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Stability of Credit Ratings - The Rating Agencies' sensitivity to the economic cycle

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Master in Finance

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PhD Paulo Viegas de Carvalho, Invited Assistant Professor
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Acknowledgements

As this project comes to an end, I find myself reminiscing of the amazing experience I have had throughout my academic path. It has been an incredible journey, filled with knowledge and the establishment of life-lasting friendships.

I would like to dedicate this project to my family and friends, who have always believed in me, and gave me the encouragement and strength to keep pushing through. Without their contribution this project would not be possible, especially my father's, to whom I am forever grateful.

A special acknowledgment to my supervisor, Prof. Paulo Carvalho, for his guidance, kind words of encouragement, and never-ending support throughout this journey.

Resumo

“Credit Ratings foster the development and smooth functioning of capital markets by providing transparent information and insight to market participants.” S&P Global

A informação relativa aos ratings corporativos tem sido um fator-chave nos mercados financeiros ao longo da história, já que as Agências de Rating desempenham o importante papel de reduzir assimetrias de informação entre empresas e investidores. Dado o funcionamento oligopolístico deste setor, aliado ao número elevado de posições questionáveis tomadas por estas agências, as mesmas têm sido sujeitas a um grande nível de escrutínio e críticas. Nesta dissertação aprofundamos o já extenso trabalho de investigação que se foca na metodologia que estas agências aplicam no seu modelo de negócio. Sendo que os mercados valorizam estabilidade e avaliações justas por parte das agências, as mesmas afirmam ter uma abordagem through-the-cycle, que foca na componente de performance individual e de longo prazo de cada rating providenciado. Através da nossa pesquisa, na qual aplicámos uma medida que captura a informação dos ratings presentes numa matriz transitória e o exprime apenas num número, apelidada de RatVol, concluímos que, na realidade, as agências parecem ser sensíveis às variações do ciclo económico. Os nossos resultados sugerem que condições económicas desfavoráveis resultam numa maior intensidade de downgrades, sendo que recentes observações indicam que as agências tendem a ser mais suscetíveis a reagir de forma exagerada a variações do ciclo económico. As alegações que as agências fazem de seguirem uma metodologia de certa forma insensível ao ciclo económico parecem, por isso, ser questionáveis.

Palavras-chave: Agências de Rating, Mudanças de rating, Volatilidade dos ratings, Estabilidade

JEL classification: G18; G24

Abstract

"Credit Ratings foster the development and smooth functioning of capital markets by providing transparent information and insight to market participants." S&P Global

Ratings information has been a key factor to financial markets over the course of the years, as Credit Rating Agencies have the important role of reducing information asymmetries between firms and investors. Because of the oligopolistic nature of this sector, coupled with a number of questionable positions taken by these agencies, they have been subjected to a high level of scrutiny and criticism. In this dissertation we deepen the investigation regarding the methodology these agencies apply in their business model. As markets crave for stability and fair assessments from CRAs, they claim to have a through-the-cycle approach that focuses on the long-term and individual performance components of each issue they release. Through our research, in which we applied a measure that encapsulates the information in a ratings transition matrix into a single number, RatVol, we find that CRAs are sensitive to business cycle variations. Unfavorable economic conditions yield a large number of downgrades, and recent observations show that agencies tend to be more prone to overreact to the business cycle variations. Their claims of a through-the-cycle methodology seem to be arguable.

Keywords: Credit Rating Agencies; Rating Changes; Volatility of Ratings; Stability
JEL classification: G18; G24

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List of abbreviations

BLUE - Best Linear Unbiased Estimators

CRA – Credit Rating Agency

GDP – Gross Domestic Product

GSM – Government Support Measures

IOSCO - International Organization of Securities Commission

NFC – Non-Financial Corporations

NRSRO – Nationally Recognized Statistical Rating Organization

OLS – Ordinary Least Squares

PiT – Point in Time

SEC – Securities and Exchange Commission

S&P – Standard and Poor’s

TTC – Through-the-cycle

US – United States

CHAPTER 1

Introduction

According to Frost (2007), Credit Rating Agencies (CRAs) provide opinions on the creditworthiness of entities and their financial obligations, a credit rating is a CRA's assessment of the credit quality of a debt issuer or a specific debt obligation.

As mentioned in the S&P Global website: "Today, investors have access to more information than ever before as markets become digitized and interconnected. Markets function best when investors of every type – from individual to institutional – draw on a wide variety of information to make educated, better-informed investment choices." Credit Rating Agencies (CRA) are then one of the most trusted institutions by investors to make educated decisions on their potential investments, as they attempt to provide transparent third-party information on firm's credit performance, which is ultimately presented in a rating scale.

Stability is a major key to prosperity in this sector, and CRAs defend that their methods are through the cycle, being "designed to achieve an optimal balance between rating timeliness and rating stability" (Altman et al., 2004:2681). Following this reasoning, macroeconomic variable changes, that have a general effect on all firms, shouldn't be a relevant factor to generate major changes in ratings. With that in mind, this study aims to understand the Credit Rating Agencies' (CRAs) process, defying the notion that the credit rating agencies' model is "through-the-cycle", as evidence shows that this is not as clear cut as they signal to the public.

To achieve the proposed goal, we use a measure previously presented by Carvalho et al (2014), focusing on the idea of ratings stability, summarizing the information in a ratings transition matrix into a single scalar number.

This study looks to further corroborate their findings, with new data, especially since we have been subject to a new global crisis (COVID-19), which had a profound impact on the global economy. Rather than exploring the accuracy vs stability nature of rating changes, as performed by the article in which this study focuses, our work will be centered on the stability component, using the parameter (RatVol) presented to further explore this issue.

To engage in such a study, it was relevant to, firstly, have a clear understanding of how rating agencies operate, their role in the market, and how that role is perceived by respected thinkers in the financial world.

This dissertation is important in the sense that it deepens the research on CRAs, entities that have become an increasingly important part of capital markets. Their signaling to investors yields an obvious impact, so their way of attributing their ratings must be carefully and continuously examined and revised, for the sake of transparency and quality information to be widely available to all users.

We used data from the CRA with the biggest market share in the US, Standard & Poor's, analyzing U.S. non-financial firms rated by them from 1994 to 2021 to understand the evolution of the measure explored (RatVol). We were also able to understand the separate contribution of downgrades (RatVolD) and upgrades (RatVolU), as the measure allows us to make that separation. Furthermore, we ran a regression for this measure, to understand its connection to business cycle variations (we utilized 5 independent variables deemed to be a good representation of the business cycle). By doing so we were able to understand the relation between the volatility surrounding rating changes and the variation of the business cycle, which shouldn't exist, as CRAs claim to have a through-the-cycle, long-term horizon approach for rating revision.

Our findings go in line with previous literature, that states a link between shifts in the economic conditions and a more aggressive position from CRAs. In fact, we found a connection between aggravated business conditions and the sharp increase of downgrades. As for upgrades, they are, in general, not related to the business cycle. There also seems to be a reputational fear associated with CRAs after the brutal scrutiny they were subjected to after the 2008 crisis, as they seem to be more eager to respond to market conditions and are more sensitive to short-term performance than they should.

This dissertation is structured in the following manner. We begin by presenting the most relevant literature that surrounds the issue at hand. Next, we present a detailed description of the data and methodology used to achieve the proposed goals. At last, we discuss the main findings and conclusions retrieved from the study.

CHAPTER 2

Literature Review

To start this literature review, we highlight the role credit rating agencies play in the market, followed by an understanding of its most meaningful players, and finally we turn our attention to the main topic – the link between the business cycle and CRAs.

2.1. The role of Credit Rating Agencies

CRAs play two key roles in capital markets. The first is the valuation role, as they distribute information to market participants. They do so by gathering and analyzing the relevant information for assessing credit quality. The second role is to facilitate contracting (theory of what kinds of deals are made between financiers and those who need financing), since letter ratings are viewed as an efficient credit quality benchmark. These two roles CRAs play can be conflicting. As information suppliers, they are expected to make the proper adjustments and make the necessary changing decisions widely available to the public at no cost. On the other hand, their contracting role relates to cautionary action, as they should promote rating stability. Unstable ratings are an alarming factor in contracting, as they can yield costly renegotiations between the parties involved.

The usefulness of credit ratings relies on rating stability. With effect, ratings should only suffer changes whenever fundamental credit risk changes, which happens quite slowly, CRAs defend. This fundamental credit risk idea is consistent with the agencies' rating approach, "in which transitory shocks that might affect a company's credit risk in the short term are given relatively little weight in the credit analysis process" (Frost, 2007:475).

As these agencies play an important role in capital markets, many issues have been raised regarding the legitimacy of how they operate. In his paper, Frost (2007), through the revision of previous empirical studies, highlights and analyzes the following issues: Disclosure Adequacy (should the rating process be clearer and publicly disseminated?); Potential Conflicts of Interest (May arise when a CRA has an economic interest in basing a credit rating on anything other than an issuer's creditworthiness); Alleged Anticompetitive or Unfair Practices (with special focus on unsolicited ratings issued by some agencies and their alleged notching practices); Diligence and Competence (Some events, such as the accounting scandals revealed in 2000-02, led many investors to question the credibility and trustworthiness of these agencies).

Some empirical studies have been performed regarding the potential conflicts of interest, which arise from CRA's reliance on issuer fees. Covitz and Harrison (2003), tested "whether rating agency actions systematically vary in a manner which suggests they favor issuer interests – the "conflict of interest hypothesis" – or investor interests – the "reputation hypothesis". They found that, rather than conflicts of interest, reputational incentives are the biggest influence for CRAs.

Many authors have focused on this issue and have examined the effects of rating upgrades and downgrades on certain types of financial instruments (stocks and bonds being the principal), with the U.S. being the focal point of interest for many of these studies, as it is the market that draws more attention from investors.

By understanding the importance they have and the role these agencies play, the scrutiny they're subjected to cannot come as a surprise.

2.2. NRSRO

With the development of the bond market in the US, in the beginning of the 20th century, bank regulators incentivized banks to make safe bond investments. To this end, they issued a set of regulatory measures that stated that banks were only allowed to hold bonds that were "investment grade" – in today's terminology. Banks were now restricted to investing in bonds that were recognized by publishers of the "recognized ratings manual" – which were, at the time, four agencies: Moody's, Poor's, Standard and Fitch. These agencies have now gained a massive influence in the bond market.

In 1975, the U.S. Security and Exchange Commission (SEC) introduced the term Nationally Recognized Statistical Rating Organization (NRSRO). Three agencies were given this designation - Standard and Poor's, Moody's, and Fitch, as they were the ones with national presence at the time. By doing so, SEC "crystallized the centrality of the three rating agencies" White, 2010:213, as these were the only agencies "whose credit ratings could be used to determine net capital requirements for broker-dealers" Cantor and Packer, (1995:18).

These regulatory measures were responsible for the strength and power these three agencies accumulated over the decades that followed, and to this day these are the agencies that play the most influential part in securities markets. Not surprisingly, research concerning the impact of credit rating announcements has used mostly data from these three companies.

In the US, the agencies are dominant to the point that the remaining agencies' market participation is almost negligible. As Table 1 shows, of the three, S&P is the most relevant, in fact, according to the U.S. Securities and Exchange Commission's latest report, they were responsible for 50,4% of the totality of ratings issued as of December 31, 2020.

Table 1: Total Outstanding Credit Ratings

Percentage by Rating Category of Each NRSRO's Outstanding Credit Ratings of the Total Outstanding Credit Ratings of all NRSROs as of December 31, 2020. Source: OCR Staff Report January 2022

NRSRO	Financial Institutions	Insurance Companies	Corporate Issuers	Asset-Backed Securities	Government Securities	Total Ratings	Change in % of Total Ratings from 2019 to 2020
AMB	N/R	34.1%	0.8%	0.0%	N/R	0.4%	0.00%
DBRS	7.8%	0.9%	3.4%	15.0%	1.3%	2.9%	0.18%
EJR	7.1%	4.6%	7.4%	N/R	N/R	1.0%	0.11%
Fitch	23.4%	15.1%	16.0%	21.8%	10.5%	12.6%	-0.47%
HR	0.6%	N/R	0.3%	N/R	0.0%	0.1%	0.01%
JCR	0.7%	0.4%	2.3%	N/R	0.0%	0.2%	0.01%
KBRA	0.9%	0.6%	0.2%	9.3%	0.0%	0.8%	0.09%
MIS	24.1%	12.0%	25.8%	30.3%	33.2%	31.7%	-0.23%
S&P	35.5%	32.2%	43.9%	23.6%	54.9%	50.4%	0.30%

We can further verify that S&P and Moody's account for 82,1% of Total Ratings. This clear oligopolistic nature of the credit rating industry has been a factor of concern for many years. SEC played a huge role in this reality, with the designation of NRSROs, using them to evaluate the amount of capital which financial institutions are required to hold. In fact, Ekins and Calabria (2012) state that reputational factors are natural barriers to entry in the credit rating agency market, but most barriers are a direct result from the regulatory designation of NRSRO credit rating agencies.

Although CRAs have been subjected to extensive regulation from SEC throughout the 20th century, the problems with their business-model became bluntly obvious after the financial crisis of 2008, when it was observable that the lack of competition in the industry was a disservice to the financial markets. In fact, "massive downgrading and defaults during the 2008 financial crisis have led politicians, regulators, and the popular press to conclude that the rating agencies' business-model is fundamentally flawed" (Opp et al., 2013:46). This occured when the scrutiny became heavily present in this industry, with CRAs becoming a focal point of interest to the general media, rather than just the parties directly interested in their services.

2.3. Ratings Methodology

Borio, Furfine and Lowe (2001) defend that there is a level to which financial systems are "inherently procyclical", and so, measures of financial activity present a tendency to increase during times of economic expansion more notably than when in the presence of a downswing.

This procyclicality, some authors defend, can be explained by the asymmetry of information available in the markets, as well as by the countercyclical nature of risk. CRAs have the role of mitigating these risks, using their "tools and methodologies to assess securities risks are more efficient than relying on the investors making their own imperfect assessment" (Huan and Mohamed, 2021:53).

"Each agency applies its own methodology in measuring creditworthiness and uses a specific rating scale to publish its rating opinions" (S&P, 2022). As this is true, their philosophy is based upon the pursuit of a rating system that is accurate, but also one that signals stability. As a credit rating adjustment has the power to shift the market's perception on a given issuer or individual debt issue, these adjustments "speak to the credit quality of an individual debt issue, such as a corporate or municipal bond, and the relative likelihood that the issue may default" (S&P, 2022)

As overalls shifts in the economy can be a factor in rating changes, this cannot be their focus, with both main agencies (S&P and Moody's) highlighting the individual and independent nature of their assessments.

Taking this into consideration, we can defend the idea that changes in macroeconomic variables should have a general effect on all firms, thus not resulting in drastic changes in ratings.

That being said, CRAs claim to have a "through-the-cycle" (TTC) methodology, with the intent of achieving an optimal balance between rating timeliness and rating stability. Their long-term default horizon is linked with the idea that ratings should not be extensively tied to short-term performance, as they prioritize the perceived permanent component of credit-quality changes. This forward-looking through-the-cycle methodology, used mainly to achieve rating stability, contrasts with the notion of a Point in Time (PiT) rating approach, which focuses on the current cyclical conditions.

The behavior of rating changes is much more complex than agencies signal to the market. Many factors are in play when it comes to CRAs' behavior, and reputational incentives are certainly in the equation, as stated above.

Mingyi et al. (2022) study the effects of market power variations on CRAs' standards, suggesting that two conflicting forces shape CRAs' rating decisions. One being the issuer-pay model, that may lead agencies to favor their paying issuers, to uplift their market position; this view is supported by several studies (Griffin and Tang, 2011; Jiang et al., 2012; Kashyap and Kovrijnykh, 2016; Beatty et al., 2019). The other force lies in the fact that CRAs are punished for optimistically biased ratings, this is directly tied to their potential reputational losses, which obviously has a direct impact on the temptation to issue favorable ratings. Bar-Isaac and Shapiro (2013) are firm believers of the idea that reputational concerns influence CRAs, going on to say that these concerns actually “discipline their behavior”. They reason that ratings quality is countercyclical, meaning that throughout the business cycle, changes in economic variables will yield different responses from CRAs’ issuing methods. The logic is to reinforce their reputation in times of distress, and “milk” it when facing favorable conditions. Dimitrov et al. (2015) go on to say that too optimistic ratings are counter-productive, as they are more likely to be accounted for as optimistically biased, which ultimately leads to a higher level of scrutiny, either legal or regulatory. This can lead them to lower some ratings to levels further than justifiable, to protect, or regain, their reputation.

The International Organization of Securities Commissions (2021) issued a report on the observed impact of COVID-19 Government Support Measures (GSM) on credit ratings, in which they found that no substantial changes were observed on the rating methodology because of the effects of the pandemic or the GSMs, but they noted that certain assumptions have been updated to reflect macro-economic conditions. As CRAs aim for long-term financial health of a corporation, there seems to have been a larger sectorial component in the assessment during the pandemic, as during this period there were sectors largely more affected than others (leisure, transport, consumer/retail), these were targeted with lower credit profiles, as the recovery path was seen as more uncertain. The report goes on to say that negative rating actions were mainly observed in the non-investment grade category.

There is a vast literature dedicated to the analysis of the through-the-cycle credit rating systems. Nickell, Perraudin, and Varotto (2000) used a probit model to quantify the dependence of ratings transition probabilities on the industry and on the stage of the business cycle. Through their study they found that business cycle effects make a difference, largely to lowly graded issuers.

Moreover, Bangia, Diebold, and Schuermann (2002) utilized an S&P database to analyze in detail the issue of procyclicality considering credit migration matrices free from business cycle conditions. Through the separation of the economy into two states, expansion, and contraction, and conditioning the migration matrix they show that the loss distribution of credit portfolios can differ significantly over the business cycle. Amato and Furfine (2004) assess the level of procyclicality of rating agencies in their assignment of ratings, by studying ratings produced by S&P using annual data on US firms, reaching the conclusion that the fact that credit ratings vary with regards to the business cycle may be connected to cyclical changes to business and financial risks, and not to cycle-related changes to rating standards.

More recently, several studies focused on the implications of the through-the-cycle methodology for rating stability and accuracy. Kiff, Kisser and Schumacher (2013) considered a market value approach to risk default estimation. Afterwards, with the same intent, we saw "a new measure of ratings stability that summarizes the information in a ratings transition matrix into a single scalar number" Carvalho et al. (2014:1). Through this measure they explored the intensity with which CRA's issue rating changes, defying their through-the-cycle claims. Their findings showed that during times of distress the volatility of credit ratings is considerably high, tying the nature of these rating changes to the business cycle, which shouldn't be the case, as macroeconomic variables have a generalized effect on all firms. In this study we will use this same approach, as it seems to be a solid measure to study ratings' stability.

We can conclude, through the literature review, that, in fact, there seems to be a strong case that ties the business cycle variations to the behavior of credit rating changes, which leads us to believe that their claims of a through-the-cycle method is not observable in practice.

CHAPTER 3

Data

This study comprises a sample of all domestic long-term credit ratings announced by Standard and Poor's for all U.S. non-financial firms between 1994 and 2021 was used. For the period between 1994 and 2011 the credit rating announcements were retrieved from the agencies' own databases (Moody's Default and Recovery Database and Standard & Poor's Capital IQ Database). As for the following 10 years (2012-2021), the credit ratings announcements were gathered from Bloomberg. The domestic long-term issuer credit rating was the rating type used for each firm.

The ratings were polished to serve the study. To that end, we only included the firms that were featured in the first sample, to maintain the same sample "universe", granting further coherence to the study. This will allow us to make a more meaningful comparison between time periods and see the evolution of CRAs' behavior in the last 10 years.

The CRAs' notation was converted into a numerical scale, that respected the following disposition: AAA = 1, AA+ = 2, …, D/C = 22. As the number grows, its corresponding credit quality declines (1 = highest credit quality/ 22 = lowest credit quality).

Since there is not a specific time frame for ratings revision, different CRAs revise the ratings of a given firm over different periods of time. With this in mind, and following the authors of the previous study's reasoning, we deemed a given rating to be valid for a period of 2 years after its announcement, or until the issuance of a new rating takes place, whichever occurs first. Therefore, a firm was included in the sample after the first rating announcement was observed, and promptly removed two years following the last announcement.

The time-series analysis was run at a quarterly-frequency. The authors defend that such frequency is ideal to capture rating changes between the different periods, as well as appropriate to analyze business cycle effects. Thus, the sample analyzed in this study is comprehended between 1994Q1 and 2021Q4.

The data used to conduct the regression, composed by the business cycle variables chosen for this purpose, were obtained from: OCDE's website (GDP); Federal Reserve Bank of St. Louis (Yield Slope; Credit Spread); CBOE Exchange (VIX); Federal Reserve Bank of Philadelphia (ADS). The regression was performed for the periods of 1997Q1 to 2021Q4.

CHAPTER 4

Methodology

4.1. RatVol

In order to measure the stability of credit ratings, as previously stated, we explored the measure proposed by Carvalho et al. (2014), which focuses on the volatility of ratings. As they explain, the measure is based on the same information required to compute a standard ratings transition matrix. The focal point being to condense the information of all rating changes into a single scalar.

Let t measure time in quarters and t = 1,2, …, T denote the end of each quarter in the sample. Let

$$w_t(s,f) := \frac{n_t(s,f)}{\sum_{s=1}^{K}\sum_{f=1}^{K} n_t(s,f)} \tag{1}$$

Where $w_t(s,f)$:= represents the numbers of firms that finished the last quarter (t-1) with rating s and ended the present quarter (t) with rating f. Through the usage of the actual number of firms we are able to give more weight to the transition paths with more observations. K represents the number of rating classes (K = 22, 22 representing default).

The volatility of ratings is defined as

$$RatVol_t := \sqrt{\sum_{s=1}^{K}\sum_{f=1}^{K} w_t(s,f) \times (f-s)^2} \tag{2}$$

As rating stability is the focal point of the study, this measure is useful to test its existence, since $RatVol_t$ "uses all information in the ratings transition matrix and thus captures more fully the concept of ratings' instability". The authors compare this measure to a standard-deviation. It ($RatVol_t$) will be high whenever large rating changes take place during the quarter, but a big amount of small rating changes will also take the measure to high values. This is relevant because they argue that instability can also emerge from frequent widespread rating changes, even in a small nature.

4.2. Decomposition into downgrades and upgrades (RatVolD;RatVolU)

Upgrades and downgrades produce different consequences for the market, so to understand their individual contribution to this measure is highly relevant.

In order to accurately separate their contribution, $RatVol_t$ allows us to break down the two, as it indexes the effects of both. The total squared volatility can be decomposed into

$$RatVol_t^2 = \sum_{s=1}^{K}\sum_{f=1}^{K} w_t(s,f) \times (f-s)^2\left(I_{\{f<s\}} + I_{\{f>s\}}\right) = RatVolU_t^2 + RatVolD_t^2$$

$$= RatVolU_t^2 + RatVolD_t^2 \tag{3}$$

Where the corresponding volatilities due to upgrades ($RatVolU_t$) and downgrades ($RatVolD_t$) are

$$RatVolU_t \coloneqq \sqrt{\sum_{s=1}^{K}\sum_{f=1}^{K} w_t(s,f) \times (f-s)^2 I_{\{f<s\}}} \tag{4}$$

$$RatVolD_t \coloneqq \sqrt{\sum_{s=1}^{K}\sum_{f=1}^{K} w_t(s,f) \times (f-s)^2 I_{\{f>s\}}} \tag{5}$$

In which the indicator function $I_{\{f<s\}}$ equals 1 when the number associated with the final rating (*f)* is lower than the initial rating (*s*), i.e., whenever an upgrade occurs.

The individual contribution of each of these elements can be observed in Figure 2, showcased below in the discussion of results.

4.3. Business cycle variables – MLRM

To test the relationship between the business cycle and the evolution of the RatVol measure, and achieve a deeper understanding of whether rating changes trends are tied to the business cycle, and fluctuate accordingly, we ran a multiple linear regression. We followed the reasoning of Carvalho et al. (2014), thus, for the representation of the business cycle in the regression, the following standard macroeconomic variables were chosen:

GDP_t: Real GDP growth over quarter *t*

$YieldSlope_t$: Yield curve slope (10-year minus 2-year Treasury Bond yields) at t

$CreditSpread_t$: Credit spread (BBB – AAA yields) at *t*

VIX_t: CBOE volatility index at *t*

ADS_t: Aruoba-Diebold-Scotti Business Conditions Index at *t*

The GDP of the US provides a signaling of the size and performance of the economy. The yield curve slope is a relevant measure to be considered, as a negative yield slope has historically been viewed as precursor to a recessionary period. Credit spread can be an indicator of adverse times, when presenting high values. The CBOE volatility index, or simply VIX, is an indicator that represents the market's expectations for volatility, hence its suitability in this model. Finally, the Aruoba-Diebold-Scotti (ADS) Business Conditions Index, is a real-time indicator that covers the business conditions for the U.S. economy.

Multiple Linear regression analysis

With the macroeconomic variables above described taken into consideration, the following regressions were performed for S&P:

$$RatVol_t = \alpha + \beta_1 GDP_t + \beta_2 YieldSlope_t + \beta_3 CreditSpread_t + \\ + \beta_4 VIX_t + \beta_5 ADS_t + \varepsilon_t \qquad (6)$$

$$RatVolU_t = \alpha + \beta_1 GDP_t + \beta_2 YieldSlope_t + \beta_3 CreditSpread_t + \\ + \beta_4 VIX_t + \beta_5 ADS_t + \varepsilon_t \qquad (7)$$

$$RatVolD_t = \alpha + \beta_1 GDP_t + \beta_2 YieldSlope_t + \beta_3 CreditSpread_t + \\ + \beta_4 VIX_t + \beta_5 ADS_t + \varepsilon_t \qquad (8)$$

We account for the presence of multicollinearity between the business variables in use, by performing the required specification test (Appendix - E).

As we want to get BLUE (Best Linear Unbiased Estimators) estimators, we test the regression for the presence of heteroskedasticity and autocorrelation, as the presence of one of these conditions will indicate we are not in the presence of BLUE estimators.

To resolve the issue that these two conditions may present, the OLS estimators retrieved followed the Newey-West standard error method (4 lags), as this is a robust estimator when there is presence of heteroskedasticity and autocorrelation. By doing so, we may obtain the most efficient model to study the relation between the dependent and independent variables. The regression was carried out from 1997Q1 to 2021Q4, and its results are further discussed during the next chapter.

CHAPTER 5

Results

5.1 Rating Volatility

Being that the purpose of this study is to have a broader understanding of the process of credit rating agencies, their behavior, and consequential outcomes, we gathered individual rating information and subsequently summarized said data into one time series for S&P. As the authors that proposed this measure defend, and unlike most studies that wish to explore the cross-section of CRAs' updates, RatVol targets the overall effect of credit rating changes, as our purpose is to understand the rationale behind CRAs ways of acting.

Table 2, below presented, shows an overview of the time-series elaborated for S&P, for both the totality of the period (1994-2021) and for the portion of added contribution that this study provides

Table 2: Descriptive statistics

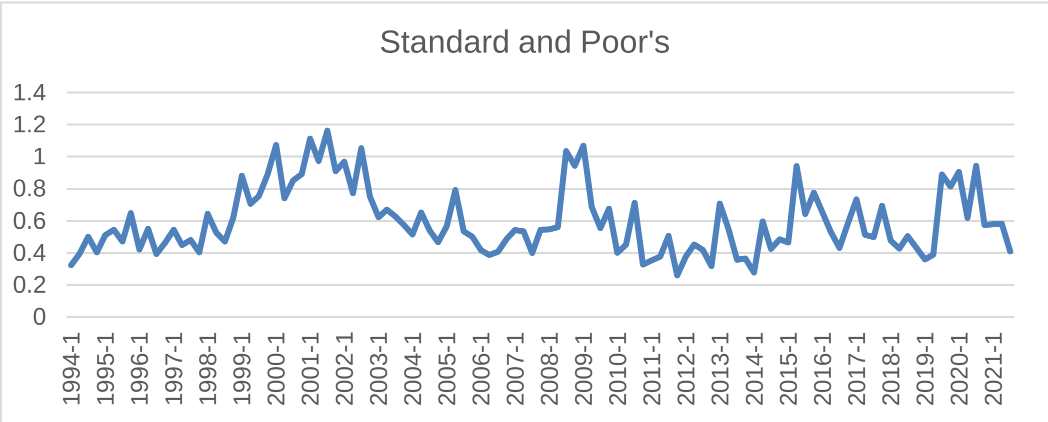
This table summarizes the statistics for the time series of CRA's ratings issuance. There is a separation between the total period and the period that corresponds to this study's contribution.

	Mean	Std. Dev.	Min	Median	Max
Total period (1994Q1-2021Q4)					
Average rating level	11.8299	0.3954	11.0151	11.8468	12.6497
Volatility of ratings (RatVol)	0.5959	0.2060	0.2591	0.5442	1.1626
Vol. from upgrades (RatVolU)	0.2923	0.1286	0.0709	0.2763	0.7099
Vol. from downgrades (RatVolD)	0.4915	0.2330	0.1251	0.4419	1.1339
(2012Q1-2021Q4)					
Average rating level	11.7710	0.1965	11.2735	11.7661	12.173
Volatility of ratings (RatVol)	0.5562	0.1776	0.2769	0.5130	0.9431
Vol. from upgrades (RatVolU)	0.3156	0.1556	0.0709	0.2842	0.7099
Vol. from downgrades (RatVolD)	0.4274	0.1875	0.1637	0.3873	0.8913

Compared with Paulo et al.'s findings, that studied the measure's evolution between 1994 and 2011, the time-series mean of RatVol we got is similar, but lower, being approximately 0.6. This decrease is easily understanded by the lower value of the RatVol's mean for the subsequent period (2012-2021), where we can also understand that the volatility of upgrades (RatVolU) was more impactful - RatVolU presents bigger values across the board. The minimum value for the total period of RatVol was 0.2591 (2011-4) and the maximum value corresponds to 1.16 (2001-3). For the period of 2012Q1-2021Q4 the minimum was 0.28 (2014-1) and the maximum 0.9431 (2020-3) As we can see, for the latest period in analysis, the variation of this measure through time has been less considerable, nonetheless, there are still notable points of instability throughout, as we will further dissect below.

Figure 1: Ratings' Volatility

This figure displays RatVol, focusing on the volatility of the ratings issued by Standard and Poor's, for the periods between 1994Q1 and 2021Q4. This measure is defined above in (2)



Through the observation of Fig 1, there are 4 moments that are specially characterized by instability in ratings: 2000-2 (average: 0.9383; max: 1.1626) , 2008-2009 (average: 0.7235; max: 1.0679), 2015-16 (average: 0.6402; max: 0.8405) and 2020 (average: 0.7903; max: 0.9431). The obvious cases of the early 2000s recession, followed by the financial crisis of 2008 are now coupled with the cases of 2016, and the most recent health/financial crisis of 2020. This clearly showcases the highly volatile nature of credit changes, and its connection to the business cycle variations.

Unfavorable macroeconomic conditions seem to result in the immediate trigger to issue new ratings, but if rating agencies operate based on long-term performance, as previously stated, there shouldn't be such a clear overreaction, as they are supposed to be more unsensitive to the business cycle. As Amato and Furfine (2004) elude, "ratings need not to reflect an absolute measure of default risk, but are rather intended to be ordinal rankings of risk across a class of bonds or firms at a particular point in time".

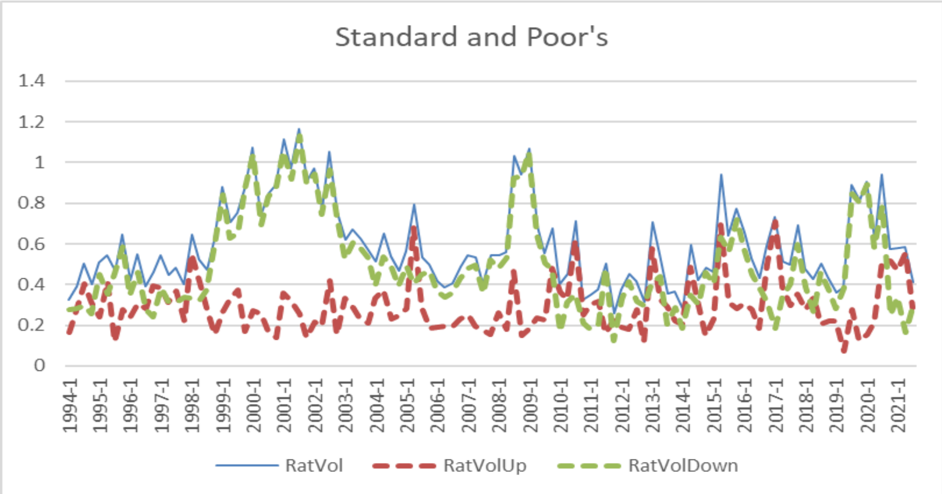
By seeing the evident relation between the volatility of ratings and the changes in the macroeconomic scope, one can argue that CRAs are targeting an absolute level of credit risk, rather than providing a fair assessment of relative credit risk of issuers and individual debt issues.

5.2 Volatilities related to rating downgrades and rating upgrades

Focusing now on the individual contribution of each of these elements, Figure 2, showcased below, enables us to visually comprehend the evolution of these two measures for the period in analysis.

Figure 2: RatVolU/RatVolD

RatVolU corresponds to the volatility explained by upgrades, defined in (4), whereas RatVolD is the volatility due to downgrades, represented in (5)



As periods of greater economic stability account for lower levels of volatility, during these times the total weight of the measure is shared by downgrades and upgrades. The same reasoning is not applied, expectingly so, for unfavorable times, as the large portion of ratings' volatility is due to the massive downgrading, easily observable.

For the cases of volatility that stand out, only for the case of the years 2015-16 does the weight of downgrades and upgrades seems to be shared, but there seems to be a panic response from agencies towards the end of 2015, that continued throughout the year of 2016. The measure was at its peak during the second quarter of 2015 (RatVol = 0.9405; RatVolU = 0.69; RatVolD = 0.63), but by the end of the year downgrades took over for most of the rating changes, which was the trend throughout the year of 2016. What follows further corroborates our disbelief of the through-the-cycle methodology, since we can observe that after a period of slower growth (2016), marked predominantly by downgrades, we observe a drastic change of events on 2017. During this year, marked by more favorable market conditions, with higher levels of GDP growth, and economic growth in general, upgrades take over, accounting for almost all the explanatory power for the volatility of ratings.

There seems to be a link between short-term business cycle variations and the intensity with which volatility of upgrades and downgrades are present. The fact of the matter is that CRAs defend that short-term performance, either positive or negative, shouldn't be reason to attribute higher or lower ratings to companies, hence their supposedly through-the-cycle methodology. Our findings are not in line with this logic, the sensitivity to the market variations displayed by CRAs is alarming, they should not behave like other market agents. Their role is to promote stability and not to intensify the uncertainty already present in the market.

As for the case of 2020, according to IOSCO (International Organization of Securities Commission), non-financial corporations (NFCs) "experienced a high number of downgrades due to the pandemic's substantial effect on already vulnerable corporate sectors". It's observable that the downgrading trend had already begun during the later stages of 2019, nonetheless, during 2020 there was still a high level of volatility displayed throughout the year, mainly due to downgrades.

5.3 Multiple Linear Regression Analysis

Table 3, showcased below, illustrates the results obtained by performing the regressions, which verify our previous findings that CRAs behave differently when facing different business cycle variables.

Table 3 - Regression

The table below contains the OLS estimates for the regressions defined in (6), (7) and (8), for the period of 1997Q1 to 2021Q4. Values in parenthesis are t-ratios. Stars account for the level of statistical significance, with the following rules: 10% (*), 5% (**), 1% (***)

	RatVol		RatVolD		RatVolU	
Constant	0.38	(6.97)	0.26	(4.76)	0.29	(7.35)
GDP	0.07	(4.07)	0.07	(4.72)	0.02	(1.12)
YieldSlope	-0.05*	(1.72)	-0.1**	(-2.54)	0.05***	(2.61)
CreditSpread	0.04	(0.69)	0.11	(1.49)	-0.08***	(-2.78)
VIX	0.01***	(2.63)	0.01**	(2.02)	0	(0.81)
ADS	-0.1**	(-2.52)	-0.12***	(-3.04)	0	(-0.03)
R-squared	0.3169		0.41		0.14	
Adjusted R-squared	0.2802		0.38		0.1	
F-statistic	8.63		12.76		3.2	

For RatVol the independent variables statistically significant were the Yield Slope, VIX and ADS, and the explanatory power of the model reached a level of approximately 32%. When the market's expectation for volatility increases (VIX), RatVol increases as well, and when business conditions for the US economy suffer a decrease (ADS), the measure seems to be positively influenced. In the presence of unfavorable market conditions the number of rating changes increases. As for GDP, surprisingly, we found a positive relation, contrarily to the findings of Carvalho et al. (2014). This can be the result of the different response conducted by CRAs in the period we added to the analysis. As the rating agencies suffered severe reputational damage during the 2008 financial crisis, where they were accused of aggravating the situation with their optimistic ratings, for the subsequent period they seem to play a game of anticipation. This was observable for the period of 2016, when economic growth was less visible, but GDP, even if on a smaller scale, was still growing, they proceeded to implement downgrades in a timely and heavily manner.

RatVolD, the measure that accounts for the volatility of downgrades, is clearly the most tied to the business cycle variations, as the regression performed for this component has the biggest explanatory power (r-square is 41%). The F-Statistic is also high, which means that there is a good relationship between the explanation of RatVolD and the business cycle variations. Which means that CRAs downgrade more when facing adverse business conditions – when volatility is expected to increase in the market (VIX), and the US market condition are expected to deteriorate (ADS), volatility of downgrades increases. This is not surprising, as we observed that the periods of crisis were heavily marked by massive downgrading from CRAs.

RatVolU, on the other hand, seems to be unrelated to the business cycle, the explanatory power of the model is quite lower (14%), and the only coefficients statistically significant are the Yield Slope and Credit Spread. Meaning that worse market conditions influence downgrading, but the opposite does not imply the observation of an increase in the intensity of upgrades.

CHAPTER 5

Conclusion

The purpose of this dissertation is to challenge the methodology that CRAs claim to apply in their assessments, which are supposed to be independent opinions of credit risk regarding a given entity or certain debt issue. These assessments are supposed to be forward looking, focusing on the long-term performance, as this is a way of promoting stability. The power they hold in financial markets has been clear throughout the years, which invites scrutiny as to the legitimacy of their business model.

By analyzing a set of data from 1994 to 2021, our empirical body of work is focused on a measure of ratings stability, previously introduced by Carvalho et al. (2014), from where can summarize the information presented in a transition matrix into a single number. This measure, RatVol, allowed us to understand the intensity with which S&P, the CRA responsible for the biggest issuance of credit ratings, changes their ratings across time. Unlike other authors that focused on the tradeoff between accuracy and stability, we only explored the stability component of rating changes, it could be interesting for future work to explore RatVol's unique characteristics and explore the relationship between these two components.

Our purpose was to study the behavior of rating changes of the two most important agencies (S&P and Moody's) and compare the results found for each of them. This would enable us to understand if their approach has been similar and would allow us to arrive at more meaningful conclusions, as the inclusion of Moody's would enrich our study. This was not possible because of data limitations; we weren't able to retrieve data that enabled us to have a consistent empirical study, as there was a big asymmetry between the first and second sets of data for this agency. Despite this fact, we were still able to retrieve rating changes for S&P, which is responsible for the biggest number of ratings issued.

With our findings, we are able to understand that rating changes have a connection with the business cycle variations, which goes against the agencies' claims of a through-the-cycle approach, supposed to have a level of unsensitivity to the business cycle. Times of adverse economic conditions yield larger levels of volatility in rating changes, as the authors of the measure proved. Our findings, with the addition of rating changes from 2012 to 2021, further confirm the unstable nature of rating changes. Although our period is mainly composed of economic stability, where levels of volatility are under control, and the weight between downgrades and upgrades is shared, two periods stand out in our contribution. Lower levels of economic growth occurred by the end of 2015 and as a result we observe the agencies were fast to start downgrading more frequently, which was followed by a period dominated by upgrades by the end of 2016, when the economy was rebounding.

Agencies seem to have been affected by the reputational damage suffered during the 2008 crisis, as our data indicates that they seem to be targeting an absolute level of credit risk, with a wider concern for short-term performance than what is expected of them. The other period that is relevant to highlight is the COVID-19 pandemic, which caused great damage to the global economy. From our evidence, there is another clear episode of instability in ratings tied to business cycle variations.

Credit rating agencies seem to be playing more of an anticipation game, after the reputational damages they have been suffering through history (the 2008 being a very impactful one), they seem to be focusing more and more on short-term performance, triggering downgrades at a fast pace whenever unfavorable business conditions are present. The results of the regressions we performed also indicate this, as we found that the overall increase in volatility in the markets and the presence of worse market conditions are responsible for the increase in the volatility in rating changes. We also found that volatility of downgrades is associated with business cycle variations, but the same does not apply to the volatility of upgrades .

It is possible to affirm that there is more to the ratings' methodology than agencies wish to signal, but they certainly seem to be biased to the variations in the conditions of the economy.

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Appendix

A. Scale used to compute the measure

Grade	S&P	Numerical Scale
Investment Grade	AAA	1
	AA+	2
	AA	3
	AA-	4
	A+	5
	A	6
	A-	7
	BBB+	8
	BBB	9
	BBB-	10
Non-investment grade	BB+	11
	BB	12
	BB-	13
	B+	14
	B	15
	B-	16
	CCC+	17
	CCC	18
	CCC-	19
	CC	20
	C	21
	SD	22
	RD	22
	D	22

B. RatVol Regression

X1: GDP; X2: Yield Slope; X3: Credit Spread; X4: VIX; X5: ADS

```
Call:
lm(formula = Y ~ X1 + X2 + X3 + X4 + X5, data = thesis)

Residuals:
    Min       1Q   Median       3Q      Max
-0.43637 -0.11991 -0.02005  0.09155  0.48557

Coefficients:
             Estimate Standardized Std. Error t value Pr(>|t|)
(Intercept)0.383109    NA        0.059307  6.460  4.74e-09 ***
X1          0.073346    0.460578   0.022569   3.250  0.00161 **
X2         -0.053599   -0.228779   0.026707  -2.007  0.04766 *
X3          0.042888    0.135006   0.047400   0.905  0.36790
X4          0.008301    0.298173   0.003376   2.459  0.01580 *
X5         -0.109285   -0.496536   0.033565  -3.256  0.00158 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.179 on 93 degrees of freedom
Multiple R-squared:  0.3169,    Adjusted R-squared:  0.2802
F-statistic: 8.628 on 5 and 93 DF,  p-value: 9.537e-07
```

NEWEY-WEST STANDARD ERRORS WITH 4 LAGS

```
> coeftest(reg1, df=Inf, vcov=NeweyWest(reg1, lag=4, prewhite=FALSE))


z test of coefficients:

            Estimate Std. Error z value  Pr(>|z|)
(Intercept) 0.3831094  0.0549538  6.9715 3.136e-12 ***
X1          0.0733464  0.0180035  4.0740 4.621e-05 ***
X2         -0.0535987  0.0309871 -1.7297  0.083682 .
X3          0.0428879  0.0617213  0.6949  0.487140
X4          0.0083008  0.0031555  2.6306  0.008523 **
X5         -0.1092852  0.0433634 -2.5202  0.011728 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

C. RatVolD Regression

D1: GDP; D2: Yield Slope; D3: Credit Spread; D4: VIX; D5: ADS

```
Call:
lm(formula = Q ~ D1 + D2 + D3 + D4 + D5, data = ratd)

Residuals:
    Min       1Q   Median       3Q      Max
-0.49868 -0.13962 -0.02406  0.12767  0.53611

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.259074   0.062635  4.136 7.74e-05 ***
D1          0.073191   0.023835   3.071 0.002799 **
D2         -0.101054   0.028205  -3.583 0.000543 ***
D3          0.114688   0.050059   2.291 0.024219 *
D4          0.007522   0.003566   2.110 0.037587 *
D5         -0.120053   0.035448  -3.387 0.001038 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1891 on 93 degrees of freedom
Multiple R-squared:  0.407,      Adjusted R-squared:  0.3751
F-statistic: 12.76 on 5 and 93 DF,  p-value: 1.895e-09
```

NEWEY-WEST STANDARD ERRORS WITH 4 LAGS

```
> coeftest(reg5, df=Inf, vcov=NeweyWest(reg5, lag=4, prewhite=FALSE))

z test of coefficients:

             Estimate Std. Error z value  Pr(>|z|)
(Intercept)
B            0.2590741  0.0543146  4.7699 1.843e-06 ***
D1           0.0731912  0.0154963  4.7231 2.322e-06 ***
D2          -0.1010539  0.0398245 -2.5375   0.01117 *
D3           0.1146884  0.0767715  1.4939   0.13520
D4           0.0075216  0.0037172  2.0235   0.04302 *
D5          -0.1200527  0.0394317 -3.0446   0.00233 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

D. RatVolU Regression

U1: GDP; U2: Yield Slope; U3: Credit Spread; U4: VIX; U5: ADS

```
Call:
lm(formula = W ~ U1 + U2 + U3 + U4 + U5, data = ratu)

Residuals:
     Min       1Q   Median       3Q      Max
-0.20114 -0.08078 -0.02132  0.05154  0.40949

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.2920535  0.0417178   7.001  3.9e-10 ***
U1          0.0161417  0.0158751   1.017   0.3119
U2          0.0525119  0.0187860   2.795   0.0063 **
U3         -0.0851330  0.0333418  -2.553   0.0123 *
U4          0.0017727  0.0023748   0.746   0.4573
U5         -0.0007698  0.0236098  -0.033   0.9741
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1259 on 93 degrees of freedom
Multiple R-squared:  0.147,	Adjusted R-squared:  0.1011
F-statistic: 3.205 on 5 and 93 DF,  p-value: 0.01029
```

NEWEY-WEST STANDARD ERRORS WITH 4 LAGS

```
> coeftest(reg3, df=Inf, vcov=NeweyWest(reg3, lag=4, prewhite=FALSE

z test of coefficients:

              Estimate  Std. Error z value  Pr(>|z|)
 (Intercept)0.29205349  0.03973769  7.3495 1.989e-13 ***
U1          0.01614168  0.01415046  1.1407  0.253988
U2          0.05251195  0.02011342  2.6108  0.009033 **
U3         -0.08513298  0.03058369 -2.7836  0.005376 **
U4          0.00177273  0.00219886  0.8062  0.420126
U5         -0.00076983  0.02633647 -0.0292  0.976681
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

E. Multicollinearity test

```
> mctest(reg1, all = T, type = "i")

Call:
imcdiag(mod = mod, method = method, corr = FALSE, vif = vif,
    tol = tol, conf = conf, cvif = cvif, ind1 = ind1, ind2 = ind2,
    leamer = leamer, all = all)


All Individual Multicollinearity Diagnostics in 0 or 1

   VIF TOL Wi Fi Leamer CVIF Klein IND1 IND2
X1   0   0  1  1      0    0     1    1    0
X2   0   0  1  1      0    0     1    0    0
X3   0   0  1  1      0    0     1    1    0
X4   0   0  1  1      0    0     1    0    0
X5   0   0  1  1      0    0     1    1    0

1 --> COLLINEARITY is detected by the test
0 --> COLLINEARITY is not detected by the test

X3 , coefficient(s) are non-significant may be due to multicollinearity

R-square of y on all x: 0.3169
```