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Beyond Price: The Influence of Credit Rating Changes on Stock Market Volumes

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Introduction

Credit rating agencies are essential players in the global financial markets. They evaluate the creditworthiness of a broad set of entities, from corporations to governments, and provide credit ratings to inform investors about different security levels of risk. However, there is an ongoing debate about the real effectiveness and value of these credit ratings. This thesis tries to contribute to this debate as it investigates the stock market's response to credit rating changes.

The debate about whether credit rating changes provide actionable additional information to the market is highly contested. Authors such as Partnoy (1999) and Chava et al. (2018) argue that these ratings may be redundant, meaning that the market effectively prices in the relevant information. This skepticism is further supported by evidence showing that bond rating upgrades do not result in positive abnormal returns, implying that such upgrades do not deliver new critical information to market participants.

This investigation explores whether the observed patterns in the bond markets concerning the consequences of rating changes are found in stock markets. The research also contributes to the broader question of understanding how stock markets respond to upgrades and downgrades, assesses the information value of rating changes, and contributes to the design of more informed regulatory policies and investment strategies.

To do so, the thesis investigates how the stock market reacts in the form of abnormal returns around rating changes. Abnormal returns are tested to see if they are consistent with the findings in the previous literature. This consists of using a market model to infer the expected returns and then calculating the differences between the actual and expected returns over the event window surrounding the announcement of the rating change. Because this intends to compare the results obtained to the benchmark literature, revealing whether the rating changes bring relevant new information that impacts the prices of the stocks, it is worth noting that, according to the literature, preliminary results suggest evidence of a lack of significant abnormal returns around upgrades, which indicates that upgrades do not bring new relevant information to the market. This observation relates to the arguments of the scholars of market efficiency, believing that the prices in the market already include any information that exists.

Therefore, the main objective of the thesis proceeds, which is the analysis of the abnormal trading volumes as a complementary approach to the reaction in the market. Previous studies (for example, Beaver, 1968; Bamber et al., 2011) have encouraged the use of volume tests in addition to studying abnormal returns. Another very important measure is the trading volume, which in principle measures the level of interest and activity investors have with the new information. In contrast to returns, trading usually has non-normal distributions, making it challenging to develop an adequate statistical method appropriate to the nature of trading.

With a view to improving the power of the analysis, this research follows the strategy used in other papers (Brogaard, Koski, Siegel, 2019) by creating normalized rank scores for the observations of the event window and comparing these scores to benchmarks. This procedure eliminates problems with skewed data and allows a better, purer detection of the abnormal trading volumes. It is, therefore, the ambition of this research to examine in detail only the stock market and describe these dynamics clearly.

In conclusion, abnormal trading volume without corresponding abnormal returns is a significant phenomenon that reveals the intricacies of market behavior and investor psychology. It demonstrates that even when the overall market does not revalue a security, individual investors may react differently based on their unique interpretations of information. This results in substantial trading activity driven by diverse beliefs and regulatory requirements rather than a unified market response. Understanding this divergence is crucial for financial analysts, policymakers, and investors as it highlights the necessity of considering both trading volume and price movements to fully capture market dynamics. Ultimately, this nuanced perspective provides deeper insight into how information dissemination and investor behavior influence market activity beyond mere price changes.

Chapter 1: Literature Review and Theory

In general, the literature suggests that firms tend to lose value when their ratings are downgraded and gain no value when their ratings are upgraded.

As a general perspective, this is confirmed in the majority of past studies, despite some out of these trends. For example, Dichev and Piotroski (2001) reviewed the long-term stock returns following bond rating changes and found a small but significant positive stock return after upgrades. Yet, despite these findings, the common view is that credit rating upgrades have negligible material impact on either investor behavior or stock prices.

In contrast, downgrades usually have a much greater impact, and there is a huge fall in stock prices, especially three months into the announcement of the news, and such a decline may last for one year. For that reason, downgrades result in market changes as they are considered a warning to an entity's future profitability, but this is not the case with upgrades. This was then further proven that the reversal of actions on smaller and lower-credit-quality firms inflicted significantly more underperformance, possibly reflecting some form of market underreaction. Therefore, a more detailed view of this is the importance of examining whether stock market reactions to credit rating changes are considered necessary.

The study emphasizes that when downgrades exhibit a dangerous effect on stock return, more probing is necessary to understand why the stock market responds as it does.

Liquidity theory is based upon the effect of credit rating to a firm on its stock's liquidity. Liquidity is the ability to buy or sell an asset without changing the price of the asset. A downgrade will decrease liquidity, mostly as investors become more cautious to trade after increased perceived risk, and conversely, an upgrade will enhance liquidity.

In view of that, Amihud and Mendelson (1986) find the relationship between asset liquidity and expected returns is supported by a lot of research that has shown assets that are less liquid offer higher expected returns in order to compensate for bigger transaction costs and risks. According to this theory, credit rating changes would increase transaction costs and perceived risks, lowering the liquidity of the stock and increasing required returns, showing negative abnormal returns in response to portfolio changes made to reflect increased illiquidity. Experimenting with high liquidity ensures that the price reflects information available to the agents and aids in ensuring the efficient functioning of a market. Theoretically, thus, the price of a liquid market should fluctuate less because large trades can be absorbed without changing the rates to a great extent. In a liquid market, bid-ask spreads are small; the costs of trading are reduced. Liquidity also enhances confidence among investors since it assures them of opening and closing positions with least friction.

Changes in credit rating have the potential to seriously impact the liquidity of an asset. Most often a downgrade would trigger selling, and consequently inflated trading volumes — this might overload market liquidity when buyers are not sufficient. An upturn might not necessarily trigger similar selling if investors view the change as non-material.

Downgrades could increase bid-ask spreads as market makers demand more compensation for increased risk and uncertainty. Upgrades may have less of an impact on spreads — if perceived risk is reduced. As noted in studies such as Beaver (1968) and Bamber et al. 2011, trading volume tends to increase on or around major information events such as credit rating revisions. The trading activity captures changes in liquidity and naturally also mimics general market sentiment.

According to information theory, credit rating changes of an entity pass valuable information about its financial health and future prospects. In fact, the upgrading or downgrading of a firm by a credit rating agency passes on new information that is likely to change the perceptions and behaviors of investors regarding an entity, with implications for stock prices and trading volumes. Several studies have examined the informational content of credit ratings. For instance, Holthausen and Leftwich (1986) found that bond rating downgrades elicited significantly adverse abnormal stock returns, suggesting that downgrades announce negative information about a firm's future cash flow prospects. On the other hand, Kliger and Sarig (2000) proved that rating upgrades released positive information, although its effect in absolute value was not as large as that produced by downgrades. Particularly pertinent here is the efficient market hypothesis. According to this hypothesis, if really markets happen to be effectively efficient, then all kinds of information available would have already been factored into the stock prices, including that one which is implied by various credit ratings. Therefore, changes in ratings would not exert a substantial effect on prices. But suppose the markets were less than truly efficient. In that case, these rating changes could indeed provide information not yet factored into stock prices that lead to substantial market reactions. Here, one of the critical roles that information asymmetry plays is in the area of credit rating agencies that help to reduce asymmetries in information. Assessment of the credit risk is done through a standardized process and helps to provide informed investment decisions. Especially on the cases of financial markets, where access to reliable information might be uneven, this is important. When credit rating agencies announce changes, their action will either confirm the market's pre-existing expectation or do something that was unexpected and so affect stock prices and trading volumes.

Behavioral finance studies how psychological factors and biases impact financial markets and investment decisions. While the traditional approach to finance considers investors to be perfectly rational beings and therefore assumes perfectly working markets, the behavioral approach has it that investors act quite irrationally under the influence of cognitive biases and emotional responses. Credit rating changes can lead to multiple investor behavioral biases. For instance, a downgrade that leads to an overreaction occurs because investors sell off their stocks excessively out of fear and loss aversion. Upgrades may also not elicit much positive reaction if the investor is anchored to previous negativity toward a company. These biases could therefore go a long way in explaining why market reaction to rating change is usually quite unpredictable.
For example, herding behavior may result in amplification of the market reaction to downgrades: higher price drops than those warranted by fundamentals would really occur.

According to signaling theory, companies communicate information to the market through their own actions. Changes in the credit rating can be perceived as signaling information about the state at which a firm's finances exist and what its future holds.
A drastic decline in the rating could be interpreted as an indication of possible financial difficulties or an unfavorable future business environment, which elicits share selling by investors. Whereas an upgrade is probably going to indicate increased financial stability and growth opportunities. The market response would therefore be a function of the credibility of the signal and whether it jibes with other information then being transmitted. The credibility of the rating agencies and consistency of their assessments with other market indicators are what really allow one to get a reading on market reactions. For example, if a downgrade by a reputable agency is pari passu with some other negative financial indicators in the marketplace, then the market reaction will be more extensive or determined.

Therefore, the theory focuses on the processes of mechanisms through which securities get traded, including the behaviors of market participants, trading protocols, and the formation of prices.

The theory of differential information and trading mechanisms explains how markets respond to changes in credit ratings. For instance, that could be more visible in markets with higher degrees of information asymmetry: some traders know better information than others. It also points at the role of market makers and liquidity providers in absorbing the impact of large trades resulting from rating changes. Much remains to be understood about the dynamics within which markets fully reflect new information quickly and efficiently. For instance, how soon or how fast does the change in ratings elicit reactions? In high-frequency trading markets, this is instant; it will, of course, take some time in markets that are not so liquid. Relevance of the Thesis It is thus with the backdrop of not only signaling, market microstructure theories, and behavioral finance but also theories of liquidity and information. Through the trading volumes, we can learn how the changes in the liquidity condition are influenced by the changes in the credit ratings. In fact, around downgrades, enhanced trading volumes suggest increased activity in the markets, and perhaps a few hiccups in terms of liquidity. There is thus a close relationship between liquidity and the speed and accuracy with which information is impounded into asset prices.

An examination of both returns and trading volumes is a way by which stock market efficiency can be determined in responding to new information from credit rating changes. The behavioral finance theory can be used to explain why, in trying to coherently explain anomalies in stock price movements and trading volumes that cannot be explained by the theories of traditional finance alone, investors both overreact and underreact to credit rating changes. The theory of signaling supports an assessment of how papers in credit ratings provide information to the market about the consequent effect on stock prices and trading volumes. Moreover, market microstructure theory deepens the research inquiry into how the mechanics of trading and information asymmetry trigger the reaction of the market to changes in the credit rating; it also singles out factors that have an impact on liquidity and trading behavior around the announcement of rating changes. This thesis will contribute to the debate on efficiency and information values of credit ratings to the stock market and its participants. On the other hand, it will embed theoretical research in terms of information and liquidity effects, behavioral finance, signaling, and market microstructure theories, with straight implications into better regulations and investment strategies.

Chapter 2: Data Collection and Analysis

This section outlines the criteria and the method involved in choosing samples. The sample consists of firms with publicly traded equity that have undergone alterations in credit ratings. The analysis is done mainly based on data from two extensive financial databases: the Mergent Fixed Income Securities Database (FISD) and the Center for Research in Security Prices (CRSP).

2.1 FISD: Credit Rating Changes

The FISD provides an extensive database related to changes in credit ratings. The database includes date and rating histories from all major agencies, such as Moody, Standard and Poor, Fitch, Duff & Phelps, and others. Therefore, this paper examines rating announcements of upgrade and downgrade of the U.S. firm ratings between January 2010 and December 2023. The reasoning behind taking this period forward is to analyze market behavior in a post-financial crisis. The granularity of the database allows for a detailed insight into each rating change's timing and nature. The FISD was queried to extract the data about all upgrade and downgrade listed events over the period considered in the study. For an econometric event window defined as a firm-rating change pair, events are combined using an event date. Then they are further screened to ensure that only trading days are selected. In the interest of ensuring the integrity of the analysis, one rating change is at least 30 trading days apart from another one. This way, the effects of one rating change can be isolated from the second.

A second requirement of the study was that there existed non-zero TRACE bond volume throughout a ±30 day window around each event. This is probably a strict requirement, but it is what gives the final sample of 3,255 upgrades and 3,186 downgrades a really high degree of confidence.

There are 3,255 upgrade events and 3,186 downgrade events in the dataset so that the database has a wide scope of how credit rating changes of a firm are related to public companies. For the upgrade events, 20% is accounted for by upgrades involving more than one agency, so that there is strong information consensus on a company's improvement by rating agencies. These are likely to be based on relevant factors about the widely known company financial health improvement. A different note is that of 18%, rate various issues by the same company in more than one bond. This indicates that whenever a company is upgraded, the resulting effect would typically be broad-based for all its debt instruments. The 24% mean that change is more than one notch, so there are many significant upgrades that have proved to be compelling in financial markets since more massive upgrades can as well affect the investor perceptions and trading behavior. More so, upgrade events account for 11 percent of the whole from the junk status, indicating commendable times when the trimming affects the borrowing costs and attractiveness of investing.

On the other side of the downgrade, the data shows that: 21% of the downgrade events are made by more than a rating indicates a strong consensus by the rating agencies in the diminution of the firm's credit quality. The data further identifies that 17% of the downgrades affect the issues of more than one bond, which again points out that rating downgrades also have a broad impact on a company's debt profile. Even more importantly, 31% of all downgrades are multi-notch ones, and that is regarded as a sure sign of a significant weakening of the credit standing of the companies. Thus, these are the strong signals of severe concerns about the companies' financial health, so such sizable moves to the downside can be expected to evoke a significant market response. In addition, 11% of them move the company's rating to junk status, so critical transitions are made which have severe implications for the company's access to capital and, in general, its market perception. This systematic approach to the event of change in rating is going to lay the foundation on which to appreciate the development regarding stock prices and trading volumes in the next sections.

Summary statistics for rating changes

In Table 1, it is reported the summary characteristics regarding the rating change events, studying more specifically, those events that are reported by multiple rating agencies, happen on multiple bonds, involve more than one notch, and regard an upgrade from or a downgrade to a junk status. In Figure 1, I show the frequency of these events.

The highest counts are observed in 2010, with a steady decrease in subsequent years. In the initial years (2010-2012), the upgrades consistently outnumber the downgrades. From 2013 onwards, the difference between the two categories narrows, with occasional years where the red category (downgrades) surpasses the blue (upgrades). In recent years, there is a significant drop in the counts for both categories post-2019, especially in 2020 and 2021. The year 2022 shows the lowest counts for both categories, indicating a sharp decline.

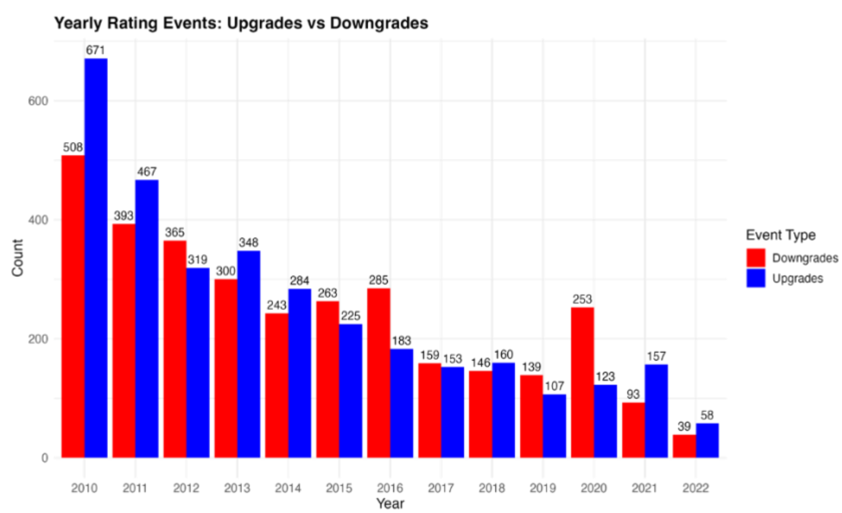
Table 1: Characteristics of Upgrade and Downgrade Events

This table provides a summary of the characteristics of credit rating upgrade and downgrade events. For each category, the table lists the number and percentage of events involving multiple agencies, multiple bonds, changes of more than one notch, and movements from or to junk status. Data are retrieved from FISD Mergent.

	Upgrades		Downgrades	
	N	%	N	%
Upgrades by multiple agencies	657	20%	662	21%
Upgrades of multiple bonds	583	18%	525	17%
Upgrades more than one notch	795	24%	991	31%
Upgrades from junk	366	11%	353	11%
Total	2401		2531	

Figure 1. Rating Events Per Year

Figure 1 reports the number of upgrades and downgrades per year, the red bars represent the downgrades, while the blue bars represent the upgrades. The bar plot shows decline through the years, for both upgrades and downgrades.



2.2 CRSP: Stock Data

The CRSP provides a detailed set of stock data to include daily trading volumes and stock prices for companies under rating change. Around the world, people recognize CRSP's historical stock market data for its accuracy and integrity. It is an indispensable database for conducting research on the effects of a credit rating change on the stock market. The sample period begins January 2010 and ends December 2023, aligning with the rating change data from the Mergent Fixed Income Securities Database (FISD).

The analysis will be around the time window preset for each event of a rating change: the event window [-10, +10] days around the event day. This covers 21 trading days over the period. Such a window covers the most crucial event: that is, the immediate reaction of the market to any announcement of a rating change. From this event window, changes in stock prices, trading volumes, and other activities in the market can clue in analysts about investor sentiments on how the event really affected the value of the firm.

For that purpose, two benchmark periods are established to provide a perspective on the market's behavior and correctly gauge the effect of the event: [-30, -11] days before the event and [+11, +30] days after the event. Accordingly, the surrounding event day volatility would be stripped, and a benchmark, or "normal," market behavior would be defined. For each of these benchmark periods, information will now be provided on the "normal" market conditions, free from the additional noise created by expectations or post-event sentiment about the rating change. The FISD dataset identifies the corresponding firms and dates from the CRSP stock data; each rating change event will have the corresponding firm's stock data from CRSP on the same date. It matches the event date, key to the correct alignment of relevant events across two data files. The event date makes possible the identification of firms and events by matching each firm's CRSP stock data with the FISD-rated change event of that firm with unique mergers based on firm identifiers and unique events based on announcement dates. Further, the abnormal returns and trading volumes are calculated by taking the difference between the actual returns and volumes during the event window and the expected return and volume derived from the benchmark periods.

According to Table 2, Panel A, the average daily trading volume, which characterizes the amount of trading activity in dollar terms for stocks undergoing the downgrade event, is about $5.62 billion. At the same time, events belonging to the upgrade category have an increased average daily trading volume and reach about $6 billion. The fact that the mean volume increases for upgrades signifies the event that brings other implications. The average dollar trading volume is the mean volume per trading day related to the amount of trading activity. It implies that positive rating changes might be related to an increased trading interest, thus reflecting overall investor activity, which might bring buying pressure after good news. The higher mean daily volume for upgrades, compared with downgrades, suggests that market participants might react more vigorously to positive rating changes, potentially due to the perception of improved creditworthiness and financial health of the companies. In contrast, using the ranks, the median trading volume is only $1.4 billion for downgrades and $1.7 billion for upgrades. The fact that medians are lower than means in both cases means that the distribution is skewed to the right, with a few very high-volume trading days driving up the mean. Such skewness is quite typical for financial markets, where only very large trades or very large trading days cause the average to increase a lot. The percentage of trading days with non-zero volume provides a measure of how frequently the stocks are traded. In the case of downgrade events, the percentage is 99.74%; for upgrade events, it is 99.72%.

Table 2. Univariate Statistics

Panel A reports mean and median daily volume and the percentage of days with trading (non-zero volume) during the benchmark period CRSP (overall stock trading). Panel B reports abnormal stock returns around upgrades and downgrades. Cumulative abnormal returns (CARs) are estimated over a two-day trading window [0,1] using a market model relative to the CRSP value-weighted index, estimated during the benchmark period days [-30, -11] and [+11, +30].

Panel A: Trading activity	Mean	Median	
	Volume ($billions)	Volume ($billions)	% Trading Days
Upgrades	5,6	1,4	99.72%
Downgrades	6,0	1,71	99.74%
Panel B. Abnormal Returns			
	CAR [0; +1] %	CAR [0; +1] %	T-stat
Upgrades	0.32	0.48	0.65
Downgrades	-0.33	-1.34	- 6.02 *

These high percentages indicate that the stocks experiencing the rating changes are almost always actively traded. In other words, almost all trading days during the benchmark periods have shown some level of trading activity.

2.3 Abnormal Stock Returns

Most prior studies examining the market reaction to rating changes focus on abnormal stock or bond returns or changes in CDS spreads. To compare the study with prior research, it is reported abnormal stock returns around rating changes. Cumulative abnormal returns (CARs) are estimated over a two-day trading window [0,1] using a market model relative to the CRSP value-weighted index, with the benchmark period defined as [-30, -11] and [+11, +30].

The thesis analysis focuses exclusively on stock returns. Consistent with prior research, we find significantly negative stock CARs around downgrades for the two-day event window, but no significant CARs around upgrades. This result suggests that the market reacts more strongly to negative news, such as downgrades, compared to positive news, such as upgrades (Bessembinder et al., 2009; May 2010).

The calculation of abnormal returns involves estimating the expected returns using a market model. This model regresses the firm's stock returns against market returns during the benchmark periods. The difference between the actual returns during the event window and the expected returns constitutes the abnormal return. These abnormal returns indicate how much of the stock's performance can be attributed to the rating change announcement, isolated from overall market movements.

The results in Table 2, Panel B reveal a mean CAR around downgrades at -0.33%, a median CAR of -1.34% and a t-statistic of -6.02, being the result in which a fair degree of significance in statistical tests is achieved. No doubt about it: if a downgrade is announced, the market reacts in a drastic reduction of the stock price. Around upgrades, the mean CAR is 0.32% and the median is 0.48%, while the t-statistic is a mere 0.65, the result showing that the reaction to upgrade announcements is positive but not statistically significant. The importance of this significant negative CAR around downgrades corresponds to the intuition that negative news affect investor sentiment more heavily and, therefore, the stock market reaction is much more pronounced. The highly negative reaction implied in the very significant t-statistic underlines the point that downgrades result in extremely negative stock returns. The lack of significant CARs around upgrades might reflect some skepticism of the market or that the market faces any positive news with moderation, perhaps accelerated by the opinion that the market had already anticipated these upgrades or that they were perceived as rather non-eventful.

In conclusion, the analysis confirms the results present in the literature: there is a significant abnormal return around the announcements of downgrades but not for upgrades. The results reveal that the market shows asymmetric behavior in reaction to changes in credit ratings: downgrades reflect the stronger market reaction compared to upgrades. That reaction is asymmetric, and one of the most important results emerging from the research is the importance of understanding investor behavior and market dynamics in response to credit rating changes. Since the analysis of abnormal returns indeed only confirms the results of other earlier studies, we therefore change gears and delve into the abnormal trading volumes. An analysis on the abnormal volumes can help one draw some inference on the market behavior since changes in trading activity often reflect price changes and resemble the overall investor reaction to ratings changes. The abnormal volumes can help one to grasp the extremity and character of the trading activity around some rating change announcements, giving out some valuable information of the reaction in the market beyond the price movement.

Chapter 3: Abnormal Stock Volume and Rating Changes

In line with existing research, the results in the previous section show that there are no abnormal returns associated with upgrades. This suggests that upgrades do not provide significant information. Previous studies (e.g., Beaver, 1968; Bamber et al., 2011) suggest using volume tests in addition to examining abnormal returns. However, trading volume often has a highly non-normal distribution. In this section, a new nonparametric test statistic is derived and compared to previous nonparametric tests used in the literature to demonstrate that it has higher power. This statistic then analyzes abnormal volume around the rating change events. Once the abnormal stock volume is estimated, the next step is to use a multivariate regression setting to estimate the relationship between abnormal stock volume and its potential determinants.

3.1 Nonparametric Test for Abnormal Volume

Stock trading volume can be highly skewed, therefore, to analyze abnormal volume, is important to adopt nonparametric methods. In this thesis is adopted a nonparametric test, developed and used in previous studies (Jonathan Brogaard, Jennifer L. Koski, Andrew F. Siegel; 2019), with improved power given the highly non-normal distributions typical of volume data. While much has been written on the properties of the t-test with non-normal data (Benjamini, 1983), one conclusion is that the non-normal distribution causes traditional t-statistics to have low power. As a single data point becomes unboundedly large, the t-statistic tends to 1 because this outlier inflates both the numerator and denominator. Thus, the t-test will tend not to reject the null hypothesis at conventional test levels in the presence of extreme skewness. Therefore, a nonparametric alternative is preferred.

The intuition behind the nonparametric initial phase is that under the null hypothesis of zero average abnormal event-window volume, any event-window day may be exchanged with any given benchmark day without materially affecting the overall distribution of the observed volume data. This is called the exchangeability property. Given the volumes for a particular event-window day and for the benchmark days for particular ratings change event, it would have been equally likely to observe, instead, any data configuration where the event-window day volume is switched with any particular benchmark day. If there is nothing special about an event-window day of a rating change event, then the rank of its actual abnormal volume should be uniformly distributed within the abnormal volumes of the associated benchmark days. This process is done separately for each day in the event window, beginning by specifying day t_0 in the event window [-10, +10]. For rating change event *i*, let $V_{i,t}$ denote volume on day *t*, where day 0 represents the day of the credit rating change announcement. As discussed above, days [-30, -11] and days [+11, +30] define the benchmark period, and days [-10, +10] represent the event window. The abnormal volume $A_{i,t0}$ for event *i* on event window day t_0 is the excess of this event window day's volume above the average volume for the benchmark period:

$$A_{i,t0} = V_{i,t0} - AverageBenchmarkVolume = V_{i,t0} - V_{i,,benchmark} \qquad (1)$$

We denote the average benchmark volume $V_{i,,benchmark}$ as follows:

$$V_{i,benchmark} = \sum_{t=-30}^{-11} V_{i,t} + \sum_{t=11}^{30} V_{i,t} \quad (2)$$

Abnormal volume $A_{i,t}$ is also defined for each benchmark day t by exchanging the volume on day t with the volume on day t_0, so that "other than day t" refers to the event-window day t_0, together with all benchmark days except day t:

$$A_{i,t} = V_{i,t} - \frac{1}{40}\left(V_{i,t0} + \sum_{s=-30}^{-11} V_{i,s} + \sum_{s=11}^{30} V_{i,s} - V_{i,t}\right) \quad (3)$$

The normalized rank score is the percentage of the benchmark abnormal volumes $A_{i,-30}$, $A_{i,-29}$, ..., $A_{i,30}$ that are smaller than the actual event-window day's abnormal volume, $A_{i,t0}$. Splitting ties, the normalized rank score $R_{i,t0}$ for event i on event-window day t_0 is defined as:

$$R_{i,t0} \equiv \frac{1}{40}\left[\#(A_{i,benchmark} < A_{i,event-window\ day}) + \frac{1}{2}\#\,(A_{i,benchmark} = A_{i,event-window\ day})\right] = \frac{1}{40}\left(\sum_{t=-30}^{-11}\left[I(A_{i,t} < A_{i,t0}) + \frac{1}{2}I(A_{i,t} = A_{i,t0})\right]\right) \quad (4)$$

where I denotes the indicator function.

3.2 Other nonparametric event study test statistics

The thesis, as already stated, uses a non-parametric test to detect abnormal volume, a test developed by Jonathan Brogaard, Jennifer L. Koski, and Andrew F. Siegel (2019) in their study. This advanced test offers higher power and sensitivity, making it well-suited for analyzing trading activity around credit rating changes and capturing the intensity of market reactions. Researchers derive nonparametric test statistics to detect abnormal returns in event studies (e.g., Brown and Warner, 1980, 1985; Corrado, 1989; Corrado and Zivney, 1992; Campbell and Wasley, 1993). Several adapt these statistics to test for abnormal volume (Sivakumar and Waymire, 1993; Campbell and Wasley, 1996; Landsman and Maydew, 2002; Ryan and Taffler, 2004; Bailey et al., 2006; Garfinkel and Sokobin, 2006). Many of the statistical tests represent variations of Corrado's (1989) test statistic. The statistic used in this thesis is taken from the study by Jonathan Brogaard, Jennifer L. Koski, and Andrew F. Siegel (2019) and has some similarities with Corrado's; both test statistics are valid, but the one selected for this thesis has a main testing innovation, which is higher power.

Under the null hypothesis of no abnormal volume, both statistics use unbiased (but distinct) variance estimates in their denominators. The numerator of the used t-statistic is identical to that of Corrado (1989), except for a constant scaling, whose effects are canceled by the denominators of the statistics. Any difference in the two test statistics therefore arises from the standard errors in the denominators.

The main reason for the higher power of the nonparametric test used in this thesis is twofold: the denominator of the used t-statistic has less variability due to its greater degrees of freedom, and it makes use of lower variability under the alternative hypothesis while remaining valid under the null hypothesis. This is because the reference variability comes from the event-day reactions (and this variability is likely to be smaller when the event effect is greater, leading to a larger t-statistic and greater power), whereas Corrado's test's reference variability comes from non-event days (which do not respond to the effect of the event). In addition to the differences in the standard errors, the nonparametric test utilized in this thesis has been optimized for higher sensitivity to detect abnormal volumes. This is achieved by focusing on the event-day variability, which tends to be more pronounced in the presence of significant market reactions. This methodological refinement ensures that the test remains robust under various market conditions and provides more reliable results compared to traditional methods.

3.3 Abnormal Volume Results

From the tables, it can be observed that there is significant abnormal volume, indicated by the t-statistics, on several days within the event window for both upgrades and downgrades. Besides, volume is extremely high in the stock market around days of downgrade announcements. For instance, average daily volume on an announcement day of a downgrade (day 0) amounts to around 7 billion and is highly significantly different compared to days prior to the announcement day, with a t-statistic equal to 7.562. However, returns are not significant around upgrades. For upgrades, average daily volume on an announcement day (day 0) amounts to around 7 billion and is at a t-statistic level of 5.322. This would indicate a very strong market reaction in trading activity. Hence, it can indeed be concluded that, although upgrades do not provoke large changes in the price of securities, trading volume is significantly raised. As the significant abnormal volumes are found for both upgrades and downgrades, this underlines that market participants are actively selling or buying in the event of a rating change. This means there is more general investor interest and involvement.

Table 3. Overall daily volume by event day

Table 3 reports abnormal stock market (CRSP) volume by event day relative to rating change announcement day 0. Panel A provides information about upgrade events, while Panel B covers downgrade events.

Panel A:Upgrades			
Day	N	Average Daily Volume ($millions)	t-statistic
-3	3255	4,4	2.045*
-2	3255	6,9	4.270*
-1	3255	5,3	3.021*
0	3255	7,1	5.322*
1	3255	5,6	3.873*
2	3255	5,8	4.607*
3	3255	4,1	1.428
Panel B: Downgrades			
Day	N	Average Daily Volume ($millions)	t-statistic
-3	3186	4,0	3.683*
-2	3186	4,9	4.020*
-1	3186	6,7	6.491*
0	3186	6,9	7.562*
1	3186	5,8	6.882*
2	3186	6,1	5.798*
3	3186	6,7	6.112*

The analysis has therefore confirmed that downgrades lead to significant negative abnormal returns. However, at the same time, significant abnormal trading volumes are identified around both upgrades and downgrades indicate that trading activity is critically important in addition to price changes. Such results indicate that the market reaction to credit rating changes makes investors' reactions very strong, with a significant increase in trading volume even in cases when the price effects are asymmetric. This further underlines the need to analyze price and volume together in order to understand market dynamics completely in response to credit rating announcements.

3.4 Multivariate regression

Abnormal volume around rating change announcements may reflect trading as investors react to the information in the announcement, or trading because investors respond to some other ratings-based constraint. These explanations are not mutually exclusive. In this section, a multivariate regression setting is used to estimate the relationship between abnormal stock volume and its potential determinants.

To estimate the relationship between abnormal stock volume and its potential determinants, it is employed a multivariate regression model. The model takes the form:

$$Abnormal\ Volume = \alpha + \beta_1 Multiple\ Agencies + \beta_2 Multiple\ Notches + \beta_3 \text{Multiple Bonds} + \beta_4 \text{Ln}(1 + \text{Market Cap}) + \beta_5 Stock\ Volatility + \epsilon \quad (5)$$

The rating variables in the regressions have been discussed in the literature as potentially motivating trading volume around rating changes for information, regulatory, or other reasons. (See Appendix A for more detailed definitions of the explanatory variables.) The anticipation is that (other things equal) rating changes by Multiple Agencies, of Multiple Notches, or for more than one bond by the same issuer (Multiple Bonds) will have greater information content than less material changes. Stock prices will change more in absolute value (CAR) when the information content of the announcement is greater.

Some of the rating variables described above (for example, whether the firm has multiple bonds) may be correlated with firm-specific factors such as firm size. Therefore, we also include firm size [Ln (1 + Market Cap)] and stock return volatility (Stock Volatility) as control variables. We do not have strong priors on the signs of these variables since predictions are mixed. For example, a higher market capitalization could lead to lower abnormal volume as these firms tend to have more analyst coverage (Bhushan, 1989). In this case, the new information generated from a rating agency may be more marginal, so large firms have lower abnormal volume. Alternatively, larger firms are more dependent on debt markets for funding (Rajan and Zingales, 1995) and may be more sensitive to their credit rating, resulting in larger firms having higher abnormal volume.

Table 4. Summary statistics for regression explanatory variables

Table 4 presents a summary of statistics for the explanatory variables in the regressions. See Appendix A for definitions of the variables. Panel A reports statistics for events in the upgrade sample, and Panel B for downgrades.

	Upgrades		Downgrades	
Variable	Mean	Standard Deviation	Min	Max
Multiple Agencies	0.065	0.321	0	1.00
Multiple Notches	0.07	0.29	0	1.00
Multiple Bonds	0.76	0.52	0	1.00
CAR%	0.81	1.98	0	56.30
Ln (1 + Market Cap) ($ billions)	1.76	1.2	0.28	6.50
Stock Volatility	3.27	1.64	0	18.90
Panel B: Downgrades				
Variable	Mean	Standard Deviation	Min	Max
Multiple Agencies	0.08	0.27	0	1.00
Multiple Notches	0.13	0.41	0	1.00
Multiple Bonds	0.72	0.54	0	1.00
CAR%	1.65	3.98	0	97.40
Ln (1 + Market Cap) ($ billions)	1.43	4.26	0.33	35.80
Stock Volatility	5.46	1.23	0.03	5.97

Table 5. Multivariate regression

Table 5 reports the results of regressions of the determinants of abnormal stock (CRSP) volume from equation (5). Determinants include rating variables and control variables. Variable definitions are provided in Appendix A. Four of the rating variables (Multiple Agencies, Multiple Notches, Multiple Bonds, and CAR) serve as information variables. We first report the results of these interaction tests. Then, we report the control variables (Ln (1 + Market Cap), Stock Volatility). We report results for upgrades and for downgrades. The table reports coefficient estimates and p-values for t-tests of whether the coefficients are significantly different from zero.

	Upgrades		Downgrades	
Variable	Estimate	P-value	Estimate	P-value
Multiple Agencies	223.221**	0	65.368**	0.000
Multiple Notches	10.390**	0.541	13.734**	0.326
Multiple Bonds	8.534	0.641	1.934	0.789
CAR%	9.330**	0	7.465**	0.000
Ln (1 + Market Cap) ($ billions)	1.428	0.676	3.953*	0.054
Stock Volatility	-2.781	0.218	-4.180**	0.000
R squared	0.282	-	0.271	-

The coefficients in Table 5 show that Multiple Agencies and CAR are statistically significant, indicating a substantial impact on abnormal stock volume. For upgrades, the estimate for Multiple Agencies equals 223.221, and the p-value equals 0.000 and is therefore highly significant. This finding suggests that the abnormal volume associated with a stock undergoing upgrade is much higher, respectively, when there is upgrading by more than one agency, proving that multi-agency upgrades tend to be more successful for increasing trading. Multiple Notches average is 10.390, with a p-value of 0.541; hence, it is not significant; it can be inferred that abnormal changes in abnormal volume during an upgrade with multiple notches are insignificant. The estimate for Multiple Bonds is 8.534, but its p-value comes out to be 0.641, which means, in general, upgrades involving multiple bonds are not significantly related to abnormal volume.

The estimate for CAR is 9.330, with a p-value of 0.000, suggesting it to be significant and indicating that there is a strong positive association between cumulative abnormal returns and abnormal volume. This implies that an upgrade that gives a significant absolute return on stock will increase the trading volume. The Ln (1 + Market Cap) estimate is 1.428; its p-value was 0.676. This result shows that firm size is not significantly material to abnormal volume days before an upgrade. The Stock Volatility estimate is –2.781, and the p-value is 0.218. As a result, it is not statistically significant, thus also indicating that stock volatility has no considerable influence on abnormal volume during upgrades. The R-squared is 0.282, implying that the model states around 28.2% of the variability in the volumes of abnormal stock.

In the case of downgrades, Multiple Agencies is estimated at 65.368, with a high significance level, considering the p-value is 0.000, hence corrupting abnormal volumes to a greater extent by downgrades and by multiple agencies is that much, further supporting the conclusions for upgrades. The estimate is 13.734; multiple notch downgrades have a p-value of 0.326, which is insignificant, and therefore, numerous notch downgrades do not significantly affect abnormal volume. The estimate for multiple bonds is 1.934, with a p-value of 0.789; it indicates that downgrades concerning various bonds have no significant change in abnormal volume. This means that abnormal volume is more prominently higher in abnormal volumes associated with downgrades because the estimate for CAR is 7.465 with a p-value of 0.000, meaning it is highly significant. This is only marginally significant and suggests that larger firms may experience higher abnormal volume during downgrades. The estimate for Ln (1 + Market Cap) is 3.953, with a p-value of 0.054. The estimate for Stock Volatility is -4.180, and this goes with an enormously significant p-value of 0.000, proving to be enormously significant and negative. From this, we infer that where stock volatility is high, abnormal volume is low during the downgrades. The R-squared of 0.271 indicates that the model for downgrades explains approximately 27.1% of the total variability in abnormal stock volume. In other words, and to sum up, it can be stated that both more Agencies and CAR are strong predictors of the abnormal volume both for upgrades and downgrades. In other words, this signals that more information is included in such changes relevant to multiple agencies and such high cumulative abnormal returns.

The response for the rating variable is not uniform, and some variables, in this case, Multiple Notches and Multiple Bonds, do not yield any substantial results, suggesting that all the rating changes do not impact volume. Firm size (Ln (1 + Market Cap)) and stock volatility also have differential effects. Firm size has a very marginal effect in the case of downgrades and has a significant negative impact for downgrades; the same is the case with stock volatility. The R-squared values show that the models do explain a decent proportion of the variability in abnormal volume; however, it is very likely that other factors are driving trading volume around rating changes. In sum, the results perfectly align with salient rating changes, particularly of the multi-agency or high-absolute-return type, bringing in an enormous amount of trading activity as a response to news information.

Chapter 4: Discussion on Volume vs Return

The effect of rating changes on the stock market is a topic of considerable interest and discussion among finance researchers and practitioners.

While prior research has mostly focused on abnormal returns around rating changes, the examination of abnormal trading volume helps provide a further, but often more fruitful, insight into market reactions. The difference between volume and returns is very important per se because it displays the basics of investor behavior and mechanics of the market. Abnormal returns are usually considered the immediate reaction of the market to new information, resulting from the new equilibrium level of stock prices. In contrast, abnormal trading volume shows an increased trading activity, which can be very large in relative terms but is not necessarily associated with changes in stock prices. This may take place because investors have heterogeneous beliefs, and even if informed, they react differently. Moreover, some investors may be of the belief that a trade should be executed based on the release of a rating, while others may be totally indifferent. These results are presented in Panel 7. For most of the samples, we have strong evidence of abnormal trading volume around the time of the rating change, while abnormal returns look to be marginally significant or even weak, as in Panel 6. This result suggests that a significant change in trading activity is triggered by rating changes, even if such changes do not correspond to immediate price adjustments. The increase in trading volume reflects heterogeneity in investor reaction to and belief revision of the change in the credit quality of the firms' securities rather than a unified revaluation of the securities. This implies that the trading volume and return series warrant a joint examination to fully understand the market's reaction to the rating transition.

4.1 Abnormal volume without abnormal returns?

Observing the abnormal trading volume without corresponding abnormal returns around such events as rating changes can be intriguing. In a completely revealing, rational expectation equilibrium, new information makes prices adjust immediately and trend to equilibrium without further trades. In that ideal world, abnormal returns around announcements should be observed, but no abnormal volume should accumulate. With no lag, prices reflect all the available information, leaving no further source for trading. Markets in real life are, however, populated with investors with different beliefs and interpretations of heterogeneous information. This diversity makes volumes accumulate without translating into price changes.

Several provide insight. Kandel and Pearson (1995) model a world where the same public signal is available, but the agents have different likelihood functions. This differential in the interpretation of the information can create significant volume without changing the price. Kim and Verrecchia (1997) suggest that pre-event period trading should be related to absolute price changes, while event period information-based volume should not be related to price changes. Volume which is abnormal but with no corresponding abnormal return may be due to varied information interpretation and not a common belief. The evidence supports this. Bamber and Cheon (1995) provided documentary evidence of large volume reactions with no accompanying price reaction. They concluded that such volume spikes are likely to occur when announcements lead to differential belief revisions amongst investors. Beaver (1968) argues that while returns are the change in market wide expectations, volume is the change in individual expectations. Thus, the news may not cumulatively change the market's expected return but will change the expectation of the traders' returns. The same information can lead to higher volumes of trading without substantial changes in prices. Some of the news, which does not signal new information that will change the stock's intrinsic value, might require trading because of the existing regulatory provision or need for portfolio rebalancing. For instance, an improved credit rating might not change the perceived risk or value of the firm, but it might mean some repair action by institutional traders to bring their asset allocation in line with investment guidelines.

Conclusion

This thesis analyzed stock market reactions to credit rating changes in terms of abnormal returns and abnormal trading volumes. From the analyses provided, it can be inferred that downgrades cause highly significant negative abnormal returns, while upgrades are found to have a close-to-zero effect on stock prices. The asymmetry indicates the existence of the market's negative information sensitivity to deteriorating creditworthiness and its heightened concerns.

The results highlight substantial abnormal trading volumes observed around upgrades and downgrades, even when price reactions are insignificant. This suggests that credit rating changes trigger different investor reactions and belief adjustments, and hence, an increase in trading activity. Abnormal volumes were quite significant around upgrades, which, contrary to what could be discerned from price changes, would mean that upgrades actually do trigger a lot of activity. This suggests that investors respond actively to rating upgrades, reflecting their interest and engagement with the new information.

The present study, in contrast, analyzes abnormal returns and trading volumes to draw inferences not only regarding efficiency but also regarding investor behavior. Thus, it emphasizes an approach in which several dimensions of market response need to be considered to capture the full implications of credit rating changes. In conclusion, the analysis of credit rating changes reveals significant market activity that goes beyond mere price adjustments.

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Appendix A: Variables Definitions

Rating Variables

Multiple Agencies = an indicator variable equal to one if more than one rating agency changed its rating on the bond on the same day, and zero otherwise.
Multiple Notches = an indicator variable equal to one if the rating changed more than one notch, and zero otherwise.

Multiple Bonds = an indicator variable equal to one if more than one bond for that firm had a rating change on that date, and zero otherwise.

CAR = the stock's absolute percentage return on days [0,1] around the rating change (in percent).

Control Variables

Stock Volatility = firm's daily average high minus low stock price, scaled by the midpoint price and calculated during the benchmark period (percent).

Ln (1 + Market Cap) = firm's daily average market capitalization during the benchmark period, calculated as the number of shares outstanding multiplied by the closing share price ($ billions).

Appendix B: Univariate Statistics

Table B.1. Upgrade and Downgrade Event Selection

Table B.1 reports the sample selection criteria and the number of events surviving each successive screen, for both upgrades and downgrades. The first selection is based on distinct company events. Weekend announcements are excluded, and only publicly traded companies are considered. Additionally, only events occurring with at least 30 days between each other are included.

	Upgrades	Downgrades
Number of distinct companies events	13657	15865
Non-weekend announcement date	13611	15813
Publicly traded company	3673	3634
At least 30 trading days from another rating change	3255	3186

Table B.2 Rating Events by Rating Prior to Rating Change

Table B.2 shows the number of events in each rating category before the announcement of the rating change. The table indicates that higher-rated entities tend to experience more downgrades, while lower-rated entities have more opportunities for upgrades. This distribution reflects the typical movement within rating scales, where entities with higher ratings have limited room for improvement and are more likely to be downgraded, whereas those with lower ratings have more potential for upgrades.

	Rating Events	
Rating	Upgrades	Downgrades
AAA	0	27
AA+	3	9
AA	3	22
AA-	23	57
A+	58	91
A	78	197
A-	123	190
BBB+	207	243
BBB	316	316
BBB-	297	223
BB+	261	186
BB	229	184
BB-	218	184
B+	227	170
B	205	129
B-	233	114
CCC+	117	87
CCC	90	79
CCC-	27	47
CC	35	41
C	17	22
D	38	4
NA	2	0