Does the current influenza activity generate stock market responses?

An analysis of US data from 1997-2015

Björn Norrby[1] & Ida Florestedt[2]

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Abstract

This paper investigates if the release of influenza activity information during influenza seasons on the US aggregate level, from 1997 to 2015, generates any stock market responses. The hypothesis is that certain companies (i.e. heath insurance companies/pharmacies) might disadvantage/advantage from an unexpected mild/severe influenza season. We have tested the hypothesis by conducting event studies on historical dates when the seasonal influenza hit the US, but find no indication of influenza activity generating any stock market responses. The null hypothesis cannot be rejected on most seasons and the CAARs frequently trend in the wrong direction. Perhaps focusing on a state wise level and examining the accounting reports following an influenza season, will shed more light on where the missing costs/revenues are located. If not, perhaps the cost/revenues are too small and/or too uncertain to generate any significant stock market responses. In the end, the aim with this paper is to illuminate a previously unexplored topic in the financial markets, with the hope of leaving the door a bit more open than it was before, and thereby encouraging further research on the topic.

Keywords: influenza season, influenza epidemic, event study, stock market reaction

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[1] 22949@student.hhs.se
[2] 22701@student.hhs.se

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1. Introduction

According to the efficient markets hypothesis, it is impossible to "beat the market" since stock market efficiency causes existing share prices to always reflect and incorporate all relevant information (Investopedia, LLC 2015). In this thesis, the statement's verity will be tested by investigating if information about the current influenza activity generates any stock market reactions. It is to our belief that influenza seasons affect certain companies' costs and revenues, creating an opportunity for aware traders to short and long certain shares to reflect and incorporate all relevant information into the share prices. However, if the efficient market hypothesis is correct, the share prices should already be adjusted to reflect these cost and revenues. The aim of this thesis is thus to investigate if the efficient market hypothesis is correct or if there possibly still exists an arbitrage opportunity to make money on the release of influenza activity.

Previous research has showed that when influenza activity is higher than normal, costs increases through loss of sales, paid sick leave and loss of productivity for companies whose labor and/or customers are ill. The estimated costs for the annual seasonal influenza varies depending on research study but has been estimated to be significant in most cases. A report from (Molinari, Noelle-Angelique M 2007) estimated the annual costs of the influenza to be $111.75 billion (95% confidence interval, $54.14, $191.81) ($2015). For companies selling influenza related products (i.e. pharmacies), the effects of the seasonal influenza are the opposite. The CNBC wrote in an article from 2014 (CNBC News Friday 3 Jan 2014) stating that pharmacies sales increased with 9.2% during the 2013-2014 influenza season due to an increase in sales of over-the counter medicines and tissues. The same article also wrote that Walgreens pharmacies administrated almost 1 million more flu shots during the influenza season than what they did one year earlier.

As the seasonal influenza seems to have a significant impact on some industries it is our belief that information about influenza activity would be valuable for traders. We have therefore chosen to study information provided on influenza activity in order to investigate any potential trading based on this information.

The US National Public Health Institute "The Centers of Disease Control and Prevention" (CDC) provides weekly updated information about the current influenza activity in the US. The information is provided through the influenza activity measurement "Percentage of hospitalized patients with Influenza like Illness" (ILI). Even though not all persons infected will be hospitalized, the measurement is commonly used in related research as an indicator of the overall influenza activity in US.

Receiving this information, traders become aware of the intensity of the seasonal influenza and can easily reason around what impact a severe or mild seasonal influenza will have on a specific industry/company. In order to reflect this impact they can short or long shares depending on if a company will profit or disadvantage from the current influenza activity.

This thesis aim is thus to investigate how and if influenza activity rates are used by traders. The research question is explored by looking at historical information provided on influenza activity rates (ILI-rates) and then investigating the abnormal returns on share prices during influenza epidemics. The abnormal returns are investigated through performing event studies on influenza seasons from 1997 to 2015. The event studies are made on a selection of S&P 500 companies divided into categories based on the effect the influenza is believed to have on the companies. The execution of the event studies are based on the article "Event Studies in Economics and Finance" (MacKinlay,A.Craig 1997) where abnormal returns during a specific event window are identified by estimating companies normal returns and then investigating any deviations from this return. If the influenza activity rates are used for trading we would thus expect positive or negative abnormal returns during the influenza seasons where the Influenza activity rate is very low or high, since this deviation from the average influenza intensity would be unexpected to the market.

With this thesis we hope to be able to contribute to the research on the impact of influenza epidemics on the financial markets in a way that has previously not been explored. We want to, in contrast to the research that has been made more purely on the socio economic burden associated with the influenza, rather investigate the practical financial use of knowing when these impacts will emerge. We also believe that our research question will help contribute to the research on the Efficient Market Hypothesis.

Looking at the results from our event studies we see no implications of influenza activity rates being used for trading. For most performed event studies we generate insignificant results, making it impossible to reject the null hypothesis stating that CAAR=0 during the event window. Even though we do find evidence of abnormal returns occurring during some of the influenza epidemics, the abnormal returns seem to appear randomly and to not have any connection to the presented influenza rates during that season. We draw this conclusion as negative abnormal returns occur for industries that reasonably should be positively affected during a seasonal influenza and vice versa.

Since the results did not show that the information about influenza activity generates any stock market reactions, the question thus becomes, why not? Did we do something wrong when performing the event studies? Is there possibly an arbitrage opportunity to make money on information about influenza activity? Is the cost/revenues associated with the seasonal influenza too small to affect share prices or is it perhaps too difficult to estimate the costs/revenues that will occur for the affected companies?

Personally, we believe that the reason to why we did not find any implications of influenza activity rates being used for trading is most in line with the two last possibilities (the cost/revenues being too small and/or too uncertain too estimate). This, as the previous research' estimations on cost and revenues occurring due to the seasonal influenza being inadequate, presenting numbers ranging from $3-8 billion (Liang Mao, Yang Yang, Youliang Qiu and Yan Yang 1981) up to $268.71 billion (Meltzer MI, Cox NJ, Fukuda K. 1999) ($2015).

Also, we believe that the larger numbers presented might have been overestimated, including costs, such as projected statistical life values for deaths, that possibly not fully would be reflected and incorporated into security prices on the financial markets.

For future research we thus leave an open door to investigate where these costs and revenues are shown. Our suggestion to future research is to investigate the possibility of the cost/revenues being shown in the quarterly reports after an influenza season. If not, then perhaps the impacts are too small and previous research estimations has been overestimated. If yes, do we have an arbitrage opportunity?

2. Related literature

Trading behavior based on information about influenza activity is an unexplored topic, hence there is little to none related literature on the specific topic. However, there is previous research that explores the costs associated with the seasonal influenza and on the Swine Flu pandemic in 2009. Also some articles investigates the increase in sales that some industries might experience (CNBC News Friday 3 Jan 2014). These researches become relevant for this thesis in order to understand what effect we expect to see on the financial markets during an influenza epidemic.

Many of the previous studies focus on the cost-benefits associated with vaccination against the seasonal flu (Nichol,K.L. 2009) (Bridges, Carolyn Buxton 2000) other studies focus on the cost-benefits on paid sick leave plans contra no paid sick leave (Puhani, Patrick A 2010) (Colla, Carrie H 2014). Some studies focus mainly on the direct medical costs (Fairbrother, Gerry 2010) but most of them try to split up the costs between direct and indirect costs (Molinari, Noelle-Angelique M 2007) (Mao, Liang 2012). In our case we care about both the direct medical costs and the indirect costs associated with productivity loss from work absence, working while ill (i.e., presenteeism days) and cost associated with death (using projected statistical life values).

Also, we have found a study from (Karve, Sudeep 2013) that investigates the direct and indirect costs associated with the Swine Flu in 2009. Even though, we are not particularly interested in looking into the effects of the Swine Flu, we find the presented results to be useful when trying to estimate the impact of a seasonal influenza epidemic with a similar level of severity.

The above mentioned studies' estimations of the annual average cost associated with the seasonal influenza seem to vary a lot, presenting numbers ranging from $3-8 billion (Liang Mao, Yang Yang, Youliang Qiu and Yan Yang 1981) up to $268.71 billion (Meltzer MI, Cox NJ, Fukuda K. 1999) ($2015). The great variation is due to the researches including different costs aspects and/or using different methods for estimations, which makes it difficult to know what estimations are most accurate. Consequently, in order for us to calculate the average cost associated with a seasonal influenza epidemic on the financial markets we will have to extrapolate information from all the studies and estimate the total economic burden by ourselves. This processes of estimating the cost is described in section “4. Estimating the costs associated with the seasonal influenza”.

Regarding the industries that might profit from the influenza the research, in contrast to the cost perspective, is almost non consisting, but there are articles that investigate trading strategies (Thomson Reuters Jan 21, 2013) during seasonal influenza epidemics and other articles that investigate what products are boosted in sales during an influenza epidemic (CNBC News Friday 3 Jan 2014). These articles become important for this research paper in order to understand what industries are positively affected by the influenza season and in what way. We will investigate this topic further below in the section “5. Influenza exposure depending on industry”.

3. Background

To provide an overview of the central definitions used in this research paper, the following section will present relevant background information. General information about the influenza and where information about it is released will firstly be presented. Secondly, we will look at the characteristics of the average influenza season, and lastly, we will present and reflect on the costs/revenues associated with the seasonal influenza and what industries are most likely exposed to these costs/revenues. The last two parts will be based on previous literature and conclusions being drawn from it.

3.1 What is the Influenza?

The influenza is a virus spread and a contagious illness. When discussing the influenza, one often refers to either the Pandemic Flu or the Seasonal Flu.[3] The pandemic and the seasonal influenza are different in both severity and frequency of occurring. The pandemic influenza is more severe in its nature and occurs when the influenza virus has gone through mutations and changes its structure. The virus thus becomes much more dangerous to people infected as they have no immunity for the virus and thus can be spread faster. The pandemic, compared to the seasonal influenza, is rare and only occurred three times during the 20th century; The Spanish Flu (1918), the Asian Flu (1957) and the Hong Kong Flu (1998). Our most recent pandemic influenza outbreak was the so called Swine Flu (H1N1) virus that occurred in 2009 (Metropolitan Emergency Managers Committee 2010).

The influenza virus is spread between humans and the symptoms come on quickly and result in the individual feeling too unwell to continue with their usual activities. Symptoms are usually shown about 1 to 4 days after being infected, and one can infect other about 1 day before symptoms are shown and up to 5-7 days after becoming sick. As a result one can infect other without being aware of themselves being infected (CDC 2015).

[3] In this research paper we will always spell out if we are referring to the seasonal or pandemic influenza. The word “flu” will only be used in names such as the “Swine Flu”.

3.2 How the intensity of the common flu is measured?

Influenza activity is measurement through the unit "Percentage of hospitalized patients with Influenza like Illness (ILI)". Even though, not all persons infected will be hospitalized, the measurement becomes a good indicator of the overall public influenza activity and the current ILI can be compared to the national baseline of 2% (CDC 2015). Almost all related literature on the seasonal influenza uses the ILI-rate as the base line indicator for estimating the total economic burden/spread of the influenza within a region.

3.3 Sources providing information about Influenza activity

There are two sources providing information about the current Influenza activity; The Centers of Disease Control and Prevention and Google Flu trends.

The Centers of Disease Control and Prevention (CDC) is the US National Public health institute with the mission to protect the public health. In order to accomplish its mission, CDC conducts critical science and delivers health information. The CDC provides a weekly update on the current ILI rate in the US, on both nationwide aggregate level and State level. The revealed ILI rates are based on information provided by the U.S. Outpatient Influenza-like Illness Surveillance Network (ILINet), consisting of more than 2900 outpatient health care providers in all 50 states. The influenza activity rates are compiled and released every Friday, thus making the revealed data 1-2 weeks old. CDC has been providing this information every week since 1997 (CDC 2015).

The other source providing this information is the Google Flu trends. Google Flu trends was released in 2008 and provides information about influenza activity based on aggregated Google Search Data. Google has found that people feeling ill tend to google their symptoms which make certain search queries great indicators of Influenza activity. Google Flu trends has been successful with estimating the current ILI rate, but its information have multiple times deviated from numbers delivered by CDC. This has resulted in Google Flu trends updating their models almost annually in order to make it more accurate (Google Flu Trends 2015). Due to the fact that Google Fu trends has been showing inaccurate ILI numbers several times we have chosen to not include this data in our research paper. This, as we believe that the market would find Google Flu trends ILI-rates too uncertain to base their trades on.

3.4 Characteristics of the average influenza season

By looking at all influenza seasons occurring from 1997 to 2015 we have been able to compile some of the characteristics of the average influenza season. The compiled characteristics are based on ILI-rates presented by CDC. Each year's influenza season is identified through the highest ILI-rate presented that year. The length of each influenza season has been defined as the time from when the ILI first crosses the baseline of 2%[4] until it returns back below the baseline. Presented in ***Figure 1*** and ***Graph 1*** are some of the characteristics of the average seasonal influenza. As we are interested in the characteristics of the seasonal influenza, the 2009 pandemic (Swine Flu) has been excluded. The characteristics are thus based on 17 influenza seasons from 1997-2015.

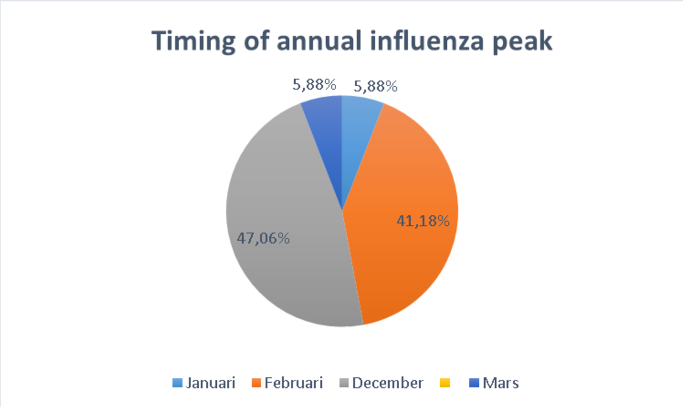
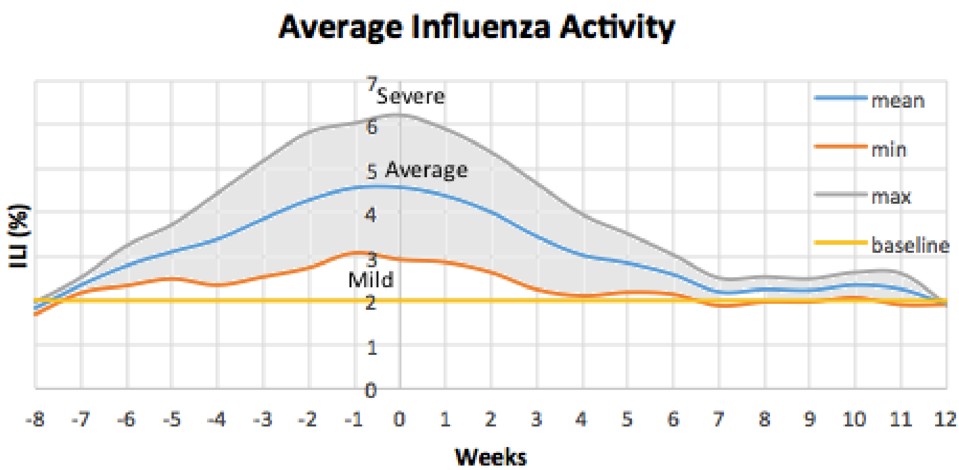


Figure 1: *The graph illustrates the distribution of the seasonal influenza peak-dates. The graph is based on 17 seasons occurring from 1997-2015.*

As can be seen from ***Figure 1***, the seasonal influenza peaks in the period December-Mars, with a majority of the seasons peaking in December. ***Graph 1*** illustrates the development curve for the average seasonal influenza. It peaks at an ILI-rate of around 4.5%, lasts for about 16 weeks and the time for it to reach its peak is approximately as long as the time it takes for it to go back to the baseline level again.

The characteristics of the average influenza season is important in order to identify unexpectedly mild or severe seasons, regarding its intensity. In this paper a mild and a severe influenza season are referred to as when the peak ILI-rate is below respectively above one standard deviation from the average influenza curve. These characteristics are important when investigating what the market is expecting of the seasonal influenza.



Graph 1: *This graph illustrates the average influenza activity curve. Approximately 68% out of all annual influenza seasons are captured between the "min" curve and the "max" curve (the grey area). If an influenza season peaks above the "max" or below the "min" curve they are regarded to be severe respectively mild seasons. The graph is based on 17 influenza seasons occurring from 1997-2015.*

[4] ILI-rates lower than 2% is regarded as normal ILI-rates according to CDC. Above 2% is regarded as an influenza epidemic.

4. Estimating the costs associated with the seasonal influenza

In order to understand what effect we expect to see on the financial markets during the seasonal influenza we have to estimate the costs associated with the influenza. As mentioned earlier, previous research cost estimations vary a lot from each other since they chose to include different types of costs. In this section we will thus discuss what costs are relevant for the scope of this research paper.

Later in this research paper, we will calculate the cumulative abnormal average returns (CAAR) for specific industry groups during the different influenza seasons. In order to do that, we will focus on the indirect costs and the direct medical costs associated with the annual influenza.

The direct medical costs will mostly affect the health insurance companies in contrast to the indirect costs that would affect a broader industry selection of companies. These costs should be reflected in the future expected cash flows when calculating the present value of security prices.

A large part of the estimated costs from previous research constitutes of the costs from projected life values from deaths. When determining whether to include these costs or not, we have to reason about if this cost should affect the pricing of company securities. If a severe non expected pandemic influenza hits the US and results in the death of a large percentage of the population, then both productivity losses in the form of lost workers and losses in consumption are expected in the future. The results thus should be a decrease in the value of the companies affected. Even though, this is an extreme and unlikely case, it demonstrates that it is reasonable to consider the costs associated with deaths when investigating the effects on the financial markets.

As we are interested in the costs that are above or below expected it becomes interesting to compare the costs of a severe/mild influenza season, with the costs of an average influenza season.

THE CDC estimates that the average number of hospitalizations and missed workdays associated with the seasonal influenza every year is estimated to 200 000 and 111 million respectively, with an attack rate from 5% to 20% (CDC 2015).

According to the most cited study (Molinari, Noelle-Angelique M 2007) within the topic of the economic burden of an average seasonal influenza hitting the US market, the total cost is \$111.75 billion (95% confidence interval, \$54.14, \$191.81). This is based on an estimated 27.18 million people (8.5% of the population) getting sick every season. The major part of these costs (about 65%) is due to death and the rest is medical costs and costs associated with work absenteeism. What is interesting to consider with this research paper is that the costs of presenteeism (costs of working while ill) are not considered in this study. A study from 2009 (Nichol,K.L. 2009) estimates that employees on average work for more than 4 days while still symptomatic with the median level of work effectiveness being 70%–75%. This implies that not all relevant costs are included and the total cost of $111.75 billion might be even higher when considering the cost for presenteeism.

In order to estimate the economic burden occurring when the US is hit by a severe (20% attack rate) influenza we investigate the costs associated with the 2009-pandemic which had an attack rate of 20.0% (approximately 60 million cases). This, as it could be useful when estimating the economic burden occurring when the US is hit by a severe influenza (20% attack rate). In a study from 2013 (Karve, Sudeep 2013) they calculated the relative higher economic burden between the regular seasonal influenza in 2005-2006 with the pandemic in the 2009. The total costs associated with influenza-related productivity loss (not including deaths) were 4.6 times higher between the two seasons. Some reasons for the costs developing faster than the estimated cases of influenza (≈2.5x cases; ≈4.6x productivity costs) are the loss of mobility to prevent the spread of the pandemic. With the 2009 pandemic being low in severity, the costs were dominated by productivity losses due to illness and social distancing interventions, such as closing of schools and workplaces (Kelso,J.K. 2013). Interestingly, the closing of schools and workplaces during the pandemic were done in a cost-beneficial purpose, whereas if the interventions had not been done, the costs would have been even larger (Mao, Liang 2013). However, the use of interventions is not a regular procedure when considering the seasonal influenza, even though they may have similar, or even higher, attack rates. This implies that the indirect costs may be larger relatively speaking for a severe seasonal influenza than they were for the pandemic in 2009. For example, another season that had similar ILI rates as the pandemic season of 2009, was the severe influenza season of 2012-2013 with adults missing an estimated 230 million workdays due to infection (CNBC News Friday, 3 Jan 2014). This makes us believe that it is possible that the costs associated with productivity losses on a severe seasonal influenza can be 4.6 times higher than a regular season.

As can be seen by the presented numbers, the differences in costs between a severe and mild season of influenza can vary very much. During a severe season, with many deaths, missed workdays, presenteeism days and hospitalizations days the costs could indeed go above $200 billion. This would comprise approximately 1% of the entire S&P 500 market capitalization (S&P Dow Jones Indices LLC April 30, 2015). Focusing only on industries with a higher exposure to the costs associated with the seasonal influenza, the relative impact should be even higher.

5. Influenza exposure depending on industry

In order to choose what industries to investigate, it becomes relevant to reflect on what industries reasonably should be most affected by the influenza. Considering that companies have different main sources of income and are dependent on different inputs, it is reasonable to think that the impact of the seasonal influenza may vary dependent on the industry. Industries can either profit from the seasonal influenza, or disadvantage from it, but the risk exposure should vary depending on industry.

The companies that profit from the seasonal influenza would reasonably do so by an increase in sales from selling influenza related products. CNBC wrote an article about the 2014 influenza and stated that pharmacy companies increased their sales with 9.2% during the most severe influenza month, thus strengthening our assumption (CNBC News January 7th 2015).

In contrast, the companies that would disadvantage from the seasonal influenza would either experience increased costs through, for example, loss of productivity, loss of sales and/or increased paid sick leave costs as a result of ill staff and/or customers.

In the same article mentioned earlier, CNBC wrote that while the pharmacy companies benefit from seasonal influenza, health insurance companies take a hit. This as the health insurance companies has to pay for medicine costs and medical costs from hospitalizations during the influenza season.

As the influenza virus spreads between humans it is reasonable that staff dense industries should be more exposed to the indirect costs associated with the seasonal influenza, as the virus can be spread faster. Also, the nature of the work should have an impact on the exposure to the indirect costs. For industries where the workers perform manual work, so called “blue collar”-industries, this exposure should be larger. This as physical work is more difficult to perform ill and also since the companies’ revenues are more dependent on the physical presence and productivity of their workers. Also, a study on vaccination rates made on occupational groups show that white-collar industries have a 35 % higher vaccination coverage compared to blue-collar industries (Caban-Martinez, Alberto J 2010), which would imply a higher risk for blue-collar workers becoming ill.

Some industries may also be affected by the seasonal influenza trough a decrease in sales as a result of their customers becoming ill. Citigroup concluded in a 2005 report a trading strategy in the event of an avian flu outbreak. The report stated that investors should short companies whose revenues come from malls, casinos, air travel, and tourism. Analysts were also bearish on labor-intensive industries and countries with "inflexible" labor laws (most of Europe) because companies not being able to easily fire workers if demand for their products fall (Thomson Reuters Jan 21, 2013). Even though this trading strategy applies for a pandemic influenza, we believe it indicates what industries are more exposed to the risk of a severe influenza season. The impact of a seasonal influenza may be smaller but the distribution of where the effects are shown should be similar.

5.1 Industry categorization

Based on this information we have categorized each industry after the impact we assume the seasonal influenza to have on that industry. The industries have been divided into three categories shown below;

1. **Broad industry selection of companies believed to be negatively affected by the seasonal influenza (NEG)** – Here we have included all industries whose business operations are believed to have inputs with a higher relative exposure to influenza illness than other industries, thus making these industries more negatively affected by the seasonal influenza compared to other industries. In order to ease the reading, this category of industries/companies will be referred to as "NEG"-industries.
2. **Companies that are assumed to be strongly positively affected by the seasonal influenza (STRONG POS)** – Here we have include companies whose business operations have a strong correlation with illness and which would be very positively affected by the seasonal influenza. In order to ease the reading, this category of industries/companies will be referred to as "STRONG POS"-companies.
3. **Companies that are assumed to be strongly negatively affected by the seasonal influenza (STRONG NEG)** - Here we have included companies whose business operations have a strong correlation with illness and which would be very negatively affected by the influenza. In order to ease the reading, this category of industries/companies will be referred to as "STRONG NEG"-companies.

Category 1: (NEG)

Construction, Manufacturing, Retail trade* *(Exception: Pharmacies and Drug Stores)	• Productivity losses due to work absteeism and preesenteism (working while ill)
Air Transportation	• Decreases in sales
Direct Health and Medical Insurance Carriers	• Increases in costs
Art, Entertainment, Recreation Accommmodation and Food Services	• Decreases in sales

***Table 1:** This table shows what industries are included in the broad selection of companies that are believed to be negatively affected by the seasonal influenza ("NEG"-industries). The right column describes what impact the seasonal influenza is assumed to have on the industry/company.*

Based on the previous information, the included companies should reasonably be negatively affected by the seasonal influenza through either productivity losses, decreases in sales or increases in costs. The included companies' business operations are believed to have inputs that have a higher exposure to the seasonal influenza than a "general" company on the market, but lower than the more narrow industry selections below.

Category 2: (STRONG POS)

CVS Pharmacies Walgreens Boots Alliance Inc.	• Increases in sales

Table 2: *This table shows what companies are included in the narrow selection of companies believed to be strongly positively affected by the seasonal influenza ("STRONG POS"-companies). The right column describes what impact the seasonal influenza is assumed to have on the companies.*

For the "STRONG POS"-companies we have included only pure-pharmacy companies. Pharmacies incorporated in other retail chains, such as Walmart Pharmacies, were excluded since the pharmacies is such a small part of their total sales and also because of the assumed negative effect that is believed to affect the other parts of their businesses. Pharmaceutical companies were also excluded, as influenza medicines are a very small part of their total revenues. Finally, Rite Aid Pharmacies was excluded because of the company being under financial distress for several of the included periods in this study. This resulted in only two companies being included for the positive selection group; CVS Pharmacies and Walgreens Boots Alliance Inc. These two companies are the major players when considering the US Pharmacy industry, encompassing approximately 42% of the total US market (Storify Aug 2014).

Category 3: (STRONG NEG)

Direct Health and Medical Insurance Carriers	• Increases in costs

Table 3*: This table shows what companies are included in the narrow selection of companies believed to be strongly negatively affected by the seasonal influenza ("STRONG NEG"-companies). The right column describes what impact the seasonal influenza is assumed to have on the companies.*

When choosing the "STRONG NEG"-companies, we made the selection based on the NAICS (North American Industry Classification System) codes representing the "Direct Health and Medical Insurance Carriers" (NAICS code: 524114). We excluded companies such as "Dental insurance carriers", that are also included in 524114, because they are not believed to be negatively affected by the seasonal influenza.

6. Hypothesis

H_0: $CAAR = 0$ (when ILI-rate is as expected)

H_1: $CAAR \neq 0$ (when ILI-rate is low or high)

The efficient market hypothesis (EMH) states that share prices always incorporate and reflect all relevant information in the market. If the EMH holds, we would thus expect that the information provided on influenza activity should be reflected in share prices as increased influenza activity may lead to an increase in costs or sales depending on the business of the companies and industries.

The seasonal influenza occurs on an annual basis and usually hits the market in the period December-February every year. The intensity of the seasonal influenza peaks around 4.5 % every year and it is therefore reasonably to say that the aggregated costs for it should be approximately equally large every season. Since the seasonal influenza has these characteristics it should be expected by the market. According to the EMH, this means that share prices already are adjusted to reflect the effects of the average seasonal influenza.

However, we should be able to find abnormal returns for the years where the influenza activity was very low or very high compared to the average seasonal influenza. This, as the effects on companies for those years would be larger or smaller than what was expected and thus the previous adjustment in share prices would not be sufficient to reflect it.[5]

Based on this, we have formulated the hypothesis showed above, which states that we expect to have abnormal returns during the influenza season were ILI-rates are very low or very high. Very low respectively very high ILI-rates are defined as mild respectively severe influenza seasons and occur when the ILI-rate peaks below respectively above one standard deviation from the average influenza curve (for further explanation of a mild and severe influenza season see ***Graph 1*** under section "3.4 Characteristics of the average influenza season").

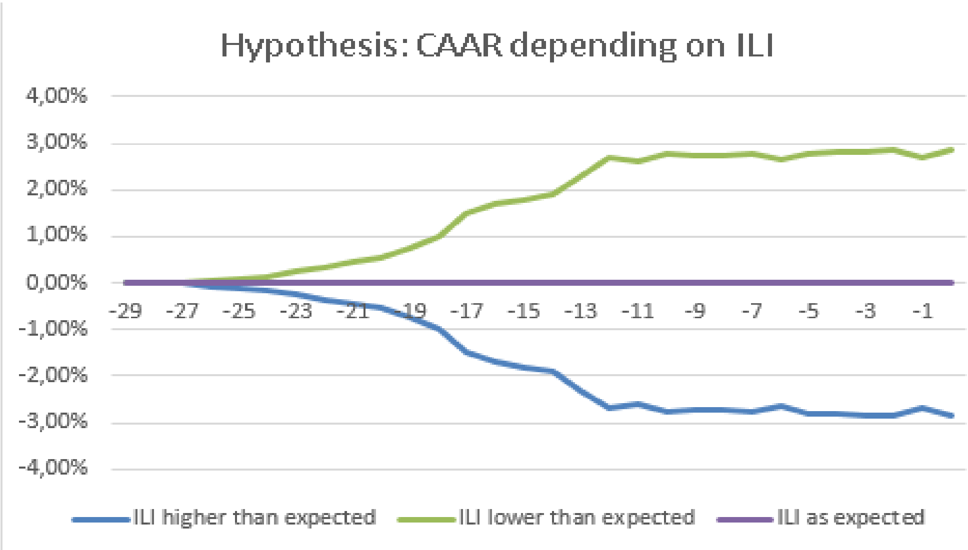
Depending on the industry and the specific influenza season's ILI-rate we expect to have positive or negative abnormal returns during the event window for the season. Companies who are positively affected by the seasonal influenza, i.e. pharmacies, would be expected to show negative abnormal returns for mild seasons and positive abnormal returns for severe

[5] One could argue that if the average seasonal influenza was expected by the market every year then, no changes would affect the share prices for the mild or severe seasons as well, due to these being averaged over time to fit the long run expected cost/profit. However, the discussion then becomes how long of a time horizon the average investor has. Furthermore, other possibilities to question if they are expected by the market are new vaccination policies and effectiveness changing over time and institutional changes over time such as paid sick leave contra no paid sick leave. Moreover, other effects such as a higher density of people with bigger cities and more cramped production within agriculture creating a faster spreading and more aggressive mutation possibilities for the influenza virus over time, may not be expected by the market. However, the scope of this research paper is to explore *if* there are any stock market reaction due to influenza activity and we will leave further discussion of how the average influenza may or may not be expected by the market to the reader.

seasons. This is as the sales would increase more than expected for the severe seasons and less than expected for the mild seasons.

For the companies who are negatively affected by the influenza we would expect the opposite, positive abnormal returns during mild seasons and negative abnormal returns during severe seasons. This is, as the costs would increase more than expected for the severe seasons and less than expected for the mild seasons.

Presented in ***Graph 3***, the estimated CAAR (Cumulated Abnormal Average Return) is illustrated based on this hypothesis. For further explanation on CAAR see section "8.1 Event study".



Graph 2: *The graph illustrates the assumed CAAR for a company who would be negatively affected by the influenza. For a company who would be positively affected by the influenza, the graph would show the opposite. Thus, the green and blue line would switch places. The x-axis shows days, and the y-axis shows the CAAR (Cumulated Abnormal Average Returns) in %. For further explanations on CAAR see section "8.1 Event study".*

7. Data

For this research paper we have limited our focus to the US market. The reason for this is that the US market has the most complete data for historical released ILI-rates.

Regarding the choice of data used for the market model proxy we decided to use index data from the S&P 500. The S&P 500 captures approximately 80% of the coverage of available market capitalization and thus becomes the most representative index for the US market (S&P Dow Jones Indices LLC April 30, 2015).

Considering that we are only focusing on the US market regarding influenza seasons, we want major companies exposed to the total wideness of an influenza epidemic, affecting the entire nation. Therefore, we choose to use larger companies with the major part of their operational business in the US market, thus making the S&P 500 constituents good candidates for our event studies. All stock market data and index data are collected from the COMPUSTAT database.

The influenza activity rates have been collected from CDC's database (CDC 2015). As CDC has ILI information since 1997 we will conduct our study on the period 1997 until 2015 in order to capture as many seasons as possible. From the period 1997-2015 the US experienced 18 influenza epidemics of which 16 seasons have been included for this research. The influenza epidemics 2002-2003 and 2008-2009 has been excluded due to the market instability occurring from the internet bubble bursting in 2002 and the financial crisis in 2008. The great volatility in share prices makes it difficult to perform correct event studies for those seasons.

8. Method

In this section we lay out the empirical framework used to investigate if the release of influenza activity generates any stock market responses. First, the average seasonal influenza was calculated using historical influenza periods from 1997 to 2015. Once the average influenza curve was estimated we split up the different seasons between mild, medium and severe seasons. In this section we will estimate the trading strategy used by the market on influenza activity information. By combining the information from influenza activity and the estimated trading strategy we can locate the event window and the estimation window. We then calculate the normal and abnormal returns during the event to see if any interesting stock market responses are generated. Investigations on stock market responses are made on the "NEG"-, "STRONG POS"- and "STRONG NEG"-industry selections. Because of event-date clustering we choose to use the adjusted Z-BMP test statistic (Kolari, James W 2010) that accounts for event-induced volatility, serial correlation and cross-sectional correlation. Finally, we show our results period-wise and regarding the level of severity of the influenza.

8.1 Event study

In order to investigate the market's reaction to the release of influenza activity information we perform a so-called event study. This is done by identifying several historical periods when information about increased influenza activity were released and then studying what happens to security prices during these periods. In finance and accounting research, event studies have been applied to a variety of firm specific and economy wide events for over 50 years and is a common tool used to identify stock market responses to distinct event types. The conduction of our event study is based on the article "Event Studies in Economics and Finance" (MacKinlay,A.Craig 1997), which summarizes how an event study should be performed and potential biases done in event studies.

To identify any stock market responses during our event we first have to calculate the normal performance of the stock. MacKinlay suggest several different methods to estimate the normal performance. One of the simpler and more common used models for this is the CAPM (Capital Asset Pricing Model), specified as following:

$$E(r_i) = r_f + \alpha_i + \beta_{mkt,i}(r_{mkt} - r_f) + \varepsilon_i$$

r_i = logarithmic stock return for security i

r_f = risk free rate

α_i = performance of security i after accounting for the systematic risk

$\beta_{mkt,i}$ = measure of the systematic risk

r_{mkt} = return of the market

As a proxy for the market return we have chosen to use the S&P 500 index. The daily risk free rate is collected from the Fama/French database (Kenneth R. French 2015). As specified on his website, this is the simple daily rate that, over the number of trading days in the month, compounds to a 1-month T-Bill rate from Ibbotson and Associates, Inc.

The abnormal returns are then calculated:

$$AR_{i,t} = r_{i,t} - [r_{f,t} + \alpha_i + \beta_{mkt,i}(r_{mkt,t} - r_{f,t})]$$

$AR_{i,t}$ = abnormal return for security i on day t

$r_{f,t}$ = risk free rate on day t

α_i = performance of security i after accounting for the systematic risk on day t

$\beta_{mkt,i}$ = estimated using the CAPM

r_{mkt} = estimated using the CAPM

As MacKinlay suggests we use an estimation window of 120 days before the event window. The event window is not included in the estimation window to prevent the event from influencing the normal performance model parameter estimates. By regressing each security's excess return (security i's return on day t minus the risk free rate) with the market excess return, within the estimation window, we can estimate each security's beta and alpha. By then using these estimates in the event window we can estimate each security's normal performance during the event window. The abnormal return is then calculated by taking the actual return minus the estimated normal return for each security and day in the event window.

However, to see if there are any actual stock market responses occurring because of the event we need to test if the abnormal returns are significantly different from zero. In our case, having a long event window, we are not especially interested with each abnormal return on a stand-alone basis, but more interested in the cumulated abnormal return (CAR) during the event. The formula calculating the CAR for each security is:

$$\mathrm{CAR_i} = \sum_{\mathrm{t=T_1+1}}^{\mathrm{T_2}} \mathrm{AR_{i,t}}$$

$\mathrm{CAR_i}$ = cumulated abnormal return for security i

$\mathrm{T_1}$ = the latest day in the estimation window

$\mathrm{T_2}$ = the latest day in the event window

$\mathrm{AR_{i,t}}$ = abnormal return for security i on day t

Furthermore, there are many securities in the sample and we are interested in the total cumulated abnormal effect among all securities as a group during the entire event window. Therefore, we have to calculate the cumulated abnormal average return (CAAR). The formula for calculating the CAAR is as follows:

$$\mathrm{CAAR} = \frac{1}{N} \sum_{\mathrm{t=T_1+1}}^{\mathrm{T_2}} \mathrm{CAR_i}$$

CAAR = cumulated abnormal average return for all securities as a group during the event window

N = number of securities in the event

The hypothesis test now becomes:

$$\mathrm{H_0} = \mathrm{CAAR}$$

$$\mathrm{H_1} \neq \mathrm{CAAR}$$

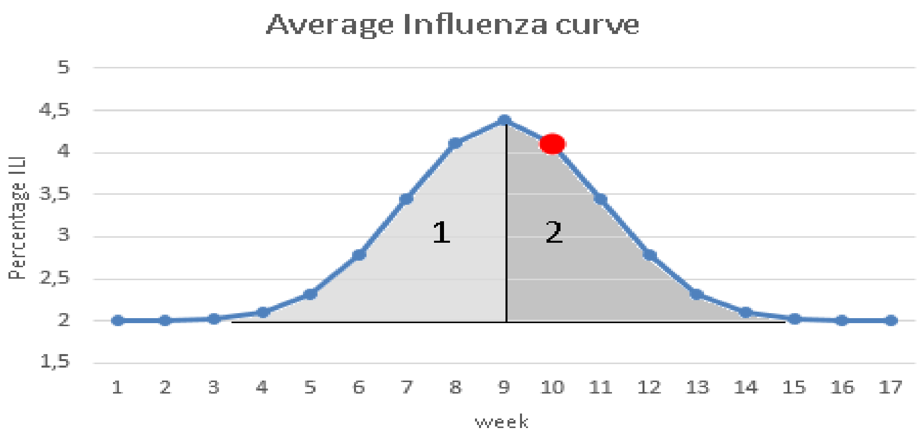
By rejecting the null hypothesis ($\mathrm{H_0}$) we can say that there indeed is a significant stock market response during the distinct event.

To test the null hypothesis we need a test statistic to test the CAAR against. Specifically in our case we have event-date clustering, because of the seasonal influenza (the event) occurring at the same time for all the firms (securities). This poses a problem leading to cross-sectional correlation of the abnormal returns and distortions from event-induced volatility changes. Cross-sectional correlation emerges when studies focuses on an event which occurs for several firms at the same day. Event-induced volatility changes, on the other hand, is a phenomenon common to many event types and also becomes a problem when events are clustered. Consequently, both issues introduce a downward bias in the standard deviation, thus overstating the t-statistic. This leads to a falsely over-rejection of the null hypothesis. There have been several attempts to address these statistical issues, with one of the latest solutions for solving them being the adjusted Z-BMP test statistic developed by (Kolari, James W 2010). This test statistic accounts for both the event-induced volatility, serial correlation and cross-sectional correlation, hence making it a good test statistic for testing our null hypothesis.[6]

[6] To see the calculations for the adjusted Z-BMP test statistic see Appendix "12.4 Adjusted Z-BMP test statistics calculations".

8.2 Event window

As information on influenza activity is released solely through the current ILI it becomes impossible for the market to know in advance how large the influenza activity will become and for how long it will last. However, looking at the characteristics of the average seasonal influenza, we have been able to form an assumption about traders reasoning. From section "3.4 Characteristics of the average influenza" we know that the average seasonal influenza curve is formed as a normal distribution curve with 6-8 weeks long tails and peaking one time in the middle, on average at an ILI-rate of 4.5%. These two characteristics together make it a reasonable assumption to say that when a lower ILI-rate compared to the previous week is revealed (red dot in ***Graph 3***), the market knows the severity of that year's seasonal influenza. This as, by looking at the first half of the seasonal influenza curve, easily can calculate the length and intensity of the later half.



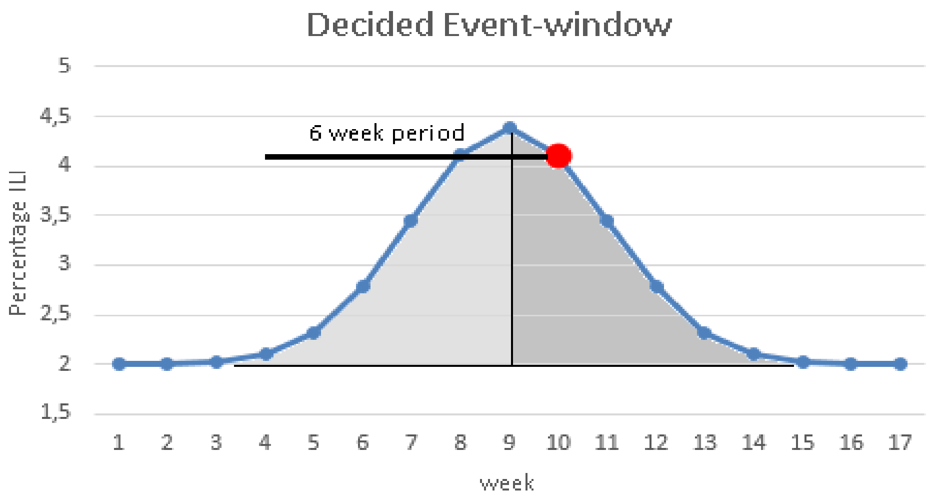
Graph 3: *This graph demonstrates at what time the market knows the severity of the seasonal influenza. The point is here shown as the red dot and is the first released lower ILI-rate compared to the previous week of the influenza period. It is possible for the traders to, by this point in time, know the severity of the whole period, as area 1 is approximately as large as area 2. (The curve is for explanatory purpose regarding the trading strategy on ILI-rates and do not represent correct numbers considering the length of the tails and height of the curve.)*

Given that our assumption is correct, it should not occur any trading on influenza activity information after the market knows that the influenza season has had its peak. This means that the last date of the event window should be set equal to the date at the red dot for all influenza seasons used in our event study.

However, the first date of the chosen event window is not as easy to decide since the ILI trading trigger may vary between traders. In order to capture all potential trades on the ILI information, we strive to make the start date as early as possible. However, longer event windows come at the cost of lower significance levels when running the regressions. The choice of the event window's length thus has to be a compromise that captures as many potential trades due to the event as possible, but without immediately generating too low significant results in our event studies.

By looking at the historical influenza seasons we have come to the conclusion that, around 6 weeks before the season hits its peak, it starts becoming obvious that the seasonal influenza is present. This as, the revealed ILI-rate increases faster compared to earlier weeks and the ILI is at least 1 percentage point above the national baseline of 2%. Going shorter than 6 weeks strengthens the risk of losing valuable information from stock market responses caused by the event.

Because of the above mentioned reasons we have decided that our event window will be set to 6 weeks (or 30 trading days) before the first revealed lower ILI point. The event window is demonstrated graphically in ***Graph 4***.



Graph 4: *This graph illustrates the method for identifying the event window for each seasonal influenza epidemic. The event window is chosen from the first reveled lower ILI rate compared to the previous week, and 6 weeks earlier. (The curve is for explanatory purpose regarding the trading strategy on ILI-rates and do not represent correct numbers considering the length of the tails and height of the curve.)*

8.3 Performed event studies

To see if there are any significant stock market responses due to the seasonal influenza we have chosen to run event studies on the three different industry/company selections mentioned in section "5.1 Industry categorization"; "NEG", "STRONG POS" and "STRONG NEG".

The three event studies will be done for each and every of the 16 included influenza seasons occurring from 1997 to 2015. The pandemic of 2009 (Swine Flu) has been included in the event studies and been classified as a severe influenza season. This as the Swine Flu was unexpected by the market due to the fact that no one new if or how large the impact would be if it hit the US. This implies that the market would react to the Swine Flu first when the ILI-rates were released of its presence, thus making it possible to accurately calculate the costs/revenues from it.

All the event studies are done on an individual basis for each season in able to investigate if there are any differences between mild, normal and severe seasons. This implies that we will run a total of 48 regressions: 16 on the “NEG”-industry selection, 16 on the “STRONG POS”-companies and 16 on the “STRONG NEG”-companies. The pandemic of 2009 (Swine Flu) is included to see if there are any differences between this special event and the other “regular” events.

8.3.1 Drop-outs of companies when running the regressions

As mentioned under the section “7. Data” we choose to look at S&P 500 companies under the period 1997 to 2015. When running the regression on the “NEG”-industries we first dropped all the companies being classified as not being part of the affected industries using the NAICS codes collected from the COMPUSTAT database. Next we dropped all companies not having 30 active trading days in the event window or not having 120 trading days in the estimation window. Finally, we winsorized the returns to the 1-percentile and 99-percentile level. Winsorization is done to limit extreme values in the statistical data to reduce the effect of possibly spurious outliers.[7] However, this is done by first checking that no returns in the event window is affected, due to the risk of losing important stock market responses occurring during the event.

After the drop-outs there are 275 to 366 companies in the “NEG”, 2 companies in the “STRONG POS” and 10 to 16 companies in the “STRONG NEG” depending on season.

9. Results

The main result in this research is that traders do not seem to trade on information about influenza activity in the US. First we present the results for the ”NEG”-industry selection, next the results for the “STRONG POS”-companies and lastly the “STRONG NEG”-companies.

9.1 Results from “NEG”-industries

After performing the event studies on the industries that were assumed to be negatively affected by the seasonal influenza, “NEG”-industries, we conclude that there are not any significant stock market responses due to the release of ILI-rates.

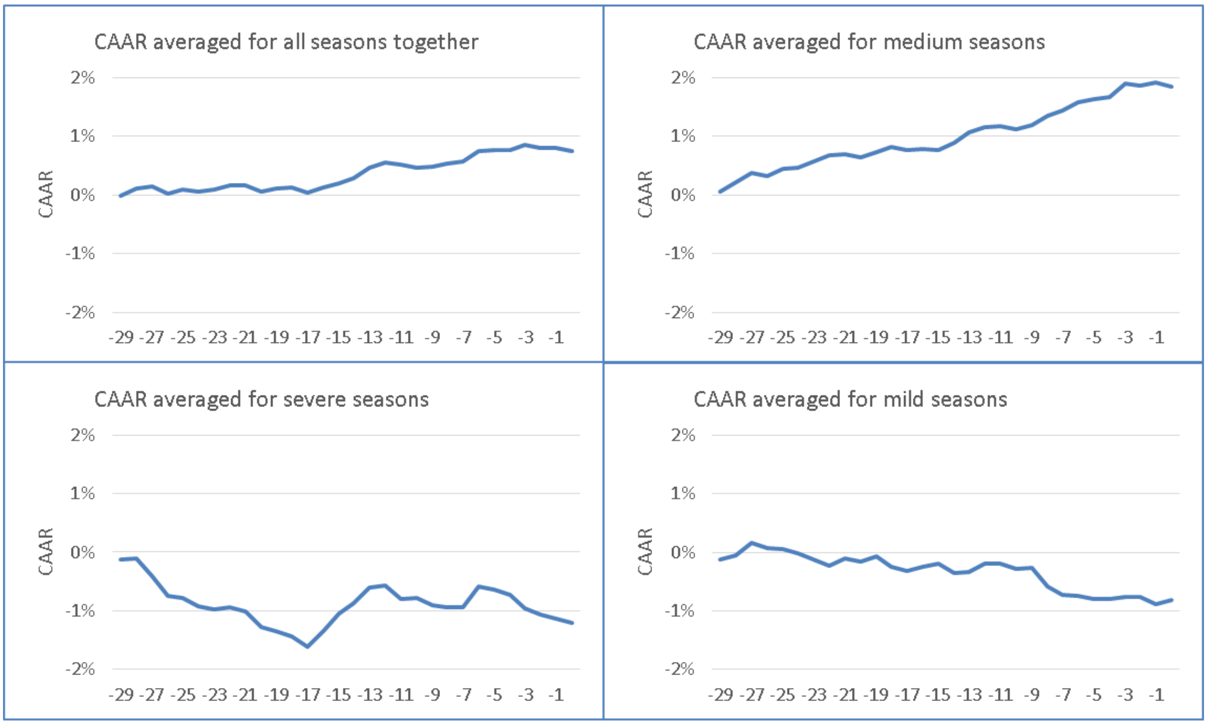
Of the 16 included seasons we have 2 mild, 10 medium[8] and 4 severe. During the mild influenza seasons the cost should be unexpected lower than the market has anticipated and

[7] For example, when checking our data we had one security price that went from 325 to 32.5 and back to 325 on three consecutive days. This generated extreme values in the return variable which were due to wrong values from the COMPUSTAT database. One could argue that trimming or trunking then would be a better choice of action, but then the risk is that we lose important information regarding volatility for a specific security, which later on is used to estimate the standard deviation in the event window. In the end, winsorizing and trimming usually generates similar results.

[8] Medium seasons are referred to as the ”regular” average influenza season. See section ”4. Characteristics of the average influenza season” for more explanations on mild, medium and severe seasons.

therefore the CAARs should be positive. The opposite should apply for the severe seasons, and the medium seasons should not generate any CAARs at all. Therefore, according to our hypothesis we want to reject the null hypothesis on 2 seasons due to positive CAARs, 4 seasons due to negative CAARs, and on 10 seasons we do not want to be able to reject it at all. However, our results show that we only can reject the null hypothesis for 1 out of 16 seasons. The season we could reject the null hypothesis for was during a mild seasons, with a rejection in the right direction.[9]

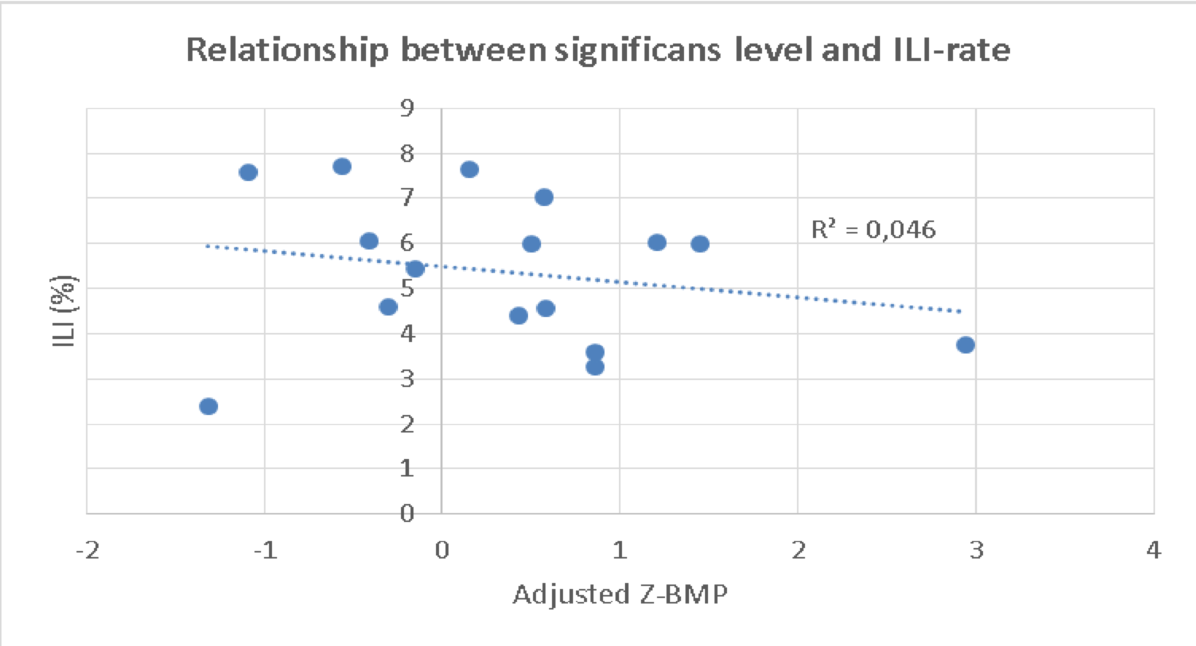
Even though the rejection rates between the seasons are not as expected we further investigate if the CAARs are generated in the right direction regarding if the season were mild, medium or severe. As shown in ***Graph 5***, the average CAAR for all the 16 seasons combined show a slight increase of less than 1%. This implies that the seasonal influenza already is incorporated in the pricing of securities. However, when then looking closer between if the seasons were mild, medium or severe we conclude that the mild seasons on average have positive CAARs, with the low and severe seasons on average having negative CAARs. This implies that the release of influenza activity does not generate any stock market responses.



Graph 5: *This graph shows the results for the event studies made on the "NEG"-industries. The results are presented as average CAAR for all seasons combined, for the medium seasons, the severe seasons and the mild seasons. The averaged CAAR for all seasons combined indicates that the information of influenza activity is already incorporated in the pricing of securities. However, looking at the CAAR averaged for medium seasons we see a slight positive trend and for the mild and severe seasons we see a slight negative trend. This implies that the release of influenza activity does not generate any stock market responses.*

[9] We are only looking at the 95% level of significance when talking about rejection. Therefore, the adjusted Z-BMP test statistic must take a value of (-1.96 < adj Z-BMP < 1.96) not to be rejected, take a value of (adj Z-BMP < -1.96) to be rejected due to a negative CAAR and take a value of (1.96 < adj Z-BMP) to be rejected due to a positive CAAR.

Furthermore, to understand if there is any relation between the CAARs and the level of influenza activity released during an influenza season we plotted the adjusted Z-BMP test statistic for the CAARs corresponding to each season against the peak ILI-rate measured during that season. The higher peak ILI-rate during a season implies a higher unexpected cost during that season, which would lead to a more negative CAAR and thus a more negative value of the adjusted Z-BMP test statistic. In contrast, a lower peak ILI-rate would lead to lower unexpected costs, a more positive CAAR and thus a more positive value of the adjusted Z-BMP test statistic. The relationship between the value of the adjusted Z-BMP test statistic and the peak ILI-rate should then be a line leaning downwards from the top left corner to the bottom right corner of the graph. As shown in ***Graph 6***, the slope of the line is leaning in the right direction, but the explanation value is very low, which implies further that ILI-rates are not affecting the pricing of securities.

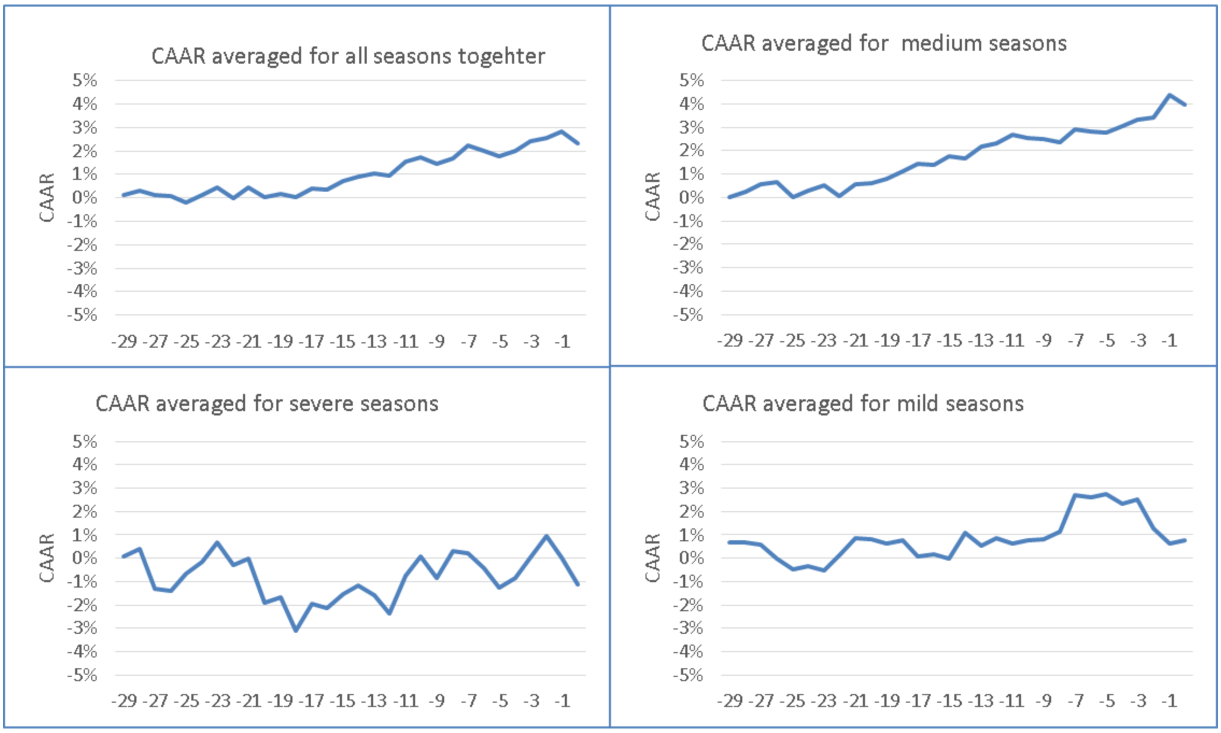


Graph 6: *This graph shows the relationship between the value of the adjusted Z-BMP test statistic and the peak ILI-rate for each season from 1997 to 2015 for the "NEG"-industries. When a mild influenza season occurs "NEG"-industries are believed to incur lower unexpected costs and therefore generate positive CAARs, in contrast to severe season, where the opposite is believed to happen. This implies positive values of the adjusted Z-BMP test statistics for mild seasons and negative values of the adjusted Z-BMP test statistics for severe seasons. We thus expect a trend in the relationship between the test statistics and the peak ILI-rates from the top left corner to the bottom right corner. Even though we have a slight trend in the right direction the explanation value of the trend is very low with a* R^2 *value of 0.046. This implies that ILI-rates are not affecting the pricing of securities.*

9.2 Results from “STRONG POS”-companies

When look at the “STRONG POS”-companies, believed to be affected in a strong positive way due to the seasonal influence, we use the same procedure as with the “NEG”-industries. However, due to “STRONG POS”-companies being believed to be effected in a positive way from increased sales during the seasonal influenza, we want the results to be in the opposite direction compared to the “NEG”-industries. Out of 16 seasons we want to see 2 negative CAARs (due to lower unexpected sales from a mild season), 4 positive CAARs (due to higher unexpected sales from a severe season) and 10 CAARs to be zero (due to nothing unexpected happening during a medium season). When looking at our results we can reject the null hypothesis for 6 out of 16 seasons. However, the rejections of the null hypothesis is during 2 severe seasons and 4 medium seasons and with the rejection being in the wrong direction for one of the severe seasons.

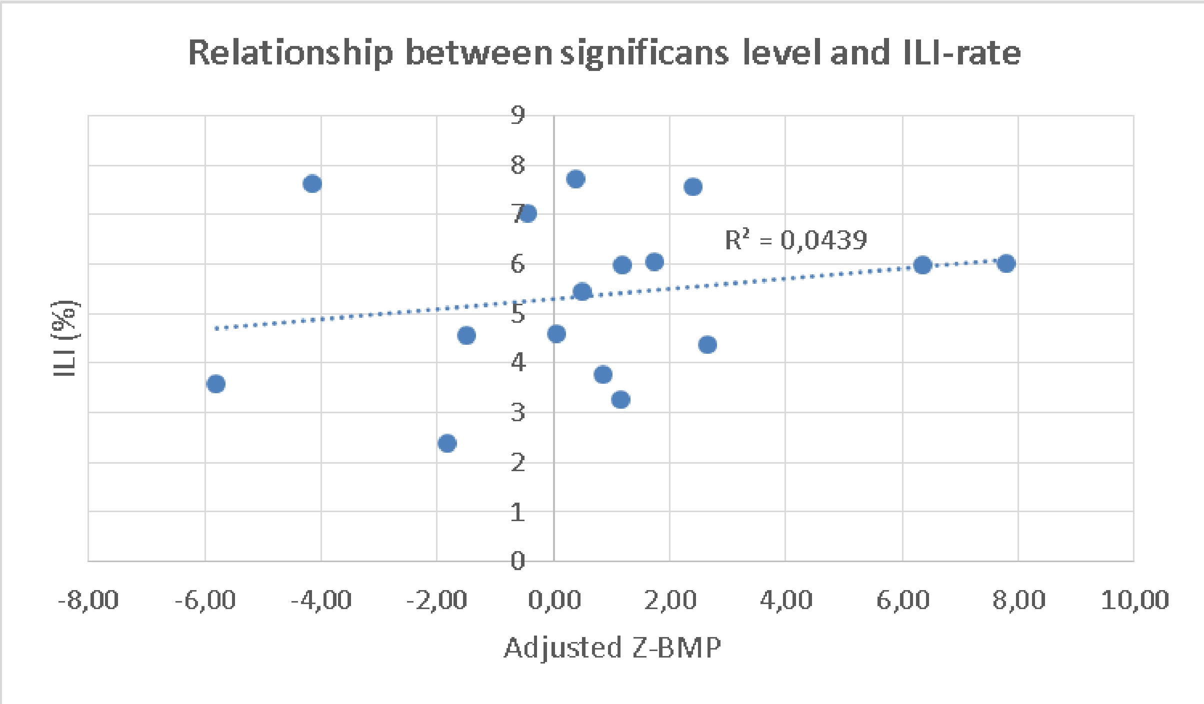
Once again, taking a closer look at the CAAR averaged over all the seasons together we actually see a slight increase of almost 3%. However, as shown in ***Graph 7***, the split up between CAARs generated during mild, medium and severe seasons indicates that the release of influenza activity has nothing to do with the stock market responses shown in the CAARs averaged for



Graph 7: *This graph shows the results for the event studies made on the “STRONG POS”-companies. The results are presented as average CAAR for all seasons combined, for the medium seasons, the severe seasons and the mild seasons. The averaged CAAR for all seasons combined indicates that the information of influenza activity does generate stock market reactions in the right direction. However, splitting up the CAARs between mild, medium and severe seasons we see that the medium seasons generate the positive CAARs and that mild and severe seasons more or less do not generate any CAARs at all. This implies that it is not the release of influenza activity that is generating the positive CAARs during medium seasons.*

all seasons together. The severe and mild seasons show CAARs being quite steady around the zero mark with only the medium influenza seasons generating steady positive CAARs.

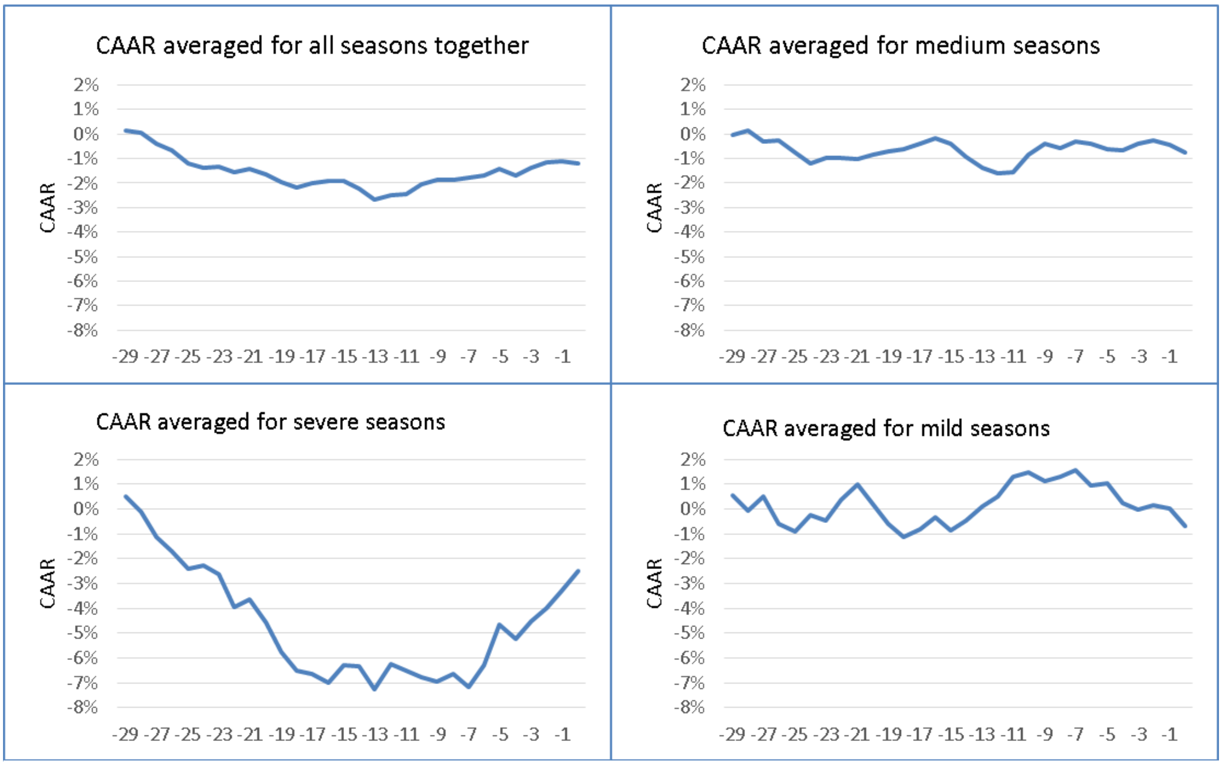
Furthermore, as done with the “NEG”-industries, we look at the relationship between the value of the adjusted Z-BMP test statistic and the peak ILI-rate for each season. We should, in contrast to the “NEG”-industries graph, expect a positive trend between the two. When an unexpected severe influenza season occurs it should generate unexpected increases in sales for the “STRONG POS”-companies and therefore generate positive CAARs, hence giving positive values of the adjusted Z-BMP test statistic, with the opposite occurring for an unexpected mild influenza season. As seen in ***Graph 8***, we in fact see a slight positive relation between the two, however, the explanation value is, as it was with the “NEG”-industries, also here very low. This implies further that ILI-rates are not affecting the pricing of securities.



Graph 8: *This graph shows the relationship between the value of the adjusted Z-BMP test statistic and the peak ILI-rate for each season from 1997 to 2015 for “STRONG POS”-companies. When a mild influenza season occurs “STRONG POS”-companies are believed to have lower unexpected sales and therefore generate negative CAARs, in contrast to severe season, where the opposite is believed to happen. This implies negative values of the adjusted Z-BMP test statistics for mild seasons and positive values of the adjusted Z-BMP test statistics for severe seasons. We thus expect a trend in the relationship between the test statistics and the peak ILI-rates from the bottom left corner to the top right corner. Even though we have a slight trend in the right direction the explanation value of the trend is very low with a* R^2 *value of 0.0439. This implies that ILI-rates are not affecting the pricing of securities.*

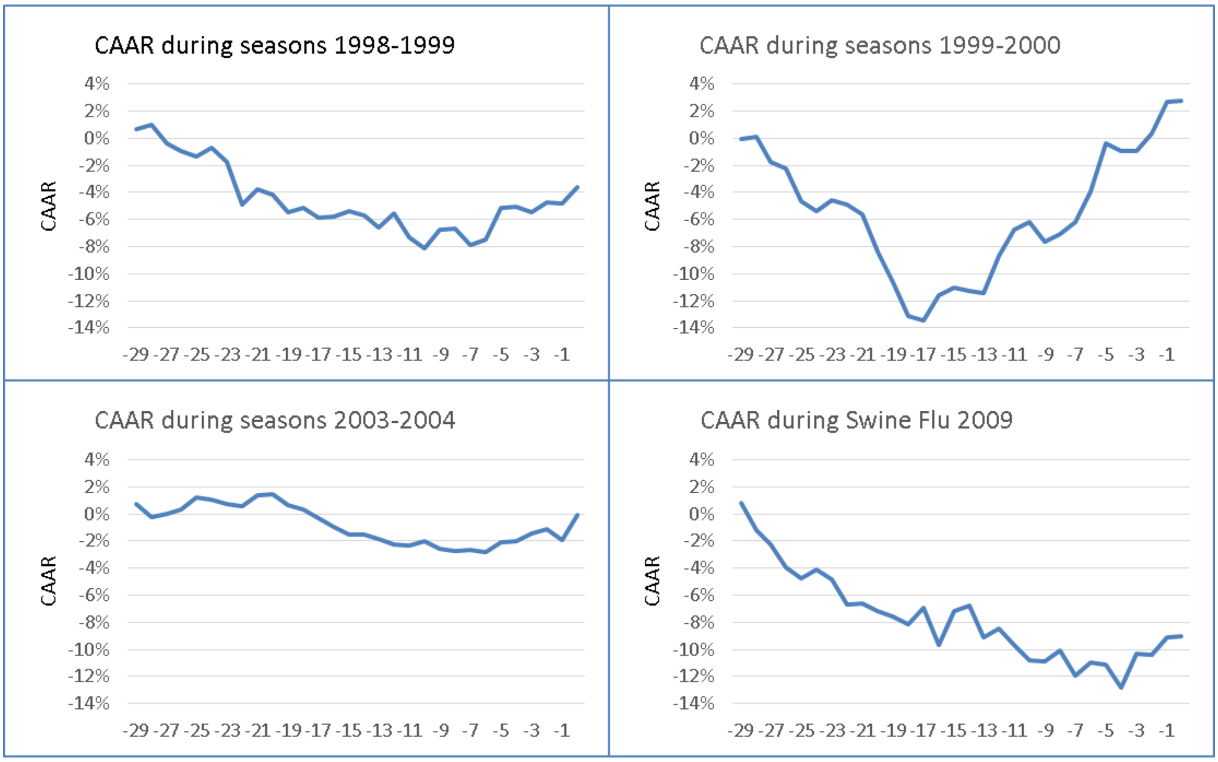
9.2 Results from "STRONG NEG"-companies

Lastly the results from the "STRONG NEG"-companies, that are the companies believed to be affected in a strong negative way due to the seasonal influenza, show that we only have 1 out of 16 seasons where the null hypothesis can be rejected. This was for a medium season that showed a positive CAAR. According to our hypothesis we want to see 2 positive CAARs (due to lower unexpected costs from a mild season), 4 negative CAARs (due to higher unexpected costs from a severe season) and 10 CAARs to be zero (due to nothing unexpected happening during a medium season). Looking further at the CAARs averaged for all seasons together we see a slight negative trend of 1% to 2% (see ***Graph 9***). However, showing the averaged CAARs split into mild, medium and severe seasons we do see a big negative trend for the severe seasons, as proposed by our hypothesis. On the other hand, the mild seasons do not show any trend what so ever and the CAARs are quite steady around the zero mark.



Graph 9: *This graph shows the results for the event studies made on the "STRONG NEG"-companies. The results are presented as average CAAR for all seasons combined, for the medium seasons, the severe seasons and the mild seasons. The averaged CAAR for all seasons combined indicates slight negative CAARs for the "STRONG NEG"-companies. However, splitting up the CAARs between mild, medium and severe seasons we see that severe seasons generate strong negative CAARs but that mild seasons more or less do not generate any CAARs at all.*

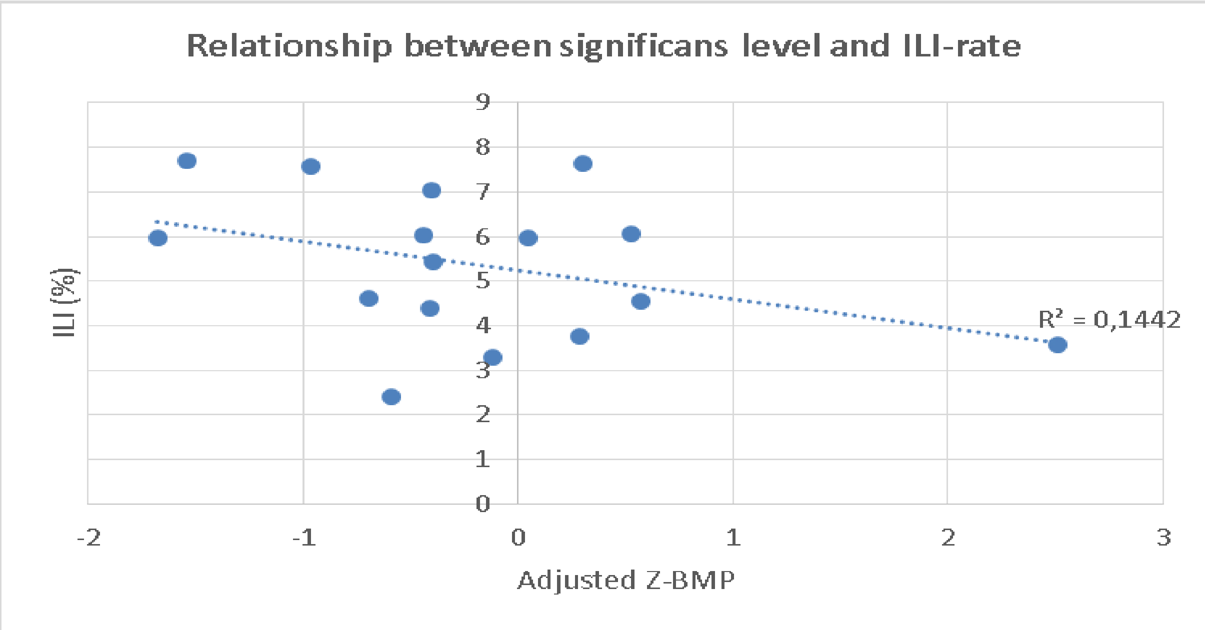
To further investigate why the severe seasons generate such negative CAARs but mild seasons have quite steady CAARs around the zero mark, we split up the four severe seasons to look at them separately as shown in ***Graph 10***. All these seasons were very severe with peak ILI-rates ranging from 7% to 8%. We see that the two seasons 1998-1999 and 1999-2000 both show large downturns that seem to recover almost fully respectively more than fully, before the influenza season has reached its peak. From section "8.2 Event window" the last day in the event window is the first day when a lower peak ILI-rate is released compared to the previous week. This means that we do not want to see a recovery effect, and instead no movement at all in the CAARs during the last days of the event window. The season of 1999-2000 is a bit special in the case that CDC reported an unexpected high count of deaths attributed to pneumonia and influenza (P&I). However, later that season they stated the P&I figures had to be interpreted with caution due to changes in the case definition that may be contributing to higher estimates of P&I mortality than in previous seasons (CDC 2015). This could have induced an overreaction and a rebound effect in the pricing of health insurance companies ("STRONG NEG"-companies). Though, that this rebound would take a positive CAAR before the season reached its' peak, is highly unlikely. This implies that we might have captured some other event during these seasons, causing the health insurance companies to drop and recover in price. Furthermore, the season of 2003-2004 did not show any significant decreases at all. Despite these results, the most interesting result is the one for the 2009 pandemic season. Here we see a steady and long decrease in the CAAR with a slight flattening in the end, exactly what our hypothesis proposes. The severity of the pandemic was large, but compared with the other seasons it was quite similar. However, the media attention surrounding the pandemic was much larger. With a regular influenza season hardly attracting any media



Graph 10: *This graph shows the CAARs for the "STRONG NEG"-companies (health insurance companies) during the most severe influenza seasons. The two seasons 1998-1999 and 1999-2000 both show big decreases in the CAARs that seem to recover almost fully respectively more than fully before the season has reached its' peak ILI-rate. The season of 2003-2004 shows small changes in the CAAR mostly surrounding the zero line. These three seasons imply that it is not the ILI-rate affecting security prices in the health insurance companies, with the two first seasons' event window probably capturing some other event during the seasonal influenza. The most interesting season is the pandemic, where we see a steady decrease in the CAAR, with a slight flattening of it in the end of the event window. The huge difference in media attention during this season, in comparison to other regular influenza seasons, might be the cause of these differences between the severe seasons' CAARs.*

coverage, the pandemic was closely monitored. This might have induced a higher level of fear in the market, with the most obvious exposed companies to the costs associated with the pandemic, taking the largest hit.

As done with the "NEG"-industries and "STRONG POS"-companies, we look at the relationship between the value of the adjusted Z-BMP test statistic and the peak ILI-rate for each season. We should expect to see a negative trend between the two. When an unexpected severe influenza season occurs it should generate unexpected increases in costs for the "STRONG NEG"-companies and therefore generate negative CAARs, hence giving negative values of the adjusted Z-BMP test statistics, with the opposite occurring for an unexpected mild influenza season. As ***Graph 11*** shows, we in fact see a slight negative trend that both is more negative and has a higher explanation value than the "NEG"-industries. However, this is mainly due to an "outlier" season. Trimming the graph from this "outlier" season makes the explanation value go from 0.1442 down to 0.0664, slightly higher than the 0.046 shown in the "NEG"-industries, but still very low. This implies that ILI-rates are not affecting the pricing of securities. [10]



Graph 11: *This graph shows the relationship between the value of the adjusted Z-BMP test statistic and the peak ILI-rate for each season from 1997 to 2015 for "STRONG NEG"-companies. When a mild influenza season occurs "STRONG NEG"-companies are believed to have lower unexpected costs and therefore generate positive CAARs, in contrast to severe season, where the opposite is believed to happen. This implies positive values of the adjusted Z-BMP test statistics for mild seasons and negative values of the adjusted Z-BMP test statistics for severe seasons. We thus expect a trend in the relationship between the test statistics and the peak ILI-rates from the top left corner to the bottom right corner. As shown by the graph we both have a more negative trend and a higher explanation value than shown in the "NEG"-industries. However, this is mainly due to an "outlier" season. Trimming the graph from this "outlier " season makes the* R^2 *go from 0.1442 down to 0.0664, slightly higher than the 0.046 shown in the "NEG"-industries, but still very low. This implies that ILI-rates are not affecting the pricing of securities.*

[10] To see all the CAARs and adjusted Z-BMP test statistic values for each influenza season on a stand-alone basis see Appendix sections "12.1 CAARs seasons 1997-2015, "NEG"-industries", "12.2 CAARs seasons 1997-2015, "STRONG POS"-companies" and "12.3 CAARs seasons 1997-2015, "STRONG NEG"-companies".

9.3 Robustness test

For robustness, we redid all 46 event studies for the "NEG"-industries, "STRONG POS"-companies and "STRONG NEG"-companies but with an extended estimation window of 180 days to investigate if our results varied in any significant way. As expected, the results did not change in any significant way, and were still very insignificant, with CAARs trending in the wrong direction, as proposed in our hypothesis.

10. Limitation and suggestions for future research

Since our results showed no indication of trading based on ILI-rates it becomes important to understand the implications of our results and what future research can contribute with to bring more understanding to this topic. It is possible that the information on ILI-rates are not used for trading, but it is also possible that we are missing something in this research paper. In order to understand the implications of our results, it is important to understand the limitations of our research to see what we potentially have missed and to understand what needs to be done next.

The following section will firstly present the limitations with our research paper and next present what future research can do to help further understand why our research paper showed the results it did.

10.1 The event studies are performed on aggregate level instead of state level

The main potential bias in our study is that our event studies are performed on aggregate US level. The aggregate US ILI-rate used in this paper is an average of ILI-rates on state level. Some states may have little to none exposure to the seasonal influenza while other states has a widespread epidemic. This means that several companies may have their operations in a state where the ILI-rate is very low, but they have been included due to high ILI-rates in the rest of the country. Even though, ILI-rates are released state-wise, there is no database that compiles where US companies have their business operations, making it impossible for us to perform event studies on state level. For this reason, some stock market reactions from several companies may happen before or after our selected event window, due to their exposure to the seasonal influenza depending on where their business operations are located.

This bias is a large issue for our research credibility, but it is important to consider that a lot of the information needed is very difficult, or in some cases impossible, to receive. Many companies' information about revenue distribution between states are not available for the public. One possibility would be to manually investigate and estimate every company's relative business exposure between states, but this would be very time consuming, and probably quite unreliable. The forming of a trading strategy on companies believed to be strongly affected from the seasonal influenza, when regarding business exposure on state level, may be a possibility, but is left for future research.

10.2 Previous research on the economic impact of the influenza is overestimated

As previously mentioned in the section "2. Related literature", the estimations of the total economic burden associated with the seasonal influenza vary a lot between different research papers. The high variations in the cost estimations indicate that they may be overestimated and that the impact of the seasonal influenza on companies may be smaller than what previous research papers have suggested. Furthermore, the inclusion of projected statistical life values for deaths in the cost estimations might possibly not fully be reflected and incorporated in the pricing of securities. If this is the case, the reason to why we see no indications of trading on ILI-rates occurring may be because of the costs/revenues being too small to show any significant impact on the pricing of securities.

10.3 The available information is too uncertain to be used for trading

Another limitation with our research, and alternative interpretation, is that the information provided is too uncertain to be used for trading. First, almost all previous research papers uses the CDC ILI data as a gold standard when estimating the costs. However, this source has potential biases of its own. First of all, only about 1800 out of the 2900 health care sentinels provide ILI surveillance data any given week. Also, each health care sentinel serves areas that vary in population size/density, which may lead to a skew in reporting. Additionally, increased media attention of an influenza season may lead to health care sentinels reporting more potential ILI cases than they would have otherwise. Furthermore, when previous research papers estimate the total number of infected cases, hospitalizations and deaths occurring each influenza season on an aggregate level, they use different types of multipliers, which makes the cost estimations even more uncertain.

Moreover, the selection of companies that are believed to either strongly profit or disadvantage from the seasonal influenza, are based on news articles or different analysts' estimations. The lacking of research based sources on these companies, in conjunction with the exposure to the seasonal influenza being highly dependent on where their business operations are located, makes the estimations of the costs/revenues for the affected companies very uncertain.

All these reasons imply that trader's may think that the information provided is not sufficient and too unreliable to be used for trading. If this is the case, the implication of this research would be that no trading occurs because it is yet not possible, since the information is too uncertain.

10.4 Suggestions for future research

As discussed previously the amount of people being affected by the market and its cost impact is significant and does affect the market. The total costs of the impact, however, is up for discussion. For future research we suggest that the costs/revenues are investigated through accounting reports released after the influenza, instead of investigating it through the financial markets during the event.

We did not find any significant stock market reactions, but as mentioned in the previous section, screening the believed strongly positively/negatively affected companies on a state-wise level, might yield more significant results. Additionally, if no stock market reactions are found during the event, the believed costs/revenues might instead be reflected in the quarterly reports following the influenza season. By comparing the expected EBITDA with the actual EBITDA, in the quarterly reports following an unexpected mild/severe influenza season, one should capture the operational costs/revenues not reflected and incorporated in the share prices during the event. If nothing is found here, it might imply that the costs/revenues are too small or that the bigger part of the costs, associated with deaths, is spread over time, making the leftover costs too small to be captured during the event.

11. Conclusion

We have examined if the release of influenza activity generated any significant stock market responses in the US during the influenza seasons from1997 to 2015. By using the historical influenza periods from 1997 to 2015 we calculated the average seasonal influenza and used this to estimate a potential trading strategy on ILI-rates released from the CDC. Our hypothesis was, that if an unexpected severe seasonal influenza hit the US, this would generate negative or positive abnormal returns depending on company. For companies exposed to the costs associated with illness we would expect to find negative abnormal returns (productivity losses due to ill workers or paid sick leave costs) and positive abnormal returns would be found for companies who would experience an increase in sales (i.e. pharmacies). Other companies, such as health insurance companies, would disadvantage from the severe season, due to higher costs associated with increased insurance payouts from illness. The opposite was proposed for an unexpected mild seasonal influenza hitting the US. The classification for a mild respectively severe influenza season was when the peak ILI-rate was below respectively above one standard deviation from the average seasonal influenza curve. We tested our hypothesis by performing event studies on all seasons from 1997 to 2015 (excluding the 2002-2003 and 2008-2009 season due to market instabilities generated from the internet bubble bursting and financial crisis).

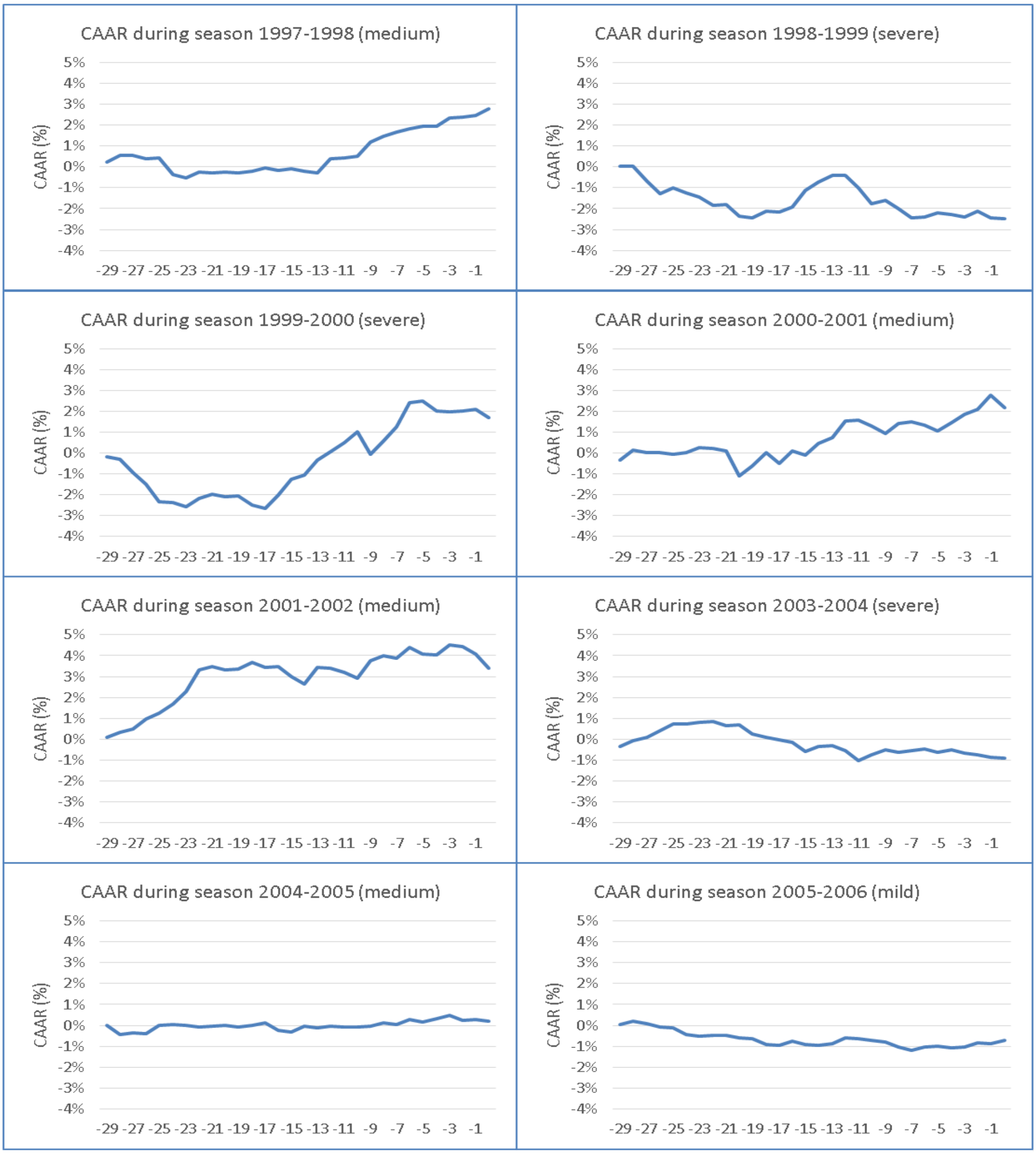
After running 48 regressions for all seasons regarding different industries/companies believed to be either positively/negatively affected from the seasonal influenza we conclude that we did not find any significant stock market responses generated from the release of influenza activity. The null hypothesis ($H_0: CAAR = 0$) was randomly rejected and many times, the abnormal returns were in the wrong direction. When looking at the relationship between the value of the test statistic for the CAARs and the peak ILI-rates for each season, we could see an indication of the believed costs/revenues being generated as proposed in our hypothesis. However, the explanation value of these findings were very low ($R^2 \approx 6\% - 8\%$). This further implies that ILI-rates were not affecting the pricing of securities.

Additionally, we found a strong negative decrease in the CAAR during the pandemic in 2009 for companies believed to be strongly negatively affected (health insurance companies) due to a severe influenza season. These companies dropped about 13% during the pandemic, but however, showed unexpected movements during other severe influenza seasons. The increased media coverage of the pandemic, in comparison with the regular seasonal influenza, might be the underlying cause for creating the large downturn in health insurance companies during this specific event. If this is the case, it implies that the media attention on the seasonal influenza might be a cause for creating stock market responses instead of the actual ILI-rates released by CDC.

For future research we suggest to conduct the event studies on a state level, by first estimating every companies' operational business exposure on state level. This, as one can more accurately account for the cost/revenues associated with seasonal influenza between companies. If no stock market responses are found on state level, then maybe they are reflected in the quarterly reports following the seasonal influenza. By comparing the expected EBITDA with the actual EBITDA, in the quarterly reports following an unexpected mild or severe influenza season, one should capture the operational costs/revenues not reflected and incorporated in the share prices during the event. If not, then perhaps the impacts are too small and previous research estimations has been overestimated. However, with this research paper we have illuminated a previously unexplored topic in the financial market, and now we leave the door slightly more open than it was before, and thereby hope to inspire further work on this topic.

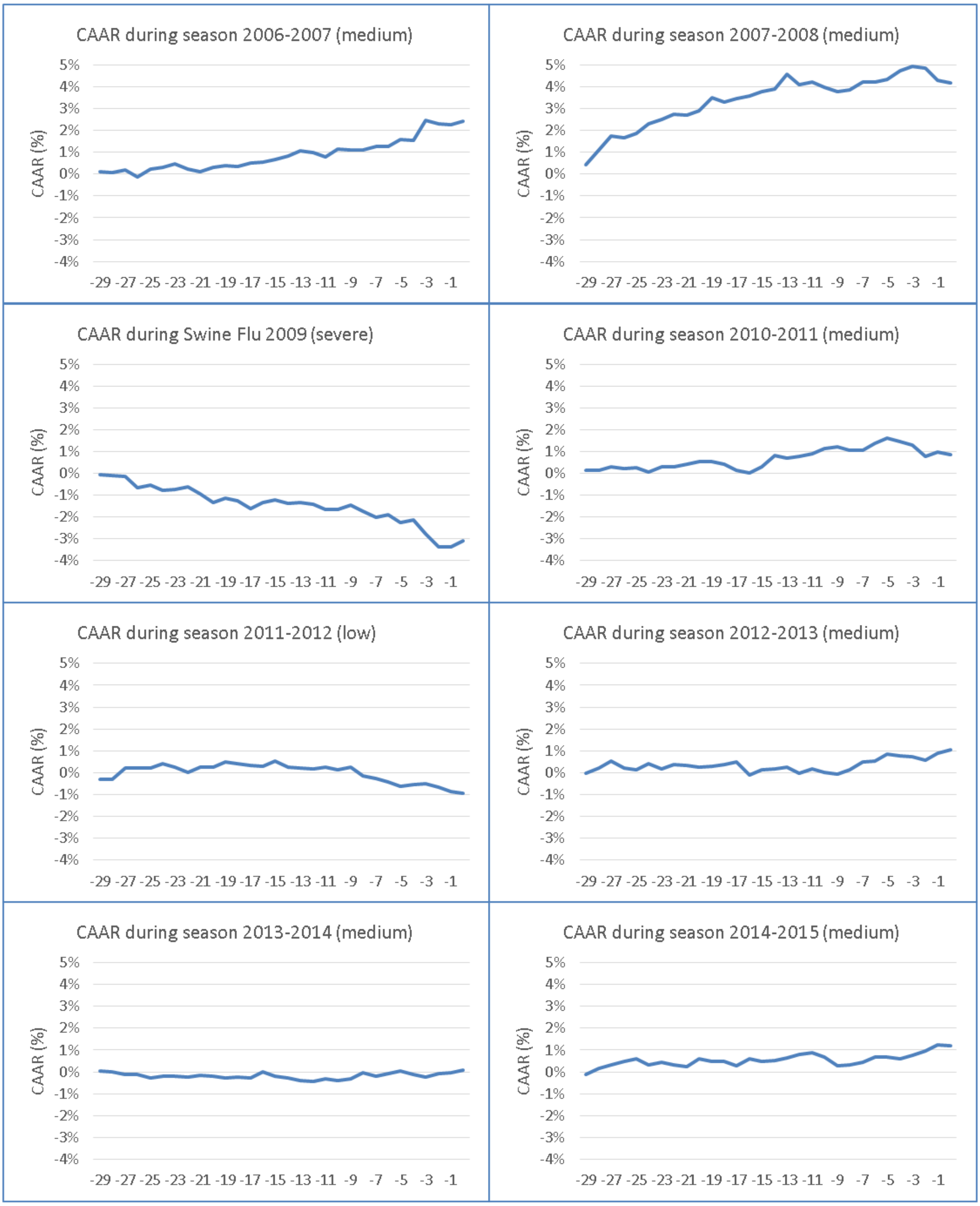
12. Appendix

12.1 CAARs season 1997-2015, "NEG"-industries



Influenza class	Medium	Severe	Severe	Medium	Medium	Severe	Medium	Low
Season	97-98	98-99	99-00	00-01	01-02	03-04	04-05	05-06
Companies	366	365	348	342	346	351	350	346
Z-BMP	2,817	-3,124	1,414	1,559	7,980	0,358	-0,3283	2,1969
average corr	0,008	0,019	0,014	0,035	0,018	0,013	0,0112	0,0158
Adjusted Z-BMP	1,450	-1,089	0,574	0,426	2,944	0,151	-0,1474	0,8574

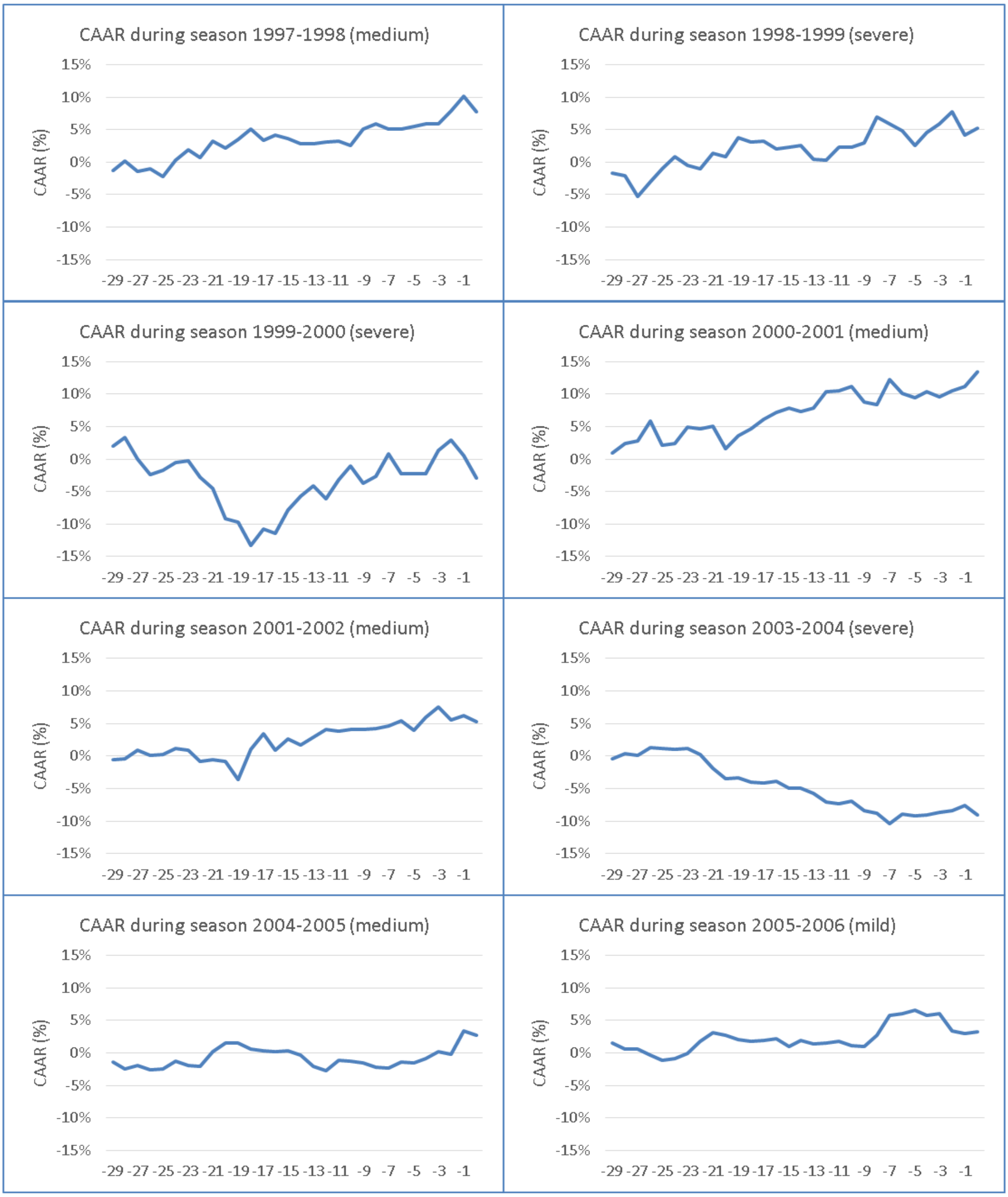
Appendix 1: *The graphs show the CAAR for each season from 1997 to 2006 for the "NEG"-companies (excluding season 2002-2003). The table shows descriptive statistics for each season's event study. The adjusted Z-BMP test statistic is calculated using the regular Z-BMP test statistic and the average of the sample cross correlation of the estimation periods abnormal returns (average corr).*



Influenza class	Medium	Medium	Severe	Medium	Low	Medium	Medium	Medium
Season	06-07	07-08	Swine Flu	10-11	11-12	12-13	13-14	14-15
Companies	333	321	305	299	293	284	278	275
Z-BMP	1,979	1,289	-1,930	1,478	-3,709	-0,956	-0,624	2,596
average corr	0,013	0,017	0,034	0,018	0,023	0,015	0,012	0,013
Adjusted Z-BMP	0,861	0,505	-0,561	0,583	-1,314	-0,412	-0,301	1,204

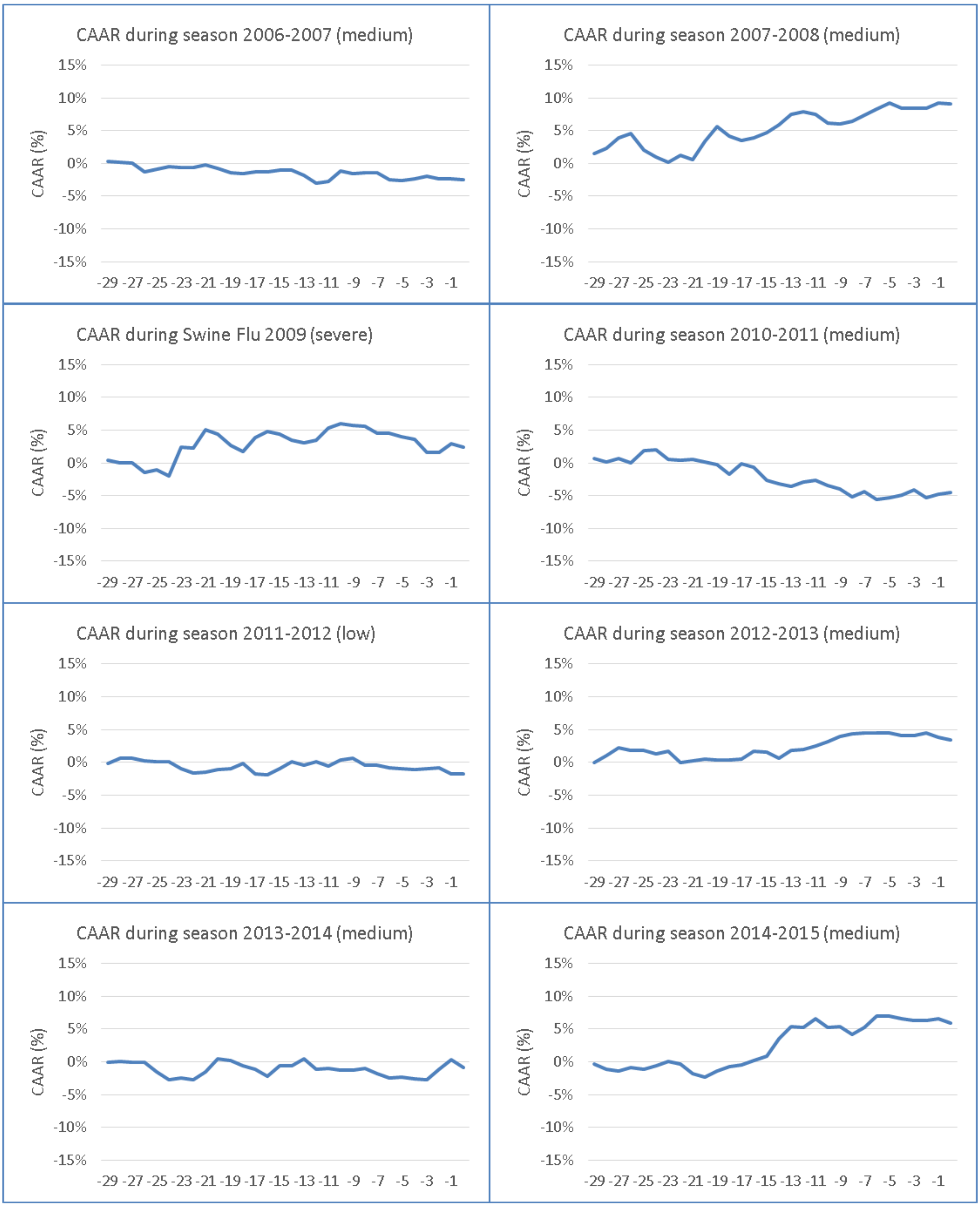
Appendix 2: *The graphs show the CAAR for each season from 2006 to 2015 for the "NEG"-companies (excluding season 2008-2009). The table shows descriptive statistics for each season's event study. The adjusted Z-BMP test statistic is calculated using the regular Z-BMP test statistic and the average of the sample cross correlation of the estimation periods abnormal returns (average corr).*

12.2 CAARs season 1997-2015, “STRONG POS”-companies



Influenza class	Medium	Severe	Severe	Medium	Medium	Severe	Medium	Low
Season	97-98	98-99	99-00	00-01	01-02	03-04	04-05	05-06
Companies	2	2	2	2	2	2	2	2
Z-BMP	7,192	4,037	-0,668	4,652	1,445	-6,278	0,6199	1,7365
average corr	0,126	0,474	0,351	0,508	0,492	0,392	0,2199	0,3889
Adjusted Z-BMP	6,338	2,412	-0,463	2,657	0,843	-4,150	0,4957	1,1518

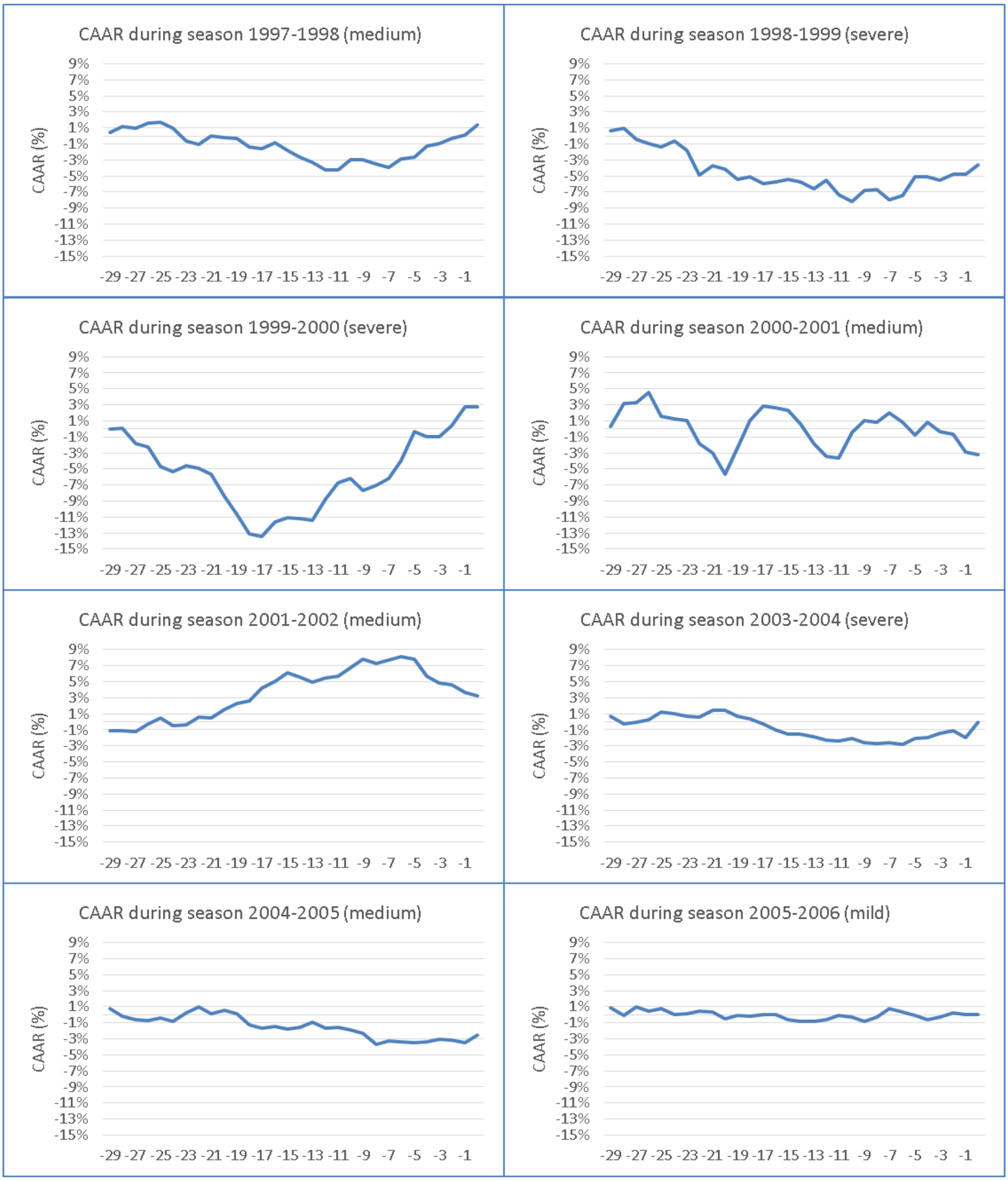
Appendix 3: *The graphs show the CAAR for each season from 1997 to 2006 for the “STRONG POS”-companies (excluding season 2002-2003). The table shows descriptive statistics for each season’s event study. The adjusted Z-BMP test statistic is calculated using the regular Z-BMP test statistic and the average of the sample cross correlation of the estimation periods abnormal returns (average corr).*



Influenza class	Medium	Medium	Severe	Medium	Low	Medium	Medium	Medium
Season	06-07	07-08	Swine Flu	10-11	11-12	12-13	13-14	14-15
Companies	2	2	2	2	2	2	2	2
Z-BMP	-14,197	2,060	0,603	-2,320	-1,904	1,621	0,054	10,781
average corr	0,714	0,509	0,450	0,417	0,042	-0,062	0,288	0,315
Adjusted Z-BMP	-5,798	1,175	0,371	-1,488	-1,826	1,725	0,040	7,783

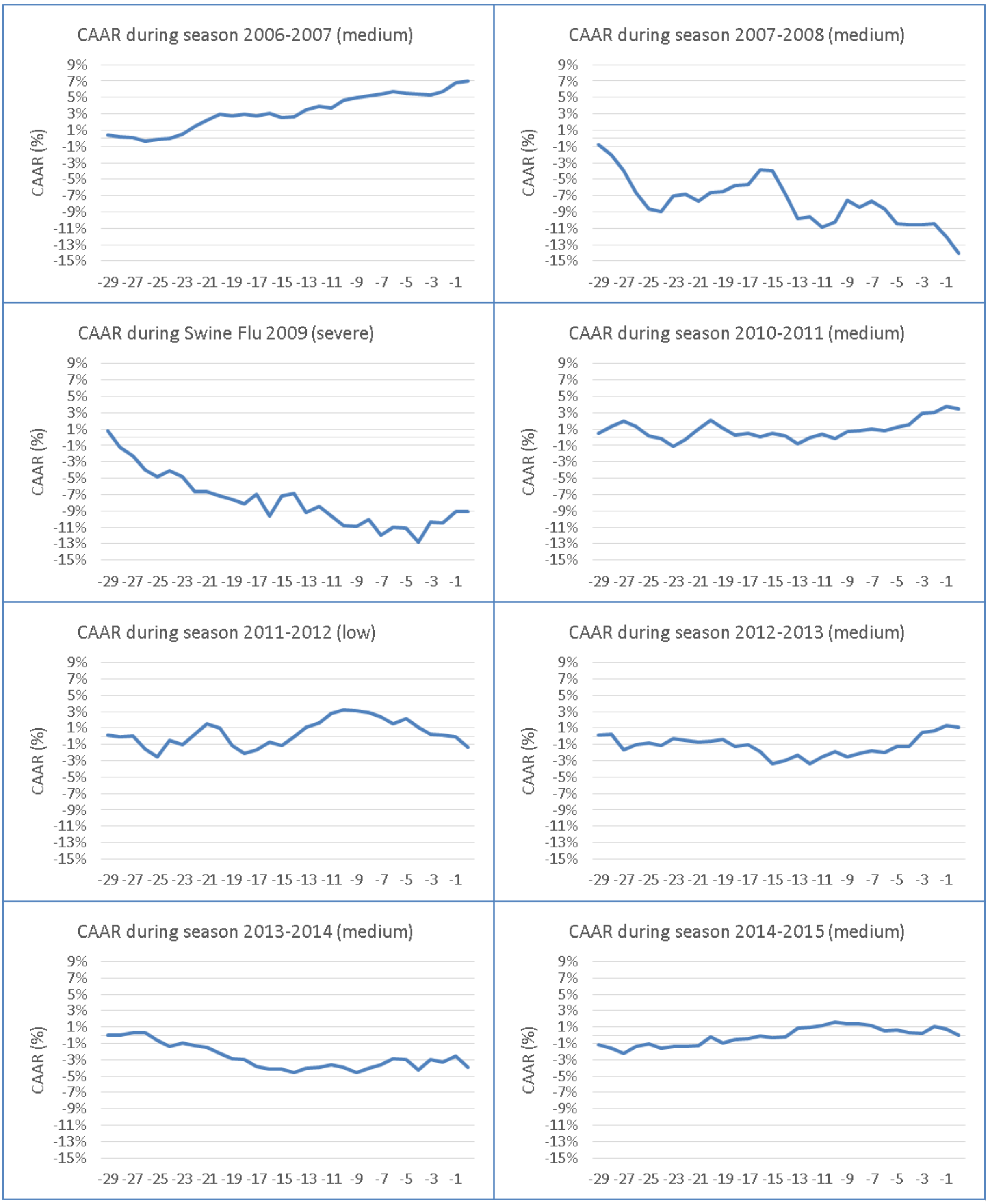
Appendix 4: *The graphs show the CAAR for each season from 2006 to 2015 for the "STRONG POS"-companies (excluding season 2008-2009). The table shows descriptive statistics for each season's event study. The adjusted Z-BMP test statistic is calculated using the regular Z-BMP test statistic and the average of the sample cross correlation of the estimation periods abnormal returns (average corr).*

12.3 CAARs season 1997-2015, “STRONG NEG”-companies



Influenza class	Medium	Severe	Severe	Medium	Medium	Severe	Medium	Low
Season	97-98	98-99	99-00	00-01	01-02	03-04	04-05	05-06
Companies	10	12	10	11	12	15	16	16
Z-BMP	0,059	-1,242	-0,623	-0,757	0,492	0,484	-0,671	-0,198
average corr	0,070	0,053	0,124	0,179	0,136	0,098	0,108	0,109
Adjusted Z-BMP	0,044	-0,962	-0,401	-0,410	0,290	0,299	-0,391	-0,115

Appendix 5: *The graphs show the CAAR for each season from 1997 to 2006 for the “STRONG NEG”-companies (excluding season 2002-2003). The table shows descriptive statistics for each season’s event study. The adjusted Z-BMP test statistic is calculated using the regular Z-BMP test statistic and the average of the sample cross correlation of the estimation periods abnormal returns (average corr).*



Influenza class	Medium	Medium	Severe	Medium	Low	Medium	Medium	Medium
Season	06-07	07-08	Swine Flu	10-11	11-12	12-13	13-14	14-15
Companies	14	12	12	12	12	12	12	11
Z-BMP	4,559	-3,054	-3,686	0,951	-1,106	0,926	-1,389	-0,942
average corr	0,141	0,162	0,282	0,129	0,175	0,148	0,201	0,243
Adjusted Z-BMP	2,509	-1,677	-1,542	0,571	-0,587	0,527	-0,693	-0,442

Appendix 6: *The graphs show the CAAR for each season from 2006 to 2015 for the "STRONG NEG"-companies (excluding season 2008-2009). The table shows descriptive statistics for each season's event study. The adjusted Z-BMP test statistic is calculated using the regular Z-BMP test statistic and the average of the sample cross correlation of the estimation periods abnormal returns (average corr).*

12.4 Adjusted Z-BMP statistics calculations

The following calculations are based on the research platform "Event Study Tools" (Event Study Tools 30 Mar 2015).

First we calculate the standard deviation over the estimation window as following:

$$S_{AR_i}^2 = \frac{1}{M_i - 2} \sum_{t=T_0}^{T_1} (AR_{i,t})^2$$

$\mathrm{M_i}$ = the count of non missing return values in the estimation window for firm i

$\mathrm{T_0}$ = the earliest day of the estimation window

$\mathrm{T_1}$ = the latest day of the estimation window

$\mathrm{AR_{i,t}}$ = abnormal return for firm i on day t

We then calculate the forecast error corrected standard deviation from (Mikkelson and Partch 1988). The Mikkelson and Partch correction adjusts the test statistic for each firm for serial correlation in the returns. The correction term for the market model is as follows:

$$S_{CAR_i} = S_{AR_i}^2 \left(L_i + \frac{L_i^2}{M_i} + \frac{\left(\sum_{t=T_1+1}^{T_2} (R_{m,t} - \overline{R}_m) \right)^2}{\sum_{t=T_0}^{T_1} (R_{m,t} - \overline{R}_m)^2} \right)$$

$\mathrm{L_i}$ = the count of non missing return values in the event window for firm i

$\mathrm{T_2}$ = the latest day of the event window

$\overline{\mathrm{R}}_{\mathrm{m}}$ = the mean of the market returns in the estimation window

$\mathrm{R_{m,t}}$ = the market return at day t

The regular Z-BMP test statistics for testing $H_0: CAAR = 0$ is given by:

$$z_{BMP} = \sqrt{N} \frac{\overline{SCAR}}{S_{\overline{SCAR}}}$$

Where $\overline{SCAR}$ is the averaged standardized cumulated abnormal returns across the ***N*** firms, with standard deviation:

$$\overline{SCAR} = \frac{1}{N}\sum_{i=1}^{N} SCAR_i$$

$$S^2_{\overline{SCAR}} = \frac{1}{N-1}\sum_{i=1}^{N}\left(SCAR_i - \overline{SCAR}\right)^2$$

$$SCAR_i = \frac{CAR_i}{S_{CAR_i}}$$

Finally, to account for cross-sectional correlation between firms, due to event-date clustering, the adjusted Z-BMP test statistic for testing $H_0: CAAR = 0$ is given by:

$$adj\ z_{BMP} = z_{BMP}\sqrt{\frac{1-\bar{r}}{1+(N-1)\bar{r}}}$$

$\bar{r}$ = the average of the sample cross correlation of the estimation periods abnormal returns

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