Time Series Analysis of BBB-bonds spreads

Sofya Tsay

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Abstract

This work is the final essay in Time series and Panel Data Analysis course in 4th year HSE ICEF. It aims to investigate properties of BBB-bonds spreads, including stationarity, cointegration, and focusing on fitting Markov Switching Models.

1 Introduction

Credit spread is generally defined as the yield difference between a risky bond and a risk-free benchmark. They are actively used by authorities, practitioners, and researchers as indicators of the financial stability of the system. BBB-rated bonds represent the lowest credit quality of the issuing counter-party. Thus, they are usually most sensitive to stress conditions in the market. We expect that the bahaviour of BBB spreads is far from (trend-) stationary. Thus, more adavanced models need to be applied to this series. The paper aims to investigate the properties of BBB-bonds spreads since 1997.

For our analysis we use Option-Adjusted Spread (OAS) of the ICE BofA BBB US Corporate Index taken from Fred.

The aim of this essay is to investigate the time series properties of BBB corporate bond spreads, focusing on fitting Markov Switching models and evaluating predictions based on it.

The structure of the paper is as follows. First, we investigate stationaruty of BBB-bonds spreads. Then, we turn to the main part with calibration of Markov Switching models to the series, as well as evaluating their in-sample performance and predictive abilities. Furthermore, the data is investigated for the presence of structural breaks. After that, we turn to multivariate analysis by testing cointegraion with Treasury yields. Finally, some conclusions are drawn.

2 Results

2.1 Data analysis

In this essay we further analyze daily BBB US Corporate Index Option-Adjusted spread, measured in percent, from 1996-12-31 to 2025-11-12. Missing data was

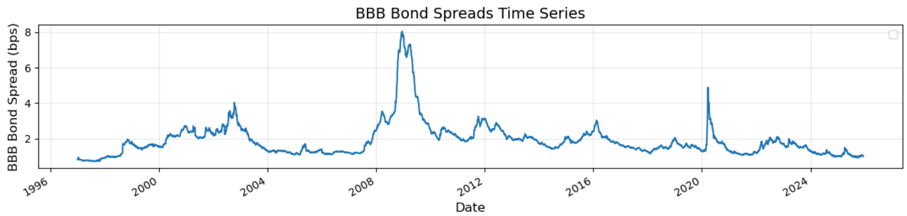

Figure 1: Visualization of the series.

excluded from the analysis due to the presence of a large amount of available data.

From Figure 1, we can recognize some major economic and financial events. Spreads elevated above 200 bps in 2000-2002, reflecting the market stress and credit risk following the collapse of the tech bubble and the 2001 recession. 2003-2007 experienced a prolonged period of historically low and stable spreads. This reflects a strong economic growth, low volatility, and high risk appetite. After that, The Global Financial Crisis of 2008-2009 broke out, indicated by an extreme vertical spike in spreads, exceeding 600 bps at its peak in late 2008 / early 2009. A second sharp spike occured during COVID-19 Pandemic in 2020, though spreads dropped quickly. The latter part of the series (2022-2024) shows increased volatility and a gentle upward trend in BBB spreads.

2.2 Stationarity

Visually, this series is likely to be not stationary. Despite the presence of long periods with low levels of spreads, two spikes in 2008 and 2020 indicate non-stationarity. Similar conclusions apply to variance. Let us check our hypothesis statistically.

The results of the Augmented Dickey-Fuller test for stationarity are presented in Table 1. The null hypothesis of the ADF test is that the time series contains a unit root (non-stationary). The alternative hypothesis is that the series is stationary.

Parameter	**Value**
Test Statistic	-3.4
p-value	0.01
Lags Used	27
Critical Values	
1% level	-3.4
5% level	-2.9
10% level	-2.6

Table 1: Results of the ADF Test for BBB-spreads

The test results also suggest that the original series is not stationary.

Now we apply the same ADF to first difference of the spreads. The output is the following.

Parameter	**Value**
Test Statistic	-17.2
p-value	0
Lags Used	17
Critical Values	
1% level	-3.4
5% level	-2.9
10% level	-2.6

Table 2: Results of the ADF Test for the first differences of BBB-spreads

The first differences are stationary. Thus, we conclude that our series is integrated of order 1.

2.3 Markov Switching Models

2.3.1 MSwM with switching intercept and two regimes

We define the regression equation in this model in the following way. Let y_t be the value of BBB-spread at time t. Then

$$y_t = \begin{cases} \mu_0 + \varepsilon_t, & \text{if } S_t = 0, \\ \mu_1 + \varepsilon_t, & \text{if } S_t = 1, \end{cases} \quad \varepsilon_t \sim N(0, \sigma^2) \tag{1}$$

where S_t follows a Markov chain with transition probability matrix:

$$\mathbb{P} = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix} = \begin{bmatrix} p[0 \to 0] & 1 - p[0 \to 0] \\ p[1 \to 0] & 1 - p[1 \to 0] \end{bmatrix}$$

Regime 0 indicats period with low spreads, while regime 1 is the one with the high spreads.

Parameters are estimated via MLE. The results of fitting this model on the whole dataset can be seen below in Tables 2.3.1 and 2.3.1.

Statistic	**Value**
Model Type	Markov Regression
Log Likelihood	-7,420
Akaike Information Criterion (AIC)	14,849
Bayesian Information Criterion (BIC)	14,884

Table 3: MSwM with switching intercept Summary Statistics

Parameter	Coeff.	Std. Err.	z	p	[0.025	0.975]
Regime 0 (Low mean)						
μ_0 (const)	1.767	0.008	232.27	0.000	1.752	1.782
Regime 1 (High mean)						
μ_1 (const)	6.201	0.055	111.77	0.000	6.092	6.310
Non-switching parameters						
σ_ε (sigma2)	0.414	0.007	61.459	0.000	0.401	0.428
Transition probabilities						
p_{00} (p[0→0])	0.999	0.000	5,241.212	0.000	0.999	1.000
p_{10} (p[1→0])	0.008	0.006	1.441	0.150	−0.003	0.021

Table 4: MSwM with switching intercept parameter estimates

2.3.2 MSwM with switching intercept and variance, and two regimes

Keeping the notations as in Equation (1), the model is defined in the following way

$$y_t = \begin{cases} \mu_0 + \varepsilon_{0,t}, & \text{if } S_t = 0, \\ \mu_1 + \varepsilon_{1,t}, & \text{if } S_t = 1, \end{cases} \quad \varepsilon_t \sim N(0, \sigma^2_{S_t}) \tag{2}$$

Notice, that now volatility is also regime-dependent. So here we also account for the fact that during recessions, both spreads and their volatility rise, while during booms the opposite takes place.

Parameters were also estimated using MLE. The model output is presented in the tables 5 and 6 below.

Statistic	Value
Model Type	Markov Regression
Log Likelihood	-5,486
Akaike Information Criterion (AIC)	10,983
Bayesian Information Criterion (BIC)	11,025

Table 5: MSwM with switching intercept and variance Summary Statistics

Overall, model 1 (switching intercept only) assumes constant volatility across regimes. It identifies clear low- and high-spread regimes but does not capture changes in volatility, which is unrealistic during stress periods (e.g., 2008, 2020) when volatility spikes. Model 2 (switching intercept and variance) allows both the mean and volatility to switch between regimes. It better reflects economic intuition—volatility rises in high-spread periods—and fits the in-sample data significantly better (lower AIC/BIC). However, while model 2 is more realistic and fits historical data better, model 1, though simpler, turned out to be more robust for forecasting.

Parameter	Coeff.	Std. Err.	z	p	[0.025	0.975]
Regime 0 (Low Volatility)						
μ_0 (const)	1.406	0.006	242.770	0.000	1.395	1.417
σ_0^2 (sigma2)	0.069	0.002	27.458	0.000	0.064	0.073
Regime 1 (High Volatility)						
μ_1 (const)	2.606	0.027	97.581	0.000	2.554	2.658
σ_1^2 (sigma2)	1.474	0.040	37.157	0.000	1.396	1.552
Transition probabilities						
p_{00} (p[0→0])	0.998	0.001	1,456.902	0.000	0.997	0.999
p_{10} (p[1→0])	0.003	0.001	3.036	0.002	0.001	0.005

Table 6: MSwM with switching intercept parameter estimates

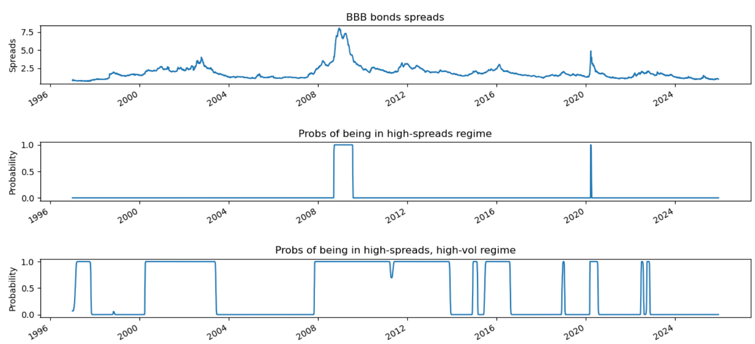

Figure 2: Comparison of MSwMs

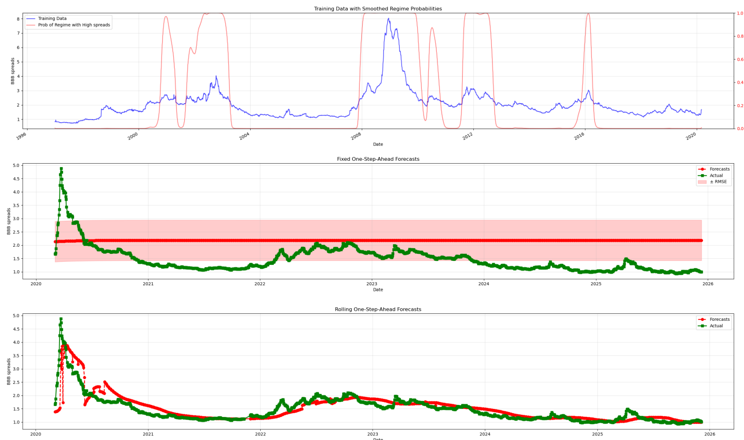

Figure 3: Comparison of fixed and rolling forecasts of MSwM

2.4 Constructing forecasts

To evaluate the predictive performance of the Markov-switching model 1 with switching intercept only, we estimated model parameters and regime transition probabilities by MLE using the first 80% of the data as a training set. Forecasts were then generated in two ways: first, using static window, second, using rolling-window predictions that update parameters over time to reflect more recent information. This allows us to assess both the model's historical fit and its dynamic adaptability to new data. One can see graphical represenation of the forecasts in Figure 3.

The rolling-window forecast ($RMSE = 0.074$) substantially outperforms the static forecast ($RMSE = 0.762$), indicating that updating the model parameters over time greatly improves prediction accuracy due to changing macroeconomic reality. BBB spreads exhibit time-varying dynamics that are better captured by a method that adapts to recent observations. While the Markov-switching framework is useful for identifying regimes, its forecasting power is enhanced through recursive re-estimation, particularly during volatile periods.

2.5 Structural breaks

Following the regime-switching analysis, we examine whether the BBB spread series exhibits structural breaks, persistent shifts in its underlying mean or volatility. While visual inspection suggests significant disruptions around the

2008–2009 Global Financial Crisis and the 2020 COVID-19 pandemic, we formally test for breaks using two approaches:

1. The Quandt Likelihood Ratio (QLR) test for an unknown break date;
2. Chow test applied at known candidate dates (2008 and 2020) to confirm whether these events correspond to statistically significant structural breaks.

2.5.1 QLR Test

For QLR test we first specify a range of possible break tests, which in our case is every day for which the observation is present, while excluding first and last 15% of the observations. As a result, we obtained

$$QLR_{test} = 2177,$$

which is larger than any critical value from the table. Thus there is indeed a structural break at some points of time.

2.5.2 Chow test

For Chow test we create the following regression equation

$$y_t = \alpha_1 + \beta_1 t + \gamma_1 d_t + \gamma_2 d_t t + \varepsilon_t, \text{ where} \tag{3}$$

d_t is a dummy for post-break period, i.e. $d_t = \mathbb{I}\{t > T_1\}$. Then we test the following hypothesis

$$H_0 : \gamma_1 = \gamma_2 = 0 \, (\text{no break})$$

vs the alternative via a standard $F - test$. We have two candidates for the break dates. The first is 2008-09-15 which is the day of bankrupcy of Lehman Brothers, which marks the beginning of 2008-2009 Global Crisis. The second date is 2020-01-30, when the World Health Organization declared the outbreak a public health emergency due to COVID-19 virus.

Chow tests applied to both dates showed

$$p - value \approx 0,$$

thus, we conclude that at both of these dates, BBB-spreads experienced a structural break.

2.6 Cointegration

The final part of this essay is devoted to multivariate analysis.

To further explore the long-term dynamics of BBB credit spreads within a broader macroeconomic context, we examine their relationship with the slope of the Treasury yield curve, measured as the difference between the 10-year and

2-year Treasury yields, which is also taken from Fred as daily percent for the same time period as BBB-spreads.

The theoretical motivation is the following: BBB spreads reflect the credit risk premium demanded by investors, while the yield curve slope (10Y–2Y) is a widely monitored indicator of economic growth expectations and monetary policy stance. A steep, positively sloped curve typically signals anticipated economic expansion and higher future inflation, conditions associated with lower credit risk and compressed spreads. Conversely, a flat or inverted curve often precedes economic slowdowns or recessions, periods during which credit risk premiums, and, thus, BBB spreads tend to widen.

This suggests the potential for a stable, long-run equilibrium relationship between the two series. After confirming that both the BBB spread and the yield curve slope are integrated of order one, $I(1)$, we apply the Engle-Granger cointegration test. For this test

$$p - value = 0.008,$$

thus the results provide statistical evidence of a significant cointegrating relationship, confirming that the two variables move together over the long term in a manner consistent with economic theory.

3 Conclusions

This essay has investigated the time series properties of BBB corporate bond spreads since 1997, applying a range of econometric methods to capture their dynamics. We found that the series is non-stationary and integrated of order one. Markov switching models revealed two distinct regimes: low- and high-spread states—with the model featuring switching intercept and variance offering the best in-sample fit. However, the simpler switching-intercept model proved more reliable for forecasting, especially when parameters were updated recursively via rolling-window estimation. Structural break tests confirmed significant disruptions during the 2008–2009 financial crisis and the 2020 COVID-19 pandemic. Finally, we established a long-run cointegrating relationship between BBB spreads and the slope of the Treasury yield curve, supporting the theoretical link between credit risk premiums and macroeconomic expectations.

Overall, these results indicate that BBB spreads are driven by both regime-dependent behavior and structural shifts.

4 Future work

In the future work on this topic, I would like to focus on exploring volatility of BBB-spreads, fitting GARCH models with Markov Switching regimes. Additionally, we found out in the esssay the presence of regime-dependent volatility. So it would also be interesting to fit models with fractional Brownian motion to investigate, whether such constructions could better capture bond spreads behaviour.

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