“The Stock Market Reaction to Credit Rating Changes: A Multi-Perspective Approach”

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Abstract

This dissertation examines the US stock market reaction to Credit Rating Changes by Standard & Poor's, focusing on both Downgrades and Upgrades across different Time Periods, Magnitudes, and Industries. Using a rating dataset of 6,985 US public companies between 1985 and 2021, my research aims to identify patterns in stock returns around the Rating Change event. The study calculates Average Abnormal Returns (AAR) for three distinct periods: the month before the change, the month of the change, and the month after the change. Including distinction between Investment Grade and Speculative Grade securities. Downgrades consistently show negative abnormal returns, particularly in the months before and during the change. While Upgrades tend to generate milder reactions, with positive returns often observed in the month before and during the change, suggesting market anticipation. Slightly negative reactions are noticed in the month after the positive change, probably indicating market corrections. Results also stronger market reactions during economic downturns, with Speculative Grade securities showing higher volatility compared to Investment Grade ones. Additionally, the study confirms that larger magnitude changes result in stronger reactions, especially for Downgrades. The industries analysis, based on SIC and NAICS classifications, reveals variations in market sensitivity, with certain industries exhibiting reacting louder than others. Overall, this thesis contributes to the literature by adding evidence of the impact of Credit Rating Agencies on Stocks prices.

Title: The Stock Market Reaction to Credit Rating Changes: A Multi-Perspective Approach
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Abstrato

Esta dissertação examina a reação do mercado de ações dos EUA às mudanças de classificação de crédito pela Standard & Poor's, focando tanto nos rebaixamentos quanto nas atualizações em diferentes períodos de tempo, magnitudes e indústrias. Utilizando um conjunto de dados de 6,985 empresas públicas dos EUA entre 1985 e 2021, minha pesquisa busca identificar padrões nos retornos das ações em torno do evento de mudança de classificação. O estudo calcula Retornos Anormais Médios (AAR) para três períodos distintos: o mês antes da mudança, o mês da mudança e o mês após a mudança, incluindo uma distinção entre títulos de Grau de Investimento e Grau Especulativo. Os rebaixamentos mostram consistentemente retornos anormais negativos, especialmente nos meses antes e durante a mudança. Já as atualizações tendem a gerar reações mais suaves, com retornos positivos observados no mês anterior e durante a mudança, sugerindo antecipação do mercado. Reações ligeiramente negativas são observadas no mês após a mudança positiva, provavelmente indicando correções de mercado. Os resultados destacam reações mais fortes durante recessões econômicas, com títulos especulativos mostrando maior volatilidade em comparação aos de Grau de Investimento. Além disso, o estudo confirma que mudanças de maior magnitude geram reações mais intensas, especialmente para rebaixamentos. A análise setorial, baseada nas classificações SIC e NAICS, revela variações na sensibilidade do mercado, com algumas indústrias reagindo mais fortemente que outras. No geral, esta dissertação contribui para a literatura ao adicionar evidências do impacto das agências de classificação de crédito nos preços das ações.

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Palavras-chave: Alterações de notação de crédito, mercado acionista, estudo de eventos, agências de notação de crédito

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Introduction

Credit rating agencies (CRAs) are key financial institutions playing a crucial role in the financial market landscape. With their decision, they not only influence investment decisions but also overall financial stability. There are three main agencies vastly known and recognized which hold the major share in the market: Moody's, Standard & Poor's and Fitch. All three are US-based companies and, along with a few selected others, are officially recognized by the Security Exchange Commission (SEC) as trusted guarantor in credit rating assessment by the <NRSRO= status (Nationally recognized statistical rating organization); which confers a high degree of credibility and authority to a credit rating agency due to the stringent criteria of integrity and transparency that it must meet. Their role is to provide a rating on the creditworthiness of a debt securities' issuers, whether they be private/public companies or governments, assessing their likelihood to fully meet their financial obligations on time. The rating scale consists in letters, varying from AAA (Top-ranked and almost null probability of default) to D (Lowest grade indicating high default probability), all grades above BBB- are deemed as <Investment Grades= while from BBB- to D are regarded as <Speculative Grades=. The majority of Governments, Pension Funds and Sovereign Wealth Funds and, the so called, Institutional Investors are not allowed to buy speculative grades securities, which lead to huge differences in capital collection between entities just above and entities just under this threshold.

Credit Rating and Credit Rating Changes, such as Downgrades or Upgrades, are highly relevant information to both investors and companies. From the investor perspective, they provide assessment about the risk associated with purchasing a debt title, thus influencing their investment decisions and capital allocation within portfolios. While, for companies, this leads to changes in bonds prices, raising (reducing) borrowing costs and eventually affecting their capital structure, financing capability and the business as a whole. It is precisely because of this immense power that the role and integrity of the rating agencies have been continuously questioned over the year until culminating in the 2008 Great Financial Crisis, where CRA had been heavily criticized for underestimating the risk connected to many securities, particularly those related to subprime mortgages, which were rated as safe investments just before the crash. Many investors before the GFC used credit ratings as a preliminary scrutiny method when selecting investing opportunities, blindly relying on them and fully trusting CRA. Extensive literature has been written about the topic. The vast majority agrees that the main concerns started in the early 1970s when rating agencies shifted their revenue model from an "investor pays" to an "issuer pays" model. The former was the standard from the inception and expansion of the rating market in the early 1900s, where investors were actively seeking for third parties' ratings and would directly pay agencies for their services. Then, as demand by companies to get rated in order to attract investors increased, financial instruments grew in numbers and complexity and competition between CRAs intensified, the market conditions made the <Issuer pays= model more suitable and way more profitable. As its name states, there the debt-issuer entity is the one directly purchasing the rating. Having a solid score became more and more as a credibility badge and necessary to attract funds at sustainable interest rates over the long run. This of course raised not few concerns among investors, <The sluggishness of these changes raises an even more central question: whether the three major credit rating agencies actually provide useful information about default probabilities to the financial markets (and, indeed, whether they have done so since the 1930s). As evidence of their value, the rating agencies themselves point to the generally tight relationship over the decades between their rankings and the likelihoods of defaults.= (White, 2010). The biggest concern for investors relates to the phenomenon of credit shopping, a practice that involves the issuer soliciting rating services from multiple agencies and then only considering the most favourable one. This phenomenon was particularly called into question in the years following the Global Financial Crisis (GFC), strong anecdotal evidence suggests that <rating shopping= and pressures by issuers on the major CRAs were occurring during the 2005–2007 period and further econometric studies indicate both that issuers did shop for preferable ratings and that this shopping did induce more favourable ratings for issuers (White, 2010).

After the GFC, rating agencies suffered severe reputational damage, policymakers and regulators began procedures aimed at improving transparency and objectivity within the practices used during the rating process. An example of that is the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, where it becomes mandatory for CRAs to disclose their methodologies and rating assumptions. Integrating new liability standards that make it easier for investors to challenge agencies' judgement, minimizing the use of credit ratings in the decision-making processes of institutional investors by employing new standards of creditworthiness and the disclosure of information regarding the fees received from issuers and about potential conflicts of interest. Coming to nowadays, the landscape for credit rating agencies has indeed undergone changes with regulatory reforms influencing operational practices, transparency and accountability. To address these newly imposed conditions and market requirements, CRAs have expanded their offerings beyond credit assessments. They now provide risk evaluation tools, market analysis and analytical services; this diversification does not only help with buffering the effects of shifts on their core rating activities but also positions them as comprehensive providers of financial market insights. The reputation of CRAs has seen some improvement since the aftermath of the Global Financial Crisis, now they operate in a more critical and demanding setting where investors and issuers are scrutinizing ratings closely and more and more often conducting independent due diligence instead of solely relying on CRAs evaluations. Furthermore, there is debate about the lasting impact of changes on rebuilding trust in CRAs: while some argue that these agencies are now more accountable and transparent, others believe that issues such as conflicts of interest and rating accuracy persist. While CRAs have adjusted to these shifts and continue to be players, in financial markets industry evolution is still ongoing: the constant obstacles linked to trust, rivalry and adjusting to technologies and market changes, imply that the responsibilities and image of CRAs are likely to develop. In the future is expected to see further innovation in credit risk assessment, possibly reshaping or even expanding the role of traditional credit rating agencies in the financial ecosystem.

This historical introduction emphasizes once again the great relevance that the topic has had in recent decades. That's why, starting from the 1970s, the theme of credit ratings has been addressed in an extremely detailed and varied manner, presented under a myriad of lights and perspectives. No matter how many theories and speculations may be developed, there will always be an objective truth in the consequences of credit rating changes, and this truth becomes even more undeniable when it is expressed and measured empirically. To understand the real influence of CRAs over the years and measure their power, one can only look at how investors and major players in the financial system have reacted to their actions. This is numerically and systematically expressed by the price changes of financial instruments related to debt instruments (and especially the debt instruments themselves) at the time these instruments are either rated for the first time or, especially, undergo changes in their current rating, whether these are positive (upgrades) or negative (downgrades). These percentage variations are an indirect measure of how much investors think the opinion of CRAs is authoritative and what informative content it brings to the market. For instance, when an instrument is downgraded, we can assert that if the price change is negative, it means the market did not expect it; therefore, in an ideal world where the market believes that the opinion of

CRAs is authoritative, the thought is that the CRAs have conducted thorough research and have come to know of information previously overlooked, leading to a correction of the risk associated with that instrument to its fair value. In a world where the opinion of CRAs is not considered authoritative, then despite the rating downgrade, the instrument will not undergo statistically significant changes because the market believes that the information it has is more valuable than that brought to light by the CRAs. Now, the power of the agencies is subject to variation over time, field of application, and market trends; thus, considering a single period or a limited statistical sample could lead to bias, but by extending the time horizon and the population, a significant estimate is obtained due to the effect of the mean. In conclusion, how investors decide to react, thus changing the allocation of their capital following the manoeuvres of the CRAs, tells us much about the real power of the latter. Now, debt instruments are the directly involved parties, but corporate shares (common stocks), besides being highly correlated to them, are more easily assessable and the price data is much more readily available. This makes them the most suitable tool for conducting an analysis of this type and the reason why they are at the centre of this dissertation.

Literature Review

As previously mentioned, the topic has been extensively discussed over the last four decades; studies range in scope, historical period analysed, methodological approach, business sectors of application, indicators considered, several rating changes from different agencies using distinct evaluation models, various types of securities taken into account etc. This Literature Review aims to explore the existing studies and theories concerning the effects of credit rating alterations, on securities market values. It starts from the early research and progresses to the most recent ones capturing the evolution that has taken place over time. The goal is to provide an overview of the understanding in this area by analysing empirical studies, theoretical frameworks and historical case studies that delve into how, changes in credit ratings, impact investor actions, market trends and stock values.

Pinches and Singleton (1978) investigate whether bond rating changes bring new information to investors; authors find that in the pre-announcement period, both upgrades and downgrade come along with significant abnormal returns, while post-announcement returns tend to be normal, even slightly reversing the pre-announcement abnormality; meaning that the market already possess these information and act accordingly. The authors examine the lag between actual change and market anticipation and find that the market starts to move 15 to 18 months before the announcement, concluding that the market is highly efficient in reflecting information in common stock prices. A few years later, Griffin and Sanvicente (1982), argue that the conclusions by Pinches and Singleton are potentially biased by the methodology used and <Since a rating change, to a degree, is also a reflection of publicly available market information and accounting data, such public information should be carefully controlled for if any observed price adjustments at or before the time of announcement are to be attributed to the rating per se=. They find that <bond downgradings convey new information to common stockholders pertinent to the assessment of security return=, examining the stock reaction in the month of the announcement and in the previous eleven months. For upgrades, they come to a counterintuitive conclusion: price changes in the announcement month are statistically not significant, while, in the eleven months prior, firms get significant positive abnormal returns. Griffin and Sanvicente conclude their work by stating: <Future research should be directed to an analysis of daily or even intraday price adjustments=. A few years later Hand, Holthausen and Leftwich (1992) present a research paper addressing this request: they examine daily excess bond (especially) and stocks returns associated with announcements of additions to Standard and Poor's Credit Watch List, and to rating changes by Moody's and Standard & Poor's. They divide the sample between <anticipated= and <unexpected changes= observations, the first being contaminated by public information flow, the second being not publicly disclosed before the event. Addition to the Credit Watch List generally returns insignificant results. They find statistically significant negative average excess returns for downgrades in both stock and bonds, results are stronger when a non-investment grade bond is considered. While for upgrades they observe significant results for bonds in the <unexpected= sample, however no effects for stocks. They do find asymmetric results; actual rating downgrades provide significant negative average excess returns for both bonds and stock, unlike upgrades that provide weak positive average excess returns (no sample distinction here). Eventually, despite the inconsistencies, they do affirm that there is a correlation between market price reaction and Credit Watching List and actual rating change announcements.

Moving forward, in the early 2000s, researchers keep adding knowledge to the topic by roaming to different markets intended as both securities, sector and geographic perspective. Dichev and Piotroski (2001) investigate long-run stock performance after the rating change event by Moody's from 1970 to 1997. They find no abnormal reaction for upgrades but do notice it after downgrades. Having more negative performances in the first months and an average duration of a year, the effect is pronounced for small and low credit ranked firms. They conclude that downgrades are strong predictors of future earning deterioration. Norden and Weber (2004) explore the CDS and stock market response to credit rating announcements (by all main CRAs: Standard & Poor's, Moody's, Fitch) between 2000 and 2002. They find that both markets anticipate downgrades for all three CRAs and prices start to move approximately 60-90 days before the announcement. Their results are consistent with previous literature and show that for downgrades negative average abnormal return is statistically significant, while for upgrades such a thing does not happen. Interestingly, they find that negative reviews by S&P and Moody’s are associated with significant abnormal returns (both CDS and stock market), while this is not happening for Fitch. Linciano (2004) does a country specific research, looking at a sample of 299 rating actions by the big three CRAs on Italian Public companies from 1991 to 2003, she gets to conclusions aligned with previous literature: reactions are statistically significant just for negative addition to the CWL or actual negative re-rating. To Linciano CRAs <do not seem to act on the basis of private information= and <the hypothesis that rating agencies act in line with the financial market regulation prohibiting selective disclosure of significant corporate events, supports the argument that the information content of ratings is modest=. Concluding that, of course, rating can be a valid resume of the financial condition of the issuer, but investment decisions can’t be based on that, not even partially. Di Cesare (2006) looks specifically at large-cap banking institutions and the reaction of stocks, CDS spread, and Bond spreads to both rating announcements and reviews. He concludes that <All indicators are found to contain useful information to anticipate rating actions from the main international agencies, especially for negative events. It must be said, however, that all indicators give also many false signals=, CDS spreads are found to be more efficient in predicting negative rating changes than common stocks, which, along with bond spreads, exhibit more accuracy for positive events. A few years later (and after the biggest financial turmoil in history), also Galil and Soffer (2011) explore CDS as a market indicator, confirming prior literature as <CDS spreads change abnormally following announcements of rating changes and rating reviews.= but <Nevertheless, this study is the first to test whether this abnormal behaviour is indeed caused by rating announcements.=. Moving away from the traditional approach of excluding clustered announcements from the sample, they look instead for sensible information across other channels, controls for them and conclude that <Rating changes draw a lesser market response than reviews.= and "It appears that news coverage and market response complement each other. The market is more sensitive to negative news.= As Di Cesare, also Jones and Mulet-Marquis (2013) examine reaction to changes in the banking sector, especially 43 US-listed banks. Using different estimation windows and different

estimation models for abnormal returns their conclusions are aligned with previous literature, i.e. downgrades are correlated with significant negative abnormal returns happening around the event window and especially on the event day. What is not aligned with previous literature is that upgrades are followed by positive post-announcement performances and significant abnormal returns on the event day, authors state that: <The results regarding upgrades contrast with most of past literature and provide support regarding the theory that due to their inherent importance to the local economy, ratings of banks should exhibit significant abnormal returns.= Most recent literature focus on analysing shorter time spans to better capture information leakage, Even-Tov and Bugra Ozel (2021) use intraday price data, they bring evidence that <Credit rating analysts looking to change jobs likely disclose private information.=. Their study <provide initial evidence on the variation in intraday timing of credit rating changes across rating agencies and between upgrades and downgrades.= and <Document that only announcements of issuer rating changes elicit a significant price reaction and that those for instrument rating changes are not broadly statistically significant".

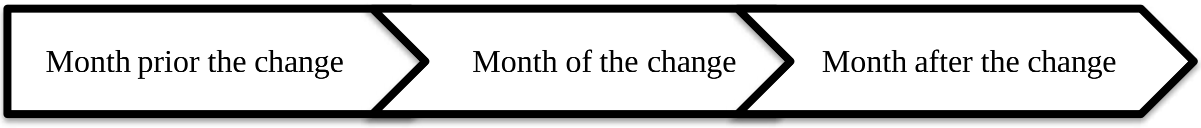
Data & Methodology

My research focus is to evaluate how stock markets react to credit rating changes. The goal is to find whether there is a common pattern among stock returns. The starting point of this dissertation is a dataset including Standard & Poor's monthly Credit Rating of 6,985 US Public Companies from January 1985 to December 2021. Each company is identified by S&P <Gvkey= Identification number. To better understand the data sample I show Summary Statistics. In *Table 1.0,* I show the all the rating observations in the initial Dataset (Raw Sample). In *Table 1.1,* I show all rating changes from the initial Dataset after cleaning operations (explained afterwards). In *Table 1.2* I show all rating changes per year, including the number of upgrades, downgrades, and companies involved (1985 and 2021 are not shown as they have zero observations).

In the first part of the dissertation, I focus on the stock's reaction around the rating change event, computing Monthly Average Abnormal Returns in three-time spans, the month prior to the change, the actual month of the change, and the month after the change. In the month prior I test whether it may happen that information regarding a downgrade (upgrade) circulates before the actual change influencing investors' sentiment. Stock returns are extracted from the

CRSP database and matched to Gvkey through Permno code, then averaged to get the mean return of each month.[1]

Prior literature uses shorter time spans (mostly daily returns) and often makes the distinction between anticipated and unanticipated rating changes using Standard & Poor’s Credit Watch List or news reported by the main authoritative media (Financial Times, Bloomberg, Reuters etc.) as reference, which lead to changes in investors’ sentiment hence driving stock’s reaction. Before going into a detailed analysis I have to state that monthly data is quite a large span for stock returns hence this could be subject to different data selection problems which effect is not taken into account in this study due to lack of access to other S&P dataset as the credit watch list or where the exact day of the rating change is available, eventually preventing me on using a shorter time span. Still, it is reasonable to say that the large number of companies and the 36 years of data composing the sample mitigate the potential distortions.



From the original Dataset I have to remove observation that can lead to distortions in the final results thus I perform the following data cleaning operations: removal of all observations with an <anomalous= credit rating as <NR, R, SD, NM, Suspended=; stock prices when companies are given an anomalous rating tend to be really volatile and are influenced more by events like scrutiny procedures by regulators (R), bankruptcy proceedings or liquidation processes (SD), or just not enough information (NM), rather than the usual market responses to credit rating adjustments. Removal of all "defaulted companies" with a rating of "D" ("D" rated companies are the ones not fulfilling their debt payments obligations facing huge difficulties, possibly defaulting or in distress). Removal of the so-called <Penny Stocks= companies; this was done by getting the monthly closing prices on CRSP (variable PRC keeping the real closing price and not bid-ask average values) and removing stock priced under 5$ (Due to a higher associated risk thus a higher price volatility related to low market liquidity and minor reliability on the company classified as <Penny=, the stock behaviour can lead to potential biases thus I want to minimize this effect). Finally, I trimmed the sample by dropping 1% top and bottom of observation to not consider outliers that present extreme returns in both directions for reasons

[1] Returns without Dividend ($retx$).

related to external factors like corporate scandals (financial fraud or falsification of financial statements, sudden legislative changes, natural disasters or accidents, political crises, rapid technological changes, etc.). Afterwards I had 11,738 observations left in total. Eventually, it worth making the distinction and showing the behavioural difference between Investment Grade companies (From BBB- upwards) and Speculative Grade ones (From BBB- excluded downwards); speculative grade companies are perceived as with a higher likelihood of default by investors, thus, averagely speaking, they are more volatile than investment grade ones. In the next section, <Results Data= I will highlight how after the cleaning procedures both type of securities behave in a similar way.

Average Abnormal Returns (AAR) follow Jones and Mulet-Marquis (2013), using two of the most widely known and used in literature models: the S&P 500 index market model and the Fama-French Three-Factor Model.[2]

Abnormal Returns (AR) are calculated as the difference between observed returns and expected returns obtained with the S&P 500 market model and the Fama-French Three-Factor Model:

$$AR_{it} = R_{it}\ 2\ E(R_{it})$$

Where:

AR_{it} is the Abnormal Return of stock i on month t.
$E(R_{it})$ is the expected return of security i on month t.
R_{it} is the observed returns of security i on month t.

In the S&P 500 market model, $E(R_{it})$ is calculated as:

$$E(R_{it}) = \alpha_i + \beta_i \times Rm_t + \varepsilon_{it}$$

Where:

- Rm_t is the log-return of the market portfolio (S&P500) on month t.[3]

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[2] Average Abnormal Returns (AAR) are calculated as: $AAR_{it} = \frac{1}{n}\sum_{i=0} \mathrm{AR}_{it}$.

[3] Return on S&P Composite Index ($sprtrn$).

- α_i is the intercept of the Ordinary Least Squares regression of the stock returns for security i on the market returns for the estimation period.
- β_i is the slope of the Ordinary Least Squares regression of the stock returns for security i on the market returns for the estimation period.
- ε_{it} is the zero mean disturbance term which is assumed as null.

<u>In the Fama-French Three-Factor Model</u>, $E(R_{it})$ is calculated as:

$$E(R_{it}) = \alpha_i + Rf_t + \beta_{market_i} \times (Rm_t \; 2 \; Rf_t) + \beta_{HML_i} \times HML + \beta_{SMB_i} \times SMB + \varepsilon_{it}$$

Where:

- α_i is the intercept of the model. This term represents the stock's i return that is not explained by the factors in the model.
- (Rm_t- Rf_t) is the excess return on the market at month t.
- HML (High Minus Low) and SMB (Small Minus Big) refer to the average returns of two portfolios designed to mimic the effects of book-to-market equity and size on stock performance.
- β_{market_i}, β_{HML_i} , β_{SMB_i} are the results of a multivariate regression of the returns of security i on the three factors Rm_t- Rf_t, HML and SMB for the estimation period.
- ε is the zero mean disturbance term which is assumed as null.

The statistical test used to assess the significance of the findings at a 1% confidence level is the one-sample t-test:

$$t \; 2 \; test = \frac{\text{AAR}}{\text{sdt(AAR)}/\sqrt{\text{n}}}$$

Where, AAR is the Average Abnormal Returns of a sample of n observations and $std(AAR)$ is the standard deviation of the AAR.

After looking at the whole sample span (Jan 1985 – Dec 2021), the focus will be directed on distress times: Dot com Bubble (March 2000 - Oct 2002); Great Financial Crisis (Feb 2007-

Feb 2009); Covid-19 (Feb 2020-Dec 2021). Even though these periods are financial market turndowns originated by different causes, they can be deemed as the major distress times of the last 25 years. I expect to find stronger negative stock market responses to downgrade due to a pronounced sense of uncertainty and negative sentiment affecting investors; while concerning the few upgrades in these sample spans, I expect a similar result as in the entire sample. Regarding Covid-19, data allows for a partial study; it captures the whole initial part and disease's evolution until December 21'. In the US, the pandemic lasted until May 11th, 2023, when the end of PHE (Public Health Emergency) was officially declared it over. But since January 2021 COVID-19 deaths have declined by 95% and hospitalizations were down nearly 91%, so data until Dec 21' definitely reflects the core part.[4] Afterwards, the decade prior and the decade afterward the Great Financial Crisis (GFC) are taken into consideration: due to the GFC lots of regulations were introduced and consequently credit ratings became more stringent, so the next thing examined is the possible differences encountered between the decade prior to the GFC (Jan 1997 - Dec 2006) and the decade post (2010 Jan - Dec 2019). That could provide an indirect measure of the impact of new regulations and GFC aftermath on the credit rating ecosystem.

Periods	
Dot-com Bubble Burst	Mar 2000 - Oct 2002
Great Financial Crisis	Feb 2007 - Feb 2009
Covid-19 Epidemic	Feb 2020 - Dec 2021
Decade Prior New Regulations	Jan 1997 - Dec 2006
Decade Post New Regulations	Jan 2010 - Dec 2019

In the second part of the dissertation, the focus is directed on relating stocks' reaction to rating change's magnitude. Since it's expected that stronger (weaker) abnormal returns should correspond to larger (smaller) downgrades (upgrades) of higher magnitude. I run the previously described analysis and get the average abnormal return for different levels of changes. For example, the goal is to assess if a 1-notch downgrade (upgrade) (for instance, from A to A-) produces a weaker market reaction than a 2-notch downgrade (upgrade) occurs (for instance,

[4] https://www.hhs.gov/about/news/2023/05/09/fact-sheet-end-of-the-covid-19-public-health-emergency.html, https://www.cdc.gov/coronavirus/2019-ncov/your-health/end-of-phe.html.

from A to BBB+). I analyse changes up to 5-notches. Furthermore, the same magnitude changes will be compared within categories. By "categories" I mean the different parts that make up the Rating Scale adopted by Standard & Poor's. The present categories are four: A, B, C, D. In the categories are found all the subcategories, for instance, category A is composed by AAA, AA+, AA, AA-, A+, A, A-. The same applies to categories B and C (with slight differences in the number of subcategories, for instance, B has 9 and C has 5). Obviously, category D, which refers to companies in Default, is not considered. For instance, a 3-notch downgrade (upgrade) in A category (Ex. AAA to AA-) may result in a stronger (weaker) negative (positive) average abnormal return than a 3-notch downgrade (upgrade) that happens within category B (Ex. BBB to BB). In *Table 1.3,* I show the Summary Statistics of all rating changes magnitudes (from 14 notches Downgrade to 14 notches Upgrade) divided by the previously considered periods.

The third and final part of this thesis focuses on Industries and if the previously seen effects are more dominant and persistent for specific ones. The whole sample is divided into nine major economic Industries identified by The Standard Industrial Classification (SIC) code by matching them to Gvkey on CRSP and the previously described analysis is run to see if there are glaring differences in average abnormal returns between businesses.[5] In conclusion, the same procedure is employed, this time using the North American Industry Classification System (NAICS), the sample is divided into nineteen major economic Industries and results are compared to check for any additional findings with respect to SIC classification.[6] I take in consideration both SIC and NAICS because in the sample a small percentage of companies can't be identified by SIC code, so they would have not been included in the comparison. With NAICS Code no company stays out of the categorization. In addition, the NAICS classification counts more Industries and is more specific. In *Table 1.4,* I show the Summary Statistics of all rating changes as companies are identified and sorted by SIC Sector of belonging. In *Table 1.5,* I show the Summary Statistics of all rating changes as companies are identified and sorted by NAICS Sector of belonging.

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[5] https://www.sec.gov/corpfin/division-of-corporation-finance-standard-industrial-classification-sic-code-list.
[6] https://www.census.gov/naics/?58967?yearbck=2017.

Returns Data

As previously mentioned, I show how the behaviour differs between Investment and Speculative grades. Although it is normal to expect more volatility in the reactions of speculative grades, we see how the most extreme values are very similar. This indicates the effectiveness of data cleaning and how homogeneous the data is. This table below provide summary statistics for all the companies' returns in the month of the change, divided by Whole Sample, Investment Grade, and Speculative Grade. The headers are Count, meaning the number of observations we have; MR, the abbreviation of Mean Return, is the average of the observations; Std, is Standard Deviation; Min, the minimum return value; 0,25, is the 25th percentile; 0,5, is the 50th percentile; 0,75, is the 75th percentile; Max, the maximum return value.

Whole Sample

Count	MR	Std	Min	0,25	0,5	0,75	Max
11738	0,0053	0,1104	-0,3511	-0,0529	0,0056	0,0646	0,4016

Investment Grade

Count	MR	Std	Min	0,25	0,5	0,75	Max
6615	0,0052	0,0919	-0,3500	-0,0426	0,0059	0,0551	0,3976

Speculative Grade

Count	MR	Std	Min	0,25	0,5	0,75	Max
5123	0,0054	0,1305	-0,3511	-0,0719	0,0046	0,0799	0,4016

This table shows how the average returns are very similar across all three groups. Also, the Maximum and Minimum values recorded are practically identical from the Whole Sample to the Investment Grade Sample to the Speculative Grade Sample. What stands out are the differences in the Standard Deviations. As expected, I find the highest Std value in the Speculative Grade Sample (0,13), the lowest in the Investment Grade Sample (0,09), and the average of these in the Whole Sample (0,11). It is interesting to note that at the 50th percentile, I find a Mean Return of about 0,5% in all three Samples, while at the 25th and 75th percentiles, I see Speculative Companies having higher absolute returns, respectively -7,19% and 7,99%.

Results

Results are presented as follows: I first show the <3-Month Whole Sample= analysis, then the <Time-periods Analysis= followed by the <Magnitude Analysis= and finally the <Industries Analysis= (divided by SIC and NAICS codes). The results from the <Market Model= and the <Fama French Three Factor Model= are presented and compared for each section. For each group, the results for the Speculative Grade and Investment Grade Sample are presented. Unless otherwise specified, all mentioned results have a significance level of 1%. The t-statistics are reported in parentheses next to each described AAR value. Among the observed results, it is notable that Downgrades, in the Month Before the Change and the Month of the Change, tend to be negative AARs. However, in the Month After the Negative Change, there are more positive AARs. For Upgrades, in the Month Before and the Month of the Change, tend to be positive AARs, while in the Month After the Change, the AARs tend to be slightly negative. This could be a sign that the market is anticipating Upgrades. In absolute terms, Downgrades result in greater AARs, and the "Speculative Grade" sample reacts slightly more strongly than the "Investment Grade" sample.

3-Month Whole Sample Analysis

Market Model

In the <Whole Sample=, *Table 3.0,* I note that the largest AAR refers to the <Month Before Negative Change= and the <Month of the Negative Change,= which are -1,29% and -1,53%, respectively. Both results are highly significant, with t-statistics of -9,48 and -10,66, respectively. For Upgrades, I find milder AARs but still highly significant. On both sides, the results are in line with the literature. In the <Speculative & Investment Sample=, *table 3.1*, in absolute terms, I notice the greater reaction in the <Month of Change (Negative Speculative Grade)= with an AAR of -2,19% (-8,44), while for upgrades, I see a max AAR of 1,00% (4,48) in the <Month before Change (Positive Speculative Grade),= both results being highly significant. Generally, I notice much larger reactions in Downgrades for the Speculative Sample, as expected.

Fama French

The Fama French Three-Factor Model, considered more accurate by the literature, presents more <severe= results. As seen in *Table 3.2,* <Whole Sample=, the <Month After= Downgrade shows the highest return in absolute terms, 1.31% (5.59). The <Month Before= and the <Current Month= show significant but weak negative abnormal returns. Regarding Upgrades, none of the AARs are significant. Regarding *table 3.3* for the <Speculative & Investment Sample= I notice only one return in line with the 1% significance level, 2.12% (6,03), in the <Month after Change (Negative Speculative Grade)=. This result is consistent with the whole sample and with expectations of greater volatility in Speculative Grade Changes.

Time-periods Analysis

Market Model

In *table 4.0* <Whole Sample=, I notice that Negative AARs are consistently found before and during Downgrades, particularly for Speculative Grades, aligning with the expectation of increased risk perception leading to negative abnormal returns. Positive AARs tend to occur before Upgrades, suggesting anticipation of improved creditworthiness, and after Downgrades, potentially reflecting market correction or recovery. The strongest reactions that I find are Month before Negative Change (Covid-19 Epidemic), -3,1% (-3,63), Month after Positive Change (Great Financial Crisis), -2,8% (-6,37), and Month before Positive Change (Dot-com Bubble Burst), 2,1% (2,74). These results suggest that broader market conditions heavily influence the market sensitivity to rating adjustments, especially during in economic instability markets tend to price in credit rating changes before they occur, and downgrades trigger deeper reassessments of a firm’s long-term viability. While in *Table 4.1,* for <Speculative & Investment=, I show that the strongest reaction is in the Month after Change (Positive Investment Grade) (Great Financial Crisis), -4,1% (-7,97). Then, in the Month before Change (Negative Speculative Grade) (Covid-19 Epidemic), I get a -3,7% (-3,31) AAR. Eventually, in the Month after Change (Negative Speculative Grade) (Covid-19 Epidemic) a -3,34% (-2,79) AAR is displayed. Here I find more extreme reactions than in the Whole Sample and surprisingly an Investment Grade change gives louder negative reactions than a Speculative one. Overall, Covid-19 has returned the strongest Negative reactions, including in the Month After Change where usually positive returns are observed.

Fama French

In *Table 4.2* I also find that Negative AARs are consistently found before and during downgrades and there are slightly negative AARs after upgrades, which aligns with expectations that markets react more heavily to bad news than to good news. Contrary to the expected pattern, Positive AARs are not averagely observed before and during Upgrades, especially in the Whole Sample, where the month after Downgrades do not consistently show positive AARs. In the Whole Sample, I find the strongest reaction during the Decade Post New Regulations, in the Month before Positive Change, 9,19% (32,85), and in the Month after Negative Change, 9,6% (28,38). In *Table 4.3*, for the <Speculative & Investment=, I observe a huge and highly significant reaction, 11,5% (36,39), in the Month before Change (Positive Investment Grade) (Decade Post New Regulations). Then another highly marked one, 11,2% (35,83), in Month of Change (Positive Investment Grade) (Decade Post New Regulations). And eventually, a 12,8% (33,86) AAR, in the Month after Change (Negative Investment Grade) (Decade Post New Regulations). All those, being also in the Decade Post Regulation and surprisingly from Investment Grade changes.

Magnitude Analysis

Market Model

In *Table 5.0,* for the Whole Sample, considering just the strongly significant AARs, the data show that 2-notches Downgrades have more negative AARs both in the Month Before and During the Change compared to 1-notch Downgrades. This suggests that the more significant downgrades is, the stronger market reaction it produces. The same observation applies to Upgrades. 2-notches Upgrades show higher (positive) AARs Before and During the Change compared to 1-notch Upgrades. Meaning the bigger the Upgrade the stronger the market reaction. Consistent with expectations, I notice that in absolute terms, Upgrades produce weaker reactions compared to Downgrades. In *Table 5.1,* for the <Speculative & Investment= Sample, I can draw the same conclusions: I do not find significant t-statistics beyond 1 notch and 2 notches Changes (Only one is the 4 notches Downgrade in the Month of the Change,

producing a -4,8% (-2,76) return). For both Speculative and Investment Grade companies, a 2-notches Downgrade tends to produce a stronger market reaction than a 1-notch Downgrade. For Upgrades, I do not have statistically significant terms to compare.

Fama French

In *Table 5.2 “*Whole Sample=, for Upgrades, I can affirm that in all three scenarios (Month Before the Change, Of the Change, and After the Change), they produce positive AARs of 4-4,50% with highly significant t-statistics (all above 4,20). But there is not much room for comparisons since the only significant Upgrade that is not <3-notches= is the 1-notch <After Change= which produces a reaction of -0,8% (-3,07). On the Downgrade side, the comparison is made between <After Change= 1, 2, and 3 notches changes: I have respectively 1,38% (5,02), -0,62% (-1,03), and 4,21% (4,85). I can’t notice a progressively stronger reaction as I could expect, but I do notice a big jump between the 1 and 3 notches (which aligns with expectations). In *Table 5.3* <Speculative & Investment=, for 2-notches Downgrades (Investments), significant negative AARs are observed before and during the Month of the Change, both returning -4,30% (-5,48 and -5,38). For 3-notches Downgrades (Investments), strong positive reactions are reported, 5,00% (4,12), 4,4% (3,73), and 5,03% (4,28). That stands out as not aligned with expectations, probably due to unique circumstances or market interpretations not immediately apparent. And I have the same strong positive significant reactions in 3-notches Upgrades (Investments). From 1 to 3 to 4 notches Upgrades, I can notice a progressively stronger positive reaction, -1,67% (-4,67) (Investments, After Change), 5,19% (4,70), 11,72% (3,13) (Speculative, After Change). However, for the 4 notches one, I rely on just 26 observations. Overall, that’s aligned with expectations.

Magnitudes Within Categories

Market Model

In *Table 6.0,* for the Whole Sample, I will change the significance criteria extending it to 5%. Reason is that I had no data to compare since this analysis is quite specific with many fields of less than 30 observations and no significant t-statistics. Even with this condition, I can just compare 1-notch Downgrades: within category B[7], it has -1,98% AAR (-8,05). Within category A, the reaction is -0,54% (-2,31), and from category A to B, I have -1,38% (-2,83). A slightly stronger reaction is noticed in lower categories, suggesting that the lower it happens, the riskier it is perceived by investors. I also notice that a 2-notches downgrade has a stronger, -2,53% (4,44), reaction than a 1-notch negative change, both within category B. As for Upgrades, I can just take as a reference the 2-notches change from C to B, provoking a positive 5,76% (2,48) return. In *Table 6.1* for the <Speculative & Investment= sample, I have slightly more valid data. A 1-notch Downgrade Within B (Investment) has a stronger negative reaction, -1,55% (-4,58), than a 1-notch Downgrade Within A (Investment), -0,54% (-2,31), and slightly stronger than a 1-notch Downgrade from A to B (Investment), -1,39% (-2,83). That's perfectly aligned with expectations. I can also notice a stronger reaction for a 1-notch downgrade Within B (Speculative), -2,19% (-6,67). On the contrary, a 2-notches Downgrade Within B Investment has a much stronger reaction, -4,30% (-3,27), than a 2-notches Downgrade Within B but Speculative, -2,22% (-3.54).

Fama French

In *Table 6.2,* for the Whole Sample, I surprisingly find that a 2-notches Downgrade Within A has a stronger negative reaction, -6,92% (-5,30), than a 2-notches Downgrade Within B, -2,24% (-2,80). In *Table 6.3,* for <Speculative & Investment= I find the same. A 2-notches Downgrade Within A (Investment) returns a -6,91% (5,30), while a 2-notches Downgrade Within B (Investment) is -5,24% (-2,80). Another unexpected result is found in the 1-notch Upgrade Within A (Investment), returning a negative -2,94% (-5,35). And a 3-notches Upgrade from B to A (Investment) reaction, 11,37% (8,90), is stronger than a bigger magnitude 4-notches Upgrade from B to A (Investment), 8,66% (4,24).

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[7] In this case, for <category B= I mean all the B-ratings according to Standard & Poor's Rating Scale, specifically those ratings are: BBB+, BBB, BBB-, BB+, BB, BB-, B+, B, B-.

Industries Analysis

Market Model - SIC

In *Table 7.0,* for the Whole Sample, I have many Industries with Significant Negative reactions to Downgrades. I notice that Office of <Trade & Service, Manufacturing=, <Energy & Transportation=, <Industrial Applications and Services=, <Finance= and <Real Estate & Construction= returns negative AARs in the Month Before and in the Month of the Change. Stand out <Office of Trade & Services= in the Month Before a Downgrade, -2,00% (-4,87), and <Office of Energy & Transportation= in the Month of the Downgrade, -1,96% (-5,97). While, among industries with Significant Positive reactions to Upgrades, I notice that <Office of Trade & Service, Manufacturing, Energy & Transportation= returns positive AARs in the Month Before and in the Month of the Change. <Office of Trade & Service= in the Month before an Upgrade has a 1,39% (3,81) AAR. Overall Industries have mixed, non-univocal reactions. In absolute terms, the strongest and most significant reactions are always Negative Downgrade-Related. In *Table 7.1,* for the <Speculative & Investment= sample, I find similar conclusions to the Whole Sample, with <Office of Finance= and <Office of Real Estate & Construction= being the most sensitive to Downgrades (Month Before and Month of the Change). <Office of Trade & Services= and <Office of Energy & Transportation= are the most sensitive to Upgrades (Month Before the Change). As previously mentioned, the strongest and most significant reactions (in absolute terms) are always Negative Downgrade and Speculative, in this case, both in the Month of the Change: <Office of Finance,= -4,96% (-3,81) and <Office of Real Estate & Construction,= -4,69% (-4,07).

Market Model - NAICS

Table 7.2 refers to the Whole Sample. Industries such as <Manufacturing= <Finance and Insurance= <Mining, Quarrying, and Oil and Gas Extraction= <Retail Trade= and <Utilities= show Negative AARs in the Month Before and the Month of the Change. The "Finance and Insurance" industry shows an AAR of -1,77% (-6,29) in the Month of the Downgrade, and <Retail Trade= shows an AAR of -2,94% (-4,49) in the Month Before the Negative Change. As for Upgrades, <Wholesale Trade= <Utilities= and <Manufacturing= show positively significant reactions, especially in the Month Before the Change. In fact, <Wholesale Trade= shows an AAR of 1,97% (2,91) in the Month Before (Speculative). And <Utilities= shows an AAR of 1,01% (2,92) in the Month Before (Speculative). As for <Speculative & Investment= section,

Table 7.3. I find almost the same results. In both samples, significant reactions often occur before the actual rating change, and this is especially true for upgrades <Wholesale Trade= and <Utilities= and "Retail Trade" and <Finance and Insurance= for Downgrades; the speculative segment has an overall louder reaction.

Fama French - SIC

Table 8.0 refers to the Whole sample. Consistently with expectations I find results similar to the Market Model. Sectors such as <Office of Trade & Services= <Manufacturing= <Energy & Transportation= <Industrial Applications and Services= <Real Estate & Construction= show negative AARs in the Month Before and during the Downgrade. <Office of Real Estate & Construction= has an AAR of -4,54% (-3,79) in the Month of the Downgrade. While <Office of Life Sciences= and <Office of Finance= display particularly positive AARs. <Office of Life Sciences= in the Month after the Negative Change has an AAR of 6,18% (4,38), which is the strongest reaction in absolute terms. I find the same conclusions in *Table 8.1* for <Speculative & Investment=. <Office of Trade & Services= and <Office of Energy & Transportation= are most sensitive to Downgrades. <Office of Trade & Services= AAR is -3,64% (-3,10) in the Month before Investment Negative Change. <Office of Energy & Transportation= AAR is -2,75% (-3,83) in the Month of Investment Negative Change. Also, "Office of Trade & Services" is the most responsive when it comes to Upgrades. While the biggest positive reaction is from <Office of Life Sciences= 7,83% (4,64), in the Month of Investment Negative Change. And the most negative one is from <Office of Trade & Services= -3,64% (-3,10) in the Month before Investment Negative Change.

Fama French - NAICS

In *Table 8.2,* Whole Sample (always considering a 1% significance coefficient) I don't observe any prevalent trend (there are not enough significant AARs to define a trend). Aligned with expectations, I find two positive AARs, both in the Month after a Downgrade, for <Finance and Insurance=, 2,95% (6,50), and for <Manufacturing=, 1,49% (3,61). Most Negative reactions are found for Upgrades, in <Mining, Quarrying, and Oil and Gas Extraction,= during the Month of the Change, -3,82% (-4,07), and in <Construction=, -6,70% (-2,86), in the Month of the Change. In *Table 8.3,* for the <Speculative & Investment= sample, I can notice positive returns after both positive and negative rating changes in the <Finance and Insurance= sector. In <Transportation and Warehousing= I see strong positive returns before and after negative rating

changes, which could indicate a market reaction where lower credit quality ratings lead to an initial drop but then present buying opportunities, leading to positive returns shortly after the Downgrade. <Mining, Quarrying, and Oil and Gas Extraction= consistently shows negative returns around positive rating changes, particularly for Investment-Grade ratings, which potentially imply that even when ratings improve, the market remains pessimistic due to broader industry challenges or expectations not being met despite the Upgrade. The most negative AAR is in the Month after Positive Change (Investment Grade) in <Mining, Quarrying, and Oil and Gas Extraction=, -6,97% (-3,99). The most positive AAR is in <Transportation and Warehousing= in the Month after Negative change (Speculative Grade), 5,16% (4,14).

In conclusion, I report the main limitations of this study. As for <Returns= I always intend Monthly Returns, which captures a ± 30 days' time span. With the large sample of data is impossible to control for external variables and events occurring and influencing the price of a single stock or generally the whole market and investors' sentiment. Furthermore, the exact day of the change is not specified, this means that if the actual change happens at the beginning of the month the return value factors in also the whole remaining days. And if the actual change happens at the end of the month all the previous days' effect is counted.

Thus, in further research, the ideal thing would be having access to data of the exact day of the change and using daily or even intra-day returns. On the other hand, an interesting point is to repeat this study on different markets, which previous literature often ignores. And on other securities of the company which price is strictly affected by Credit Rating Changes like bonds. The distinction between Expected and Unexpected changes (regarding the additions to the Credit Watch List) is also an aspect that could be deepened. Eventually, given my findings, it would be useful to test different trading strategies on portfolios that aim to profit from buying and selling stocks timing the price movement based on the rating change.

Conclusion

Starting from a (cleaned) Standard & Poor's dataset containing 11,738 rating changes of 6,985 US public companies from January 1985 to December 2021, by calculating the Average Abnormal Returns for three-time spans (the month before, the month of, and the month after the rating change) using both the Market Model and the Fama-French Three-Factor Model, following the calculation methodology of Jones & Mulet Marquis (2013), I can conclude that the results are in line with previous literature. Downgrades tend to cause the strongest reactions in absolute terms, particularly negative ones. Moreover, as hypothesized, Speculative Grade securities tend to display more pronounced reactions compared to Investment Grade securities, although the difference is never excessive, and opposite cases are also observed. Specifically, Downgrades lead to significantly negative reactions in the month before and in the month of the rating change, showing, on average, slightly positive reactions in the month after the change. Upgrades, in contrast, show slight positive reactions in the month before and the month of the rating change, and slightly negative reactions in the month after the change. Regarding time periods, it is observed that during periods of market distress, negative reactions are accentuated, especially during the Global Financial Crisis (GFC) and COVID-19. In the magnitude analysis, while there are specific divergent cases, expectations are confirmed: the larger the rating notch change, the stronger the reaction in absolute terms. Similarly, (although contrary cases are not absent), changes within a category or rating jumps from one category to another are perceived as more severe (stronger reaction) when a security moves from A to B or when the Downgrade happens within a lower category. Lastly, the Industries Analysis suggests that some industries are more sensitive than others, but generally reconfirms that negative reactions following downgrades are the most significant and strongest in absolute terms. Comparing the models, the Fama-French Three-Factor Model typically provides more pronounced results than the Market Model. In conclusion, the multi-perspective approach adopted in this research expands upon previous literary findings and provides further confirmatory evidence while remaining aligned with them. At the same time, it suggests new paths for analysis.

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Appendix

Please access the Appendix via the following link: Appendix[8]

[8]< https://www.dropbox.com/scl/fi/owmiw5bmw0ej50efbmw9w/Master-Thesis-Vittorio-Sacchi-Appendix.docx?rlkey=j66wqxhxsybetq4tw8pky26c6&st=07vyiwe4&dl=0