DETERMINANTS OF CREDIT RATINGS OF STRUCTURED FINANCE PRODUCTS IN THE UNITED STATES

BARBARA WANJIKU NGANDU

A RESEARCH PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS OF THE DEGREE OF MASTER OF SCIENCE IN FINANCE, FACULTY OF BUSINESS AND MANAGEMENT SCIENCE, UNIVERITY OF NAIROBI

2022

DECLARATION

I, the undersigned, declare that this is my original work and has not been submitted to any institution or university other than the University of Nairobi for examination.

Signed ______________ Date 01/12/2022

BARBARA WANJIKU NGANDU

D63/34963/2019

The research project has been submitted for examination with my approval as the University Supervisor

Signed ______________ Date 01 December 2022

PROF. CYRUS IRAYA (PhD)

Associate Professor & Chairman, Department of Finance & Accounting

Faculty of Business & Management Sciences

University of Nairobi

ACKNOWLEDGEMENT

This research project has been accomplished through the support and encouragement of various people who I appreciate and am greatly indebted to. First and Foremost, all thanks and praise to the God Almighty for it is by his grace I have been able to undertake and complete this research project. I am extremely grateful to my Supervisor, Prof. Cyrus Iraya for his guidance, insightful reviews and immense knowledge. His guidance, patience and understanding helped me during the research period.

To my parents, siblings and friends thank you for your love, prayers, care and encouragement during my entire Msc. Finance course. Your support gave me the strength and confidence to forge ahead and believe in a better future.

DEDICATION

I dedicate this work to my parents Mr. and Mrs. Githinji and my siblings Bryan and Cynthia. I thank you for all the love, support and sacrifices you have made for me.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ABS	Asset Backed Securities
BIS	Bank for International Settlements
CDO	Collateralized Debt Obligations
CLO	Collateralized Loan Obligations
CMBS	Commercial Mortgage Backed Securities
CRAs	Credit Rating Agencies
MBS	Mortgage Backed Securities
RMBS	Residential Mortgage Backed Securities
SPSS	Statistical Package for Social Sciences
VIF	Variance Inflation Factors

ABSTRACT

Credit Rating is an appraisal of the credit worthiness of an individual, business, government or financial product. This appraisal is done by Credit Rating Agencies based on capability of account holder to repay the borrowings or honor the financial commitments stipulated within the established time frame. Credit Ratings have a crucial part in the financial markets of helping bridge the informational gap between investors and borrowers on the security and reliability of the assets being traded. This informational gap is larger in the market for structured finance products due to increased complexity of the structured finance products; therefore credit ratings have an even more important part in this market. Developing a grasp of the elements/variables that determine credit rating is therefore crucial in the structured finance products market because there is a huge reliance of investors on CRAs providing some assurance on the safety of the products. This research sought to identify and assess the determinants of structured finance products credit ratings in the United States (US). The predictor variables were maturity, default probabilities and recovery rates of the underlying assets and seniority and the response variable was credit rating. The population of the study was the new issuances of US Consumer Asset Backed Securities in 2019. Data was collected from the Fitch Ratings website and the Financial Industry Regulation Authority (FINRA) website. A sample of 152 issues was determined by use of stratified sampling. Multiple linear regression was performed to ascertain the connection between the variables and a descriptive research design was utilized. The data analysis utilized SPSS version 28.. An R square score of 0.711 was obtained which was translated to mean 71.1% of the variations in credit rating for US Consumer ABS can be explained by the 4 chosen predictor variables. 28.9% of the variation in credit rating was said to be explained by other variables/factors that were not part of this research. Further analysis showed that maturity and default probabilities had a negative correlation with credit rating while recovery rates and seniority had a positive correlation with credit rating. Additionally, results showed that maturity and seniority had a statistically significant influence on credit rating while recovery rates and default probabilities were not statistically significant predictors of credit rating. The study concluded that maturity of underlying assets and seniority were the most significant factors influencing credit rating. Seniority was shown to have the strongest influence on credit rating and therefore the priority of distribution of payments to investors of structured finance products was concluded to be one of the most significant determinants of credit quality. The study recommended that Credit Rating Agencies should also examine the relevant characteristics of the underlying assets of the structured finance products as these characteristics have been shown to influence credit rating of structured finance instruments. The study recommended the need for further research on other variables such as level of collateralization, level of excess spread, performance of collateral managers and macroeconomic variables such as inflation and interest rates and their influence on credit ratings of structured finance products.

CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

Demand for structured finance credit ratings; the risk evaluations that credit rating organizations provide to issues of structured finance products has grown significantly in recent years. However credit ratings have not always provided a true picture to investors in the financial markets, most notably is their role in the 2007 global financial crisis. Rating assignments that are lower than anticipated often prompt investors to question the consistency and rationale of structured finance credit ratings.

How clear are the criteria underlying structured finance products credit ratings? Wealth of data now available allows us to estimate which indicators are weighed most heavily in the determination of ratings. This research focuses on the seniority, tranche size, maturity, recovery rates multiplier and default probability multiplier as the main factors used in determining a credit rating. Without carrying out an empirical test it can be easily inferred from reasoning that a more senior tranche of a structured finance product will have a high credit rating than a junior. A structured finance product with a longer maturity will have a high probability of default and therefore a lower credit rating than one with a shorter maturity with all other factors being equal. However more needs to be known on which of these factors are most weighed heavily in determining a credit rating, do of all these factors mentioned actually have an effect on a credit rating, are there any correlations between the factors?

Credit Scoring theory, Information Asymmetry theory and Reputation theory underline this study. The Credit Scoring theory and Competitive Pricing of Default is the anchor theory and it states that potential borrowers are assessed on their ability and willingness to repay the debt based on 5Cs i.e. Character, Capacity, Collateral, Conditions and Capital (Satyajit, 2005) . The 5Cs can be used to identify credit ratings determinants in Structured Finance by analyzing what factors lead to a good score on e.g. capacity (done by analysis of underlying assets cashflows), conditions (what macroeconomic factors are favorable for loan repayment) etc. The Information Asymmetry theory was developed by 3 economists; Akerlof , Stiglitz and Spence. The theory posits that there exists an information gap between the buyers (investors) and sellers (borrowers) in a market (Financial Markets). The sellers have more information regarding the degree of quality of the products than the buyers. This leads to the buyers questioning the quality of the items and diminishes the price they are ready to pay for the product. Akerlof (1970) emphasizes the need for counteracting institutions to reduce the information asymmetry. This theory argues in favor of necessity of credit ratings, particularly in the structured finance markets where the information asymmetry between lenders and investors is greater due to the complexity of the products. A credit rating serves as a signal to buyers (investors) on which products are of high quality (safe). The Reputation theory by Shapiro (1983) posits that reputation plays an important role by enabling businesses to gain trust and relationships in the market. Partnoy (1990) argues that CRAs have been able to survive due to their ability to build and retain their reputation which is critical in fostering a high trust environment in financial markets. In order to retain their reputation credit rating agencies should strive to give accurate credit ratings. A reputation of accurate credit rating by CRAs builds trust with investors and makes investors more likely to purchase unfamiliar products (e.g. structured finance products) that have been deemed safe by the CRAs.

The study focused on structured finance market and this choice arises from the fact that nowhere do credit ratings hold more importance than in the structured finance market. Why is this the case? Structured finance products are created by pooling assets such as student loans, aircraft leases, mortgages and other types of loans and creating a priority structure for claims against the underlying assets. Issuers and the rating companies that grade the bonds work closely together to structure the bonds (Josephson & Shapiro, 2019).There is also the issue of high information asymmetry in the structured finance market. The complexity of the structured finance securities requires credit ratings to provide an assurance on whether senior securities as they have been structured are safe. The study focuses on the structured finance market in the US as it is the largest and most developed structured finance market. Therefore investigating the variables that affect structured finance product credit ratings is crucial.

1.1.1 Determinants of Credit Ratings

A determinant is defined as a factor that controls or affects what happens in a particular situation. It is an exploratory variable of a given phenomenon. Fender and Kiff (2004) find that the factors that determine credit ratings for structured finance products are recovery rate assumptions, correlation of the underlying assets, the concentration rate of issuers in a specific industry and the maturity of the debt. Maris and Segal (2002) identified the factors that have the most influence on credit ratings as default probability, tranche size and transaction size. Their findings were as a result of empirical study on yield spreads and credit ratings of Commercial Mortgage Backed securities. Nickerson (2020) adds that credit ratings are not only determined by the quantitative factors thus mentioned but are also affected by qualitative factors such as the past performance of collateral managers. This study aims to look into factors such as seniority, tranche size, maturity, recovery rates and default probability and determining how they affect credit ratings and also which factors are weighed most heavily in determining credit ratings.

The development of an understanding of factors that determine credit ratings is crucial in the structured finance market especially because there is a huge reliance of investors on CRAs providing some assurance on the safety of the products. According to Adams, Burton, and Harwick (2003), knowing the factors that influence credit ratings can help regulators and investors when making a choice whether to depend on the ratings provided by credit rating agencies. Therefore, based on the findings of the credit rating determinants, investors might modify their investment portfolio. Kim and Gu (2014) in their study to identify credit rating determinants for Brazilian bonds found that a model that could predict bond ratings based on its determinants enabled firms to take actions to reduce their perceived risk and lower their borrowing costs. Therefore by gaining an understanding of the determinants of credit ratings, firms would work on adjusting factors such as cash flows, dividend payout so as to get a better credit rating and therefore cheaper access to credit. Guasti (2016) holds the same view as he states that knowing the variables that influence credit rating can assist companies with their investment and financing decisions taken over time. Therefore the understanding of what determines credit ratings is very useful work as it allows stakeholders to build risk management mechanisms and to learn what factors may influence the movement of the credit rating.

Some factors used in determining credit ratings such as par amount and maturity can be easily measured while other factors specifically the qualitative factors like the performance of the collateral manager are not as easy. Maturity of a structured finance product will be the average maturity of the product's underlying assets. There seems to be no divergence in the measurement of maturity among researchers. Vioili (2010) measures seniority based on three levels i.e. senior, mezzanine and junior and assigns a factor of 1 to senior tranche, a factor of 2 to the mezzanine tranche and a factor of 3 to the junior tranche. Wotjowitcz (2011) measures recovery rates as a function of the loss severity. The recovery rate = 1 - Loss Severity. The tranche size is measured as an amount equal to the sum of the principal amount of the aggregate tranche (De Marzo, 2004). Fabiano, Camila and Rodrigo (2016) measure the probability of default as a debt ratio of an issuer i.e. Debt/EBITDA which tells us the ability of the issuer to pay debts.

1.1.2 Credit Ratings

Minardi (2006) defines credit ratings as an assessment of a company's ability to honor its financial commitments within the time established in the contract. Letters are used to describe the ratings in order of the scale of risk. Caouette et al (2008) adds that the assessment also takes into account business specific information like market share, corporate governance standards and competitive strategy in addition to information about the financial and accounting condition of the company. Committee on the Global Financial System (2005) gives a more specific definition of credit ratings with regards to structured finance, the committee describes a structured finance credit rating as an appraisal on the probability that cashflows from the underlying receivables pool will be sufficient to pay the claims related to a specific tranche. Scope Ratings defines structured finance credit rating as a forward-looking opinion on relative credit risks of a debt instrument, or a synthetic credit instrument. A rating describes the expected loss that is associated with payments that are promised contractually by an instrument on a payment date or date of maturity

From the various definitions mentioned it is clear that credit ratings are meant to provide an assessment on an issuer's or asset's ability to meet the cashflows agreed upon. Does this assessment provided by credit rating agencies hold for the future? After the 2007 financial crisis, Fitch ratings stated that approximately 60% of global structured products that were graded AAA had been downgraded to junk status by the end of 2008. In recent times, a study by Nickerson (2020) found that between March and August 2020 S&P and Moody's downgraded approximately 25% of collateral feeding into Collateralized Loan Obligations. This leads us to wonder what makes credit rating in the structured finance market have such a huge variance over a short period of time. One explanation is the complexity due to structured finance products which consist of portfolios of heterogeneous obligors with each tranche reflecting a different position in the deal's capital structure. Due to this, credit rating agencies need to comprehend not only the risk of default that is embodied in the asset pool but also other non default risks in the underlying asset pool that affect the credit quality of the tranches arising from the structure of the transaction.

The credit rating industry is dominated by 3 agencies that have a market share of 95% of the rating business, namely Moody's Investor Services, Fitch Ratings and Standard and Poor's (S&P) . Each credit rating agency uses letter-based scores to show if a debt has a high or low risk of default and the financial stability of its issuer. S&P Global has a rating scale that ranges from AAA with the capacity of repayment being extremely strong to the lowest rating, D meaning the borrower has already defaulted

Structured finance ratings have the subscript “(sf)” and national scale ratings have a country-specific identifier “(xx)” (e.g., “(ZA)” for South Africa). Score Ratings also uses the ‘SF’ suffix for structured finance instruments in line with Regulation No. 1060 of the European Council and European Parliament. This applies to instruments such as collateralized loan obligations (CLOs), consumer asset backed securities (ABS), mortgage backed securities (MBS) and collateralised debt obligations (CDO). The suffix is not applied to covered bonds and non-tranched asset securitisations.

1.1.3 Credit Ratings and its Determinants

Arguments have been made regarding the connection between credit ratings and its determinants. For a factor to be considered a determinant of credit rating, it must be a statistically significant predictor variable of credit rating. Therefore a relationship must already exist between credit rating and its determinants, however what kind of relationship is it? Does an increase in determinant 1 lead to a better credit rating while an increase in determinant 2 lead to a lower credit rating? To answer this we examine the individual determinants and their relationship to credit rating (is it inverse or direct) by reviewing theoretically expected relationships and empirically confirmed relationships.

One of the credit rating determinants of Structured Finance Products is maturity. Structured finance products have different maturities depending on their underlying assets According to the normal yield curve, bonds with longer maturity will have higher yield than bonds with a shorter maturity due to compensation to investors for the higher interest rate risk. The higher the yield of a security/bond, the higher the risk of default hence a lower credit rating is expected. Radhakrishnan, Fenghua and Vijay (2013) carried out a study that explored the relationship between credit quality and maturity of investment grade and speculative grade rated firms. The findings of the study revealed that longer maturity bonds issued by the firms traded at higher yield spreads, showing that investors are aware of the rollover risk arising from a firm’s debt maturity. We can infer from this study that a longer maturity asset will most likely have a lower credit rating than a shorter term one if all other factors are equal.

Dominic (2021) defines default probability as a financial risk management term that gives an estimate of the probability that a borrower will be unable to meet its obligations. The probability of default of the underlying assets is a significant determinant of credit ratings.

Probability of default/default risk is one the two components of credit risk. It has an inverse relationship with credit ratings. The higher the default probability of the underlying assets, the lower the underlying pool credit quality and therefore a lower credit rating is assigned. To come up with a forward looking default probability Scope Ratings incorporates historical default rates of the underlying assets with macroeconomic factors that are correlated to defaults in the relevant asset class such as GDP and unemployment rates. The forward looking probability estimated is used to approximate the portfolio default rate distribution which is then used to calculate the expected loss.

Nada (2016) defines recovery rates as a measure of the extent to which a creditor recovers back the accumulated interest and principal on a defaulted loan. Nada notes that recovery rates are systematically related to default rates because both variables are driven by common factors such as business cycle, industry type, seniority. Recovery rates have an inverse relationship to default rates (another determinant of credit ratings). Altman (2001) carried out a study on recovery rates and credit risk and found that the higher the recovery rate the lower the credit risk will be. Hanouna and Das (2008) state that the recovery rate used in modelling risk is often a constant based on historical averages, such as a recovery rate of between 40% and 50% on US corporate debt and 25% on debt issued by sovereign borrowers and is also independent of default probabilities. However in practice actual recovery rates as previously stated are related to default probabilities and vary significantly and as a result assuming constant recovery rates can lead to an inaccurate assessment of potential losses.

Seniority of the tranches in structured finance products is another determinant of credit rating. Structured finance products are created by pooling of receivables/assets and dividing them into slices or tranches based on similar characteristics. The tranches are senior, mezzanine and junior based on priority of repayment of principal and accrued interest. Altman and Karlin (2009) carried out a study on a sample of bond issues from 1978 to 2008 consisting of senior bond issues and subordinated bonds. The results showed that more often than not a higher seniority is associated with higher payoffs in case of bankruptcy. Higher payoffs meaning higher recovery rates lead to lower expected loss on default and therefore an assignment of a higher rating. The notching process of credit rating agencies also supports this finding. S&P's approach to corporate debt credit rating is notching up secured debt with reference to the company's credit rating and notching down subordinated debt. This means if the company's credit rating is BBB+, the company's long term secured debt will be A- and the long term subordinated debt will be BBB. This shows that seniority has a direct positive relationship with credit ratings. A higher seniority means a higher credit rating and vice versa. The explanation is simple, the more senior a debt is the higher the priority it receives with regard to the order of payment in the case of a bankruptcy or default.

Collateral Manager's performance is another factor that determines credit ratings. Some structured finance products such as CLOs have managers taking on an active role by sourcing, developing, working out, exchanging and removing assets from the collateral pool. In this case the performance of the manager has an impact on the structured finance securities credit quality. Nickerson (2020) found that CRAs may be including qualitative factors, into their assessments e.g. the historic performance of collateral managers. If a person managing a Collateralized Loan Obligation is more experienced, CRAs might be more willing to give a higher rating.

1.1.4 Structured Finance Products in the United States

The term "structured finance" is often perceived as the pooling of receivables though it is more applicable to the offering of a structured system to help borrowers and investors accomplish their end goal. This end goal involves meeting the unique and complex financing needs of large financial institutions that cannot be met by traditional financial products such as loans and mortgages. Fahad (2017) states that structured finance involves the pooling of receivables/assets (mortgages, loans) and repackaging them into tranches before selling to investors in form a tradable bond in a process known as securitization. Structured finance has 3 distinct features 1) pooling of the receivables 2) tranching of liabilities backed by the underlying asset s 3) the use of a Special Purpose Vehicle that separates the credit risk of the pool of collateral assets from the credit risk of the originator, or the bank that granted the loans and mortgages .

The securities that the SPV owns can be classified as collateralized debt obligations (CDOs), mortgage-backed securities (MBS), and asset-backed securities (ABS) . A type of security known as an asset-backed security is one that is secured by an underlying collection of assets (usually ones that generate a cash flow from debt). A mortgage-backed security is one in which the source of the security's payment is a mortgage loan (MBS). In contrast, CDOs may also include MBS in addition to mortgages, corporate loans, credit card receivables, royalties, and leases (Schwarz, 2008).

The tranches (meaning a slice or portion) created from the asset pool are based on the maturity and risks of the underlying assets. Each tranche is securitized and priced when issued to give the appropriate yield to investors. The high grade tranche (credit ratings of BBB or higher) are the most highly priced, providing a low yield but with low risk attached. This is because the underlying assets are less risky and also because the tranche (known as the senior tranche) is insured in a credit default swap by an insurance company. A credit default swap (CDS) is a derivative instrument in which the seller of a CDS (usually an insurance company) agrees to pay the buyer (who is a lender) if the borrower defaults on loan repayment in exchange of a premium for the service. On the other end is the junior tranche which is priced with a high but very risky yield. The intermediate or mezzanine tranche sits between the two tranches. When borrowers provide cash flows in the form of interest payments and loan repayments, the senior tranche is paid first until their obligation is satisfied, followed by the mezzanine tranche, and any remaining funds are paid to the junior tranche (Fahad, 2017).

New issuance of structured finance products has rebounded since the 2007 financial crisis and has continued to grow yearly. According to the S&P Global Ratings Report (2022) new issuance volume in the United States was the largest in 2021 at $520 billion followed closely by China at $500 billion. Auto loan ABS issuance in 2021 was approximately $83 billion. The top six 2020 auto loan issuers in the US were; GM Financial/AmeriCredit at $8.3 billion, Toyota Motor Credit at $7.9 billion, Ford Credit at $7.4 billion, Santander Consumer USA at $7.0 billion, American Honda Finance Co. at $5.0 billion and CarMax Business Services at $5.6 billion. Commercial ABS issuance in 2021 was $28 billion in 2021, up by $7 billion from 2020.

1.2 Research Problem

From the beginning of the 1980s the evolution of capital markets has been extremely rapid. This has brought about a departure from the use of more traditional finance products by financial institutions to more complex products such as structured finance products. Due to the increasing complexity and information asymmetry in financial markets, there is a huge reliance on credit ratings to bridge the information gap. Questions have been raised about the effectiveness of CRAs' rating processes, the robustness of their historical default models, and their rating surveillance procedures as a result of the delay in the downgrade process for structured finance securities. In a study conducted by the Centre for Economic and Social Research in 2020, respondents questioned if CRAs would be able to keep up with the rapid wave of financial innovation. Another issue brought up by respondents was notching, which is the practice of downgrading by one or more "notches" the rating of an underlying asset given by a competitor. It is necessary to assess the transparency of CRAs rating methodologies and techniques, their application, and their implications in order to increase market comprehension of structured finance ratings and rating revisions.

There is a lack of understanding by investors on the role of credit ratings in the structured finance market in the United States. The extent of comparability between, for instance, an AAA-rated corporate bond and an AAA-rated CDO tranche appears to be widely misunderstood, according to the Bank of International Settlements (2020), indicating that there is a general lack of understanding regarding the information that structured finance ratings provide or do not provide. In contrast to the United States, countries in the Eurozone have pushed financial institutions and other businesses to do their own credit evaluations rather than relying on the main three rating agencies. Another issue in the United States structured finance market is the issuer paid rating system, which leads to a conflict of interest by the CRAs because they are being paid by the issuers to rate their securities and are therefore likely to give favorable ratings to issuers'products.

In current times, the ratings of structured financial products have all been adjusted differently based on the performance of the underlying assets. According to S&P Global Ratings report (2022) Auto lease ABS ratings remained stable in 2021. Ford Motor's issuer credit rating was reduced by S&P Global Ratings to "BB+" (speculative grade) due to poorer performance in 2020 as a result of the pandemic . The ratings of auto lease ABS are negatively impacted as an auto manufacturer's rating drops to speculative-grade status. S&P has cut airline ratings by several notches since the start of the Covid outbreak, and around two-thirds of those ratings are now in the "B+" and below rating categories, underlining the gloomy prognosis for the aviation industry. As a result, credit ratings for aircraft lease ABS have decreased.

There are several studies conducted on credit ratings, credit score and the factors that have significant influence on them. Both credit ratings and credit scores are indicators of one's creditworthiness, however credit ratings are used for governments and enterprises, whilst credit scores are utilized for consumers and small businesses. Dimasceno (2016) used an ordered Probit model to predict the credit ratings of Brazilian non-financial companies. The model found that the main factors influencing credit ratings were profitability and capital structure. Soares (2017) carried out a similar study, using a model to predict credit ratings of Brazilian companies. The model had corporate governance in addition to profitability and capital structure as statistically significant predictor variables of credit ratings of Brazilian companies.

Cowan (2006) carried out a survey assessment on the use of credit scoring by Financial Institutions for small business lending in Kenya. The survey found that Financial Institutions can increase the accuracy of their credit scores by correctly identifying the factors that affect the credit worthiness of an SME. Milimu, (2013) carried out a similar study and went further in identifying the factors that determine a credit score for an SME were the sector of operation, type of collateral held, previous credit history, existing and projected cashflows and status of SME's financial statements. Kibet and Wagacha (2018) carried out a study on the factors influencing a credit score for a KWFT client and found that marriage status, age and group membership status (of KWFT) were significant determinants an individual's loan performance.

Vink and Thibeault (2007) and Hu and Cantor (2006) carried out similar studies on significance of credit ratings in structured finance market. Their studies found that credit ratings were the most significant determinant of credit spread which is the difference in yield between two debt securities with different credit quality but with the same maturity. Therefore credit ratings were the most significant factor in pricing of structured finance products. Maris and Segal (2002) carried out an analysis on yield spreads of Commercial Mortgage Backed Securities. The study found that default probability, transaction size and tranche size had the most significant influence on CMBS credit spreads.

From the empirical review, there exists conceptual and contextual gaps. Contextually, the available local and global studies on the determinants of credit ratings are not in the context of structured finance products in the US. The global studies available about the determinants of credit ratings are of companies (e.g. Brazilian companies in this study's empirical review) and governments(i.e. sovereign ratings) . The available local studies about the determinants of credit ratings are of SMEs and individuals' credit scores. The available studies in the context of credit ratings in structured finance products have a conceptual gap. Maris and Segal (2002) found that probability of default, tranche size and transaction size were determinants of credit spread while Vink and Thibeault (2007) and Hu and Cantor (2006) found that credit rating was the most important determinant of credit spread. Are the determinants of credit spread by Maris and Segal i.e. probability of default, transaction size and tranche size actually the determinants of credit rating. If this relation turns out to be true, then we can conclude that Maris & Segal also find that credit ratings are the main determinants of credit spread. The current research leveraged on this gap by answering the research question; what are the determinants of credit ratings in structured finance products in the US?

1.3 Research Objective

To identify and assess the determinants of credit ratings in the structured finance market in the United States.

1.4 Value of the Study

The findings of this study will be useful to academics and future researchers who would like to undertake similar research on determinants of credit ratings in structured finance. Additionally the study will benefit future researchers in identifying gaps in the current literature and areas that could use with further intensive research.

The study will be beneficial in the development of theory and practice in rating structured finance products using the expected probability of default. The analysis can also be used in development of theory in the related research of pricing complexity in an asset pricing model.

The findings of the study will be useful to policy makers who want to implement a regulatory framework for rating of structured finance products and for reducing financial complexity.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter examines relevant literature from various researchers on credit ratings and its determinants. It begins with a review of theories related to credit ratings. A review of empirical studies carried out by researchers on credit ratings and its determinants is undertaken.

2.2 Theoretical Review

This next section reviews the Credit Scoring theory, Information Asymmetry theory and Reputation theory. These theories are relevant to the study as they give an understanding of what factors CRAs utilize in assigning a credit rating and why credit ratings are important in the financial markets.

2.2.1 Credit Scoring Theory

In 2005, Satyajit created the competitive price of default and the credit scoring theory. Screening clients to make sure they have the willingness and ability to repay a debt is the first step taken in lowering credit risk. Banks assess a customer as a possible borrower using the 5Cs model of credit, according to Abedi (2000). Character, capacity, collateral, capital, and condition are the 5Cs. They enable a bank or a lender to assess their potential borrowers and thereby increase loan performance. Character is defined as the integrity and trustworthiness of the potential borrower and represents the willingness of the applicant to pay back the debt. Capacity is an evaluation that determines if the borrower's cashflows can support loan repayments. The potential borrower's assets and obligations are referred to as capital. Collateral refers to access to an asset by the lender that the potential borrower is willing to give up to the lender in case they are unable to pay principal and accrued interest or a guarantee by an entity/person to pay back a debt that has defaulted. Conditions refers to factors that relate to the loan such as interest rate, the purpose of the credit that is being requested and also includes forces in the external environment such as macroeconomic factors e.g. inflation.

According to Constantinescu (2010), the credit scoring model is a categorization process that divides credit applicants into credit risk classes using information gathered from application forms. Structured Finance credit rating follows a similar assessment methodology but instead of assessing a potential borrower’s ability and willingness to repay a debt, it assesses the structured finance instrument’s ability to repay a debt. For example in capacity assessment, the underlying pool of assets cashflows are analyzed. Conditions relating to macroeconomic factors such as unemployment need to be assessed, an increase in unemployment may lead to more defaults on mortgages (the underlying assets of MBS).

2.2.2 Information Asymmetry Theory

Joseph Stiglitz, George Akerlof and Michael Spence are the three economists credited with the creation of the asymmetric information theory. Information asymmetry is the absence of information transfer between any two parties. Akerlof (1970) identified that sellers in many markets had more knowledge about the quality of the product than purchasers in a paper titled "The Market for Lemons: Quality Uncertainty and Market Mechanism." Due to the information asymmetry caused by this discrepancy in information, there is a gap in the product quality. Because of this, consumers who lack access to knowledge begin to doubt the items' quality and reduce the price they are ready to pay, which deters manufacturers and sellers of high-quality goods from selling their goods. Akerlof finds that where this asymmetry exists, high quality product sellers are driven out of the market due to low prices, leaving behind only sellers of poor-quality products. This affects transactions that are mutually beneficial and eventually the markets will collapse. Akerlof emphasizes the need to distinguish good quality and poor-quality products in the markets and therefore puts forth a suggestion of some counter acting institutions such as guarantees, licensing and brand names to minimize the information asymmetry.

In a paper titled "Job Market Signalling," Spence (1973) noted that those who have superior market knowledge will take steps to improve their market outcome. He identified characteristics of job applicants and grouped them into two categories i.e. indices which includes characteristics that cannot be changed such as gender, age and race and signals which are characteristics that can be altered such as work experience and qualifications. In order to be able to indicate their productive skills to the employer and to lessen information asymmetry between the job candidate and the employer, he advised sellers (applicants) of high quality to adopt observable steps, such as seeking training and qualifications. This is relevant to the financial market whereby an issuer of structured finance securities would want request a rating from CRAs for their securities so as to be able to signal to buyers (investors) that their product (e.g. CDOs) is of high quality (safe).

In his essay "The theory of screening, education, and distribution of income," Stiglitz (1975) went even deeper into the process of signalling through screening. He describes screening as a method of determining the various attributes of products, brands, people, and other stuff. He contends that screening can lessen the market's information asymmetry.

According to Rousseau (2006), CRAs are intended to replace the inefficient efforts made by investors who independently conduct research on the financial instruments they are interested in. By assessing the characteristics of the financial instruments and giving suitable credit ratings to them, CRAs are designed to reduce the information asymmetry between investors and issuers. The credit ratings act as a signal to the investors, enabling them to distinguish between high and poor quality financial products.

2.2.3 Reputation Theory

Shapiro (1983) initially emphasized the importance of reputation in his study titled "Premiums for High Quality Products as Returns to Reputations." He contends that reputation plays a key role in how companies build relationships and trust with customers. Partnoy (1990) argues that CRAs have survived due to their ability to build and retain their reputation which is critical in fostering a high trust environment in financial markets. Due to the reputation of the top 3 CRAs, S&P, Moody's, and Fitch, investors are more likely to buy unfamiliar financial instruments that have been regarded safe (given favourable ratings). Revenues are not as crucial as reputation according to S&P. Moody's have claimed that reputation is the backbone of their business and the reason for its success.

It is then clear that reputation is very important to CRAs and that they strive to maintain it. However this is not always the case, during the 2007 financial crisis, CRAs were accused of assigning undeservedly high ratings and failing to downgrade the ratings on issues when warranted. This was attributed to the CRAs desire to appease issuers who are their paying customers and not the investors. The CRAs were willing to compromise their reputation of being reliable credit raters in order to appease their customers. Credit rating agencies (CRAs) compromise on their reputation for two key reasons, according to Hunt (2009) in his work "Credit Rating Agencies and the Worldwide Credit Crisis; The Limits of Reputation, the Insufficiency of Reform and Proposals for Improvement." These reasons are high hurdles to entry in the rating agency market plus the fact that CRAs are exempt from both civil and criminal prosecution for misconduct because of limited agency liability meaning that the benefits of overrating outweigh the costs of such ratings for CRAs.

2.4 Empirical Studies

We take a look at past studies that have been done on the significance of structured finance credit ratings and credit ratings determinants. The aim is to establish any gaps, convergence, disagreements that will help justify this research study.

2.4.1 Global Studies

Damasceno (2016) conducted research to examine any potential improvement in the rating agencies' ability to accurately assess credit risk for Brazilian companies. Brazilian public enterprises from the years 2007 to 2013 made up the sample. An ordered Probit model, which uses a predictive approach for credit ratings based on financial data, was utilized in the study. 64.1% of the ratings in the sample were properly predicted by the model. The proxies for profitability, capital structure, and a dummy variable representing whether or not the enterprise was a member of the Sao Paulo stock exchange's (BOVESPA) index were the model's statistically significant explanatory factors. Therefore the study found that the main determinants of credit rating for publicly listed issuers was profitability and capital structure.

In a study comparable to Damasceno's, Soares (2017) added an indicator of corporate governance standards as one of the credit ratings explanatory variables. 72 Brazilian non-financial enterprises from the years 2010 to 2014 made up the sample, and the explanatory variables employed in the analysis depended on data from the financial statements. 59% of the ratings were accurately predicted by the model. The model's findings also demonstrated that corporate governance, asset size, and the interest coverage ratio all contributed to the explanation of business ratings. Contrary to expectations, corporate governance had an inverse relationship to credit ratings. In other words, businesses with higher standards of corporate governance typically have lower credit ratings.

Vink and Thibeault (2007) carried out an empirical study to determine the most important variables influencing the credit spread of structured finance products. The Structured Finance International Magazine, which compiles historical data on the full population of non-US asset securitization from January 1999 to March 2005, provided the statistics. The study was carried out on a sample of 2,427 ABS issues, including both fixed rate and variable rate issues, that were issued in non-US markets during the years of 2000 to 2004. The credit spread was the response variable in the regression analysis, with the predictor variables being the credit rating, loan to value, asset type, currency risk, time of issue, maturity, transaction size, and country of origin. The study discovered that while the asset-backed securities' credit ratings were the most crucial factor in determining credit spreads, it was not a sufficient statistic for the determination of credit spread.

A quantitative analysis was conducted by Hu and Cantor (2006) to examine the relationship between securitization issuance credit spreads, credit ratings, and credit performance. The credit spread, which is the difference in yields between two bonds of the same maturity but that have a difference in credit quality, acts as a stand-in for the bond's credit risk. The study included a sample of 16,516 CDO, MBS, and ABS securitization securities that were issued in the US market between 1998 and 2004. The sample also included fixed- and floating-rate securities that were rated Baa3 or above at the time of issuance. According to the analysis, credit ratings were the most influential factor in the pricing of structured finance products. The study also showed that, although there is still a positive correlation between them, spreads on structured finance products are typically wider than those on corporate securities with comparable ratings (conventional corporate bonds).

An investigation of the yield spreads of Commercial Mortgage Backed Securities was done by Maris and Segal in 2002. (CMBS). The goal of the study was to determine the causes of the sharp drop in yield spreads on CMBS from 1992 to 1997 and the rise in yield spreads in 1998 and 1999. In order to assess the degree to which trends observed in CMBS yield spreads may be explained by changes in other observable factors, the link between the CMBS credit spreads and other variables was estimated using linear regression. A sample of 479 variable and 1600 fixed rate CMBS tranches were used to conduct the study. According to the analysis, the most important factors influencing CMBS credit spreads were, respectively, default probability, tranche size, and transaction size. In accordance with the Hu and Cantor investigation, the study also discovered that credit spreads on securitization instruments were greater than those on corporate bonds.

2.4.2 Local Studies

In order to analyze how financial institutions in Kenya employ credit scoring for small business lending, Cowan (2006) conducted a survey. Commercial bank clients and SMEs in Nairobi's central business district made up the sample of SMEs that was used. The study found that SMEs might lessen their dependency on collateral and qualify for loans with lower interest rates if credit scoring of SMEs was well developed and managed. Due to the banks' ability to quantify risk, credit scoring makes it easier for SME's to acquire financing. The study found that by first accurately identifying the variables that would influence a SME's credit worthiness, banks can improve the accuracy of the credit scores they assign to SMEs.

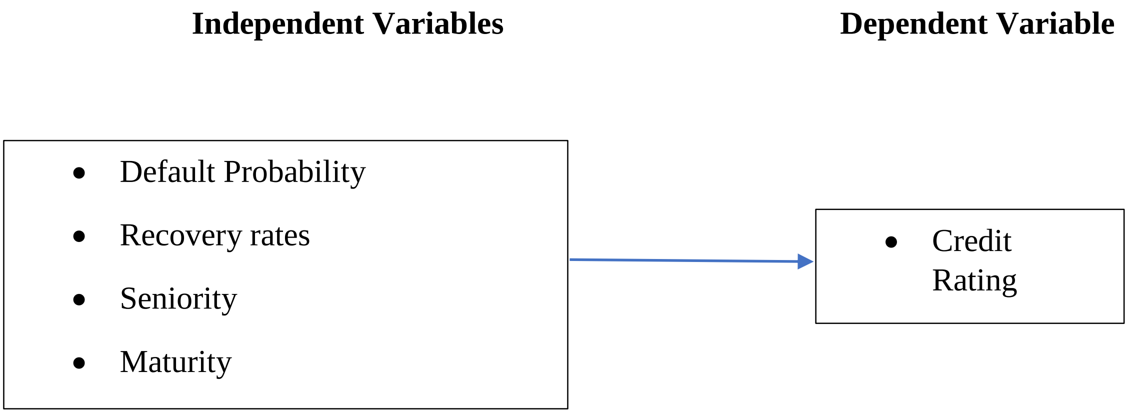
A study on the connection between commercial banks' credit scoring and the availability of loans for SMEs in Kenya was conducted by Milimu (2013). All 43 of Kenya's commercial banks were included in the study's sample, which included both primary and secondary data. The study discovered a significant positive association between commercial banks' credit score and SMEs' ability to get loans. The study also found that the parameters that determine a credit score for an SME were the sector of operation, type of collateral held, previous credit history, existing and projected cashflows and status of SME’s financial statements. The results of this study support Cowan's study from 2006 in that credit scoring by banks improves SMEs' access to credit. However, this study adds to Cowan's research by defining the variables that go into calculating a SME's credit score. The commercial banks function as credit rating agencies in regard to our study on credit ratings in structured finance by determining the credit worthiness of the SMEs and giving them a credit score.

A study on developing a credit scoring model for Kenyan microfinance institutions was conducted by Kibet and Wagacha (2018). Kenya Women Fund Trust (KWFT) served as the study's case study. The credit scoring model is for an individual customer i.e. a KWFT client, while the previous studies mentioned are about credit scoring an SME (borrower) by the banks (lender). The study used data from 20 of the best credit performers and 20 of the worst credit performers across all branches in Nairobi. Logistic regression was employed as a modeling tool. The study found that marriage status, age and group membership status (of KWFT) were significant determinants of an individual’s loan performance. Therefore these factors could be used in determining the credit score of a KWFT client.

2.5 Conceptual Framework

A conceptual framework is a diagram that lists the variables that taken together, describe the problem of concern. The conceptual framework creates a link between the study's title, objectives, research methodolog, and literature review (Coulthard, 2004). Below is a diagram illustrating the link between the independent variables and the dependent variable.

Figure 2.1 The Conceptual Model



2.6 Summary of the Literature Review

The literature review covers three theories that are related to the factors that are assessed during credit scoring and theories that highlight the significance of credit ratings in the structured finance market and in general the financial markets. The theories are Credit Scoring theory, Information Asymmetry theory and Reputation theory. Local and global empirical studies on factors determining credit rating of Brazilian companies and factors determining the credit score of SMEs in Kenya have been discussed.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

The research process used to identify the determinants of credit ratings in the US market for structured finance products needed to be outlined in a methodology. This chapter focuses on the techniques used for data collection, organization, and analysis. Research design, Population, Sample Design, Data Collection, and Data Analysis are sections that are included in this chapter.

3.2 Research Design

Research Design is a technique, outline or plan that a researcher employs in order to formulate answers to their research problem. This study used a descriptive research design to explain the factors that influence an issue's credit rating. A descriptive study accurately represented the variables, which helped in delivering an answer to the research objective (Schindler & Cooper, 2013).

3.3 Population

Burns and Burns (2008) defined a population as the totality of observations of interest from a collection such as events or persons. This study’s population compromised of Consumer Asset Backed Securities issued in 2019 coming in at a volume of $157.7 billion. The average transaction size of a consumer ABS in the United States is approximately $80 million, therefore the approximate number of new issuances was 1,972.

3.4 Sample Design

According to Saijad (2016), sample design refers to the strategies and procedures to be used while choosing a representative sample from the target population. This study used stratified sampling that involved subdividing the population into sub-groups based on a relevant characteristic. The population was divided into 4 sub-groups based on the credit ratings assigned i.e. 1)’AAA’ to ÁA’ 2) ‘AA-‘ to ‘A’ 3) ‘A-‘ to ‘BBB’ 4) ‘BBB-‘ to ‘BB’. Sample selected from each sub-group depended on the ratio of the observations in a sub-group over the total population. The sample size selected consisted of 152 US Consumer Asset Backed Securities.

3.5 Data Collection

This study was based on data of secondary nature. Data on new issuances of US consumer ABSs in 2019 was collected from the Financial Industry Regulation Authority (FINRA) website. The specific data that was collected included issuer name, the underlying asset name, seniority, the maturity date and tranche size. Historical default rates and recovery rates of the underlying assets of Consumer ABS i.e. credit card receivables, auto loans and student loans were sourced from the Fitch Ratings website. Information about the predictor and response variables was the end outcome.

3.6 Data Analysis

The next step was to check and clean the data for any errors that may have arisen due to inconsistencies in recording and also checking for any missing figures. For data analysis, the SPSS computer program version 28 was used. The metrics of central tendency and dispersion along with the standard deviation for each variable were computed using descriptive statistics. The Univariate Analysis was done to enable us to identify potential significant variables that have an effect on the credit ratings. This was done by taking the correlation of a single explanatory variable e.g. default probability with the response variable i.e. credit rating. We also checked for the correlation between recovery rates and credit rating. At this point it was not entirely clear whether the recovery rate is a key driver of credit rating or whether the effect was caused by a variable correlated to recovery rates for example default probabilities. To determine this we needed to carry out further analysis i.e. correlation analysis between the recovery rates and other predictor variables. In order to ascertain the relationship between the response variable and the predictor variables, a multivariate regression analysis was used.

3.6.1 Diagnostic Tests

In order to determine the viability of the research structure, diagnostic tests were conducted. First, the Kolmogorov-Smirnov test was used to test for normality. This test is suited for sample sizes above 30, and an insignificant finding (p value larger than 5%) was taken as proof of normality. The Variance Inflation Factor, an SPSS statistic that gauges the correlation and intensity of correlation between predictor variables in a regression model, was utilized in the study to test for multicollinearity. A VIF of greater than 5 indicates potentially severe correlation among predictor/independent variables. To ascertain the functional form of the regression model and the predictor variables to be used, a model specification test was conducted. If the R^2 of the regressor is close to 1, then the regressor produces a good prediction of the dependent variable.

3.6.2 Analytical Model

Default probability, recovery rates, maturity, and seniority are the four predictor variables that have been postulated to have an effect on the credit ratings of structured finance products.

The regression model below will be utilized:

$Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \varepsilon$ Where;

Y = Credit rating measured as the natural logarithm of assigned values from an ordinal scale of 16 categories ranging from 1 for 'B-' to 16 for 'AAA' class

β_0 = y intercept of the regression equation

β_1, β_2, β_3, and β_4 = Regression Slope

X_1 = Default probability measured mean historical rates of default of underlying assets

X_2 = Recovery rates measured as the mean historical recovery rates of underlying assets

X_3 = Seniority measured as the natural logarithm of assigned values from a scale with senior tranche =2 and non-senior tranche = 1

X_4 = Maturity as measured as the natural logarithm of average maturity of underlying in n years

ε = Error term

3.6.3 Tests of Significance

In order to establish the statistical significance of the overall model as well as the statistical significance of the individual parameters, parametric tests were run. The statistical significance of the overall model was established using the F test from the ANOVA, and the statistical significance of the individual variables was established using T test.

CHAPTER FOUR: DATA ANALYSIS, RESULTS AND DISCUSSION

4.1 Introduction

The analysis, conclusions and discussion of the data from the websites of the Financial Industry Regulatory Authority and Fitch Ratings are detailed in this section. The study's goal was to determine and evaluate the factors that affect credit ratings for structured finance products. The independent variables for the study were maturity, seniority, default probabilities and recovery rates. The dependent variable was credit rating which is graded in letter based format. The dependent and independent variables were measured in either ratio form (i.e. recovery rates, default probabilities) or in logarithmic form (i.e. maturity, seniority and credit rating) to improve the fit of the model. The relationship between the study variables in relation to the research objective was examined using multiple regression analysis. ANOVA was used to determine whether the analytical model was appropriate. Tables and figures are used to present the analysis' findings.

4.2 Descriptive Analysis

The statistics produced from descriptive analysis help describe and summarize the features of a data set. The analysis produced the mean, median, standard deviation, variance of each variable, both dependent and independent variables. An output of each variable was extracted using SPSS software version 28 for a cross section of 152 new issuance of US Consumer ABS from the year 2019.

Table 4.1 Descriptive Statistics

	Minimum	Maximum	Mean		Std. Deviation	Variance
	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic
Maturity	2.4849	5.8861	4.148803	.0791522	.9758545	.952
Default Probability	.03	.27	.1410	.00499	.06151	.004
Recovery rate	.30	.75	.5663	.00735	.09056	.008
Seniority	.0000	.6931	.446898	.0269962	.3328320	.111
Credit Rating	.0000	2.7726	2.218991	.0493445	.6083596	.370

Source: Research Findings (2022)

4.3 Diagnostic Tests

Diagnostic tests were performed on the acquired data. Tests are run to see if the estimated model and the assumptions about the data and the model are accurate and match the data that has been gathered. A 95% confidence level and a significance level of 5% were used in this study. To evaluate which hypothesis the data supports, we compare the significance level to the p value. You can reject the null hypothesis if the p value is lower than the significance level. The diagnostic tests run were multicollinearity and normalcy tests.

4.3.1 Multicollinearity Test

When independent variables in a correlation have strong correlations, multicollinearity results. In order to isolate the relationship between each predictor variable and the response variable, which is the main objective of regression analysis, the predictor variables should be independent of one another. The independent variables' statistical significance is diminished by multicollinearity. Values more than 10 for VIF and Tolerance values lower than 0.1 indicate severe multicollinearity exists. VIF values and Tolerance values were used. A VIF score of above 4 or a tolerance value below 0.25 suggest the possibility of multicollinearity. From the results, all the variables had VIF values lower than 4 and Tolerance values above 0.25 suggesting no multicollinearity.

Table 4.2 Multicollinearity Test

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	1.806	.314		5.754	<.001		
	Maturity	-.113	.030	-.182	-3.724	<.001	.824	1.214
	Default Probability	-.626	.607	-.063	-1.031	.304	.522	1.916
	Recovery rate	.706	.447	.105	1.577	.117	.443	2.256
	Seniority	1.280	.123	.700	10.385	<.001	.432	2.314

a. Dependent Variable: Credit Rating

Source: Research Findings (2022)

4.3.2 Normality Test

In order to check for normality, the Shapiro-Wilk and Kolmogorov-Smirnov tests were used. The study's level of significance was 5%. The null hypothesis was that the data is distributed normally. The null hypothesis is not rejected if the p value for the tests is larger than 0.05. The Kolmogorov-Smirnov test is preferred over the Shapiro-Wilk test when they conflict because it is more statistically sound. The test's results are shown in table 4.3. All of the variables tested in both tests' p values—aside from recovery rates—are less than 0.05. So, we reject the null hypothesis.

Table 4.3 Normality Test

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	df	Sig.
Credit Rating	.221	152	<.001	.803	152	<.001
Seniority	.415	152	<.001	.605	152	<.001
Recovery rate	.080	152	.019	.984	152	.080
Default Probability	.099	152	.001	.968	152	.001
Maturity	.121	152	<.001	.936	152	<.001

a. Lilliefors Significance Correction

Source: Research Findings (2022)

4.4. Correlation Analysis

The results of a correlation analysis reveal whether there is a relationship between two variables as well as how strong the relationship might be. A positive correlation indicates that both variables rise together, whereas a negative correlation indicates that as one variable falls, the other rises. The association between credit rating and maturity, seniority, recovery rates, and default likelihood was examined using the Pearson correlation in the study. The range of the Pearson correlation efficiency, r, is from -1 (strongly negatively correlated) to +1. (a strong positive relation). No correlation is present when the coefficient is 0. A two-tailed test was used, and a confidence level of 95% was used. If the p value is less than 0.05, the correlation between two variables is considered to be statistically significant.

Table 4.4 Correlation Analysis

Correlations

		Credit Rating	Maturity	Default Probability	Recovery rate	Seniority
Credit Rating	Pearson Correlation	1	-.212	-.600	.663	.807
	Sig. (2-tailed)		.009	<.001	<.001	<.001
Maturity	Pearson Correlation	-.212	1	.257	-.247	.017
	Sig. (2-tailed)	.009		.001	.002	.835
Default Probability	Pearson Correlation	-.600	.257	1	-.614	-.607
	Sig. (2-tailed)	<.001	.001		<.001	<.001
Recovery rate	Pearson Correlation	.663	-.247	-.614	1	.677
	Sig. (2-tailed)	<.001	.002	<.001		<.001
Seniority	Pearson Correlation	.807	.017	-.607	.677	1
	Sig. (2-tailed)	<.001	.835	<.001	<.001	

Source: Research Findings (2022)

Credit ratings and maturity were found to have a negative and statistically significant connection ($r = -.212$, $p = 0.009$). Additional findings showed a negative and statistically significant correlation between credit rating and default probability ($r = -.600$, $p = .001$). Recovery rates and credit ratings were shown to be positively correlated and statistically significant, as shown by ($r = .663$, $p = .001$). Seniority and credit ratings showed a fairly strong positive and statistically significant correlation ($r = .807$, $p = .001$).

4.5 Regression Analysis

A Regression Analysis was carried out at significance level of 5% between credit rating and the four predictor variables (i.e. maturity, seniority, recovery rates and default probability). The F calculated value was contrasted with the F critical value.

Table 4.5 Model Summary

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.843[a]	.711	.703	.3314175	.711	90.450	4	147	<.001

a. Predictors: (Constant), Seniority, Maturity, Default Probability, Recovery rate
b. Dependent Variable: Credit Rating

Source: Research Findings (2022)

According to table 4.5, the R Square value was 0.711, meaning that variation in maturity, seniority, recovery rates, and default probabilities account for 71.1% of the variation in credit ratings of US consumer ABS. The remaining 28.9% of the change in credit rating is attributable to additional factors that were not considered in the model. A fairly strong association exists between the dependent variable, credit rating, and the independent variables, as indicated by the correlation co-efficient (R) value of 0.843.

The results of the ANOVA are shown in Table 4.6. The significance of the F test was to determine the overall model's significance.

The F test table yielded a critical value of 2.43308. The entire model is significant in predicting credit rating since the F statistic, which was indicated in the study findings as being 90.450, is higher than the critical number.

Table 4.6 ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	39.739	4	9.935	90.450	<.001[b]
	Residual	16.146	147	.110		
	Total	55.885	151			

a. Dependent Variable: Credit Rating
b. Predictors: (Constant), Seniority, Maturity, Default Probability, Recovery rate

Source: Research Findings (2022)

It was crucial to conduct a t test in order to assess the significance of each individual variable in this study as a predictor of credit rating. The significance of the relationships between the individual predictor variables and the response variable was determined using a p value. A p value less than 0.05 was used as a measure of the independent variables' statistical significance at a 95% confidence level. A variable is shown to be insignificant if its p value is higher than 0.05. Table 4.7 presents the results.

Table 4.7 Model Coefficients

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	1.806	.314		5.754	<.001		
	Maturity	-.113	.030	-.182	-3.724	<.001	.824	1.214
	Default Probability	-.626	.607	-.063	-1.031	.304	.522	1.916
	Recovery rate	.706	.447	.105	1.577	.117	.443	2.256
	Seniority	1.280	.123	.700	10.385	<.001	.432	2.314

Source: Research Findings (2022)

We determined the direction and extent of the association between the dependent variable and the independent variables using the coefficients shown in table 4.7. The T values are used to illustrate the significance of the relationship between the dependent variable and the independent variables. The critical values were compared to the analysis's T values. At 95% confidence interval and a two-tailed test, the critical value is +/-1.975799 . A significant t test value is one that is outside of this range.

The findings indicate that while maturity and default probability have a negative influence on credit rating, recovery rate and seniority have positive influence. This indicates that an increase of one unit in either the recovery rate or seniority will result in an increase of 0.706 and 1.280, respectively, in credit rating. The credit rating will drop by -0.113 and -0.626 points for every unit increase in maturity and default probability, respectively. Due to the p values being less than 0.05, the findings further demonstrate that maturity and seniority have a statistically significant impact on credit rating. Recovery rates and default probabilities do not have a statistically significant influence on credit rating because they have p values above 0.05. The constant coefficient of 1.806 indicates that the credit rating will be equal to 1.806 when the values of the four independent variables are zero.

The regression equation below was estimated.

$$\mathbf{Y = 1.806 - 0.626\ X_1 + 0.706\ X_2 + 1.208\ X_3 - 0.113\ X_4}$$

Where;

Y = Credit rating measured as the natural logarithm of assigned values from an ordinal scale of 16 categories ranging from 1 for 'B-' to 16 for 'AAA' class

X_1 = Default probability measured as the mean historical rates of default of underlying assets

X_2 = Recovery rates measured as the mean historical recovery rates of underlying assets

X_3 = Seniority measured as the natural logarithm of assigned values from a scale with senior tranche =2 and non-senior tranche = 1

X_4 = Maturity as measured as the natural logarithm of average maturity of underlying in n years

4.6 Discussion of Research Findings

The goal of the study was to identify and evaluate the determinants of credit ratings for structured finance products. The study evaluated the impact of four factors—seniority, maturity, recovery rates, and default probabilities—on credit ratings. To see if the data met the criteria for a regression, diagnostic tests were initially performed. Using the F test, the whole model's suitability for predicting credit rating was evaluated. Each independent variable's degree and direction of influence on the dependent variable were also investigated.

The results of the Pearson correlation demonstrate a positive and statistically significant association between recovery rates and credit ratings. This implies that the credit quality and, consequently, the credit rating of the structured financing product increase when the recovery rates of the underlying assets of US consumer ABS rise. The same is true for seniority, which has been found to correlate positively and statistically significantly with credit rating. The higher the seniority of an ABS tranche, means a higher priority in distribution of proceeds to investors, this increases the credit worthiness of an ABS security resulting in higher credit ratings. Results of the correlation analysis also revealed the existence of a negative and statistically significant correlation between credit ratings and maturity and credit ratings and default probability. This means that if maturity and default probability increase, it will have a negative effect on credit rating.

Both the overall model and each of the individual independent variables underwent a test of significance using the F test and T test, respectively. The findings of the F test show that the model is applicable when predicting and explaining how the independent variables affect credit rating. The T test results showed that seniority and maturity had a statistically significant impact on credit rating.

The results of this study agree with Altman and Karlin (2009) who carried out a study on a sample of bond issues from 1978 to 2008 consisting of senior bond issues and subordinated bonds. Their research was on the association between seniority and credit rating in traditional bonds. According to the findings, higher seniority is typically linked to higher payoffs in bankruptcy cases. Higher payoffs meaning higher recovery rates lead to lower expected loss on default and therefore an assignment of a higher rating. The study we have carried finds that seniority has a positive and statistically significant association with credit rating in agreement with Altman and Karlin's findings.

This research supports a study from Radhakrishnan, Fenghua, and Vijay (2013) that looked at the relationship between credit quality and maturity of investment grade and speculative grade rated companies. The study's findings showed that longer-term bonds issued by the companies traded at bigger yield spreads, demonstrating that bond buyers are aware of the risk of rollover associated with a company's debt maturity. This tells us that a longer maturity bond will most likely have a lower credit rating than a shorter term one if all other factors are equal. The research we carried out is in agreement with this as it shows that maturity has a negative relation with credit rating.

CHAPTER FIVE: SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The major objective of this study was to determine and evaluate the factors that influence the credit ratings of structured finance products. This chapter provides a summary of the findings from the preceding chapter, the study's conclusions, and its limitations. This chapter offers suggestions for future academics as well as measures that policymakers might adopt.

5.2 Summary

The research's objectives were to identify the factors that affect credit ratings in structured finance products and to evaluate the nature and importance of the relationships between the factors and credit ratings. To conduct the study, credit rating (response variable) was measured as the natural logarithm of assigned values from an ordinal scale of 16 categories ranging from 1 for 'B-' to 16 for 'AAA' class. Seniority was measured as the natural logarithm of the assigned values i.e. 2 for Senior and 1 for Non – Senior. Maturity was measured as the natural logarithm of average maturity of underlying in n years. Default probabilities and Recovery rates were measured as the mean historical rates of the underlying assets. In order to comprehend the generally recognized relationship between the independent variables of seniority, maturity, recovery rates, and default probabilities and the dependent variable, credit rating, the research analyzed the relevant theories and empirical studies.

The research design used was descriptive. The research's target population was the 2019 issuances of US consumer ABS. Data on new issuances of US consumer ABSs in 2019 was collected from the Financial Industry Regulation Authority (FINRA) website and Fitch Ratings website. Stratified sampling was employed, where the issues were divided into 4 sub-groups based on the credit ratings assigned i.e. 1)'AAA' to ÁA' 2) 'AA-' to 'A' 3) 'A-' to 'BBB' 4) 'BBB-' to 'BB'. A sample was selected from each sub-group depending on the ratio of the observations in a sub-group over the total population. The sample collected was 152 issues of US consumer ABS.

Before using inferential statistics, the researcher performed diagnostic tests to ensure that the data had the necessary characteristics. This was done to ensure that the data was fit for analysis. To determine whether there is a relationship between two variables and how strong that relationship might be, correlation analysis was conducted. Regression analysis was used to examine the degree to which the independent variables and the dependent variable were significantly related, as well as the importance of both the overall model and its individual parameters.

The findings of the Pearson Correlation showed that there was a statistically significant negative correlation between credit rating and maturity. Additional findings showed a statistically significant negative correlation between default probability and credit rating. Credit ratings and recovery rates were found to be positively and statistically significantly correlated. Seniority and credit ratings showed a substantial positive and statistically significant correlation.

The variation in the response variable caused by changes in the predictor variables was demonstrated by the coefficient of determination, indicated as R square. The R Square score was 0.711, indicating that differences in maturity, seniority, recovery rates, and default rates can account for 71.1% of the variation in credit ratings. The remaining 28.9% of the change in credit rating is attributable to additional factors that were not considered in the model. A fairly strong association exists between the dependent variable, credit rating, and the independent variables, as indicated by the correlation co-efficient (R) value of 0.843. The F statistic was significant at the 5% level of significance with p value being lower than 0.05, according to additional ANOVA test results. This indicates that the model is appropriate for describing the relationship between the research variables.

The findings also indicated that a unit increase in seniority and recovery rate will cause an increase in credit rating of 0.706 and 1.280, respectively. The credit rating will drop by -0.113 and -0.626 points for every unit increase in maturity and default probability, respectively. Due to the p values being less than 0.05, the findings further demonstrate that maturity and seniority have a statistically significant influence on credit rating. Due to their p values being above 0.05, default probabilities and recovery rates do not statistically affect credit rating. The credit rating would be equal to 1.806 if all of the variables seniority, maturity, default probabilities, and recovery rates had a value of zero.

5.3 Conclusion

The results of this study demonstrate that the average maturity of the underlying assets as well as the seniority of the tranche have a significant influence on the credit rating of US consumer ABS. Although default probabilities and recovery rates have a negative and positive influence on credit rating respectfully, they do not have a statistically significant influence on credit rating. The study shows that a unit increment in recovery rates and seniority increases the credit rating of a consumer ABS. A unit increment in maturity and default probability decreases the credit rating of a consumer ABS. The study concludes that seniority has the strongest influence on credit rating and therefore a change in seniority status results in a more significant change in credit rating than a change in the other three predictor variables. This indicates that one of the most significant factors affecting credit quality is the priority in which payments are distributed to investors in structured finance products.

According to the study's findings, 71.1% of the variation in the credit rating of US Consumer ABS can be explained by the independent variables included in this study. As a result, we can say that seniority and the maturity of the underlying assets are two of the key factors affecting a structured finance product's credit rating. However they are not the only factors that affect credit rating as evidenced by the remaining 28.9% unexplained variation. Other factors such as the level of credit enhancement and the performance of collateral managers could have a significant effect on credit ratings.

5.4 Recommendations for Policy and Practice

These policy and practice suggestions have been drawn from the study's findings. It has been demonstrated that underlying asset characteristics, such as maturity, significantly influence the structured finance products credit ratings. Therefore, when the risk factors of the receivables/assets underpinning a structured finance product change significantly, credit rating agencies should assess the suitability of the current approaches and models used to assign credit ratings to structured products.

The study showed that maturity and seniority have a significant influence with credit rating of consumer ABS and also that the four predictor variables explain 71.1% of the variation in credit rating. Since some of the key factors affecting credit ratings are known, it is advised that CRAs push structured finance issuers to make pertinent information about these factors publicly available. This will enable other CRAs and investors to do their own independent analysis of structured finance products credit quality without relying on the CRA that has been hired by the issuers to provide a rating.

According to the empirical review and data analysis, there are differences between the factors that affect the credit ratings of traditional bonds and structured finance products. It is therefore advised that CRAs use a separate credit rating symbology, where possible, in order to distinguish structured finance products credit ratings from other credit ratings. The question of the comparability of ratings of structured finance products and traditional financial products will be allayed by this distinction.

5.5 Limitations of the Study

The analysis section of the study focused on US consumer ABS, however in reality there are several other types of structured finance products. These include Collateralized Debt Obligations (CDOs). Residential Mortgage Backed Securities (RMBS), Collateralized Loan Obligations (CLOs) and Commercial Mortgage Backed Securities (CMBS). These structured finance products are likely to have different factors that are significant in determining credit ratings. For example, the performance of the collateral manager is hypothesized to be a significant factor affecting credit rating in CLOs, however not significant in other types of structured finance products.

Due to a lack of data on structured finance products' credit ratings in Kenya, the study's backdrop was structured finance products in the United States. As a result, the study was not able to be localized. The Kenya Mortgage Refinance Company (KMRC) has been collaborating with banks to develop Mortgage Backed Securities, and as a result, the structured finance industry in Kenya is expanding. Future research on the factors affecting structured finance products' credit ratings in the Kenyan market are possible.

The study concentrated on a few variables that are thought to affect structured finance products credit ratings in the US. This study focused on four predictor variables. However, in practice, additional factors/variables, including the degree of credit enhancement, the performance of the collateral manager and macroeconomic factors like inflation and interest rates, are likely to affect the credit rating of structured finance products. The study's results show that the predictor variables used in this study are unable to account for 28.9% of the variation in credit rating.

The study used a highly scientific analytical approach. Qualitative information that can clarify other elements that influence or determine the credit rating of structured finance products was not taken into consideration in the study. Qualitative methods such as interviews, focus group discussions can help develop more concrete results.

5.6 Suggestions for Further Research

The research did not take into account all the factors that can have an impact on structured finance products' credit ratings. It is advised that more research be done, taking into consideration additional factors including the degree of collateralization, the degree of excess spread, the effectiveness of the collateral managers, and macroeconomic factors like inflation and interest rates. Policymakers will be able to understand what influences variation in credit rating by determining each variable's effect on credit rating.

It is suggested that additional research be done on factors that influence credit ratings of other types of structured finance products . Knowing the factors that are particular to certain types of structured finance products and the factors that apply to all of them is crucial.

The United States' structured finance market was the main focus of the study. The study's conclusions and suggestions call for more research to be done in the future on the Kenyan structured finance market.

REFERENCES

Abedi, N. (2000). HIghway to Success. *Credit Management Journal*. Retrieved from http://leathersprinters.com

Adams, M. B. (2003). The Determinants of Credit Ratings in the United Kingdom Insurance Industry. *Journal of Business Finance and Accounting*. doi: https://doi.org/10.1111/1468-5957.00007

Akerlof, G. (1970). The Market for Lemons: Quality Uncertainity and the Market Mechanism. *The Quarterly Journal of Economics, 84*, 488-500. doi:https://doi.org/10.2307/1879431

Altman, E. (2002). Managing Credit Risk: A Challenge for the New Millenium. *Economic Notes, 31*(2). doi:https://doi.org/10.1111/1468-0300.00084

Altman, E., & Karlin, B. (2009). The Re-Emergence of Distressed Exchanges in Corporate Restructurings. *NYU Working Paper*. Retrieved from https://ssrn.com/abstract=1469130

Bank of International Settlements. (2020). *Annual Economic Report.*

Brunnermeier, M., & Oehmke, M. (2009). *Complexity in Financial Markets.* Princeton University Working Paper Series. Retrieved from http://www.princeton.edu/~markus/research/papers/Complexity.pdf

Burns, R., & Burns, R. (2008). *Business Research Methods and Statistics using SPSS.* SAGE Publications.

Caouette, J., Altman, E., Narayanan, P., & Nimmo, R. (2008). *Managing Credit Risk: The Great Challenge for Global Financial Markets* (2nd ed.). Wiley.

Carron, A. (2003). *Credit Ratings for Structured Products: A Review of Analytical Methodologies, Credit Assessment Accuracy and Issuer Selectivity.* National Economic Research Associates. Retrieved from https://www.nera.com/content/dam/nera/publications/archive1/6384.pdf

Committee on the Global Financial System. (2005). *The Role of Ratings in Structured Finance Isuues and Implications.* Bank of International Settlements.

Damasceno, L., Artes, R., & Minardi. (2008). Determining the Credit Ratings of Brazilian Companies using accounting indices.

Das, S., & Hanouna, P. (2008). Implied Recovery. *Journal of Economic Dynamics and Control, 33*, 1837-1857. doi:https://doi.org/10.1016/j.jedc.2009.04.005

Dominic, J. (2021). Estimating Credit Default Probabilities using Stochastic Optimization. *Journal of Data Science, 1*(3). doi:https://doi.org/10.3934/DSFE.2021014

Faggen, J. (1994). *The Market for Commercial Mortgage Backed Securities among Life Insurance Companies and Pension Funds.* Massachusetts Institute of Technology Working Paper.

Fender, I. K. (2004). *CDO Rating Methodology: Some Thoughts on Model Risk and Its Implications.* Bank of International Settlements. Retrieved from https://www.bis.org/publ/work163.pdf

Guasti, F., Veneo, C., & Franco, R. (2016). The Determinants of Credit Rating Levels. Evidence from Brazilian Non-Financial Companies. Retrieved from https://www.researchgate.net/publication/305919274_The_determinants_of_credit_rating_levels_evidence_from_Brazilian_non-financial_companies

Hu, J., & Cantor, R. (2006). The Relationship between Issuance Spreads and Credit Performance of Structured Finance Securities. *The Journal of Fixed Income*. doi:http://dx.doi.org/10.3905/jfi.2006.640273

Josephson, J., & Shapiro, J. (2019). *Credit Ratings and Structured Finance.* Center for Economic Policy Research. Retrieved from https://ssrn.com/abstract=3336793

Kim, H., & Gu, Z. (2004). Financial Determinants of Corporate Bond Ratings. An Examination of Hotel and Casino Firms. *Journal of Hospitality and Tourism Research, 28*(1). doi:https://doi.org/10.1177/1096348003261217

Maris, B., & Segal, W. (2002). Analysis of Yield Spreads of Commercial Mortgage Backed Securities. *Journal of Real Estate Research, 23*(3), 235-252. doi:https://doi.org/10.1080/10835547.2002.12091083

Minardi, A. (2006). The Impact of Credit Rating Changes in Latin American Stock Markets. *Brazilian Administration Review*. doi:https://doi.org/10.1590/S1807-76922013000400005

Mora, N. (2012). What determines creditor recovery rates? *Fed. Reserve Bank Kansas City Economics Review, 97*.

Nafiz, F., & Mehnaz, L. (2017). Complexity in Structured Finance and Difficulties faced by Market Participants - A Critical Assessment of the Role of the Complexity in Financial Crisis. *Asian Economics and Financial Review, 7*(9). doi:http://dx.doi.org/10.18488/journal.aefr.2017.79.907.920

Radhakrishnan, G., Fenghua, S., & Vijay, Y. (2013). Debt Maturity Structure and Credit Quality. *Journal of Financial and Quantitative Analysis, 49*(4). Retrieved from http://www.jstor.org/stable/43303971.

Satyajit, C., & Dean, C. (2005). *Credit Scoring and Competitive Pricing of Default Risk.* USC FBE Macroeconomics and International Finance Workshop.

Shapiro, C. (1983). Premiums for High Quality Products as Returns to Reputations. *The Quarterly Journal of Economics, 98*(4), 659-680. doi:https://doi.org/10.2307/1881782

Spence, M. (1973). Job Market Signaling. *The Quarterly Journal of Economics, 87*(3), 355-374. doi:https://doi.org/10.2307/1882010

Stafford, E., Coval, J., & Jurek, J. (2008). The Economics of Structured Finance. *Journal of Economic Perspectives, 23*. doi:http://dx.doi.org/10.2139/ssrn.1287363

Stiglitz, J. (1975). The Theory of Screening, Education and the Distribution of Income. *The*

http://www.jstor.org/stable/1804834

Vincenzo, B. (2013). Financial Innovation and Structured Finance. The Case of Securitization. *The Company Lawyer, 34*(1), 3-12. doi:https://dx.doi.org/10.2139/ssrn.2012042

Vink, D., & Thibeault, A. (2008). ABS, MBS and CDO compared: An Empirical Analysis. *14*, 27-45. Retrieved from https://ssrn.com/abstract=1016854

Violi, R. (2010). *Credit Ratings in Structured Finance and the Role of Systemic Risk.* Bank of Italy Temi di Discussione. doi:https://dx.doi.org/10.2139/ssrn.1733562

Wojtowicz, M. (2011). *CDOs and the Financial Crisis: Credit Ratings and Fair Premia.* Tinbergen Institute, Amsterdam. doi:https://dx.doi.org/10.2139/ssrn.1568309

APPENDICES

Appendix I: Moody's, S&P and Fitch Bond Rating Scales

Moody's	S&P	Fitch	Rating description
Long-term	Long-term	Long-term	Rating description
Aaa	AAA	AAA	Prime
Aa1	AA+	AA+	High grade
Aa2	AA	AA	High grade
Aa3	AA−	AA−	High grade
A1	A+	A+	Upper medium grade
A2	A	A	Upper medium grade
A3	A−	A−	Upper medium grade
Baa1	BBB+	BBB+	Lower medium grade
Baa2	BBB	BBB	Lower medium grade
Baa3	BBB−	BBB−	Lower medium grade
Ba1	BB+	BB+	Non-investment grade speculative
Ba2	BB	BB	Non-investment grade speculative
Ba3	BB−	BB−	Non-investment grade speculative
B1	B+	B+	Highly speculative
B2	B	B	Highly speculative
B3	B−	B−	Highly speculative
Caa1	CCC+	CCC	Substantial risks
Caa2	CCC	CCC	Extremely speculative
Caa3	CCC−	CCC	Default imminent with little prospect for recovery
Ca	CC	CCC	Default imminent with little prospect for recovery

Ca	C	CCC	Default imminent with little prospect for recovery
C	D	DDD	In default
/	D	DD	In default
/	D	D	In default

Appendix II: Research Data

Issuer Name	Maturity	Default Probability	Recovery Rate	Seniority	Credit Rating
Sandtader Consumer USA	4.4308	0.10	0.70	0.6931	2.4849
Ford Motor	4.0943	0.12	0.72	0.6931	2.5649
Nissan Motor	4.2047	0.13	0.56	0.6931	2.5649
Toyota Motor Corp.	4.3820	0.17	0.73	0.6931	2.4849
Hyundai Capital America	3.8067	0.10	0.65	0.6931	2.6391
Capital One Financial Corporation	4.1744	0.11	0.62	0.6931	2.5649
JN Family Enterprises Inc.	3.8067	0.10	0.60	0.6931	2.5649
Volkswagen AG	3.6376	0.10	0.50	0.0000	2.0794
Bayerische Motoren Werke AG	3.8501	0.12	0.48	0.0000	1.9459
Ally Financial Inc.	4.0254	0.03	0.73	0.6931	2.6391
Consumer Portfolio Services Inc.	3.8712	0.03	0.65	0.6931	2.6391
American Credit Acceptance	4.1744	0.06	0.50	0.6931	2.6391
Drivetime Automotive Group Inc.	4.1589	0.08	0.40	0.6931	2.5649
Lithia Motors Inc.	4.3567	0.09	0.60	0.6931	2.4849
Harley Davidson Inc.	3.9890	0.13	0.45	0.0000	2.1972
United Auto Credit	3.5835	0.10	0.54	0.6931	2.7081
Foursight Capital LLC	3.8712	0.15	0.59	0.0000	1.7918
United Services Automobile Association	4.4308	0.05	0.68	0.6931	2.3979
Pentagon Federal Credit Union	4.2767	0.04	0.65	0.6931	2.4849
JP Morgan Chase & Co.	4.3307	0.03	0.56	0.6931	2.5649
Arivo Acceptance LLC.	3.8286	0.06	0.61	0.6931	2.6391
Orient Corporation	3.7377	0.04	0.61	0.6931	2.6391
Americas Car-Mart Inc.	4.2195	0.03	0.75	0.0000	1.9459
Cox Enterprises Inc.	4.4308	0.08	0.60	0.6931	2.3979
Waterfall Asset Management	4.1589	0.07	0.65	0.6931	2.3026
Oregon Community Credit Union	4.0254	0.14	0.45	0.0000	1.7918
US Auto Finance	4.1589	0.15	0.43	0.0000	1.6094
Automotive Credit Corp.	3.6636	0.12	0.50	0.0000	1.9459
RAC Asset Holdings	3.7377	0.13	0.53	0.0000	1.9459
Car Max Business Services	3.8286	0.15	0.43	0.0000	1.7918
Hankey Group	3.8712	0.11	0.67	0.6931	2.4849
Flagship Credit Acceptance	4.0254	0.10	0.63	0.6931	2.4849
Carvana Group LLC	4.3820	0.14	0.58	0.6931	2.3979
Drivetime Automotive Group	4.0254	0.07	0.67	0.6931	2.7081
Exeter Finance	3.5835	0.13	0.73	0.6931	2.7081
General Motors Company	4.1589	0.14	0.65	0.6931	2.5649
Consumer Portfolio Services Inc.	4.0943	0.12	0.60	0.6931	2.7081
Credit Acceptance Corporation	3.8712	0.14	0.56	0.0000	1.6094
Onemain Financial	3.8286	0.05	0.56	0.6931	2.3979
Stellantis Financial Services	4.4308	0.11	0.43	0.0000	1.3863

United Auto Credit	4.2767	0.08	0.74	0.6931	2.5649
Foursight Capital LLC	3.9890	0.03	0.67	0.6931	2.6391
Pagaya Technologies Ltd.	4.0254	0.10	0.65	0.0000	1.3863
Arivo Acceptance LLC	4.3307	0.06	0.58	0.6931	2.4849
Americas Car- Mart Inc.	3.8286	0.12	0.45	0.0000	1.9459
Prestige Financial Services	3.8067	0.05	0.65	0.6931	2.5649
First Help Financial LLC	4.4308	0.17	0.41	0.0000	1.0986
US Auto Finance	4.3820	0.13	0.53	0.0000	1.0986
Automotive Credit Corp (ACC)	3.8712	0.12	0.58	0.0000	1.7918
Tricolor Holdings	4.0254	0.11	0.72	0.6931	2.6391
Lendbuzz Inc.	3.8712	0.12	0.72	0.6931	2.7081
Veros Credit LLC	3.6889	0.08	0.68	0.6931	2.7726
JD Byrider	4.4308	0.19	0.45	0.0000	1.0986
Capital One Financial Corporation	3.1781	0.23	0.51	0.0000	1.7918
American Expresss	2.9957	0.21	0.48	0.0000	1.6094
Discover Financial Services	2.8904	0.08	0.64	0.6931	2.7726
Bank of America	2.4849	0.10	0.63	0.6931	2.7726
Brex	2.7726	0.11	0.56	0.6931	2.6391
Mercury Financial	3.4012	0.15	0.63	0.6931	2.5649
JP Morgan Chase & Co.	3.5835	0.16	0.53	0.6931	2.3979
Continental Finance	3.2189	0.11	0.65	0.6931	2.5649
Brazos Higher Education Service Corp Inc.	4.7875	0.18	0.30	0.0000	1.3863
North Texas Higher Education Authority Inc.	5.0106	0.18	0.30	0.0000	1.0986
Navient Corp	5.2983	0.15	0.54	0.6931	2.5649
Education Credit Management Corp	5.7683	0.17	0.53	0.6931	2.4849
Higher Education Loan Authority of the State of Missouri	5.8861	0.19	0.54	0.6931	2.3979
Nelnet Inc.	5.1930	0.14	0.58	0.6931	2.5649
Pennsylvania Higher Education Assistance Agency	5.5215	0.20	0.43	0.0000	1.3863
Michigan Finance Authority	5.7038	0.22	0.43	0.0000	1.3863
Iowa Student Loan Corp.	5.6348	0.13	0.56	0.6931	2.3026
Kentucky Higher Education Student Loan Corp.	5.1930	0.10	0.60	0.6931	2.6391
Education Credit Management Corp	4.9416	0.10	0.60	0.6931	2.7081
Utah State Board of Regents	5.3230	0.14	0.57	0.6931	2.3026
New Hampshire Higher Education Loan Corp	5.3471	0.16	0.54	0.6931	2.3979
Goldman Sachs Group Inc	5.5215	0.23	0.43	0.0000	1.0986
Educational Services of America	5.7038	0.25	0.40	0.0000	0.6931
Rhode Island Student Loan Authority	5.7683	0.21	0.48	0.0000	0.0000
Goal Structured Solutions Inc.	5.3471	0.12	0.59	0.6931	2.3026

ISM Educational Loans	5.4806	0.22	0.42	0.0000	1.3863
South Carolina Student Loan Corp	5.5607	0.14	0.58	0.6931	2.5649
Mississipi Higher Education Assistance Corp	5.4806	0.20	0.49	0.0000	1.6094
Rhode Island Student Loan Authority	5.3936	0.14	0.58	0.6931	2.6391
Educational Services of America	5.1930	0.10	0.60	0.6931	2.6391
Pennsylvania Higher Education Assistance Agency	4.9416	0.08	0.58	0.6931	2.6391
Iowa Student Loan Corp.	4.7875	0.10	0.62	0.6931	2.7081
Michigan Finance Authority	5.5607	0.14	0.54	0.6931	2.4849
ALL Student Loan Group	5.6348	0.16	0.69	0.6931	2.6391
Navient Corp	5.7683	0.27	0.39	0.0000	1.0986
Nelnet Inc.	5.4806	0.20	0.48	0.0000	1.3863
Vermont Student Assistance Corporation	5.7038	0.24	0.39	0.0000	0.0000
New Mexico Educational Assistance Foundation	5.8861	0.18	0.58	0.6931	2.3979
Oklahoma Student Loan Authority	5.6699	0.16	0.56	0.0000	1.6094
Access Group Inc.	5.2470	0.20	0.48	0.6931	2.5649
South Carolina Student Loan Corp	5.2730	0.15	0.65	0.6931	2.4849
Arkansas Student Loan Authority	5.1648	0.13	0.65	0.6931	2.7081
Northstar Education Finance Inc.	5.6490	0.20	0.53	0.6931	2.3979
North Texas Higher Education Authority Inc.	5.2730	0.20	0.50	0.0000	2.0794
North Carolina State Education Assistance Authority	5.3936	0.15	0.62	0.6931	2.5649
Educational Funding of the South Inc.	5.3471	0.17	0.57	0.6931	2.4849
Academic Loan Group	5.2470	0.25	0.45	0.0000	2.1972
Montana Higher Education Student Assistance Corporation	5.1930	0.23	0.42	0.0000	1.3863
Panhandle Plains Higher Education Authority	5.7170	0.23	0.55	0.6931	2.5649
New Mexico Educational Assistance Foundation	5.6525	0.19	0.60	0.6931	2.3026
ALL Student Loan Group	5.1930	0.16	0.60	0.6931	2.7726
Vermont Student Assistance Corporation	5.7104	0.22	0.49	0.6931	2.4849
Access Group Inc.	5.6560	0.24	0.54	0.6931	2.3026
Mississipi Higher Education Assistance Corp	5.1240	0.17	0.63	0.6931	2.4849
North Carolina State Education Assistance Authority	5.1930	0.18	0.58	0.6931	2.3979
Capital One Financial Corporation	2.4849	0.12	0.58	0.6931	2.7081

American Expresss	2.7726	0.08	0.68	0.6931	2.7726
Discover Financial Services	3.4012	0.22	0.52	0.0000	2.0794
Synchrony Financial	3.3322	0.20	0.54	0.0000	1.9459
Bank of America	3.1781	0.13	0.62	0.6931	2.7081
JP Morgan Chase & Co.	2.7726	0.22	0.52	0.0000	2.1972
Mercury Financial	2.7726	0.10	0.67	0.6931	2.7726
Barclays Bank Plc	2.7726	0.22	0.56	0.0000	2.1972
Mission Lane LLC	2.8904	0.12	0.59	0.6931	2.7726
Brex Inc.	2.9957	0.11	0.45	0.6931	2.7726
Continental Finance	3.2581	0.11	0.58	0.6931	2.7726
Barclays Bank Plc	3.1781	0.25	0.53	0.0000	2.1972
Mercury Financial	3.1781	0.25	0.51	0.0000	2.0794
Royal Bank of Canada	3.2581	0.08	0.67	0.6931	2.7081
Bank of Nova Scotia	3.3322	0.10	0.63	0.6931	2.7081
Avant LLC	3.4012	0.14	0.68	0.6931	2.6391
Mission Lane LLC	2.4849	0.08	0.69	0.6931	2.7726
Genesis Financial Solutions	2.7726	0.06	0.68	0.6931	2.7726
New Day Ltd	3.4657	0.27	0.50	0.0000	1.6094
Fair Square Financial	3.5835	0.27	0.49	0.0000	1.7918
American Expresss	2.7726	0.07	0.65	0.6931	2.7726
Capital One Financial Corporation	2.8904	0.21	0.53	0.0000	2.7081
Lloyds Banking Group LLC	2.7726	0.06	0.68	0.6931	2.7726
World Financial Network	2.9957	0.23	0.47	0.0000	1.7918
Synchrony Financial	3.1781	0.26	0.48	0.0000	1.6094
Bank of Nova Scotia	3.3322	0.27	0.49	0.0000	1.6094
Genesis Financial Solutions	3.4657	0.12	0.63	0.6931	2.6391
First National Bank	3.2581	0.11	0.65	0.6931	2.5649
Citigroup Inc.	3.3322	0.10	0.62	0.6931	2.6391
Bank of America	3.4012	0.11	0.56	0.6931	2.4849
Mercury Financial	3.3322	0.08	0.67	0.6931	2.7081
JP Morgan Chase & Co.	3.2581	0.13	0.58	0.6931	2.3026
Mission Lane LLC	3.1781	0.19	0.47	0.0000	2.1972
Synchrony Financial	2.8904	0.19	0.49	0.0000	2.0794
Bank of America	2.8332	0.09	0.59	0.6931	2.5649
Continental Finance	2.7726	0.10	0.58	0.6931	2.4849
American Expresss	3.5835	0.13	0.60	0.6931	2.6391
Barclays Bank Plc	3.4657	0.19	0.50	0.0000	1.0986
Brex Inc.	3.2189	0.22	0.49	0.0000	0.6931
Discover Financial Services	3.2581	0.25	0.53	0.0000	0.6931
Capital One Financial Corporation	3.3322	0.08	0.63	0.6931	2.7081
Bank of Nova Scotia	2.8904	0.10	0.62	0.6931	2.7726
Avant LLC	2.9957	0.25	0.49	0.0000	0.0000
NewDay Ltd	3.4012	0.11	0.60	0.6931	2.7081