Takeover Announcements and Illegal Insider Trading Activity

- An Empricial Investigation of the Scandinavian Markets -

Magnus Rakneberg Haug (93820)

&

Mikkel Behrens Mæhlum (94544)

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ABSTRACT

The purpose of this thesis is to answer three main questions; does illegal insider trading occur prior to takeovers of Scandinavian-listed companies? If so, when is it more likely to occur? And thirdly, how can our findings be applied by authorities in their objective to uncover illegal insider trading? In order to investigate the occurrence of insider trading, we conduct an event study where we examine potential abnormal returns and abnormal trading volumes preceding the release of takeover news. Following the approach of MacKinlay (1997), the event study defines an estimation window, event window and post-event window, all set relative to the timing of the event of interest – the "event date". For reliable and confident inference of our results the selected data is controlled for noise creating elements. We start with wide selection criteria and progress gradually more detailed on deal and company specifics until we obtain a representative sample of 263 takeover announcements in the initial sample and 207 announcements in an adjusted sample. The event study uncovers a significant run-up in both abnormal returns and abnormal trading volume prior to the event date, in line with the information leakage hypothesis.

In addressing our second analysis, we find several statistical relationships between abnormal returns and specific deal and company characteristics, among them abnormal trading volume, target firm size, the number of advisors and the relative valuation of the target firm. Although some findings are in line with our initial expectations and hypotheses, we also observe the contrary and several differences across the three markets.

Finally, we make several suggestions to future enforcement of insider trading laws and how our findings can be applied by authorities in their endeavour to prevent and uncover illegal insider trading prior to material events. We direct our focus towards the implementation of software robotics and how its superior processing power can be utilised to detect suspicious trades, automatically map networks and conduct ongoing run-up analyses.

A vast majority of previous studies discussed in this paper have found evidence of illegal insider trading prior to acquisitions and this thesis is no exception. However, to the best of our knowledge, this thesis is the first to analyse insider trading in the Scandinavian markets. Thus, the contribution of this thesis is a validation of the methodology and findings of previous scholars, suggesting that illegal insider trading is not concentrated to select geographies but is a global concern.

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1 INTRODUCTION

“Greed – for lack of a better word – is good”

Mistaken by many, these words are not originally Gordon Gekko’s, protagonist in the 1987 movie ‘Wall Street’, but those of Ivan Boesky, the man on which Michael Douglas’ character is based. At the height in the mid-1980s, he managed an estimated $3 billion, primarily making money on takeover information he bargained for. And not discreetly so; he would often buy tens of thousands of shares only days before announcement, leading to his incarceration in 1987 (Sterngold, 1987; Meserve, 2012).

Maybe not so coincidental, the merger manic 1980’s was also the decade when Keown and Pinkerton (1981) pioneered the method used for investigating illegal insider trading prior to the release of price-sensitive information. Assuming semi-strong market efficiency (Fama, 1970), they argue that if stock prices reflect all public information, market participants holding private information of an impending takeover offer can make abnormal returns by trading before the release of said information. And their findings are accordingly, suggesting that insider trading did in fact prevail prior to public takeovers.

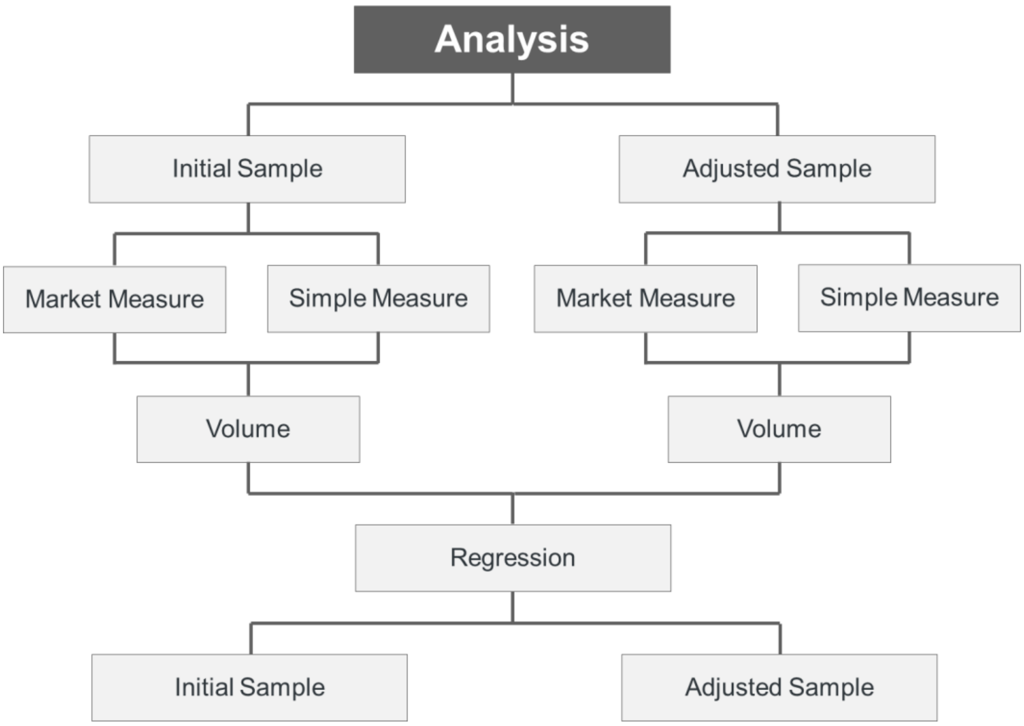
Illegal insider trading is, however, not a thing of the past, should one believe the findings of later scholars inspired by the aforementioned, and several convictions. Among them the 11-year sentence of Raj Rajaratnam in 2011, dubbed one of the largest insider trading cases to date and a modern-day pendant to Ivan Boesky (Hilzenrath, 2011). However, there is friction in the academic environment and among practitioners about whether and why insider trading is inherently bad. Jarrell and Poulsen (1989) find weak evidence of pre-bid run-up substituting for the bid premium, suggesting that this additional cost is the acquirer’s burden. The findings are later supported by Schwert (1996), accentuating a case where Maxus sued Kidder Peabody, Martin Siegel and Ivan Boesky due to allegations of the price they paid for Natomas in 1983 was inflated by the latter’s insider trading. Boesky was again the man of the hour when FMC Corporation sued him, among others, due to inflated prices from insider trading prior to their recapitalisation in 1986 (ibid.) To this comes the deterioration of trust in and integrity of the capital markets; how can you know whether someone exchanging a stock with you does not hold private information incentivising the trade? It is a question of protecting both the acquiring entities and the efficiency of the capital markets.

As there previously have been no investigations as the one by Keown and Pinkerton on the Scandinavian markets, we find great motivation in conducting such an analysis. In the second section we review the distinction between legal and illegal insider trading, the efficient market hypothesis and two competing hypotheses regarding pre-event run-ups as well as trading behaviour and insider trading networks. This lays the necessary foundation for the next section, where we formulate the preliminary hypotheses for the thesis. Subsequently, in section 4, we review previous studies with respect to the methodology and findings, as well as criticism of the approach of former scholars. This section serves the purpose of comparing previous methodologies and applying the criticism to create, in our optic, a more robust model.

Section 5 on methodology and data comprise three parts, firstly our data collection and screening process. Our point of departure is all public takeovers from January 1999 to December 2018. Following several screens, we arrive at a sample of 263 takeover announcements, on which an additional liquidity screen is performed. Secondly, we review the event study methodology and its main components, namely the overall structure and calculation of the necessary measures. Lastly, we review the OLS regression methodology, including, but not limited to, assumptions, variable description and model selection criteria. The variables are selected based on the institutional background, previous studies and intuition.

In section 6 we report the findings of our model, following the structure depicted in Figure 1 below. We first report the event study, starting with the initial sample and subsequently the adjusted sample. For each sample we compare our two measures of abnormal returns and subsequently compare with the trading volume for a coherent picture. These findings make the foundation for the following OLS regression, where we seek to uncover event characteristics making illegal insider trading more or less likely. Subsequently, we revisit our initial hypotheses and whether they are to be kept or rejected based on the empirical results. Lastly, we conduct a robustness check of our methodology to validate that it is indeed reliable for investigating the occurrence of illegal insider trading.

Figure 1: Structure of analysis



Lastly, in section 7, we recapitulate and discuss our preliminary findings. As a robustness check we conduct an event study of a small sample exclusively comprising public takeovers in which there have been convictions of illegal insider trading. Finally, we discuss our findings' implications for regulators and initiatives for insider trading law enforcement in the future.

1.1 RESEARCH QUESTIONS

The purpose of this thesis is to assess whether illegal insider trading prevails prior to public takeover offers in the Scandinavian stock markets. While this has been an established academic area since the 1980's, particularly focused on the US, Canada and Australia, we are yet to see the exercise applied to the Scandinavian markets. Going beyond answering the preliminary question with a simple 'yes' or 'no' – and given the answer is the former – we are motivated to investigate under which circumstances illegal insider trading thrives by applying a regression methodology.

We find great inspiration to our methodology in the early and pioneering studies of Keown and Pinkerton (1981) and Jarrell and Poulsen (1989), and the later and highly cited work of King (2009). Following the empirical conclusions, we discuss how our results can be utilised in exposing informed trading and the initiatives for future enforcement of insider trading laws.

Thus, in conclusion, the thesis seeks to answer the following three questions:

1) Does illegal insider trading pervasively occur in the Scandinavian stock markets prior to public takeover offers?
2) Is illegal insider trading prior to public takeover offers more likely given specific deal and company characteristics?
3) How can the findings in 1) and 2) be applied by regulators in future insider trading law enforcement?

1.2 DELIMITATION

As for any other economic study, this thesis comes with several delimitations. The most pronounced and obvious is our focus solely on the Scandinavian markets, and subsequently exclusively on takeover offers. Illegal insider trading extends to far more forms than the one investigated by us, both in execution and event of interest. While inside knowledge can be materialised through a range of trades, such as options, forwards and shorting, our focus is exclusively on stock purchases, as this has the most apparent price/volume dynamic. To this comes our disregard of offers below closing price the preceding trading day. We are thus left with a proportionate relationship between the returns of the trader and the returns on the stock, i.e. the returns of a trader are directly observable in the stock returns, as elaborated in section 5.1.2.

The delimitation has the implication that we will not and cannot make certain inferences beyond the spectre of the thesis. The reason for this focus is twofold; firstly, the takeover premium tends to be substantial, thus greatly increasing the incentive to act on insider information; secondly, the time required to retrieve data on all "positive" announcements and subsequent illogic in selecting only some. Furthermore, investigating other events such as earnings announcements would remove the possibility of investigating the influence of characteristics of the acquiring entity in takeover events, which we suspect to be influential. The focus thus enables a more in-depth assessment of both underlying mechanisms, as unfolded in the institutional background, and analysis of empirical results.

Thus, the focus of our institutional background is to briefly explain theoretical stock market dynamics and the process of a public takeover, as well as the behaviour and incentives of traders and information flow in an insider network. Combined, we believe this lays the foundation for a better understanding of the forces at work in our hypotheses and subsequent analysis.

2 INSTITUTIONAL BACKGROUND

2.1 HISTORICAL VIEW OF TAKEOVERS

The M&A-activity for the last 100 years has varied greatly. Periods with high activity are referred to as acquisition waves in the literature, and since the end of 1890 there have been seven waves (DePamphilis, 2012). The waves are characterised by a cyclical pattern where economic upswing is followed by a downturn. Each wave has unique characteristics as a result of different economic factors. The beginning of each takeover wave typically coincides with a number of economic, political and regulatory changes.

The fifth takeover wave started in 1993. It surged along with the increasing economic globalisation, technological innovation, deregulation and privatisation, as well as the economic and financial markets' boom. A feature of the fifth takeover wave is its international nature. The European takeover market was about as large as its US counterpart in the 1990's. Moreover, a substantial proportion of acquisitions was cross-border transactions. The fifth wave ended as a consequence of the equity market collapse in 2000 (Renneboog & Martynova, 2005; DePamphilis, 2012).

Globalisation, private equity, and shareholder activism were the key features that characterise the acquisition-wave from 2003-2008. Shareholders became more involved, leading to shareholder activism, where they displayed more influence and power over the actions and behaviour of a corporation by the simple exercise of their ownership rights over the management (Renneboog & Martynova, 2005). However, in December 2007, the subprime mortgage crisis in the US, which caused the recession of the US economy, marked the end of the Sixth Wave.

After several years with low activity for acquisitions, the market took a turn in 2011. In this ongoing wave, the BRIC-countries are taking to the forefront of M&A-activity. The cooperation among these countries directs a lot of focus on commercial and corporate activities, and it would definitely come as no surprise if acquisition activity in the coming years will be heavily concentrated to these countries and their respective continents (DePamphilis, 2012).

2.2 THE TAKEOVER PROCESS

A takeover occurs when one company makes a bid to assume control over or acquire another. Takeovers can be voluntarily, meaning they are the result of a mutual decision between the two companies. In other cases, they may be unwelcomed. In which case the larger company goes after the target without its knowledge. By law, shareholders are obliged to receive a fair value for their shares if they are forced to sell, in both friendly and hostile takeovers (retsinformation.dk, 2014). This fair value is typically referred to as the value excluding any value that arises because of the merger itself. Therefore, it is unlikely that a bidder will acquire a target firm for less than its current market value. Instead, it is normal that the acquirer pays a premium, which is the percentage difference between the acquisition price and the premerger price of the target firm. Historically, acquirers have paid an average premium of 43% over the premerger price (DeMarzo & Berk, 2017). However, for most investors, an investment in the stock market is a zero-net present value (NPV) investment. How can then an acquirer pay a premium for a target firm and still see the investment as a positive-NPV investment opportunity? This is due to the acquirer's ability to add economic value as a result of the acquisition. These synergies can include (DeMarzo & Berk, 2017, p.999-1002):

Economies of scale and scope

Large companies can enjoy economies of scale that are not available to small companies. Furthermore, large firms can also benefit from economies of scope, which are savings that come from combining the marketing and distribution of different types of related products.

Vertical integration

The principal benefit of vertical integration is coordination. By putting two companies under central control, management can ensure that both companies work towards a common goal.

Monopoly gains

Merging with or acquiring a major rival may enable a firm to substantially reduce competition within the industry and thereby increase profits.

Diversification

Diversification is often mentioned as a benefit of merging two firms. The justifications come in three forms.

1) Risk reduction: Large firms bear less idiosyncratic risk, so often mergers are justified on the basis that combined firms are less risky.
2) Debt capacity and borrowing costs: Larger, more diversified firms have a lower probability of bankruptcy given the same degree of leverage. Therefore, such firms can increase leverage further without incurring significant costs of financial distress.
3) Liquidity: Shareholders of private companies are often under-diversified because they have a disproportionate share of their wealth invested in private companies. Consequently, when an acquirer buys a private target, it provides the target's owners with a way to reduce their risk exposure by cashing out their investment in the private target and reinvesting in a diversified portfolio.

Once the acquirer has completed the valuation process, it is in the position to make a tender offer, which is an offer to purchase some or all of shareholders' shares in a corporation for a specified price. A bidder can use either of two methods to pay for a target: cash or stock – or a combination. In a cash transaction, the bidder pays for the target, including any premium, in cash. In a stock-swap transaction, the acquiring firm essentially uses its own stock as cash to purchase the company. The price offered is determined by the exchange ratio, which is the number of bidder shares received in exchange for each target share, multiplied by the market price of the acquirer's stock. Once a tender offer is announced, there is no guarantee that the takeover will take place at this price. Often acquirers must raise the price to consummate the deal. Alternatively, the offer may fail. Moreover, when an acquirer bids for a target, the target firm's board may not accept the bid, and recommend their existing shareholders to not tender their shares, even when the acquirer offers a significant premium over the pre-offer share price. Because of this uncertainty about whether the takeover will succeed, the market price generally does not rise by the amount of the premium when the takeover is announced. This uncertainty creates an opportunity for investors to speculate on the outcome of the deal (DeMarzo & Berk, 2017, p.1006).

For a merger to proceed, both the target and the acquiring board of directors must approve the deal and put the question to a vote of the shareholders of the target. In a friendly takeover, the target board of directors supports the merger, negotiates with potential acquirers and agrees on a price that is ultimately out to a shareholders' vote. In a hostile takeover, the board of directors fights the takeover. To succeed, the acquirer must garner enough shares to take control of the target and replace the board of directors DeMarzo & Berk, 2017, p.1009).

2.3 LEGAL DEFINITIONS

For a better understanding of the scope of this thesis, it is necessary to define the term "inside information" and what it covers whenever used hereafter.

Denmark and Sweden are covered by the European Union's Market Abuse Regulation (MAR) of 2014[1], defining insider information as:

[…] information of a precise nature, which has not been made public, relating, directly or indirectly, to one or more issuers or to one or more financial instruments, and which, if it were made public, would be likely to have a significant effect on the prices of those financial instruments or on the price of related derivative financial instruments (MAR, Regulation (EU) No 596/2014, 7.1.a)

[1] Entered into force July 3rd 2016, replacing the Danish and Swedish equivalent acts with similar definitions

The Norwegian Securities Trading Act of 2007 uses a highly similar definition, validating the choice of investigating the three countries together, defining inside information as:

[…] information of a precise nature relating to financial instruments, the issuers thereof or other circumstances which has not been made public and is not commonly known in the market and which is likely to have a significant effect on the price of those financial instruments or of related financial instruments (LOV-2007-06-29-75, §3-2.1)

Trading in financial instruments on the basis of inside information is unlawful. This applies regardless of whether it is carried out wilfully or through negligence. By trading on inside information, individuals can exploit profitable trading opportunities that are not available to outside investors. If they were allowed to trade on their information, their profits would come at the expense of outside investors and, as a result, outside investors would be less willing to invest in corporations, with the capital market efficiency at risk. Insiders of a company are defined broadly to include managers, directors and anyone else who has access to material non-public information, including temporary insiders such as lawyers and advisors. Courts have defined that for information to be material, it must be a significant factor in an investor’s decision about the value of the security (DeMarzo & Berk, 2017). The law is especially strict regarding takeover announcements, prohibiting anyone with non-public information about a pending or ongoing tender offer from trading on that information or revealing it to someone who is likely to trade on it (DeMarzo & Berk, 2017, p.1040).

2.1.1 Legal and illegal insider trading

Insider trading can be defined in several ways, and it is therefore vital to separate between insider trading and illegal insider trading. *Insider trading* carried out in accordance with the rules and regulations is of course legitimate and represents an important source of information for the market. If a primary insider purchases shares in a company, the market often interprets this as a signal that the individual has confidence in the company and its activities. In the same way, the market will often draw an adverse conclusion if primary insiders sell shares. It is therefore important to have clear rules for reporting insider trading. Primary insiders are required to maintain high standards in meeting their duties so that their trading remains in the insider trading category (Oslo børs, 2019).

Illegal insider trading takes place when a primary insider or an employee, an advisor to the company or anyone else trades on the basis of inside information, as formerly defined.

2.4 The market anticipation and the information leakage hypothesis

The market anticipation hypothesis is an investment theory whereby investors speculate on whether a given firm will be subject to a takeover. The speculations are based on rumours and in-house analyses of industries. The speculation on a potential takeover lead to anticipation in the market which will, whether accurate or not, become incorporated into prices through trading. This will lead to a stock price run-up ahead of the first public announcement to acquire the target firm (Jensen & Ruback, 1983).

Keown and Pinkerton (1981) introduce an alternative hypothesis, the information leakage hypothesis. This is based on the theory where individuals with access to non-public information trade illegally to profit from the future price jump when the takeover is announced. Both hypotheses have empirical support in the literature, and it is only natural to assume that run-ups prior to acquisitions are caused by some combination of both hypotheses. In order to separate anticipation from information leakage, it is useful to apply the models introduced by Kyle (1985) and Admati and Pfleiderer (1988). The models are used to examine how a trader with inside information will trade to maximise profits by introducing two kinds of traders: informed traders who trade on the basis of private information that is not known to all other traders, and a liquidity trader who trade for reasons that are not related directly to the future payoffs of financial assets, such as hedging positions. Informed traders trade more actively in periods when liquidity trading is concentrated. Furthermore, trades executed by informed traders determine to a large extent at what price the stock will stabilise. This is because the informed trader will, unlike the liquidity trader, only execute trades that will accumulate positively and thus push up the stock price (Kyle, 1985). Furthermore, Admati and Pfleiderer (1988) argue that insider traders and non-discretionary traders generate a higher liquidity, in turn incurring discretionary liquidity traders to act, thus resulting in a concentration of abnormal volume in these periods.

2.5 The efficient market hypothesis

The efficient market hypothesis is an investment theory by Fama (1970) whereby share prices reflect all information and consistent abnormal returns is impossible. Theoretically, neither technical nor fundamental analysis can produce risk-adjusted excess returns consistently and only inside information can result in abnormal risk-adjusted returns. This implies that securities will be fairly priced, based on their future cash flows, given all information that is available to investors (DeMarzo & Berk, 2017). The underlying rationale for the efficient market hypothesis is the presence of competition. The degree of competition, and therefore the accuracy of the efficient market hypothesis, will depend on the number of investors who possess this information. To illustrate the above, we can look at two different cases. In the first case we assume that information is public and easily interpretable. In this situation, we expect competition between investors to be fierce and the stock price to react nearly instantaneously to news. Most investors would find that the stock price already reflect the new information before they were able to trade on it. Thus, in such cases with high degree of information symmetry, the efficient market hypothesis is expected to hold.

In the second case, we assume that information is private or difficult to interpret. When private information is possessed by a relatively small number of investors, these investors may be able to capitalise on their informational advantage. In this case, the strong-form market efficiency does not hold. However, as these informed traders begin to trade, they tend to move prices, so over time prices will begin to reflect their information. If the potential gains of capitalising on this information are great, other market participants will strive to even out their informational disadvantage. As more individuals become better informed, competition to exploit this information will increase. Thus, in the long run, we should expect that the degree of inefficiency in the market will be limited by the costs of obtaining the information (DeMarzo & Berk, 2017, p.335).

2.6 PRICE AND VOLUME RUN-UP AS AN INDICATORS OF ILLEGAL INSIDER TRADING

Several studies on insider trading have shown that stock prices and trading volume tend to increase significantly prior to announcements of public takeover bids or rumours of such (DeMarzo & Berk, 2017). One of these studies shows that the majority of suspected insider trading takes place in the 25 days prior to the release of market sensitive information (Olmo, Pilbeam, & Pouliot, 2011), while others find concentration within the last 10 days (Aitken & Czernkowski, 1992; King M. R., 2009; Borges & Gairifo, 2013). While some researchers attribute these run-ups to be evidence of illegal insider trading, others are convinced that run-ups are evidence of the efficient market hypothesis, stating that stock prices at any time reflect all publicly available information (Jarrell & Poulsen, 1989). Based on the two contradictory hypotheses, it is natural to question whether a stock price run-up *actually* serves as a robust indicator of illegal insider trading.

Research done by Jarrell and Poulsen (1989) disclose that abnormal volume and abnormal return tend to increase in the period prior to the public announcement of the takeover. Furthermore, Cornell and Sirri (1992) found that abnormal returns solely coincide with days on which informed traders are active. Additionally, the study showed that the presence of informed traders with inside information in the market brought falsely informed traders to transact, leading to a surprising increase in liquidity. Moreover, Meulbroek's study from 1992 showed that the abnormal price movement on insider trading days is 40% to 50% of the subsequent price reaction to the public announcement of the inside information. In addition, 43% of the stock price run-up over the twenty days preceding the takeover announcement occurs on insider trading days.

McInish, Frino and Sensenbrenner (2011) investigated whether insiders trade strategically to avoid detection. The results show that insiders are more likely to trade on high volume days which indicate an effort to hide their trades by attracting as little attention as possible. Illegal insider trades should therefore be identified by both abnormal return and abnormal volume on the same day.

2.7 Trading behaviour

2.7.1 Uninformed investors and the effect on stock run-ups

As discussed in section 2.4 the market anticipation hypothesis postulates that increases in stock prices prior to acquisitions are due to in-house analysis made by investors who do not violate law when investing. In the following section we will discuss the implications of these trades.

Prior to takeovers, skilled institutional investors and speculators actively manage portfolios by taking long-short positions in the target and the acquiring firm. These investors strive to uncover signals of impending takeovers by analysing industries and company-specific factors. As opposed to the private information of informed traders, most of the information institutional investors hold is less reliable. Consequently, they know neither the eventual takeover price nor the timing, leading to their speculative trading having less of an imprint on the stock behaviour than that of the trading of a confident, informed trader. The public information identifying a firm as a takeover candidate is perceived and analysed by institutional investors in several ways and there will be both hedging and speculative trading. If the skilled, uninformed traders have opposing views on the offer price and the timing, the increased trading volume should not generate price changes (Grundy & McNichols, 1989).

As the event day approaches, the target firm will be more attractive to speculators as rumours abound. As a consequence, institutional investors will speculate more aggressively and trade large quanta. Therefore, one should observe that stock returns correlates positively with abnormal volume. However, there will always be some uncertainty related to the stock price after the acquisition and we will therefore expect the stock price to react to the announcement, depending on the accuracy of the market's speculation (King, 2009).

2.7.2 Inside information networks

Ahern (2017) disclosed that individual characteristics, such as age, gender, wealth and occupation, are related to insider trading behaviour. Insider traders have incentive to share information with people they trust. This means that social networks will spread information in insider trading networks. In this paragraph we will therefore present an analysis of the social relationships that underlie illegal insider trading networks.

Stein (2008) presents a model which predicts that valuable information remains local. The logic behind this is based on the fact that the more people that have the information, the less valuable the information becomes because stock prices will reflect the information as insiders capitalise on it. Therefore, when inside information is more valuable, the informed investors are more likely to share the information with closer contacts. Conversely, as the information loses value, the informed investor is more likely to share the information more broadly. Thus, as information spreads away from the original source, the social relationships become more peripheral (Stein, 2008).

A study carried out by Ahern (2017) investigates how information transmits away from the original source through social networks by introducing “tip chains”. An illegal insider trader’s order in the tip chain is “the number of links he is removed from the original source” (Ahern, 2017, p. 39). The first link in the tip chain is the connection between the original source and the person who receives a tip, referred to as a “tippee”. The tippers that are in the first link in the tip chain are the original sources and tend to be primary insiders or advisory professionals. As the information moves away from the original source, officers become less common tippers. In contrast, buy-side managers and analysts are increasingly the tippers as the information travels further from the source. As for social connections, the study reveals a clear pattern. In the first link, tippers and tippees are primarily friends (42,4%) and family members (26,4%) and then become more peripheral as the tip moves further from the source. In assessing the amount invested, Ahern’s research showed that the median amount invested for the first tippee is $200.400 while the fourth and subsequent tippees have a median investment of $492.700. Trading return, on the other hand decline over the tip chain, indicating that the information become less valuable as stock prices begin to reflect the information. Finally, the research show that the average time between receiving information and sharing it with others decreases over the tip chain. The original source waits 12,1 days on average before tipping the information, while for the fourth and higher links, the delay is 0,4 days.

Furthermore, Ahern’s (2017) paper studied how illegal insider traders are connected to each other by investigating social relationships, geographic proximity and shared attributes. Of the total 461 cases of illegal insider trading, 23% are familial, 35% are business-related, 35% are friendship and 21% do not have any clear relationships. As for geographic proximity in relationships, the paper showed that illegal insider traders are more likely to share information with people who live close by. Logically, close geographic proximity facilitates social interaction. In the context of insider trading, greater social interaction could reduce uncertainty in a relationship and increase trust between a tipper and a tippee. Finally, the paper disclose shared attributes of insider traders. The connections between tippers and tippees by occupation showed that top executives are by far the most frequent tippers. Their tippees are spread over all occupations. In contrast, buy-side analysts are the next most common tippers, but their tippees are concentrated to other buy-side analysts. Furthermore, tippers and their tippees tend to be close in age.

Finally, Ahern's (2017) study disclose how stock returns depend on the identities and relationships of insider traders. The results show that insider traders' age, gender, wealth, occupation and network positions do not have significant relationships with stock returns. However, when traders receive information from a family member, stock returns are significantly higher. This could indicate that tips from family members are more reliable, which leads to more aggressive trading. In contrast, tips from business associates and friends are unrelated to stock returns.

3 HYPOTHESIS DEVELOPMENT

In order to answer the research questions, we will test several hypotheses based on theory, logical intuition and previous studies. The first hypothesis will assess whether illegal insider trading prevails prior to public takeover offers in the Scandinavian markets. The subsequent eleven hypotheses examine if illegal insider trading prior to takeovers are more likely given specific deal and company characteristics. This section will only elaborate on the reasoning behind our hypotheses. For a detailed explanation of each variable used for the hypotheses, we refer to section 5.3.3.

3.1 HYPOTHESIS ON OCCURRENCE OF INSIDER TRADING IN SCANDINAVIAN TAKEOVER TARGETS

As discussed in section 2.4, the literature points out two popular hypotheses to explain run-ups in stock prices prior to acquisitions of publicly listed companies. The first hypothesis, the information leakage hypothesis, states that pre-event run-ups are caused by informed insiders trading illegally to profit from the future price jump when the takeover is announced. This tend to generate abnormal returns but also abnormal volume, as uninformed traders are induced to trade by the increased order flow when insiders are active. Illegal insider trading should therefore be identified by the coincidence of abnormal return and abnormal volume on the same day (King, 2009). The other hypothesis, the market anticipation hypothesis, argues that investors speculate on whether a firm will be subject to a takeover based on in-house analyses that do not violate law (Jensen & Ruback, 1983). The analysis, accurate or not, will lead to a stock price run-up prior to the public announcement of the acquisition.

Based on the two contradictory hypotheses presented above, it is natural to question whether a stock price run-up actually serves as a robust indicator of illegal insider trading. However, if both abnormal trading volume and abnormal return are observed prior to the public announcement of the acquisition, it serves as a robust indicator of insider trading (King, 2009). Furthermore, previous research disclose that stock prices trades at abnormal return and volume as early as 25 days prior to the public announcement of the acquisition with concentration within the final 10 days (Aitken & Czernkowski, 1992; King M. R., 2009; Olmo, Pilbeam, & Pouliot, 2011; Borges & Gairifo, 2013). For the above reasons, we hypothesise that:

H.1.1: Illegal insider trading prevails prior to public takeover offers in the Scandinavian stock markets

3.2 HYPOTHESES ON DEAL AND COMPANY CHARACTERISTICS

Research by Admati & Pfleiderer (1988) showed that insiders have incentive to trade when the stock is liquid. This is based on the argument that it is easier for the insider traders to hide their trade when the stock trades frequently. Furthermore, King (2009) disclosed that abnormal returns should occur on days with abnormal turnover, as uninformed traders are induced to trade by the increased order flow when insiders are active. Based on the above, we hypothesise that:

H.2.1: Illegal insider trading is increasing in abnormal trading volume

As previously stated, illegal insider traders prefer to trade in a fashion that keeps them out of authorities' search light. Larger deals tend to attract the attention of media and regulators, giving us a reason to believe that market participants with inside information will to a greater extent refrain from materialising their knowledge if it concerns a large company, in turn leading to less illegal insider trading prior to such takeovers. Further research on this topic shows that run-ups are larger for relatively small target companies (Hackbarth & Morellec, 2008). Thus, we hypothesise:

H.2.2: Illegal insider trading is less likely the larger the target firm

As discussed in section 2.6, illegal insider traders have a strategic approach when trading on inside information. More specifically, they are more likely to trade on already high-volume days. This is because they have an incentive to invest so their trades have as little influence on the stock price as possible (McInish, Frino, & Sensenbrenner, 2011). The more liquid the stock is in general, the better the insider's order blend in with the ordinary trading pattern. Thus, we suspect more insider trading to occur in high-volume stocks, but harder to observe in terms of irregular stock behaviour. Therefore, we hypothesise that:

H2.3: The more liquid the stock, the less likely it is that illegal insider trading is statistically observable

As formerly discussed, globalisation and international trade have characterised the M&A market for the last decades (Renneboog & Martynova, 2005; DePamphilis, 2012). A larger proportion of the transactions are made by international players. This makes it difficult for federal governments to investigate illegal insider trading as the exchange of sensitive Financial Supervisory Authority (FSA) data across borders is often a troublesome process (Bromberg, Ramsay, & Gilligan, 2017). This implies that foreign investors are less likely to be prosecuted when trading on inside information. Consequently, the possibility of leakage of sensitive information is higher when the acquirer of a target firm is foreign. Therefore, it is only natural to assume that illegal insider trading is more likely to occur when the acquiring firm is foreign. Furthermore, a formal investigation is more likely when the takeover is made by a foreign bidder (Madura & Marciniak, 2014). Based on the above, our hypothesis is:

H.2.4: Takeover offers by foreign acquirers are more prone to illegal insider trading

In firms with dispersed share ownership, no single individual or entity has a majority interest, meaning ownership of more than 50% of the voting shares. This implies that none of the shareholders control a large enough position to determine corporate policy and influence the strategic direction of the company. As a consequence, each shareholder will have limited insight into sensitive information and strategic decisions made by the management. Conversely, in cases with a concentrated ownership structure, the majority shareholder normally takes part in daily operations and has insight into sensitive information. Recalling Ahern's (2017) paper where he disclosed a noteworthy close linkage between corporate insiders and buy-side investors, it is only natural to assume that some of this inside information is forwarded to insider traders. Based on this, we hypothesise that:

H.2.5: Illegal insider trading is more likely to occur when the target firm is owned by a majority shareholder

Section 2.7.2 disclosed that deal advisors leak sensitive information during the takeover process. On average, insider tips originate from corporate executives and reach buy-side investors after three links in the network (Ahern, 2017). Therefore, we expect that more advisors on a deal makes insider trading more likely. Furthermore, research carried out by Brigida & Madura (2012) disclose a positive correlation in the run-up period between the target's stock price and the number of advisors. Therefore, we hypothesise that:

H.2.6: The higher the number of deal advisors, the more likely is illegal insider trading

Historically, the announcement effect of cash-only deals has been significantly higher than that of a full or partial stock-swap (Rappaport & Sirower, 1999). In a stock-swap the shareholders of the acquired company obtain a share in the acquiring company for which the acquiring company is not willing to pay the same price. Thus, a cash-only deal represents a higher upside for an insider trader. Furthermore, in a cash-only deal, the trader can easily sell his shares post-announcement, whereas shares involved in a swap may be more illiquid. This is further supported by Masulis, Wang and Xie (2007), who showed that takeovers paid in cash had a positive impact on the target stock cumulative abnormal returns (CAR) from two days before the event date till two days after. A payment made in stock, on the other hand, had a negative impact on CAR. Moreover, Wansley, Lane and Yang (1983) compared CAR for cash mergers against stock mergers in a 40-day window prior to the public announcement of the merger. The results showed that CAR for cash mergers was 38,7%, while the equivalent for stock mergers was 25,4%. Hence, an investor trading on inside information would prefer to trade on acquisitions where the payment is made in cash. Our hypothesis is therefore:

H.2.7: Illegal insider trading is more likely for cash-only offers

The financial crisis of 2007-2008 took the financial markets by storm. Governance failure in adequately judging and assigning risk measures to key financial instruments led to a full-blown international banking crisis. However, the response by banks and supervisors in the aftermath of the crisis was immediate and has brought about changes in the desired direction (Dudley, 2018). In fact, research has shown that financial misconduct has fallen since the financial crisis (Rao & Reddy, 2014). Therefore, we expect that takeovers after the Financial Crisis generally have a lower attraction to illegal insider traders. Consequently, we hypothesise that:

H.2.8: Illegal insider trading is less present after the financial crisis

A significant amount of the firms in our sample are penny stocks[2]. Penny stocks are stocks that are considered highly speculative due to their lack of liquidity and small capitalisation (DeMarzo & Berk, 2017). This makes them risky, but still, some investors prefer to trade penny stocks because the low stock price makes it possible to hold a large number of shares for a relatively small amount of capital. This means that investors can make a profit with just a minor gain per share. Given the speculative nature and volatility of penny stocks, it is natural to assume that penny stocks are a popular choice for insider traders who want to hide their trades among already volatile stock behaviour. Therefore, we hypothesise that:

H.2.9: Illegal insider trading is more likely to occur when the target firm trades as a penny stock

A study carried out by Borges & Gairifo (2013) show that undervalued firms are more likely to be exposed to acquisition bids. As a means to identify undervalued or overvalued stocks we introduce the market-to-book ratio. If the market value of a company is trading lower than its book value per share, it is considered to be undervalued. Therefore, we expect the run-up in stock price to be higher when the target firm is undervalued and has a low market-to-book value. Based on this we hypothesise that:

[2] Stocks trading at a per-share price lower than $1 (King, 2009)

H2.10: Illegal insider trading is more likely to occur in takeovers of undervalued companies

Employees of a financially distressed firm usually have lower morale and higher stress caused by the increased chance of bankruptcy (DeMarzo & Berk, 2017). It is therefore natural to assume that individuals who experience financial distress on their workplace are more likely to commit financial misconduct. Based on this, we hypothesise that:

H.2.11: Illegal insider trading is more likely to occur when the target firm is financially distressed

4 LITERATURE REVIEW

The purpose of this chapter is to review selected previous research on the occurrence of illegal insider trading. Firstly, we review the methodologies of previous scholars, including, among others, the ambiguity regarding event dates and correctly setting the event window (Halpern, 1982; Jarrell & Poulsen, 1989). We then present the findings of studies having investigated abnormal returns and trading volume as a proxy for insider trading, such as Meulbroek (1992), Bris (2005), Chae (2005) and King (2009). We subsequently review the common criticism of said approach, for example that of Aspris, Foley and Frino (2014), emphasising the potential mistakes in solely attributing pre-bid run up to insider trading. To complement our hypotheses 2.1-2.11 we review studies going beyond a pre-bid stock price run-up analysis investigating the influence of specific event characteristics.

4.1 METHODOLOGY AND RESEARCH DESIGN

Prior to going into detail on the results of previous research, setting the expectations to our own study, we summarise similarities and differences in the research designs of studies on the area. The common research design defines initial sampling and subsequent data screens, determining the event date and window, and the calculation of abnormal returns (AR) and volume (AV).

The common approach to investigate the potential occurrence of insider trading is the event study, specifically on the pre-event stock price run-up (Halpern, 1982). This approach seeks to examine potential abnormal returns and abnormal trading volumes preceding the publication of takeover news of significance to the target stock price. In the event of the market anticipating said takeover and/or insiders trading on their private information, one would expect a stock price run-up and rush in trading volume pre-event. The common measures of this is cumulated abnormal returns (CAR) and cumulated abnormal volume (CAV), suggesting that leakage of such information leads to irregular stock behaviour. Conversely, if there is no anticipation or leakage, CAR and CAV are expected to fluctuate around zero, cementing the measures' position as validators of the information leakage hypothesis (Keown & Pinkerton, 1981; Meulbroek, 1992; Bris, 2005; King, 2009).

The existing literature is dispersed in terms of geographies and time period analysed, ranging from national to global and three years to fifteen years. Common for all, however, is a meticulous data screen to minimise bias and noise for a more reliable and representative data foundation. A first screen is commonly excluding observations for which another bid occurred within a given period before, where Borges and Gairifo (2013) set the length of this "clean" period to one year, King (2009) uses two years and Bris (2005) uses a conservative four years. This is to ensure that stock prices are not influenced by market anticipation from the previous bid, where some scholars also exclude follow-up bids from the same acquirer despite the time between exceeding said clean period, to ensure no anticipation of the offer (Bris, 2005; Aspris, Foley, & Frino, 2014).

Furthermore, for reliable AR and AV calculations, it is common to exclude offers for which stock price and volume is not available for a given number days in the estimation window and event window, usually corresponding to maximum 25% of the days in the two windows separately (Boehmer, Musumeci, & Poulsen, 1991; King, 2009). To mitigate the potential bias of thinly traded stocks on the return and volume, some also exclude stocks which are not traded sufficiently to move the price more than 75% of the days in the event window (King, 2009; Borges & Gairifo, 2013).

An important issue of event studies is determining the event date. In Halpern's (1982) review of several studies on the topic, all scholars used the date of the first public announcement as event date. Later scholars, led by Jarrell and Poulsen (1989), use a news-adjusted event date, arguing that this date to a greater extent isolates the information leakage effect, as the market's anticipation of a takeover will increase with media coverage, thus introducing a bias in measuring the run-up (Aitken & Czernkowski, 1992; King M. R., 2009; Borges & Gairifo, 2013; Aspris, Foley, & Frino, 2014). These rather set the event date as the date of the first public, well-founded rumour by analysing media coverage prior to the official stock exchange announcement date.

To compute ARs Brown and Warner (1980) and MacKinlay (1997) suggest several approaches, two of which being the constant mean model and the market model. In the former, the mean return of the estimation window is subtracted from the daily returns in the event window. Previous literature predominantly lean towards the latter approach in which event window returns are predicted from a regression of stock returns on index returns in the estimation window, and subsequently subtracted from the actual daily returns.

For AV, Chae (2005) uses a constant mean model similar to the one for AR, whereas Bris (2005) and King (2009) subtract the mean plus two standard deviations, setting this to zero if the calculation returns a negative AV. AR and AV are both averaged and cumulated cross-sectionally to return AAR, AAV, CAAR and CAAV[3], with the period of accumulation ranging from 20 days (Jarrell & Poulsen, 1989) to 60 days (King, 2009) preceding the event date. These are subsequently tested using the student's t-test, to evaluate the presence of statistically significant abnormal daily and cumulated stock behaviour.

4.2 FINDINGS FROM PREVIOUS STOCK RUN-UP STUDIES

Keown and Pinkerton (1981) were among the first to analyse abnormal pre-bid price movements applying the event study methodology and attributing this to illegal insider trading. In their study of 194

[3] (Cumulative) Average abnormal return and volume

successful transactions in the US between 1975-1978 they find almost exclusively significant market-modelled ARs the last ten days before the takeover announcement, cumulating to a 20-day pre-event CAAR of 12,2%. They also find a considerable rush in trading volume beyond transactions by registered insiders, underpinning Ahern's (2017) study suggesting traders with no direct affiliation to the target company possess inside information, either to cover for registered insiders or due to word of mouth.

Jarrell and Poulsen (1989) reach similar conclusions in their study of 172 US takeover offers. With an 11% CAAR (-20, -1) relative to the news-adjusted event date, they conduct a cross-sectional OLS regression to investigate factors influencing takeover premiums and stock price run-up. They find that media speculation significantly reduce the takeover premium on the event day and greatly increase the run-up as the prices start reflecting the impending takeover offer. Although not significant, the same results apply for cases where the acquirer had accumulated significant shareholdings in the target company, as is common before launching formal offers for control. They also distinguish between hostile and friendly bids, based on the hypothesis that there is more secrecy involved in a hostile bid to prevent the target from taking defensive moves. As expected, hostile takeovers result in a higher takeover premium and a lower run-up, however, it is only significant for the (-20, -5) run-up. Lastly, they include a dummy for whether government agencies later alleged insider trading violations based on former scholars attributing all run-up to insider trading. As opposed to expectations, cases with insider trading allegations had significantly higher takeover premiums and (insignificantly) lower run-up, leading the authors to speculate in whether authorities more frequently prosecute in cases where illegal insider traders made substantial profits, i.e. a higher takeover premium.

A much larger dataset was used by Bris (2005) in his study of close to 4.500 announcements worldwide from 1990 through 1999. In two of eight world regions he finds a statistically significant CAAR (-50, -11) relative to the news-adjusted event date, which increases to six of the regions for the period (-10, -2). Using a volume calculation of subtracting the mean plus two standard deviations from the actual daily volume, he also finds corresponding significant CAAV for both (-60, -5) and (-30, -5). This study has a particular focus on the efficiency of insider trading legislation, thus including a dummy for the year in which the law was enforced for the first time. Contrary to immediate expectations, he finds inside trading profits had increased after enforcement, justifying this with the higher the marginal cost, i.e. punishment, the higher the required benefit.

A similar approach in calculating AR and AV was used by King (2009) in his analysis of 399 takeover announcements of publicly listed Canadian firms. The statistically significant AARs cluster in the interval (-10, -1) with CAAR turning significant five days preceding the event date. There are no significant daily AAVs, however the CAAV is exclusively and increasingly significant from 38 days preceding the event date. In the cross-sectional analysis, instead of regressing CAR for a given period, the dependent variable is daily AR in the window (-50, -1). Of the most notable results from the regression are the negative and significant impacts of the size of the target company and cash-only offers, the former consistent with insider traders avoiding attention thus also larger deals and the attention that follows. Consistent with expectations, the more volatile penny stocks experience greater AR, and AV coincides with days of AR. All findings were robust to changes in calculation methods for AR and AV, where both a constant mean and factor model was applied for AR and mean-deviation and market model for AV.

4.3 CRITICISM OF PREVIOUS METHODOLOGIES

While Keown and Pinkerton's (1981) study received great praise for pioneering the academic area, it has also been criticised for its bombastic conclusion of attributing the significant run-up to illegal insider trading, largely due to the authors' use of the announcement date as event date. As mentioned, this has later been refined by applying a news-adjusted event date, to account for anticipatory trading. In later studies, Bris (2002) and Ravid and Spiegel (1999) provide theoretical evidence of toehold purchases creating rumours resulting in target stock price run-ups. Direct, empirical evidence is however conflicting. Jarrell and Poulsen (1989), Betton and Eckbo (2000) and Borges and Gairifo (2013), have all tried to further capture market anticipation by including potential toeholds, however with the former obtaining negative, yet insignificant, coefficients, the second negative and significant, and the latter positive and significant.

Some of the more pronounced critics of previous studies are Aspris, Foley and Frino (2014). Crediting the aforementioned for controlling for toeholds and their triggering effect on perfectly legal speculation, they argue that a simple dummy is insufficient, with more information contained in the timing of the toehold acquisition. By distinguishing between long-term and short-term toehold holdings (relative to event date) and controlling for media speculation and price sensitive announcements, they find that the market activity generated by these factors explains a significant share of the pre-bid run-up. Through conducting a robustness test of toehold acquisitions with no later takeover bid, they also find a significant run-up, concluding that toehold acquisitions drive market anticipation. Running the same model on takeover announcements with no short-term toeholds, they obtain no significant run-up. This suggests that the run-up previous studies had largely attributed to illegal insider trading, to a great extent can be explained by legal factors associated with market anticipation.

5 Methodology and Data

To empirically assess the occurrence of illegal insider trading prior to takeover announcements of Scandinavian listed companies, we will conduct an event study and subsequently a cross-sectional OLS regression analysis following the methodology seen in Jarrell and Poulsen (1989), King (2009) and Aspris, Foley and Frino (2014). This two-fold approach allows us to first analyse potential pre-bid abnormalities in stock price and trading volume, for later to test whether said abnormalities can be explained by certain deal and company characteristics.

5.1 Data collection and screening

5.1.1 Data collection

We retrieve a list of all publicly announced takeover offers for Scandinavian-listed companies from January 1999 through December 2018 from Moody's Bureau van Dijk Zephyr database. With a minimum requirement of the offer at some point being announced by the stock exchanges, we also include offers that in the end did not result in a takeover, as this could not be anticipated prior to the launch of a formal bid. In this process we also retrieve information on deal and company characteristics that later lay the foundation for our OLS variables, such as acquiring entity, deal type, payment structure, number of advisors, etc. This leaves us with a raw sample of 946 offers.

Using the target companies' unique ISIN[4] number, we retrieve daily data on adjusted stock prices, trading volumes and market capitalisation from Datastream by Thomson Reuters. However, all data from Datastream is padded, meaning that for banking holidays, data is merely repeated from the previous trading day. This results in zero returns for these days, which can potentially distort both the expected returns from the constant mean and market model and the actual daily return from which the expected returns are subtracted, leaving us with unreliable abnormal returns and abnormal volume. To account for this, we find that Bloomberg leaves banking holidays blank instead of padded. We thus retrieve index data from Bloomberg, which we first make sure is equal to that of Datastream, and subsequently match the stock data with their respective index and delete blanks. When collecting data, we also retrieve market-to-book ratios and interest coverage ratios for the target companies, for later use in the cross-sectional analysis.

5.1.2 Data screening

To be able to rely on and confidently interpret our results, a data screen is required. We start with wide selection criteria for our sample of 946 takeover offers and progress increasingly more detailed on deal

[4] International Securities Identification Number

and company specifics until we obtain a representative sample, which is then screened based on data quality.

Screen 1 – Excluding offers with no stock price or volume data

The first screen is merely on data availability to ensure that the remaining sample has sufficient data to calculate the stock price and volume run-up. We exclude all offers for which Datastream could not supply a stock price or volume, which led us to remove 163 offers, thus ending up with 783.

Screen 2 – Excluding offers not of interest

Despite filtering for mergers and acquisitions when retrieving data, our sample contained offers and transactions that for different reasons are not of interest, and thus required review (Bris, 2005). We exclude minority stake purchases we regard too small to trigger price movements, thus are unlikely to be traded on by insiders. For good measure we therefore also exclude bids for unknown stakes.

We also exclude recapitalisations and debt conversions as these in all cases in our sample resulted in a negative return upon announcement. While it is perfectly possible and also evidence of short-selling prior to the release of negative price-sensitive information, thus making an abnormal positive return (Khan & Lu, 2013), we have delimited our scope to focus on AR serving as a direct proxy for the returns achieved by illegal inside trading.

Lastly, we exclude all instances of a company transferring all shares in a wholly-owned subsidiary to themselves and cases of carve-outs, asset sales and sales of Special Purpose Vehicles, as neither of these have substantial impact on stock price.

Following this screen, we exclude 186 offers, arriving at 597 observations.

Screen 3 – Excluding offers with noise in the period preceding the event date

This screen serves to exclude observations with elements in the period prior to the event data with the potential to bias our calculations. Firstly, we exclude offers that were announced within a year after a previous bid on the same company, as do Borges and Gairifo (2013). This is due to the potentially increased attention these companies achieve both from media and market participants, thus being more prone to speculative trading in the anticipation of a follow-up or competing bid. This, in the end, would downplay the run-up in the event of a subsequent bid, also making it more difficult to distinguish between the run-up caused by perfectly legal anticipatory and speculative trading and that of illegal insider trading (King, 2009). Adding to this, we also exclude offers where the target company underwent an initial public offering (IPO) in the estimation or event window, as the IPO underpricing phenomena tend to result in significant AR on the first day of trading followed by unstable trading patterns (Ritter & Welch, 2002).

Where Aspris, Foley and Frino (2014) distinguished between long-term and short-term toeholds, we have taken the conservative approach of excluding all offers where the acquiror over time has ramped up their stake in the target company. Here as well it is due to the market's anticipation of the incoming bid and our inability to obtain the dates of the toeholds for an equivalent distinction. Furthermore, our focus is illegal insider trading, not other factors explaining the run-up.

Lastly, we exclude all offers that were at a discount to the average share price over the last ten days prior to the bid, for the same reason as when excluding debt conversions and recapitalisations (Jarrell & Poulsen, 1989).

This screen leads to the exclusion of 274 observations, resulting in a preliminary sample of 323 observations.

Screen 4 – Exclude offers with insufficient data

While the first screen excluded observations where Datastream could not provide data, this screen serves the purpose of ensuring sufficient data for our remaining sample, as Datastream for whatever reason do not necessarily have data for all days in the event period. Following the example of Boehmer, Musumeci and Poulsen (1991) and King (2009) we exclude offers with more than 20 days of missing price or volume data in (-120, -31), more than 25% missing in (-30, -1) and more than 1 missing in (-2, 1) for more reliable calculations.

From this screen 60 offers are omitted, leaving us with 263 announcements. This will henceforth be referred to as the *initial sample*.

Screen 5 – Liquidity screen

After looking deeper into the initial sample, we realised that a large share of the observations seemed to be illiquid in that they had a substantial number of zero-return days in the period (-120, 0), which coincided with a low trading volume. Such illiquidity has the potential to distort the calculation of expected returns and volume, and subsequently also AR and AV. Illiquidity in the estimation period yields both a low mean return and beta used to calculate the expected return in the event window, thus inflating the abnormal returns if the stock is more frequently traded in the event window. Furthermore, as stated previously, illegal insider traders tend to avoid illiquid stocks as their trades to a greater extent stand out, making these observations less relevant for us (McInish, Frino, & Sensenbrenner, 2011). To account for this, we do a final screen excluding all observations with more than 25% zero-return days in the period (-120, 0).

Following this, we exclude 56 observations, arriving at 207 takeover announcements. This sample will henceforth be referred to as the *adjusted sample* and will be used in parallel with the initial sample.

5.2 THE EVENT STUDY METHODOLOGY

Event studies are frequently applied to measure the economic effects of an event on firms, as the effect will immediately be reflected in security prices, given the efficient market hypothesis to some extent holds (MacKinlay, 1997). In the following section we will present how to properly structure and conduct an event study, including defining the different windows and calculating the measures of interest.

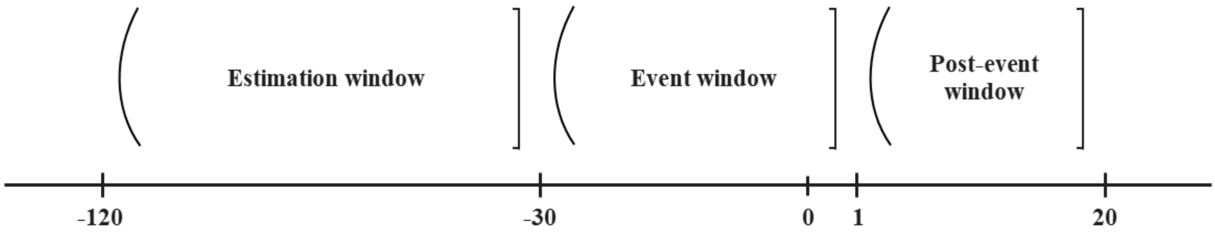
5.2.1 Event study structure

Following the approach of MacKinlay (1997), an event study should have a defined estimation window, event window and post-event window, all set relative to the timing of the event of interest – the event date. The event window is the period for which the returns and volume will be examined, and usually includes multiple days prior to and after the event date to examine the behaviour surrounding the event date, as is the case for this study. Preceding the event window is an estimation window, which represents a period of ‘normal’ behaviour, and thus lays the foundation for the calculation of the *expected* returns and volume for the event window. The estimation and event window should not overlap to avoid the expected parameters from being influenced by behaviour around the event date (ibid.). Lastly, a post-event window is defined to examine any sustaining effects of the event.

In the case of this study, the 90-day period of (-120, -31) is deemed a representative period of normal behaviour with no unexpected events, and will thus be used as the estimation window, as do Keown and Pinkerton (1981). Following the approach of the aforementioned, we set the event window to (-30, 1). However, an important distinction from “traditional” event studies is our focus on the pre-event dynamics rather than the actual event effect, as illegal insider trading will occur *prior* to the event in question, i.e. the release of the at the time non-public information. Thus, our focus will mainly be on the pre-event days of the event window, i.e. (-30, -1).

As mentioned previously, there have been discussions regarding what is the proper event date. Halpern (1983) found that most scholars used the date of the announcement, however, acknowledged the implications of this, as there may have been rumours surrounding the takeover prior to the formal announcement, thus contaminating the run-up. This is recognized by later scholars, who rather use the earlier of the date of the first public rumour and the announcement date (Jarrell & Poulsen, 1989; King, 2009; Aspris, Foley, & Frino, 2014), which will also be our approach. The rumour dates are included when retrieving data from the Zephyr database, ensuring that we limit the number of data sources. Figure 2 below depicts our event study timeline.

Figure 2: Event study timeline



5.2.2 Calculating abnormal returns

The first step towards calculating abnormal returns is computing the daily returns of each target share using the following formula (King, 2009):

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

When we have computed the daily returns for (-120, 20) we proceed by estimating the daily expected return for the period (-30, 20). Brown and Warner (1980) suggest several different approaches of which two are highlighted by Halpern (1983) and MacKinlay (1997), namely the market model and the constant mean model. The market model takes point of departure in the Capital Asset Pricing Model (CAPM) first developed independently by Treynor (1961), Sharpe (1964), Lintner (1965) and Mossin (1966). It is a single-factor market model where the daily returns for the estimation period (-120, -31) are regressed on the equivalent daily returns of the market, resulting in a prediction of a stock's returns at time *t* depending on the constant and slope of the regression and the market return at time *t*:

$$E[R_{i,t}] = \alpha_i + \beta_i * R_{m_t} \qquad t = -30, \dots, 20 \tag{2}$$

Where α_i is the expected constant return excess of the market, β_i is the stock's sensitivity to market fluctuation and R_{m_t} is the market return at time t. Critics of the CAPM argue that the model will be biased in its estimates, as there exists no market portfolio. However, as this study is delimited to focus on the Scandinavian markets, we will use Nasdaq OMX Copenhagen All-Share Index, Oslo Børs All-Share Index and OMX Stockholm All-Share index as reference indices. These are the value-weighted indices of all shares listed on the Danish, Norwegian and Swedish stock exchanges, respectively, thus all being appropriate approximations of the three markets. Alternative market proxies are the STOXX 600 or the MSCI ACWI index. The former is a value-weighted index of 600 companies from 17 European companies, and the latter constitutes 2.784 companies covering approximately 85% of the global investible equity (STOXX, 2019; MSCI, 2019). However, these indices would not to the same extent reflect economic cycles of the three markets, which in turn influence the target firm's stock price. We thus believe the selected indices better reflect the markets in which the target companies operate.

To arrive at abnormal returns, the expected returns from the CAPM regression above are subtracted from the actual daily returns of the target company, which will henceforth be referred to as the *market measure* ARs:

$$AR_{i,t} = R_{i,t} - E[R_{i,t}] = R_{i,t} - (\alpha_i + \beta_i * R_{m_{,t}}) \tag{3}$$

We calculate a second AR measure for robustness, which is the aforementioned constant mean model, henceforth referred to as the *simple measure.* In this model, the expected return is merely the average daily return of the estimation window, which is subsequently subtracted from the daily return in the event window to calculate the AR:

$$AR_{i,t} = R_{i,t} - \frac{\sum_{t=-120}^{-31} R_{i,t}}{90} \tag{4}$$

Now having calculated the daily ARs for each stock with both measures, we aggregate each day across the samples to return the average abnormal returns (AAR). Thus, the daily AAR for a given day across the samples with *n* events is:

$$AAR_t = \frac{\sum_{i=1}^{n} AR_{i,t}}{n} \tag{5}$$

As illegal insider trading can occur on any day prior to the event date, we accumulate the ARs and AARs to get a better picture of the stock price run-up. Beneath is exemplified with CAR(-30, 20) and subsequently the average equivalent:

$$CAR = \sum_{t=-30}^{t=20} AR_{i,t} \tag{6}$$

$$CAAR = \frac{\sum_{i=1}^{n} CAR_{i,t}}{n} \tag{7}$$

Following the method of Keown and Pinkerton (1981), Bris (2005) and King (2009) we test whether the AARs and CAARs are significantly different from zero using a one-tailed[5] student's t-test, as exemplified with CAAR below:

$$T_t = \frac{CAAR_t}{\left(\frac{sd(CAAR_t)}{\sqrt{n}}\right)} \tag{8}$$

[5] One-tailed as we only regard positive ARs

5.2.3 Calculating abnormal volume

To substantiate the evidence of illegal insider trading, we also examine trading volume, as any abnormalities in the trading pattern should be reflected in the trading volume as well. In calculating abnormal volume (AV) we find inspiration in Chae (2005), Bris (2005) and King (2009). Alike the aforementioned, we use a standardised volume, which is calculated as the daily trading volume divided by the number of shares outstanding, resulting in the turnover of each share per day. For AV, the calculation is:

$$AV_{i,t} = \begin{cases} Volume_{i,t} - \left(\overline{Volume_i} + \sigma_i\right) & if \quad Volume_{i,t} > \overline{Volume_i} + \sigma_i \\ 0 & otherwise \end{cases} \tag{9}$$

Where $\overline{Volume_i}$ and σ_i are the mean and standard deviation of the daily volume for firm *i* over the estimation window. Importantly, with this notion, AV will always be positive, with the logical reason that volume necessarily cannot be negative. The volume measure is aggregated, averaged and cumulated in the same fashion as the returns, as seen below, respectively (MacKinlay, 1997):

$$AAV_t = \frac{\sum_{i=1}^{n} AV_{i,t}}{n} \tag{10}$$

$$CAV = \sum_{t=-30}^{t=20} AV_{i,t} \tag{11}$$

$$CAAV = \frac{\sum_{i=1}^{n} CAV_{i,t}}{n} \tag{12}$$

The volume measures are subsequently tested whether they are significantly greater than zero, using a one-tailed t-test[6], as exemplified with CAAV below:

$$T_t = \frac{CAAV_t}{\left(\frac{sd(CAAV_t)}{\sqrt{n}}\right)} \tag{13}$$

5.3 OLS REGRESSION METHODOLOGY

5.3.1 Multiple regression models, assumptions and statistical tests

5.3.3.1 The multiple linear regression

The multiple linear regression attempts to model the relationship between two or more independent variables and a dependent variable by fitting a linear equation to the observed data. In our model, we

[6] One-tailed, as volume measures are by construction greater than or equal to zero

examine on which variables the abnormal return on stock prices depend. Furthermore, it tells us whether the predictive power increases when adding several independent variables. The multiple regression model is defined as:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + u \tag{14}$$

Where y is the dependent variable equivalent to the abnormal return, β_0 denotes the intercept, β_k represents the slope and X_k is the chosen independent variable. The random error term u indicates the variation in y that is not estimated by the linear relationship (Newbold, Carlson, & Thorne, 2013). By using the statistical software program R, we have computed the regression coefficients so the estimated regression line is as close as possible to the observed data using the *Ordinary Least Squares* (OLS) estimator. The multiple linear regression will generate several statistical measures explaining our dataset. First, the coefficient of determination, denoted R^2, is the proportion of the variance in the dependent variable that is explained by the independent variables. A higher R^2 indicates a more accurate regression model. Adjusted R^2, on the other hand, estimates the percentage of variation explained by only those independent variables that in reality affect the dependent variable. Second, the t-value of the model test for the significance of the intercept and each of the independent variables. In this paper we have chosen significance levels of 1%, 5% and 10% to test for a statistically significant relationship between abnormal returns and our independent variables. The rejection region is a set of values of the test statistic for which the null-hypothesis is rejected. That is, the sample space for the test statistic is portioned into two regions; one region will lead us to reject the null hypothesis, while the other will lead us to not reject the null hypothesis (Stock & Watson, 2011).

5.3.3.2 Assumptions

The multiple regression requires the fulfilment of five assumptions which will all be presented in the following (Newbold, Carlson, & Thorne, 2013).

Linearity

The first assumption states that there must be a linear relationship between the independent variable and the dependent variable. The assumption is tested using scatter plots with residual values against predicted values. The linearity assumption is obtained when the observed points are symmetrically distributed around the predicted regression line. Moreover, a linear regression model with a dummy variable will always be linear (Newbold, Carlson, & Thorne, 2013).

Furthermore, we assume that the error u has an expected value of zero given any values of the independent variables:

$$E(u|X_1, X_2 \ldots X_k) = 0 \tag{15}$$

Omitting an important factor that is correlated with any of $X_1, X_2 \ldots X_k$ will lead to bias and inconsistency in all of the OLS estimators, called omitted variable bias (Stock & Watson, 2011).

Normality

The second assumption states that error terms are normally distributed. To test this assumption, we use the Jarque-Bera test, which is an adoption of the chi-squared procedure with *S*, *K* and *N* denoting the sample skewness, the sample kurtosis and the sample size, respectively (Newbold, Carlson, & Thorne, 2013).

$$Jarque - Bera = \frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \qquad (df = 2) \tag{16}$$

The test for a normal distribution is based on the closeness to 0 for the skewness and the closeness to 3 for the kurtosis, where the test statistic is held up against a critical value from the chi-squared distribution.

If the residuals are not normally distributed, normality in the error terms is only required in small samples. According to Gujarati and Porter (2009), the normality assumption becomes of importance when the sample contains less than 100 observations. However, Wooldridge (2009) claims that in some cases you only need 30 observations. A rejection of the normality assumption indicates that the significance tests of the coefficients may be misleading (Newbold, Carlson, & Thorne, 2013).

Independence of residuals

The third assumption states that the residuals are independent of each other. This implies that there is no correlation between the error terms in the multiple regression model (Newbold, Carlson, & Thorne, 2013).

To test for residual correlation, we use the Durbin-Watson test, for which the null-hypothesis states that there is no correlation. The test is rejected if the test statistic is below the lower bound and accepted if it is above the upper bound. If it is between the two bounds, the test is non-conclusive. If the residuals are not independent the estimated standard errors for the coefficients may be biased, the t-statistic can be inaccurate and this could lead us to reject the null hypothesis when, in fact, the null hypothesis should not be rejected (Newbold, Carlson, & Thorne, 2013).

Constant variance

The fourth assumption states that the sample must be homoscedastic, meaning that the residuals have a constant variance. In order to test for homoscedasticity, we use the White test (1980), with the null hypothesis stating that the error variances are all equal. If the null hypothesis is rejected, it means that the residuals are heteroscedastic and subject to non-constant variance. Consequently, the calculation of the p-value becomes more insecure (Newbold, Carlson, & Thorne, 2013). In the event of heteroscedastic residuals, we use White-corrected standard errors (White, 1980).

Multicollinearity

Multicollinearity occurs when two or more independent variables are highly correlated (Newbold, Carlson, & Thorne, 2013). A consequence of multicollinearity is large standard errors, and the regression coefficients may not be estimated precisely. This will lead to wide confidence intervals and the results become less reliable when multicollinearity is present.

In order to assess the level of multicollinearity, the *Variance Inflation Factor* (VIF) has been applied. VIF tells us how much larger the standard error is, compared with what it would be if the variable had zero correlation to the other independent variables in the dataset. Setting a cut-off value for VIF above which we conclude multicollinearity is a problem is arbitrary and not especially helpful. However, we have chosen to set the VIF-limit equal to 10, which is line with Bowerman et al. (2005). If VIF is above 10, we conclude that multicollinearity is a problem for estimating β. Still, it must be noted that VIF is just an indicator and not a test. Therefore, a VIF above 10 does not mean that the standard deviation of $\hat{\beta}$ is too large to be useful because the standard deviation also depends on σ and total sum of squares. Contrary, a VIF just below 10 may also be subject to multicollinearity (Stock & Watson, 2011).

5.3.2 Logarithm Approach

The following section will elaborate on the use of logarithmic values in our dataset. However, for a systematic presentation of each variable and its use of natural logarithm we refer to section 5.3.3. Natural logarithm is the logarithm to the base e of a number and is given by the formula (Newbold, Carlson, & Thorne, 2013):

$$\ln(e^x) = x \tag{17}$$

Transforming into natural logarithmic values have several advantages. Logarithmically transformed variables in a regression model is a common way to handle situations where there exists a non-linear relationship between the independent and the dependent variable (Benoit, 2011).

As formerly discussed in section 5.3.1, one of the assumptions for a linear regression model is homoscedasticity (Newbold, Carlson, & Thorne, 2013). This assumption is not always met as it is common to observe heteroscedasticity. As a consequence, the confidence intervals and hypothesis tests will be of great uncertainty. However, by transforming into lognormal values the problem with heteroscedasticity will be significantly reduced (Michener, 2003). Furthermore, logarithmic transformation is a great mean for reducing the skewness in the dataset.

Lastly, we have used the logarithmic transformation, because the estimated coefficients in a logarithmic regression are easy to interpret. This means that the coefficient is a measure of absolute change in abnormal return as a result of a relative change in the independent variable (Michener, 2003).

5.3.3 Description of variables

The foundation for our regression analysis is the selection of variables. These variables will be presented and carefully explained throughout this section. In the linear regression, we have a pool of 11 independent variables related to insider trading theory, six of which are dummies. These will be described below, in accordance with their theoretical relevance.

5.3.2.1 Dependent variable

CAR

To test whether specific event characteristics have significant influence on the run-up, we regress each target firm's CAR(-10, -1). We select this specific accumulation length as previous scholars consistently find significantly positive ARs to occur within ten days of the event (Aitken & Czernkowski, 1992; King M. R., 2009; Borges & Gairifo, 2013). Furthermore, we use the market measure CAR, as this is primarily the method used by former scholars, thus enabling a comparison.

5.3.2.2 Explanatory variables related to inside trading theory

CAV

Similar to King (2009) we investigate the price/volume dynamics preceding takeover announcements. For this we use each firm's CAV(-30, -1), i.e. the cumulation for the whole event window. As opposed to CAR we use this accumulation length, as Kyle (1985) found that the trading volume of illegal insiders accumulate positively, while that of non-discretionary traders do not necessarily, causing a lag in the price's response.

Target company market value

As stated in hypothesis 2.2, insider traders prefer to trade in a manner that does not attract attention by avoiding large deals as they usually receive a great deal of attention from media and regulators. As a means to assess the relationship between the size of the target firm and the abnormal return we estimate market value of the target firm. This is done by multiplying the number of shares outstanding with the average share price of the target firm in the period (-120;-31). We use the (-120;-31) window to avoid any possible bias in the share price from a potential run-up in the event window. Furthermore, we have used the natural logarithm of the original value. This will give us the absolute change in abnormal return for a relative change in target market value. This is advantageous when the market value in the dataset varies. Furthermore, we use the natural logarithm to standardise and avoid heteroscedasticity. Market value is given by the following formula:

$$MV_i = \bar{P}_i * shares\ outstanding_{i,t}$$

Where $\bar{P}_{i,t}$ is the average share price of the target firm over the period (-120;-31), and shares outstanding is the total number of shares outstanding of target company i at time t. Based on the arguments presented above, we expect that a lower market value for the target firm will yield higher abnormal return.

lnVol

Previous studies have found that illegal insider traders prefer liquid stocks, as they more easily can hide their orders in the already high order flow. Thus, illegal insider trading is more likely to occur in liquid stocks, however, is less statistically observable. We measure the stock's liquidity as the logarithm of the average daily trading volume in the estimation period:

$$lnVol = \ln(\overline{volume_i})$$

With illegal insider trading being less statistically observable the higher the volume, we expect a negative sign.

Foreign acquirer

In section 3.2 we presented a hypothesis stating that illegal insider trading is more likely to occur when the target firm is acquired by a foreign acquirer. Therefore, we expect higher AR and AV when the acquiring firm is foreign. In order to analyse this, we introduce a dummy based on the acquiring firm's nationality. That is, if the acquiring firm is foreign, it will be given a value of 1 and 0 otherwise.

$$Foreign = 1\ if\ foreign; 0\ otherwise$$

Majority shareholders

Hypothesis 2.5 states that illegal insider trading is more likely to occur when a majority shareholder owns the target firm. In order to analyse this, we downloaded data of ownership structure from Zephyr. Our dummy variable is given the value 1 in cases where a person or entity owns and controls more than 50% of the target company, and 0 otherwise.

$$Majority = 1\ if\ majority\ shareholder; 0\ otherwise$$

Number of deal advisors

As presented in section , studies by Ahern (2017) disclose that 35% of all the cases of inside trade in his sample was business related. Furthermore, on average, insider tips originate from corporate executives and reach buy-side investors after three links in the network (Ahern, 2017). Therefore, as deal advisors facilitate the process by guiding their clients through these transformative corporate decisions, we will model the relationship between CAR and the number of deal advisors. Based on the findings presented above, we expect that more advisors will yield a higher CAR. We have used the Zephyr database to extract number of deal advisors and their identity. Their identity varies, but consists mainly of investment banks, auditing firms and law firms.

Interaction: target company market value and number of advisors

Hypotheses 2.2 and 2.6 state that market participants with inside information will shy away from trading on the biggest deals due to the greater attention they receive, thus reducing insider trading in such deals, and that more advisors increase the likelihood of insider trading. We do, however, quite intuitively observe a fairly high positive correlation between the two variables. As they are positively correlated, but we hypothesise opposite signs for the coefficients, we construct an interaction term for the two to investigate the simultaneous effect.

Payment structure

Hypothesis 2.7 postulates that illegal insider trading is more likely to occur when the payment is made entirely in cash. To analyse this, we gathered information on the payment structure on each deal by using the Zephyr database. Our dummy variable is given the value 1 if the payment was made in cash and zero if it includes anything else than cash. In cases where the deal is not made in cash entirely, it typically consists of stock deals or a combination where both cash and stock is used.

$$Cash = 1\ if\ cash, 0\ otherwise$$

Financial crisis

The financial crisis in 2007-2008 brought about big changes in the financial markets. To assess whether these changes have had any effect on the occurrence of inside trading we introduce a dummy. An acquisition made in 2008 or later is given the value of 1, and a value of 0 if it took place before 2008.

$$Crisis = 1\ if\ \geq 2008, 0\ otherwise$$

As merger waves follow economic cycles, and the financial crisis represents a shift in cycles and enforcement in the middle of our sample, this variable is to control for this shift.

Penny stocks

As explained in section 3.2, penny stocks are defined by their lack of liquidity and small capitalisation. In our sample, we have chosen to categorise firms that trade for 5 kroner or less as penny stocks. Our dummy is given the value of 1 if the stock price is 5 kroner or below and 0 otherwise. The stock price is estimated as the average stock price in the (-120, -31) estimation window. This is done in order to avoid possibly biased stock prices in the price run-up prior to the rumour date. In line with the hypothesis, we expect a positive sign.

$$Penny = 1 \; if \leq 5kroner, 0 \; otherwise$$

Market-to-book ratio

In section 3.2 we hypothesised that the target firm's stock price run-up is higher when the target firm is undervalued. Therefore, we expect a higher run-up when the target firm has a low market to book ratio. As a means to disclose undervalued and overvalued stocks we use the market-to-book ratio. The variable was collected manually from Datastream. We will use the natural logarithm of the variable to obtain a standardised value for the same reason as explained earlier. The ratio is given by the following formula where a low ratio indicates an undervalued target firm.

$$Market - to - book \; ratio = \frac{market \; capitalisation}{book \; value \; of \; equity}$$

We did, however, see instances of a negative market-to-book ratios due to negative equity value. As one cannot take the logarithm of a negative number, we added a minimum constant to turn all observations positive.

$$lnM2B = \ln(M2B + \epsilon)$$

Where ϵ is the minimum value ensuring only positive values.

Financial distress

Hypothesis 2.11 states that insider trading is more likely to occur when the target firm is financial distressed. To assess this we include a liquidity variable. We chose the interest coverage ratio (ICR) because it provides us with a precise estimate of the long-term liquidity risk. More specifically, the ratio shows how many times operating profit covers net financial expenses. The higher the ratio, the lower long-term liquidity risk (Plenborg, Kinserdal, & Christian, 2017).

$$Interest \; coverage \; ratio = \frac{Cash \; flow \; from \; operations}{Net \; financial \; expenses}$$

The interest coverage ratio varies greatly within our samples. We have therefore included four dummy variables to categorise the level of financial distress. That is, the variable is given the value of 1 if the interest coverage ratio ranges within the intervals we have chosen, and 0 otherwise. D3 is set as the base level. This implies that D1 and D2 represent very high and high levels of financial distress, while D4 indicates a very low level of financial distress. The intervals are defined in the following way:

$$D1\begin{cases}1\ if\ ICR < -9\\ 0\ otherwise\end{cases} \qquad D2\begin{cases}1\ if -9 \leq ICR < 1\\ 0\ otherwise\end{cases}$$

$$D3\begin{cases}1\ if\ 1 \leq ICR < 10\\ 0\ otherwise\end{cases} \qquad D4\begin{cases}1\ if\ ICR \geq 10\\ 0\ otherwise\end{cases}$$

5.3.4 Model selection criteria

Our initial selection of independent variables is not random; each variable serves the purpose of answering one of our hypotheses regarding factors influencing the occurrence of illegal insider trading prior to a public takeover. Immediately formulating an appropriate regression function is often difficult, as there is a question of which variables to include. Thus, in the event of insignificant variables, a structured approach to model selection is required.

One such approach is adding and excluding variables in a fashion that maximises the adjusted R^2 (Johnson & Wichern, 2013). The adjusted R^2 is similar in interpretation as the ordinary R^2, in that it tells how much of the variance in the dependent variable the model explains, but punishes models with excessive independent variables (Fox, 2016). Despite the intuitive rationale, however, there is little justification for using the adjusted R^2 as selection criterion (ibid.)

Another approach is the stepwise regression, which comes in two variations; backward and forward selection (Johnson & Wichern, 2013). In the former, all variables are included, and subsequently the variables with largest p-value above a predetermined threshold are omitted one by one until all p-values are below the threshold.

In the forward selection all possible *simple* linear regression models are first considered. Subsequently, the predictor that explains the largest significant proportion of variance in the independent variable is added to the model. The next variable to be added is the one that makes the largest significant contribution to the regression sum of squares, based on an F-test. This is repeated until all possible additions are insignificant and all exclusions are significant. However, this process is deemed time consuming and there is no guarantee that his approach will select the best regressors (Johnson & Wichern, 2013).

A third approach, and our criterion of choice, is the *Akaike information criterion* (AIC) and *Bayesian information criterion* (BIC), which are penalised model-fit statistics, and two of the most commonly used selection criteria (Fox, 2016). The measures balance the residual sum of squares with the number of regressors in the model, i.e. it rewards a model for minimising residual sum of squares, but penalises for too many regressors (Johnson & Wichern, 2013). AIC and BIC differ in that BIC penalises harder the greater the *n*, and thus nominates models with fewer parameters (Fox, 2016). Our method of choice is a combination of backward selection and AIC. First we estimate the full model, and subsequently exclude insignificant variables based on AIC.

After obtaining a final model with which we are satisfied, we test whether the omitted variables were jointly insignificant in the model comprising all variables. Using an F-test we only proceed with the final model if we do not reject the null hypothesis. The final models are also tested for heteroscedasticity applying the same method as mentioned in 5.3.1.

5.3.5 Measuring influence and outlier detection

As our samples, particularly on country basis, are not very large in a statistical context, a small number of outliers can have crucial influence on the estimation of coefficients. We investigate possible outliers by measuring the influence of all observations on the different coefficients in the full model.

We measure each observation's influence using a DFBETAS test (Fox, 2016):

$$D_{ij}^{*} = \frac{D_{ij}}{SE_{-i}(\beta_j)} \tag{18}$$

Where

$$D_{ij} = \beta_j - \beta_{j(-i)} \quad for\ i = 1, \dots, n\ and\ j = 0, 1, \dots, k \tag{19}$$

Where β_j are the lest-square coefficients calculated for all the data, and $\beta_{j(-i)}$ are the least-square coefficients with the *i*th observation omitted. More precisely, this tells us by how much the coefficient will change by omitting a given observation. We use a critical value of |2| to evaluate a potential outlier (Belsley, Kuh, & Welsch, 1980).

6 EMPIRICAL ANALYSIS

This section, in which we present results from our analyses, is structured in the following order; we first present the descriptive statistics for all countries and both samples. Second, we present the results from the event study on the initial sample, and thirdly the results from the adjusted sample. Fourth, we present the results from the cross-sectional regression analysis on the initial sample, and subsequently the adjusted sample. Lastly, we revisit our hypotheses and discuss whether our initial suspicions hold or not.

6.1 DESCRIPTIVE STATISTICS - INITIAL AND ADJUSTED SAMPLE

In our 20-year sample, we can see that the majority of the observations occurred in the second half, i.e. after the onset of the global financial crisis. For a single year, most observations occur in 2008 for Denmark (15%) and Norway (18%), while for Sweden it is 2007 (11%), with a slight change in distribution for the adjusted sample (appendix 1). The distribution of most variables later used in the cross-sectional analysis is summarised below, for all countries separately. Some notable mentions are the days between the first public rumour and the formal announcement, which ranges from the same timing to close to three-and-a-half years. One might question how this affect the validity of our window selection. However, the event in question is the first public rumour of the takeover, and there may be numerous reasons for the 'delay' of the formal announcement. We seek to uncover whether market participants capitalise on their information before it is public. Thus, a long rumour period before a formal announcement does not impede our ability to investigate this phenomenon.

Great variance can also be seen in the market capitalisation and trading volume of the target company, both of which's minimum value increases in the adjusted sample, implying that the smallest companies also are less liquid. The initial Norwegian sample also seem to comprise larger and more liquid target companies. Foreign acquirers are far more prominent in Denmark, at 44% and 45%, respectively, while closer to every third acquirer is of another nationality for the Norwegian and Swedish markets. Lastly, cash-only offers make up 73% of the bids on Norwegian-listed companies, far more than is the case of its neighbours.

Lastly, the Danish and Norwegian samples, the former in particular, are quite small. This should be kept in mind for the OLS regression as it may affect our ability to obtain significant coefficients.

Table 1: Descriptive statistics – initial sample

	Denmark			Norway			Sweden		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Days between rumour and bid	92	0	1 274	32	0	450	28	0	1 018
Target market value	3 428 435	6 844	25 882 320	4 760 875	56 814	107 018 363	2 818 686	2 875	63 641 340
Avg. volume (-120, -31)	198 963	127	3 593 981	698 875	3 162	10 594 764	159 634	297	5 074 269
Number of advisors	3	0	22	4	0	21	4	0	14
Market-to-book	1,8	-0,3	10,8	1,7	-11,9	7,8	3,7	-5,9	70,7
Interest coverage ratio	41	-101	1 644	115	-76	5 934	-279	-41 936	13 775
% with foreign acquiror		44 %			32 %			28 %	
% with majority shareholder		65 %			61 %			65 %	
% cash-only offers		48 %			73 %			58 %	
% post-crisis offers		63 %			66 %			66 %	
% penny stocks		21 %			18 %			19 %	
n		48			62			144	

Table 2: Descriptive statistics – adjusted sample

	Denmark			Norway			Sweden		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Days between rumour and bid	118	0	1 274	36	0	450	30	0	1 018
Target market value	4 809 050	43 267	25 882 320	5 597 447	98 798	107 018 363	2 750 939	9 286	56 204 271
Avg. volume (-120, -31)	252 576	127	3 593 981	820 992	5 016	10 594 764	188 428	1 237	5 074 269
Number of advisors	4	0	22	4	0	21	4	0	14
Market-to-book	1,6	0,2	4,9	1,9	-0,5	7,1	3,6	-5,9	58,5
Interest coverage ratio	59	-101	1 644	136	-76	5 934	-302	-41 936	13 775
% with foreign acquiror		45 %			35 %			28 %	
% with majority shareholder		61 %			62 %			65 %	
% cash-only offers		42 %			73 %			63 %	
% post-crisis offers		58 %			69 %			68 %	
% penny stocks		15 %			19 %			18 %	
n		33			52			116	

6.2 EVENT STUDY – INITIAL SAMPLE

In the following we present the results of the event study on the initial sample, which are visualised in Table 3 to Figure 5: CAAV, all countries - initial sample

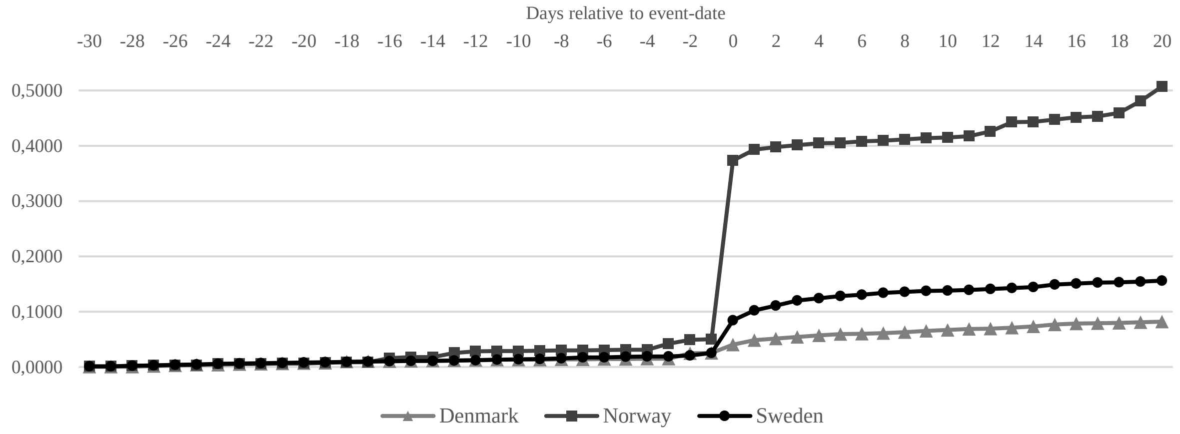


Table 5 and Figure 3 to Figure 11. Different accumulation lengths of CAAR can be viewed in appendices 2-6.

6.2.1 Market measure of abnormal returns – initial sample

Looking at all countries as a whole, AAR turns significantly positive at the 10% level with 0,38% on day -28 relative to the event date, largely driven the by the larger Swedish sample's significance at the 5% level with an AAR of 0,69%. Further positively significant cross-sample AARs can be observed on days, -11, -9, -4, -2 and -1, with the latter's 0,98% highly significant at the 1% level. The cross-sample event date AAR – the announcement effect – is 15,31%, significant at the 0,1% level. For CAAR there is a small cluster of significantly positive observations in (-28, -24) until they again turn positive and increasingly more significant from day –8. The 30-day pre-event run-up across all countries is 3,81%, significant at the 0,1% level.

For Denmark, the first significantly positive AAR occurs on day -26 with 1,07%, significant at the 5% level. Further positive significance is observed on days -16 and -9, ending with an event day AAR of 11,73% significant at the 0,1% level – the lowest announcement effect of the three markets. CAAR turns significantly positive on day -26 and remains so throughout the event study period, leading to a pre-event run-up of 5,34% - the highest among the countries – significant at the 5% level. Looking at other accumulation lengths, it is evident that the highest AARs occur early in the 30-day window, seeing as 20 days is the only other significant length at the 10% level.

For the Norwegian market we are as close as day -9 for the first significantly positive AAR at 0,47%, and then day -4 and -1, both of which significant at the 5% level. The announcement effect is 17,07%, which is the highest of the three markets. The pre-event run-up for the Norwegian sample is a mere 2,25%, however not statistically significant. However, all alternative, and shorter, accumulation lengths display an increasingly more significant run-up – no surprise seeing as of the ten earliest days in the event window, six display negative AARs.

As mentioned, Sweden experiences the first significantly positive AAR on day -28, with other significant observations on days -11, -4, -2 and -1, the latter rather high at 1,15%, significant at the 1% level. The announcement effect for the Swedish sample is 15,67%, significant at the 0,1% level. Occasional statistically positive CAAR can be seen on days -28, -23, -17, -11 and then from -7 and forth, with a pre-event run-up of 4,03%, significant at the 1% level. The significance in run-up is robust across different accumulation lengths, with the starting day varying from day -8 to -2.

Figure 3: Market measure CAAR, all countries - initial sample

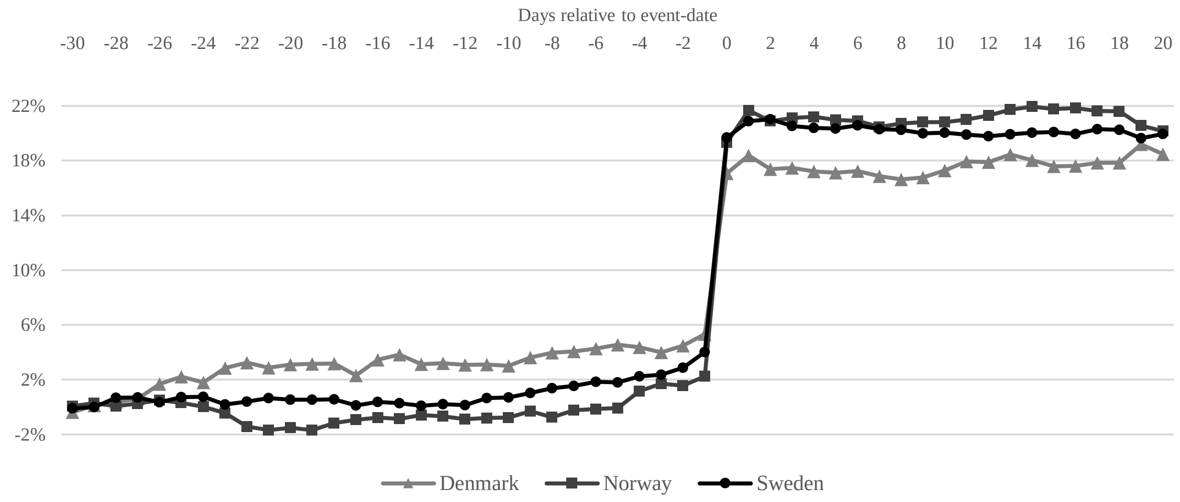


Table 3: Market measure AAR and CAAR – initial sample

	All countries		Denmark		Norway		Sweden	
Day	AAR	CAAR	AAR	CAAR	AAR	CAAR	AAR	CAAR
-30	-0,11%	-0,11%	-0,37%*	-0,37%*	0,07%	0,07%	-0,10%	-0,10%
-29	0,20%	0,09%	0,50%	0,13%	0,22%	0,29%	0,10%	0,00%
-28	0,38%*	0,47%*	0,25%	0,37%	-0,22%	0,07%	0,69%**	0,69%**
-27	0,10%	0,57%*	0,23%	0,61%	0,18%	0,26%	0,01%	0,70%*
-26	0,07%	0,64%*	1,07%**	1,68%*	0,25%	0,51%	-0,34%	0,36%
-25	0,26%	0,90%**	0,54%	2,22%*	-0,20%	0,31%	0,38%	0,74%
-24	-0,14%	0,75%*	-0,40%	1,81%*	-0,30%	0,01%	0,02%	0,75%
-23	-0,25%	0,51%	1,04%	2,85%**	-0,46%	-0,45%	-0,57%	0,18%**
-22	-0,06%	0,44%	0,39%	3,24%**	-0,98%	-1,42%	0,21%	0,39%
-21	0,02%	0,46%	-0,36%	2,88%**	-0,25%	-1,67%	0,26%	0,65%
-20	0,02%	0,48%	0,22%	3,11%**	0,17%	-1,51%	-0,11%	0,55%
-19	-0,03%	0,45%	0,06%	3,16%**	-0,17%	-1,68%	0,00%	0,55%
-18	0,15%	0,59%	0,01%	3,17%**	0,51%	-1,17%	0,02%	0,57%
-17	-0,34%	0,25%	-0,85%	2,32%*	0,24%	-0,94%	-0,44%	0,13%*
-16	0,38%	0,64%	1,14%**	3,46%**	0,16%	-0,78%	0,24%	0,37%
-15	0,00%	0,64%	0,38%*	3,84%**	-0,08%	-0,86%	-0,08%	0,29%
-14	-0,16%	0,48%	-0,70%	3,14%*	0,29%	-0,57%	-0,18%	0,10%
-13	0,05%	0,53%	0,07%	3,21%*	-0,10%	-0,67%	0,12%	0,22%
-12	-0,12%	0,41%	-0,13%	3,08%*	-0,21%	-0,88%	-0,07%	0,14%
-11	0,31%*	0,73%	0,04%	3,12%*	0,08%	-0,80%	0,51%**	0,65%**
-10	0,02%	0,75%	-0,11%	3,01%*	0,03%	-0,78%	0,06%	0,71%
-9	0,41%*	1,16%	0,62%*	3,63%*	0,47%*	-0,30%	0,32%	1,03%
-8	0,15%	1,31%*	0,34%	3,96%*	-0,44%*	-0,74%	0,36%	1,38%
-7	0,24%	1,54%*	0,11%	4,07%*	0,51%	-0,23%	0,15%	1,53%*
-6	0,24%	1,78%**	0,20%	4,27%**	0,09%	-0,13%	0,32%	1,86%*
-5	0,04%	1,82%**	0,28%	4,55%**	0,07%	-0,07%	-0,06%	1,80%*
-4	0,53%**	2,35%**	-0,18%	4,37%**	1,24%**	1,17%	0,43%*	2,23%**
-3	0,14%	2,49%**	-0,37%	4,00%*	0,54%*	1,72%	0,12%	2,35%**
-2	0,34%*	2,83%***	0,49%	4,49%*	-0,16%	1,56%	0,52%*	2,88%**
-1	0,98%***	3,81%****	0,85%	5,34%**	0,69%**	2,25%	1,15%***	4,03%***
0	15,31%****	19,12%****	11,73%****	17,07%****	17,07%****	19,32%****	15,67%****	19,69%****
1	1,50%****	20,62%****	1,30%**	18,37%****	2,35%***	21,67%****	1,18%**	20,87%****
2	-0,29%	20,33%****	-0,98%	17,39%****	-0,78%	20,89%****	0,15%	21,03%****
3	-0,20%	20,13%****	0,09%	17,47%****	0,23%	21,13%****	-0,49%	20,54%****
4	-0,10%	20,03%****	-0,27%	17,21%****	0,09%	21,22%****	-0,14%	20,40%****
5	-0,11%	19,92%****	-0,09%	17,12%****	-0,25%	20,97%****	-0,05%	20,35%****
6	0,14%	20,06%****	0,13%	17,25%****	-0,06%	20,91%****	0,23%	20,58%****
7	-0,33%	19,72%****	-0,37%	16,88%****	-0,45%	20,46%****	-0,27%	20,31%****
8	-0,02%	19,71%****	-0,25%	16,63%****	0,26%*	20,72%****	-0,07%	20,24%****
9	-0,09%	19,62%****	0,15%	16,78%****	0,10%	20,81%****	-0,25%	19,99%****
10	0,12%	19,73%****	0,50%	17,28%****	0,00%	20,81%****	0,04%	20,04%****
11	0,10%	19,83%****	0,66%**	17,94%****	0,20%	21,01%****	-0,13%	19,90%****
12	0,01%	19,84%****	-0,05%	17,90%****	0,30%	21,31%****	-0,11%	19,79%****
13	0,28%**	20,12%****	0,55%	18,44%****	0,43%	21,73%****	0,12%	19,92%****
14	0,06%	20,17%****	-0,41%	18,03%****	0,22%	21,95%****	0,14%	20,05%****
15	-0,10%	20,07%****	-0,44%	17,60%****	-0,17%	21,78%****	0,04%	20,09%****
16	-0,05%	20,02%****	0,03%	17,62%****	0,06%	21,84%****	-0,13%	19,96%****
17	0,18%	20,20%****	0,22%	17,84%****	-0,20%	21,64%****	0,35%	20,30%****
18	-0,04%	20,16%****	0,01%	17,85%****	-0,03%	21,61%****	-0,06%	20,25%****
19	-0,37%	19,80%****	1,34%**	19,19%****	-1,04%	20,56%****	-0,61%	19,64%****
20	-0,06%	19,74%****	-0,72%	18,47%****	-0,41%	20,15%****	0,31%*	19,95%****
n	254		48		62		144	

Significance indicators: *10%, **5%, ***1%, ****0,1%

6.2.2 Simple measure of abnormal returns – initial sample

For the simple measure, the pattern is quite similar to that of the market measure. The first significantly positive observation is again at day -28, also this time heavily influenced by the Swedish sample. While AAR for day -2 is no longer significant, day -16 has turned significant at the 5% level with 0,50%. Both days -4 and -1 are now more significant and higher than for the market measure, as is the event day AAR at 15,35%, with same significance as previously. For CAAR there is still a cluster of significantly positive observations at (-28, -24), however now higher and more significant. The run-up becomes significant one day later and results in a pre-event run-up of 3,80%, marginally lower than for the market measure.

For Denmark, the first positively significant observation is now on day -29, three days earlier than for the market measure. For this measure, however, day -9 is no longer significant, resulting in only two days with positively significant AAR, until an event date AAR of 11,73%. There is also great similarity regarding CAAR, which also here becomes significant on day -26, which with the exception of day -17, remains significant for the remainder of the event period, resulting in a pre-bid run-up of 4,91% - which is 0,4 percentage points lower than for the market measure. The simple measure run-up for different accumulation lengths is similar to those seen for the market measure, with the notion that the (-25, -1) run-up has become insignificant.

For the Norwegian sample, the first significantly positive AAR is now on day -26 with 0,57%, 17 days earlier than for the market measure. Days -9 and -3 are not significant in this case, however, day -4 is higher and more significant with 1,60% at the 1% level. The announcement effect is marginally higher at 17,18%, also this significant at the 0,1% level. Aside from a single day at -26, CAAR never becomes significant, leading to an insignificant yet higher pre-bid run-up than the market measure at 2,68%. In terms of significance, the different accumulation lengths yield identical results as the market measure, while in terms of size, the run-up varies between being higher and lower.

Again, the first significantly positive observation occurs on day -28 for Sweden, while subsequent positive and significant observations occur on the same days as for the market measure. Now, however, days -4 and -1 have increased in both magnitude and significance at 0,60% and 1,26%, respectively. The event date AAR is very similar both in magnitude and significance at 15,70% at the 0,1% level. The pattern in CAAR is also somewhat similar to that of the market measure. In this case, day -25 becomes significant, while days -17 and -11 are insignificant. A bigger difference, however, is the run-up becoming significant three days later, on day -4, resulting in a pre-bid run-up of 3,95%, slightly lower than for the market measure. For the different accumulation lengths, the length of the significant run-up is slightly shorter than for the market measure, lying both above and below in size.

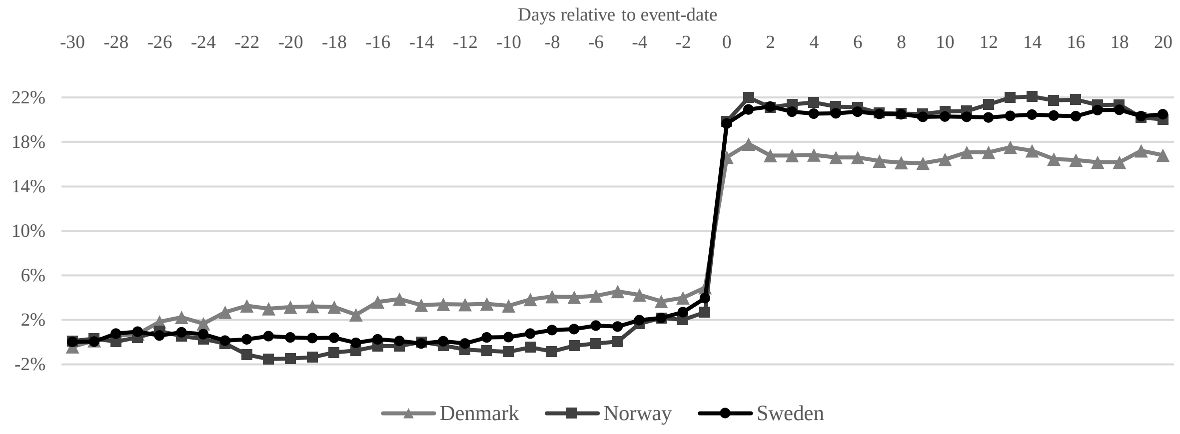
The low variation in results creates robustness around our calculations and confirms Brown and Warner's (1980) findings of the simple model often yielding similar results to those of more sophisticated models.

Table 4: Simple measure AAR and CAAR – initial sample

	All countries		Denmark		Norway		Sweden	
Day	AAR	CAAR	AAR	CAAR	AAR	CAAR	AAR	CAAR
-30	-0,04%	-0,04%	-0,41%	-0,41%	0,10%	0,10%	0,01%	0,01%
-29	0,17%	0,13%	0,56%*	0,15%	0,20%	0,30%	0,04%	0,05%
-28	0,41%**	0,54%**	0,43%	0,58%	-0,24%	0,06%	0,71%**	0,76%**
-27	0,22%	0,76%**	0,17%	0,75%	0,37%	0,42%	0,17%	0,93%**
-26	0,16%	0,92%**	1,07%**	1,82%*	0,57%*	0,99%*	-0,32%	0,60%
-25	0,12%	1,05%**	0,42%	2,24%*	-0,45%	0,54%	0,29%	0,89%*
-24	-0,28%*	0,77%*	-0,57%	1,67%*	-0,27%	0,27%	-0,19%	0,70%
-23	-0,24%	0,53%	1,04%	2,71%*	-0,40%	-0,13%	-0,57%	0,13%
-22	-0,09%	0,44%	0,55%	3,26%**	-1,00%	-1,13%	0,13%	0,25%
-21	0,01%	0,46%	-0,24%	3,01%**	-0,40%	-1,53%	0,28%	0,54%
-20	-0,02%	0,44%	0,15%	3,16%**	0,04%	-1,49%	-0,10%	0,43%
-19	0,01%	0,45%	0,06%	3,22%**	0,13%	-1,35%	-0,06%	0,37%
-18	0,12%	0,56%	-0,06%	3,16%*	0,44%	-0,92%	0,03%	0,40%
-17	-0,35%*	0,21%	-0,71%	2,45%	0,15%	-0,77%	-0,47%	-0,07%
-16	0,50%**	0,70%	1,16%**	3,61%**	0,40%	-0,37%	0,32%	0,25%
-15	-0,03%	0,67%	0,26%	3,88%**	0,01%	-0,36%	-0,14%	0,11%
-14	-0,13%	0,54%	-0,56%	3,31%*	0,37%	0,01%	-0,22%	-0,11%
-13	0,04%	0,58%	0,09%	3,40%*	-0,29%	-0,28%	0,18%	0,07%
-12	-0,21%	0,38%	-0,01%	3,39%*	-0,38%	-0,67%	-0,19%	-0,12%
-11	0,29%*	0,67%	0,06%	3,45%*	-0,11%	-0,78%	0,55%**	0,43%
-10	-0,04%	0,63%	-0,18%	3,27%*	-0,10%	-0,88%	0,03%	0,46%
-9	0,37%*	1,00%	0,56%	3,83%*	0,42%	-0,46%	0,29%	0,75%
-8	0,13%	1,13%	0,26%	4,09%*	-0,38%	-0,84%	0,32%	1,08%
-7	0,18%	1,31%	-0,04%	4,05%*	0,50%	-0,34%	0,10%	1,18%
-6	0,25%	1,56%*	0,10%	4,15%*	0,23%	-0,11%	0,31%	1,49%
-5	0,06%	1,62%*	0,42%	4,57%**	0,16%	0,05%	-0,11%	1,38%
-4	0,69%***	2,31%**	-0,33%	4,24%*	1,60%***	1,64%	0,60%**	1,98%*
-3	0,15%	2,45%**	-0,56%	3,68%*	0,54%	2,19%	0,19%	2,18%*
-2	0,30%	2,75%***	0,30%	3,98%*	-0,18%	2,00%	0,52%*	2,69%**
-1	1,05%****	3,80%***	0,93%	4,91%*	0,68%*	2,68%	1,26%****	3,95%***
0	15,35%****	19,15%****	11,72%****	16,64%****	17,18%****	19,86%****	15,70%****	19,65%****
1	1,48%****	20,63%****	1,19%*	17,82%****	2,11%***	21,97%****	1,28%**	20,93%****
2	-0,27%	20,37%****	-1,04%	16,79%****	-0,85%	21,12%****	0,25%	21,18%****
3	-0,20%	20,17%****	-0,01%	16,78%****	0,26%	21,38%****	-0,47%	20,71%****
4	-0,04%	20,12%****	0,06%	16,83%****	0,16%	21,54%****	-0,17%	20,54%****
5	-0,11%	20,01%****	-0,22%	16,62%****	-0,36%*	21,18%****	0,03%	20,57%****
6	0,05%	20,06%****	-0,02%	16,59%****	-0,07%	21,12%****	0,13%	20,70%****
7	-0,29%	19,77%****	-0,31%	16,28%****	-0,51%	20,61%****	-0,19%	20,51%****
8	-0,06%	19,71%****	-0,14%	16,14%****	-0,07%	20,54%****	-0,03%	20,49%****
9	-0,14%	19,57%****	-0,05%	16,09%****	-0,02%	20,52%****	-0,22%	20,27%****
10	0,12%	19,70%****	0,35%	16,43%****	0,22%	20,74%****	0,01%	20,28%****
11	0,11%	19,81%****	0,63%*	17,07%****	0,04%	20,78%****	-0,03%	20,25%****
12	0,13%	19,94%****	0,01%	17,07%****	0,61%***	21,39%****	-0,05%	20,20%****
13	0,31%**	20,25%****	0,45%	17,52%****	0,60%*	21,99%****	0,13%	20,33%****
14	0,04%	20,29%****	-0,30%	17,22%****	0,10%	22,09%****	0,13%	20,46%****
15	-0,28%	20,01%****	-0,76%	16,46%****	-0,36%	21,72%****	-0,08%	20,38%****
16	-0,04%	19,97%****	-0,09%	16,37%****	0,08%	21,81%****	-0,08%	20,30%****
17	0,15%	20,12%****	-0,20%	16,17%****	-0,49%	21,32%****	0,55%**	20,86%****
18	0,03%	20,16%****	0,01%	16,18%****	0,03%	21,35%****	0,04%	20,90%****
19	-0,44%	19,72%****	1,03%*	17,21%****	-1,16%	20,19%****	-0,59%	20,31%****
20	-0,02%	19,70%****	-0,41%	16,80%****	-0,17%	20,02%****	0,18%	20,49%****
n	254		48		62		144	

Significance indicators: *10%, **5%, ***1%, ****0,1%

Figure 4: Simple measure CAAR, all countries - initial sample



6.2.3 Abnormal volume – initial sample

For AAV we observe varying degrees of significance. While only three pre-event days have insignificant AAVs, twelve days experience significance on at least the 1% level, two of which on the 0,1% level. CAAV becomes significant at the 0,1% level on day -28, and remains so until day -3, not to be confused with a decreasing CAAV.

Denmark and Norway experience far more dispersed significance in AAV in the pre-event period. Of the 30 pre-event days, Denmark experience significant AAV on 19, seven of which at the 5% level. Although insignificant, there is a large spike in AAV on day -2 for Denmark, caused by two takeover targets with extremely high AAV on this day. CAAV is significant on at least the 10% level from day -30, with an 18-day stretch of 1% significance from (-20, -3). The Norwegian sample experiences the fewest significant observations, with only seven on at least the 10% level, just one of which on the 5% level. Although insignificant, Norway experience the by far highest event day AAV at 0,3230. CAAV is significant in the period (-27, -4), clearly affected by the lacking significance in AAV.

As the Swedish sample is undoubtedly the largest one, it is no surprise that the pattern in AAV follows that of all countries combined. Only six days experience insignificant AAV and seven experience significance on at least the 1% level. CAAV is continuously significant at the 0,1% level from day -21.

The size of AAV and CAAV is more complex to interpret. Basically, it tells how many more times each individual stock is traded than normal, where normal is within the boundaries of the mean plus one standard deviation. Our expectations are more on the development than the size, where we expected a steady run-up before a sharp increase on the event date. We observe this for all countries, however, the announcement effect for Norway is puzzling. Looking into the data, we find 2-3 observations causing this. They do not, on the other hand, bias the run-up which otherwise looks more comparable, and thus we do not exclude them.

There are, however, some common features for all three countries, the first being high abnormal volume post-event despite no significantly positive AARs – in many cases even negative. There may be many reasons for this. In some cases, the rumour date is the date of the formal announcement, after which the share tends to stabilise on the bid price. Here the acquirer may also have started buying shares at the offered price, which would explain the high volume and little price movement. In the cases where it is merely a rumour, the increased volume may be caused by the extra attention from media coverage, and some investors are also willing to sell at what they believe is a peak.

Another common feature is the 'wave' pattern in AAV. One could only speculate in the reasons for this pattern, but previously mentioned theory states that uninformed market participants react to what they believe are more informed trades. This, in turn, has a cascading effect on the trading volume which peaks and then returns. Illegal insider trading *could*, among many others, be such a trigger.

Figure 5: CAAV, all countries - initial sample

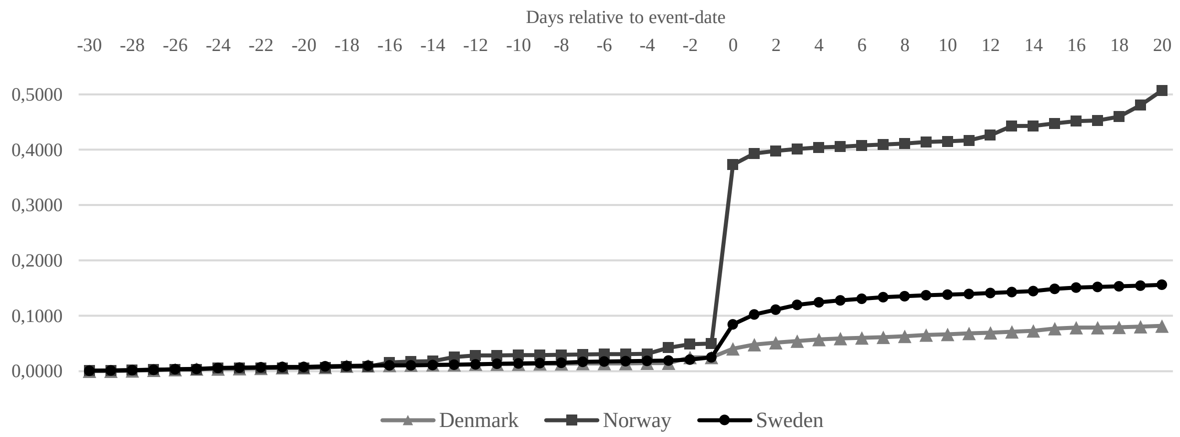


Table 5: AAV and CAAV – initial sample

	All countries		Denmark		Norway		Sweden	
Day	AAV	CAAV	AAV	CAAV	AAV	CAAV	AAV	CAAV
-30	0,0009**	0,0009**	0,0003*	0,0003*	0,0013	0,0013	0,0010**	0,0010**
-29	0,0002*	0,0012***	0,0001	0,0005**	0,0000	0,0013	0,0004	0,0013**
-28	0,0006***	0,0017****	0,0003*	0,0007***	0,0007	0,0020	0,0006**	0,0020***
-27	0,0009***	0,0026****	0,0012	0,0019*	0,0010	0,0030*	0,0008**	0,0027****
-26	0,0009*	0,0035****	0,0010	0,0029**	0,0002	0,0032**	0,0012	0,0039***
-25	0,0005**	0,0040****	0,0011	0,0040**	0,0000	0,0032**	0,0006	0,0045***
-24	0,0013**	0,0053****	0,0002*	0,0042**	0,0022	0,0054**	0,0013***	0,0057***
-23	0,0005***	0,0059****	0,0007	0,0049***	0,0003	0,0057**	0,0006**	0,0063***
-22	0,0006***	0,0065****	0,0006**	0,0055***	0,0003*	0,0060**	0,0008**	0,0071***
-21	0,0005***	0,0070****	0,0010*	0,0065***	0,0001	0,0061**	0,0005**	0,0076****
-20	0,0002****	0,0072****	0,0003*	0,0068****	0,0001*	0,0062**	0,0003****	0,0079****
-19	0,0009***	0,0081****	0,0004**	0,0071****	0,0012*	0,0074**	0,0010**	0,0089****
-18	0,0010**	0,0091****	0,0026	0,0097****	0,0009	0,0083**	0,0005***	0,0093****
-17	0,0004*	0,0095****	0,0004**	0,0101****	0,0001**	0,0085**	0,0006	0,0099****
-16	0,0023	0,0118****	0,0005**	0,0106****	0,0075	0,0160**	0,0005**	0,0104****
-15	0,0008*	0,0126****	0,0005**	0,0111****	0,0019	0,0178**	0,0004**	0,0108****
-14	0,0003***	0,0130****	0,0005**	0,0116****	0,0002	0,0180**	0,0004**	0,0111****
-13	0,0022	0,0152****	0,0001	0,0118****	0,0074	0,0254*	0,0005**	0,0117****
-12	0,0012*	0,0165****	0,0011*	0,0129****	0,0030	0,0284*	0,0005***	0,0122****
-11	0,0008**	0,0172****	0,0001*	0,0130****	0,0003	0,0287*	0,0012**	0,0134****
-10	0,0004****	0,0176****	0,0002*	0,0132****	0,0002	0,0289*	0,0005***	0,0139****
-9	0,0004***	0,0180****	0,0001*	0,0132****	0,0003	0,0292*	0,0006***	0,0145****
-8	0,0007**	0,0187****	0,0003*	0,0135****	0,0005*	0,0297*	0,0009	0,0153****
-7	0,0011**	0,0198****	0,0005	0,0141****	0,0005*	0,0302*	0,0016*	0,0170****
-6	0,0004***	0,0202****	0,0002	0,0143****	0,0004*	0,0306*	0,0005**	0,0175****
-5	0,0005*	0,0207****	0,0001**	0,0143****	0,0003	0,0309*	0,0007	0,0183****
-4	0,0005***	0,0212****	0,0004	0,0148****	0,0004	0,0313*	0,0006***	0,0188****
-3	0,0030	0,0242***	0,0001*	0,0149****	0,0110	0,0423	0,0003*	0,0191****
-2	0,0046**	0,0288***	0,0100	0,0248***	0,0066	0,0488	0,0018*	0,0210****
-1	0,0028**	0,0316***	0,0004*	0,0252***	0,0013	0,0501	0,0044*	0,0254****
0	0,1190*	0,1506*	0,0153****	0,0405****	0,3230	0,3731	0,0591****	0,0844****
1	0,0165****	0,1672**	0,0077**	0,0482****	0,0200****	0,3931	0,0179****	0,1023****
2	0,0066****	0,1738**	0,0032****	0,0514****	0,0046**	0,3978	0,0086***	0,1110****
3	0,0066**	0,1803**	0,0030**	0,0544****	0,0035***	0,4012	0,0091**	0,1201****
4	0,0037****	0,1840**	0,0028*	0,0572****	0,0031**	0,4044	0,0043***	0,1244****
5	0,0027****	0,1867**	0,0021****	0,0593****	0,0010***	0,4053	0,0036****	0,1280****
6	0,0023****	0,1890**	0,0008***	0,0601****	0,0024**	0,4078	0,0027****	0,1307****
7	0,0023**	0,1912**	0,0012	0,0613****	0,0015**	0,4092	0,0030*	0,1338****
8	0,0019****	0,1931**	0,0019**	0,0632****	0,0022	0,4114	0,0017***	0,1355****
9	0,0021****	0,1952**	0,0021***	0,0653****	0,0025	0,4139	0,0020****	0,1374****
10	0,0011****	0,1963**	0,0015**	0,0667****	0,0011***	0,4150	0,0009****	0,1383****
11	0,0015****	0,1978**	0,0020**	0,0687****	0,0022	0,4172	0,0010****	0,1393****
12	0,0034*	0,2012**	0,0007*	0,0694****	0,0089	0,4261	0,0018***	0,1411****
13	0,0057	0,2069**	0,0018*	0,0712****	0,0167	0,4428	0,0018**	0,1429****
14	0,0014****	0,2082**	0,0019**	0,0731****	0,0004**	0,4433	0,0017***	0,1446****
15	0,0042**	0,2124***	0,0037**	0,0768****	0,0041	0,4474	0,0044*	0,1490****
16	0,0025***	0,2150***	0,0018**	0,0786****	0,0042	0,4516	0,0020***	0,1510****
17	0,0012***	0,2161***	0,0005**	0,0791****	0,0013*	0,4530	0,0013**	0,1523****
18	0,0024*	0,2185***	0,0004***	0,0795****	0,0068	0,4598	0,0010**	0,1533****
19	0,0064	0,2248**	0,0014	0,0808****	0,0212	0,4809	0,0011**	0,1544****
20	0,0080**	0,2328***	0,0011*	0,0820****	0,0265*	0,5074	0,0017**	0,1561****
n	254		48		62		144	

Significance indicators: *10%, **5%, ***1%, ****0,1%

Figure 6: Market measure AAR and AAV, Denmark – initial sample

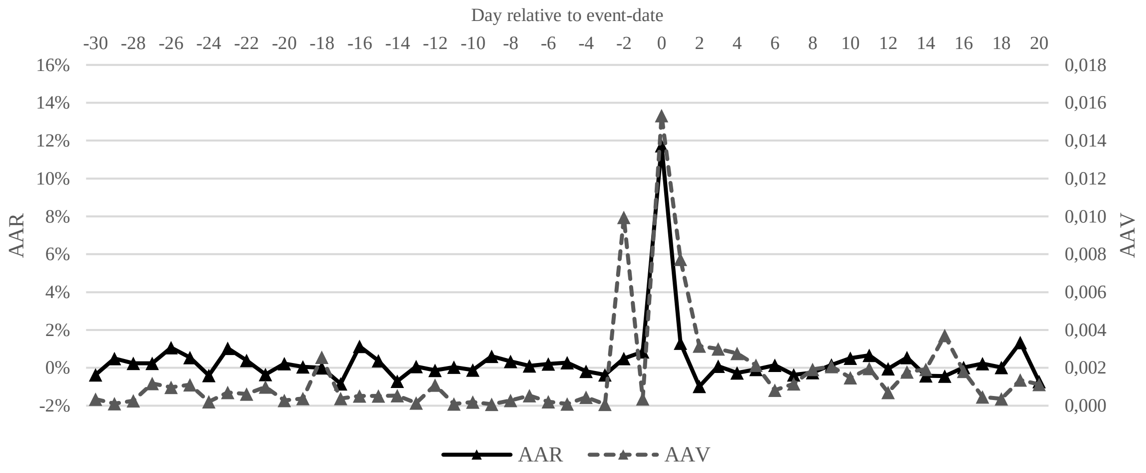


Figure 7: Market measure AAR and AAV, Norway – initial sample

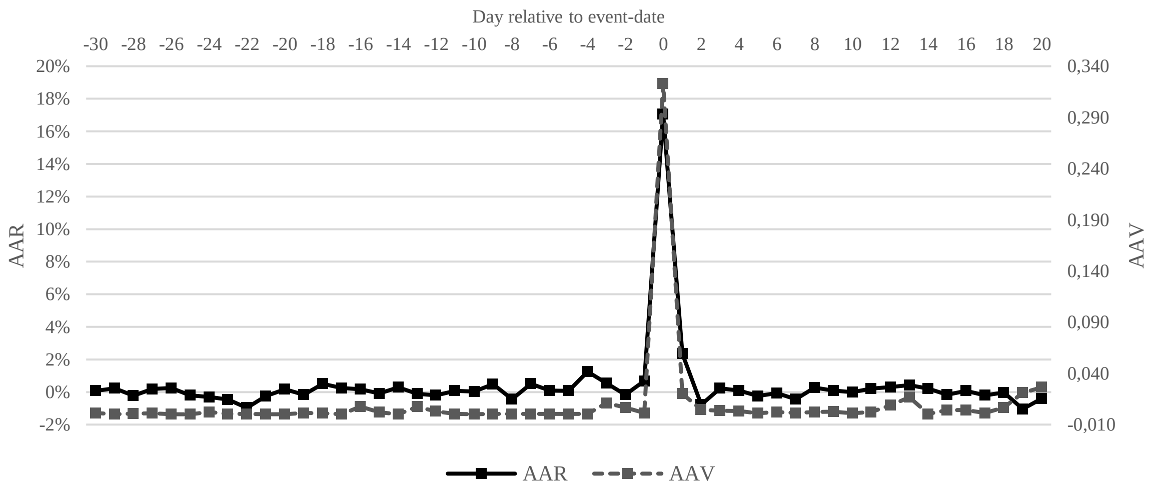


Figure 8: Market measure AAR and AAV, Sweden – initial sample

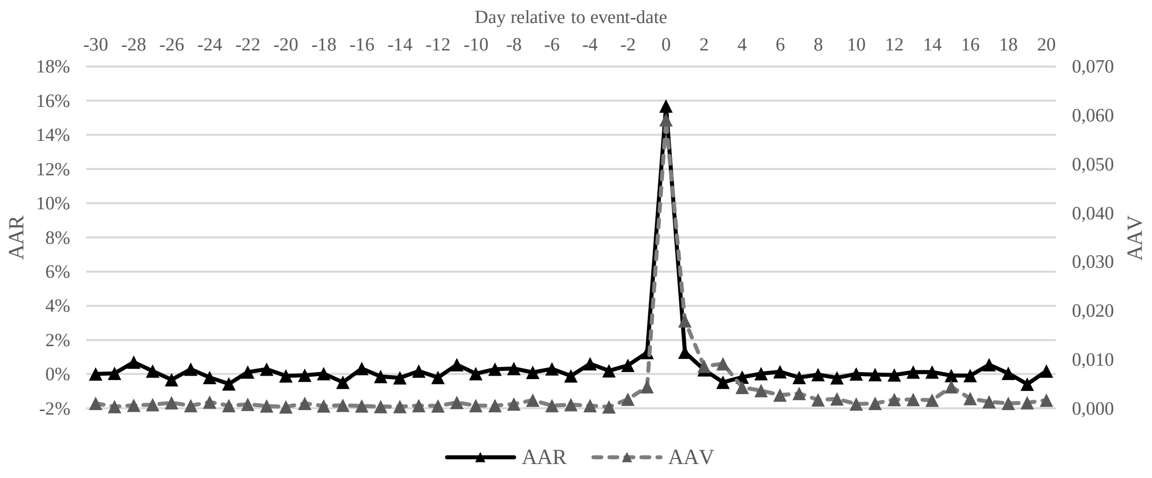


Figure 9: Simple measure AAR and AAV, Denmark – initial sample

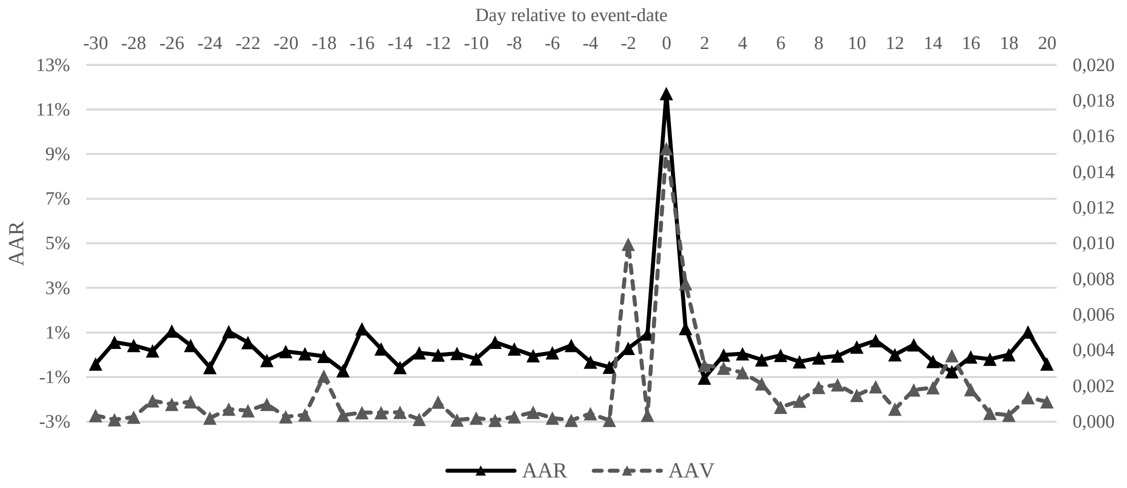


Figure 10: Simple measure AAR and AAV, Norway – initial sample

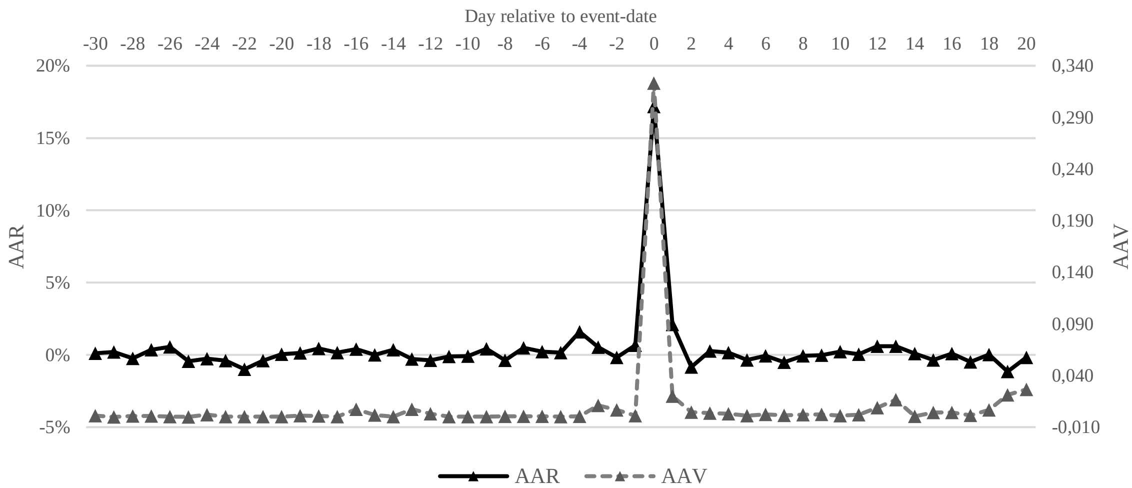
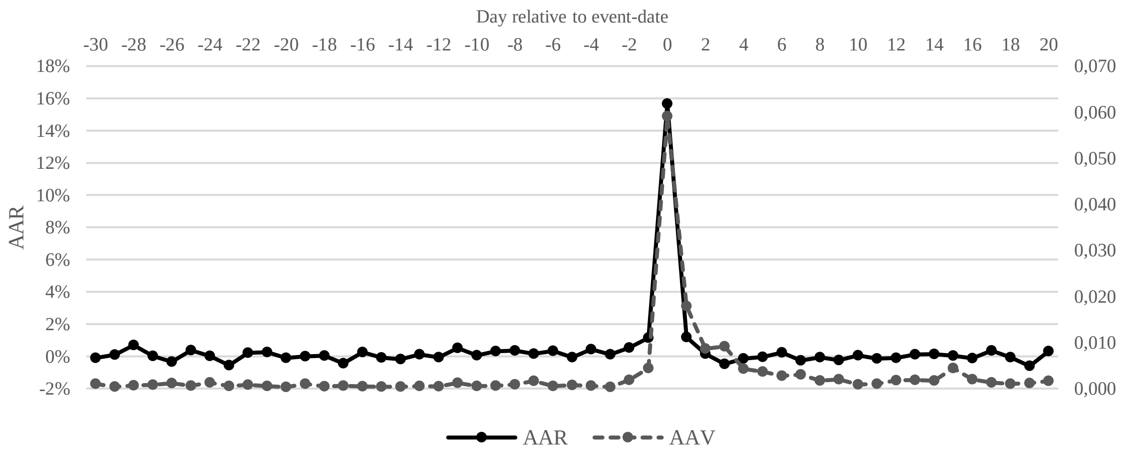


Figure 11: Simple measure AAR and AAV, Sweden – initial sample



6.3 EVENT STUDY – ADJUSTED SAMPLE

In the following we present the results of the event study on the adjusted sample, which are visualised in Figure 12: Market measure CAAR, all countries – adjusted sample

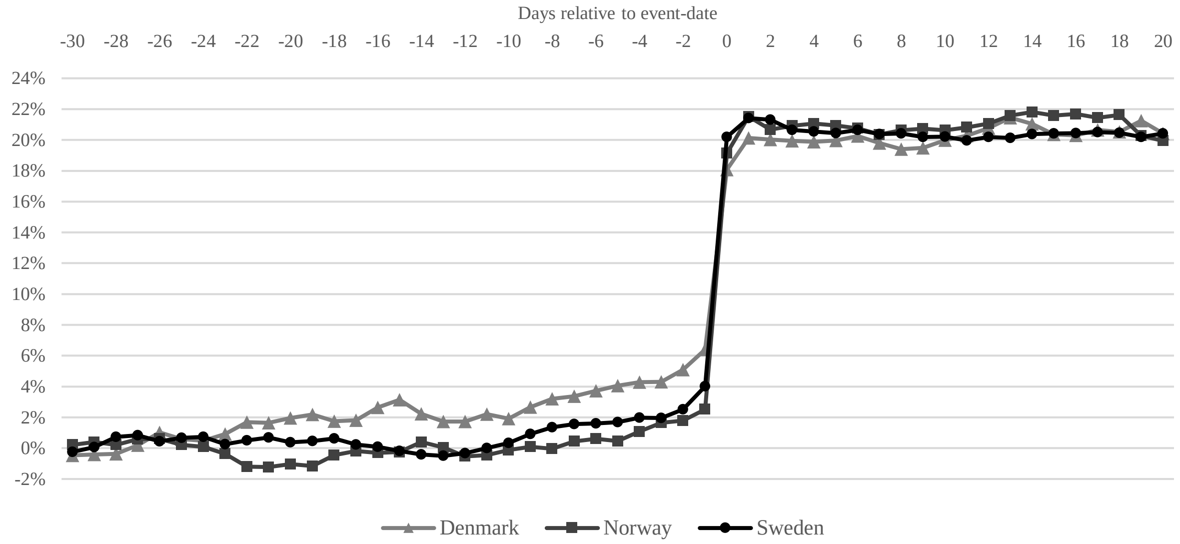


Table 6 to Table 8 and Figure 12 to Figure 20. Different accumulation lengths of CAAR can be viewed in appendices 7-11.

6.3.1 Market measure of abnormal returns – adjusted sample

As for the initial sample, the first significant and positive observation is on day -28, looking at all countries combined (Figure 12: Market measure CAAR, all countries – adjusted sample

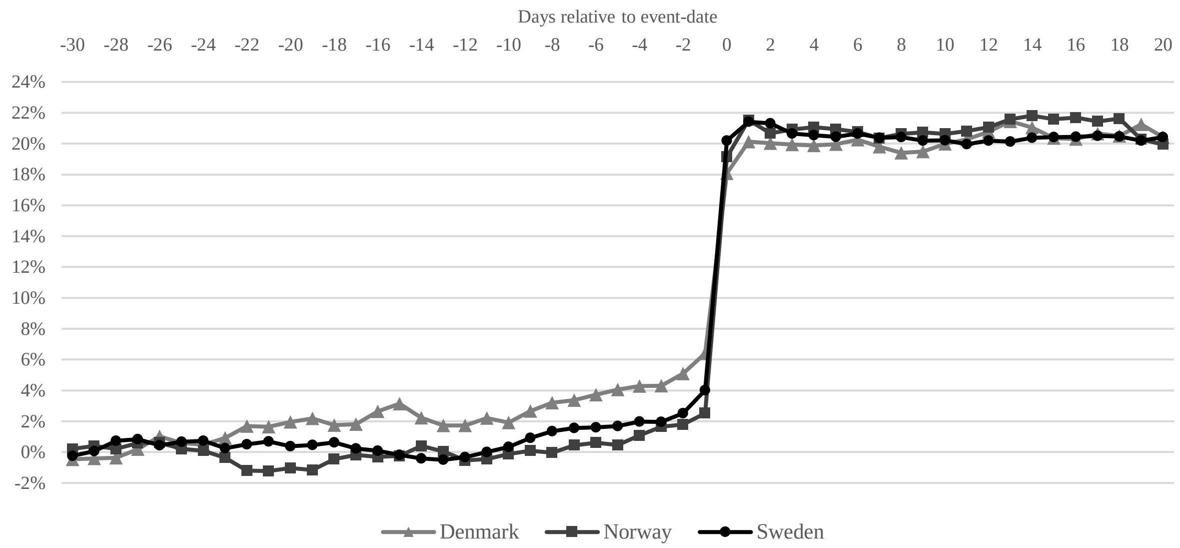


Table 6). Here as well, further significance can be observed on days -11, -9, -4, -2 and -1, with the latter substantially higher than for the initial sample with 1,26%, significant at the 0,1% level. The adjusted sample also produces a slightly higher announcement effect of 15,57%, an increase of 0,26 percentage points from the initial sample. On CAAR we yet again see a cluster of significant observations early in the event window, although now becoming insignificant two days earlier. The run-up becomes consistently significant one day later at -7, culminating in a pre-bid run-up of 3,99%.

For Denmark, the days with significantly positive AAR are the same as for the initial sample, namely -16, -15 and -9. Despite its insignificance, the highest AAR occurs one day before the event date at 1,31%. A more substantial difference from the initial sample can be seen on the CAAR, which for the initial sample became significant on day -26 and remained so throughout the event period. For the adjusted sample, on the other hand, the CAAR is low and insignificant until day -5, where it picks up pace and produces a significant pre-event run-up of 6,39%, more than 1 percentage point higher than for the initial sample. For accumulation lengths of 25, 20 and 10 days, the run-up is significant at the 10% level as well, while the remaining two are insignificant.

For Norway, the first significant and positive observation occurs on day -14, as opposed to -9 in the initial sample. While day -9 is insignificant for the adjusted sample, days -4 ,-3 and -1 remains significantly positive before the announcement effect of 16,61%. While CAAR for the initial sample experienced occasional negative and significant observations, the Norwegian run-up in the adjusted sample remains insignificant with a pre-event run-up of 2,52%. As for the initial sample, the cluster of negative AARs influence the 30-day run-up, resulting in a significant run-up for shorter accumulation lengths.

As for the initial sample, the first positive and significant observation in Sweden occurs on day -28. Contrary to the initial sample, following this, only days -2 and -1 are significant, the latter with an AAR as high as 1,50%, significant at the 0,1% level. The announcement effect of 16,19% is half a percentage point higher than in the initial sample. While CAAR in the initial sample had drops of significance throughout the event window, only days -28 and -27 display significance here. The run-up becomes continuously significant only on day -2, five days later than for the initial sample, leading to a similar pre-event run-up of 4,01%, significant at the 5% level. The run-up is significant on at least the 5% level across all accumulation lengths, beginning from day -8 to –2.

We can see that for the most part, the two samples yield similar results, with the CAAR for Denmark being a great exception to this norm. This, however, is no surprise, seeing as Denmark suffered the greatest loss from the additional screen, reducing the number of observations by 28%, compared to 15% and 20% for Norway and Sweden, respectively.

Figure 12: Market measure CAAR, all countries – adjusted sample

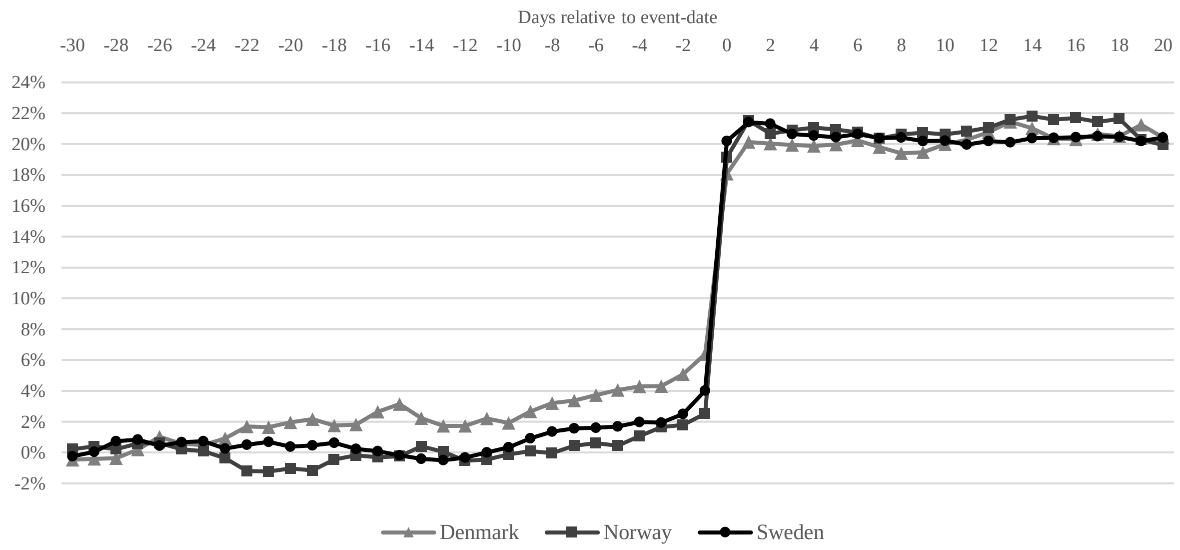


Table 6: Market measure AAR and CAAR, all countries – adjusted sample

	All countries		Denmark		Norway		Sweden	
Day	AAR	CAAR	AAR	CAAR	AAR	CAAR	AAR	CAAR
-30	-0,15%	-0,15%	-0,46%	-0,46%	0,21%	0,21%	-0,23%	-0,23%
-29	0,22%	0,07%	0,05%	-0,41%	0,19%	0,40%	0,29%	0,06%
-28	0,33%*	0,41%*	0,05%	-0,37%	-0,19%	0,21%	0,67%**	0,73%**
-27	0,26%	0,67%**	0,55%	0,19%	0,39%	0,60%	0,11%	0,84%*
-26	-0,08%	0,59%**	0,83%	1,02%	0,02%	0,62%	-0,40%	0,45%
-25	-0,06%	0,53%	-0,44%	0,58%	-0,41%	0,21%	0,22%	0,67%
-24	-0,02%	0,51%	-0,09%	0,49%	-0,13%	0,08%	0,06%	0,73%
-23	-0,32%	0,19%	0,43%	0,92%	-0,46%	-0,38%	-0,48%	0,25%
-22	0,04%	0,23%	0,77%	1,68%	-0,83%	-1,21%	0,25%	0,50%
-21	0,09%	0,32%	-0,03%	1,66%	-0,02%	-1,22%	0,19%	0,68%
-20	-0,07%	0,25%	0,31%	1,97%	0,19%	-1,04%	-0,30%	0,38%
-19	0,04%	0,30%	0,21%	2,18%	-0,13%	-1,16%	0,08%	0,46%
-18	0,22%	0,52%	-0,43%	1,75%	0,71%	-0,45%	0,17%	0,63%
-17	-0,14%	0,38%	0,06%	1,81%	0,27%	-0,19%	-0,39%	0,24%
-16	0,02%	0,41%	0,83%*	2,64%	-0,12%	-0,31%	-0,14%	0,10%
-15	-0,05%	0,35%	0,49%*	3,14%*	0,07%	-0,23%	-0,27%	-0,17%
-14	-0,10%	0,25%	-0,91%	2,23%	0,64%**	0,40%	-0,23%	-0,40%
-13	-0,24%	0,01%	-0,50%	1,72%	-0,36%	0,04%	-0,10%	-0,50%
-12	-0,06%	-0,05%	0,00%	1,73%	-0,57%	-0,53%	0,17%	-0,33%
-11	0,29%*	0,24%	0,47%	2,20%	0,08%	-0,45%	0,34%	0,01%
-10	0,24%	0,48%	-0,29%	1,91%	0,34%	-0,12%	0,34%	0,34%
-9	0,51%**	0,99%	0,76%*	2,67%	0,21%	0,09%	0,58%	0,93%
-8	0,29%	1,28%	0,54%	3,21%	-0,12%	-0,03%	0,42%	1,35%
-7	0,27%	1,55%*	0,15%	3,36%	0,46%	0,43%	0,21%	1,56%
-6	0,13%	1,68%*	0,36%	3,72%	0,18%	0,61%	0,04%	1,60%
-5	0,05%	1,73%*	0,33%	4,05%*	-0,16%	0,45%	0,08%	1,68%
-4	0,38%*	2,11%**	0,23%	4,29%*	0,62%**	1,08%	0,31%	1,99%
-3	0,14%	2,25%**	0,01%	4,30%*	0,57%*	1,65%	-0,04%	1,95%
-2	0,48%**	2,74%**	0,79%	5,08%*	0,14%	1,79%	0,56%*	2,51%*
-1	1,26%****	3,99%***	1,31%	6,39%*	0,73%*	2,52%	1,50%****	4,01%**
0	15,57%****	19,56%****	11,69%****	18,08%****	16,61%****	19,13%****	16,19%****	20,20%****
1	1,68%****	21,24%****	2,05%**	20,13%****	2,40%***	21,53%****	1,21%*	21,41%****
2	-0,30%	20,93%****	-0,11%	20,02%****	-0,85%	20,68%****	-0,10%	21,32%****
3	-0,33%	20,60%****	-0,07%	19,95%****	0,23%	20,91%****	-0,68%	20,64%****
4	-0,02%	20,58%****	-0,08%	19,87%****	0,16%	21,07%****	-0,09%	20,55%****
5	-0,08%	20,50%****	0,08%	19,96%****	-0,13%	20,94%****	-0,10%	20,45%****
6	0,11%	20,61%****	0,29%	20,24%****	-0,19%	20,75%****	0,20%	20,65%****
7	-0,33%	20,28%****	-0,45%	19,80%****	-0,39%	20,36%****	-0,27%	20,38%****
8	0,03%	20,31%****	-0,39%	19,41%****	0,27%	20,63%****	0,03%	20,41%****
9	-0,09%	20,22%****	0,07%	19,48%****	0,10%	20,73%****	-0,22%	20,19%****
10	0,07%	20,29%****	0,51%	19,98%****	-0,10%	20,63%****	0,02%	20,21%****
11	-0,04%	20,25%****	0,28%	20,27%****	0,19%	20,82%****	-0,24%	19,97%****
12	0,27%*	20,52%****	0,50%	20,77%****	0,26%	21,07%****	0,21%	20,19%****
13	0,22%	20,74%****	0,68%*	21,45%****	0,52%	21,59%****	-0,07%	20,12%****
14	0,14%	20,88%****	-0,41%	21,03%****	0,22%	21,81%****	0,26%*	20,38%****
15	-0,16%	20,73%****	-0,67%	20,37%****	-0,22%	21,59%****	0,03%	20,41%****
16	0,04%	20,76%****	-0,07%	20,30%****	0,11%	21,70%****	0,03%	20,44%****
17	0,02%	20,78%****	0,35%	20,65%****	-0,26%	21,44%****	0,06%	20,50%****
18	0,01%	20,79%****	-0,14%	20,51%****	0,19%	21,62%****	-0,04%	20,47%****
19	-0,40%	20,39%****	0,73%	21,25%****	-1,35%	20,27%****	-0,27%	20,20%****
20	-0,09%	20,30%****	-0,83%*	20,42%****	-0,32%	19,95%****	0,23%	20,43%****
n	201		33		52		116	

Significance indicators: *10%, **5%, ***1%, ****0,1%

6.3.2 Simple measure of abnormal returns – adjusted sample

Similar to preceding measures and samples, the first significant and positive AAR occurs on day -28, this time with 0,38% (Table 7). As opposed to before, day -27 is now significant at the 10% level with 0,41%. While day -11 AAR is now lower and no longer significant, similar magnitude can be observed on days -4, -2 and -1, the latter very much so with 1,36% at the 0,1% level. Across all countries, we see an average announcement effect of 15,60%.

For Denmark, we only observe a single significantly positive pre-event AAR, namely day -16 with 0,87%, as opposed to previous measures and samples where we observed three to four significantly positive days. The announcement effect remains more or less equal to before at 11,73%, also here significant at the 0,1% level. As was the case for the market measure, the run-up becomes significant on day -5, far later than for the initial sample equivalents. Here, however, the run-up becomes insignificant on day -3 due to the now negative AAR on the same day, resulting in a pre-event run-up of 6,16%, significant at the 10% level. The run-up for different accumulation lengths is similar in its significance to the market measure.

The first significant and positive AAR for the Norwegian sample occurs on day -14, as for the market measure, although now at 0,68%. While day -3 is insignificant both days -4 and -1 become higher in magnitude. This especially goes for the former, which increases almost 0,4 percentage points to 1,00%. Although lower than for the initial sample, the announcement effect remains the highest among the markets, at 16,61%, significant at the 0,1% level. The run-up is still insignificant and the lowest among the three at a mere 2,66%. Again, we see great influence on CAAR from the negative AARs early in the event window, as the run-up is both higher and significant for the alternative accumulation lengths, however, usually becomes significant later than for the market measure.

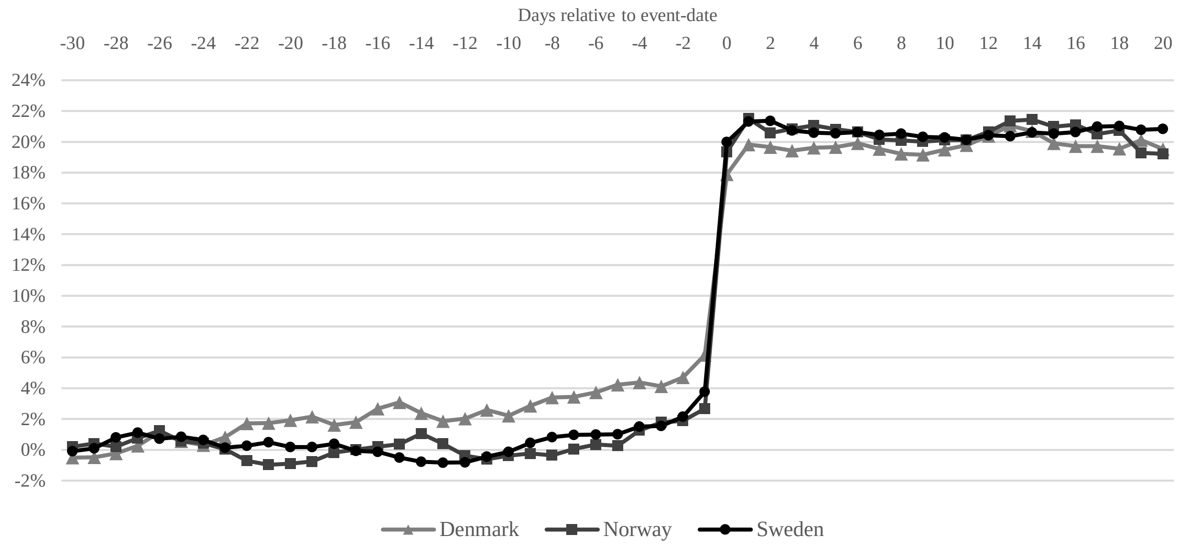
As also observed previously, the first significantly positive Swedish AAR is observed on day -28, now at 0,71% and significant at the 5% level. Day -4 has now become significant with an 0,5% AAR, significant at the 10% level. Days -2 and -1 are still significant, however the latter has increased to a staggering 1,63% with a 0,1% significance. The announcement effect for Sweden experiences a marginal increase to 16,19%, also this the highest compared to previous measures and samples. In terms of CAAR, we observe a small, significant three-day cluster succeeding day -28 . Following this, the run-up returns to significance only on day -1 – one day later than for the market measure – leading to a pre-event run-up of 3,77%, significant at the 5% level. For the alternative accumulation lengths, the run-up is similar to those of the market measure in terms of both size and significance.

Table 7: Simple measure AAR and CAAR – adjusted sample

	All countries		Denmark		Norway		Sweden	
Day	AAR	CAAR	AAR	CAAR	AAR	CAAR	AAR	CAAR
-30	-0,08%	-0,08%	-0,51%	-0,51%	0,20%	0,20%	-0,09%	-0,09%
-29	0,17%	0,09%	0,03%	-0,48%	0,21%	0,41%	0,20%	0,10%
-28	0,38%**	0,47%*	0,23%	-0,25%	-0,21%	0,20%	0,71%**	0,81%**
-27	0,41%*	0,88%**	0,51%	0,27%	0,57%	0,77%	0,31%	1,12%**
-26	0,06%	0,94%**	0,89%	1,16%	0,47%	1,24%*	-0,39%	0,73%*
-25	-0,22%	0,72%	-0,61%	0,55%	-0,68%	0,56%	0,11%	0,84%
-24	-0,19%	0,53%	-0,25%	0,30%	-0,13%	0,43%	-0,20%	0,64%
-23	-0,31%	0,22%	0,52%	0,82%	-0,39%	0,04%	-0,51%	0,13%
-22	0,01%	0,23%	0,90%	1,72%	-0,75%	-0,71%	0,12%	0,25%
-21	0,06%	0,29%	0,01%	1,73%	-0,26%	-0,97%	0,23%	0,48%
-20	-0,12%	0,17%	0,20%	1,93%	0,07%	-0,90%	-0,31%	0,17%
-19	0,08%	0,25%	0,21%	2,14%	0,14%	-0,75%	0,01%	0,18%
-18	0,19%	0,43%	-0,53%	1,61%	0,57%	-0,18%	0,21%	0,39%
-17	-0,18%	0,26%	0,19%	1,81%	0,20%	0,02%	-0,47%	-0,08%
-16	0,16%	0,41%	0,87%*	2,68%	0,18%	0,20%	-0,07%	-0,14%
-15	-0,09%	0,33%	0,40%	3,08%	0,16%	0,36%	-0,35%	-0,50%
-14	-0,09%	0,24%	-0,70%	2,38%	0,68%**	1,05%	-0,29%	-0,79%
-13	-0,29%	-0,06%	-0,53%	1,86%	-0,66%	0,38%	-0,04%	-0,83%
-12	-0,18%	-0,23%	0,17%	2,02%	-0,77%	-0,39%	0,02%	-0,81%
-11	0,24%	0,01%	0,56%	2,58%	-0,22%	-0,61%	0,37%	-0,44%
-10	0,18%	0,19%	-0,37%	2,21%	0,23%	-0,37%	0,31%	-0,13%
-9	0,47%*	0,66%	0,65%	2,87%	0,14%	-0,24%	0,57%	0,44%
-8	0,27%	0,92%	0,53%	3,40%	-0,13%	-0,36%	0,38%	0,83%
-7	0,20%	1,13%	0,04%	3,43%	0,42%	0,06%	0,15%	0,98%
-6	0,14%	1,26%	0,29%	3,73%	0,29%	0,34%	0,02%	0,99%
-5	0,07%	1,34%	0,50%	4,23%*	-0,08%	0,26%	0,02%	1,01%
-4	0,57%***	1,91%*	0,13%	4,37%*	1,00%***	1,26%	0,50%*	1,51%
-3	0,13%	2,04%**	-0,25%	4,12%	0,52%	1,78%	0,05%	1,55%
-2	0,46%*	2,50%**	0,60%	4,72%*	0,11%	1,89%	0,59%*	2,14%
-1	1,36%****	3,86%***	1,45%	6,16%*	0,77%*	2,66%	1,63%****	3,77%**
0	15,60%****	19,47%****	11,73%****	17,89%****	16,69%****	19,35%****	16,21%****	19,98%****
1	1,66%****	21,13%****	1,93%**	19,82%****	2,15%**	21,51%****	1,34%**	21,32%****
2	-0,25%	20,87%****	-0,16%	19,67%****	-0,94%	20,57%****	0,05%	21,37%****
3	-0,32%	20,55%****	-0,23%	19,44%****	0,28%	20,85%****	-0,64%	20,73%****
4	0,02%	20,57%****	0,18%	19,62%****	0,23%	21,08%****	-0,13%	20,60%****
5	-0,10%	20,47%****	0,05%	19,67%****	-0,26%	20,82%****	-0,06%	20,54%****
6	0,04%	20,51%****	0,24%	19,91%****	-0,19%	20,63%****	0,09%	20,63%****
7	-0,29%	20,22%****	-0,38%	19,52%****	-0,48%	20,15%****	-0,18%	20,46%****
8	-0,02%	20,20%****	-0,30%	19,22%****	-0,06%	20,09%****	0,08%	20,53%****
9	-0,16%	20,04%****	-0,06%	19,16%****	-0,09%	20,01%****	-0,22%	20,31%****
10	0,06%	20,10%****	0,33%	19,49%****	0,12%	20,12%****	-0,04%	20,27%****
11	-0,03%	20,08%****	0,30%	19,79%****	-0,01%	20,11%****	-0,13%	20,15%****
12	0,41%**	20,48%****	0,60%	20,39%****	0,55%**	20,66%****	0,28%*	20,43%****
13	0,27%*	20,75%****	0,67%*	21,05%****	0,70%*	21,36%****	-0,06%	20,37%****
14	0,10%	20,85%****	-0,36%	20,69%****	0,08%	21,44%****	0,24%	20,61%****
15	-0,30%	20,55%****	-0,79%	19,90%****	-0,46%	20,98%****	-0,08%	20,53%****
16	0,07%	20,62%****	-0,18%	19,72%****	0,13%	21,12%****	0,11%	20,64%****
17	0,03%	20,65%****	0,01%	19,73%****	-0,60%	20,51%****	0,34%**	20,98%****
18	0,06%	20,71%****	-0,17%	19,55%****	0,23%	20,74%****	0,05%	21,03%****
19	-0,45%	20,26%****	0,56%	20,11%****	-1,46%	19,29%****	-0,25%	20,78%****
20	-0,08%	20,18%****	-0,58%	19,53%****	-0,07%	19,22%****	0,06%	20,84%****
n	201		33		52		116	

Significance indicators: *10%, **5%, ***1%, ****0,1%

Figure 13: Simple measure CAAR, all countries – adjusted sample



6.3.3 Abnormal volume – adjusted sample

For the total sample, with the exception of days -29 and -16, we see exclusively significant AAVs with varying degrees of significance – as was also the case for the initial sample (Table 8). For 13 of the pre-event days we observe AAVs significant on at least the 1% level. CAAV becomes continuously significant at the 1% level on day -25.

It is evident that the additional liquidity screen has influenced the significance of the Danish and Norwegian observations. The Danish sample has nine fewer significant pre-event observations than the initial sample, while Norway has four fewer. Revisiting formula 8 for calculating t-statistic, this may be due to the screen having ambiguous effects on the standard deviation, but strictly negative influence on the number of observations, thus returning a lower t-statistic. The two Danish stocks causing the AAV spike on day -2 are still in the sample, and the spike is thus still present.

We also see that the extreme Norwegian announcement effect is now gone with the screening. As it was a liquidity screen this may at first glance seem counterintuitive. However, we calculated AV as the daily volume less the estimation period mean and standard deviation. For an illiquid stock the mean and standard deviation are both low, but the market ignores previous illiquidity in the event of a takeover rumour. That is, if there is a rumour of a 20% takeover premium, the market will react accordingly with both price and volume, and the announcement effect on volume will therefore be relatively higher than for more liquid stocks.

For the Swedish sample, on the other hand, the number of significant pre-event observations has increased by two to 26, however the number of significant AAVs on at least the 1% level has decreased by three to now four observations. Following the screening, the Swedish sample now experiences the highest announcement effect with 0,0726 in excess of the mean and standard deviation. We observe a pattern in CAAV similar to that of the initial sample, although here becoming continuously significant at the 0,1% level seven days later on day -14.

Table 8: AAV and CAAV, all countries – adjusted sample

	All countries		Denmark		Norway		Sweden	
Day	AAV	CAAV	AAV	CAAV	AAV	CAAV	AAV	CAAV
-30	0,0006**	0,0006**	0,0002	0,0002	0,0002	0,0002	0,0009*	0,0009*
-29	0,0003	0,0008**	0,0001	0,0003	0,0001	0,0002*	0,0004	0,0013*
-28	0,0007**	0,0015***	0,0002	0,0005**	0,0009	0,0011*	0,0007*	0,0020**
-27	0,0010***	0,0025****	0,0017	0,0022	0,0010	0,0021	0,0009**	0,0029***
-26	0,0008*	0,0033***	0,0014	0,0036*	0,0002	0,0023	0,0009	0,0037**
-25	0,0004**	0,0037****	0,0014	0,0050*	0,0000	0,0023*	0,0002**	0,0040**
-24	0,0010*	0,0047****	0,0001	0,0052**	0,0026	0,0049	0,0006**	0,0046***
-23	0,0003**	0,0051****	0,0007	0,0058**	0,0003	0,0053*	0,0003*	0,0048**
-22	0,0008***	0,0058****	0,0008**	0,0066**	0,0003	0,0055*	0,0010**	0,0058***
-21	0,0005***	0,0063****	0,0012	0,0078***	0,0002	0,0057*	0,0004**	0,0062***
-20	0,0002****	0,0065****	0,0002	0,0080***	0,0001	0,0058*	0,0003***	0,0065***
-19	0,0011***	0,0076****	0,0004	0,0083***	0,0015*	0,0073**	0,0011**	0,0076***
-18	0,0010**	0,0087****	0,0030	0,0114***	0,0011	0,0085**	0,0004**	0,0081***
-17	0,0002****	0,0089****	0,0005**	0,0119***	0,0001**	0,0086**	0,0002**	0,0083***
-16	0,0013	0,0102****	0,0006**	0,0125***	0,0037	0,0123*	0,0004**	0,0086***
-15	0,0003***	0,0105****	0,0006*	0,0131***	0,0002	0,0125*	0,0003**	0,0089***
-14	0,0004***	0,0109****	0,0007**	0,0138****	0,0002	0,0127**	0,0004**	0,0093****
-13	0,0005**	0,0114****	0,0002	0,0140****	0,0004	0,0130**	0,0007*	0,0099****
-12	0,0008***	0,0121****	0,0016*	0,0156****	0,0007	0,0137**	0,0005**	0,0105****
-11	0,0009**	0,0131****	0,0001*	0,0157****	0,0003	0,0140**	0,0015**	0,0120****
-10	0,0005****	0,0135****	0,0003	0,0159****	0,0001	0,0141**	0,0007***	0,0127****
-9	0,0005***	0,0140****	0,0001	0,0160****	0,0001	0,0142**	0,0007***	0,0134****
-8	0,0007*	0,0147****	0,0004*	0,0164****	0,0005	0,0147**	0,0009	0,0143****
-7	0,0010*	0,0157****	0,0008	0,0172****	0,0005	0,0152**	0,0013	0,0156****
-6	0,0004***	0,0161****	0,0003	0,0175****	0,0004	0,0156**	0,0005**	0,0161****
-5	0,0002**	0,0164****	0,0001*	0,0176****	0,0003	0,0160**	0,0003**	0,0163****
-4	0,0005***	0,0168****	0,0006	0,0182****	0,0001	0,0160**	0,0006***	0,0170****
-3	0,0002*	0,0171****	0,0001	0,0183****	0,0001*	0,0161**	0,0003*	0,0173****
-2	0,0037*	0,0208****	0,0146	0,0329***	0,0001	0,0162**	0,0023*	0,0196****
-1	0,0036**	0,0244****	0,0005*	0,0334***	0,0016	0,0178**	0,0055*	0,0251****
0	0,0576****	0,0820****	0,0187***	0,0521****	0,0509****	0,0686****	0,0726****	0,0977****
1	0,0194****	0,1014****	0,0102**	0,0623****	0,0221****	0,0908****	0,0208***	0,1185****
2	0,0059****	0,1072****	0,0033***	0,0657****	0,0053**	0,0960****	0,0068****	0,1253****
3	0,0041****	0,1114****	0,0036*	0,0692****	0,0027***	0,0987****	0,0049****	0,1302****
4	0,0031****	0,1145****	0,0020**	0,0713****	0,0036**	0,1024****	0,0031****	0,1333****
5	0,0024****	0,1169****	0,0019***	0,0732****	0,0012***	0,1036****	0,0032****	0,1365****
6	0,0022****	0,1191****	0,0008**	0,0740****	0,0015**	0,1051****	0,0029****	0,1394****
7	0,0016****	0,1207****	0,0015	0,0755****	0,0019**	0,1070****	0,0015***	0,1409****
8	0,0016***	0,1223****	0,0027**	0,0782****	0,0024	0,1094****	0,0009****	0,1418****
9	0,0021****	0,1244****	0,0021***	0,0803****	0,0031	0,1125****	0,0017****	0,1435****
10	0,0012****	0,1256****	0,0019**	0,0822****	0,0013**	0,1138****	0,0009****	0,1444****
11	0,0011****	0,1268****	0,0022**	0,0844****	0,0010**	0,1148****	0,0009***	0,1453****
12	0,0012****	0,1279****	0,0006*	0,0850****	0,0012**	0,1160****	0,0013***	0,1466****
13	0,0065	0,1344****	0,0023	0,0873****	0,0206	0,1366****	0,0010****	0,1476****
14	0,0012****	0,1356****	0,0024*	0,0897****	0,0006**	0,1372****	0,0012****	0,1488****
15	0,0022***	0,1379****	0,0051*	0,0948****	0,0005*	0,1377****	0,0023**	0,1510****
16	0,0016****	0,1395****	0,0020*	0,0968****	0,0014	0,1391****	0,0017**	0,1527****
17	0,0011***	0,1406****	0,0004**	0,0973****	0,0016*	0,1407****	0,0010***	0,1537****
18	0,0029*	0,1435****	0,0004**	0,0977****	0,0085	0,1492****	0,0010**	0,1547****
19	0,0008****	0,1443****	0,0004	0,0981****	0,0016**	0,1508****	0,0006**	0,1553****
20	0,0055*	0,1498****	0,0005*	0,0986****	0,0160	0,1668****	0,0019**	0,1572****
n	201		33		52		116	

Significance indicators: *10%, **5%, ***1%, ****0,1%

Figure 14: CAAV, all countries – adjusted sample

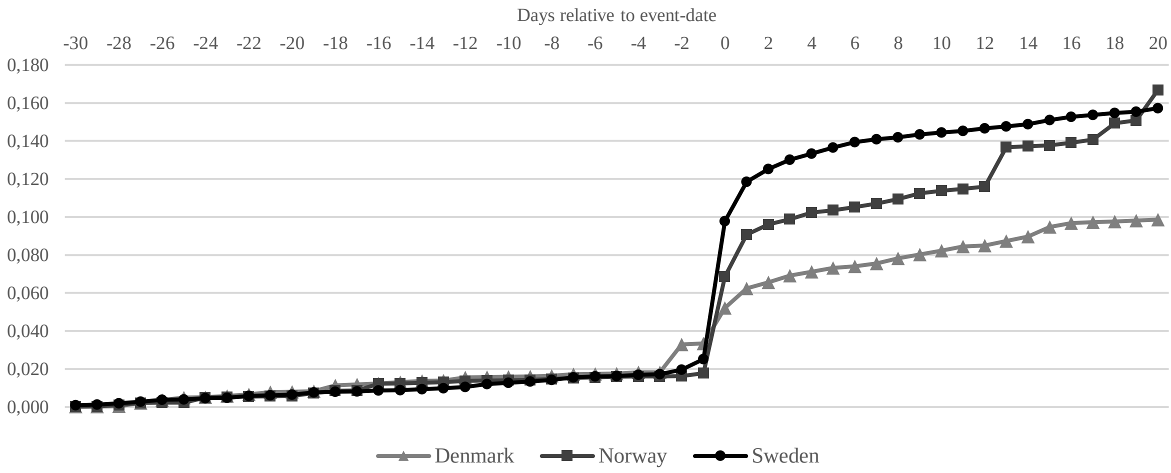


Figure 15: Market measure AAR and AAV, Denmark – adjusted sample

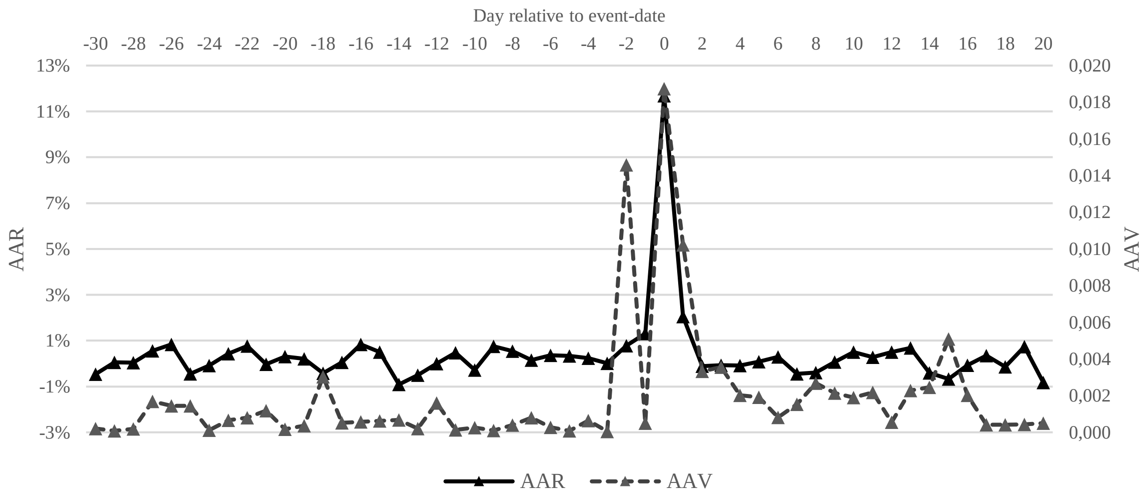


Figure 16: Market measure AAR and AAV, Norway – adjusted sample

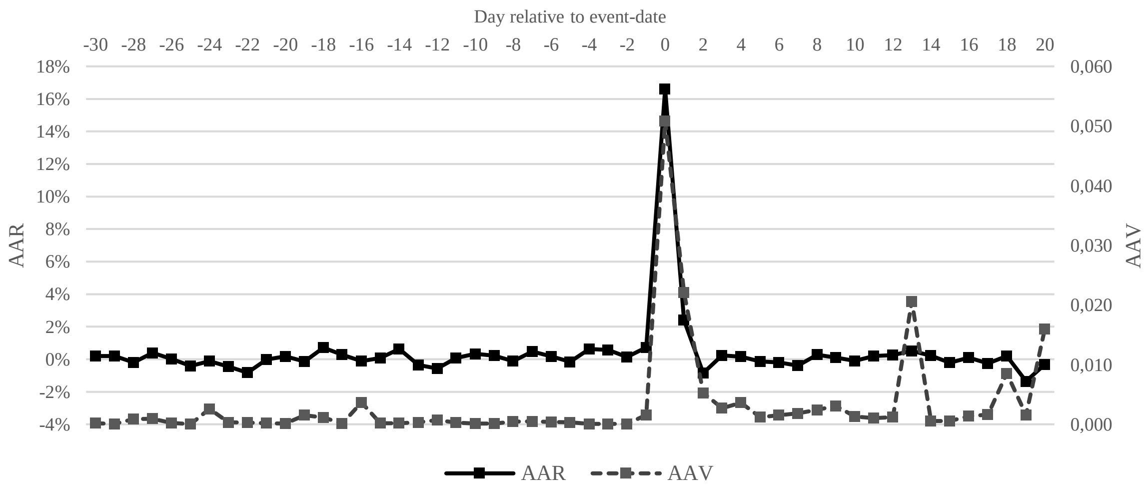


Figure 17: Market measure AAR and AAV, Sweden - adjusted sample

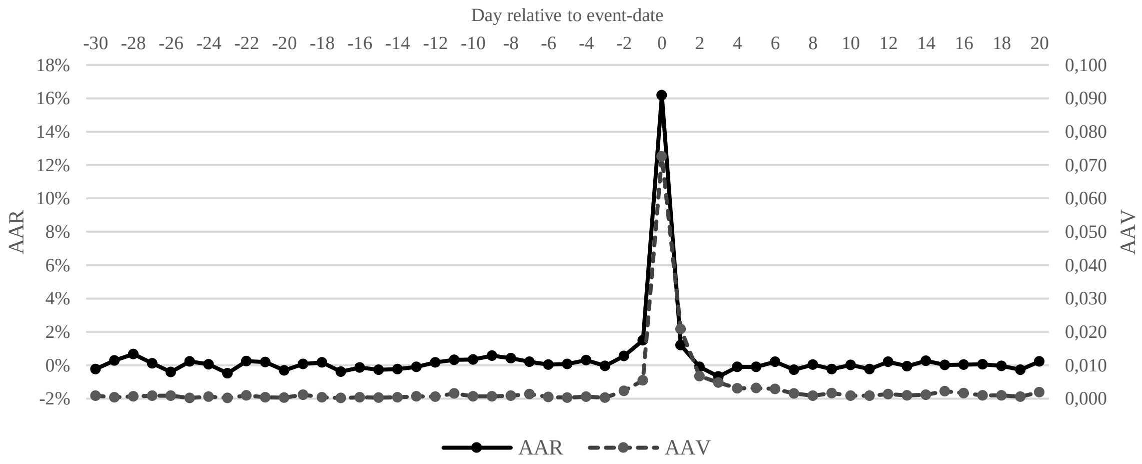


Figure 18: Simple measure AAR and AAV, Denmark – adjusted sample

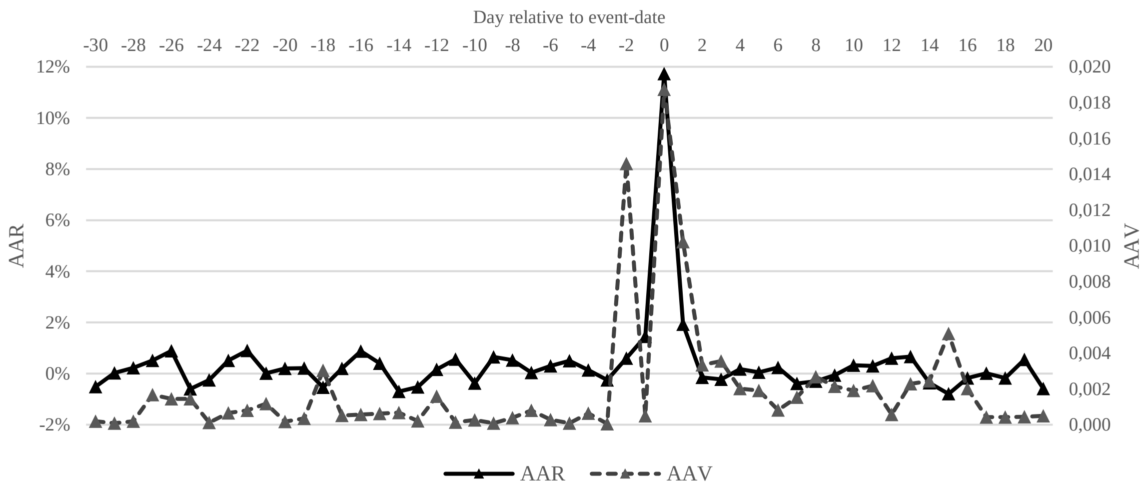


Figure 19: Simple measure AAR and AAV, Norway - adjusted sample

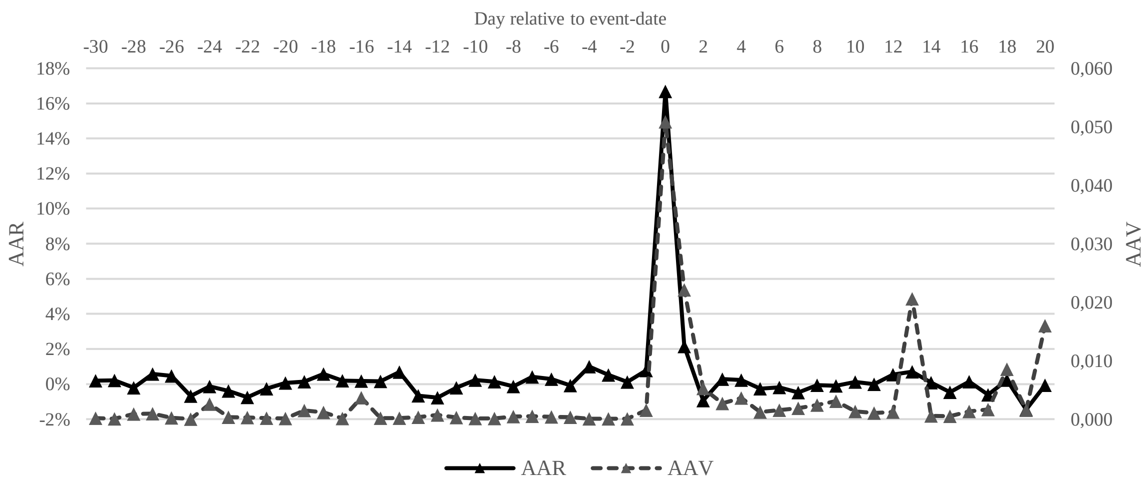
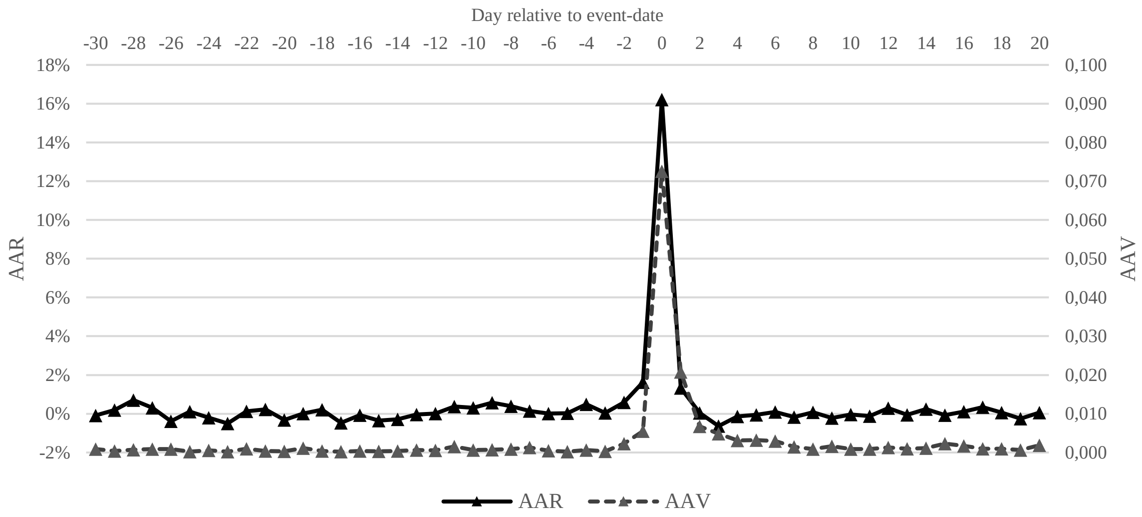


Figure 20: Simple measure AAR and AAV, Sweden - adjusted sample



6.4 SUMMARY OF EVENT STUDY

Denmark experiences close to consistently higher stock price run-up than its neighbouring countries, however, it is also almost consistently less significant. In only one instance – the market measure on the initial sample – it is significant at the 5% level, otherwise at the 10% level or insignificant. We do, on the other hand, keep in mind that Denmark represent the smallest sample, which can affect the significance.

Due to a run of negative AARs within the ten first days of the event window, the longer accumulation lengths yield an insignificant run-up for Norway. The run-up is far more significant and robust when accumulating within the 20 latest days, for which Norway in fact experience the highest run-ups. This *may* indicate that illegal insider trading occurs closer to the event date in Norway than in Denmark, and may also be caused by a small sample size.

Sweden is the only one of the three displaying a run-up significant on at least the 5% level across both samples and measures. The results are robust across different accumulation lengths, where the run-up becomes significant on day -2 at the latest and -9 at the earliest. As it is also the largest sample, this emphasises the influence of the number of observations.

Common for most samples is a consistently positive CAAV from early in the event window, apart from Norway in the initial sample, which returns to insignificance on day -3. We thus see abnormalities for all countries which are quite robust across different samples, measures and accumulation lengths, where Norway and Sweden are similar. Denmark stands out with its low significance, which may be due to the small samples. We thus see pervasive evidence of the information leakage hypothesis for all countries, especially Norway and Sweden.

6.5 MULTIPLE LINEAR REGRESSION

6.5.1 Test of assumptions

To be able to infer on and draw reliable conclusions from the cross-sectional analysis, we test whether the final models for each market in both samples fulfil the assumptions stated in section 5.3.1. The results from the tests are summarised in Table 9 below, while the plots for linearity and normality and table of VIFs can be viewed in appendices 12-24. Note that the tests were conducted after the exclusion of outliers uncovered in 6.5.2.

Table 9: Summary of OLS assumptions tests

	Linearity	Normality			Independent residuals			Homoscedasticity			Multicollinearity
	Evaluation	Test stat	p-value	Evaluation	Test stat	p-value	Evaluation	Test stat	p-value	Evaluation	Evaluation
Initial sample											
Denmark	Yes	4,171	0,12	Yes	1,845	0,58	Yes	10,521	0,01	No	No
Norway	Yes	6,871	0,03	Borderline	2,109	0,69	Yes	3,384	0,18	Yes	No
Sweden	Yes	177,390	< 2,2E-16	No	2,058	0,71	Yes	27,174	1,26E-06	No	No
Adjusted sample											
Denmark	Yes	0,737	0,69	Yes	1,515	0,14	Yes	6,595	0,04	Borderline	No
Norway	Yes	12,442	0,00	No	1,876	0,68	Yes	1,527	0,47	Yes	No
Sweden	Yes	85,815	< 2,2E-16	No	2,242	0,19	Yes	33,562	5,16E-08	No	No

Looking at the plots of standardised residuals we can see an even distribution above and below the horizontal line. Moreover, the residuals are independent, and the models show no signs of multicollinearity, using a critical VIF value of 10 (Bowerman, O'Connell, & Koehler, 2005).

Regarding normality, only the Danish sample fulfils the requirement, while the initial Norwegian more or less fulfils it. Looking at the residual Q-Q plots in appendices 18-23 we see that the residuals form more or less a straight line, except from an upswing in the right tail in some cases. Knowing this, we proceed with the notion that coefficients may be biased and ought to be interpreted with care.

Looking at the test for homoscedasticity, the Norwegian sample is the only one for which we do not reject the null hypothesis. For good measure, we estimate all models with White heteroscedasticity-robust standard errors, as explained in section 5.3.1.

6.5.2 Outliers

As explained in section 5.3.5, we conduct a DFBETAS test on the full model to investigate whether our samples contain outliers that could distort our coefficient estimates, which was our suspicion regarding some illogical coefficients, e.g. *CAV* for Norway being extremely negative. This led to the exclusion of eight observations from the initial sample, of which four were also in the adjusted sample. They all had in common an extremely negative CAR, caused by one or two observations in the run-up, combined with a high CAV. Following this, the initial sample now comprise 254 observations and the adjusted sample 201 observations.

6.5.3 Regression

In section 3 we formulated a number of hypotheses regarding 1) the occurrence of illegal insider trading prior to public takeover offers, and 2) event characteristics affecting the pre-bid stock price run-up. We will in the following revisit our hypotheses and compare them to our empirical results from both the initial and adjusted sample to evaluate whether they hold or not.

All of our final models passed the F test mentioned in section 5.3.4 where we jointly tested whether all the excluded variables were jointly zero in the model containing all variables. The output from the final models can be seen in

Table 10, and all hypotheses are assessed with respect to this. The full model selection can be viewed in appendices 25-30.

Table 10: OLS regression final models

	Dependent variable: CAR (-10, -1)					
	Initial sample			Adjusted sample		
	Denmark	Norway	Sweden	Denmark	Norway	Sweden
Constant	-0.548***	-0.033	-0.015	-0.143	0.198*	-0.082
	(0.201)	(0.124)	(0.107)	(0.250)	(0.102)	(0.135)
CAV	3.253***	3.858***	0.365*	3.190***	3.945***	0.307
	(0.748)	(0.918)	(0.216)	(0.663)	(1.204)	(0.214)
lnMV	0.028**	0.016	0.005	0.010	0.0002	0.011
	(0.012)	(0.011)	(0.009)	(0.016)	(0.005)	(0.011)
lnVol		-0.015*			-0.014**	
		(0.009)			(0.006)	
Foreign	0.042			0.053		
	(0.027)			(0.034)		
Advisors	-0.009***	0.001	0.063**	-0.008***		0.069**
	(0.003)	(0.002)	(0.025)	(0.003)		(0.027)
Crisis	0.044*		-0.058***	0.042	-0.032	-0.073**
	(0.027)		(0.023)	(0.030)	(0.025)	(0.029)
Penny		0.064*				
		(0.037)				
lnM2B	0.009**		-0.002**	0.0003		-0.003**
	(0.004)		(0.001)	(0.010)		(0.002)
D1ICR	-0.015	-0.066**	0.062	-0.097		0.088*
	(0.040)	(0.027)	(0.039)	(0.074)		(0.050)
D2ICR	0.035	-0.056*	-0.014	-0.028		-0.003
	(0.040)	(0.032)	(0.023)	(0.059)		(0.030)
D4ICR	-0.053	0.001	-0.004	-0.083**		0.004
	(0.034)	(0.027)	(0.017)	(0.038)		(0.019)
lnMV*Advisors			-0.004**			-0.004**
			(0.002)			(0.002)
AIC	-75.5	-118	-203.4	-43.9	-115	-148.9
Observations	48	62	144	33	52	116
R^2	0.542	0.456	0.168	0.624	0.401	0.198
Adjusted R^2	0.433	0.374	0.112	0.477	0.350	0.130
Residual Std. Error	0.099 (df = 38)	0.086 (df = 53)	0.115 (df = 134)	0.104 (df = 23)	0.075 (df = 47)	0.121 (df = 106)
F Statistic	4.993*** (df = 9; 38)	5.554*** (df = 8; 53)	3.002*** (df = 9; 134)	4.240*** (df = 9; 23)	7.859*** (df = 4; 47)	2.903*** (df = 9; 106)
Note:						*p<0.1; **p<0.05; ***p<0.01

As can be seen above, the final models contain variables that are insignificant. This is due to our partial use of AIC as model selection criterion and not significance alone, which may have included the variable due to its influence on other variables thus increasing the explanatory power of the model. Seeing as our models all have sufficiently low VIFs, we are not worried about multicollinearity by including the insignificant variables. In the smallest samples, the number of observations may also be the reason for AIC including them while a p-value selection criterion alone would dismiss them. Included or not, this does not change how we interpret the coefficients with respect to our hypotheses.

It is evident that the liquidity screening has had an influence on the Norwegian sample in particular, seeing as the regression equations are not equal cross-sample. Although identical equations, we also see differences in significance for Denmark and Sweden. The constant is no longer as negative and significant for Denmark, whereas it has changed sign and significance for Norway. Naturally, we never assumed all variables to be zero, such that expected CAR (-10, -1) for a Danish takeover target is -54,8%, but the starting point in the adjusted sample is more reassuring. Furthermore, *lnMV* is no longer significant for the Danish model in the adjusted sample, as is the case for *lnM2B*, which experienced a substantial decrease in variance following the screen (table 1).

For Norway, significant variables *Penny* and the *ICR* dummies, of which two were significant, are all excluded from the final model in the adjusted sample. The adjusted sample model for Norway is the most spartan one with only three variables, two of which significant.

As for Denmark, the Swedish model is the same across samples. While *D1ICR* and *CAV* change in significance, *Advisors*, *lnM2B* and *lnMV*Advisors* are robust, which may be due to the larger sample.

Between the countries, only two variables are significant with opposing signs, namely *lnM2B* and *Advisors* for Denmark and Sweden. Looking at the descriptive statistics, the former is likely to be caused by a large difference in variance between the two countries. For *Advisors* on the other hand, the variable is interacted with *lnMV* for Sweden. As can be seen in the model selection process in appendices 25, 26, 28 and 29, the interaction influences the Danish and Norwegian models, however not significantly. This could be due to the smaller samples or data quality, as will be discussed, or there is quite simply no significant interaction.

Once again, before proceeding to the assessment of the hypotheses, we again stress that the number of observations may have an influence on the lack of significant variables.

6.6 ASSESSMENT OF HYPOTHESES

In light of the findings from the event study and regression, we will in the following revisit our hypotheses and assess whether they hold or ought to be rejected.

H.1.1: Illegal insider trading prevails prior to public takeover offers in the Scandinavian stock markets

Denmark

From the event study, we clearly see indications of illegal insider trading in the Danish sample. For both measures in the initial sample CAAR becomes consistently significant at the 10% level on day -26 with drops of significance at the 5% level towards the event date. The market measure yields 30-day pre-event holding period abnormal returns of 5,34%, significant at the 5% level, and the simple measure 4,91%, significant at the 10% level. This is supported by CAAV becoming consistently significant at the 5% level on day -26 and the 1% level on day -23.

The adjusted sample, on the other hand, paints a less bombastic picture. Having adjusted for illiquid stocks, CAAR became far less significant with no pre-event days significant beyond the 10% level. For the market measure CAAR first becomes significant on day -15 and consistently so from day -6, while the simple measure CAAR is significant on days -5, -4, -2 and -1, with 30-day pre-event run-ups of 6,39% and 6,16%, respectively. CAAV becomes consistently significant at the 5% level on day -24 and the 1% level on day -21.

Furthermore, for both samples and measures we observe some days, e.g. -26 and -16, with high and significant AAR. While this may also be driven by market anticipation, scholars reviewed earlier argue that particularly high AAR cannot be driven by uninformed anticipation alone.

Despite the great differences between the initial and adjusted sample, the material significance of the former and the low but present significance in the latter cannot be ignored. Thus, we do not reject the hypothesis of illegal insider trading prior to public takeovers in Denmark.

Norway

The initial Norwegian sample displays no significant CAAR for the market measure and a single day on -26 for the simple measure, much due to some quite negative AARs early in the event window. If we look at shorter windows, all the alternatives shorter than 25 are significant at the 5% level for the market measure, and a mix of 5% and 10% for the simple measure (appendices 2-11). This could be an indication of illegal insider trading occurring closer to the event date in Norway. Looking at AAR there are in particular two days that stand out, namely -4 and -1. On the volume side, CAAV is significant at the 5% level from (-26, -14), which extends to (-27, -4) on the 10% level in the initial sample.

The adjusted sample displays the same pattern for CAAR – no and one significant observation for the market measure and simple measure CAAR (-31, -1), but increased significance for shorter windows. CAAV is consistently significant at the 10% level from day -23 and from -14 at the 5% level.

Thus, we observe irregular pre-bid trading volumes relative to the estimation window and significant stock price run-up closer to the event date, we do not reject the hypothesis of illegal insider trading in Norway.

Sweden

In the initial Swedish sample, we observe occasional significance in the CAAR (-30, -1), before it becomes consistently significant on days -7 and -4 for the market measure and simple measure, respectively. The pre-event run-up is significant at the 1% level for all six lengths of the event window (appendices 2-11). We also observe high and significant pre-event AARs, in particular days -29 and -1. CAAV is consistently significant at the 5% level throughout the event window and becomes significant at the 0,1% level on day -22.

The adjusted sample follows the same pattern, although more downplayed in terms of significance. CAAR (-30, -1) is significant for some days early in the window, returns to significance on days -2 and -1 for the market measure and simple measure, respectively. Shorter event windows are also highly significant, and we yet again observe particularly positive and significant AARs on days -28 and -1.

Considering the above evidence, we do not reject the hypothesis of illegal insider trading prior to public takeover offers in Sweden.

As we observe significant values for the different accumulation periods of CAAR across all markets and measures, supported by significant CAAV, we feel confident in investigating the relationship between CAR and the selected variables.

H.2.1: Illegal insider trading is increasing in abnormal trading volume

Denmark

For both the initial and adjusted sample we observe a consistently positive coefficient for *CAV* with significance on the 1% level, ending up at 3,253 and 3,190, respectively. As expected, and found by King (2009), abnormal volume coincides with abnormal returns, thus we do not reject the hypothesis for Denmark,

Norway

We make the same observations for the Norwegian samples, with consistently significant coefficients, increasing as the model is refined, ending up at 3,858 and 3,945, respectively. With consistency in sign and significance, we do not reject the hypothesis, and believe the higher the CAV (-30, -1) the higher the CAR (-10, -1).

Sweden

For the initial Swedish sample, we end up with a *CAV* coefficient of 0,365, significant at the 10% level, whereas the coefficient of 0,307 for the adjusted sample is not significant. This is far lower than for the neighbouring markets, which can also explain the only partial significance. With significance only at the 10% level we hesitantly do not reject our hypothesis for the initial sample and fully reject it for the adjusted sample, leaving the CAV's influence on CAR in the Swedish market highly doubtful.

H.2.2: Illegal insider trading is less likely the larger the target firm

Denmark

Contradictory to our hypothesis, we find a positive coefficient for *lnMV* in the initial sample of 0,028, significant at the 5% level – and more or less consistently so (appendix 25). This implies that a 1% increase in the average market capitalisation results in a decrease in *CAR* of 0,028. For the adjusted sample we also observe a positive coefficient, which is increasing with the model selection (appendix 28), however insignificant. This may be due to the liquidity screen excluding many small companies, thus making the size variable less impactful.

The positive sign may be exactly due to the media coverage, which can be a driver for uninformed market anticipation and therefore also a stock price run-up. Whatever the reason, we reject the initial hypothesis for the Danish market.

Norway

For the initial Norwegian sample, we obtain a coefficient of 0,016, and a far lower 0,0002 for the adjusted sample. This follows the pattern of the Danish market, and the cause of this may be the same. For Norway, however, the coefficient is insignificant for both samples. With both insignificant and positive coefficients, we reject the hypothesis.

Sweden

The Swedish models differ from the other two in that we obtained a significant interaction term with *Advisors*. This has the implication on interpretation that we do not have a unique effect of target firm size on the stock price run-up, but one that also depends on the unit change in number of advisors. An insignificant main effect and significantly negative interaction term, suggest that the main effect of target firm size is zero, however decreasing for all values of *Advisors* higher than zero by 0,4 percentage points per advisor. Thus, the conclusion on the hypotheses depends on the number of advisors on the deal; it is rejected for zero advisors but not rejected for number of advisors higher than this.

H2.3: The more liquid the stock, the less likely it is that illegal insider trading is statistically observable

Denmark

The variable for general liquidity, *lnVol*, is not included in the final Danish model for neither the initial nor adjusted sample. Throughout the model selection for the initial sample (appendix 27), in which it is included in the final model, the coefficient ranges between 0,008 to 0,004, and a bit higher between 0.013 to 0.014 for the adjusted sample (appendix 30). This is the opposite sign of what we expected but may be caused by a high correlation between liquidity and firm size, which turned out to be significant and positive. On the basis of insignificance and opposite sign of what we expected we reject the hypothesis.

Norway

For the initial sample, we observe a coefficient of -0,015, significant at the 10%. This implies that a 1% increase in average daily trading volume incurs a statistically significant reduction in *CAR* of 0,015. At -0,014, the coefficient is similar for the adjusted sample, however significant at the 5% level. With negative and significant coefficients, we do not reject the hypothesis

Sweden

The variable is not included in the final models for the initial nor adjusted sample. Where it is included in the model selection, it ranges insignificantly between -0,0002 to 0,0001 for the initial sample, and between -0,013 to -0,010 for the adjusted sample. Thus, for the adjusted sample, the coefficient is similar to that of the Norwegian models and in line with our expectations, and it is evident that the liquidity screen influenced the coefficient. However, due to the insignificance we reject the hypothesis.

H.2.4: Takeover offers by foreign acquirers are more prone to illegal insider trading

Denmark

The coefficient of *Foreign* ends up at 0,042 in the initial sample and 0,053 in the adjusted sample, implying that in the event of a foreign acquirer, *CAR* is expected to increase by 4,2 and 5,3 percentage points, respectively. Considering a CAAR (-10, -1) of 2,22% and 4,19% for the two samples, this is quite a remarkable impact. However, the coefficient is only significant in models 3-5 and not in the final model for the initial sample, and never becomes significant in the adjusted sample. Thus, we reject the hypothesis of foreign traders' lower risk of being prosecuted making insider trading more likely.

Norway

The *Foreign* variable is not included in the final model for neither the initial sample nor the adjusted sample. For the models in which it is included, the coefficient ranges between 0,032 to 0,036 and 0,014 to 0,019 for the initial and adjusted sample, respectively (appendices 26 and 29). This as well is a considerable impact, but the variable was omitted due to insignificance, and we are therefore forced to reject the hypothesis.

Sweden

For the Swedish sample as well, *Foreign* is excluded, but ranges from 0,020 to 0,021 and 0,034 to 0,045 for the initial and adjusted sample, respectively, in the models in which it is included. In the adjusted sample, it is significant at the 10% level in the first model but becomes insignificant as the model is refined. We therefore reject the hypothesis for the Swedish sample.

H.2.5: Illegal insider trading is more likely to occur when the target firm is owned by a majority shareholder

Denmark

For both the initial and adjusted sample, *Majority* is excluded from the final model. In the models in which it is included in the model selection, the coefficient ranges between -0,005 to 0,0003 and -0,039 to -0,018 for the two samples, respectively. The sign is contrary to our expectation, but as it never is significant, we reject the hypothesis.

Norway

The variable is excluded from the Norwegian models as well, however with the ranges 0,016 to 0,018 for the initial sample and constant at 0,025 for the adjusted sample in the model selection. This is according to our hypothesis, however, it is insignificant and omitted, thus we reject the hypothesis.

Sweden

The variable is excluded from the Swedish sample as well, with a coefficient of 0,05 in the one model it is included for the initial sample and 0,20 and 0,018 in the two models for the adjusted sample. Again, this is according to our expectations, but the variable is insignificant and therefore the hypothesis is rejected.

H.2.6: The higher the number of deal advisors, the more likely is illegal insider trading

Denmark

For the initial sample, we obtain an *Advisors* coefficient of -0,009 with significance at the 1% level. While we expected the number of advisors to increase the likelihood of illegal insider trading, the coefficient rather suggests that for every additional advisor on the deal, *CAR* decreases by 0,009. This is also the case for the adjusted sample with a coefficient of -0,008, significant at the 1% level. When applying an interaction term *lnMV*Advisors*, the sign for *Advisors* changed with a negative coefficient for the interaction term, which would be more according to our expectations. However, the interaction term made *Advisors* insignificant, was insignificant itself and increased the AIC, and was therefore excluded.

The negative sign may be due to the data quality regarding the number of advisors. Many of our observations were registered with zero advisors, which is quite unlikely. Calculating the correlation between *CAR* and *Advisors* for the Danish samples, returns a negative correlation, which may explain the negative coefficient.

However, with a consistently negative and significant coefficient with no interaction, we are inclined to reject the hypothesis and cannot reject that the number of advisors has a negative effect on *CAR*. We encourage further research on the topic given access to better data.

Norway

For the initial sample, we obtain a coefficient of 0,001, implying that an additional advisor increases the run-up, in line with our hypothesis. When including an interaction term, the coefficient increased to 0,019 and the interaction term at -0,001, which implies that the number of advisors increases *CAR* but is decreasing in combination with increasing deal size. The interaction did, however, turn out insignificant and increased AIC, and was therefore excluded (appendices 26 and 29).

The results are similar for the adjusted sample, where, on the other hand, the variable is omitted in the final model. Where it is included, the coefficient is 0,002 and 0,003 without interaction and 0,11 with firm size interaction.

We thus observe results in line with our hypothesis for both the initial and adjusted sample. However, as the coefficient is insignificant in the former and omitted in the latter, we reject the hypothesis.

Sweden

By including a market value interaction we both obtained significant coefficients and a lower AIC, contrary to Denmark and Norway. In the final model for the initial sample, we observe a coefficient of 0,063 and an *lnMV*Advisors* interaction coefficient of -0,004 – both significant at the 5% level. This implies that a unit increase in the number of advisors, *ceteris paribus*, increase CAAR by 0,063, but the effect is decreasing in target market capitalisation by 0,004 for every 1% increase. This is in line with our hypotheses; the number of advisors increases the network to which information can leak, but market participants with inside knowledge are more reluctant to capitalise on their knowledge for larger deals.

We obtain almost identical results for the adjusted sample, with an *Advisor* coefficient of 0,069 and interaction coefficient of -0,004. As the coefficient is robust across both samples and all models, we do not reject our hypothesis for the Swedish samples.

H.2.7: Illegal insider trading is more likely for cash-only offers

Denmark

The *Cash* variable is omitted from the final model for both samples but ranges between -0,035 to -0,032 for the initial sample and -0,018 to -0,012 for the adjusted sample in the model selection. This implies that cash-only offers experience a substantially lower run-up in the target share, contrary to our hypothesis and the findings of previous scholars. However, as the coefficient is insignificant, the variable's influence on *CAR* is inconclusive, and we reject our hypothesis.

Norway

For the Norwegian samples as well, the variable is omitted in the final model, ranging from -0,026 to -0,015 and -0,036 to -0,030 for the initial and adjusted sample, respectively. As it is insignificant and omitted, we reject the hypothesis.

Sweden

The same applies to the Swedish samples, however with a constant -0,005 and between -0,023 to -0,010 for the initial and adjusted sample. Here as well, the variable is insignificant and omitted, thus we reject the hypothesis.

H.2.8: Illegal insider trading is less present after the financial crisis

Denmark

In the final model for the initial sample, the *Crisis* coefficient is 0,044 and significant at the 10% level. This implies that offers made after the onset of the financial crisis on average have a 4,4 percentage-point higher run-up. This is a material impact and the opposite sign of what we hypothesised. Bris (2005) found that while the number of illegal insider cases decreased following the first enforcement of an insider trading law, however the severity of the felonies increased substantially, as a higher benefit was required for a higher cost in terms of potential punishment. We can draw a parallel from these findings in that regulators increased their focus on financial misconduct following the financial crisis, thus increasing the risk of being caught. A larger order is more likely to trigger abnormal stock behaviour, and thus also increase the run-up. However, this is mere speculation and would require deeper research. Due to a positive and significant coefficient, we are forced to reject our hypothesis and cannot reject the hypothesis that illegal insider trading is *more* present after the financial crisis.

For the adjusted sample we obtain a positive coefficient as well at 0,042, although insignificant. We thus reject our hypothesis for the adjusted sample.

Norway

The *Crisis* variable is excluded from the final model for the initial sample but ranges between -0,012 and -0,007 in the three models in which it is included in the model selection. This is the opposite of the

Danish samples and according to our hypothesis. As the coefficient is insignificant and omitted from the final model, we reject the hypothesis.

For the adjusted sample, the variable is included with a coefficient of -0,032, also here in line with our hypothesis. While it is insignificant in the final model, it is significant at the 10% level for models 3-8 in the model selection, ranging between -0,047 and -0,041. As the coefficient changes sign two times, it may be dependent on one or more other variables to be significant. However, as it is insignificant in our final model, we reject the hypothesis.

Sweden

For the initial sample we obtain a coefficient of -0,058, which is significant at the 1% level, implying that offers made after the onset of the financial crisis on average experience a 5,8 percentage-point lower pre-bid run-up. This is in line with our hypothesis and is reinforced by a similar coefficient of -0,073 for the adjusted sample, with significance at the 5% level. We therefore do not reject the hypothesis for neither sample.

H.2.9: Illegal insider trading is more likely to occur when the target firm trades as a penny stock

Denmark

The *Penny* variable is not included in the final model for neither sample, however, is negative at -0,027 and -0,16 for the initial and adjusted sample in the model selection, respectively, not considering the interaction model. Comprising only 20% and 15% of already small samples of 48 and 33 observations, respectively, this may influence the estimates. Due to the penny stock's speculative nature we find it a particularly interesting hypothesis worth further research with larger samples, but on the basis of our data we reject the hypothesis.

Norway

For the initial sample we obtain a coefficient of 0,064, significant at the 10% level. This implies that penny stocks on average experience a 6,4 percentage-point higher pre-bid run-up, in line with our expectations. We thus do not reject the hypothesis for the initial sample.

The variable is excluded from the final model in the adjusted sample but ranges between 0,028 and 0,042 in the model selection. However, due to insignificance we reject the hypothesis for the adjusted sample.

Sweden

For the Swedish samples the variable is excluded from both models. In the model selection the coefficient is -0,007 and -0,005 for the initial sample, and with opposite signs for the adjusted sample with coefficients ranging from 0,002 to 0,008. Due to insignificance we reject the hypothesis.

H2.10: Illegal insider trading is more likely to occur in takeovers of undervalued companies

Denmark

In the final model of the initial sample we obtain a coefficient for *lnM2B* of 0,009, significant at the 5% level. This implies that an increase in market-to-book ratio of 1% increases *CAR* by 0,9 percentage points, contrary to our expectations. We therefore reject our hypothesis for the initial sample meanwhile we cannot reject the hypothesis of a positive relation between market-to-book ratio and *CAR*.

For the adjusted sample, the coefficient has shifting signs as the model is refined but ends up at a small and insignificant 0,0003. The difference from the initial sample may be due to the screening excluding extreme observations in both ends. Due to insignificance we reject the hypothesis.

Norway

The variable is omitted from both of the final models, however with opposite signs in the model selection. It is constant at 0,004 in the initial sample and ranges between -0,0004 and -0,0002 in the adjusted sample. This may be due to the liquidity screen eliminating an extreme minimum value at -11,9 for the initial sample, contrary to -0,5 for the adjusted sample. As the variable is insignificant in both samples, we reject the hypothesis.

Sweden

For the initial sample, we obtain a coefficient of -0,002 in the final model, significant at the 5% level. This implies that a 1% increase in the market-to-book ratio yields an expected decrease in CAR of 0,2 percentage points, in line with our expectations. Our expectations are confirmed in the adjusted sample as well, with a coefficient of -0,003, also this significant at the 5% level.

H.2.11: Illegal insider trading is more likely to occur when the target firm is financially distressed

Denmark

For the initial sample, we observe a negative coefficient for the dummy indicating a very high degree of financial distress, namely *D1ICR*. This indicates, contrary to our expectations, that a very high degree of financial distress leads to lower *CAR* than is the case of low degree of financial distress, as that is our baseline. For a high degree of financial distress, *D2ICR*, the coefficient of 0,035 indicates a higher *CAR* than for a low degree, in line with our hypothesis. Lastly, for a very low degree of financial distress, *D4ICR*, the coefficient of -0,053 indicates a 5,3-percentage point lower *CAR* than for a low degree of financial distress, also this in line with our expectations. However, due to insignificance of all coefficients, we reject the hypothesis for the initial sample.

For the adjusted sample, we observe a highly negative and a slightly less negative coefficient for *D1ICR* and *D2ICR*, i.e. very high and high degree of financial distress, respectively. This is not according to our expectations, but *D4ICR*, on the other hand, also has negative coefficient of -0,083, significant at the 5% level. The two former coefficients are insignificant, which to some extent makes our hypothesis inconclusive. On one hand we have the insignificant coefficients calling for a rejection, but on the other hand we have the one significant coefficient in line with our hypothesis. We can however avoid rejecting a less bombastic hypothesis, namely that a very low degree of financial distress has a negative relation to *CAR*.

Norway

For the initial sample, we obtain coefficients of -0,066, -0,056 and 0,001 for *D1ICR*, *D2ICR* and *D4ICR*, respectively. According to our hypothesis, we would expect completely opposite signs. Furthermore, the coefficients for both *D1ICR* and *D2ICR* are significant at the 5% and 10% significance level, respectively, indicating that very high and high degrees of financial distress reduce *CAR* by 6,6 and 5,6 percentage points, respectively. Thus, we reject our hypothesis and cannot reject the opposite hypotheses, namely that *CAR* is decreasing as financial distress increases.

For the adjusted sample, the dummies are omitted from the final model. Where they are included in the model selection, *D1ICR* is all negative, *D2ICR* starts off as positive and then switches, and *D4ICR* is consistently negative, i.e. only the latter consistently in line with our hypothesis. As they are all insignificant, we reject the hypothesis for the adjusted sample.

Sweden

For the initial sample, we obtain coefficients of 0,062, -0,014 and 0,004 for *D1ICR, D2ICR* and *D4ICR*, respectively, with the former and latter in line with our hypothesis. However, *D1ICR* is significant only in models 1-4 in the model selection and otherwise they are all insignificant. Therefore, we reject the hypothesis for the initial sample.

For the adjusted sample, we obtain coefficients of 0,088, -0,003 and 0,004 for the three dummies. Only the former is according to our expectations, and coincidentally the only significant of the three at a 10% level. Again, we cannot be bombastic in not rejecting the hypothesis, but we can keep the hypothesis that firms suffering under a very high degree of financial distress on average experience a higher *CAR*.

6.6.1 Summary of hypotheses

Table 11 below provides a quick summary of the hypotheses in light of the regression results, including our preliminary expectations to the hypotheses, the sign of the variable if significant and significance level. For a better overview, only the significant coefficients are denoted.

Table 11: Summary of OLS hypotheses

		Denmark		Norway		Sweden	
Hypothesis	Expectation	Initial	Adjusted	Initial	Adjusted	Initial	Adjusted
H.2.1: CAV	+	+***	+***	+***	+***	+*	
H.2.2: lnMV	-	+**				(-)**	(-)**
H.2.3: lnVol	-			-*	-*		
H.2.4: Foreign	+						
H.2.5: Majority	+						
H.2.6: Advisors	+	-***	-***			+**	+**
H.2.7: Cash	+						
H.2.8: Crisis	-	+*				-***	-**
H.2.9: Penny	+			+*			
H.2.10: lnM2B	-	+*				-**	-**
H.2.11:D1ICR	+			-**			+*
H.2.11: D2ICR	+			-*			
H.2.11: D4ICR	-		-**				

Significance indicator: *p<0,1; **p<0,05; ***p<0,01

As can be seen above, the final models are far more robust for Sweden, most likely due to the larger samples. The brackets around the sign for H.2.2 are due to its dependency on *Advisors* being greater than zero.

6.7 ROBUSTNESS CHECK

Working with two samples and two AR measures parallelly has provided us with a continuous robustness check. The following section seeks to create further robustness and enhance our ability to conclude on the pervasive presence of abnormal stock behaviour prior to takeover announcements, cementing our suspicions that these are not random movements aggregating to abnormality. In the following we will exclusively use the market measure AAR and CAAR.

The robustness check will take the form of a comparative analysis where we apply the same methodology as previously, with the important distinction of substituting the timing of the CAR calculations, as inspired by King (2009). More precisely, we will compare our findings with those of applying the same methodology to an “uneventful” period. To avoid the takeover announcement biasing the results to the extent possible, we select a period as far from the event date as possible on which we have data, namely (-120, -91), where day -90 would equal the “event” day. In our preliminary screening process, we eliminated all takeover offers with noise-creating elements within one year of the event. However, we cannot be certain there have not been any other corporate events in this window, such as new partnerships, R&D stage advancement, etc., with material influence on the stock price.

6.7.1 Event study

The first step in the robustness check is the "event" study to analyse occurrence of AARs and the accumulation hereof. There may be many reasons for abnormal returns on a given day. However, as there is no event on day -90, we expect any significant AARs to be offset by the preceding and following random walk, and thus we expect there to be no significant run-up in CAAR. Table 12 and Table 13 below show the results from the analysis, for the initial and adjusted sample, respectively.

Table 12: Market measure AAR and CAAR (-120, -90), all countries - initial sample

	All countries		Denmark		Norway		Sweden	
Day	AAR	CAAR	AAR	CAAR	AAR	CAAR	AAR	CAAR
-120	0,10%	-0,08%	1,14%	0,20%	0,03%	0,03%	-0,21%	-0,21%
-119	-0,06%	-0,23%	0,65%	0,39%	0,38%	0,40%	-0,49%	-0,69%
-118	0,09%	-0,20%	0,17%	0,23%	0,34%	0,74%	-0,04%	-0,74%
-117	-0,05%	-0,15%	-0,94%*	-0,25%	-0,60%	0,14%	0,49%*	-0,25%
-116	-0,13%	-0,29%	-0,24%	-0,58%	0,23%	0,37%	-0,24%	-0,48%
-115	-0,05%	-0,42%	1,14%	0,18%	-1,12%	-0,73%	0,01%	-0,47%
-114	0,20%	-0,22%	0,15%	0,38%	0,36%	-0,38%	0,14%	-0,33%
-113	-0,17%	-0,37%	-0,31%	0,16%	-0,05%	-0,42%	-0,18%	-0,51%
-112	-0,48%	-0,90%*	0,13%	0,04%	-0,73%	-1,14%	-0,57%	-1,09%
-111	-0,31%	-1,17%**	-0,53%	-0,27%	-0,14%	-1,29%	-0,30%	-1,39%
-110	0,01%	-1,12%**	-0,20%	-0,26%	-0,04%	-1,33%	0,10%	-1,29%
-109	0,27%	-0,81%	0,60%	0,58%	0,26%	-1,07%	0,17%	-1,12%
-108	-0,24%	-1,17%**	-0,19%	-0,34%	-0,81%	-1,88%	0,00%	-1,12%
-107	-0,02%	-1,13%*	0,27%	0,32%	0,07%	-1,81%	-0,16%	-1,29%
-106	0,37%	-0,86%	0,37%	0,16%	-0,10%	-1,91%	0,57%	-0,72%
-105	0,31%	-0,50%	-0,33%	0,04%	0,09%	-1,82%	0,61%	-0,10%
-104	0,18%	-0,32%	-0,96%	-0,98%	0,60%*	-1,22%	0,38%	0,27%
-103	0,29%	0,01%	0,50%	-0,27%	-0,09%	-1,31%	0,38%	0,66%
-102	-0,01%	-0,04%	0,04%	-0,38%	0,10%	-1,21%	-0,08%	0,58%
-101	0,09%	0,07%	0,55%	0,28%	-0,07%	-1,29%	0,01%	0,58%
-100	0,18%	0,21%	0,61%	0,72%	0,56%	-0,73%	-0,12%	0,47%
-99	0,06%	0,27%	1,16%*	1,98%	0,17%	-0,56%	-0,36%	0,11%
-98	-0,48%	-0,24%	-0,60%	1,21%	0,01%	-0,55%	-0,66%	-0,55%
-97	-0,02%	-0,26%	-0,12%	1,06%	-0,18%	-0,72%	0,08%	-0,47%
-96	0,08%	-0,15%	0,89%	2,24%	-0,41%	-1,14%	0,01%	-0,45%
-95	0,19%	0,07%	-0,38%	1,94%	0,02%	-1,12%	0,46%	0,00%
-94	-0,12%	-0,12%	0,26%	1,85%	-0,05%	-1,17%	-0,27%	-0,27%
-93	0,07%	-0,05%	0,48%	2,34%	0,25%	-0,91%	-0,15%	-0,41%
-92	-0,13%	-0,17%	-0,27%	2,13%	-0,26%	-1,18%	-0,03%	-0,45%
-91	-0,01%	-0,14%	-0,50%	1,85%	0,29%	-0,89%	0,02%	-0,42%

Significance indicators: *p<1%; **p<5%; **p<1%; ****p<0,1%

Table 13: Market measure AAR and CAAR (-120, -90), all countries - adjusted sample

	All countries		Denmark		Norway		Sweden	
Day	AAR	CAAR	AAR	CAAR	AAR	CAAR	AAR	CAAR
-120	0,11%	-0,01%	0,84%	0,12%	0,07%	0,07%	-0,06%	-0,06%
-119	-0,17%	-0,26%	0,75%	0,45%	0,37%	0,43%	-0,69%	-0,74%
-118	0,12%	-0,21%	0,12%	0,08%	0,41%	0,83%	-0,04%	-0,78%
-117	-0,06%	-0,25%	-0,31%	-0,07%	-0,57%	0,27%	0,20%	-0,58%
-116	0,02%	-0,21%	-0,35%	-0,36%	0,27%	0,53%	0,00%	-0,58%
-115	-0,26%	-0,49%	0,72%	0,32%	-1,46%	-0,89%	0,01%	-0,57%
-114	0,27%	-0,21%	0,29%	0,69%	0,35%	-0,55%	0,21%	-0,36%
-113	-0,21%	-0,44%	-0,13%	0,45%	-0,26%	-0,80%	-0,19%	-0,55%
-112	-0,65%	-1,07%	-0,93%	-0,41%	-0,78%	-1,57%	-0,52%	-1,07%
-111	-0,26%	-1,34%	0,44%	0,05%	-0,08%	-1,65%	-0,52%	-1,59%
-110	-0,16%	-1,47%	-0,95%	-0,82%	-0,20%	-1,84%	0,10%	-1,50%
-109	0,29%	-1,18%	0,26%	-0,57%	0,23%	-1,61%	0,32%	-1,17%
-108	-0,49%	-1,69%	-0,18%	-0,85%	-1,23%	-2,85%	-0,27%	-1,44%
-107	-0,07%	-1,74%	0,00%	-0,69%	0,13%	-2,72%	-0,17%	-1,61%
-106	0,23%	-1,54%	0,36%	-0,59%	-0,23%	-2,95%	0,41%	-1,20%
-105	0,37%	-1,21%	0,21%	-0,66%	0,46%	-2,49%	0,39%	-0,81%
-104	0,04%	-1,19%	-1,25%	-2,14%	0,70%*	-1,79%	0,09%	-0,72%
-103	0,54%**	-0,63%	1,41%	-0,49%	-0,13%	-1,92%	0,61%**	-0,11%
-102	-0,15%	-0,80%	-0,34%	-0,96%	0,28%	-1,64%	-0,32%	-0,43%
-101	0,13%	-0,67%	-0,11%	-1,10%	-0,18%	-1,82%	0,28%	-0,15%
-100	0,22%	-0,47%	0,51%	-0,69%	0,84%	-0,98%	-0,17%	-0,32%
-99	-0,01%	-0,51%	1,75%*	1,07%	0,14%	-0,84%	-0,67%	-0,99%
-98	-0,14%	-0,62%	-1,11%	0,00%	0,21%	-0,63%	-0,01%	-1,00%
-97	0,04%	-0,59%	0,39%	0,42%	-0,08%	-0,71%	0,00%	-1,00%
-96	-0,14%	-0,73%	-0,09%	0,34%	-0,67%	-1,38%	0,11%	-0,89%
-95	0,32%	-0,37%	0,44%	0,99%	0,03%	-1,35%	0,44%	-0,45%
-94	-0,05%	-0,46%	-0,29%	0,45%	0,31%	-1,04%	-0,13%	-0,58%
-93	0,31%	-0,18%	0,98%	1,33%	0,01%	-1,03%	0,25%	-0,33%
-92	0,07%	-0,11%	-0,22%	1,08%	-0,40%	-1,43%	0,38%	0,04%
-91	-0,29%	-0,34%	-0,61%	0,77%	0,43%	-1,00%	-0,53%	-0,49%

Significance indicators: *p<1%; **p<5%; **p<1%; ****p<0,1%

There are sporadically significant AARs for all countries, as expected. Several factors can cause this, in which we can only speculate, but most importantly, we clearly do not observe a significant run-up moving towards day -90. In addition to insignificance, the "run-up" is far lower than for the actual event window.

This is reinforced when looking at different accumulation lengths of CAAR, as displayed in

Table 14. We observe a single significant observation at the 10% level for CAAR (-105, -90) across all countries in the adjusted sample. As it is a single cross-country incident with minor significance, we regard it as immaterial with respect to robustness of our model.

Table 14: Different accumulation lengths of market measure CAAR (-120, -90)

	All countries		Denmark		Norway		Sweden	
	Initial	Adjusted	Initial	Adjusted	Initial	Adjusted	Initial	Adjusted
CAAR (-120, -90)	-0,26%	-0,34%	1,21%	0,77%	-0,89%	-1,00%	-0,42%	-0,49%
CAAR (-115, -90)	0,04%	-0,13%	1,82%	1,13%	-1,26%	-1,53%	0,06%	0,09%
CAAR (-110, -90)	0,95%	0,99%	1,71%	0,72%	0,40%	0,65%	0,96%	1,11%
CAAR (-105, -90)	0,68%	1,20%*	1,48%	1,36%	1,03%	1,95%	0,29%	0,71%
CAAR (-100, -90)	-0,25%	0,33%	1,37%	1,87%	0,40%	0,82%	-1,01%	-0,34%
CAAR (-95, -90)	0,15%	0,38%	0,42%	0,43%	0,25%	0,38%	0,03%	0,41%

Significance indicators: *p<1%; **p<5%; **p<1%; ****p<0,1%

Our expectations of an insignificant “run-up” are to a great extent met. We therefore conclude that the run-up uncovered prior to takeover announcements is indeed unique for the event and not coincidental, and thus also worth further investigation.

6.7.2 Regression

As a means to validate our regression models, they will in the following be estimated although with the substitution of CAR (-10, -1) and CAV (-30, -1) for CAR (-100, -90) and CAV (-120, -90), respectively. As previously established, CAR (-100, -90) is not significant, i.e. it is statistically zero. Thus, our expectation for the regression is no significant coefficients, as zeros are best explained by zeros. The output of the final models for all countries is displayed in As can be seen, there are significant coefficients in some of the models, such as Denmark and Norway in the initial sample, and Denmark again in the adjusted sample. For no models but the Danish in the initial sample is the hypothesis of all coefficients being jointly zero rejected, indicating that any significant coefficients in these models is immaterial. Regarding the initial sample Danish model, we do see that its adjusted equivalent, which is the exact same model, is insignificant. Furthermore, when regressing CAR (-10, -1) the hypothesis is rejected for both samples at a 99,9% confidence level. Combined with the fact that CAR (-100, -90) is insignificant, we assume that the minor significance observed here is due to noise from illiquid stocks

Table 15, while the full model selection can be viewed in appendices 31-36.

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Table 15: OLS regression on CAR (-100, -90), all countries

	Dependent variable: CAR (-100, -90)					
	Initial sample			Adjusted sample		
	Denmark	Norway	Sweden	Denmark	Norway	Sweden
Constant	0.113	-0.253	-0.079	0.034	-0.129	0.064
	(0.116)	(0.222)	(0.090)	(0.141)	(0.194)	(0.112)
CAV120	-0.214	0.134	-0.061	0.082	0.252	-0.017
	(0.401)	(0.178)	(0.312)	(0.322)	(0.196)	(0.602)
lnMV	-0.002	0.042^{**}	0.003	-0.005	0.013	-0.005
	(0.007)	(0.018)	(0.007)	(0.009)	(0.017)	(0.008)
lnVol		-0.031^{**}			-0.006	
		(0.013)			(0.014)	
Foreign	-0.069^{***}			0.016		
	(0.023)			(0.027)		
Advisors	-0.003	0.001	-0.015	-0.003		-0.012
	(0.002)	(0.004)	(0.026)	(0.002)		(0.030)
Crisis	-0.066^{***}		0.016	0.004	0.010	0.021
	(0.023)		(0.015)	(0.022)	(0.040)	(0.015)
Penny		0.049				
		(0.056)				
lnM2B	-0.001		0.001	0.004		-0.0002
	(0.005)		(0.001)	(0.014)		(0.001)
D1ICR	0.073^{*}	0.099^{**}	0.027	0.090^{**}		-0.001
	(0.038)	(0.039)	(0.036)	(0.035)		(0.027)
D2ICR	0.093^{***}	0.094^{**}	-0.008	0.036		-0.039
	(0.032)	(0.047)	(0.022)	(0.041)		(0.032)
D4ICR	0.033	0.023	-0.007	0.012		0.0002
	(0.024)	(0.044)	(0.017)	(0.025)		(0.014)
lnMV*Advisors			0.001			0.001
			(0.002)			(0.002)
AIC	-94.2	-65.8	-213.4	-74.4	-68.3	-185.5
Observations	48	62	144	33	52	116
R^2	0.333	0.206	0.039	0.343	0.047	0.029
Adjusted R^2	0.175	0.086	-0.025	0.085	-0.034	-0.053
Residual Std. Error	0.081 (df = 38)	0.130 (df = 53)	0.111 (df = 134)	0.067 (df = 23)	0.118 (df = 47)	0.104 (df = 106)
F Statistic	2.104^{*} (df = 9; 38)	1.715 (df = 8; 53)	0.605 (df = 9; 134)	1.332 (df = 9; 23)	0.576 (df = 4; 47)	0.353 (df = 9; 106)
Note:						*p<0,1; **p<0,05; ***p<0,01

Test of significantly different price/volume dynamics

Following the approach of King (2009), we test whether there is a difference in the price/volume relation between the two timings of CAR. More precisely, we conduct an F-test with the hypothesis that the *CAV* coefficient is equal in the regression on CAR (-10, -1) as for the one on CAR (-100, -91). A stronger relationship between CAR and CAV in the event window is consistent with the presence of illegal insider trading (King, 2009). As the coefficient in our event window model is significant, and significant for all but the Swedish model for the adjusted sample, we expect the hypothesis to be rejected, with the exception of the latter.

Table 16: CAV coefficient difference test, all countries

	Denmark		Norway		Sweden	
	Initial	Adjusted	Initial	Adjusted	Initial	Adjusted
F-statistic	18,827***	21,308***	16,888***	10,00**	2,204	0,732

Significance indicators: *p<1%; **p<5%; **p<1%; ****p<0,1%

Table 16As can be seen in Table 16 above, the hypothesis is indeed rejected, however, surprisingly it is not rejected for the model for neither the initial nor adjusted Swedish sample. Looking back at our regression output, the *CAV* coefficient was only significant at the 10% level and far lower than for the Danish and Norwegian models, which explains why the coefficients are not significantly different.

As we have found there to be no significant run-up for any accumulation of AARs in the window (-120, -90) and applying the same regression models did not yield any significant explanatory power of CAR (-100, -90), we have solidified our suspicions of abnormal stock behaviour prior to takeover announcements. A further indication of this being caused by insider trading is the significant difference in price/volume dynamics in the event window compared to a seemingly uneventful period. We thus consider our methodology to be robust in uncovering the pre-bid run-up and explaining its occurrence.

7 DISCUSSION

7.1 PRELIMINARY CONCLUSIONS

Based on the above analysis, there is empirical evidence to conclude that CAAR is positive and significant in the event window from (-30,-1) for both the initial and the adjusted sample in all three markets. This is in accordance with findings from other researchers, such as (Jarrell & Poulsen, 1989), Meulbroek (1992), Bris (2005) and King (2009). Although significant, abnormal returns alone hardly serve as sufficient proof of insider trading. However, our empirical analysis also disclose a significantly positive CAAV in the event window. Therefore, we find it reasonable to expect illegal insider trading to occur prior to takeovers in the Scandinavian stock market as we observe both significant CAAV and CAAR. Yet, it is important to note that not all observations of abnormal volume serve as proof of illegal insider trade. As King (2009) postulates, uninformed traders may be induced to trade by the increased order flow when insiders are active. As a consequence, more uninformed traders will follow. Therefore, we humbly acknowledge that CAAV and CAAR do not necessarily coincide with insider trading. Nevertheless, the robustness check suggests that the run-up in CAAR and CAAV is unique for the final days preceding the announcement and is not coincidental. Thus, we find it reasonable to use abnormal returns and volume as proxies for illegal insider trading.

7.1.1 The two measures of abnormal return as a robustness check

As a means to further explain our results from the analysis, we find it relevant to compare our two measures of abnormal return; the market measure and simple measure. Assessing similarities and differences between two measures that test the same hypothesis, will strengthen our final conclusion. Recalling section 5.2.2, the market measure estimates abnormal return as the actual daily return minus the expected return expressed as CAPM. In the simple measure, the expected return is merely the average daily return of the estimation period, which is subsequently subtracted from the daily return in the estimation window (-120, -31).

When comparing the market measure with the simple measure in both the initial and adjusted sample we see a very similar pattern. In many instances, significant observations are seen on the same day, often at the same significance level. However, in the initial sample, the simple measure includes less significant observations than the market measure. Even though the difference is moderate, it can be seen in all three markets. The difference might be explained by CAPM's effect on the market measure. More specifically, the market measure is sensitive to externalities such as macroeconomic announcements throughout the period (-120;-31). Moreover, firm specific news will not affect the abnormal return as it is highly unlikely that such news will move the market index. This contrasts with the simple measure, where the abnormal return is only affected by movements in the firm's own stock price which may be due to both systemic and idiosyncratic risk.

Due to the limitations of the thesis, it is not possible for us to analyse if there is reason to believe that any of the two methods for estimating abnormal return will yield the most correct abnormal returns over time. However, we believe that the many similarities in abnormal return between market measure and simple measure serve as a solid proof of abnormal return in the pre-event window.

7.1.2 The initial sample versus the adjusted sample

Throughout the thesis, we have worked with the initial and adjusted sample parallelly. While this has worked as a continuous robustness check, we have also in some cases obtained different results for the two. The rationale behind the liquidity screening leading to the adjusted sample was illiquid target firm stocks having the potential to distort the abnormal returns and volume calculations.

For our simple measure, a large number of zero-return days would incur a small mean return in the estimation period, to be subtracted from the actual daily returns in the event window to arrive at abnormal returns. Following the screening, the sample mean return increases from -0,026% to -0,017%, which at first glance does not seem like much, but represents an increase of over 36%.

As for the market measure, illiquidity would for the most part be reflected in the beta. As it measures the stock's response to market movements, the beta would be biased towards zero due to the number of zero-return days when the market otherwise fluctuates. As for the simple measure, this would understate the expected returns while the actual returns might be far higher if the stock is more frequently traded pre-event, leading to inflated abnormal returns. Between the two samples, the average beta is almost 12% higher for the adjusted sample, supporting the above argument.

Thus, one would expect the AARs of the initial sample to be higher, however, this is not the case. Of the pre-event days in the initial sample, only 37% have a higher AAR than the adjusted sample for Denmark, while the equivalent for Norway and Sweden is 43% and 47%.

While this immediately is counterintuitive, a closer look at AAV for the pre-event days reveals that only 29% of the days in the initial sample have a higher AAV than the adjusted sample for Denmark, while for Norway and Sweden the shares are more even at 45% and 48%, respectively. Recall that the ARs of these stocks would be inflated *if* they were more frequently traded in the event window than the estimation window, i.e. we can clearly see that they are most likely not. This is consistent with the strategic trading model (section 2.6), suggesting that illegal insider traders prefer trading in liquid stocks to blend in with the ordinary trades and not trigger an abnormal stock response.

With respect to the above, we regard the adjusted sample to be more representative and superior to the initial sample for investigating illegal insider trading. Thus, going forth we will exclusively focus on the adjusted sample.

7.1.3 Hypotheses regarding the results from the adjusted sample

H.1.1: Illegal insider trading prevails prior to public takeover offers in the Scandinavian stock markets

We observe sporadic significant and positive AARs in the event window for all markets, which accumulates to a significant run-up. This is robust across the market and simple measure as well as for different accumulation lengths within the event window, varying from 5-30 days. Sweden experience the most significant run-up on at least the 5% significance level across all lengths and measures. Denmark is consistently significant at the 10% level for the market measure, whereas Norway is consistently significant from 20 days, indicating that abnormalities occur closer to the event date in Norway.

The same observations apply to trading volume. For Sweden, however, significant AAV is the norm in the event window, leading to a volume run-up significant at the 0,1% level, contrary to 1% and 5% for Denmark and Norway, respectively. We thus observe that abnormal stock behaviour is more pervasive in Sweden than in the neighbouring countries.

Our findings are validated when investigating a presumably more representative period when applying the same model to the window (-120, -90). We observe no significance in market measure CAAR for any of the equivalent accumulation lengths, indicating that the run-up revealed in the event window is indeed related to the impending takeover announcement. Following the approach of King (2009), we estimated the same regression model and tested for a difference in the volume coefficient, and found a significantly stronger relationship in the event window for Denmark and Norway. We could not reject no difference in the coefficient for Sweden, as the coefficient was not significant in the first place.

We thus have found pervasive evidence of abnormal stock behaviour prior to public takeover announcements in Scandinavia, and indications of illegal insider trading. To what extent these abnormalities are fully attributable to illegal insider trading will be discussed in section 7.3, but as the findings are consistent with the information leakage hypothesis, we do not reject the hypothesis of the occurrence of illegal insider trading.

H.2.1: Illegal insider trading is increasing in abnormal trading volume

The rationale behind this hypothesis is two-fold; firstly, increased liquidity incentivises insiders to trade as they can more easily hide their trades in the high order flow. Secondly, illegal insider trading may cause abnormal volume inducing uninformed market participants to trade based on the order flow.

For Denmark and Norway, we observe highly positive and significant coefficients. Conversely and surprisingly, for Sweden we obtain an insignificant coefficient, despite Sweden consistently displaying the most significant CAAR and CAAV. This may, on the other hand, be exactly the reason. If both the dependent and an independent variable are high with little variance, the independent variable has little explanatory power.

Our findings are according to our expectations and in line with Admati and Pfleiderer (1988) and King (2009), with respect to Denmark and Norway. We thus conclude that for these markets, abnormal trading volume may be caused by illegal insider trading and a tool to hide it.

H.2.2: Illegal insider trading is less likely the larger the target firm

Our initial suspicion was that illegal insider traders prefer to avoid attention, and thus also avoid larger takeovers, as these gain exactly this from media and regulators. For all markets we obtain an insignificant coefficient, leading us to reject the initial hypothesis. For Sweden, however, we obtain a significant interaction term between *lnMV* and *Advisors*. This implies that there is no overall effect of *lnMV,* but in combination with more than zero advisors, there is a significant reduction, and thus to some extent in line with the findings of King (2009).

Thus, not to say that Swedish regulators should ignore the larger deals, attention should be directed towards small-medium sized transactions. Conversely, in Denmark and Norway, with no relation between target firm size and run-up, regulators should not discriminate on the deal size in their attention.

H2.3: The more liquid the stock, the less likely it is that illegal insider trading is statistically observable

We previously argued that illegal insider trading is more likely to occur in liquid stocks. However, the positive relation revealed in that case was due to the combination of observable abnormal volume. Here, on the other hand, we hypothesise that the volume generated by illegal insider trading has a smaller imprint on the stock price of generally liquid stocks, as the trades blend in with the uninformed trading pattern. The variable is excluded from the final models of Denmark and Sweden, but we obtain a negative and significant coefficient for the Norwegian model. However, we cannot be sure whether it is due to illegal insider trading being less observable or in fact not as pervasive in liquid stocks. However, logic and previous literature (McInish, Frino, & Sensenbrenner, 2011) point towards the former, and takeovers of Norwegian companies with liquid stocks should not necessarily be written off due to lower run-up.

H.2.4: Takeover offers by foreign acquirers are more prone to illegal insider trading

The rationale behind this hypothesis is that an increasing proportion of public takeovers today are cross-border transactions and FSA data exchange is troublesome, supported by an increased likelihood of initiation of formal investigation for such transactions. In sum, the incentives to commit illegal insider trading are greater for foreign market participants.. However, contrary to Bromberg, Ramsay and Gilligan (2017), *Foreign* is only included in the final model for Denmark, in which it is positive, yet insignificant. While we thus cannot infer any influence of foreign acquirers, we have difficulties seeing why the Scandinavian markets should be an exception to the norm, as found by previous and recent scholars. The location of the target firm should be irrelevant, as it is more a matter of the origination of the acquirer. There may be some bilateral FSA data exchange agreements in place, thus reducing the incentives of a foreign trader with inside information. However, this is mere speculation and would require deeper research.

H.2.5: Illegal insider trading is more likely to occur when the target firm is owned by a majority shareholder

We reasoned this hypothesis with a majority shareholder being more likely to know about a takeover before the announcement, as there may well be a lag between the time of first buy-side and sell-side contact and the first public rumour. The hypothesis builds on Ahern's (2017) network findings, where including one or more links increases the network exponentially. The variable is, however, excluded from the final model for all countries. Consequently, we cannot state whether regulators should keep particular attention to the network surrounding an eventual majority owner. We do, however, recommend a higher degree of granulation in the variable. We worked with a single dummy equalling one if a shareholder owns more than 50%, but investors with smaller holdings than these may well be close to takeover news, e.g. two investors holding 25% theoretically increase the network more than one owning 50% while being equally involved in operations. One could measure the ownership concentration by calculating the Herfindahl-Hirschman Index, commonly used for measuring the market share concentration (Cabral, 2017). This would, however, require data on the stake of all investors, which we consider to be too time consuming.

H.2.6: The higher the number of deal advisors, the more likely is illegal insider trading

As briefly explained in the previous hypothesis, we expect there to be a positive relationship between illegal insider trading and the network surrounding the respective takeover. In the final models we observe conflicting coefficients across the markets; Denmark has a significantly negative, in the Norwegian the variable is excluded, and in Sweden it is positive and significant, although significantly interacted with target firm size. The latter, with a significantly negative interaction term, implies that the main effect of the number of advisors is an increase in run-up, however decreasing in target firm size. These findings are in line with those of Brigida and Madura (2012).

For Denmark and Norway, on the other hand, we are forced to reject the hypothesis, and for the former we cannot reject that the number of advisors has the opposite effect. We do, however, wish to avoid such a bombastic conclusion, as we suspect the data quality of this variable to be suboptimal, combined with small samples. *Advisors* is the number of advisory *firms* as a proxy for number of professionals, as we could not find detailed information on the number of professionals. Thus, on a takeover with two advisory firms, there may be far more individuals involved than for a takeover with four advisory firms, thus also a larger network. Furthermore, several of the transactions in our sample are reported with zero advisors, where we cannot be certain whether these are true zeros or unavailable information to Zephyr as well. Thus, we regard more research necessary to make more robust inferences on the Scandinavian markets.

H.2.7: Illegal insider trading is more likely for cash-only offers

History has seen the announcement effect of cash-only deals being larger than those involving an exchange of stock, as control in the acquiring entity calls for a lower price paid by the acquirer. As a full or partial stock-swap may not lead to as high a valuation of the target firm, the upside for a potential insider trader is lower and thus the incentive to act on it as well. The *Cash* variable is excluded from all final models due to insignificance, as opposed to previous scholars who find significantly higher CAR for cash-only financed takeovers (Wansley, Lane & Yang, 1983; Masulis, Wang & Xie, 2007). Thus, we believe there is little reason to direct neither more nor less attention to cash-only deals in Scandinavia.

H.2.8: Illegal insider trading is less present after the financial crisis

A direct cause or not, the immediate response by banks and supervisors following the financial crisis has led to a decrease in convictions for financial misconduct, justifying this hypothesis. The coefficients are, however, conflicting across the three markets; in Denmark it is consistently positive and significant, and in Norway consistently negative with significance at the 10% level for a handful of the models, although not the final. Lastly, in Sweden, the coefficient is consistently negative and significant at the 5% level, obstructing a unison conclusion. For Denmark and Norway, we do not observe any difference between prior to and after the onset of the financial crisis, while the difference is distinctively more present in Sweden. One should, however, note the findings of Bris (2005), revealing that along with stricter regulation, the number of insider trading cases has decreased, but the severity of each case has increased. As the problem is still pervasive, there is naturally still a need for strict law enforcement.

H.2.9: Illegal insider trading is more likely to occur when the target firm trades as a penny stock

The rationale behind the hypothesis is that penny stocks are highly volatile and react sharply to news, making them speculative in nature, and thus also a suited stock for illegal inside traders wanting to hide their trades among ordinary volatility. As opposed to King (2009) we do not find the variable to be significant, as it is excluded from all final models. Thus, there is little reason to believe penny stocks are more prone to illegal insider trading than stocks with higher capitalisation.

H2.10: Illegal insider trading is more likely to occur in takeovers of undervalued companies

As undervalued companies are more likely takeover objects, we hypothesised that the stock price run-up is higher for such companies. The variable is insignificant and excluded from the final Danish and Norwegian models, respectively. For Sweden, on the other hand, we observe a significantly negative coefficient, contrary to our hypothesis and the findings of Borges and Gairifo (2013). While there is no difference in the Danish and Norwegian markets, relatively overvalued companies seem to be more prone to illegal inside trading in Sweden.

H.2.11: Illegal insider trading is more likely to occur when the target firm is financially distressed

Due to higher stress and lower morale from the financial situation, we hypothesise that individuals who experience financial distress at their work place are more prone to commit financial misconduct. For the Norwegian sample, the set of dummies is excluded from the final sample, while one dummy is significant for Denmark and Sweden. While they are on the opposite side of the "distressed scale", they paint the same picture; in Denmark the coefficient for very low degree of financial distress is significantly negative, while the coefficient for very high degree of distress is significantly positive in Sweden. We thus consider illegal insider trading to be more likely in financially distressed target firms, which can serve as a red flag for regulators.

7.2 METHODOLOGY APPLICATION TO PROVEN INSIDER TRADING CASES

In section 3.1 and 3.2 we hypothesise that abnormal return and abnormal volume serve as robust indicators of illegal insider trading. Several theories question this. Among them, we find the market anticipation hypothesis, stating that run-ups prior to acquisitions are caused by professional investors who do qualified investments based on analyses that do not violate the Securities Trading Act. Therefore, we want to test whether AR and AV *actually* serve as solid proof of insider trading. As a means to test this, we conduct an event study on a new sample of cases where insider trading has been proved and one or several individuals were convicted and legally sentenced. The results from this event study will be held up against our adjusted sample. However, it does not make sense to break the proven cases into country groups, as the samples would be far too small, e.g. only three observations for Denmark.

7.2.1 Data collection and screening

We retrieve a list of all cases where people have been sentenced for insider trading according to the Securities Trading Act from January 1999 to December 2018. For Sweden and Denmark we have used data from Karnov's law collection while for Norway we have used Lovdata – a database with public access to all Norwegian laws and court rulings. As a means to filter out only those cases of insider trading where people have traded prior to acquisitions, we have used two different methods. In the first screen we search the databases for convictions for breach of the Securities Trading Act. To find any cases that were not included in the first screen we conduct a second screen, where we search for newspaper articles on insider trading cases prior to public acquisitions in Scandinavia. Based on this, we end up with a total of 15 takeover offers where people have been convicted and sentenced for insider trading prior to public takeovers.

Next, we retrieve daily data on adjusted stock prices and trading volumes from Datastream by Thomson Reuters. Two of the cases did not provide us with sufficient data to calculate AR and AV. Therefore, our final sample of proven cases includes 13 takeovers, three of which included in the adjusted sample.

7.2.2 Market measure of abnormal returns – proven cases

For the market measure we observe that AAR turns significant and positive at the 5% significance level with 0,95% on day -21. Moreover, we see a positive significance on day -15, -10, -4, -2 with a significance level of 5% and 10%. As for the event date, the announcement is highly significant with an AAR of 29,55% at the 0,1% significance level.

When comparing AAR for proven cases with the adjusted sample, we see that the total number of significant days is very close. In the sample with proven cases, we observe a total of five days with significant AAR, while the adjusted sample has six days with significant AAR. In both cases, we observe an arbitrary pattern where significant days seem to occur rather randomly.

Moving to CAAR, we observe a clear pre-event run-up with a total of five significant observations concentrated in a cluster from day -5 to -1. Days -5, -4, -3 are significant at the 10 % significance level, while day -2, -1 are significant at a level of 5% and 1%. In comparison, the total number of significant observations in the adjusted sample is ten. Again, we see a build-up prior to the event day.

Even though the adjusted sample includes a larger number of significant AARs than the sample based on proven cases, we can still observe a clear pattern in proven cases that can strengthen the theory and our approach to creating evidence. Firstly, we notice a distinct increase in CAAR throughout the pre-event run-up period. From day -14 to -1, we observe an almost perfect daily increase in CAAR from 1,77 % to 8,25 %. Moreover, we see an even stronger run-up in the last five trading days with a significance level of 10%, 5% and 1%. The higher run-up than for the adjusted sample serves as a clear indication that information about a takeover has leaked to the market before the takeover announcement. Naturally, we do not assume illegal insider trading to occur prior to all public takeovers, such that the lower run-up for the adjusted sample is expected. However, the mere existence of a significant run-up is an indication of it occurring.

Table 17: Market measure AAR and CAAR - proven cases and adjusted sample

	Proven cases		Adjusted sample	
Days	AAR	CAAR	AAR	CAAR
-30	0,72%	0,72%	-0,15%	-0,15%
-29	0,48%	1,20%	0,22%	0,07%
-28	-1,24%	-0,04%	0,33%*	0,41%*
-27	0,32%	0,28%	0,26%	0,67%**
-26	-0,54%	-0,25%	-0,08%	0,59%**
-25	0,41%	0,16%	-0,06%	0,53%
-24	-0,53%	-0,37%	-0,02%	0,51%
-23	0,84%	0,46%	-0,32%	0,19%
-22	-0,28%	0,18%	0,04%	0,23%
-21	0,95%**	1,13%	0,09%	0,32%
-20	-0,73%	0,41%	-0,07%	0,25%
-19	0,33%	0,74%	0,04%	0,30%
-18	-0,44%	0,30%	0,22%	0,52%
-17	-0,22%	0,08%	-0,14%	0,38%
-16	0,30%	0,38%	0,02%	0,41%
-15	1,76%**	2,14%	-0,05%	0,35%
-14	-0,36%	1,77%	-0,10%	0,25%
-13	-0,27%	1,51%	-0,24%	0,01%
-12	-0,15%	1,36%	-0,06%	-0,05%
-11	0,14%	1,50%	0,29%*	0,24%
-10	0,67%*	2,17%	0,24%	0,48%
-9	0,47%	2,64%	0,51%**	0,99%
-8	-0,13%	2,52%	0,29%	1,28%
-7	1,02%	3,54%	0,27%	1,55%*
-6	-0,01%	3,52%	0,13%	1,68%*
-5	0,17%	3,69%*	0,05%	1,73%*
-4	0,62%*	4,31%*	0,38%*	2,11%**
-3	0,36%	4,67%*	0,14%	2,25%**
-2	1,51%*	6,17%**	0,48%**	2,74%**
-1	2,08%	8,25%***	1,26%****	3,99%***
0	29,55%****	37,80%****	15,57%****	19,56%****
1	0,19%	37,99%****	1,68%****	21,24%****
2	-0,78%	37,21%****	-0,30%	20,93%****
3	0,01%	37,21%****	-0,33%	20,60%****
4	0,49%**	37,71%****	-0,02%	20,58%****
5	0,31%*	38,02%****	-0,08%	20,50%****
6	0,33%	38,36%****	0,11%	20,61%****
7	-0,02%	38,33%****	-0,33%	20,28%****
8	-0,12%	38,21%****	0,03%	20,31%****
9	-0,03%	38,18%****	-0,09%	20,22%****
10	-0,06%	38,12%****	0,07%	20,29%****
11	-0,14%	37,98%****	-0,04%	20,25%****
12	-0,29%	37,68%****	0,27%*	20,52%****
13	0,31%*	37,99%****	0,22%	20,74%****
14	1,21%**	39,19%****	0,14%	20,88%****
15	-0,21%	38,98%****	-0,16%	20,73%****
16	-0,64%	38,34%****	0,04%	20,76%****
17	-0,53%	37,81%****	0,02%	20,78%****
18	0,31%**	38,12%****	0,01%	20,79%****
19	0,39%	38,51%****	-0,40%	20,39%****
20	-0,10%	38,42%****	-0,09%	20,30%****
n	201		13	

Significance indicator: *p<10%; **p<5%; ***p<1%; ****p<0,01%

7.2.3 Simple measure of abnormal returns – proven cases

As for the simple measure, we recognize a pattern that is very much the same as we observed in the market measure. The first positive significant AAR observation is again at day -21. Days -15 and -2 are significant at the same significance level as in the market measure. The only difference is that day -10 is no longer significant, and day -4 has increased in significance level from 10% to 5%.

In comparing proven cases of insider trading with the adjusted sample we see that the pattern is very much the same as we saw for the market measure. Both samples are characterised by a pattern where AAR seems to occur rather randomly.

Finally, we move to CAAR and compare market measure for proven cases of insider trading with the corresponding simple measure. The first significant observation is now on day -4, one day later than for the market measure. Day -1 is still significant, but only at the 5% significance level compared to 10% in the market measure.

As we saw in the market measure, the adjusted sample includes a larger number of significant CAARs than the sample with proven cases. Proven cases have a total of four days with significant CAAR where the first significant observation is day -4. In comparison, the total number of significant days in the adjusted sample is seven. Moreover, we see a cluster of significant observations early in the event window. Even though there are some differences in trading pattern between proven cases and adjusted sample, we still observe similarities that strengthen our evidence of insider trading prior to acquisitions. Most importantly, we see a run-up in CAAR prior to the public announcement in both samples. Even though not always significant, there is an almost perfect daily increase in CAAR from 1,54% on day -15 to 8,17% on day -1. Thus, it is natural to assume that someone else in the market knew about the pending takeover and acted on it prior to the public announcement.

Table 18: Simple measure AAR and CAAR - proven and adjusted sample

	Proven cases		Adjusted sample	
Days	AAR	CAAR	AAR	CAAR
-30	1,00%	1,00%	-0,08%	-0,08%
-29	0,58%	1,59%	0,17%	0,09%
-28	-1,35%	0,24%	0,38%**	0,47%*
-27	0,12%	0,36%	0,41%*	0,88%**
-26	-0,71%	-0,35%	0,06%	0,94%**
-25	0,36%	0,01%	-0,22%	0,72%
-24	-0,59%	-0,58%	-0,19%	0,53%
-23	0,79%	0,21%	-0,31%	0,22%
-22	-0,40%	-0,19%	0,01%	0,23%
-21	0,78%*	0,58%	0,06%	0,29%
-20	-0,88%	-0,29%	-0,12%	0,17%
-19	0,41%	0,11%	0,08%	0,25%
-18	-0,22%	-0,11%	0,19%	0,43%
-17	-0,32%	-0,43%	-0,18%	0,26%
-16	0,31%	-0,12%	0,16%	0,41%
-15	1,66%**	1,54%	-0,09%	0,33%
-14	-0,53%	1,01%	-0,09%	0,24%
-13	-0,61%	0,39%	-0,29%	-0,06%
-12	0,18%	0,58%	-0,18%	-0,23%
-11	-0,17%	0,41%	0,24%	0,01%
-10	0,54%	0,95%	0,18%	0,19%
-9	0,54%	1,49%	0,47%*	0,66%
-8	-0,09%	1,40%	0,27%	0,92%
-7	1,06%	2,45%	0,20%	1,13%
-6	0,34%	2,79%	0,14%	1,26%
-5	-0,15%	2,64%	0,07%	1,34%
-4	0,72%**	3,36%*	0,57%***	1,91%*
-3	0,73%	4,09%*	0,13%	2,04%**
-2	1,79%*	5,88%**	0,46%*	2,50%**
-1	2,29%	8,17%**	1,36%****	3,86%***
0	29,59%****	37,76%****	15,60%****	19,47%****
1	0,48%	38,24%****	1,66%****	21,13%****
2	-0,75%	37,49%****	-0,25%	20,87%****
3	-0,13%	37,35%****	-0,32%	20,55%****
4	0,14%	37,50%****	0,02%	20,57%****
5	0,40%*	37,89%****	-0,10%	20,47%****
6	0,27%	38,17%****	0,04%	20,51%****
7	0,11%	38,28%****	-0,29%	20,22%****
8	0,06%	38,34%****	-0,02%	20,20%****
9	0,01%	38,35%****	-0,16%	20,04%****
10	-0,02%	38,33%****	0,06%	20,10%****
11	-0,04%	38,29%****	-0,03%	20,08%****
12	-0,14%	38,15%****	0,41%**	20,48%****
13	0,16%	38,31%****	0,27%*	20,75%****
14	1,13%*	39,44%****	0,10%	20,85%****
15	-0,16%	39,28%****	-0,30%	20,55%****
16	-0,44%	38,84%****	0,07%	20,62%****
17	-0,42%	38,42%****	0,03%	20,65%****
18	0,21%	38,64%****	0,06%	20,71%****
19	0,31%	38,95%****	-0,45%	20,26%****
20	-0,01%	38,94%****	-0,08%	20,18%****
n	201		13	

Significance indicator: *p<10%; **p<5%; ***p<1%; ****p<0,01%

7.2.4 Abnormal volume – proven cases

As a second indicator for illegal insider trading we examine if we can observe abnormal volume in the pre-event period. Out of the 30 days in the run-up period, we observe six days with significant AAV. It is difficult to detect any pattern in abnormal volume as significant days seem to occur rather randomly. However, in the last three days before the event date we observe significant AAVs at a 10% significance level. Furthermore, AAV in the post-event window is remarkably significant despite few significant AARs for the same period.

When comparing AAV for proven cases with the adjusted sample, we see that the total number of significant observations is substantially higher for the adjusted sample. In the adjusted sample there is a total of 28 days with significant AAV, while proven cases only contain six days with significant AAV. This may contradict with logic as one would expect more days with abnormal volume in takeover announcements where illegal insider trading has been proven. However, as proven cases only involve 13 takeover announcements, it will naturally include many days where none of the 13 cases show abnormal volume. As a consequence, AAV will have a value of zero. This is the case for a total of nine observations in the sample with proven cases compared to none in the adjusted sample. For this reason, it may be deceptive to compare AAV for proven cases with the adjusted sample. Such a low number of observations also makes significance less likely. Nevertheless, studying AAV over the event window, we see that from day -8 and forth, there is a total of five days with abnormal trading volume. Though only significant at the 5% and 10% levels, it serves as an indication that information about a pending takeover has leaked.

Moving to CAAV, we observe 17 days with abnormal volume at a significance level of 10% and 5%. This is considerably less than what we observe for the adjusted sample, but as explained above, it may be misleading to hold CAAV for proven cases up against the adjusted sample. However, we can still observe a pattern in CAAV for proven cases that may serve as proof of insider trading. First and foremost, it is noteworthy to observe the pattern at which significant days occur. From day -6 and forth there is a run-up with significance at a level of 10% and 5%. Furthermore, we see the same pattern from day -24 to -14. There may be several reasons why significant observations are concentrated in clusters, but King (2009) postulates that uniformed traders are induced to trade by the increased order flow when insiders are active. Consequently, more uniformed traders will follow and there will be a snowball effect.

Table 19: AAV and CAAV - proven cases and adjusted sample

	Proven cases		Adjusted sample	
Days	AAV	CAAV	AAV	CAAV
-30	0,0000	0,0000	0,0006**	0,0006**
-29	0,0000	0,0000	0,0003	0,0008**
-28	0,0000	0,0000	0,0007**	0,0015***
-27	0,0000	0,0000	0,0010***	0,0025****
-26	0,0002	0,0002	0,0008*	0,0033***
-25	0,0001	0,0003	0,0004**	0,0037****
-24	0,0016*	0,0018*	0,0010*	0,0047****
-23	0,0000	0,0018*	0,0003**	0,0051****
-22	0,0002	0,0020**	0,0008***	0,0058****
-21	0,0014	0,0034**	0,0005***	0,0063****
-20	0,0000	0,0034**	0,0002****	0,0065****
-19	0,0000	0,0034**	0,0011***	0,0076****
-18	0,0000	0,0034**	0,0010**	0,0087****
-17	0,0002	0,0035**	0,0002****	0,0089****
-16	0,0002	0,0038**	0,0013	0,0102****
-15	0,0001	0,0039**	0,0003***	0,0105****
-14	0,0045	0,0084*	0,0004***	0,0109****
-13	0,0062	0,0145	0,0005**	0,0114****
-12	0,0000	0,0146	0,0008***	0,0121****
-11	0,0000	0,0146	0,0009**	0,0131****
-10	0,0000	0,0146	0,0005****	0,0135****
-9	0,0000	0,0146	0,0005***	0,0140****
-8	0,0001*	0,0147	0,0007*	0,0147****
-7	0,0005	0,0153	0,0010*	0,0157****
-6	0,0003**	0,0156*	0,0004***	0,0161****
-5	0,0086	0,0242*	0,0002**	0,0164****
-4	0,0001	0,0242**	0,0005***	0,0168****
-3	0,0009*	0,0251**	0,0002*	0,0171****
-2	0,0003*	0,0254**	0,0037*	0,0208****
-1	0,0003*	0,0256**	0,0036**	0,0244****
0	0,1251*	0,1507*	0,0576****	0,0820****
1	0,0193****	0,1700**	0,0194****	0,1014****
2	0,0116**	0,1816**	0,0059****	0,1072****
3	0,0045**	0,1861**	0,0041****	0,1114****
4	0,0042***	0,1903**	0,0031****	0,1145****
5	0,0044**	0,1947**	0,0024****	0,1169****
6	0,0011**	0,1958**	0,0022****	0,1191****
7	0,0046***	0,2004**	0,0016****	0,1207****
8	0,0011**	0,2014**	0,0016***	0,1223****
9	0,0018*	0,2032**	0,0021****	0,1244****
10	0,0028**	0,2061**	0,0012****	0,1256****
11	0,0003	0,2064**	0,0011****	0,1268****
12	0,0036**	0,2100**	0,0012****	0,1279****
13	0,0008**	0,2108**	0,0065	0,1344****
14	0,0006**	0,2114**	0,0012****	0,1356****
15	0,0041**	0,2155**	0,0022***	0,1379****
16	0,0036	0,2191**	0,0016****	0,1395****
17	0,0016*	0,2208**	0,0011***	0,1406****
18	0,0002	0,2209**	0,0029*	0,1435****
19	0,0035	0,2244**	0,0008****	0,1443****
20	0,0190	0,2434***	0,0055*	0,1498****
n	201		13	

Significance indicator: *p<10%; **p<5%; ***p<1%; ****p<0,01%

7.2.5 Regression

In an attempt to further validate our method, we will in the following estimate a regression model on the proven cases. As the final models for the three countries are not equal, we have to choose variables that have the same sign, and preferably significance across all countries, as to avoid opposing effects on the variables. However, with a sample of only 13, there are constraints to how many regressors one can include. With constraints both on which and the number of variables, we decide to regress on *CAV* and *lnMV*.

Table 20: OLS regression - proven cases

	Dependent variable:
	CAR
Constant	0.169*
	(0.093)
oneCAV	0.146
	(0.408)
lnMV	-0.014
	(0.012)
AIC	-21.9
Observations	13
R^2	0.091
Adjusted R^2	-0.091
Residual Std. Error	0.087 (df = 10)
F Statistic	0.498 (df = 2; 10)
Note:	*p<0.1; **p<0.05; ***p<0.01

As can be seen in Table 20Table 20 above, the regression does not yield results worth interpreting, as the coefficients are jointly insignificant and the adjusted R^2 is a mere -0,091. This is in line with our expectations, as the sample is simply too small to regress and therefore does not impede the robustness of our methodology.

7.2.6 Conclusion proven cases

The results from the event study based on proven cases indicate a clear run-up both for abnormal return and abnormal volume. Even though not always significant, we observe an almost continuous increase in CAAR in the last days of the event period. As for CAAV, 17 out of the 30 days in the event period are significant. We find the stock price run-up to be higher for the proven sample, substantiating the method’s validity in using the run-up as an indication of information leakage. Therefore, we still find it reasonable to use abnormal return and abnormal volume as proxies for illegal insider trading.

7.3 LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

As addressed several times throughout the paper, using abnormal returns and abnormal volume as indicators for illegal insider trading comes with several limitations. Firstly, it is not possible to completely isolate for the market anticipation effect as increases in stock prices might be caused by professional investors who make qualified investments based on analyses that are in accordance with the law. Therefore, a large proportion of the run-ups may be due to natural speculation. However, as we find a significant run-up for all countries and samples, we do not expect that skilled investors have anticipated every takeover, i.e. anticipation cannot be the sole cause of the run-up. Secondly, abnormal volume might be explained by the information leakage hypothesis. More specifically, illegal trades executed by insiders will cause abnormal volume as uninformed traders will notice unusual activity in the stock, and thus copy these trades. As a consequence, there will be a snowball effect where a large proportion of the abnormal volume does not come from illegal insider trading, but uninformed investors. We have tried to control for this problem by running a robustness check where we held the results from our adjusted sample up against a sample of proven cases. Once again, we cannot with certainty fully attribute the run-up in these cases to information leakage, and certainly not illegal insider trading alone. However, we know that information has been leaked for all of these takeovers, and the systematically higher run-up indicates that the market reacts to this. Thus, as there is a significant run-up for the adjusted sample we have reasons to believe that illegal insider trading is partly the cause.

As our data covers the period 1999 through 2018, there might be issues in establishing inference about the presence of illegal insider trading prior to acquisitions in the Scandinavian market as of today. During this period, new technologies that have significant impact on insider trading have been introduced. Internet, smartphones and other personal devices provide a constant online connection where people have access to more information than ever before. But more importantly, with an increasing number of tools available, regulators can use technology to more effectively conduct surveillance of securities markets. As a consequence, technological development is likely to change the nature of insider trading activity, and we can therefore not guarantee that the methods and data used in this paper is adequate to disclose insider trading prior to acquisitions in 2019. Moreover, there have been significant changes in legislation and enforcement over the period subject to analysis. In 2005, EU implemented MAD, the Market Abuse Directive (Christensen, 2015), a legal framework intended to ensure efficient, transparent and trustworthy European financial markets. Since 2005, MAD (now MAR) has been replaced twice and it is natural to assume that such changes has an impact on the incentive structure of illegal insider traders.

Other sources of potential limitations to our study are related to econometric issues. Firstly, the event-window is measured over an arbitrary time period of 30 days. Even though this is in accordance with practitioners, such as Keown and Pinkerton (1981), it might be the case that the periods are either too long or too short. If so, this may have biased the calculation of AR and AV. Consequently, we cannot claim that our event window will serve as the most correct window for estimating abnormal stock behaviour prior to takeovers.

Another implication for our results is the sample size needed to be representative of a given population. A study performed by Krejcie and Morgan (1970) states that a population size of 946 requires a sample size of at least 274 observations when the value of alpha is assumed to be 5%. As both the initial and adjusted sample is below this threshold, our results may be subject to low statistical power. Moreover, as our explanatory variables are estimated as an average, it does not account for macroeconomic cycles. We therefore recommend that future studies estimate the explanatory variables on a yearly basis using dummies. This will disclose a more precise relationship between insider trading and macroeconomic cycles in the regression analysis. However, as the adjusted Danish and Norwegian samples only include 33 and 52 observations, we believe that it would be extensive to add 20 more dummies.

In order to ensure that the estimation of AR and AV does not suffer from other company-specific news or events, it would be useful to control for quarterly reports. Each report has the potential to significantly affect the value of a company's stock, and thus bias our estimates. As a consequence, our results may be prone to company-specific news that are not solely due to acquisitions. Furthermore, we acknowledge that it might be a limitation that we did not add more dummies to assess what effect the financial crisis had on the occurrence of insider trading. By adding a second dummy, we would be able to evaluate the level of abnormal returns before, during and after the financial crisis, and thus yield a more precise result of the financial crisis effect on insider trading.

7.4 IMPLICATIONS FOR FUTURE ENFORCEMENT: DIGITAL ENHANCEMENT

The institutional background, and to some extent the cross-sectional analysis, revealed the importance of uncovering the network surrounding illegal insider traders. Logically, illegal insider trading *cannot* occur without the individual having a direct or indirect link to primary insiders. Substantiating this, the formerly mentioned case of Raj Rajatnam unravelled an illegal insider trading ring involving people in the higher echelons of the financial world and other major corporations, leading to the indictment of six others (SEC, 2009).

With respect to uncovering such networks, software robotics, such as machine learning and artificial intelligence, could be of good use. The internationalisation of markets has spurred the emergence of alternative market places beyond the traditional stock exchanges, complicating the monitoring of the financial markets (Riise, 2010). However, all market participants have a unique ID tag which software could pull from all the different databases to construct the trader's link to individuals on the insider list prescribed the FSA by exchange-listed companies. Simultaneously, an equivalent network can be constructed from the trader's social media data and social registers to be compared to the previous list to uncover potential channels through which inside information may have leaked. These networks can be constructed immediately as the software detects a suspicious order, e.g. AV coinciding with AR, or in retrospect as a standard procedure following material events, such as takeover announcements, earnings announcements or stage advancements for R&D projects. Artificial intelligence could also be utilised to continuously calculate a stock's moving CAR and CAV over a certain period while trawling the internet for rumours about the stock, thus potentially uncover a run-up before the release of a public rumour of a material event.

Having uncovered a network or link to primary insiders, software robotics and big data analytics come into play again when analysing the vast amounts of data needed for insider trading cases. Robotics have the capabilities to process more data and analyse patterns better and quicker than humanly possible. Furthermore, machine learning can utilise historical information and data to assess when illegal insider trading is more likely to occur for different events, much like the regression analysis conducted in section 6.5. The superior data processing power of software robotics can also allow FSAs to uncover networks or affiliates by analysing the trading patterns of different traders and whether they frequently make the same profitable trades, and subsequently uncover their potentially common insider source.

Implementing such systems could aid FSAs in identifying and prioritising specific cases for which to commence a special investigation. Software robotics provide a clear advantage in both speed and capacity. An example of the time-consuming nature of such cases is the already mentioned case of Raj Rajaratnam, which took three years from indictment to trial, and likely even longer from suspicion to indictment. Another advantage is the objectivity of the analysis, thus providing FSAs with unbiased analysis and prioritisation of possible cases for which to initiate a formal investigation and subsequently hand over the prosecuting authorities.

Lastly, Bromberg, Ramsay and Gilligian (2017) found the process of data exchange between FSAs to be a troublesome process. While we rejected the hypothesis of a foreign acquirer increasing the likelihood of illegal inside trading, this does not imply that foreigners do not trade on inside information in Scandinavian stocks. By implementing said technologies, FSAs can retrieve data and analysis in a standard format, easing the exchange process and ensuring a satisfactory data quality, and thus deteriorate the current incentives of foreign traders.

It should, however, be noted that a complete dehumanisation of the analysis comes with the risk of labelling an innocent person as a criminal, thus some subjectivity is still required. Furthermore, such technology is still on the advance and implementing systems like machine learning and artificial intelligence requires a long trial period for the software to become “smart”. In setting up such a system, on the other hand, we regard our methodology and findings to be a fine starting point as to what can be indications worth further investigation.

8 CONCLUSION

The purpose of this thesis was to answer three main questions; does illegal insider trading occur prior to takeovers of Scandinavian-listed companies? If so, when is it more likely to occur? And thirdly, how can our findings be applied by authorities in their objective to uncover illegal insider trading? Following an event study of historical takeovers, we conclude that illegal insider trading has prevailed on the Scandinavian markets the last 20 years. These findings take form of an event study analysis of the run-up in stock price and trading volume pre-announcement, which displays robustness across two measures of abnormal returns and two samples.

Based on these findings, we further investigate specific event characteristics potentially influencing the likelihood of illegal insider trading to occur. Between the three markets, our findings are ambiguous. Denmark and Norway have in common great explanatory power attributed the cumulative abnormal volume of the last 30 days pre-announcement. Quite surprisingly, we find the number of advisors to have a negative relation with illegal insider trading in Denmark, which is contrary to previous studies using similar methodology and qualitative ones. For Sweden, on the other hand, we obtain a result in line with expectations, where the number of advisors increase the presence of illegal insider trading, however, decreasing in the size of the target firm. Furthermore, for Sweden we also find indications of illegal insider trading being less pronounced in acquisitions of firms with a high relative valuation. Conversely, it is more likely to occur in target companies in severe financial distress. Similarly, we find illegal insider trading to be less likely in Danish companies with very low degree of financial distress. Lastly, as opposed to the neighbouring countries, we find illegal insider trading to be either less present or less statistically observable for more liquid target companies in Norway, with previous literature arguing for the latter.

Over the last 20 years the enforcement has become stricter and more efficient, leading to fewer cases of illegal insider trading, however an increase in the severity of the individual cases. Having uncovered indicators of when it is more likely to occur, we use our findings for suggestions to how enforcement can be enhanced. We direct our focus towards the implementation of software robotics and how its superior processing power can be utilised to detect suspicious trades, automatically construct the link between traders and people on the insider list and conduct ongoing run-up analyses. To this comes the ability to work in a standard format, easing the data exchange between FSAs, which historically has been a bureaucratic obstacle increasing the incentives of foreign traders to commit illegal insider trading.

We believe our findings contribute to the existing literature in that the Scandinavian markets were yet to be investigated applying this methodology. Evidently, the Scandinavian markets are no exception to the norm and joins the list of markets with a history of some individuals materialising their informational advantage at the cost of the lawful majority.

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10 APPENDIX

Appendix 1: Distribution per year – initial and adjusted sample

	Initial sample						Adjusted sample					
Year	Denmark		Norway		Sweden		Denmark		Norway		Sweden	
1999	0	0 %	0	0 %	1	1 %	0	0 %	0	0 %	0	0 %
2000	1	2 %	0	0 %	3	2 %	1	3 %	0	0 %	3	3 %
2001	2	4 %	0	0 %	1	1 %	2	6 %	0	0 %	0	0 %
2002	1	2 %	0	0 %	1	1 %	1	3 %	0	0 %	1	1 %
2003	0	0 %	0	0 %	1	1 %	0	0 %	0	0 %	0	0 %
2004	1	2 %	1	2 %	3	2 %	0	0 %	0	0 %	2	2 %
2005	4	8 %	1	2 %	3	2 %	4	12 %	1	2 %	0	0 %
2006	1	2 %	3	5 %	6	4 %	1	3 %	2	4 %	5	4 %
2007	1	2 %	5	8 %	16	11 %	1	3 %	5	10 %	15	13 %
2008	7	15 %	11	18 %	14	10 %	4	12 %	8	15 %	11	9 %
2009	1	2 %	6	10 %	5	3 %	1	3 %	5	10 %	4	3 %
2010	3	6 %	5	8 %	15	10 %	1	3 %	5	10 %	11	9 %
2011	4	8 %	4	6 %	9	6 %	2	6 %	4	8 %	6	5 %
2012	6	13 %	5	8 %	4	3 %	4	12 %	5	10 %	3	3 %
2013	3	6 %	2	3 %	3	2 %	2	6 %	2	4 %	3	3 %
2014	2	4 %	7	11 %	12	8 %	2	6 %	6	12 %	11	9 %
2015	2	4 %	3	5 %	13	9 %	0	0 %	2	4 %	12	10 %
2016	3	6 %	2	3 %	10	7 %	3	9 %	2	4 %	8	7 %
2017	1	2 %	2	3 %	9	6 %	1	3 %	2	4 %	6	5 %
2018	5	10 %	5	8 %	15	10 %	3	9 %	3	6 %	15	13 %
Total	48		62		144		33		52		116	

Appendix 2: AAR and CAAR(-25, 1) market and simple measure – initial sample

	Denmark		Norway		Sweden	
Day	Market	Simple	Market	Simple	Market	Simple
-25	0,54 %	0,42 %	-0,15 %	-0,42 %	0,38 %	0,29 %
-24	0,18 %	-0,11 %	-0,31 %	-0,56 %	0,41 %	0,11 %
-23	1,22 %	0,93 %	-0,68 %	-0,90 %	-0,16 %	-0,47 %
-22	1,62 %*	1,48 %	-1,37 %**	-1,60 %**	0,06 %	-0,33 %
-21	1,25 %	1,23 %	-1,44 %**	-1,83 %**	0,33 %	-0,03 %
-20	1,42 %	1,33 %	-1,23 %*	-1,73 %*	0,25 %	-0,11 %
-19	1,52 %*	1,43 %	-1,38 %**	-1,54 %*	0,24 %	-0,19 %
-18	1,57 %	1,41 %	-0,88 %	-1,15 %	0,26 %	-0,16 %
-17	0,75 %	0,73 %	-0,77 %	-1,09 %	-0,19 %	-0,64 %
-16	1,90 %*	1,91 %*	-0,44 %	-0,55 %	0,04 %	-0,32 %
-15	2,19 %*	2,08 %*	-0,58 %	-0,60 %	-0,04 %	-0,46 %
-14	1,47 %	1,50 %	-0,05 %	0,02 %	-0,23 %	-0,70 %
-13	1,52 %	1,57 %	-0,21 %	-0,39 %	-0,13 %	-0,52 %
-12	1,41 %	1,58 %	-0,62 %	-0,95 %	-0,25 %	-0,77 %
-11	1,48 %	1,67 %	-0,39 %	-0,99 %	0,26 %	-0,21 %
-10	1,37 %	1,49 %	-0,14 %	-0,84 %	0,32 %	-0,18 %
-9	2,04 %	2,10 %	0,23 %	-0,53 %	0,66 %	0,13 %
-8	2,33 %	2,32 %	-0,08 %	-0,75 %	1,01 %	0,45 %
-7	2,49 %	2,32 %	0,66 %	-0,05 %	1,20 %	0,59 %
-6	2,84 %*	2,56 %*	0,84 %	0,28 %	1,52 %*	0,91 %
-5	3,07 %*	2,94 %*	1,02 %	0,47 %	1,48 %*	0,81 %
-4	2,82 %*	2,54 %	2,40 %	2,16 %	1,93 %**	1,43 %
-3	2,49 %	2,02 %	2,94 %	2,74 %	2,06 %**	1,64 %*
-2	2,89 %	2,22 %	2,86 %	2,65 %	2,61 %**	2,18 %**
-1	3,71 %*	3,12 %	3,68 %*	3,52 %*	3,81 %***	3,49 %***
0	15,56 %****	14,96 %****	20,62 %****	20,58 %****	19,35 %****	19,06 %****
1	16,93 %****	16,22 %****	22,82 %****	22,57 %****	20,54 %****	20,35 %****

Appendix 3: AAR and CAAR(-20, 1) market and simple measure – initial sample

	Denmark		Norway		Sweden	
Day		Simple	Market	Simple	Market	Simple
-20	0,17 %	0,10 %	0,21 %	0,10 %	-0,08 %	-0,08 %
-19	0,27 %	0,20 %	0,05 %	0,29 %	-0,10 %	-0,16 %
-18	0,32 %	0,18 %	0,56 %	0,68 %	-0,07 %	-0,13 %
-17	-0,50 %	-0,50 %	0,67 %	0,74 %	-0,53 %	-0,61 %*
-16	0,66 %	0,68 %	1,00 %	1,28 %	-0,29 %	-0,30 %
-15	0,95 %	0,85 %	0,86 %	1,23 %	-0,37 %	-0,44 %
-14	0,23 %	0,27 %	1,39 %	1,85 %	-0,57 %	-0,67 %
-13	0,28 %	0,34 %	1,23 %	1,44 %	-0,46 %	-0,50 %
-12	0,16 %	0,35 %	0,82 %	0,88 %	-0,58 %	-0,74 %
-11	0,24 %	0,44 %	1,05 %	0,84 %	-0,07 %	-0,18 %
-10	0,12 %	0,26 %	1,30 %	0,99 %	-0,01 %	-0,15 %
-9	0,79 %	0,87 %	1,67 %	1,30 %	0,32 %	0,16 %
-8	1,09 %	1,09 %	1,36 %	1,08 %	0,67 %	0,48 %
-7	1,24 %	1,09 %	2,10 %	1,78 %	0,86 %	0,62 %
-6	1,59 %	1,33 %	2,28 %	2,11 %	1,19 %*	0,94 %
-5	1,82 %	1,71 %	2,45 %	2,30 %	1,14 %*	0,84 %
-4	1,58 %	1,31 %	3,84 %*	3,99 %*	1,60 %**	1,46 %*
-3	1,25 %	0,79 %	4,38 %**	4,57 %**	1,73 %**	1,67 %**
-2	1,64 %	0,99 %	4,30 %**	4,48 %**	2,28 %**	2,21 %**
-1	2,46 %	1,89 %	5,12 %**	5,35 %**	3,48 %****	3,52 %***
0	14,31 %****	13,73 %****	22,06 %****	22,41 %****	19,02 %****	19,09 %****
1	15,68 %****	14,99 %****	24,26 %****	24,40 %****	20,21 %****	20,38 %****

Appendix 4: AAR and CAAR(-15, 1) market and simple measure – initial sample

	Denmark		Norway		Sweden	
Day	Market	Simple	Market	Simple	Market	Simple
-15	0,29 %	0,17 %	-0,14 %	-0,05 %	-0,08 %	-0,14 %
-14	-0,43 %	-0,41 %	0,39 %	0,57 %	-0,28 %	-0,38 %
-13	-0,38 %	-0,35 %	0,22 %	0,16 %	-0,17 %	-0,20 %
-12	-0,49 %	-0,33 %	-0,18 %	-0,40 %	-0,29 %	-0,44 %
-11	-0,42 %	-0,24 %	0,04 %	-0,44 %	0,22 %	0,11 %
-10	-0,54 %	-0,43 %	0,30 %	-0,29 %	0,28 %	0,15 %
-9	0,14 %	0,19 %	0,67 %	0,02 %	0,61 %	0,46 %
-8	0,43 %	0,40 %	0,36 %	-0,21 %	0,96 %*	0,77 %
-7	0,59 %	0,41 %	1,10 %	0,50 %	1,15 %**	0,91 %*
-6	0,93 %	0,65 %	1,27 %	0,82 %	1,48 %**	1,23 %**
-5	1,16 %	1,02 %	1,45 %	1,02 %	1,43 %**	1,14 %*
-4	0,92 %	0,63 %	2,84 %*	2,71 %*	1,89 %***	1,76 %**
-3	0,59 %	0,10 %	3,38 %**	3,29 %*	2,02 %***	1,96 %**
-2	0,99 %	0,31 %	3,30 %**	3,20 %**	2,57 %***	2,51 %***
-1	1,80 %	1,21 %	4,11 %**	4,07 %**	3,77 %****	3,81 %****
0	13,65 %****	13,05 %****	21,06 %****	21,13 %****	19,31 %****	19,38 %****
1	15,02 %****	14,30 %****	23,25 %****	23,12 %****	20,50 %****	20,67 %****

Appendix 5: AAR and CAAR(-10, 1) market and simple measure – initial sample

	Denmark		Norway		Sweden	
Day	Market	Simple	Market	Simple	Market	Simple
-10	-0,12 %	-0,19 %	0,25 %	0,15 %	0,06 %	0,04 %
-9	0,56 %	0,43 %	0,62 %	0,46 %	0,39 %	0,35 %
-8	0,85 %	0,64 %	0,31 %	0,23 %	0,74 %	0,66 %
-7	1,00 %	0,65 %	1,05 %	0,94 %	0,93 %*	0,80 %
-6	1,35 %*	0,89 %	1,23 %	1,26 %	1,26 %**	1,12 %*
-5	1,58 %*	1,26 %	1,41 %*	1,45 %	1,21 %**	1,02 %*
-4	1,34 %	0,87 %	2,80 %**	3,15 %**	1,67 %**	1,65 %**
-3	1,01 %	0,35 %	3,33 %***	3,72 %**	1,80 %**	1,85 %**
-2	1,41 %	0,55 %	3,26 %***	3,63 %***	2,35 %***	2,40 %***
-1	2,22 %	1,45 %	4,07 %***	4,51 %***	3,55 %****	3,70 %****
0	14,07 %****	13,29 %****	21,01 %****	21,56 %****	19,09 %****	19,27 %****
1	15,44 %****	14,54 %****	23,21 %****	23,56 %****	20,28 %****	20,56 %****

Appendix 6: AAR and CAAR(-5, 1) market and simple measure – initial sample

	Denmark		Norway		Sweden	
Day	Market	Simple	Market	Simple	Market	Simple
-5	0,23 %	0,37 %	0,18 %	0,19 %	-0,05 %	-0,10 %
-4	-0,01 %	-0,02 %	1,57 %**	1,89 %**	0,41 %	0,53 %
-3	-0,34 %	-0,54 %	2,10 %***	2,46 %***	0,54 %	0,73 %*
-2	0,05 %	-0,34 %	2,03 %***	2,37 %***	1,09 %**	1,28 %**
-1	0,87 %	0,56 %	2,84 %****	3,25 %****	2,29 %****	2,58 %****
0	12,72 %****	12,40 %****	19,78 %****	20,30 %****	17,83 %****	18,15 %****
1	14,09 %****	13,66 %****	21,98 %****	22,30 %****	19,02 %****	19,44 %****

Appendix 7: AAR and CAAR(-25, 1) market and simple measure – adjusted sample

	Denmark		Norway		Sweden	
Day	Market	Simple	Market	Simple	Market	Simple
-25	-0,48 %*	-0,75 %**	-0,32 %	-0,07 %	0,23 %	-0,11 %
-24	-0,48 %	-1,27 %***	-0,32 %	0,10 %	0,31 %	-0,28 %
-23	-0,07 %	-0,64 %	-0,76 %	0,14 %	-0,19 %	-1,01 %*
-22	0,71 %	1,03 %	-1,47 %**	-0,80 %*	0,05 %	-0,77 %
-21	0,67 %	1,01 %	-1,49 %**	-1,06 %*	0,25 %	-0,68 %
-20	0,92 %	1,26 %	-1,28 %*	-0,84 %	-0,06 %	-0,94 %
-19	1,20 %	1,66 %	-1,41 %**	-0,79 %	0,04 %	-0,86 %
-18	0,82 %	1,40 %	-0,71 %	0,05 %	0,21 %	-0,73 %
-17	0,94 %	1,53 %	-0,47 %	0,34 %	-0,16 %	-1,14 %
-16	1,79 %	2,41 %	-0,43 %	1,00 %	-0,32 %	-1,28 %*
-15	2,16 %*	2,59 %*	-0,45 %	0,93 %	-0,57 %	-1,55 %*
-14	1,21 %	1,75 %	0,19 %	1,37 %	-0,80 %	-1,93 %*
-13	0,66 %	1,27 %	-0,35 %	0,58 %	-0,91 %	-2,18 %*
-12	0,70 %	1,42 %	-0,96 %	-0,21 %	-0,74 %	-1,99 %*
-11	1,23 %	2,04 %	-0,76 %	0,32 %	-0,40 %	-1,86 %*
-10	0,93 %	1,59 %	-0,31 %	0,29 %	-0,05 %	-1,46 %
-9	1,77 %	2,49 %	-0,11 %	0,55 %	0,54 %	-0,97 %
-8	2,26 %	2,54 %	-0,23 %	0,65 %	0,97 %	-0,64 %
-7	2,47 %	2,76 %	0,45 %	0,47 %	1,18 %	-0,34 %
-6	3,05 %*	3,25 %*	0,64 %	0,72 %	1,20 %	-0,35 %
-5	3,31 %*	3,66 %*	0,55 %	0,65 %	1,28 %	-0,31 %
-4	3,47 %*	3,35 %*	1,29 %	1,63 %	1,60 %	0,20 %
-3	3,55 %*	3,35 %*	1,90 %	1,92 %	1,57 %	0,45 %
-2	4,21 %*	3,51 %	2,09 %	2,54 %	2,11 %*	0,89 %
-1	5,49 %*	5,18 %*	2,96 %*	3,16 %	3,61 %**	2,69 %**

0	17,34 %****	18,01 %****	20,09 %****	18,22 %****	19,86 %****	18,81 %****
1	19,51 %****	20,22 %****	22,28 %****	20,34 %****	21,10 %****	20,10 %****

Appendix 8: AAR and CAAR(-20, 1) market and simple measure – adjusted sample

	Denmark		Norway		Sweden	
Day	Market	Simple	Market	Simple	Market	Simple
-20	0,25 %	0,24 %	0,22 %	0,22 %	-0,32 %*	-0,26 %
-19	0,52 %	0,65 %	0,08 %	0,26 %	-0,22 %	-0,18 %
-18	0,14 %	0,39 %	0,78 %	1,10 %	-0,04 %	-0,05 %
-17	0,27 %	0,52 %	1,03 %	1,40 %	-0,41 %	-0,46 %
-16	1,12 %	1,40 %	1,06 %	2,06 %	-0,57 %	-0,60 %
-15	1,49 %	1,58 %	1,05 %	1,99 %	-0,82 %	-0,86 %
-14	0,54 %	0,74 %	1,68 %	2,43 %	-1,06 %	-1,25 %
-13	-0,01 %	0,26 %	1,15 %	1,64 %	-1,16 %	-1,50 %*
-12	0,03 %	0,41 %	0,53 %	0,85 %	-0,99 %	-1,31 %*
-11	0,56 %	1,03 %	0,74 %	1,37 %	-0,65 %	-1,18 %
-10	0,25 %	0,57 %	1,18 %	1,35 %	-0,30 %	-0,78 %
-9	1,10 %	1,48 %	1,38 %	1,61 %	0,29 %	-0,29 %
-8	1,58 %	1,53 %	1,27 %	1,71 %	0,72 %	0,05 %
-7	1,80 %	1,75 %	1,95 %	1,52 %	0,93 %	0,34 %
-6	2,37 %	2,24 %	2,13 %	1,78 %	0,95 %	0,34 %
-5	2,63 %	2,65 %*	2,05 %	1,71 %	1,03 %	0,37 %
-4	2,80 %*	2,34 %	2,79 %*	2,69 %	1,35 %	0,88 %
-3	2,87 %*	2,34 %	3,39 %**	2,97 %*	1,31 %	1,13 %
-2	3,54 %*	2,49 %	3,59 %**	3,59 %*	1,85 %*	1,58 %*
-1	4,81 %*	4,17 %*	4,45 %**	4,22 %**	3,36 %***	3,37 %***
0	16,67 %****	17,00 %****	21,58 %****	19,27 %****	19,61 %****	19,50 %****
1	18,84 %****	19,21 %****	23,77 %****	21,40 %****	20,84 %****	20,79 %****

Appendix 9: AAR and CAAR(-20, 1) market and simple measure – adjusted sample

	Denmark		Norway		Sweden	
Day	Market	Simple	Market	Simple	Market	Simple
-15	0,37 %	0,18 %	-0,02 %	-0,07 %	-0,25 %	-0,26 %
-14	-0,58 %	-0,66 %	0,62 %	0,37 %	-0,48 %	-0,65 %
-13	-1,13 %**	-1,15 %**	0,08 %	-0,42 %	-0,59 %	-0,90 %
-12	-1,09 %	-0,99 %	-0,53 %	-1,21 %*	-0,42 %	-0,71 %
-11	-0,56 %	-0,37 %	-0,32 %	-0,69 %	-0,08 %	-0,58 %
-10	-0,86 %	-0,83 %	0,12 %	-0,71 %	0,27 %	-0,18 %
-9	-0,02 %	0,08 %	0,32 %	-0,45 %	0,86 %	0,31 %
-8	0,46 %	0,13 %	0,20 %	-0,35 %	1,29 %*	0,65 %
-7	0,68 %	0,35 %	0,88 %	-0,53 %	1,51 %**	0,94 %
-6	1,26 %	0,84 %	1,07 %	-0,28 %	1,52 %**	0,94 %
-5	1,52 %	1,25 %	0,99 %	-0,35 %	1,60 %**	0,98 %
-4	1,68 %	0,94 %	1,72 %*	0,63 %	1,92 %**	1,48 %*
-3	1,76 %	0,94 %	2,33 %**	0,91 %	1,89 %**	1,73 %**
-2	2,42 %	1,09 %	2,52 %**	1,54 %	2,43 %**	2,18 %**
-1	3,70 %	2,77 %	3,39 %**	2,16 %*	3,93 %****	3,97 %****
0	15,55 %****	15,60 %****	20,52 %****	17,21 %****	20,19 %****	20,10 %****
1	17,72 %****	17,80 %****	22,71 %****	19,34 %****	21,42 %****	21,39 %****

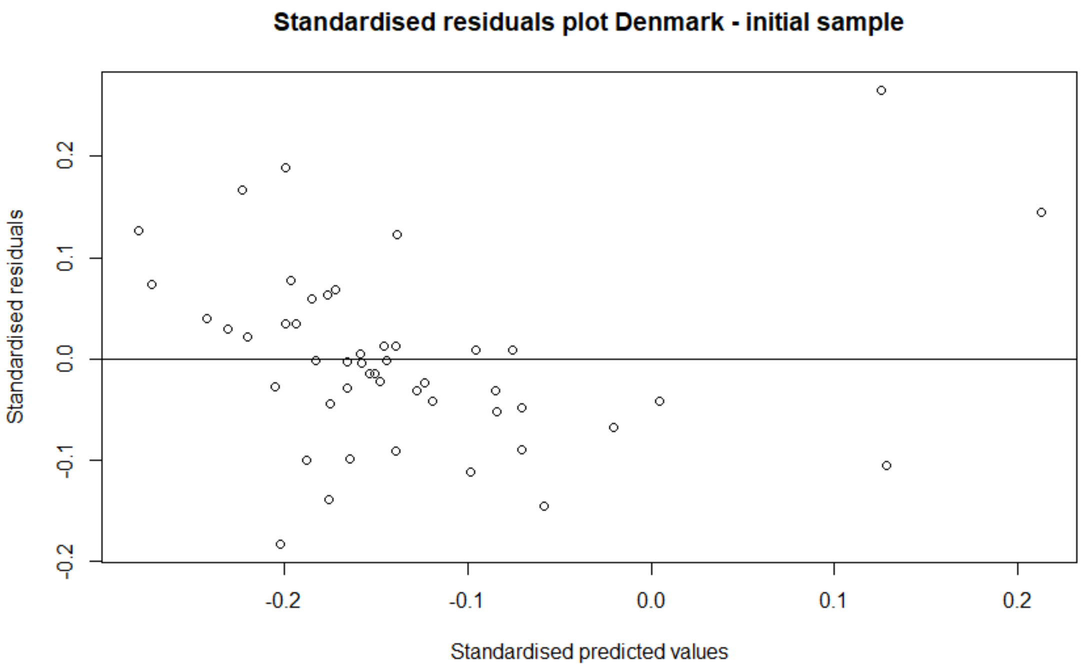
Appendix 10: AAR and CAAR(-10, 1) market and simple measure – adjusted sample

	Denmark		Norway		Sweden	
Day	Market	Simple	Market	Simple	Market	Simple
-10	-0,30 %	-0,39 %	0,44 %	0,36 %	0,35 %	0,31 %
-9	0,54 %	0,34 %	0,64 %	0,49 %	0,94 %*	0,88 %
-8	1,02 %	0,82 %	0,53 %	0,40 %	1,37 %**	1,27 %*
-7	1,24 %	0,92 %	1,21 %*	1,04 %	1,58 %**	1,42 %**
-6	1,82 %*	1,42 %	1,39 %*	1,35 %	1,60 %**	1,43 %**
-5	2,08 %*	1,87 %*	1,31 %*	1,28 %	1,68 %**	1,45 %**
-4	2,24 %*	1,93 %*	2,05 %**	2,33 %*	2,00 %**	1,95 %**
-3	2,32 %*	1,73 %	2,65 %***	2,93 %**	1,96 %**	1,99 %**
-2	2,98 %*	2,20 %	2,85 %***	3,10 %**	2,50 %**	2,58 %**
-1	4,26 %*	3,62 %*	3,72 %***	4,10 %***	4,00 %****	4,21 %****
0	16,11 %****	15,52 %****	20,85 %****	21,31 %****	20,26 %****	20,42 %****
1	18,28 %****	17,56 %****	23,03 %****	23,28 %****	21,49 %****	21,76 %****

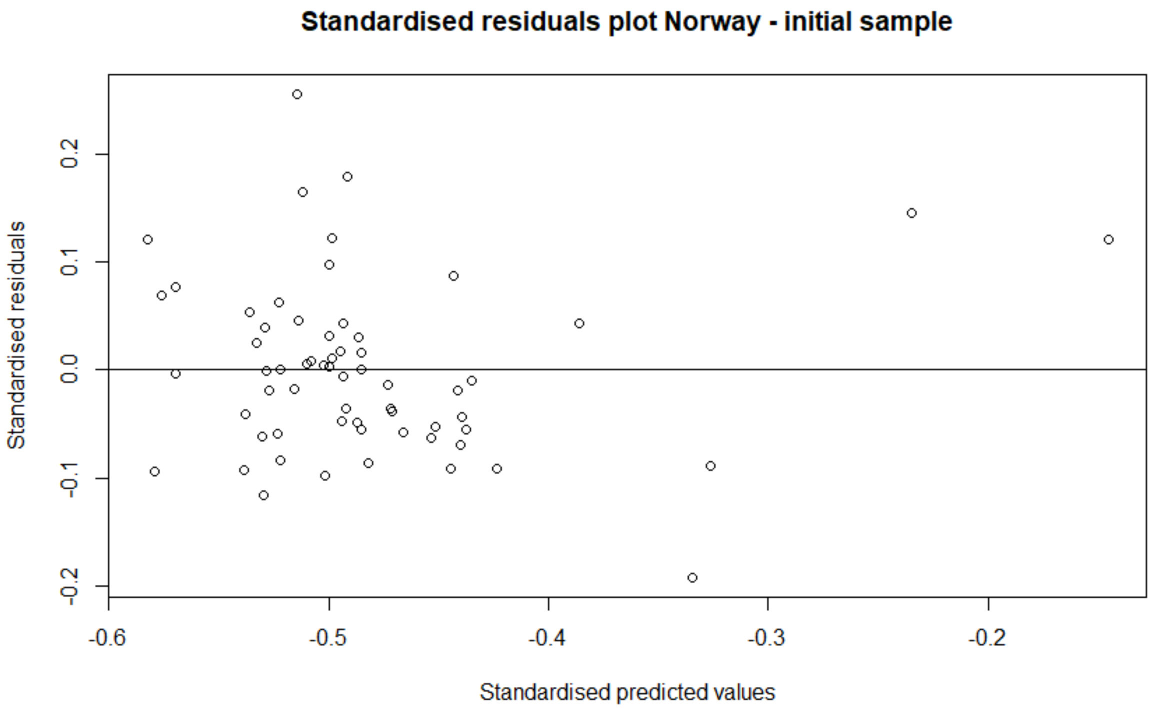
Appendix 11: AAR and CAAR(-5, 1) market and simple measure – adjusted sample

	Denmark		Norway		Sweden	
Day	Market	Simple	Market	Simple	Market	Simple
-5	0,26 %	0,41 %	-0,08 %	-0,07 %	0,08 %	0,04 %
-4	0,43 %	0,10 %	0,65 %*	0,91 %*	0,40 %	0,54 %
-3	0,50 %	0,10 %	1,26 %**	1,19 %**	0,36 %	0,79 %
-2	1,16 %	0,25 %	1,46 %**	1,82 %***	0,90 %*	1,24 %**
-1	2,44 %	1,93 %	2,32 %***	2,44 %***	2,40 %***	3,04 %****
0	14,29 %****	14,76 %****	19,45 %****	17,50 %****	18,66 %****	19,16 %****
1	16,47 %****	16,97 %****	21,64 %****	19,62 %****	19,89 %****	20,45 %****

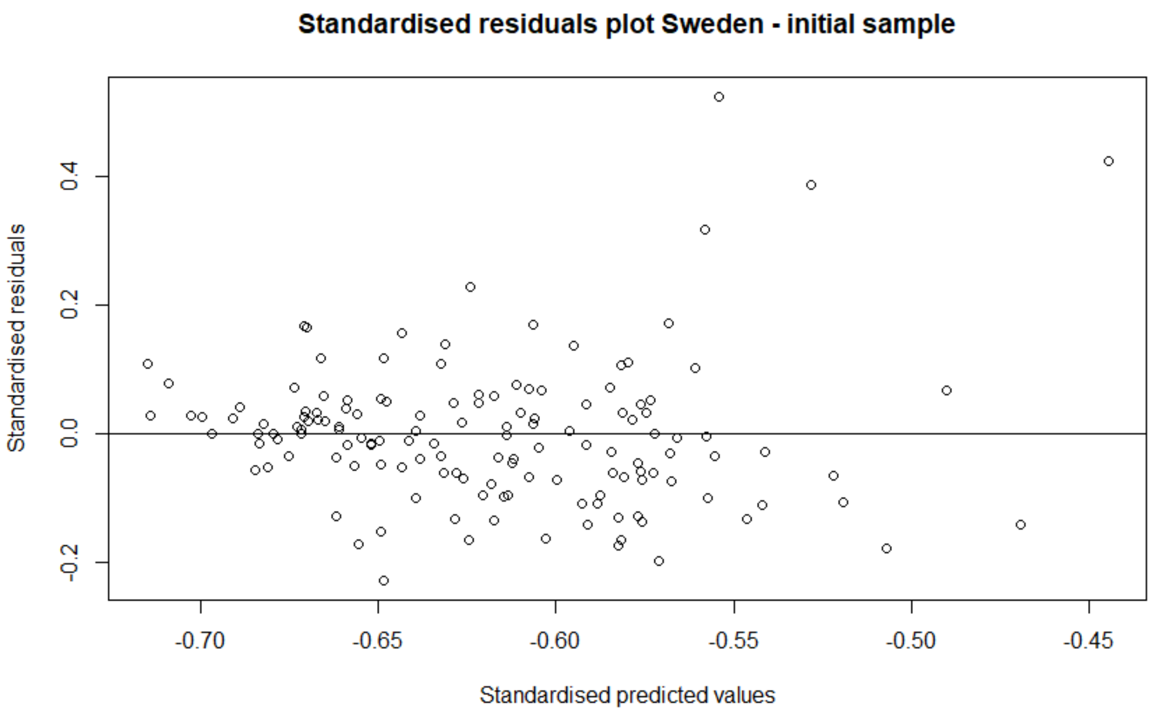
Appendix 12: Standardised residual plot, Denmark - initial sample



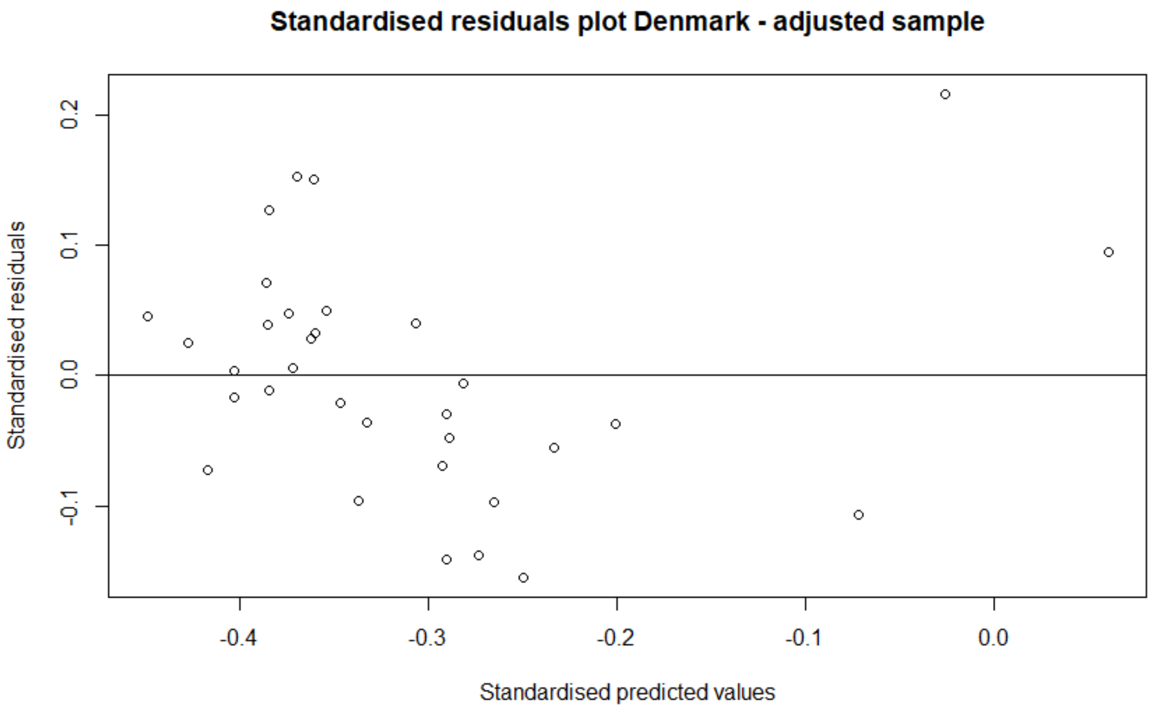
Appendix 13: Standardised residuals plot, Norway - initial sample



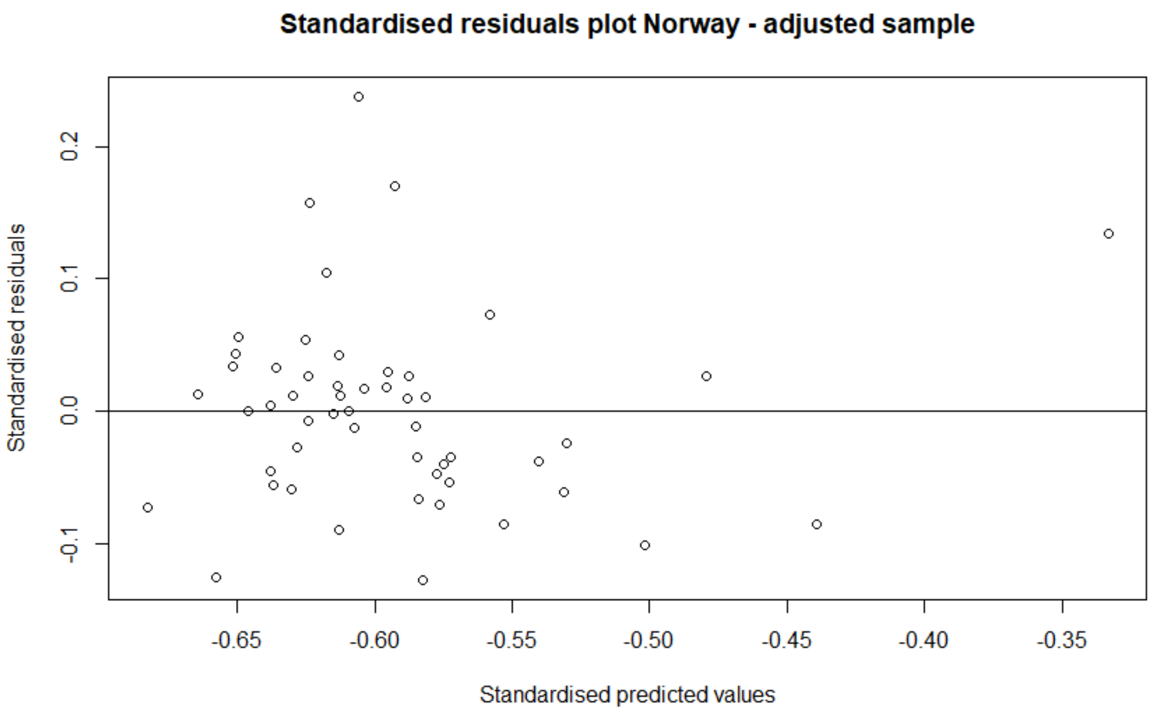
Appendix 14: Standardised residuals plot, Sweden - initial sample



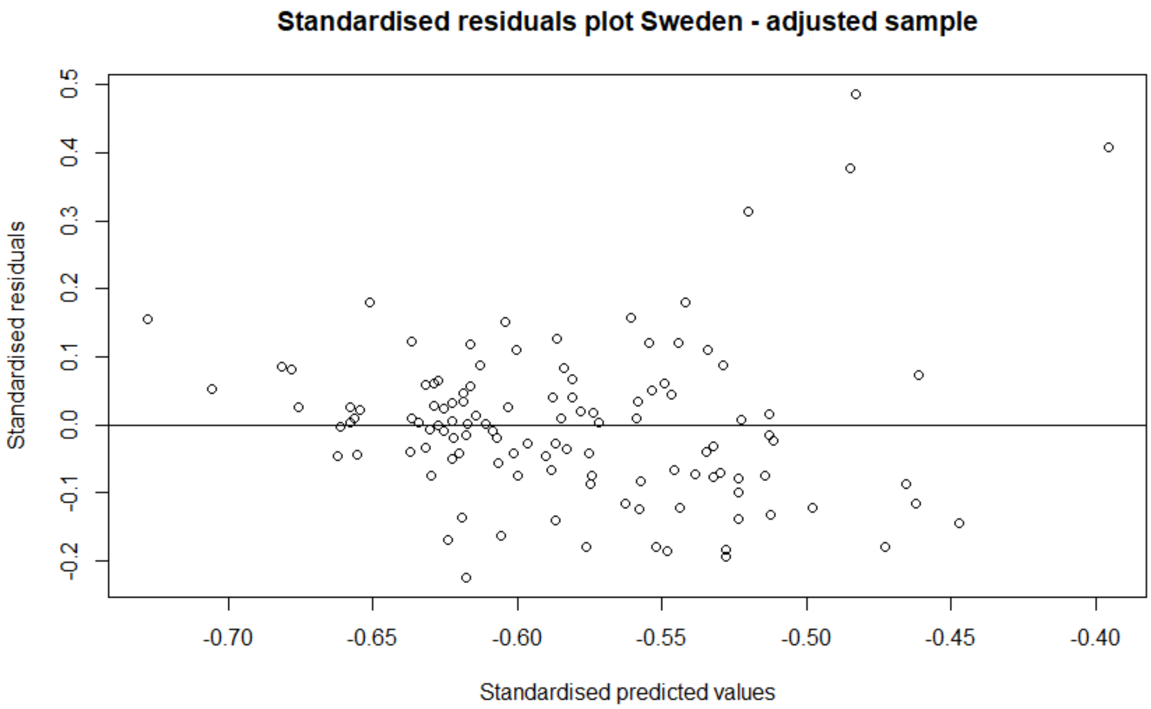
Appendix 15: Standardised residuals plot, Denmark - adjusted sample



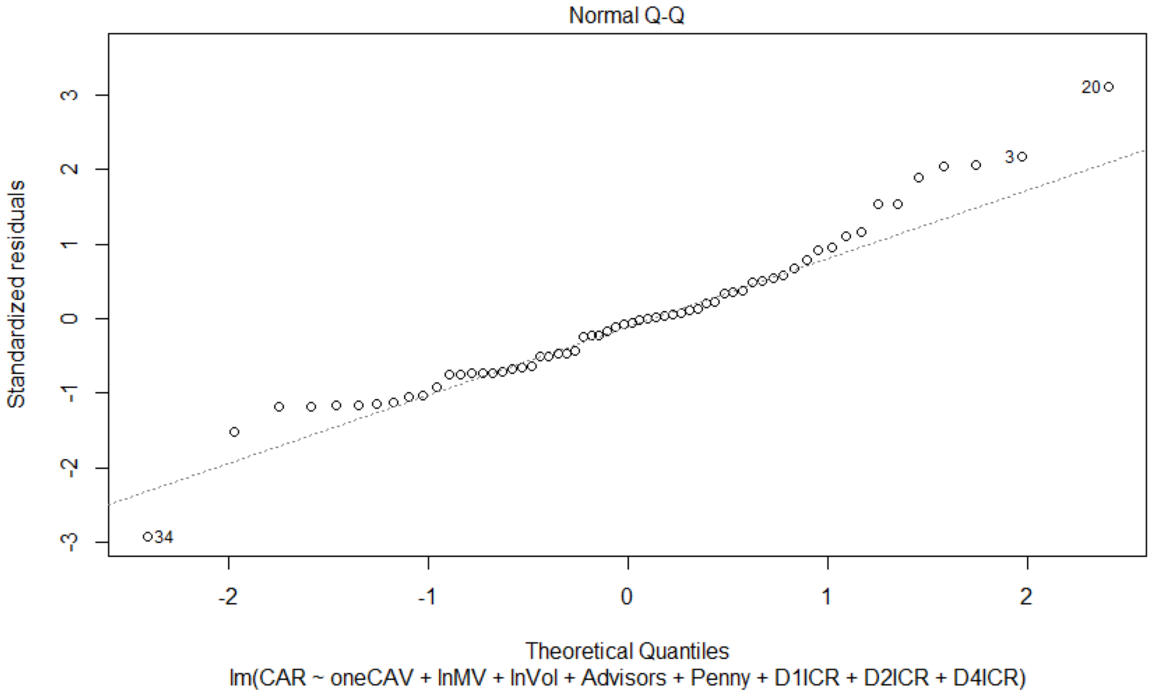
Appendix 16: Standardised residuals plot, Norway - adjusted sample



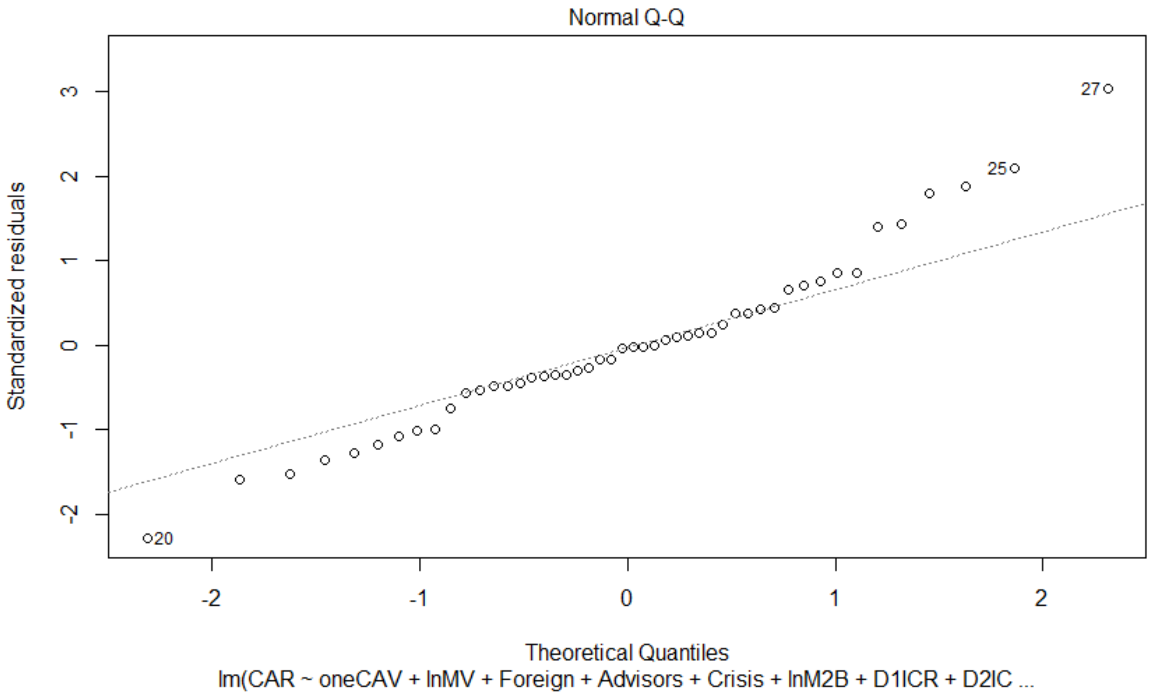
Appendix 17: Standardised residuals plot, Sweden - adjusted sample



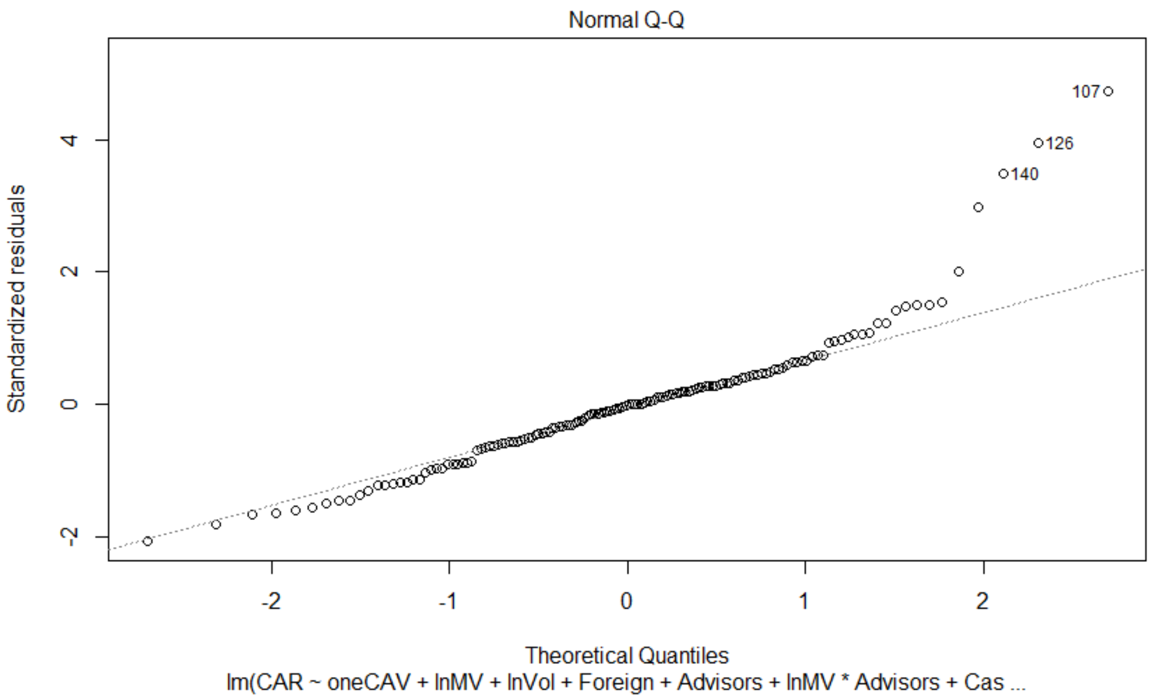
Appendix 18: Residuals Q-Q plot, Denmark - initial sample



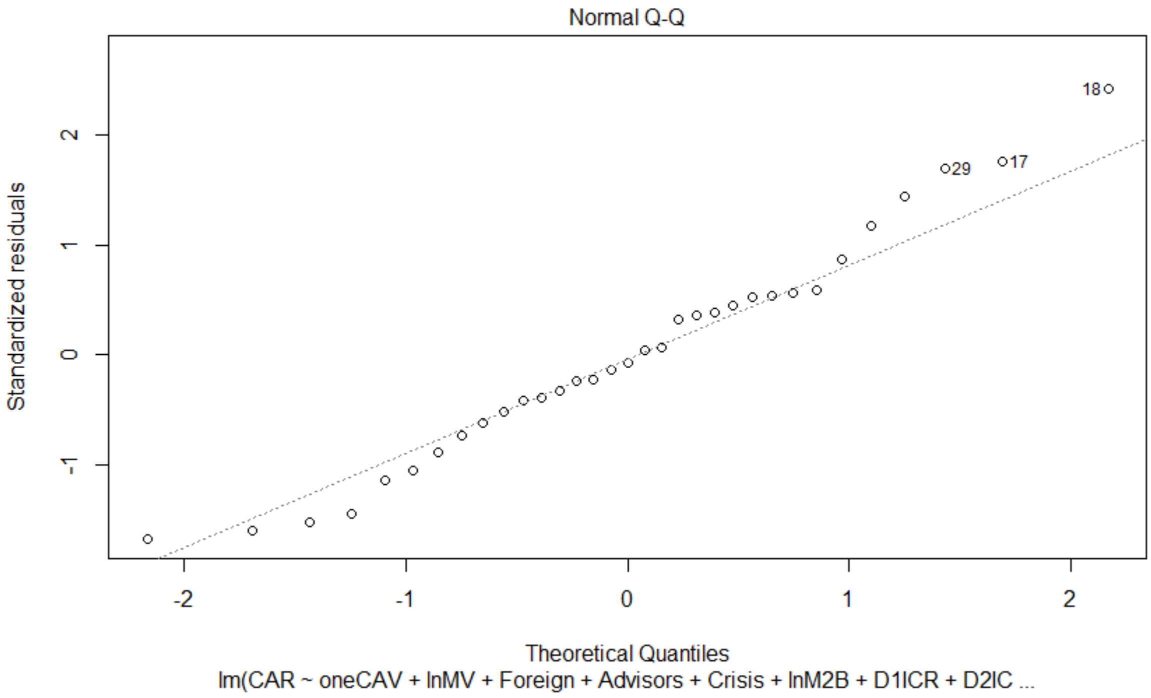
Appendix 19: Residuals Q-Q plot, Norway - initial sample



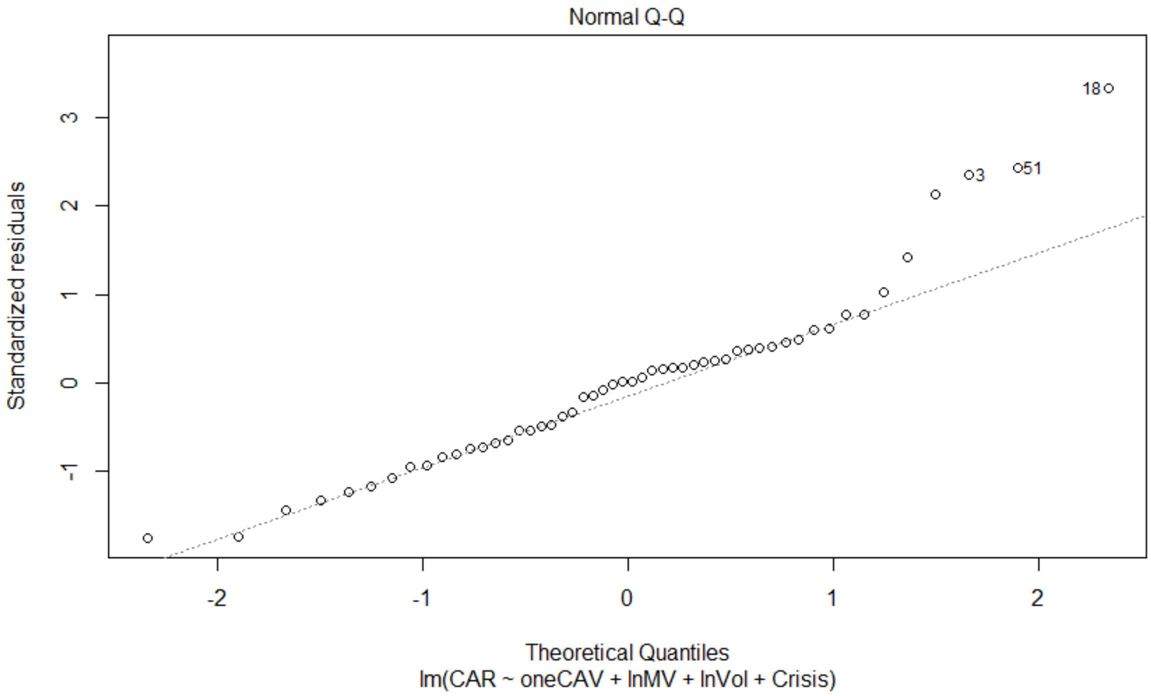
Appendix 20: Residual Q-Q plot, Sweden - initial sample



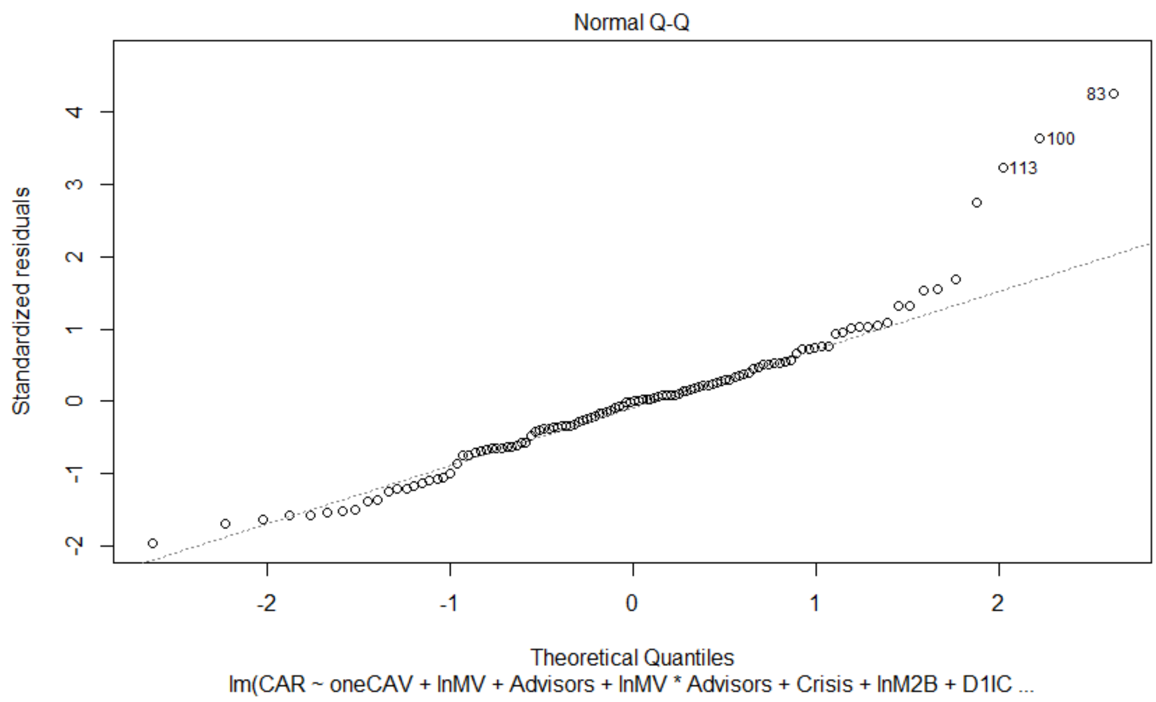
Appendix 21: Residual Q-Q plot, Denmark - adjusted sample



Appendix 22: Residual Q-Q plot, Norway - adjusted sample



Appendix 23: Residual Q-Q plot, Sweden - adjusted sample



Appendix 24: VIFs final models, all countries - initial and adjsuted sample

	Denmark		Norway		Sweden	
Variable	Initial	Adjusted	Initial	Adjusted	Initial	Adjusted
CAV	1,215	1,346	1,129	1,238	1,088	1,086
lnMV	2,179	2,872	1,995	1,147	2,681	2,759
lnVol	-	-	1,464	1,165	-	-
Foreign	1,163	1,313	-	-	-	-
Majority	-	-	-	-	-	-
Advisors	1,564	1,681	1,188	-	65,294	63,547
Cash	-	-	-	-	-	-
Crisis	1,359	1,36	-	1,255	1,066	1,089
Penny	-	-	1,759	-	-	-
lnM2B	1,109	1,272	-	-	1,085	1,115
D1ICR	1,673	1,896	1,128	-	1,503	1,595
D2ICR	1,405	2,084	1,268	-	1,494	1,581
D4ICR	1,307	1,407	1,138	-	1,418	1,447
lnMVAdvisors	-	-	-	-	73,556	72,139

Appendix 25: Model selection, Denmark - initial sample

	Dependent variable:					
	CAR (-10, -1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.492**	-0.521**	-0.520***	-0.523***	-0.523***	-0.548***
	(0.201)	(0.211)	(0.193)	(0.187)	(0.187)	(0.201)
CAV	3.056***	3.095***	2.981***	3.088***	3.087***	3.253***
	(0.840)	(0.842)	(0.791)	(0.776)	(0.742)	(0.748)
lnMV	0.021	0.023	0.024*	0.026**	0.026**	0.028**
	(0.015)	(0.015)	(0.013)	(0.011)	(0.011)	(0.012)
lnVol	0.007	0.008	0.004			
	(0.009)	(0.010)	(0.009)			
Foreign	0.044	0.040	0.046*	0.045*	0.045*	0.042
	(0.027)	(0.026)	(0.027)	(0.027)	(0.027)	(0.027)
Majority	-0.005	-0.002	-0.005	0.0003		
	(0.032)	(0.033)	(0.032)	(0.030)		
Advisors	-0.010***	0.005	-0.009***	-0.009***	-0.009***	-0.009***
	(0.003)	(0.025)	(0.003)	(0.003)	(0.003)	(0.003)
Cash	-0.035	-0.033	-0.035	-0.033	-0.032	
	(0.022)	(0.023)	(0.023)	(0.024)	(0.024)	
Crisis	0.043*	0.042	0.044*	0.045*	0.045*	0.044*
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.027)
Penny	-0.027	-0.028				
	(0.052)	(0.052)				
lnM2B	0.010**	0.009*	0.010**	0.011**	0.011**	0.009**
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
D1ICR	-0.024	-0.029	-0.030	-0.017	-0.017	-0.015
	(0.055)	(0.055)	(0.054)	(0.040)	(0.040)	(0.040)
D2ICR	0.020	0.020	0.021	0.023	0.023	0.035
	(0.041)	(0.042)	(0.040)	(0.039)	(0.038)	(0.040)
D4ICR	-0.057	-0.059*	-0.056	-0.057	-0.057	-0.053
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.034)
lnMV:Advisors		-0.001				
		(0.002)				
AIC	-69.3	-67.6	-71.1	-72.8	-74.8	-75.5
Observations	48	48	48	48	48	48
R^2	0.559	0.561	0.557	0.555	0.555	0.542
Adjusted R^2	0.391	0.375	0.405	0.419	0.434	0.433
Residual Std. Error	0.102 (df = 34)	0.103 (df = 33)	0.101 (df = 35)	0.100 (df = 36)	0.098 (df = 37)	0.099 (df = 38)
F Statistic	3.319*** (df = 13; 34)	3.016*** (df = 14; 33)	3.664*** (df = 12; 35)	4.077*** (df = 11; 36)	4.609*** (df = 10; 37)	4.993*** (df = 9; 38)
Note:						*p<0.1; **p<0.05; ***p<0.01

Appendix 26: Model selection, Norway - initial sample

	Dependent variable:						
	CAR (-10, -1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-0.060	-0.103	-0.040	-0.059	-0.018	-0.030	-0.033
	(0.124)	(0.153)	(0.119)	(0.120)	(0.119)	(0.117)	(0.124)
CAV	3.736***	3.785***	3.738***	3.794***	3.788***	3.858***	3.858***
	(0.991)	(0.989)	(0.946)	(0.898)	(0.895)	(0.869)	(0.918)
lnMV	0.016	0.020	0.017*	0.017	0.017	0.016	0.016
	(0.011)	(0.013)	(0.011)	(0.011)	(0.011)	(0.010)	(0.011)
lnVol	-0.018*	-0.019**	-0.020**	-0.019**	-0.018**	-0.017**	-0.015*
	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)
Foreign	0.034	0.036*	0.034	0.034	0.032	0.032	
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	
Majority	0.018	0.016					
	(0.025)	(0.025)					
Advisors	0.001	0.019	0.002	0.001	0.001	0.001	0.001
	(0.002)	(0.025)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cash	-0.023	-0.026	-0.023	-0.022	-0.015		
	(0.027)	(0.028)	(0.027)	(0.028)	(0.027)		
Crisis	-0.007	-0.009	-0.012				
	(0.025)	(0.026)	(0.026)				
Penny	0.062	0.063	0.074**	0.069*	0.066*	0.068*	0.064*
	(0.040)	(0.041)	(0.035)	(0.036)	(0.036)	(0.036)	(0.037)
lnM2B	0.004	0.004	0.004	0.004			
	(0.003)	(0.003)	(0.003)	(0.003)			
D1ICR	-0.061	-0.063*	-0.063*	-0.067*	-0.064*	-0.069**	-0.066**
	(0.037)	(0.038)	(0.036)	(0.035)	(0.034)	(0.033)	(0.027)
D2ICR	-0.054	-0.054*	-0.061*	-0.059*	-0.060*	-0.057*	-0.056*
	(0.033)	(0.032)	(0.033)	(0.033)	(0.033)	(0.032)	(0.032)
D4ICR	-0.008	-0.011	-0.013	-0.010	-0.002	0.0003	0.001
	(0.024)	(0.024)	(0.023)	(0.023)	(0.025)	(0.025)	(0.027)
lnMV:Advisors		-0.001					
		(0.002)					
AIC	-111.9	-110.1	-113.3	-115.1	-116.3	-118	-118
Observations	62	62	62	62	62	62	62
R^2	0.490	0.492	0.485	0.483	0.477	0.474	0.456
Adjusted R^2	0.352	0.341	0.359	0.370	0.374	0.383	0.374
Residual Std. Error	0.088 (df = 48)	0.088 (df = 47)	0.087 (df = 49)	0.086 (df = 50)	0.086 (df = 51)	0.085 (df = 52)	0.086 (df = 53)
F Statistic	3.545*** (df = 13; 48)	3.254*** (df = 14; 47)	3.844*** (df = 12; 49)	4.253*** (df = 11; 50)	4.650*** (df = 10; 51)	5.205*** (df = 9; 52)	5.554*** (df = 8; 53)
Note:							*p<0.1; **p<0.05; ***p<0.01

Appendix 27: Model selection, Sweden - initial sample

	Dependent variable:					
	CAR (-10, -1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.006	-0.002	-0.001	-0.005	-0.014	-0.015
	(0.125)	(0.119)	(0.119)	(0.119)	(0.123)	(0.107)
CAV	0.340	0.337	0.344^{*}	0.348^{*}	0.366^{*}	0.365^{*}
	(0.214)	(0.210)	(0.204)	(0.206)	(0.218)	(0.216)
lnMV	0.004	0.004	0.004	0.005	0.005	0.005
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
lnVol	0.0001	-0.00002	-0.0004	-0.001	-0.0001	
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	
Foreign	0.021	0.021	0.021	0.020		
	(0.020)	(0.020)	(0.020)	(0.019)		
Majority	0.005					
	(0.021)					
Advisors	0.060^{**}	0.060^{**}	0.059^{**}	0.059^{**}	0.063^{**}	0.063^{**}
	(0.025)	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)
Cash	-0.005	-0.005				
	(0.019)	(0.019)				
Crisis	-0.056^{**}	-0.056^{**}	-0.056^{***}	-0.057^{**}	-0.058^{***}	-0.058^{***}
	(0.023)	(0.022)	(0.022)	(0.022)	(0.022)	(0.023)
Penny	-0.007	-0.007	-0.005			
	(0.033)	(0.033)	(0.034)			
lnM2B	-0.002^{***}	-0.002^{**}	-0.002^{**}	-0.002^{**}	-0.002^{**}	-0.002^{**}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
D1ICR	0.064^{*}	0.064^{*}	0.064^{*}	0.063^{*}	0.062	0.062
	(0.037)	(0.038)	(0.038)	(0.038)	(0.039)	(0.039)
D2ICR	-0.012	-0.012	-0.012	-0.013	-0.015	-0.014
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.023)
D4ICR	-0.001	0.00003	-0.001	-0.001	-0.004	-0.004
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
lnMV:Advisors	-0.004^{**}	-0.004^{**}	-0.004^{**}	-0.004^{**}	-0.004^{**}	-0.004^{**}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
AIC	-194.4	-195.5	-197.4	-200.3	-201.4	-203.4
Observations	144	144	144	144	144	144
R^2	0.174	0.173	0.173	0.173	0.168	0.168
Adjusted R^2	0.084	0.091	0.097	0.104	0.105	0.112
Residual Std. Error	0.116 (df = 129)	0.116 (df = 130)	0.116 (df = 131)	0.115 (df = 132)	0.115 (df = 133)	0.115 (df = 134)
F Statistic	1.935^{**} (df = 14; 129)	2.096^{**} (df = 13; 130)	2.282^{**} (df = 12; 131)	2.507^{***} (df = 11; 132)	2.681^{***} (df = 10; 133)	3.002^{***} (df = 9; 134)
Note:						*p<0.1; **p<0.05; ***p<0.01

Appendix 28: Model selection, Denmark - adjusted sample

	Dependent variable:					
	CAR(-10, 1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.078	0.011	-0.083	-0.142	-0.149	-0.143
	(0.241)	(0.266)	(0.235)	(0.254)	(0.251)	(0.250)
CAV	2.852^{***}	2.724^{***}	2.807^{***}	3.076^{***}	3.135^{***}	3.190^{***}
	(0.834)	(0.879)	(0.759)	(0.716)	(0.682)	(0.663)
lnMV	0.0002	-0.006	0.001	0.010	0.009	0.010
	(0.018)	(0.019)	(0.017)	(0.015)	(0.015)	(0.016)
lnVol	0.014	0.013	0.013			
	(0.010)	(0.009)	(0.009)			
Foreign	0.061	0.067	0.060	0.061	0.052	0.053
	(0.042)	(0.043)	(0.040)	(0.041)	(0.035)	(0.034)
Majority	-0.033	-0.039	-0.032	-0.018		
	(0.044)	(0.046)	(0.044)	(0.043)		
Advisors	-0.010^{***}	-0.036	-0.010^{***}	-0.008^{**}	-0.008^{***}	-0.008^{***}
	(0.003)	(0.027)	(0.003)	(0.004)	(0.003)	(0.003)
Cash	-0.014	-0.018	-0.014	-0.012	-0.013	
	(0.036)	(0.035)	(0.036)	(0.036)	(0.035)	
Crisis	0.044	0.044	0.044	0.043	0.040	0.042
	(0.029)	(0.029)	(0.029)	(0.030)	(0.029)	(0.030)
Penny	-0.016	-0.012				
	(0.062)	(0.061)				
lnM2B	-0.003	-0.002	-0.003	0.002	0.003	0.0003
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.010)
D1ICR	-0.154^{*}	-0.151^{*}	-0.159^{*}	-0.114	-0.099	-0.097
	(0.089)	(0.090)	(0.090)	(0.084)	(0.075)	(0.074)
D2ICR	-0.038	-0.040	-0.039	-0.033	-0.029	-0.028
	(0.059)	(0.057)	(0.059)	(0.061)	(0.058)	(0.059)
D4ICR	-0.077^{*}	-0.071^{*}	-0.076^{*}	-0.083^{**}	-0.081^{**}	-0.083^{**}
	(0.040)	(0.041)	(0.039)	(0.039)	(0.038)	(0.038)
lnMV:Advisors		0.002				
		(0.002)				
AIC	-37.5	-39.3	-37.8	-41.3	-42	-43.9
Observations	33	33	33	33	33	33
R^2	0.642	0.646	0.641	0.627	0.625	0.624
Adjusted R^2	0.396	0.371	0.426	0.432	0.455	0.477
Residual Std. Error	0.112 (df = 19)	0.114 (df = 18)	0.109 (df = 20)	0.108 (df = 21)	0.106 (df = 22)	0.104 (df = 23)
F Statistic	2.617^{**} (df = 13; 19)	2.348^{**} (df = 14; 18)	2.976^{**} (df = 12; 20)	3.213^{**} (df = 11; 21)	3.673^{***} (df = 10; 22)	4.240^{***} (df = 9; 23)
Note:						$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix 29: Model selection, Norway - adjusted sample

	Dependent variable:								
	CAR(-10, -1)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.129	0.104	0.127	0.172	0.185	0.157	0.163	0.142	0.198*
	(0.150)	(0.181)	(0.147)	(0.130)	(0.126)	(0.116)	(0.121)	(0.120)	(0.102)
CAV	3.281**	3.233**	3.288***	3.679***	3.838***	3.588***	3.910***	3.940***	3.945***
	(1.288)	(1.290)	(1.258)	(1.035)	(1.027)	(0.989)	(1.098)	(1.188)	(1.204)
lnMV	0.008	0.010	0.008	0.008	0.007	0.008	0.005	0.007	0.0002
	(0.008)	(0.011)	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)	(0.005)
lnVol	-0.016*	-0.017*	-0.016*	-0.020***	-0.019**	-0.019**	-0.017**	-0.017**	-0.014**
	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)
Foreign	0.019	0.019	0.018	0.014					
	(0.025)	(0.026)	(0.023)	(0.021)					
Majority	0.025	0.025	0.025						
	(0.032)	(0.032)	(0.032)						
Advisors	0.003	0.011	0.003	0.003	0.003	0.003	0.002		
	(0.002)	(0.026)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)		
Cash	-0.034	-0.036	-0.034	-0.033	-0.030	-0.033			
	(0.025)	(0.024)	(0.025)	(0.024)	(0.025)	(0.023)			
Crisis	-0.047	-0.047	-0.046*	-0.047*	-0.044*	-0.047*	-0.044*	-0.041*	-0.032
	(0.029)	(0.030)	(0.025)	(0.026)	(0.025)	(0.025)	(0.026)	(0.025)	(0.025)
Penny	0.029	0.028	0.028	0.042	0.036	0.034	0.032	0.033	
	(0.042)	(0.042)	(0.041)	(0.034)	(0.033)	(0.033)	(0.033)	(0.033)	
lnM2B	-0.0004	-0.0002							
	(0.006)	(0.006)							
D1ICR	-0.027	-0.027	-0.027	-0.035	-0.037				
	(0.036)	(0.036)	(0.033)	(0.032)	(0.030)				
D2ICR	0.002	0.002	0.002	-0.008	-0.007				
	(0.031)	(0.031)	(0.031)	(0.029)	(0.028)				
D4ICR	-0.011	-0.012	-0.012	-0.023	-0.024				
	(0.026)	(0.026)	(0.025)	(0.021)	(0.022)				
lnMV:Advisors		-0.001							
		(0.002)							
AIC	-103.2	-101.2	-105.2	-106.2	-107.8	-112.2	-112.4	-113.9	-115
Observations	52	52	52	52	52	52	52	52	52
R^2	0.467	0.468	0.467	0.458	0.453	0.436	0.416	0.410	0.401
Adjusted R^2	0.285	0.266	0.303	0.309	0.320	0.346	0.338	0.346	0.350
Residual Std. Error	0.079 (df = 38)	0.080 (df = 37)	0.078 (df = 39)	0.077 (df = 40)	0.077 (df = 41)	0.075 (df = 44)	0.076 (df = 45)	0.075 (df = 46)	0.075 (df = 47)
F Statistic	2.565** (df = 13; 38)	2.323** (df = 14; 37)	2.851*** (df = 12; 39)	3.070*** (df = 11; 40)	3.400*** (df = 10; 41)	4.859*** (df = 7; 44)	5.345*** (df = 6; 45)	6.402*** (df = 5; 46)	7.859*** (df = 4; 47)
Note:									*p<0.1; **p<0.05; ***p<0.01

Appendix 30: Model selection, Sweden - adjusted sample

	Dependent variable:						
	CAR (-10, -1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.140	-0.045	-0.026	-0.018	-0.004	-0.023	-0.082
	(0.109)	(0.148)	(0.138)	(0.139)	(0.138)	(0.143)	(0.135)
CAV	0.297	0.307	0.295	0.289	0.306	0.313	0.307
	(0.211)	(0.213)	(0.207)	(0.216)	(0.207)	(0.222)	(0.214)
lnMV	0.003	0.017	0.016	0.015	0.013	0.014	0.011
	(0.011)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)	(0.011)
lnVol	-0.013	-0.012	-0.012	-0.011	-0.011	-0.010	
	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	
Foreign	0.045^{*}	0.036	0.035	0.036	0.034		
	(0.026)	(0.025)	(0.025)	(0.023)	(0.024)		
Majority	0.020	0.018					
	(0.026)	(0.026)					
Advisors	0.005	0.065^{**}	0.067^{**}	0.067^{**}	0.060^{**}	0.067^{**}	0.069^{**}
	(0.005)	(0.028)	(0.028)	(0.028)	(0.027)	(0.028)	(0.027)
Cash	-0.010	-0.023	-0.021	-0.022			
	(0.022)	(0.022)	(0.022)	(0.023)			
Crisis	-0.068^{**}	-0.076^{**}	-0.074^{***}	-0.074^{***}	-0.072^{***}	-0.072^{**}	-0.073^{**}
	(0.029)	(0.029)	(0.028)	(0.028)	(0.028)	(0.028)	(0.029)
Penny	0.002	0.006	0.008				
	(0.046)	(0.046)	(0.046)				
lnM2B	-0.003^{*}	-0.003^{*}	-0.003^{*}	-0.003^{*}	-0.003^{*}	-0.003^{**}	-0.003^{**}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
D1ICR	0.091^{*}	0.089^{*}	0.092^{*}	0.093^{*}	0.092^{*}	0.091^{*}	0.088^{*}
	(0.049)	(0.047)	(0.050)	(0.049)	(0.050)	(0.050)	(0.050)
D2ICR	0.011	0.003	0.006	0.007	0.006	0.001	-0.003
	(0.030)	(0.029)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
D4ICR	0.009	0.008	0.012	0.012	0.008	0.003	0.004
	(0.019)	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)	(0.019)
lnMV:Advisors		-0.004^{**}	-0.004^{**}	-0.004^{**}	-0.004^{**}	-0.004^{**}	-0.004^{**}
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
AIC	-140.9	-143.6	-145.1	-147.1	-148.2	-148.4	-148.9
Observations	116	116	116	116	116	116	116
R^2	0.198	0.230	0.226	0.226	0.220	0.208	0.198
Adjusted R^2	0.096	0.123	0.128	0.136	0.138	0.133	0.130
Residual Std. Error	0.124 (df = 102)	0.122 (df = 101)	0.121 (df = 102)	0.121 (df = 103)	0.121 (df = 104)	0.121 (df = 105)	0.121 (df = 106)
F Statistic	1.935^{**} (df = 13; 102)	2.153^{**} (df = 14; 101)	2.296^{**} (df = 13; 102)	2.508^{***} (df = 12; 103)	2.669^{***} (df = 11; 104)	2.762^{***} (df = 10; 105)	2.903^{***} (df = 9; 106)
Note:							*p<0.1; **p<0-05; ***p<0.01

Appendix 31: Model selection robustness regression, Denmark - initial sample

	Dependent variable:					
	CAR (-100, -90)					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.144	0.192	0.125	0.112	0.110	0.113
	(0.130)	(0.137)	(0.119)	(0.116)	(0.116)	(0.116)
CAV120	-0.186	-0.166	-0.164	-0.236	-0.223	-0.214
	(0.404)	(0.405)	(0.404)	(0.420)	(0.424)	(0.401)
lnMV	-0.002	-0.005	0.00005	-0.002	-0.002	-0.002
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
lnVol	-0.005	-0.008	-0.007			
	(0.008)	(0.008)	(0.007)			
Foreign	-0.071***	-0.066***	-0.070***	-0.070***	-0.069***	-0.069***
	(0.022)	(0.023)	(0.022)	(0.023)	(0.023)	(0.023)
Majority	0.013	0.008	0.013	0.006		
	(0.029)	(0.031)	(0.030)	(0.030)		
Advisors	-0.002	-0.029	-0.002	-0.003	-0.003	-0.003
	(0.003)	(0.018)	(0.003)	(0.002)	(0.002)	(0.002)
Cash	0.014	0.012	0.015	0.013	0.014	
	(0.021)	(0.021)	(0.021)	(0.021)	(0.020)	
Crisis	-0.070***	-0.068***	-0.069***	-0.069***	-0.068***	-0.066***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.022)	(0.023)
Penny	-0.014	-0.014				
	(0.036)	(0.035)				
lnM2B	-0.002	-0.0001	-0.001	-0.002	-0.002	-0.001
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
D1ICR	0.098**	0.108**	0.096**	0.076*	0.073*	0.073*
	(0.043)	(0.043)	(0.043)	(0.039)	(0.039)	(0.038)
D2ICR	0.097***	0.100***	0.098***	0.098***	0.097***	0.093***
	(0.031)	(0.031)	(0.031)	(0.032)	(0.031)	(0.032)
D4ICR	0.033	0.037	0.033	0.035	0.034	0.033
	(0.022)	(0.023)	(0.022)	(0.023)	(0.023)	(0.024)
lnMV:Advisors		0.002				
		(0.001)				
AIC	-69.3	-86.8	-89.6	-90.7	-92.6	-94.2
Observations	48	48	48	48	48	48
R^2	0.354	0.368	0.352	0.339	0.338	0.333
Adjusted R^2	0.106	0.100	0.130	0.137	0.159	0.175
Residual Std. Error	0.084 (df = 34)	0.085 (df = 33)	0.083 (df = 35)	0.083 (df = 36)	0.082 (df = 37)	0.081 (df = 38)
F Statistic	1.430 (df = 13; 34)	1.373 (df = 14; 33)	1.585 (df = 12; 35)	1.678 (df = 11; 36)	1.890* (df = 10; 37)	2.104* (df = 9; 38)
Note:						*p<0.1; **p<0.05; ***p<0.01

Appendix 32: Model selection robustness regression, Norway - initial sample

	Dependent variable:						
	CAR (-100, -90)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-0.337	-0.453*	-0.332	-0.260	-0.263	-0.253	-0.253
	(0.228)	(0.256)	(0.212)	(0.202)	(0.207)	(0.217)	(0.222)
CAV120	0.143	0.171	0.145	0.087	0.087	0.115	0.134
	(0.214)	(0.217)	(0.217)	(0.186)	(0.189)	(0.183)	(0.178)
lnMV	0.036**	0.047**	0.037**	0.037**	0.037**	0.041**	0.042**
	(0.017)	(0.021)	(0.018)	(0.019)	(0.019)	(0.018)	(0.018)
lnVol	-0.022	-0.026*	-0.023	-0.026*	-0.026*	-0.029**	-0.031**
	(0.015)	(0.016)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)
Foreign	-0.037	-0.033	-0.037	-0.036	-0.035	-0.033	
	(0.035)	(0.036)	(0.035)	(0.035)	(0.035)	(0.035)	
Majority	0.005	-0.002					
	(0.037)	(0.036)					
Advisors	-0.001	0.047	-0.001	-0.0002	-0.0001	0.001	0.001
	(0.005)	(0.039)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Cash	0.034	0.023	0.034	0.032	0.032		
	(0.047)	(0.049)	(0.047)	(0.047)	(0.047)		
Crisis	0.045	0.041	0.044				
	(0.051)	(0.052)	(0.049)				
Penny	0.019	0.022	0.022	0.039	0.040	0.042	0.049
	(0.053)	(0.052)	(0.050)	(0.054)	(0.055)	(0.056)	(0.056)
lnM2B	0.001	0.002	0.001	-0.0004			
	(0.004)	(0.004)	(0.004)	(0.005)			
D1ICR	0.081*	0.077*	0.081*	0.093**	0.093**	0.102**	0.099**
	(0.042)	(0.040)	(0.042)	(0.040)	(0.040)	(0.040)	(0.039)
D2ICR	0.107**	0.105**	0.105**	0.100**	0.100**	0.095**	0.094**
	(0.045)	(0.045)	(0.048)	(0.048)	(0.048)	(0.046)	(0.047)
D4ICR	0.042	0.033	0.041	0.029	0.028	0.024	0.023
	(0.043)	(0.041)	(0.044)	(0.046)	(0.045)	(0.043)	(0.044)
lnMV:Advisors		-0.003					
		(0.002)					
AIC	-59.6	-58.5	-61.6	-62.5	-64.5	-65.8	-65.8
Observations	62	62	62	62	62	62	62
R^2	0.241	0.252	0.240	0.227	0.227	0.218	0.206
Adjusted R^2	0.035	0.029	0.054	0.056	0.075	0.083	0.086
Residual Std. Error	0.134 (df = 48)	0.134 (df = 47)	0.132 (df = 49)	0.132 (df = 50)	0.131 (df = 51)	0.130 (df = 52)	0.130 (df = 53)
F Statistic	1.170 (df = 13; 48)	1.129 (df = 14; 47)	1.292 (df = 12; 49)	1.331 (df = 11; 50)	1.494 (df = 10; 51)	1.613 (df = 9; 52)	1.715 (df = 8; 53)
Note:							*p<0.1; **p<0.05; ***p<0.01

Appendix 33: Model selection robustness regression, Sweden - initial sample

	Dependent variable:					
	CAR(-100, -90)					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.054	0.051	0.033	0.002	-0.003	-0.079
	(0.131)	(0.129)	(0.131)	(0.117)	(0.117)	(0.090)
CAV120	0.027	0.020	0.072	0.189	0.178	-0.061
	(0.414)	(0.413)	(0.401)	(0.433)	(0.421)	(0.312)
lnMV	-0.002	-0.002	-0.001	0.003	0.004	0.003
	(0.008)	(0.008)	(0.009)	(0.007)	(0.007)	(0.007)
lnVol	-0.008	-0.008	-0.006	-0.010	-0.009	
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	
Foreign	0.014	0.015	0.017	0.013		
	(0.022)	(0.022)	(0.023)	(0.022)		
Majority	-0.004					
	(0.017)					
Advisors	-0.035	-0.036	-0.023	-0.021	-0.019	-0.015
	(0.033)	(0.033)	(0.030)	(0.029)	(0.028)	(0.026)
Cash	0.039*	0.038*				
	(0.021)	(0.022)				
Crisis	0.018	0.017	0.020	0.018	0.017	0.016
	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)
Penny	-0.025	-0.025	-0.035			
	(0.035)	(0.035)	(0.038)			
lnM2B	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
D1ICR	0.031	0.031	0.032	0.027	0.026	0.027
	(0.033)	(0.034)	(0.034)	(0.036)	(0.036)	(0.036)
D2ICR	-0.003	-0.003	-0.004	-0.008	-0.009	-0.008
	(0.024)	(0.024)	(0.024)	(0.022)	(0.022)	(0.022)
D4ICR	-0.015	-0.015	-0.008	-0.011	-0.012	-0.007
	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)	(0.017)
lnMV:Advisors	0.003	0.003	0.002	0.002	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
AIC	-211.1	-211.1	-209.5	-212	-213.5	-213.4
Observations	144	144	144	144	144	144
R^2	0.089	0.089	0.064	0.056	0.053	0.039
Adjusted R^2	-0.010	-0.002	-0.022	-0.023	-0.018	-0.025
Residual Std. Error	0.110 (df = 129)	0.110 (df = 130)	0.111 (df = 131)	0.111 (df = 132)	0.110 (df = 133)	0.111 (df = 134)
F Statistic	0.899 (df = 14; 129)	0.973 (df = 13; 130)	0.749 (df = 12; 131)	0.712 (df = 11; 132)	0.748 (df = 10; 133)	0.605 (df = 9; 134)
Note:						*p<0.1; **p<0.05; ***p<0.01

Appendix 34: Model selection robustness regression, Denmark - adjusted sample

	Dependent variable:					
	CAR(-100, -90)					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.051	0.027	0.050	0.049	0.048	0.034
	(0.160)	(0.167)	(0.155)	(0.155)	(0.152)	(0.141)
CAV120	0.051	0.087	0.051	0.054	0.011	0.082
	(0.328)	(0.325)	(0.325)	(0.318)	(0.312)	(0.322)
lnMV	-0.004	-0.002	-0.004	-0.003	-0.004	-0.005
	(0.012)	(0.013)	(0.011)	(0.010)	(0.010)	(0.009)
lnVol	0.001	0.001	0.001			
	(0.008)	(0.009)	(0.007)			
Foreign	0.026	0.024	0.026	0.026	0.018	0.016
	(0.024)	(0.025)	(0.024)	(0.025)	(0.027)	(0.027)
Majority	-0.017	-0.017	-0.017	-0.017		
	(0.031)	(0.031)	(0.030)	(0.029)		
Advisors	-0.003	0.006	-0.003	-0.003	-0.003	-0.003
	(0.002)	(0.019)	(0.002)	(0.002)	(0.002)	(0.002)
Cash	0.019	0.020	0.019	0.019	0.017	
	(0.028)	(0.029)	(0.029)	(0.028)	(0.027)	
Crisis	0.010	0.009	0.010	0.009	0.007	0.004
	(0.022)	(0.023)	(0.022)	(0.021)	(0.022)	(0.022)
Penny	-0.001	-0.001				
	(0.039)	(0.038)				
lnM2B	-0.001	-0.001	-0.001	-0.001	0.0003	0.004
	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)	(0.014)
D1ICR	0.075	0.073	0.075	0.077^{*}	0.091^{**}	0.090^{**}
	(0.046)	(0.046)	(0.047)	(0.040)	(0.037)	(0.035)
D2ICR	0.033	0.033	0.033	0.033	0.036	0.036
	(0.045)	(0.046)	(0.045)	(0.045)	(0.044)	(0.041)
D4ICR	0.009	0.007	0.009	0.009	0.010	0.012
	(0.024)	(0.026)	(0.024)	(0.024)	(0.024)	(0.025)
lnMV:Advisors		-0.001				
		(0.001)				
AIC	-67.3	-65.4	-69.3	-71.3	-72.9	-74.4
Observations	33	33	33	33	33	33
R^2	0.360	0.363	0.360	0.360	0.353	0.343
Adjusted R^2	-0.077	-0.133	-0.023	0.025	0.059	0.085
Residual Std. Error	0.073 (df = 19)	0.075 (df = 18)	0.071 (df = 20)	0.069 (df = 21)	0.068 (df = 22)	0.067 (df = 23)
F Statistic	0.824 (df = 13; 19)	0.731 (df = 14; 18)	0.939 (df = 12; 20)	1.075 (df = 11; 21)	1.200 (df = 10; 22)	1.332 (df = 9; 23)
Note:						*p<0.1; **p<0.05; ***p<0.01

Appendix 35: Model selection robustness regression, Norway - adjusted sample

	Dependent variable:

	CAR(-100, -90)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	-0.144	-0.132	-0.109	-0.155	-0.128	-0.118	-0.119	-0.092	-0.129
	(0.224)	(0.235)	(0.223)	(0.211)	(0.214)	(0.203)	(0.212)	(0.192)	(0.194)
CAV120	0.268	0.267	0.275	0.274	0.260	0.240	0.255	0.248	0.252
	(0.213)	(0.212)	(0.216)	(0.216)	(0.198)	(0.207)	(0.185)	(0.194)	(0.196)
lnMV	0.017	0.016	0.018	0.016	0.013	0.014	0.011	0.008	0.013
	(0.015)	(0.018)	(0.017)	(0.016)	(0.016)	(0.018)	(0.018)	(0.017)	(0.017)
lnVol	-0.010	-0.010	-0.010	-0.006	-0.004	-0.006	-0.004	-0.004	-0.006
	(0.013)	(0.013)	(0.013)	(0.010)	(0.012)	(0.013)	(0.013)	(0.013)	(0.014)
Foreign	0.026	0.026	0.030	0.032					
	(0.036)	(0.036)	(0.036)	(0.035)					
Majority	-0.031	-0.030	-0.030						
	(0.044)	(0.044)	(0.044)						
Advisors	-0.002	-0.006	-0.002	-0.002	-0.002	-0.001	-0.002		
	(0.003)	(0.046)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)		
Cash	-0.041	-0.040	-0.037	-0.034	-0.030	-0.040			
	(0.039)	(0.041)	(0.037)	(0.034)	(0.033)	(0.037)			
Crisis	0.033	0.033	0.028	0.034	0.035	0.018	0.019	0.015	0.010
	(0.040)	(0.040)	(0.037)	(0.043)	(0.043)	(0.040)	(0.040)	(0.040)	(0.040)
Penny	0.017	0.017	0.026	0.008	-0.006	-0.018	-0.020	-0.021	
	(0.042)	(0.042)	(0.043)	(0.035)	(0.034)	(0.031)	(0.032)	(0.031)	
lnM2B	0.008	0.008							
	(0.010)	(0.010)							
D1ICR	-0.100	-0.099	-0.092	-0.088	-0.086				
	(0.068)	(0.066)	(0.065)	(0.067)	(0.071)				
D2ICR	-0.056	-0.056	-0.052	-0.039	-0.037				
	(0.043)	(0.042)	(0.041)	(0.037)	(0.038)				
D4ICR	-0.025	-0.024	-0.018	-0.004	-0.004				
	(0.033)	(0.034)	(0.030)	(0.028)	(0.028)				
lnMV:Advisors		0.0003							
		(0.003)							
AIC	-56.6	-54.6	-58.1	-59.5	-60.5	-63.9	-64.8	-66.5	-68.3
Observations	52	52	52	52	52	52	52	52	52
R^2	0.154	0.154	0.147	0.136	0.120	0.076	0.055	0.049	0.047
Adjusted R^2	-0.135	-0.166	-0.115	-0.101	-0.094	-0.071	-0.071	-0.054	-0.034
Residual Std. Error	0.123 (df = 38)	0.125 (df = 37)	0.122 (df = 39)	0.121 (df = 40)	0.121 (df = 41)	0.120 (df = 44)	0.120 (df = 45)	0.119 (df = 46)	0.118 (df = 47)
F Statistic	0.533 (df = 13; 38)	0.483 (df = 14; 37)	0.561 (df = 12; 39)	0.575 (df = 11; 40)	0.560 (df = 10; 41)	0.514 (df = 7; 44)	0.435 (df = 6; 45)	0.478 (df = 5; 46)	0.576 (df = 4; 47)
Note:									*p<0.1; **p<0.05; ***p<0.01

Appendix 36: Model selection robustness regression, Sweden - adjusted sample

	Dependent variable:						
	CAR(-100,-90)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.193	0.227	0.213	0.159	0.163	0.171	0.064
	(0.119)	(0.153)	(0.150)	(0.134)	(0.136)	(0.139)	(0.112)
CAV120	0.312	0.293	0.243	0.217	0.217	0.204	-0.017
	(0.560)	(0.572)	(0.569)	(0.600)	(0.597)	(0.592)	(0.602)
lnMV	-0.007	-0.009	-0.009	0.0004	-0.0001	-0.0004	-0.005
	(0.013)	(0.013)	(0.012)	(0.008)	(0.008)	(0.008)	(0.008)
lnVol	-0.009	-0.009	-0.009	-0.017	-0.017	-0.017	
	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	
Foreign	-0.010	-0.008	-0.008	-0.015	-0.016		
	(0.023)	(0.021)	(0.021)	(0.018)	(0.019)		
Majority	-0.014	-0.013					
	(0.016)	(0.015)					
Advisors	0.004	-0.007	-0.009	-0.008	-0.009	-0.013	-0.012
	(0.004)	(0.027)	(0.027)	(0.027)	(0.028)	(0.030)	(0.030)
Cash	-0.013	-0.011	-0.012	-0.006			
	(0.015)	(0.014)	(0.014)	(0.014)			
Crisis	0.021	0.022	0.021	0.021	0.021	0.021	0.021
	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Penny	-0.054	-0.054	-0.056				
	(0.051)	(0.051)	(0.051)				
lnM2B	-0.001	-0.001	-0.001	-0.0004	-0.0004	-0.0003	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
D1ICR	0.011	0.012	0.010	0.003	0.003	0.003	-0.001
	(0.029)	(0.029)	(0.029)	(0.026)	(0.027)	(0.027)	(0.027)
D2ICR	-0.035	-0.034	-0.036	-0.037	-0.037	-0.035	-0.039
	(0.031)	(0.030)	(0.030)	(0.030)	(0.029)	(0.029)	(0.032)
D4ICR	-0.001	-0.0004	-0.003	-0.004	-0.005	-0.003	0.0002
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
lnMV:Advisors		0.001	0.001	0.001	0.001	0.001	0.001
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
AIC	-186.9	-185.1	-186.7	-186.3	-188.3	-189.7	-185.5
Observations	116	116	116	116	116	116	116
R^2	0.105	0.107	0.104	0.085	0.084	0.080	0.029
Adjusted R^2	-0.009	-0.017	-0.011	-0.022	-0.013	-0.007	-0.053
Residual Std. Error	0.101 (df = 102)	0.102 (df = 101)	0.101 (df = 102)	0.102 (df = 103)	0.101 (df = 104)	0.101 (df = 105)	0.104 (df = 106)
F Statistic	0.918 (df = 13; 102)	0.861 (df = 14; 101)	0.906 (df = 13; 102)	0.797 (df = 12; 103)	0.871 (df = 11; 104)	0.916 (df = 10; 105)	0.353 (df = 9; 106)
Note:							$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$