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The Effect of Credit Rating Announcements on the GICS Market Sectors

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Abstract

The purpose of this paper is to test the effect on the GICS sectors stock returns found on the S&P 500 from credit rating announcements provided by Standard & Poor's and Moody's through an event study spanning from 2000 to 2019. We find that the GICS sectors exhibit different effects in stock returns, where the magnitude depends on the rating announcement. The more timely indicators of creditworthiness found in the outlook sample produce the greatest effects for the negative rating announcements. Whereas for the positive announcements more publicly available information decreases the effect. Suggesting that the negative rating announcements can be found to reduce the information asymmetry more.

Keywords: Abnormal returns, Rating Announcements, Credit Rating Changes, Credit Outlooks, Credit Reviews, Standard & Poor's, Moody's

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1 Introduction

The purpose of this paper is to test the effect on the Global Industry Classification Standard (GICS) sectors stock returns found on the S&P 500 from credit rating announcements provided by Standard & Poor's and Moody's through an event study spanning from 2000 to 2019. Three samples of rating announcements are tested; credit rating changes, credit rating outlooks and reviews as well as a combined sample of both, where each sample is tested individually. This is done in order to answer the questions; which sample of announcements produces the greatest cumulative average abnormal returns ($\overline{CAR}s$) and which sectors experience the greatest effect in the stock returns. To measure the effect in a comprehensive manner, the $\overline{CAR}s$ are compared in absolute values across the announcements and event windows as well as portrayed over time to determine the behavior. Extensive research has been conducted in this area, testing the effect following the credit rating announcements, which announcements that matter and their informational value, such as; Choy, Gray, & Ragunathan (2006), Ederington & Goh (1998), Followill & Martell (1997), Glascock, Davidson, & Henderson (1987), Hand, Holthausen, & Leftwich (1992), Holthausen & Leftwich (1986), Kenjegaliev, Duygun, & Mamedshakhova (2016), Kliger & Sarig (2000) and Micu, Remolona, & Wooldridge (2006). These studies conclude that negative rating announcements cause abnormal returns, that outlooks and reviews cause a greater effect and that the announcements carry informational value to the market. However, these studies do not observe the underlying characteristics, such as the business activity that in the end constitutes the GICS sectors, as they only test the effect using broad market indices. The S&P 500 is an important economic indicator made up of the 500 largest companies on the New York Stock Exchange that is divided into 11 sectors based on their business activity. As the business activities differ between the sectors, their characteristics differ and could therefore impact the return following a rating announcement. Consequently, we contribute to the existing research by testing the effect of rating announcements on the GICS market sectors found on the S&P 500, allowing us to draw conclusions based on the characteristics in more detail. As such, this study can be of importance regarding financial decision making, as to help investors to make wiser decisions concerning investments in the GICS market sectors.

Thus, a credit rating agency is an independent player who assigns ratings to different entities, measuring their creditworthiness. With the help of credit rating agencies, investors can get an assessment of the entity's credit risk, indicating its financial health. On one hand, the credit rating agencies act as intermediaries between the companies, investors and debtors, decreasing the information asymmetry. While on the other hand, due to the existing asymmetry, investors could react upon rating announcements, possibly causing abnormal returns (Calvo & Mendoza, 2000). However, as the market is made up of different sectors, the announcements might affect each sector differently.

We find that the GICS sectors exhibit different reactions in stock returns, where the magnitude of the effect differs depending on the rating announcements. The more timely indicators of creditworthiness found in the negative outlook sample produces the greatest effect for the majority of the sectors. Where the reaction of these announcements are limited to the day prior of the event, as such, we argue that they carry information to the market, classifying them as more unexpected. The health care, information technology and utilities sectors are found to exhibit the greatest effect following the negative rating announcements, three sectors with a high level of long-term debt per share. On the other hand, the positive rating announcements are found to produce a smaller reaction in stock returns, where pinpointing the announcement causing the greatest effect is more ambiguous. A result that can be attributed to the fact that firms prioritize communicating good information to the public. Where the two sectors with some of the highest return over the sample period and a relatively low level of long-term debt are found to exhibit the greatest effect, these are consumer discretionary and consumer staples. As a last remark, our results suggest that the negative rating announcements help to reduce the information asymmetry the most.

This thesis is structured as follows; in section one an overview of the previous research, the rating announcements and the S&P 500 and the GICS market sectors are given. Section two describes the event study methodology, the testing procedure and data with summary statistics. In section three the empirical results are presented, followed by section four where the results obtained are discussed. Lastly, in section five we present our concluding remarks.

1.1 Literature Review

The effect of rating announcements on security returns has been tested extensively over time. Early studies used monthly data to test the effect, with inconclusive results. Katz (1973) tested for a semi-strong efficiency of the U.S. bond market using bond rating reclassification's from Standard & Poor's, whereas Weinstein (1977) conducted a similar study with bond rating announcements from Moody's. Katz (1973) showed that an effect existed for both positive and negative rating announcements, dis-proving the efficient market hypothesis, whereas, Weinstein (1977) could not find any effect, providing results for a semi-strong form of the efficient market hypothesis. In contrast, Pinches & Singleton (1978) and Griffin & Sanvicente (1982) tested for an effect in common stock prices. Using credit rating announcements from Moody's, Pinches & Singleton (1978) failed to detect any effect, concluding that this was due to anticipation in the market. On the other hand, Griffin & Sanvicente (1982) found negative abnormal returns following negative credit rating announcements from both Moody's and Standard & Poor's.

In a highly cited paper, Holthausen & Leftwich (1986) investigated the effect of bond rating changes on common stock prices using daily data. The study classified the rating announcements into two categories, either as contaminated or non-contaminated; contaminated being when information such as news from other sources was released within the event window and non-contaminated classified as unexpected. They hypothesized that abnormal returns were partly driven by this additional information. By removing the contaminated data and using rating announcements from Moody's, Standard & Poor's and additions to the Standard & Poor's watchlist, their results showed that significant negative abnormal returns were found to follow negative rating changes and watchlist additions. Whereas no abnormal returns were found following the positive rating changes, a small effect was observed for the positive watchlist additions. Additionally, Glascock et al. (1987) could show that the abnormal returns following a negative rating announcement exhibited a reversal after the date of the rating announcement. However, from the positive rating announcements no effect was found on the event date, but a significant downturn was observed shortly thereafter. In an extension to their previous study, Hand et al. (1992) tried to explain the effect on both common stock and bond returns. With a similar classification of the rating announcements, they could show that stock and bond returns experienced abnormal returns following negative rating announcements. However, removing announcements classified as expected increased the significance for the stock returns while the effect disappeared for bonds. Following a positive rating announcement, significant results were found for unexpected rating announcements for bond returns while no effect was found for stocks. Whereas the previously conducted studies used both rating changes and rating reviews, Elayan, Maris, & Young (1996) solely used watchlist placements from Standard & Poor's, with an objective to identify any firm characteristics causing the abnormal returns. The results proved that negative credit reviews provided significant negative abnormal returns and concluded that this was due to the liquidity of the firm as measured by the current ratio. Followill & Martell (1997) could also show that rating reviews had the most statistically significant impact on equity returns, while subsequent rating changes had an inconsequential impact. The paper also provided evidence showing that press releases surrounding a rating review influenced the equity returns, whereas publication of this information in the financial press caused a smaller market reaction.

The research, starting with Holthausen & Leftwich (1986), conducted up until this point had reached a consensus regarding the effect of rating announcements on stock prices - with a significant effect following negative rating announcements and a less significant effect following positive rating announcements. However, few had tried to explain this consensus. One explanation was presented by Ederington & Goh (1998) who could show that the abnormal returns following a negative rating announcement were significant, where part of the significance was driven by the fact that the market values the negative rating announcements as new information. The results showed that the effect as well as analysts revisions were due to the negative rating announcement itself, not due to information or earning figures in the market. On the other hand, an effect following the positive rating announcements could not be found as this information was already publicly available in the market, where analyst revisions were less pronounced than for negative rating announcements. They concluded that this could be due to the fact that firms prioritize communicating good news to the public. Further, Kliger & Sarig (2000) provided evidence that since firms disclose inside information to rating agencies, who in turn produce reports and ratings without disclosing specific details of the inside information to the public, the rating agencies help to reduce the information asymmetry. Moreover, the informational value was found to be higher for high-leveraged firms than for low-leveraged firms. These findings were complimented by Dichev & Piotroski (2001) that made use of the Fama & French (1993) three-factor model, concluding that the effect was most pronounced for low-credit-quality firms.

In contrast to the previous studies mentioned, that are all based on the U.S. market, Choy et al. (2006) conducted a study on the Australian market. In this study, the rating announcements were classified as either expected or unexpected. Where the expected and unexpected effect was also tested across the regulation of the market, as it was hypothesised that heavily regulated markets produce more publicly available information, increasing the expectation of these rating announcements. They could conclude that the results were similar to those found for U.S. stocks, where the significance of the negative abnormal returns held whether or not the rating announcements were classified as expected or unexpected and the effect was much greater if the firm belonged to an unregulated market. Additionally, their results proved that the effect from a sample of unexpected events was limited to the day prior to the event. Micu et al. (2006) extended the event study methodology to the credit default swap (CDS) market. By using daily data and three rating announcements; credit rating changes, credit outlooks and credit reviews, their results showed that all rating announcements have a significant effect on CDS spreads, whether positive or negative, where the effect was most pronounced when an issuer was given a negative credit review. Concluding that if the rating announcements carry information to the market, this should be observed on the day of the event or on the day thereafter.

According to economic theory, bearing a higher risk should be rewarded with a higher return, however, as noted, low credit risk firms realize higher returns than firms with high credit risk. Avramov, Chordia, Jostova, & Philipov (2009) tried to explain this puzzle by utilizing multiple market models. Their results showed that low credit risk firms earned a higher return than firms with a high credit risk, where this return could not be attributed to any of the market anomalies in the Fama & French (1993) three-factor model with a momentum factor. They concluded that the puzzle was rather due to arbitrageurs' inability to exploit the mis-pricing of these stocks and a short-sale constraint of high credit-risk stocks.

Kenjegaliev et al. (2016) investigated the impact of credit rating changes on the German stock market for the three major rating agencies; Standard & Poor's, Moody's and Fitch. The results were consistent with the previous research, additionally showing that the adjustment in stock prices began 30 to 60 days before the actual rating announcements. Reddy, Bosman, & Mirza (2019) tested the effect over the global financial crisis of 2007-2008, by dividing the sample into three sub-samples; pre-crisis, crisis and post-crisis. Providing results in accordance with earlier studies, where the results held for all of the three sub-periods. Further, they found that the sensitivity of rating announcements from specific agencies had increased since the crisis.

1.2 Credit Ratings, Outlooks and Reviews

A credit rating agency is an independent player in the market, providing investors and institutions with an opinion regarding an issuer's ability to meet its outstanding obligations, where the issuer can be either a corporation, government, state or a municipality (Calvo & Mendoza, 2000). A credit rating presents a forward-looking, long-term projection, of the financial stability of an issuer. The agencies are inclined to "rate through the cycle", meaning that the ratings are taking a long-term view and are not based on temporary events, such as a momentary decrease in profit margins. Even though credit ratings present the financial stability of an issuer, the ratings are not a definitive measure of default risk, rather a tool to clarify standardised risk measures (Micu et al., 2006).

The three largest rating agencies are Standard & Poor's, Moody's and Fitch. Only these three rating agencies control about 95% of the market, where Standard & Poor's and Moody's make up approximately 80% (Frost, 2007). These are large international companies operating in many markets, rating a wide variety of issuers. A difference between the rating agencies is in the way they structure their ratings, or risk categories, the issuer is given one of the following symbols based on the measured creditworthiness[1] (Micu et al., 2006):

Standard & Poor's:	AAA,	AA,	A,	BBB,	BB,	B,	CCC,	CC,	SD,	D		
Moody's:	Aaa,	Aa,	A,	Baa,	Ba,	B,	Caa,	Ca,	C			
Fitch:	AAA,	AA,	A,	BBB,	BB,	B,	CCC,	CC,	C,	DDD,	DD,	D

In the 1980's the rating agencies decided to keep the issuers that they had rated under surveillance, and began using the watchlist. A watchlist placement, or review, is issued when a considerable rating change can be expected in the coming 90 days, with a 50% likelihood (Standard & Poor's Rating Services, 2009). The reviews are issued due to a significant event in the short-term, such as a merger or decline in profits of the issuer, where the influence of the event on the credit quality of the issuer is not fully recognized. If the rating agency anticipates that a new rating change would occur within six to 24 months, a credit outlook may be issued, considering the underlying economic and business conditions. They are issued if there is roughly a 30% likelihood of a rating change in the medium-term due to an event or deviation from an economic trend (Standard & Poor's Rating Services, 2009). A negative (positive) review or outlook therefore indicates a potential downgrade (upgrade) of the credit rating in the short to medium term. Thus, the reviews and the credit outlooks

[1]These are the risk categories for the long-term issuer ratings.

are more timely indicators of the creditworthiness of an issuer, a characteristic different from the credit rating changes that are more sticky (Micu et al., 2006).

The rating process begins by the issuer and the rating agency establishing a contract where the analysts of the rating agency go through the issuers financial information. The risk factors considered are dependent on the given issuer, typically including information of competitive position, economic and regulatory influences, management and key performance indicators. When the creditworthiness and likelihood of default has been determined, the analysts propose a rating in front of the agency's committee, where a rating is decided by a voting process. When these steps have been conducted and the agency's rating fee has been paid by the issuer, an issuance to the public is made. The issuer is then kept under surveillance by the rating agency in case a new rating change, outlook or review is needed (Standard & Poor's Financial Services, 2018).

1.3 The S&P 500 and the GICS Sectors

Standard & Poor's has for long been an important institution on the U.S. market. In 1957 the first value-weighted index was started, covering 500 companies with the largest market capitalization on the New York Stock Exchange. This became the S&P 500, with a purpose to represent the overall U.S. economy. Since its creation, the S&P 500 has served its purpose well, and is now also seen as a proxy for the U.S. equity market (S&P Dow Jones Indices, 2020). The index covers roughly 80% of the market capitalization of U.S. domicile firms, with an additional USD 6.6 trillion benchmarked to the index (S&P Dow Jones Indices, 2021). To be included in the index a company needs to satisfy five basic requirements: (*i*) be a U.S. company (*ii*) have a market capitalization of at least USD 11.8 billion (*iii*) be highly liquid (*iv*) have a public float of at least 10% of the shares outstanding (*v*) the current and the sum of the four trailing quarter's earnings must be positive (S&P Dow Jones Indices, 2020). As the index is value-weighted, meaning that each company's contribution to the index is proportional to the market capitalization of that company, the largest companies will have the greatest influence on the return of the index. Some of these large companies include; Apple Inc., Alphabet Inc., Amazon.com, Johnson & Johnson, JPMorgan Chase & Co. and Microsoft Corp.[2]

[2]This is just an example of companies with some of the largest market capitalization's of the GICS market sectors found on the S&P 500, as such this is not the exact order of size.

The Global Industry Classification Standard (GICS) was started in 1999 by Morgan Stanley Capital International (MSCI) and S&P Dow Jones, with the purpose of a more accurate, complete and long-term definition of the industries based on the underlying business activity. GICS is a four-level hierarchical system with sectors, industry groupings, industries and sub-industry categorizations. Each company is attributed to one of the 11 sectors, 24 industry groups, 69 industries and 158 sub-industries (MSCI, 2021). The GICS sectors included in the S&P 500 are communication services, consumer discretionary, consumer staples, energy, financials, health care, industrials, information technology, materials, real estate[3] and utilities. For a new company, the decision of which sector it should belong to is based on the initial company description in the prospect, while for already listed companies, the decision is based on annual reports and financial statements. If a company's business activity is related to two different sectors, the selection is based on which business activity that provides the majority of the earnings (S&P Global Market Intelligence, 2018).

The S&P 500 covers many companies, industry groupings, industries and sub-industries that in the end constitute the GICS market sectors. With different business activities of the companies, the characteristics of the sectors differ. In table 1, the 11 market sectors and their characteristics of size, return, long-term debt per share and market beta are displayed over the period 2000-01-01 to 2019-12-31.

Table 1.

The GICS Sectors on the S&P 500

Sector	Market Cap (bn)	Value of S&P 500 (%)	Return	Long-Term Debt Per Share	Beta
Communication Services	335.72	10.39%	-43.07%	36.78	0.90
Consumer Discretionary	315.15	9.75%	238.48%	128.12	1.20
Consumer Staples	232.71	7.20%	216.80%	103.72	0.60
Energy	140.42	4.35%	120.96%	117.28	1.70
Financials	418.40	12.95%	66.47%	276.24	1.20
Health Care	458.85	14.20%	256.52%	215.23	0.80
Industrials	292.42	9.05%	158.89%	138.39	1.20
Information Technology	749.44	23.20%	94.28%	141.85	1.10
Materials	85.77	2.65%	145.39%	87.05	1.10
Real Estate	94.55	2.93%	21.51%	75.52	0.70
Utilities	107.35	3.32%	136.66%	186.76	0.30
S&P 500	3230.78	100%	122.01%	726.38	1.00

Note: The market capitalization and long-term debt per share are presented as of 2019-12-31. The market beta is presented as of 2020-11-20. The return is given over the period 2000-01-03 to 2019-12-31. For real estate the return is given over the period 2016-09-20 to 2019-12-31. *Source: https://www.spglobal.com/spdji/en/indices/equity/sp-500/*

[3]The real estate sector was separated from the financial sector in September 2016, while mortgage REITs are still included in the financial sector (S&P Dow Jones Indices, 2016).

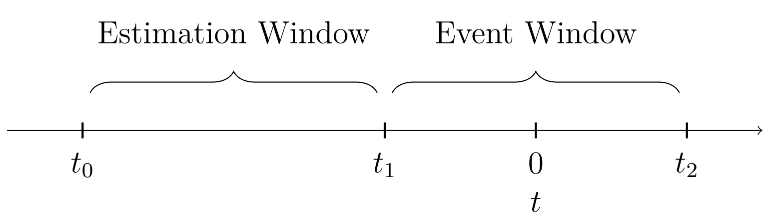
2 Methodology

An event study is a tool for measuring the impact of a specific event of interest on the value of a firm's outstanding security prices. Looking at a specific event one wants to measure, in this case credit rating announcements, and given a rational market the event should lead to an immediate effect on the firm's outstanding security prices (MacKinlay, 1997).

2.1 Event Window and Window of Estimation

The first step when conducting an event study is to define the event window, the period for which the stock returns of the chosen firms are to be examined (Campbell, Lo, & MacKinlay, 1997). The event window can be the day of the event, however, as the event may take place after the market has closed or that it might be anticipated, the window is usually extended to the days before and after the event (MacKinlay, 1997). For this study two event windows are used, [-2, +2] consisting of five days; two days prior to the event and two days after the event, as well as [-5, +5] five days prior and five days following the event, thus consisting of eleven days. The next step is to define the estimation window, the time interval providing the normal returns. The chosen estimation window will be 60 trading days, providing the returns from approximately three calendar months. In figure 1 an illustration of the timeline of the event study methodology is provided.

Figure 1.
Timeline of Event Study



2.2 Normal and Abnormal Returns

The second step is to define the normal and abnormal return. MacKinlay (1997) noted that the use of factor models help to reduce the variance of the abnormal returns, thus, allowing the abnormal returns to explain more of the variation in the normal returns. The reduction in variance was the greatest when the firms in the sample shared some common characteristic, such as belonging to the same market sector. As this paper will test the effect of rating announcements on the GICS sectors, the Fama & French (2015) five-factor model will be used as the market model, a risk-adjusted model factoring in the following characteristics; return of the market (R_{mkt}), size (SMB), value (HML), profitability (RMW) and investments (CMA). Defined by the following equation:

$$R_{i,t} = \alpha_i + \beta_1 R_{mkt} + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \varepsilon_{i,t} \tag{1}$$

The parameters of the market model are to be estimated with ordinary least squares (OLS), as OLS under general conditions is a consistent estimator (Campbell et al., 1997). Given that the parameters of the market model have been estimated, one can measure the abnormal returns. The abnormal returns are defined as the realized ex post returns in the event window less the normal return over the estimation window (Campbell et al., 1997). Defined algebraically as:

$$\varepsilon_{i,t} = AR_{i,t} = R_{i,t} - E[R_{i,t}] \tag{2}$$

Where $\varepsilon_{i,t}$ is the abnormal return, $R_{i,t}$ defines the actual return[4] and $E[R_{i,t}]$ is the estimated normal return. Thus, the abnormal return is the disturbance term of the five-factor market model (MacKinlay, 1997).

2.3 Testing Procedure

To test whether the credit rating announcements have any impact on the stock returns, the abnormal returns must first be aggregated as to allow for overall inferences. The aggregation will be defined over time and security, as well as across securities (MacKinlay, 1997). The aggregation for an individual security over time will be examined first. We define $CAR_i(t_1, t_2)$ as the cumulative abnormal return for security i from time t_1 to t_2, as:

$$CAR_i(t_1, t_2) = \sum_{t_1=1}^{t_2} AR_{i,t} \tag{3}$$

From equation (3) a test-statistic can be established for security i by using the standardized cumulative abnormal returns, in order to test whether the credit rating announcements have an effect on security i's return (Campbell et al., 1997). Defined as:

[4]The actual return is given by: $R_{i,t} = (P_{i,t}/P_{i,t-1}) - 1$

$$S\widehat{CAR}_i(t_1,t_2) = \frac{\widehat{CAR}_i(t_1,t_2)}{\hat{\sigma}_i(t_1,t_2)} \tag{4}$$

However, the above result can only be used for one event, thereby, a sample of many events have to be aggregated in order to test the effect of the GICS sectors. Given that the abnormal returns have been estimated from equation (2), we calculate the average abnormal return ($\overline{AR}$) for each security over the event window. Given a sample of N events, the average abnormal returns for security i are given by (MacKinlay, 1997):

$$\overline{AR}_t = \frac{1}{N}\sum_{i=1}^{n} AR_{i,t} \tag{5}$$

After finding the average abnormal return for each security, they are firstly aggregated by their respective sector, by the direction of the rating announcement; positive or negative and the sample of rating announcements; credit rating changes, credit outlooks and reviews and a combination of both. These aggregations are defined as the cumulative average abnormal return ($\overline{CAR}$), estimated within the event window by the following equation using OLS (MacKinlay, 1997):

$$\overline{CAR}(t_1,t_2) = \sum_{t=t_1}^{t_2} \overline{AR}_t \tag{6}$$

The cumulative average abnormal returns can be used to test whether the rating announcements have an effect on the stock returns in each sector. In order to do so, we test if the $\overline{CARs}$ are statistically different from zero on the event date, with the following test statistic and hypothesis (MacKinlay, 1997):

$$\theta_i = \frac{\overline{CAR}_t(t_1,t_2)}{var(\overline{CAR}_t(t_1,t_2))^{1/2}} \sim \mathcal{N}(0,1) \tag{7}$$

$$H_0 : \overline{CAR}_t = 0$$
$$H_A : \overline{CAR}_t \neq 0$$

Where θ_i is the test statistic approximated by a normal distribution. Rejection of the null hypothesis implies that there are statistically significant abnormal returns present and that the rating announcements have an effect on the stock returns. The testing procedure is a cross sectional study where the above methodology will be used for each sector, the direction of the rating announcements and each sample of individual rating announcement.

2.4 Data and Summary Statistics

Daily stock prices, adjusted close, for the companies listed on the S&P 500 were obtained from Yahoo Finance over a time interval spanning from 2000-01-01 to 2019-12-31, this time period was chosen as it adequately captures the stock returns and provides good estimates allowing us to generalize the results. As the Fama & French (2015) five-factor model will serve as the market model, daily data for the factors was obtained from the Kenneth French website[5], providing data for all the factors. The chosen time interval includes periods of financial distress and high market volatility, time periods such as the crash of the Dot-com bubble of 2001-2002 and the financial crisis of 2007-2008. It is noticed that periods of financial distress and high market volatility can have a direct influence on the stock returns, creating extreme values that in the end can have an effect on the final results. Kim, Kim, & Ergün (2015) noted that the distortions from extreme values can have a substantial effect, for example, by affecting both the results as well as the normality of the data. They note that by removing the top two extreme values on either side of the distribution help to overcome this problem. Further, Galai, Kedar-Levy, & Schreiber (2008) noted that a relatively small sample of daily extreme values, 2.03%, can have a substantial impact on the final result. Thus, as to control for the influence of periods of financial distress and high market volatility we remove 2% of the observations on either side of the distribution. The Shapiro-Wilks goodness-of-fit test was also conducted as to ensure normality of the data, which can be found in appendix A.

The use of daily data has two primary advantages: first, it allows for a more powerful testing if the exact event date can be identified, secondly, the use of daily data and a narrow event window will reduce the likelihood of other economic and non-economic events to influence the effect of rating announcements on the stock prices (Holthausen & Leftwich, 1986). Nevertheless, Brown & Warner (1985) highlights the issues following the use of daily data. The authors provided evidence that the use of daily data tends to be non-normal, and that non-synchronous trading causes biased estimates as securities can be traded at different frequencies. Although problematic, the authors concluded that the central limit theorem (CLT) ensures that the abnormal returns of the stocks converged to normality as the number of stocks increased[6]. Moreover, the use of cross-sectional average abnormal returns will reduce the departures from normality more than the use of individual security abnormal

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

[6] Brown & Warner (1985) noted that the central limit theorem ensures normality for a sample size of 50 observations, however Hogg, Tanis, & Zimmerman (2015) observed that it is usually sufficient with a sample size of 25 to 30 observations.

returns (Brown & Warner, 1985). The effect of non-synchronous trading causes the beta estimates of the market model to become biased and inconsistent. An adjustment model to correct for the inconsistency of the parameters in the market model was developed by Scholes & Williams (1977), where they showed that an adjustment is especially needed for thinly traded stocks. However, Jain (1986) investigated the distribution of the adjustment model and the unadjusted OLS market model, concluding that the differences between them were small and that adjustments for thin-trading are not necessary.

Lastly, data for long-term issuer ratings, credit outlooks and reviews from both Standard & Poor's and Moody's were obtained through S&P Capital IQ and Moody's website. The long-term issuer ratings indicate an issuer's overall ability to meet its long- and short-term obligations. The reason for using these two agencies is that they are large international rating agencies and control 80% of the market, as such, providing the data needed with ease. Fitch holds a proportionally smaller market share, and was excluded from this research due to time availability. From the obtained announcements, three samples were created; a combined sample consisting of all rating announcements, a rating change sample consisting of solely rating changes and an outlook sample consisting of both outlooks and reviews. This provided a total sample of 386 companies, where 114 companies were dropped due to their lack of rating announcements. From the included companies, a total of 3593 rating announcements were collected, consisting of 2043 negative announcements and 1550 positive announcements. Where the negative rating announcements consist of 1154 credit outlooks and reviews and 889 rating changes, and the positive consists of 648 credit outlooks and reviews and 902 rating changes. See table 2 for an overview of the total sample and the announcement groupings.

After gathering all the announcements, a total of 243 announcements were removed due to overlap of the event and estimation window, as to ensure that the normal returns are not influenced by the event (MacKinlay, 1997). Additionally, some of the events lacked sufficient data in the estimation period, thus, a total of 178 events were further dropped for the 5-day event window and 183 for the 11-day window. As a result we obtained two final samples for the event windows. The final sample for the 5-day event window consists of 3105 events, whereof 1721 negative rating announcements and 1384 positive announcements. Similarly, the 11-day event window consists of 3100 events, whereof 1717 negative announcements and 1383 positive announcements. An overview of the final samples are presented in table 3 and 4.

2.5 Limitations

One limitation to consider is the aspect of using only two of the major rating agencies, by excluding rating announcements from other agencies there might be information in the market that is already incorporated into the security prices, a factor that could affect the final results. It should also be noted that the paper suffers from survivorship bias, as the sample consists of those companies listed on the S&P 500 as of 2019-12-30. A last limitation to consider is that the gathered ratings are all classified with equal importance. Meaning that the effect is not tested when moving over the different risk categories; such as from speculative to investment grade, over multiple ratings or over the notches within a rating.

Table 2.
Total Sample

Sector	Companies			Combined Sample			Outlook Sample			Rating Change Sample		
	Negative	Positive	Total	Negative	Positive	Total	Negative	Positive	Total	Negative	Positive	Total
Communication Services	14	13	15	88	56	144	54	22	76	34	34	68
Consumer discretionary	41	45	49	271	256	527	142	104	246	129	152	281
Consumer Staples	27	20	30	186	67	253	117	31	148	69	36	105
Energy	19	18	21	111	89	200	66	34	100	45	55	100
Financials	54	41	56	395	206	601	226	90	316	169	116	285
Health Care	37	35	43	192	169	361	109	72	181	83	97	180
Industrials	47	39	54	287	177	464	149	69	218	138	108	246
Information Technology	31	41	47	138	173	311	69	66	135	69	107	176
Materials	20	18	22	127	84	211	80	33	113	47	51	98
Real Estate	17	23	25	63	121	184	41	57	98	22	64	86
Utilities	24	22	24	185	152	337	101	70	171	84	82	166
Total	331	315	386	2043	1550	3593	1154	648	1802	889	902	1791

Note: The combined sample is the sum of the rating change sample and the outlook sample. Negative indicates a downgrade for the rating changes and a potential downgrade following the outlook sample. Positive indicates an upgrade for the rating changes and a potential upgrade for the outlook sample. The number of companies are based on the combined sample.

Table 3.

Final Sample for the 5-day Event Window

	Companies			Combined Sample			Outlook Sample			Rating Change Sample		
Sector	Negative	Positive	Total	Negative	Positive	Total	Negative	Positive	Total	Negative	Positive	Total
Communication Services	13	12	15	66	45	111	43	18	61	23	27	50
Consumer discretionary	45	41	49	233	233	466	127	97	224	106	136	242
Consumer Staples	27	20	30	162	59	221	101	27	128	61	32	93
Energy	18	18	21	97	79	176	59	30	89	38	49	87
Financials	49	43	56	330	187	517	193	84	277	137	103	240
Health Care	37	33	43	176	150	326	100	61	161	76	89	165
Industrials	46	38	54	229	150	379	141	65	206	88	85	173
Information Technology	30	39	47	121	156	277	63	59	122	58	97	155
Materials	19	16	22	108	68	176	67	27	94	41	41	82
Real Estate	16	23	25	54	113	167	36	53	89	18	60	78
Utilities	24	22	24	145	144	289	81	66	147	64	78	142
Total	324	305	386	1721	1384	3105	1011	587	1598	710	797	1507

Note: The combined sample is the sum of the rating change sample and the outlook sample. Negative indicates a downgrade for the rating changes and a potential downgrade following the outlook sample. Positive indicates an upgrade for the rating changes and a potential upgrade for the outlook sample. The number of companies are based on the combined sample.

Table 4.

Final Sample for the 11-day Event Window

Sector	Companies			Combined Sample			Outlook Sample			Rating Change Sample		
	Negative	Positive	Total	Negative	Positive	Total	Negative	Positive	Total	Negative	Positive	Total
Communication Services	13	12	15	66	45	111	43	18	61	23	27	50
Consumer discretionary	41	41	49	233	233	466	127	97	224	106	136	242
Consumer Staples	27	20	30	162	59	221	101	27	128	61	32	93
Energy	18	18	21	97	79	176	59	30	89	38	49	87
Financials	49	43	56	327	187	514	191	84	275	136	103	239
Health Care	37	33	43	176	150	326	100	61	161	76	89	165
Industrials	46	38	54	229	150	379	141	65	206	88	85	173
Information Technology	30	39	47	121	156	277	63	59	122	58	97	155
Materials	19	16	22	108	68	176	67	27	94	41	41	82
Real Estate	16	23	25	54	113	167	36	53	89	18	60	78
Utilities	24	22	24	144	143	287	80	66	146	64	77	141
Total	320	305	386	1717	1383	3100	1008	587	1595	709	796	1505

Note: The combined sample is the sum of the rating change sample and the outlook sample. Negative indicates a downgrade for the rating changes and a potential downgrade following the outlook sample. Positive indicates an upgrade for the rating changes and a potential upgrade for the outlook sample. The number of companies are based on the combined sample.

3 Empirical Results

In this section the empirical results are presented. This section is divided for the sample of rating announcements, firstly the results for the combined sample are presented, secondly the credit rating change sample, and lastly the outlook sample. Where each section is observed by the negative and positive direction of the rating announcements and the two event windows. Finally, the $\overline{CAR}s$ for all three samples are illustrated over time.

3.1 Combined Sample of Rating Announcements

The results from testing whether the $\overline{CAR}s$ following the combined sample are different from zero on the event day are presented in this section. In table 5 the results for the 5-day and 11-day event windows following the negative rating announcements are presented. As can be seen, the overall effect is that a negative rating announcement has a negative effect on the stock returns. This is clearly illustrated in the 5-day event window when looking at the coefficients for the $\overline{CAR}s$, which are negative for all of the 11 sectors, where the null hypothesis can be rejected for ten sectors. The null hypothesis can be rejected at the one percent significance level for eight sectors, providing evidence that negative rating announcements cause negative stock returns. Moreover, two of the sectors are significant at the five percent level, providing a similar result. The sector experiencing the greatest effect, in absolute value rounded to two decimal places, is health care, with a $\overline{CAR}$ roughly equal to -1.03%, closely followed by utilities and information technology at -0.82% and -0.74%, respectively. Only one sector stands out in this event window, consumer discretionary, where we fail to reject the null hypothesis, suggesting that the negative rating announcements do not have any effect on the stock returns for this sector. Followingly, the sectors with the least effect are; consumer discretionary, consumer staples and real estate, with an effect of -0.03%, -0.23% and -0.27%, respectively.

For the 11-day event window, the results are similar to those found for the 5-day window. Where, for eight of the sectors the null hypothesis can be rejected at the one percent significance level, and one sector at the five percent significance level. As for the 5-day event window, health care, utilities and information technology exhibit the greatest effects of -1.01%, -0.82% and -0.74%, respectively. Correspondingly, we fail to reject the null hypothesis for consumer discretionary, as well as for real estate. Thereby, the sectors with the least effect are consumer discretionary, consumer staples and real estate with effects of -0.07%, -0.25% and -0.28%.

Table 5.
Results for the Combined Sample for the Negative Rating Announcements

	5-day Event Window				11-day Event Window			
Sector	$\overline{CAR}_i$	Robust Std. Error	θ_i	Prob.	$\overline{CAR}_i$	Robust Std. Error	θ_i	Prob.
Communication Services	-0.00704	0.00163	-4.32	0.0000***	-0.00692	0.00170	-4.80	0.0001***
Consumer discretionary	-0.00030	0.00130	-0.25	0.7994	-0.00065	0.00130	-0.50	0.6161
Consumer Staples	-0.00226	0.00102	-2.20	0.0289**	-0.00248	0.00100	-2.46	0.0151**
Energy	-0.00651	0.00114	-5.74	0.0000***	-0.00390	0.00110	-3.56	0.0006***
Financials	-0.00538	0.00122	-4.40	0.0000***	-0.00474	0.00137	-3.46	0.0006***
Health Care	-0.01029	0.00190	-5.41	0.0000***	-0.01014	0.00188	-5.39	0.0000***
Industrials	-0.00279	0.00117	-2.39	0.0176**	-0.00327	0.00112	-2.94	0.0037***
Information Technology	-0.00736	0.00188	-3.91	0.0002***	-0.00737	0.00190	-3.88	0.0002***
Materials	-0.00724	0.00179	-4.04	0.0000***	-0.00696	0.00177	-3.94	0.0001***
Real Estate	-0.00266	0.00045	-5.92	0.0000***	0.00282	0.00174	1.62	0.1116
Utilities	-0.00819	0.00114	-7.16	0.0000***	-0.00822	0.00113	-7.28	0.0000***

Note: $\overline{CAR}_i$ is the cumulative average abnormal return following from a combined sample of rating changes, outlooks and reviews that is tested on the event dates. The robust standard errors are corrected for heteroscedasticity. θ_i is the test statistic approximated by a normal distribution. *, **, *** represents statistical significance at the 10%, 5% and 1% significance level.

Correspondingly, the $\overline{CARs}$ following the positive rating announcements are also tested on the event dates and are presented in table 6. For the 5-day event window, eight of the sectors can be seen to exhibit a positive effect following these announcements, suggesting that positive rating announcements will increase the stock return for these sectors. Out of these, the effect is significant for seven sectors, four at the one percent level, one at the five percent level and two at the ten percent significance level. The remaining sectors are not significant, as we fail to reject the null hypothesis. The sectors experiencing the greatest effects are real estate, consumer discretionary and consumer staples with an effect of 0.58%, 0.38% and 0.37%, respectively. Followingly, utilities, financials and industrials are the sectors that exhibit the least effects of 0.02%, -0.06% and -0.12%, respectively, where these sectors are also found to be insignificant.

For the 11-day event window, seven sectors exhibit a positive $\overline{CAR}$ suggesting a positive effect in the stock returns. Out of these, four are significant; three at the one percent level and one at the ten percent level, while the remaining three are insignificant. Four of the sectors exhibit a negative effect, where real estate turns negative when moving from the 5-day to the 11-day event window. The sectors experiencing the greatest effect are consumer discretionary, consumer staples and health care with an effect of 0.40%, 0.37% and 0.31%, while the sectors exhibiting the least effect are real estate, utilities and financials with effects of -0.02%, 0.03% and 0.05%, respectively.

Table 6.
Results for the Combined Sample for the Positive Rating Announcements

	5-day Event Window				11-day Event Window			
Sector	$\overline{CAR}_i$	Robust Std. Error	θ_i	Prob.	$\overline{CAR}_i$	Robust Std. Error	θ_i	Prob.
Communication Services	0.00226	0.00122	1.86	0.0693*	0.00208	0.00127	1.64	0.1076
Consumer discretionary	0.00380	0.00070	5.88	0.0000***	0.00400	0.00065	6.20	0.0000***
Consumer Staples	0.00370	0.00072	5.14	0.0000***	0.00370	0.00075	4.94	0.0000***
Energy	-0.00132	0.00131	-1.01	0.3151	-0.00129	0.00132	-0.97	0.3332
Financials	-0.00056	0.00040	-1.38	0.1690	-0.00050	0.00041	-1.22	0.2240
Health Care	0.00321	0.00090	3.57	0.0000***	0.00311	0.00087	3.59	0.0004***
Industrials	-0.00119	0.00086	-1.37	0.1720	-0.00128	0.00095	-1.35	0.1775
Information Technology	0.00141	0.00085	1.65	0.0999*	0.00150	0.00085	1.76	0.0801*
Materials	0.00126	0.00055	2.29	0.0250**	0.00096	0.00062	1.54	0.1286
Real Estate	0.00577	0.00215	2.68	0.0096***	-0.00022	0.00036	-0.62	0.5338
Utilities	0.00015	0.00056	0.28	0.7835	0.00028	0.00057	0.50	0.6211

Note: $\overline{CAR}_i$ is the cumulative average abnormal return following from a combined sample of rating changes, outlooks and reviews that is tested on the event dates. The robust standard errors are corrected for heteroscedasticity. θ_i is the test statistic approximated by a normal distribution. *, **, *** represents statistical significance at the 10%, 5% and 1% significance level.

Overall, we can see that the combined sample for the negative rating announcements presents great statistical significance as the sample allows us to reject the null hypothesis for ten sectors, where eight sectors can be rejected at the 1% significance level across both event windows. We also find that the sample produces negative $\overline{CARs}$ for nearly all the sectors. Although the two event windows present analogous results, the 5-day event window captures the effect more efficiently, since it allows us to reject the null hypothesis for a higher number of sectors. We notice that health care, utilities and information technology exhibit the greatest effect, in absolute values, throughout both event windows. The sectors experiencing the least effect following the negative rating announcements are consumer discretionary, consumer staples and real estate, for both event windows. For the positive rating announcements we notice that real estate, consumer discretionary and consumer staples experience the greatest effect for the 5-day event window. Whereas, for the 11-day event window the greatest effects are found for consumer discretionary, consumer staples and health care. It is also noted that the least effect for the positive rating announcements varies over the event windows. In appendix C, an overview of the percentage effect across the rating announcements for both event windows is presented.

3.2 The Rating Change Sample and the Outlook Sample

As presented above, we wish to distinguish which type of rating announcement that has the greatest effect on the stock returns. Therefore, in this section the rating change and outlook samples are tested individually. This section presents the results for the 5-day event window as the results are closely comparable to the 11-day window. The results for the 11-day window can be found in appendix B.

The results for the sample of rating changes are presented in table 7. Following the negative rating changes we observe that ten out of 11 sectors exhibit a negative $\overline{CAR}$. However, only two out of the 11 sectors experience a significant impact in the stock returns, where utilities is statistically significant at the one percent level and energy at the ten percent significance level. For the remaining sectors, the effect following the negative rating changes does not have a statistically significant impact on the stock returns, as we fail to reject the null hypothesis. The sectors exhibiting the greatest effect are utilities, energy and communication services at -0.88%, -0.64% and -0.38%, while the sectors experiencing the least effect are industrials, health care and consumer discretionary at -0.06%, -0.11% and 0.15%, respectively. On the other hand, following the positive rating changes, eight of the sectors produce positive $\overline{CAR}s$, while negative coefficients are found for communication services, energy and financials. Only consumer discretionary experiences a significant effect, along with the greatest effect of 0.57%, closely followed by industrials and information technology with effects of 0.32% and 0.29%, although not significant. The sectors exhibiting the least effects are utilities, energy and materials at 0.02%, -0.04% and 0.05%, respectively.

Table 7.

Results for the Rating Change Sample

	Negative				Positive			
Sector	$\overline{CAR}_i$	Robust Std. Error	θ_i	Prob.	$\overline{CAR}_i$	Robust Std. Error	θ_i	Prob.
Communication Services	-0.00376	0.00329	-1.14	0.2662	-0.00112	0.00131	-0.86	0.3996
Consumer discretionary	0.00146	0.00263	0.55	0.5811	0.00574	0.00084	6.82	0.0000***
Consumer Staples	-0.00203	0.00280	-0.73	0.4710	0.00155	0.00129	1.12	0.2730
Energy	-0.00639	0.00367	-1.74	0.0903*	-0.00042	0.00138	-0.30	0.7645
Financials	-0.00251	0.00241	1.04	0.2994	-0.00120	0.00093	-1.29	0.2012
Health Care	-0.00111	0.00269	-0.41	0.6805	0.00179	0.00110	1.63	0.1070
Industrials	-0.00062	0.00186	-0.33	0.7398	0.00316	0.00194	1.63	0.1093
Information Technology	-0.00304	0.00339	-0.90	0.3733	0.00290	0.00235	1.23	0.2203
Materials	-0.00175	0.00284	-0.61	0.5426	0.00046	0.00102	0.45	0.6546
Real Estate	-0.00214	0.00657	-0.33	0.7480	0.00074	0.00070	1.05	0.2975
Utilities	-0.00882	0.00252	-3.50	0.0001***	0.00022	0.00046	0.47	0.6383

Note: $\overline{CAR}_i$ is the cumulative average abnormal return following from a sample of rating changes. The robust standard errors are corrected for heteroscedasticity. θ_i is the test statistic approximated by a normal distribution. *, **, *** represents statistical significance at the 10%, 5% and 1% significance level.

In table 8 the results for the outlook sample are presented. Following the negative announcements, ten out of the 11 sectors exhibit a negative $\overline{CAR}$, where only the real estate sector exhibits a positive $\overline{CAR}$. The effect is statistically significant for nine sectors, seven at the one percent level and two at the five percent significance level. The sectors exhibiting the greatest effects are health care, utilities and information technology at -1.82%, -1.68% and -1.1%, respectively. The sectors with the least effect are found to be real estate, consumer discretionary and consumer staples at 0.14%, -0.19% and -0.37%, respectively. Following the positive announcements for the outlook sample, four sectors produce positive $\overline{CARs}$ where only two of these sectors are significant; consumer discretionary and consumer staples. The remaining seven sectors produce negative $\overline{CARs}$, suggesting that the positive outlook sample causes negative abnormal returns for these sectors, however, they are insignificant. The sectors exhibiting the greatest effect are consumer discretionary, consumer staples and energy with an effect of 0.39%, 0.31% and -0.27%, respectively. The sectors with the least effect are information technology, materials and communication services at -0.01%, 0.01% and -0.07%, respectively.

Table 8.
Results for the Outlook Sample

	Negative				Positive			
Sector	$\overline{CAR}_i$	Robust Std. Error	θ_i	Prob.	$\overline{CAR}_i$	Robust Std. Error	θ_i	Prob.
Communication Services	-0.00875	0.00283	-3.10	0.0035***	-0.00067	0.00244	-0.27	0.7879
Consumer discretionary	-0.00190	0.00245	-0.78	0.4386	0.00542	0.00177	3.06	0.0029***
Consumer Staples	-0.00371	0.00182	-2.04	0.0438**	0.00307	0.00099	3.09	0.0044***
Energy	-0.00660	0.00244	-2.70	0.0091***	-0.00268	0.00358	-0.75	0.4600
Financials	-0.00469	0.00186	-2.53	0.0123**	-0.00111	0.00140	-0.79	0.4310
Health Care	-0.01819	0.00458	-3.97	0.0001***	0.00188	0.00245	0.77	0.4464
Industrials	-0.00548	0.00194	-2.83	0.0059***	-0.00139	0.00116	-1.19	0.2444
Information Technology	-0.01133	0.00338	-3.35	0.0014***	-0.00007	0.00195	-0.04	0.9720
Materials	-0.01112	0.00401	-2.77	0.0073***	0.00018	0.00258	0.07	0.9436
Real Estate	0.00140	0.00159	0.88	0.3880	-0.00114	0.00101	-1.13	0.2634
Utilities	-0.01684	0.00301	-5.59	0.0000***	-0.00118	0.00134	-0.88	0.3815

Note: $\overline{CAR}_i$ is the cumulative average abnormal return following from a sample of credit outlooks and reviews. The robust standard errors are corrected for heteroscedasticity. θ_i is the test statistic approximated by a normal distribution. *, **, *** represents statistical significance at the 10%, 5% and 1% significance level.

In appendix D, the percentage impact for both the negative and the positive rating announcements in each event window are presented as well as the rating announcement that causes the greatest effect for each sector. A clear result is presented for the negative rating announcements, where the outlook sample causes the greatest effect for the majority of the sectors, specifically nine out of 11 sectors in both event windows. As presented above, the greatest effect is found for health care, utilities and information technology, a result that is consistent for both the outlook sample[7] and the combined sample. For two of the sectors, the largest effect effect cannot be attributed solely to the outlook sample; where in the 5-day event window, financials and real estate experience the greatest effects from the combined sample, while in the 11-day window, energy and real estate experience the greatest effects from the rating change sample and combined sample, respectively. The least effects for the negative rating announcements are found for consumer discretionary, real estate and consumer staples, a result found to be consistent over both event windows.

For the positive rating announcements a pattern can be observed, where for ten of the sectors the greatest effect is found to be caused by an individual rating announcement across both event windows. It is noted that the greatest effect found for communication services, consumer staples, health care and materials is caused by the combined sample, for consumer discretionary, financials, industrials and information technology the rating change sample, and for energy and utilities the outlook sample. However, for real estate the rating announcements causing the greatest effect differ between the event windows. The sectors with the greatest effect for the 5-day event window are; real estate, consumer discretionary and consumer staples, while for the 11-day window; consumer discretionary, consumer staples and industrials. The least effect is found for utilities, financials and materials in the 5-day event window and real estate, materials and utilities in the 11-day window. As such, for the positive rating announcements there is a larger variation in the rating announcements causing the greatest effect.

3.3 The $\overline{CARs}$ over the Event Window

To illustrate the results presented above, this section presents figures of the $\overline{CARs}$ over time, for both the negative and positive rating announcements. This allows us to determine when an effect takes place, as an effect closer to the event date is hypothesized to be more unexpected whereas an earlier effect could be regarded as more expected. We will utilize the 11-day window as this provides us with a better overview, but also captures most of the effect from the 5-day event window with comparable results. Three $\overline{CARs}$ are shown within each figure; one for the combined sample, one for the rating change sample and one

[7] The order of the greatest effect changes when moving across the event windows for the outlook sample, where for the 5-day event window the greatest effect is found for health care, utilities and information technology, while in the 11-day window it is found for health care, information technology and utilities.

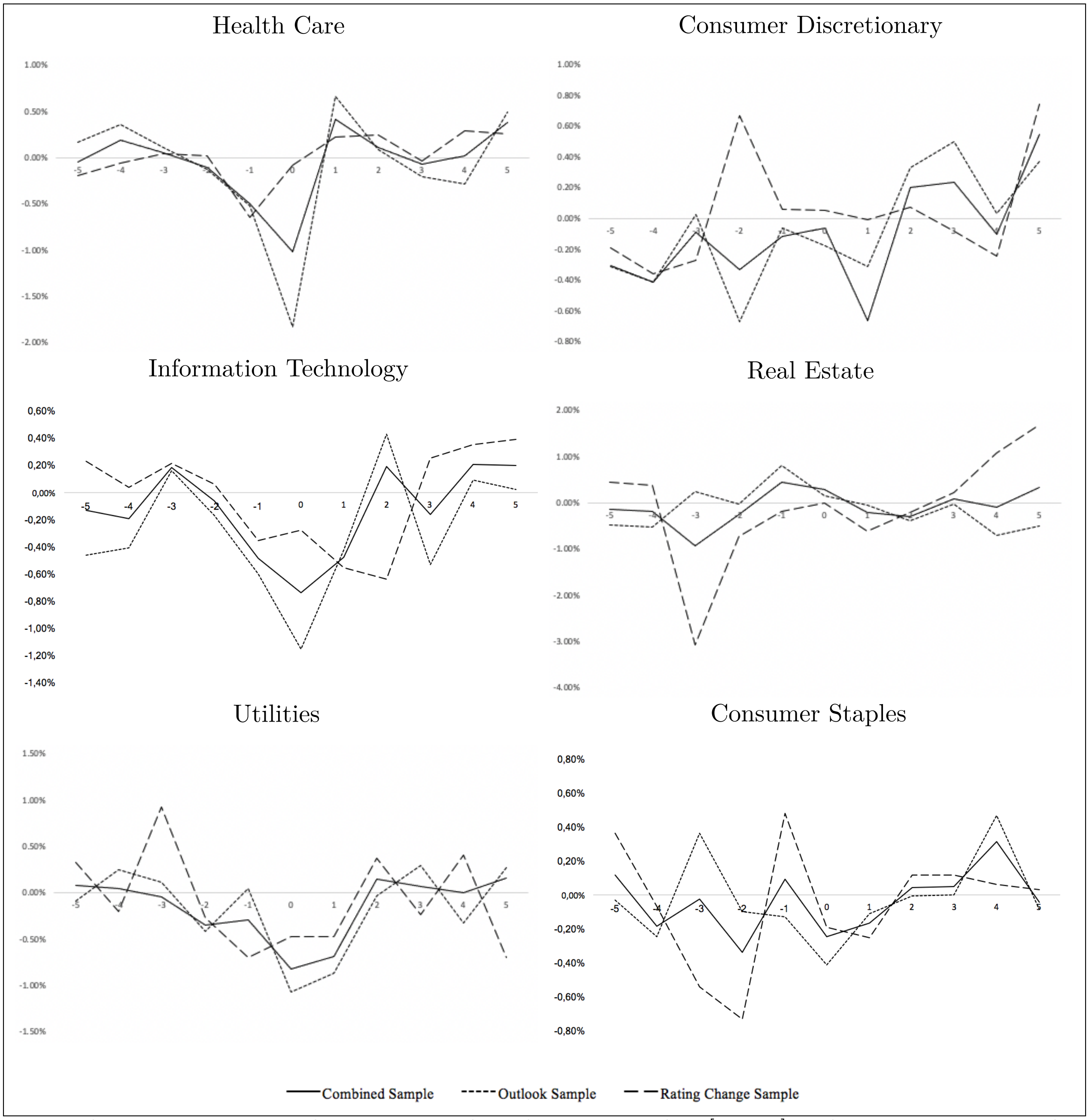
for the outlook sample. Presented are those sectors that are found to exhibit the greatest effect in the empirical results section, where the remaining sectors can be found in appendix E.

In figure 2, and figure E1, the $\overline{CAR}s$ for each sector following the negative rating announcements are presented. An overview of the illustrations reveal a general pattern, with higher dispersion of the $\overline{CAR}s$ for the time prior to the event date followed by a more dense pattern after the event date. For all the sectors, the figures present a result where the effect takes place before the actual event date for each rating announcement. Additionally, the figures present a result where the effect occurs closer to the actual event date when looking at both the combined and the outlook sample, whereas a somewhat earlier movement is observed for the rating change sample. As presented earlier, following the negative rating announcements the greatest effects are found for health care, information technology and utilities where the effects can be attributed to the outlook sample. A result that can also be seen in figure 2, with a substantial drop in the $\overline{CAR}s$ following the outlook and combined sample close to the event date. We also note that consumer discretionary, real estate and consumer staples exhibit the least effect, where the effect can be seen to take place close to the event date, however, the drop is of smaller magnitude. Furthermore, strong market movements are observed on the day following the event, where these movements can be seen as a reversal of the $\overline{CAR}s$ to their initial level. Overall, the individual rating announcements can be seen to cause negative $\overline{CAR}s$, as negative reactions in the stock returns can be observed. It is also noted that the rating change sample tends to remain closer to the x-axis, or even above on the event date, suggesting a lower effect for these rating announcements. Whereas, the combined sample and the outlook sample provide more negative movements on the days surrounding the event, suggesting a stronger effect following these samples of announcements.

In figure 3, and figure E2, three $\overline{CAR}s$ for each sector following the positive rating announcements are shown. As found for the negative announcements, the effect can be seen to take place before the actual event date, followed by a reversal in the $\overline{CAR}s$, where they converge towards their initial values. The effect following a positive rating announcement is not as clearly presented, as many of the sectors experience large movements throughout the event window, see for example, industrials, or movements closer to the x-axis, for example real estate. Two of the sectors exhibiting the greatest effect are consumer discretionary and consumer staples. As noted previously, consumer discretionary is the only sector exhibiting a significant effect following the positive rating change sample. Further, consumer discretionary and consumer staples are the only two sectors found to be significant following the positive outlook sample. For these two sectors, large jumps in their $\overline{CAR}s$ can be observed for these rating announcements, where the effect can also be seen to take place close to the actual event date. Whereas, two of the sectors with the least effects are materials and utilities, where we once again can observe movements closer to the x-axis on the event date. However, it is also noted that materials experiences a substantial increase in the $\overline{CAR}s$ when moving from [0, +1]. As we test the null hypothesis on the event date, day 0, this effect is not captured by the testing procedure.

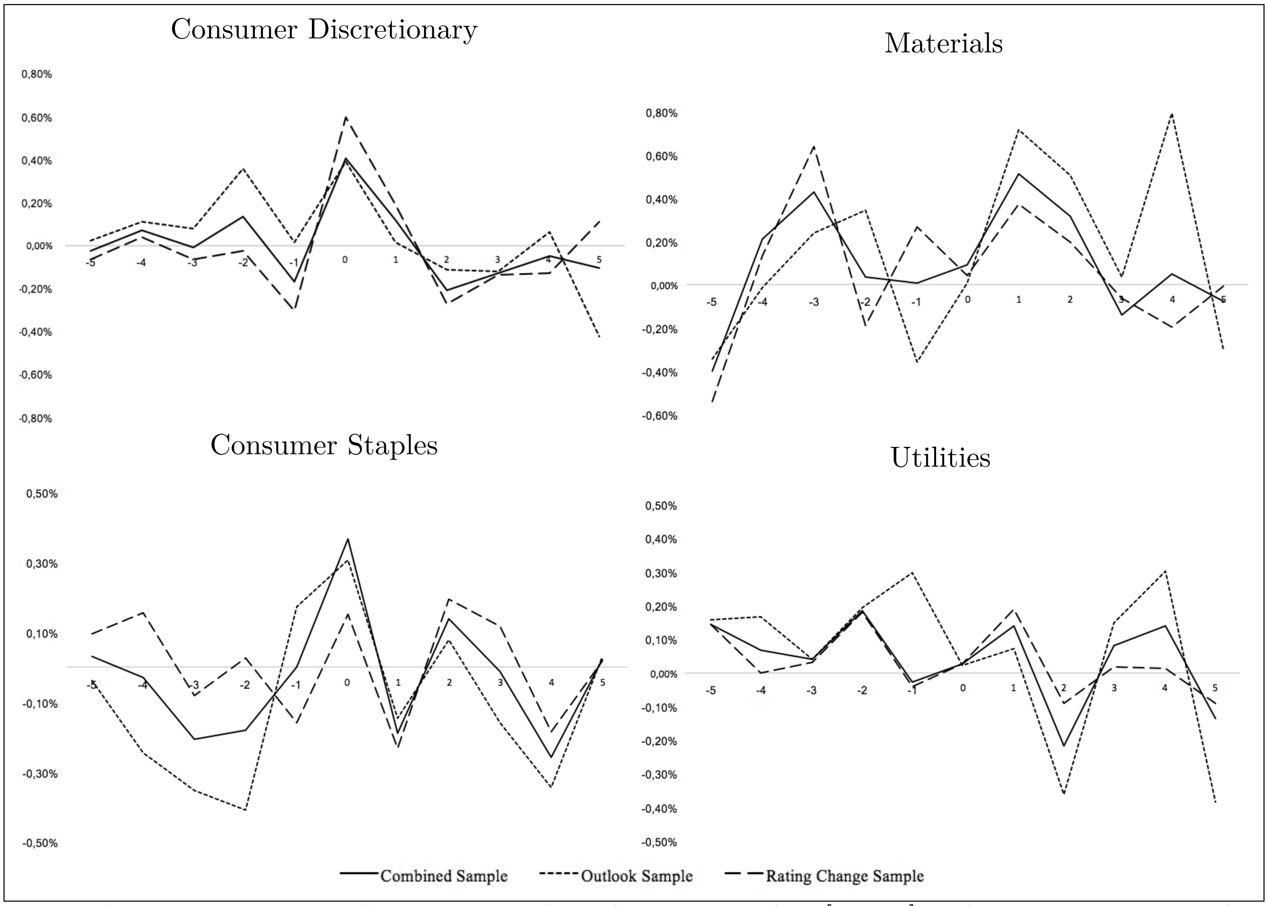
Figure 2.

$\overline{CAR}s$ Over the Event Window Following Negative Rating Announcements



Note: The x-axis represents the time interval in the event window [-5, +5]. The y-axis represents the percentage impact in the stock returns through the cumulative average abnormal return ($\overline{CAR}$).

Figure 3.
$\overline{CAR}s$ Over the Event Window Following Positive Rating Announcements



Note: The x-axis represents the time interval in the event window [-5, +5]. The y-axis represents the percentage impact in the stock returns through the cumulative average abnormal return ($\overline{CAR}$).

4 Discussion

Our results seem to go hand in hand with the results from previous research, where negative rating announcements cause a significant reaction in the stock returns, while a more subtle result is presented for positive rating announcements (Choy et al., 2006; Hand et al., 1992; Holthausen & Leftwich, 1986). While the combined sample produces the most significant sectors, the outlook sample produces the greatest effect in the stock returns, as also found by Followill & Martell (1997) and Micu et al. (2006). Further, the anticipation in the market differs between the announcements and a reversal is observed, in accordance with Glascock et al. (1987) and Kenjegaliev et al. (2016). We therefore argue that the results presented can be attributed to the informational value, the characteristics of the sectors and the expectation of the rating announcement, following the results of Ederington & Goh (1998) and Kliger & Sarig (2000).

4.1 Negative Rating Announcements

For the negative rating announcements, we find high significance among the sectors for the combined sample and the outlook sample, whereas the rating change sample only allows us to reject the null hypothesis for two sectors. We find that the combined sample in the 5-day event window has the highest significance, as it allows us to reject the null hypothesis for more sectors. With comparable significance across the event windows in the outlook sample, for the rating change sample a slightly higher significance is observed for the 5-day window. Overall, these results suggest that the 5-day window captures the effect more efficiently compared to the 11-day window. These findings are similar to those of Choy et al. (2006), where they report that the majority of the reaction is limited to the two days surrounding the event date. One explanation for a slightly lower significance in the 11-day event window might be the inclusion of other information that contaminates the data, as defined by Hand et al. (1992), lowering the overall significance and effect. One limitation is also noted with the event windows in this paper, utilizing two relatively short event windows hinders us from determining when the effect in the $\overline{CARs}$ disappears and when the stock returns have fully moved back to their initial levels.

The greatest effect for the negative rating announcements is found to be produced by the outlook sample. The effect is the greatest for nine of the 11 sectors, over both event windows. Therefore, we can see that the negative announcements in the outlook sample are of most importance to the GICS sectors, similar to the results found by Followill & Martell (1997). We note that both the rating reviews and outlooks typically precede the actual rating changes, as such, the informational value is already incorporated into the security prices when a rating change is due. Choy et al. (2006) note that the effect following a sample of unexpected events is limited to the days [-1, 0]. Further, Micu et al. (2006) found that the unexpected effect is limited to [0, +1], proving that these announcements carry informational value to the market. As noted, the effect for the $\overline{CAR}s$ in the outlook sample is observed to take place closer to the event date than for the other two announcement samples. As such, following the reasoning of Choy et al. (2006) and Micu et al. (2006) our results suggest that the announcements in the outlook sample are more unexpected as they seem to occur within the [-1, +1] interval surrounding the event, as suggested by these studies. This as a substantial drop in the $\overline{CAR}s$ is typically seen to occur on the day leading up to the event, followed by a strong market movement on the day following the event. The strong movement that follows on the day of the event suggests a reversal from the negative effect, moving the $\overline{CAR}s$ back to their initial levels, an effect that was also found by Glascock et al. (1987).

Thus, following the arguments presented by Hand et al. (1992) and Holthausen & Leftwich (1986), that an unexpected event will increase the significance for the stock returns, it can be seen that the combined and outlook sample have a higher unexpected value compared to the rating change sample. A result that seems to be consistent for the sectors with a significant effect, as the effect is of greater magnitude. For the rating change sample, we observe that the effect takes place somewhat earlier, since the information is already incorporated into the security prices through the more timely indicators of creditworthiness in the outlook sample. Additionally, Kenjegaliev et al. (2016) found that the adjustments in stock prices following a rating change starts [-60, -30] days before the actual event, suggesting a higher expectation of these announcements. Equivalently, our results seem to suggest a higher expectation for these announcements and an effect that is already incorporated into the security prices, as the significance level and the effects are found to be lower. Lastly, the number of significant sectors are found to be the most for the combined sample. Where the number of significant sectors can be due to a larger sample, as each announcement is treated as an individual event. Although, the following effect is found to be of intermediate magnitude, as it can be expected that the combination of announcements leads to a somewhat higher expectation than the outlook sample, however, a lower effect due to the inclusion of the rating change sample.

As noted, the greatest effects for the negative announcements, in absolute values, are observed for health care, utilities and information technology, where the order of effect is changed for information technology and utilities in the 11-day event window. For the remaining sectors, the order of greatest effect stays the same across both event windows. We note that the three sectors with the greatest effect have some of the highest long-term debt per share among the GICS sectors, suggesting that the informational value of rating announcements is more pronounced for high leveraged firms, which was also noted by Kliger & Sarig (2000). Although financials is the sector with the highest long-term debt per share, nevertheless experiencing a smaller effect. Choy et al. (2006) found that more heavily regulated industries provides more publicly available information, reducing the effect from the rating announcements. As this sector is comprised of banks, investment companies, insurance companies, etc., the regulation of this sector is high, which can explain its lower effect. The effect for health care, utilities and information technology can also be observed over the event window, where the individual $\overline{CAR}s$ exhibits substantial drops, where the drop is especially pronounced for the outlook sample. On the contrary, the least effects following the negative rating announcements are found for consumer discretionary, real estate and consumer staples, once again, a result that is consistent over both event windows. The long-term debt per share for these sectors is lower, as compared to the sectors exhibiting the greatest effect. However, the debt level is lower or relatively low, meaning that these are not the sectors with the lowest long-term debt per share.

4.2 Positive Rating Announcements

The two event windows following the positive rating announcements present a lower number of significant sectors, which is especially true for the rating change and outlook sample. The significance for the rating change and outlook sample is equivalent across both event windows, however, we note that the 5-day event window produces somewhat more significant sectors in the combined sample, suggesting that this event window captures the effect more efficiently. Once again, the higher significance found for the combined sample could be attributed to its larger sample size.

For the positive rating announcements, defining the rating announcement causing the greatest effect is more ambiguous. For the 5-day event window we observe that for five sectors the greatest effect is produced by the combined sample, for four sectors the rating change sample and for the last two the outlook sample. Out of these, we find that only six sectors experience a significant effect in their stock returns. Additionally, for the 11-day event window, the greatest effect is observed following the combined sample for four sectors, for another four sectors the rating change sample and for three sectors the outlook sample. Where only three of these sectors experience a significant effect. Ederington & Goh (1998) argue that companies are more inclined to release positive information, as such the positive information will be publicly available and incorporated into security prices, causing the positive rating announcements to be more expected. Our results seem to confirm this as the $\overline{CAR}s$, the significance of the $\overline{CAR}s$ and the absolute effects are found to be of lower magnitude. We observe that real estate, consumer discretionary and consumer staples exhibit the greatest effects for the 5-day event window, while in the 11-day window the greatest effects are found for consumer discretionary, consumer staples and industrials. Consumer discretionary experiences a great significant effect for all the positive rating announcements across both event windows, where the same holds for consumer staples, although not significant for the rating change sample.

One observation made is that real estate exhibits the greatest effect in the 5-day event window, however, in the 11-day window this sector is found to exhibit the least effect. This suggests that the 11-day window captures unnecessary information regarding the events for this sector. Further, industrials experiences low significance across all the positive rating announcements. As such, we limit our attention to consumer discretionary and consumer staples, as the possible inclusion of unnecessary information and a low significance level for real estate and industrials does not provide meaningful inferences. The long-term debt per share for consumer discretionary and consumer staples is relatively low, which could suggest that the positive rating announcements produce stronger effects for sectors with a lower level of long-term debt per share. Although, we note that these sectors do not have the smallest long-term debt per share, as such this is just one explanation for the results. It is also noted that these sectors have some of the highest returns over the sample period, where only health care experiences a higher return. As such, the relatively low level of long-term debt per share in combination with a high return could be the explanation for the greater effect found. The great effect for these sectors is also observed over the event window, where a substantial increase in the $\overline{CAR}s$ for all the rating announcements is observed on day [-2, 0]. For consumer discretionary, the effect following all the rating announcements can be seen to take place at the same time, more specifically the day prior to the event. Whereas, for consumer staples we note that the effect following the combined and the outlook sample can be observed somewhat earlier. In contrast to the argument brought forward by Ederington & Goh (1998), the announcements for these sectors seem to be accompanied by limited information. Subsequently, the increase observed on the day prior to the event is followed by a substantial decrease in the $\overline{CAR}s$ on the event date. For the remaining sectors, there is higher variation in the $\overline{CAR}s$, where the effect for some sectors can be seen to occur before the actual event date, followed by a substantial decline on the day prior to the event. One interesting result is presented, where the sectors experiencing the greatest effect following the positive rating announcements are the sectors experiencing the least effect following the negative rating announcements, which is especially true for consumer discretionary and consumer staples.

For the 5-day event window, the sectors experiencing the least effects are utilities, financials and materials, whereas for the 11-day event window the least effects are found for real estate, materials and utilities. As real estate likely suffers from contaminated data we limit our attention to financials, materials and utilities in regards to the least effect, where the effect is consistent across both event windows for the two latter sectors. Utilities and financials both have higher long-term debt per share compared to the sectors with the greatest effect. Once again, financials is likely affected by the higher regulation which causes the information to already be publicly available, as suggested by Choy et al. (2006). Although materials experiences one of the least effects, we observe a substantial increase in the $\overline{CAR}s$ from day [0, +1]. As we measure the effect solely on the event date, we fail to capture this effect when the effect might actually be much greater.

Kliger & Sarig (2000) showed that the rating agencies help to reduce the asymmetric information by disclosing inside information in the ratings. Where the companies being rated are more inclined to release positive information into the ratings, reducing the information asymmetry, whereas the negative information is not as easily available, as noted by Ederington & Goh (1998). With this in mind, the results obtained in this paper can be seen to confirm these findings. We find that the negative rating announcements cause a greater reaction in the stock returns, evidence for a higher degree of asymmetric information contained in these announcements. As such, the new information that these announcements bring about, help to reduce the asymmetry. While the asymmetry is less pronounced for the positive announcements, as the information is already publicly available, a result attributed to the smaller reaction in the sectors stock returns.

5 Conclusion

The purpose of this paper was to test the effect in the GICS sectors stock returns found on the S&P 500 from credit rating announcements provided by Standard & Poor's and Moody's through an event study spanning from 2000 to 2019. Three samples of rating announcements are tested individually and observed over time. Where we try to answer which rating announcement produces the greatest abnormal returns and which sector experiences the greatest effect. We find that the GICS sectors exhibit different reactions in stock returns, where the magnitude of the effect differs depending on the rating announcements. As this has not been tested before, we contribute to the existing research with results indicating that the more timely indicators of creditworthiness found in the outlook sample produce the greatest effects for the negative rating announcements. Whereas, for the positive announcements more publicly available information decreases the reaction in stock returns. As such, the negative rating announcements can be found to reduce the information asymmetry more. Lastly, our results indicate that some of the individual sector characteristics can help to explain the magnitude of the effect.

For the negative rating announcements, the outlook sample produces the greatest abnormal returns for the majority of the sectors. As the outlooks and reviews, that constitute the outlook sample, are more timely indicators of creditworthiness and where these rating announcements precede the actual rating changes they carry more information to the market. The informational value brought forward by the outlook sample generates a lower expectancy for these announcements, resulting in a greater effect. By using absolute values of the $\overline{CAR}s$, we observe that the sectors with a higher long-term debt per share are also those that exhibit a greater effect following the negative rating announcements, these sectors are; health care, utilities and information technology. We can also observe that a relatively lower level of long-term debt per share produces a smaller effect, which is found for consumer discretionary, real estate and consumer staples.

For the positive rating announcements, less significance is observed for the sectors as well as a lower absolute effect. Where this can be explained by the phenomenon that companies are more inclined to release positive information causing them to be more expected. Concluding which announcement that causes the greatest effect is more ambiguous as the source of the greatest effect varies to a higher degree between the announcement samples. As such we fail to conclude which announcement sample that causes the greatest effect. On the other hand we find that the sectors exhibiting the greatest significant effects are consumer discretionary and consumer staples. These are sectors with relatively low long-term debt per share and with some of the highest returns over the sample period, a relationship that might help to explain this finding. One interesting observation is made, where the sectors with the least effect following the negative rating announcements are those that experience the greatest effect following the positive rating announcements, which is especially true for consumer discretionary and consumer staples. Whereas, the least effect can be seen to be as ambiguous, where utilities and materials are found to have the least effect in both event windows.

For further research we propose to include ratings from more rating agencies, for example from Fitch. Focusing on the rating announcements could also lead to conclusions, as to see if there is a larger effect when a company goes from investment grade to speculative grade, or vice versa. It could also be of interest to test the effect if the rating changes are over multiple ratings, such as from BBB to C or over multiple notches within a rating. Dividing the outlook sample into outlooks and reviews and testing the effect individually could also be of interest, as we find that this sample produces the greatest effect. It would therefore be interesting to see which component of this sample that produces the greatest effect. Another aspect that could be of importance is to include additional parameters in the regression model, such as the level of debt and the return of the sectors in order to see if these factors could explain the results found. Further, dummy variables could be included in the regression for periods surrounding the financial crises, as to see whether the effect is consistent over these periods. Lastly, it would be interesting to see if the results in this paper hold for the market sectors of other geographical locations.

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Appendices

A Shapiro-Wilks Test of Normality

The Shapiro-Wilks goodness-of-fit test was conducted as to ensure normality of the data. The test was chosen as it is a powerful test of normality, even for smaller sample sizes (Razali & Wah, 2011). The Shapiro-Wilks test can be conducted to ensure that a random sample comes from a normal distribution (Shapiro & Wilk, 1965). Where Z is the test statistic, approximated by a normal distribution under the null hypothesis. The test statistic W is estimated by the following equation:

$$W = \frac{(\sum_{i=1}^{n} a_i y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{A1}$$

Where, y_i are random sample values and a_i are constants from a normally distributed sample. The null hypothesis to be tested is that a sample of random variables comes from a normal distribution.

Table A1.
Shapiro-Wilks Test for the 5-day Event Window, Combined Sample

	Negative			Positive		
Sector	W-statistic	Z	Prob.	W-statistic	Z	Prob.
Communication Services	0.93795	2.742	0.0031***	0.87524	1.431	0.0762*
Consumer discretionary	0.90827	2.426	0.0076***	0.96717	2.819	0.0024***
Consumer Staples	0.90937	2.013	0.0221**	0.86937	2.275	0.0115**
Energy	0.88853	1.794	0.0364**	0.88988	1.769	0.0384**
Financials	0.97023	2.536	0.0056***	0.97743	2.639	0.0042***
Health Care	0.97957	0.524	0.3002	0.95078	1.079	0.1402
Industrials	0.90383	2.310	0.0104**	0.93135	2.012	0.0221**
Information Technology	0.93248	1.579	0.0572*	0.93917	1.803	0.0357**
Materials	0.89847	1.688	0.0457**	0.94044	1.928	0.0269**
Real Estate	0.88601	1.753	0.0398**	0.95755	1.771	0.0383**
Utilities	0.97306	0.909	0.1816	0.94885	0.525	0.2997

Note: *, **, *** represents statistical significance at the 10%, 5% and 1% significance level.

Table A2.
Shapiro-Wilks Test for the 11-day Event Window, Combined Sample

Sector	Negative			Positive		
	W-statistic	Z	Prob.	W-statistic	Z	Prob.
Communication Services	0.94707	2.456	0.0070***	0.87903	1.371	0.0852**
Consumer discretionary	0.90118	2.581	0.0049***	0.91390	2.789	0.0026***
Consumer Staples	0.89258	2.362	0.0091***	0.87970	2.109	0.0175**
Energy	0.89204	1.730	0.0418**	0.89088	1.751	0.0400**
Financials	0.90496	2.915	0.0018***	0.95816	2.541	0.0055***
Health Care	0.97673	0.807	0.2099	0.97506	1.224	0.1105
Industrials	0.88614	2.659	0.0039***	0.84454	2.544	0.0055***
Information Technology	0.93380	1.537	0.0622*	0.93918	1.802	0.0358**
Materials	0.89602	1.736	0.0412**	0.94893	1.562	0.0591*
Real Estate	0.88404	1.955	0.0253**	0.88771	2.120	0.0170**
Utilities	0.92906	0.889	0.1869	0.94805	0.557	0.2888

Note: *, **, *** represents statistical significance at the 10%, 5% and 1% significance level.

Table A3.
Shapiro-Wilks Test for the 5-day Event Window, Rating Change

Sector	Negative			Positive		
	W-statistic	Z	Prob.	W-statistic	Z	Prob.
Communication Services	0.93705	0.946	0.1720	0.95056	0.587	0.2786
Consumer discretionary	0.88747	2.852	0.0022***	0.90495	2.830	0.0023***
Consumer Staples	0.95975	1.626	0.0520*	0.95356	0.958	0.1690
Energy	0.93132	2.013	0.0221**	0.89756	1.625	0.0521*
Financials	0.90561	2.901	0.0019***	0.94890	1.347	0.0890*
Health Care	0.96482	0.332	0.3699	0.97203	1.382	0.0835*
Industrials	0.97464	-0.446	0.3022	0.97020	0.685	0.2467
Information Technology	0.96885	1.012	0.1558	0.92739	2.083	0.0186**
Materials	0.96713	0.467	0.3203	0.91350	0.926	0.1772
Real Estate	0.94887	-0.331	0.3295	0.94721	1.175	0.1200
Utilities	0.94475	0.541	0.2543	0.96853	-0.526	0.2743

Note: *, **, *** represents statistical significance at the 10%, 5% and 1% significance level.

Table A4.
Shapiro-Wilks Test for the 11-day Event Window, Rating Change

Sector	Negative			Positive		
	W-statistic	Z	Prob.	W-statistic	Z	Prob.
Communication Services	0.92670	1.034	0.1505	0.95355	0.460	0.3228
Consumer discretionary	0.90118	2.581	0.0049***	0.91756	2.530	0.0057***
Consumer Staples	0.95926	1.652	0.0493**	0.95559	0.816	0.2073
Energy	0.93770	1.808	0.0353**	0.91655	1.214	0.1123
Financials	0.90496	2.915	0.0018***	0.93906	1.622	0.0524*
Health Care	0.96566	0.282	0.3889	0.93885	1.319	0.0935*
Industrials	0.96196	0.393	0.3472	0.94061	0.611	0.2705
Information Technology	0.96790	1.077	0.1408	0.96500	2.294	0.0109**
Materials	0.96067	-0.536	0.2740	0.94893	1.562	0.0591*
Real Estate	0.95482	-0.541	0.2859	0.95180	2.045	0.0204**
Utilities	0.95564	0.302	0.3812	0.94805	0.557	0.2888

Note: *, **, *** represents statistical significance at the 10%, 5% and 1% significance level.

Table A5.

Shapiro-Wilks Test for the 5-day Event Window, Outlook Sample

Sector	Negative			Positive		
	W - Statistic	Z	Prob.	W - Statistic	Z	Prob.
Communication Services	0.94946	1.231	0.1091	0.90997	1.525	0.0637*
Consumer discretionary	0.93397	1.975	0.0241**	0.92363	2.189	0.0143**
Consumer Staples	0.89772	2.262	0.0119**	0.91623	2.025	0.0214**
Energy	0.95281	1.904	0.0284**	0.92542	1.892	0.0292**
Financials	0.94759	1.776	0.0379**	0.98350	0.059	0.4766
Health Care	0.96097	2.253	0.0121**	0.94628	1.940	0.0262**
Industrials	0.91791	1.810	0.0352**	0.89717	1.714	0.0433**
Information Technology	0.94364	2.318	0.0102**	0.95368	1.832	0.0335**
Materials	0.95610	1.994	0.0231**	0.91779	1.689	0.0456**
Real Estate	0.92195	2.139	0.0162**	0.94197	2.177	0.0148**
Utilities	0.96838	1.768	0.0386**	0.84416	2.709	0.0034***

Note: *, **, *** represents statistical significance at the 10%, 5% and 1% significance level.

Table A6.

Shapiro-Wilks Test for the 11-day Event Window, Outlook Sample

Sector	Negative			Positive		
	W - Statistic	Z	Prob.	W - Statistic	Z	Prob.
Communication Services	0.88219	1.222	0.1109	0.90768	1.575	0.0576*
Consumer discretionary	0.91907	2.402	0.0081***	0.96425	2.321	0.0102**
Consumer Staples	0.92169	1.713	0.0434**	0.93456	1.402	0.0804*
Energy	0.88248	1.813	0.0349**	0.92935	1.780	0.0376**
Financials	0.94527	1.867	0.0309**	0.98501	-0.150	0.5594
Health Care	0.96866	1.794	0.0364**	0.95273	1.631	0.0514*
Industrials	0.93203	1.422	0.0775*	0.92879	1.743	0.0407**
Information Technology	0.96447	1.536	0.0623*	0.96447	1.536	0.0623*
Materials	0.95382	2.103	0.0177**	0.91597	1.733	0.0415**
Real Estate	0.92080	2.169	0.0150**	0.93892	2.214	0.0134**
Utilities	0.96982	1.666	0.0479**	0.84106	2.749	0.0023***

Note: *, **, *** represents statistical significance at the 10%, 5% and 1% significance level.

B Results for Rating Change and Outlook Sample for the 11-day Event Window

Table B1.

Result for the Rating Change Sample

	Negative				Positive			
Sector	$\overline{CAR_i}$	Robust Std. Error	θ_i	Prob.	$\overline{CAR_i}$	Robust Std. Error	θ_i	Prob.
Communication Services	-0.00271	0.00341	-0.80	0.4352	-0.00104	0.00147	-0.71	0.4853
Consumer discretionary	0.00051	0.00262	0.19	0.8473	0.00596	0.00085	7.03	0.0000***
Consumer Staples	-0.00194	0.00277	-0.70	0.4868	0.00155	0.00143	1.07	0.2935
Energy	-0.00738	0.00366	-2.02	0.0507*	-0.00043	0.00137	-0.32	0.7527
Financials	-0.00226	0.00238	-0.95	0.3437	-0.00136	0.00090	-1.51	0.1334
Health Care	-0.00081	0.00271	-0.30	0.7645	0.00179	0.00100	1.11	0.2682
Industrials	-0.00059	0.00179	-0.33	0.7392	0.00334	0.00192	1.54	0.1753
Information Technology	-0.00283	0.00351	-0.81	0.4235	0.00290	0.00111	0.65	0.5155
Materials	-0.00175	0.00292	-0.60	0.5523	0.00046	0.00101	0.00	0.9964
Real Estate	-0.00004	0.00571	-0.01	0.9936	0.00066	0.00070	0.95	0.3439
Utilities	-0.00477	0.00279	-1.71	0.0917*	0.00029	0.00045	0.64	0.5270

Note: $\overline{CAR_i}$ is the cumulative average abnormal return following from a sample of rating changes. The robust standard errors are corrected for heteroscedasticity. θ_i is the test statistic approximated by a normal distribution. *, **, *** represents statistical significance at the 10%, 5% and 1% significance level.

Table B2.

Result for the Outlook Sample

	Negative				Positive			
Sector	$\overline{CAR_i}$	Robust Std. Error	θ_i	Prob.	$\overline{CAR_i}$	Robust Std. Error	θ_i	Prob.
Communication Services	-0.00912	0.00284	-3.21	0.0026***	-0.00134	0.00248	-0.54	0.5961
Consumer discretionary	-0.00177	0.00246	-0.72	0.4732	0.00389	0.00172	2.26	0.0262**
Consumer Staples	-0.00415	0.00180	-2.30	0.0233**	0.00310	0.00083	2.01	0.0556*
Energy	-0.00636	0.00240	-2.65	0.0105**	-0.00257	0.00356	-0.72	0.4751
Financials	-0.00498	0.00187	-2.66	0.0085***	-0.00086	0.00140	-0.62	0.5402
Health Care	-0.01830	0.00453	-4.04	0.0001***	0.00188	0.00231	0.49	0.6276
Industrials	-0.00600	0.00188	-3.19	0.0020***	-0.00167	0.00144	-1.16	0.2577
Information Technology	-0.01155	0.00336	-3.44	0.0011***	0.00017	0.00198	0.08	0.9327
Materials	-0.01037	0.00394	-2.71	0.0087***	0.00012	0.00312	0.04	0.9707
Real Estate	0.00152	0.00150	1.01	0.3193	-0.00095	0.00103	-0.93	0.3570
Utilities	-0.01067	0.00169	-6.12	0.0000***	0.00024	0.00160	0.17	0.8649

Note: $\overline{CAR_i}$ is the cumulative average abnormal return following from a sample of credit outlooks and reviews. The robust standard errors are corrected for heteroscedasticity. θ_i is the test statistic approximated by a normal distribution. *, **, *** represents statistical significance at the 10%, 5% and 1% significance level.

C Summary of the $\overline{CAR}s$

Table C1.
$\overline{CAR}s$ for the Negative Rating Announcements

Sector	5-day Event Window			11-day Event Window		
	Combined Sample	Rating Change Sample	Outlook Sample	Combined Sample	Rating Change Sample	Outlook Sample
Communication Services	-0.70%	-0.38%	-0.88%	-0.69%	-0.27%	-0.91%
Consumer discretionary	-0.03%	0.15%	-0.19%	-0.07%	0.05%	-0.18%
Consumer Staples	-0.23%	-0.20%	-0.37%	-0.25%	-0.19%	-0.42%
Energy	-0.65%	-0.64%	-0.66%	-0.39%	-0.74%	-0.64%
Financials	-0.54%	-0.25%	-0.47%	-0.47%	-0.23%	-0.50%
Health Care	-1.03%	-0.11%	-1.82%	1.01%	-0.08%	-1.83%
Industrials	-0.28%	-0.06%	-0.55%	-0.33%	-0.06%	-0.60%
Information Technology	-0.74%	-0.30%	-1.13%	-0.74%	-0.28%	-1.16%
Materials	-0.72%	-0.17%	-1.11%	-0.70%	-0.17%	-1.04%
Real Estate	-0.27%	-0.21%	0.14%	0.28%	0.00%	0.15%
Utilities	-0.82%	-0.88%	-1.68%	-0.82%	-0.48%	-1.07%

Table C2.
$\overline{CAR}s$ for the Positive Rating Announcements

Sector	5-day Event Window			11-day Event Window		
	Combined Sample	Rating Change Sample	Outlook Sample	Combined Sample	Rating Change Sample	Outlook Sample
Communication Services	0.23%	-0.11%	-0.07%	0.21%	-0.10%	-0.13%
Consumer discretionary	0.38%	0.57%	0.54%	0.40%	0.60%	0.39%
Consumer Staples	0.37%	0.16%	0.31%	0.37%	0.16%	0.31%
Energy	-0.13%	-0.04%	-0.27%	-0.13%	-0.04%	-0.26%
Financials	-0.06%	-0.12%	-0.11%	-0.05%	-0.14%	-0.09%
Health Care	0.32%	0.18%	0.19%	0.31%	0.18%	0.19%
Industrials	-0.12%	0.32%	-0.14%	-0.13%	0.33%	-0.17%
Information Technology	0.14%	0.29%	-0.01%	0.15%	0.29%	0.02%
Materials	0.13%	0.05%	0.02%	0.10%	0.05%	0.01%
Real Estate	0.58%	0.07%	-0.11%	-0.02%	0.07%	-0.10%
Utilities	0.02%	0.02%	-0.12%	0.03%	0.03%	0.02%

D The Greatest Effect for each Sector by Rating Announcement

Presented in this section is the greatest effect for each sector and the rating announcement that causes the effect. The greatest effects are presented in absolute values for both event windows. Absolute values are used since we do not want to limit the effect in any direction, for example, following the negative rating announcements the effect is not solely limited to a negative $\overline{CAR}$. This as we find that some sectors exhibit a positive reaction following the negative announcements, whereas some exhibit a negative reaction following the positive announcements. As such, we argue, that this allows for a more comprehensive result and inference.

Table D1.
The Greatest Effect Following Negative Rating Announcements

	5-day Event Window		11-day Event Window	
Sector	Rating Type	Effect	Rating Type	Effect
Communication Services	Outlooks	-0.88%	Outlooks	-0.91%
Consumer discretionary	Outlooks	-0.19%	Outlooks	-0.18%
Consumer Staples	Outlooks	-0.37%	Outlooks	-0.42%
Energy	Outlooks	-0.66%	Rating Change	-0.74%
Financials	Combined	-0.54%	Outlooks	-0.50%
Health Care	Outlooks	-1.82%	Outlooks	-1.83%
Industrials	Outlooks	-0.55%	Outlooks	-0.60%
Information Technology	Outlooks	-1.13%	Outlooks	-1.16%
Materials	Outlooks	-1.11%	Outlooks	-1.04%
Real Estate	Combined	-0.27%	Combined	0.28%
Utilities	Outlooks	-1.68%	Outlooks	-1.07%

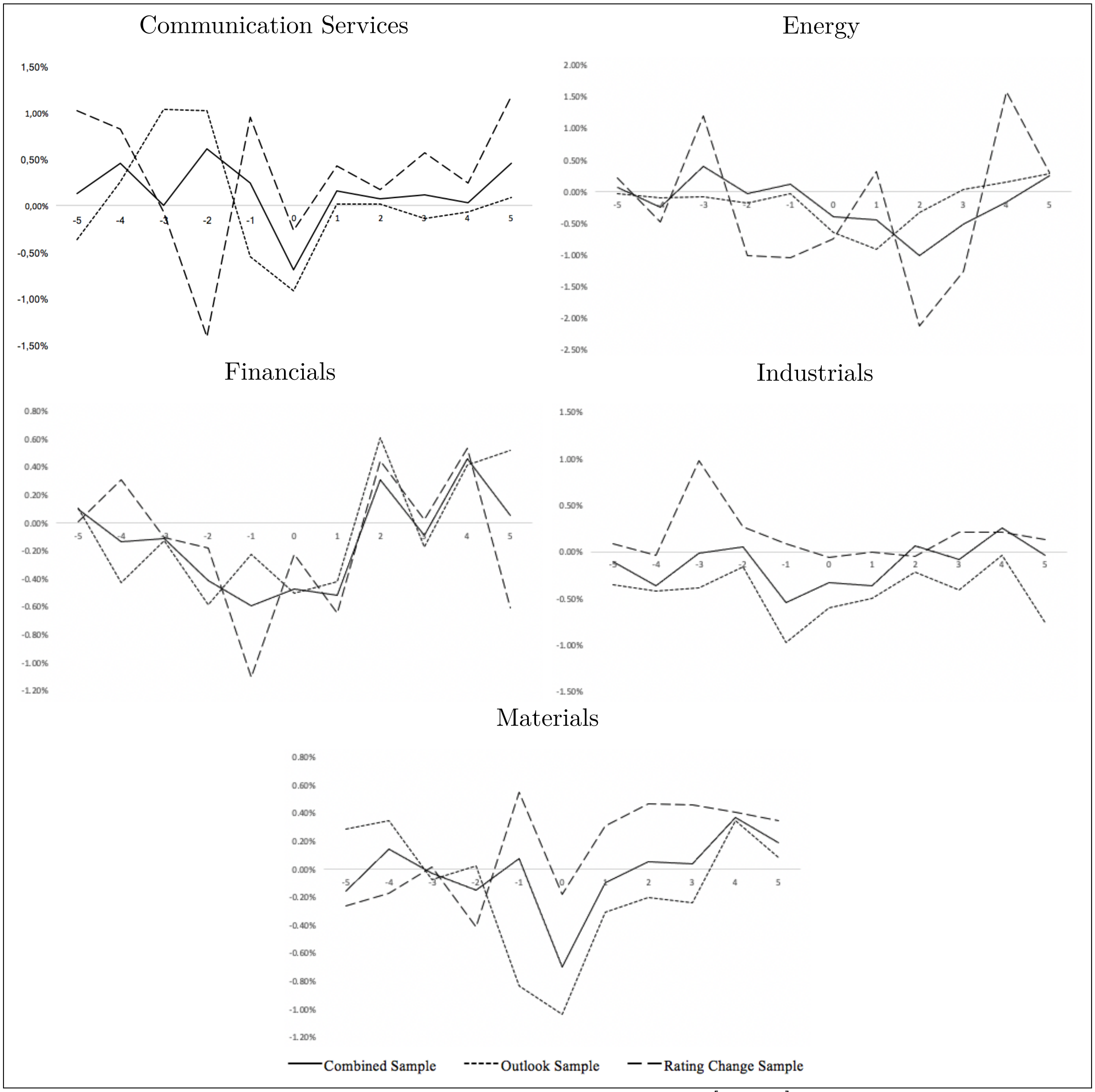
Table D2.
The Greatest Effect Following Positive Rating Announcements

	5-day Event Window		11-day Event Window	
Sector	Rating Type	Effect	Rating Type	Effect
Communication Services	Combined	0.23%	Combined	0.21%
Consumer discretionary	Rating Change	0.57%	Rating Change	0.60%
Consumer Staples	Combined	0.37%	Combined	0.37%
Energy	Outlooks	-0.27%	Outlooks	-0.26%
Financials	Rating Change	-0.12%	Rating Change	-0.14%
Health Care	Combined	0.18%	Combined	0.31%
Industrials	Rating Change	0.32%	Rating Change	0.33%
Information Technology	Rating Change	0.29%	Rating Change	0.29%
Materials	Combined	0.13%	Combined	0.10%
Real Estate	Combined	0.58%	Outlooks	-0.10%
Utilities	Outlooks	-0.12%	Outlooks	0.12%

E $\overline{CAR}s$ Over the Event Window

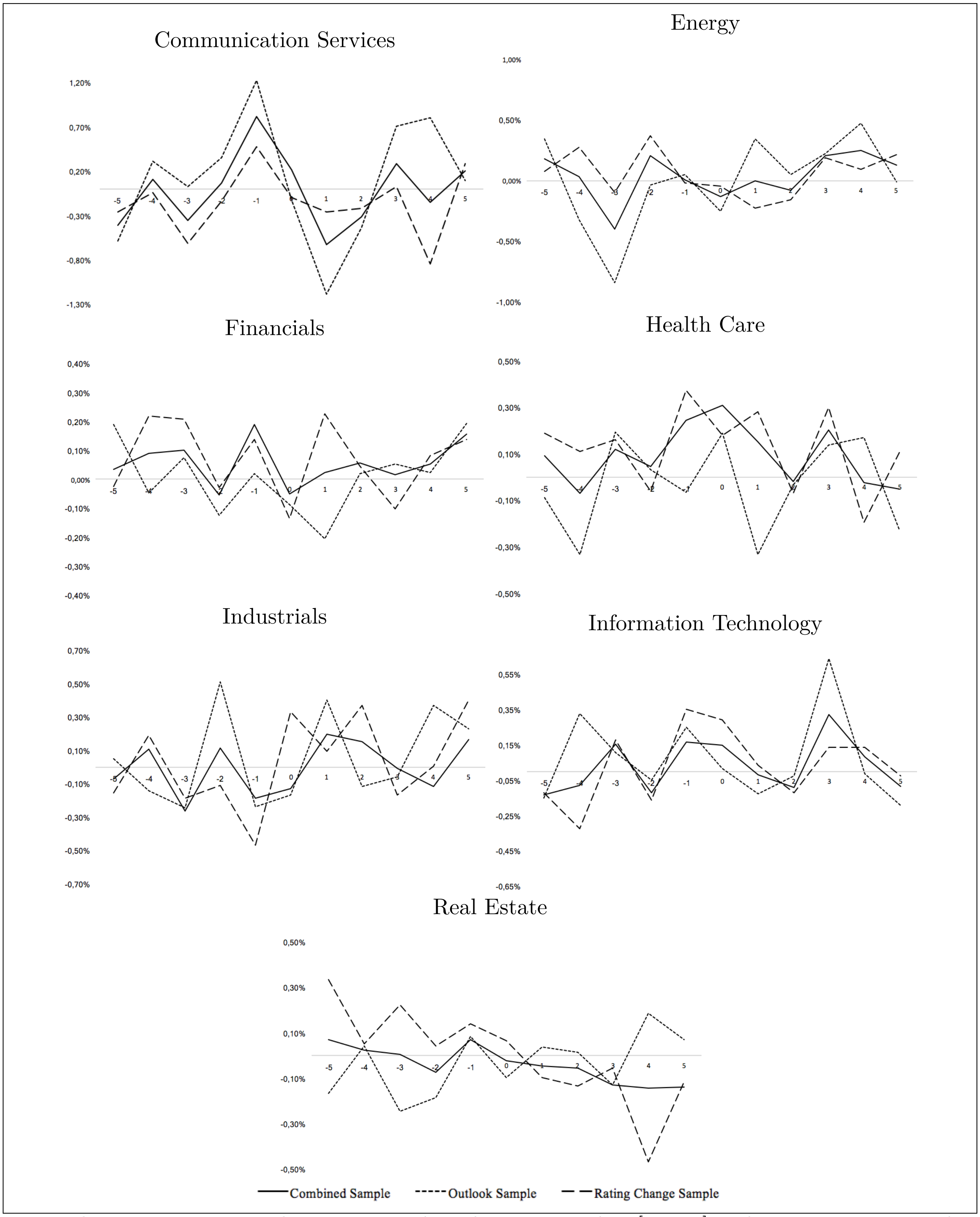
Figure E1.

$\overline{CAR}s$ Over the Event Window Following Negative Rating Announcements



Note: The x-axis represents the time interval in the event window [-5, +5]. The y-axis represents the percentage impact in the stock returns through the cumulative average abnormal return ($\overline{CAR}$).

Figure E2.
$\overline{CARs}$ Over the Event Window Following Positive Rating Announcements



Note: The x-axis represents the time interval in the event window [-5, +5]. The y-axis represents the percentage impact in the stock returns through the cumulative average abnormal return ($\overline{CAR}$).