INSTITUTO
UNIVERSITÁRIO
DE LISBOA

Trading Strategies in Corporate Credit using Cross Sectional Relative Value Analysis

Rui Pinto Caeiro Trancoso Torres

Master in Finance

Supervisor: PhD, Joaquim Paulo Viegas Ferreira de Carvalho, Assistant Professor, ISCTE-IUL

March, 2024

Trading Strategies in Corporate Credit using Cross Sectional Relative Value Analysis

Department of Finance

Rui Pinto Caeiro Trancoso Torres

Master in Finance

Supervisor: PhD, Joaquim Paulo Viegas Ferreira de Carvalho, Assistant Professor, ISCTE-IUL

March, 2024

Acknowledgments

Authoring a dissertation is in many ways a testament to one´s spirit of sacrifice. It is a long hard and sometimes tedious battle. Authoring a dissertation while working full time is that times ten. Nevertheless, is doable and will only give you more tools which will help you in the future – so the first acknowledgment has to go to me in finishing this epic battle.

I would also like to appreciate my supervisor, professor Joaquim Viegas for all his help and encouragement during this work. He was always available to me and made the development of this dissertation easier.

Of course, I cannot express in words the support my family gave me throughout this tough process and the countless times they said, "you can make it", "go for it". Always inspiring to hear that. I have to point out the support of my older brother, João. He was a pillar to me from encouragement calls to his expertise in the matter referred in this work. Indeed, his help is something that I will take with me for life.

One word of appreciation to BNP Paribas, company where I work, for facilitating access to Bloomberg so I could get access to the data needed for this job, for letting me use the facilities to work on my dissertation.

And last, a big thanks to Dire Straits as they were the unofficial soundtrack of this work.

Abstract

Factor investing is in the equities world well known and studied broadly across the world. The same thing doesn't happen in credit markets, especially in corporate credit markets so we set out to try and figure a way to constantly beat the market through a factor model. The developed model is a multi linear regression model having as dependent variable, the Option Adjusted Spread (OAS) and independent variables are common factors to all corporate bonds, such as maturity, rating, sector of business of the issuer and the issuer's location. Through the reading of existing literature, we were able to restrict the universe of bonds that were used for analysis in regard to liquidity as to have not only a theoretical conclusion but also one that can be readily applied in real trading activities. With the model it is possible to create a portfolio that yields not only better returns but significantly better volatility-adjusted returns than the market and several other typically used factor portfolios in the trading floors across the world.

Keywords: Bond Market, Corporate Credit, Relative Value, Linear Regression, Portfolio Management

JEL Classification: G10, G12

Resumo

O investimento por fatores de risco é bem conhecido no mundo das ações e amplamente estudado em todo o mundo. A mesma coisa não acontece nos mercados de crédito, especialmente nos mercados de crédito corporativo, por isso a proposta é tentar descobrir uma maneira de bater constantemente o mercado através de um modelo de fatores. O modelo desenvolvido é um modelo de regressão multilinear onde as variáveis independentes são fatores comuns a todos os obrigações corporativas, como maturidade, rating, setor de atuação do emissor e localização do emissor e a variável dependente o *Option Adjusted Spread* (OAS). Através da literatura existente, conseguimos restringir o universo de obrigações que foram utilizadas para análise no que diz respeito à liquidez, de modo a ter não apenas uma conclusão teórica, mas também uma que possa ser facilmente aplicada em atividades reais de negociação. Com o modelo é possível criar uma carteira que rende não apenas melhores retornos, mas também retornos significativamente melhores ajustados à volatilidade do que o mercado e várias outras carteiras de fatores normalmente usadas nos *trading floors* em todo o mundo.

Palavras-chave: Mercado de Obrigações, Crédito Corporativo, Valor Relativo, Regressão Linear, Gestão de portefólios

Classificação JEL: G10, G12

Index

Table index

Figure Index

Equation Index

Index of acronyms

CAPM - Capital Asset Pricing Model

C0A0 - ICE BofA US Corporate Index Effective Yield

IG - Investment Grade

ISIN - International Securities Identification Numbering system

HY - High Yield

OAS - Option Adjusted Spread

OLS - Ordinary Least Squares

US – United States

1.Introduction

Factor investing is an investment strategy that involves selecting securities based on specific characteristics or factors that are believed to contribute to the securities performance. Instead of focusing solely on the overall market return, factor investing aims to capture the returns associated with certain factors or attributes that have historically demonstrated a premium or excess return. While this has been extensively researched and reported in the equity universe, there is not a lot of literature on this topic for credit markets. This work addresses the issue of factor investing in bonds from a real-world application point of view through an easily applicable methodology.

This work aims to create and execute a viable approach to consistently outperform the corporate credit market. While investors usually rely on relative value methods using time-series analysis, our approach diverges by employing cross-sectional analysis.

To facilitate this, we have developed a model that assesses the appropriate pricing of a corporate bond through its spread.

The model to develop the trading strategies are created through a multi linear regression model where the independent variables will be common factors to all corporate bonds, such as maturity, rating, sector of business of the issuer and the issuer's location.

With the model it is possible to create a portfolio that yields not only better returns but significantly better volatility-adjusted returns than the market. This work is oriented for practitioners as that is the focus of our work is with this theorical results try to replicate in a real-life scenario. Since there´s still little literature on the topic this work will also be a valuable addition to the existing literature.

The structure of this work is then followed by a literature review where we get acquainted with already existing work in this field as well as existing literature on the corporate credit market, brief overview of the data used in this work as well as all relevant work done to the data in analysis before working with it. We also explain in detail the methodology used in this work, carefully explaining the step-by-step work done to arrive at a strategy. We continue to analyze the model validity and also the relevant premia factors and how they behave throughout time. Furthermore, we also analyze the results of the trading strategy implemented by using the model through back testing over a period of 23 years. We also compare our trading strategy with common trading strategies used every day.

2.Literature review

Factor investing operates on the premise that investors receive a premium as compensation for being exposed to the specific risks associated with each factor. For instance, an investor who is exposed to beta, or the risk associated with the overall market, should receive an additional return as compensation for taking on that risk. This concept aligns with the Capital Asset Pricing Model (CAPM), which was the first-ever model to incorporate factors into investment analysis.

In their seminal work, (Fama & French, 1993) made a pivotal contribution to the field of finance by introducing a significant enhancement to the Capital Asset Pricing Model (CAPM) and the broader literature on factor-based portfolios. Their innovation lies in the incorporation of two fundamental factors, namely size, and value, into the framework of equity markets.

The introduction of these new factors marked a substantial departure from the traditional CAPM, which primarily relied on the single factor of market beta to explain asset returns. Fama and French's insight was to recognize that other factors were at play in explaining the variations in asset returns, and size and value were among the most influential.

The size factor often referred to as the Small Minus Big (SMB) factor, captures the phenomenon where small-cap stocks tend to outperform large-cap stocks over the long term. This factor acknowledges that investors often require a risk premium for investing in smaller, potentially less liquid, and more volatile companies.

Conversely, the value factor, known as the High Minus Low (HML) factor, addresses the tendency of value stocks to outperform growth stocks. Value stocks are typically characterized by lower price-to-book ratios, indicating that they are undervalued relative to their fundamentals. Investors may demand a risk premium for investing in these undervalued assets.

The addition of size and value factors represented a paradigm shift in asset pricing theory, as it demonstrated that systematic risk and expected returns were influenced by multiple factors beyond the market risk premium. Fama and French's work ignited a rich area of research and laid the foundation for the development of multi-factor models that have since become integral tools for portfolio management, asset pricing, and risk assessment in finance.(Blitz & Vidojevic, 2019)

Factor investing has gained traction across various types of assets, but surprisingly, it has not gained as much popularity in credit markets. There are two straightforward explanations.

Firstly, studying credit markets systematically is notably challenging. Corporate bonds in these markets exhibit a wide range of characteristics, such as varying seniority, maturity periods, and optional features, making them highly diverse. Additionally, to focus on the credit aspect, it is essential to separate the interest rate component from bond yields. Furthermore, the over-the-counter nature of the credit market poses difficulties in collecting data.

The second reason is how costly it is to trade credit instruments. Trading corporate credit is considerably costlier than other asset classes (Edwards et al., 2007).

Corporate bonds are a popular source for publicly listed and non-publicly listed companies to finance themselves. It becomes then important to understand what the drivers for corporate bonds' excess returns are. Israel et al. (2018) reach the conclusion that much like what happens in the equity markets value, momentum, quality, and carry are key drivers in explaining returns on these securities.

This research shares common goals with the study conducted by Henke et al. (2020), yet it diverges in its approach to handling and analyzing the data. While both works aim to address comparable objectives, they take distinct paths in their execution, emphasizing unique methodologies and strategies to achieve their research goals.

The authors have used five factors: Value, Equity Momentum, Carry, Quality, and Size.

The Value effect in equity markets can be described as follows: cheap stocks outperform, while expensive stocks underperform. The value concept can be applied in credit markets by comparing the market's required compensation for the credit spread to fundamental risk measures (L'Hoir et al. 2010).

Corporate bond value is determined by comparing the market spread to the estimated fair spread through a multiple linear regression model whose independent variables are volatility, market cap, profitability, and leverage ratio. Also used are bond rating and modified duration as these are relevant determinants of corporate bond spreads (Fridson et al. 1998).

Houweling & Van Zundert, 2017 take a different approach to defining a value factor, limiting their analysis to bond-only factors such as rating, time to maturity and 3-month spread change.

In turn, momentum describes the observed phenomenon wherein securities on an upward trajectory tend to persist in their upward movement, while those in a downward trend tend to continue declining. In the extended run, securities displaying stronger momentum often surpass the market's performance, a phenomenon commonly known as the momentum premium. (Kaufmann & Messow, 2019)

The examined paper utilizes a 3-month equity momentum factor to predict forthcoming bond returns. This factor entails dividing the return index at a specific date by the return index from three months prior.

Regarding carry, it can be defined as the future returns assuming the price remains constant, so the return of a security can be defined as its carry plus its price appreciation (Koijen et al., 2018).

As for quality, this work determines it using variables related to a company's balance sheet, focusing on profitability, liquidity, and operating efficiency.

The study finds evidence of various factor premiums in the corporate bond market. Within Investment Grade (IG), Value, Momentum, Carry, and Size offer excess returns, while in High Yield (HY), Quality becomes beneficial. However, Carry and Value, which rely on Option adjusted spread, perform less effectively in HY due to bond-specific complexities.

The study suggests that investors in the corporate bond market should consider using systematic strategies, like an integrated multifactor approach.

3.Data

The ICE BofA US Corporate Index Effective Yield (C0A0), often simply referred to as the "Corporate Bond Yield," is an important financial metric used in the fixed-income market to gauge the interest rate or yield that investors can expect to earn from investing in a specific basket of US corporate bonds.

The ICE BofA US Corporate Index is maintained and published by ICE (Intercontinental Exchange) and Bank of America Merrill Lynch (BofA). This index tracks the performance of investment-grade corporate bonds issued by US-based companies. It is one of the most relevant benchmarks for corporate credit markets in the US and therefore the main reason why we used it in the context of our work.

Portfolio managers and investors often use the ICE BofA US Corporate Index Effective Yield as a benchmark to compare the performance of their corporate bond investments.

The data used in this study is the monthly constituents of the index and the timespan goes from January 2000 to July 2023. Data retrieved for each month contained almost all the information needed for the proposed analysis, such as ISIN, rating, maturity, country of bond issuance, a breakdown of sector levels, type of bond, percentage of weight of each bond in the index, effective duration, credit spread, prior month end credit spread and month-to-date excess return.

The data is to be analyzed at the beginning of each month and having that in mind the data was retrieved at the end of each month but with the beginning of the month constituents. This allowed us to have direct access to the monthly excess returns of each bond. The sector in this index is categorized into 4 different levels. Sector level 1 is common for all bonds and refers to the nature of the issuer. Since this is a corporate bond only index sector level 1 is identical to all: Corporate. Sector Level 2 refers to the area of business of the issuer: *Industrials, Financial,* and Utility. Sector Level 3 refers to the activity of the issuer and will be the one in focus in this work: Basic Industry, Banking, Insurance, Retail, Healthcare, Consumer Goods, Utility, Financial Services, Energy, Technology & Electronics, Real Estate, Transportation, Services, Automotive, Telecommunications, Capital Goods, Media, Leisure.

On Table 1 are descriptive statistics of relevant characteristics of the ICE BofA US Corporate Index Effective Yield (C0A0) such as average face value, sector representation, Duration, Credit Spread and Rating.

	Mean	Median	10%	25%	75%	90%
Face Value	668	473	245	326	811	1270
Sector	7.51	7.17	2.00	3.12	10.23	15.04
Time since issue	4.2	3.2	0.6	1.5	6.0	8.8
Duration	6.53	5.49	1.81	3.12	9.18	13.58
Credit Spread	162	142	70	100	198	273
Rating	6.97	7.47	3.68	5.45	8.98	10.00
Bonds	5506					

Table 1 - Descriptive Statistics for C0A0 index.

The sector statistics were computed by assigning a value to each sector level. Basic Industry = 1, Banking = 2, Insurance = 3, Retail = 4, Healthcare = 5, Consumer Goods = 6, Utility = 7, Financial Services = 8, Energy = 9, Technology & Electronics =10, Real Estate = 11, Transportation =12, Services = 13, Automotive = 14, Telecommunications =15, Capital Goods = 16, Media = 17, Leisure =18. Credit score was also computed in this way: AAA = 1, AA3 = 2, AA2 = 3, AA1 = 4, A3 = 5, A2 = 6, A1 = 7, BBB3 = 8, BB2 = 9, BBB1 = 10.

Over 23 years, there were 283 monthly observations of bonds. In total, there were 1.04 million bonds during this time. Back in January 2000, the total outstanding amount was 1.02 trillion dollars. The index in this month was comprised of about 3,300 diverse bonds. The average duration of the bonds in the index was 5.47 years. Throughout these 23 years, most bonds in the index originated from companies in the Financial Services sector, suggesting their prominence in bond issuance. Additionally, the predominant credit rating for these bonds remained consistently at A2, signifying a strong level of creditworthiness. Fast forward to July 2023, and the total amount outstanding is 8.4 trillion dollars. Now, there are roughly 9,900 different types of bonds in the index. The average duration of these bonds increased to 6.69 years.

The most common type of bond in this index now comes from the Utility sector, indicating a shift in the types of companies issuing bonds. Despite these changes, the credit rating didn't change much, suggesting that these bonds are still considered quite reliable in terms of creditworthiness.

4.Methodology

The main output from the current research work consists of a model that estimates the fair value of a corporate bond. The model is used as a basis for trading strategy to outperform pure long-only strategies. The intuition of the proposed strategy is to take advantage of discrepancies between the model-based fair value and the current market price at which bonds are trading in the market.

The above idea matches what is typically considered a Relative Value strategy. Relative value strategies are trading strategies used in financial markets to profit from price differences between related assets or securities. The idea behind relative value trading is to identify opportunities where one asset appears overvalued or undervalued relative to another asset or a benchmark, and then take positions to profit from the expected convergence of the prices. This technique is commonly used across trading floors in different asset markets (see, for example, Lee et al. (2017) for FX strategies and Goetzmann et al. (2006) for pairs trading strategies).

In credit markets, Relative Value strategies have been mostly used in the context of time series relative value analysis (Flavell et al., 1994). In brief, Time Series Relative value analysis makes use of statistical techniques such as time series regression or co-integration to assess the likelihood that a price differential between two securities is likely to mean revert back to equilibrium allowing for a profitable strategy. In such a way, the investor takes a long position in the relatively undervalued security and a short position in the relatively overvalued.

The model proposed in this work is also based on the concept of relative value. However, it fundamentally differs from a typical time series relative value technique by using cross-sectional analysis for a large universe of corporate bonds. So instead of looking into an asset's price time series, we focus on many assets in a single period and infer a fair value for each corporate bond. Each bond of the universe is described by its key characteristics (ratings, maturity, region, sector, etc.). Those characteristics are the drivers of fair value differences for each corporate bond.(Kahn, 1991) Our ultimate goal is to calculate a fair value for each bond and identify undervalued and overvalued bonds that can outperform a benchmark portfolio based on the idea that cheap/rich bond prices should ultimately converge towards estimated fair value.

4.1.Model Portfolio

Corporate bond prices are affected by credit risk but also by risk-free rates (Weinstein, 1981). Drivers of credit risk are very different from drivers of "risk-free" interest rates risk (commonly referred to as duration risk). To analyze credit performance, it is important to focus on measures that remove interest rate risk from the analysis. To model the fair value of credit risk for a corporate bond, we used a measure which is called the Option Adjusted Spread (OAS).

The option-adjusted spread (OAS) is a measure used in finance to evaluate the yield spread of a fixed-income security, typically a bond, over the risk-free rate, considering the value of any embedded options. In simple terms, it describes the excess in yield for a corporate bond when compared to a benchmark “risk-free” bond with a similar cash flow schedule profile.

The model we propose estimates a fair value of OAS for bonds in the universe which is later compared to the traded credit spreads which allows us to evaluate if a bond is cheap or expensive and thus points towards an investment decision.

To confirm if the proposed strategy works, we performed a monthly backtest of the model going back to the year 2000. For that reason, the first step of our work was building the database of corporate bond data. We used monthly data, given its easy accessibility and ease of use for the current work.

4.1.1.Model Factors

The proposed strategy will be composed through the development of a model that will evaluate if the fair value of a bond´s OAS is correct vis-à-vis what is the actual traded OAS value of the bond. The model will rely on a multiple linear regression method. The dependent variable is the OAS of the bond, and the independent variables are a set of factors which are determinants of the bond spread such as the time-to-maturity, bond´s rating, sector level in which the bond´s issuer operates, and region of domicile of the bond´s issuer as presented on Table 2.

Time to maturity	Rating		Sector Level			Region
3-5Y	AAA	BBB3	Basic Industry	Utility	Services	U.S.
5-7Y	AA3	BB2	Banking	Financial Services	Automotive	Euro
7-10Y	AA2	BBB1	Insurance	Energy	Telecommunications	
10-15Y	AA1		Retail	Technology & Electronics	Leisure	
>15Y	A3		Healthcare	Real Estate	Media	
	A1		Consumer Goods	Transportation		

Table 2 - Proposed coefficients for the Fair Value Model

4.1.1.1.Time to Maturity Factors

Knowing that all bonds vary on their time to maturity which impacts the duration of each bond's time to maturity, we use the time to maturity as a factor of the proposed model. All bonds have different time to maturity, so we formed time to maturity intervals which will serve as independent variables for the regression. Six intervals of time to maturity were created to later convert them into a dummy variable. All the bonds with a maturity shorter than 3 years are identified in the interval “*< 3Y*”, and all the bonds with a maturity greater or equal to 3 years and shorter than 5 years are identified in the interval

“*3-5Y”*. Bonds with a maturity greater or equal to 5 years and shorter than 7 years are identified in the interval “*5-7Y”.* Bonds with maturity greater or equal to 7 years and shorter than 10 years are identified in the interval “*7-10Y”.* Bonds with maturity greater or equal to 10 years and shorter than 15 years are identified in the interval “*10-15Y”*. Finally, all bonds with maturity greater or equal to 15 years are identified in the interval >15*Y.*

4.1.1.2.Rating factor

Another factor in the study is the rating of the bond. Each rating will serve as an independent variable. Bond ratings are important in financial markets. They guide investors by indicating creditworthiness — higher ratings imply lower risk. Bond ratings provide a standardized measure crucial for assessing credit risk, shaping investment decisions, and impacting market dynamics.(Collin-Dufresne et al., 2001).

4.1.1.3.Sector Factor

Another factor in the study is the sector level in which the issuer operates. Each sector level is an independent variable totaling eighteen different variables: Basic Industry, Banking, Insurance, Retail, Healthcare, Consumer Goods, Utility, Financial Services, Energy, Technology & Electronics, Real Estate, Transportation, Services, Automotive, Telecommunications, Capital Goods, Media, and Leisure.

4.1.1.4.Region Factor

One significant aspect of our trading strategy was the fact that not all bonds in the portfolio are from United States-domiciled companies. The region is therefore one of the factors included in our model. Consequently, we categorized these bonds based on the country of their issuer and subsequently mapped them to their corresponding regions (Cavallo et al, 2010).

To achieve this, a mapping system was established that categorized bonds into one of three regions: the United States (US), Europe (Euro), or Other.

4.1.2.Data preparation for analysis

Each dataset contains valuable information such as ISIN, rating, maturity, country of bond issuance, a breakdown of sector levels, type of bond, percentage of weight of each bond in the index, effective duration, and credit spread (OAS). Although each dataset already contains enough data to be worked on and to build the model some refinements and additions are made.

For the purposes of our analysis, we felt the need to calculate specific fields from the original data set. An example is the age of a corporate bond. Although the time to maturity is present in the data set, the issuance date of each bond is not present. We retrieved the issuance data from Bloomberg for every ISIN of all the bonds included in our database. Computation of age and time to maturity on each bond then followed having in mind the month under analysis.

4.1.2.1.Restrictions for Liquidity

Corporate bonds are less liquid instruments than equities and government bonds. Therefore, the implementation of systematic strategies, such as the one we envisage in this work, is constrained by the applicability of prescribed strategies in practice. Through interviews with traders and strategists across a Major European Investment Bank, we gathered information on a variety of filters which allow us to exclude the illiquid bonds from our analysis. This is important to ensure that the output strategies can correspond to bonds that actively trade and that can be easily purchased/sold at prevailing market prices. The filters we applied are based on (2) seniority, (3) age and (4) time to maturity.(Chen et al., 2007)

4.1.2.2.Seniority

Senior debt represents a category of financial obligation with a superior position in the repayment hierarchy within a company's or organization's capital structure. This higher priority becomes evident in situations of financial distress or bankruptcy, where senior debt takes precedence over other forms of debt. In such circumstances, senior debt holders are granted the foremost right to receive payments from the liquidation of the company's assets to settle outstanding debts. Their claim on these assets surpasses that of other creditors. Due to the increased likelihood of repayment, senior debt holders are viewed as less risky when compared to creditors or investors holding subordinated debt, which is often considered separately in investment analysis (Henke et al., 2020). In simpler terms, most individuals perceive senior and subordinated debt as belonging to entirely different investment categories.

4.1.2.3.Age and time to maturity

The bonds included in the dataset underwent a filtering process based on their age and maturity. Specifically, a defined time interval for maturity was established, encompassing bonds with a maturity period equal to or greater than 2 years but no longer than 25 years. Similarly, bonds were filtered based on their age, with those having an age at the time of analysis equal to or exceeding 15 years being excluded from the analysis.

Newly issued bonds tend to experience more active trading due to a range of factors associated with these financial instruments and investor behavior (Alexander et al., 2000). Investors are naturally curious about new investment opportunities and may engage in trading activities early in the bonds' lifecycle to position themselves for potential profit or diversify their investment portfolios. This initial enthusiasm can create a heightened demand for recently issued bonds, resulting in increased trading activity. Additionally, as investors react to the latest information, trading activity can further intensify (Hotchkiss et al., 2007).

4.1.2.4.Dummy variables

Applying the dummy variable to rating and sector level is straightforward. If the bond has a rating of *AA3* and the issuer belongs to the *Automotive* sector, then this bond will be characterized as having *AA3* as 1 and 0 for all other ratings and following the same logic will have for *Automotive,* 1 and 0 for all other sector levels. Regarding the time to maturity, some adjustments are made. Since every bond can have a different time to maturity it becomes impossible to convert the individual time to maturity into a dummy variable because it is not qualitative but quantitative data. For that reason, six intervals of time to maturity were created as explained previously.

4.1.3.Regression and Portfolio.

After completion of the previous and necessary data processing at the beginning of the month, a regression is done having as independent variables the rating of bonds, time to maturity, and sector level of the issuer of the bond and region where the issuer is domiciled. The dependent variable on the regression is the OAS at the beginning of the month. There are two key factors to take into consideration while applying the multiple linear regression model. The dependent variable distribution is heavily skewed. On average the skewness of the credit spread was 1.68, and so a log-linear relation was computed, and the natural logarithm of the OAS was computed before regression. This brought down the skewness level of the OAS to -0.10 which suggests a much better result to apply the linear regression model.

$$\ln(\text{Fair OAS}) = \alpha + \text{Time to Maturity} \times \beta_{(1\ldots5)} + \text{Rating} \times \beta_{(6\ldots14)} + \text{Sector} \times \beta_{(15\ldots31} + \text{Region} \times \beta_{(32\ldots33)} + << e \quad (4.1)$$

Factor	Coefficient	Beta
Time to Maturity	3-5Y	B1
Time to Maturity	5-7Y	B2
Time to Maturity	7-10Y	B3
Time to Maturity	10-15Y	B4
Time to Maturity	<15Y	B5
Rating	AAA	B6
Rating	AA1	B7
Rating	AA2	B8
Rating	AA3	B9
Rating	A1	B10
Rating	A3	B11
Rating	BBB3	B12
Rating	BBB2	B13
Rating	BBB1	B14
Sector	Basic Industry	B15
Sector	Banking	B16
Sector	Insurance	B17
Sector	Retail	B18
Sector	Healthcare	B19
Sector	Consumer Goods	B20
Sector	Services	B21
Sector	Energy	B22
Sector	Financial Services	B23
Sector	Utility	B24
Sector	Technology & Electronics	B25
Sector	Real Estate	B26
Sector	Transportation	B27
Sector	Automotive	B28
Sector	Telecommunications	B29
Sector	Media	B30
Sector	Leisure	B31
Region	US	B32
Region	Euro	B33

Table 3 - Factors to coefficients map for equation 4.1

Having completed the regression at the beginning of each month, the fair value for the credit spread is then computed by multiplying each coefficient of the regression by the dummy variable of the bond exponentiated to the power of e.

To analyze if the bond is correctly priced, the market spread is subtracted from the fair value yielded by the model. If the result is negative (positive), the bond is expensive (cheap) relative to the market and that allows us to form a portfolio. The bonds were ordered from the most negative difference in spreads to the biggest and were then divided into terciles for the completion of the different portfolios on cheap, neutral, and rich bonds. All the other factors analyzed in this work will be divided into terciles for comparison purposes.

4.1.4.Further restrictions on liquidity

To analyze the impact of liquidity on the results we have obtained, we opted to create a universe that was even more strict regarding liquidity constraints. In this way, we attempted to create a universe where we have a higher degree of likelihood to screen for bonds that can be traded at prevailing market prices. Only bonds with a maturity equal to or greater than 3 years and shorter than 7 years were considered. Like what was done previously, bonds were filtered based on their age, this time having an age at the time of analysis equal to or shorter than 3 years. Two new restrictions were introduced. For the analysis, only bonds with a size of 500M dollars or more are considered as bigger issues tend to be more liquid. Also, the region of the issuer was filtered, and only US-domiciled issuers were included. It is worth mentioning that, on average, the sample with these new restrictions was reduced by about 95%. In January 2000, the universe suitable for analysis was only composed of 98 bonds while in July 2023 that universe was 600 bonds.

After applying these restrictions, the process was similar to the first model. Some adjustments were needed on the dummy variables regarding the intervals in time to maturity. Since the filter was smaller, new intervals were created. All bonds with a maturity greater or equal to 3 years and shorter than 4 years are identified in the interval *3-4Y*. Bonds with a maturity greater or equal to 4 years and shorter than 5 years are identified in the interval *4-5Y.* Bonds with a maturity greater or equal to 5 years and shorter than 6 years are identified in the interval *5-6Y.* Bonds with a maturity greater or equal to 6 years and shorter than 7 years are identified in the interval *6-7Y.* The sector level remained untouched, as no restriction was imposed there, and the region factor used previously was dropped since we are only using US-based issuers bonds.

4.2.Factor Portfolio

One of the goals of this work is to assess the performance of the developed model in generating market-beating strategies. We therefore conducted a comparison of the performance of the current model against different common style factors that are usually used as benchmarks for performance. In this study, we compared our performance against the following factor strategies: Carry, Momentum, Beta, Duration, Rating and, Age.

In this study, the factor portfolios we will study to compare with the created portfolio are the following:

Carry Portfolio

Momentum Portfolio

Beta Portfolio

Duration Portfolio

Rating Portfolio

Age Portfolio

These portfolios contain bonds that are part of the ICE BofA US Corporate Index Effective Yield index and were subjected to the same liquidity restrictions that the bonds for the model portfolio were subjected. These restrictions can be found on chapter 4.1.2.1. This way, we not also can assure the same liquidity on the portfolios but direct comparability between portfolios.

4.2.1.Carry Portfolio

Carry can be interpreted as the potential return or profit that an investor can earn just from having the bond on a portfolio regardless of price changes given that a bond pays coupons. Investment strategies based on carry are a popular strategy for investors looking for higher returns. In simple terms, a carry-driven strategy can be taking a long position on a higher-yielding bond and a short position on a lower-yielding bond (Burgess, 2023).

To account for specific carry associated with credit risk, we evaluate spreads instead of yields. Bonds with higher spreads will provide higher returns when compared with lower spread bonds if market risk is unchanged and rating/default events are avoided. At the beginning of each month, the bonds that constitute the index are ordered from smaller OAS to biggest and divided into terciles, which represent three different carry portfolios. After that division, for each portfolio, the time series for the returns are computed. The bonds in each portfolio are not equally weighted. They maintain in the newly created portfolio the same adjusted weight they had originally.

4.2.2.Momentum portfolio

Momentum refers to a trading or investment strategy that relies on the idea that assets that have had positive performance tend to continue to provide positive returns in the future, and assets that have performed poorly are more likely to continue performing poorly. There is proof of momentum in corporate bonds (Jostova et al., 2011).

Every month the percentage of change in spread was computed for each bond. That value is then used in the following month to order the bonds from a smaller percentual change in spread to biggest and divided in terciles for portfolio creation. As with every portfolio, the times series of returns and the portfolio´s duration were computed.

4.2.3.Beta portfolio

The dataset in its original state did not issue any information regarding the bond´s beta against the index. For the implementation of a beta portfolio, a proxy for the beta computation was used. Essentially "beta" refers to a measure of a security's or investment's volatility in relation to the overall market, therefore the beta for each bond in this work was computed as being the bond excess return divided by the entire index return. That information computed at the end of every month to be used in the next month, which means that the portfolio is limited to the information that was available in the previous month. Following the same chain of thought the portfolios were then ordered from smaller beta to biggest beta and divided in terciles whilst also computing portfolio returns times series and duration.

4.2.4.Duration Portfolio

Implementation of a duration portfolio is easier and there is no need to look at the previous month's data. The index was ordered from smallest effective duration to biggest and divided in terciles with respective returns times series computed.

4.2.5.Age Portfolio

Age portfolio was formed by ordering bonds from lowest age to highest and divided in terciles with respective returns times series computed.

4.2.6.Rating Portfolios

A slightly different approach was used. Rather than just ordering the bonds by their credit rating and dividing them in terciles, the bonds were separated into three different groups for the creation of portfolios. AA group contains all bonds with *AAA, AA3, AA2* and *AA1* ratings. A group contains all bonds with *A1*, *A2* and *A3* credit ratings and finally BBB group contains all bonds with credit ratings *BBB1*, *BBB2* and *BBB3* rating. Like what happened for all other portfolios, the returns times series was computed.

5.Model Analysis

In this chapter, the model and the respective coefficients are going to be analyzed. For each month, a regression was done which means a total of 283 regressions. The variables in the study remained the same throughout the period in analysis even though in some months a few coefficients were not statistically significant. However, across the entire period, there is statistical relevance in all the coefficients used, hence the decision to have the model constant through time.

5.1.Model Coefficients

The coefficients represent the relationships between the independent variables and the dependent variable. These coefficients are also known as regression coefficients or beta coefficients. The coefficients are estimated from the data using an ordinary least squares (OLS) regression. These coefficients provide valuable information about the strength and direction of the relationships between the independent variables (factors) and the dependent variable (OAS spread) in the model.

5.1.1.Time-to-maturity coefficients

The time-to-maturity coefficients on the model equation are 3-5Y, 5-7Y, 7-10Y, 10-15Y and >15Y. Below on Table 4 are some descriptive statistics of the results obtained throughout the period in study.

	Mean	Median	Std Dev	Max	Min
3-5Y	0,15	0,15	0,07	0,35	-0,07
	(0,0212)	(0,0000)	(0,1125)	(0,9501)	(0,0000)
5-7Y	0,31	0,33	0,14	0,67	-0,11
	(0,0108)	(0,0000)	(0,0735)	(0,8627)	(0,0000)
7-10Y	0,45	0,47	0,19	0,80	-0,20
	(0,0075)	(0,0000)	(0,0698)	(0,9367)	(0,0000)
10-15Y	0,44	0,46	0,25	0,93	-0,26
	(0,0374)	(0,0000)	(0,1443)	(0,9708)	(0,0000)
>15Y	0,72	0,76	0,33	1,30	-0,23
	(0,0040)	(0,0000)	(0,0368)	(0,4849)	(0,0000)

Table 4 - Descriptive statistics of the regression coefficients for the time-to-maturity variables.

Max (Min) represents the maximum (minimum) value obtained for each specific coefficient. The values in parenthesis represent the p-values of t-statistics of the coefficient.

On average, the coefficient for the 3-5Y variable was 0.15, while the maximum value observed for this variable was 0.35 and the minimum value observed was -0.07. What is observed is that the greater the time to maturity, the higher is the coefficient for that variable. The variable >15Y has an average coefficient of 0.72 and a maximum value of 1.30. This causes the higher time-to-maturity values to have a greater impact on the fair OAS spread value of the bonds. This makes sense since bonds with longer time to maturity are more exposed to risks such as interest rate risk, inflation risk and default risk than those with shorter time to maturity, so the spread needs to increase to compensate for the exposure to those risks. All coefficients were generally statistically significant for a significance level of 0.05 confirming the validity of the time to maturity variables. With the time-to-maturity coefficients, there were few times when the variables were not statistically significant. The variable most affected by this is the *10-15Y* which was not statistically significant in 22 different months. That comes out to a small percentage of 7.7%. This further corroborates the importance of time-to-maturity in explaining bond spreads.

Below on Figure 1 on we can see the impact on the spreads of the time-to-maturity coefficients throughout the period analyzed.

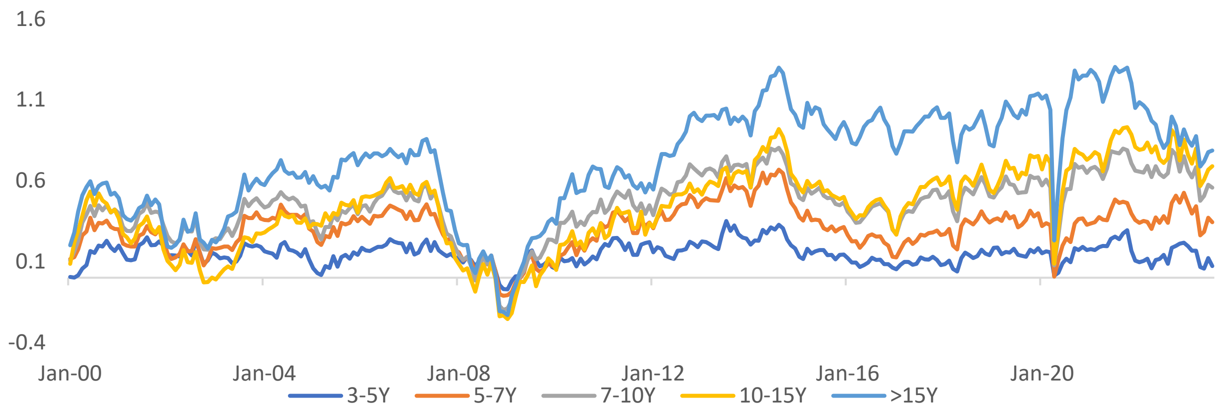

Figure 1 - Graph plot of evolution of the coefficient values for time-to-maturity variables

Analyzing Figure 1, the coefficients behave almost the same way through time. In periods of financial distress, credit spread curves tend to invert as the market usually prices in imminent stress and default/downgrade situations. In fact, during recessions when companies are close to default/downgrades the likelihood that conditions improve in the upcoming years is higher for longer maturities than those for shorter maturities. In addition, longer-term bonds are usually held in a higher proportion by liability-driven investors which tend to hold bonds to maturity and therefore not join the aggregate selling activity which tends to happen during periods of stress which also helps explain why curves tend to invert. The >15Y variable coefficient assumes the highest value throughout time and it is consistently higher than the following variables which means it is the variable related to maturity that influences most changes in the fair value of the spreads. On the other hand, the coefficients of variable 3-5Y assume generally the smaller values, thus not contributing a lot to explaining the fair value of the OAS spreads. Between 2000 and 2003, it is possible to see that all variables sit closer in their weight explaining the spreads. The differences in explanatory power become more notable after 2012 and remain like that until 2022. One interesting aspect of analyzing the graph plot is the way these variables behave in times of economic distress.

Immediately observable is the financial crisis of 2008 and the crisis generated by the 2020 pandemic. All variables lose explanatory power in times of economic distress, especially those who normally, through the years, have more power in explaining the spreads.

5.1.2.Rating coefficients

The Rating coefficients on the model equation are AAA, AA1, AA2, AA3, A1, A3, BBB3, BBB2, BBB1. Below on Table 5 are some descriptive statistics of the results, such as Mean, Median, Standard Deviation, Maximum and Minimum Value obtained throughout the period in study.

	Mean	Median	Std Dev	Max	Min
AAA	-0,47	-0,44	0,14	-0,19	-0,98
	(0,0000)	(0,0000)	(0,0001)	(0,0021)	(0,0000)
AA1	-0,39	-0,37	0,16	-0,08	-1,18
	(0,0183)	(0,0000)	(0,0903)	(0,6480)	(0,0000)
AA2	-0,28	-0,27	0,11	0,02	-0,55
	(0,0096)	(0,0000)	(0,0679)	(0,7170)	(0,0000)
AA3	-0,27	-0,27	0,08	-0,09	-0,51
	(0,0000)	(0,0000)	(0,0001)	(0,0011)	(0,0000)
A1	-0,12	-0,11	0,06	0,08	-0,31
	(0,0271)	(0,0000)	(0,1091)	(0,8386)	(0,0000)
A3	0,16	0,17	0,06	0,32	0,00
	(0,0045)	(0,0000)	(0,0557)	(0,9254)	(0,0000)
BBB3	0,77	0,80	0,15	1,11	0,43
	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)
BBB2	0,53	0,54	0,10	0,75	0,27
	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)
BBB1	0,37	0,37	0,08	0,58	0,17
	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)

Table 5 - Descriptive statistics of the regression coefficients for the credit rating variables.

Max (Min) represents the maximum (minimum) value obtained for each specific coefficient. The values in parenthesis represent the p-values of t-statistics of the coefficient.

The variables for rating are all the credit ratings that can be found in the index. The bonds in the index are considered investment grade bonds and have lower risk, issued by financially stable and creditworthy organizations. On average the coefficient for the *AAA* variable was -0.47 which ultimately results in a low impact in explaining the spread on a bond. This variable kept a low impact throughout the time in analysis, having reached a maximum value of -0.19. These results make sense since higher-rated bonds are less likely to default and pose threats to investors, which is reflected in lower bond spreads. Throughout the various credit ratings, from higher credit rating (*AAA*) to lower credit rating (*BBB3*) we see the mean of the coefficients growing constantly and again this is perfectly in line with what is expected. The lower the bond credit rating, the higher the investor´s demand to be compensated for bearing that risk. Once again statistical significance was not an issue regarding the credit rating variables. On average, and for all credit rating variables, the coefficients were statistically significant with very small p-values. The variable most affected by non-statistical significance was *A1* and the number of times it was not statistically significant was 20 times, roughly 7% of the time, which is a very small number and further proves the importance of credit rating in explaining the dependent variable (OAS spread). As both the credit spreads and time-to-maturity are essential in explaining the spreads the decision to keep the model intact throughout time was made. The reference rating is A2, so higher ratings than A2 will have lower coefficients meaning lower risk and lower ratings than A2 will have a higher coefficient which will mean a higher risk.

Below on Figure 2 on we can see the impact on the spreads of the Rating coefficients throughout the period analyzed.

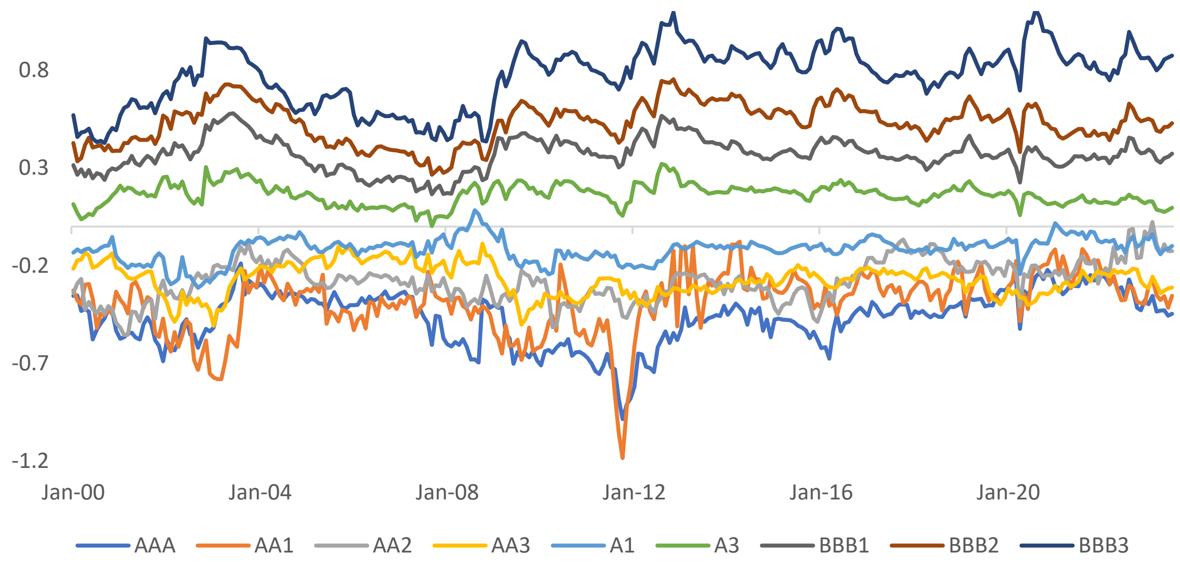

Figure 2 - Graph plot of the evolution of the coefficient values for Rating variables.

It is straightforward to see on Figure 2 that the coefficients of the lower credit ratings variables (A3, BBB1, BBB2, BBB3) behave identically through time and assume always positive values. The *BBB3* variable coefficient assumes the highest value throughout time and the coefficients remain constant in time. The behavior of the higher credit ratings is neither similar nor symmetrical to the previous ratings. Although the tendency for higher credit ratings to have less impact on spreads is generally verified, the behavior is irregular between credit ratings. The variable that suffers more with great shifts is the *AA1.* One interesting aspect to note is the behavior of all the variables during the financial crisis in 2008. It is possible to see an inversion in the explanatory power of the variables. Lower credit ratings tend to explain less of the spreads while higher credit rating variables gain explanatory power. This can be possibly attributed to a higher demand for these ratings from investors around this time. After the 2008 crisis, the behavior of almost all the variables remains constant. Important to note that during periods of crisis, investors will try to sell what is possible to sell, not what they want to sell. Higher rates assets become more liquid and are unloaded by investors first thus decreasing in value. That is behind the rise in higher-rated coefficients and the drop in lower-rated coefficients during economic distress times.

5.1.3.Sector-Level Coefficients

Analysis of the variables for the sector level is not as straightforward as the previously studied factors, mainly because of the statistical relevance of the regression coefficients. Sector level wise the number of non-statistical relevant coefficients rises substantially when compared to previous factors.

5.1.3.1.Industrial Sector Level

The Industrial Sector Levels coefficients on the model equation are Basic Industry, Retail Healthcare, Consumer Goods, Services, Energy, Technology & Electronics, Real Estate, Transportation, Automotive, Telecommunications, Media, Leisure and on Table 6 we can find some descriptive statistics of the results, such as Mean, Median, Standard Deviation, Maximum and Minimum value obtained throughout the period in study.

	Mean	Median	Std Deviation	Max	Min
Basic Industry	0.12	0.10	0.08	0.35	-0.02
	(0.0606)	(0.0001)	(0.1554)	(0.9219)	(0.0000)
Retail	0.03	0.01	0.10	0.33	-0.21
	(0.1932)	(0.0608)	(0.2704)	(0.9971)	(0.0000)
Healthcare	0.04	0.05	0.07	0.27	-0.23
	(0.2420)	(0.1073)	(0.2907)	(0.9994)	(0.0000)
Consumer Goods	-0.01	-0.02	0.08	0.31	-0.17
	(0.2241)	(0.0624)	(0.2908)	(0.9896)	(0.0000)
Services	0.18	0.17	0.12	0.50	-0.08
	(0.0763)	(0.0002)	(0.1971)	(0.9631)	(0.0000)
Energy	0.12	0.11	0.13	0.72	-0.21
	(0.1217)	(0.0001)	(0.2363)	(0.9978)	(0.0000)
Technology & Electronics	0.13	0.12	0.11	0.53	-0.12
	(0.0794)	(0.0002)	(0.2195)	(0.9982)	(0.0000)
Real Estate	0.26	0.21	0.17	0.76	-0.02
	(0.0198)	(0.0000)	(0.0773)	(0.5665)	(0.0000)
Transportation	-0.08	-0.06	0.10	0.21	-0.48
	(0.1974)	(0.0353)	(0.2775)	(0.9914)	(0.0000)
Automotive	0.26	0.24	0.26	1.26	-0.34
	(0.0437)	(0.0000)	(0.1579)	(0.9296)	(0.0000)
Telecommunications	0.18	0.16	0.18	1.00	-0.17
	(0.1043)	(0.0000)	(0.2292)	(0.9885)	(0.0000)
Media	0.08	0.08	0.14	0.88	-0.22
	(0.1558)	(0.0028)	(0.2621)	(0.9867)	(0.0000)
Leisure	0.21	0.18	0.14	0.67	-0.09
	(0.1169)	(0.0025)	(0.2297)	(0.9737)	(0.0000)

Table 6 - Descriptive statistics of the regression coefficients for the industrial sector level variables.

Max (Min) represents the maximum (minimum) value obtained for each specific coefficient. The values in parenthesis represent the p-values of t-statistics of the coefficient.

The industry sector level is the one that comprises the most sub-sectors and seems to be the sector level where each variable less contributes to explain the spreads on corporate bonds. *Leisure*. *Automotive* and *Real Estate* are on average the variables that have the highest coefficients ranging between 0.21 and 0.28 and are also the sectors where the highest coefficients were obtained. The sector levels that influence corporate bond spreads the least are *Transportation*, *Consumer Goods* and *Media* with values ranging from -0.08 and 0.08. Out of all variables, the Industrial sector level is the one that suffers most from non-statistically significant coefficients. Throughout time, only the *Services, Technology & Electronics, Real Estate and Automotive* sectors had statistically significant coefficients that explained the change in spreads. This does not mean that all the variables performed poorly over time. On this front, the variables that had more times statistically relevant coefficients were *Real Estate, Automotive and Technology & Electronics* and on the other hand, the variables that behaved the worst were *Retail, Consumer Goods and Healthcare.* The problem of the high level of statistical relevance will most likely come from multicollinearity issues between the variables. Multicollinearity occurs when two or more independent variables in a regression model are highly correlated with each other. In other words, it is a situation where there is a high degree of linear association among two or more predictor variables. It is normally resolved by removing variables that are highly correlated with other variables. For future work analysis, the model can be "dialed" down on the number of variables that are used. Instead of using individual sub-sectors, the regression can be made to maintain everything else the same and use as sector level the main sector of business of issuing corporation (*Industrial, Banking and Utility).*

The below figures (Fig 3, Fig 4, Fig5) were separated between sector levels for easier analysis.

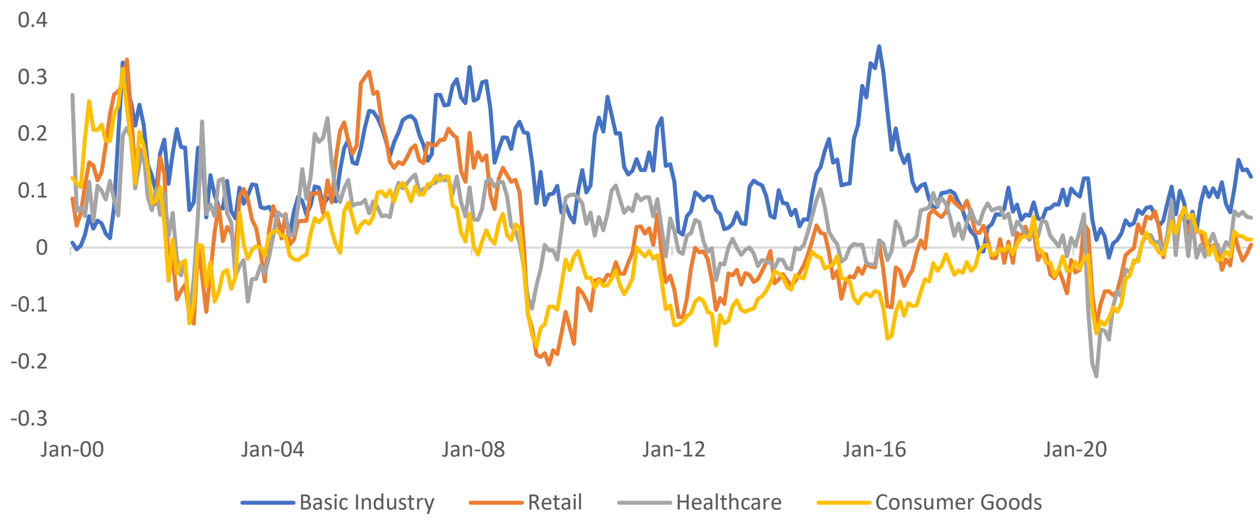

Figure 3 - Plot coefficient evolution for values of represented sector level variables.

On Figure 3, all variables tend to behave similarly. Across time the Basic Industry sector has a bigger impact on bond spreads than the rest of the variables. Between 2000 and 2004 both the behavior and value of the coefficients are identical. All variables range between roughly -0.2 and 0.3 which are relatively small values and do not seem to influence the spreads all that much. All variables but Basic Industry are affected by the 2008 financial crisis and the 2020 pandemic.

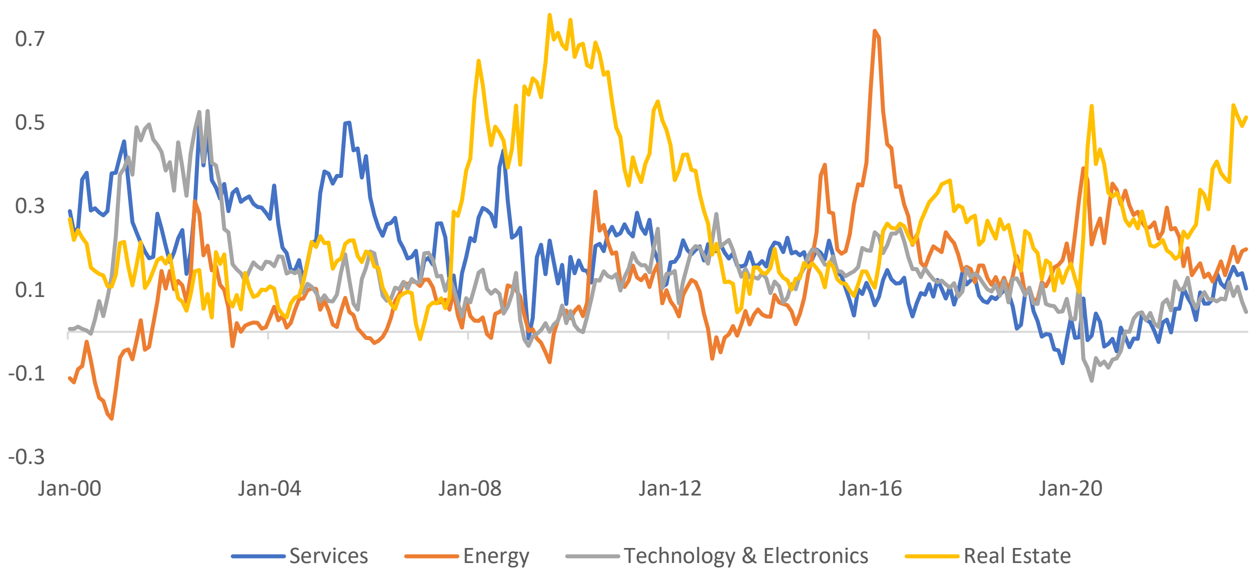

Figure 4 - Plot coefficient evolution for values of represented sector level variables.

On Figure 4 it is possible to observe that in general, the impact these variables have on bond´s spreads are higher than the previous set of variables. Both *Real Estate* and *Energy* have peaks of about 0.7. *Services* start by having relatively high values but after 2008 the impact this variable has on spreads continuously drops even reaching negative values around 2020. The variable that saw its coefficient rise the most was *Real Estate* right after the financial crisis of 2008. This makes sense since one of the drivers of the crisis was the real estate market.

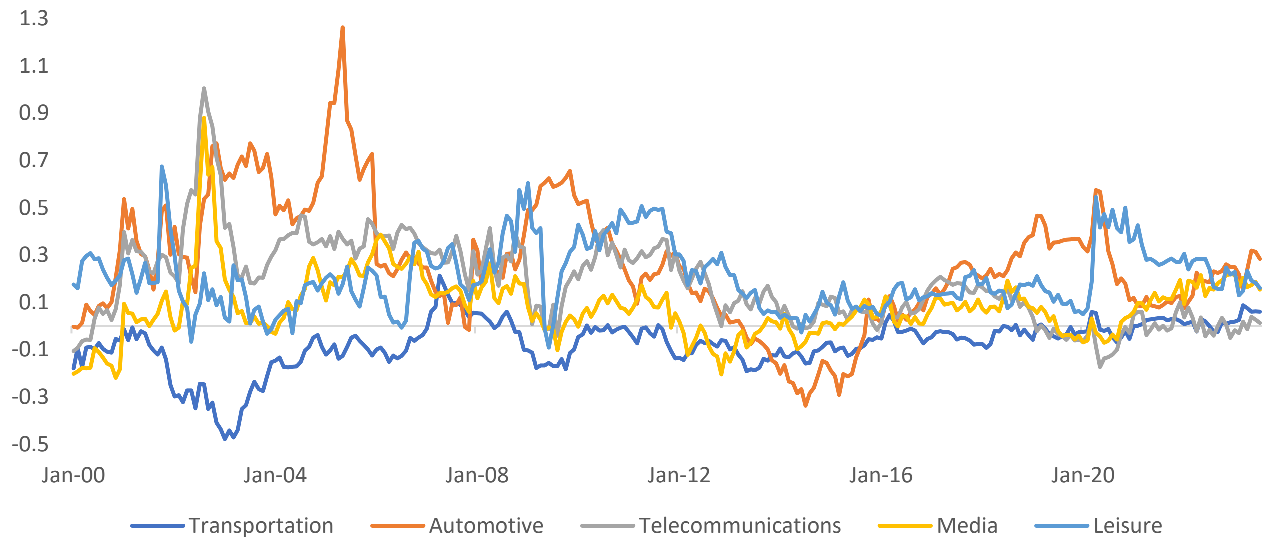

Figure 5 - Plot coefficient evolution for values of represented sector level variables.

On Figure 5, it is possible to see that, on average, the variable *Automotive* has a greater impact in explaining bond spreads than the other variables from 2000 to 2006 reaching a value of almost 1.3 in 2004, the highest of all variables. *Telecommunication* also shares higher values in this period as well as

Media. During the financial crisis of 2008, the impact on spreads of all variables tends to decrease to smaller values and that downward tendency remains the same until 2016. Transportation remains almost always with negative values contributing very little to spreading explanation.

Banking Sector Level

The Banking Sector Levels coefficients on the model equation are Banking, Insurance, Financial Services and on Table 7 we can find some descriptive statistics of the results, such as Mean, Median, Standard Deviation, Maximum and Minimum value obtained throughout the period in study.

	Mean	Median	Std Dev	Max	Min
Banking	0,35	0,26	0,23	0,99	-0,03
	(0,0208)	(0,0000)	(0,0989)	(0,9808)	(0,0000)
Insurance	0,31	0,27	0,14	0,66	0,11
	(0,0000)	(0,0000)	(0,0000)	(0,0002)	(0,0000)
Financial Services	0,41	0,35	0,19	0,85	0,02
	(0,0028)	(0,0000)	(0,0353)	(0,5613)	(0,0000)

Table 7 - Descriptive statistics of the regression coefficients for the Banking sector level variables.

Max (Min) represents the maximum (minimum) value obtained for each specific coefficient. The values in parenthesis represent the p-values of t-statistics of the coefficient.

The coefficients share, on average, similar values throughout time ranging between 0.31 and 0.41 and are statistically significant as well. The number of times that there are non-statistically significant events drops dramatically when compared to the previous sector level. Of the 283 regressions done *Banking* coefficient was non-statistically significant only 14 times, the *Financial Services* coefficients 2 times and *the Insurance* coefficients were always statistically significant, once again pointing to the fact that characterizing bonds on principal sector levels might be enough to obtain strong enough results.

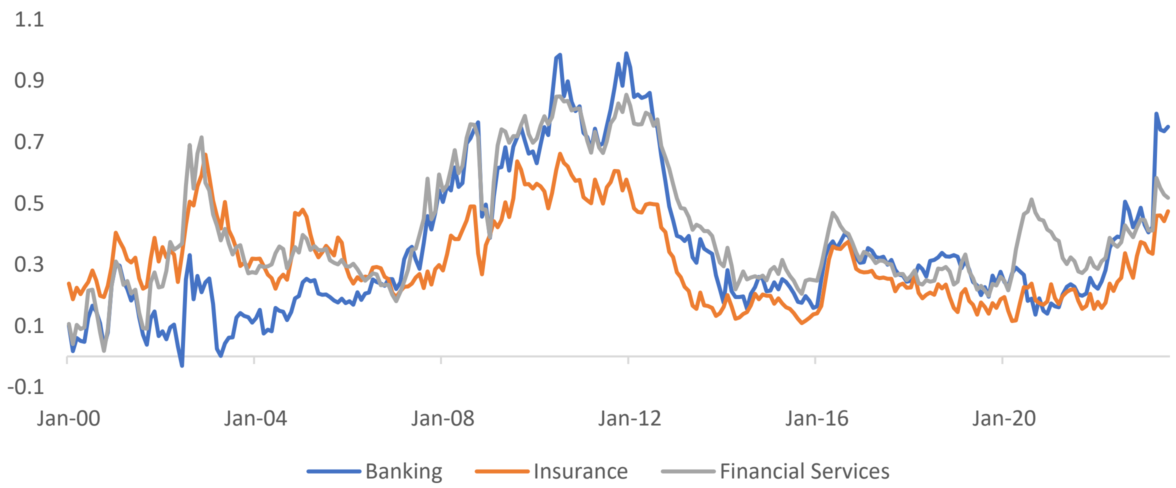

Figure 6 - Graph plot of the evolution of the coefficient values for variables Banking variables.

The behavior of coefficients is identical through time, and all three variables grow in explanatory power after the 2008 crisis which makes sense since the banking sector was greatly affected. Their explanatory power seems to be higher on average than most other sector variables which again points to a simplification of variables in the model as shown of Figure 6

5.1.3.2.Utility Sector Level

The Utility Sector Level coefficient only contains one coefficient and on Table 8 we can find some descriptive statistics of the results, such as Mean, Median, Standard Deviation, Maximum and Minimum value obtained throughout the period in study.

	Mean	Median	Std Deviation	Max	Min
Utility	0,10	0,09	0,09	0,55	-0,07
	0,1249	0,0008	0,2381	0,9926	0,0000

Table 8 - Descriptive statistics of the regression coefficients for the Utility sector level variables.

Max (Min) represents the maximum (minimum) value obtained for each specific coefficient.

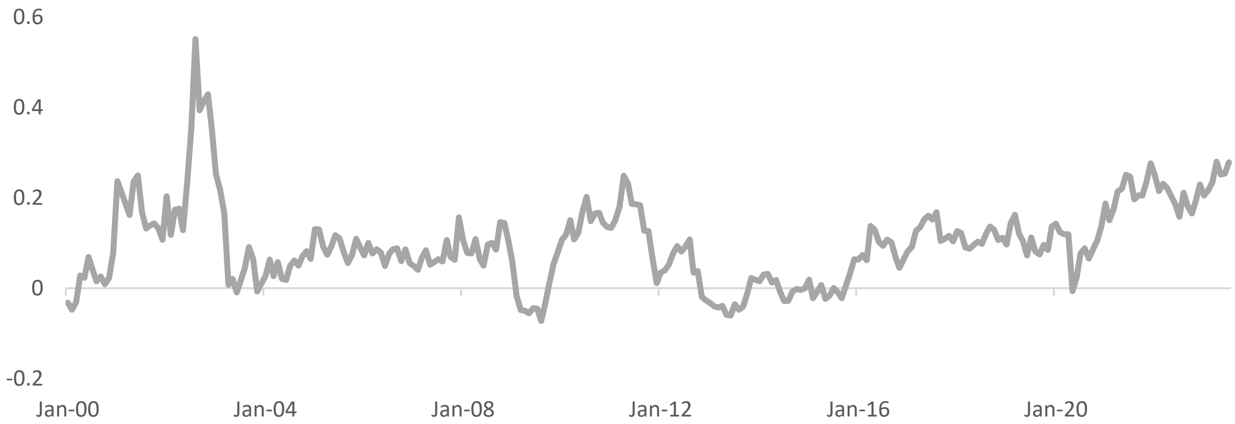

Figure 7 - Graph plot of evolution of the coefficient values for variable Utility.

The behavior of this variable is very constant through time and the amplitude is also very small, except for a spike in 2003 as seen in Figure 7. Overall, with sectors the coefficients tend to provide you with an indication of what is the relative preference of investors. 2015 China industrial crisis there is a higher premium for energy and industrial sectors. In 2020, government-imposed restrictions due to the COVID-19 pandemic affected the leisure and transportation sectors. With an increase in interest rates Real Estate coefficients rise. That is visible both in 2008 and now in 2023. The effects of the 2000 tech bubble are also visible. Important to notice that each crisis is usually driven by a particular sector weakness that depends on the specific nature and risk driver of that crisis. Overall, you can see that cyclical sectors tend to perform worse in crisis and vice versa.

5.1.4.Region Coefficients

The Region coefficients on the model equation US and Euro and on Table 9 we can find some descriptive statistics of the results, such as Mean, Median, Standard Deviation, Maximum and Minimum value obtained throughout the period in study.

	Mean	Median	Std Deviation	Max	Min
US	-0,19	-0,19	0,12	0,06	-0,42
	(0,0591)	(0,0000)	(0,1794)	(0,9894)	(0,0000)
Euro	-0,04	-0,06	0,08	0,17	-0,22
	(0,1342)	(0,0052)	(0,2430)	(0,9967)	(0,0000)

Table 9 - Descriptive statistics of the regression coefficients for the Utility sector level variables.

Max (Min) represents the maximum (minimum) value obtained for each specific coefficient. The values in parenthesis represent the p-values of t-statistics of the coefficient.

On average the explanatory power of the US variable is low with a coefficient of -0.19, a maximum of 0.06 and a minimum of -0.42, and for the Euro variable -0.04, a maximum of 0.17 and a minimum of -0.22. On average the coefficients of the US variable were not statistically significant. this variable failed to be statistically significant for a significance level of 0.10, 33 times which represents roughly only 11% of the times. With these results in mind, the domicile of the issuer is valid in explaining corporate bond spreads. Foreign issuers carry a premium against domestic issuers as investors are naturally closer to domestic issuers so have easier accessibility to information and know domestic businesses more extensively vis-à-vis foreign businesses. Foreign issuers are also exposed to foreign currency risk and that also increases the domicile premium.

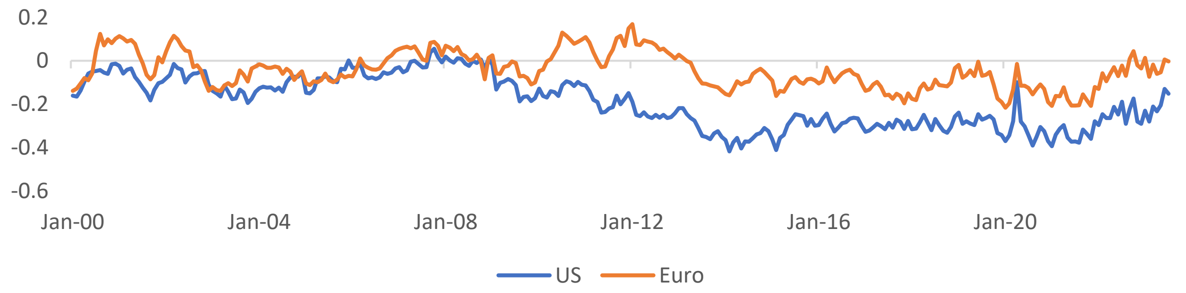

Figure 8 - Graph plot of evolution of the coefficient values for region variables.

The behavior of this variable is very constant through time and with a very low amplitude. Despite being valid, the location does not influence greatly the corporate bond spreads. This can be explained by the composition of the index. Most of the bonds present in the Index are from US-domiciled companies, so that leaves very little room for an explanation of the domicile of the issuer.

5.2.Goodness of Fit

The adjusted R-squared (or adjusted coefficient of determination) is a modified version of the R-squared statistic used in regression analysis. While the regular R-squared (R^2) measures the proportion of the variance in the dependent variable explained by the independent variables in a regression model, the adjusted R-squared considers the number of predictors in the model.

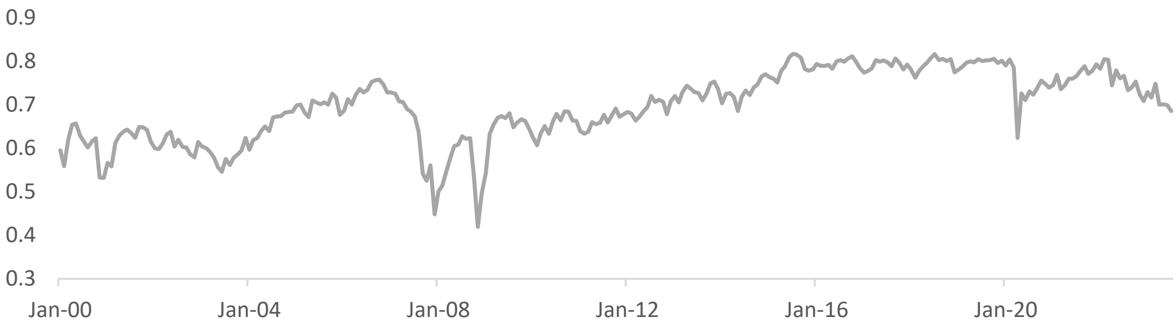

Figure 9 - Plot graph of the Adjusted R-squared of the proposed model.

Since the model used is lengthy in the number of independent variables the chosen goodness of fit indicator was the adjusted R-squared as it penalizes models with a higher number of predictors. By adding more predictors to a model, the adjusted R-squared will decrease unless those additional predictors significantly improve the model's fit. This metric ranges from 0 to 1, with higher values indicating a better fit. A value of 1 means that the model explains all the variance in the dependent variable, while a value of 0 means that the model explains none of the variance.

6.Performance analysis

In this chapter, we examine the overall performance of the model portfolio. This assessment involves a comparison with the performance of a benchmark portfolio, which is characterized by the returns of the index. Additionally, we evaluate how the model portfolio compares against the performance of various portfolios based on the aforementioned factors such as age, beta, carry, duration, momentum, and rating. This analysis aims to provide a comprehensive understanding of the model portfolio's effectiveness in comparison to both the broader market represented by the index and specific portfolios tailored to distinctive financial parameters.

	Portfolio 1	Portfolio 2	Portfolio 3	Long/Short Portfolio
Annualized Return	-0.09	1.03	3.53	1.90
Annualized Vol.	4.09	3.72	5.74	1.37
Annualized Sharpe	-0.02	0.28	0.61	1.39
Beta	0.82	0.75	1.17	0.17

Table 10 - Annualized average returns, Sharpe Ratio, and beta for all model portfolios

The portfolio formed with the factor model was a long position in the tercile with the highest Sharpe Ratio and a short position in the tercile with the lowest Sharpe Ratio. On average the annualized return of this portfolio was 1.90% with a volatility of 1.37% yielding a volatility-adjusted return of 1.39 as shown in Table 10.

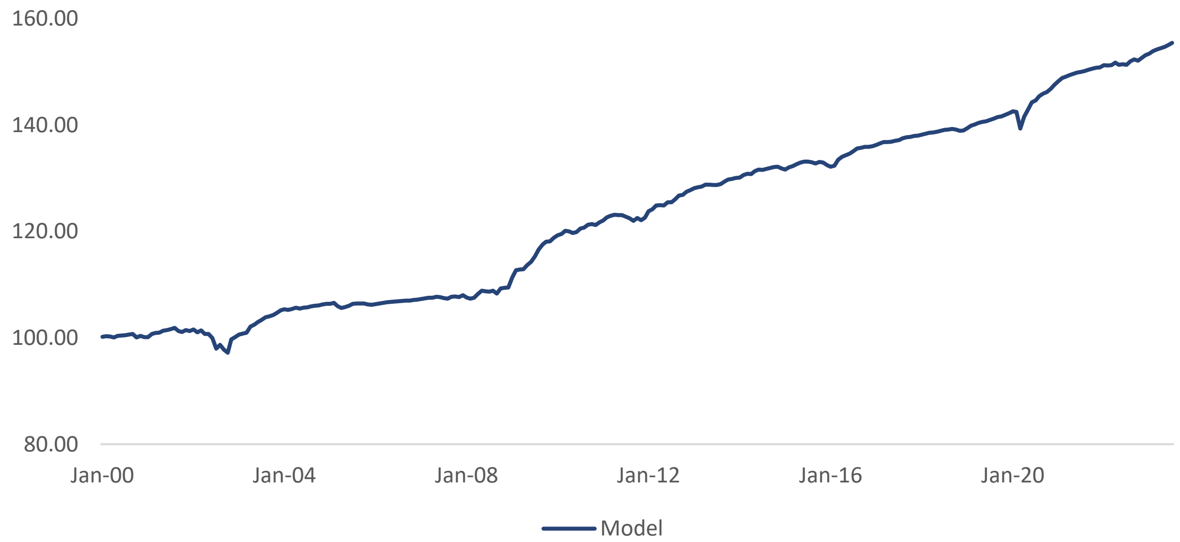

Figure 10 – Cumulative excess returns of the model portfolio.

6.1.Model Portfolio Performance vs. Index Performance

The first comparison is between the model portfolio and the index. The index is simply a long position on all the bonds on the index (which suffered liquidity restrictions mentioned on chapter 4.1.2.1.) and the results of the index performance over the years can be found in Table 11.

	Index
Annualized Return	1.60
Annualized Vol.	4.83
Annualized Sharpe	0.33
Beta	1.00

Table 11 - Annualized Average Return, and Sharpe Ratio of the index portfolio

We can see that the index had an average annualized return of 1.60% and a volatility of 4.83%, yielding an annualized Sharpe Ratio of 0.33.

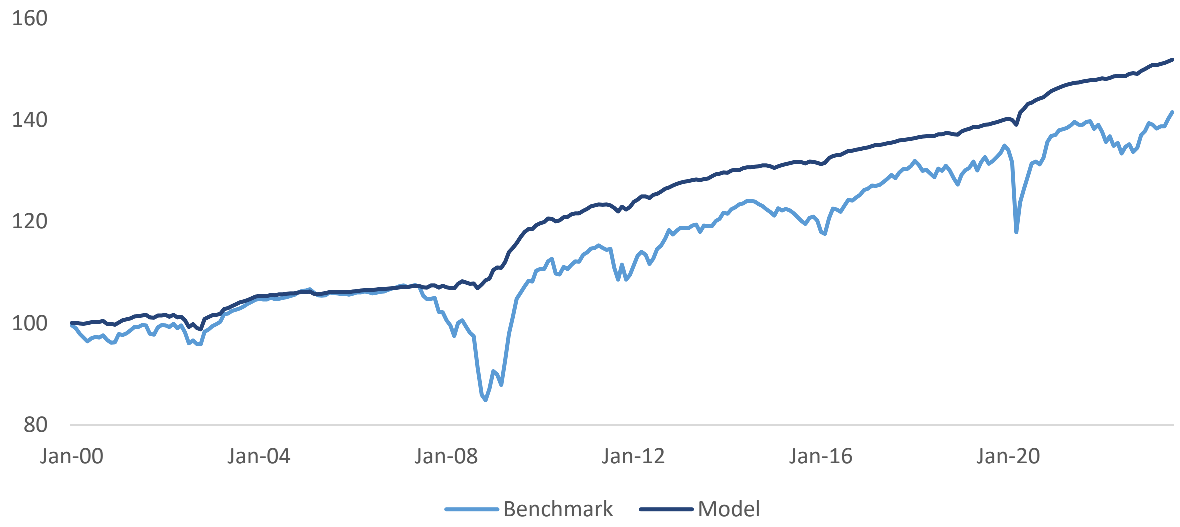

Figure 11 - Cumulative excess returns between model portfolio and index.

By looking at Figure 11 we can see that the model consistently outperforms the market and in the periods of market distress the portfolio performs positively. Looking at the 2008 crisis we can see that our portfolio values grow when the market is in a downfall.

6.2.Model Portfolio vs. Age Portfolio

In this section, the performance of the model portfolio is compared to the Age Factor portfolio. Following the same rationale, we ordered the bonds by their age and divided them into terciles thus creating three portfolios where Portfolio 1 represents the tercile with the youngest bonds and Portfolio 3 represents the tercile with the oldest bonds.

	Portfolio 1	Portfolio 2	Portfolio 3	Long/Short Portfolio
Annualized Return	1.26	1.85	1.80	0.27
Annualized Vol.	5.18	4.83	4.50	0.63
Annualized Sharpe	0.24	0.38	0.40	0.43
Beta	1.07	0.99	0.92	-0.07

Table 12 - Annualized average returns, Sharpe Ratio, and beta for all age portfolios

Portfolio 1 on average had an annualized return of 1.26%, an annualized volatility of 5.18% and a Sharpe Ratio of 0.24. Portfolio 3 had an annualized return of 1.80%, and an annualized volatility of 4.50%, yielding a Sharpe Ratio of 0.40. With the performance of both portfolios being similar to one another the long/short portfolio performs poorly over time with an annualized return of 0.27%. when comparing with the index performance we see that the volatility-adjusted returns are lower than the index.

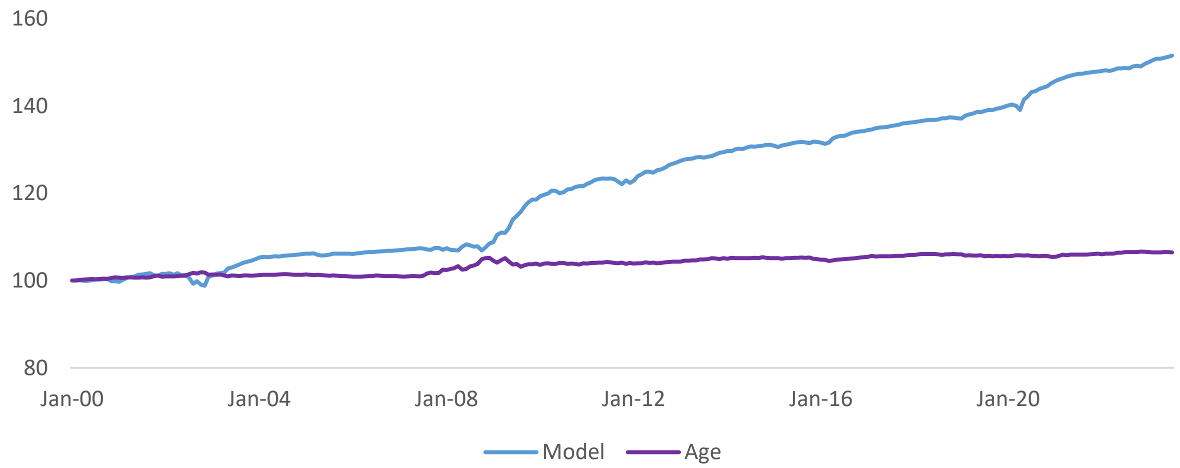

Figure 12 - Comparison of cumulative excess returns between model portfolio and age portfolio.

We can see the comparison between the age portfolio and the model portfolio and is easy to see that the model portfolio vastly outperforms the age portfolio. There is practically no creation nor destruction of wealth with this portfolio.

6.3. Model Portfolio vs. Beta Portfolio

In this section, the performance of the model portfolio is compared to the Beta portfolio. The bonds were ordered into terciles from smallest beta to highest beta with Portfolio 1 being the portfolio of bonds with smallest beta and Portfolio 3 being the portfolio of bonds with highest beta. Again, a long/short portfolio was created with a long position on the highest Sharpe Ratio portfolio and a short position on the lowest Sharpe Ratio portfolio.

	Portfolio 1	Portfolio 2	Portfolio 3	Long/Short Portfolio
Annualized Return	1.43	1.31	2.21	-0.38
Annualized Vol.	4.05	3.84	7.03	2.22
Annualized Sharpe	0.35	0.34	0.31	-0.17
Beta	0.77	0.77	1.42	0.32

Table 13 - Annualized average returns, volatilities, Sharpe Ratio, and beta for all beta portfolios.

Portfolio 1 and Portfolio 2 have similar performances with an average annualized return of 1.43% and 1.31%, respectively. Portfolio 3 has higher returns but also has a higher volatility. All three portfolios have a similar Sharpe Ratio, between 0.31 and 0.35. The index Sharpe Ratio was 0.33. A long-only position in any of these portfolios would be equivalent to holding an index portfolio. The long/short portfolio has an annualized return of -0.38%, volatility of 2.22% and a Sharpe Ratio of -0.17, considerately lower than the model long/short portfolio and index.

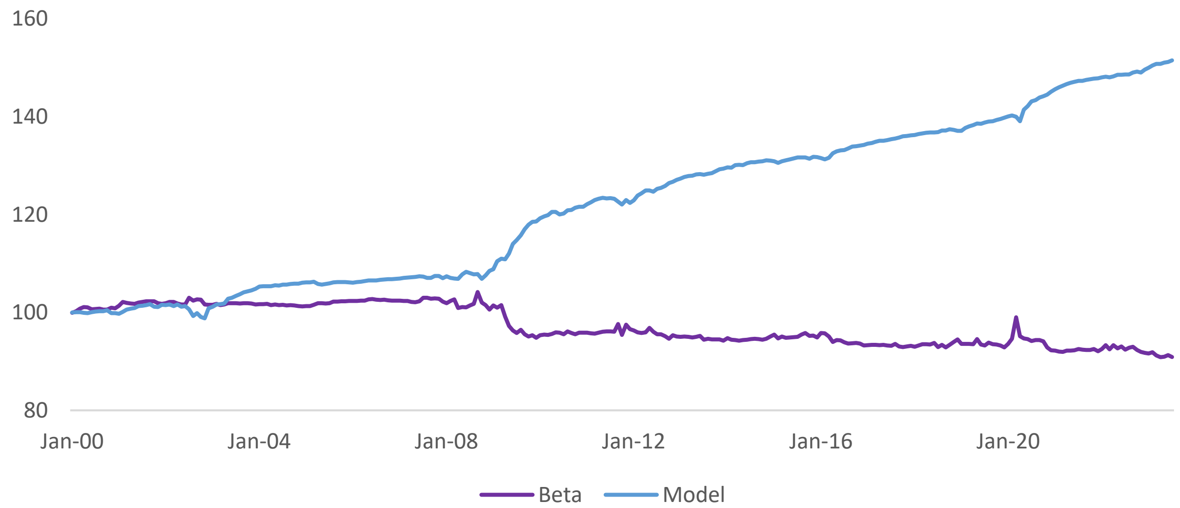

Figure 13 - Cumulative excess returns between model portfolio and beta portfolio.

By looking at the cumulative returns (Figure 13) we can see the comparison between the beta portfolio and the model portfolio, the model portfolio once again outperforms the beta portfolio. Since all the portfolios had a similar performance regarding returns, the behavior of the returns remains almost constant throughout time. Since the average return of the beta portfolio is negative, we can see a destruction of wealth with this portfolio.

6.4.Model Portfolio vs. Carry Portfolio

We analyze the performance of the model portfolio and compare it with the performance of the carry portfolio. The bonds were ordered from smallest OAS to highest and divided in terciles. Portfolio 1 contains the bonds with the smallest OAS and Portfolio 3 contains the bonds with the highest OAS. A long/short portfolio was created with a long position on the highest Sharpe Ratio portfolio and a short position on the lowest Sharpe Ratio portfolio.

	Portfolio 1	Portfolio 2	Portfolio 3	Long/Short Portfolio
Annualized Return	0.18	1.14	3.79	1.79
Annualized Vol.	2.76	4.73	7.89	2.93
Annualized Sharpe	0.06	0.24	0.48	0.61
Beta	0.53	0.96	1.59	0.53

Table 14 - Annualized average returns, Sharpe Ratio, and beta for all carry portfolios.

The portfolio containing higher spreads (Portfolio 3) vastly outperforms the portfolio containing smaller spreads (Portfolio 1) with an average annualized return of 3.79% and an average annualized volatility of 7.89% yielding a Sharpe Ratio of 0.48. The resulting long/short portfolio has an average annualized return of 1.79%, volatility of 1.69% and Sharpe Ratio of 0.63.(Table 14)

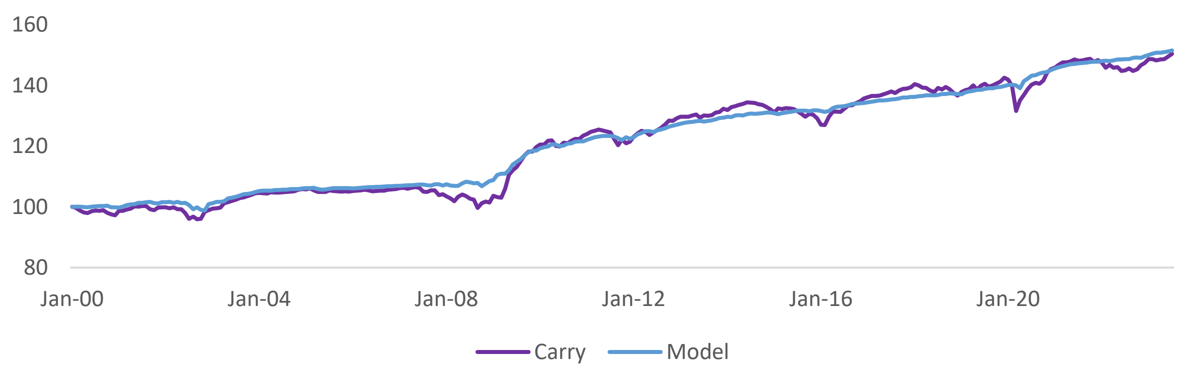

Figure 14 - Cumulative excess returns between model portfolio and carry portfolio.

It is visible on Figure 14 that the model portfolio is similar to the carry portfolio throughout the period in analysis. The behavior of both portfolios is identical in periods of market distress and before 2008 the performance was similar. The model portfolio performance grows constantly and is less prone to market volatility than the carry portfolio. After 2008 they also behave similarly throughout the rest of the period.

6.5.Model Portfolio vs. Duration Portfolio

In this section, the performance of the model portfolio is compared to the duration portfolio. The bonds were ordered into terciles from smallest effective duration to highest effective duration with Portfolio 1 being the portfolio of bonds with smallest effective duration and Portfolio 3 being the portfolio of bonds with highest effective duration. Again, a long/short portfolio was created with a long position on the highest Sharpe Ratio portfolio and a short position on the lowest Sharpe Ratio portfolio.

	Portfolio 1	Portfolio 2	Portfolio 3	Long/Short Portfolio
Annualized Return	1.58	1.75	1.40	0.01
Annualized Vol.	2.81	4.75	7.32	1.20
Annualized Sharpe	0.56	0.37	0.19	0.01
Beta	0.54	0.98	1.49	0.23

Table 15 - Annualized average returns, Sharpe Ratio, and beta for all duration portfolios.

Portfolio 1 and Portfolio 2 have similar returns with an average annualized return of 1.58% and 1.75% respectively. Portfolio 1 has marginally smaller returns but half the volatility of portfolio 2. The index Sharpe Ratio was 0.33. A long-only position in any of these portfolios would be equivalent to holding an index portfolio. The long/short portfolio has an annualized return of 0.01%, volatility of 1.20% and a Sharpe Ratio of 0.01, considerately lower than the model long/short portfolio and index (Table 14).

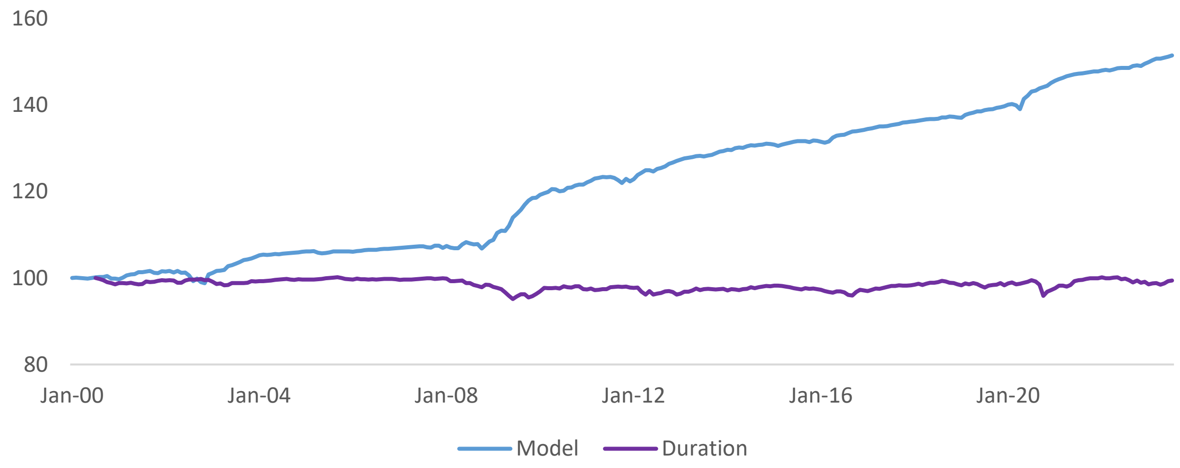

Figure 15 - Cumulative excess returns between the model portfolio and duration portfolio.

By looking at the cumulative returns graph we can see the comparison between the beta portfolio and the model portfolio, the model portfolio once again outperforms the beta portfolio. Since all the portfolios had a similar performance regarding returns, the behavior of the returns remains almost constant throughout time. Since the average return of the beta portfolio is essentially 0, we can that portfolio values remain the same throughout time (Figure 15).

6.6.Model Portfolio vs. Momentum Portfolio

We analyze the performance of the model portfolio and compare it with the performance of the momentum portfolio. The bonds were ordered from smallest change in spread in percentage to highest and divided in terciles. Portfolio 1 contains the bonds with the smallest change in the spread in percentage and Portfolio 3 contains the bonds with the highest change in spread in percentage. A long/short portfolio was created with a long position on the highest Sharpe Ratio portfolio and a short position on the lowest Sharpe Ratio portfolio.

	Portfolio 1	Portfolio 2	Portfolio 3	Long/Short Portfolio
Annualized Return	-0.33	1.75	3.53	1.92
Annualized Vol.	4.68	5.29	5.17	1.51
Annualized Sharpe	-0.07	0.33	0.68	1.27
Beta	0.92	1.08	1.02	0.05

Table 16 - Annualized average returns, Sharpe Ratio, and beta for all momentum portfolios.

The portfolio containing higher momentum (Portfolio 3) vastly outperforms the portfolio containing smaller momentum (Portfolio 1) with an average annualized return of 3.53% and an average annualized volatility of 5.17% yielding a Sharpe Ratio of 0.68. The resulting long/short portfolio has an average annualized return of 1.92%, volatility of 1.51% and Sharpe Ratio of 1.27, therefore coming very close to the model portfolio (Table 16).

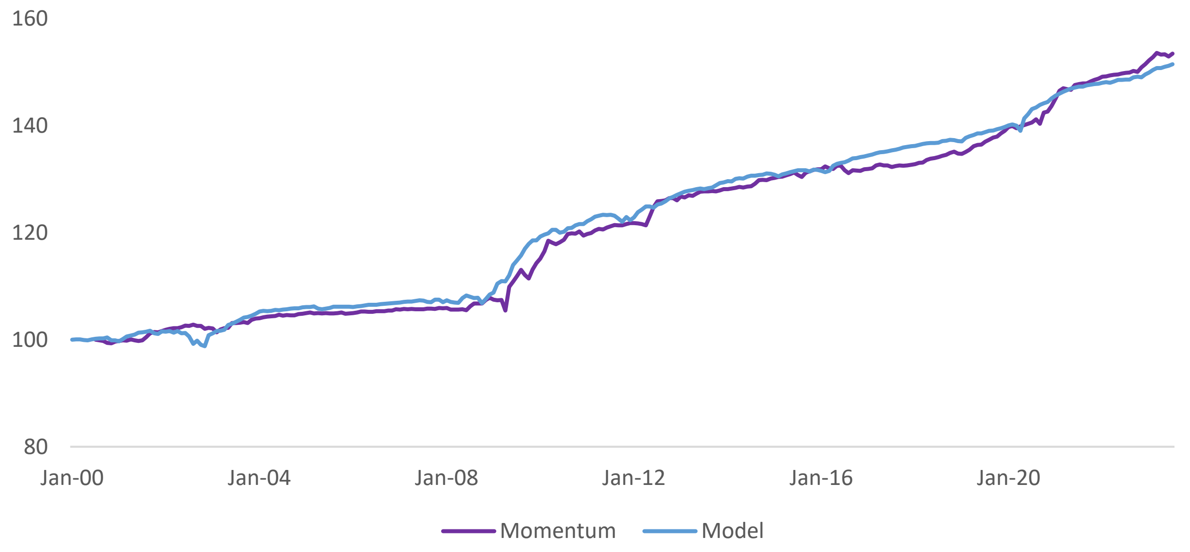

Figure 16 - Cumulative excess returns between model portfolio and momentum portfolio.

Much like the carry-based strategy the momentum strategy performs very similarly to the model. The returns of the model portfolio were marginally better than the momentum portfolio up until 2020. From 2020 onwards there is an inversion where the momentum portfolio performs marginally better than the model portfolio (Figure 16).

6.7.Model Portfolio vs. Rating Portfolio

In this section, the performance of the model portfolio is compared to the Rating portfolio. We grouped the bonds by their rating and created three portfolios where Portfolio BBB contains *BBB1*, *BBB2* and *BBB3* rated bonds, Portfolio A contains *A1*, *A2* and *A3* rated bonds and Portfolio AA contains *AAA, AA3, AA2* and *AA1* rated bonds.

	Portfolio BBB	Portfolio A	Portfolio AA	Long/Short Portfolio
Annualized Return	2.11	1.23	0.86	0.62
Annualized Vol.	6.00	4.42	3.37	1.67
Annualized Sharpe	0.35	0.28	0.26	0.67
Beta	1.22	0.90	0.67	0.28

Table 17 - Annualized average returns, Sharpe Ratio, and beta for all rating portfolios.

Portfolio BBB on average had an annualized return of 2.11%, an annualized volatility of 6.00% and a Sharpe Ratio of 0.35. Portfolio AA had an annualized return of 0.86%, and an annualized volatility of 3.37%, yielding a Sharpe Ratio of 0.26. The performance of the long/short portfolio performs poorly over time with an annualized return of 0.62%. when comparing with the model portfolio we can see that it is vastly.

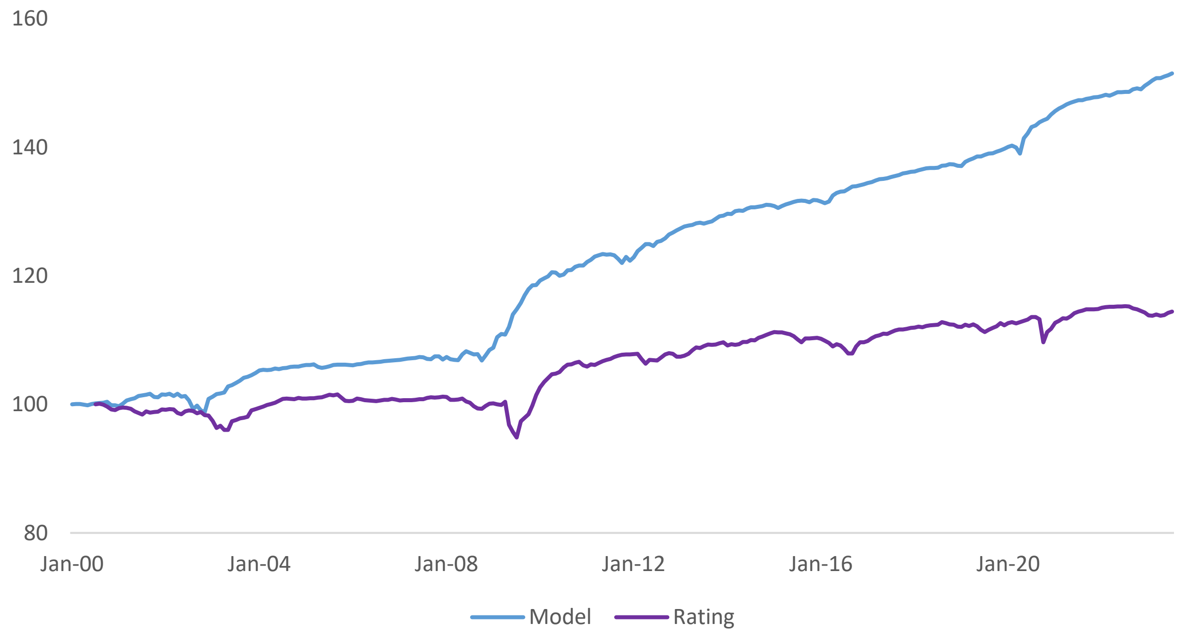

Figure 17 - Cumulative excess returns between model portfolio and rating portfolio.

By looking at the cumulative returns graph (Figure 17) we can see the comparison between the rating portfolio and the model portfolio, the model portfolio once again outperforms the beta portfolio. Since all the portfolios had a similar performance regarding returns, the behavior of the returns remains almost constant throughout time. Since the average return of the rating portfolio is small, we can that portfolio values remain the same throughout time.

6.8. Model Portfolio vs. Restricted Model Portfolio

We analyze the performance of the model portfolio and compare it with the performance of the liquidity-restricted model portfolio. We follow the same rationale and divide the universe in terciles from the bond with lowest difference between traded OAS and fair OAS to the bond with the highest.

	Portfolio 1	Portfolio 2	Portfolio 3	Long/Short Portfolio
Annualized Return	0.11	0.86	1.60	1.19
Annualized Vol.	3.07	2.85	4.76	1.11
Annualized Sharpe	0.03	0.30	0.53	1.08
Beta	0.60	0.55	1.92	0.16

Table 18 - Annualized average returns, Sharpe Ratio, and beta for all restricted model portfolios.

Portfolio 3 vastly outperforms Portfolio 1 with an average annualized return of 1.60% and an average annualized volatility of 4.76%, yielding a Sharpe Ratio of 0.53. The resulting long/short portfolio has an average annualized return of 1.19%, volatility of 1.11% and Sharpe Ratio of 1.08, therefore performing worse than the model portfolio (Table 18).

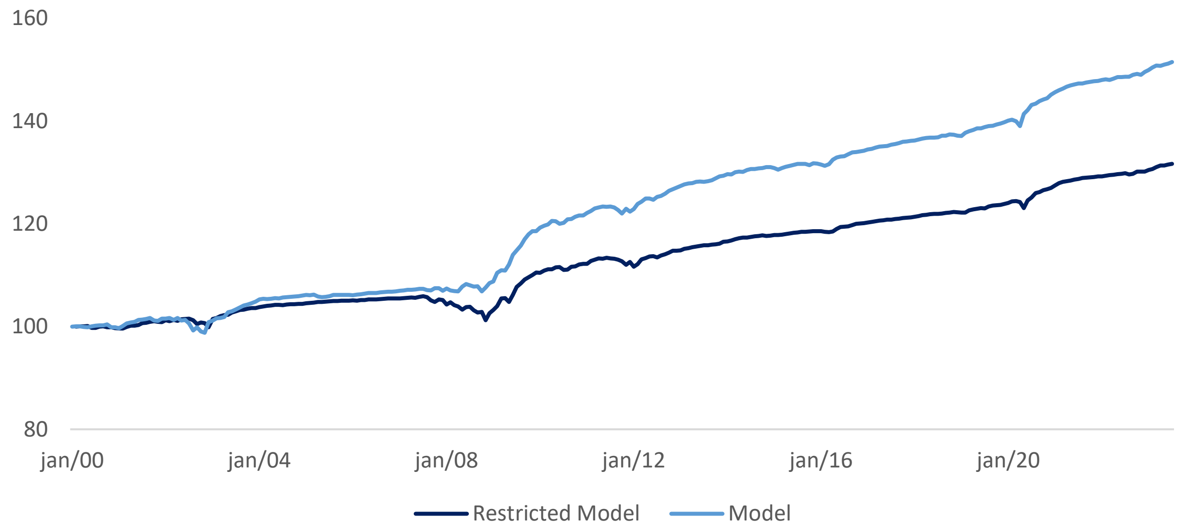

Figure 18 - Cumulative excess returns between the model portfolio and restricted model portfolio.

It is visible on Figure 18 that the model portfolio is similar to the restricted model portfolio throughout the period in analysis. The behavior of both portfolios is identical in periods of market distress and before 2008 the performance was similar. The model portfolio returns grow constantly more than the restricted model.

The restricted model underperforms the unrestricted model and the difference in the cumulative returns is considerable. With that in mind, one must look at previous results with caution. Although the unrestricted model already accounts for some restrictions on liquidity the restricted model represents only bonds that are very easily traded. The performance seen on the unrestricted model might not be able to be replicated. The fact that the performance is lower might be explained by the fact that the bonds in this portfolio are more actively traded and therefore misprices tend to be smaller than those less actively traded. When comparing the restricted model strategy with the previous strategies we still find that this strategy has the highest Sharpe ratio excluding the momentum strategy.

7.Conclusion

The main goal of this work was to develop a strategy that could consistently beat the corporate credit market. For that to be possible a model was created to evaluate if a corporate bond is correctly priced with regards to its spread. The model considers characteristics of the corporate bond, such as its maturity, rating, sector of business of the issuer and domicile of the issuer.

The model is effective in identifying corporate bond misprices because from those misprices it is possible to create a portfolio that yields not only better returns but significantly better volatility-adjusted returns than the market and the typically used strategies such as beta, carry, momentum and duration strategies. A long/short trading strategy beats a long-only position in the market portfolio by 20% while being covered by a short position for periods of economic distress. As for the returns of the model in comparison with the typically used strategies, it outperformed vastly the age, beta, duration, and rating and had slightly better returns than carry, and slightly worse returns than the momentum portfolio. As for volatility-adjusted returns, it showed the highest values amongst all the portfolios again except for the momentum portfolio which had a slightly worse Sharpe Ratio. To ensure the maximum applicability of the model in real life we demonstrated through the application of restrictions to liquidity that we also have a portfolio that beats the market and all portfolios except the momentum portfolio. We were also able to understand how the factors contribute to explaining the OAS of corporate bonds and how they behave in different periods with different economic conditions.

Trading costs are a limitation of our work. However, we believe the impact on performance would be low. Portfolios are rebalanced monthly and that suggests a low turnover of the portfolio and therefore low trading costs and we reserve this for future work.

8.References

Alexander, G. J., Edwards, A. K., & Ferri, M. G. (2000). The determinants of trading volume of high-yield corporate bonds. Journal of Financial Markets, 3(2), 177–204. https://doi.org/10.1016/S1386-4181(00)00005-7

Blitz, D., & Vidojevic, M. (2019). The Characteristics of Factor Investing. The Journal of Portfolio Management Quantitative Special Issue, 45(3), 69–86.

Burgess, N. (2023). An Introduction to Bond Carry Trading Strategies. https://ssrn.com/abstract=4434400

Cavallo, E. A., & Valenzuela, P. (2010). The determinants of corporate risk in emerging markets: an option-adjusted spread analysis. International Journal of Finance & Economics, 15(1), 59–74. https://doi.org/https://doi.org/10.1002/ijfe.398

Chen, L., Lesmond, D. A., Wei, J., Amihud, Y., Booth, L., Butler, K., Cao, M., Hull, J., Kalimipalli, M., Kan, R., Mcmcurdy, T., Roberts, G., Spatt, C., Tian, Y., White, A., & Yu, X. (2007). Corporate Yield Spreads and Bond Liquidity. In The Journal of Finance: Vol. LXII (Issue 1). http://www.sec.gov/news/speech/speecharchive/1998/

Collin-Dufresne, P., Goldstein, R. S., Spencer Martin, J., Bakshi, G., Bauer, G., Brown, D., Carrieri, F., Christoffersen, P., Chris-Toffersen, S., Duffee, G., Duffie, D., Errunza, V., Fong, G., Gallmeyer, M., Gauthier, L., Green, R., Griffin, J., Helwege, J., Jacobs, K., … Wruck, K. (2001). The Determinants of Credit Spread Changes. In The Journal of Finance: Vol. LVI (Issue 6).

Edwards, A., Harris, L. E., & Piwowar, M. S. (2007). Corporate Bond Market Transaction Costs and Transparency.JournalofFinance,62(3),1421–1451.https://EconPapers.repec.org/RePEc:bla:jfinan:v:62:y:2007:i:3:p:1421-1451

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33(1), 3–56. https://doi.org/10.1016/0304-405X(93)90023-5

Flavell, R., Meade, N., & Salkin, G. (1994). The Gilt Market: Models and Model-Based Trading. Journal of the Operational Research Society, 45(4), 392–408. https://doi.org/10.1057/jors.1994.58

Fridson, M. S., & Garman, M. C. (1998). Determinants of Spreads on New High-Yield Bonds.

Goetzmann, W., Rouwenhorst, K., & Gatev, E. (2006). Pairs Trading: Performance of a Relative Value Arbitrage Rule. Review of Financial Studies, 19, 797–827. https://doi.org/10.1093/rfs/hhj020

Henke, H., Kaufmann, H., Messow, P., & Fang-Klingler, J. (2020). Factor Investing in Credit. The Journal of Index Investing, 11(1), 33–51. https://doi.org/https://doi.org/10.3905/jii.2020.1.085

Hotchkiss, E., Carroll, W. E., & Jostova, G. (2007). Determinants of Corporate Bond Trading: A Comprehensive Analysis. http://ssrn.com/abstract=1001459https://ssrn.com/abstract=1001459Electroniccopyavailableat:http://ssrn.com/abstract=1001459

Houweling, P., & Van Zundert, J. (2017). Factor Investing in the Corporate Bond Market. In Financial Analysts Journal (Vol. 73, Issue 2).

Israel, R., Palhares, D., & Richardson, S. (2018). Common Factors in Corporate Bonds Returns. In www.joim.com Journal of Investment Management (Vol. 16, Issue 2). www.joim.com

Jostova, G., Nikolova, S., Philipov, A., Stahel, C. W., Chan, K., Dobrev, D., Flannery, M., Goldstein, M., Hanley, K., Helwege, J., Huh, S.-W., Jame, R., Martin, S., Stulz, R., & Unal, H. (2011). Momentum in Corporate Bond Returns. In Financial Management Association conference. http://ssrn.com/abstract=1651853Electroniccopyavailableat:https://ssrn.com/abstract=1651853

Kahn, R. N. (1991). Bond Performance Analysis: A Multi-Factor Approach. Journal of Portfolio Management, 18(1), 40. https://www.proquest.com/scholarly-journals/bond-performance-analysis-multi-factor-approach/docview/195588089/se-2?accountid=38384

Kaufmann, H., & Messow, P. (2019). Equity Momentum in European Credits. Journal of Fixed Income. https://api.semanticscholar.org/CorpusID:218807577

Koijen, R. S. J., Moskowitz, T. J., Pedersen, L. H., & Vrugt, E. B. (2018). Carry. Journal of Financial Economics, 127(2), 197–225. https://doi.org/10.1016/j.jfineco.2017.11.002

L'Hoir, M., & Boulhabel, M. (2010). A Bond-Picking Model for Corporate Bond Allocation. Journal of Portfolio Management, 35. https://doi.org/10.3905/jpm.2010.2010.1.001

Weinstein, M. (1981). The Systematic Risk of Corporate Bonds. The Journal of Financial and Quantitative Analysis, 16(3), 257–278. https://doi.org/10.2307/2330238