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Positively deviating
- A study on reversed profit warnings and market reactions

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Abstract

This thesis examines the initial and long-term market reactions following reversed profit warnings on the Nordic markets. Furthermore, it investigates if firm size and trading volume can explain the magnitude of the market reaction. The study is based on 118 reversed profit warnings announced on the Nordic markets during 2010-2019 applying an event study approach, measuring abnormal returns. To examine if firm size and trading volume affects the market reaction, this study uses a regression analysis to complement the event study. Results show a significant initial market reaction, confirming that the market is genuinely surprised by a profit warning. In accordance with the efficient market hypothesis, the market is also seen to correct its expectations based on the new information. The initial reaction is more substantial for smaller firms and higher trading volume is seen to increase abnormal returns. Our long-term results show a significant reversal in share price, indicating that there is an overreaction to reversed profit warnings. The long-term regression results show that neither firm size nor trading volume explain the reversal in share price.

Keywords Reversed profit warnings, abnormal returns, event study, efficient market hypothesis, Nordic markets.

1. Introduction

During recent years, both academia and practitioners have shown an increasing interest in corporate transparency and the disclosure of price sensitive information (Dye, 2001; Verrecchia, 2001). One example of disclosure that has received a lot of attention since the 1990s and contain price sensitive information are profit warnings[1]. The interest in profit warnings[2] is reflected in the extensive amount of studies, media coverage and markets speculations (Jackson and Madura, 2003; Collett, 2004; Bulkley and Herrerias, 2005; Jackson and Madura, 2007; Alves et al., 2009; Church and Donker, 2010; Spohr, 2014; Cox et al., 2017). Although traditional warnings[3] is a well-studied subject, there seem to be a lack of studies exploring reversed warnings[4], especially covering the long-term market reaction and factors impacting it.

Jackson and Madura (2003) studies traditional warnings on the U.S market between the years 1998-2000, and find that the initial market reaction, measured in abnormal returns during the announcement day to be -14.72%. In a subsequent study on the London Stock Exchange, ranging between 1995-2001, results show abnormal returns of -15.10% for the traditional warnings (Collett, 2004). Thereafter, a variety of studies have analyzed the initial market reaction following traditional warnings and report results deviating between -13.40% to -6.10% (Bulkley and Herrerias, 2005; Jackson and Madura, 2007; Alves et al., 2009; Church and Donker, 2010; Spohr, 2014; Cox et al., 2017). Consistent with these prior findings, is that new information generates a correction in share price in the same direction as the news (Fama, Fisher, Jensen and Roll, 1969; Ball and Kothari, 1991; Amir and Lev, 1996). Hence, strengthening the semi-strong form of the efficient market hypothesis by Fama (1970).

To our knowledge there are only two studies focusing on the initial market reaction following reversed warnings. Collett (2004) finds that reversed warnings yield an initial abnormal return of 4.28%. Spohr (2014) investigates the Nordic markets between 2005-2011, and find an initial abnormal return of 4.78% on the announcement day. This would further strengthen that the

[1] Voluntary trading update that signals a material deterioration in profitability and earnings relative to market expectations (Alves, Pope and Young, 2009).
[2] Henceforth referred to as "warnings".
[3] The term traditional warning is used when referring to the announcement when profits are negatively deviating from the market's expectations.
[4] A reversed warning is an announcement based on the same fundament as a traditional warning, with the one exception that the profits are positively deviating from the market's expectations (Collett, 2004; Spohr, 2014).

prevailing information asymmetry on capital markets (Jensen and Meckling, 1976) is reduced when a warning is disclosed (Healy and Palepu, 2001; Church and Donker, 2010). Thus, the quick adjustment in share price after a reversed warning seem to be comparable to the one observed for traditional warnings.

Light has also been shed on the long-term market reactions following traditional warnings. Jackson and Madura (2003) find the long-term abnormal return, measured between announcement day +11 to +60, to be positive by 1.49% and statistically significant. Their results could be interpreted as there is an overreaction to the announcement of a traditional warning, where there is a correction over time. Nevertheless, these results are in contrast to Bulkley and Herrerias (2005) and Pukthuanthong (2010) who find the long-term market reaction to be negative. Bulkley and Herrerias (2005) study the U.S market between 1998-2000 and investigate the three months after a traditional warning is announced. Their results show a negative return of -1.98%, measured in buy-and-hold abnormal returns (BHAR). Pukthuanthong (2010) studies the U.S market between 1997-2009 and find the long-term return following a traditional warning to be negative by -4.05%, investigating a six-month period after the announcement. Similar to Bulkley and Herrerias (2005), Pukthuanthong (2010) applies (BHAR) to measure the outcome. Thus, there seem to be controversies regarding the long-term reaction following traditional warnings. As these research papers are conducted in the U.S, future studies should also test if the findings remain when examining other markets. Furthermore, we find no prior study examining the long-term reaction following reversed warnings, why we argue that there is a knowledge-gap in previous research.

Regardless of studied periods, authors investigating warnings find that certain factors explain the magnitude of the market reaction (Jackson and Madura, 2003; Collett, 2004; Jackson and Madura, 2007). Jackson and Madura (2003) find a significant greater price decrease in small firms compared to large firms, when measuring the initial returns following traditional warnings. Similar results are found in Collett (2004), who observe a significant difference in share price returns when comparing small, medium and large firms by their market value. A contradictory finding is presented by Jackson and Madura (2007) where results show no significant impact of firm size. The magnitude of a market reaction following a warning is also argued to be corresponding with trading volume (Collett, 2004; Cox et al., 2017; Dayanandan, 2018). In Collett (2004), results show that there is an increased trading volume following the announcement of profit warnings. A similar result is found in Cox et al. (2017), where they observe that high trading volume increase changes in share price following issued warnings. In addition, Dayanandan et al. (2018) show that trading volume following traditional warnings have a positive impact on abnormal returns. Therefore, when examining the market reaction following warnings one should emphasize the importance of firm size and trading volume.

Our literature review shows that studies focusing on reversed warnings are underrepresented in the academic literature. Further on, no previous studies focusing on reversed warnings have examined the long-term returns following these announcements. There also seem to be an interest in how firm size and trading volume impact a market reaction. With this paper, we therefore add a deeper theoretical understanding on how markets react both initially and in the long-term, following reversed warnings. In addition, we contribute new practical knowledge for investors regarding the long-term returns following announcements of reversed warnings. As Spohr (2014) is the most recent paper studying market reactions following reversed warning, we extend his research by looking at a different time period on the Nordic markets, contributing with new insight in the long-term market reaction. Following Collett (2004) and Spohr (2014), we rely on the assumption that reversed warnings falls under the same theoretical framework as traditional warnings.

1.2 Purpose

The purpose of this study is to investigate the initial and long-term market reactions following reversed warnings on the Nordic markets. A secondary aim is to analyze if firm size and trading volume could explain the magnitude of the market reaction, measured in abnormal returns. With no known study covering more recent market conditions, this study focus on the period between 2010-2019. With the above purpose this study formulates its research questions as following:

How does the Nordic markets react to a reserved warning in an initial and long-term period?

What impact does firm's size and trading volume have on the initial and long-term market reaction following a reversed warning?

2. Theoretical framework

2.1 Efficient market hypothesis

The capital market have an important function to fill in how the economy allocates and prices securities while assessing risk. The concept of capital markets being efficient was first introduced by Fama (1970) and explicates how the stock market reacts and adjusts to the available information. How the information is interpreted further influences the share price returns. Fama (1970) determines that the efficient market hypothesis (EMH) consists of three different forms; weak, semi-strong and strong. These forms are based on the degree to which information is reflected in the share price.

Under weak market conditions, share prices will reflect all historical information of past returns (Fama, 1970). Supposing that markets are efficient under the weak form, investors cannot receive abnormal returns from performing analysis on historical returns (ibid). Prices are instead determined by random walk, where price changes are independent of previous information (Kendall, 1953). These findings are supported by Brealey and Myers (2000), who state that current share prices do not give any indications of forthcoming prices. The value of shares reflects historical prices as well as all published information available in the semi-strong form. In the case of a semi-strong market, announcements and new information are directly reflected in the share price. Consistently, when new information is announced, it will cause quick adjustments in share prices, implying that the market is effective under the semi-strong form (Kohtari, 2001). Lastly, in the strong form of market efficiency, share prices will reflect all available information, even the news that is concealed and secluded, e.g. insider information (Fama, 1970). In a market characterized by a strong form, there is no possibility for investors to outperform the market, meaning that the investors will price the securities correctly (Keown and Pinkerton, 1981). Under such market conditions, insiders should not be able to obtain excess returns from advantaged asymmetric information (Fama, 1970).

Though, there are evidence showing that capital markets are not always efficient nor correct in its pricing of securities (Ball and Kothari, 1991; DeBondt and Thaler, 1987; Subrahmanyam, 1996; Easterwood and Nutt, 1999). DeBondt and Thaler (1987) find that the market is not able to rationally price information disclosed, leading to evidence of investor overreactions. Another example is presented by Easterwood and Nutt (1999), who find indications of that investors, along with analysts, seem to overvalue positive earnings announcements while they seem to undervalue negative announcements.

2.2 Markets initial reactions following warnings

Capital markets are characterized by information asymmetry (Jensen and Meckling, 1976), where announcements of warnings are seen to reduce the asymmetry between market participants (Church and Donker, 2010). As warnings reduces diverging expectations, the market is said to revise its beliefs based on the new information (Jackson and Madura, 2003). Consequently, new information generates a correction in share price in the same direction as the news (Beaver, 1968; Fama et al., 1969; Ball and Kothari, 1991; Amir and Lev, 1996). Following the EMH, firms that disclose warnings would thereby face an almost immediate correction in share price, much because of the fact that investors and analysts have a more updated belief about the firm.

Prior research within this field find varying results regarding the initial abnormal return on the day of disclosure. The reasons for the diverging findings are further explained by the differences in scope of study, observed time-periods, and examined markets. Table 1 displays findings from prior studies considering the traditional warning as an isolated event, testing the semi-strong form of EMH.

Table 1. *Previous research showing abnormal returns (AR) on the announcement day of traditional warnings.*

Market	**AR**	**Period**	**Source**
U.S	-14.72%	1998–2000	Jackson and Madura (2003)
U.K	-15.10%	1995–2001	Collett (2004)
U.S	-13.38%	1995–2012	Cox et al. (2017)
U.S	-8.08%	1998–2000	Bulkley and Herrerias (2005)
Europe	-10.89%	1997–2007	Alves et al. (2009)
Netherlands	-6.12%	2002	Church and Donker (2010)
Nordic	-6.10%	2005–2011	Spohr (2014)

Even though the initial market reaction following a traditional warning is of varying magnitude, all the above studies find a quick adjustment in expectations, implying that the market is efficient under the semi-strong form of EMH. According to Jackson and Madura (2003), the reaction following the warnings indicate information asymmetry between the firm's management and the markets expectations. Similarly, Collett (2004) interprets it as the stock market is indeed surprised by the warning, why there is a sudden change in share price. In addition to their findings, Church and Donker (2010) argue that firms could alleviate the initial negative reaction following warnings by providing more extensive financial information to the market, thereby lowering the information asymmetry. Cox et al. (2017) concludes that the initial market reaction is significantly greater for warning firms compared to the ones who do not announce warnings. There is a significant difference in price reactions if the warning is announced during an economic expansion or during a recession (ibid).

Table 2. *Previous research showing abnormal returns (AR) on the announcement day of reversed warnings.*

Market	**AR**	**Period**	**Source**
U.K	4.28%	1995–2001	Collett (2004)
Nordic	4.78%	2005–2011	Spohr (2014)

The two known studies investigating market reactions following reversed warnings document an explicit adjustment in expectations on the announcement day (Collett, 2004; Spohr 2014). Similar as for traditional warnings, there is a clear market reaction in terms of sudden price change. Comparing findings on reversed warnings with the traditional ones, there is a greater reaction following traditional warnings. This smaller reaction observed for reversed warnings is contradicting to findings in Easterwood and Nutt (1999), showing that the market on average overvalue positive earnings announcements, resulting in greater reaction following positively deviating news. Furthermore, Spohr (2014) find that the abnormal returns following reversed warnings occur during the day of the warning, whilst it for traditional warnings continue during four days. This would indicate that the market is better at processing reversed warnings compared to traditional ones.

2.3 Markets long-term reactions following warnings

As warnings occur sporadically and vary in terms of deviation, they should be viewed as a surprise to the market (Collett, 2004; Spohr, 2014; Cox et al., 2017). When investors and analysts react to such information, correcting their expectations in line with the new information, they are sometimes incorrect in their pricing of securities (DeBondt and Thaler, 1987; Bernard and Thomas 1989; Subrahmanyam, 1996; Easterwood and Nutt, 1999). According to DeBondt and Thaler (1987), the wrongly correction to new information is due to human bias in information processing. Thus, the mispricing lead to share prices fluctuating more than usual, until there is a consensus price on the market (Subrahmanyam, 1996). If mispricing occurs, studies show that it could take days, weeks or even months until a correction is complete, known as a post-earnings-announcement drift (PEAD) (Bernard and Thomas, 1989). In case of a PEAD, the share price continues in the same direct as the news (ibid). With market reactions following warnings being of larger magnitude compared to scheduled earnings announcements, prior studies also examine the long-term abnormal returns after the announcement (Jackson and Madura, 2003; Bulkley and Herrerias, 2005; Pukthuanthong, 2010).

Table 3. *Observed long-term returns after the announcement of a negative warning.*

Market	Measure	Result	Horizon	Period	Source
U.S	BHAR	-4.05%	6 Months	1997–2009	Pukthuanthong (2010)
U.S	BHAR	-1.98%	3 Months	1998–2000	Bulkley and Herrerias (2005)
U.S	CAR	1.49%	49 Days	1998–2001	Jackson and Madura (2003)

Table 3 illustrates the results where the market reaction is either measured in buy-and-hold abnormal returns (BHAR) or cumulative abnormal return (CAR).

Jackson and Madura (2003) examine the long-term market reaction using a traditional event study approach and find a positive cumulative abnormal return of 1.49% in the period of 11 to 60 (49 days) after the negative warning is announced. Even though their results show a positive long-term return, it is still insufficient to invert the prior decrease in share price observed at the initial reaction. Nevertheless, their results show a significant reversal in share price that may indicate that there is an overreaction to the initial announcement. In contrast to Jackson and Madura (2003), the two other studies focusing on the long-term period conclude returns to be negative (Bulkley and Herrerias, 2005; Pukthuanthong, 2010). Bulkley and Herrerias (2005) measure the long-term return by BHAR, for a period of 60 days after a traditional warning has been announced. They find the long-term abnormal return to be -1.98%. Bulkley and Herrerias (2005) further test if there is a difference in share price returns depending on the warning being qualitative[5] or quantitative[6]. Their results show that the quantitative warnings result in less substantial negative abnormal return during the period. A similar approach is also applied by Pukthuanthong (2010), who examines the six months after the warning and finds the BHAR of six months to be -4.05%. Important to consider is that results may differ due to the divergence in methodological assumptions. However, there are still indications of controversies regarding the long-term reaction related to warnings.

2.4 The impact of firm size

The time it takes for the market to react to new information have been previously examined by Brennan, Jegadeesh and Swaminathan (1993) and Holden and Subrahmanyam (2002). Both studies find that that information processing on the market will be relative to the number of analysts following the firm and the size (i.e. market value) of the firm. Documented in studies focusing on both types of warnings, is that large firms experience less drastic price changes, compared to small firms (Jackson and Madura, 2003; Collett, 2004; Bulkley and Herrerias, 2005; Church and Donker, 2010). The smaller market reaction among large firms are though viewed differently among authors.

Firstly, Jackson and Madura (2003) argue that larger firms are more frequently monitored by investors, why the market is better at anticipating warnings for larger firms compared with smaller ones. Consistent with their reasoning, they find that smaller firms experience a more extensive market reaction in share price interpreting this as the market is more surprised by the warning (ibid). Secondly, Collett (2004) reasons that larger firms are often seen in media and followed by a higher number of analysts. The author further adds that there might be an overreaction among smaller firms. In his study results show that small firms observe a significantly larger return relative to medium- and large firms. Consequently, there is a more pronounced reaction for the observations having lower market values (ibid). Thirdly, Bulkley and Herrerias (2005) find that the initial- and long-term market reaction following the announcement of a traditional warning is greater for small firms. In their study they divide their

[5] Quantitative warnings differ from qualitative, by the one difference that they also contain a revised forecast for the forthcoming profits (Bulkeley and Herrerias, 2005).
[6] Qualitative warnings solely include information of whether the upcoming results will be better or worse than the markets current expectations (Bulkeley and Herrerias, 2005).

data sample into deciles based on their market value and find that there are evident differences between smaller firms (ibid). Fourthly, Church and Donker (2010) argue that there are higher transparency requirements for large firms. As a result, analysts are more correct in their estimations of larger firms, why a deviating profit is foreseen by the market, leading to a smaller observable market reaction (ibid).

However, in Jackson and Madura (2007) there is a similar reasoning as above, but with a conflicting outcome. In their study, results show that there is no significant difference in market reaction depending on firm size. Consistent with Jackson and Madura (2007), Spohr (2014) find no impact of firm size when investigating traditional warnings. Taken as a whole, findings show deviating results regarding the impact of firm size why it is motivated to test further for reversed warnings.

2.5 The impact of trading volume

The magnitude of a market reaction could also be determined by trading volume (Osborne, 1959; Ying, 1966; Beaver 1968; Kim and Verrecchia, 1991). Osborne (1959), finds that the number of traded shares generate a higher variance in a share price returns. Another early finding by Ying (1966) show that increases in trading volumes are generally accompanied by a rise or decline in share price when examining the New York Stock Exchange over a six-year period. Beaver (1968) argues that the change in share price will reflect how investors perceive new information, whilst trading volume reflects an individual's idiosyncratic[7] reactions. Recognizing that investors are diversely informed and differ in beliefs, they will revise current expectations due to new information, leading to new transactions on the market (Kim and Verrecchia, 1991).

As trading volume is perceived as an important aspect of market reactions, prior research studying warnings do also take that aspect into concern (Collett, 2004; Cox et al., 2017; Dayanandan et al., 2018). Collett (2004) find that trading volume increases to a significantly higher level on the day of the announcement and the following day, suggesting that investors are capable of obtaining and processing new information in a short time. Cox et al. (2017), studies the U.S market between 1995-2012, covering traditional warnings over a full business cycle, and find that trading volume increase the change in share price during the announcement

[7] Behavior or emotions that are unique to an individual.

day. Dayanandan et. al (2018) study the U.S market between 1995-2012, with an interest in corporate goodness following warnings. They find that higher trading volume leads to increased negative abnormal returns. Taken as a whole, prior literature show that trading volume influence the market reaction following reversed warnings.

2.6 Hypotheses formulation

The first and second hypothesis of this study is formulated upon previous research focusing on the initial and long-term market reactions of both types of warnings. Regardless of the warning being either traditional or reversed they are seen to generate a significant change in share price during the announcement day window, following in the same direction as the news (Jackson and Madura, 2003; Collett, 2004; Bulkley and Herrerias, 2005; Alves et al., 2009; Church and Donker, 2010; Spohr, 2014; Cox et al., 2017). This would further strengthen the semi-strong form of the EMH (Kothari, 2001). Thus, a similar outcome is expected in this study.

Findings on the long-term market reaction following warnings are though somewhat dubious. Jackson and Madura (2003) find results indicating that there is a reversal in share price in the long-term period suggesting an overreaction to the warning. Bulkley and Herrerias (2005) and Pukthuanthong (2010) find that the share price will continue in that same direction as the news, also known as PEAD. At the same time, findings imply that the market is not always correct in its pricing of securities when information comes as a surprise to the market (DeBondt and Thaler, 1987; Bernard and Thomas 1989; Subrahmanyam, 1996). As a result, overreactions to new information may occur. With prior studies made on traditional warnings find different outcomes for the long-term return, we expect an abnormal return, but with no assumed direction. Based on the above reasoning the first and second hypotheses of this study are formulated as following:

- **H1:** *The initial market reaction following a reversed warning is positive.*
- **H2:** *There are abnormal returns in the period following the announcement of a reversed warning.*

The third and fourth hypotheses are formulated to test whether there is any difference in market reaction depending on firm size. Previous findings indicate that small firms experience a greater initial market reaction compared to large firms, when a warning is disclosed (Jackson and Madura, 2003; Collett, 2004; Bulkley and Herrerias, 2005; Church and Donker, 2010). Thereby we hypothesize that a similar outcome is identifiable in our study. Similar as for hypothesis 2, as prior studies are somewhat contradictory, we cannot expect a certain direction of the long-term returns. This reasoning leads to the third and fourth hypotheses being formulated as following:

- **H3:** *The initial market reaction following a reversed warning is less positive for large firms compared to small firms.*
- **H4**: *There is a difference in long-term abnormal returns between large and small firms following a reversed warning.*

The fifth and sixth hypotheses relates to the secondary aim of this paper, studying the relationship between firm size and abnormal returns. Findings from prior studies show that there are several reasons for that larger firms experience a smaller price change following a warning. (Jackson and Madura, 2003, Collett, 2004; Bulkley and Herrerias, 2005; Church and Donker, 2010). One explanation for these deviating reactions is given by Church and Donker (2010), arguing that greater requirements of transparency concerning large firms generate more correct estimations of these firms. Nevertheless, Jackson and Madura (2007) as well as Spohr (2014) find no significant relation between firm size and abnormal returns studying traditional warnings. Summarizing these findings, there are controversies regarding the impact of firm size. However, most studies show that there is a negative relation between firm size and abnormal returns, why this study formulates its fifth and sixth hypothesis as follows:

- **H5:** *There is a negative relationship between firm size and the abnormal return in the initial period following reversed warning.*
- **H6:** *There is a negative relationship between firm size and the abnormal return in the long-term period following a reversed warning.*

The seventh and eighth hypotheses also relates to the secondary aim if this paper, studying the relationship between trading volume and abnormal returns. Previously observed is a significant increase in trading volume both during the announcement day of a warning and in the following day (Collett, 2004). A similar result is found in Cox et al. (2017), where they find that a high trading volume increase the change in share price following new information. In addition to Cox et al (2017), Dayanandan et. al (2018) state that higher trading volume following traditional warnings have a positive impact on abnormal returns. Consequently, we hypothesize that there is a positive relation between trading volume and observed abnormal returns in the initial period following a reversed warning. As this study strives to contribute new knowledge regarding the long-term market reaction following reversed warnings, we also create a hypothesis for the long-term relationship.

- **H7:** *There is a positive relationship between trading volume and the abnormal return in the initial period following a reversed warning.*
- **H8:** *There is a positive relationship between trading volume and the abnormal return in the long-term period following a reversed warning.*

3. Methodology

3.1 Research design

This paper aims to study the initial and long-term market reaction following reversed warnings on the Nordic markets. There is also a strive to examine the impact of firm size and trading volume. Thus, multiple cases of observations are a necessity. Consistently with the aim and formulated the research question, we rely on a quantitative research design with a deductive approach. Hence, we establish our testable hypotheses on a theoretical framework so that we can gather data, and contribute new insight on prior knowledge within the area (Bryman and Bell, 2015).

Naturally, this study have a quantitative method as the sole object of study is financial data. This approach is further motivated since it brings assurance in comparability for later studies examining the same period (Bryman and Bell, 2015). To measure abnormal returns related to reversed warnings, this study uses the traditional event study approach by MacKinlay (1997), testing hypotheses 1 and 2. We also apply separate t-tests to see if there are any differences in market reactions depending on firm size, testing hypothesis 3 and 4. As this study seek to investigate the impact of firm size and trading volume, a cross-sectional research design is motivated (Bryman and Bell, 2015). Accordingly, we apply a multiple regression analysis to test hypotheses 5–8.

3.2 Collection of data

The data sample include observations of Nordic firms that have declared a reversed warning during the period of 2010-2019. The examined period of 10 years is selected since there is a strive to produce generalizable results of the market's reaction following reversed warnings. Further on, Spohr (2014) conducts his study over a seven-year period spanning between 2005-2011, why our selected period of study is considered motivated. Announcement dates of reversed warnings are manually gathered through the database Retriever Business where specific firm, announcement date, and their country of origin are disclosed in Appendix. Before any exclusion of observations, the accumulated sample consists of 117 firms generating 138 observations. See Table 5 for data selection process. When summarizing the sample, we exclude 12 observations as they originate from lists that are not the country's primary stock exchanges. To obtain required data of share price changes, key figures and listing date, we use the financial database Thomson Reuters Eikon, accessing Datastream. When collecting data for the remaining observations it was also necessary to exclude 5 observations as Datastream did not have sufficient data on these. 3 observations were also excluded due to that the firm had not been listed throughout the whole estimation period. Furthermore, as financial data is obtained in different currencies, all figures are recalculated into Swedish Krona (SEK), using the average exchange rate of the examined period. Non-corporate financial variables, as number of analysts and consensus recommendation, used for the regression analysis, originate from Refinitive IBES, accessed via Thomson Reuters Eikon. After exclusion of the observations the final data sample constitutes of 101 firms that accumulate 118 observations. The size of our final sample is considered sufficient for the aim of this study since it is similar to the one used in Spohr (2014)[8]. Collected data is categorized and further transformed in Microsoft Excel.

Table 4. *Sample selection.*

Observations	**No. of Firms**	**No. Observations**
Total observations from Nordic markets	117	138
Listed on secondary stock markets	(9)	(12)
Missing financial data	(4)	(5)
Unsuffcient listing period	(3)	(3)
Total	**101**	**118**

As previously documented by Alves et al. (2009) and Spohr (2014), there seems to be a skewed distribution of observations originating from Finland. Although the data being skewed to observations from Finland, all observations are still assumed to originate from a normally distributed population, not affecting the reliability of the results from the statistical tests (Hand, 2008). With the aim being to measure the market reactions following reversed warnings, there is no requirement for the firms to be listed through the entire period of 2010-2019. In turn, this leads to no interest in examining if there is any survivorship bias in the observations.

8 The accumulated data sample in Spohr (2014) consists of 119 observations of reversed warnings.

Table 5. *Sample distribution.*

Observations	Index	No. of Firms	No. Observations
Danish	OMX Copenhagen GI	9	11
Finnish	OMX Helsinki GI	51	61
Norwegian	OSEAX Oslo GI	12	14
Swedish	OMX Stockholm GI	29	32
Total		**101**	**118**

3.3 Event study

MacKinlay (1997) argues that event studies are among the most suitable methods within the area of finance when measuring how certain events affect both firms and the market. With the purpose to investigate the announcement of a reversed warning, the event study approach is argued to be motivated. The method is based on the market being rational and has a semi-strong efficiency, therefore testing the EMH. Event studies are also used throughout previous research and applied for both reversed and traditional warnings (Jackson and Madura, 2003; Collett, 2004; Bulkley and Herrerias, 2005; Church and Donker, 2010; Spohr, 2014). Due to its vast pursuance in previous capital market studies (Kothari and Warner, 2005), and with Collett (2004) and Spohr (2014), to our knowledge, being the only two studies examining reversed warnings, we apply similar methodological assumptions in this study.

3.3.1 Event window and estimation period

To isolate the effect from the reversed warning, testing the first hypothesis, the cumulative abnormal return, *CAR*, is calculated for two days (day 0 to +1), defined as the event day window. MacKinlay (1997) argues that a three-day event window is needed in order to measure the full effect of an announcement, ranging from day -1 from the event today +1. In the below study, the choice is made to have a two-day window in order to be consistent with prior research with the same scope of the study. Therefore, following Collett (2004) and Spohr (2014) the event window ranges from the announcement day (0) to the following day (+1). The defined event window in this study is therefore argued to capture the full announcement effect from the reversed warning.

Armitage (1995) recommends an estimation window between 100 to 300 days depending on the purpose, while MacKinlay (1997) opines that when analyzing daily share prices, an estimation window of 120 days is suitable. On this matter Spohr (2014) follows Jackson and Madura (2003) applying an estimation period of 200 days. Further on, Spohr (2014) chooses to end the estimation period 20 days prior to the warning. Hence, this study applies an estimation period (L_1) of 200 days, ending 20 days before the event day. The reason for stopping the estimation period several days ahead of the event day is so that the estimation of normal returns is not to affected by potential information leakage (MacKinlay, 1997; Jackson and Madura 2003; Spohr, 2014). Following prior studies, we also construct a wider event window ranging from -5 to +5 to control for potential information leakage and information processing time (Jackson and Madura, 2003; Collett, 2004; Bulkley and Herrerias, 2005; Spohr, 2014).

As neither Collett (2004) nor Spohr (2014) study the long-term abnormal return following reversed warnings, this study applies the same methodological approach as in Jackson and Madura (2003). Thus, measuring *CAR* for a subsequent period after the reversed warning is announced. This is done to test the second and fourth hypotheses of this study. For the long-term measurement a period of 54 days is used, ranging from day +6 to +60 after the warning is announced. Barber and Lyon (1997), who review the methodological assumptions on measuring long-term abnormal returns, make a comparison between the BHAR-method and CAR. Findings from their study show that, if the aim is to measure a period ranging over several months, one should use the BHAR method. At the same time, they state that the CAR-method is more accurate if the period of interest ranges from several days up to a few months (ibid). For this study, where the aim is to measure the long-term reaction over 54 days, *CAR* is considered adequate.

The figure below presents estimation-, event day and post-event windows visualized in Figure 1. L_1 represent the estimation window, L_2 the event day period for the announcement and L_3 the post-event window.

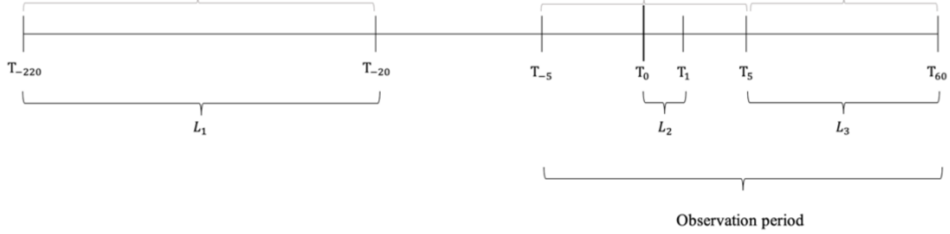

Figure 1. Illustration of estimation window, event day window and post-event window.

3.3.2 The market model

To calculate abnormal returns for the selected event periods, we apply the traditional market model. The market model is a statistical model that uses a linear relationship, interrelating the return of a particular security to the return of the market portfolio (MacKinlay, 1997). Brown and Warner (1985), as well as MacKinlay (1997), argue that the market model is suitable as it excludes the return, which is related to the variation in market return. By excluding this return, we increase the possibility of identifying effects from the reversed warnings.

Expected return E(r)

In this study, the expected return is calculated from the daily closing prices in the estimation window, where $R_{i,\tau}$ is the return for a share during period τ, α_i idiosyncratic risk for share *i*, and β_i is the systematic risk for share *i*. $R_{m,\tau}$ is the return of the market portfolio during period τ and $\varepsilon_{i,\tau}$ is the error term expected to have a mean equal to zero. The market portfolio is represented by the primary market index on respective Nordic Market[9]. The expected return is calculated as follows:

$$E(r)_{i,\tau} = \alpha_i + \beta_i R_{m,\tau} + \varepsilon_{i,\tau} \qquad (1)$$

Abnormal return (AR) and Average abnormal return (AAR)

Through the model, the expected return for α and β is estimated. Thereafter, the abnormal return is calculated as the difference between expected return and the actual return for each specific firm during its estimation window (MacKinlay, 1997). The computed abnormal return is used to estimate the reversed warnings effect on the firm's return. $AR_{i,\tau}$ is the abnormal return for the share *i* during period τ and $\hat{\beta}_i R_{m,\tau}$ is the expected return for the security *i* during period τ. Abnormal returns are calculated with the following equation:

$$AR_{i,\tau} = R_{i,\tau} - \hat{a} - \hat{\beta}_i R_{m,\tau} \qquad (2)$$

The average abnormal return is calculated by summarizing all the observations' abnormal returns for several days in the event window, dividing by the number of observations

9 For Swedish observations we use OMXSGI, for Finnish observations OMXHGI, for Norwegian observations OSEAX and for Danish observations OMXCGI.

(MacKinlay, 1997). AAR_τ represents the average abnormal return for period τ, N represents the number of observed events and $AR_{i,\tau}$, and τ is the abnormal return for the share *i* during period τ. The average abnormal return is calculated with the following equation:

$$AAR_\tau = \frac{1}{N}\sum_{i=1}^{N} AR_{i,\tau} \tag{3}$$

Variance for abnormal return (var(AR)) and Variance for average abnormal return (var(AAR))

This study uses the variance for the abnormal return, *Var(AR)*, from respectively share in the estimation window. The variance for the abnormal return is calculated as explained by MacKinlay (1997) where $\hat{\sigma}_\varepsilon^2$ is the variance for the abnormal return for the share *i*, L_1 is the size of the estimation window measure in the number of days and (formula abnormal return) is the abnormal return for the share *i*. The variance for abnormal return is calculated as follows:

$$\hat{\sigma}_\varepsilon^2 = \frac{1}{L_1-2}\sum_{\tau=T_0+1}^{\tau_1}(R_{i,\tau} - \hat{a} - \hat{\beta}_i R_{m,\tau})^2 \tag{4}$$

With the calculated variance from the abnormal return, the variance from the average abnormal return $var(AAR)_\tau$ can be estimated (MacKinlay, 1997). $\hat{\sigma}_\varepsilon^2$ is the variance for the abnormal return for share *i*, N is the number of observed events. The $var(AAR)$ is calculated as follows:

$$var(AAR)_\tau = \frac{1}{N^2}\sum_{i=1}^{N}\hat{\sigma}_\varepsilon^2 \tag{5}$$

Cumulative abnormal return (CAR) and Average cumulative abnormal return (ACAR)

The cumulative abnormal return (CAR) is calculated to see if there is any change in returns over more than one day. CAR comprises the sum of the abnormal return during a time interval for each share used in this study. $CAR_\tau(\tau_1\tau_2)$ is the cumulative abnormal return for the share *i* from period τ_1 until τ_2. $AR_{i,\tau}$ is the abnormal return for the share *i* from period τ. The cumulative abnormal return is calculated using the following equation:

$$CAR_\tau(\tau_1\tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i,\tau} \tag{6}$$

Cumulative abnormal return (CAR) and Average cumulative abnormal return (ACAR)

To estimate the average cumulative abnormal return, $ACAR_{\mathrm{i}}$, we sum up the cumulative abnormal return, CAR, for all the events and then divide them by the total number of observations. This calculation aggregates the average abnormal return in one event window (MacKinlay, 1997). $ACAR_{\mathrm{i}}(\tau_1\tau_2)$is the average cumulative abnormal return between day τ_1 and τ_2 in the event window. AAR_τ describes the average abnormal return during period τ. The average cumulative abnormal return is calculated using the following equation:

$$ACAR_i(\tau_1\tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AAR_\tau \tag{7}$$

Variance for average cumulative abnormal return (var(ACAR))

The variance for the average cumulative abnormal return is calculated by aggregating the total variances for the average abnormal returns. In line with MacKinlay (1997), the $var(ACAR_i(\tau_1\tau_2))$ is estimated from the variance for average cumulative abnormal return between day τ_1 and τ_2 in the event window and $var(AAR)_t$ is the variance for the average abnormal return for period τ. The $var(ACAR)$ is calculated using the following equation:

$$var(ACAR_i(\tau_1\tau_2)) = \sum_{\tau=\tau_1}^{\tau_2} var(AAR)_\tau \tag{8}$$

Critical value/significance test

Using a t-test the statistical significance for the average cumulative abnormal return is examined by observing the event window and the following post-event window. In the equation, $ACAR_i(\tau_1\tau_2)$ represents the average cumulative abnormal return between day τ_1 and τ_2 in the event window. $var(ACAR_i(\tau_1\tau_2))$ is the variance for the average cumulative abnormal return between day τ_1 and τ_2 in the event window.

$$\theta = \frac{ACAR_i(\tau_1\tau_2)}{var(ACAR_i(\tau_1\tau_2))} \sim N(0,1) \tag{9}$$

Lastly, to test for hypotheses three and four, a one-sample t-test is conducted in respectively time-period. The difference between the subgroups $ACARs$ is divided by the square root sum of $var(ACAR)$ for each sample. See the equation below.

$$\theta = \frac{ACAR_1 - ACAR_2}{\sqrt{\frac{Var_1}{N_1} + \frac{Var_2}{N_2}}} \sim N(0,1) \tag{10}$$

3.4 Market reactions across size groups

To test for hypotheses 3 and 4, if there is any difference in market reaction between large and small firms, at the initial and long-term period, we follow both Collett (2004) and Bulkley and Herrerias (2005). Thus, the full data sample of 118 observations is divided into two equally sized groups based on the median of natural logarithmic market value, resulting in two groups of 59 observations, ranging from the smallest to the largest. Groups are then t-tested against each other to determine if the reaction is different depending on the firm’s logarithmic market value. For the t-test we apply equation 10 illustrated above. Selecting the one-sample t-test for this cause is motivated since the aim is to compare mean CAR's of the different groups to see if they are statistically different from each other (Pallant, 2016). To see if the results from this test stands if conditions change we furthermore conduct robustness checks, presented in chapter 4.4. Robustness check.

3.5 Multiple regression analysis

3.5.1 Regression model

To test for hypotheses 5–8, if firm size or trading volume have an impact on the cumulative abnormal return, we apply a multiple regression model. Since the purpose is to examine both the initial- and the long-term reaction, we measure *CAR* for each period in two separate regressions. This application is further motivated since the study seeks to find how well the two independent variables explain the variance in the dependent variable (Tabachnick and Fidell, 2013). Furthermore, a well-developed regression model can how good predictions can be made about a specific event (ibid). Applying such an approach is also done to reveal if there is any spurious relationship, a non-real relation (Bryman and Bell, 2015). This is essentially important for the variable trading volume, as prior studies have shown that high trading volume may occur after information disclosures (Kim and Verrecchia, 1991). We are therefore restrictive when interpreting the trading volumes impact on abnormal return.

When setting up the testable regression models, this study seeks inspiration from Spohr (2014) who apply a similar model in his study. For this analysis, the dependent variable of interest is *CAR* and independent variables are the firm size (*SIZE*) and trading volume (*VOL*). When determining how precise the constructed models are in explaining the variance in *CAR*, this study takes the adjusted R-square into concern (Tabachnick and Fidell, 2013). The constructed regression model is illustrated in equation 11.

$$CAR_{i,t} = \alpha + \beta_1 SIZE_{it} + \beta_2 VOL_{it} + \beta_3 LEV_{it} + \beta_4 ROA_{it} + \beta_5 CREC_{it} + \varepsilon \quad (11)$$

To isolate the effect of each independent variable, they are first tested separately against *CAR*. After that, the full regression model with both independent variables is conducted for the respective period. Where there have been extreme values, this study applies winsorizing, replacing the extreme values with the closest observations value (Tabachnick and Fidell, 2013). The method was used to winsorize the percentile 1 and 99 for the variables, (*SIZE*), (*VOL*), return on assets (*ROA*) and leverage (*LEV*). For the variable consensus recommendation (*CREC*), winsorizing did not affect the sample. By applying the variable *CREC* in the regression model, we are required to exclude 17 observations as they lack any analyst coverage, further publishing the consensus recommendation. This reduces the total observations used in the regression model from 118 to 101.

Table 6. Definition of variables.

Variable	**Definition**	*Source*
CAR	Cumulative Abnormal returns	Manually computed (Excel).
α	Intercept	
β	Regression coefficients	
SIZE	Firm size. Calculated by natural logarithm of the firm's market value for the day before the announcement.	Thomson Reuters Eikon (Datastream).
VOL	Trading volume. Computed as the percentage of a firm's outstanding shares traded on the announcement day.	Thomson Reuters Eikon (Datastream).
ROA	Return on Assets. Computed as earnings before interest and taxes (EBIT) as a percentage of the book value of total assets.	Thomson Reuters Eikon (Datastream).
LEV	Firm leverage. Computed as total liabilities divided by total assets.	Thomson Reuters Eikon (Datastream).

CREC	Consensus recommendation. The estimated average analyst recommendation one day before the announced reversed warning. The analysts' different predictions provide a consensus recommendation based on a scale from 1 to 5. (1 = strong buy and 5 = strong sell).	Thomson Reuters Eikon (Datastream).
ε	Error term	
τ	Year-indicator	
i	Firm-indicator	

3.5.2 Dependent variable

The dependent variable is the observed cumulative abnormal return for the initial- and long-term period. The computation of *CAR* follows equation 11, and have been similarly computed in prior studies examining market reactions following warnings (Jackson and Madura, 2003; Collett, 2004; Bulkeley and Herrerias, 2005; Church and Donker, 2010; Spohr, 2014). Therefore, we argue that it is suitable to apply *CAR* as dependent variable for this study.

$$CAR_{\tau}(\tau_1\tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i,\tau} \tag{12}$$

3.5.3 Independent variables

To test hypothesis 5–8, regarding if firm size and trading volume could help to explain the variation in CAR, this study uses firm size (*SIZE*) and trading volume (*VOL*) as independent variables. *SIZE* is represented by the firm's market value for the day before the announcement and transformed by its natural logarithm. The same approach is applied in previous studies examining this variable (Jackson and Madura, 2003; Collett, 2004; Jackson and Madura, 2007; Spohr, 2014). The application of the natural logarithm is further motivated since the computation make the data more normally distributed, reducing skewness (Tabachnick and Fidell, 2013).

$$Ln(Market\ Market\ Value_{it}) = SIZE_{i,t} \tag{13}$$

Previously observed is that *VOL* could function as a proxy for estimating the magnitude of a market reaction (Collett, 2004; Cox et al., 2017; Dayanandan; 2018). In this study, *VOL* is represented by the percentage of a firm's outstanding shares traded on the announcement day. For the long-term volume we apply the mean of shares traded during the studied period. Following Collett (2004), we calculate *VOL* accordingly with equation 12.

$$\frac{Shares\ traded}{Shares\ outstanding}\,x\ 100 = VOL_{i,t} \tag{14}$$

3.5.4 Control variables

As the study strives to yield reliable causes for the market reactions related to reversed warnings, a selection of control variables is added to the regression model. It is further motivated as it functions as a control for unexplained variance in the dependent variable (Muller and Fetterman, 2002), in this study, *CAR*.

Studies focusing on warnings do often examine how a firm's financial leverage could explain the magnitude of a market reaction (Church and Donker, 2010; Spohr, 2014; Cox et al., 2017). Cox et al. (2017) argues that the probability of managing a diverging profit is decreasing as the risk of the firm increases. *LEV* is therefore applied as a control variable for this study. The performance measure, return on assets (ROA), is also seen to affect the magnitude of the market reaction after a warning (Church and Donker, 2010; Cox et al., 2017). In Church and Donker (2010), the variable *ROA* has a significant negative impact on the initial market reaction following a traditional warning. The authors also observe that firms with higher ROA respond even more negatively compared to firms with lower ROA's (ibid). This study, therefore, apply *ROA* as a control variable. Spohr (2014) identifies that consensus recommendation, being the estimated average analyst recommendation, has a significance negative impact on abnormal returns for traditional warnings while identifying a small but insignificant result for the reversed warning. Following Spohr (2014) the variable consensus recommendation (*CREC*) is applied as a control variable. *CREC* is the estimated average analyst recommendation one day before the announced reversed warning.

3.5.5 Robustness check

A fundamental part of producing generalizable results is to test how robust the findings are. For the test across size groups, we divide the full sample into quartiles based on their logarithmic market value. Thus, the full sample of 118 observations for our event study, is divided into four groups of 29 observations ranging from the smallest to the largest firm observations. As the quartiles contain 29 observations the assumptions of normal distribution are validated (Pallant, 2016). Nevertheless, the sample originates from a population that is assumed to be normally distributed, why it should be of less concern.

The common practice for regression models is to change certain variables to see if the outcome is different under specific conditions. Therefore, this study applies additional regression models, including the following control variables; number of analysts (*ANA*), previously used as a proxy for firm size (Jackson and Madura, 2007), *INDUSTRY*, *COUNTRY* and *YEAR*. Industry and country are considered relevant since the announcement of reversed warnings might be interpreted differently depending on country and industry of the firm. Previous research do also show that warnings may have different impact depending on which year they are announced in (Cox et al., 2017). Results from the robustness tests are provided in chapter 4.4 Robustness check.

3.5.6 Normality testing

To ensure that the data used in this study is normally distributed, the degree of normality is tested. The motivation behind a test is to yield information on the data or variables being either skewed or indicate kurtosis (Tabachnick and Fidell, 2013). Doing this will indicate if we are able to draw any generalizable conclusions. Since the aim is to produce as reliable results as possible, normality testing is deemed a necessity. The studied dataset is tested through descriptive statistics illustrating the data in boxplots and histograms, to show any skewness or kurtosis (Tabachnick and Fidell, 2013). Descriptive statistics are displayed in Table 9, where skewness and kurtosis are included. As some deviations from normality are accepted, there is only a need for transforming if deviating too much. Such a procedure could lead to changes in the replicability of results. Hence, it should be done with transparency and caution so the criterions of replicability and generalizability are not harmed.

3.5.7 Multicollinearity

The issue of multicollinearity occurs when independent variables included in the regression model are highly correlated i.e. a value of ± 0.9. If variables included in the model are multicollinear that would negatively impact the functionality of our regression model (Tabachnick and Fidell, 2013). In order to control for multicollinearity, a Variance Inflation Factor (VIF) test is conducted for the different variables. In the VIF-test, values exceeding five are deemed unusable to be applied as variables in a regression model (ibid). The correlation matrix, also including the VIF-test, for all variables are illustrated in Table 10.

3.6 Methodological considerations

An underlying aspect of conducting research is to generate replicable, reliable, and valid results (Bryman and Bell, 2015). Therefore, this study aims to be transparent in its methodological shortcomings, transformation of data and statistical testing to be replicable for later studies.

One limitation of concern, eventually risking the criterion of generalizability and reliability, is the data sample (Bryman and Bell, 2015). With 118 observations from 101 firms, the event study would benefit from a larger sample since it would make statistical assumptions and generalizability more accurate. Regarding the regression analysis we exclude 17 more observations when applying *CREC* as a control variable. Hence, our sample is further reduced to a total of 101 observations for the multivariate analysis. A consequence of including *CREC* is that the smallest firms, not having any analysts following them, are excluded. This might harm the criterion of generalizability as the remaining sample is not representative for all the firms that disclosed a reversed warning. Further issues with a smaller sample are presented by Tabachnick and Fidell (2013) stating that, doing multivariate analysis on small samples may cause the adjusted R-square to become negative, hence the applied model may not explain much of the outcome. A rule of thumb on this matter, is that the selected model requires a minimum of 50 observations and also additional 8 observations for each used control variable (ibid). In our case with 101 observations for the regression analysis we are close that limit as we have selected 5 control variables. Results from this study could therefore be somewhat difficult to generalize compared to studies using larger samples. Another issue related to the regression analysis, is the certainty about causal relationships. With the application of a regression analysis there is a strive to explain the outcome and in the dependent variable by using certain control variables (Bryman and Bell, 2013). As the multiple regression analysis only explains if there is a relationship between variables, there is no answer of causality (Tabachnick and Fidell, 2013). Results concerning whether the firm size or trading volume have an impact on the significance of a market reaction should be interpreted with caution.

The period of this study also needs to be emphasized from a reliability perspective. The examined period is assumed to incorporate both economic expansions and recessions; thus, a representative period. As the period spans over ten years, it is assumed that the study covers a full business cycle. Hence, the length of the studied period is considered to generate generalizable and representable results. An examination of a shorter period may, according to Cox et al. (2017), yield asymmetric results as there could be differences in market reactions in times of solely economic expansions or recessions. A data sample covering a more extended period incorporating more expansions and recessions in the economy would be considered more representative and more reliable. However, the examined period still spans over ten years, assumed to be sufficient.

Even though several studies are applying the event study approach, the method have received some criticism (Kothari, 2001; Brown and Warner, 1985; Corrado, 2011). In the review of Corrado (2011), the event study approach is criticized for not taking into consideration that stock market returns seldom are normally distributed. In addition, the market model relies on that the market is efficient, an assumption frequently contested (Kothari, 2001). There also seem to be issues related to short- and long-term event windows where evidence of expected return for a specific period could be misleading (Brown and Warner, 1985; Barber and Lyon, 1997). Another complication with an event study is to ensure that the effect of the event of interest is isolated (MacKinlay, 1997). For example, this study uses 54 days after the announcement day to see if there are any long-term abnormal returns. The issue here is that the examined period extends over other price driving events like the quarterly report. Hence, the results from an event study should be interpreted with care, but still ought to be useful for indicating certain market behaviors and testing the EMH. Therefore, this study makes assumptions based on prior studies examining similar matters, hopefully strengthening the validity. The event study application is frequently used in capital markets research and hence motivated for this paper (MacKinlay, 1997; Kothari, 2001).

4. Results and analysis

4.1 Event study

Table 7. Event study results

Event Period	Abnormal Return (in %)	t-stat
Day -5 to -1	0.029	0.059
Day 0	6.769	30.069***
Days 0–1 (L_2)	6.830	17.832***
Days 2–5	0.632	1.429
Days 6–60 (L_3)	-3.729	-2.274**

*Table 7 summarizes results from the event study of the full sample of 118 observations. The results are displayed as AR in % for day 0 and CAR in % for periods extending over several days. The t-stat column illustrates if the mean abnormal return is statistical different from zero. Level of significance is shown by an asterisk, where *= significant on a 10% level **= significant on a 5% level ***= significant on a 1% level.*

To examine the Nordic markets and test hypotheses 1 and 2, this study applies the traditional event study approach. Table 7 displays the cumulative return for the two-day event window, resulting in a *CAR* of 6.83%, representing a t-value of 17.832. This illustrates that the market reaction is significantly different from zero on a 1% level. The results in period (L_2) show that reversed warnings, disclosed by firms on the Nordic markets between 2010 and 2019, on average increase the share price by 6.83%. Therefore, results show that the first hypothesis, *the initial market reaction following a reversed warning is positive*, should be accepted. Table 7 clearly shows that the majority of the increase in share price occurs already on the announcement day, showing an AR of 6.77% for the examined firms. Results from the event-day window are also in line with prior research, represented by an almost immediate adjustment in expectations measured by the share price returns during day 0 and +1 (Jackson and Madura, 2003; Collett, 2004; Bulkley and Herrerias, 2005; Alves et al., 2009; Church and Donker, 2010; Spohr, 2014; Cox et al., 2017). For illustrative reasons we also disclose the periods covering -5 to -1 and +2 to +5 in Table 7, even though they are not included in our scope of study. The period prior to the announcement show no indications of the market anticipating the warning. As no significant *CAR* is observed the market is assumed to be surprised by the announcement of the warning, which is in line with the argumentation in Collett (2004). Findings from the period day 2 to day 5 is in line with findings in Spohr (2014) as he finds no abnormal returns subsequent to reversed warnings.

Referring to Table 7, the long-term *CAR* (L_3) is negative by -3.73%, representing a t-value of -2.27, which is significantly different from zero on a 5% level. Thus, we find a significant reversal in share price during the examined period. The results from the long-term period lead to that the second hypothesis, *there are abnormal returns in the period following the announcement of a reversed warning,* is accepted. The reversal in share price is though no enough to erase the prior increase following the initial reaction. These results are in line with Jackson and Madura (2003), showing a reversal in *CAR* when examining long-term abnormal returns following a traditional warning. However, the findings are in contrast to Bulkley and Herrerias (2005) and Pukthuanthong (2010) as they find the long-term return to follow in the same direction as the warning.

Results from our study are consistent with assumption that the market quickly revises its expectations in the same direction as new public information (Ball and Kothari, 1991; Amir and Lev, 1996). Similar to earlier studies this study also finds the most significant market reaction, measured by abnormal returns, to occur on the announcement day (Jackson and Madura, 2003; Collett, 2004; Bulkley and Herrerias, 2005; Alves et al., 2009; Church and Donker, 2010; Spohr, 2014; Cox et al., 2017). As share prices adjust after the announcement, this study finds support for the semi-strong form of the EMH presented by Fama (1970). In addition, this shows that prevailing information asymmetry is reduced when the warning is announced. Hence, results indicate that practitioners view reversed warnings as value-relevant, which is reasonable since affect a firm's future earnings. Therefore, the announcement of a reversed warning lead to a significant positive abnormal return at an initial period. A conclusion in line with the theoretical framework on which this study relies (Collett, 2004; Spohr, 2014).

As our long-term *CAR* (L_3) shows no continuous price increase, there are no indications of a PEAD following a reversed warning on the Nordic markets. Further on, our findings show a significant increase in share price during the initial period and a significant decrease in the long-term period. We interpret this as a potential overreaction by the market similar to findings in Bernard and Thomas (1989), concerning information surprises. This suggests that the market is not able to process the warning correctly, illustrating that there is a human bias in information processing, earlier observed by DeBondt and Thaler (1987). We deem this reasonable as our long-term *CAR* is -3.73%, implying that investors are too aggressive in their expectations set out by the warning. It partially suggests that Easterwood and Nutt (1999) might be correct when arguing that analysts overvalue positive earnings announcements. However, as there is no examination of the traditional warnings in our study, we cannot take this for sure. Nevertheless, we conclude that there are indications of overreactions on the Nordic markets following reversed warnings. Based on these results, this study find support that an investor could make a beneficial investment by shortening the shares of the warning firm on the announcement day.

4.2 Market reactions across size groups

Table 8 displays *CAR* when the full sample is divided into two groups based on their natural logarithmic market value. For the group containing the larger firms, we observe an event period *CAR* of 6.02%, representing a t-value of 12.43, a result that is significantly different from zero on a 1% level. For the group containing the smaller firms, we observe an event period *CAR* of 7.65%, which represents a t-value of 15.76. This result is significantly different from zero on a 1% level. When testing if the mean in the two groups are statistically different from each other, results show that they are deviating by 1.63 units of percentage. This represents a t-value of 20.01, a result significantly different from 0 on the 1% level. As there is a significant difference between the groups during the announcement day window, this study accepts the third hypothesis, *that the initial market reaction following a reversed warning is less positive for large firms compared to small firms*. Thus, we can conclude that the results are in line with previous findings (Jackson and Madura, 2003; Collett, 2004; Church and Donker, 2010).

Table 8. Event study results between firm size

Event period	**Large firms**	**Small firms**	**t-stat between groups**
Days 0–1 *(L_2)*	6.015	7.645	
	*(12.43)****	*(15.76)****	-20.012***
Days 6–60 *(L_3)*	-4.752	-2.706	
	*(-2.29)***	*(-4.79)*	-4.791***

*Table 8 summarizes the results generated from the event study where the full sample has been divided into two subgroups, one containing the small firms and one containing the large firms based on their logarithmic market value. Each group contains 59 observations each. Results are displayed as CAR in %. T-stat for each group are displayed in the parentheses. The t-stat column illustrates the statistical difference in mean CARs between the two groups. Level of significance is shown by an asterisk, where: *= significant on a 10% level **= significant on a 5% level ***= significant on a 1% level.*

The results regarding the post-event window (L_3) show that the *CAR* for the group containing the larger firms is -4.75%, representing a t-value of -2.29, a result significantly different from zero on a 5% level. For the group containing the smaller firms, results show a *CAR* of -2.7%, which is not significantly different from zero. When testing if the mean in the two groups is significantly different from each other, results show that they are by -2.05 units of percentage, representing a t-value of -4.79, a result significantly different from zero at a 1% level. Thus, there is a difference in mean *CARs* between the groups implying that there are differences in abnormal returns in the long-term. Hypothesis four, *there is a difference in long-term abnormal returns between large and small firms following a reversed warning,* is thereby accepted. Our results indicate that large firms, compared to small firms, experience a more negative price change in the long-term following a reversed warning. This is unexpected since prior literature state that large firms are less prone to react to earnings surprises due to their larger coverage by analysts and media (Jackson and Madura, 2003; Collett, 2004). To further determine what impacts the fluctuations in *CAR,* both initially and in the long-term, we apply the constructed regression models.

4.3 Multiple regression analysis

Table 9. Descriptive Statistics

VARIABLE	MEAN	MED	ST.DIV	MAX	MIN	SKEW	KURT	ST. ER
CAR (L_2)	0,064	0,053	0,060	0,311	-0,045	1,491	3,683	0,006
CAR (L_3)	-0,024	-0,016	0,143	0,283	-0,473	-0,441	0,535	0,014
SIZE	8,884	8,841	1,799	11,936	4,684	-0,281	-0,608	0,127
VOL	0,007	0,004	0,009	0,051	0	2,558	7,541	0,001
ROA	9,299	7,782	9,001	38,160	-18,020	0,678	2,269	0,633
LEV	32,749	34,221	20,790	90,500	0	0,316	-0,001	1,463
CREC	2,562	3	0,591	4,170	1	0,472	0,124	0,042

Table 9 displays descriptive statistics for the variables included in the regression models. MEAN is the average value of the variable. MED stands for median which is the center value of all measured values. ST.DIV stands for the standard deviation. MIN represents the lowest measured value whilst MAX represents the highest measured value. SKEW stands for skewness which describes the normal deviations curves distortion. KURT stands for kurtosis, describing the height of the normal distribution.

The dependent variable *CAR* (L_2)*,* for the initial period, show a mean value of 0.064, with values ranging from -0.045 to 0.311. This illustrates that the most observations respond positively to the announcement of a reversed warning. Even so, a few observations respond negative when the warning is announced. For the dependent variable, *CAR* (L_3)*,* results show a mean value of -0.024 and values ranging in an interval between -0.46 to 0.28. Hence, the average firm have a negative *CAR* after the 54 days. Table 9 further shows that the independent variable *VOL* have a kurtosis of 7.541, which can be considered a positive deviation from an expected normal distribution (Tabanick and Fidell, 2013). A high kurtosis for *VOL* is though expected, since prior studies find the similar outcome. (Collett, 2004; Cox et al., 2017; Dayanandan; 2018).

Table 10. Correlation matrix.

	CAR (L_2)	*CAR* (L_3)	*SIZE*	*VOL*	*ROA*	*LEV*	*CREC*	*VIF*
CAR (L_2)	1							
CAR (L_3)	0.158	1						
SIZE	-0.264***	-0.107	1					1,868
VOL	0.271***	0.021	0.178**	1				1,089
ROA	0.030	0.018	0.057	0.062	1			1,507
LEV	-0.072	-0.027	0.026	-0.038	-0.460***	1		1,400
CREC	0.175	-0.062	0.146**	-0.027	0.041	-0.161**	1	1,122

*Table 10 displays the correlation matrix generated when using Pearson's correlation coefficient. Level of significance are illustrated by an asterisk, where; *= significant on a 10% level **= significant on a 5% level ***= significant on a 1% level.*

In Table 10, we disclose our correlation coefficient matrix to determine the correlations between variables. Observable is that the dependent variable *CAR* (L_2), show a significant negative correlation with the independent variable *SIZE* and a significant positive correlation with *VOL*. Thus, our results are in line with prior literature also examining these variables (Osborne, 1959; Jackson and Madura, 2003; Collett, 2004; Bulkley and Herrerias, 2005; Cox et al., 2017; Dayanandan, 2018). We also find that there is a significant positive correlation between the independent variables *SIZE* and *VOL*, indicating that a larger firm will have higher amounts of shares traded. This is also expected as larger firms tend to have higher turnover in their listed shares. A high, and significant, correlation coefficient is found between *LEV* and *ROA*, a coefficient of -0.46. This can be argued logic as leverage have an effect on the assets in the balance sheet. A correlation coefficient showing a value of ± 0.5 can be argued to cause certain complications (Tabanick and Fidell, 2013). As this study have no variables with a correlation exceeding ± 0.5, we proceed keeping all selected variables. To further eliminate the risk of including variables that are highly correlated to each other, a VIF-test is conducted. The VIF-test results are shown in Table 10, and displays if there is any multicollinearity between variables. There are no indications of problems with the multicollinearity when analysing the VIF-tests.

Tabell 11. Multiple Regression Analysis

	Day 0 until + 1			Day +6 until +60		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Number of observations	101	101	101	101	101	101
R^2	0.126	0.104	0.227	0.011	0.007	0.014
Adjusted R^2	0.089	0.066	0.176	-0.029	-0.034	-0.038
F-value	3.453***	2.778**	5.584***	0.276	0.171	0.269
Coefficients						
Intercept	0.092**	0.010	0.087**	0.068	0.021	0.007
	(0.038)	(0.032)	(0.036)	(0.101)	(0.082)	(0.102)
SIZE	-0.010***		-0.012***	-0.001		-0.001
	(0.003)		0.003	(0.008)		-0.001
VOL		1.466***	1.777***		0.724	1.690
		(0.532)	(0.503)		(3.165)	(3.385)
ROA	0.000	0.000	0.001	0.000	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.002)	(0.002)	(0.002)
LEV	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
CREC	0.024**	0.019**	0.024**	-0.015	-0.016	-0.013
	(0.010)	(0.010)	(0.010)	(0.025)	(0.025)	(0.026)

Table 11 display the respective model's significance level, R-square, and beta coefficient. The sample consists of 101 observations. The dependent variable is CAR (L_2 and L_3). For a detailed overview of the independent variables see Table 6. The models 1–3 presents results from the initial period after the announcement of a reversed warning. Model 1 tests with the independent variable SIZE alone. Model 2 tests with the independent variable VOL alone. Model 3 combines the two independent variables in the regression equations. The models 4–6 presents results from the long-term period after the announcement of a reversed warning. Model 1 tests with the independent variable SIZE alone. Model 2 tests with the independent variable VOL alone. Model 3 combines the two independent variables in the regression equations.

The regression analyses are conducted to test the study's hypotheses regarding the effect of firm size and trading volume on the cumulative abnormal return. Model 1 and 2 illustrates that variable *SIZE* as well as *VOL* is statistically significant at the 1% level in their separate models. For the full model (3), using both of the independent variables, the regression analysis for the initial period (L_2) is proven to have a statistically significant relationship on the 1% level. In addition, the F-value for the model is significant at a 1% level. The regression analysis displays that one increased unit in the natural logarithm of Market Value affects the cumulative abnormal return with -1.1%, being significant on the 1% level. We thereby accept our fifth hypothesis, *there is a negative relationship between firm size and the abnormal return in the* *initial period after the reversed warning.* In other words, a large firm announcing a reversed warning generate a smaller initial abnormal return than a small firm. These results are in line with previous studies from both Collett (2004) and Spohr (2014).

For the initial period, *VOL* is significant at the 1% level, therefore accepting the seventh hypothesis, *there is a positive relationship between trading volume and the abnormal return in the initial period following a reversed warning*. With new information announced to the market, there can in short periods, be argued that volume affect the cumulative abnormal return positively. These findings are in line with the argumentation in Beaver (1968) and Kim and Verrecchia (1991) who state that trading volume reflects an individual's reactions to new information, why investors will trade shares based on their new expectations. In addition, our findings seem to be similar to Collett (2004), who state the trading volume to significantly increase during the announcement day and the following day after the warning. In the study by Dayanandan et al. (2018) it is also found that higher trading volume generates increased abnormal returns, which can also be observed in our study. Accordingly, investors seem to obtain and process the reversed warning quickly, why more shares traded results in an even higher return in the initial period following the announcement.

Furthermore, identifiable from the Table 11 are results for model 1–3. Results show that the consensus recommendation, *CREC*, is significant on the 5% level. The beta coefficient in the initial period has a positive slope, showing that the more pronounced sales recommendation (i.e. a higher number on the scale) a firm has, the more prominent the cumulative abnormal return will be. In order words, firms that outperform the markets current expectations will to a larger extent generate a more significant price increase. Building on this discussion, it seems like the amount of information asymmetry prior to the announcement of reversed warning leads to a larger market reaction.

The results for the long-term period, +6 to +60 days after the announcement of a reversed warning, is analyzed by regression models 4–6, following the same structure as the modification done for *CAR* (L_2). Based on the results in Table 11, neither variable explains the outcome in the long-term *CAR*, (L_3). Thus, both the sixth hypothesis, *there is a negative relationship between firm size and the abnormal return in the long-term period following a reversed warning*, and the eight hypothesis, *there is a positive relationship between trading volume and the abnormal return in the long-term period following a reversed warning* are rejected. Visible from Table 11, is that we have negative adjusted R-squares throughout our three regressions, indicating that our selected variables are not able to predict the outcome. As mentioned, Tabachnick and Fidell (2013) state that it might be issues when conducting multivariate analysis on a small sample, which seems to be the case here. The negative adjusted R-square throughout the three regressions could also stipulate that the model is perhaps overparameterized (ibid). Another aspect is that variables selected, especially *LEV* and *ROA*, are not good at capturing the effects. Beside statistical concerns, external reasons may be the cause for this outcome. For instance, that the market has been provided with newer and more relevant information during the time frame of +6 to +60 days after the reversed warning. One example is the quarterly report, which provides further and more detailed information of the reversed warning and future outlooks. Another factor might be the underlying motivation for the warning and how it is communicated (i.e. qualitative or quantitative), previously examined by Bulkley and Herrerias (2005).

Table 12. Summary of hypotheses.

1. The initial market reaction following a reversed profit warning is positive.	Accepted
2. There are abnormal returns in the period following the announcement of a reversed warning.	Accepted
3. The initial market reaction following a reversed warning is less positive for large firms compared to small firms.	Accepted
4. There is a difference in long-term abnormal returns between large and small firms following a reversed warning.	Accepted
5. There is a negative relationship between firm size and the abnormal return in the initial period following reversed warning.	Accepted
6. There is a negative relationship between firm size and the abnormal return in the long-term period following a reversed warning.	Rejected
7. There is a positive relationship between trading volume and the abnormal return in the initial period following a reversed warning.	Accepted
8. There is a positive relationship between trading volume and the abnormal return in the long-term period following a reversed warning.	Rejected

4.4 Robustness check

Results from our robustness check on the test across size groups, when observations have been divided into quartiles ranging from smallest to largest, are displayed in table 13.

Table 13. Test across quartile sized groups.

(L_2)	1st quartile	2nd quartile	3rd quartile	4th quartile
1st quartile	1			
2nd quartile	1,811**	1		
3rd quartile	3,225***	1,688*	1	
4th quartile	3,956***	3,053***	1,647*	1

(L_3)	1st quartile	2nd quartile	3rd quartile	4th quartile
1st quartile	1			
2nd quartile	–1,728*	1		
3rd quartile	1,023*	3,081***	1	
4th quartile	–0,706	1,932*	–1,906*	1

*Table 13 shows the differences in the t-value from paired T-tests between groups. Each group contains 29 observations *= significant on a 10% level **= significant on a 5% level ***= significant on a 1% level.*

Visible is that there are significant differences between observations when looking at the initial reaction. In line with theory, most significance is the found when comparing the 1st quartile, containing the smallest firm observations, with the 4th quartile, containing the largest firm observations. The results also decrease in a linear pattern comparing larger quartiles with each other. Hence, the difference in initial reaction results across larger and small firms are considered robust. For the long-term period the results do not show any clear pattern across size groups. One unexpected finding is also the significant difference between the 3th quartile and the 4th quartile. Findings considering the long-term difference in reaction across size-groups are therefore considered less robust and not generalizable.

To test how robust our regression results are we conducted further tests including the variables *ANA*, *COUNTRY*, *INDUSTRY* and *YEAR*. As previously found, *ANA* could be used as proxy for firm size (Jackson and Madura, 2007), why we replace *SIZE* with *ANA* to test the predictive power of our models. The inclusion of the variables *COUNTRY*, *INDUSTRY* and *YEAR* are to control for fixed effects in the data sample. Hence, to show any deviation in results based on which country, industry and year the observations originate from.

Tabell 13. Robustness checks.

	Day 0 until + 1		Day +6 until +60	
	Model 1	**Model 2**	**Model 3**	**Model 4**
Number of observations	101	101	101	101
R^2	0.174	0.243	0.008	0.031
Adjusted R^2	0.131	0.177	-0.044	-0.053
F-value	4.001**	3.684***	0.155	0.365
Coefficients				
Intercept	0.002	-3.211	0.018	-1.108
	(-0.002)	(3.734)	(0.083)	(10.346)
ANA	0.002***		-0.001	
	(0.001)		(0.002)	
SIZE		-0.011***		-0.006
		(0.003)		(0.009)
VOL	1.887***	1.854***	1.164	1.965
	(0.535)	(0.518)	(3.478)	(3.520)
ROA	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.002)	(0.002)
LEV	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.001)
CREC	0.025**	0.024**	-0.014	-0.011
	(0.010)	(0.010)	(0.027)	(0.026)
COUNTRY		-0.007		-0.015
		(0.006)		(0.017)
INDUSTRY		0.000		-0.004
		(0.002)		(0.005)
YEAR		0.002		0.001
		(0.002)		(0.005)

*Table 12 display the respective model's significance level, R-square, and beta coefficient. The table describes the coefficient with the standard errors in parentheses. Level of significance are illustrated by an asterisk, where; *= significant on a 10% level **= significant on a 5% level ***= significant on a 1% level. Model 1 tests ANA as an independent variable and proxy for SIZE in the initial period. Model 2 controls for COUNTRY, INDUSTRY and YEAR in the initial period of the full model (3) presented in table 10. Model 3 tests ANA as an independent variable and proxy for SIZE in the long-term period. Model 4 controls for COUNTRY, INDUSTRY and YEAR in the long-term period of the full model (6) presented in table 10.*

Shown in Table 13 is the results for model 8, when the variable *SIZE* have been exchanged for *ANA*. The regression output shows that *ANA* is significant, but when comparing the results, it is not as good at predicting the outcome as is *SIZE* in model 3. The same result is found when testing if ANA is better at predicting the outcome for the long-term period, model 3. When controlling for *COUNTRY*, *INDUSTRY*, and *YEAR* results show a marginal change in our adjusted R-square from 0.0176 to 0.0177. Viewing the control variables independently we find no indications of there being any fixed-effects influencing the regression results. This is accurate for both the initial and long-term models including additional control variables.

5. Conclusion

This paper studies the initial- and long-term market reaction following reversed warnings, examining the Nordic markets between 2010 to 2019. From the literature review it is clear that reversed warnings are underrepresented in the academic literature, with two known examples of Collett (2004) and Spohr (2014). From our review it is expected that reversed warnings yield initial abnormal returns, and that there is a difference in returns when comparing large and small firms. The theoretical framework regarding the long-term market reaction is somewhat deviating, why there is no expected direction for this period. Based on the review, it is also expected that firm size and trading volume could explain the magnitude of the market reactions.

Results from our event study of 118 observations show a significant positive market reaction at the initial period after a reversed warning is announced. We therefore conclude, that the Nordic markets see reversed warnings as value-relevant and that the prevailing information asymmetry is decreased after the announced warning. As the market is seen to make quick adjustments in their expectations, the Nordic markets is assumed to be genuinely surprised by the reversed warning, which is similar to findings in Collett (2004). Results also show a significant difference in initial abnormal returns between small and large firms. This insinuate that share prices of larger firms on the Nordic markets are more correctly priced compared to smaller firms, also in line with prior research (Jackson and Madura, 2003; Collett; 2004). Results from our regression analysis show that both firm size and trading volume impacts the magnitude of the market reaction, a finding confirming prior research made on traditional warnings (Jackson and Madura, 2003; Bulkley and Herrerias, 2005; Cox et al., 2017; Dayanandan, 2018). Based on our regression results for the variable consensus recommendation, CREC, we are also able to conclude that the higher information that prevails prior to the announcement, the greater market reaction is to be expected.

For the long-term period, this study finds results that are especially interesting from a practitioner's point of view. As we observe a significant reversal in share price in the long-term period, we interpret this as an overreaction to reversed warnings on the Nordic markets. Even though firms announce that they will perform better than expected, our long-term results show that their share price will not. Our test across size groups do show that large firms experience a greater reversal in price for the period after the warning is announced. Throughout the long-term period we find no significant regression results, which indicates that neither firm size or trading volume have an impact on the long-term reaction following a reversed warning.

In sum, with this study we contribute extended theoretical knowledge on how the Nordic markets react at an initial period following reversed warnings. In addition, we also fill the knowledge-gap regarding how such announcement impacts the markets in a long-term period. From a practitioner's point of view, we find support for a potential investment opportunity as there are significant price reversals in the period following a reversed warning on the Nordic markets.

5.1 Limitations and future research

One limitation of this thesis is the generalizability of the results. With our data sample being relatively small and skewed to observations originating from Finland and Sweden, 61 and 32, respectively, it makes it complicated to generalize the Nordic markets as a whole. Even if we control for this limitation, finding no indications of it being problematic, a larger data sample, including more observations from Denmark and Norway would yield more generalizable results. Hence, there seems more common to announced warnings in Finland compared to in other Nordic countries. This skewness in observations raises the question of why Finland is more keen to issue warnings, and if that is an implication of that the corporate climate in Finland is more transparent. While warnings seem to be more common in Finland, it would be of interest to see if the Finnish market is less or more prone to react to warnings, as they occur more frequently. Hence, we deem that a cross-country study is motivated to give further insights.

Another limitation of this study is the low capacity of our regression model to explain the long-term abnormal returns. The low explanatory power of our model is assumed to be connected to especially three factors. First, that the selected independent and control variables are not relevant for explaining the variance in long-term abnormal returns. Second, that our model is overparameterized in relation to the number of observations. Third, that the market have been provided with new, and more detailed, information from the quarterly report. Future research should therefore use a larger dataset and apply a revised model, including variables of higher explanatory power. Examples of variables could then be if the warning is quantitative or qualitative (Bulkeley and Herrerias, 2005) or that the warning is issued due to external factors not within the hands of the firm (Church and Donker, 2010). Accordingly, a more vigorous discussion could be held and yield more knowledge regarding the long-term market reaction following reversed warnings. As this study is not able to identify the effect from the forthcoming quarterly report, future research is suggested to examine if there is a more precise method for isolating the long-term effect of a reversed or a traditional warning. To our knowledge, one might use a regression discontinuance design, first examining the initial reaction to the warning and then observe if there is a substantial deviation in price for when the quarterly report is later disclosed. As reversed warnings are a relatively unexplored phenomenon in capital market research, and as we find results indicating an overreaction by the market, we argue that it is motivated to produce further research within this topic.

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Appendix

List of observations used in the study

Listed company	Country	Industry	Date	Size
Noho Partners	Finland	Consumer discretionary	2019-12-18	Small
Vaisala	Finland	Technology	2019-12-11	Large
Danske Bank	Denmark	Finance	2019-12-05	Large
Exel Composites	Finland	Industry	2019-11-21	Small
SAS	Sweden	Industry	2019-11-08	Large
Oma Säästöpankki	Finland	Finance	2019-11-07	Small
Carlsberg	Denmark	Consumer staples	2019-10-28	Large
AP Moller Maersk	Denmark	Industry	2019-10-21	Large
Marimekko	Finland	Consumer discretionary	2019-10-14	Small
Vestjysk Bank*	Denmark	Finance	2019-10-09	Small
Metsä Board	Finland	Commodities	2019-10-08	Large
Ålandsbanken*	Finland	Finance	2019-10-08	Small
Viking Line*	Finland	Industry	2019-09-25	Small
Incap*	Finland	Technology	2019-09-13	Small
Sparebank Norway	Norway	Finance	2019-07-11	Large
Pricer	Sweden	Industry	2019-07-10	Small
Lindab	Sweden	Industry	2019-04-11	Large
Soprano*	Finland	Technology	2019-02-26	Small
BTS	Sweden	Industry	2019-02-07	Small
Raute	Finland	Industry	2019-01-15	Small
Wulff-Yhtiöt	Finland	Industry	2018-12-14	Small
Investors House	Finland	Real estate	2018-11-28	Small
Aspocomp	Finland	Technology	2018-10-16	Small
Storytel	Sweden	Consumer services	2018-10-05	Large
Admicom	Finland	Technology	2018-10-04	Small
Talenom	Finland	Industry	2018-09-17	Small
LeoVegas	Sweden	Consumer services	2018-07-18	Large
Duroc*	Sweden	Industry	2018-06-15	Small
GN Store Nord	Denmark	Healthcare	2018-06-14	Large
Scanfil	Finland	Technology	2018-04-13	Small
Cherry	Sweden	Consumer services	2018-04-13	Large
Stora Enso	Finland	Commodities	2018-04-13	Large
TGS-Nopec	Norway	Energy	2018-04-10	Large
Cellavision	Sweden	Healthcare	2018-04-06	Small
Lehto Group	Finland	Real estate	2017-12-22	Large
Finnair	Finland	Industry	2017-11-10	Large
Ponsse	Finland	Industry	2017-10-16	Large
Honkarakenne*	Finland	Consumer discretionary	2017-10-13	Small
Alma Media	Finland	Consumer services	2017-07-21	Small

Asetek	Norway	Technology	2017-07-21	Small
Pöyry	Finland	Industry	2017-06-15	Large
Kotipizza	Finland	Consumer discretionary	2017-06-06	Small
Keskisuomalainen*	Finland	Consumer services	2017-05-18	Small
Valmet	Finland	Industry	2017-04-12	Large
Yara	Norway	Commodities	2017-02-10	Large
Raysearch	Sweden	Healthcare	2017-02-01	Small
Probi*	Sweden	Healthcare	2017-01-10	Large
Lemminkäinen	Finland	Industry	2016-10-20	Small
PGS	Norway	Energy	2016-10-12	Large
Ahlstrom-Munksjö	Finland	Commodities	2016-09-13	Small
Kotipizza	Finland	Consumer discretionary	2016-08-23	Small
Trainers´ House*	Finland	Industry	2016-08-01	Small
Ahlstrom-Munksjö	Finland	Commodities	2016-07-20	Large
Nilörngruppen	Sweden	Consumer discretionary	2016-07-18	Small
Sanoma	Finland	Consumer services	2016-07-14	Large
Grieg Seafood	Norway	Consumer staples	2016-07-05	Large
Orion	Finland	Healthcare	2016-06-15	Large
Elecster*	Finland	Industry	2016-02-08	Small
Uponor	Finland	Industry	2016-01-26	Large
Schouw & Co	Denmark	Consumer staples	2016-01-21	Large
Martela	Finland	Consumer discretionary	2016-01-15	Small
Napatech	Norway	Technology	2016-01-06	Small
Precise Biometrics*	Sweden	Technology	2015-11-03	Small
Axfood	Sweden	Consumer staples	2015-10-12	Large
Stora Enso	Finland	Commodities	2015-10-12	Large
Fingerprint	Sweden	Technology	2015-10-08	Large
Orion	Finland	Healthcare	2015-07-09	Large
Byggmax	Sweden	Consumer discretionary	2015-07-07	Small
Alma Media	Finland	Consumer services	2015-06-17	Small
Technopolis	Finland	Real estate	2015-06-12	Small
Neste Oil	Finland	Energy	2015-04-21	Large
Profilgruppen	Sweden	Industry	2015-04-07	Small
Nekkar	Norway	Industry	2015-01-27	Small
Nolato	Sweden	Industry	2014-12-19	Small
Elanders	Sweden	Industry	2014-12-17	Small
Taaleri	Finland	Finance	2014-12-05	Small
Atria	Finland	Consumer staples	2014-11-13	Small
Vestas Vind	Denmark	Industry	2014-11-07	Large
Scanfil	Finland	Technology	2014-09-15	Small
Ålandsbanken*	Finland	Finance	2014-07-10	Small
Protector Forsikring	Norway	Finance	2014-01-23	Large
Pandora	Denmark	Consumer discretionary	2014-01-17	Large

Saga Furs*	Finland	Consumer discretionary	2013-10-28	Small
Veidekke	Norway	Industry	2013-10-28	Large
Hofseth Biocare	Norway	Healthcare	2013-10-15	Small
Stora Enso	Finland	Commodities	2013-10-09	Large
Kone	Finland	Industry	2013-09-11	Large
Binero Group*	Sweden	Technology	2013-05-10	Small
Getinge	Sweden	Healthcare	2013-01-23	Large
Nobia	Sweden	Consumer discretionary	2013-01-21	Large
Nokia	Finland	Technology	2013-01-10	Large
TGS-Nopec	Norway	Energy	2012-10-08	Large
Tikkurila Oyj	Finland	Commodities	2012-09-11	Large
PGS	Norway	Energy	2012-07-17	Large
Dovre Group Oyj	Finland	Energy	2012-05-29	Small
NCC	Sweden	Industry	2012-01-26	Large
Micro systemation*	Sweden	Technology	2012-01-17	Small
Arcam*	Sweden	Technology	2012-01-16	Small
Raisio Oyj	Finland	Consumer staples	2011-12-20	Small
Pandora	Denmark	Consumer discretionary	2011-04-20	Large
Metso Oyj	Finland	Industry	2011-04-20	Large
Nokia Tyres	Finland	Technology	2011-04-04	Large
Axis	Sweden	Technology	2011-01-20	Large
Nokian Renkaat	Finland	Consumer discretionary	2011-01-17	Large
Getinge	Sweden	Healthcare	2011-01-11	Large
Huhtamäki Oyj	Finland	Consumer discretionary	2010-12-15	Large
Olvi Oyj A	Finland	Consumer staples	2010-09-24	Small
AP Moller Maersk	Denmark	Industry	2010-07-08	Large
Finnair	Finland	Industry	2010-06-10	Large
Scania	Sweden	Industry	2010-04-28	Large
SKF	Sweden	Industry	2010-04-13	Large
Metsa board	Finland	Commodities	2010-04-08	Large
Autoliv	Sweden	Consumer discretionary	2010-03-01	Large
HK Scan	Finland	Consumer staples	2010-01-29	Small
Axis	Sweden	Technology	2010-01-20	Large
BWG Homes	Norway	Real estate	2010-01-15	Small
Getinge	Sweden	Healthcare	2010-01-14	Large
NKT Holding	Denmark	Industry	2010-01-12	Large

The date is the announcement date of the reserved profit warning. If the reversed profit warning was released after the closage of the stock exchange or during a weekend the next trading day is stated. Firms with an asterisk (*) are the firms that weren't used in the regression analysis.