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The Impact of the Frequency of Credit Ratings Changes on Stock Return Volatility: Evidence from the S&P 500

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Abstract

This study investigates the relationship between the frequency of credit ratings changes and stock return volatility using a dataset of publicly listed U.S. firms with annual credit ratings from the past ten years to construct both cross-sectional and panel datasets across different time windows. The main empirical approach of this thesis is fixed effects panel regression with clustered estimator, and results consistently show a positive and statistically significant association between the frequency of credit ratings changes and stock return volatility. Through using categorical variables, directional subsamples to validate the findings, we find the key driver in credit ratings changes' impact on volatility is rating downgrades. This study contributes to the literature by highlighting the long-term implications of credit ratings activity and points to future research opportunities in the area of information persistence.

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1 Introduction

This thesis investigates the relationship between the frequency of credit rating changes and the stock return volatility, focusing on members of the S&P 500 index. While the role of credit rating has been broadly discussed, earlier studies generally paid attention to the effects of individual rating events. Based on this background, this thesis shifts focus toward the cumulative impact of frequent rating changes on firms' stock volatility i.e. the longer-term effect of credit rating. For this topic, we employ a panel data regression as our main methodology, using fixed effects to control for unobservable heterogeneity.

The empirical analysis is based on a comprehensive dataset covering 234 S&P 500 companies over a 10-year period from 2015 to 2024. Credit rating data is collected mixedly from different credit rating agencies, mainly from Standard & Poor's and Fitch. Stock return volatility is measured as the standard deviation of daily stock returns.

The remaining parts of this thesis are organized as follows. Chapter 2 first reviews the literature background regarding credit rating. During this chapter, a small discussion about the research gap – the frequency of credit rating changes is presented. Main hypotheses of this study are also introduced at the end of this chapter. Chapter 3 introduces the methodology, including panel data model specification, applied variables and econometric techniques employed for this thesis. Thereafter, chapter 4 describes the data source and how it was processed. Then the empirical results of the study are demonstrated in chapter 5, and separately discussed considering the previous literature and the research questions of this study in chapter 6. Conclusions for the study are presented in chapter 7, followed by some research limitations and potential future study directions in chapter 8 and chapter 9 respectively.

2 Literature Review

In this section, a brief introduction of credit rating history and its role in the economy would be presented. Furthermore, empirical evidence about the impact of credit rating changes on financial markets would be discussed throughout the review of earlier related research, followed by the hypotheses for this research topic.

2.1 The History of Credit Rating Agencies

From the first public bond rating was published by Moody's, the Credit Rating Agencies (CRAs) have undergone a series of evolution and transformations. Over the decades, their role has expanded from simple credit assessment to becoming an essential part of the global financial markets. Today, almost all public companies can obtain more than one credit rating and are usually monitored continuously through credit watch procedures. In 2023, ten nationally recognized statistical rating organizations (NRSROs) issued a total of 2,113,208 ratings, with Fitch, Moody's, and Standard & Poor (S&P) categorized as "large NRSROs" based on revenue accounting for 98.96% of the total (U.S. Securities and Exchange Commission, 2025, p. 3).

During the evolution of CRAs in the U.S., there was a crucial factor - the regulatory support. Since the 1930s, the insurance regulators of the 50 states successively enacted decrees to introduce the minimum capital requirements connected with the ratings of the bonds invested in by those insurance companies, followed by federal pension regulators eventually. In 1975, the Securities and Exchange Commission established the legal status of CRAs under the situation where credit rating was seen as the indicators of risk owned by those broker-dealers who needed to satisfy the minimum capital requirements from SEC. At this time, SEC published a new category - "nationally recognized statistical rating organizations" (NRSROs) - to deal with the vagueness of the "recognized rating manuals" and the differences of rating systems used by different CRAs (White, 2010).

Owing to the crisis of public confidence caused by the lagging downgrades in Enron and WorldCom debt in the early 2000s and the barriers to NRSROs entry regulated by the SEC, Congress passed the Credit Rating Agency Reform Act in 2006. It included Congress's finding that additional NRSROs competition is in the public interest and implied that the registration system, favoring no particular business model, was intended to enhance competition and provide investors with more choices, higher quality rating, and lower costs (Kane, 2020). After that, other CRAs had the opportunity to enter the credit rating market. An important turning point regarding the influence of CRAs appeared in 2008, when the Subprime Debacle significantly exacerbated the public's crisis of confidence in CRAs, as their massive failures in assessing the risks of "structured investment vehicles". To mitigate this phenomenon and solve the relevant problems arising from the Financial Crisis, Congress passed the Dodd-Frank Act in 2010 including strengthening the regulation, reducing the over-reliance on CRAs, and mandating the Office of Credit Ratings to conduct annual examinations. Both Acts authorized and directed the SEC to implement the rules concerning CRAs. Initially, CRAs reflected legal reliance rather than genuine market demand (Partnoy, 2006). However, in the following decade, the demand for accurate, reliable, and widely disseminated credit ratings has remained a constant feature of debt markets in the U.S.

Another change that cannot be ignored with regard to CRAs is the business model. In the early 1970s, the business model changed from investor-paying to issuer-paying, which means the entity issuing the bonds needs to pay the rating agencies to rate its bonds instead of investors paying for access to rating information. There are four main reasons for this change summarized by White (2010). Firstly, the development of photocopy machines squeezed the market share of rating manuals, which were previously the primary method of disseminating ratings. Secondly, the bankruptcy of one big business expanded the requirement of ratings, as other debt issuers needed to demonstrate they are reliable and low risk to obtain funding. In the meanwhile, they needed to satisfy minimum rating grade requirements for bonds to be invested by financial institutions because most of them were required to only invest "investment grade" bonds. Finally, most information industries are considered a "two-sided market", which means payments can come from one or both sides of the market (Rysman, 2009). Therefore, the shift from investor-paying to issuer-paying was a natural outcome driven by multiple factors.

The new issuer-paying business model inevitably introduced potential conflict of interest because most debt issuers had incentives to be rated higher even at a greater cost. However, after the market had undergone several major incidents that implied there existed a lot of problems in CRAs, the regulators have made more and more stringent rules to enforce effective internal control structures, good governance, transparency and robust disclosure to enhance rating quality (Kane, 2020).

Additionally, substantial empirical research supports that CRAs will prioritize their long-term reputation over short-term profit. Covitz and Harrison (2003) measured how quickly bond-yield spreads moved in advance of rating changes using cross-sectional data and found that the timing of downgrades reflected reputation-protecting behavior not following issuer's interest. More recently, Xu and Liu (2021) confirmed this reputation-driven view by employing a difference-in-difference (DiD) design that shows reputation shocks significantly affect bond yield spreads.

Today, CRAs are traditionally viewed as gatekeepers in financial markets, responsible for reducing information asymmetry and certifying the creditworthiness of issuers. Most investors will make their investment decision with reference to credit rating even if there may exist potential problems.

2.2 The Economic Role of Credit Rating

In the viewpoint of many financial researchers, credit rating has always played a significant role, especially in the context of the dynamic economic development contemporarily. Following the existing research about the functions of credit rating in the economy, we would like to point out some of the most important functions of CRAs: information role, coordination mechanism, the impact on capital structure, and market signal.

Following the argument of Boot, Milbourn and Schmeits (2006), since investors do not always readily observe the investment decisions of the firm nor their effort in economic recovery, the presence of CRAs could act as an "information equalizer" for investors to make an informed decision. In markets where comprehensive financial data is not always approachable or where firms are difficult to observe economically, rating acts as a representative for credit risk. Investors, because of the presence of CRAs, can get access to the information which is not fully revealed publicly, especially for small and less transparent firms.

Boot, Milbourn and Schmeits (2006) also highlighted the interaction between CRAs and firms by pointing out that credit rating not only provides a common risk signal to all the market participants but also helps to create a self-controlling system that keeps the rating process reliable and shapes the behaviour of firms, investors and regulators. Hence, the credit rating process can serve as a coordination mechanism enforcing discipline and reducing information asymmetry. Additionally, credit rating can be easily seen in numerous regulatory frameworks and contractual agreements. For example, in the context of banking, ratings are used as a method to classify the risk weight of assets according to the Basel II and III frameworks.

With regard to the influence of credit rating on a firm's cost of debt, Kisgen (2006) pointed out firms' behaviours where they adjust the capital structure to prevent rating downgrades. Since some institutional investors and financial regulations require a minimum rating level for their potential instruments, a downgrade below investment-rating can easily lead to the reduction in the investor's demand. Additionally, there is a fact that high-rated firms often take advantage of lower interest rates – lower default risk and vice versa.

Credit rating, especially the rating changes, can also function as market signals. There are many empirical studies concluding that investors do respond to the change in a firm's risk profile by proving that rating changes, particularly rating downgrades, are deeply related with the changes of the market. We will discuss more about the related research of credit rating changes in the next part.

2.3 The Impact of Credit Ratings Changes on Financial Market

Because of the significant existence of credit rating, its changes could exert a considerable impact on a firm in many different levels both directly and indirectly, such as capital structure or financial policy (Kisgen, 2006). However, since the impact of credit ratings changes on stock prices is especially well-researched and empirically observable, we would focus more on this aspect.

One of the earliest studies about credit ratings changes is the research of Pinches and Singleton (1978), which took into account the performance of 207 firms from 1959 to 1972 and found that for the market predicted ratings changes, abnormal returns were often observed prior to the announcement, but no significant reaction after the rating event. Similarly, according to the study of Griffin and Sanvicente (1982), by using data from Moody's and between 1960 and 1975, no anticipation was found before the ratings changes event but they noticed a negative stock market reaction in the context of downgrades, which marked a breakthrough in the history of credit ratings research.

Following the result of Griffin and Sanvicente's study, Holthausen and Leftwich (1986) not only provided a stronger evidence of negative shock by examining over 1,000 ratings changes and about 260 additions to the S&P credit watch list from 1977 to 1982, but also contributed to the literature with a new finding stating that no significant abnormal performance was found when it comes to upgrades. These findings in market reaction were then extended by Glascock et al. (1987), who found significantly negative abnormal stock returns both before and around downgrades, with some reversal after the event.

Hand, Holthausen, and Leftwich (1992) extended the conversation by including and analysing both stock and bond markets, using a large sample of 1,100 events. This research confirmed that while downgrades and unexpected additions to credit watch lists resulted in significant negative abnormal returns, upgrades faced a totally opposite situation. Specifically searching for the explanations behind the relationship between downgrades and negative stock returns, Goh and Ederington (1993) concluded deteriorating earnings as one main factor.

Studies in the 1990s and early 2000s confirmed and expanded on these findings. Followill and Martell's research in 1997 reported that although the market reaction to the announcement day of ratings changes was muted, there were still negative stock returns around downgrade reviews. To highlight this extreme phenomenon, Hite and Warga (1997) also emphasized the time period for the occurrence of significantly negative abnormal returns i.e. 6 months before downgrades. Vassalou and Xing (2003), by applying event studies for nearly 5,000 announcements over three decades, underscored the meaning of altering returns by size, book-to-market ratio, and default risk. They also reinforced the earlier finding that the reduction in stock prices typically resulted from downgrades, especially in the context of increasing default probability.

2.4 The Remaining Research Gap

Understanding the earlier studies about credit ratings changes and its impact on multiple firm levels, there remains a notable research gap in the literature. While most of the existing research has generally focused on ratings changes – single announcement effect and how short-term stock prices respond to this event, the longer-term implications of credit ratings have received particularly less attention. Thus, the broader effect of rating activity on a firm's profile might be overlooked due to this single-event method. Therefore, instead of analysing the one-time movement of stock prices due to individual credit rating announcements, we would like to shift our focus to the longer-term aspect of credit ratings – the stock volatility over time under the impact of ratings changes frequency.

In the financial market, new information is considered as one of drivers of stock return volatility. Following the Efficient Market Hypothesis (Fama, 1970), stock prices reflect all available information, which suggests that unexpected news leads to price movements. Additionally, as French, Schwert, and Stambaugh (1987) concluded, unexpected news of both firm and macro-level contributed greatly to the daily stock volatility of a firm, implying that volatility can serve as a signal of market response to information – credit ratings changes in this context. When discussing stock volatility, Campbell et al. (2001) argued in their study that there exists a close relationship between stock volatility and firms fundamentals, such as financial leverage or earnings variability. Thus, if such ratings changes happen repeatedly over time, they may intensify the financial inconsistency of the firm. Whereas individual credit ratings changes affect stock returns in the short run, the frequency of these changes may impose a cumulative impact on stock return volatility over the longer term.

Understanding this relationship, our thesis primarily focuses on the frequency of credit ratings changes and how it affects the stock volatility over time, which might offer a broader understanding of credit ratings implication in a longer-term.

Based on these findings, the hypotheses for this study are stated as follows:

H1: Firms that experience a higher frequency of credit ratings changes exhibit greater stock return volatility.

H2: The relationship between the frequency of credit ratings change and stock return volatility is stronger for firms with more frequent downgrades than upgrades.

3 Methodology

3.1 Panel Data: Model Specification

This study employs a fixed effects panel data regression model to investigate the relationship between stock return volatility and frequency of credit ratings changes among members of the S&P 500 index.

One of the biggest advantages of this method is that it exploits the complementary information dimensions, which are both variation among firms and variation within firms over time. Baltagi (2005) and Wooldridge (2010) pointed out that by using lags, panel estimators allow researchers to capture time-based characteristics such as persistence or mean reversion that pure time-series, or common one-year cross-section usually misses out. Additionally, another finance literature proved that all unobserved and time-invariant firm characteristics can be controlled and proxied by using random or fixed effects (Petersen, 2009). Altogether, these features make panel regression the most appropriate and powerful approach for those researching questions, where both firm-level characteristics and cross-firm differentiations are significant.

The main driver of applying panel data regression in this study is that it aligns well with our focus on the long-term impact of credit ratings changes – a research aspect that has been overlooked in the literature. We find that earlier studies generally focused on short-term effects of individual rating events, which often employ event study or difference-in-difference method. In contrast, our target is to capture the effects of the frequency of credit ratings changes on stock return volatility over extended periods, which can be achieved through using panel data analysis.

Since our dataset covers 234 firms with only annual credit rating for each, our sample is relatively small for applying cross-sectional analysis. Therefore, we adopted a rolling window approach with different time lengths (from 3 years to 10 years) for each regression, which then gave us 8 distinct panel datasets. This helps enlarge our data sample, and improve our model statistically. Nevertheless, applying rolling windows can lead to the problem of potential autocorrelation, as consecutive observations for the same entity may share overlapping time periods. To solve this problem, clustered standard errors were used for all panel data regressions.

It is also worth noting that employing a 10-year rolling window would include the whole time range of data in the regression. This accordingly turns the analysis into cross-sectional regression with 1 observation for each firm within the 10-year period, which is not ideal and reliable due to our small sample. Hence, analysis focuses mainly on the regressions that preserve the whole features of panel data, rather than cross-sectional one.

To formulate the panel regression model, a two-step model selection process was constructed. For each rolling window, the Hausman test was first applied to determine if it is reasonable to use random effects or fixed effects. The test results support the application of fixed effects since random effects are proved to be inconsistent. The one-way effects and two-way effects were then respectively employed for each rolling window. We compared the performance of both models using the Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), and Likelihood Ratio (LR) test. The results among all 3 criteria strictly support the presence of time fixed effects compared to the one-way effects for all rolling windows, indicating that it improves model fit. The baseline two-way fixed effects model is formulated as follows:

$$Volatility_{it} = \alpha_i + \beta_i RatingFreq_{it} + X'_{it}\beta + \gamma_t + \epsilon_{it} \qquad (1)$$

Where:

$Volatility_{it}$ is the dependent variable representing the stock return volatility of firm *i* at year *t*

$RatingFreq_{it}$ is the main regressor representing the frequency of credit ratings changes for firm *i* in year *t*

X'_{it} is a vector of control variables, including firm-specific factors which are firm size, ROA, dividend per share, leverage, P/E ratio, and sales growth

α_i captures the entity fixed effects

γ_t captures the time fixed effects

ϵ_{it} represents the error term

3.2 Variables

In line with our research objectives, we measured stock return volatility as the dependent variable using daily returns over multiple time windows. The key explanatory variable is the frequency of credit ratings changes within each window. In the selection of potential control variables, Fama and French (1992) found firm size and profitability can capture the financial stability, and Merton (1974) argued leverage ratio could account for default risk amplification. In addition, we included P/E ratio (Baker et al., 2006), dividend per share (Lintner, 1956), and sales growth (Berk et al., 1999) as potential control variables. In our regression, we followed the minimum AIC and BIC values rule to determine the most appropriate control variables in each panel. Table 3.1 summarizes the variables possibly used in the regression models, including definitions, expected theoretical sign, and economic explanation for the expected sign.

Table 3.1: Variables Summary

Variable	Description	Expected sign	Economic explanation
volatility	Standard deviation of daily returns		Proxy for firm-specific return risk; the dependent variable in our analysis
rating_change_frequency	Number of credit-rating changes	+	More frequent changes may reflect greater perceived uncertainty, increasing volatility
marketcap_avr	Average market capitalization (in USD)	−	Larger firms are typically more stable and less volatile
pe_avr	Average price-to-earnings ratio	+	Higher P/E ratios reflect market expectations and uncertainty
lvr_avr	Average leverage ratio	+	Higher leverage increases financial risk and cash-flow pressure
roa_avr	Average return on assets	−	Higher ROA indicates stable profitability and efficient asset utilization
dps_total	Total cash dividends paid per share	−	Firms with stable or high dividends are often mature and less volatile
sales_cagr	Compound annual growth rate (CAGR) of sales	+/−	High sales CAGR can boost volatility if growth is speculative, but stable growth with profitability can reduce it

3.3 Robustness Checks

To reinforce the main analysis result, several robustness checks were conducted. This robustness analysis was intended to test whether the main findings are sensitive to different model designs, alternative definitions of key variables, and subsample analyses. The results of this part will be presented in chapter 5: Empirical Results.

First, adopting panel data analysis as our main methodology means that we have to construct multiple datasets using rolling windows of varying lengths, ranging from 3 to 10 years. However, this approach can also be considered as a robustness check method since it allows us to test whether the relationship between the frequency of credit ratings changes and stock return volatility is consistent across different time ranges.

Second, we test the sensitivity of our findings to the definition of the key independent variable - the frequency of credit ratings changes. Instead of using only the number of ratings changes within each window as the main explanatory variable, we added a binary indicator by classifying firms's ratings changes into 2 categories: high and low. To be specific, "high" was defined as having a "high frequency" of ratings changes if their frequency exceeds the sample median. This alternative model design investigates how changes in the main explanatory variable affect the studied relationship.

Third, to explore potential asymmetries in the effects of credit rating activity, we performed subsample analyses that examine how rating upgrades and downgrades influence the stock return volatility separately. By conducting regressions for each subset, we assessed whether one type of rating change exerts a stronger impact on stock return volatility than the other does. This analysis also provided empirical results for the second hypothesis of this study.

4 Data

The data sample includes credit ratings announced mainly by two major CRAs, which are Standard & Poor's (S&P) and Fitch. Additionally, since this study's main focus is on the S&P 500 index companies, relevant data, such as stock return volatility or data of control variables, are collected from 234 members of the S&P 500.

4.1 Data Source

All data used in this study were collected from Bloomberg Terminal and S&P Capital IQ databases. To calculate the dependent variable, stock return volatility, daily stock price was first collected for each company from Bloomberg. Similarly, to derive the independent variable, the frequency of credit ratings changes, historical data of annual credit rating for each firm was compiled over time. The historical credit ratings data used in this study is the compilation of ratings issued by two major agencies - Standard & Poor's (S&P) and Fitch. Although the source of this historical data is not disclosed by Bloomberg and our dataset for credit ratings should be considered as a blended record of ratings from both agencies, these two agencies provide the same credit ratings scale. Table 4.1 illustrates the credit ratings scale of both S&P and Fitch.

Table 4.1: Credit Ratings Scale

Rating Category	S&P / Fitch Rating	Interpretation
Investment Grade		
Prime	AAA	Extremely strong capacity to meet financial commitments
High Grade	AA+, AA, AA$^-$	Very strong capacity; slight difference from top rating
Upper Medium Grade	A+, A, A$^-$	Strong capacity; more susceptible to adverse conditions
Lower Medium Grade	BBB+, BBB, BBB$^-$	Adequate capacity; vulnerable to economic changes
Speculative Grade		
Non-Investment Grade	BB+, BB, BB$^-$	Faces major uncertainties and ongoing risks
Highly Speculative	B+, B, B$^-$	Vulnerable to adverse conditions; weaker financial position
Substantial Risk	CCC+, CCC, CCC$^-$	Currently vulnerable; dependent on favorable conditions
Extremely Speculative	CC	Highly vulnerable; very low likelihood of repayment
Near Default	C	Extremely vulnerable or near default
In Default	D	In default on financial obligations

In order to investigate the longer-term influence of credit ratings changes, it is essential to take into account other factors that also affect firms' financial performance and risk. Accordingly, we decided to include in our model some control variables that were proved to be significant and widely used in corporate finance and asset pricing research. Most of the data was collected from the same databases with credit ratings and stock price, including leverage ratio, price-to-earnings ratio, sales growth, and dividend per share, except for the return on assets (ROA) provided by Capital IQ. The sample consists of firms that are members of the S&P 500 index, observed over the period 2015 to 2024.

4.2 Data Processing

To make sure that the consistency and completeness is achieved across the dataset, a data cleaning procedure was taken. There were 501 companies in the dataset originally; however, due to the missing data, whether related to credit ratings, daily stock price, or data of control variables, we had to exclude them from the final dataset. Furthermore, firm identifiers were employed to ensure that only matching firms with fully consistent data coverage across all the dataset remained. Throughout the dataset, we tried to get as detailed data as possible. However, when it comes to the quarterly reported data of several control variables, which are return on assets (ROA), dividend per share, leverage ratio, and sales growth respectively, they were not reported at the same timeline across companies. To address this problem, the difference between reporting dates from each firm was adjusted in a fiscal year to align quarterly observations within a unified annual system, which ensures that we can both preserve the same time-series and maintain cross-sectional comparability.

Following these steps, the final dataset includes 234 firms, each observed daily - quarterly - annually based on each variable over a time range of 10 years (2015-2024).

Based on the processed dataset, required variables for the regression were calculated. Annual number of credit ratings changes for each firm was first listed across 234 companies and the stock return volatility was calculated based on daily stock price. We then took the average of all quarterly reported control variables, except for dividend per share. To make sure that the model controls for long-term payout behavior, we chose the cumulative amount of dividend per share for each year instead, while sales growth data was used for computing the compound annual growth rate. These calculated figures are the foundation for constructing panel datasets with different time lengths from 3 years to 10 years.

4.3 Descriptive Statistics

Further detail of the dataset will be described more in this part. First, Table 4.2 represents the descriptive table for the whole dataset in a 10-year phase from 2015 to 2024, encompassing 234 firms.

Table 4.2: Descriptive Table

Variable	N	Mean	Std. Dev.	Min	P25	Median	P75	Max
Rating Frequency	234	1.201	1.186	0.000	0.000	1.000	2.000	6.000
Volatility	234	0.018	0.004	0.011	0.015	0.017	0.020	0.032
Average ROA	234	6.350	4.266	0.367	3.183	5.452	8.217	26.969
Average P/E Ratio	234	23.956	14.204	6.396	15.682	20.516	28.135	131.782
Average Leverage Ratio	234	4.663	4.671	1.552	2.326	3.153	4.903	50.634
Average Market Cap	234	70.449	153.417	6.951	16.725	30.329	64.796	1628.378
Total Dividends per Share	234	20.871	17.531	0.000	8.702	17.621	29.930	117.720
Sales CAGR	234	0.289	0.320	-0.196	0.097	0.238	0.407	2.590

Each firm experienced around 1.2 credit ratings changes over the studied period on average. The maximum number (6 changes) and the minimum number (0 change) indicates that the credit ratings results of firms over the decade were quite stable. It is understandable since the firms in the dataset are all members of the S&P 500 index. The consistency in market risk levels is also proved by analysing the volatility of companies since they seem to have a narrow interquartile range (from 0.015 to 0.020). The figures of ROA, P/E ratio, leverage ratio, market capital, and dividend per share suggest the same features across firms. However, the negative minimum of sales growth implies some companies faced revenue declines over time.

Second, some detail of the main regressor of the model would be discussed. The number of total ratings changes, including both upgrades and downgrades, through each calendar year is demonstrated in table 4.3.

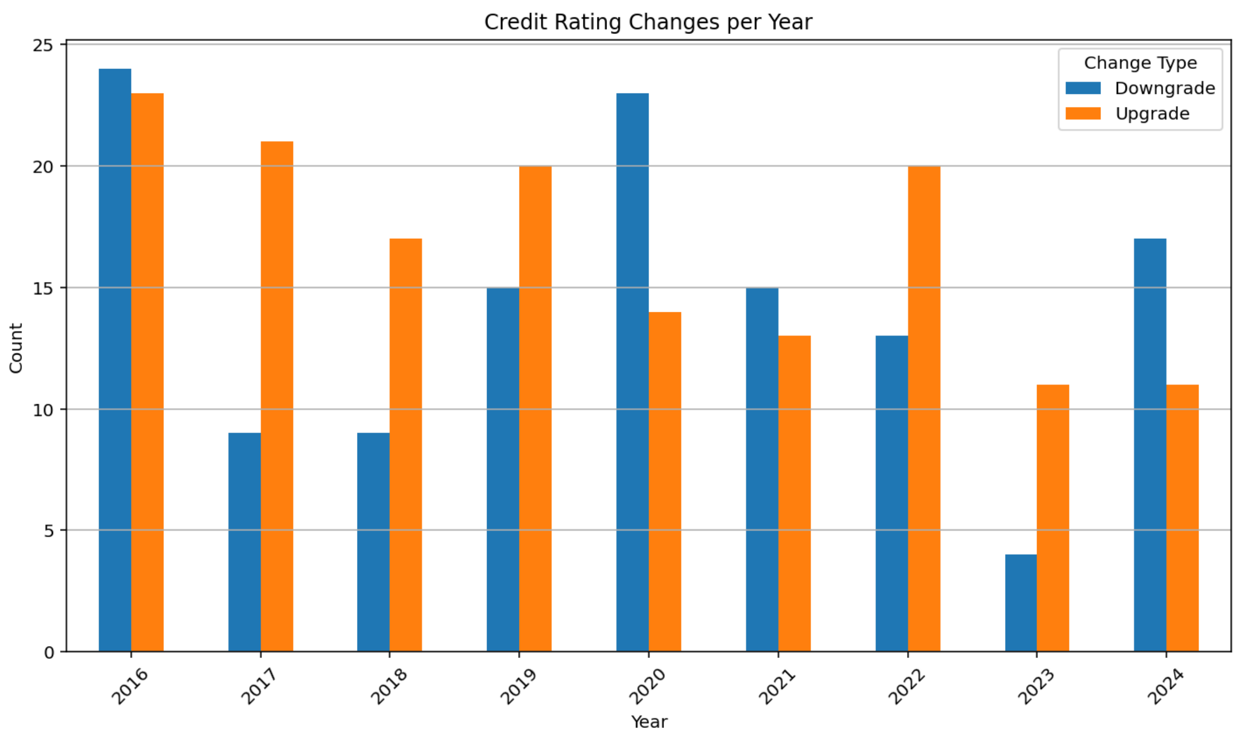
Table 4.3: Summary of Total Ratings Changes

Year	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Total	0	48	30	27	35	37	28	31	15	28

The absence of changes in 2015 is due to the limitation in the collected dataset, since the number of total credit ratings changes in each year is counted based on the comparison with the previous year and there was no data of historical credit ratings for 2014. The number of changes peaked in 2016 with 48 changes overall and then fluctuated in the next 6 years between 30 and 37 changes. 2023 witnessed the lowest figure with only 15 changes, indicating the calmer market at the time or the more stable credit assessments compared to previous years.

For the summary of total changes, all the dataset of historical credit ratings across 234 firms over a 10-year period was used. The observations are the combination of 2 major CRAs – S&P's and Fitch's. Figure 4.1 illustrates more detaily how upgrades and downgrades are accounted for over the period.

Figure 4.1: Total Numbers of Upgrades and Downgrades



Its is obvious that the number of upgrades surpasses the number of downgrades across firms for the research period, except for 2016, 2020, 2021 and 2024. The domination of downgrades to upgrades in this data sample is around the 2020s, likely due to the economic crisis in this phase. It is also notable that 2023 saw a significant decline in the number of credit ratings changes, and while the number of upgrades seems to have remained in both 2023 and 2024, the amount of downgrades in 2024 increased significantly compared to that of 2023. There might be several reasons behind this such as U.S. Sovereign Credit Downgrade by Moody's or post-pandemic rising interest rates.

Table 4.4 is a matrix showing the transition of credit ratings across firms over 10 years detailedly.

Table 4.4: Ratings Transition Matrix

	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	Total
AAA	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9
AA+	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	9
AA	0	0	23	0	0	0	0	0	0	0	0	0	0	0	0	23
AA-	0	0	3	63	3	1	0	0	0	1	0	0	0	0	0	71
A+	0	0	0	6	142	5	1	1	0	0	0	0	0	0	0	155
A	0	0	0	1	16	246	11	0	0	0	0	0	0	0	0	274
A-	0	0	0	0	3	23	297	21	0	0	0	1	0	0	0	345
BBB+	0	0	1	0	0	5	27	447	30	2	0	0	0	0	0	512
BBB	0	0	0	2	0	0	5	16	351	34	4	0	0	0	0	412
BBB-	0	0	0	0	0	0	0	2	13	148	16	0	0	0	0	179
BB+	0	0	0	0	0	0	0	0	1	1	57	13	1	0	0	73
BB	0	0	0	0	0	0	0	0	1	0	3	22	3	1	0	30
BB-	0	0	0	0	0	0	0	0	0	0	0	0	8	1	0	9
B+	0	0	0	0	0	0	0	0	0	0	0	0	0	4	1	5
Total	9	9	27	72	164	280	341	487	396	186	80	36	12	6	1	2106

(Note: total number of ratings transitions is 2106 since we have 9 transitions per firm in 10 years, including ratings that stay the same from one year to the next)

5 Empirical Results

The empirical process for this study will be described in this part. Summary of all panel data regression results will also be illustrated, including the brief statistical analysis of the main result for this research.

5.1 The Main Regression Results for Different Time Windows

We calculated the frequency of credit ratings changes over different time periods and constructed panel data using a rolling window approach. Most panels suggest the main variable has a statistical correlation with volatility of stock returns. Table 5.1 shows the summary of regression results for each rolling window.

Table 5.1: Results Summary

Time Window	Main Coef. (Std. Err.)	p-value	Within R^2	AIC	BIC	Best Model Spec.	Notes
3 years	0.0005 (0.0002)	0.0143	-0.0579	-17 594.34	-17 566.67	Two-way fixed effect	Significant at the 5% level
4 years	0.0004 (0.0002)	0.0550	-0.0727	-16 095.75	-16 068.75	Two-way fixed effect	Significant at the 10% level
5 years	0.0003 (0.0002)	0.0863	-0.1162	-14 710.08	-14 678.59	Two-way fixed effect	Marginally significant (10% level)
6 years	0.0003 (0.0002)	0.0476	-0.0014	-13 498.92	-13 478.66	Two-way fixed effect	Significant at the 5% level
7 years	0.0003 (0.0002)	0.0780	-0.0404	-11 113.03	-11 088.82	Two-way fixed effect	Marginally significant (10% level)
8 years	0.0003 (0.0002)	0.0579	0.0341	-8 676.94	-8 658.73	Two-way fixed effect	Significant at the 10% level
9 years	0.0001 (0.0001)	0.3089	-0.0074	-6 149.29	-6 128.55	Two-way fixed effect	Not statistically significant
10 years	0.0340 (0.0050)	0.0000	0.263 (adj. R^2)	–	–	Cross-sectional model	Significant at the 1% level

For all models, we can observe that AIC and BIC are negative in each time window. This is due to large log-likelihoods and is typical in well-fitting models. These metrics are interpreted on a relative scale, where lower values indicate better model fit, regardless of sign.

Additionally, we also observe negative within R-squared values in several specifications. This may occur when fixed effects absorb most of the cross-sectional variation and leave little variation within a firm to be explained. Despite this, the coefficient on the main variable remains statistically significant across nearly all time windows, indicating a robust and consistent association with return volatility. Therefore, we rely primarily on the significance and consistency of the main effect in a combination of all information.

For the regression from the 10-year sample, we have cross-sectional data. While a significant correlation between the two variables is observed, the sample size is relatively small, and the cross-sectional structure limits our ability to capture the impact of credit ratings changes within the same firm over time. Therefore, we include the cross-sectional results as supplementary evidence, but do not rely on them for deeper analysis.

5.2 Summary Table for The Main Result

The target of this study is to investigate the relationship between stock return volatility and the frequency of credit ratings changes across 234 members of the S&P 500 through a 10-year period, employing the panel data approach. After running regressions with different time ranges of rolling window (from 3-10 years), we choose the detailedly illustration and interpret the regression result of the 6-year rolling window that is considered to be the most reasonable and representational. Both entity and time fixed effects were applied for this model, and to control the within-entity correlation, the clustering standard errors technique was also employed. The detail result is presented in Table 5.2.

Table 5.2: Summary of the Main Result

	Volatility
rating_freq_6yr	0.0003**
	(0.0002)
lvr_avr_6yr	0.00004
	(0.00002)
ln_marketcap_avr_6yr	0.0004
	(0.0004)
dps_total_6yr	-0.00005**
	(0.00002)
Observations	1,170
R-squared (Within)	-0.0014
R-squared (Between)	0.7510
Entity FE	Yes
Time FE	Yes
F-statistic	10.121
F-test (p-value)	0.0000

Note: *** p<0.01, ** p<0.05, * p<0.1

Overally, the regression results suggest that there is a close relationship between frequency of credit ratings changes and the stock return volatility. However, some of the control variables are found to be statistically insignificant.

With regard to the model fit and specification, the overall r-squared is 0.7491, indicating that the model can explain about 75% of the variation in the stock return volatility, including both variation within and between firms. Nevertheless, it is noticeable that although the between r-squared is positively significant, the within r-squared is negative, suggesting that the explanatory variables are limited in explaining the within-entity volatility changes over time.

Our main regressor, the frequency of credit ratings changes, is regarded to be statistically significant with the p-value of 0.0476. The estimated coefficient of 0.0003 implies a 0.03% increase in daily stock return volatility for each additional credit rating change. This is significant since it represents a 1.5% – 3% relative increase based on typical daily volatility levels of 1% – 2%, as proved in Campbell et al. (2001). The significance of this variable is also supported by the narrow range of confidence interval and the small standard error.

After selecting the best subset of control variables, this regression only contains three control factors in the model. However, based on the p-value, only dividend per share is considered to be statistically significant at 5% confidence level. The negative coefficient suggests that firms with higher payout to shareholders are closely associated with lower stock return volatility since it represents the financial health and stability of the company. This is also supported by the not including 0 confidence interval. Meanwhile, the p-value of both leverage ratio and firm size are greater than 0.05 at around 0.1 and 0.3 respectively, which indicates that these variables do not have significant impact on the return volatility. This can also be seen easily in the wider range of confidence intervals and higher standard errors. Although their coefficients are small, we believe it supports the theory that these factors have a negative relationship with the firm return volatility. The fact that they are insignificant when it comes to the within-firm explanation does not necessarily mean that they are not significant in general since they may be more relevant in the cross-sectional analysis. The result of cross-sectional regression with a time range of 10 years supports our belief (Appendix 7).

5.3 The Results of Robustness Checks

5.3.1 Categorize Main Independent Variable

We conducted a robustness check by replacing the continuous measure of ratings change frequency with a binary dummy variable indicating whether a firm belongs to the high-frequency group. Using this specification, we estimated the panel regression model with two-way fixed effects based on the lowest AIC and the result of the likelihood ratio (LR) test ($\chi^2 = 345.31$, $p < 0.001$).

Table 5.3: Summary of the Categorization Regression Result

	Volatility
high_rating_6yrs	0.0003**
	(0.0001)
pe_avr_6yrs	0.000004
	(0.000014)
lvr_avr_6yrs	0.00004*
	(0.00002)
ln_marketcap_avr_6yrs	0.0003
	(0.0005)
dps_total_6yrs	-0.00004*
	(0.00002)
roa_avr_6yrs	0.00005
	(0.00006)
Observations	1170
R-squared (within)	-0.0220
R-squared (Between)	0.5233
Entity FE	Yes
Time FE	Yes
F-stat	5.0750
F-test (p-value)	0.0000

Note: *** p<0.01, ** p<0.05, * p<0.1

The coefficient on the high_rating_freq dummy is positive and statistically significant at the 5% level, indicating that firms with more frequent credit ratings changes tend to have higher stock return volatility compared to their low-frequency counterparts. This supports the main hypothesis that increased rating activity reflects higher volatility on stock returns. Comparatively, we also tried to make dummy variables according to tertiles and quartiles, but neither produced stronger results than the baseline binary classification, suggesting that excessive segmentation may reduce model clarity and stability.

While the within R-squared remains low and negative, which will occur in fixed effects models when limited variation within the entity is explained by the regressors, the overall model remains statistically significant. The direction and significance of the main explanatory variable are consistent with the baseline results, confirming the robustness of the effect under an alternative binary classification scheme.

5.3.2 Separate Regressions for Upgrades and Downgrades

To examine whether the direction of credit ratings changes affects the relationship with stock return volatility, we conducted separate regressions on the downgrades and upgrades subsamples using the 6-year window. Results of each subset are presented in Table 5.4 and Table 5.5 respectively.

Table 5.4: Summary of the Downgrades Subset Regression Result

	Volatility
downgrade_cnt_6yrs	0.0003**
	(0.0001)
lvr_avr_6yrs	0.00003
	(0.00002)
ln_marketcap_avr_6yrs	0.0005
	(0.0004)
dps_total_6yrs	-0.00004**
	(0.00002)
Observations	1170
R-squared (within)	0.0086
R-squared (Between)	0.7814
Entity FE	Yes
Time FE	Yes
F-stat	6.8251
F-test (p-value)	0.0000

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 5.5: Summary of the Upgrades Subset Regression Result

	Volatility
upgrade_cnt_6yrs	0.0003
	(0.0002)
pe_avr_6yrs	0.000005
	(0.000013)
lvr_avr_6yrs	0.00004*
	(0.00002)
ln_marketcap_avr_6yrs	0.0002
	(0.0005)
dps_total_6yrs	-0.00004*
	(0.00002)
roa_avr_6yrs	0.00004
	(0.00006)
Observations	1170
R-squared (within)	-0.0219
R-squared (Between)	0.4545
Entity FE	Yes
Time FE	Yes
F-stat	4.8417
F-test (p-value)	0.0001

Note: *** p<0.01, ** p<0.05, * p<0.1

For the downgrades subsample, the coefficient on the number of downgrades over 6 years is positive and statistically significant at the 5% level, suggesting that firms with more frequent downgrades tend to exhibit higher return volatility. The within R-squared, while low (0.0086), indicates a slightly improved explanatory power compared to the baseline. In contrast, the upgrades subsample yields a non-significant coefficient, indicating that upgrades are not statistically associated with volatility in our setting.

Overall, the result shows that the impact on stock return volatility from credit ratings changing frequency is mainly driven by downgrading, which is consistent with previous research and supports our hypothesis.

6 Discussion

In this section, the empirical results shown in the previous part will be discussed in relation with both ealiers research of credit ratings and the hypotheses formulated in this study. First, the general interpretation of Table 5.2, Table 5.3 and Table 5.4 will be presented in association with the first and the second hypothesis – influence of both the frequency of credit ratings changes and the rating upgrades - downgrades on stock return volatility. Additionally, the impact of other factors on return volatility will also be considered, followed by a brief comparison between the cross sectional and the panel data analysis at the end.

6.1 The Frequency of Credit Ratings Changes' Impact on Stock Return Volatility

While earlier research generally treated the credit ratings change as a single event and considered the market's reaction to this "information shock", mainly focusing on the signs of credit ratings changes (downgrades and upgrades), our study extends the literature by checking the longer-term impact of credit ratings changes on firms' financial performance. In summary, by presenting the main regression result of this study, our research supports the idea that the higher frequency of credit ratings changes that firms experience, the higher stock return volatility will be. We first find that the elevation of stock return volatility is not only drived by the sign of the rating event, which is the main conclusion of many previous studies, but also by the pace and rate of credit-quality updates.

Our finding can be explained through the lens of asymmetric information models. According to the research outcomes of Easley-O'Hara (2004), the adverse-selection costs were proved to be inflated by the high rate of private information disclosure, which directly leads to the rise in bid-ask spreads and return volatility. The frequency of credit ratings changes here functions as a type of private information revelation since it publicizes the new assessments regarding the financial health of firms such as default risk, which makes the dealers become more cautious and charge wider bid-ask spreads to protect themselves. Therefore, trading prices would reflect the greater uncertainty. This phenomenon can be considered as one of the most obvious reasons behind the larger volatility of stock return.

Another potential explanation can be provided through the framework of Bayesian learning model of Hong and Stein (2003) about the mixed-signals and its impact on investors' reaction. They believe that due to the arrival of new information, especially the private ones, investors have to update their belief about the financial value of a firm. The more often this information arrival is, including the changes of credit ratings, the more frequently investors have to adjust their evaluation. These repeated behaviors from investors directly exert a significant impact on the stock price.

6.2 Rating Upgrades and Downgrades' Impact on Stock Return Volatility

To make sure of the determinants behind the credit ratings changings' impact on stock return volatility, this study has two regressions on upgrades and downgrades separately. The results present a significant positive relationship between numbers of downgrades and stock return volatility at significance level 5%, while upgrades cannot influence volatility significantly over the same time length. It means a firm with a higher frequency of downgrading will have a higher volatility on stock return. And because higher numbers of upgrading cannot drive the changing of stock return, we can see the main factor leading to the difference of volatility in the frequency of credit ratings changing is downgrading. About this condition, Holthausen and Leftwich (1986) provided evidence that downgrades are associated with negative abnormal stock return using daily data over 3 main CRAs and suggested no abnormal performance will happen on announcement of an upgrade. Additionally, Avramov et al. (2009) stated around rating downgrades, low-rated firms experience considerable negative returns amid strong institutional selling, whereas returns do not differ across credit risk groups in stable or improving credit conditions. More importantly, under the current regulatory framework, many financial institutions are required to invest in investment-grade securities. Therefore, downgrades will bring greater impact to those firms. About upgrades, according to Tang (2009), firms with refinement upgrades will have more capital investments, less cash accumulation, and faster asset growth than downgraded firms. Hence, a firm experienced more times of upgrading will be more stable and have a lower volatility.

6.3 Other Factors' Impact on Stock Return Volatility

Beyond credit rating activity, our multivariate regressions further reveal that out of six control variables in the model, there are three firm-level factors that exert the most significant influence on the return volatility: sales growth, dividend per share, and the price-earnings (P/E) ratio. In particular, rapid sales growth is shown to be positively associated with volatility. This result implies that firms experiencing swift development often face greater uncertainty. In contrast, dividend per share displays a negative relationship with volatility, suggesting that firms with higher payouts to shareholders experience greater earnings stability and lower return volatility. Finally, a positive effect of P/E ratio is proved by the study result, which is consistent with the idea that highly valued firms are particularly sensitive to news, resulting in larger volatility.

This finding aligns closely with extant literature of main factors leading to volatility. The research result of Kim and Zhang (2016) suggests that high sales-growth entities often incur more chances of forecasting error, which raise return volatility. Similarly, DeAngelo et al. (2006) anticipate that the effect of adverse selection and information asymmetry, which is proved to be closely linked with volatility, can be reduced by the policy of higher dividends. Additionally, a study of Campbell and Shiller (1998) introduces a mechanism called “valuation sensitivity” where P/E ratio reflects the expectation of investors to the future earnings. Therefore, when the actual earnings do not meet the expectations, higher P/E firms often experience larger price adjustments, leading to more significant volatility.

6.4 Comparison: Cross-sectional Analysis - Panel Data Analysis

To assess the robustness and generalizability of our findings, we compare results derived from both cross-sectional and panel data regressions. The cross-sectional regression is based on aggregated 10-year data, where each firm contributes one observation. In contrast, the panel regression utilizes a 6-year rolling window structure, and under the evaluation of AIC, BIC and LR test, the final model employs two-way fixed effects to capture the entity-invariant and time-invariant factors.

The cross-sectional regression yields a coefficient of 0.0005 on the ratings frequency variable, which is statistically significant at the 1% level. In comparison, the panel regression returns a smaller coefficient of 0.0003, significant only at the 5% level. Both models point toward a positive association between ratings change frequency and return volatility, but the statistical strength of the effect is different. Several factors may explain this discrepancy. Firstly, due to different methods of sample composition, each firm only contributes one observation, and the total sample size is 234 observations while the 6-year rolling window has 1170 observations. The results may have bias under different sample sizes. Secondly, panel data regression could absorb time-specific heterogeneity to make the model ignore the common trend in the time period. Thirdly, the cross-sectional model captures long-term firm-level differences but is potentially biased by omitted variables, while panel regression mitigates this concern by using within-firm variation, thus enhancing causal interpretation (Wooldridge, 2010).

Moreover, the results in the literature show that market responses to credit ratings information are persistent across different modeling approaches (Hand, Holthausen, & Leftwich, 1992; Tang, 2009). The adoption of a rolling window methodology not only mitigates the impact of short-term disturbances but also reinforces the hypothesis that frequent ratings changes reflect heavier market ambiguity, which ultimately amplifies the instability of stock return.

7 Conclusion

This thesis has researched the impact of frequency of credit ratings changes on the stock return volatility. It extends the prior work by focusing on the longer-term effects of credit ratings. To investigate this relationship, a panel data model with two-way fixed effects was performed on 234 members of the S&P 500 index through different rolling windows.

Based on the panel regression results of different time ranges, the main finding of this study is that firms with higher frequency of credit ratings changes experience a higher volatility of stock return. This result can be explained through the lens of many theoretical concepts, especially the theory of information asymmetry. The regression results also suggest that other than the frequency of credit ratings changes, dividend per share, P/E ratio, and sales growth are three subfactors exerting the most influence on the volatility of stock return.

To test out the particular impact of rating downgrades and upgrades on the volatility, the same model specification was used, but focused the main explanatory variable on the subsets of each rating type. Consistent with the previous research conclusions, we find out that stock return volatility is more sensitive to rating downgrades than upgrades.

Furthermore, to strengthen the analysis, subsamples regression was conducted. The credit ratings were categorized into high, and low sections to facilitate our analysis. In addition, we also varied the rolling window length to see the difference among results of those time ranges. The results indicate that firms with more frequent credit ratings change tend to have higher stock return volatility compared to their low-frequency counterparts, which supports the main finding of this study.

8 Limitations

8.1 Data

Our primary ratings data is sourced from Bloomberg's aggregate credit-rating series, which is a combination of information from multiple CRAs, and supplementarily from Fitch. While comprehensive, Bloomberg's ratings might differ in timing and methodology from the real ratings that many institutional investors actually use, since it might aggregate all the changes of credit ratings into a single timeline. This can dilute the real market response to each CRA's announcement. Moreover, we do not have access to exclusive agency-specific ratings datasets, which would allow us to isolate and consider each CRA's unique informational impact. As a result, we cannot determine whether the changes in assessment of credit by particular agencies have greater informational content or exert differential effects on the stock return volatility.

8.2 Sample

Our analysis of credit-ratings frequency and its impact on stock-return volatility is subject to certain sample constraints. First, since we only have one ratings change per issuer each year over a 10-year period for 234 firms, credit-ratings observations are relatively sparse. This low annual frequency restricts our ability to observe within-year dynamics when it comes to credit ratings effects and may understate the true variation in rating activity generally.

Moreover, choosing to focus exclusively on members of the S&P 500 index, which are considered to be large and financially stable corporations, also means that we leave out smaller, and more financially vulnerable companies. Such large firms tend to show more predictable credit profiles and often witness fewer rating revisions, which in turn declines cross-sectional dispersion in both ratings changes and volatility. Consequently, our results may underestimate the effects that would be observable in a broader sample that also includes smaller or more credit-risky entities.

8.3 Methodology

This study mainly adopts panel data regression with fixed effects to model our variables, which can capture the entity-invariant and time-invariant factors. However, there may exist some potential model designs which are appropriate to use random effect when control variables related to firms can be selected more exactly. Additionally, the construction of panel data using overlapping rolling windows may introduce serial correlation across observations, especially in the dependent variable, which can lead to underestimated standard errors and overstated significance levels. Although clustered standard errors are used to mitigate this concern, residual autocorrelation may persist. Moreover, the explanatory power of the model is limited by using fixed effects, especially the within R-squared remaining low in several specifications. This suggests the ability to detect economically meaningful effects in the model may be reduced.

9 Potential Future Research

The results shown in this study suggest the scale of credit ratings changes' impact on volatility is comparatively small. Hence, it is necessary to include more small business to construct a larger sample. On the other hand, it is worth encouraging to conduct research on another market based on region or another kind of economy.

Other than sample resources, another promising direction lies in the application of more advanced empirical techniques. For instance, machine learning methods such as random forests, gradient boosting, or neural networks could be employed to capture nonlinear interactions and high-dimensional patterns in credit ratings behavior and market volatility.

Additionally, an important point worth considering is information persistence. As a regular method for credit risk evaluation and an effective tool to mitigate information asymmetry, credit ratings plays an important role in investment decision-making. When an investor considers relevant information for a potential investment, how long ago the information was released may affect its relevance. In other words, how long a single credit ratings change continues to have an impact is an important question for future research to explore.

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Appendix

Appendix 1: Summary of Panel Regression Results for 3-Year Rolling Volatility

	Volatility
rating_freq_3yrs	0.0005**
	(0.0002)
ln_marketcap_avr_3yrs	-0.001*
	(0.0006)
dps_total_3yrs	-0.00008
	(0.00005)
roa_avr_3yrs	0.00007
	(0.00006)
sales_cagr_3yrs	-0.000006***
	0.000002
Observations	1872
R-squared (within)	-0.0579
R-squared (Between)	-4.5652
Entity FE	Yes
Time FE	Yes
F-stat	11.965
F-test (p-value)	0.0000

Note: *** p<0.01, ** p<0.05, * p<0.1

Appendix 2: Summary of Panel Regression Results for 4-Year Rolling Volatility

	Volatility
rating_freq_4yrs	0.0004*
	(0.0002)
ln_marketcap_avr_4yrs	-0.0009
	(0.0006)
dps_total_4yrs	-0.00007*
	(0.00004)
roa_avr_4yrs	0.00009
	(0.00007)
sales_cagr_4yrs	-0.000006*
	0.000004
Observations	1638
R-squared (within)	-0.0727
R-squared (Between)	-3.6820
Entity FE	Yes
Time FE	Yes
F-stat	8.9940
F-test (p-value)	0.0000

Note: *** p<0.01, ** p<0.05, * p<0.1

Appendix 3: Summary of Panel Regression Results for 5-Year Rolling Volatility

	Volatility
rating_freq_5yrs	0.0003*
	(0.0002)
pe_avr_5yrs	0.00001
	(0.00001)
lvr_avr_5yrs	0.00001
	(0.00002)
ln_marketcap_avr_5yrs	-0.0009*
	(0.0005)
dps_total_5yrs	-0.00005
	(0.00004)
roa_avr_4yrs	0.0001*
	(0.00007)
Observations	1404
R-squared (within)	-0.1162
R-squared (Between)	-3.3263
Entity FE	Yes
Time FE	Yes
F-stat	5.9567
F-test (p-value)	0.0000

Note: *** p<0.01, ** p<0.05, * p<0.1

Appendix 4: Summary of Panel Regression Results for 7-Year Rolling Volatility

	Volatility
rating_freq_7yr	0.0003*
	(0.0002)
lvr_avr_7yr	0.00004*
	(0.00003)
ln_marketcap_avr_7yr	0.0001
	(0.0005)
dps_total_7yr	-0.00004*
	(0.00002)
roa_avr_7yr	0.00002
	(0.00007)
Observations	936
R-squared (Within)	-0.0404
R-squared (Between)	0.2413
Entity FE	Yes
Time FE	Yes
F-statistic	2.1448
F-test (p-value)	0.0584

Note: *** p<0.01, ** p<0.05, * p<0.1

Appendix 5: Summary of Panel Regression Results for 8-Year Rolling Volatility

	Volatility
rating_freq_8yr	0.0003*
	(0.0002)
pe_avr_8yr	0.00004***
	(0.00001)
lvr_avr_8yr	0.00004
	(0.00003)
dps_total_8yr	-0.00003
	(0.00002)
Observations	702
R-squared (Within)	0.0341
R-squared (Between)	0.0933
Entity FE	Yes
Time FE	Yes
F-statistic	5.0111
F-test (p-value)	0.0006

Note: *** p<0.01, ** p<0.05, * p<0.1

Appendix 6: Summary of Panel Regression Results for 9-Year Rolling Volatility

	Volatility
rating_freq_9yr	0.0001
	(0.0001)
pe_avr_9yr	0.00002
	(0.00003)
lvr_avr_9yr	0.00003
	(0.00004)
ln_marketcap_avr_9yr	-0.0007
	(0.0009)
roa_avr_9yr	-0.00003
	(0.0001)
Observations	468
R-squared (Within)	-0.0074
R-squared (Between)	-2.2921
Entity FE	Yes
Time FE	Yes
F-statistic	0.6116
F-test (p-value)	0.6911

Note: *** p<0.01, ** p<0.05, * p<0.1

Appendix 7: Summary of Cross-Sectional Regression for 10-Year Volatility

	Volatility
const	0.0344***
	(0.0050)
rating_freq_10yr	0.0005***
	(0.0002)
lvr_avr_10yr	0.0001***
	(0.0000)
ln_marketcap_avr_10yr	-0.0007***
	(0.0002)
dps_total_10yr	-0.00004***
	(0.00001)
sales_cagr_10yr	0.0041***
	(0.0007)
Observations	234
R-squared	0.278
Adj. R-squared	0.263
F-statistic	17.59
F-test (p-value)	0.0000

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$