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The Value of Equity Analysts

An Empirical Study of the Informativeness of Analyst Revisions

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Abstract

This thesis investigates the informativeness of analyst recommendation revisions and target price revisions in absence of recommendation changes. The 69 companies included in the Oslo Børs Benchmark Index (OSEBX) are examined over the period of 2011 to 2021. The analysis is conducted by the application of the event study framework, and we study whether analyst revisions are associated with abnormal returns. We separate target price revisions in absence of recommendation revisions by the degree of innovation potential in the revision signal.

Our findings suggest that recommendation revisions are associated with large abnormal returns and that the revisions are informative to investors. The evidence in the Norwegian market context is consistent with the majority of the literature focusing on short-term effects of analyst revisions. Further, target price revisions in absence of recommendation changes are associated with significant abnormal returns, and they are relevant to market participants. The economic impact of high-innovation target price revisions is larger by a factor of two to three compared to low-innovation target price revisions when the recommendation level is reiterated. The main conclusions are robust to the exclusion of revisions adjacent to earnings announcements, but we show that analysts somewhat piggyback their revisions on recent news and events. However, the evidence suggests that analysts are providing timely aggregations of the information environment and that the revisions are informative to financial markets.

Keywords: Security analyst, revisions, market efficiency, target price

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1. Introduction

Equity research analysts are highly educated professionals spending long hours trying to value companies and predict future stock returns. The job is highly reputable and typically paid well. Since investors are willing to implicitly pay a high price for advice from equity research analysts, the information content in the analyst reports must be regarded as valuable. However, under the efficient market hypothesis, there is no room for systematic outperformance by the means of fundamental analysis based on public information. As the role of the analyst should be redundant under this assumption, is there any informational value associated with analyst revisions?

The analysts' goal is to provide investors with information on the current and future prospects of companies (Bonini et al., 2010). The analyst report consists of a summary of the investment case, a level of recommendation, a target price, estimates, and key financial ratios. The analysts signal whether they recommend investors to buy, hold, or sell the stock through the recommendation level, and the target price represents the analysts' assessment of the expected fundamental value based on the desired valuation method. As such, the analysts' aggregated view on the investment case and future prospects of the firm can be summarised by the level of recommendation and the target price.

The revenue streams of the brokerage firms stem primarily from capital transactions and advisory from the investment banking division. There is a potential conflict of interest within the brokerage firm when the research department issues research reports to investors on the same clients who pay for services by the investment banking division (Dugar & Nathan, 1995). The conflict of interest may result in a direct or indirect pressure for the analyst to portray the corporate client favourably. In addition, the wave of new public listings in the Norwegian market during the last two years has intensified the bias concerns in equity research as up to 97% of newly listed companies have a buy recommendation (Bøhren & Solheimsnes, 2021). If analysts are biased, the value of the research reports should be limited.

Although the efficient market hypothesis disregards the value of analyst reports, researchers have found abnormal returns associated with recommendation changes in the short term (Asquith et al., 2005; Womack, 1996). This is aligned with the informed analyst hypothesis presented by Altınkılıç et al. (2016). The hypothesis states that analysts are valuable to investors as they are better informed and possess new information and insights that they release in their revisions. However, Altınkılıç et al. (2016) argue that the observed abnormal returns stem from piggybacking of adjacent earnings announcements and other additions to the information environment. Hence, the informative value of analyst reports is being questioned.

Moreover, target price revisions could provide a better picture on the informativeness of analysts as it introduces another dimension of information. In particular, there is reason to believe that target prices may have an additional signalling effect on instances where the recommendation level is unchanged. The majority of recommendations follow a rigid three-point system (buy, hold, sell), which makes recommendation revisions restricted on the extremes. However, the analyst is still able to revise the target price. In addition, the discrete three-point system mechanically asks for large changes in the analyst's assessment. As such, target prices could provide additional information in the absence of a recommendation change.

Further, past studies argue that analysts are reluctant to make downgrade revisions (Jegadeesh & Kim, 2006; Womack, 1996). In instances where the analyst's view of the relevant stock has deteriorated, a change in the target price, continuous in principle, may leave the analyst with more refined options. An explanation can be found in the business model of brokerage firms that might cause biases in the recommendation dimension. If the analyst is reluctant to downgrade to preserve corporate client relations, changes in the target price could be the middle road where the analyst is maintaining both client relations in the investment banking division and the credibility of the research department.

However, there are reasons to believe that not all target price revisions are equally informative. The degree of innovation in the assessment of the analyst is likely to be relevant under the informed analyst view. Thus, we differentiate high-innovation target price revisions from low-innovation target price changes as the signalling effect could be different. Specifically, this distinction separates analysts who bring new information to investors by announcing a fundamental change or a differing assessment of the company's prospects relative to the consensus.

This thesis aims to provide insights into the informativeness of analyst revisions. We examine the broader Norwegian market by including all 69 stocks of the Oslo Børs Benchmark Index (OSEBX). To the best of our knowledge, research of the broader Norwegian market has not been conducted in past studies. Analysis on the market turmoil initiated by Covid-19 is contributing to the literature in an international context. Further, the event study framework is used to extract abnormal returns associated with analyst revisions. If the informed analyst hypothesis is true, there should be corresponding abnormal returns in the direction of the revisions. The analysis is conducted exclusively on revisions. We argue that reiterations of old assessments are less likely to be informative to investors. The focus on revisions follows intuitively under the assumption of efficient capital markets. If current asset prices reflect all publicly available information, only new information should have an effect on asset prices. If analysts reiterate their previous view of the relevant firm, the potential innovations to the information environment determining stock prices should be limited. Moreover, the investigation of target prices in the Norwegian market, when the recommendation level is unchanged, introduces another dimension to the literature.

1.1 Problem Formulation and Structure

This thesis will examine the market impact of analyst revisions. In particular, our research will be conducted based on the following problem formulations:

Research question 1: Are analyst recommendation revisions informative to investors for companies listed on the Oslo Stock Exchange?

Research question 2: Are target price revisions relevant to investors in the absence of recommendation changes?

The thesis is divided into eight chapters. This first chapter has introduced our motivation, the research questions, and the structure of the thesis. The second chapter covers prior research within the same subject of our study. The third chapter introduces the theoretical framework. The fourth chapter establishes the methodological foundations to answer the research question. An extensive elaboration of the event study framework is provided in this section. Chapter five presents the data-gathering process and the data used in the study. The sixth chapter presents the results of the analysis. Chapter seven discusses our results, the limitations of our findings, and suggests proposals for future research. The last chapter summarizes the main conclusions.

2. Prior Research

Researchers have been looking into the value of analyst recommendations for decades. Cowles (1933) analyses recommendations from financial service and fire insurance companies and concludes that the advice is not valuable to investors. Decades later, researchers find that brokerage firms' recommendations are associated with significant abnormal returns (Bjerring et al., 1983; Givoly & Lakonishok, 1979; Groth et al., 1979; Barber et al., 2001).

More recent research also supports the theory of analysts' informativeness to investors. Barber et al. (2010) conclude that abnormal returns associated with recommendations stem from both the level of the recommendation and the magnitude of change in the rating. They find that a strategy of buying stocks which receive a double upgrade to buy, or strong buy, and shorting stocks receiving a double downgrade to sell, or strong sell, yields an average daily abnormal return of 5.2 basis points. Thus, they argue that the analysts' predictive power to some extent reflects the ability to generate valuable private information. Crane and Crotty (2020) find that 97% of the analysts in their sample experience abnormal returns in the direction of the recommendation and that the associated "analyst skill" is persistent.

Researchers have been analysing both the report-level and revision-level informativeness in their studies. The report-level research examines the effect of all analyst reports published, including reiterations of previous recommendations. Revision-level studies only include reports with a change, or revision, compared to the analyst's previous report. Barber et al. (2010) analyse the report-level effect of recommendations and find that there are abnormal returns associated with the level of recommendation. Bjerring et al. (1983) find similar results. However, Brav and Lehavy (2003) and Crane and Crotty (2020) show that revisions are more likely to contain information affecting security prices. Thus, they are only including revisions to better capture the effect of potential new information to market participants.

Prior literature has studied both the long-term return drift and the short-term market reaction associated with analyst revisions. Stickel (1991) finds a six-month post-revision drift in the direction of the analysts' recommendations. Womack (1996) studies both the short-term and long-term effects of recommendation revisions. In his study of the long-term effect, he finds that excess returns are significant and persistent. In addition, he shows that abnormal return mainly occurs in the first month for upgrades, while downgrades usually have a negative drift over six months. However, Altınkılıç et al. (2016) find that the post-revision return drift is not significantly different from zero between 2003 and 2010 in the American market.

Short-term studies focus on the immediate reactions to analyst reports. Mikhail et al. (2004) find excess returns of analyst revisions within a five-day event window. Other studies find similar results within a three-day event window (Francis & Soffer, 1997; Chang & Chan, 2008). Asquith et al. (2005) argue that both recommendation upgrades and downgrades are associated with significant abnormal returns and that analysts aggregate and interpret previously published information, but also provide new information. This coincides with Womack (1996) who finds statistically significant excess returns in a three-day event window; 3.3% return for recommendation upgrades and -4.7% return for recommendation downgrades. Overall, the majority view in the literature focusing on the short-term effects of revisions is aligned with the informed analyst hypothesis. However, some researchers find contradictory results, as Elton et al. (1986) do not find significant returns for downgrades within the month centred around the analyst report.

The abovementioned research papers are looking at the analyst recommendation level, often denoted by a buy, hold, or sell recommendation. Other research has examined the target price dimension of revisions. Brav and Lehavy (2003) find significant effects to target price revisions, both conditional and unconditional on recommendation and earnings forecast revisions. They argue that target prices are relevant to investors as they are the "analyst's most concise and explicit statement on the magnitude of the firm's expected value" (Brav & Lehavy, 2003, p. 1933). Hsieh and Lee (2021) add that target prices provide additional information to the investors especially when the analysts update the target price but reiterate the previous recommendation level. Asquith et al. (2005) show similar findings. However, Bonnini et al. (2010) argue that there is limited forecasting accuracy in target prices, as prediction errors are consistent, autocorrelated, large, and not mean-reverting. They also find that errors increase with the forecasted appreciation in the share price, suggesting that the research is systematically biased.

Gleason and Lee (2003) examine the innovation level of the target price revisions. They argue that revisions in the direction of the consensus forecast are low-innovation revisions, whilst revisions away from the consensus is regarded as high-innovation. They suggest that the degree of innovation is relevant to investors, and that the distinction is important as it extracts the qualitative characteristics of the forecast revision. Thus, by defining the innovation level of the forecast revision, Gleason and Lee (2003) can distinguish the analysts who bring new information to the market and those who are just “herding” by revising towards the consensus forecast. By the application of cross-sectional regressions, they find that the innovation level in the target price dimension is highly significant on post-revision returns, and that a hedge strategy based on the innovation level yields 10% abnormal return over the next year.

Jegadeesh and Kim (2006) take an international point of view by comparing the effect of analyst recommendations within the G7 countries. They find that stock prices react significantly on the revision day and the following day in every country except Italy. Furthermore, they conclude that analysts are significantly more accurate in the U.S. market compared to the rest of the G7 countries and that U.S. analysts are more skilled at identifying mispriced stocks compared to other analysts. Murg et al. (2016) examine analyst recommendations in Austria. They add to prior research by examining the analysts’ forecast accuracy in a smaller market. The authors find abnormal returns in the recommendation level and in the direction of revisions by using an ARMA-market-GARCH approach. Thus, they find that analysts provide additional information and influence the investors’ behaviour, also in smaller markets. Murg et al. (2016) are also including target price revisions into their model. However, they conclude that the effects in the target price dimension are ambiguous.

Other research investigates whether additional abnormal returns can be associated with certain characteristics. Brown and Mohd (2003) examine earnings estimation errors and find decreased forecast errors for larger brokerage houses, time length of analyst coverage, and number of analyst forecasts for the firm. Several studies also find that size and reputation of brokerage firms and analysts are associated with higher abnormal returns (Ivković & Jegadeesh, 2004; Stickel, 1995; Clement, 1999; Gleason & Lee, 2003).

Moreover, Altınkılıç et al. (2013) argue that the abnormal return stems from analysts’ piggybacking on the drift from other events, such as news releases or earnings announcements, and that analysts are not informative to investors. Thus, they take the view that analyst revisions are indicators of the information environment itself. Altınkılıç and Hansen (2009) raise the question after finding that analyst reports are often published shortly after company news. They present two possible explanations: 1) Company news is mostly about corporate operations and the news events give analysts the opportunity to apply their skills to process news into new information; 2) that analysts are strategically piggybacking on events to align their revisions with prior and future returns, thus boosting their reputation of stock picking and personal revenue. They conclude that analysts are piggybacking their revisions on news, and that analyst reports contain limited useful information to the investor. Kim and Song (2015) find supportive evidence, suggesting that earnings announcements influence both the timing and precision of analyst revisions. They find that stock price responses to analyst revisions following earnings announcements disappear after controlling for management's earnings forecast, and they conclude that the analyst's information discovery role is overstated in prior studies.

Ivković and Jegadeesh (2004) find that the frequency of recommendations in the U.S. is higher on days following earnings announcements, and that the recommendation change is in the same direction as the earnings surprise. Jegadeesh and Kim (2006) remove every recommendation revision inside a four-day window from the earnings announcement date. They show that excluding post-earnings revisions does not change the main conclusions from the original sample, suggesting that the analysts' performance is not due to piggybacking on earnings announcements. Moreover, Yezegel (2015) argues that analysts revise their recommendations after earnings announcements as they receive new information, face higher demand from investors for advice, and are more likely to find mispricing. Furthermore, he finds that the effect of earnings piggybacking is small in magnitude and that analysts rather fulfil their duties as information intermediaries rather than piggybacking other announcements.

3. Theoretical Framework

3.1 Efficient Market Hypothesis

The efficient market hypothesis (EMH) states that asset prices reflect all available information and that no risk-adjusted abnormal returns can be systematically achieved. Formally, market efficiency can be defined as follows: “A market is efficient with respect to information set Ω if it is impossible to make economic profit by trading on the basis of information set Ω” (Jensen, 1978, p. 97). Thus, in an efficient market, the price of a security will be a good estimate of its intrinsic value, as the competition from intelligent market participants eliminates mispricing (Fama, 1965). The theoretical foundation was developed 120 years ago as the random walk theory, where security prices fluctuate independently of previous price changes (Bachelier, 1900, as cited in Cootner, 1964). If prices always reflect all information, a random walk of price changes would be the natural consequence (Brodie et al., 2014).

The empirical evidence of the EMH emerged in the 1960s (Cootner, 1964; Samuelson, 1965; Fama, 1965). Fama (1970) extended the empirical evidence of the EMH by the separation of weak, semi-strong, and strong market efficiency. Weak market efficiency states that the stock price reflects all information that can be derived from historical price data (Brodie et al., 2014). This implies that historical market data has no predicative value for future asset prices. Semi-strong market efficiency states that asset prices reflect all public information available at the given time (Jensen, 1978). The strong market efficiency is the most extreme version of market efficiency, where prices reflect both public and private information (Jensen, 1978). In the state of semi-strong and strong market efficiency, there will be no portfolio managers or security analysts who can consistently beat the market as it is not possible to achieve abnormal returns by studying available information.

However, the validity of EMH has been empirically challenged ever since. Past studies find that serial correlation is not equal to zero in the short-run and reject the hypothesis of a random walk in stock prices (Malkiel, 2003; Lo & MacKinlay, 2002). The criticism of the EMH mainly lies in the existence of market anomalies and theoretical inconsistencies.

Short-term momentum in stock prices is consistent with studies of behavioural finance and psychological feedback mechanisms. Shiller (2000) described the late 1990s rise in the U.S. stock market as being a result of psychological contagion of irrational enthusiasm and optimism. Moreover, several researchers have found that stock prices tend to both overreact and underreact under certain conditions. De Bondt and Thaler (1985) find that investors' waves of optimism and pessimism cause prices to deviate from their fundamental value, before reverting towards the mean in the longer run. In fact, several research papers have seen negative serial correlation in stock returns using monthly data (Jegadeesh, 1990; Rosenberg & Rudd, 1982). In addition, Frank and Sanati (2018) find that positive price shocks following news are followed by a share price reversal, illustrating an overreaction in the case of positive news. Negative news is followed by a subsequent negative drift, illustrating an underreaction to the news. These events of mispriced securities suggest that the efficient market hypothesis does not hold in practice. However, Fama (1998) argues that as these anomalies are split randomly between underreactions and overreactions, it is still consistent with the efficient market hypothesis.

Grossman and Stiglitz (1980) continue the critique of the EMH by fronting an inconsistency of the theory. They argue that prices cannot perfectly reflect the available information as the market participants would not receive compensation for their efforts in obtaining that information. EMH is defined in a competitive equilibrium, where prices are such that all arbitrage profits are eliminated. If arbitrageurs make no profit from their costly activity, they stop gathering information and the informed price equilibrium will break down. This proposes that there must be "an equilibrium degree of disequilibrium" in situations where arbitrage is costly, where prices reflect the information cost of informed arbitrageurs, so they receive compensation for the resources spent on obtaining information (Grossman & Stiglitz, 1980, p. 393). This sets up the paradox for the EMH. If the market is semi-strong efficient, where all public information is reflected in the price, no one has the incentive to use costly resources to gather information. Then, if no one gathers information, not all information can be reflected in the price.

The efficient market hypothesis is a theory of importance for this thesis. If the prices reflect all information, analysts, and their work of obtaining information, are redundant and there should not be abnormal returns associated with the analysts' revisions. However, the role of the security analysts may be explained by the theory of Grossman and Stiglitz (1980), as gathering and processing information for investment decisions are time consuming and sometimes costly.

4. Methodology

This chapter will present the methodological framework applied to answer the research questions. The event study framework, introduced by Ball and Brown (1968) and Fama et al. (1969), is the most applied approach for examining the effect of analyst revision in the literature. We stick to this conventional approach as our main methodological framework. We will elaborate on the event study framework applied and discuss the implementation in this study.

4.1 Event Window

The first step within the event study framework is to define the event of interest. In our study, an event has occurred if analyst *i* has made a revision in either the recommendation or the target price of stock *j* in our data sample. This follows previous discussions of analyst reports and analyst revisions.

This study focuses on the short-term impact of analyst revisions. Thus, a narrow event window is most relevant to answer the research question. The event window is typically extended to include days around the event itself to account for pre- and post-event drift from potential information leakage and to allow for anomalies where prices are not immediately reflecting the new information (MacKinlay, 1997). The length of the event window is a trade-off between being certain that the full effect of the event is recognised within the event window and that adjacent events are not influencing the results.

A three-day event window centred at the event date is widely used by similar studies. Altınkılıç and Hansen (2009) argue that the three-day event window centred around the announcement date is the conventional approach in the study of analyst informativeness in the short run (Womack, 1996; Francis & Soffer, 1997; Chang & Chan, 2008). Inclusion of the day past the announcement day captures the initial market reaction of the revision and allows for possible delays in the distribution of information to the public market, as argued by Mikhail et al. (2004). This is especially important if analyst reports are published after trading hours.

The inclusion of pre-event days in the event window accounts for potential leakages of information. However, the challenges of leakages are less relevant for analyst revisions compared to other types of event studies. Analysts are working in small teams with only a handful of people within each sector. Information leakages occur more often when larger teams are involved, as it is more difficult for a larger group of people to keep information secret (Binder, 1998). Moreover, the value of the security analyst lies in digesting new information more precisely and quicker than other market participants. As such, most reports are published quickly in order to inform investors of relevant changes before others are able to digest the additional information. As the report is produced quickly, rather than built over a longer time period, information is more likely to be contained within the analyst team. Thus, leakages are limited, and we argue that it is unlikely that leakages occur several days prior to the announcement date.

In conclusion, we follow the conventional approach of prior studies by selecting a three-day event window centred at the event date.

4.2 Estimation Window

The estimation window's purpose in the event study framework is to estimate the parameters of the normal return model. The length of the estimation window typically varies from 30 to 750 days (Holler, 2012). However, as the length of the estimation window increases, the estimation window will include observations more distant in time where the estimated parameters may be different than the true parameters in the event window. The length of the estimation window is a trade-off between sampling error and timeliness. The former is shown formally in section 4.5. According to Armitage (1995) and Park (2004), the results are not sensitive to the estimation window if the length is sufficiently long, and they argue that approximately 100 days is appropriate. Thus, we choose to implement an estimation window of 100 days which is equivalent to approximately five months of trading.

Further, the estimation window cannot overlap the event window (MacKinlay, 1997). This could potentially introduce biases in the normal return estimation. As discussed in the section above, our event window will be centred three days around the event date. In addition, Binder (1998) suggests that a minimum of one day should be left between the event window and estimation window. In this study, the estimation window ends five days before the event day and the normal return parameters are estimated over the previous 100 days.

4.3 Return Computation

Our data is based on daily observations of analyst revisions and stock prices. Thus, the return computation is conducted on a daily basis. Further, the returns are calculated as the natural logarithm of the daily return. Formally, the log-returns can be expressed as:

$$r_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) = \ln(P_{i,t}) - \ln\,(P_{i,t-1}) \tag{1}$$

We calculate log-returns as they are additive over time and applicable for our three-day event window. In addition, log-returns exhibit better statistical properties in event studies than simple returns (Corrado & Truong, 2008; Henderson, 1990).

4.4 Benchmark Model

A benchmark model is required to estimate the normal return in absence of the event. A wide range of estimation procedures are available, and this section will elaborate on the different options and our preferred model specification. A meta study by Holler (2012), in a sample of more than 400 event studies, shows that 79.1% of researchers utilised the market model, 13.3% relied on the market-adjusted model, 3.6% used multifactor models, 3.3% chose the constant mean model and 0.7% used the CAPM model.

There are two main branches of benchmark models: economical and statistical. Economical models, such as the CAPM by Treynor (1961), Sharpe (1964), Lintner (1965) and Mossin (1966), are based on economic fundamentals such as utility maximisation. Statistical models rely on fewer underlying assumptions and take an analytical approach to answer the ambiguous empirical evidence of the CAPM.

The simplest benchmark model, the mean-adjusted return model, assumes that the normal return during the event window is the same as the average return in the estimation window (Brown & Warner, 1980). The model's strength is the trivial implementation. However, the model is typically ceased from most event studies as other model specifications can add significant accuracy improvements. Further, the market-adjusted model subtracts the market return from firm *i*'s return at time *t*. In this way, no parameters are estimated (Binder, 1998). Time-varying benchmark returns connected to the overall market is an obvious improvement from the mean-adjusted return model. However, exposure to systematic risk is assumed to be homogenous in the cross-section of companies and similar to the overall market itself. Thus, a model specification with heterogenous exposure to systematic risk may be preferred.

The market model is widely accepted as a benchmark model to calculate abnormal returns. The critique of the market model is that it assumes a constant risk-free interest rate over the estimation window captured in the α. To not allow for time-varying risk-free rates may bias the estimates of the parameters (Binder, 1998). In addition, the parameters for stocks with weak correlation to the market index could be less precisely estimated than for stocks with strong co-movements with the market. Nonetheless, the consideration of different exposure to systematic risk is an improvement to the market-adjusted model, and Campbell et al. (1997) argue that adjusting for the market return can enhance the ability to capture event effects.

Augmented and more sophisticated versions of the market model include Scholes-Williams beta estimation applicable for nonsynchronous trading and GARCH error estimation models (Scholes & Williams, 1977; Bollerslev, 1986). The modified version of the latter approach is utilised by Murg et al. (2016). They incorporate the sophisticated ARMA-market-GARCH approach to the Austrian market. Low market capitalisation may lead to higher autocorrelations (Schleicher, 1999). Further, the constant mean and variance assumption may be violated around the event date if event-induced volatility is present (Mestel & Gurgul, 2003). The ARMA-market-GARCH approach can mitigate these issues. However, Murg et al. (2016) find no additional value in estimating the normal return by the ARMA-market-GARCH model compared to conventional methods.

The CAPM model is practically similar to the market model, but the underlying assumptions are different. If the risk-free rate varies over time, the CAPM prediction errors control for this, contrary to the market model. However, the incremental value of the CAPM compared to the market model is likely small in our research design. This is supported by Holler (2012) who shows that the CAPM is rarely used as the benchmark model in the academic literature.

The Fama-French three-factor model describes the process of stock returns through the three factors market risk, SMB[1], and HML[2] (Fama & French, 1993). The three-factor model was extended by another factor, momentum, by Carhart (1997). The models capture the classical

[1] SMB = Small Minus Big and represents the outperformance of small versus large firms.
[2] HML = High Minus Low and represents the value premium.

empirical anomalies presented in the financial literature. However, the models are time consuming compared to the more simplistic models discussed above. In addition, MacKinlay (1997) argues that the gains from adding additional factors to the market model are small.

Another approach used for benchmark modelling is the matching approach. This approach matches the relevant firms to other firms based on different characteristics and uses the matched firms' performance as the benchmark. Altınkılıc et al. (2016) apply the matching approach in their study of analyst recommendation revisions.

The companies in the OSEBX exhibit heterogeneity. Companies like Equinor and Yara are large market leaders within capital intensive, cyclical, and commodity-based industries, and the stocks offers adequate liquidity. Others, such as Pexip, are smaller tech companies where human capital is the main resource of the business. Thus, one can argue that the more sophisticated models are relevant in our study. Nevertheless, there seems to be limited evidence that a more comprehensive benchmark model leads to more precise estimates in short-term event study analysis. Thus, we proceed with the general convention in the literature, which is the standard market model specification. The ability to control for market movements in the event window and the simple implementation makes the model practical and adequately powerful in our research framework.

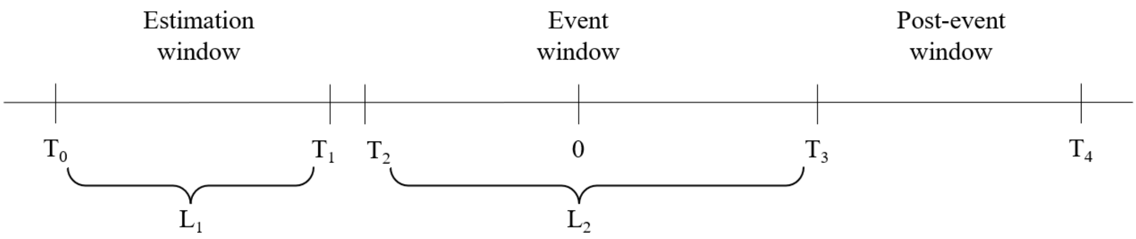
4.4.1 The Market Index

To estimate the parameters of the market model, a portfolio to proxy for the market portfolio must be chosen. A broad stock index is typically used in event studies (MacKinlay, 1997). In this thesis, we use the local OSEBX as the market proxy. The application of a local market index is common in the literature. As an example, Jegadeesh and Kim (2006) utilise local market indexes to proxy for the market portfolio in their analyst revision study in G7 countries. Further, in the initial phase of our analysis, we applied the all-share index, OSEAX, as the benchmark index in addition to the OSEBX. The results are practically identical, and we utilise the OSEBX as our proxy for the market return in this thesis.

4.5 Abnormal Return

This section will elaborate on the calculation of abnormal returns. The following illustration shows the time indexes and definitions applied in the derivation. T_0 to T_1 represents the estimation window with length L_1. Further, T_2 to T_3 is the event window with length L_2.

Figure 1: Illustrative Summary of the Definitions in Event Time



As previously discussed, the impact analysis of an event requires a measure of normal return as an estimate of the stock return if the event did not take place. Formally, MacKinlay (1997) defines abnormal return as:

$$AR_{i,t} = r_{i,t} - E(r_{i,t}|X_t) \tag{2}$$

where $r_{i,t}$ is the raw return of stock *i* at time *t*, and $E(r_{i,t}|X_t)$ is the expected normal return conditional on the normal return model. The market model, which will be applied in this study, is defined as:

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \varepsilon_{i,t} \tag{3}$$

$$E(\varepsilon_{i,t}) = 0 \qquad\qquad var(\varepsilon_{i,t}) = \sigma^2_{\varepsilon_i} \tag{4}$$

where

α_i and β_i are the model parameters, and $\varepsilon_{i,t}$ is the error term.

Thus, the abnormal return can be expressed as:

$$AR_{i,t} = r_{i,t} - \widehat{\alpha_i} - \widehat{\beta_i} r_{m,t} \tag{5}$$

Further, the parameters of the market model are estimated in the following way (MacKinlay, 1997):

$$\widehat{\beta_i} = \frac{\sum_{t=T_0+1}^{T_1}\left(r_{i,t} - \widehat{r_i}\right)\left(r_{m,t} - \widehat{r_m}\right)}{\sum_{t=T_0+1}^{T_1}\left(r_{m,t} - \widehat{r_m}\right)^2} \tag{6}$$

$$\widehat{\alpha_i} = \widehat{r_i} - \widehat{\beta_i} * \widehat{r_m} \tag{7}$$

where

$$\widehat{r_i} = \frac{1}{L_1}\sum_{t=T_0+1}^{T_1} r_{i,t} \tag{8}$$

and

$$\widehat{r_m} = \frac{1}{L_1}\sum_{T_0+1}^{T_1} r_{m,t} \tag{9}$$

The disturbance term variance is defined as:

$$\widehat{\sigma_{\varepsilon_i}^2} = \frac{1}{L_1 - 2}\sum_{t=T_0+1}^{T_1}\left(r_{i,t} - \widehat{\alpha_i} - \widehat{\beta_i} r_{m,t}\right)^2 \tag{10}$$

As shown above, the OLS estimation of the parameters is conducted in the estimation window. This means that the abnormal return is the disturbance term from the market model in the event window. Under the null hypothesis, the abnormal return will have a zero conditional mean and a variance of:

$$\sigma^2\left(AR_{i,t}\right) = \sigma_{\varepsilon_i}^2 + \frac{1}{L_1}\left(1 + \frac{\left(r_{m,t} - \widehat{r_m}\right)^2}{\hat{\sigma}_m^2}\right) \tag{11}$$

The two components of the variance term are the disturbance variance of $\sigma_{\varepsilon_i}^2$ and the sampling error of the parameters. Thus, as the length of the estimation window increases, the sampling error will converge towards zero. Under the null of no event effect, one can formally describe the distributional properties of $AR_{i,t}$ as:

$$AR_{i,t} \sim N(0, \sigma^2\left(AR_{i,t}\right)) \tag{12}$$

Further, to assess whether there is a systematic effect of the event, a cross-sectional aggregation at the time of the event is conducted by the calculation of the average abnormal return (AAR):

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \tag{13}$$

A time series aggregation is also necessary to capture the full extent of the event. Although the timing of the event itself is indisputable when it comes to analyst revisions, there might be minor leakages or a delayed reaction to the revision. Thus, under the null hypothesis and with the assumption of semi-strong efficient markets, a time series aggregation is necessary to capture the full magnitude of the event. The cumulative average abnormal return (CAAR) can formally be described as:

$$CAAR = \sum_{t=T_2}^{T_3} AAR_t \tag{14}$$

Alternatively, one can first aggregate the abnormal returns by the time series dimension and then the cross-sectional aggregation in the next step (Kliger & Gurevich, 2014). The cumulative abnormal return (CAR) can be defined as:

$$CAR_i = \sum_{t=T_2}^{T_3} AR_{i,t} \tag{15}$$

and then

$$CAAR = \frac{1}{N}\sum_{i=1}^{N} CAR_i \tag{16}$$

According to MacKinlay (1997), for estimation windows of adequate length and under the assumption of no cross-sectional dependence, the variance of AAR_t, CAR_i, and $CAAR$ can be formally described as:

$$Var(AAR_t) = \frac{1}{N^2}\sum_{i=1}^{N} \sigma_{\varepsilon_i}^2 \tag{17}$$

$$Var(CAR_i) = (T_3 - T_2 + 1)\sigma_{\varepsilon_i}^2 \tag{18}$$

$$Var(CAAR) = \sum_{t=T_2}^{T_3} Var(AAR_t) \tag{19}$$

or alternatively

$$Var(CAAR) = \frac{1}{N^2}\sum_{i=1}^{N} Var(CAR_i) \tag{20}$$

4.6 Clustering

Clustering is the phenomenon of overlapping events (Kliger & Gurevich, 2014). Overlapping can occur in several ways in the context of analyst revisions. The following examples illustrate two situations of clustering: 1) A new revision for company *c* from analyst *j* is made within the event window of analyst *i*'s revision for company *c*; 2) a new revision for company *c* from analyst *j* is made within the event window of analyst *j*'s revision for company *d*. If clustering is significant, the assumption of no cross-sectional dependence is violated, and inference may by biased. Specifically, the covariance term in the aggregate of abnormal returns will not be zero. The estimated standard deviation is typically to be found in the denominator of the test statistic, and cross-sectional correlation can lead to downward biased variance estimates and inflated test statistics.

MacKinlay (1997) argues that in the presence of cross-sectional dependence two measures could be implemented. The first is to construct calendar portfolios in accordance with Jaffe (1974), Mandelker (1974), and Fama (1998), and then perform security level analysis on the portfolio. At the portfolio level, the cross-sectional dependence is accounted for. However, the calendar portfolio method fails to account for event-induced volatility (Dutta, 2015; Kolari & Pynnönen, 2010). The second method to handle clustering is to not aggregate the abnormal returns (MacKinlay, 1997). The approach is most applied in the presence of perfect clustering. A third approach is to adjust the test statistic to account for clustering.

We believe clustering is not an important issue for our analysis. Since we are focused on the short-term effect of analyst revisions[3] over a time frame of more than 10 years, the average cross-sectional dependence will naturally be low. In addition, Kothari and Warner (2007) suggest that the statistical tests in short-term event studies are not materially affected by potential cross-sectional correlation. Further, our research design naturally mitigates cross-sectional dependence. First, a mechanical fact is that the focus on revisions naturally reduces the cross-sectional correlation compared with report-level analysis as the number of observations is reduced. Second, we remove observations where there are conflicting revisions for the same firm on the same day. In the case of multiple and agreeing reports for the same firm on the same day, we aggregate the revisions into one report date revision as discussed in section 5.2. This reduces the cross-sectional dependence and avoids idiosyncratic shocks amidst clustered events from being counted multiple times. In conclusion, our results are not likely to be severely affected by cross-sectional dependence.

4.7 Event-Induced Volatility

Event-induced volatility is a common phenomenon where the return variance increases for the period around event dates. If the volatility of abnormal returns conditional on the event is higher than in the estimation period, the estimated volatility can be understated. Event-induced volatility is present when the companies of relevance show heterogeneous reactions to the new information of the event (Boehmer et al., 1991). There is reason to believe that this might be the case for analyst revisions. This could lead to elevated test statistics and more type 1 errors (Brown & Warner, 1985). Dann (1981) shows that variance during the event period increases by a factor of more than three in the case of stock repurchases. Beaver (1968) argues that the return variance associated with earnings announcements is elevated. Our sample includes a significant proportion of revisions associated with earnings announcements[4]. Further, Penman (1982) and Mikkelson (1981) use the cross-sectional variance instead of the estimation period variance and both studies find evidence of higher variance when applying this method. Kolari and Pynnönen (2010) argue that the standard deviation in the event window is typically 1.2-1.5 times higher than in the estimation window. Nonetheless, several test statistics that are

[3] We use a three-day event window.
[4] 15.6% of the total sample.

robust in the case of event-induced volatility and applicable in our research design have been developed. This enables inference that is robust to event-induced volatility.

4.8 Significance Tests

The classical approach in terms of inference within the event study framework is to apply a t-test to the aggregate of average abnormal returns where the variance term is calculated during the estimation window. The test conditions on no serial correlation of returns, no cross-sectional dependence, normally distributed returns, and the same variance in the estimation period and the event period. In this section, we will elaborate on the significance tests chosen for this thesis that are more robust under non-idealistic conditions.

In the context of event studies, parametric and non-parametric tests have been developed to enable inference about the events of interest. Non-parametric tests separate from their parametric counterparts by being distribution-free tests based on ranks. If all requirements are met, the parametric tests are superior to non-parametric tests due to higher power. In the context of event studies, Kolari and Pynnönen (2011) find that the non-parametric tests are superior to parametric tests as they are not sensitive to the distribution of returns. MacKinlay (1997) suggests including both parametric and non-parametric test statistics for robustness. Thus, we will follow this convention and implement parametric and non-parametric tests in our analysis.

Patell (1976) argues that standardising each abnormal return improves the performance of the statistical test. Kolari and Pynnönen (2010) extend this view and argue that standardised abnormal returns are superior in the event study framework. The intuition behind the standardisation of the abnormal returns is that the process weighs each individual observation by the inverse of standard deviation (Kolari & Pynnönen, 2010). Thus, volatile observations will have smaller weights in the aggregation process. Our parametric and non-parametric test statistics utilise standardised abnormal returns.

In relation to parametric tests, Boehmer et al. (1991) introduce a modified test statistic robust to incremental volatility in the event window and applicable to multi-day event windows. The test relies on estimation window and event window information, and Harrington and Shrider (2007) argue that the parametric test is robust in short-horizon event studies of mean stock price effects. Specifically, the test re-standardises the abnormal returns by the cross-sectional variation during the event window. Simple implementation and satisfactory power make the test appealing in our research framework. Thus, we will implement the test suggested by Boehmer et al. (1991), hereafter the BMP test, in our analysis[5].

MacKinlay (1997) proposes a non-parametric rank test developed by Corrado (1989). The test has several advantages such as simple implementation and overall adequate power in the short-term event study framework. However, the original test developed by Corrado (1989) was initially designed for single-day events. A comprehensive and more effective non-parametric test has been developed which is robust against event-induced volatility, serial-correlation, the normal distribution assumption, and to some extent cross-sectional correlation. The test was introduced by Kolari and Pynnönen (2011) and is called the Generalised Rank Test, hereafter GRANK. The GRANK is a rank test that standardises the abnormal return in accordance with Patell (1976) but also the cross-sectional variation. Another innovation of the GRANK is that it aggregates the event window into a cumulative event day and compares the rank to the return ranks of the estimation window. Kolari and Pynnönen (2011) show that the test has high power in both short and longer event windows. The GRANK test will be used as the non-parametric test in our initial results section[6].

Further, in the presence of event-induced volatility, the abnormal returns may not be homoscedastic in the multivariate regression framework applied in section 6.2 (Harrington & Schrider, 2007). Thus, we utilise heteroscedasticity-robust standard errors clustered by calendar day[7] when we perform OLS regressions. The latter is to make our results more robust to any cross-sectional dependence.

4.9 High-Innovation Target Price Revisions

Most of the literature presented in section 2 focuses on the recommendation dimension of analyst reports. However, past studies find significant abnormal returns when revisions are focused on the target price dimension (Gleason & Lee, 2003; Brav & Lehavy, 2003). We add an extension to the current literature by considering target price revisions when recommendations are unchanged in the Norwegian market.

[5] Kindly refer to appendix A.2 for formal elaboration of the BMP test.
[6] Kindly refer to appendix A.3 for formal elaboration of the GRANK test.
[7] Loh and Stulz (2018) cluster the standard errors by calendar day in their study of analyst revisions during crises.

As an example, imagine a situation where an analyst has a buy recommendation for a company trading at 80 NOK per share and the target price is 100 NOK. Next month, the stock price has increased to 90 NOK, and the analyst publishes a report where he reiterates his buy recommendation, but the target price is lifted to 170 NOK. If the informed analyst hypothesis is true, then this revision could be relevant to investors. A dedicated focus on recommendation revision would treat the situation explained above as a reiteration with no possibility for new information. Since the academic literature shows evidence supporting the informed analyst view in the target price dimension, we believe target price revisions should be included in our analysis.

Gleason and Lee (2003) implement the distinction between low- and high-innovation target price revisions. They define a high-innovation revision as either: 1) The target price revision implies that analyst *i* has flipped their view from below (above) to above (below) the consensus target price; 2) the target price revision puts analyst *i* longer from the consensus target price than their previous target price. We utilise the ideas from the framework of Gleason and Lee (2003). We make the distinction between high- and low-innovation target price revisions with some modifications.

First, a high-innovation target price revision should require a revision that is significant in absolute terms and a true deviating view from the consensus. If these distinctions are not made, a minor change in the target price close to the consensus could arbitrarily lead to a flipped view or longer from consensus assessment; thus, a high-innovation revision. As a first measure to accommodate this issue, we set a minimum requirement of 10% absolute target price change for a revision to be included as high innovation. We set a second requirement that the absolute percentage deviation from the consensus must be 10% or greater. As such, we implement the flipped view and longer from consensus concepts in accordance with Gleason and Lee (2003), but we require 10% absolute target price change and 10% absolute deviation from the consensus target price in addition.

Figure 2: HITP and LITP When the Analyst's Prior Assessment is Above Consensus

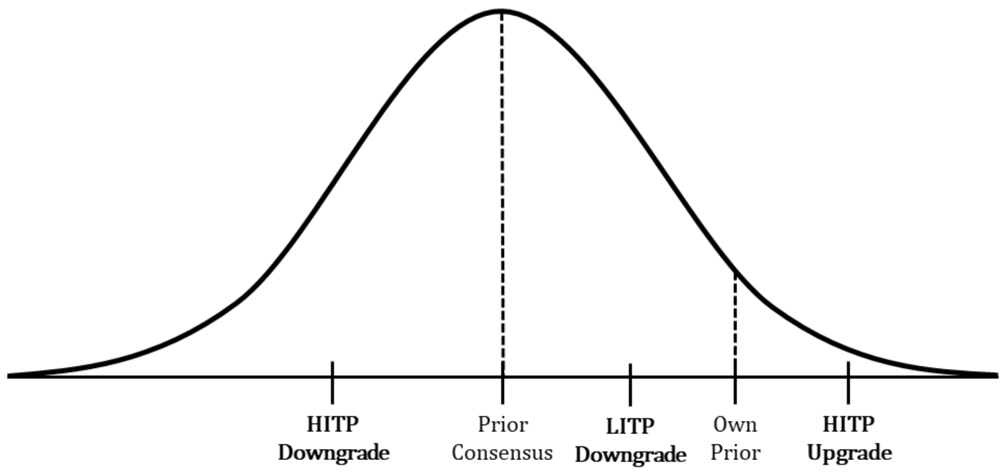


Figure 3: HITP and LITP When the Analyst's Prior Assessment is Below Consensus

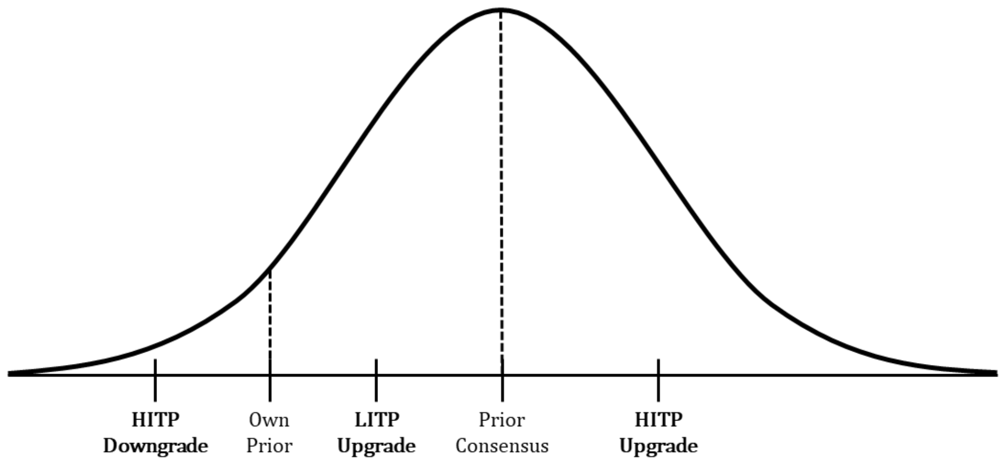


Figure 2 and 3 exemplify two situations where the target price revision is considered as high-innovation[8] and low-innovation. If the analyst's prior assessment is above (below) the consensus forecast, there will be a high-innovation target price revision if the new target price lies further away from the consensus or if the analyst is flipping their view and issue a target price below (above) the consensus. Moreover, if the analyst is only revising the target price towards the consensus, the revision is considered a low-innovation target price revision.

The flipped view specification is intuitive and appealing if revisions are truly informative to investors. If the fundamental assessment from the analyst changes from being below (above) to above (below) the consensus, the polarising revision signals a change in the overall view of

[8] Here we assume that the two additional criteria of 10% change in target price and 10% deviation from consensus are met.

the analyst. Thus, this revision is more likely to be informative to the market. Further, an analyst in strong disagreement with the consensus is likely to be aware of their differing assessment of the relevant firm. If analysts are conscious of their career prospects and reluctant to separate from the common view, a revision where the target price is revised to be longer from the consensus could increase the strength of the signal.

4.10 Low-Innovation Target Price Revisions

The third group of revisions included in our analysis is low-innovation target price revisions. These are revisions where the recommendation is reiterated but the target price is changed. To be included in the sample, we require a minimum of 2% change in the target price from the previous analyst report. This threshold is set to mitigate inclusions of false revisions from currency effects or other adjustments. Some brokerages issue target prices in different currency than NOK. Thus, a reiteration of the target price but a change in value of the currency may look like a target price change in NOK. All target price revisions passing the 2% absolute change requirement and not defined as high-innovation revisions, will be included in the low-innovation target price sample.

4.11 Multivariate Regression Analysis

A multivariate regression model is helpful to examine the association between the CARs and the attributes specific to the event observations (MacKinlay, 1997). In addition, other factors that might affect the magnitude of abnormal returns, but are not directly related to the analyst revisions, can be explicitly controlled for. The cross-sectional OLS regression models implemented in section 6.2 can generically be expressed as:

$$CAR_i = \beta_0 + \beta_1 x_{1,i} + \cdots + \beta_j x_{j,i} + \varepsilon_i \tag{21}$$

where CAR_i is the i^{th} cumulative abnormal return observation, $x_{j,i}$ are j different attributes and controls for the i^{th} observation, ε_i is the error term, which is uncorrelated with the independent variables x_j and has an expected value of zero. β_j are the model coefficients. All models are implemented using standard errors robust to heteroscedasticity and clustered by time as discussed in section 4.8.

4.12 Variable Description

This section describes the variables included in the multivariate regression analysis conducted in the results section.

4.12.1 Revision Variables

The main variables of interest for the research questions of this thesis are the revision-level dummy variables. *Rec up, HITP up,* and *LITP up* capture the difference in cumulative abnormal returns of upgrades and downgrades. If analyst revisions are informative, the difference in cumulative abnormal return between upgrades and downgrades should be statistically significant. The variable design follows the implementation of Altınkılıç et al. (2016).

4.12.2 Relative Revisions per Day (Relative RPD)

One can argue that signals from revisions are greater if several analysts make similar revisions on the same day. If several analysts make clustered revisions, the overall market is likely to be more affected than for individual revisions under the informed analyst view. Frankel et al. (2006) find that the number of revisions on the event date significantly affects abnormal returns. To account for this effect, we create a variable that captures the number of revisions in our sample for a given firm within the three-day event window of every event. Further, we normalise the variable by dividing by the number of analysts covering the relevant firm on the event day. Thus, the variable represents the percentage of analysts covering the firm that make a revision within the relevant event window. Lastly, the variable is converted to a dummy variable equal to one if the relative revisions per day are in the top quintile for the relevant firm over the entire sample time period. Formally, the relative revisions per day formulation can be described as:

$$RPD_{i,t} = \frac{Rev_{i,t}}{TAC_{i,t}} \tag{22}$$

where

$Rev_{i,t}$ represents the number of analyst revisions for firm *i* within the three-day event window. $TAC_{i,t}$ is the total number of analysts covering firm *i* at time *t*.

4.12.3 Market Presence

If the process of acquiring information is costly, one can argue that a large institutional system with great focus on the Norwegian stock market is more likely to release informative revisions. Moreover, Clement (1999) and Cowen et al. (2006) find that analysts in brokerage houses with larger market coverage, measured by number of published reports, are more informative. To capture the possible relationship between the brokerage firm's market presence and the informativeness of revisions, we include a dummy variable that separates the top five brokerage firms from the rest. Specifically, the dummy variable is equal to one if the relevant brokerage firm was in the top five in terms of total number of revisions in the previous calendar year.

4.12.4 Firm Size

A single analyst revision is expected to have greater informational value to investors in small-cap stocks compared to the large-cap stocks. Ivković & Jegadeesh (2004) find that smaller firms react more strongly to analyst recommendations compared to larger firms. This could be explained by the availability of information, where large firms are already heavily analysed by other market participants, and the marginal effect of one new revision is likely to be smaller than for the less analysed small-cap stocks. Moreover, the firm size variable will also control for differences in trading costs, as they tend to be higher for smaller firms (Stoll & Whaley, 1983). Thus, we create a dummy variable equal to one if the relevant firm's market capitalisation is in the top ten of our sample at the end of the previous year.

4.12.5 Momentum

Altınkılıç et al. (2016) argue that stocks experiencing higher momentum are associated with more favourable revisions, as the analysts rely on the momentum from prior earnings data in their analysis. In addition, Jegadeesh & Titman (1993) find that a strategy selecting stocks based on their past six-month returns is associated with significant excess returns. Moreover, Carhart (1997) finds that momentum is a market anomaly associated with higher returns, and he extends the Fama and French (1993) three-factor model by including momentum as an additional factor.

We construct a momentum variable inspired by the method presented by Altınkılıç et al. (2016). The returns are computed in a five-month window starting at six months and ending one month before the event date. The momentum variable is converted to a dummy that equals one if the stock's -120 to -20 trading day return is in the top quartile compared to the other stocks in our sample.

$$Return_{i,t} = \frac{p_{i,t-20}}{p_{i,t-120}} - 1 \tag{23}$$

4.12.6 Covid-19 Crash

The Covid-19-initiated turmoil in financial markets during February and March 2020 caused a drop in the OSEBX of approximately 32%. This rapid and broad market reaction represents a very unusual event that can potentially affect our revision-level coefficients and the revision signal. In addition, Loh and Stulz (2018) find that analyst revisions are associated with greater abnormal return in the direction of the revision amidst market crises. Thus, we include a Covid-19 crash dummy equal to one for the period between February 20th, 2020, and March 20th, 2020.

4.12.7 Covid-19 Recovery

In the aftermath of the Covid-19-initiated market crash, financial markets recovered quickly, and the rapid market surge was broad. The market turmoil may also reduce the accuracy of our normal return parameters. To avoid any adverse effects to our analysis of the rapid market recovery, we add a time dummy which is equal to one if the revision is made between March 21st, 2020, and November 30th, 2020.

4.12.8 Company News

As presented in section 2, Altınkılıc et al. (2013) find that analysts piggyback value-relevant company news in their revisions. To address the effect of analyst piggybacking on value-relevant news in the information environment, we include a dummy variable that will be equal to one if news in the form of M&A, equity capital transactions, or contract announcements is announced during the three-day event period. The variable is naturally not exhaustive, but the news categories captured in the variable are likely to be value-relevant as shown by Altınkılıc and Hansen (2009).

4.12.9 Standardised Unexpected Earnings (SUE)

To examine whether there are different effects of analyst revisions in conjunction with unexpected earnings surprises, we include a variable that captures the change in the information environment. Consider the following: Equinor publishes an earnings announcement significantly above the market expectations at day *t*. At day *t* or *t+1* an analyst makes a revision to incorporate the unexpected earnings from Equinor into the assessment. Thus, mechanically, the revision will be associated with abnormal returns due to the earnings announcement piggybacking. In the literature, this issue is typically controlled for or analysed by the means of the standardised unexpected earnings (SUE) variable (Altınkılıç et al, 2016; Brown & Mohd, 2003; Datta & Dhillon, 1993). We define SUE formally for firm *i* at time *t* in the following way:

$$SUE_{i,t} = \frac{AE_{i,t} - F_{i,t}}{\sigma_{i,t_{-1}-t_{-8}}} \tag{24}$$

where

$AE_{i,t}$ is the actual earnings per share in the last completed fiscal quarter for firm *i*. $F_{i,t}$ represents the latest available consensus EPS forecast for firm *i* in the last completed fiscal quarter. $\sigma_{i,t_{-1}-t_{-8}}$ is the standard deviation of the forecast error of the last eight quarters for firm *i*.

For newly listed firms, we use the standard deviation of the first four quarters in the first reporting year. Next, the variable is converted into two dummy variables that separate the bottom and the top SUE quartiles from the two middle quartiles in our full firm sample. Specifically, the variable is equal to one if the revision event is associated with an earnings announcement in the top (bottom) SUE quartile and zero otherwise. In this way, we are able to explicitly control for unexpected earnings surprises.

4.12.10 Earnings Announcement

In addition, we aim to control for other earnings announcement effects by including a dummy variable equal to one if the company releases an earnings announcement within the event window. This follows the finding of earnings announcement piggybacking by Altınkılıç and Hansen (2009). Stickel (1995) implements a similar control. The earnings dummy will capture other relevant innovations to the information environment that are not captured in the SUE variable.

4.12.11 Book-to-Market

Fama and French (1993) show that companies with higher book-to-market ratios outperform companies with smaller ratios. One can think of this as the value versus growth effect. Most high-growth firms, especially within the technology sector, have low book-to-market ratios, while mature industrial companies with limited growth opportunities represent the contrary. Our variable is constructed as a dummy variable. It separates the bottom quartile from the other firms calibrated at the end the previous year. Specifically, the variable is equal to one if the relevant firm's book-to-market ratio is in the lowest quartile. Thus, our variable will separate stocks that are typically classified as growth stocks from the rest of the sample firms.

4.13 Variable Design

To examine whether the variables have different effects for upgrades and downgrades, and to mitigate convergence in the coefficients, we split most variables into two, separated by whether they are associated with an upgrade or a downgrade. The exceptions are the Covid-19 recovery variable, which is added as a standard time dummy, and the SUE dummy variables, which are split by whether the event is associated with a SUE in the top or bottom quartile independent of the revision direction.

The first reason to split the variables based on whether they are associated with upgrades or downgrades is that we avoid the convergence in the coefficients if there are true effects related to the absolute value of CAR. As an example, if market presence increases the effect in the direction of the revision, and this is true for both upgrades and downgrades, then the coefficient will converge to zero[9]. Under the informed analyst hypothesis, positive (negative) CARs for upgrade (downgrade) revision events are expected. The second reason for splitting the variables is that it allows us to investigate whether effects are symmetrical for upgrades and downgrades. In the results section, we will investigate whether our findings are sensitive to assuming symmetrical effects. To conclude, our independent control variables will be

[9] If the effects are symmetrical.

multiplied with upgrade and downgrade dummies corresponding to the associated revision. A similar methodology is used by Altınkılıc and Hansen (2009). In section 6.2.4, where we assume symmetrical effects in the coefficients, we transform the control dummies into categorical variables of -1, 0, 1 where -1 and 1 represent the dummy variable values for downgrades and upgrades, respectively. Gleason and Lee (2003) apply a corresponding method.

The variable split makes the interpretation of the up and down coefficients similar to interaction terms. To include a single dummy variable for each regressor and an interaction term with the main revision variable is equivalent to our specification derived above. All else equal, the base effect of a downgrade is captured in the constant. Further, the down coefficients capture the different effect of a downgrade when the relevant regressor is one. The up coefficients capture the different effect of an upgrade when the regressor is one.

5. Data

This section will elaborate on the data sample used in this study. We will discuss the data cleaning process and the main characteristics of our data. In addition, descriptive statistics will be presented.

5.1 Data Collection

The analyst report data were retrieved from the Bloomberg Terminal. We consulted several data source applications, such as Refinitiv I/B/E/S and FactSet, to assess the extensiveness and accuracy of the data. The Bloomberg Terminal offers a significantly more comprehensive database of analyst revisions than the alternatives. For several companies in our sample, the data sources could differ in the reported analyst coverage by a factor of two. Other market and firm data were primarily collected from Bloomberg, but we relied on the Refinitiv I/B/E/S database for company news data.

5.1.1 Companies

We consider all 69 companies included in the OSEBX as of September 2021 in our analysis. By focusing on a broader market index, we are able to capture the effects of revisions on a wider range of company characteristics. OSEBX offers a broad spectrum of industries, as well as large differences in market capitalisation, daily volume, and analyst coverage. As an example, Equinor is the largest company in our sample with a market capitalisation of 750 billion NOK, while in comparison, PCI Biotech has the lowest market capitalisation at 480 million NOK.

The time period of the analysis ranges from January 1st, 2011, to September 30th, 2021. The ten years and three quarters ensures a rich time dimension in our data while at the same time provides adequate timeliness for current applications. Interestingly, our data include revisions from the market turmoil during the winter and spring of 2020 where the Covid-19 pandemic became a global phenomenon.

5.1.2 Brokerages

We include 38 brokerage firms with recommendation and target price data available from the Bloomberg Terminal. This sample includes both large and small Norwegian brokerage firms, as well as international peers. Originally, data from 100 brokerages were collected. However, 62 companies did not make our minimal requirement of more than 50 revisions between 2011 and 2021. This process is further explained in section 5.2.

5.2 Data Cleaning Process

The initial revision sample has 94 083 analyst reports from 100 brokerages gathered from the Bloomberg Terminal. The data set consists of a date, recommendation, report type, target price, stock ticker, brokerage firm, analyst name, consensus target price on the publication date, and the target price implied return.

The first step in the cleaning process was to eliminate observations related to termination of coverage or other observations that did not provide true analyst updates. This included initiation of coverage and other reports that mechanically did not represent a revision. Further, we removed all observations without a complete set of recommendations and target prices, duplicates, and observations before our defined time period. Some observations had questionable data recordings, such as unnaturally large and quick target price changes. In one instance, the target price went from stable reiterations of 50 NOK, to quickly dropping to five NOK, and then returning to 50 NOK in a matter of days. These unnatural fluctuations were regarded as errors and removed from the sample.

Moreover, brokerages with less than 50 total revisions in our full time period were removed, reducing the number of brokerage firms from 100 to 38. Thus, we omitted observations from small international brokerage houses with limited reach and focus on the Norwegian market. These 38 brokerages represent 95% of the revisions in our original sample. This emphasises that we only removed smaller brokerage firms with limited or discontinued market coverage of the Oslo Stock Exchange. To get from the report-level sample to the revision-level sample, we eliminated all analyst reports that were not recommendation revisions or target price revisions in accordance with the definitions in section 4.9 and 4.10. After this process, the sample was reduced to 21 370 observations.

Further, the data were separated into recommendation, high-innovation target price, and low-innovation target price samples. The recommendation sample only consists of recommendation upgrades and downgrades and does not consider target price changes. The high- and low-innovation target price samples are reiterations of the recommendation level but revisions in the target price dimension. Low-innovation target price changes below the 2% threshold were removed, as some smaller changes in target price were caused by currency effects.

As discussed in section 4.6 on clustering, if there were multiple revisions within an event window, the collection of revisions was aggregated into one report date revision. This corresponds with the practice of Frankel et al. (2006)[10]. If all revisions were made in the same direction, one revision was randomly selected and kept while the others were removed from the sample. If revisions were conflicting, where one analyst published an upgrade and another analyst published a downgrade, we removed all observations due to the ambiguous signal. Thus, by removing conflicting observations, we eliminated misleading CAR observations that were affected by two separate and conflicting assessments. However, conflicting observations, where more than 75% of the revisions signalled in the same direction, were aggregated into one report date revision in correspondence with the majority view. As such, we included revisions where there was a clear aggregate signal to the market while still removing conflicting revisions.

Lastly, the revision observations were combined with a comprehensive data set covering the regressors presented in section 4.12. All variables were constructed from data gathered from the Bloomberg Terminal, except for the company news data collected from the Refinitiv I/B/E/S database. Data from Bloomberg were gathered on daily, quarterly, and yearly frequency based on the characteristics of the variable. Missing or misleading data due to ticker changes or currency adjustments were manually revised to ensure the quality and consistency of our constructed variables. The last steps of the data cleaning process removed 7 744 observations resulting in the final data sample of 13 526 analyst revisions.

5.3 Revisions

The analysis will be conducted on three samples: A recommendation revision sample, a high-innovation target price revision sample and a low-innovation target price sample. A descriptive summary of the samples is presented in Table 1.

[10] Brav and Lehavy (2003) follow a similar logic, and they remove identical return observations.

Low-innovation target price revisions make the largest sample with 7 705 observations. This is intuitive as a large change in the opinion of the analyst should occur less frequently than smaller adjustments. The recommendation revision sample is the second largest, consisting of 3 701 observations, which makes the high-innovation target price sample the smallest in our study with 2 120 revisions.

There are more upgrades than downgrades in our samples as there are 7 540 upgrades and a total of 5 986 downgrades. However, in the recommendation sample, there are more downgrades than upgrades. This is in conflict with past studies which argue that analysts are hesitant to downgrade, especially during bull markets (Jegadeesh & Kim, 2006; Womack, 1996). A possible explanation could be found in the rigidness of recommendation levels. Most analysts are already issuing a buy recommendation and are unable to upgrade within the three-point system. Subsequent positive revisions will only be possible through the target price dimension. This is aligned with the HITP and LITP sample characteristics where the number of upgrades is higher than the number downgrades.

Table 1: Revision Sample Statistics

The table presents the recommendation, HITP, and LITP revision samples separated into upgrade and downgrade revisions.

	Rec	**HITP**	**LITP**	**Total**
Upgrades	1 819	1 220	4 501	**7 540**
Downgrades	1 882	900	3 204	**5 986**
Total	**3 701**	**2 120**	**7 705**	**13 526**

5.3.1 Companies

The samples, consisting of the 69 OSEBX companies, are mainly small and medium sized companies in an international context, as Oslo Stock Exchange is a smaller market in general. There are six micro-cap, 34 small-cap, 20 mid-cap, and nine large-cap companies in the sample[11]. Along with the variation in company size, the companies receive a different level of attention both from market participants and analysts.

[11] We define firms with market capitalisation between 0.5 and 3.0 billion NOK as micro-cap, 3.0 and 20 billion NOK as small-cap, 20 and 100 billion NOK as mid-cap, and firms larger than 100 billion NOK are considered large-cap stocks.

A descriptive summary of the covered companies is presented in Table 2. The companies with the most revisions are Equinor, DNB, and Norsk Hydro, with 670, 549 and 530 revisions, respectively. The connection between the revision intensity and firm size is evident as Equinor and DNB are the two largest in terms of market capitalisation while Norsk Hydro is the 6th largest company at the time of writing. In fact, 61.1% of the revisions are from companies included in the OBX index, defined as the 25 stocks with the highest turnover during the last six months. Nevertheless, the bottom 20 companies represent only 3.8%, and the bottom half make up 14.5% of the total revisions. This spread in the number of revisions between the companies is due to several factors. First, there is a large difference in analyst coverage of the stocks, and the larger stocks are followed by more analysts. Equinor is currently covered by 34 analysts according to the Bloomberg Terminal, while Carasent, PCI Biotech, and Ultimovacs are covered by two analysts. In addition to lower analyst coverage, the analysts tend to update smaller companies less frequently. Lastly, several companies in our sample have been publicly listed during our defined time period.

Arcticzymes Technologies is the only company in the OSEBX with no revisions according to our definitions within the defined time period. Carasent, Aker Horizons, PCI Biotech, Ultimovacs, and Pexip are the following companies with the lowest number of revisions. The characteristics of these companies are that they are either newly publicly listed or companies within the biotech sector, a smaller industry at the Oslo Stock Exchange.

Table 2: Company Statistics

The table presents the OSEBX companies included in our samples, as well as the number of revisions associated with each company in total and in each sample.

Company	All	Rec	HITP	LITP	Company	All	Rec	HITP	LITP
ABG Sundal Collier	13	2	0	11	Kitron	38	8	5	25
Adevinta	79	20	13	46	Kongsberg Automotive	102	20	12	70
AF Gruppen	108	22	10	76	Kongsberg Gruppen	233	74	28	131
Aker	237	39	53	145	Lerøy Seafood	383	93	56	234
Aker BP	460	118	81	261	Mowi	436	163	56	217
Aker Horizons	5	0	2	3	MPC Container Ships	50	6	20	24
Aker Solutions	316	94	73	149	Multiconsult	52	12	6	34
Arcticzymes Tech	0	0	0	0	Nel	58	14	20	24
Atea	211	76	20	115	Nordic Nanovector	33	1	8	24
Avance Gas Holding	234	59	63	112	Nordic Semiconductor	219	55	50	114
B2Holding	73	10	19	44	Norsk Hydro	530	154	78	298
Bakkafrost	363	109	35	219	Norwegian Air Shuttle	328	91	93	144
Bank Norwegian	78	16	8	54	Orkla	295	90	8	197
BergenBio	15	0	4	11	PCI Biotech	5	0	0	5
Bonheur	13	3	2	8	Pexip	10	0	2	8
Borregaard	126	31	17	78	Photocure	69	21	3	45
Bouvet	48	8	4	36	REC Silicon	228	70	66	92
BW LPG	251	62	72	117	SalMar	383	128	54	201
Carasent	1	0	0	1	Sats	32	1	7	24
Crayon	46	3	14	29	Scatec	147	32	24	91
DNB Bank	549	166	55	328	Schibsted	328	88	42	198
DNO	360	96	78	186	SpareBank 1 SR-Bank	278	56	34	188
Elkem	83	12	23	48	Stolt-Nielsen	211	44	30	137
Entra	134	40	6	88	Storebrand	334	82	54	198
Equinor	670	232	77	361	Subsea 7	507	151	86	270
Europris	126	32	16	78	Telenor	450	134	31	285
Fjordkraft	36	6	2	28	TGS	437	137	69	231
Flex LNG	101	14	27	60	Tomra Systems	222	78	20	124
Frontline	406	79	123	204	Ultimovacs	8	0	2	6
Gaming Innovation	44	20	3	21	Veidekke	165	47	12	106
Gjensidige Forsikring	339	99	18	222	Vow	32	7	6	19
Golden Ocean Group	300	64	63	173	Wal. Wilhelmsen	239	54	56	129
Hexagon Composites	113	38	18	57	XXL	170	53	26	91
Kahoot!	30	1	16	13	Yara International	487	164	38	285
Kid	59	2	3	54	**Total**	**13 526**	**3 701**	**2 120**	**7 705**

5.3.2 Brokerages

Statistics of the 38 brokerages included in our sample is presented in Table 3. ABG Sundal Collier, DNB Markets, and Pareto Securities have the highest market presence with 1 133, 1 132, and 985 total revisions, respectively. The three mentioned brokerages are also the greatest contributors in the HITP and LITP samples, while DNB Markets, SpareBank 1 Markets, and Arctic Securities have the highest number of recommendation-level revisions. Furthermore, Mediobanca, BMO Capital Markets, and Nomura have the lowest total market presence. The sample includes 18 brokerage firms with analyst teams located in Norway, while the other 20 are primarily international analyst teams. The top 10 brokerage firms in terms of revisions are located in Norway, while Goldman Sachs is the greatest contributor among international peers.

In addition to having the most revisions in our sample, ABG Sundal Collier has the greatest coverage over the defined time period, conducting research on 61 out of the 69 sample companies. DNB Markets and Pareto Securities follow with company coverage of 56 and 54 firms, respectively. The large company coverage is the main determinant of the leading market presence in terms of number of revisions. On average, the included brokerages are covering 24.4 companies each, despite Evercore and Mediobanca which only cover two companies. The international brokerage firms have less companies covered compared to the Norwegian peers. The average company coverage of the international brokerages is 11.0 companies, while the Norwegian average is 39.4. This clearly demonstrates the difference in having Norway as the main market compared to the international brokerage firms. The international peers are covering the larger firms with greater global interest.

Table 3: Brokerage Statistics

The table displays the 38 brokerage firms included in our study. It also presents the number of revisions by each brokerage in each sample.

Broker	All	Rec	HITP	LITP
ABG Sundal Collier	1 133	227	187	719
Arctic Securities	837	242	152	443
Barclays	199	43	29	127
Berenberg	110	23	15	72
Beringer Finance	393	132	36	225
Bernstein	94	18	19	57
BMO Capital Markets	33	7	1	25
Canaccord Genuity	56	22	5	29
Carnegie	533	151	88	294
Clarksons Platou Securities	225	63	48	114
Cleaves Securities	109	17	29	63
Credit Suisse	175	45	18	112
Danske Bank	726	185	129	412
Deutsche Bank	192	36	21	135
DNB Markets	1 132	324	160	648
Evercore ISI	71	12	18	41
Exane BNP Paribas	192	42	31	119
Fearnley Securities	377	145	59	173
Goldman Sachs	413	85	42	286
HSBC	178	65	27	86
Jefferies	122	30	19	73
JPMorgan	262	62	38	162
Keefe Bruyette & Woods	66	20	7	39
Kepler Chevreux	384	88	65	231
Macquarie	101	29	18	54
Mediobanca	31	1	4	26
Morgan Stanley	249	57	37	155
Nomura	49	11	9	29
Nordea	701	196	140	365
Norne Securities	412	174	39	199
Pareto Securities	985	237	166	582
RBC Capital	124	25	20	79
SEB Bank	736	233	143	360
Société Générale	85	28	13	44
SpareBank 1 Markets	745	294	99	352
Svenska Handelsbanken	668	145	99	424
Swedbank	473	147	72	254
Terra Markets	155	40	18	97
Total	**13 526**	**3 701**	**2 120**	**7 705**

6. Results

6.1 Initial Results

This section presents the initial results of our analysis of the 69 companies included in the OSEBX. We examine whether there are significant abnormal returns associated with the revisions in the three dimensions relevant to this thesis. The preliminary findings will add insights to answer the research questions.

6.1.1 Recommendation Revisions

Table 4: Market Reactions to Recommendation Revisions

The table presents CAARs for recommendation upgrades and downgrades over a three-day event window centred at the event day. The sample includes 3 701 recommendation revisions from January 1st, 2011, to September 30th, 2021. The market model is utilised as the normal return model, and the parameters are estimated over a 100-day estimation window [-105, -5]. The table presents the non-parametric GRANK test and the parametric BMP test statistics. ***, **, and * denote the 10%, 5%, and 1% significance level, respectively. Pos and Neg CAR represent the number of events in each revision direction associated with positive and negative CARs.

	CAAR	**GRANK**	**BMP**	**Pos CAR**	**Neg CAR**	***N***
Rec up	1.74%	14.57***	10.62***	1 220	599	1 819
Rec down	-1.92%	-11.05***	-11.65***	577	1 305	1 882

Table 4 illustrates the CAARs for recommendation revisions, as well as the parametric and non-parametric test statistics presented in section 4.8. Upgrades are associated with 1.74% abnormal returns conditional on the market model, while downgrades show abnormal returns of -1.92% over the event window. The sign of the abnormal returns is supportive of the informed analyst hypothesis. The market reaction is economically significant. 67.1% of the upgrades have positive CARs in our recommendation sample. Our findings show similar proportions in the direction of the revision for downgrades where 69.3% of the revisions have negative CARs. The impact of recommendation upgrades and downgrades are statistically significant at the one per cent level. The results are robust under the parametric as well as the non-parametric test statistics.

The findings of significant abnormal returns in the direction of the recommendation revision are consistent with the conclusions of several past studies which find a large economic impact associated with upgrades and downgrades (Ivković & Jegadeesh, 2004; Womack, 1996).

Further, the larger absolute effects associated with downgrades coincide with the results of the abovementioned research papers.

6.1.2 Target Price Revisions

Table 5 and 6 show the CAARs for revisions where the recommendation level is reiterated but the target price is revised. The distinction between HITP and LITP follows the definition in section 4.9 and 4.10.

Table 5: Market Reactions to High-Innovation Target Price Revisions

The table presents CAARs for HITP upgrades and downgrades over a three-day event window centred at the event day. The sample includes 2 120 HITP revisions from January 1st, 2011, to September 30th, 2021. The market model is utilised as the normal return model, and the parameters are estimated over a 100-day estimation window [-105, -5]. The table presents the non-parametric GRANK test and the parametric BMP test statistics. ***, **, and * denote the 10%, 5%, and 1% significance level, respectively. Pos and Neg CAR represent the number of events in each revision direction associated with positive and negative CARs.

	CAAR	**GRANK**	**BMP**	**Pos CAR**	**Neg CAR**	***N***
HITP up	2.07%	6.66***	5.83***	775	445	1 220
HITP down	-1.43%	-4.14***	-3.91***	367	533	900

The CAAR for high-innovation upgrades is 2.07% and -1.43% for downgrades. The results are aligned with the informed analyst hypothesis and suggest that target price revisions of high innovation are informative to investors. 63.5% of high-innovation target price upgrades show positive CARs, while 59.2% of the high-innovation target price downgrades are associated negative abnormal returns over the three-day event window. The parametric and non-parametric test statistics are significant at the one per cent level for both upgrades and downgrades. Nonetheless, partly due to smaller sample size, the average test statistic drops by approximately 50% for upgrades and 65% for downgrades compared to recommendation revisions. Our initial findings are consistent with Gleason and Lee (2003) who argue that high-innovation target price revisions are associated with significant abnormal returns and that they are relevant to investors.

Table 6: Market Reactions to Low-Innovation Target Price Revisions

The table presents CAARs for LITP upgrades and downgrades over a three-day event window centred at the event day. The sample includes 7 705 LITP revisions from January 1st, 2011, to September 30th, 2021. The market model is utilised as the normal return model, and the parameters are estimated over a 100-day estimation window [-105, -5]. The table presents the non-parametric GRANK test and the parametric BMP test statistics. ***, **, and * denote the 10%, 5% and, 1% significance level, respectively. Pos and Neg CAR represent the number of events in each revision direction associated with positive and negative CARs.

	CAAR	**GRANK**	**BMP**	**Pos CAR**	**Neg CAR**	***N***
LITP up	0.93%	7.67***	8.65***	2 540	1 961	4 501
LITP down	-0.70%	-5.04***	-6.03***	1 409	1 795	3 204

In the LITP sample, the economic magnitudes are smaller than the findings in the HITP sample. However, the effects are still statistically significant. LITP upgrades show CAAR of 0.93%, while the corresponding downgrades are associated with -0.70% abnormal return. 56.4% of low-innovation target price upgrades exhibit positive CARs, while 56.0% of low-innovation target price downgrades showcase negative CARs. The parametric and non-parametric test statistics are significant at the one per cent level. The statistical significance is generally higher than in the HITP sample due to much larger sample size but lower than the findings for recommendation revisions. The economic magnitude of HITP revisions is generally greater than LITP revisions by a factor of more than two. The difference in CAAR between HITP upgrades and LITP upgrades is statistically significant at the one per cent level[12]. The difference in the corresponding downgrades is significant at the five per cent level.

Our initial findings suggest that target price revisions in absence of recommendation revisions are informative to investors. The results correspond with the main conclusions in past studies and suggest that the degree of innovation in target price revisions, in absence of recommendation revisions, is relevant (Brav & Lehavy, 2003; Gleason & Lee, 2003).

6.1.3 Piggybacking and CAAR Development

As shown above, all the significance tests of upgrades and downgrades in our three samples of interest are significant at the one per cent level. The results are aligned with the informed analyst hypothesis. However, as shown by Altınkılıç and Hansen (2009), analysts are likely to piggyback company specific events that are driving abnormal returns. As an example, if

[12] We test the difference by the application of Welch’s t-test. The implementation is derived in appendix A.1.

Equinor reports unexpectedly strong earnings in the last completed fiscal quarter, the earnings announcement itself is likely to yield abnormal returns as good news is provided to the markets. If on the same day, or the day after, the analysts revise their assessments in the same direction as the news surprise, the analysis in the previous section will capture the company specific news as abnormal return related to analyst revisions. This has implications for inference. A strict causal interpretation of the results in the previous section adds spuriousness concerns. Further, if analysts primarily piggyback the information environment, our findings could be indicators of the news environment itself. A first measure to analyse the extensiveness of piggybacking is to examine the abnormal returns on the days surrounding the event date.

Table 7: Average Abnormal Returns Around the Revision Date

The table presents AARs for recommendation, HITP, and LITP revisions separated into upgrades and downgrades. ***, **, and * denote the 10%, 5% and, 1% significance level, respectively, from the non-parametric GRANK significance test.

	AAR -1	AAR 0	AAR 1	AAR 2	AAR 3
Rec up	0.24%***	1.08%***	0.41%***	0.03%	0.04%
Rec down	-0.12%*	-1.13%***	-0.68%***	-0.10%*	-0.11%*
HITP up	0.47%***	1.27%***	0.33%*	-0.05%	-0.06%
HITP down	-0.42%*	-1.04%***	0.04%	-0.10%	0.00%
LITP up	0.22%***	0.55%***	0.16%***	-0.06%	-0.06%
LITP down	-0.11%	-0.44%***	-0.15%**	-0.01%	0.19%**

Figure 4: Cumulative Average Abnormal Return Around the Revision Date

The figure presents the CAAR development [-2, 3] for recommendation, HITP, and LITP revisions separated into upgrades (U) and downgrades (D).

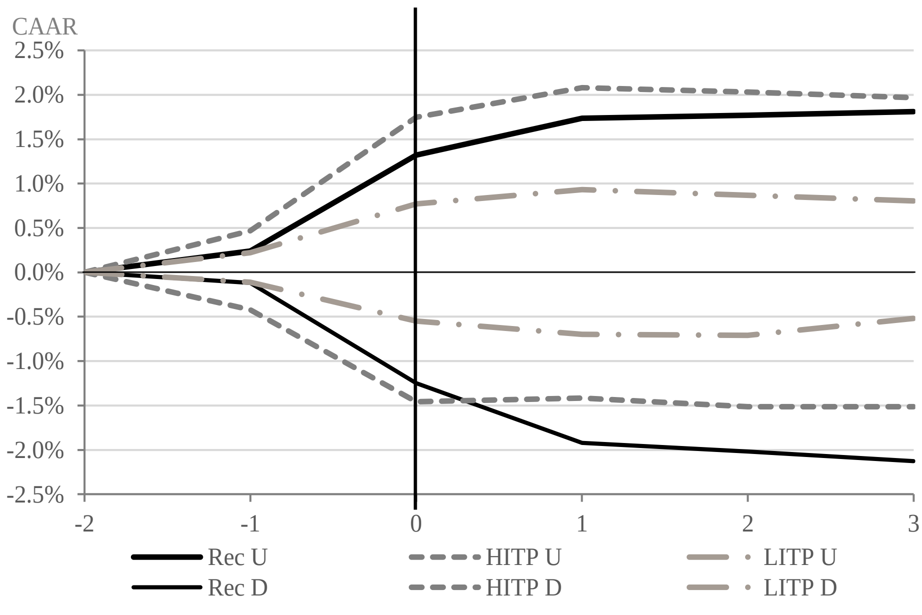


Figure 4 illustrates the development in the cumulative abnormal return around the event date. Upgrade revisions in all samples on the day before the event day have statistically significant abnormal returns at the one per cent level in the direction of the revision. This is evident from Table 7. The evidence indicates that analysts piggyback innovations to the information environment and make timely revisions to incorporate the new information into their analysis. We believe this is natural as analysts are employed to make assessments about the future prospects of the covered firms conditional on the information environment. This is consistent with the argumentation of Yezegel (2015). Nevertheless, there are no statistically significant[13] abnormal returns associated with downgrades on the day before the event day in any sample. Thus, if analysts piggyback the value-relevant changes to the news environment, the effect of this is stronger for upgrades than downgrades. Overall, there seems to be some evidence that analysts piggyback the information environment in their revisions.

Other insights from the table and figure above include that the information release adjacent to analyst revisions is quickly reflected in market prices and limited post-event drift is present in our revision samples. A quick response to innovations in the information environment is consistent with the EMH. Further, the abnormal returns on the day after the event day is statistically significant for both revision directions in the recommendation and LITP sample. This illustrates the importance of a wider event window than the event date itself.

6.1.4 Results in Absence of Earnings Announcements

In this section, we extend the analysis conducted above by excluding observations related to earnings announcements. The analysis corresponds with the methods of Jegadeesh and Kim (2006) presented in section 2. As such, all events where the event window and the earnings announcement dates overlap are removed from the sample, and the analysis is further conducted in the same manner as in the earlier parts of section 6.1.

15.6% of our total revision sample are revisions in conjunction with earnings announcements. The clustering around these news releases is expected as the company reports are comprehensive information documents from the management and are likely to provide new information to analysts and other market participants. This is also the finding of Ivković and

[13] At the five per cent significance level.

Jegadeesh (2004). Thus, if our initial results are changed due to the removal of events affiliated with earnings announcements, the value of analyst revisions will be more questionable.

Table 8: Market Reactions to Revisions Excluding Earnings Announcements

The table presents CAARs for recommendation, HITP, and LITP revisions over a three-day event window centred at the event day. The revisions are separated into upgrades (U) and downgrades (D). The Full sample includes all the 13 526 revisions in our study, whilst the Modified sample excludes all revisions where the event window overlaps earnings announcement dates. The table displays the non-parametric GRANK test and the parametric BMP test statistics. ***, **, and * denote the 10%, 5%, and 1% significance level, respectively. Difference is the deviation in CAAR between the Full sample and the Modified sample. Welch's t-test is utilised to test the statistical significance of the difference.

	Full sample				*Modified sample*				
	CAAR	**GRANK**	**BMP**	***N***	**CAAR**	**GRANK**	**BMP**	***N***	**Difference**
Panel A: Recommendations									
Rec U	1.74%	14.57***	10.62***	1 819	1.66%	14.42***	11.39***	1 525	0.08%
Rec D	-1.92%	-11.05***	-11.65***	1 882	-1.86%	-12.03***	-12.57***	1 568	-0.06%
Panel B: HITP									
HITP U	2.07%	6.66***	5.83***	1 220	1.77%	5.63***	4.89***	978	0.30%
HITP D	-1.43%	-4.14***	-3.91***	900	-0.74%	-2.65***	-2.68***	748	-0.69%*
Panel C: LITP									
LITP U	0.93%	7.67***	8.65***	4 501	-0.59%	5.08***	5.32***	3 826	0.34%***
LITP D	-0.70%	-5.04***	-6.03***	3 204	-0.24%	-2.38**	-3.29***	2 775	-0.46%***

Table 8 displays the results for the full sample and when events adjacent to earnings announcements are omitted from the analysis. In the modified sample, recommendation upgrades and downgrades show a small decline in the absolute level of CAAR compared to the full sample, but the change is neither economically nor statistically significant. Thus, the evidence suggests that earnings announcement piggybacking is not a factor changing our results in the recommendation revision dimension.

The economic magnitude of HITP revisions decreases in the modified sample. Nonetheless, the difference is not statistically significant, and the results are broadly consistent with the findings in section 6.1.2. Further, we note that HITP upgrades still show the highest economic magnitude of all specified upgrades. In addition, HITP revisions are associated with asymmetrical market reactions as the economic magnitude of HITP downgrades is approximately halved in the modified sample compared to the full sample. This suggests that HITP downgrades are associated with economically large market reactions clustered around earnings announcement releases. However, partly due to the smaller sample size, the decrease is only statistically significant at the 10 per cent level. The signal effects remain statistically significant at the one per cent level for the parametric and non-parametric tests alike. Thus, our results suggest that HITP revisions are relevant to investors in absence of earnings announcements in the information environment.

Abnormal returns associated with LITP revisions are statistically different at the one per cent level in the modified sample compared to the full sample. The difference is consistent with a smaller market reaction in the direction of the revision. The reduction in the economic magnitude of the revisions is large, especially for downgrades. Thus, earnings announcements are significantly enhancing the revision signal amidst LITP revisions, and the results are consistent with piggybacking. Nonetheless, the signal effects remain statistically significant in the direction of the revision. Thus, while earnings announcements enhance the economical magnitude of LITP revisions, the evidence suggests that the revision signal is relevant to investors in absence of earnings news.

Overall, our initial findings in section 6.1 are to some extent supportive of Altınkılıç and Hansen's (2009) argument that analyst piggybacking of innovations to the information environment can explain some of the evidence in the literature in support of the informed analyst hypothesis. However, the main conclusions from the full samples in support of the informed analyst view remain largely unchanged when revisions in conjunction with earnings announcements are removed from the sample. This result coincides with the findings of Jegadeesh and Kim (2006). Nonetheless, the removal of revisions adjacent to earnings announcements eliminates only one type of news event from the information environment. Thus, the greater part of the information environment is likely intact, and a strict causal interpretation of the results may not be warranted. This is discussed more is section 7. We find some evidence that revisions represent indicators of the information environment itself.

6.2 Multivariate Regression Analysis

Our initial results suggest that analyst revisions are informative to investors. The sign of the CAARs is supportive of the informed analyst view. However, this section will add a more comprehensive analysis controlling for other factors that affect abnormal returns amidst analyst revisions. We follow the general convention in the literature and conduct a multivariate regression analysis (MacKinlay, 1997; Kliger & Gurevich, 2014). We will discuss the key revision variables and comment on the controls.

We separate the regression analysis into three the samples of recommendation, HITP, and LITP revisions, consistent with the previous section. In this way, our analysis will answer whether the different dimensions of analyst revisions relevant to this thesis are informative to investors. The key variable of interest is the revision-level upgrade variable in each regression, specifically *Rec up*, *HITP up*, and *LITP up*. These variables capture the difference in CAR of an upgrade compared to a downgrade, conditional on controls. If the analyst revisions are informative, there should be a statistically significant difference between upgrades and downgrades. A comprehensive description of the variables and the variable design is presented in section 4.12 and 4.13.

Further, the multivariate regression analysis will present two model specifications: Base model and Full model. The former model controls for factors not directly affiliated with analyst revisions. The latter model adds two additional controls: The brokerage level variable market presence and the revision event variable relative RPD. The models run on all three samples mentioned in the paragraph above. Thus, a total of six regressions will be presented initially. To further examine the potential impact of analyst piggybacking on our coefficients, and for robustness, Table 10 will present the regression results when revision events overlapping earnings announcements are dropped from the samples. A third model will complete this section, where we assume symmetrical effects for the control variables in our model design.

6.2.1 Base Model

This section will present and discuss the regression results from the Base model specification.

Table 9: CAR on Analyst Revisions

The table presents pooled OLS regressions where CAR [-1, 1] associated with analyst revisions is the dependent variable. *Rec up*, *HITP up*, and *LITP up* are dummy variables equal to one for upgrade revisions. All control variables presented as *up* and *down* are separated into upgrade and downgrade effects. All control variables are dummy variables. *Relative RPD* is equal to one if the relative number of revisions within the event window is in the top quintile for the relevant firm. *Market presence* is equal to one if the revision is made from an analyst employed at a top five brokerage firm in terms of market presence in the Norwegian market. *Firm size* is equal to one if the relevant firm is among the top ten largest firms in terms of market capitalisation at the end of the previous year. *Momentum* is equal to one if the relevant firm's [-6, -1] month return is in the top quartile across the sample. *Covid-19 crash* is equal to one if the revision was made between February 20th, 2020, and March 20th, 2020. *Covid-19 recovery* is equal to one if the revision was made between March 21st, 2020, and November 30th, 2020. *Company news* is equal to one if company specific news is released in the event window. *Pos (Neg) SUE* is equal to one if the revision is associated with a top (bottom) quartile SUE announcement. *Earnings* is equal to one if the revision event window overlaps an earnings announcement release. *Book-to-market* is equal to one if the relevant firm's ratio is in the bottom quartile at the end of the previous year. Standard errors (in parenthesis) are robust and clustered by day. ***, **, and * denote the 10%, 5%, and 1% significance level, respectively, of a two-sided t-statistic.

	Dependent variable:					
	CAR [-1,1]					
		Base model			Full model	
	(Rec 1)	(HITP 1)	(LITP 1)	(Rec 2)	(HITP 2)	(LITP 2)
Rec up	0.047***			0.040***		
	(0.004)			(0.003)		
HITP up		0.032***			0.021***	
		(0.005)			(0.005)	
LITP up			0.011***			0.010***
			(0.002)			(0.002)
Relative RPD up				0.013***	0.024***	0.021***
				(0.004)	(0.005)	(0.002)
Relative RPD down				0.005	-0.025***	-0.020***
				(0.004)	(0.006)	(0.003)
Market presence up				0.005*	0.009**	0.002
				(0.003)	(0.004)	(0.001)
Market presence down				-0.006**	0.001	-0.0001
				(0.003)	(0.006)	(0.002)
Firm size up	-0.012***	-0.014***	-0.006***	-0.011***	-0.016***	-0.007***
	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)
Firm size down	0.013***	0.003	0.001	0.012***	0.007	0.002
	(0.003)	(0.005)	(0.002)	(0.003)	(0.005)	(0.002)
Momentum up	-0.012***	-0.012***	-0.006***	-0.012***	-0.011***	-0.007***
	(0.003)	(0.004)	(0.001)	(0.003)	(0.004)	(0.001)
Momentum down	-0.009***	-0.012	-0.011***	-0.009***	-0.013*	-0.012***
	(0.003)	(0.007)	(0.003)	(0.003)	(0.007)	(0.003)
Covid-19 crash up	-0.028	0.010	0.017	-0.029	0.029	0.016
	(0.019)	(0.097)	(0.022)	(0.019)	(0.108)	(0.022)
Covid-19 crash down	-0.005	-0.040***	-0.032	-0.003	-0.038***	-0.031
	(0.035)	(0.012)	(0.021)	(0.035)	(0.013)	(0.021)
Covid-19 recovery	0.003	0.023***	0.009***	0.002	0.023***	0.010***
	(0.007)	(0.005)	(0.002)	(0.007)	(0.005)	(0.002)
Company news up	0.023**	0.009	0.005*	0.021**	0.008	0.005*
	(0.009)	(0.007)	(0.003)	(0.009)	(0.007)	(0.003)
Company news down	0.008	0.006	0.008**	0.008	0.006	0.007**
	(0.007)	(0.016)	(0.004)	(0.006)	(0.016)	(0.004)
Pos SUE	0.021***	-0.010	0.011***	0.017***	-0.006	0.010***
	(0.006)	(0.011)	(0.004)	(0.005)	(0.009)	(0.003)
Neg SUE	-0.024***	-0.033**	-0.017***	-0.028***	-0.035***	-0.021***
	(0.006)	(0.013)	(0.005)	(0.006)	(0.012)	(0.004)
Earnings up	0.002	0.023***	0.018***			
	(0.005)	(0.008)	(0.003)			
Earnings down	0.001	-0.024***	-0.024***			
	(0.005)	(0.009)	(0.004)			
Book-to-market up	-0.006	-0.003	-0.0002			
	(0.004)	(0.004)	(0.001)			
Book-to-market down	-0.002	0.002	0.002			
	(0.005)	(0.006)	(0.002)			
Constant	-0.022***	-0.009**	-0.003*	-0.021***	-0.006	-0.002
	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)	(0.001)
N	3,701	2,120	7,705	3,701	2,120	7,705
Adjusted R^2	0.131	0.106	0.082	0.136	0.117	0.087
F statistic	35.766***	16.658***	44.079***	37.376***	18.505***	46.694***

The three revision variables of interest, *Rec up*, *HITP up*, and *LITP* up, are all significant at the one per cent level and the sign is aligned with the informed analyst view. In general, the results are consistent with the findings of Chang and Chan (2008), Asquith et al. (2005), and Gleason and Lee (2003). The economic magnitude of HITP revisions is larger by a factor of approximately three compared to LITP revisions. This suggests that the degree of innovation is relevant for the informativeness of analyst revisions in absence of recommendation revisions. Further, the signal is strongest in the recommendation dimension where the difference in CAR between upgrades and downgrades is 4.7 percentage points. The evidence suggests a hierarchy where the signalling is strongest in the recommendation dimension and weakest amidst LITP revisions.

The *Firm size up* coefficients suggest that the upgrade signal is weaker when the revision firm is large in terms of firm size. Specifically, the abnormal return associated with upgrade revisions in the recommendation and HITP samples are 1.2 and 1.4 percentage points smaller, respectively, if the revision firm is among the top ten largest companies in our sample at the end of the previous year. Large firms have greater analyst coverage; thus, the marginal revision should be less informative also if analyst revisions are informative to investors in general. Past studies find similar effects (Ivković & Jegadeesh, 2004; Chang & Chan, 2008). Further, transaction costs are typically lower for larger firms. The variable may capture differences in transaction costs across the event samples such that smaller firms have higher gross returns. The results are more ambiguous for downgrades where the effects are symmetrical in the Rec 1 model but statistically insignificant in the HITP 1 and LITP 1 models. A cautionary note should be made about potential risk factors in the true asset pricing model that are omitted in the market model used in our analysis. If the loadings to these risk factors are large and different for large and small firms, inference could be spurious.

The momentum coefficients are negative and significant at the one percentage level in all models but when revisions are HITP downgrades. Thus, the overall evidence is corresponding with a broad sell-off effect for all types of revisions. A possible explanation could be that investors holding the stock exploit the extra attention and interest in the stock to realise profits. Analyst revisions are extensively referred to in the financial media. Thus, a revision might trigger attention and liquidity from a wider audience than the clientele of the respective brokerage firms. The reasoning is supported by Jegadeesh & Kim (2006) who find evidence of abnormal trading volume in conjunction with recommendation revisions.

The Covid-19 crash variables capture differences in the revision signal during the market turmoil in February and March 2020. Loh and Stulz (2018) find that analyst recommendations are associated with larger effects in the direction of the revision during crises periods. One could argue that an upgrade during the market crash would be exceptionally surprising and potentially be associated with a stronger signal. However, this is not supported in our empirical findings as the *Covid-19 crash up* coefficients are insignificant in all models. The *Covid-19 crash down* coefficient is insignificant in the LITP 1 model, but also in the Rec 1 model, contrary to the finding of Loh and Stulz (2018). Nevertheless, in the HITP 1 model, the effect is economically and statistically significant at the one per cent level in the direction of the revision. The great volatility during this period suggests that the information environment was unstable and highly dynamic. Thus, one can argue that the amount of new information was inflated and that the cost of acquiring all value-relevant information was higher than normal. The results are ambiguous, but there is some evidence that analysts made timely and relevant aggregations of the information flow as the HITP revision signal is strengthened.

The SUE coefficients are statistically significant at the one per cent level with the expected sign for all dimensions except the top quartile SUE in conjunction with HITP revisions[14]. The control variable seems well specified for the purpose of controlling for the unexpected result component in quarterly earnings announcements.

The earnings coefficients are insignificant in the Rec 1 model. This suggests that after controlling for SUE, the signal from recommendation revisions adjacent to earnings announcements is not stronger than normal. This is consistent with our findings in section 6.1.4. However, the earnings coefficients in the HITP and LITP dimensions are significant, economically large, symmetrical, and indicate higher abnormal returns in the direction of the revision. This suggests that the effect of analyst piggybacking is relatively stronger in the target price dimensions around earnings announcements, but also that target price revisions are to some extent indicators of the value-relevant qualitative information in earnings releases.

The company news variable examines the effects of M&A, capital transactions, as well as contract announcements adjacent to analyst revisions. The *Company news up* coefficient is

[14] We highlight that the SUE coefficients are not conditional on the revision direction as for most of the other control variables. See section 4.12 and 4.13 for more details.

statistically significant at the five per cent level in the Rec 1 model. Thus, the signal from recommendation upgrades is stronger in conjunction with releases of company specific news. Nonetheless, the overall results are ambiguous as *Company news down* is significant with the unexpected sign in the LITP sample. Contrary to the findings of Altınkılıç and Hansen (2009), the evidence is not supportive of a broad company news effect in line with the direction of the revision. A possible explanation could be that the I/B/E/S data for Norwegian companies are less refined and noisier compared to larger capital markets such as the United States. In addition, the company news variable is not exhaustive, and a great part of the information environment may be intact despite our controls. This is discussed more in section 7.

The book-to-market variables are included to capture differences in relation to analyst revisions for growth stocks. Nonetheless, there are no significant effects in any model in our study. Thus, we conclude that growth stocks are not reacting differently to analyst revisions.

6.2.2 Full Model

In the Full model, we add the market presence and relative RPD variables to the regression models. We remove the book-to-market variable due to insignificant effects in all samples under the Base model specification. In addition, the earnings dummies are excluded due to high correlations with the relative RPD variable[15]. Since the other controls have been discussed extensively above, we proceed with discussions only if there are significant changes in the coefficients.

Our *Rec up*, *HITP up*, and *LITP up* coefficients remain statistically significant at the one per cent level in the Full model specification, and the conclusions are unchanged from the Base model. The results are broadly consistent with the findings of Francis and Soffer (1997) and Brav and Lehavy (2003). In addition, the results are supportive of Grossman and Stiglitz's (1980) argumentation that costly information gathering and processing should be compensated. However, the economic magnitudes are reduced in all samples compared to the Base model and especially in the HITP sample. The results are aligned with the informed analyst view in all dimensions and are generally consistent with most of the academic literature focused on the short-term effects of analyst revisions.

[15] See appendix A.5 for VIF tests and correlation matrixes.

The most interesting invention in our Full model specification is the relative RPD variable. As evident from Table 9, the revision signal is strengthened in all dimensions and revision directions except for recommendation downgrades. The practical interpretation is that a high number of revisions for the relevant firm within the event window increase the magnitude of the revision signal. If analysts are truly informative to investors, this is intuitively appealing. Frankel et al. (2006) find similar effects. Nonetheless, the variable captures events where the number of revisions for the relevant firm is abnormally large. Analysts are naturally revising their assessment of the relevant firm if a change to the overall information environment causes a change in the fundamental value of the company. Thus, the variable may be an indicator of a change in the information environment itself. This is supported by the high correlation between the relative RPD variables and the earnings announcement dummies[16]. If analysts are excellent at aggregating information and make timely revisions to large changes to the information environment, then some of the effect of this could be captured in the relative RPD coefficients.

The *Market presence up* variable is significant at the five per cent level if the analyst revision is a HITP upgrade but fails to be statistically significant at the five per cent level under any other revision dimension. The *Market presence down* variable is only statistically significant at the five per cent level in the Rec 2 model. If the analyst belongs to an institution with a top five market presence in the Norwegian market, there might be synergies in the information gathering process that could potentially result in superior research that is informative to investors. In addition, as suggested by Stickel (1995), brokerage firms with a higher market share are likely to have larger marketing budgets and potentially greater reach of their information. Overall, our empirical results are ambiguous across the three dimensions. However, there is some evidence suggesting that the signal is stronger in the recommendation dimension if the brokerage firm has a top five market presence in the Norwegian market.

6.2.3 Excluding Earnings Announcements

This section will present the regression results where events adjacent to earnings announcements are removed from the samples.

[16] See appendix A.5

Table 10 shows that our key coefficients of interest, *Rec up, HITP up,* and *LITP up,* are slightly reduced in terms of economic magnitude compared to the full sample coefficients in Table 9. However, all main conclusions remain unchanged and aligned with the informed analyst view. The results are broadly consistent with our findings in section 6.1.4 and the conclusion of Jegadeesh and Kim (2006). Thus, the evidence suggests that revisions are informative to market participants when earnings announcement news is eliminated from the information environment.

Interestingly, the relative RPD variables are similar in terms of economic and statistical significance compared to the coefficients in Table 9. The exception is the *Relative RPD down* coefficient in the LITP sample which is halved in economic magnitude and only significant at the 10 per cent level. However, since the coefficients are generally similar in absence of revisions in conjunction with earnings announcements, the evidence is more robust that the revision signal is stronger, especially for upgrades, when a large number of analysts make revisions at the same time for the relevant firm. Nevertheless, the great correlation between the relative RPD variable and the earnings dummies suggests that the clustered revisions are associated with major news events. However, a possible interpretation of the results in Table 10 is that the relative RPD variable captures other types of large changes to the information environment, as discussed in section 6.2.2. The variable itself adds insights to the effect of revisions, and since this study focuses on the individual revision-level effect, the variable is an important control.

The other coefficients are largely unchanged, but we note that the market presence variable is statistically significant for both recommendation upgrades and downgrades. Thus, the evidence is strengthened that a top five market presence enhances the revision signal in the recommendation dimension. The *Company news up* variable turns statistically significant at the five per cent level in the HITP 2 model and the *Company news down* variable is no longer significant with the unexpected sign in the LITP 2 regression. Thus, the overall evidence from this section is more supportive of the findings of Altınkılıç and Hansen (2009) for upgrades.

Table 10: CAR on Analyst Revisions Excluding Earnings Announcements

The table presents pooled OLS regressions where CAR [-1, 1] associated with analyst revisions is the dependent variable. *Rec up*, *HITP up*, and *LITP up* are dummy variables equal to one for upgrade revisions. All control variables presented as *up* and *down* are separated into upgrade and downgrade effects. All control variables are dummy variables. *Relative RPD* is equal to one if the relative number of revisions within the event window is in the top quintile for the relevant firm. *Market presence* is equal to one if the revision is made from an analyst employed at a top five brokerage firm in terms of market presence in the Norwegian market. *Firm size* is equal to one if the relevant firm is among the top ten largest firms in terms of market capitalisation at the end of the previous year. *Momentum* is equal to one if the firm's [-6, -1] month return is in the top quartile across the sample. *Covid-19 crash* is equal to one if the revision was made between February 20th, 2020, and March 20th, 2020 (note: *Covid-19 crash up* is omitted from HITP 1 and HITP 2 due to zero associated observations). *Covid-19 recovery* is equal to one if the revision was made between March 21st, 2020, and November 30th, 2020. *Company news* is equal to one if company news is released in the event window. Standard errors are robust and clustered by day. ***, **, and * denote the 10%, 5%, and 1% significance level, respectively, of a two-sided t-statistic.

	Dependent variable:					
	CAR [-1,1]					
		Base model			Full model	
	(Rec 1)	(HITP 1)	(LITP 1)	(Rec 2)	(HITP 2)	(LITP 2)
Rec up	0.044***			0.037***		
	(0.004)			(0.004)		
HITP up		0.030***			0.019***	
		(0.004)			(0.005)	
LITP up			0.010***			0.007***
			(0.002)			(0.002)
Relative RPD up				0.020***	0.021***	0.019***
				(0.006)	(0.005)	(0.003)
Relative RPD down				0.005	-0.022***	-0.009*
				(0.006)	(0.007)	(0.005)
Market presence up				0.006**	0.007*	0.002
				(0.003)	(0.004)	(0.001)
Market presence down				-0.007**	0.004	0.001
				(0.003)	(0.006)	(0.002)
Firm size up	-0.010***	-0.014***	-0.006***	-0.009***	-0.015***	-0.006***
	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)
Firm size down	0.012***	0.0002	-0.0002	0.010***	0.003	-0.0001
	(0.003)	(0.005)	(0.002)	(0.003)	(0.005)	(0.002)
Momentum up	-0.013***	-0.012***	-0.005***	-0.013***	-0.011***	-0.005***
	(0.003)	(0.004)	(0.001)	(0.003)	(0.004)	(0.001)
Momentum down	-0.011***	-0.012	-0.009***	-0.012***	-0.013*	-0.010***
	(0.003)	(0.008)	(0.003)	(0.003)	(0.007)	(0.003)
Covid-19 crash up	-0.025		0.027	-0.028		0.027
	(0.019)		(0.025)	(0.019)		(0.025)
Covid-19 crash down	-0.001	-0.036***	-0.040*	0.001	-0.034**	-0.040*
	(0.035)	(0.013)	(0.022)	(0.035)	(0.013)	(0.023)
Covid-19 recovery	0.002	0.023***	0.008***	0.001	0.023***	0.008***
	(0.008)	(0.006)	(0.003)	(0.008)	(0.006)	(0.003)
Company news up	0.022**	0.018**	0.003	0.020**	0.017**	0.003
	(0.011)	(0.008)	(0.003)	(0.010)	(0.007)	(0.003)
Company news down	0.010	0.003	0.005	0.011	0.003	0.005
	(0.007)	(0.017)	(0.004)	(0.007)	(0.017)	(0.004)
Constant	-0.022***	-0.008**	-0.001	-0.019***	-0.005	-0.001
	(0.003)	(0.003)	(0.001)	(0.003)	(0.004)	(0.001)
N	3,056	1,703	6,341	3,056	1,703	6,341
Adjusted R^2	0.122	0.072	0.023	0.131	0.091	0.034
F statistic	43.581***	15.736***	15.643***	33.944***	14.149***	16.782***

6.2.4 Symmetrical Effects

In this section, we show the results assuming symmetrical effects for the control variables that we separated into dummies associated with upgrades and downgrades in Table 9. In general, if the effects are symmetrical, the number of upgrades and downgrades in each sample will be irrelevant. If the effects are asymmetrical, the coefficients assuming symmetrical effects will show the direction weighted average effect for upgrades and downgrades in the sample.

The *Rec up*, *HITP up*, and *LITP up* coefficients remain economically and statistically unchanged. The R^2 does not materially change by assuming symmetrical effects which suggests that the overall loss of information is low. Thus, our main conclusions are robust to the symmetrical model specification.

Relative RPD becomes insignificant under the symmetrical assumption in model Rec 2. This follows naturally from Table 9 where the coefficients in the recommendation sample are clearly not symmetrical. In addition, we note that the *Market presence* variable is significant at the one per cent level assuming symmetrical effects in model Rec 2 in Table 11. The overall conclusion that a brokerage firm's market presence seems to be relevant in the recommendation dimension remains unchanged from previous discussions.

In section 6.2.1, we detect that there seems to be a general sell-off effect for high momentum stocks regardless of the direction of the revisions in all samples. Thus, the *Momentum* variable is misspecified in the symmetrical effects models in Table 11. Further, the *Company news* variable is insignificant in both model specifications and all samples under the symmetrical effect assumption. This follows naturally as the coefficients from Table 9 have the same sign in relation to both upgrades and downgrades.

In conclusion, if most effects are symmetrical, the model design in this section may be preferred. However, if the effects are not symmetrical, the specification presented in Table 9 will be more informative. This section illustrates that the model specification assuming symmetrical effects does not affect the main conclusion of this study and information loss is minimal. However, some control variables change in terms of statistical significance and to some extent economic interpretation.

Table 11: CAR on Analyst Revisions Assuming Symmetrical Effects

The table presents pooled OLS regressions where CAR [-1, 1] associated with analyst revisions is the dependent variable. *Rec up*, *HITP up*, and *LITP up* are dummy variables equal to 1 for upgrade revisions. All control variables except *Covid-19 recovery* assume symmetrical effects for downgrade and upgrade revisions (-1, 0, 1). *Relative RPD* is equal to 1 (-1) if the relative number of revisions within the event window is in the top quintile for the relevant firm and the associated revision is an upgrade (downgrade). *Market presence* is equal to 1 (-1) if the revision is made from an analyst employed at a top five brokerage firm in terms of market presence in the Norwegian market and the associated revision is an upgrade (downgrade). *Firm size* is equal to 1 (-1) if the relevant firm is among the top ten largest firms in terms of market capitalisation at the end of the previous year and the associated revision is an upgrade (downgrade). *Momentum* is equal to 1 (-1) if the firm's [-6, -1] month return is in the top quartile across the sample and the associated revision is an upgrade (downgrade). *Covid-19 crash* is equal to 1 (-1) if the revision was made between February 20th, 2020, and March 20th, 2020, and the associated revision is an upgrade (downgrade). *Covid-19 recovery* is equal to 1 if the revision was made between March 21st, 2020, and November 30th, 2020. *Company news* is equal to 1 (-1) if company news is released in the event window and the associated revision is an upgrade (downgrade). *SUE* is equal to 1 (-1) if the revision is associated with a top (bottom) quartile SUE announcement. *Earnings* is equal to 1 (-1) if the revision event window overlaps an earnings announcement release and the associated revision is an upgrade (downgrade). *Book-to-market* is equal to 1 (-1) if the relevant firm's ratio is in the bottom quartile at the end of the previous year and the associated revision is an upgrade (downgrade). Standard errors (in parenthesis) are robust and clustered by day. ***, **, and * denote the 10%, 5%, and 1% significance level, respectively, of a two-sided t-statistic.

	Dependent variable:					
	CAR [-1,1]					
		Base model			Full model	
	(Rec 1)	(HITP 1)	(LITP 1)	(Rec 2)	(HITP 2)	(LITP 2)
Rec up	0.047***			0.040***		
	(0.004)			(0.003)		
HITP up		0.034***			0.020***	
		(0.005)			(0.005)	
LITP up			0.012***			0.010***
			(0.002)			(0.002)
Relative RPD				0.004	0.023***	0.020***
				(0.003)	(0.004)	(0.002)
Market presence				0.006***	0.006*	0.001
				(0.002)	(0.003)	(0.001)
Firm size	-0.013***	-0.009***	-0.004***	-0.012***	-0.011***	-0.005***
	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)
Momentum	-0.001	-0.006*	-0.001	-0.001	-0.006*	-0.001
	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)
Covid-19 crash	-0.015	0.037***	0.026	-0.015	0.036***	0.025
	(0.014)	(0.010)	(0.017)	(0.014)	(0.011)	(0.017)
Covid-19 recovery	0.004	0.024***	0.010***	0.004	0.024***	0.010***
	(0.007)	(0.005)	(0.002)	(0.007)	(0.005)	(0.002)
Company news	0.006	0.003	-0.001	0.006	0.002	-0.0002
	(0.005)	(0.008)	(0.002)	(0.005)	(0.008)	(0.002)
SUE	0.022***	0.013	0.014***	0.022***	0.014*	0.015***
	(0.003)	(0.008)	(0.002)	(0.003)	(0.008)	(0.002)
Earnings	0.0005	0.020***	0.020***			
	(0.003)	(0.006)	(0.002)			
Book-to-market	-0.001	-0.003	-0.001			
	(0.003)	(0.003)	(0.001)			
Constant	-0.025***	-0.015***	-0.006***	-0.021***	-0.009***	-0.005***
	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)
N	3,701	2,120	7,705	3,701	2,120	7,705
Adjusted R^2	0.121	0.096	0.075	0.124	0.107	0.080
F statistic	57.657***	25.974***	70.788***	59.137***	29.257***	75.482***

7. Discussion and Future Research

This section will discuss our findings, limitations in our research design, and elaborate on possible future extensions to our research.

This study has found empirical evidence aligned with the informed analyst view. An explanation for the findings can be found in the work of Grossman and Stiglitz (1980). They argue that prices reflect the cost of information. Thus, informed arbitrageurs should receive compensation for the resources spent on obtaining information. If the analysts are intermediaries and release their assessments from their costly information gathering process by the means of recommendation and target price revisions, our results could be explained by this argument in the literature. Our findings are consistent with a disequilibrium in prices that compensates information acquirers.

However, a discussion of the interpretation of our results is warranted. Our empirical findings suggest that analysts to some degree piggyback their revisions on changes in the overall information environment. A strict causal interpretation of our results, that the revisions directly cause abnormal returns of the magnitudes presented in section 6, adds spuriousness concerns. This interpretation of our results implicitly assumes that we are successful at controlling for all exogenous changes to the information environment. This is highly unlikely as we only capture and control for a small portion of the information flow that in aggregate determines stock prices. In addition, the evidence that analysts piggyback their revisions to innovations in the information environment is not surprising. In fact, if this was not the case, we could argue that analysts are not doing what they are employed to do: Analyse the stocks' prospects conditional on the information environment. We find that analysts indeed make timely revisions to reflect the information environment of the stock and that these revisions are relevant to market participants. However, an interpretation that analysts themselves create new information and release this to financial markets by their revisions is more questionable.

Our research asks several questions that we are not able to answer on how analyst revisions are affecting stock prices. A first possible extension to this thesis is to examine the role of target price changes conditional on the recommendation change in the Norwegian market. The interaction between the two revision dimensions could reveal incremental or heterogeneous signalling effects. This analysis is left to future research. A second extension could be to examine the interactions between the different elements of the analyst report. Analyst reports are extensive documents, and a study of the information value of each element will add to this thesis, especially if these characteristics are examined conditional on the revision change. Further, the relative RPD variable could be researched more closely. Specifically, since the number of aggregate analyst revisions are relevant, then a natural extension would be to investigate the interaction between the individual reports and whether the publishing order or characteristics at the report-level are relevant when revisions are clustered. This will also enable an investigation of whether analysts are affected by the revisions of other analysts.

Another extension to our analysis is to investigate smaller time increments similar to Altınkılıç and Hansen (2009). This thesis focuses exclusively on daily observations. If the analysis were to be conducted at minutely or hourly return observations, the spuriousness concern addressed in this section would be mitigated as the potential changes to the information environment would be less predominant.

Further, a more comprehensive measure of news controls could be implemented. Sophisticated techniques such as the application of textual analysis similar to Frank and Sanati (2018) could potentially reveal associations not detected in our study and mitigate noise in the variable design. Textual analysis facilitates more refined categorisation of the news. Thus, differences in the revision signal associated with different news types could be examined more closely.

This study does not examine the characteristics of the investors acting on the revision signals. A natural extension to our thesis is to investigate this question in the Norwegian market context. Hsieh and Lee (2021) find that foreign institutions and domestic mutual funds are the primarily users of analyst reports and that individual investors are liquidity providers to institutions. As our results are consistent with a sell-off effect in the Norwegian market amidst analyst revisions for high momentum stocks, an analysis of the characteristics of liquidity providers and takers is an interesting extension to our study.

Another natural continuance of our research would be to examine the post-revision drift over a longer time interval in the Norwegian market context. Specifically, an interesting analysis could be to investigate if the effects in support of the informed analyst view are persistent. Future research could also extend this thesis by applying the calendar portfolio approach (Jaffe, 1974). This would add a different methodological framework for robustness and enable analysis of long-short portfolios based on the revision signals. The calendar approach would also be the preferred analytical framework for analysis over longer time intervals.

Our data sample is limited to the 69 companies on the OSEBX as of September 2021. Thus, survivorship bias as well as introduction bias might be present in our study. Future research would benefit from a sample of all stocks that have entered the OSEBX within the relevant time period and a restriction on new listings may be added.

8. Conclusion

This study examines the informational value of analyst recommendation revisions and target price revisions in absence of recommendation changes in the broader Norwegian market. By the application of the event study framework, we investigate whether analyst revisions are associated with abnormal returns and whether the informed analyst hypothesis is supported in a Norwegian market context. Since there is reason to believe that the relevance of target price revisions in absence of recommendation revisions is conditional on the degree of innovation by the analyst, we separate target price revisions by their innovation potential.

Our results suggest that recommendation revisions are informative to investors. The revisions are associated with economically large and statistically significant abnormal returns for both upgrades and downgrades. In addition, the conclusions are robust to different model specifications and the exclusion of revisions adjacent to earnings announcements. Thus, our findings in the broader Norwegian market are in support of the informed analyst view and consistent with the majority of the academic literature.

The findings support that target price revisions in absence of recommendation revisions are informative to investors. The revisions are associated with economically meaningful and statistically significant abnormal returns in both revision directions. The results align with the informed analyst view, and the thesis adds more evidence to the literature about the relevance of target price revisions. The degree of innovation is relevant as the economic effect of high-innovation target price revisions is larger by a factor of two to three compared to low-innovation target price revisions.

We observe that the market reaction following analyst revisions is larger under certain conditions. Overall, the signalling effect of analyst revisions is magnified if a large number of analysts are making revisions for the relevant firm at the same time. The effect of recommendation revisions is stronger if the analyst is employed at a brokerage firm with high market presence in the Norwegian market and weaker if the company size is large. In addition, we detect a sell-off effect where high-momentum stocks are associated lower nominal CARs regardless of the revision dimension and direction.

We find evidence that the revision signals are magnified by innovations to the information environment in terms of news and events not directly related to the analyst. This is not surprising, but it questions the validity of a strict causal interpretation of our results. In conclusion, our findings suggest that analysts are providing timely aggregations of the information environment and that the revisions are relevant to market participants.

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Appendix

A.1 Welch's Test

Welch's t-test is utilised to determine whether there is a difference between the abnormal returns in the full sample compared to the modified sample where revisions in conjunction with earnings announcements are removed. In addition, the test is applied to examine the difference in abnormal return between HITP and LITP revisions. The parametric t-test is extensively applied in the literature to test differences in means (Gleason & Lee, 2003; Womack, 1996). Welch's t-test assumes sample independence and normality. We use the cross-sectional variance in the calculation due to the established mean effects in the revisions (MacKinlay, 1997):

$$T = \frac{CAAR_1 - CAAR_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{25}$$

where

$$s_i^2 = \frac{\sum_{j=1}^{n_i}(CAR_{j,i} - CAAR_i)^2}{n_i - 1} \tag{26}$$

$CAAR_i$ and s_i^2 are the sample i^{th} cumulative average abnormal return and sample variance.

A.2 BMP Test

The BMP test developed by Boehmer et al. (1991) standardises the abnormal returns by the estimation period prediction errors and then the cross-sectional standard deviation to make the test robust to event-induced volatility. Thus, the test can be viewed as a combination of the test developed by Patell (1976) and the standard cross-sectional t-test.

The standardised abnormal return (SAR) is calculated according to Patell (1976):

$$SAR_{i,t} = \frac{AR_{i,t}}{\widehat{s}_i \sqrt{C_{i,t}}} \tag{27}$$

where

$$C_{i,t} = 1 + \frac{1}{T_i} + \frac{\left(r_{m,e} - \overline{r_m}\right)^2}{\sum_{T=1}^{T_i}\left(r_{m,t} - \overline{r_m}\right)^2} \tag{28}$$

$AR_{i,t}$ represents the abnormal return at time t, $\widehat{s}_i$ is the standard deviation of the estimation period disturbance term defined in section 4.5, $C_{i,t}$ is the forecast-error adjustment for predictions outside the estimation period, T represents the length of the estimation window, $r_{m,t}$ is the market return on day t, $r_{m,e}$ is the market return on event day e, and $\overline{r_m}$ is the average market return during the estimation window.

The BMP test statistic for H_0: $AAR = 0$ is defined as:

$$t_{BMP} = \sqrt{n}\frac{\overline{SAR_t}}{S_{\overline{SAR_t}}} \tag{29}$$

where n represents the sample size, $\overline{SAR_t}$ is the sample average standardised abnormal return at event time t. $S_{\overline{SAR_t}}$ is the cross-sectional standard deviation of $\overline{SAR_t}$ where the variance can be formalized as:

$$Var(\overline{SAR_t}) = \frac{1}{n-1}\sum_{i=1}^{n}\left(SAR_{i,t} - \overline{SAR_t}\right)^2 \tag{30}$$

Further, we follow the practice of Kolari and Pynnönen (2010) and define the BMP test statistic for H_0: $CAAR = 0$ as:

$$t_{BMP} = \sqrt{n}\frac{\overline{SCAR}}{S_{\overline{SCAR}}} \tag{31}$$

where

$\overline{SCAR}$ represents the sample average standardised cumulative abnormal return and $S_{\overline{SCAR}}$ is the cross-sectional standard deviation of $\overline{SCAR}$.

A.3 GRANK Test

The Generalised rank test (GRANK) was developed by Kolari and Pynnönen (2011). The test relies on the standard assumption of stock returns being white noise continuous random variables with:

$$E[r_{i,t}] = \mu_i \text{ for all t} \tag{32}$$

$$var[r_{i,t}] = \sigma_i^2 \text{ for all t} \tag{33}$$

$$cov[r_{i,t}, r_{iu}] = 0 \text{ for all t} \neq \text{u} \tag{34}$$

where i is a stock index, and u and t are time indexes.

The GRANK utilises the standardised abnormal returns (SAR) with the estimation period residuals as the variance estimate.

$$SAR_{i,t} = \frac{AR_{i,t}}{S_{AR_i}} \tag{35}$$

where S_{AR_i} represents the standard deviation of the prediction errors in the abnormal returns.

The CAR of security i over d event days (event period) is formalized by:

$$CAR_{i,t} = \sum_{t=t_1+1}^{t_1+d} AR_{i,t} \tag{36}$$

where $T_1 \leq t_1 \leq T_2 - d$ and $1 \leq d \leq L_2$.

Kolari and Pynnönen (2011) define the standardised cumulative abnormal return, SCAR, as:

$$SCAR_{i,d} = \frac{CAR_{i,d}}{S_{CAR_{i,d}}} \tag{37}$$

where $S_{CAR_{i,d}}$ is the standard deviation of the prediction errors of the cumulative abnormal returns.

Further, to be robust against event-induced volatility, the SCARs are re-standardised by the cross-sectional standard deviation in accordance with Boehmer et al. (1991). According to Kolari and Pynnönen (2011), the re-standardised SCAR is given by:

$$SCAR_i^* = \frac{SCAR_{i,d}}{S_{SCAR}} \tag{38}$$

where

$$S_{SCAR} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(SCAR_{i,d} - \overline{SCAR_d})}^{2} \tag{39}$$

represents the cross-sectional standard deviation of $SCAR_{i,d}$. $\overline{SCAR_d}$ is the average SCAR.

Further, Kolari and Pynnönen (2011) consider $SCAR_i^*$ as a single observation of abnormal return, the cumulative event day, and define the Generalised Standardised Abnormal Return (GSAR):

$$GSAR_{i,t} = SAR_{i,t} \; in \; estimation \; window, SCAR_i^* \; in \; event \; window$$

The test will consider the estimation period (abnormal) returns and the last cumulative event day return so that the standardised abnormal rank will have $L_1 + 1$ observations and be given by:

$$U_{i,t} = \frac{Rank\left(GSAR_{i,t}\right)}{L_1 + 2} - 0.5 \tag{40}$$

where *i* is stock 1 to *n* and *t* is the time index of the estimation window observations and the cumulative event day.

The null hypothesis of no mean effect for all *i* is:

$$E\left[U_{i,0}\right] = 0 \tag{41}$$

where time index 0 is the cumulative event day.

The GRANK test can then be defined as[17]:

$$T_{grank} = Z\left(\frac{L_1 - 1}{L_1 - Z^2}\right)^{\frac{1}{2}} \tag{42}$$

where

$$Z = \frac{\overline{U_o}}{S_{\bar{U}}} \tag{43}$$

and

$$S_{\bar{U}} = \sqrt{\frac{1}{L+1}\sum_{t\in T^*}\frac{n_t}{n}\bar{U}_t^2} \tag{44}$$

$$\bar{U}_t = \frac{1}{n_t}\sum_{i=1}^{n_t} U_{i,t} \tag{45}$$

T^* represents the available elements in the combined window of the estimation period and the cumulative event day. n_t is the number of $GSAR_{i,t}$ at time t. $\overline{U_o}$ is the $\overline{U_t}$ at the cumulative event day. The test of H_0: $AAR = 0$ is straightforward with minor adjustments to the elaboration above.

[17] Kolari and Pynnönen (2011) defines $T = L_1 + 1$.

A.4 Symmetrical Effects Ex. Earnings Announcements

Table 12: CAR on Revisions Ex. Earnings Announcements with Symmetrical Effects

The table presents pooled OLS regressions where CAR [-1, 1] associated with analyst revisions is the dependent variable. *Rec up*, *HITP up*, and *LITP up* are dummy variables equal to 1 for upgrade revisions. All control variables except *Covid-19 recovery* assume symmetrical effects for downgrade and upgrade revisions (-1, 0, 1). *Relative RPD* is equal to 1 (-1) if the relative number of revisions within the event window is in the top quintile for the relevant firm and the associated revision is an upgrade (downgrade). *Market presence* is equal to 1 (-1) if the revision is made from an analyst employed at a top five brokerage firm in terms of market presence in the Norwegian market and the associated revision is an upgrade (downgrade). *Firm size* is equal to 1 (-1) if the relevant firm is among the top ten largest firms in terms of market capitalisation at the end of the previous year and the associated revision is an upgrade (downgrade). *Momentum* is equal to 1 (-1) if the firm's [-6, -1] month return is in the top quartile across the sample and the associated revision is an upgrade (downgrade). *Covid-19 crash* is equal to 1 (-1) if the revision was made between February 20th, 2020, and March 20th, 2020, and the associated revision is an upgrade (downgrade). *Covid-19 recovery* is equal to 1 if the revision was made between March 21st, 2020, and November 30th, 2020. *Company news* is equal to 1 (-1) if company news is released in the event window and the associated revision is an upgrade (downgrade). Standard errors (in parenthesis) are robust and clustered by day. ***, **, and * denote the 10%, 5%, and 1% significance level, respectively, of a two-sided t-statistic.

	Dependent variable:					
	CAR [-1,1]					
	Base model			Full model		
	(Rec 1)	(HITP 1)	(LITP 1)	(Rec 2)	(HITP 2)	(LITP 2)
Rec up	0.045***			0.038***		
	(0.004)			(0.004)		
HITP up		0.029***			0.018***	
		(0.004)			(0.005)	
LITP up			0.010***			0.007***
			(0.002)			(0.002)
Relative RPD				0.007	0.022***	0.015***
				(0.004)	(0.004)	(0.003)
Market presence				0.006***	0.003	0.0005
				(0.002)	(0.003)	(0.001)
Firm size	-0.011***	-0.008***	-0.003***	-0.010***	-0.010***	-0.003***
	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)
Momentum	0.0002	-0.006*	-0.001	0.0003	-0.005	-0.001
	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)
Covid-19 crash	-0.014	0.036***	0.035**	-0.015	0.035***	0.035**
	(0.014)	(0.013)	(0.017)	(0.014)	(0.013)	(0.017)
Covid-19 recovery	0.004	0.025***	0.008***	0.004	0.024***	0.009***
	(0.008)	(0.006)	(0.003)	(0.008)	(0.006)	(0.003)
Company news	0.004	0.009	-0.001	0.003	0.008	-0.0004
	(0.006)	(0.009)	(0.002)	(0.006)	(0.009)	(0.002)
Constant	-0.024***	-0.011***	-0.004***	-0.020***	-0.006**	-0.002*
	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)
N	3,056	1,703	6,341	3,056	1,703	6,341
Adjusted R^2	0.110	0.066	0.018	0.113	0.085	0.028
F statistic	63.658***	21.013***	20.464***	49.856***	20.775***	23.903***

A.5 VIF Analysis and Correlation Matrixes

Table 13: VIF Analysis of the Regression Variables

The table presents VIF analysis of the regression variables presented in Table 9. Rec 1 and Rec 2 are recommendation sample models, HITP 1 and HITP 2 are HITP sample models, and LITP 1 and LITP 2 are LITP sample models.

	Rec 1	**HITP 1**	**LITP 1**	**Rec 2**	**HITP 2**	**LITP 2**
Rec up	2.64			3.29		
HITP up		2.73			2.99	
LITP up			2.81			3.04
Relative RPD up				1.30	1.42	1.30
Relative RPD down				1.32	1.34	1.24
Market presence up				1.30	1.33	1.29
Market presence down				1.34	1.34	1.41
Firm size up	1.37	1.16	1.26	1.37	1.19	1.28
Firm size down	1.38	1.19	1.34	1.39	1.20	1.37
Momentum up	1.16	1.30	1.20	1.16	1.30	1.21
Momentum down	1.19	1.09	1.09	1.19	1.09	1.09
Covid-19 crash up	1.01	1.01	1.01	1.01	1.01	1.01
Covid-19 crash down	1.01	1.04	1.01	1.02	1.04	1.01
Covid-19 recovery	1.02	1.04	1.01	1.02	1.02	1.01
Company news up	1.05	1.04	1.04	1.04	1.04	1.03
Company news down	1.05	1.06	1.05	1.04	1.06	1.05
Pos SUE	1.58	1.60	1.61	1.15	1.16	1.18
Neg SUE	1.56	1.51	1.52	1.12	1.04	1.12
Earnings up	1.65	1.87	1.81			
Earnings down	1.77	1.54	1.60			
Book-to-market up	1.12	1.24	1.19			
Book-to-market down	1.12	1.35	1.26			

Table 14: Correlation Matrix of the Variables in the Recommendation Dimension

The table presents the correlation matrix of the independent variables from Table 9 in the recommendation sample. All control variables presented as U and D are separated into upgrade and downgrade effects. The Covid-19 variables are uncorrelated with the other variables and omitted from the presentation.

	Rec U	Relative RPD U	Relative RPD D	Market pres. U	Market pres. D	Firm size U	Firm size D	Momen-tum U	Momen-tum D	Company news U	Company news D	Pos SUE	Neg SUE	Earnings U	Earnings D	Book-to-market U	Book-to-market D
Rec U	1																
Relative RPD U	0.375	1															
Relative RPD D	-0.383	-0.144	1														
Market presence U	0.462	0.190	-0.177	1													
Market presence D	-0.473	-0.177	0.186	-0.219	1												
Firm size U	0.497	0.151	-0.190	0.138	-0.235	1											
Firm size D	-0.485	-0.182	0.182	-0.224	0.089	-0.241	1										
Momentum U	0.349	0.148	-0.134	0.146	-0.165	0.096	-0.169	1									
Momentum D	-0.373	-0.140	0.141	-0.172	0.166	-0.185	0.076	-0.130	1								
Company news U	0.185	0.108	-0.071	0.126	-0.087	0.044	-0.089	0.073	-0.069	1							
Company news D	-0.191	-0.072	0.060	-0.088	0.113	-0.095	0.082	-0.067	0.070	-0.035	1						
Pos SUE	0.006	0.216	0.210	0.020	0.019	-0.009	-0.026	0.022	0.002	0.0005	-0.005	1					
Neg SUE	-0.029	0.152	0.206	-0.011	0.022	-0.035	-0.033	-0.014	0.011	0.024	-0.003	-0.051	1				
Earnings U	0.310	0.645	-0.119	0.185	-0.147	0.084	-0.150	0.139	-0.116	0.082	-0.059	0.346	0.273	1			
Earnings D	-0.308	-0.115	0.635	-0.142	0.184	-0.153	0.066	-0.107	0.119	-0.057	0.050	0.327	0.380	-0.095	1		
Book-to-market U	0.281	0.106	-0.108	0.174	-0.133	0.031	-0.136	0.129	-0.105	0.154	-0.054	0.004	0.013	0.142	-0.086	1	
Book-to-market D	-0.266	-0.100	0.081	-0.123	0.185	-0.132	-0.001	-0.093	0.188	-0.049	0.130	-0.013	0.055	-0.083	0.133	-0.075	1

Table 15: Correlation Matrix of the Variables in the HITP Dimension

The table presents the correlation matrix of the independent variables from Table 9 in the HITP sample. All control variables presented as U and D are separated into upgrade and downgrade effects. The Covid-19 variables are uncorrelated with the other variables and omitted from the presentation.

	HITP U	Relative RPD U	Relative RPD D	Market pres. U	Market pres. D	Firm size U	Firm size D	Momen-tum U	Momen-tum D	Company news U	Company news D	Pos SUE	Neg SUE	Earnings U	Earnings D	Book-to-market U	Book-to-market D
HITP U	1																
Relative RPD U	0.438	1															
Relative RPD D	-0.447	-0.195	1														
Market presence U	0.475	0.192	-0.212	1													
Market presence D	-0.492	-0.215	0.267	-0.233	1												
Firm size U	0.338	0.189	-0.151	0.024	-0.166	1											
Firm size D	-0.372	-0.163	0.262	-0.176	0.110	-0.126	1										
Momentum U	0.463	0.146	-0.207	0.262	-0.228	0.075	-0.172	1									
Momentum D	-0.254	-0.111	0.052	-0.120	0.161	-0.086	0.024	-0.118	1								
Company news U	0.172	0.091	-0.077	0.074	-0.085	0.014	-0.064	0.067	-0.044	1							
Company news D	-0.207	-0.091	0.038	-0.098	0.085	-0.070	0.009	-0.096	0.106	-0.036	1						
Pos SUE	0.132	0.336	0.009	0.057	-0.065	0.023	-0.039	0.048	-0.052	0.018	-0.042	1					
Neg SUE	-0.062	0.086	0.190	-0.039	0.079	-0.055	0.013	-0.045	-0.010	-0.036	-0.017	-0.056	1				
Earnings U	0.318	0.586	-0.142	0.145	-0.156	0.037	-0.118	0.116	-0.081	0.039	-0.066	0.532	0.234	1			
Earnings D	-0.335	-0.147	0.553	-0.159	0.280	-0.113	0.086	-0.155	0.040	-0.058	0.011	0.066	0.421	-0.106	1		
Book-to-market U	0.435	0.229	-0.194	0.169	-0.214	0.144	-0.161	0.212	-0.110	0.014	-0.090	0.062	-0.023	0.137	-0.146	1	
Book-to-market D	-0.487	-0.213	0.232	-0.231	0.241	-0.165	0.237	-0.226	0.049	-0.084	0.041	-0.058	0.004	-0.155	0.124	-0.212	1

Table 16: Correlation Matrix of the Variables in the LITP Dimension

The table presents the correlation matrix of the independent variables from Table 9 in the LITP sample. All control variables presented as U and D are separated into upgrade and downgrade effects. The Covid-19 variables are uncorrelated with the other variables and omitted from the presentation.

	LITP U	Relative RPD U	Relative RPD D	Market pres. U	Market pres. D	Firm size U	Firm size D	Momen-tum U	Momen-tum D	Company news U	Company news D	Pos SUE	Neg SUE	Earnings U	Earnings D	Book-to-market U	Book-to-market D
LITP U	1																
Relative RPD U	0.321	1															
Relative RPD D	-0.347	-0.111	1														
Market presence U	0.448	0.184	-0.155	1													
Market presence D	-0.513	-0.165	0.226	-0.230	1												
Firm size U	0.422	0.123	-0.146	0.059	-0.216	1											
Firm size D	-0.492	-0.158	0.157	-0.220	0.121	-0.207	1										
Momentum U	0.386	0.144	-0.134	0.209	-0.198	0.041	-0.190	1									
Momentum D	-0.277	-0.089	0.095	-0.124	0.163	-0.117	0.069	-0.107	1								
Company news U	0.172	0.088	-0.060	0.078	-0.088	0.031	-0.085	0.070	-0.048	1							
Company news D	-0.207	-0.066	0.071	-0.093	0.109	-0.087	0.088	-0.080	0.042	-0.036	1						
Pos SUE	0.103	0.361	0.042	0.090	-0.050	0.012	-0.058	0.030	-0.023	0.030	-0.027	1					
Neg SUE	-0.078	0.086	0.270	-0.010	0.074	-0.064	0.009	-0.044	0.039	-0.001	0.023	-0.050	1				
Earnings U	0.294	0.615	-0.102	0.220	-0.151	0.035	-0.145	0.115	-0.081	0.091	-0.061	0.522	0.202	1			
Earnings D	-0.322	-0.103	0.575	-0.144	0.239	-0.136	0.073	-0.124	0.113	-0.055	0.095	0.121	0.445	-0.095	1		
Book-to-market U	0.383	0.132	-0.133	0.140	-0.196	0.133	-0.188	0.141	-0.106	-0.009	-0.079	0.043	-0.041	0.069	-0.123	1	
Book-to-market D	-0.447	-0.144	0.158	-0.200	0.197	-0.188	0.223	-0.173	0.077	-0.077	0.036	-0.049	-0.001	-0.132	0.095	-0.171	1