Eric Guangcheng Hua, Jesper Thuestad Jacobsen

# Stability and Accuracy of Credit Ratings

## Examining the stability and accuracy of Nordic credit ratings with relation to the business cycle

Master's thesis in Industrial Economics and Technology Management
Supervisor: Petter Eilif de Lange
June 2020

**Master's thesis**

**NTNU**
Norwegian University of Science and Technology
Faculty of Economics and Management
Dept. of Industrial Economics and Technology Management

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# Abstract

This master's thesis examines the stability and accuracy of credit ratings from two Norwegian savings banks and a Nordic Credit Rating Agency (CRA) called Nordic Credit Rating (NCR). We utilize recently developed measures for rating stability that compress the information present in traditional transition matrices into a single scalar for each time period. Despite a wish from investors for ratings to be stable and independent of the business cycle, we find contradictory evidence from the banks. The intensity of their rating changes - both upgrades and downgrades - vary over time and according to the business cycle. In particular, we observe a higher intensity of both upgrades and downgrades in worse economic times, so-called troughs, for one bank (Bank A). The other bank (Bank B) appears to have overall rating volatility and upgrades that are inversely related to the business cycle. This is inconsistent with CRAs' claim that ratings are a relative ranking of firms and largely independent of the business cycle. Characterizing their methodology as through-the-cycle is thus problematic. Surprisingly, the accuracy of credit ratings show contrasting dependency on the business cycle for the banks. Whereas one bank (Bank A) appears to have higher accuracy in periods of higher economic growth, the other bank (Bank B) appears to have lower accuracy during such times. We do not find evidence that higher ratings volatility leads to higher ratings accuracy. In fact, *lower* volatility appears to be associated with higher ratings accuracy. As anticipated, the data from NCR is generally insufficient to draw any meaningful conclusions regarding the relationships between stability and the state of the business cycle.

# Preface

This master's thesis is conducted by Eric Guangcheng Hua and Jesper Thuestad Jacobsen as part of achieving a Master of Science degree at the Norwegian University of Science and Technology (NTNU) in Trondheim. The field of specialization is in Finance at the Department of Industrial Economics and Technology Management. The work is an extension of our previous paper and, therefore, builds on our previous work. In particular, we implement several *additional* methods in this paper, including OLS multiple regressions with accompanying variance inflation factors (VIF), as well as Ridge, Lasso and Elastic Net regressions. We also include several additional proxies for the business cycle to improve our models. Finally, we perform all these and previous analyses on an additional data set from a bank in a different region, and compare our results. We would like to thank our supervisor, Assosicate Professor Petter Eilif de Lange, with stimulating and valuable guidance, support and continuous feedback throughout the whole semester, despite the worldwide coronavirus pandemic and global financial downturn. We also appreciate his crucial assistance in acquiring necessary data so we could perform our desired analyses. We would also like to extend our gratitude to Professor Alexei A. Gaivoronski.

Trondheim, June 5th, 2020

Eric Guangcheng Hua　　Jesper Thuestad Jacobsen

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# Acronyms & Abbreviations

| | | |
|---|---|---|
| AR | = | Accuracy Ratio |
| CAP | = | Cumulative Accuracy Profile |
| CRA | = | Credit Rating Agency |
| GDP | = | Gross Domestic Product |
| LRC | = | Large Rating Changes |
| NCR | = | Nordic Credit Ratings |
| RR | = | Rating Reversals |
| VIF | = | Variance Inflation Factor |
| VIX | = | Volatility Index |

# Chapter 1

# Introduction

Credit rating agencies (CRAs) specialize in the task of evaluating the creditworthiness of an obligor, thereby helping investors and banks in assessing the riskiness of issuers and their securities [22]. These agencies are confronted with a difficult trade-off dilemma when assigning credit ratings. On the one hand, they are expected by relevant stakeholders to deliver as accurate estimates of default risks as possible, at a particular point in time. On the other hand, certain stakeholders expect stable ratings that do not change in the short term to match the stakeholders' own decision-making horizons.

Originally, credit ratings were designed for long-term investors. These buy-and-hold type investors were less concerned with short-run and temporary changes in risk profiles that did not have a considerable impact on the probability of default of a company. Therefore, credit ratings were assigned "through the cycle" based on fundamental data. Today, the approach most CRAs use is still based on this principle, and the majority of agencies claim that their ratings are through-the-cycle and thus should be immune to short-run changes in the business cycle, as noted by Amato and Furfine (2004) [2]. However, some studies claim that this might not be the case, particularly for U.S. firms (Lobo, Paugam, Stolowy, and Astolfi (2017) [15]). It is, therefore, of interest to investigate these contradicting results using credit rating data from Europe. By analyzing whether there is evidence of a trade-off for higher accuracy in exchange for lower stability over time, we can examine the claim that ratings are procyclical - i.e., that short-lived economic changes, such as high or low GDP growth, affect credit ratings in a particular direction.

This master's thesis utilizes several statistical methods, some of which were developed by Paulo Carvalho, Paul Laux, and João Pereira (Carvalho, Laux, and Pereira (2014) [9]), for testing the characteristics of credit rating processes. We apply these methods to new ratings data from a different part of the world, namely Northern Europe. Whereas Carvalho et al. (2014) uses data sets from CRAs based in the U.S., we predominantly utilize data sets from two Norwegian savings and loan banks, referred to as Bank A and Bank B. We also use a data set of limited size from Nordic Credit Rating (NCR), an ESMA-registered credit rating agency based in the Nordics. All three data sets span the period 2009-2018.

Our literature study covers mostly solicited ratings to which rating adjustments are made when a CRA determines that a change in the creditworthiness of its rated entities has actually occurred. However, the data from the two banks are snapshots of the year-end credit ratings of their customers, irrespective of changes in their customers' creditworthiness occurring during each year. Our conclusions, therefore, differ slightly from that of previous studies and the same conclusions cannot always be drawn even if the result from a particular analysis is identical. Throughout this paper, we occasionally use the term "CRA" to refer to both traditional credit rating agencies *and* banks responsible for credit assessments. Furthermore, due to the limited size of the NCR data set, our analysis will focus on the larger data sets from the banks unless otherwise explicitly specified.

The aim of this thesis is to quantify and test the stability and accuracy of credit ratings, investigate whether the state of the business cycle influences rating adjustments, and analyze the trade-off between accuracy and stability. We jointly analyze the results from a CRA and two banks with exposure to different industry-specific risks to assess whether this affects their credit rating methodology. At the core of our analysis is a measure for ratings volatility and instability developed by Carvalho et al. (2014) [9]. It condenses the information contained in a two-dimensional transition matrix into a single number for each time period and thus captures both the number of changes as well as the magnitude of rating changes.

First, we calculate transitions matrices, unconditional and conditional, in order to offer insight into probabilities of rating changes of firms. Next, we calculate five different measures of volatility - two traditional measures of credit rating volatility (*Large Ratings Changes* (LRC) and *Rating reversals* (RR)) and the three measures developed by Carvalho et al. ($RatVol$, $RatVolU$, and $RatVolD$). We observe that the trend of rating volatility for the two banks differ in a way that appears to be independent of Norwegian mainland GDP, i.e., independent of the business cycle. Finally, we assess the quality of the ratings by calculating the measure *Accuracy ratio (AR)*.

Recognizing that the state of the business cycle is likely to affect the rate of default, this paper studies the impact of the business cycle on CRAs' credit rating methodologies. We investigate this using two approaches: 1) by analyzing transition matrices conditioned on the business cycle and 2) by performing several linear regressions. Our results from performing univariate and multivariate regressions on rating volatility and the business cycle, seem to be partially consistent with that of Lobo et al. (2017) [15]. For Bank A and Bank B, we find evidence suggesting that credit ratings are indeed dependent on the business cycle and hence not through-the-cycle. On the other hand, we do not find conclusive evidence that NCR does not adhere to a through-the-cycle methodology.

Examining the relationship between accuracy and the state of the business cycle, we find contradicting evidence for the two banks. Whereas Bank B achieves higher accuracy in times of low GDP growth, in line with previous studies such as Bar-Issac and Shapiro (2013) [3], we find evidence for the opposite for Bank A. A possible explanation for the conflicting results is that banks do not face the same potential conflict of interest as CRAs, whose ratings are often paid for by the rated firm. Therefore, banks do not have the same financial incentive as CRAs to be overly optimistic in good times, as this will not generate higher income for these entities.

Cantor and Mann (2006) [7] conclude that investors want stable credit ratings, even though this leads to trade-offs regarding rating accuracy. Therefore, we jointly analyze these two measures - rating stability and rating accuracy. Our results show that rating accuracy is positively correlated with rating stability - i.e., an inverse relationship between accuracy and volatility - for both banks, despite only Bank A yielding statistically significant results. This contradicts our original hypothesis. Our conclusion of a lack of trade-off between stability and accuracy is in agreement with the conclusions of Carvalho et al. (2014) [9].

This thesis seeks to apply new rating volatility measures to Nordic credit ratings. Our work contributes to existing research in several ways. We demonstrate how to determine the way in which different business cycle variables affect rating stability and accuracy. Furthermore, we analyze credit ratings from other financial institutions besides only CRAs, namely banks. Banks have different incentives as compared to CRAs and we thus contribute with new results not seen in previous credit rating studies. Lastly, we implement sophisticated multivariate regression methods, some of which, to our knowledge, are unused in previous credit rating research.

Chapter 2

# Literature Review

Through conversations with investors, issuers and regulators, Cantor and Mann (2006) [7] find that many market participants have a preference for stable and accurate credit ratings. For instance, some users of credit systems base important decisions on credit ratings. Frequent rating changes can thus potentially prove costly for investors who rely on credit ratings for trading decisions. For instance, as a result of portfolio governance rules, credit ratings are often employed in the composition of fixed-income portfolios. Because changes in credit ratings might result in investors incurring rebalancing costs, market participants do not want temporary or minor changes in credit risk of obligors to lead to credit rating adjustments. Thus, credit ratings are expected not to be point-in-time measures of credit risk, but to be through-the-cycle, reflecting credit risk over the long term. Consequently, one would expect credit ratings not to be significantly correlated with the business cycle. It is also reasonable to expect that frequent credit rating adjustments would result in more accurate ratings. However, several studies claim to have found evidence contradicting both of these claims.

The financial system is mostly procyclical. Measures of financial activity, e.g. new bond issuance, bank lending, and equity offering, tend to be more prevalent during booms than downturns (Bernanke et al. (1999) [4]). At the same time, CRAs claim only to adjust credit ratings when permanent changes in the risk profiles of companies occur. Several studies investigate the causes of credit rating changes and whether CRAs have a motive for frequent changes. Carvalho et al. (2014) [9] analyze the motivations for CRAs to modify their ratings by examining the stability and accuracy of credit ratings. They conclude that CRAs have more volatile ratings during bad economic times, which is inconsistent with the claim that ratings are simply a relative measure of obligors' riskiness and thus should be independent of the business cycle. This implies that credit ratings are point-in-time measures rather than through-the-cycle, consistent with the findings of Amato and Furfine (2004) [2], but at least partially contradicting the work of Altman and Rijken (2006) [1]. Amato and Furfine find that cyclical changes to individual businesses and financial risk attributes play a significant role for rating changes, contrary to a through-the-cycle methodology. Furthermore, they find little evidence of procyclicality in U.S. firms en masse. By contrast, they find evidence for procyclicality in *initial ratings* and in *rating changes*. They reason that CRAs rarely change the rating of a particular firm and generally do not adjust ratings based on small movements in the risk profile of firms. However, when they *do* adjust the ratings, they tend to overreact by being overly optimistic during booms and overly pessimistic during downturns. While Amato and Furfine use ratings from 1984 to 2000, Lobo et al. (2017) [15] use a larger data set with ratings from 1984 to 2012. They do find procyclical tendencies in credit ratings, particularly in the latest period. Lobo et al. contribute their diverging results to differences in the data sets. They argue that Amato and Furfine look at credit ratings during a period with lower economic and market fluctuations and that evidence for procyclicality is only found when including the additional 12 years of credit ratings. If the evidence provided by Carvalho et al. and Amato and Furfine is correct, the riskiness of issuers and bonds today cannot be directly compared to issuers and debt instruments which have been rated similarly in the past, as noted by Cantor and Mann (2003) [8].

The variation in the accuracy of credit ratings over time suggests a dependency on the business cycle. In an influential theoretical paper, Bar-Issac et al. (2013) [3] find that credit rating quality is countercyclical, i.e., moving in the opposite direction to that of the overall state of the economy. They reason that CRAs have incentives to improve their reputation, i.e., accuracy, in bad times when analyst labor is cheap and rating mistakes are less likely to be noticed, in order to increase their income in better times when labor is scarcer and fewer firms default. The same conclusion is reached by Bolton, Freixas, and Shapiro (2012) [5]. They suggest that, due to the conflict of interest for CRAs, they have a tendency to understate risk to attract new business during recessions, leading to rating bias. This, in addition to decreased due diligence in such periods, is a possible reason for decreased ratings accuracy in economic downturns. Erel, Julio, Kim, and Weisbach (2012) [13] find evidence that appears to substantiate the conclusions of Bolton et al. when examining the relationship between credit ratings, the business cycle and the raising of capital. Their results suggest that a borrower's credit quality is a significant factor in its ability to raise capital during macroeconomic downturns. Particularly, they find that sub-investment grade firms appear to be shut out of the public capital markets during poor economic conditions. As a result, it is likely that companies perform rating shopping, choosing the CRA that gives them the most favorable credit rating. CRAs thus have an incentive to assign too high ratings during good times to attract new business, thus reducing their rating accuracy.

Carvalho et al. (2014) also find indications of this phenomenon. They conclude that higher rating volatility, i.e., more frequent changes, does not lead to higher ratings accuracy. Instead, their results suggest that CRAs modify ratings not to achieve higher accuracy, but to increase revenue. The reasoning behind this claim is the observation of more intense rating adjustments shortly before new issuance in the primary bond market for seemingly no apparent reason. In their view, more frequent changes may lead to a more credible view of a CRA among investors, which in turn may cause new issuers to choose this CRA when purchasing a credit rating.

Although credit ratings primarily are relative risk measures distinguishing the credit risk of a company from peers in other rating categories, they can also be used to directly estimate the probability of default. By analyzing the frequency of rating changes from a given rating to another, an estimate of the risk associated with different ratings can be obtained. The distribution of such rating changes plays a crucial role in many risk models. By generating both unconditional and conditional transition matrices, Nickell, Perraudin, and Varotto (2000) [20] quantify how rating transition probabilities depend on the industry that the obligors operate in and the state of the business cycle. They find significant differences between the transition probabilities of banks and industrials, and in good and bad economic times - referred to as peaks and troughs. The latter result implies that credit ratings are dependent on the business cycle and thus not a through-the-cycle measure of risk, consistent with the findings of Carvalho et al. (2014), Amato and Furfine (2004) and Lobo et al. (2017).

Chapter 3

# Data

This master's thesis examines the stability and accuracy of credit ratings and attempts to determine how the state of the business cycle influences the frequency and intensity of rating adjustments. In order to perform such an analysis, two types of data are necessary: (1) historical time series data for the credit ratings and (2) several proxies for the business cycle that can be used for measuring the effect that the business cycle has on credit ratings. We further attempt to relate some of our results to the historic Brent crude oil price. We also look at financial indicators, which often are thought to be forward looking indicators of the general economy and the state of the business cycle. This gives us an additional comparative measure for interpreting our results in addition to the different economic variables' exposure to the the petroleum industry.

## 3.1 Credit Ratings

The methods presented in the following section are implemented on three different data sets. Two of the data sets are from large Norwegian savings and loans banks. In this thesis, we will refer to them as Bank A and Bank B. The third data set is from a newly founded Nordic credit rating agency called "Nordic Credit Rating" (NCR). Due to the limited size of the NCR data, not all methods are applied to this data set.

### 3.1.1 Norwegian Bank A

The first data set is provided by a Norwegian savings and loans bank that we refer to as Bank A. The data set includes the bank's own estimated probabilities of default and their corresponding letter ratings for 8,724 Norwegian companies. All rated companies are the bank's own customers - i.e., companies that have loans at the bank. The first ratings were assigned in December 2009 and the final ratings were assigned in late December 2018 and early January 2019, with annual adjustments for as long as the firms remained solvent and remained a customer. Letter ratings range from $A$ to $K$, where $A$ denotes the lowest probability of default and $J$ and $K$ denote companies currently in default. The outstanding debt of companies with rating $K$ has been registered as written off, while the debt of companies with rating $J$ has not been written-off. We also assume that previously rated firms that are not rated in a particular year, have decided to retire their status as customers of the bank.

Figure 3.1 illustrates the distribution of credit ratings over the time period 2009-2018 for Bank A. Except for a slight decrease in the number of ratings from 2010 to 2011 in the aftermath of the financial crisis, the total number of ratings has increased every year in the period. Nevertheless, the percentage distribution among different ratings classes remains approximately the same, as Figure 3.2 demonstrates, with a slight increase in the percentage of ratings in the higher ratings classes $A$ to $G$ towards the end of the period. Figure 3.3 displays a summary of the distribution of credit ratings for the bank over the ten-year period. The majority of companies are assigned a rating between rating $B$ and $G$, whereas very few companies are assigned the highest and lowest ratings, i.e., $A$, $J$, and $K$.

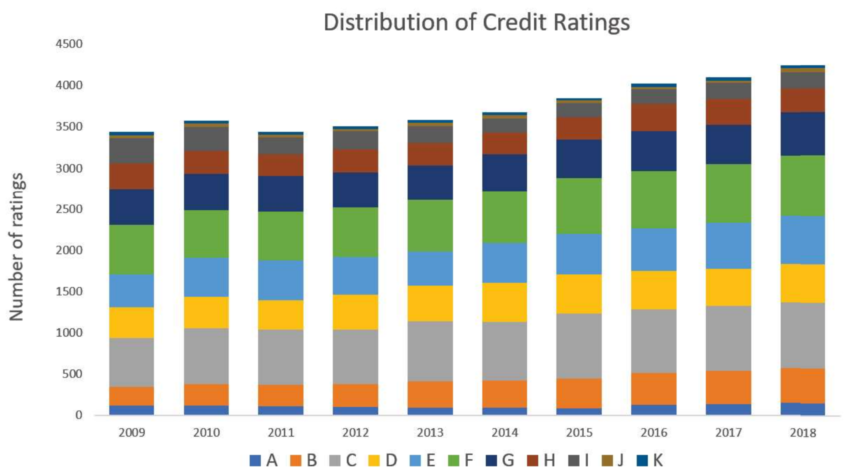


**Figure 3.1:** Distribution of credit ratings in absolute numbers from Bank A during the period 2009-2018.

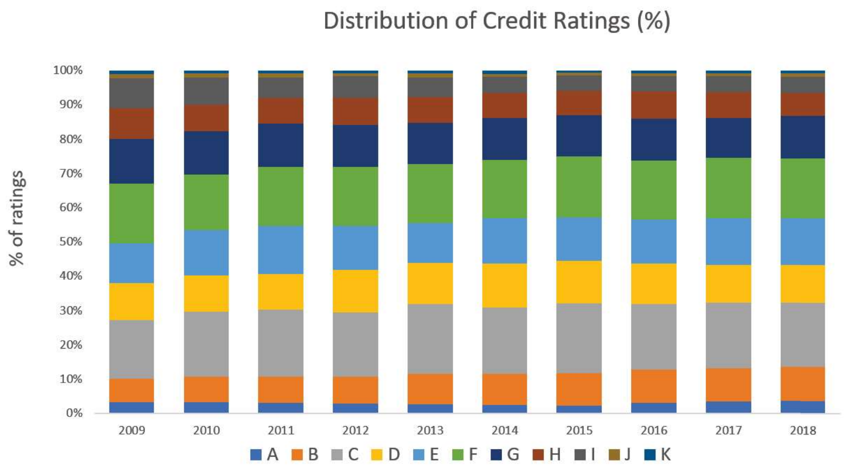


**Figure 3.2:** Percentage distribution of credit ratings assigned each year from Bank A during the period 2009-2018.

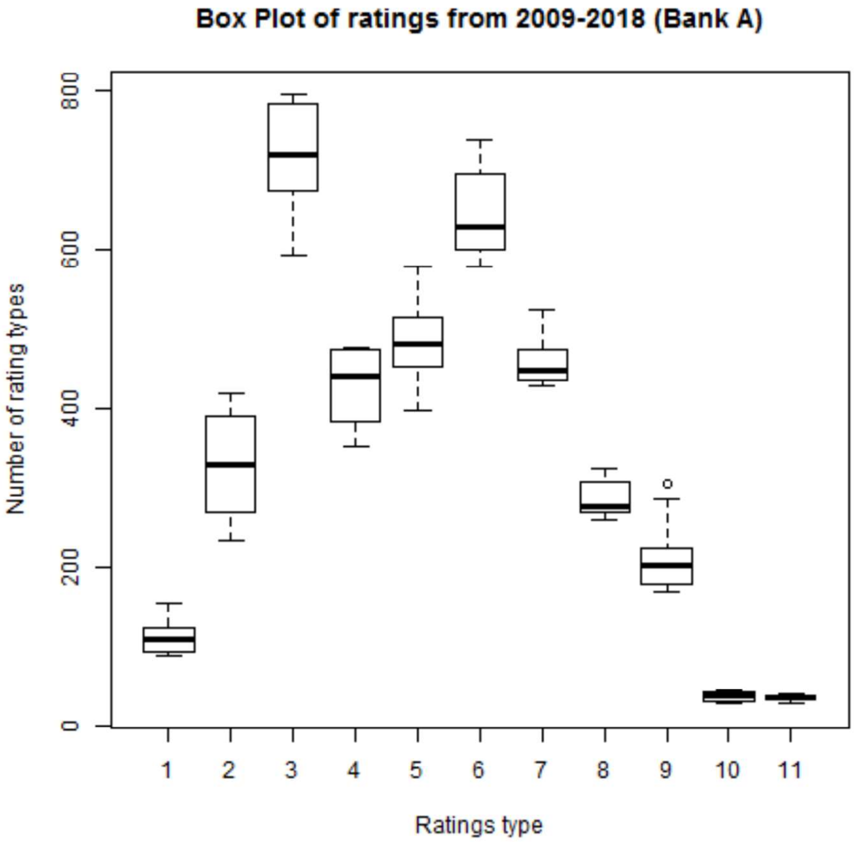


**Figure 3.3:** Box Plot of credit ratings assigned each year from Bank A during the period 2009-2018. A rating of 1 on the x-axis is equivalent to rating $A$ and 11 is equivalent to $K$.

Table 3.1 shows the default frequency and default rates per year for Bank A. Before calculating the statistics, we adjusted the data by registering companies that remained in one of the default states - i.e., are assigned rating $J$ or $K$ - for two or more consecutive years as defaulting the *first* time they were assigned the rating. However, companies that leave the bankruptcy state by being assigned a higher rating and then once more enter bankruptcy will receive a second bankruptcy count. In other words, we don't remove bankrupt companies from the data set altogether, but we adjust the data set to take such occurrences into consideration.

**Table 3.1:** Annual data from Bank A for (1) the number of new default ratings and (2) the default rate as a percentage of total ratings that year.

| | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|---|---|---|---|
| Number of new ratings *J* | 40 | 34 | 24 | 19 | 32 | 28 | 22 | 19 | 21 | 31 |
| Number of new ratings *K* | 39 | 16 | 15 | 15 | 20 | 23 | 13 | 24 | 14 | 14 |
| Total new default | 79 | 50 | 39 | 34 | 52 | 51 | 35 | 43 | 35 | 45 |
| Default rate (J) [%] | 1.16 | 0.95 | 0.70 | 0.54 | 0.89 | 0.76 | 0.57 | 0.47 | 0.51 | 0.73 |
| Default rate (K) [%] | 1.13 | 0.45 | 0.44 | 0.43 | 0.56 | 0.63 | 0.34 | 0.60 | 0.34 | 0.33 |
| Total (J & K) [%] | 2.30 | 1.40 | 1.13 | 0.97 | 1.45 | 1.39 | 0.91 | 1.07 | 0.85 | 1.06 |

### 3.1.2 Norwegian Bank B

The second data set is provided by another Norwegian savings and loans bank, hereafter referred to as Bank B. Its customers are located along the west coast of Norway. The bank is, therefore, heavily invested in the petroleum industry and exposed to the oil price. Their credit ratings are updated at a monthly frequency. However, the ratings used in this thesis were annualized to maintain anonymity. The data set includes the bank's own estimated probabilities of default and their corresponding letter ratings for 5,615 Norwegian companies. All rated companies are the bank's own customers - i.e., companies that have loans at the bank. The first ratings were assigned in 2009 and the final ratings were assigned in 2018, with yearly adjustments for as long as the firms remained solvent and remained a customer. Letter ratings range from $A$ to $N$, where $A$ denotes the lowest probability of default and $M$ and $N$ denote companies currently in default. The outstanding debt of companies with rating $N$ has been registered as written off, while the debt of companies with rating $M$ has not been written-off. We also assume that previously rated firms that are not rated in a particular year, have decided to retire their status as customers of the bank.

Figure 3.4 displays a summary of the distribution of credit ratings for Bank B over the whole ten-year period. Most companies are assigned ratings $B, C, D, E,$ and $F$. Relatively few companies are assigned the highest and lowest ratings, i.e., rating $A$, $J$, and $K$. Figure 3.5 illustrates the distribution of credit ratings over the time period 2009-2018 for Bank B. The total number of ratings has steadily decreased over time, from 2,870 in 2009 to 2,243 in 2018. This decrease is due to customers suspending their relationship with the bank after the exogenous oil price shock in 2014-2015. It is thus likely that some of these companies actually defaulted. However, since they discontinued being customers at the bank, this does not show up in the default rating categories. The percentage distribution among different ratings classes remains approximately the same for the higher rating classes $A$ to $F$ at the beginning of the period as compared to the end. However, as Figure 3.6 demonstrates, there is a slight increase in companies of higher rating classes in the years 2010 to 2014 - years with extraordinarily high oil prices. The share of firms distributed to the lower rating classes $G$ to $N$, however, decreases steadily, making up about 38% of all ratings in 2008 and 21% in 2018.

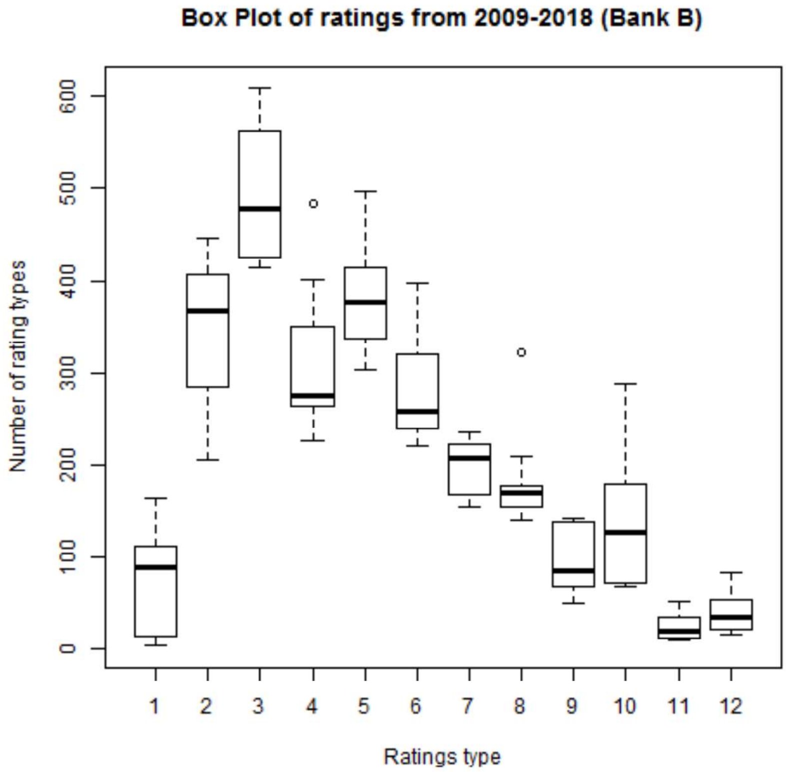


**Figure 3.4:** Box Plot of credit ratings assigned in each year from Bank B during the period 2009-2018. A rating of 1 on the x-ais is equicalent to rating $A$ and 12 is equivalent to $N$.

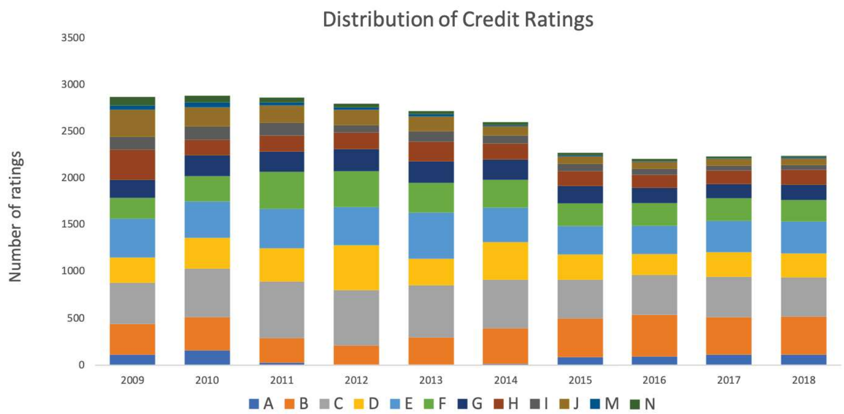


**Figure 3.5:** Distribution of credit ratings in absolute numbers from Bank B during the period 2009-2018.

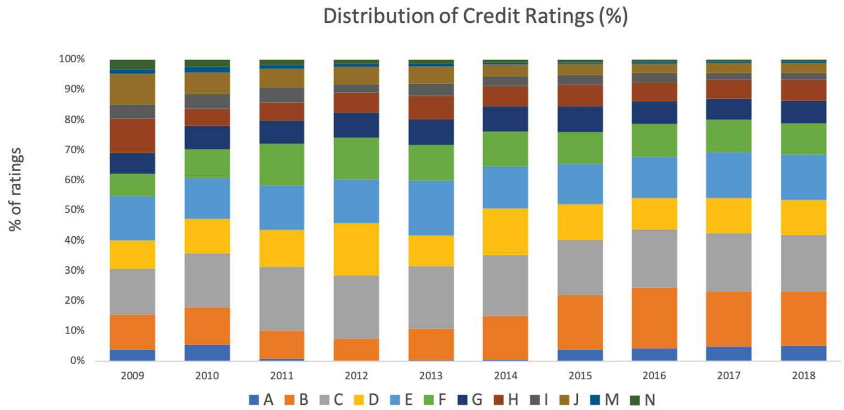


**Figure 3.6:** Percentage distribution of credit ratings assigned each year from Bank B during the period 2009-2018.

Table 3.2 shows the default frequency and default rates per year for Bank B. We repeat the same procedure for Bank B as we did for Bank A. We adjust the data by registering companies that remained in one of the default states - i.e., rating $M$ or $N$ - for two or more consecutive years as defaulting the *first* time they were assigned the rating. Furthermore, we let companies that leave the bankruptcy state by being assigned a higher rating and then once more enter bankruptcy receive a second bankruptcy count. Again, we note that the true default rates are probably higher in the years following 2014 than presented in the table. Due to defaulting firms discontinuing their customer relationship with the bank before being assigned a default rating, this does not appear in the data from the bank - the companies are simply removed from the bank's customer list.

**Table 3.2:** Annual data from Bank B for (1) the number of new default ratings and (2) the default rate as a percentage of total ratings that year.

| | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|---|---|---|---|
| Number of new ratings *M* | 45 | 36 | 16 | 17 | 18 | 11 | 7 | 11 | 10 | 12 |
| Number of new ratings *N* | 93 | 32 | 24 | 22 | 12 | 12 | 11 | 8 | 7 | 6 |
| Total new default | 138 | 68 | 40 | 39 | 30 | 23 | 18 | 19 | 17 | 18 |
| Default rate (M) [%] | 1.62 | 1.28 | 0.57 | 0.62 | 0.67 | 0.43 | 0.31 | 0.50 | 0.45 | 0.54 |
| Default rate (N) [%] | 3.35 | 1.14 | 0.85 | 0.80 | 0.45 | 0.47 | 0.49 | 0.37 | 0.32 | 0.27 |
| Total (M & N) [%] | 4.97 | 2.42 | 1.42 | 1.41 | 1.12 | 0.89 | 0.80 | 0.87 | 0.77 | 0.81 |

### 3.1.3 Nordic Credit Rating (NCR)

The third data set contains credit ratings from the rating agency "Nordic Credit Rating" (NCR). NCR assigns credit ratings to financial institutions and corporate entities based primarily in Denmark, Finland, Iceland, Norway, and Sweden. The data set contains 3,119 credit ratings assessments from 562 different companies, and is adjusted to annual frequency. Letter ratings vary from the lowest probability of default, $AAA$, to the highest probability of default, $C$. A rating $D$ represents companies who have defaulted. There are a total of 20 possible rating states. More information about NCR's credit rating system can be found in Table 6.1 in the Appendix. The rating company uses, like the bank, a 1-year time horizon in their estimates. Unlike the bank, they adjust credit ratings *when necessary* rather than once a year. The data is cleaned such that annual ratings will be the last rating the firms have in each year. This does not reflect rating changes within a year and information that is uniquely held by the CRA might be missed during this type of data cleansing. In spite of this, by using exactly the same format of data, we can compare the results from the rating agency with that of the bank. However, due to the smaller size of this data set, we have omitted certain tests. Also, we only include general descriptive statistics, as shown in Figure 3.7.

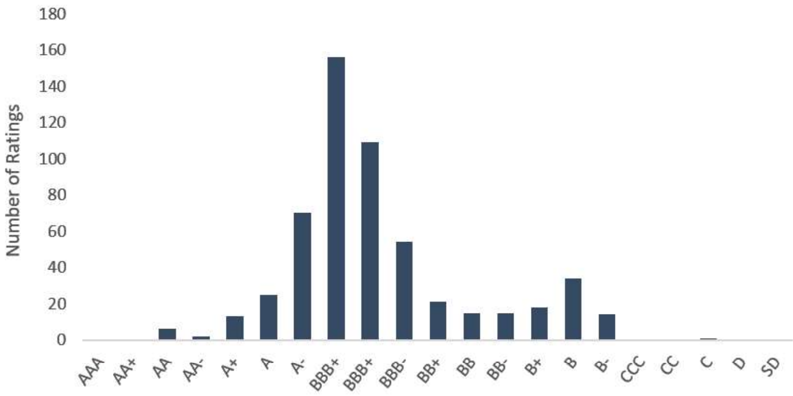


**Figure 3.7:** Distribution of *current* credit ratings from NCR as of September 2019. Note that currently the highest rated company is rated $AA$ and the lowest rated company is rated $C$.

## 3.2 Brent Crude Oil Price

The Norwegian economy is undoubtedly affected by the oil price. This has been confirmed by, among others, the Norwegian Central Bank (2008) [23]. Although some sectors in the Norwegian economy primarily experience increased demand as a result of a higher oil price, other sectors - e.g. the transportation sector - primarily experience higher costs. Nevertheless, the central bank finds that the net effect of a higher oil price is an increase in Norwegian mainland GDP growth in the short term. In order to briefly analyze this effect, we collect annual data from the U.S. Energy Information Administration (EIA) on the European Brent spot price [10]. Note that data on the oil price is not used frequently in this paper and no formal statistical tests are performed on this data set. Still, we refer to the oil price on several occasions and use it as a comparative measure. Figure 3.8 depicts the evolution of the yearly average Brent crude oil price over the period 2009 to 2018. The financial crisis in 2007-2008 throttled demand for oil and gas, sending energy prices sharply downwards. The economic recovery in the following years, however, sent prices soaring back up to over 100 USD/bbl in 2011-2013. The subsequent year, oil prices again declined sharply. This time, the drop in prices was largely due to lower import demand from the US and Canada, combined with a continued high oil production in Saudi Arabia.

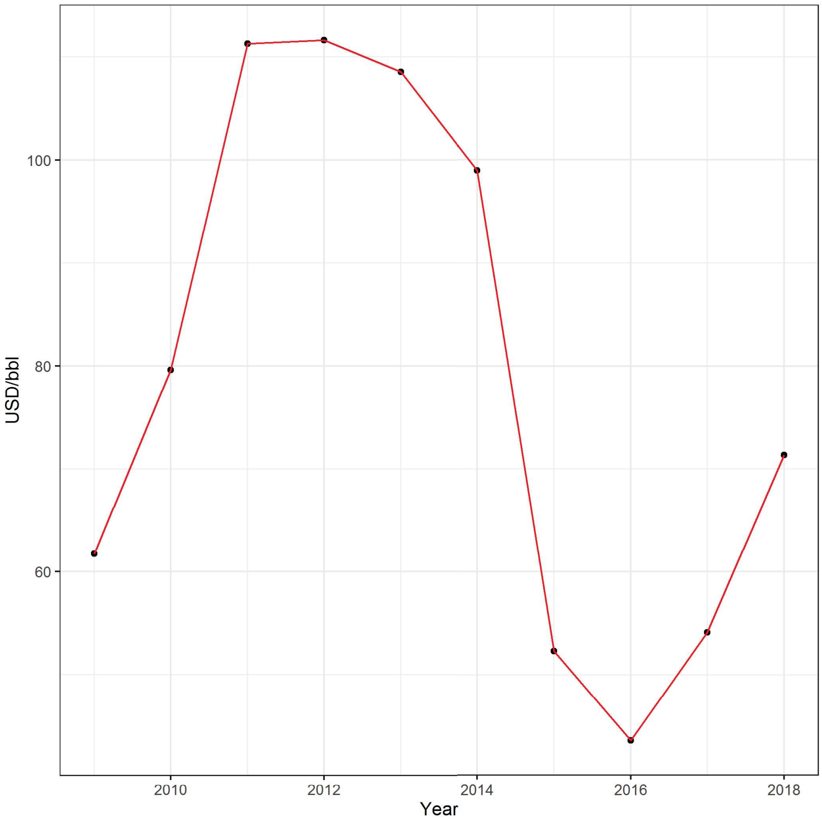


**Figure 3.8:** Europe Brent prices (USD/bbl) from 2009 to 2018. The decline in prices from 2014 to 2016 can explain decline in GDP of Norway in the same period.

## 3.3 Measures of Business Cycle

Financial markets are usually a leading indicator of the business cycle. The reasoning behind this is simple. The overall pattern of the current financial market is well-known to all investors. The future, however, is for obvious reasons uncertain. Consequently, investors attempt to act just before the business cycle turns; they increase their risky positions when they *believe* the business cycle to be at the end of a trough, and they reduce risk right before they *believe* the business cycle to be at a peak, as noted by Calverley (2002) [6]. Real GDP is a macroeconomic measure of economic output - a good indicator for the state of the economy. The change in real GDP is lower (or negative) during troughs and higher during peaks. Empirical studies have shown that financial variables can be leading indicators of recessions (see, e.g., Estrella and Mishkin (1998) [11]). Such variables include, but are not limited to, the yield curve spread and the swap rate. The CBOE Volatility Index (VIX) can also be seen as an indicator for the state of the economy. Since this paper employs credit ratings from banks and not traditional CRAs, we also include the change in the monetary value of new bond issuance and loans as a potential measure of the business cycle. Applying the above reasoning, we wish to examine how CRAs are affected by financial market cycles.

### 3.3.1 Real GDP

As a proxy for the state of the business cycle, many studies use real GDP, as noted by Wong et al. (2016) [28] and Carvalho et al. (2014) [9]. Real GDP provides a relatively good measure because it contains data covering a broad range of economic activity, thereby reflecting the real economic situation in a country. With the purpose of investigating the effect that the state of the business cycle has on credit ratings, we collect data from Statistics Norway [25]. It contains annual real, Mainland GDP in Norway spanning the time period 2009-2018, as depicted in Figure 3.9. However, GDP data consists of two separate components: 1) a long-run trend component and 2) a business cycle component. As our analysis focuses on the state of the business cycle, we are more interested in the business cycle component. Hence, we isolate this component using a Hodrick-Prescott (HP) filter as described later, thereby removing the long-run trend component. The business cycle component, which is equal to the deviation of GDP from its long-run trend, is shown in Figure 3.10. Evidently, the deviation is negative in 2015-2017, showing signs of correlation with the oil price.

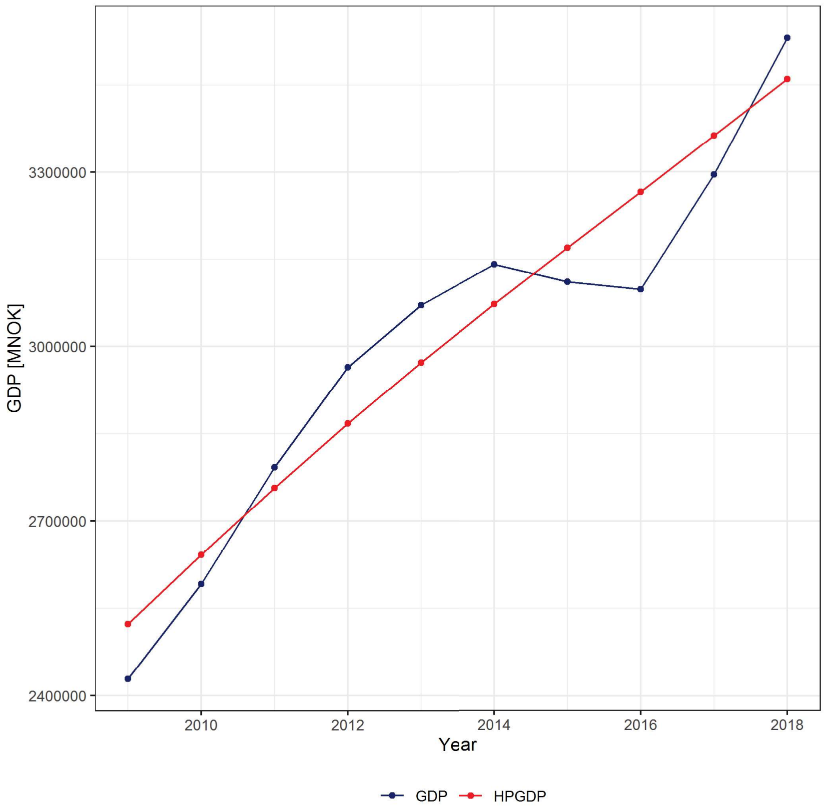


**Figure 3.9:** Real GDP and GDP trend in Norway in the period 2009-2018. There is a decline in GDP from 2014 to 2016, indicating a correlation with the coinciding decline in the oil price.

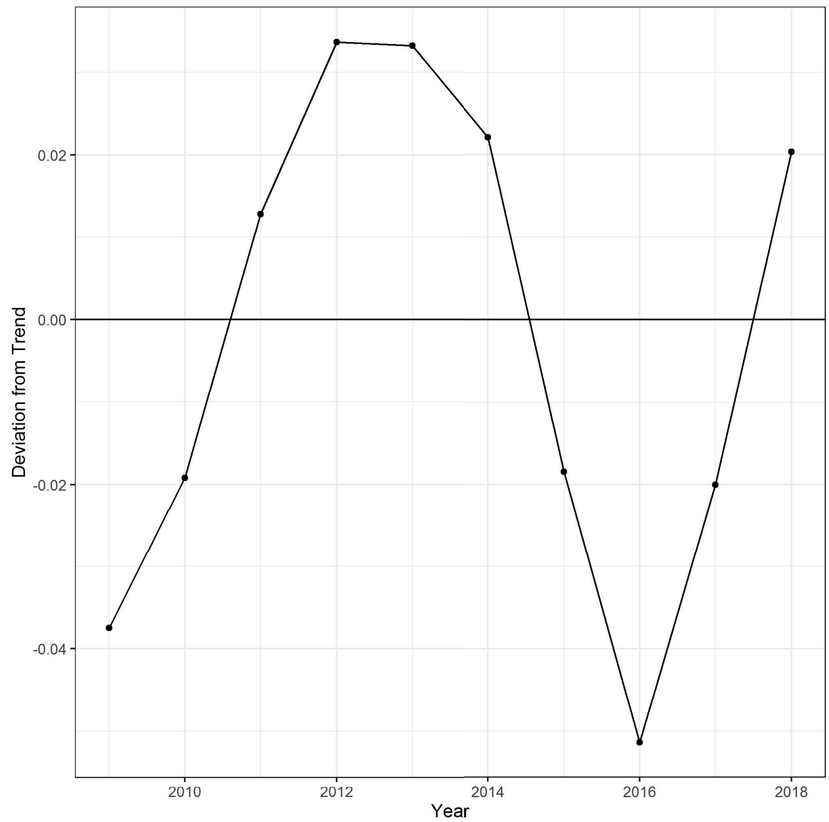


**Figure 3.10:** Deviation of GDP from trend (also known as the business cycle component of GDP) in Norway in the period 2009-2018.

### 3.3.2 Swap rates

As suggested above, the yield curve slope is another potential indication for the condition of the business cycle. In normal times with inflation, the yield curve is positive. This indicates a positive expectation of financial performance in the future and thus increased risk premiums for long-term investments. If the slope is negative - i.e., an inverted yield curve - this could indicate an impending recession. The same rationale applies to the swap rate curve. In other words, prior to recessions, long-term rates can become lower than short-term rates. To model this relationship between long-term and short-term rates, similar studies employing credit data from the United States have considered the difference between 10-year and 2-year U.S Treasury bond yields and analyzed its effect on credit rating adjustments. Our data, however, is collected mostly from Norway. Thanks to high income from petroleum-related activities, the Norwegian government does not rely heavily on debt financing. The low demand for Norwegian treasuries leads to poorer liquidity in these securities. Therefore, for our purposes, Norwegian government bond yields are probably not a good proxy for the ”true” yield curve as they do not reflect the true risk of government debt. Instead, we utilize the difference between swap rates of the same maturities - 10-year maturity minus 2-year maturity, which we collect from Macrobond. The two swap rates are shown in Figure 3.11. Between 2009 and 2020, the swap rates for the shorter maturity has been higher than the longer maturity for the whole period, except for the very last year. Since then, many experts have warned of an impending recession. Next, in order to match the frequency of our credit rating data, we proceed to annualize the swap rate data and calculate the difference between 10-year maturity and 2-year maturity swap rates. The resulting graph is presented in Figure 3.12. There is a clear decreasing trend in the graph, with the swap rate difference narrowing and actually reversing as 2020 approaches. This could reflect declining interbank interest rates set by the central bank of Norway during the energy crisis of 2016.

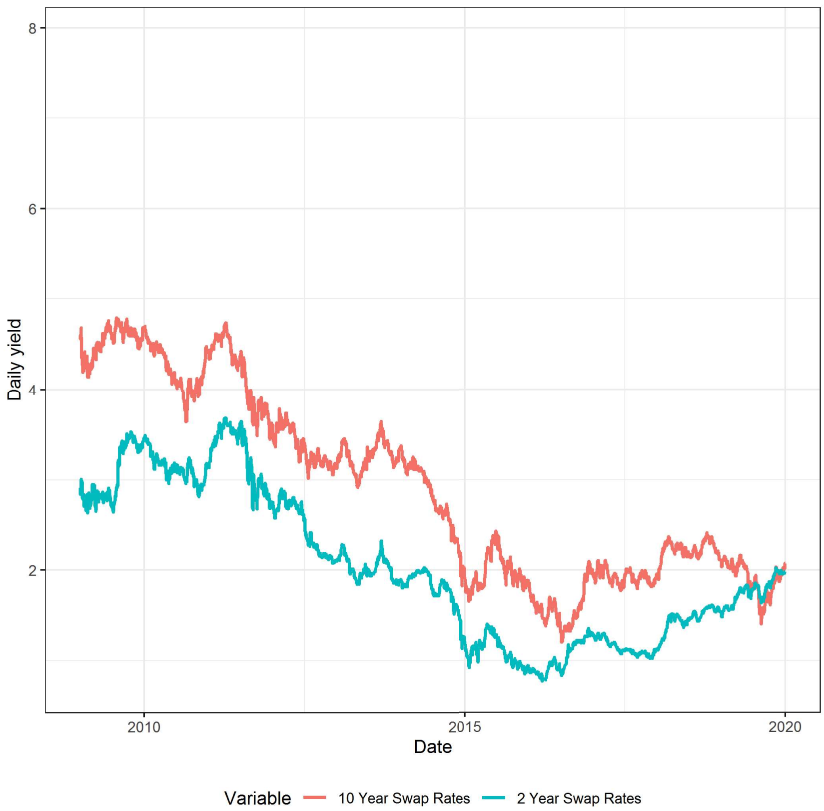


**Figure 3.11:** Daily Swap rates (10 years and 2 years) for the period 2009 - 2019. Except the very last months, swap rates with longer maturity are higher than swap rates with shorter maturity.

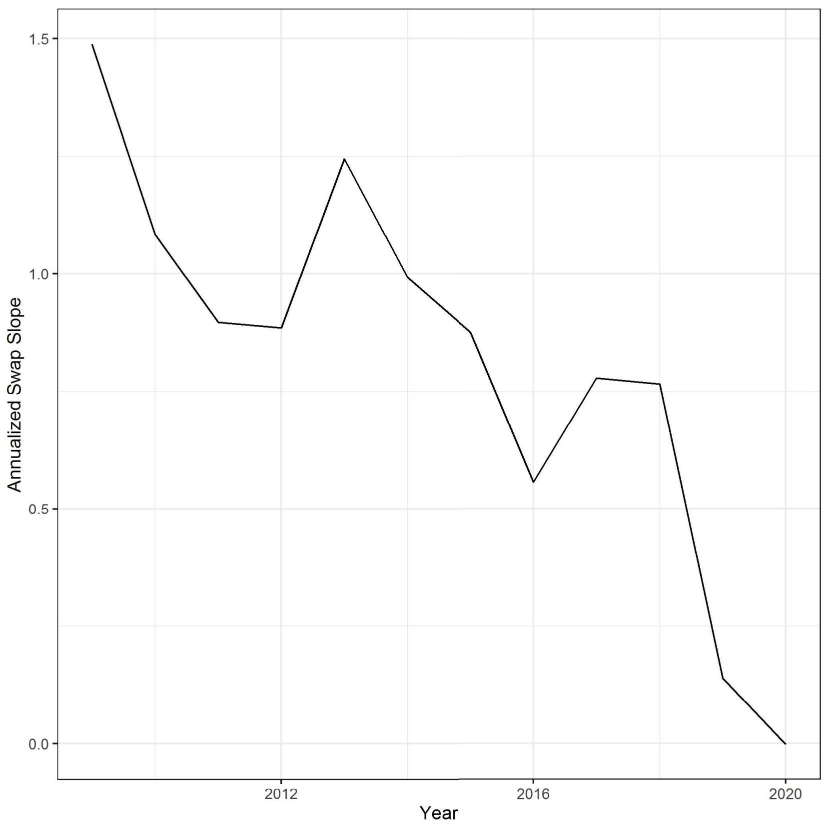


**Figure 3.12:** Annualized values of the difference in Swap rates (10 years - 2 years) for the period 2009 - 2019, referred to as the Swap slope. The Swap slope decreases over the period and reaches its lowest point at the end of the 2019.

### 3.3.3 Volatility Index

As a third indicator for the state of the economy, we need a proxy for economic uncertainty. In times of high or low levels of uncertainty, banks and CRAs could potentially decide to make changes in credit ratings. A possible such proxy could be historical volatility for the Oslo Stock Exchange Index; however, this risk measure does not reflect future expectations. Since it is expectations that are indicative of uncertainty - and not necessarily real volatility, and since historical volatility will not be available to CRAs when assessing credit risks at a particular point in time, the Volatility Index (VIX) is a better proxy than historical volatility. The Volatility Index (VIX), created by the Chicago Board Options Exchange (CBOE), represents the market's expectation of the 30-day forward-looking volatility by calculating the implied volatility based on S&P 500 index options. To our knowledge, there are no good Nordic or European alternatives to the VIX index. Since previous studies have found a significant correlation between Norwegian and US stock indices [16], we conclude that the VIX can be used as a proxy for forward-looking volatility in the Norwegian equity market. We obtain daily VIX data from Macrobond as shown in Figure 3.13. From 2009 until 2020, the VIX peaks at around 53 in 2009 and bottoms at around 9 in 2017. It can be observed from the graph that there are several occasions of high uncertainty in the market. In 2009, the financial crisis caused a record high VIX. The year after, in 2010, there was a sovereign debt crisis in the Eurozone [18] (which is now of course returning), followed by the US debt ceiling crisis in 2011 when Standard & Poor's downgraded the long-term sovereign debt credit rating for US Treasuries from AAA to AA+ for the first time in history [14]. In the following years, Chinese currency devaluation in 2015 and uncertainty of the fallout from the trade war between the US and China since 2018 have led to several short-lived spikes in the VIX [17].

To match the frequency of our rating data, we proceed to annualize the VIX data by calculating the average yearly VIX. The results are shown in Figure 3.14. As can be observed, the annualized VIX follows a clear downward trend, falling steadily since the global financial crisis.

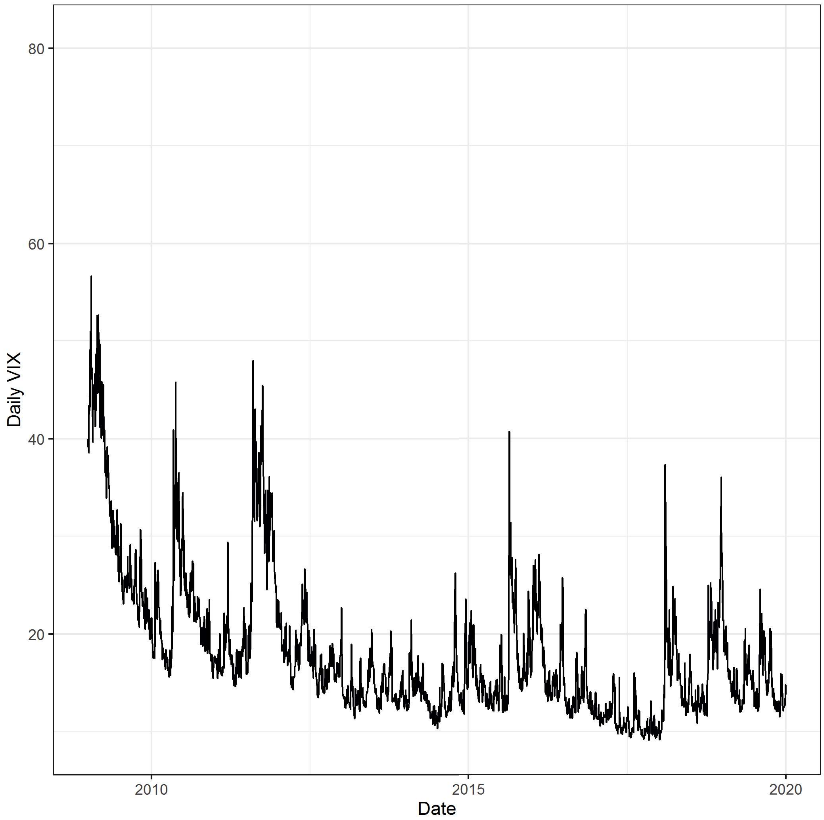


**Figure 3.13:** Daily VIX for the period 2009 - 2019. The VIX has spiked in 2009 (financial crisis), 2010 (Eurozone crisis), 2011 (US debt ceiling crisis), 2015 (Chinese currency devaluation), and several times since the beginning of 2018 (US-China trade war).

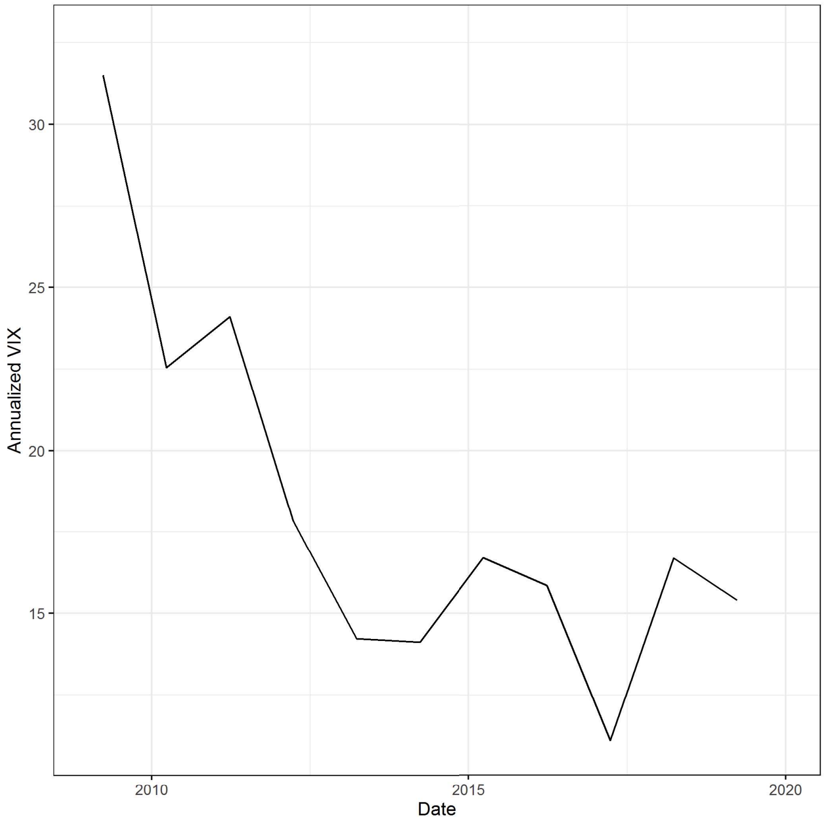


**Figure 3.14:** Annualized values of VIX for the period 2009 - 2019 shows a clear downward sloping trend, falling from its peak during the financial crisis.

### 3.3.4 New Bond Issuance and New Loans

New corporate debt could potentially be related to the propensity of credit rating adjustments and their accuracy (see e.g. Carvalho et al. (2014) [9]). If the interests of bond issuers and CRAs align when corporations want to take on new debt, CRAs should perform more upgrades and less downgrades on average leading up to periods of increased new debt financing. The reasoning behind this is that a positive rating change by a CRA will lead to better terms when raising capital for corporations. Banks assessing credit risks and providing loans to the respective clients, will however have an incentive to reflect the *true* credit risk. We want to examine how the appetite for new corporate debt relates to the rating stability and accuracy of credit ratings. Generally speaking, corporations have two means of debt financing; they can issue corporate bonds, or they can apply for bank loans. Corporate bonds are perceived as more risky, but are more liquid and often offer higher yields than bank loans.

We collect data from two different sources to use as a proxy for investors' willingness to take on new debt. Then, we use these proxies to assess whether obtaining debt capital influences rating volatility and accuracy.

The first proxy is the the total annual value of new bond issuance in Norway, shown in Figure 3.15. The total market value of new bond issuance in Norway from 2009 to 2018 is collected from Nordic Trustee's Norwegian Bond Market Report (2018) [27]. Nordic Trustee is the leading provider of trustee and agency services for bonds and direct lending in the Nordic region.

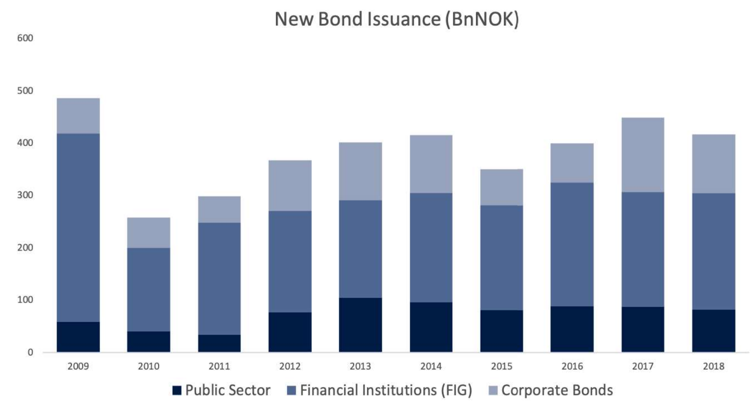


**Figure 3.15:** Total value of new bond issuance in Norway from 2009 to 2018 in NOK billion.

The second data set is the balance sheet of all Norwegian banks from 2009 to 2018, shown in Figure 3.16 and collected from the Norway Statistics Bureau (2020) [24]. Due to missing data from the first quarter of 2009, we will be using the average monthly change in the balance sheet of ”loans to and claims of customers” - both companies and private individuals - for each year. The point-in-time measure of loans to customers is not a perfect measure for gauging the value of new loans to banks' clients. However, the net change in the banks' assets will reflect the lending behavior of banks to an acceptable degree. The proxy for new debt in terms of bank loans will be the average monthly net change in asset values of bank loans for each year.

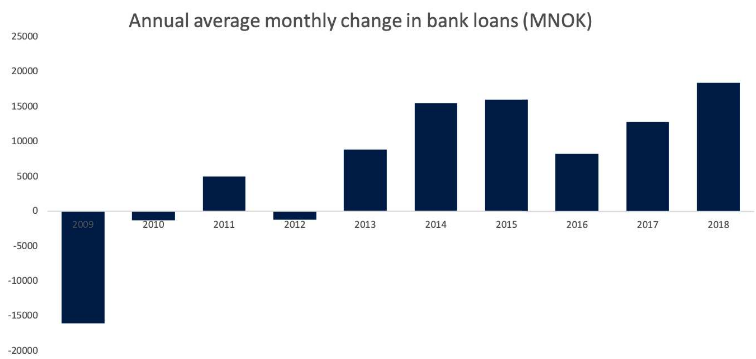


**Figure 3.16:** Annualized average monthly change in bank loans to end claims of customers from 2009 to 2018 in NOK million.

Chapter 4

# Methodology

We wish to analyze ratings stability and ratings quality or accuracy using data sets containing ratings data from two Norwegian savings and loans banks, as well as a smaller data set from the credit rating agency NCR. In order to do so, we employ several statistical methods. First, we construct unconditional and conditional transition matrices. Then, we employ a measure developed by Carvalho et al. (2014) [9] that condenses the information contained in two-dimensional transition matrices into a single scalar representing the volatility of ratings for each time period. We further analyze ratings stability by calculating two different alternative measures: 1) *Large Rating Changes* ($LRC$) and 2) *Rating Reversals* ($RR$). This is followed by an analysis of the accuracy of ratings, evaluated using the measure *Accuracy Ratio* ($AR$), representing rating quality. In order to understand the effect that the state of the business cycle has on the volatility and quality of ratings, we employ several simple linear regressions. We also run a simple linear regression to find the relationship between the state of the business cycle and the accuracy ratio. We then expand the simple linear regression analysis by performing multivariate analyses, examining the effect of the business cycle on rating volatility and rating quality. Finally, we analyze the relation between accuracy and stability by employing simple linear regressions.

## 4.1 Transition Matrix

Transition matrices provide an approximation of the probability of a transition from one rating class to another in the course of a predefined time period. Migration matrices are typically based on the continuous Markov Chain Model. Given the nature of our data sets and the frequency of revisions of credit ratings, it is more reasonable for us to look at a discrete model rather than a continuous model. The probability estimates are calculated by first collecting historical credit rating changes over a given time period. Next, the frequency with which obligors move from the initial rating $i$ to the next rating $j$ is collected, denoted $N_{ij}$. Finally, this measure is transformed into a transition probability by dividing the frequency by the total number of firms in a given rating category $i$ in the beginning of a period, denoted $N_i$. The formula for calculating the probability of migration from a specific rating class to another specific rating class during a single period thus is

$$\widehat{p}_{ij} = \frac{N_{ij}}{N_i} \qquad \forall\ i, j \tag{4.1}$$

By repeating this calculation for all rating migration possibilities and for all time periods, the result is a transition matrix containing the *average* empirical probability of rating transitions for a given sample.

In order to identify what impact different variables have on the transition probabilities, we calculate both unconditional and conditional transition matrices. The unconditional transition matrix is calculated based on the whole sample. It illustrates the rating migrations for all obligors included in the data set. The conditional transition matrices are calculated by splitting the data into two different subsets. The two subsets are distinguished by the state of the business cycle, one containing rating transitions in years with positive deviation from the GDP trend (peak) and one containing rating transitions in years with negative deviation from the GDP trend (trough).

## 4.2 Measure of Rating Volatility

Carvalho et al. (2014) [9] construct a new measure for the stability of credit ratings denoted *Ratings Volatility* ($RatVol$). It is an estimate of the volatility of credit ratings and is very similar to a standard deviation. The measure condenses all information that is contained in a two-dimensional ratings transition matrix, into a single scalar for each time period. Hence, the measure can be utilized in time-series tests. It is based on the same information required to compute a standard ratings transition matrix.

### 4.2.1 Definition of RatVol

To calculate $RatVol$, let $t$ denote the time in years so that $t = 1, 2, ..., T$ represents the end of each year. Let the weights for all possible rating transitions from rating $s$ to rating $f$ from period $t-1$ to period $t$ equal

$$w_t(s, f) := \frac{n_t(s, f)}{\sum\limits_{s=1}^{N} \sum\limits_{f=1}^{N} n_t(s, f)} \tag{4.2}$$

where $n_t(s, f)$ is the number of firms that ended the last year (time $t-1$) with rating s and ended the current year (time $t$) with rating $f$. In this context, $s$ and $f$ are assigned a numerical value, e.g. $1$ for ratings $A$ and $11$ for ratings $K$. $N$ denotes the total number of possible ratings classifications in the data set. The term in the denominator represents the total number of movements in the transition matrix. The ratings volatility is then defined as

$$RatVol_t := \sqrt{\sum_{s=1}^{N} \sum_{f=1}^{N} w_t(s, f) \times (f - s)^2} \quad \forall \ \ t \in T \tag{4.3}$$

Unlike normal transition matrices, the measure above gives more weight to transition paths with more observations and less weight to paths with fewer observations. It also penalizes larger ratings movements more than smaller ratings adjustments. Therefore, Carvalho et al. (2014) [9] argue that it more correctly depicts the true volatility of ratings compared to transition matrices.

### 4.2.2 Decomposition of RatVol into Upgrades and Downgrades

$RatVol$ includes the total volatility effects of both upgrades and downgrades. In order to analyze these effects separately, we split them into the volatility due to upgrades, $RatVolU_t$, and downgrades, $RatVolD_t$. These measures are defined as

$$RatVolU_t := \sqrt{\sum_{s=1}^{N}\sum_{f=1}^{N} w_t(s,f) \times (f-s)^2 I_{\{f<s\}}} \quad \forall \ t \in T \tag{4.4}$$

$$RatVolD_t := \sqrt{\sum_{s=1}^{N}\sum_{f=1}^{N} w_t(s,f) \times (f-s)^2 I_{\{f>s\}}} \quad \forall \ t \in T \tag{4.5}$$

where the indicator function $I_{\{f<s\}}$ is equal to 1 when the final rating $f$ is lower than the initial rating $s$, i.e., when an upgrade occurs. Conversely, $I_{\{f>s\}}$ is equal to 1 when a downgrade occurs.

## 4.3 Alternative Measures of Rating Volatility

### 4.3.1 Large Rating Changes

Credit ratings are based on fundamental data and hence are not expected to change frequently. Nevertheless, unexpected changes in the economy or within a company may lead to large changes in a company's credit rating - so-called multi-notch rating adjustments. A measure known as *Large Rating Changes* ($LRC$) is used to estimate the frequency of such events [8]. It estimates the stability of credit ratings and is defined as

$$LRC_t = \frac{\sum_{i=1}^{R_t} lrc_{it}}{R_t} \quad \forall \ t \in T \tag{4.6}$$

where

$i$ is the index of the customers of the bank with credit rating

$R_t$ is the total number of all credit ratings apart from defaults in period $t$

$lrc_{it}$ is a binary variable equal to 1 if the rating change is three or more notches from period $t-1$ to period $t$ , and 0 otherwise

Intuitively, this measure describes the ratio of ratings that received an update of 3 or more notches from one period to the next, to the total number of ratings.

A large and sudden increase in the frequency of large rating changes - i.e., a high LRC - could indicate that CRAs have been too slow to incorporate the change in the risk of a company in their credit ratings. However, there are instances where large rating changes are justified. Therefore, LRC is not an objective measure that should be used to infer definite statements about the quality of the rating process over time. Nevertheless, large rating changes should *only* occur if there is a substantial shift in a company's risk profile.

### 4.3.2 Reversal of Ratings

Another measure used to estimate the stability of credit ratings is known as *Rating Reversals* ($RR$). It is defined as

$$RR_t = \frac{\sum_{i=1}^{R_t} rr_{it}}{R_t} \quad \forall \ t \in T \tag{4.7}$$

where

$i$ is the index of the customers of the bank with credit rating

$R_t$ is the total number of all credit ratings apart from defaults in period $t$

$rr_{it}$ is a binary variable equal to $1$ if a rating change is an upgrade preceded by a downgrade or vice versa, and $0$ otherwise. In other words, a value of $1$ is assigned if a rating in period $t-2$ is equal to a rating in period $t$ and different than the rating in period $t-1$

Intuitively, this measure describes the ratio of ratings experiencing a change in one direction two periods ago and then changed the other direction during the previous period, to the total number of ratings.

An increase in the frequency of rating reversals may indicate that CRAs are overly sensitive to temporary shocks, resulting in rating adjustments that are based on erroneous risk assessments. However, like LRC, there are instances where rating reversals are justified. Therefore, RR is not an objective measure that can be analyzed directly over time, and it should be carefully interpreted with reference to the underlying macroeconomic situation. These measures of volatility are more applicable to CRAs where rating assessments happen when the rating entity deems it necessary.

## 4.4 Accuracy of Ratings

The Cumulative Accuracy Profile (CAP) can be used to evaluate the accuracy of a rating system through time. A CAP curve is constructed by plotting the share of defaulters for each of the rating categories, as seen in Figure 4.1. This curve can then be used to derive a measure known as the *Accuracy Ratio* ($AR$) [8].

The Accuracy ratio (AR) is the summary index of the Cumulative Accuracy Profile (CAP). It compresses all the information depicted in the CAP curve into a single statistic and is equal to the area between the CAP curve and the 45-degree line, divided by the total area above the 45-degree line - i.e., $AR = X/(X+Y)$ as shown in Figure 4.1. The measure is commonly used to compare the relative accuracy and quality of credit ratings by measuring the correlation coefficients between rating categories and defaults. Furthermore, it is a measure of the discriminatory power of credit score models - i.e., the ability to distinguish *ex ante* between defaulting and solvent firms. Thus, the AR measures how accurate a credit model predicts the probability of default. If only firms in the lowest rating category default ($J$ and $K$ in our data set), the AR will approach $1$. If firms in all rating categories default - i.e., defaults are unrelated to rating categories - the AR will be $0$. If only firms in the highest rating category default (A in our data set), the AR will approach $-1$ .

Building on the work of Cantor and Mann (2003) [8] and Carvalho et al. (2014) [9], the AR at time *t* can be computed using the equation

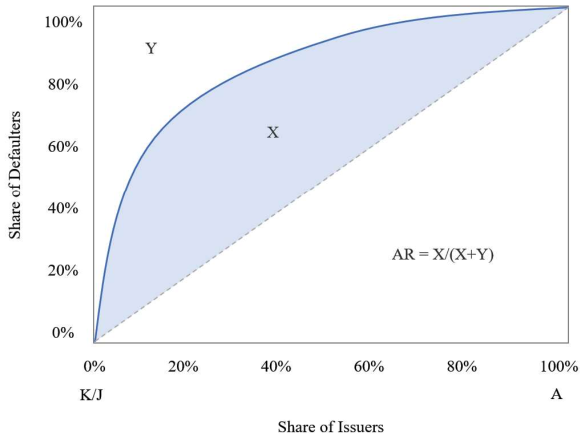


**Figure 4.1:** Example of a Cumulative Accuracy Profile (CAP) plot and the derivation of the Accuracy Ratio (AR). Note that the percentages on the y-axis are not necessarily equivalent to the rating stated below due to the ordinal data structure of credit ratings.

$$AR_t = \frac{\sum_{\underline{r}}^{\overline{r}}[n(i) - n(i-1)][d(i) - n(i) + d(i-1) - n(i-1)]}{1 - \frac{D}{N}} \tag{4.8}$$

where

$\underline{r}$ = minimum $r$ in the sample at $t$.

$\overline{r}$ = maximum $r$ in the sample at $t$.

$n(r)$ = $\sum_{\underline{r}}^{r} N_i/N$, for $r \geq 1$, and $n(0) = 0$

$d(r)$ = $\sum_{\underline{r}}^{r} D_i/D$, for $r \geq 1$, and $d(0) = 0$

$N_r$ = number of issuers with rating $r$ at $t$.

$D_r$ = number of issuers with rating $r$ at $t$ that defaulted over the following year.

$N$ = total number of issuers at $t$.

$D$ = total number of defaults over the following year.

## 4.5 Adjusting the Business Cycle Variable

As previously mentioned, a common proxy for the state of the business cycle is the quarterly or annual change in real GDP. However, GDP data consists of two separate components: 1) a long-run trend component and 2) a short-run business cycle component. As our analysis focuses on the state of the business cycle, we are only interested in the business cycle component. In order to isolate this component from the trend component, we apply a statistical technique developed by Hodrick and Prescott (1997) [12] known as the Hodrick-Prescott (HP) filter.

Let $y_t$ denote the logarithms of Norway's real GDP for years $t = 1, 2, ..., T$. The variables $y_t$ contain a short-term trend component $\tau_t$ and a cyclical component $c_t$. The value of $y_t$ equals $y_t = \tau_t + c_t$. The HP-filter creates a measure for the smoothness of the path of $\tau_t$ and involves solving the following minimization problem:

$$\min_{\tau} \left( \sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \right) \tag{4.9}$$

The first term is the cyclical component, $c_t = y_t - \tau_t$. It penalizes deviations of $\tau_t$ from $y_t$. The second term is a multiple $\lambda$ that penalizes variability in the second differences of the trend component. The parameter $\lambda$ is a subjectively chosen positive scalar that places a relative weight on variability in the trend components as compared to the cyclical component. A lower $\lambda$ means a lower cyclical component $c_t$, while a higher $\lambda$ means a higher cyclical component. For quarterly data, Hodrick and Prescott (1997) [12] suggest $\lambda = 1600$, and for annual data $\lambda = 100$ has been proposed. Since our data is annual, we use $\lambda = 100$.

For the other business cycle variables and financial indicators (swap rate, VIX index, balance sheet of banks' assets and new bond issuance) we annualized the data as explained in the previous section.

## 4.6 Analysis of Volatility of Ratings

It is natural that the credit ratings of companies change to some extent over a period of time. With data sets containing ratings for several thousand companies, it is of interest to investigate whether there is a fundamental explanatory reason underlying rating upgrades and downgrades. In this paper, we ask if the state of the business cycle, represented by several macroeconomic variables, might be a cause of ratings changes. In order to examine the effect that the state of the business cycle has on rating changes, we first perform several simple linear regressions before proceeding to more complex multivariate regressions.

### 4.6.1 Univariate Analysis

Initially, we perform a univariate analysis, regressing real GDP deviation from trend ($GDP.Dev_t$) as a proxy for the business cycle, on several measures of ratings volatility. The real GDP deviation from trend is obtained by applying an HP filter to GDP data for Norway, thereby isolating the cyclical component of GDP. $RatVol_t$, $RatVolU_t$, $RatVolD_t$, $AR_t$, $LRC_t$, and $RR_t$ are separately used as the dependent variables. They represent the total intensity of rating changes, intensity of upgrades, intensity of downgrades, Accuracy Ratio, Large Rating Changes, and Rating Reversals for each year, respectively. We run the following linear regressions using the ordinary least squares (OLS) method:

$$RatVol_t = \alpha + \beta GDP.Dev_t + \epsilon_t \tag{4.10}$$

$$RatVolU_t = \alpha + \beta GDP.Dev_t + \epsilon_t \tag{4.11}$$

$$RatVolD_t = \alpha + \beta GDP.Dev_t + \epsilon_t \tag{4.12}$$

$$LRC_t = \alpha + \beta GDP.Dev_t + \epsilon_t \tag{4.13}$$

$$RR_t = \alpha + \beta GDP.Dev_t + \epsilon_t \tag{4.14}$$

A positive correlation between $GDP.Dev_t$ and $RatVol_t$, $RatVolU_t$, and $RatVolD_t$ indicates that better economic times are associated with higher total volatility, more frequent upgrades, and more frequent downgrades, respectively. Likewise, a positive relation between the state of the business cycle and $LRC_t$ and $RR_t$, corresponds to a higher frequency of rating adjustments of three or more notches and a higher frequency of rating reversals, respectively.

### 4.6.2 Multivariate Analysis

After performing univariate analyses, we proceed to investigate business cycle effects by performing multivariate regressions. To represent the business cycle, we employ $GDP.Dev_t$, $SwapRate_t$, $VIX_t$, $NewBonds_t$, $NewLoans_t$, and $RateDef_t$ as explanatory variables. The following multivariate regressions are run for each data set:

$$\begin{aligned} RatVol_t = \alpha + \beta_1 GDP.Dev_t + \beta_2 SwapRate_t + \beta_3 VIX_t + \beta_4 NewBonds_t \\ + \beta_5 NewLoans_t + \beta_6 RateDef_t + \epsilon_t \end{aligned} \tag{4.15}$$

$$\begin{aligned} RatVolU_t = \alpha + \beta_1 GDP.Dev_t + \beta_2 SwapRate_t + \beta_3 VIX_t + \beta_4 NewBonds_t \\ + \beta_5 NewLoans_t + \beta_6 RateDef_t + \epsilon_t \end{aligned} \tag{4.16}$$

$$\begin{aligned} RatVolD_t = \alpha + \beta_1 GDP.Dev_t + \beta_2 SwapRate_t + \beta_3 VIX_t + \beta_4 NewBonds_t \\ + \beta_5 NewLoans_t + \beta_6 RateDef_t + \epsilon_t \end{aligned} \tag{4.17}$$

$$\begin{aligned} LRC_t = \alpha + \beta_1 GDP.Dev_t + \beta_2 SwapRate_t + \beta_3 VIX_t + \beta_4 NewBonds_t \\ + \beta_5 NewLoans_t + \beta_6 RateDef_t + \epsilon_t \end{aligned} \tag{4.18}$$

$$\begin{aligned} RR_t = \alpha + \beta_1 GDP.Dev_t + \beta_2 SwapRate_t + \beta_3 VIX_t + \beta_4 NewBonds_t \\ + \beta_5 NewLoans_t + \beta_6 RateDef_t + \epsilon_t \end{aligned} \tag{4.19}$$

Higher values of $GDP.Dev_t$, $SwapRate$, $NewBonds$, $NewLoans$ are indicative of better economic times. By contrast, better times are associated with lower values of $VIX$ and $RateDef$. As a result, a positive correlation between the business cycle measures $GDP.Dev_t$, $SwapRate$, $NewBonds$, $NewLoans$ (a negative correlation between the business cycle measures $VIX$ and $RateDef$) and the volatility measures $RatVol_t$, $RatVolU_t$, and $RatVolD_t$ indicate that better economic times are associated with higher total volatility, more frequent upgrades, and more frequent downgrades, respectively. Likewise, a positive relation between $GDP.Dev_t$, $SwapRate$, $NewBonds$, $NewLoans$ (a negative relation between $VIX$ and $RateDef$) and $LRC_t$ and $RR_t$, corresponds to a higher frequency of rating adjustments of three or more notches and a higher frequency of rating reversals, respectively.

## 4.7 Analysis of Quality of Ratings

CRAs' credit ratings are not perfect assessments of default probabilities. Occasionally, even companies with high credit ratings default. As previously described, the discriminatory measure known as the Accuracy Ratio (AR) can measure how well a CRA performs at assigning "correct" ratings to companies that actually do default. In other words, the AR is a measure of the quality of a CRA's credit ratings. By analyzing the relation between AR and the state of the business cycle, it is possible to determine whether the business cycle has an effect on rating quality. We first perform a univariate analysis using a single macroeconomic variable and subsequently expand our analysis by including multiple macroeconomic measures in multivariate analyses.

### 4.7.1 Univariate Analysis

In order to examine the business cycle effect on the quality of credit ratings, we perform a simple linear regression. We use the deviation of recorded GDP from the long-term trend component as the independent variable, denoted $GDP.Dev_t$. As the dependent variable, we employ the Accuracy Ratio, denoted $AR_t$. We run the following linear regression using the ordinary least squares (OLS) method:

$$AR_t = \alpha + \beta GDP.Dev_t + \epsilon_t \tag{4.20}$$

A positive correlation between the two variables, i.e., $\beta > 0$, indicates that better economic times results in a higher accuracy. This implies that less companies with higher credit ratings default in better times, and that most defaulting companies are correctly located in the lower range of the credit rating spectrum.

### 4.7.2 Multivariate Analysis

To gain deeper insight into which macroeconomic variables are associated with higher quality of ratings, we expand our linear regression models to include several macroeconomic variables, which will be explained below. After careful consideration, we employ the following explanatory variables: $GDP.Dev_t$, $SwapRate_t$, $VIX_t$, $NewBonds_t$, $NewLoans_t$, and $RateDef_t$. We also include $RatVol_t$ to test the effect of our measure of ratings' volatility. Hence, the following multivariate regression is run for each individual bank:

$$\begin{aligned} AR_t = \alpha + \beta_1 GDP.Dev_t + \beta_2 SwapRate_t + \beta_3 VIX_t + \beta_4 NewBonds_t \\ + \beta_5 NewLoans_t + \beta_6 RateDef_t + \gamma_1 RatVol_t + \epsilon_t \end{aligned} \tag{4.21}$$

$SwapRate_t$ is the difference between swap rates of 10-year maturity and 2-year maturity. $NewBonds_t$ is the total annual value of new bond issuance in Norway. $NewLoans_t$ is the average monthly change in loans to Norwegian bank customers. $VIX_t$ is the average annual market expectation of the 30-day forward-looking volatility of the S&P 500 index. $RateDef$ is the default rate among each bank's customers per year. A positive coefficient for $GDP.Dev_t$, $SwapRate_t$, $NewBonds_t$, and $NewLoans_t$ indicates that AR is positively related with business cycle peaks and inversely related with business cycle troughs. In other words, the quality of ratings is higher when the economy is performing well and lower when it is performing poorly. Conversely, a positive coefficient for $VIX_t$ and $RateDef$ indicates that the rating accuracy is higher during economic troughs and lower during peaks.

## 4.8 Analysis of Relation between Accuracy and Stability

Cantor and Mann (2006) [7] claim that CRAs trade off accuracy for higher stability. If this is the case, the relationship between the accuracy ratio (AR) and rating volatility ($RatVol$), rating reversals (RR) and Large Rating Changes (LRC), should be positive. The reason for an expected positive relation is because these three measures - $RatVol$, RR, and LRC - in different ways express the degree of volatility of ratings. Therefore, if CRAs do indeed trade off accuracy in order to attain more stable changes, a lower accuracy should be accompanied by higher stability, i.e., less volatility, or vice versa.

### 4.8.1 Relationship between AR and RatVol, LRC, and RR

To examine the relationship between AR and $RatVol$, LRC, and RR, we run the following simple linear OLS regressions, with $AR_t$ as the dependent variable and $RatVol_t$, $LRC_t$, and $RR_t$ as the independent variables:

$$AR_t = \alpha + \beta RatVol_t + \epsilon_t \tag{4.22}$$

$$AR_t = \alpha + \beta LRC_t + \epsilon_t \tag{4.23}$$

$$AR_t = \alpha + \beta RR_t + \epsilon_t \tag{4.24}$$

A negative $\beta$ for any of the regressions indicates a negative correlation between the two variables. Such a relation *could* imply a trade-off between accuracy and stability, meaning that CRAs intentionally accept less accurate ratings in order to achieve more stable ratings. However, such a correlation by itself, even if statistically significant, is not enough to conclude that CRAs *actively* pursue such a trade-off. It would, however, strengthen the argument that the particular CRA's ratings are through-the-cycle rather than point-in-time measures, as noted by Altman and Rijken (2006) [1].

## 4.9 Multivariate Regression Methods

Multicollinearity occurs when allegedly independent variables actually are correlated. When such explanatory variables in a linear regression model exhibit tendencies of multicollinearity, the standard errors of the estimated coefficients can be falsely inflated resulting in inaccurate, non-significant p-values when using the Ordinary Least Squares (OLS) method. Therefore, the potential problem of multicollinearity has to be solved. Correlation can be identified by analyzing the correlation matrix and scatter plots for the independent variables in question, as well as using the variance inflation factor (VIF). Variables with high values of VIF can be removed from the OLS regression. The problem can also be mitigated using, e.g., Ridge regression, Lasso regression, and Elastic Net regression - methods frequently used in machine learning due to their predictive power.

Ridge regression reduces the coefficients of highly-correlated variables, while Lasso eliminates some of the variables. Ridge also penalizes the largest $\beta$-values more than the smaller ones, while Lasso penalizes them uniformly. Elastic Net regression combines both of these techniques to find a model that fits better than each model on their own.

### 4.9.1 Testing multicollinearity

The variance inflation factor (VIF) is a measure used to identify multicollinearity (see, e.g., Rawlings, Pantula, and Dickey (1998) [21]). It calculates the correlation between the independent variables and the strength of that correlation by quantifying how much the variance of the estimated coefficients are inflated. The VIF value for an estimated regression coefficient $\beta_j$ is given by:

$$VIF_j = \frac{1}{1 - R_j^2} \tag{4.25}$$

where $R_j^2$ is the $R^2$-value when regressing the variable $j$ on the other variables. A VIF-value of 1 indicates no correlation between the particular variable and the remaining variables. Higher values suggest more multicollinearity issues connected to that particular variable. Suggestions for cut-off values of VIF are typical between 5 and 30. When multicollinearity is observed, mitigation should be attempted.

### 4.9.2 Ridge Regression

Ridge regression is a method used to mitigate the problem of multicollinearity by calculating shrinkage estimators that shrink estimators closer to the "true" population parameters (see Marquardt and Snee (1975) [19]). The method is a more advanced variation of OLS multivariate regression and is used when the data is suspected of suffering from multicollinearity. The simple OLS method finds unbiased coefficients that best fit the data by minimizing the residual sum of squares. It treats all explanatory parameters equally and does not consider the case when some independent variables have more explanatory power than others. Ridge regression, on the other hand, adds a degree of bias to the regression estimates and reduces the standard errors. Thus, it balances the trade-off between variance and bias of the estimated betas and improves the least-squares estimate.

In normal OLS regression, the relation between the predicted coefficients and the betas has the following cost function:

$$\arg\min_{\beta \in \mathbb{R}} \sum (y_i - \hat{y}_i)^2 = \arg\min_{\beta \in \mathbb{R}} \sum (y_i - X_i \hat{\beta}_i)^2 \tag{4.26}$$

where, $y_i$ is dependent variable $i$, and $X_i$ is the vector of explanatory variables. Ridge regression adds a penalty term, $\lambda$, to the sum of the squared values of the estimated coefficients and betas. Thus, the cost function becomes:

$$\arg\min_{\beta \in \mathbb{R}} \sum (y_i - X_i \hat{\beta}_i)^2 + \lambda \sum (|\hat{\beta}_i|)^2 \tag{4.27}$$

The value of $\lambda$ can vary from 0 and $\infty$. When $\lambda = 0$, the Ridge regression is equivalent to a least squares regression. As the penalty term increases, the ridge regression coefficients will decrease, leading to a smaller variance. Using cross-validation, we select the $\lambda$-value that produces the lowest Mean Squared Error (MSE) in the training model. This value is applied across the testing of the data set. Ridge regression does not eliminate coefficients, only shrinks them, and it thus never yields sparse models. A potential problem with Ridge regression is that the regression model can shrink the coefficients so much that it might not accurately predict future values.

### 4.9.3 Lasso Regression

Another method used to mitigate the problem of multicollinearity is Least Absolute Shrinkage and Selection Operator (Lasso) regression (see Tibshirani (2011) [26]). Lasso regression is similar to ridge regression in that it uses shrinkage, a method where data points are shrunk towards a central point. To do so, a penalty term is added to the absolute value of the estimated coefficients. The cost function will have a form of:

$$\underset{\beta \in \mathbb{R}}{\arg\min} \sum (y_i - X_i \hat{\beta}_i)^2 + \lambda \sum |\hat{\beta}_i| \tag{4.28}$$

Like Ridge regression, the selection of the value of $\lambda$ in Lasso regression is also performed using cross-validation. The value of $\lambda$ can vary between 0 and $\infty$. When $\lambda = 0$, no parameters in the model are eliminated and the estimate is equal to a least squares regression. As the value of $\lambda$ increases, more coefficients are eliminated. When $\lambda$ is sufficiently high, *all* coefficients are eliminated. A problem with Lasso is that, unlike Ridge, high values of the penalty term, $\lambda$, can force the coefficients of certain explanatory variables to be eliminated from the model, not just reduced as they are in Ridge. This can yield sparse models. It also doesn't take into account *which* correlated explanatory variables should be eliminated as it tries to simplify the model to decrease the variance error. When variables are sufficiently correlated, it simply retains one variable and sets all other variables to zero. This could lead to loss of information and a less accurate model.

### 4.9.4 Elastic Net Regression

Elastic Net regression is a combination of Lasso and Ridge regression. It combines the penalty terms of the Lasso and Ridge methods linearly (see Zou and Hastie (2005) [29]). The resulting cost function is:

$$\underset{\beta \in \mathbb{R}}{\arg\min} \sum (y_i - X_i \hat{\beta}_i)^2 + \lambda \sum (1 - \alpha)|(\hat{\beta}_i|)^2 + \alpha |\hat{\beta}_i| \tag{4.29}$$

$\lambda$ is the penalty term, where $\alpha$ decides how much to weight to put on the Lasso and Ridge penalty terms. The value of $\alpha$ can vary from 0 to 1. When $\alpha = 0$, the resulting regression corresponds to Ridge. Likewise, when $\alpha = 1$, the resulting regression is corresponds to Lasso. Values of $\lambda$ and $\alpha$ can be decided using cross-validation by selecting values that produces the least mean squared errors.

Chapter 5

# Results and Discussion

In this Chapter, we present the results from implementing the methods outlined in Chapter 4 on the three data sets presented in Chapter 3. First, we present the unconditional and conditional transition matrices summarizing the rating migration probabilities. Next, we demonstrate the stability of the credit ratings as represented by rating volatility ($RatVol$, $RatVolU$, and $RatVolD$), Large Rating Changes (LRC), and Rating Reversals (RR). Next, we evaluate the quality of the ratings as measured by the accuracy ratio (AR). In an attempt to relate credit ratings to the business cycle, we regress our three volatility measures against several macroeconomic variables. We also regress AR against rating volatility and macroeconomic variables. Finally, we mention possibilities for future expansion of our work.

Due to insufficient data, we perform only some of the methods described in the previous Chapter on the data set from NCR. For this data set, we only construct the unconditional transition matrix, calculate the three RatVol measures ($RatVol$, $RatVolU$, and $RatVolD$), and perform both univariate and multivariate regressions examining the relationship between the volatility measures and the business cycle. Due to insufficient quantitative evidence, we cannot draw final conclusions about the underlying credit rating process from the NCR data set. Therefore, discussion and interpretation of results will refer to the data sets from the two banks, unless NCR is explicitly noted.

## 5.1 Transition Matrices

A transition matrix provides an approximation for the probability of a transition from one rating category to another. The unconditional transition matrices are presented in Table 5.1 for Bank A, Table 5.2 for Bank B, and Table 5.3 for NCR. We also calculate the standard deviations of the transition rates for the bank, shown in parentheses below the probabilities. In Tables 5.4, 5.5, 5.6, and 5.7, we calculate the conditional transition matrices for Bank A and B by isolating the years with positive and negative deviations from GDP trend and calculating the transition probabilities. These values are, therefore, conditioned on the state of the business cycle.

The diagonal probabilities in the matrices can be interpreted as the probability of retaining a particular rating for two consecutive years. Due to limited quantity of data, NCR's unconditional transition matrix contains mostly probabilities along the diagonal and its immediate adjacent cells. This means that companies in this particular data set are likely to remain assigned with their current credit rating over time. Comparing this outcome to other studies, this is common for CRAs.

### 5.1.1 Unconditional Transition Matrices

In the unconditional transition matrix for Bank A, shown in Table 5.1, the highest probabilities for each row are mostly located along the diagonal, varying between 26.87% and 94.63%. There is one exception for the row representing rating migrations originating from rating category $D$, where the probability of moving from $D$ to $C$ is higher than that of remaining in $D$. We observe that for companies with ratings $A, B, C, I, J$, and $K$, it is more likely to remain in their current rating category than to migrate to another rating category - i.e., the probability is higher than 50%. These categories represent the upper and lower range of rating categories. We, therefore, conclude that it is more likely for companies with high ratings to remain in the upper range and companies with low ratings to remain in the lower range.

Meanwhile, companies with ratings in the center of the rating spectrum - ratings $D, E, F, G$, and $H$ - are more likely to be upgraded or downgraded than to remain in the same state. From a purely probabilistic standpoint, this conforms with a higher possible range of rating choices for CRAs to select from when assigning new ratings. In the center of the matrix, CRAs can assign both upgrades and downgrades to all companies. At the edges, however, there are fewer possible assignment choices in the immediate vicinity. Also, at the edges the CRAs' rating options are mostly tied to one direction: for high ratings, most possibilities for rating adjustments are downgrades and upgrades for low ratings. As a result, the probabilities are generally lower in the middle of the diagonal than at the edges. This pattern *could* indicate that CRAs are less certain about the credit worthiness of firms that are located at the center of the rating categories, although we do not have any conclusive evidence for such a claim. Note, for instance, that the ratings with the highest probabilities of remaining in the current rating category are $A$ (96.63%), and the two default categories $J$ (79.05%) and $K$ (79.69%).

In the unconditional transition matrix for Bank B, shown in Table 5.2, probabilities along the diagonal of the matrix are mostly lower than those of Bank A. We thus note that rating changes are more likely to occur with Bank B than with Bank A. Probabilities along the diagonal of the matrix are still high - varying between 16.90% and 71.32% - but not as high as those of Bank A. For the rating categories $A, B, C, E, F, H, J, M$ and $N$, the diagonal entry contains the highest value for all rows in the matrix. However, firms with initial ratings $D, G$, and $I$ are more likely to migrate than to remain in their current rating category. For the period covered by our data set, companies with rating $D$ are more likely to be upgraded to rating $C$ than to retain rating $D$. Likewise, for companies with ratings $G$ and $I$, the probability of being upgraded to ratings $F$ and $H$, respectively, is higher than remaining in their current rating categories.

Just as was the case for Bank A, it is more likely for companies with the highest ratings $A$ and $B$ or the lowest ratings $M$ and $N$ to retain their current ratings due to their probabilities being higher than 50%. Meanwhile, companies with ratings in the center of the rating spectrum, namely, ratings $C, D, E, F, G, H, I$, and $J$, are more likely to be upgraded or downgraded than remaining in their current rating categories. As noted above for Bank A, this could be due to a higher possible range of rating choices to select from, when starting from these rating categories. For Bank B, however, the diagonal values at the edges are smaller than for Bank A. For instance, the values for Bank A are 96.63% and 64.40% for ratings $A$ and $B$, respectively. The equivalent values for Bank B are 54.19% and 52.98% - significantly lower than Bank A's values. For the two default states - $J$ and $K$ for Bank A and

$M$ and $N$ for Bank B - the values are 79.05% and 79.69%; 62.50% and 71.32%, respectively. The difference between the two banks are smaller in the default states, but still noticeable. Purely judging by the unconditional transition matrices for the two banks, it seems as if rating changes are more common in Bank B than in Bank A. Later in this section, our measures of volatility ($RatVol$, $RatVolU$, and $RatVolD$) will further strengthen this claim.

**Table 5.1:** Unconditional Transition Matrix for Bank A (2009-2018) with annual frequency. Data is in percentages where values in parenthesis are standard deviations.

| From/to | A | B | C | D | E | F | G | H | I | J | K |
|---|---|---|---|---|---|---|---|---|---|---|---|
| A | **96.63** | 1.20 | 0.47 | 0.60 | 0.45 | 0.11 | 0.19 | 0.00 | 0.14 | 0.21 | 0.00 |
| | **(1.63)** | (0.80) | (0.27) | (0.52) | (0.48) | (0.26) | (0.23) | (0.05) | (0.16) | (0.23) | (0.05) |
| B | 0.85 | **64.40** | 22.13 | 7.37 | 3.48 | 1.26 | 0.32 | 0.03 | 0.06 | 0.00 | 0.10 |
| | (0.44) | **(4.88)** | (4.36) | (2.87) | (1.37) | (0.37) | (0.17) | (0.03) | (0.60) | (0.61) | (2.73) |
| C | 0.42 | 14.97 | **54.19** | 13.97 | 9.52 | 5.13 | 1.24 | 0.33 | 0.09 | 0.03 | 0.10 |
| | (0.29) | (3.70) | **(9.74)** | (5.27) | (3.64) | (1.95) | (0.20) | (0.87) | (0.76) | (0.58) | (2.53) |
| D | 0.32 | 4.51 | 30.84 | **26.87** | 18.61 | 12.11 | 4.95 | 1.23 | 0.36 | 0.18 | 0.03 |
| | (0.31) | (1.75) | (11.57) | **(13.93)** | (1.74) | (1.87) | (0.79) | (0.21) | (0.13) | (0.10) | (0.03) |
| E | 0.39 | 2.29 | 16.94 | 21.30 | **27.86** | 19.12 | 8.05 | 2.76 | 0.90 | 0.18 | 0.22 |
| | (0.22) | (0.91) | (6.38) | (2.53) | **(9.86)** | (1.98) | (0.67) | (0.97) | (0.21) | (0.09) | (0.12) |
| F | 0.20 | 0.76 | 8.18 | 10.08 | 19.01 | **34.91** | 15.95 | 7.30 | 2.85 | 0.52 | 0.24 |
| | (0.13) | (0.30) | (3.08) | (2.10) | (4.45) | **(3.05)** | (1.04) | (1.84) | (0.83) | (0.30) | (0.07) |
| G | 0.11 | 0.32 | 3.12 | 5.63 | 10.53 | 27.05 | **30.23** | 14.48 | 6.85 | 0.90 | 0.76 |
| | (0.15) | (0.12) | (1.14) | (1.31) | (2.43) | (2.28) | **(1.31)** | (1.92) | (0.71) | (0.72) | (0.16) |
| H | 0.15 | 0.10 | 1.34 | 2.74 | 5.17 | 14.93 | 24.89 | **33.18** | 14.72 | 1.51 | 1.27 |
| | (0.08) | (0.19) | (0.50) | (0.86) | (1.27) | (2.12) | (2.66) | **(1.38)** | (1.72) | (2.19) | (0.63) |
| I | 0.00 | 0.00 | 0.16 | 0.45 | 1.23 | 4.05 | 12.44 | 21.90 | **50.71** | 4.98 | 4.07 |
| | (0.04) | (0.34) | (0.25) | (0.22) | (0.82) | (0.90) | (1.05) | (2.13) | **(7.72)** | (3.63) | (1.14) |
| J | 0.74 | 0.00 | 0.00 | 0.74 | 0.00 | 0.00 | 1.45 | 1.53 | 6.64 | **79.05** | 9.84 |
| | (0.82) | (0.56) | (0.48) | (0.82) | (0.50) | (1.03) | (1.74) | (5.15) | (7.16) | **(17.77)** | (2.72) |
| K | 0.00 | 0.00 | 0.00 | 0.00 | 1.31 | 2.58 | 1.87 | 1.61 | 6.98 | 5.95 | **79.69** |
| | (0.00) | (1.78) | (1.55) | (0.00) | (1.02) | (1.23) | (0.87) | (1.24) | (3.08) | (6.38) | **(11.08)** |

**Table 5.2:** Unconditional Transition Matrix for Bank B (2009-2018) with annual frequency. Data is in percentages where values in parenthesis are standard deviations.

| From/to | A | B | C | D | E | F | G | H | I | J | M | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A | **54.19** | 31.31 | 7.57 | 3.70 | 2.35 | 0.22 | 0.48 | 0.07 | 0.00 | 0.00 | 0.00 | 0.10 |
| | **(11.76)** | (7.59) | (3.45) | (1.73) | (1.47) | (0.23) | (0.51) | (0.08) | (0.00) | (0.00) | (0.00) | (0.11) |
| B | 6.89 | **52.98** | 28.53 | 6.52 | 3.34 | 1.00 | 0.34 | 0.19 | 0.06 | 0.14 | 0.00 | 0.00 |
| | (2.44) | **(5.94)** | (4.26) | (1.85) | (0.82) | (0.42) | (0.18) | (0.10) | (0.05) | (0.08) | (0.00) | (0.00) |
| C | 1.03 | 24.46 | **45.97** | 14.36 | 7.91 | 3.52 | 1.24 | 0.70 | 0.25 | 0.39 | 0.04 | 0.12 |
| | (0.37) | (2.89) | **(2.30)** | (2.35) | (1.07) | (0.46) | (0.17) | (0.17) | (0.15) | (0.17) | (0.03) | (0.05) |
| D | 0.68 | 6.96 | 29.70 | **27.83** | 20.02 | 8.07 | 2.94 | 2.10 | 0.85 | 0.65 | 0.12 | 0.08 |
| | (0.36) | (0.75) | (1.66) | **(2.27)** | (2.97) | (0.88) | (0.35) | (0.35) | (0.28) | (0.30) | (0.09) | (0.06) |
| E | 0.47 | 3.26 | 15.23 | 21.89 | **31.20** | 15.07 | 6.64 | 3.28 | 1.56 | 1.11 | 0.03 | 0.26 |
| | (0.33) | (0.65) | (1.01) | (3.11) | **(1.34)** | (1.56) | (0.64) | (0.31) | (0.29) | (0.30) | (0.03) | (0.11) |
| F | 0.05 | 1.69 | 8.16 | 11.38 | 23.97 | **26.48** | 14.11 | 8.07 | 3.30 | 2.03 | 0.32 | 0.46 |
| | (0.05) | (0.39) | (1.13) | (0.98) | (1.12) | **(1.47)** | (1.37) | (0.83) | (0.29) | (0.51) | (0.17) | (0.13) |
| G | 0.45 | 1.19 | 4.71 | 6.57 | 15.78 | 22.68 | **19.78** | 15.64 | 6.75 | 4.63 | 0.69 | 1.13 |
| | (0.48) | (0.29) | (0.89) | (1.00) | (0.99) | (0.97) | **(1.43)** | (1.60) | (0.97) | (0.66) | (0.18) | (0.23) |
| H | 0.20 | 0.76 | 3.25 | 4.60 | 9.93 | 16.21 | 20.33 | **23.74** | 9.48 | 8.93 | 1.09 | 1.48 |
| | (0.21) | (0.49) | (1.15) | (1.02) | (0.89) | (1.38) | (1.56) | **(2.24)** | (1.07) | (0.93) | (0.19) | (0.32) |
| I | 0.00 | 0.21 | 1.70 | 2.69 | 7.67 | 11.90 | 15.29 | 24.64 | **16.90** | 15.26 | 1.95 | 1.79 |
| | (0.00) | (0.15) | (0.57) | (0.68) | (1.04) | (1.46) | (1.57) | (1.61) | **(1.30)** | (1.78) | (0.42) | (0.56) |
| J | 0.05 | 0.14 | 0.57 | 1.35 | 2.86 | 7.55 | 8.51 | 12.05 | 13.23 | **45.58** | 4.54 | 3.59 |
| | (0.05) | (0.11) | (0.26) | (0.32) | (0.96) | (1.30) | (1.72) | (1.20) | (1.63) | **(2.02)** | (0.75) | (0.91) |
| M | 0.00 | 0.00 | 0.00 | 0.00 | 0.41 | 0.00 | 2.44 | 1.27 | 0.41 | 26.03 | **62.50** | 6.94 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.44) | (0.00) | (1.81) | (0.96) | (0.44) | (10.95) | **(9.59)** | (2.39) |
| N | 0.00 | 0.62 | 0.47 | 1.53 | 3.37 | 4.14 | 4.09 | 2.82 | 1.53 | 5.05 | 5.05 | **71.32** |
| | (0.00) | (0.46) | (0.34) | (0.82) | (0.99) | (1.57) | (2.11) | (1.71) | (0.94) | (1.87) | (1.28) | **(2.93)** |

**Table 5.3:** Unconditional Transition Matrix using annual credit rating data from Nordic Credit Rating (NCR) in the period 2009-2018.

| From/to | Aaa | Aa+ | Aa | Aa- | A+ | A | A- | Bbb+ | Bbb | Bbb- | Bb+ | Bb | Bb- | B+ | B | B- | Ccc | Cc | C | D |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Aaa | **0.00** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Aa+ | 0.00 | **0.00** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Aa | 0.00 | 0.00 | **100.00** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Aa- | 0.00 | 0.00 | 11.11 | **88.89** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| A+ | 0.00 | 0.00 | 2.94 | 0.00 | **88.24** | 8.82 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| A | 0.00 | 0.00 | 0.00 | 0.00 | 10.00 | **75.00** | 14.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| A- | 0.00 | 0.00 | 0.33 | 0.00 | 0.00 | 10.60 | **71.19** | 16.89 | 0.33 | 0.33 | 0.00 | 0.33 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Bbb+ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.23 | 11.53 | **79.16** | 8.96 | 0.12 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Bbb | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.67 | 21.53 | **72.54** | 4.98 | 0.27 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Bbb- | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 2.25 | 26.69 | **62.06** | 9.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Bb+ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 7.14 | 38.78 | **53.06** | 1.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Bb | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 4.17 | 4.17 | 25.00 | **62.50** | 4.17 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Bb- | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 57.14 | **42.86** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| B+ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 15.79 | **36.84** | 31.58 | 10.53 | 0.00 | 5.26 | 0.00 | 0.00 |
| B | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 5.56 | 0.00 | **77.78** | 16.67 | 0.00 | 0.00 | 0.00 | 0.00 |
| B- | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | **100.00** | 0.00 | 0.00 | 0.00 | 0.00 |
| Ccc | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 100.00 | **0.00** | 0.00 | 0.00 | 0.00 |
| Cc | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | **0.00** | 0.00 | 0.00 |
| C | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | **0.00** | 0.00 |
| D | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | **0.00** |

### 5.1.2 Conditional Transition Matrices

By applying the same method as above separately on years in which GDP deviates positively (peak) and negatively (trough) from trend, we calculate conditional transition probabilities. These are conditioned on the state of the business cycle being in a peak or a trough, as calculated using the Hodrick-Prescott method previously described. The conditional transition matrices for peak years are shown in Table 5.4 for Bank A and 5.5 for Bank B. Similarly, conditional transition matrices for trough years are shown in Table 5.6 for Bank A and Table 5.7 for Bank B.

Comparing the diagonals of the two matrices for Bank A, we observe that the probability of remaining within the same rating state for two consecutive peak or trough years is mostly higher during peaks than troughs. This phenomenon applies to all rating classes except for the 2 default states, ratings $J$ and $K$. This indicates that the probability for defaulted companies to get a rating change is marginally higher during peaks and lower during troughs.

For Bank B, the opposite is the case. The probability of remaining within the same rating state for two consecutive peak or trough years is mostly higher during troughs than peaks. The exceptions are ratings $E$, $G$, and $J$, and with very small margins. Disregarding these exceptions, Bank B seems to perform more rating adjustments during periods of low GDP growth than in periods of high GDP growth. However, we find no evidence from the conditional matrices that these changes are due to more frequent downgrades. Adjustments seem to be approximately equally common for upgrades in percentage terms.

**Table 5.4:** Conditional Transition Matrix for Bank A (2009-2018) with positive deviation from GDP trend, referred to as peaks. Data is in percentages where values in parenthesis are standard deviations.

| From/to | A | B | C | D | E | F | G | H | I | J | K |
|---|---|---|---|---|---|---|---|---|---|---|---|
| A | **97.74** | 0.85 | 0.40 | 0.68 | 0.00 | 0.00 | 0.34 | 0.00 | 0.00 | 0.00 | 0.00 |
| | **(2.22)** | (0.95) | (0.28) | (0.76) | (0.00) | (0.00) | (0.38) | (0.00) | (0.00) | (0.00) | (0.00) |
| B | 0.72 | **65.04** | 21.38 | 7.99 | 3.14 | 1.43 | 0.14 | 0.06 | 0.11 | 0.00 | 0.00 |
| | (0.81) | **(1.76)** | (1.07) | (1.05) | (0.63) | (0.55) | (0.10) | (0.06) | (0.12) | (0.00) | (0.00) |
| C | 0.12 | 14.89 | **55.06** | 14.67 | 9.27 | 4.56 | 1.06 | 0.25 | 0.03 | 0.03 | 0.06 |
| | (0.13) | (1.22) | **(1.75)** | (0.51) | (1.26) | (0.18) | (0.24) | (0.11) | (0.04) | (0.03) | (0.07) |
| D | 0.10 | 3.71 | 30.80 | **27.26** | 20.16 | 12.10 | 4.61 | 0.98 | 0.18 | 0.10 | 0.00 |
| | (0.11) | (0.54) | (1.86) | **(1.18)** | (1.61) | (0.80) | (0.98) | (0.36) | (0.08) | (0.07) | (0.00) |
| E | 0.28 | 1.84 | 15.38 | 21.49 | **29.30** | 19.76 | 7.97 | 2.38 | 1.18 | 0.18 | 0.25 |
| | (0.32) | (0.31) | (0.85) | (1.62) | **(1.38)** | (0.54) | (0.67) | (0.19) | (0.24) | (0.09) | (0.22) |
| F | 0.10 | 0.60 | 8.06 | 9.67 | 19.18 | **35.31** | 16.27 | 7.22 | 2.76 | 0.60 | 0.23 |
| | (0.11) | (0.30) | (0.52) | (0.51) | (0.67) | **(0.81)** | (0.63) | (0.44) | (0.50) | (0.20) | (0.08) |
| G | 0.05 | 0.16 | 2.68 | 5.87 | 9.54 | 27.62 | **30.84** | 14.44 | 6.78 | 1.06 | 0.97 |
| | (0.06) | (0.07) | (0.47) | (0.48) | (0.45) | (1.09) | **(1.47)** | (1.53) | (0.53) | (0.20) | (0.23) |
| H | 0.09 | 0.00 | 1.19 | 2.68 | 5.15 | 13.03 | 25.79 | **33.91** | 15.45 | 1.69 | 1.02 |
| | (0.10) | (0.00) | (0.40) | (0.83) | (0.61) | (1.16) | (2.65) | **(1.96)** | (2.77) | (0.53) | (0.30) |
| I | 0.00 | 0.00 | 0.13 | 0.30 | 0.84 | 3.62 | 11.16 | 22.44 | **50.83** | 6.02 | 4.67 |
| | (0.00) | (0.00) | (0.14) | (0.21) | (0.34) | (0.87) | (0.49) | (1.37) | **(0.81)** | (1.02) | (0.69) |
| J | 1.33 | 0.00 | 0.00 | 1.33 | 0.00 | 0.00 | 1.43 | 2.76 | 4.11 | **77.99** | 11.05 |
| | (1.49) | (0.00) | (0.00) | (1.49) | (0.00) | (0.00) | (1.60) | (1.89) | (1.94) | **(6.01)** | (3.02) |
| K | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 4.02 | 1.69 | 1.79 | 9.14 | 4.23 | **79.13** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (1.19) | (1.17) | (1.26) | (4.13) | (2.30) | **(3.65)** |

**Table 5.5:** Conditional Transition Matrix for Bank B (2009-2018) with positive deviation from GDP trend, referred to as peaks. Data is in percentages where values in parenthesis are standard deviations.

| From/to | A | B | C | D | E | F | G | H | I | J | M | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A | **44.95** | 36.13 | 9.47 | 4.28 | 3.77 | 0.40 | 0.87 | 0.13 | 0.00 | 0.00 | 0.00 | 0.00 |
| | **(21.05)** | (13.93) | (6.62) | (2.88) | (2.67) | (0.44) | (0.97) | (0.15) | (0.00) | (0.00) | (0.00) | (0.00) |
| B | 2.44 | **48.28** | 34.96 | 8.49 | 4.16 | 1.05 | 0.29 | 0.20 | 0.06 | 0.06 | 0.00 | 0.00 |
| | (1.05) | **(10.66)** | (6.50) | (3.29) | (1.40) | (0.78) | (0.21) | (0.14) | (0.07) | (0.07) | (0.00) | (0.00) |
| C | 0.51 | 21.38 | **45.45** | 16.67 | 8.68 | 4.03 | 1.53 | 0.91 | 0.30 | 0.30 | 0.08 | 0.17 |
| | (0.30) | (3.41) | **(2.58)** | (3.81) | (2.02) | (0.73) | (0.16) | (0.30) | (0.29) | (0.08) | (0.05) | (0.08) |
| D | 0.13 | 7.03 | 29.77 | **25.87** | 23.06 | 7.28 | 2.88 | 1.93 | 0.92 | 0.92 | 0.14 | 0.07 |
| | (0.10) | (1.44) | (2.67) | **(3.72)** | (5.04) | (1.48) | (0.52) | (0.44) | (0.50) | (0.55) | (0.15) | (0.08) |
| E | 0.00 | 2.81 | 13.79 | 23.62 | **31.25** | 15.88 | 6.60 | 3.16 | 1.27 | 1.16 | 0.00 | 0.47 |
| | (0.00) | (1.05) | (1.23) | (6.01) | **(2.14)** | (2.49) | (0.74) | (0.59) | (0.16) | (0.56) | (0.00) | (0.14) |
| F | 0.00 | 1.23 | 7.88 | 10.73 | 23.35 | **26.07** | 15.97 | 7.92 | 3.35 | 2.68 | 0.48 | 0.35 |
| | (0.00) | (0.48) | (1.43) | (1.74) | (1.83) | **(2.45)** | (1.37) | (0.90) | (0.37) | (0.84) | (0.29) | (0.15) |
| G | 0.00 | 1.16 | 4.78 | 6.05 | 14.41 | 22.63 | **19.90** | 17.14 | 7.76 | 4.84 | 0.50 | 0.82 |
| | (0.00) | (0.49) | (0.69) | (1.65) | (0.85) | (0.86) | **(1.39)** | (2.05) | (1.25) | (1.11) | (0.30) | (0.28) |
| H | 0.00 | 0.35 | 2.80 | 4.48 | 8.78 | 17.65 | 21.15 | **21.86** | 9.85 | 10.13 | 0.89 | 2.06 |
| | (0.00) | (0.25) | (0.66) | (1.41) | (1.26) | (2.11) | (2.22) | **(2.94)** | (1.84) | (1.36) | (0.31) | (0.31) |
| I | 0.00 | 0.21 | 1.53 | 3.66 | 7.27 | 11.61 | 14.60 | 26.33 | **15.32** | 16.73 | 1.54 | 1.20 |
| | (0.00) | (0.24) | (0.82) | (0.63) | (1.57) | (2.19) | (1.61) | (2.28) | **(1.71)** | (2.18) | (0.38) | (0.41) |
| J | 0.00 | 0.17 | 0.68 | 1.63 | 4.29 | 5.20 | 8.00 | 14.29 | 10.27 | **47.29** | 4.91 | 3.26 |
| | (0.00) | (0.19) | (0.37) | (0.25) | (1.19) | (1.17) | (2.87) | (1.17) | (1.24) | **(2.12)** | (1.24) | (1.35) |
| M | 0.00 | 0.00 | 0.00 | 0.00 | 0.74 | 0.00 | 4.40 | 2.28 | 0.74 | 19.75 | **61.72** | 10.38 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.83) | (0.00) | (3.23) | (1.71) | (0.83) | (8.25) | **(2.99)** | (3.05) |
| N | 0.00 | 0.74 | 0.48 | 0.00 | 3.08 | 6.13 | 2.77 | 3.17 | 1.43 | 5.48 | 6.10 | **70.62** |
| | (0.00) | (0.83) | (0.53) | (0.00) | (1.59) | (2.48) | (1.91) | (2.71) | (1.60) | (2.29) | (2.12) | **(4.76)** |

**Table 5.6:** Conditional Transition Matrix for Bank A (2009-2018) with negative deviation from GDP trend, referred to as troughs. Data is in percentages where values in parenthesis are standard deviations.

| From/to | A | B | C | D | E | F | G | H | I | J | K |
|---|---|---|---|---|---|---|---|---|---|---|---|
| A | **95.23** | 1.64 | 0.55 | 0.51 | 1.02 | 0.26 | 0.00 | 0.00 | 0.32 | 0.47 | 0.00 |
| | **(2.90)** | (1.39) | (0.38) | (0.59) | (1.18) | (0.29) | (0.00) | (0.00) | (0.37) | (0.54) | (0.00) |
| B | 1.00 | **63.60** | 23.07 | 6.60 | 3.91 | 1.05 | 0.54 | 0.00 | 0.00 | 0.00 | 0.22 |
| | (0.41) | **(1.83)** | (0.90) | (1.40) | (0.58) | (0.44) | (0.24) | (0.00) | (0.00) | (0.00) | (0.26) |
| C | 0.80 | 15.07 | **53.10** | 13.10 | 9.85 | 5.84 | 1.46 | 0.42 | 0.17 | 0.04 | 0.15 |
| | (0.54) | (0.71) | **(1.17)** | (1.12) | (0.67) | (0.48) | (0.20) | (0.13) | (0.09) | (0.04) | (0.12) |
| D | 0.58 | 5.52 | 30.89 | **26.38** | 16.68 | 12.12 | 5.37 | 1.55 | 0.58 | 0.27 | 0.06 |
| | (0.39) | (0.28) | (1.52) | **(0.58)** | (1.01) | (0.99) | (0.89) | (0.11) | (0.26) | (0.18) | (0.07) |
| E | 0.51 | 2.86 | 18.89 | 21.06 | **26.06** | 18.31 | 8.15 | 3.24 | 0.55 | 0.19 | 0.18 |
| | (0.38) | (0.61) | (1.42) | (1.23) | **(0.63)** | (0.46) | (0.14) | (0.88) | (0.06) | (0.13) | (0.07) |
| F | 0.33 | 0.95 | 8.34 | 10.58 | 18.81 | **34.41** | 15.54 | 7.40 | 2.96 | 0.41 | 0.26 |
| | (0.27) | (0.32) | (0.56) | (0.61) | (1.41) | **(0.79)** | (0.14) | (0.59) | (0.38) | (0.22) | (0.09) |
| G | 0.19 | 0.51 | 3.67 | 5.33 | 11.78 | 26.34 | **29.48** | 14.54 | 6.94 | 0.71 | 0.51 |
| | (0.21) | (0.21) | (0.53) | (0.84) | (0.84) | (0.35) | **(1.64)** | (0.91) | (1.24) | (0.19) | (0.12) |
| H | 0.22 | 0.23 | 1.53 | 2.82 | 5.20 | 17.30 | 23.75 | **32.26** | 13.81 | 1.29 | 1.59 |
| | (0.15) | (0.27) | (0.52) | (0.48) | (1.23) | (1.23) | (1.05) | **(1.71)** | (2.27) | (0.19) | (0.38) |
| I | 0.00 | 0.00 | 0.21 | 0.65 | 1.72 | 4.59 | 14.04 | 21.23 | **50.55** | 3.69 | 3.31 |
| | (0.00) | (0.00) | (0.24) | (0.48) | (0.90) | (1.30) | (1.33) | (1.49) | **(2.16)** | (0.99) | (0.51) |
| J | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.47 | 0.00 | 9.81 | **80.38** | 8.34 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (1.70) | (0.00) | (4.29) | **(8.57)** | (3.32) |
| K | 0.00 | 0.00 | 0.00 | 0.00 | 2.95 | 0.78 | 2.10 | 1.39 | 4.27 | 8.11 | **80.40** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (1.97) | (0.90) | (1.49) | (1.60) | (1.66) | (3.95) | **(5.87)** |

**Table 5.7:** Conditional Transition Matrix for Bank B (2009-2018) with negative deviation from GDP trend, referred to as troughs. Data is in percentages where values in parenthesis are standard deviations.

| From/to | A | B | C | D | E | F | G | H | I | J | M | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A | **65.75** | 25.28 | 5.18 | 2.97 | 0.58 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.23 |
| | **(9.43)** | (5.99) | (1.51) | (2.48) | (0.40) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.27) |
| B | 12.46 | **58.86** | 20.50 | 4.05 | 2.31 | 0.95 | 0.40 | 0.17 | 0.07 | 0.24 | 0.00 | 0.00 |
| | (3.94) | **(4.63)** | (1.50) | (0.47) | (0.69) | (0.37) | (0.37) | (0.19) | (0.08) | (0.18) | (0.00) | (0.00) |
| C | 1.68 | 28.31 | **46.61** | 11.47 | 6.95 | 2.88 | 0.89 | 0.44 | 0.19 | 0.51 | 0.00 | 0.07 |
| | (0.68) | (5.20) | **(5.05)** | (2.59) | (0.31) | (0.49) | (0.26) | (0.07) | (0.07) | (0.43) | (0.00) | (0.08) |
| D | 1.36 | 6.89 | 29.61 | **30.28** | 16.21 | 9.05 | 3.01 | 2.32 | 0.75 | 0.31 | 0.11 | 0.11 |
| | (0.73) | (0.53) | (2.65) | **(2.71)** | (2.47) | (0.95) | (0.63) | (0.70) | (0.36) | (0.12) | (0.12) | (0.12) |
| E | 1.06 | 3.82 | 17.03 | 19.72 | **31.14** | 14.07 | 6.69 | 3.43 | 1.91 | 1.05 | 0.07 | 0.00 |
| | (0.69) | (0.90) | (1.41) | (0.85) | **(2.15)** | (2.35) | (1.39) | (0.21) | (0.67) | (0.27) | (0.08) | (0.00) |
| F | 0.11 | 2.26 | 8.52 | 12.19 | 24.74 | **27.00** | 11.78 | 8.26 | 3.23 | 1.22 | 0.11 | 0.59 |
| | (0.12) | (0.63) | (2.32) | (0.91) | (1.60) | **(2.10)** | (2.39) | (1.87) | (0.60) | (0.22) | (0.13) | (0.26) |
| G | 1.02 | 1.22 | 4.62 | 7.21 | 17.50 | 22.76 | **19.62** | 13.78 | 5.48 | 4.36 | 0.92 | 1.52 |
| | (1.18) | (0.41) | (2.17) | (1.39) | (1.81) | (2.32) | **(3.33)** | (2.83) | (1.60) | (0.93) | (0.20) | (0.35) |
| H | 0.44 | 1.26 | 3.83 | 4.75 | 11.36 | 14.42 | 19.30 | **26.09** | 9.02 | 7.44 | 1.34 | 0.75 |
| | (0.51) | (1.17) | (2.90) | (1.97) | (1.08) | (1.72) | (2.78) | **(3.99)** | (1.40) | (1.02) | (0.18) | (0.36) |
| I | 0.00 | 0.22 | 1.92 | 1.48 | 8.17 | 12.26 | 16.15 | 22.53 | **18.86** | 13.42 | 2.46 | 2.53 |
| | (0.00) | (0.25) | (1.04) | (1.18) | (1.78) | (2.54) | (3.50) | (2.36) | **(1.93)** | (3.37) | (0.89) | (1.21) |
| J | 0.11 | 0.11 | 0.42 | 1.00 | 1.06 | 10.48 | 9.15 | 9.24 | 16.92 | **43.44** | 4.07 | 4.00 |
| | (0.12) | (0.12) | (0.49) | (0.71) | (1.22) | (1.64) | (2.49) | (1.23) | (2.31) | **(4.16)** | (1.05) | (1.61) |
| M | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 33.88 | **63.49** | 2.63 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (26.13) | **(25.24)** | (3.04) |
| N | 0.00 | 0.47 | 0.47 | 3.45 | 3.73 | 1.66 | 5.73 | 2.38 | 1.66 | 4.51 | 3.73 | **72.20** |
| | (0.00) | (0.54) | (0.54) | (1.38) | (1.52) | (1.30) | (4.81) | (2.75) | (1.30) | (3.90) | (1.52) | **(4.48)** |

## 5.2 Rating Stability

Since credit ratings are based on fundamental data and most CRAs claim they are through-the-cycle, ratings should not change frequently. Occasionally, however, macroeconomic or firm-specific changes lead to adjustments of credit ratings. If a CRA is successful at assessing the creditworthiness of its obligors, rating adjustments should not occur frequently, be large, or change direction regularly. To investigate if this is the case, we calculate and analyze five different measures of volatility for the two banks. These are Rating Volatility ($RatVol$), Rating Volatility due to downgrades ($RatVolD$), Rating Volatility due to upgrades ($RatVolU$), Large Rating Changes (LRC) and Rating Reversals (RR). Due to insufficient historical data, LRC and RR are not computed on the NCR data set.

### 5.2.1 Rating Volatility

$RatVol$ is a measure for volatility that condenses volatility data from the two-dimensional ratings transition matrix into a single scalar for each time period. The measure can be further split into volatility caused by downgrades ($RatVolD$) and upgrades ($RatVolU$) as shown in Figures 5.1 and 5.2. All three measures represent data over the previous year - e.g $RatVol_t$ describes the volatility from year $t-1$ to $t$. When performing a Dickey-Fuller test on RatVol for both banks separately, we find that the measures are stationary at a $1\%$ significance level, fulfilling the condition for regression analysis. For Bank A, there has been an upward trend both in total volatility and volatility due to upgrades and downgrades. Because all three measures represent data over the previous year, Bank A achieves a low volatility "score" in the year leading up to 2011. Likewise, its high is reached in the year leading up to 2016.

From the second graph in Figure 5.1, we conclude that Bank B's ratings are generally more volatile, in absolute terms, than Bank A. In other words, its ratings are less stable over time. The graph also exhibits a negative trend in both total volatility and volatility due to upgrades and downgrades for Bank B, contrary to the positive trend in Bank A.

The figure indicates that the volatility started to pick up between 2014 and 2015 for Bank A. This is also the period that the oil price hit its ten-year low. Consequently, the period 2015-2017 clearly stands out as a period of strong instability of ratings for this bank. However, there is only insignificant differences between volatility due to upgrades and downgrades. In other words, both upgrades and downgrades contribute with approximately the same proportion to the total volatility throughout the whole time period.

For Bank B on the other hand, $RatVol$ and $RatVolU$ continue to decrease following the year 2014, despite this bank's strong dependency on the oil and gas sector. One possible reason is that since Bank B is more exposed to oil and gas sector, it might be more reluctant to provide loans *and assign credit ratings* to firms that pose high credit risk. An even more likely reason is that the total number of firms that remain customers of Bank B has declined since 2014. The data set from Bank B only contains current customers, so if a firm defaults before being assigned a default ratings, it does not show up in the default statistics. Thus, these defaulting companies do not affect $RatVol$ and other volatility measures the way they should, so that the actual measures could be somewhat different than the results imply.

For NCR, the value for $RatVol$ is lower than for the banks, but it fluctuates more. Also, unlike bank ratings volatility, the NCR volatility *decreases* during years in which the Norwegian GDP deviation is negative, following the oil price drop starting in late 2014. One possible reason is that while the banks only assigns ratings to *Norwegian* companies, NCR assigns ratings to *Nordic* companies. Nordic companies as a whole are less dependent on the oil price than Norwegian companies. Consequently, we should not necessarily expect that the ratings behavior of a CRA is ”identical” to that of a bank. We should also point out that the NCR data set reveals a great increase in the number of rating adjustments over the last year, for companies with no ratings prior to 2018. Therefore, the volatility measures surge from 2018 to 2019 and should be interpreted with care.

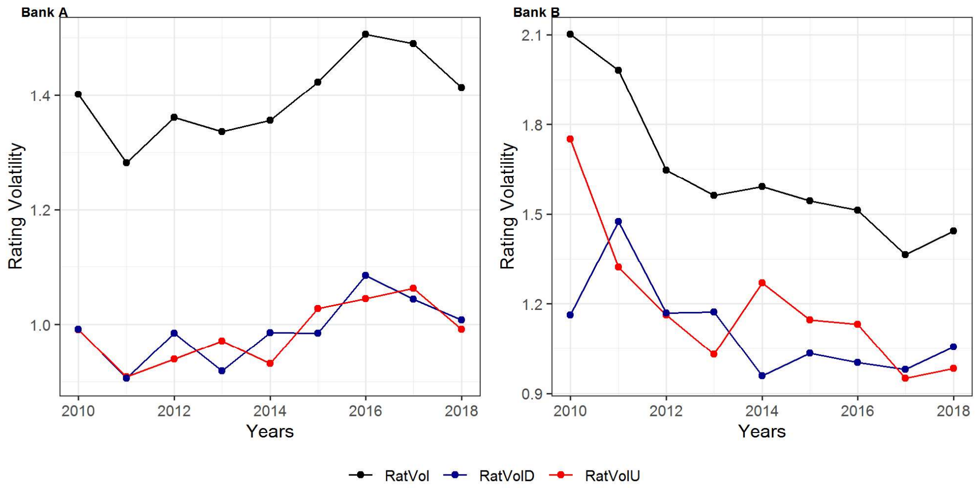


**Figure 5.1:** Total rating volatility ($RatVol$), and volatility caused by downgrades ($RatVolD$) and upgrades ($RatVolU$) for Bank A and B during the period 2009-2018. Note that the spacing for the values on the vertical axes on the two subplots are not of equal magnitude.

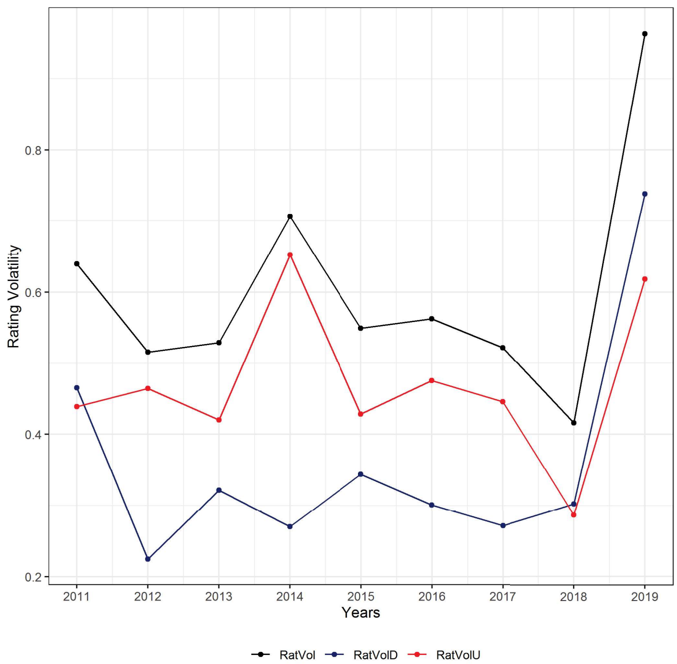


**Figure 5.2:** NCR: Total rating volatility ($RatVol$), and volatility caused by downgrades ($RatVolD$) and upgrades ($RatVolU$) for Nordic Credit Rating (NCR) during the period 2010-2019.

### 5.2.2 Large Rating Changes

Large Rating Changes (LRC), i.e., adjustments of three or more notches over two consecutive years during the ten-year period, is shown in Figure 5.3 for both banks. It is shown in blue on the left axis.

For Bank A, we can see an increase in LRC from 0.7% of annual rating changes at its lowest in 2011 to 1.3% of all rating changes in 2017. Although representing a limited amount of all ratings, LRC almost doubles from 2011 to 2017. Such a drastic increase could be justified if, for instance, there was a change in the business cycle from a peak to a trough. We investigate this possibility and present the results later in this section. In general, however, a rise in the value for LRC may suggest that a CRA has been too slow at incorporating the changes of credit risk in its obligors. For our data, this claim has to be somewhat adjusted. Credit ratings in our data set are only updated at an annual frequency, not at the bank's own desired frequency. Therefore, one would expect a higher value for LRC at a bank than for a regular CRA, and we cannot directly conclude that the bank is slow to incorporate the change in risk for its obligors.

For Bank B, LRC reaches its highest level at about 4% of annual rating changes in 2011 and its lowest at about 1.2% in 2017. From Figure 3.6 in the Data Chapter of this paper, we observe that almost all companies in rating class $A$ are downgraded between 2010 and 2011, which could partly explain the sharp increase in LRC in 2011.

Compared to Bank A's high of 1.3% and low of 0.7%, LRC for Bank B, with its high of 4% and low of 1.2%, is much higher than for Bank A throughout the whole duration of our data, except for in 2017. Also, as can be seen in Figure 5.3, the trend for LRC is *increasing* for Bank A and *decreasing* for Bank B.

Later in this Chapter, we examine whether the state of the business cycle affects the value of LRC. We also explore whether the banks trade off accuracy for increased volatility, as measured by AR and LRC respectively.

### 5.2.3 Rating Reversals

The ratio of Rating Reversals (RR) - i.e., a rating adjustment in one direction followed by a rating change in the opposite direction - to the total number of ratings during the ten-year period for Bank A and B, can be seen in Figure 5.3, in red on the right axis.

For Bank A, we see that the occurrence of rating reversals is stable throughout the whole time period. Nevertheless, rating reversals overall occur at a relatively high frequency, with between 8% and 9% of all rating changes being rating reversals. Again, part of the reason for this could be the annual frequency of credit rating updates. However, RR should not be affected by the update frequency to the same degree as LRC. In fact, it can be argued that a lower credit update frequency should result in a lower RR since the lower frequency acts as an averaging process. As a result, the RR should be lower than if updates occurred more regularly. Since we do not have any direct comparable data for this, we only mention it but cannot verify if this is the case.

Rating Reversals (RR) for Bank B vary between 8% and 14% of all rating changes. RR spikes in 2014, the same year that the oil price fell from over 100 USD/bbl to less than 50 USD/bbl. Interestingly, Figure 3.6 from the Data Chapter, shows that the rating classes that increased from 2013 to 2014 were $B$, $C$, $D$ and $E$. Meanwhile, the percentage distribution of all companies in ratings classes $G$ through $N$ actually decreased from about 30% of all ratings to 25%. Also, as Table 3.2 indicates, the total default rate - i.e., new companies assigned ratings $M$ and $N$ - appears to fall from 1.12% in 2013 to 0.89% in 2014. Due to this bank's high exposure to the oil industry, we expected the default rate to increase during this period. However, as previously explained, the seemingly lower rate of default is due to the data set only containing current customers, so it does not capture the higher number of defaults in this period. This results in volatility measures that have to be interpreted with care.

When comparing RR for both banks simultaneously in Figure 5.3, it becomes clear that Rating Reversals are higher and more volatile for Bank B than for Bank A through most of the period. Whereas RR for Bank A varied between 8% and 9%, between 8% and 14% of all rating changes were rating reversals for Bank B.

Later in this section, we investigate whether the state of the business cycle affects the value of RR. We also investigate whether the banks trade off accuracy for increased volatility, as measured by AR and RR respectively.

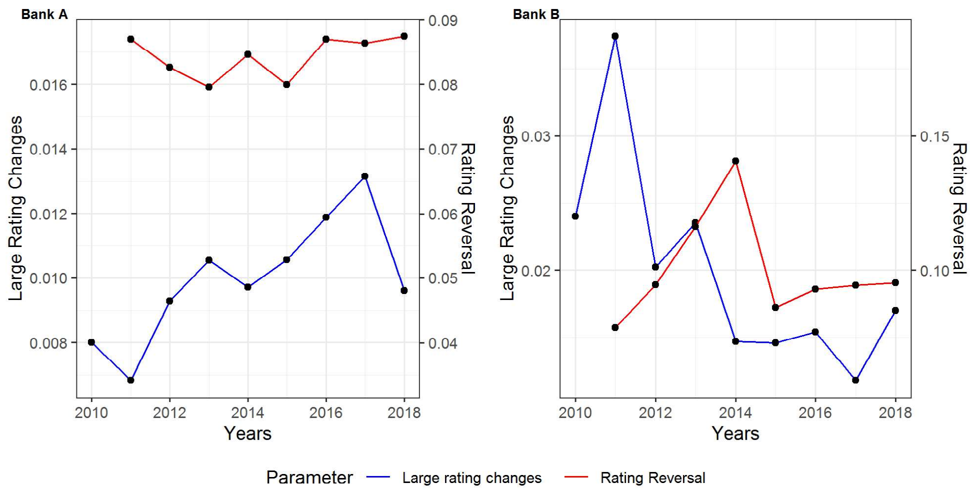


**Figure 5.3:** Large rating changes (LRC) and rating reversals (RR) for both Bank A and Bank B during the period 2009-2018. Note that the spacing for the values on the vertical axes on the two subplots are not of equal magnitude.

## 5.3 Relationship between Measures of Volatility

In order to compare our measures of volatility - $RatVol$, $RatVolU$, and $RatVolD$ - with more conventional measures of volatility, we calculate the correlations between them on the data set for the two banks. The results in Table 5.8 and 5.9 show some intriguing relationships.

For Bank A, we observe high, significant correlations between LRC and our three novel measures of volatility: $RatVol$, $RatVolU$, and $RatVolD$. The correlation is slightly higher for $RatVolU$ (0.81) than for $RatVolD$ (0.68), suggesting that large rating changes are slightly more frequent or of a larger magnitude among upgrades than downgrades. We note small and insignificant correlations between our three volatility measures and RR. This indicates that rating reversals are not significantly more frequent in periods of higher total volatility, nor in periods of higher volatility due to upgrades or downgrades. From this, we conclude that credit rating reversals seem to occur independently of overall rating volatility.

For Bank B, we observe high, significant correlations between LRC and $RatVol$ and

$RatVolD$. As seen in the Table 5.9, the correlation is very high for $RatVolD$ (0.98). This suggests that large rating changes are quite frequent among downgrades. The lower, *insignificant* correlation between LRC and $RatVolU$ (0.44) implies that large rating changes do not occur as frequently for upgrades. As was the case for Bank A, we note relatively small and insignificant correlations between our three volatility measures and RR.

Our analysis shows insignificant correlations between RR and the RatVol measures for both banks. If all measures contained mostly the same information regarding rating volatility, the correlations would ideally be high and significant. The lack of suck a relationship suggests that our measures for volatility contain some information absent in traditional measures of stability. For instance, our measures include a full account of rating transitions because they include not only small or large rating changes, but also the direction of the adjustment. Therefore, it can be argued that our measures combine information present in the traditional stability measures and provide a more accurate account of rating stability.

**Table 5.8:** Correlation between traditional measures of rating stability and our alternative measures of volatility for Bank A. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

| | $RatVol$ | $RatVolU$ | $RatVolD$ | LRC | RR |
|---|---|---|---|---|---|
| $RatVol$ | - | 0.93*** | 0.94*** | 0.79** | 0.26 |
| $RatVolU$ | 0.93*** | - | 0.75** | 0.81*** | 0.06 |
| $RatVolD$ | 0.94*** | 0.75** | - | 0.68** | 0.42 |
| LRC | 0.79** | 0.81*** | 0.68** | - | -0.05 |
| RR | 0.26 | 0.06 | 0.42 | -0.05 | - |

**Table 5.9:** Correlation between traditional measures of rating stability and our alternative measures of volatility for Bank B. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

| | $RatVol$ | $RatVolU$ | $RatVolD$ | LRC | RR |
|---|---|---|---|---|---|
| $RatVol$ | - | 0.91*** | 0.70** | 0.77** | 0.23 |
| $RatVolU$ | 0.91*** | - | 0.34 | 0.44 | 0.07 |
| $RatVolD$ | 0.70** | 0.34 | - | 0.98*** | 0.45 |
| LRC | 0.77** | 0.44 | 0.98*** | - | 0.32 |
| RR | 0.23 | 0.07 | 0.45 | 0.32 | - |

## 5.4 Rating Quality

The Accuracy Ratio (AR) is a measure for the discriminatory power of rating systems. It measures how well a credit rating system captures and predicts the default risk of companies. A value of AR equal to 1 indicates that a CRA perfectly predicts which companies will default. Values closer to 0 indicate that a CRA's ratings do not possess any predictive power of which firms will default. In Figure 5.4, the resulting accuracy ratios for the two banks are presented, Bank A in blue and Bank B in red. When performing a KPSS test on AR for both banks separately, we find that the measures are trend stationary at a 10% significance level, fulfilling the condition for regression analysis. Due to inadequate default data for companies rated by NCR, ARs can not be calculated for this CRA and are, therefore, excluded from the analysis.

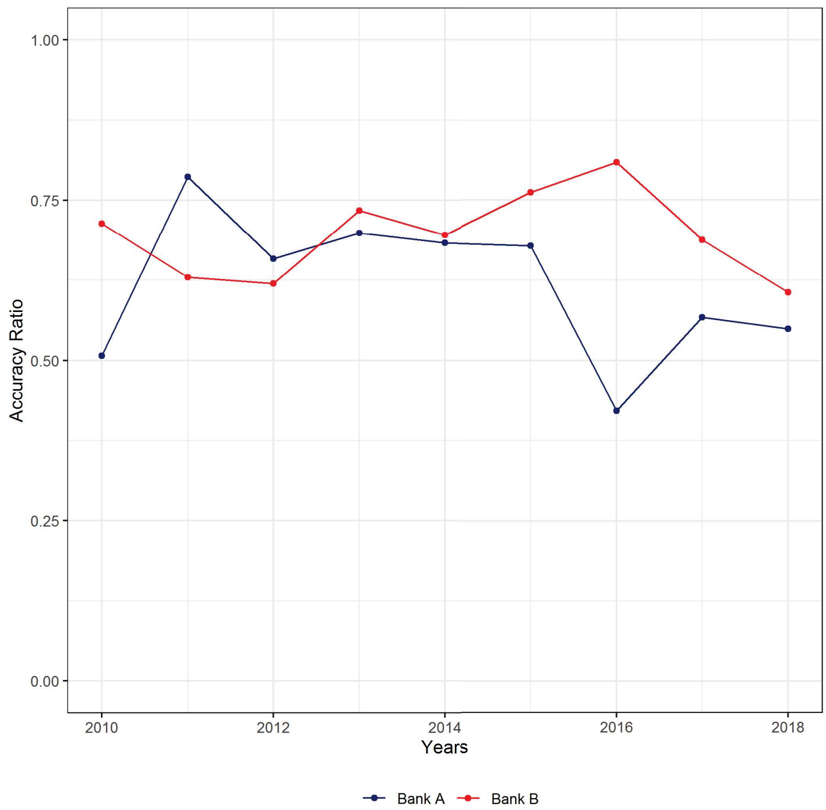


**Figure 5.4:** Accuracy ratio for both banks in the period 2010-2018. Values closer to 1 indicate more accurate predictions of default. Bank B outperforms Bank A in terms of more accurately predicting default rates in 7 out of the 9 years.

The Accuracy Ratio is higher than 0 for both banks throughout the nine-year period. For Bank A, the mean value is 0.62, while it is slightly higher for Bank B, at 0.70. In comparison, a previous study calculated the AR for Moody's and Standard & Poor's during the period 1994-2011 to be 0.71 and 0.73, respectively (Carvalho et al. (2014) [9]). We can, therefore, conclude that both banks in question have relatively high values for AR, implying that their rating systems overall seem to predict defaults adequately.

In 7 out of the 9 years that our data spans, Bank B is more accurate at predicting defaults than Bank A. Nevertheless, the values for the two banks are reasonably similar up until 2015, at which point they begin to diverge. As previously mentioned in the Data Chapter, the Norwegian Central Bank identifies a clear correlation between Norway's GDP and the oil price [23]. In 2014-2016, the oil price declined sharply. Consequently, the state of the Norwegian business cycle in the same period was in a so-called trough, with negative deviation from the GDP trend, as shown in Figure 3.10 in the Data Chapter.

The divergence between the Accuracy Ratio of Bank A and Bank B occurs at exactly the same time as the oil price collapses and the trough materializes. During this period, the default prediction accuracy of Bank A decreases. Meanwhile, despite its higher exposure to oil, the AR for Bank B improves. One possible explanation for this seemingly inverse relationship between the Accuracy Ratio of the two banks and the oil price, is the difference in the amount of experience with distressed oil companies that each of them have. Since Bank A has less customers in the petroleum industry, its default prediction models might not be as well-suited at assigning correct default probabilities to such companies as Bank B. Tables 3.1 and 3.2 in the Data Chapter show that Bank B consistently has lower default rates as a percentage of total ratings than Bank A, ever since the reversal of the state of the business cycle in 2014. Consequently, another possible reason for Bank B's higher AR could be that it is less difficult to correctly predict which *oilfield service* companies will default in periods of low oil prices, than it is to predict default probabilities in *non-oil* sectors in the same economic environment. If the companies associated with Bank B that did default were indeed mostly petroleum related companies, and considering its higher competence and experience with such companies, this could explain the higher prediction accuracy. A third possible reason is the previously explained termination of customer relation of defaulting companies not showing up as a default rating in the data set, resulting in a higher accuracy measure than is actually the case. Since we do not have access to sector-specific default rates of either bank, we cannot confirm any of these hypotheses.

## 5.5 Business Cycle Effects

As noted by Altman and Rijken (2006) [1], CRAs advertise a through-the-cycle methodology in their rating assignments. In this context, this means that credit ratings should not be significantly dependent on the state of the business cycle. In this paper, we use data from two *banks* and only one CRA - a CRA that is relatively new and with limited historical data. Consequently, our results could, due to legitimate and understandable reasons, differ from that of previous studies performed on data from large CRAs with a long history (such as Standard & Poor's and Moody's). Nevertheless, we analyze the effect that the state of the business cycle has on the volatility and quality of credit ratings, in order to assess whether banks and smaller CRAs can claim to follow the same methodology as larger CRAs.

### 5.5.1 Business Cycle Effects on Volatility of Ratings

#### 5.5.1.1 Univariate Analysis

We run several simple linear regressions on the three credit rating data sets. The results of the regressions are presented in Table 5.10 for the two banks and Table 5.11 for NCR. We only include scatter plots for relationships showing statistically significant results for either of the banks.

Previous studies find contradictory evidence for a through-the-cycle methodology (see, e.g., Carvalho et. al (2014) [9]), even among the biggest, leading CRAs. Naturally, we expected the same to be the case for our data, with ratings volatility varying with the state of the business cycle. We initially expected positive $GDP.Dev$ to be accompanied by a higher $RatVolU$, a lower $RatVolD$, and a lower or insignificant $RatVol$. The rationale behind these initial assumptions is that good economic times results in more upgrades, less downgrades and more stability in credit ratings, i.e., lower total volatility. For the two volatility measures LRC and RR, we expected them to be either less dependent or completely independent of the state of the business cycle since these measures can be either high or low in both good or bad economic times.

**Table 5.10:** OLS estimates of the regressions examining the relationship between $GDP.Dev_t$ and $RatVol_t$, $RatVolU_t$, $RatVolD_t$, $LRC_t$, and $RR_t$ for both banks. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

| | **Bank A** | | | **Bank B** | | |
|---|---|---|---|---|---|---|
| | Intercept | $GDP.Dev_t$ | $R^2$ | Intercept | $GDP.Dev_t$ | $R^2$ |
| $RatVol_t$ | 1.40*** | -1.89** | 0.61 | 1.64*** | 0.28 | 0.001 |
| t-ratio | (87.20) | (-3.30) | | (18.79) | (0.09) | |
| $RatVolU_t$ | 0.99*** | -1.36** | 0.58 | 1.20*** | -1.29 | 0.03 |
| t-ratio | (80.14) | (-3.10) | | (14.00) | (-0.43) | |
| $RatVolD_t$ | 0.99*** | -1.31** | 0.49 | 1.11*** | 1.81 | 0.11 |
| t-ratio | (70.34) | (-2.61) | | (20.74) | (0.94) | |
| $LRC_t$ | 0.01*** | -0.03 | 0.18 | 0.02*** | 0.08 | 0.10 |
| t-ratio | (16.31) | (-1.25) | | (7.48) | (0.90) | |
| $RR_t$ | 0.08*** | -0.03 | 0.09 | 0.10*** | 0.25 | 0.15 |
| t-ratio | (71.36) | (-0.77) | | (14.16) | (1.03) | |

Table 5.10 shows the results of the univariate regressions for both banks. Figures 5.5, 5.6, and 5.7 illustrate the relationship between our three volatility measures ($RatVolU$, $RatVolD$, and $RatVol$) and GDP deviation. The results show a statistically significant negative relationship between the three RatVol measures for Bank A and GDP deviation, at a significance level of 0.05. The negative relation is displayed by the downward sloping regression lines in Figures 5.5, 5.6, and 5.7. Our results for Bank A are consistent with the result found in previous studies, such as Amato and Furfine (2004) [2] and Carvalho et al. (2014) [9]. The evidence implies that rating adjustments are more intense during worse economic times and less so during better times, as indicated by all five regressions, despite the fact that only the RatVol measures are showing statistically significant correlation with GDP deviation. The stability of credit ratings in better times indicates a procyclical rating policy. In these periods, there will be less incentive to change credit assessments compared to bad times due to less overall default risk. A possible explanation for higher rating volatility in periods when the economy underperforms, is that defaults are more common in such periods. Thus, CRAs may attempt to increase default prediction by over-eagerly reassessing ratings leading to higher volatility and lower stability.

The same conclusions cannot be drawn for Bank B. Table 5.10 shows that the regressions yield no statistically significant results between any of the RatVol measures of volatility and GDP deviation. Nevertheless, our analysis shows that Bank B's rating adjustments are *less* intense during bad economic times, as indicated by the upward sloping regression lines in Figure 5.5 and Figure 5.7. The only exception is in volatility due to upgrades ($RatVolU$ in Figure 5.6), suggesting that the bank executes more upgrades when the economy underperforms. The relationship is ambiguous for all the measures for Bank B and accompanied by a low $R^2$. Additionally, unlike Bank A, it is important to stress that none of the regressions for Bank B are statistically significant.

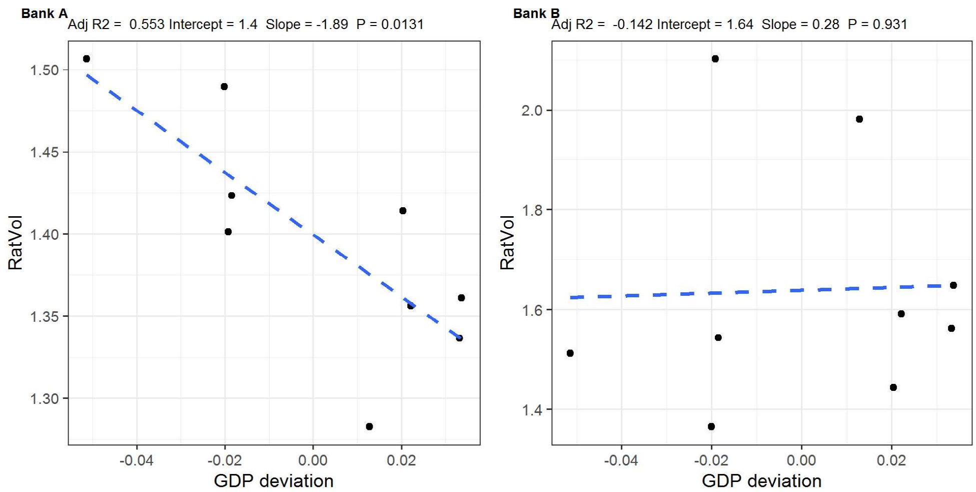


**Figure 5.5:** Relationship between deviation from long-term growth in real GDP and $RatVol$ for both banks in the period 2009-2018.

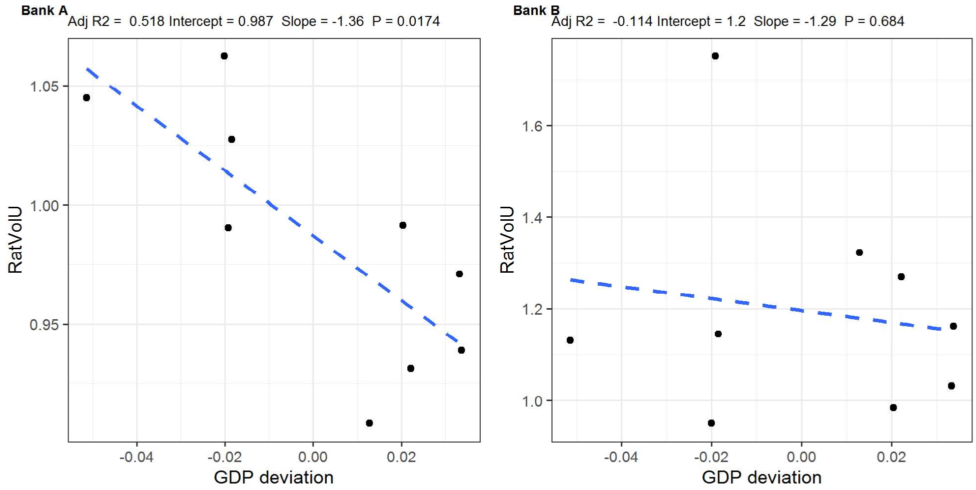


**Figure 5.6:** Relationship between deviation from long-term growth in real GDP and $RatVolU$ for both banks in the period 2009-2018.

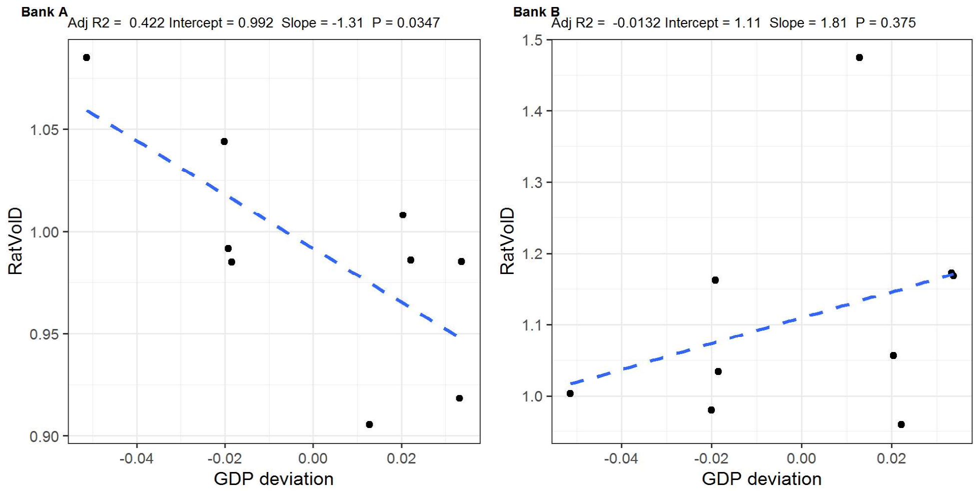


**Figure 5.7:** Relationship between deviation from long-term growth in real GDP and $RatVolD$ for both banks in the period 2009-2018.

As seen in Table 5.10, the relationship between the state of the business cycle and the volatility measures LRC and RR are negative for Bank A and positive for Bank B. However, the regressions show statistically insignificant results, as expected, so we do not include plots for these relationships.

As previously described, credit ratings issued by CRAs measure relative business risk. Many CRAs claim to follow a through-the-cycle methodology when assigning credit ratings. The ratings should, therefore, be unaffected by the business cycle. Clearly, this is not the case for the ratings of Bank A since the three volatility measures $RatVol$, $RatVolU$, and $RatVolD$ are significantly negatively correlated with the state of the business cycle. In other words, rating assignments appear to *be* affected by the business cycle. We conclude that the stability of ratings is positively correlated with the state of the business cycle and that Bank A's credit ratings are point-in-time measures of credit risk.

Bank B on the other hand, *could* claim to be following a through-the-cycle methodology.

Based on our analysis, we could not dismiss such a claim due to statistically insignificant results. There is no clear pattern for the relationship between the different measures of rating volatility and the business cycle, i.e., rating adjustments appear to be independent of the business cycle. However, these results may well be attributed to the limited size of our data set, covering a period of only nine years. Also, our measure for the business cycle, GDP deviation from trend growth, is not a perfect proxy. Therefore, we cannot conclude from this univariate analysis that Bank B's ratings are indeed independent on the business cycle, i.e., that this bank adheres to a through-the-cycle methodology. We attempt to mitigate this problem by including additional business cycle measures in the following multivariate analysis.

**Table 5.11:** OLS estimates of the regressions examining the relationship between $GDP.Dev$ and $RatVol$, $RatVolU$, and $RatVolD$ for NCR. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

| **Nordic Credit Rating (NCR)** | | | |
|---|---|---|---|
| | Intercept | $GDP.Dev_t$ | $R^2$ |
| $RatVol_t$ | 0.60*** | 1.98 | 0.14 |
| t-ratio | (11.39) | (1.06) | |
| $RatVolU_t$ | 0.47*** | 1.68 | 0.21 |
| t-ratio | (13.56) | (1.36) | |
| $RatVolD_t$ | 0.36*** | 0.87 | 0.03 |
| t-ratio | (6.49) | (0.44) | |

Due to insufficient data, LRC and RR have not been computed on the NCR data set. However, we perform the same linear regressions to assess the relationship between GDP deviation and the three Rating Volatility measures. As seen in Table 5.11, there are no significant relationships between $GDP.Dev$, and $RatVol$, $RatVolU$, and $RatVolD$. Consequently, we cannot make any definitive conclusions on the relationship between the variables derived from this data set. Note that although they are insignificant, the relationships between the variables are positive for NCR, whereas they are statistically significant negative for Bank A. If this trend continues as the size of the data set grows, infrequent outliers that currently influence the insignificance in the relationship will be given less weight. We may, therefore, *speculate* that the relation could be significant in the future. If this is the case, the results are quite interesting as they directly contradict the results we get using data from Bank A. A possible reason for this contradictory result is the uncertain relation between Nordic credit ratings and Norwegian Mainland GDP. It could well be the case that *Nordic* credit ratings are independent of *Norwegian* GDP, and that this is why our results are insignificant and the relationship negative. Due to this data set's insufficient size, we do not proceed with a multivariate analysis.

#### 5.5.1.2 Multivariate Analysis

Next, we continue with a more comprehensive multivariate analysis of the effect that the business cycle might have on the volatility of ratings. Previously in this chapter, we presented evidence that our measures of volatility better explain the volatility of credit ratings than LRC and RR. Therefore, we only perform multivariate regressions on $RatVol$, $RatVolU$, and $RatVolD$. In addition to $GDP.Dev$, we include five more business cycle proxies: $SwapRate$, $VIX$, $NewBonds$, $NewLoans$, and $RateDef$. When performing a multivariate regression with all six measures as independent variables, the results produce only one statistically significant coefficient for either bank (see Table 6.2 in the Appendix). We suspect that this is due to the presence of multicollinearity among the independent variables, which Figures 6.1 and 6.2 in the Appendix seem to suggest. Therefore, we calculate the variance inflation factor (VIF) for both of the banks to assess which variables are likely to be exhibiting indications of multicollinearity, i.e., VIF values typically higher than 30, before removing these variables. Then, we proceed to run multivariate regressions on the remaining independent variables. When performing similar multivariate regressions for the data from NCR, the results yield no statistically significant coefficients as shown in Table 6.3 in the Appendix. Removing variables in a similar fashion as is done for the banks and re-running the regressions yield no significant results. This is likely due to the small size of the data set. We do not discuss our results for NCR further.

The VIF values for Bank A and B are presented in Table 5.12. Analyzing the VIF values of both banks jointly, we see that the values are high for $VIX$ and $NewBonds$. These variables are highly correlated, with a correlation of -0.92 as seen in Figure 6.2 in the Appendix. The VIF value is also quite high for $SwapRate$, a variable that shows signs of correlation with $GDP.Dev$. Due to their high VIF values, these variables are removed as independent variables. We also believe that these variables ($VIX$, $NewBonds$, and $SwapRate$) are proxies for the business cycle that affect credit ratings of CRAs more than banks, so their removal from the model can be justified regardless. The resulting multivariate regression is, therefore, composed of the explanatory variables $GDP.Dev$, $NewLoans$, and $RateDef$ since they appear to be uncorrelated.

**Table 5.12:** Variance inflation factor (VIF) values for the following measures: $GDP.Dev$, $SwapRate$, $VIX$, $NewBonds$, $NewLoans$, and $RateDef$. Higher VIF values indicate multicollinearity between independent variables.

| | **Bank A** | **Bank B** |
|---|---|---|
| | VIF | VIF |
| $GDP.Dev_t$ | 9.37 | 5.98 |
| $SwapRate_t$ | 17.70 | 7.76 |
| $VIX_t$ | 43.81 | 26.18 |
| $NewBonds_t$ | 57.89 | 35.09 |
| $NewLoans_t$ | 1.92 | 3.84 |
| $RateDef_t$ | 3.66 | 8.79 |

After eliminating correlated independent variables, we run a multivariate regression with the remaining variables. The results are presented in Table 5.13. For Bank A, we see that all three volatility measures show significantly negative relationships with $GDP.Dev$. This is consistent with the result in the previous univariate analysis - higher volatility during troughs. The values for adjusted $R^2$ in the multivariate analysis are lower than the values for $R^2$ in the univariate regression, indicating that the added predictors improve the model by less than that to be expected by chance. Therefore, the univariate model appears to better explain the variance of the volatility measures.

For Bank B on the other hand, only $RatVol$ and $RatVolU$ have significant coefficients. They both appear to be positively related to the rate of default, $RateDef$, suggesting higher total volatility and upward adjustments when the rate of default is higher. Higher default rates are presumably more common during troughs, implying more volatility in ratings during bad economic times. In other words, rating volatility appears to be inversely related to the business cycle, as expected. However, as previously argued, the measure of the default rate for Bank B is likely to be too low. If we had access to the *real* default rate for this bank, this *could* alter the results of this regression analysis, but not necessarily. Since we do not have access to this data, we do not discuss it any further. The values for $R^2$ in the univariate analysis for Bank B were very low, varying between 0.001 and 0.11 for the three RatVol measures. In the multivariate analysis, the adjusted $R^2$ were much higher for $RatVol$ (0.69) and $RatVolU$ (0.77). This suggests that the multivariate model better explains the variance of the volatility measures for bank B.

**Table 5.13:** Results from the multivariate regression examining the relationship between business cycle measures ($GDP.Dev$, $NewLoans$, and $RateDef$) and our volatility measures ($RatVol$, $RatVolU$, and $RatVolD$) for both banks. As before, asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

| **Bank A** | $RatVol_t$ | $RatVolU_t$ | $RatVolD_t$ |
|---|---|---|---|
| Intercept | 1.46*** | 1.02*** | 1.04*** |
| t-ratio | (14.22) | (13.21) | (10.65) |
| $GDP.Dev_t$ | -1.71** | -1.24** | -1.18* |
| t-ratio | (-2.79) | (-2.68) | (-2.02) |
| $NewLoans_t$ | 0.00 | 0.00 | 0.00 |
| t-ratio | (0.86) | (1.05) | (0.45) |
| $RateDef_t$ | -0.07 | -0.05 | -0.05 |
| t-ratio | (-0.82) | (-0.72) | (-0.65) |
| Adj.$R^2$ | 0.54 | 0.52 | 0.30 |

| **Bank B** | $RatVol_t$ | $RatVolU_t$ | $RatVolD_t$ |
|---|---|---|---|
| Intercept | 1.08*** | 0.46 | 1.13** |
| t-ratio | (3.87) | (-1.03) | (3.54) |
| $GDP.Dev_t$ | 0.14 | -1.43 | 1.75 |
| t-ratio | (0.09) | (-1.03) | (0.95) |
| $NewLoans_t$ | 0.00 | 0.00 | 0.00 |
| t-ratio | (0.30) | (1.19) | (-0.66) |
| $RateDef_t$ | 0.45** | 0.53*** | 0.05 |
| t-ratio | (2.87) | (3.98) | (0.28) |
| Adj.$R^2$ | 0.69 | 0.77 | 0.06 |

As an alternative method to mitigate the problem of multicollinearity without discriminately hand-picking which independent variables to remove from the regression, which could be subject to bias, we perform several regularization regression techniques as mentioned in Chapter 4. The techniques are known as Lasso, Ridge and Elastic Net. We expected these techniques to produce parsimonious models with greater predictive power and to explain which explanatory variables are more important in affecting rating volatility. The results are presented in Table 6.5 in the Appendix. The Ridge regressions produce no statistically significant coefficients and very low values of adjusted $R^2$. Likewise, no coefficients in the Lasso regression are statistically significant. Interestingly, the results indicate that none of the independent business cycle variables should be included in the model. This results in a sparse model with only a constant term, suggesting that none of the explanatory variables have very much explanatory power on the volatility measures. Note that its values for adjusted $R^2$ are very low. The Elastic Net regression produces identical results as the Lasso regression for both banks, so the same reasoning applies. Due to an insufficient amount of data, the results of these regression methods yield little useful information. As a consequence, we do not discuss the results further. If the data sets were larger, these methods could potentially yield interesting results and the models could potentially predict volatility.

### 5.5.2 Business Cycle Effects on Quality of Ratings

Previous studies find evidence for increased rating quality during recessions (see Bar-Isaac and Shapiro (2013) [3] and Bolton et al. (2012) [5]). We investigate if this is the case for our data sets by examining the dependency that the state of the business cycle has on the quality of ratings. We run several regressions on the two banks, both univariate and multivariate. We do not perform these analyses on the data from NCR due to insufficient default data - i.e., none of the companies in the data set have been assigned the credit ratings $D$ or $SD$, indicating default. Initially, we expected that firms with higher credit risks underperform when the economy underperforms, thus exposing their actual creditworthiness to CRAs. CRAs in turn end up with more accurate ratings in such periods. In other words, we expected rating quality to be countercyclical, implying a negative relation between accuracy and the state of the business cycle.

#### 5.5.2.1 Univariate Analysis

The results for the univariate analysis is presented in Table 5.14 and Figure 5.8. They show contrary relationships between rating quality and the state of the business cycle for each of the individual bank.

**Table 5.14:** OLS estimate of the simple linear regressions examining the relationship between $GDP.Dev$ and $AR$ for both banks. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

| | **Bank A** | | | **Bank B** | | |
|---|---|---|---|---|---|---|
| | Intercept | $GDP.Dev_t$ | $R^2$ | Intercept | $GDP.Dev_t$ | $R^2$ |
| $AR_t$ | 0.61*** | 2.60** | 0.47 | 0.70*** | -1.64** | 0.48 |
| t-ratio | (20.82) | (2.48) | | (34.68) | (-2.35) | |

For Bank A, there is a statistically significant positive relationship between deviation from GDP trend ($GDP.Dev$) and the accuracy ratio ($AR$) at a significance level of 0.05. This implies that the rating entity does a better job of correctly assigning low credit ratings to companies with high probability of default in periods when the economy is doing well. Therefore, the quality of its ratings are higher in such periods. Conversely, Bank A is *less* accurate in assigning low ratings to defaulting companies in times when the economy performs below average, indicating lower quality of ratings. This could imply that the bank finds it more challenging to anticipate which companies will struggle in worse economic conditions than under better conditions. This counter-intuitive result contradicts previous work such as Bar-Issac and Shapiro (2013) [3] and Bolton et al. (2012) [5]. The crucial difference between these studies and this master's thesis is the source of the data sets. Bolton et al. (2012) posit that, due to the conflict of interest of CRAs, they have a tendency to understate risk to attract new business in periods when the economy performs well, leading to rating bias. This, in addition to due diligence potentially decreasing in such periods, is a possible reason for decreased accuracy in such periods. Bank A on the other hand, does not face the same conflict of interest, as it only assigns ratings to its own customers. Therefore, the inverse conclusion is justifiable.

Bank B on the other hand, has a statistically significant negative relationship between positive deviation from GDP trend ($GDP.Dev$) and the accuracy ratio ($AR$) at a significance level of 0.05, indicating that this bank achieves higher accuracy in its default prediction in times when the economy is struggling. The results for Bank B are, unlike Bank A, consistent with the results of Bar-Issac and Shapiro (2013) [3] and Bolton, Freixas, and Shapiro (2012) [5]. As previously argued in this section, this *could* be due to Bank B: 1) being comparatively more experienced with distressed companies (particularly oil service companies) than Bank A, 2) being more conservative and cautious when extending debt, resulting in lower overall default rates than Bank A even in times of plunging oil prices, and therefore having better predictions of which companies *actually* do default during such periods, or 3) having a too high AR due to the bank's handling of some of its defaulting customers by removing them from the data set, thus not appearing as a default statistic.

If we assume that the default rates of Bank B are indeed correct, our results show that the rating accuracy of Bank B surpasses Bank A after the oil price decline in 2014-2015. A possible reason for this could be that the plunging oil price caused Bank B's rating policy to becoming more conservative and thus more accurate. By regressing $AR$ against $GDP.Dev$ in two separate univariate regressions - one during 2010-2014 and another during 2015-2018 - we see evidence that could indicate a change in policy (see Table 5.15).

**Table 5.15:** OLS estimate of the simple linear regressions examining the relationship between $GDP.Dev$ and $AR$ in two separate time periods (2010-2014 and 2015-2018). Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

| | **2010-2014** | | | **2015-2018** | | |
|---|---|---|---|---|---|---|
| **Bank B** | Intercept | $GDP.Dev_t$ | $R^2$ | Intercept | $GDP.Dev_t$ | $R^2$ |
| $AR_t$ | 0.69*** | -0.56 | 0.06 | 0.67*** | -2.81* | 0.87 |
| t-ratio | (20.43) | (-0.43) | | (28.08) | (-3.64) | |

Before 2015, there is an insignificant, weak negative relation between the two variables. After 2015, there is a much stronger, significant negative relation. Although we cannot conclude definitively due to very few data points in both regressions, the results *could* indicate a change to a more conservative rating policy.

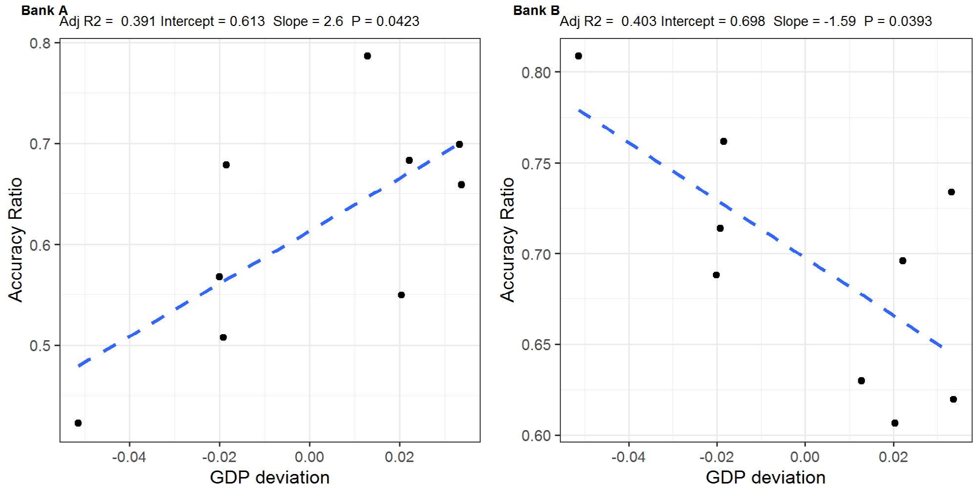


**Figure 5.8:** Relationship between adjusted short-term GDP growth in Norway and Accuracy Ratio (AR) for both banks in the period 2009-2018

#### 5.5.2.2 Multivariate Analysis

Next, we proceed to perform a more comprehensive multivariate analysis of the effect that the business cycle might have on the quality of ratings. When running a multivariate regression with all seven independent variables, the results have some complications (see Table 6.4 in the Appendix). Several of the coefficients for Bank A seem to have a statistically significant effect on the accuracy. However, an adjusted $R^2$ equal to 1 is unreasonable and suggests a spurious regression. The results for Bank B on the other hand yield *no* statistically significant coefficients. We suspect that this is due to the presence of multicollinearity among our independent variables, which could also be present in Bank A. Therefore, we first calculate the variance inflation factor (VIF) for both of the banks. Then, we remove the variables exhibiting indications of multicollinearity, i.e., variables with high VIF values, typically higher than 30, and run multivariate regressions on the remaining independent variables.

**Table 5.16:** Variance inflation factor (VIF) values for the following measures: $GDP.Dev$, $SwapRate$, $VIX$, $NewBonds$, $NewLoans$, $RateDef$, and $RatVol$. Higher VIF values indicate multicollinearity between independent variables.

| | **Bank A** | **Bank B** |
|---|---|---|
| | VIF | VIF |
| $GDP.Dev_t$ | 11.08 | 7.07 |
| $SwapRate_t$ | 20.04 | 10.47 |
| $VIX_t$ | 53.27 | 41.51 |
| $NewBonds_t$ | 60.84 | 35.99 |
| $NewLoans_t$ | 1.96 | 3.91 |
| $RateDef_t$ | 3.68 | 10.67 |
| $RatVol_t$ | 9.58 | 23.79 |

The VIF values for Bank A and B are presented in Table 5.16. Higher VIF values indicate multicollinearity between independent variables. Analyzing the VIF values of both banks jointly, we see that $VIX$ and $NewBonds$ have the highest VIF values. These variables are too highly correlated, which is an issue in OLS regression. In addition, we believe that these measures are more relevant when analyzing credit ratings from CRAs and not banks. Consequently, we remove them as independent variables. This result implies that $GDP.Dev$, $SwapRate$, $NewLoans$, $RateDef$, and $RatVol$ are the only sufficiently uncorrelated variables and thus included in the following multivariate regression.

After removing the correlated independent variables, we run a multivariate regression with the remaining variables for each bank. The results are presented in Table 5.17. For Bank A, there is a statistically significant *negative* relationship between $AR$ and the independent variable $RateDef$ at the 10% level. The negative relationship between the two variables implies that the accuracy, i.e., quality, of ratings is higher when the rate of default is lower. Generally, the rate of default is lower during better times, so the regression implies higher accuracy when the economy performs well. This is consistent with the result we find in the preceding univariate analysis and inconsistent with the work of Bar-Issac and Shapiro (2013) [3] and Bolton et al. (2012) [5] due to the same reasoning as explained in the univariate analysis. We also find a surprising significant relationship between $AR$ and $RatVol$ at the 5% level. After controlling for business cycle effects, higher rating volatility seems to be associated with lower accuracy. We will briefly explore this in the next section. The remaining explanatory variables are insignificant.

For Bank B, the adjusted $R^2$ is -0.26 before removing variables suspected of multicollinearity (see Table 6.4 in the Appendix) and 0.57 afterwards, indicating an improvement in the model. There is a statistically significant *negative* relationship between $AR$ and the independent variable $GDP.Dev$ at the 5% level. In other words, worse economic times seem to be associated with higher accuracy. This is consistent with our conclusion in the univariate analysis and previous studies (see Bar-Issac and Shapiro (2013) [3] and Bolton et al. (2012) [5]). The coefficient for $SwapRate$ is *positive* at a significance level of 10%. This implies that the accuracy is higher when the difference between long (10 year) and short (2 year) swap rates are higher. A larger spread in swap rates is indicative of better times. The relationship between $AR$ and $SwapRate$, therefore, could suggest that the accuracy is higher when the economy is doing well. However, considering the small value of this coefficient (0.32) combined with the fact that the value of $SwapRate$ varies little during the period that our data spans (between 0.75% and 1.5%, see Figure 3.12 in the Data Chapter during 2010-2018), this is essentially treated as a constant when compared to the effect the other significant variable, $GDP.Dev$, has on the regression. The latter explanatory variable has a coefficient of -2.82 and a much larger variation in its value during the period (varying between -5% and +3%). We can thus conclude that the result of the multivariate analysis is reasonably, although not perfectly, consistent with that of the univariate analysis and previous studies. The remaining explanatory variables are insignificant.

**Table 5.17:** Results from the multivariate regression examining the relationship between business cycle measures ($GDP.Dev$, $SwapRate$, $NewLoans$, $RateDef$), a volatility variable ($RatVol$), and the rating quality measure ($AR$) for both banks. As before, asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

| | **Bank A** | | **Bank B** | |
|---|---|---|---|---|
| | $AR_t$ | t-ratio | $AR_t$ | t-ratio |
| Intercept | 3.12** | (4.78) | 0.56** | (2.81) |
| $GDP.Dev_t$ | -0.90 | (-0.91) | -2.82** | (-3.89) |
| $SwapRate_t$ | 0.25 | (1.66) | 0.32* | (2.53) |
| $NewLoans_t$ | 0.00 | (1.89) | 0.00 | (-1.04) |
| $RateDef_t$ | -0.29* | (-2.67) | -0.13 | (-1.31) |
| $RatVol_t$ | -1.74** | (-3.97) | 0.02 | (0.15) |
| $Adj.R^2$ | 0.82 | | | 0.57 |

As we did in the previous section, we also perform some alternative methods to mitigate the problem of multicollinearity when analyzing the business cycle effects on the quality of ratings. These techniques are known as Lasso, Ridge and Elastic Net. The results are presented in Table 6.6 in the Appendix.

Due to the same reasoning as in the previous section, the results presented in Table 6.6 in the Appendix show no statistically significant results. The Ridge regressions produce no statistically significant coefficients and very low values for adjusted $R^2$. In the Lasso regressions, all variables were deemed insignificant in determining the relationship with rating accuracy and were, therefore, removed from the model. This results in a sparse model with only a constant term. The Elastic Net regressions produce results equal to Lasso regressions for Bank B and Lasso *and* Ridge regressions for Bank A. As argued in the previous section where we analyzed the effect of the business cycle on rating volatility, the results of these regression methods yield little useful information due to an insufficient amounts of data. As a consequence, we do not discuss the results further.

## 5.6 Relationship between Accuracy and Stability

Cantor and Mann (2006) [7] claim that CRAs follow a through-the-cycle methodology and trade off accuracy for increased stability. Therefore, if CRAs do indeed trade off accuracy in order to attain more stable ratings, a lower accuracy should be accompanied by a higher stability, i.e, lower volatility. If that is the case, we should observe an upward sloping relationship in the figures below. The reasoning behind this assumption is that rating changes of a higher frequency or magnitude should more accurately predict the relative risk of the firm. Table 5.18 displays the results of the univariate linear regressions for $AR$ and the three volatility measures, $RatVol$, $LRC$, and $RR$ for both banks.

For Bank A, we conclude that the results are significant for $RatVol$ (Figure 5.9) and insignificant for $LRC$ and $RR$. Moreover, for all three volatility measures, a higher volatility is associated with a lower AR - i.e., there is a negative correlation between the measures. In other words, accuracy is higher when the volatility is lower. This contradicts common sense, as you would expect that more frequent rating adjustments (higher $RatVol$) would result in more accurate ratings (higher $AR$). We speculate whether Bank A's increased stability during better times could arise from less pressure from management to accurately predicting defaults due to overall lower default rates. When the economy underperforms, higher default rates result in larger and more frequent rating adjustments as shown in the previous section. This might compel CRAs to attempt to more accurately predict defaults by reassessing ratings too frequently, resulting in higher volatility *and* lower accuracy in such periods and possibly explaining the inverse relationship. Our results do, however, not indicate that Bank A trades off accuracy for stability of its credit ratings.

For Bank B, the results indicate no statistically significant relationships. Nevertheless, we find the same negative relationship between $AR$, and $RatVol$ and $LRC$ as we did for Bank A, but a positive relation for $RR$. We stress that the results for Bank B are insignificant, so no definitive unambiguous conclusions can be drawn. However, as a consequence of weak and insignificant relationships between accuracy and stability, one could claim that this indicates a lack of a trade-off between the two measures. Thus, Bank B appears to *not* trade off stability for accuracy.

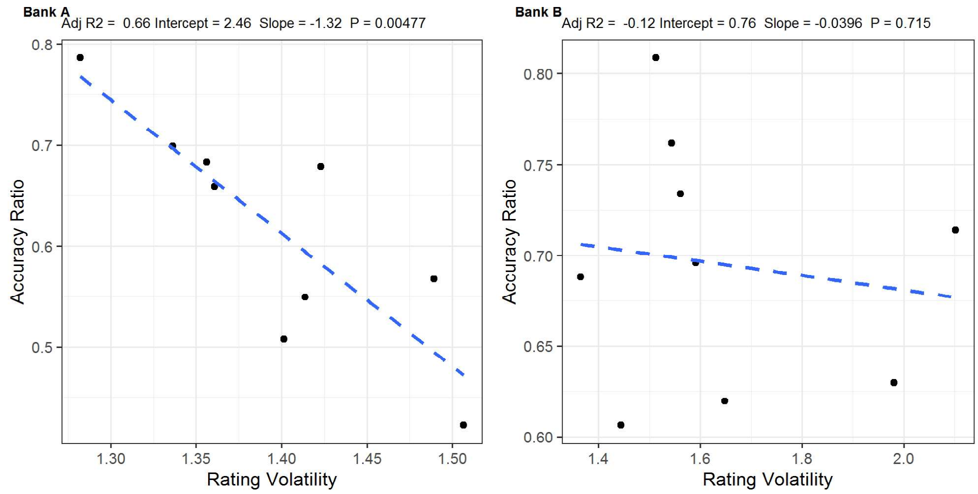


**Figure 5.9:** The relationship between the accuracy (AR) and rating volatility ($RatVol$) for both banks. Each point in the figure represents data for a given year.

**Table 5.18:** OLS estimates of the regressions examining the relationship between $AR$ and $RatVol$, $LRC$, and $RR$ for both banks. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

| | Bank A | | | | | Bank B | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Intercept | $RatVol_t$ | $LRC_t$ | $RR_t$ | $R^2$ | Intercept | $RatVol_t$ | $LRC_t$ | $RR_t$ | $R^2$ |
| $AR_t$ | 2.46*** | -1.32*** | | | 0.70 | 0.76*** | -0.04 | | | 0.02 |
| t-ratio | (5.42) | (-4.07) | | | | (4.41) | (-0.38) | | | |
| $AR_t$ | 0.89*** | | -27.22 | | 0.21 | 0.76*** | | -3.09 | | 0.13 |
| t-ratio | (4.39) | | (-1.36) | | | (11.59) | | (-1.00) | | |
| $AR_t$ | 1.90 | | | -15.00 | 0.18 | 0.65*** | | | 0.44 | 0.01 |
| t-ratio | (1.74) | | | (-1.16) | | (4.28) | | | (0.29) | |

A possible explanation for the lack of quantitative evidence for a trade-off in accuracy for rating stability as described above, is that our data set consists of ratings from Norwegian savings and loans *banks* and not *CRAs*. Unlike CRAs which regularly update their credit ratings, the data sets from banks include ratings reassessed at a *fixed frequency of once a year*, regardless of firm-specific changes in creditworthiness or changes in the economic environment. As a result, we cannot make as definitive conclusions as previous studies have done, such as Cantor and Mann (2006) [7]. They conclude that there is a lack of quantitative evidence supporting their hypothesis of the CRAs' willingness to induce higher rating accuracy to achieve more stability. We only conclude that there is a negative relationship between AR and volatility. Whether this is intentional or not, we can only speculate and neither confirm nor deny due to the nature of our data sets. Since rating assessment frequency is fixed, however, it is very unlikely that this is in fact intentional.

Chapter 6

# Summary and Suggestions for Future Work

Credit ratings are a vital component of financial markets, providing information to investors and regulators about the riskiness of financial debt securities and their issuers. Credit rating agencies (CRAs) therefore have a very important responsibility of assigning credit ratings reflecting the ”true” creditworthiness of obligors. At the same time, many CRAs claim they attempt to apply a *through-the-cycle* methodology to assigning credit ratings. This means, among other things, that users of credit ratings expect that credit ratings are stable over time and that only permanent changes in credit risk should result in a credit rating adjustment. This methodology also implies that the state of the business cycle should not have a significant impact on credit ratings because ratings are simply a measure of risk *relative* to other firms. However, stable ratings are achieved at the expense of accuracy. CRAs thus have to balance two competing goals: a low rating stability and a high rating accuracy.

## 6.1 Summary

In this master’s thesis, we apply different quantitative models and tests to quantify and analyze the stability and accuracy of credit ratings, examine the influence of the business cycle on rating adjustments, and analyze the trade-off between accuracy and stability. We perform these tests on three different data sets: 1) A large data set from a Norwegian savings and loans bank (Bank A), 2) another large data set from a somewhat smaller Norwegian savings and loans bank (Bank B) heavily exposed to the oil-service sector, and finally 3) a smaller data set from a Nordic CRA called ”Nordic Credit Rating” (NCR).

We aim at applying new rating volatility measures to Nordic credit ratings, contributing to existing research in several ways. We examine how different business cycle variables affect rating stability and accuracy. Furthermore, we analyze credit ratings from other financial institutions besides only CRAs, namely banks. CRAs and banks have different incentives for their credit ratings, and we thus contribute with new results not seen in previous credit rating studies. Lastly, we implement sophisticated multivariate regression methods, some of which, to our knowledge, are not used in previous credit rating research. Despite these methods not producing statistically significant results using our relatively small data sets, the same methods might produce significant results using larger data sets.

At the core of our analysis is a measure for rating volatility and instability developed by

Carvalho et al. (2014) [9] known as *RatVol*. It summarizes the information contained in a two-dimensional transition matrix into a single scalar for each time period. This allows us to perform time-series tests rarely seen in previous literature.

Our results indicate that the intensity of both upgrades and downgrades varies through time for both banks and NCR. Rating volatility for Bank A follows an upward trend during the period of our data sets, whereas Bank B appears to be following a downward trend. NCR has more stable ratings, and no apparent trend is visible. Interestingly, we observe that the intensity of both upgrades and downgrades for Bank A is higher during worse economic times, so-called troughs. Bank B appears to have overall rating volatility and upgrades that are inversely related to the business cycle. These results are not only surprising - they are also *inconsistent* with CRAs' claim that ratings are a relative ranking of firms and largely independent of the business cycle. Despite a wish from investors for ratings to be stable and independent of the business cycle, we find contradicting evidence and the banks appear to unintentionally target absolute levels of risk at a specific point in time. Characterizing their rating methodology as through-the-cycle is thus problematic. NCR on the other hand appears to produce ratings volatility that is independent of the business cycle and could, therefore, adhere to a through-the-cycle methodology. However, the limited size of the data set prohibits a definitive conclusion.

Surprisingly, we find that the accuracy of ratings is procyclical, i.e., higher during better economic times, for Bank A. This result contradicts previous findings of Bar-Isaac and Shapiro (2013) [3] and Bolton et al. (2012) [5] that rating quality is countercyclical. Rating accuracy for Bank B on the other hand appears to be consistent with these studies, with higher accuracy during worse economic times. In these periods, it *could* be easier for this bank to separate companies with high probability of default from companies with low probability of default, resulting in a higher accuracy. However, a more likely reason is that the accuracy measure (AR) for Bank B is higher than its real value. Evidence from the data set suggests that not all companies that default were assigned default ratings before they were removed as customers of the bank - some were removed as customers still with a non-default rating. Consequently, these companies will not show up with a default rating in the default statistics and will thus not influence the value of AR.

Notably, we do not find evidence that higher ratings volatility leads to higher ratings accuracy. In fact, higher volatility is instead associated with *lower* accuracy for Bank A and uncorrelated with accuracy for Bank B. Unlike other studies that have performed similar analysis, we cannot make as definitive conclusions as to why we see this unanticipated relationship in Bank A due to the fixed frequency of rating adjustments. However, we speculate that Bank A's increased stability during better times could arise from less pressure from management to accurately predicting defaults due to lower default rates overall. Conversely, when the economy underperforms, higher default rates possibly result in larger and more frequent rating adjustments. This compels banks to attempt to more accurately predict defaults by reassessing ratings too frequently, resulting in higher volatility *and* lower accuracy in such periods and possibly explaining the inverse relationship. The insignificant relationship between accuracy and stability for Bank B suggests that they do not actively trade off stability for accuracy.

## 6.2 Suggestions for Future Work

We have examined the relationship between different proxies for the business cycle and credit rating stability and accuracy. When adjusting our analyses to overcome suspected problems of multicollinearity, our results yield *some* statistically significant relationships, although varying for the two banks. It is quite possible that this is due to their differing customer locations and thus different relations to the business cycle. However, a more likely reason is differing policies in regards to handling adjustments to their customers' credit ratings, thus affecting the data sets and our analyses. Although we do not have any clear evidence of such differing policies between the two banks, we suspect this to be the case. Since our data is not sufficient for this kind of interpretation, we leave this for future work.

The data sets we utilize are sufficient for the purposes of our analyses. However, performing the same analyses on more comprehensive data sets would yield more complete results and enable the possibility of making more definitive conclusions. Although we were not able to obtain more frequently updated data in a similar fashion as CRAs, many banks have such data in their possession. With such data, entities (either banks or actual CRAs) update their credit ratings not on a fixed basis, but whenever they consider the creditworthiness of a particular company as changed. The results from the methods provided in this paper would then allow direct comparison to those of previous work on CRAs. We could also more confidently conclude on the banks' or CRAs' motivations *behind* rating adjustments, rather than simply describing the relationship between rating adjustments and different measures. Using data with more frequent updates and stretching over a longer time period would allow the use of additional quantitative methods such as Quantile regression. Also, a longer period will naturally include data from several business cycles, leading to a better analysis.

Furthermore, this paper analyzes ratings from *regional* banks in Norway and compare how rating volatility and stability changes with the business cycle. An extension of our work could look at additional national and international banks or CRAs both in the Nordics or Europe, exposed to a wider geographical region and to different industry-specific risks, and investigate whether this is reflected in their rating changes.

Finally, it would be very interesting to analyze how the economic shutdown due to the current coronavirus pandemic affects credit ratings. In particular, the circumstances are likely to influence their stability and accuracy. Performing the tests and analyzes presented in this thesis on credit rating data that includes the year 2020, could give completely new insight into the effects that global pandemics have on credit ratings.

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# Appendix

**Table 6.1:** Credit rating system for NCR. NCR assigns long-term credit ratings on a scale ranging from 'AAA', reflecting the strongest credit quality, to 'D', reflecting the lowest credit quality. Rating categories from 'AA' to 'B' are modified by plus (+) and minus (-) where required to show their relative position within the rating category. This results in a rating scale with 20 levels (notches) in total.

| Comment | Rating | NCR description |
|---|---|---|
| Prime rating | AAA | 'AAA' rated entities and instruments demonstrate the highest credit quality and lowest expectation of default risk |
| High Grade | AA | 'AA' rated entities and instruments demonstrate very high credit quality with a very low default risk |
| Upper medium grade | A | 'A' rated entities and instruments demonstrate high credit quality with a low default risk |
| Lower medium grade | BBB | 'BBB' rated entities and instruments demonstrate medium credit quality with a moderate default risk |
| Speculative | BB | 'BB' rated entities and instruments demonstrate speculative credit quality with a slightly increased default risk |
| Highly speculative | B | 'B' rated entities and instruments demonstrate highly speculative credit quality with an increased default risk |
| Extremely speculative | CCC | 'CCC' entities and instruments demonstrate very low credit quality with a high default risk |
| | CC | 'CC' rated entities and instruments demonstrate very low credit quality and an event of default is very likely |
| Default imminent | C | 'C' rated entities and instruments demonstrate the lowest credit quality and an event of default is imminent |
| In default | D/SD | 'D' rated entities and instruments have defaulted, as defined by NCR. 'SD' (selective default) rated entities have only defaulted on certain debt obligations |

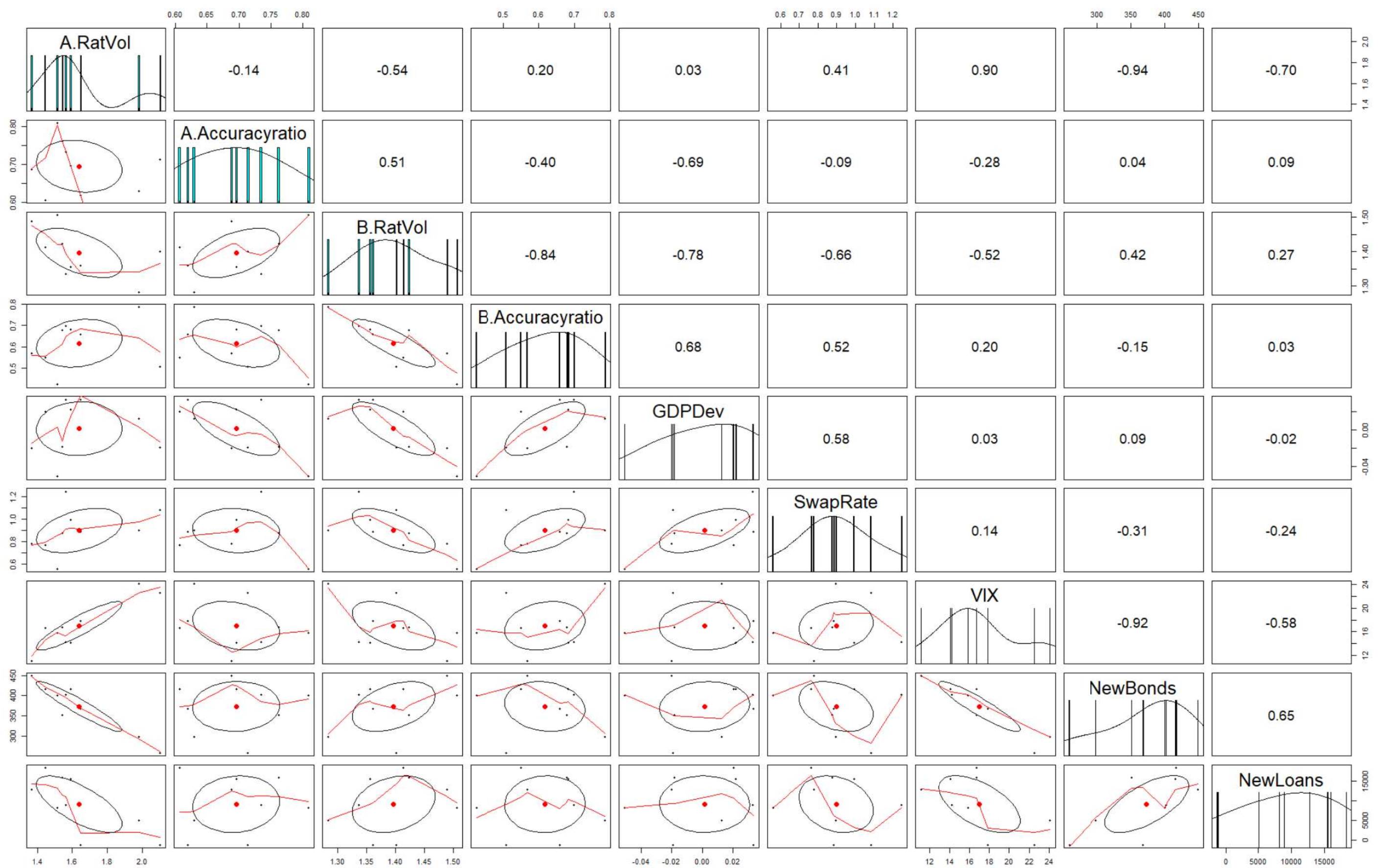


**Figure 6.1:** Combined correlation and scatter plots for the variables $RatVol$, $AR$, $GDP.Dev$, $SwapRate$, $VIX$, $NewBonds$, and $NewLoans$. Plots for the variables are along the diagonal. Correlations between different variables are shown in the top triangle of the matrix of plots. Scatter plots and correlation eclipses showing the relationship between different variables are shown in the bottom triangle of the matrix of plots.

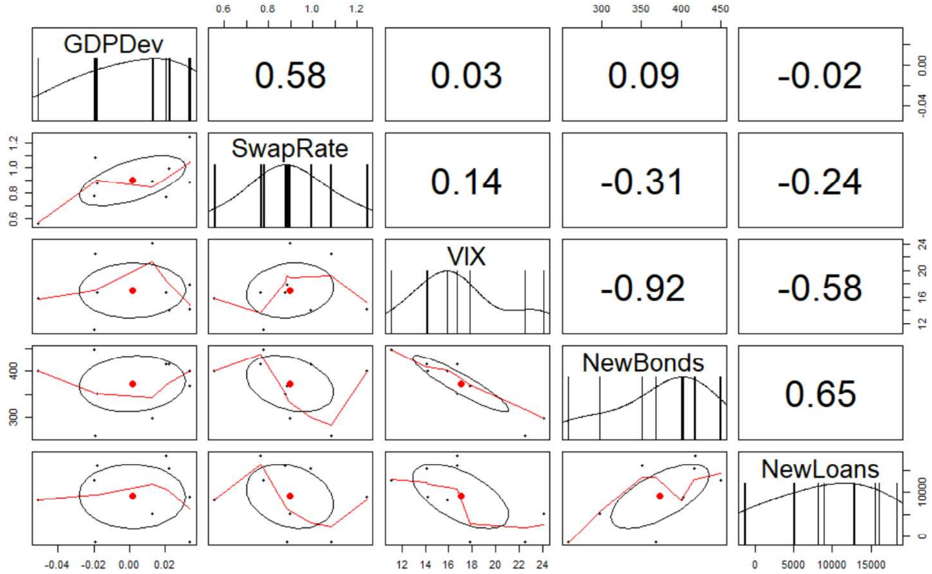


**Figure 6.2:** Combined correlation and scatter plots for the variables $GDP.Dev$, $SwapRate$, $VIX$, $NewBonds$, and $NewLoans$. Plots for the variables are along the diagonal. Correlations between different variables are shown in the top triangle of the matrix of plots. Scatter plots and correlation eclipses showing the relationship between different variables are shown in the bottom triangle of the matrix of plots.

**Table 6.2:** Results from the multivariate regression examining the relationship between business cycle measures ($GDP.Dev_t$, $SwapRate_t$, $VIX_t$, $NewBonds_t$, $NewLoans_t$, and $RateDef_t$) and volatility measures ($RatVol_t$, $RatVolU_t$, $RatVolD_t$, $LRC_t$, and $RR_t$) for both banks. As before, asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

| **Bank A** | $RatVol_t$ | $RatVolU_t$ | $RatVolD_t$ | $LRC_t$ | $RR_t$ |
|---|---|---|---|---|---|
| Intercept | 2.09 | 0.68 | 2.27 | 0.00 | -0.01 |
| t-ratio | (1.51) | (0.62) | (2.36) | (0.29) | (-0.11) |
| $GDP.Dev_t$ | -1.02 | -1.94 | 0.49 | -0.04* | -0.06 |
| t-ratio | (-0.60) | (-1.46) | (0.41) | (-3.11) | (-0.45) |
| VIF | 9.37 | | | | |
| $SwapRate_t$ | -0.18 | 0.18 | -0.44 | 0.00 | 0.00 |
| t-ratio | (-0.52) | (0.66) | (-1.79) | (1.45) | (0.08) |
| VIF | 17.70 | | | | |
| $VIX_t$ | -0.02 | 0.00 | -0.03 | 0.00 | 0.00 |
| t-ratio | (-0.66) | (0.11) | (-1.45) | (-0.64) | (1.04) |
| VIF | 43.81 | | | | |
| $NewBonds_t$ | 0.00 | 0.00 | 0.00 | 0.00 0.00 | |
| t-ratio | (-0.32) | (0.38) | (-1.08) | (1.46) | (1.03) |
| VIF | 57.89 | | | | |
| $NewLoans_t$ | 0.00 | 0.00 | 0.00 | 0.00 0.00 | |
| t-ratio | (-0.21) | (0.01) | (-0.44) | (-1.90) | (-0.05) |
| VIF | 1.92 | | | | |
| $RateDef_t$ | 0.02 | -0.11 | 0.13 | 0.00 | 0.00 |
| t-ratio | (0.11) | (-0.96) | (1.29) | (-2.10) | (-0.17) |
| VIF | 3.66 | | | | |
| Adj.$R^2$ | 0.58 | 0.53 | 0.66 | 0.96 | -0.08 |

| **Bank B** | $RatVol_t$ | $RatVolU_t$ | $RatVolD_t$ | $LRC_t$ | $RR_t$ |
|---|---|---|---|---|---|
| Intercept | 0.03 | 1.82 | -1.74 | -0.18 | -0.07 |
| t-ratio | (0.01) | (0.47) | (-0.75) | (-2.33) | (-0.08) |
| $GDP.Dev_t$ | -1.77 | -0.34 | -2.05 | -0.17 | 0.03 |
| t-ratio | (-0.61) | (-0.07) | (-0.71) | (-1.74) | (0.02) |
| VIF | 5.98 | | | | |
| $SwapRate_t$ | 0.42 | -0.14 | 0.73 | 0.05 | 0.05 |
| t-ratio | (0.84) | (-0.17) | (1.49) | (2.85) | (0.20) |
| VIF | 7.76 | | | | |
| $VIX_t$ | 0.05 | -0.01 | 0.08 | 0.01* | 0.00 |
| t-ratio | (1.08) | (-0.20) | (1.94) | (3.51) | (0.00) |
| VIF | 26.18 | | | | |
| $NewBonds_t$ | 0.00 | 0.00 | 0.00 | 0.00 0.00 | |
| t-ratio | (0.23) | (-0.40) | (1.00) | (2.18) | (0.21) |
| VIF | 35.09 | | | | |
| $NewLoans_t$ | 0.00 | 0.00 | 0.00 | 0.00 0.00 | |
| t-ratio | (-0.19) | (0.71) | (-1.67) | (-2.10) | (0.04) |
| VIF | 3.84 | | | | |
| $RateDef_t$ | 0.13 | 0.42 | -0.29 | -0.01 | 0.01 |
| t-ratio | (0.65) | (1.27) | (-1.52) | (-1.82) | (0.2) |
| VIF | 8.79 | | | | |
| Adj.$R^2$ | 0.83 | 0.53 | 0.62 | 0.82 | -1.91 |

**Table 6.3:** Results from the multivariate regression examining the relationship between business cycle measures ($GDP.Dev_t$, $SwapRate_t$, $VIX_t$, $NewBonds_t$ and $NewLoans_t$) and volatility measures ($RatVol_t$, $RatVolU_t$, $RatVolD_t$) for NCR. As before, asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels; however, in this analysis all results are insignificant.

| **NCR** | $RatVol_t$ | $RatVolU_t$ | $RatVolD_t$ |
|---|---|---|---|
| Intercept | -2.06 | -2.34 | 0.27 |
| t-ratio | (-0.44) | (-0.80) | (0.05) |
| $GDP.Dev_t$ | -0.52 | -1.46 | 1.54 |
| t-ratio | (-0.09) | (-0.41) | (0.24) |
| $SwapRate_t$ | 0.42 | 0.57 | -0.17 |
| t-ratio | (0.46) | (0.99) | (-0.16) |
| $VIX_t$ | 0.06 | 0.05 | 0.01 |
| t-ratio | (0.64) | (0.99) | (0.11) |
| $NewBonds_t$ | 0.00 | 0.00 | 0.00 |
| t-ratio | (0.48) | (0.84) | (-0.01) |
| $NewLoans_t$ | 0.00 | 0.00 | 0.00 |
| t-ratio | (0.74) | (0.57) | (0.65) |
| Adj.$R^2$ | -0.63 | -0.34 | -1.10 |

**Table 6.4:** Results from the multivariate regression examining the relationship between business cycle measures ($GDP.Dev_t$, $SwapRate_t$, $VIX_t$, $NewBonds_t$, $NewLoans_t$ and $RateDef_t$), a volatility variable ($RatVol_t$), and the rating quality measure ($AR_t$) for both banks. As before, asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

| | **Bank A** | | | **Bank B** | | |
|---|---|---|---|---|---|---|
| | $AR_t$ | t-ratio | VIF | $AR_t$ | t-ratio | VIF |
| Intercept | 5.40*** | (61.11) | | 0.46 | (0.25) | |
| $GDP.Dev_t$ | -1.74** | (-21.65) | 11.08 | -3.06 | (-1.26) | 7.07 |
| $SwapRate_t$ | 0.02 | (1.48) | 20.04 | 0.37 | (0.84) | 10.47 |
| $VIX_t$ | -0.02** | (-19.32) | 53.27 | 0.01 | (0.13) | 41.51 |
| $NewBonds_t$ | 0.00* | (-8.85) | 60.84 | 0.00 | (0.07) | 35.99 |
| $NewLoans_t$ | 0.00** | (18.07) | 1.96 | 0.00 | (-0.62) | 3.91 |
| $RateDef_t$ | -0.26** | (-41.68) | 3.68 | -0.12 | (-0.74) | 10.67 |
| $RatVol_t$ | -2.73*** | (-88.34) | 9.58 | -0.04 | (-0.08) | 23.79 |
| $Adj.R^2$ | 1.00 | | | -0.26 | | |

**Table 6.5:** Results from the Ridge, Lasso and Elastic Net regressions examining the relationship between business cycle measures ($GDP.Dev_t$, $SwapRate_t$, $VIX_t$, $NewBonds_t$, $NewLoans_t$ and $RateDef_t$), and our rating volatility measures ($RatVol_t$, $RatVolU_t$, and $RatVolD_t$) for both banks. The results are on the form: Bank A / Bank B.

| | **Ridge** | | | **Lasso** | | | **Elastic Net** | | |
|---|---|---|---|---|---|---|---|---|---|
| | $RatVol_t$ | $RatVolU_t$ | $RatVolD_t$ | $RatVol_t$ | $RatVolU_t$ | $RatVolD_t$ | $RatVol_t$ | $RatVolU_t$ | $RatVolD_t$ |
| Intercept | 1.51 / 1.47 | 1.1 / 0.57 | 0.99 / 1.11 | 1.39 / 1.60 | 0.98 / 1.14 | 0.99 / 1.11 | 1.39 / 1.60 | 0.98 / 1.14 | 0.99 / 1.11 |
| $GDP.Dev_t$ | -0.44 / 0.34 | -0.52 / 0.34 | -0.02 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 |
| $SwapRate_t$ | -0.11 / 0.17 | -0.09 / 0.73 | -0.01 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 |
| $VIX_t$ | 0.00 / 0.01 | 0.00 / 0.01 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 |
| $NewBonds_t$ | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 |
| $NewLoans_t$ | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 |
| $RateDef_t$ | -0.06 / 0.06 | -0.05 / 0.05 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 | 0.00 / 0.00 |
| $Adj.R^2$ | 0.00 / 0.03 | 0.00 / 0.10 | 0.00 / 0.01 | 0.01 / 0.09 | 0.00 / 0.13 | 0.00 / 0.01 | 0.01 / 0.09 | 0.00 / 0.13 | 0.00 / 0.01 |

**Table 6.6:** Results from the Ridge, Lasso and Elastic Net regressions examining the relationship between business cycle measures ($GDP.Dev_t$, $SwapRate_t$, $VIX_2$, $NewBonds_t$, $NewLoans_t$ and $RateDef_t$), a volatility variable ($RatVol_t$), and the rating quality measure ($AR_t$) for both banks.

| | Ridge | | Lasso | | Elastic Net | |
|---|---|---|---|---|---|---|
| | **Bank A** $AR_t$ | **Bank B** $AR_t$ | **Bank A** $AR_t$ | **Bank B** $AR_t$ | **Bank A** $AR_t$ | **Bank B** $AR_t$ |
| Intercept | -0.82 | 0.67 | 0.65 | 0.67 | -0.82 | 0.67 |
| $GDP.Dev_t$ | -0.30 | 0.00 | 0.00 | 0.00 | -0.30 | 0.00 |
| $SwapRate_t$ | 0.21 | 0.00 | 0.00 | 0.00 | 0.21 | 0.00 |
| $VIX_t$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| $NewBonds_t$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| $NewLoans_t$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| $RateDef_t$ | 0.03 | 0.00 | 0.00 | 0.00 | 0.03 | 0.00 |
| $RatVol_t$ | -0.21 | 0.00 | 0.00 | 0.00 | -0.21 | 0.00 |
| $Adj.R^2$ | 0.03 | 0.01 | 0.03 | 0.01 | 0.03 | 0.01 |

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