI} Friday_i + \beta_{NORECDAY} NoRecsThisDay_i + \beta_{BR} Broker_i + \beta_{YR} Year_i + \varepsilon_i
\end{aligned}
$$

The explanatory variables are defined in exactly the same way as for the previous model, and the results are presented in Table 16 below.

Most of the results are slightly different in size, but not in which direction they impact the effect of a recommendation change on AR. The only exception is the term "Friday". For the two groups with significant coefficients, downgrades to buy and hold, recommendation changes announced on Fridays seem to increase the impact on AR. This is consistent with the findings presented by Kudryavtsev (2019).

Determining factors

Summarizing the models explained above, we can say that the reaction to an analyst recommendation revision can be influenced by several factors. Depending on the type of revision, different explanatory variables might be more or less significant.

Among some of the important explanatory variables, we find 1) the magnitude of the change, 2) if other revisions are announced on the same day and how many, 3) trading volume of the stock, 4) market cap of the stock, and 5) the potential, which the analyst believes the stock has. In some cases, the markets can be significantly different, the liquidity of the stock measured by the relative bid-ask spread can be a predictor, and announcements on Fridays tend to cause less reaction than the rest of the week when we measure the day 0 abnormal return.

Table 16 - Regression models AR Day 0

AR	**DOWNGRADE to**			**UPGRADE to**		
	BUY	**HOLD**	**SELL**	**BUY**	**HOLD**	**SELL**
Movement2		-0.0002	0.0002	0.003**	0.003	
		(0.002)	(0.002)	(0.001)	(0.004)	
Movement3			-0.008**	0.006**		
			(0.003)	(0.002)		
Movement4			-0.005	0.008*		
			(0.004)	(0.003)		
Potential	-0.005	-0.006***	0.004	0.002***	-0.014***	-0.004
	(0.003)	(0.002)	(0.003)	(0.001)	(0.004)	(0.012)
Potential^2	0.001	-0.009***	-0.010	-0.0001***	0.013*	0.023
	(0.001)	(0.003)	(0.005)	(0.00002)	(0.006)	(0.022)
No_Recs	-0.0001	0.0003***	0.0004***	-0.0003***	-0.001***	0.001
	(0.0001)	(0.00005)	(0.0001)	(0.00004)	(0.0001)	(0.0004)
MarketUS	0.004	0.015***	0.015***	-0.011***	-0.006	-0.008
	(0.007)	(0.003)	(0.003)	(0.002)	(0.004)	(0.013)
ln(Volume)	-0.003***	-0.009***	-0.008***	0.007***	0.008***	0.002
	(0.001)	(0.0003)	(0.0005)	(0.0003)	(0.001)	(0.002)
Multiple	0.030***	0.023***	0.040***	-0.029***	-0.074***	0.032
	(0.005)	(0.002)	(0.004)	(0.002)	(0.006)	(0.022)
ln(Marketcap)	0.004***	0.008***	0.007***	-0.006***	-0.005***	-0.003
	(0.001)	(0.0003)	(0.001)	(0.0003)	(0.001)	(0.002)
Dist_Consensus	0.0001	-0.005***	-0.001	0.001*	0.003	0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.005)
Spread_Rel	-1.354*	-0.024	-0.013	0.004	-0.003	0.044**
	(0.634)	(0.019)	(0.008)	(0.008)	(0.018)	(0.015)
Friday	0.004	-0.002**	-0.003	0.005***	0.003	-0.007
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.007)
No_Recs_This_Day	-0.018***	-0.016***	-0.024***	0.019***	0.043***	-0.009
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.009)
Constant	-0.072*	-0.128**	-0.047	0.039	0.009	-0.042
	(0.028)	(0.046)	(0.045)	(0.038)	(0.049)	(0.058)
Broker fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,087	21,409	7,089	24,028	5,334	220
R^2	0.209	0.162	0.231	0.120	0.196	0.454
Adjusted R^2	**0.148**	**0.147**	**0.196**	**0.105**	**0.148**	**0.197**
F Statistic	0.031 (df = 1937)	0.046 (df = 21016)	0.043 (df = 6775)	0.038 (df = 23616)	0.046 (df = 5031)	0.024 (df = 149)

Note: *p<0.05; **p<0.01; ***p<0.001

Post-event effect

As stated in hypothesis 2, we want to investigate whether the immediate effect, as found in the previous section, is the full effect of the recommendation change or if there seems to be any additional reaction being incorporated into the stock price in the time period after the recommendation change. This section is meant to present the main results from the analysis graphically and to examine if there seem to be certain clear tendencies in the development of the long-term BHAR.

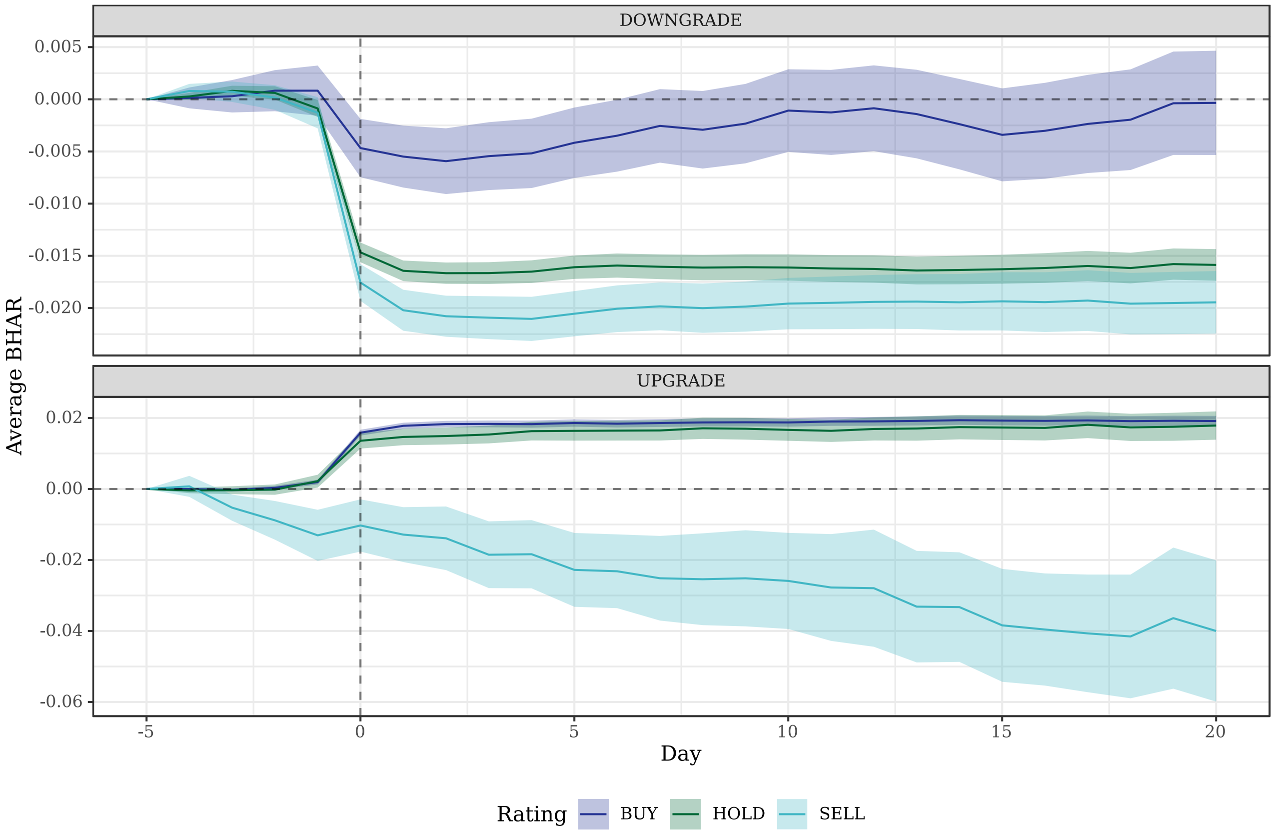
When we discuss the long-term effect we are interested in finding out what is happening after the event and up to 6 months after to detect if the immediate effect seems to be a new permanent level, or if there are indications of a continued drift or mean reversion. As discussed in the literature review, several previous studies have found a post-event drift following recommendation changes (Womack, 1996; Stickel, 1995; Park & Park, 2019b).

Compounding these abnormal returns for the individual recommendation changes over days as described in the methodology section, we get the buy-and-hold abnormal return (BHAR) relative to day -5. The average of these across stocks, the average BHAR, is depicted in Figure 10.

Here we see indications of a pre-event movement on day -1 as well as the greater return on day 0. The movements on day 0 are the one-day AR (immediate effect) discussed earlier in the analysis. After that, the post-event movement is illustrated. Upgrades to buy and hold recommendations seem to react to the new information and stay relatively stable at the new level. Downgrades to sell and holds follow a similar pattern but in the other direction. It might also seem like the abnormal return is still positive for day 1, indicating that there is a slight delay in the short-term effect. We know from earlier in the analysis that the slight movements on day -1 and day 1 are significantly different from zero, and this illustration shows how this affects the BHAR over the entire period. After day 1, there does not seem to be a clear change in BHAR for the four groups. These findings are in line with the findings of Stickel (1995), Womack (1996), and Park & Park (2019b) who find the effect of analyst recommendation changes to be a new level, and not just temporary price change that reverts back to the original level.

Downgrades-to-buy and upgrades-to-sell follow a much more volatile and unclear path. Downgraded recommendations to buy (a strong buy that is changed to a buy) show an immediate negative reaction as anticipated, but also show signs of mean reversion to a level not significantly different from before the recommendation change. Opposite, upgrades-to-sell seem to have a somewhat constant negative development. These results might be related to our interpretation of the two groups; that they are inherently mixed signals. As frequently mentioned in this thesis, upgrades-to-sell constitute recommendation changes that still have a negative level, but a positive direction. Downgrades to buy are changes with a positive level but a negative direction. How the market should interpret these signals are not entirely clear, and that might be the cause of these two graphs being somewhat difficult to interpret.

Figure 10 - Average BHAR by Day, Direction and Level of Recommendation Change

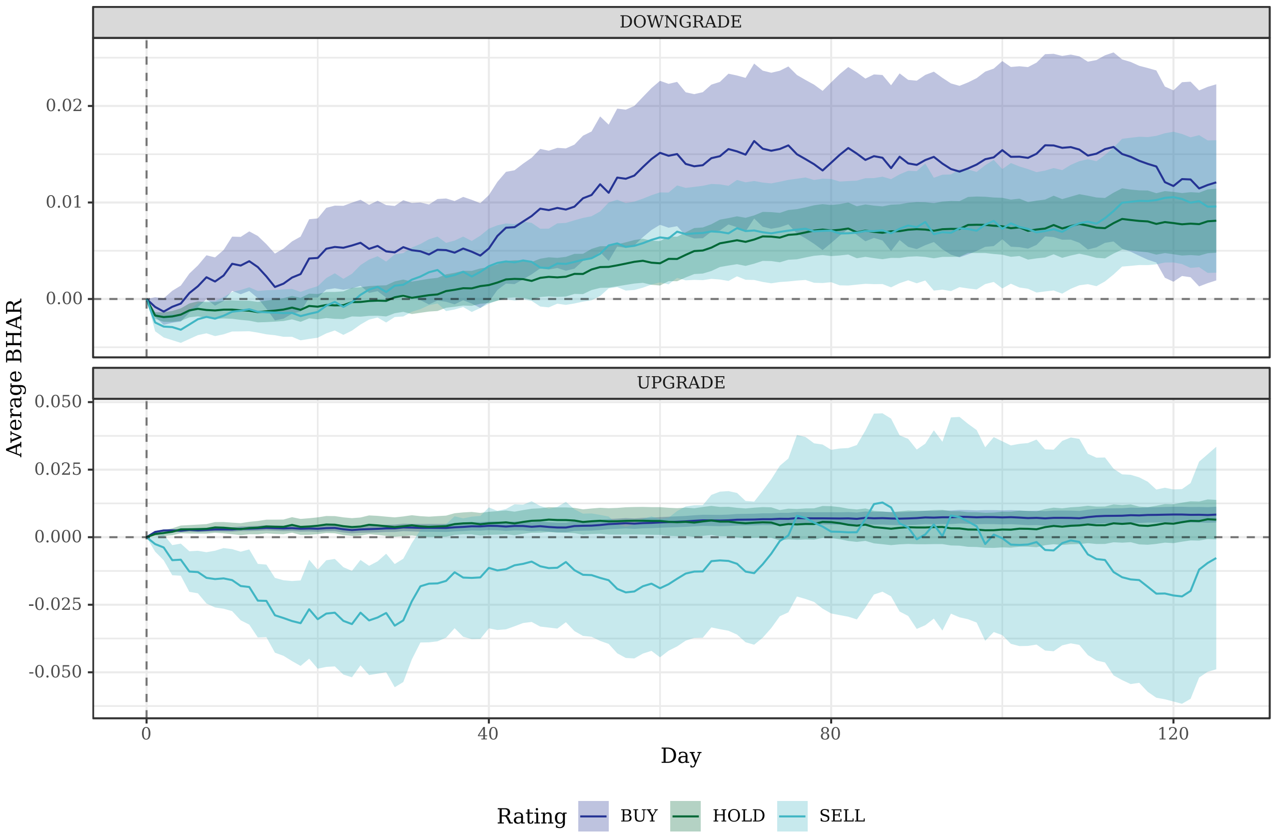


By expanding the time to 6 months after the event and starting from day 0, we get the depiction shown in Figure 11. This is a representation of the abnormal drift or mean reversion that a potential investor would experience by following the recommendation and thus buying (shorting) a stock on the day of the recommendation announcement.

A slight positive drift is suggested by this representation for upgrades to buy and hold (which are significantly different from zero but not significantly different from each other). This drift seems to revert towards zero for hold recommendations after approximately three months (around 60 trading days) but continues a slight increase for the buy recommendations. Surprisingly, we see that downgrades revert with the BHAR of hold and sell recommendations not being significantly different from 0 at around day 15 and being significantly positive from around day 45-50. It could seem like the downgrades to “hold” and “sell” have a more persistent drift, as the average BHAR has almost reached 10% at the end of the six-month period, while the average BHAR of upgrades to buy and hold never exceed 2%. This is in line with the results presented by Park & Park (2019b), which indicate that negative recommendation changes have a stronger and longer-lasting post-event drift than positive changes in analyst recommendation changes.

The “mixed signal” recommendations of upgrades to sell and downgrades to buy stand out with their volatile development and large standard errors. The downgrade is not significantly different from 0 and quickly turns to a positive return after only a few trading days and continues to increase until around trading day 60 (3 months). By expanding the timeline, a different development than before is observed for upgrades to sell. After the initial negative drift, it shows signs of a mean reversion and stays negative or indistinguishable from 0 for the whole 6-month period.

Figure 11 - Average BHAR 6 months after Recommendation Change by Direction and Rating



We explore the average BHAR further by splitting the development of the different groups down to our two markets: Denmark and the United States. This is presented in Figure 12 below. First, the uncertainty regarding the results seems to be much greater for Danish stocks than for U.S. stocks. This is probably because of the smaller sample size, but the effects also seem to differ drastically among the two markets.

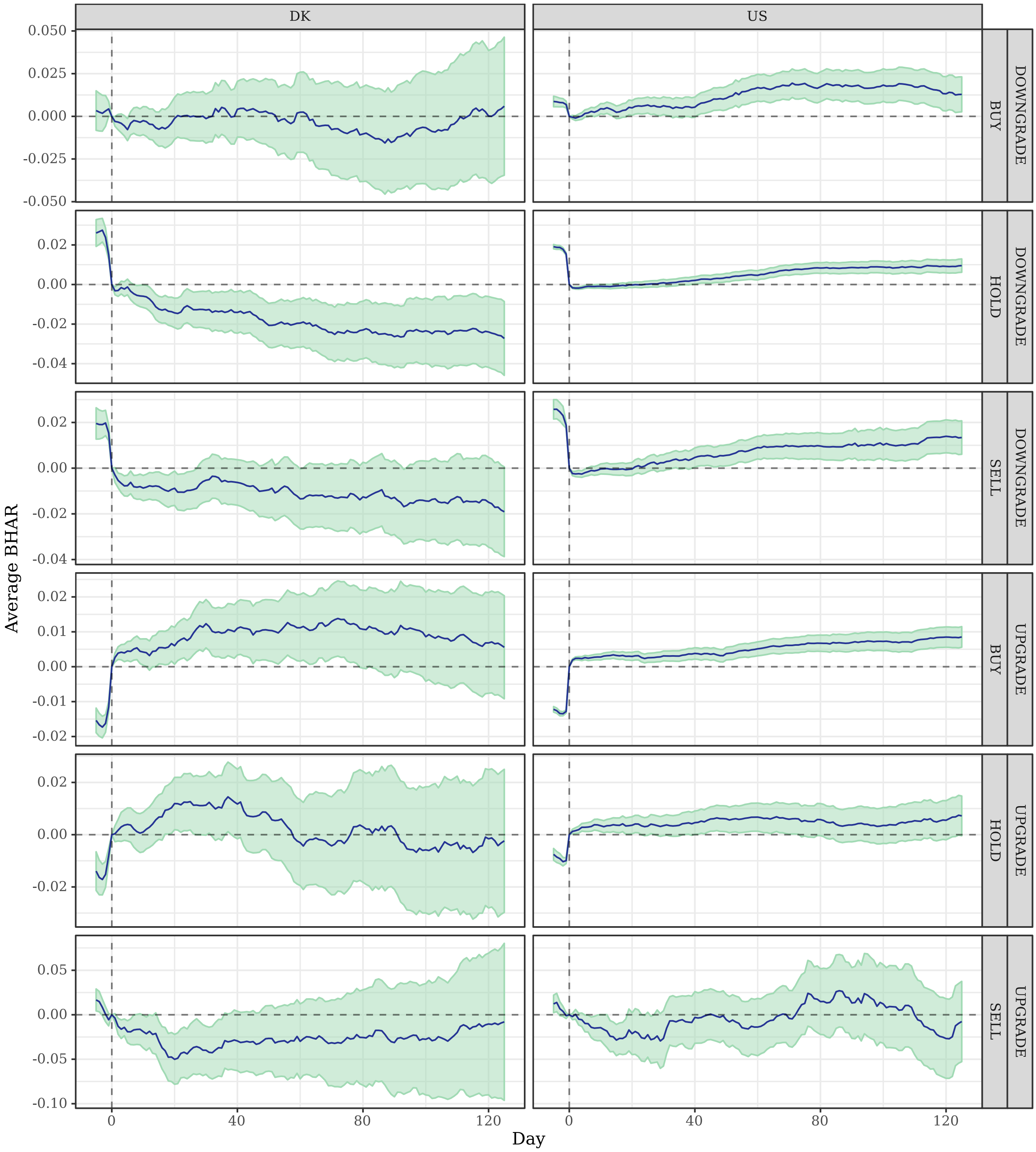
Starting from the top, downgrades-to-buy in Denmark simply produce average BHAR values indistinguishable from zero over the entire period. The same is not true for U.S. stocks, which seem to increase slightly before reverting partly back towards zero. The bottom plots, upgrades to sell, are hardly ever significantly different from zero. This is possibly due to the "mixed signal" effect discussed above.

Downgrades to hold and sell show very different results in the two markets. The development in Denmark seems to be either insignificant or negatively drifting. This is directly opposed to the results from the United States, where the negative recommendation changes seem to be followed by a partly mean-reversion. These findings are in contrast to the literature, which states that the negative recommendation changes in the U.S. resulted in average BHAR's which showed signs of a negative drift for up to six months after the event (Park & Park, 2019b). Ironically, this seems to be the case for the Danish stocks instead.

For upgrades to buy and hold, the markets show different signs of developments again, but now in the opposite directions as before. For these upgrades, Danish stocks show tendencies of a mean reversion after the initial positive effect of the recommendation change. U.S. stocks, on the other hand, do not indicate the same mean reversion. This is more in line with the findings of Park & Park (2019b). However, upgrades to buy drift upwards for the entire duration of the sample period, which is not consistent with the literature, as this drift has previously been found to last for a shorter time. Upgrades-to-hold show similar tendencies but are not significantly different from zero at the end of the six-month period.

Our findings for this section thus indicate strongly that a post-event drift is present, as proposed in hypothesis 2 and that the price-relevant information of analyst recommendation changes is not immediately incorporated into the stock price.

Figure 12 – Average BHAR 6 months by Market, Rating Level and Direction



Trading strategy

In the following section, we propose and test trading strategies based on the findings from the previous analyses. A trading strategy will be based on the analysis of abnormal returns after day 0, as it is not possible to trade prior to the announcement of the recommendation and thus obtain the abnormal return of day 0.

As found, stocks that receive a positive change in recommendation (defined as an upgrade to buy or strong buy) experience significantly positive abnormal returns on day 1 after the announcement, and stocks that are subject to a negative recommendation change (downgrade to hold, sell or strong sell) show negative abnormal returns on the following day. Thus, at the end of each trading day, we form portfolios of the positive and negative recommendation changes announced during the trading day[4].

We propose a trading strategy where each day at market close, one buys (sells short) stocks which since previous market close have received a positive (negative) change of recommendation. We test this “main” strategy over the 20-year period we have data for, with different assumptions imposed. We also test it in both the Danish and U.S. market, and we test it against strategies of only trading based on the signal of either level or direction of change in the recommendations. All variants are illustrated and compared in Figure 13.

General for all strategies tested are the following assumptions:

1. Every day, recommendation changes are observed, and a positive and a negative portfolio are formed.
2. The strategy is zero-cost, meaning selling short the same amount as buying long positions for, so initial capital is only required as margin for the short positions.
3. There must be at least one buy position and one short position, in order to maintain the zero-cost nature of the strategy. On days with no stocks in any or both portfolios, only prior positions are closed, and the amount is held in cash for the next day. No yield is assumed for this holding.
4. If there are multiple recommendations for a stock on a particular day, no position is taken in that stock.

[4] If a recommendation change is announced after market close, the stock enters our portfolios on the following trading day, as Barber et al. (2010) does.

5. All trading takes place at market close. We thus explicitly exclude the day 0 recommendation return in order to reflect that many investors (especially smaller investors) will likely learn about a change of recommendation with a delay.
6. All positions are held for one trading day then closed.
7. Equal weighting in each portfolio as equal dollar investment in each recommendation, meaning one recommendation change = one part of the portfolio. The difference in prices and any imbalance from this is not considered.
8. In order to account for part of the transaction costs, we buy (sell) at the last ask (bid) price of trading hours. We thus account for the bid-ask spread as one sort of transaction costs.
9. We assume no other transaction costs.
10. Profits are reinvested and thus compounded.

First, we test the most basic version of the strategy. Only the assumptions listed above are imposed on the test. Every day a long position is taken in the positive portfolio, and a short position is taken in the negative portfolio. This strategy turns 1 dollar into 10,733 dollars after 20 years, yielding a total return[5] over the 20-year period of 1,073,279%, equaling 59% per year compounded. The average daily return is .19%, which annualized[6] for a Sharpe Ratio calculation is 46.84%. The associated risk with this strategy is determined by its annualized standard deviation[7] , which is estimated to be 18.1% resulting in a Sharpe ratio of 2.59.

In comparison, the S&P 500 index returned an annualized 5.63% over the same period with a standard deviation of 18.6% (so close to the same risk as our strategy), resulting in a Sharpe ratio of 0.30. Our strategy thus performs much better on a return to risk basis that the S&P 500 index.

Next, we carry out this trading strategy in both markets individually. Trading only Danish stocks, we practically lose our investment, as we obtain a negative return of the 20-year period of 99.98% equaling -34.4% per year with a standard deviation of 25.4% per year. This, of course, results in a

[5] Note that this is gross return only accounting for transaction costs in terms of bid-ask spread. It is not adjusted for the market return.

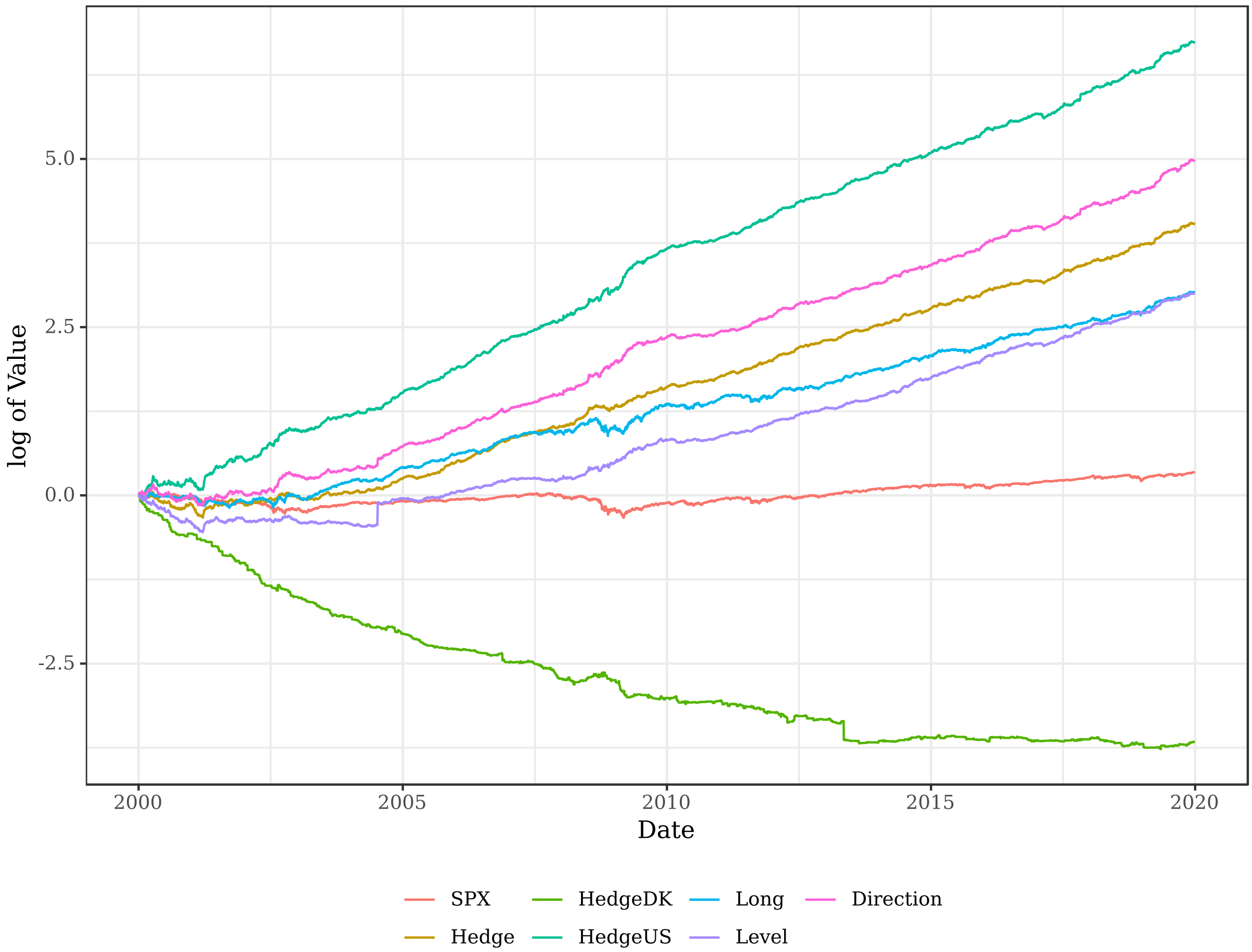
[6] We annualize the mean daily return for the Sharpe ratio calculation as $\overline{r_D} * 252$ where $\overline{r_D}$ is the mean daily return and we multiply by the number of trading days per year.

[7] We annualize the standard deviation by $\sigma_A = \sigma_D * \sqrt{252}$, where σ_D is the daily standard deviation

negative Sharpe ratio of -1.48. The average daily return for the strategy in the Danish market is negative .15%. So even though we were able to detect positive (negative) returns to the positive (negative) recommendation changes in Denmark earlier, we were not able to trade on them.

In the United States, the strategy yields 535,835,900% return over the 20 years. This is an average daily return of 0.31% and corresponds to 117% per year compounded (78% when multiplied) with a standard deviation of 22.3%. It thus seems impossible to obtain consistent positive abnormal returns from this strategy in Denmark, whereas the U.S. market consistently yields exorbitant positive abnormal returns.

Figure 13 – Trading strategies compared, log of value, 2000-2019



**As the value of the investment is exponentially increasing, we show here the log-transformed value of the investment. The raw value is depicted in Appendix A.*

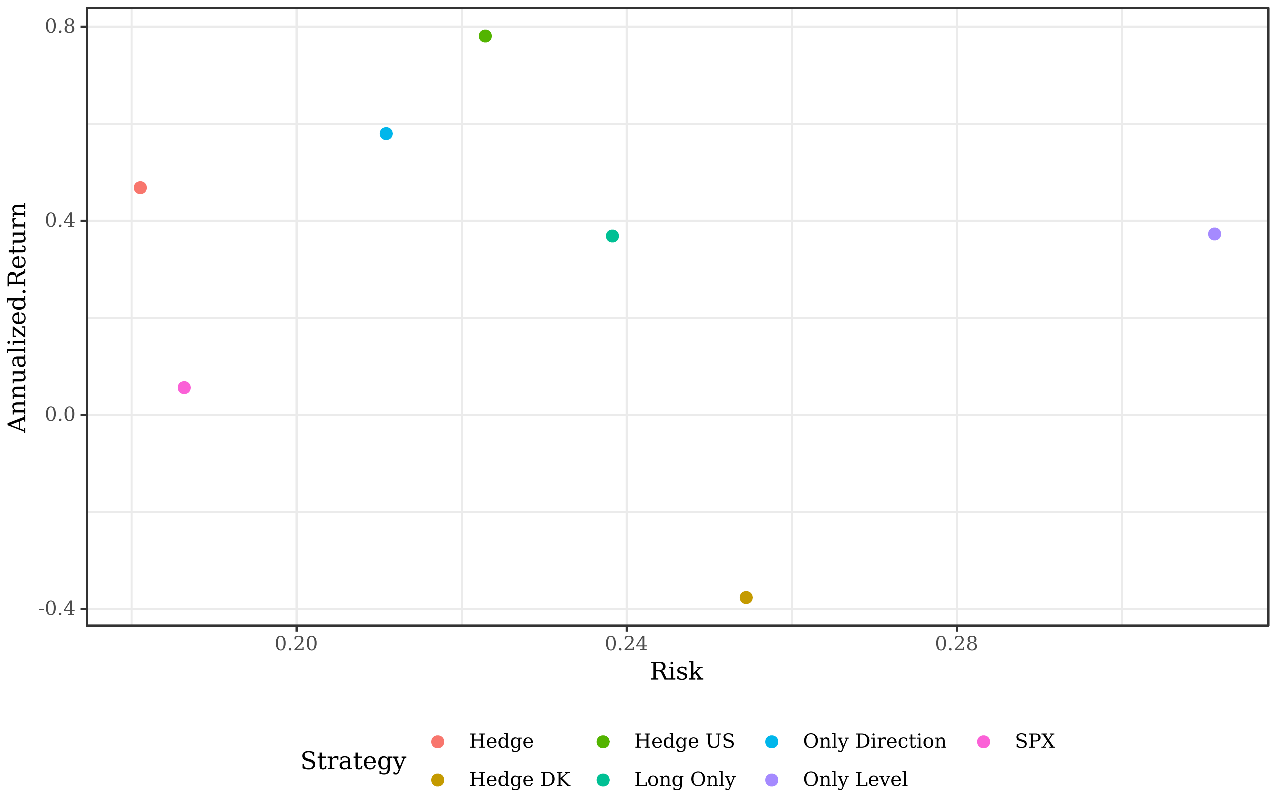
As a second strategy, we will impose a shorting constraint, meaning that it is not possible to short stocks but only possible to buy the stock in the positive portfolio. This also requires an initial amount of capital, as a zero-cost hedging strategy is not possible without shorting. This strategy turns our 1 dollar into 1,040.48 dollars after 20 years, which is a total return of 104,047% over the 20-year period, corresponding to a compounded annual return of 41.5%. The mean daily return is .15% and is associated with a standard deviation of 23.8%, which results in a Sharpe ratio of 1.55.

We compare these strategies with strategies of only forming portfolios from only recommendation level or change direction, respectively. A strategy of buying (shorting) stocks getting a buy or strong buy (hold, sell or strong sell) recommendation in both markets, yields a total return of 99,387% from 2000 through 2019, which equals 41.2% annually with a standard deviation of 31.1% per year. The average daily return is .15%, which annualized by multiplication results in a Sharpe ratio of 1.20.

The strategy of buying (shorting) stocks getting an upgraded (downgraded) recommendation leads to a total 20-year return of 9,329,168%, corresponding to 77.2% annually with a standard deviation of 31.1% per year. The average daily return is .23%, which multiplied by 252 trading days results in a Sharpe ratio of 2.75.

The different strategies are also compared by their return-to-risk performance in the following figure.

Figure 14 – Trading Strategies Return to Risk



6 | Perspective

Discussion

Our interest in this subject was sparked by the question, “Should we listen to them?” whenever we noticed that a brokerage house announced a recommendation change. If their actions affect the price of the stock they are covering, then surely the market can predict this and react immediately. Right? Not exactly.

As mentioned in the literature review, according to the market efficiency hypothesis, stock prices should at any given point in time reflect all available information; thus, investors should not be able to obtain any abnormal profit from listening to and trading on analyst recommendations. However, our results indicate that there are significant abnormal returns associated with the days of recommendation changes. Even more relevant in the market efficiency debate, there seemed to be small but significant abnormal returns the following day as well!

As discussed in the data section, we are aware of a potential problem with the dates reported by the I/B/E/S database, potentially causing the estimated abnormal returns to be incorrect. However, assuming that the estimates are accurate, two aspects need to be investigated in order to interpret the findings: The role of analysts in the price formation process and the speed at which the effect of the recommendation change is fully incorporated into the price.

First, since our results indicate significant abnormal returns associated with analyst recommendation changes, investors seem to use analysts as a source of information for investment decisions. Under the semi-strong form efficient market hypothesis, this means that the analysts must have access to private information. This might be the case, as these analysts often are in direct contact with the firm. They might also recognize some qualitative aspects of the firms that would not be available to the public otherwise. An alternative explanation could be that the analyst’s opinion itself is one of the constituents of the firm value. Either way, our findings indicate that recommendation changes lead to stock price reactions.

Second, the efficient market hypothesis assumes that all new price-relevant information is incorporated into stock prices immediately. The significant abnormal returns found on the day following the announcement of the recommendation change indicate that the same-day price effect is incomplete. This seems to be a delay in the market response to new information, which means that the market is not efficient.

Future research

This thesis explores the field of analyst recommendation revisions in Denmark. Our work is limited, and many questions still pertain. For future research, we propose several topics, which could be of great interest.

The choice of looking at daily returns as the measure of immediate reaction to revision announcements could favorably be changed to a focus of intra-day, with shorter data intervals such as hourly or even shorter. This would give an interesting view of how quickly the reaction happens, and if there are any patterns intra-day. This would also add to the discussion on the ability to trade on signals.

Another topic, related to the possibility to trade and obtain abnormal profits from the signals of recommendation revisions, is to further investigate and estimate transaction costs. Future research can account better for transaction costs than we have been able to in this thesis.

Others who want to study this field should have a better proxy or filtering method for confounding events as, e.g., earnings announcements. Controlling adequately for such events would improve the robustness of the findings and make causality more probable. Furthermore, controlling for other factors, which we might not even have thought of, can also be of interest for future studies.

Also, we know that there are potential problems with erroneous dates in the I/B/E/S database. Future research should investigate the extent of this problem.

Another new area of research is that of passive investments. Combining these two and investigating if the trend of passive investing makes analyst recommendations less relevant, would be interesting.

7 | Conclusion

This thesis investigates the market reaction in stock prices associated with changes in analysts' recommendations for Danish and U.S. stocks in the period January 2000 through December 2019.

Newspapers sometimes use changes in recommendations to explain large changes in stock prices, and much of the literature provides evidence that this causality is true (Stickel, 1995; Womack, 1996). However, recent literature finds this effect to be shrinking (Park & Park, 2019b), and the literature studying markets outside the U.S. is scarce and indicates a smaller effect than in the United States (Jegadeesh & Kim, 2006).

In our analysis, we find that the stock market has a significant price reaction to recommendation changes in both Denmark and the United States. By estimating average buy-and-hold abnormal returns (BHAR) over an event window of three days around the recommendation change, as a measure of the short-term reaction, we are able to compare the effects in the two markets. We find that both the direction of the recommendation change and the level of the new recommendation is determining the effect on the stock price. As expected, upgrades (downgrades) tend to result in positive (negative) abnormal returns when announced, as well as recommendations giving a buy (sell) rating tend to lead to price increases (decreases).

When we combine the two signals of rating level and direction of change, we observe the abnormal return in the event window associated with an upgrade-to-buy (downgrade-to-sell) rating change in Denmark is 1.86% (-1.26%) and 1.62% (-1.91%) in the U.S. These estimates are significantly different from zero at the 1% significance level.

We find that only the combination of downgrades to "hold" revisions experience significantly different abnormal returns between the two markets. All other combinations of directions and levels result in differences between the two markets that are not significantly different from zero.

Surprisingly, we find Danish stocks to be more affected by these types of recommendation changes than the U.S stocks, but for most of the groups of revisions, we cannot conclude a difference in reaction between the markets. Jegadeesh & Kim (2006) found that stock price reactions in the United States were larger than any of the other G7 countries, so our findings stand in contrast to theirs.

Examining the daily abnormal returns in the days following a recommendation change leads to an interesting result: The information of the event is not immediately incorporated into the price. There are significant abnormal returns on the first day after the event in both Denmark and the United States for all groups of levels and changes. This is in line with previous studies (R. K. Loh, 2010; Ryan & Taffler, 2006; Womack, 1996) which find that there is a delay in reaction to recommendation changes in the United States, and so our findings indicate that the Danish stock market is subject to the same delay in reaction. Using a longer event period, we find that downgrades seem to have at least a partial mean-reversion after the initial effect in the United States, while in Denmark, they tend to drift even further away from zero. The opposite is true when examining upgrades: After the initial reaction, U.S. stocks tend to drift even further in the direction of the immediate effect, while stocks in Denmark seem to revert back towards zero.

We find that the reaction to an analyst recommendation revision can be influenced by several factors, and depending on the type of revision, different explanatory variables might be significant. Some of the important explanatory variables we find are 1) the magnitude of the change, 2) if other revisions are announced on the same day and how many, 3) trading volume of the stock, 4) market cap of the stock, and 5) the potential, which the analyst believes the stock has. In some cases, the two markets can be significantly different, as well as the liquidity of the stock measured by the relative bid-ask spread as being of importance, and announcements on Fridays tend to cause less reaction than the rest of the week.

We find a significant abnormal return on the day preceding analyst recommendation revisions in both markets. We explain that this can be caused either by revisions being announced due to confounding news, information leakage and insider trading, or erroneous dates in the data sample.

Our findings suggest that the market is not informationally efficient in the semi-strong form when defining *immediate response* as within one trading day or less, because we see a significant reaction beyond the first trading day of the announcement. We propose several possible explanations for this delayed reaction. Whether this definition is correct, and the question about market efficiency in general, we will leave for future research.

We also find tendencies of stock price drifts following the changes in analyst recommendations, where the price-relevant information of the analyst recommendation revision is not immediately incorporated into the stock price.

In attempting to answer whether or not investors can profitably exploit recommendation changes, we test a trading strategy of buying (selling short) upgrades-to-buy (downgrades-to-sell) on the announcement day and selling (buying back) the stocks on the following day. This resulted in an exorbitant return of 59% per year when tested over the previous 20 years, and only accounting for bid-ask spread as a transaction cost (in comparison, the S&P 500 index yielded, on average, 5.6% per year in the same period). The Sharpe ratio of annualized return to risk for this strategy is estimated at 2.59. Another strategy with constraints on shorting yielded a compounded annual return of 41.5%. We also find that the whole profit is generated in the U.S. market, as testing the strategy in Denmark results in loss of the invested capital.

Unsurprisingly, the key here is transaction costs. Using the same proportional estimates as Barber et al. (2001) would quickly diminish the portfolio value to zero, as these strategies require very frequent trading with little return on each trade, and thus most transactions would cost more than they yield. Therefore, whether investors can profitably trade based on the signal of recommendation revisions remains uncertain, but with our test, we believe it would not be feasible due to the high transaction costs. This is in line with Barber et al. (2001), who find that abnormal returns after transaction costs are not significantly different from zero, but in contrast to the most recent study (Park & Park, 2019a).

In conclusion, we find that changes in analyst recommendations do cause the market to react by adjusting stock prices. In the short term, the market follows the changes in recommendations and generate reactions in the direction laid out by the recommendation revision. In the long term, the findings are still inconclusive.

Table of tables

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Appendices

Appendix A