Do Rating Agencies' Decisions Impact Stock Returns?

Evidence From US Market

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Abstract

This dissertation analyses the effect of credit rating decisions on stock returns for the US Market, considering two kinds of events: Upgrades and Downgrades. The data used to conduct the study ranges from 1985 to 2017. To understand the impact of the changes in credit ratings on stock returns, the analysis was applied before and after the event occurred within 10 to 25 days prior and post the event. The abnormal returns are calculated to see if the returns following credit rating changes differ considerably from the expected returns with no change in rating. To see if the discrepancies between the abnormal returns and the expected returns are statistically significant, a standard paired t-test is used on three different windows, T-10 to T+10, T-10 to T+15, and T-15 to T+15, for robustness checks.

The results suggest that the credit rating downgrades have a significant impact on stock returns for the whole sample. On the contrary, credit rating upgrades have no significant impact. As for the average predicted returns, for the T-10 to T+10 window, the result for upgrades is 0.02% and for downgrades is -0.09%. For AAR, the result for upgrades is 0.01% and for downgrades is 0.05%.

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Resumo

A presente dissertação analisa o efeito das decisões de classificações de crédito nos retornos das ações para o Mercado dos EUA, tendo em consideração: *Upgrades* e *Downgrades*. Os dados variam entre 1985 e 2017. Para compreender o impacto das alterações nas classificações de crédito, no retorno das ações, a análise foi aplicada no período de 10 a 25 dias antes e depois do evento ocorrer. Os retornos anormais são calculados para ver se os retornos na sequência das alterações de classificação de crédito diferem consideravelmente dos retornos esperados, sem qualquer alteração na classificação. Para ver se as discrepâncias são estatisticamente significativas, é desempenhado um *t-test* padrão em três janelas diferentes, T-10 a T+10, T-10 a T+15 e T-15 a T+15 como teste de robustez. Os resultados sugerem que, para toda a amostra, as reduções da classificação de crédito têm um impacto significativo nos retornos das ações, e pelo contrário, os aumentos das classificações de crédito não têm impacto significativo. Quanto aos *average predicted returns*, para a janela de T-10 a T+10, o resultado em *upgrades* é de 0,02% e em *downgrades* é de -0,09%. Já para o AAR, o resultado em *upgrades* é 0,01% de e para *downgrades* é de 0,05%.

Título: As decisões das agências de classificação de crédito de risco têm impacto nos retornos das ações? Evidência do mercado dos Estados Unidos da América

Autor: Sofia Estácio Simões

Palavras-chave: Aumento da classificação de crédito, Diminuição da classificação de crédito, Estudo de Evento, Categoria de Investimento, Categoria de Especulação

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1. Introduction

Nowadays, Credit Rating Agencies have an essential role in the financial markets. Historically, credit ratings have been a significant benchmark for regulators as they rely their decisions on the nationally recognized credit rating agencies (NRSROs).[1] The Office of Credit Ratings (OCR) is responsible for protecting investors, promoting capital formation, and maintaining fair, orderly, and efficient markets throughout the oversight credit rating agencies considered for the NRSROs, such as Standards & Poor's (S&P), Moody's and Fitch.

Credit ratings are considered an essential input as they are able to impact a firm's cost of capital (Kisgen & Strahan, 2010), and managers are aware of them when making financial decisions (Grahama & Harvey, 2001).

Over the years, many have been the opinions on the importance of credit ratings, questioning and trying to understand their need. However, credit ratings have persisted. One of the reasons that can explain this is the perceived lack of alternatives to credit ratings. Even though there are other ways of analysing a company's probability of default, such as bond spreads or CDSs, credit ratings are still an important source of information. On the one hand, bonds can differ on yield, maturity, callability, and other covenants (Chava, et al., 2010), which can lead to market segmentation and illiquidity.[2] On the other hand, pure credit risk measures should only be influenced by systematic factors to the extent that fundamental credit quality is a function of such (Karagozoglu & Jacobs, 2010), and CDSs are influenced by systematic and unsystematic factors independently, not respecting such premiss.

This study aims to investigate if a specific firm rating change (upgrade or downgrade) has any impact on the firm's stock returns and to understand if the impact is positive or negative according to the type of rating change, and thus, it presents an extension on past literature. According to Mokoaleli-Mokoteli & Thabang, (2019), understanding the impact of credit rating changes is important as a downgrade can result in investors stopping investing in firms, which in turn results in volatility in stock yields and a decrease in stock returns.

To conduct this study, I use an event study methodology to assess the impact of the credit rating changes on stock returns. Only upgrades and downgrades are considered as they hold new information that the market typically reacts to. The data used to conduct the study

[1] NRSRO is a credit rating agency that provides an assessment of the creditworthiness of a firm or financial instrument(s) that is registered and approved by the Securities and Exchange Commission (SEC).

[2] Callability is the ability of a bond issuer to redeem its bonds early than its defined maturity date.

ranges from 1985 to 2017.[3] To understand the impact of changes in credit ratings on the return of stocks, the analysis was applied before and after the event occurred within 10 to 25 days prior and post the event. The abnormal returns are calculated to see if the returns following credit rating changes differ considerably from the expected returns with no change in rating. To see if the discrepancies between the abnormal returns and the expected returns are statistically significant, a standard paired t-test is used on three different windows, T-10 to T+10, T-10 to T+15, and T-15 to T+15, for robustness checks. Furthermore, t-tests are used to determine which periods and events investors react more powerfully to. For the overall sample, the results for the downgrades lead to significant changes in stock returns, and upgrades are only significant for the wider window (T-15 to T+15), meaning that upgrades do not show consistent results, therefore not having a significant impact on stock returns.

2. Literature Review

Credit Rating Agencies aim to measure the creditworthiness of an issuer or specific issue. With the use of financial and non-financial information, they can provide each entity/issue with a forward-looking estimation regarding credit risk. According to different authors, credit risk is an opinion regarding the creditworthiness of an entity, debt or financial obligation, debt security, preferred share, or another financial instrument issued using an established and defined ranking system of rating categories (Adamko, et al., 2014). In this way, Credit Rating Agencies can provide investors with an opinion on the ability of the company to repay their obligations and allows a comparison between issuers.

The most well-known Credit Rating Agencies in the US Market are Standards & Poor's (S&P), Moody's, and Fitch, in which investors rely their decisions on. The mentioned agencies allow investors to evaluate the financial health and creditworthiness of a firm they are interested in, or they can evaluate the credit quality of an individual debt issue, such as a corporate or municipal bond, and the relative probability that the issue may default.

By analysing the creditworthiness of the issuers, credit rating agencies are expected to provide investors with information that allows accurate pricing of securities that help investors and regulators to make significant credit judgments. Considering this, it is possible to say that investors are influenced by credit ratings when deciding in which stocks, they want to invest

[3] The data base used in this dissertation is from 1985 to 2017 because as of the end of February 2017, the Compustat S&P Ratings database has been discontinued and will no longer be updated.

their money on (Avramov, et al., 2009). However, based on symmetric information, Wakeman, (1981) says that credit rating agencies only have available public information. Therefore, it is not expected that credit rating changes have any impact on the stock prices.

According to Kisgen, (2009) firms reduce leverage in the aftereffects of credit rating downgrades. Compared to other firms, downgraded firms issue approximately 1.5–2.0 percent less net debt than net equity as a percentage of assets in the year following a downgrade. Within an empirical model of target leverage behaviour, this relationship persists. The impact of a downgrade is greater when it happens within a speculative-grade class and when commercial paper access is impacted. Firms downgraded to speculative grade class are roughly twice as likely to reduce debt. Rating upgrades do not affect subsequent capital structure activity, implying that firms target minimum rating levels.

Previous literature shows that there are still different opinions regarding the effect of credit rating changes on stock returns. The first view of credit rating agencies is that they hold information that is not public to the investors (Millon & Thakor, 1985). Therefore, in the context of asymmetric information, credit rating agencies can be seen as an easy and not costly way of providing information to the investors throughout their insight on the ratings they provide (Holthausen & Leftwich, 1986). This way, credit rating agencies are seen as influencing security prices improving market efficiency.

Even though there is still the question of whether credit rating agencies have an impact on the stock prices, according to studies (Nordberg, 2011), "credit ratings are only opinions and not recommendations to buy, sell or hold a security".

The study is carried out using Standards and Poor's (in S&P Global Ratings) credit ratings as it employs a specific rating framework covering country risk, industry risk, competitive position, and financial risk. After establishing a preliminary rating with the previous risks, it will be subjected (or not) to changes via "modifiers," which include information such as diversification, capital structure, financial policy, liquidity, and management/governance. To evaluate issue ratings (more specifically, bond ratings), S&P considers the issuer rating, whether investment grade or speculative grade, and applies an evaluation based on the issue's priority, company asset valuation, jurisdictions, and recovery percentage in the event of default.[4] According to S&P, this information is also obtained by the rated company and may not yet be available to public investors.

[4] Guide to Credit Rating Essentials: What are credit ratings and how do they work?

Each agency uses its own method to evaluate the creditworthiness and publishes its ratings opinions using a specific rating scale. Ratings are typically expressed as letter grades ranging from 'AAA' to 'D' to communicate the agency's opinion of the relative level of credit risk.

On the S&P's rating scales, it is possible to see the difference between investment grade and speculative grade. From AAA to BBB-, the companies are considered in an investment grade rating, which means the company has the capability to make timely payments. In contrast, from BB+ to D, companies are vulnerable to making timely payments, facing the probability of default. Therefore, they are considered speculative grade ratings.

Even though S&P investment grade ratings suggest a secure investment, high ratings do not guarantee that a company is a reliable investment, according to S&P Global Ratings, "Our ratings are not indications of investment merit. In other words, the ratings are not buy, sell, or hold recommendations, or a measure of asset value. Nor are they intended to signal the suitability of an investment. They speak to one aspect of an investment decision—credit quality—and, in some cases, may also address what investors can expect to recover in the event of default".[5] Even an entity with a AAA rating (the highest credit rating) has a 1 in 600 chance of defaulting over a five-year period.

[5] S&P Global Ratings: www.spglobal.com.

Table 1 - Summary of Rating Scales

The table shows a summary of the rating scales used by Standard & Poor's rating agency.

	Description	S&P Scale	Approx. probability of default over 5 years
Speculative Grade	Default	D	1 in 1
	Currently Highly Vulnerable	CC	1 in 2
	Currently Vulnerable	CCC	
		CCC-	
		CCC+	
	More Vulnerable	B-	
		B	
		B+	1 in 5
	Less Vulnerable	BB-	
		BB	
		BB+	1 in 10
Investment Grade	Adequate	BBB-	
		BBB	
		BBB+	1 in 30
	Strong	A-	
		A	
		A+	1 in 150
	Very Strong	AA-	
		AA	
		AA+	1 in 300
	Extremely Strong	AAA	1 in 600

(Source: Reddy, Bosman, Mirza, (2019))

When talking about credit rating agencies, what I aim to study is the impact on stock returns following changes in credit rating (upgrades and downgrades), and over the past years, many have been the studies where event study methodology was used to understand the impact of credit rating changes, such as upgrades and downgrades on stock returns. Having this in consideration, the studies, so far, have had very different results.

Bissoondoyal-Bheenick & Brooks, (2015) reports that rating downgrades significantly impact Australian and Japanese stock returns, and upgrades have no significant impact.

When looking at early studies that use monthly returns, there is no evidence of a significant bond prices or stock prices change in response to a change in bonds rating change (Pinches & Singleton, 1978). However, recent studies use daily stock returns (Poomima, et al., 2015) and show that there is a significant impact of rating upgrades and downgrades on the stock returns of the investor, with an immediate and long-term significant impact on a firm's value.

Furthermore, when looking at the impact in detail by upgrades and downgrades, recent studies show that credit rating agencies convey adverse private information about a company through downgrades. Consequently, the market reacts significantly negatively to credit rating downgrades in emerging and transitional economies as much as they do in developed countries, such as the United States (Mokoaleli-Mokoteli & Thabang, 2019).

Kenjegaliev, et al., (2016) shows that stock prices do not react significantly to upgrades on credit ratings. However, downgrading credit ratings have a significant impact on the stock returns. Nonetheless, in both cases, adjustments to stock prices start long before the rating announcement date, both for upgrades and for downgrades. This study (Kenjegaliev, et al., 2016) has the same conclusions as Jorion & Zhang, (2007), Norden & Weber, (2004), Goh & Ederington, (1999) and Hand, et al., (1992) in terms of the character of market reaction to rating downgrades.

Additionally, previous studies also conduct analysis to understand the impact in different periods of time or within investment grade or speculative grade. The study from Reddy, et al., (2019) shows that there is a different impact according to the class of rating being analysed. The market reacts strongly to upward changes with a company that goes from speculative grade to investment grade. However, the impact is only significant for downgrades when the downgrade is within the investment grade category.

Although the empirical research has provided mixed results, with studies with different periods of time and different areas observed, such as the US, Europe, or Australasia, common features can be underlined.[6] The authors Holthausen & Leftwich, (1986), Ilia D Dichev, (2001), and Galil & Soffer, (2011) generally observe significant negative abnormal returns in case of downgrades. Previous research tends to conclude a lack of significant impact in upgrades, suggesting no information content (May, (2010) explains a significant impact of upgrades on the bond market, but not on the stock market).

The discretionary disclosure hypothesis, which holds that managers have discretion over information disclosure and prefer to announce good news immediately while allowing bad news to be released more slowly, can explain the differences in market reactions to rating upgrades and downgrades (Chen, 2001), (Bae, 2006), (Alsakka, 2012). As a result, the good news is associated with increased disclosure and decreased information asymmetry. On the other hand,

[6] Australasia is a region that comprises Australia, New Zealand, and some neighboring islands.

the bad news is associated with reduced disclosure and greater information asymmetry (He et al., 2011).

3. Research methodology

3.1 Data and data sources

The sample used in this study comprises firms listed on the S&P 500 index from January 1985 to February 2017 that have a long-term credit rating assigned by Standard & Poor's credit agency. The proposed timeframe in this study is ideal as it allows us to see equity prices reactions throughout very different periods of time, such as the 1999-2000 dot-com crisis, the 2008 financial crisis, and the period of recovery from the global financial crisis. Data for security prices and credit ratings are retrieved from Wharton Research Data Services, namely the Center for Research of Security Prices (CRSP) and Compustat database. After retrieving the data, the sample was analysed, and the total amount of upgrades and downgrades was 1712. For those, 875 were upgrades, and 837 were downgrades.

To analyze the impact of the credit rating changes on stock prices, the sample was subdivided into 4 subsamples: January 1985 to December 2000 (including the dot-com crises), January 2001 to December 2006 (before the financial crisis), January 2007 to December 2009 (during the financial crises) and January 2010 to February 2017 (after the financial crisis). As shown in Table 2, the period from 2007 to 2009, even though it only comprises 2 years, has a total amount of 265 upgrades and downgrades, showing that in periods of crisis, companies are more volatile and credit ratings change more often than in periods of stability. Table 2 shows the sample’s description in terms of upgrades and downgrades.

Table 2 - Changes in Credit Ratings by Periods of Time

The table shows a description of the sample, providing a summary of the overall changes in the credit ratings observed during the sample period and in subsample periods.

Changes in Credit Ratings by Class of Rating			
Observations of Rating Changes within different periods of time			
	Upgrades	**Downgrades**	**Total**
Total Rating Changes	875	837	1712
Subsample: Jan 1985 - Dec 2000	284	296	580
Subsample: Jan 2001 - Dec 2006	167	203	370
Subsample: Jan 2007 - Dec 2009	99	166	265
Subsample: Jan 2010 - Feb 2017	325	172	497

Furthermore, the sample was also analysed according to the type of credit rating category, meaning the sample was subdivided into 4 subsamples: changes within investment grade class, changes up from speculative to investment grade class, changes down from investment to speculative grade class, and changes within speculative grade class. Table 3 shows that most credit rating changes occur within investment grade class, followed by changes within speculative grade class.

Table 3 - Changes in Credit Ratings within Rating Classes

The table shows a description of the sample, providing a summary of the overall changes in the credit ratings observed according to the type of credit rating.

Changes in Credit Ratings by Class of Rating			
Observations of Rating Changes within and between Rating Classes			
	Upgrades	**Downgrades**	**Total**
Total Rating Changes	875	837	1712
Changes within Investment Grade Class	539	652	1191
Changes up from Speculative to Investment Grade	106		106
Changes down from Investment to Speculative Grade		66	66
Changes within Speculative Grade Class	230	119	349

To understand better the changes in credit ratings, Table 4 shows a summary relating to the changes in the ratings announced for different classes within different periods of time.

Table 4 - Changes in Credit Ratings within Rating Classes and Periods of Time

The table shows a description of the sample, providing a summary of the overall changes in the credit ratings observed according to the type of credit rating.

Changes in Credit Ratings by Class of Rating			
Observations of Rating Changes within and between Rating Classes			
	Upgrades	**Downgrades**	**Total**
Total Rating Changes	875	837	1712
Changes within Investment Grade Class	539	652	1191
Subsample: Jan 1985 - Dec 2000	195	244	439
Subsample: Jan 2001 - Dec 2006	96	155	251
Subsample: Jan 2007 - Dec 2009	52	117	169
Subsample: Jan 2010 - Feb 2017	196	136	332
Changes up from Speculative to Investment Grade	106		106
Subsample: Jan 1985 - Dec 2000	31		31
Subsample: Jan 2001 - Dec 2006	22		22
Subsample: Jan 2007 - Dec 2009	19		19
Subsample: Jan 2010 - Feb 2017	34		34
Changes down from Investment to Speculative Grade		66	66
Subsample: Jan 1985 - Dec 2000		23	23
Subsample: Jan 2001 - Dec 2006		18	18
Subsample: Jan 2007 - Dec 2009		12	12
Subsample: Jan 2010 - Feb 2017		13	13
Changes within Speculative Grade Class	231	119	350
Subsample: Jan 1985 - Dec 2000	58	29	87
Subsample: Jan 2001 - Dec 2006	49	30	79
Subsample: Jan 2007 - Dec 2009	28	37	65
Subsample: Jan 2010 - Feb 2017	95	23	118

3.2 Methodology

Most of the previous literature that aims to study the market's reaction to rating changes announcements, such as Hand, et al., (1992) and Choy, et al., (2006) have used the event study methodology considering the day of the rating announcement as day 0 and measuring daily returns for different windows, depending on what they intend to study. The event study method assesses the influence of a specific event on a company's stock price by calculating the abnormal returns (performance) that result from the event. The goal is to calculate the significance of the abnormal returns due to the new and unexpected information present in the credit rating upgrade or downgrade.

The event study methodology is predicated on the assumption that the market is efficient. In an efficient market, the impacts of the event will be reflected immediately in the company's stock prices. This allows to observe the event's economic impact over a relatively short period of time.

When looking at studies that have event windows such as -120 to +90 (Galil & Soffer, 2011), it is possible that the results are influenced by other rating changes as larger event windows can gather information not only about the event they are trying to study but also other credit rating changes or other relevant information. To contrast with this type of analysis, other authors such as Choy, et al., (2006), state that the ideal event window is a smaller window to have only in consideration the event itself and minimize other potential events in the period of observation, such as windows of day -10 to day +10 or from day -5 to day +5 or even from day -1 to day +1. Some rating announcements are accompanied by one or more concurrent disclosures that could have an impact on the outcome. Therefore, smaller windows should be addressed.

To circumvent the constraint mentioned above, the data in this study is analysed over a 21-day period, as the event window, with an estimation window of [-25; -10] days prior to the event date and [10;25] days after the event date.

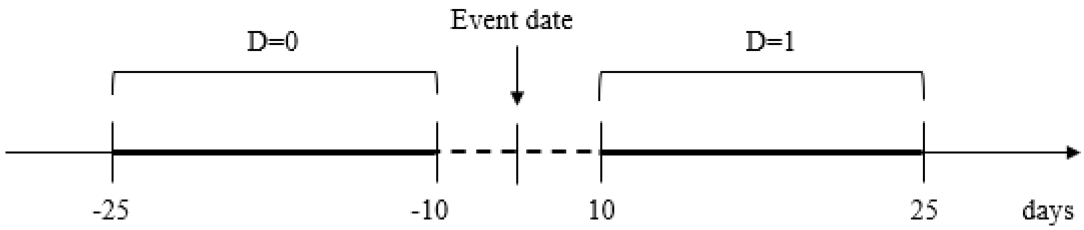

Figure 1- Event and Estimation Window

Where:

D	Dummy variable
———	Estimation window
- - - - -	Event window

In this study, a standard event study methodology is used to evaluate market reactions to changes in credit ratings. The expected and abnormal returns are calculated using daily data extracted from CRSP. I use daily log returns as they are more convenient for multiperiod returns (John Y. Campbell, 1998) and avoid negative security prices in security return models. As previously indicated, an appropriate event window for testing the influence of credit rating changes on asset prices is 21 days, from day T-10 to day T+10. In order to have a detailed view of the results, event windows such as T-10 to T+15 and T-15 to T+15 are also analysed for robustness checks.

The market-adjusted return model, which captures the price effect of a firm's shares due to changes in credit rating, is used to calculate abnormal returns (AR_{it}) (MacKinlay, 1997). The following method computes daily log returns (R_{it}):

$$r_{it} = \ln\left(\frac{P_{it}}{P_{it-1}}\right)$$

Where:

- r_{it} is the actual stock return over the period t;
- P_{it} and P_{it-1} represent the stock price for periods t and t – 1, respectively.

The market model is used to determine the expected or normal returns for each entity and for each previously mentioned event. A regression model was used to calculate the alpha and the beta for each event. As the benchmark, the S&P500 index was taken into consideration as it is where all companies gathered in the study are listed. Having this said, the regression model used was:

$$r_{it} = \alpha_i + \beta_i r_{mt} + e_{it}$$

Where:

- r_{it} = daily return on a stock;
- α_i = alpha or intercept of the stock;
- β_i = beta value of the stock;
- r_{mt} = market returns, given by S&P500 returns.
- e_{it} = zero mean error term

The abnormal returns were calculated by subtracting the expected return (benchmark returns) from the actual or normal returns (firm returns) to see if the event resulted in returns that exceeded expectations:

$$AR = r_{it} - E(r_{it})$$

Where:

- AR = abnormal return;
- r_{it}= the actual return of the stock for the respective day;
- $E(r_{it})$ = expected return on the stock for the respective day.

To derive a conclusion based on evidence and reasoning, observations on abnormal returns were aggregated across time to calculate the cumulative abnormal returns (CARs), as in MacKinlay, (1997) and Mokoteli-Mokoaleli, Taffler, and Agarwal, (2009). The cumulative abnormal returns are the sum of the abnormal returns:

$$CARs_{it} = \sum\nolimits_{t=t1} AR$$

Where:

- $CARs_{it}$ = Cumulative abnormal returns
- AR = Abnormal returns

The abnormal returns are calculated to see if the returns following credit rating changes differ considerably from the expected returns with no change in rating. To see if the discrepancies between the abnormal and expected returns are statistically significant, a standard paired t-test is used. Furthermore, t-tests are used to determine whether investors react more powerfully to changes in firm credit ratings before or after the dot-com crisis and the global financial crisis, thus, using t-tests accordingly to the 4 subsamples of periods of time. T-tests are also used to understand whether investors react more strongly to changes within investment grade class, within speculative grade class, or upgrades or downgrades for different grading classes.

4. Results

As mentioned before, 1713 events were analysed, and to understand better the reasoning of the results, it is essential to see the effect of the events by groups. Moreover, it is vital to understand what are the type of events or in which periods of time it is possible to see a significant impact on the stock returns.

To drive the analysis, standard paired t-tests were undertaken to determine whether the differences between the abnormal returns observed, and the expected returns are statistically significant. The paired t-tests aim to look at are the differences in the values of the abnormal returns and expected returns, testing if the mean of the difference is equal to zero. The paired t-test is defined as follows:

$$\text{T (paired)} = \frac{AAR - APR}{\sqrt{S_{AAR}^2 + S_{APR}^2 - 2rS_{AAR}^2 S_{APR}^2}}$$

$$S_{AAR\,APR} = \sum_i (AR_{i1} - AAR_2)(AR_{i2} - AAR_2)/(n-1)$$

$$r = \frac{S_{AAR\,APR}}{S_{AAR} S_{APR}}$$

Where:

- S_j = estimation of the standard error of the mean of group j
- r = correlation between average abnormal returns and average predicted returns
- n = total number of pairs
- AR = Abnormal returns
- AAR = Average abnormal returns
- APR = Average predicted returns

This way, in this section, it will be possible to see the results of the t-tests accomplished. The analysed groups are upgrades and downgrades, upgrades and downgrades for each period of time, and upgrades and downgrades according to the type of event.

4.1 Upgrades and Downgrades

Tables 5 and 6 show the descriptive information for returns and abnormal returns, respectively, of upgrades and downgrades before and after the event take place considering the total amount of events.

Table 5- Return Descriptive Statistics For The Estimation Window

The table shows descriptive information for returns of upgrades and downgrades before and after the upgrade or downgrade date considering the total amount of upgrades and downgrades (1713). Panel A reports the summary statistics for credit rating upgrades on the estimation window [-25; -10] and [10, 25]. Panel B reports the summary statistics for credit rating downgrades on the estimation window [-25; -10] and [10; 25].

Panel A

Upgrades in Credit Rating	**Estimation Window: [-25; -10] [10;25]**	
	Before event date	**After event date**
Mean	0,02%	0,01%
Variance	0,0007	0,0006
Min	-72,15%	-7,11%
Percentile 25%	-0,93%	-0,96%
Percentile 50%	0,00%	0,00%
Percentile 75%	1,00%	0,97%
Max	19,72%	21,87%

Panel B

Downgrades in Credit Rating	**Estimation Window: [-25; -10] [10;25]**	
	Before event date	**After event date**
Mean	-0,27%	-0,08%
Variance	0,003	0,001
Min	-270,47%	-66,82%
Percentile 25%	-1,33%	-1,21%
Percentile 50%	0,00%	0,00%
Percentile 75%	1,15%	1,14%
Max	35,85%	28,29%

Table 6- Abnormal Return Descriptive Statistics for The Estimation Window

The table shows descriptive information for abnormal returns of upgrades and downgrades before and after the upgrade or downgrade date considering the total amount of events (1713). Panel A reports the summary statistics for credit rating upgrades on the estimation window [-25; -10] and [10, 25]. Panel B reports the summary statistics for credit rating downgrades on the estimation window [-25; -10] and [10; 25].

Panel A

Upgrades in Credit Rating	Estimation Window: [-25; -10] [10;25]	
	Before event date	After event date
Mean	0,00%	-0,01%
Variance	0,0005	0,0004
Min	-67,63%	-63,80%
Percentile 25%	-0,79%	-0,81%
Percentile 50%	0,00%	-0,03%
Percentile 75%	0,78%	0,76%
Max	17,00%	21,41%

Panel B

Downgrades in Credit Rating	Estimation Window: [-25; -10] [10;25]	
	Before event date	After event date
Mean	-0,07%	0,08%
Variance	0,002	0,001
Min	-263,87%	-65,15%
Percentile 25%	-0,96%	-0,93%
Percentile 50%	0,00%	-0,03%
Percentile 75%	1,02%	0,94%
Max	32,94%	35,16%

As it is possible to see, credit rating upgrades have a negative effect on returns and abnormal returns' mean. Before the event occurs, the mean of the returns was 0,02% moving down to 0,01% as the upgrade happens. The same appears to happen on the abnormal returns' mean. Before the event, the abnormal returns' mean was 0%, lowering to -0,01% after the upgrade occurs. On the other side, a credit rating downgrade has a positive effect on the returns and abnormal returns' mean. Before a credit rating downgrade, the returns' mean was -0,27%, moving upwards to -0,08% after it occurs. As for the abnormal returns' mean before a downgrade happen was -0,07%, changing up to 0,08%, showing a vast increase. One reason that may explain the results is the fact that when there is an upgrade, the company's value is expected to increase. Therefore, the stock price will also increase its value, which results in a decrease in the stock returns. Having this said, the credit rating downgrades are also aligned with this point of view, in which the company's value is expected to decrease. Therefore, the stock's value is also expected to decrease, and the stock returns will increase.

Furthermore, Table 7 shows the statistics for the cumulative abnormal returns across all changes in credit ratings, treated as a group, in which we can denote that in both cases, the cumulative abnormal returns are not significant as the t-test as lower than 1,96 (for 5% significance), and p-values are higher than 0,05.

Table 7- Cumulative Abnormal Return Across All Events

The table shows a regression on the cumulative abnormal returns (CAR) across all upgrades and downgrades treated as a group. The regression is undertaken to understand if the event window is significant in upgrades and downgrades. Panel A reports the t-statistics for the credit rating upgrades for the event window T-10 to T+10 for the years 1985 to 2017. Panel B reports the t-statistics for the credit rating upgrades for the event window T-10 to T+10 for the years 1985 to 2017.

Panel A

Upgrade in Credit Rating	**Cumulative Abnormal Returns**
Coef.	0,001
Robust Std. Deviation	0,002
Observations	876
df	875
R-squared	0
Root MSE	0,06
t-Stat	0,71
P(T>|t|) two-tail	0,48

Panel B

Downgrade grade in Credit Rating	**Cumulative Abnormal Returns**
Coef.	0,006
Robust Std. Deviation	0,004
Observations	837
df	836
R-squared	0
Root MSE	0,115
t-Stat	1,610
Pr(T>|t|) two-tail	0,109

Panel A and B from Table 8 shows the paired t-test results for the differences in means for the credit rating upgrades and downgrades for the three different event windows, used as robustness checks. Panel A reports the t-test statistics for the differences in mean for the credit rating upgrades for the event windows T-10 to T+10, T-10 to T+15, and T-15 to T+15 for the years 1985 to 2017. Panel B reports the t-test statistics for the differences in mean for the credit rating downgrades for the event windows T-10 to T+10, T-10 to T+15, and T-15 to T+15 for the years 1985 to 2017.

Table 8 -T-Tests for Differences in Mean for Credit Ratings

The table shows a paired t-test for differences in mean for credit ratings. Panel A reports the t-test statistics for the differences in mean for the credit rating upgrades for the event windows T-10 to T+10, T-10 to T+15, and T-15 to T+15 for the years 1985 to 2017. Panel B reports the t-test statistics for the differences in mean for the credit rating downgrades for the event windows T-10 to T+10, T-10 to T+15, and T-15 to T+15 for the years 1985 to 2017. AAR and APR are the average abnormal returns and the average predicted returns, respectively.

Panel A

Upgrade in Credit Rating	**T-10 to T+10**		**T-10 to T+15**		**T-15 to T+15**	
	AAR	APR	AAR	APR	AAR	APR
Mean	0,01%	0,02%	0,001%	0,03%	0%	0,04%
Std. Deviation	0,43%	0,45%	0,01%	0,02%	0,26%	0,43%
Observations	875	875	875	875	875	875
Hypothesized Mean Difference	0		0		0	
df	874		874		874	
t-Stat	-0,619		-1,613		-2,389	
Pr (| T | > | t |) two-tail	0,536		0,107		0,017	
t Critical two-tail	1,96		1,96		1,96	

Panel B

Downgrade grade in Credit Rating	**T-10 to T+10**		**T-10 to T+15**		**T-15 to T+15**	
	AAR	APR	AAR	APR	AAR	APR
Mean	0,05%	-0,09%	0,04%	-0,1%	0,01%	-0,12%
Std. Deviation	0,78%	1,10%	0,63%	1,05%	0,49%	1,04%
Observations	837	837	837	837	837	837
Hypothesized Mean Difference	0		0		0	
df	836		836		836	
t-Stat	2,885		3,103		3,269	
Pr (| T | > | t |) two-tail	0,004		0,002		0,001	
t Critical two-tail	1,96		1,96		1,96	

It is possible to denote that the results are aligned with previous studies. For all the event windows, from 1985 to 2017, the results for the downgrades lead to significant changes in stock returns, and upgrades are only significant for the wider window (T-15 to T+15), which can mean that other events may influence the results, therefore, they can be biased. As for the results in Panel B, the t-Stats are all much higher than the t-critical value (for 5% significance level), implying that we reject the null hypothesis and that there are undoubtedly significant changes in stock returns in reaction to credit rating downgrades. The *p*-values for all three windows for downgrade events are lower than 0,01, meaning that these results are statistically significant at

1% significance level. The results for the AAR' mean for either upgrades or downgrades, on all event windows are positive. On the other hand, results of the APR' mean, for upgrades are positive, and for downgrades are negative.

4.2 Upgrades and downgrades for the different periods of time

This section serves the purpose to analyse the effect of upgrades and downgrades on stock returns by focusing on the different periods of the dataset. Table 9 to 12 show the results for the statistical paired t-tests on the mean of abnormal returns observed, and the mean of expected returns for the periods described in section 3.1 (Data and Data sources). The test is undertaken in 3 different windows for robustness checks, such as T-10 to T+10, T-10 to T+15 and T-15 to T+15.

Table 9 exhibits the results from 1985 to 2000. It is interesting to analyze this period since, in terms of how information was spread and perceived by investors is different from now. In this period, investors did not had access to information as easily and fast as today, so it was not expected that stockholders reacted to credit ratings upgrades or downgrades as fast as it is expected to happen nowadays. This period is also marked by the dot-com crises. During the late 1990s bull market and investments in Internet-based companies fuelled a rapid rise in U.S. technology stock equity valuations, resulting in the dot-com bubble. During this time, the value of equity markets increased exponentially, with the technology-dominated Nasdaq index rising from under 1,000 to more than 5,000 between 1995 and 2000. The bubble burst around 2000.

Table 9 - T-Tests for Credit Ratings From 1985 to 2000

The table shows the results for the paired t-tests for credit ratings for the differences in mean of abnormal returns observed, and the mean of expected returns for the credit rating upgrades and downgrades. Panel A reports the t-test statistics for the credit rating upgrades for the period 1985 to 2000. Panel B reports the t-test statistics for the credit rating downgrades for the period 1985 to 2000.

Panel A

Upgrade in Credit Rating	**T-10 to T+10**	**T-10 to T+15**	**T-15 to T+15**
Observations	284	284	284
t-Stat	-0,410	-1,266	-1,521
Pr (| T | > | t |) two-tail	0,682	0,207	0,129
t Critical two-tail	1,96	1,96	1,96

Panel B

Downgrade in Credit Rating	**T-10 to T+10**	**T-10 to T+15**	**T-15 to T+15**
Observations	296	296	296
t-Stat	1,512	1,589	1,530
Pr (| T | > | t |) two-tail	0,132	0,113	0,127
t Critical two-tail	1,96	1,96	1,96

Table 9 reports that upgrades and downgrades of credit ratings over the three windows tested have no significant impact on security returns. Since the t-values, in this case, are lower than the t-critical value, the null hypothesis cannot be rejected, implying that changes in credit ratings do not result in significant stock abnormal returns.

Table 10 reports the results for the period before the global financial crisis, meaning the period from 2001 to 2006. This test also shows that a credit rating change has no significant impact on stock' returns for all windows, for both upgrades and downgrades the t-value is lower than 1,96.

Table 10- T-Tests for Credit Ratings For 2001 to 2006

The table shows the results for the paired t-tests for credit ratings for the differences in mean of abnormal returns observed, and the mean of expected returns for the credit rating upgrades and downgrades. Panel A reports the t-test statistics for the credit rating upgrades for the period 2001 to 2006. Panel B reports the t-test statistics for the credit rating downgrades for the period 2001 to 2006.

Panel A

Upgrade in Credit Rating	**T-10 to T+10**	**T-10 to T+15**	**T-15 to T+15**
Observations	167	167	167
t-Stat	0,161	-0,558	-0,995
Pr (| T | > | t |) two-tail	0,873	0,578	0,321
t Critical two-tail	1,96	1,96	1,96

Panel B

Downgrade in Credit Rating	**T-10 to T+10**	**T-10 to T+15**	**T-15 to T+15**
Observations	203	203	203
t-Stat	1,251	1,196	1,697
Pr (| T | > | t |) two-tail	0,212	0,233	0,091
t Critical two-tail	1,96	1,96	1,96

Table 11 shows the t-tests for the period of the Financial Global Crises. It is to denote that what happens in this period is different from what happened in the periods before. The period from 2007 to 2009 was defined by the Financial Global Crises (FGC). The GFC represents a period of severe stress in the world's banking systems and financial markets. During the GFC, a recession in the US housing market acted as a basis for a financial crisis that spread from the US to the rest of the world via global financial system linkages.

Table 11 -T-Tests for Credit Ratings For 2007 to 2009

The table shows the results for the paired t-tests for credit ratings for the differences in mean of abnormal returns observed, and the mean of expected returns for the credit rating upgrades and downgrades. Panel A reports the t-test statistics for the credit rating upgrades for the period 2007 to 2009. Panel B reports the t-test statistics for the credit rating downgrades for the period 2007 to 2009.

Panel A

Upgrade in Credit Rating	**T-10 to T+10**	**T-10 to T+15**	**T-15 to T+15**
Observations	99	99	99
t-Stat	0,785	0,413	-0,113
Pr (| T | > | t |) two-tail	0,435	0,681	0,911
t Critical two-tail	1,96	1,96	1,96

Panel B

Downgrade in Credit Rating	**T-10 to T+10**	**T-10 to T+15**	**T-15 to T+15**
Observations	166	166	166
t-Stat	2,193	2,276	2,496
Pr (| T | > | t |) two-tail	0,030	0,024	0,014
t Critical two-tail	1,96	1,96	1,96

As a severely stressful period, the results from Table 11 show that downgrades in credit rating had a significant impact on the stock returns. The t-values were 2,1931 for the window T-10 to T+10, 2,276 for the window T-10 to T+15, and 2,496 for the window T-15 to T+15, rejecting the null hypothesis for a 5% significance level.

Table 12 reports the t-tests for credit ratings for 2010 to 2017, the period after the FGC.

Table 12- T-Tests for Credit Ratings For 2010 to 2017

The table shows the results for the paired t-tests for credit ratings for the differences in mean of abnormal returns observed, and the mean of expected returns for the credit rating upgrades and downgrades. Panel A reports the t-test statistics for the credit rating upgrades for the period 2010 to 2017. Panel B reports the t-test statistics for the credit rating downgrades for the period 2010 to 2017.

Panel A

Upgrade in Credit Rating	**T-10 to T+10**	**T-10 to T+15**	**T-15 to T+15**
Observations	325	325	325
t-Stat	-1,499	-1,464	-1,831
Pr (| T | > | t |) two-tail	0,135	0,144	0,068
t Critical two-tail	1,96	1,96	1,96

Panel B

Downgrade in Credit Rating	**T-10 to T+10**	**T-10 to T+15**	**T-15 to T+15**
Observations	172	172	172
t-Stat	0,184	0,773	0,160
Pr (| T | > | t |) two-tail	0,854	0,440	0,873
t Critical two-tail	1,96	1,96	1,96

The results are aligned with the results for the periods of 1985 to 2000 and from 2001 to 2006, in which neither upgrades nor downgrades show a significant impact on the stock returns, for a 5% significance level. The other windows tested are also aligned with these results.

4.3 Upgrades and downgrades according to the different types of events

The aim of this section is to understand which type of upgrade or downgrade imply a bigger impact on the stock returns after the event is disclosed, that is: which credit rating change (within investment grade, within speculative grade or between different grade classes) have a significant impact on stock returns. To better understand the impact individually of the upgrades and downgrades on stock returns, the sample was also subdivided by subperiods in Tables 14 to 17.

Table 13 shows the results for the paired t-tests for credit ratings for the differences in mean of abnormal returns observed, and the mean of expected returns for the whole sample (1985-2017) subdivided by type of credit rating change.

Table 13 - T-Tests for Between and Within Different Credit Ratings for the Period 1985 to 2017

The table reports t-statistics of the differences in mean of abnormal returns observed, and the mean of expected returns for between and within different types of credit ratings for the period 1985 to 2017. Panel A reports the t-test statistics for the credit rating upgrades between and within different grading classes for the period 1985 to 2017. Panel B reports the t-test statistics for the credit rating downgrades between and within different grading classes for the period 1985 to 2017.

Panel A

Upgrade in Credit Rating	**Upgrade within Investment Grade**			**Upgrade from Speculative to Investment grade**			**Upgrade within Speculative grade**		
	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15
Observations	539	539	539	106	106	106	230	230	230
t-Stat	0,872	0,182	-0,648	0,247	-0,056	-0,191	-2,74	-3,22	-3,25
Pr (| T | > | t |) two-tail	0,384	0,855	0,517	0,805	0,956	0,849	0,007	0,002	0,001
t Critical two-tail	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96

Panel B

Downgrade in Credit Rating	**Downgrade within Investment Grade**			**Downgrade from Investment to Speculative grade**			**Downgrade within Speculative grade**		
	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15
Observations	652	652	652	66	66	66	119	119	119
t-Stat	2,412	2,504	2,654	0,057	0,414	0,791	2,077	2,122	1,973
Pr (| T | > | t |) two-tail	0,016	0,013	0,008	0,955	0,68	0,432	0,039	0,036	0,044
t Critical two-tail	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96

The results shown in Table 13 are mixed. Announcements of credit rating upgrades only have a significant impact on abnormal returns when considering an upgrade within speculative grade class. When testing for credit rating downgrades, the results are different. In this case, rating changes have a significant impact on downgrades within investment grade and downgrades within speculative grade. For all the windows of these robustness checks, the results are aligned with previous studies such as Freitas & Minardi, (2013) and Choy, et al., (2006). These studies show that credit rating downgrades announcements across classes have a significant impact on stock returns, but no significant impact observed for credit rating upgrades.

Table 14 reports the results for the for the paired t-tests for credit ratings for the differences in mean of abnormal returns observed, and the mean of expected returns for between and within different types of credit ratings for the period of 1985 to 2000.

Table 14 - T-Tests for Between and Within Different Credit Ratings for the Period 1985 to 2000

The table reports t-statistics of the differences in mean of abnormal returns observed, and the mean of expected returns for between and within different types of credit ratings for the period 1985 to 2000. Panel A reports the t-test statistics for the credit rating upgrades between and within different grading classes for the period 1985 to 2000. Panel B reports the t-test statistics for the credit rating downgrades between and within different grading classes for the period 1985 to 2000.

Panel A									
Upgrade in Credit Rating	**Upgrade within Investment Grade**			**Upgrade from Speculative to Investment grade**			**Upgrade within Speculative grade**		
	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15
Observations	195	195	195	31	31	31	58	58	58
t-Stat	0,565	-0,487	-0,855	-1,275	-0,887	-0,358	-1,169	-1,112	-1,268
Pr (| T | > | t |) two-tail	0,573	0,627	0,394	0,212	0,382	0,723	0,247	0,271	0,21
t Critical two-tail	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96
Panel B									
Downgrade in Credit Rating	**Downgrade within Investment Grade**			**Downgrade from Investment to Speculative grade**			**Downgrade within Speculative grade**		
	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15
Observations	244	244	244	23	23	23	29	29	29
t-Stat	-0,028	-0,206	0,373	1,196	1,476	1,304	1,913	1,971	1,086
Pr (| T | > | t |) two-tail	0,977	0,837	0,709	0,244	0,154	0,206	0,07	0,05	0,287
t Critical two-tail	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96

Table 14 shows that for both upgrade and downgrade announcements, there are no significant results, except downgrades within speculative grade for the T-10 to T+15 window, with a t-value of 1,971, however, since it is not consistent with the other window-s results, it is not possible to say that downgrades within speculative grade have a significant impact on stock-returns. These results do not match those of the full data set.

Table 15 reports the results for the paired t-tests for credit ratings for the differences in mean of abnormal returns observed, and the mean of expected returns for between and within different types of credit ratings for the period of 2001 to 2006.

Table 15 - T-Tests for Between and Within Different Credit Ratings for the Period 2001 to 2006

The table reports t-statistics of the differences in mean of abnormal returns observed, and the mean of expected returns for between and within different types of credit ratings for the period 2001 to 2006. Panel A reports the t-test statistics for the credit rating upgrades between and within different grading classes for the period 2001 to 2006. Panel B reports the t-test statistics for the credit rating downgrades between and within different grading classes for the period 2001 to 2006.

Panel A									
Upgrade in Credit Rating	**Upgrade within Investment Grade**			**Upgrade from Speculative to Investment grade**			**Upgrade within Speculative grade**		
	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15
Observations	96	96	96	22	22	22	49	49	49
t-Stat	1,219	0,803	0,476	0,126	-0,785	-1,261	-2,237	-3,228	-3,12
Pr (| T | > | t |) two-tail	0,226	0,424	0,635	0,901	0,441	0,221	0,03	0,002	0,003
t Critical two-tail	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96
Panel B									
Downgrade in Credit Rating	**Downgrade within Investment Grade**			**Downgrade from Investment to Speculative grade**			**Downgrade within Speculative grade**		
	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15
Observations	155	155	155	18	18	18	30	30	30
t-Stat	1,091	1,4	1,439	-0,966	-0,848	-0,458	2,327	1,652	1,325
Pr (| T | > | t |) two-tail	0,277	0,164	0,152	0,348	0,408	0,653	0,027	0,109	0,195
t Critical two-tail	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96

Regarding the results of the period before the FGC, from 2001 to 2006, the events within speculative grade class have an impact on either upgrades or downgrades. For upgrades, all windows have the same results, they are all significant for a 5% significance level, and for downgrades, only the smaller window (T-10 to T+10) has a significant impact.

Table 16 reports the results for the for the paired t-tests for credit ratings for the differences in mean of abnormal returns observed, and the mean of expected returns for between and within different types of credit ratings for the period of 2007 to 2009.

Table 16 - T-Tests for Between and Within Different Credit Ratings for the Period 2007 to 2009

The table reports t-statistics of the differences in mean of abnormal returns observed, and the mean of expected returns for between and within different types of credit ratings for the period 2007 to 2009. Panel A reports the t-test statistics for the credit rating upgrades between and within different grading classes for the period 2007 to 2009. Panel B reports the t-test statistics for the credit rating downgrades between and within different grading classes for the period 2007 to 2009.

Panel A									
Upgrade in Credit Rating	**Upgrade within Investment Grade**			**Upgrade from Speculative to Investment grade**			**Upgrade within Speculative grade**		
	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15
Observations	52	52	52	19	19	19	28	28	28
t-Stat	1,635	1,727	0,813	0,694	0,313	0,623	-0,535	-0,948	-1,02
Pr (| T | > | t |) two-tail	0,108	0,09	0,42	0,496	0,758	0,541	0,597	0,351	0,317
t Critical two-tail	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96
Panel B									
Downgrade in Credit Rating	**Downgrade within Investment Grade**			**Downgrade from Investment to Speculative grade**			**Downgrade within Speculative grade**		
	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15
Observations	117	117	117	12	12	12	37	37	37
t-Stat	2,373	2,464	2,856	-0,88	-0,784	-0,645	0,893	0,885	0,947
Pr (| T | > | t |) two-tail	0,019	0,015	0,005	0,398	0,449	0,532	0,378	0,382	0,35
t Critical two-tail	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96

Table 16 reflects the results for the FGC period, in which its possible to see that in the case of an upgrade event, there is no significant impact on the stock prices. However, when examining downgrade announcements, the results have a significant impact only when a downgrade is announced for movements within investment grade ratings.

Table 17 reports the results for the for the paired t-tests for credit ratings for the differences in mean of abnormal returns observed, and the mean of expected returns for between and within different types of credit ratings for the period of 2010 to 2017.

Table 17 - T-Tests for Between and Within Different Credit Ratings for the Period 2010 to 2017

The table reports t-statistics of the differences in mean of abnormal returns observed, and the mean of expected returns for between and within different types of credit ratings for the period 2010 to 2017. Panel A reports the t-test statistics for the credit rating upgrades between and within different grading classes for the period 2010 to 2017. Panel B reports the t-test statistics for the credit rating downgrades between and within different grading classes for the period 2010 to 2017.

Panel A									
Upgrade in Credit Rating	**Upgrade within Investment Grade**			**Upgrade from Speculative to Investment grade**			**Upgrade within Speculative grade**		
	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15
Observations	196	196	196	34	34	34	95	95	95
t-Stat	-1,669	-1,413	-1,554	0,762	0,689	0,224	-1,688	-1,839	-1,997
Pr (| T | > | t |) two-tail	0,097	0,159	0,122	0,452	0,496	0,825	0,095	0,069	0,049
t Critical two-tail	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96
Panel B									
Downgrade in Credit Rating	**Downgrade within Investment Grade**			**Downgrade from Investment to Speculative grade**			**Downgrade within Speculative grade**		
	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15	T-10 to T+10	T-10 to T+15	T-15 to T+15
Observations	136	136	136	13	13	13	23	23	23
t-Stat	0,262	0,207	-0,979	-0,456	-0,412	-0,447	0,247	2,012	1,933
Pr (| T | > | t |) two-tail	0,794	0,836	0,329	0,657	0,688	0,663	0,807	0,057	0,066
t Critical two-tail	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96	1,96

Lastly, for the period of 2010 to 2017, the findings indicate that an announcement on an upgrade within speculative grade class has a significant impact on the window T-15 to T+15, and an announcement on downgrades within speculative grade classes has a significant impact on the window T-10 to T+15.

5. Conclusion

This dissertation proposes an extension of prior studies on the effect of a credit rating upgrade or downgrade. All the examined credit rating changes are from the US Market for the S&P500 between January 1985 to February 2017. The total amount of upgrades and downgrades studied was 1712, where 875 were upgrades, and 837 were downgrades. For the analysis, the sample was subdivided by periods of time. This is the period of 1985 to 2000, including the dot-com crisis, the period of 2001 to 2006 before the Financial Global Crisis (FGC), the period of the FGC, from 2007 to 2009, and finally the period of the recovery from the crisis until now, from 2010 to 2017. Afterward, the sample was subdivided by type of credit rating change, that is, by upgrades within investment grade class, upgrade from speculative grade to investment grade class, upgrade within speculative grade class, downgrade from speculative grade class, downgrade from investment grade to speculative grade and finally downgrade within speculative grade class.

To test whether companies' stock returns are significantly affected by credit rating changes, an event study methodology was applied by using the stock market data extracted from CRSP. For robustness, three windows were tested, from T-10 to T+10, from T-10 to T+15, and lastly from T-15 to T+15.

For the overall sample, the results for the downgrades lead to significant changes in stock returns, and upgrades are only significant for the wider window (T-15 to T+15), meaning that upgrades do not show consistent results, therefore not having a significant impact on stock returns. These results are aligned with those of Bissoondoyal-Bheenick & Brooks, (2015), that state that credit rating downgrades have a significant impact on Australian and Japanese stock returns, and that upgrades have no significant impact on security prices. These results suggest that credit rating upgrades are widely anticipated by investors when they are made public, thus having little impact on the stock's returns. Credit rating downgrades, on the other hand, present investors with new information that was not available before. This makes it evident that there is asymmetric information, contradicting the efficient market hypothesis (EMH), which claims that investors, thus stock prices react rapidly to sensitive new information (Mokoaleli-Mokoteli & Thabang, 2019).

The analysis of the different years shows inconsistent results regarding downgrade events, as downgrades only have significant results in the case of a downgrade from 2007 to 2009. Upgrades, in contrast, are insignificant for all the periods tested being aligned with the previous results.

As for the different credit rating events, announcements of credit rating upgrades only have a significant impact on abnormal returns when considering an upgrade within the speculative grade class. When testing for credit rating downgrades, rating changes have a significant impact on downgrades within investment grade and downgrades within speculative grade.

As for the results by the subdivided samples, even though there is evidence of mixed results, there is a common feature. For all tests, it is possible to see significance on downgrades within speculative grade class except for the period of extreme stress, the FGC, where only a downgrade within investment grade class had a significant impact on the stock returns. An upward event only has a significant impact if it happens within a speculative grade, but it is only possible to see that for the period before and after the GFC, which represents, in both cases, a cycle of recovery. It is to denote that this is more in line with the results of previous studies.

Although this dissertation provides useful insights, some limitations can be discussed, potentially opening new future research directions.

It is critical to have a sufficient sample size when conducting a study in order to draw valid conclusions. The larger the size of the sample, the more precise the results are. It is difficult to identify significant relationships in the data when the sample size is too small.

Outliers in the dataset are unusual values that can distort statistical analyses and violate their assumptions. Outliers raise the variability of the data, reducing statistical power. Kim, Kim and Ergun (2015), as a matter of example, remove the top two outliers on opposite sides of the distribution and reach the conclusion that outliers can create huge distortions. Galai, Kedar-Levy, and Schreiber (2008) observe that a slight number of daily return outliers, namely 2.03 percent of the sample, has a significant impact on empirical estimation. Therefore, this study could have been done also removing the outliers by 1% and 2% such as in Reddy, et al., (2019).

Statistical tests typically require a larger sample size to ensure that the sample is sufficiently representative, and that the statistical outcome can be extrapolated to a bigger population. Even though the total amount of upgrades and downgrades represents a large sample (1712 events), when testing for subsamples such as Downgrade from Investment to Speculative grade from 1985 to 2000 where there are only 23 events, the size of the sample is not large enough to say that the results can represent the population. A way to improve the results would be by using bootstrap. Bootstrapping is a resampling method proposed by Bradley Efron (1979). It is used to approximate distribution in the sample of a statistical survey.

Finally, it would be interesting to see, in future research, the impact of credit rating decicions by other credit rating agencies, such as Moody's or Fitch. Also, it would be interesting to analyze the impact on stock returns of bigger changes in terms of notches (2 or more notches).

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