Investigating the VIX Index Relationship with High Yield & Investment Grade Bond Spreads: Exploring Structural Breaks & Threshold Effects

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Abstract

In this study, we investigate the relationship between implied equity volatility (VIX) and corporate bond spreads, covering both investment-grade and high-yield sectors. Our dataset spans three significant periods of recent volatility: the 2008/09 financial crisis, the COVID-19 pandemic, and the regional banking crisis of 2023. To identify structural breaks, we employ the Bai & Perron (1998, 2003) methodology and conduct ordinary least squares linear regression analyses (OLS). By examining structural breaks over time, our research offers a fresh perspective on the VIX-spread relationship. We also use threshold regressions to categorize VIX into low, intermediate, and elevated ranges, exploring how different volatility levels impact these interactions. Additionally, we introduce the Federal Funds Effective Rate (FEDL) as a moderator in this relationship. Our findings confirm multiple structural breaks in spread relationships and underscore the significant influence of both VIX levels and FEDL rates on the VIX-spread relationship. Our results reveal that implied volatility has a notably stronger association with high yield spreads during the most elevated levels of VIX when compared to investment grade. Furthermore, we demonstrate that changes in interest rates minimally affect high-yield bond spreads, regardless of the absolute level of FEDL.

Keywords: Market Risk, Volatility, Setar, Fed Funds, VIX, Spreads

1. Introduction

In the aftermath of significant market events such as the 2008 financial crisis, the COVID-19 pandemic, and the 2023 regional banking crisis, the financial landscape experienced profound shifts. Due to the severe market volatility during these periods, further investigation into how volatility changed and how VIX influenced credit markets seems warranted. The motivation for our study arises from the assumption that the association between the VIX and bond spreads exhibits structural breaks of varying degrees through time. Additionally, we argue that this association changes at various levels of the VIX, especially when this relationship is moderated by levels of the Federal Funds Effective Rate.

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Our focus is on detecting structural breaks in this relationship and evaluating responses across different market regimes. Additionally, we aim to test the impact of varying levels of VIX and the Federal Funds Effective Rate (FEDL) on this association. This multifaceted analysis seeks to offer insights into the evolving nature of bond spreads in response to changes in the VIX and interest rate conditions.

Bond spreads refer to the difference in yields between corporate bonds and U.S. Treasury bonds of the same duration, essentially representing the risk premium over risk-free assets. Past research consistently shows a positive link between VIX and bond spreads. However, these studies often explored connections over fixed time periods, potentially limiting the comprehension of the relationship amid changing market conditions. Moreover, most empirical studies have not examined this relationship across various levels of VIX or FEDL. In response to these limitations, we extend the existing analysis in several ways. First, we test for the presence of structural breaks in the relationship between the VIX and bond spreads over time. To do this, we follow Bai & Perron (1998, 2003). Second, we analyze how these spreads respond to changes in the VIX throughout each regime. Third, using self-exciting threshold autoregressive models (SETAR), we identify low, intermediate, and elevated zones (Tong, 1977b; Tong & Lim, 1980). This assists us in examining how relationships change during the three zones of volatility. Fourth, following the same methodology, we define three interest rate zones based on the Federal Funds Effective Rate and test for changes to the relationships. Last, we enhance the robustness of our findings by incorporating an expanded dataset that encompasses multiple periods characterized by severe market volatility. This includes prominent events such as the 2008/09 financial crisis, the COVID-19 pandemic, and the 2023 regional banking crisis, allowing for a comprehensive analysis of the relationship between bond spreads and the VIX.

Implied equity volatility, or the VIX, is widely known as the "fear index" and is crucial to examine in the context of financial markets. Many investors consider it the gold standard of market sentiment indices (Chen & Gao, 2020). VIX has also been identified as a driver of fear transmission from the U.S. to other global markets (Peng & Ng 2012). Both the VIX and Federal Reserve policy rates have independently demonstrated a significant positive correlation with credit spreads. As such, investors should carefully consider the impact of VIX shocks and changes in the Federal Funds rate on their positions in credit markets (Mensi, Shahzad, Hammoudeh, Hkiri, & Yahyee, 2019). We use the VIX rather than other commonly used measures, such as the Economic Policy Uncertainty Indices (EPU) (Baker, Bloom & Davis, 2016), because of the VIX's reliance on market-traded option prices of the S&P 500 Index. This is in contrast to the EPU's dependency on news articles and social media, which takes into account the opinions of business leaders, journalists, and even general consumers. This text-based approach lacks precision, produces a high rate of erroneous matches, and introduces noise that hampers the indices' explanatory and predictive capacity for market volatility. By focusing strictly on investor risk premiums implied from options data, the VIX provides a tighter signal filtered for just the market impacts of interest. Additionally, using the VIX ensures a quantitative and objective measure of expected volatility, allowing for a more robust and data-driven examination of the relationship between VIX and bond spreads through the lens of market participants.

Extensive research has consistently demonstrated a positive correlation between changes in equity volatility and bond spreads. Collin-Dufresne, Goldstein & Martin (2001) found a positive relationship between the VIX and bond spreads. They tested spread changes against VIX and other firm and market-specific control variables, such as leverage, 10-year yields, yield curve spread, volatility smirk, and stock market returns. Bhar & Handzic (2011) identified three key factors that drive bond spreads, namely the VIX, the long bond rate, and S&P 500 returns. Afonso & Jalles (2019) tested VIX and other factors on Euro-Area sovereign government yield spreads using a panel VAR approach. They found that higher movements in implied volatility increase spreads.

We would also suspect that the behavior of investment-grade and high-yield spreads would react differently to changes in volatility. Yields on high-quality securities, which include U.S. Treasuries and investment-grade bonds, typically fall when the perception of market-wide risk increases. Spreads on high yield bonds widen when investors move into bonds they perceive to be safer (Jubinski & Lipton, 2012). This leads to a divergence of spread reactions to movements in the VIX. Shahzad, Aloui, & Jammazi (2020) established a robust and enduring positive relationship between the VIX and CDS spreads. Their analysis revealed variations across industry sectors in shorter time periods, while the overall trend demonstrated a strong positive correlation over the long term. The study encompassed both investment-grade and high-yield CDS index spreads, examining two distinct high and low periods of volatility. The results showed a positive association between the VIX and CDX spreads, with variations observed across the identified periods. Specifically, during the volatile period, which included the financial crisis of 2008/09, investment grade spreads displayed greater sensitivity to the VIX, whereas high yield spreads exhibited higher sensitivity during tranquil market conditions.

While previous studies have shed light on the positive relationship between VIX and bond spreads, there is a need to investigate this association across multiple periods of volatility, including significant market events. Identifying and utilizing structural breaks found in time series analyses adds more precision to the results, especially when the breakpoints are specifically identified Pesaran, Pettenuzzo, & Timmermann (2006). Detecting where regime changes occur enables the segmentation of the sample into discrete periods, which facilitates the estimation of time-varying model parameters across low, intermediate, and high volatility states. Discrete breaks often occur around major financial events or policy moves – detecting these allows focused investigation of market unrest and central bank impacts. This approach strengthens model realism, forecasting accuracy, and usefulness. Ultimately, findings and forecasts produced without accounting for structural changes prove limited in usefulness due to reliance on assumptions of no meaningful variability over time. Break analysis tackles this directly by exposing discrete transitions in core relationships.

It is more common to test for structural breaks in a univariate series, but a few studies have utilized the Bai & Perron (1998, 2003) process in multiple variable relationships, including the VIX and equity returns (Andrangi, Chetrath, Kolay & Raffiee, 2021) and VIX and break-even inflation (Orlowski & Soper, 2019).

We expand our analysis by testing the influence of the VIX on bond spreads at different interest rate levels, as measured by the FEDL. Similar to the VIX, macroeconomic factors, including the FEDL, significantly affect markets and, specifically, bond spreads. Thus, it is important to investigate how the level of interest rates moderates the impact of the VIX on spreads. Research indicates that increases in the FEDL result in negative equity returns and wider bond spreads (Bernanke & Kuttner, 2005; Nodari, 2015). Furthermore, Dupoyet, Jiang, & Zhang (2023) highlight that interest rate movements have a greater impact on high-yield bond spreads compared to investment-grade spreads. We utilize FEDL rather than other interest rate measures, as it often acts as a baseline rate for other short-term rates such as Treasury Bills. FEDL is directly set by Federal Reserve policy, and its changes may be enacted to stimulate growth and lending during economic weakness or to tighten conditions in response to unwanted inflationary pressures. As such, the absolute FEDL level provides important context about macroeconomic conditions and monetary policy, and it has been used in models to predict recessions and expansions (Conover, Jensen, Johnson & Mercer, 2008). Moreover, it strongly influences baseline short-term rates economy-wide. The combination of signal and rate anchor roles makes FEDL levels useful for examining bond spread changes.

The existing body of literature consistently supports the notion of a positive relationship between implied equity volatility and bond spreads. These findings underscore the importance for investors to be diligent in monitoring both the directional movements in the VIX and its level when managing fixed-income portfolios. Furthermore, this research underscores the significance of getting more granular in evaluating the credit quality of bonds to ascertain their unique responsiveness to fluctuations in volatility.

Our findings demonstrate a significant association between implied volatility and bond spreads, with differential effects observed between investment-grade and high-yield bonds. Previous studies, such as Shahzad et al. (2020), have reported a positive correlation between bond spreads and implied volatility. However, most of these studies were conducted over arbitrary time intervals or specific high-volatility periods, such as the financial crisis of 2008-09. Our study goes beyond this and includes multiple periods of volatility, including the financial crisis, COVID-19, and the regional banking crisis of 2023.

In sum, our study brings new perspectives to the relationship between implied equity volatility and bond spreads, introducing a multifaceted analysis that considers structural breaks, market regime responses, and the nuanced effects of VIX and FEDL levels.

2. **Data and Methodology**

2.1 Data

This study incorporates a dataset consisting of high yield and investment grade bond spreads, implied volatility (VIX), and the Federal Funds Effective Rate (FEDL). The data used in this analysis spans from November 1, 2006, to April 27, 2023, and was obtained from Bloomberg and the Federal Reserve Economic Data Database (FRED).

The high yield spread data is the Treasury option-adjusted spread (OAS) sourced from the Bloomberg US Corporate High Yield Total Return Index Value Unhedged USD. The investment grade spread data is obtained from the Treasury OAS of the Bloomberg US Corporate Total Return Index Value Unhedged USD. Descriptive statistics are reported in Table 1.

The bond spread change and log change of VIX data exhibit near zero means and leptokurtic data distribution, with noticeable kurtosis. The distribution of high-yield spread changes has minimal positive skewness, while log changes in VIX and investment grade spread data display positive skewness, implying an asymmetric distribution with a tail towards higher values.

2.2 Methodology

We examined the influence of log changes in implied volatility on the changes in high-yield and investment-grade bond spreads using various methods. To ensure stationarity and mitigate autocorrelation, we employed first differences in spreads. Furthermore, we incorporated a one-period lag of the dependent variable in each model to address autocorrelation, as identified through a partial autoregression test.

Table 1: Descriptive Statistics

	Δ HY	**Δ IG**	**Log(VIX)**	**HY**	**IG**	**VIX**	**FEDL**
Mean	0.000	0.000	0.000	5.226	1.279	20.191	1.075
Median	-0.004	-0.001	-0.007	4.589	0.919	17.890	0.190
Maximum	1.250	0.688	0.768	19.619	7.006	82.690	5.410
Minimum	-0.870	-0.389	-0.351	2.298	0.400	9.140	0.040
Std. Dev.	0.113	0.035	0.077	2.522	1.114	9.222	1.503
Skewness	0.972	4.540	1.074	2.679	3.038	2.323	1.633
Kurtosis	17.632	92.017	8.993	12.212	12.997	11.053	4.593
Jarque-Bera	37501	1378113	6977	19547	23558	14878	2274
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	4130	4130	4130	4130	4130	4130	4130

In our analysis, we first run a standard OLS regression of bond spreads regressed against log(VIX) and spreads lagged by one period as shown in Equation 1 below.

$$\Delta SPR = B_o + B_1(\log \Delta VIX) + B_2(\Delta SPR_{(t-1)}) + e \qquad (1)$$

Where ΔSPR and $\Delta SPR_{(t-1)}$ are changes in bond spreads and their one-period lag. Log ΔVIX is the difference in natural log changes in VIX. The disturbance term, *e* captures unobserved or random variations that can affect the dependent variable. Results of the base regressions are presented in Tables 2 and 3 in Section 3.

Next, using the same regression framework, we employed the Bai & Perron (1998, 2003) multiple breakpoint test to identify potential structural breaks in the relationship between bond spreads and the VIX. This approach allows us to detect shifts or discontinuities in the association between these variables. Bai & Perron identifies specific break dates, which is a more robust process when compared to other empirical methods. For example, Bai & Perron tests are more objective in determining the number and locations of breaks. The Chow test requires you to subjectively specify the breakpoint to test, while the Bai & Perron procedures have algorithms to estimate the number and timing of breaks endogenously from the data.

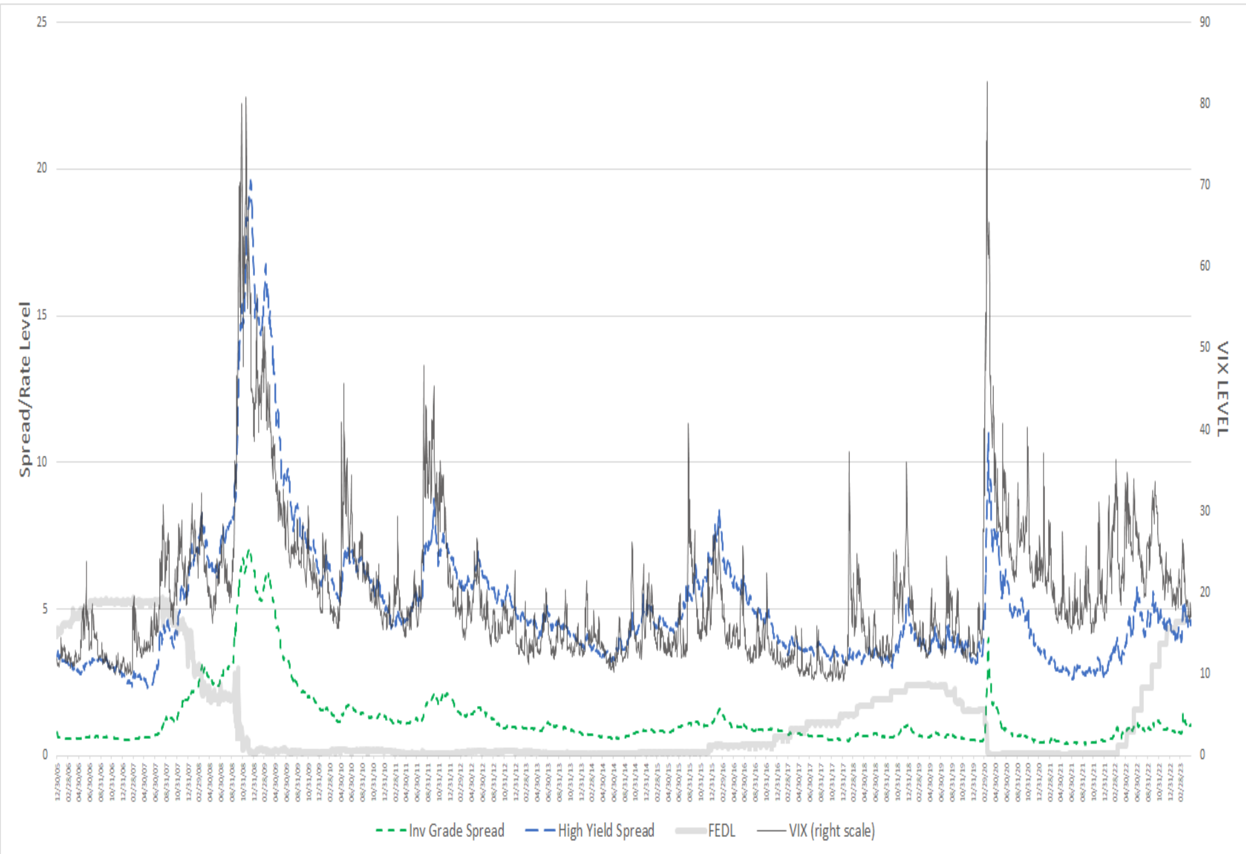
Furthermore, we performed SETAR threshold regressions to identify three distinct levels of low, intermediate, and elevated for both the FEDL and the VIX index.

These levels serve as reference points for examining the relationship between the VIX (Eq 1) and spreads at different intensities of either FEDL or the VIX itself. Through this approach, we aim to explore potential non-linear relationships and shed light on the dynamics between the VIX and bond spreads across various levels of the respective variables.

2.2.1 Bai & Perron Structural Break Tests

We begin our analysis by investigating the potential changes in the relationship between the VIX and spreads over time. We found the existence of structural breaks, indicating that the regression coefficients do not remain constant for extended periods. We optimized this model by minimizing the Akaike Information Criterion (AIC). These findings highlight the importance of recognizing the dynamic nature of the VIX-spread relationship and call for further exploration of its underlying factors.

Figure 1: VIX, FEDL Rates, High Yield, and Investment Grade Spreads (2006-2023)



We use the Bai & Perron (1998, 2003) multiple breakpoint tests to identify structural breaks in these relationships. Our approach is similar to the methodology employed by Orlowski & Soper (2019) in examining the impact of breakeven inflation on market risk. In our analysis, we identify four structural breaks in the high yield-VIX series and two structural breaks in the relationship between investment grade spreads and VIX. These findings highlight the presence of distinct shifts in these relationships, emphasizing the need to consider the evolving dynamics between them. The results of these tests are presented in Tables 4 and 5 in Section 3, and a visualization of the data is found in Figure 1.

2.2.2 Identification of Volatility and Interest Rate Zones

In order to objectively set low, intermediate, and elevated zones of interest rates and volatility, we employ a SETAR(2,p) model. Tong (1990) extended his seminal threshold autoregressive (TAR) model (Tong & Lim, 1980) to create the original SETAR model.

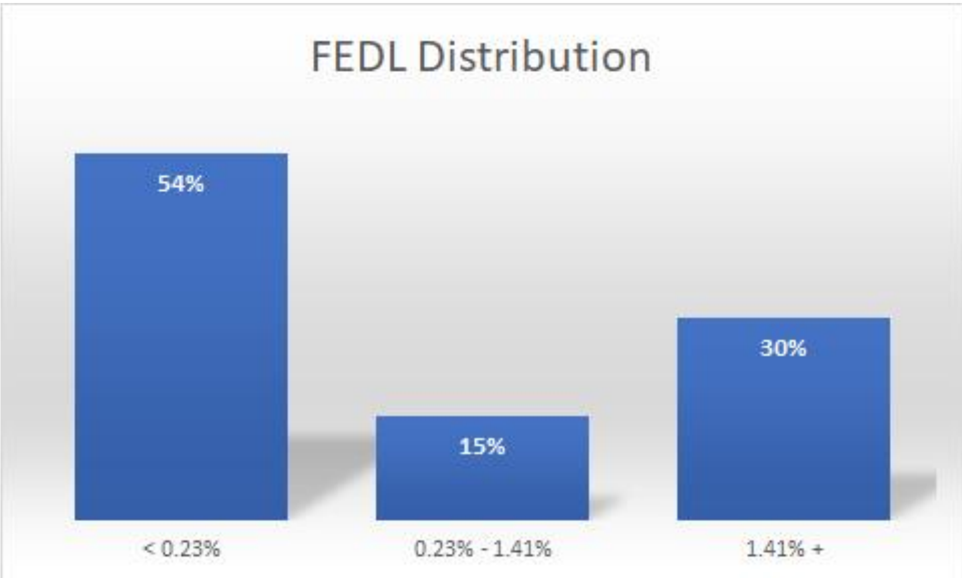
Generalized SETAR (1.p) model which is set for one threshold and two regimes (or zones):

$$X_t = \begin{cases} \alpha_{10} + \alpha_{11}X_{t-1} + \varepsilon_t \text{ if } X_{t-p} < r \\ \alpha_{10} + \alpha_{11}X_{t-1} + \varepsilon_t \text{ if } X_{t-p} \geq r \end{cases} \qquad \textbf{(2)}$$

Where α_{10} is a constant, X is the lagged explanatory variable and r is the threshold value.

In our analysis, we expand this general model to estimate two thresholds with three regimes. To estimate the threshold zones for VIX and FEDL we used a lag length of 1 period after running a partial autocorrelation analysis (PAC). We set the selection range from (-3 to -6) with (-5) chosen as the displacement parameter (p). The zones determined from the analysis of FEDL and VIX are in Figures 2 and 3 below and Tables 6 and 9 in Section 3, respectively.

Figure 2: Distribution of FEDL (low, intermediate, and elevated)



Notes: November 2, 2006 – April 27, 2023 full sample period (4130 observations)

2.2.3 Relationship of VIX and Spreads across various levels of the Fed Funds Rate

The relationships between financial variables can be influenced by economic policy, prompting us to investigate the interplay between volatility and spreads by examining the impact of Fed rate policy. To achieve this, we employed threshold regressions to determine the specific ranges of the FEDL rate within our sample. Subsequently, we conducted OLS regressions, incorporating interaction variables between log changes in VIX and low, intermediate, and elevated values of FEDL interest rates. The interaction variables were generated using dummy variables multiplied by the log change in VIX. These dummy variables were coded with a value of 1 when VIX fell within each designated range and 0 otherwise.

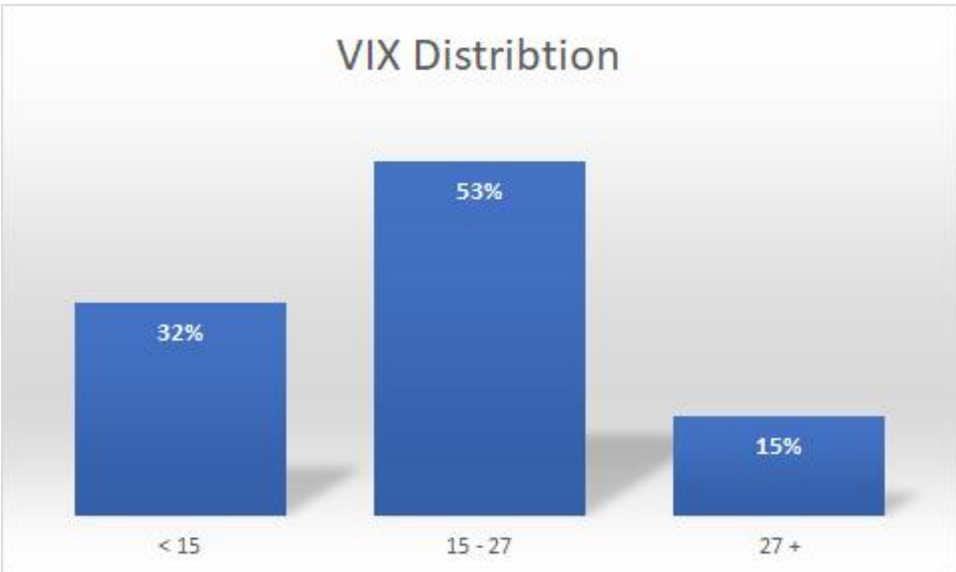
We use a fully partitioned approach that isolates the response of each variable in each level of the VIX or FEDL. We use this method rather than the more common model that includes interaction variables with a main effect with offsets to the main effect. Our approach involves reporting each interaction variable individually. While both methodologies yield the same results, the fully partitioned approach provides several advantages, including ease of interpretation and a clearer understanding, particularly when there are multiple coefficients to be analyzed (Yip & Tsang, 2007). We utilize Equation 3 to estimate the coefficients. The results are presented in Tables 7 and 8.

$$\Delta SPR = B_o + B_1(\log \Delta VIX_{low}) + B_2(\log \Delta VIX_{intermediate}) + B_3(\log \Delta VIX_{elevated}) + B_4(\Delta SPR_{(t-1)}) + e \tag{3}$$

Equation 3 builds off of Equation 1 and adds the interaction terms. Where *log* ΔVIX_i represents the log change in VIX when FEDL is in a low, intermediate, and elevated zone as defined by the SETAR threshold regression process.

2.2.4 Relationship of VIX and Spreads across various levels of the VIX

Figure 3: Distribution of the VIX (low, intermediate, and elevated)



Notes: November 2, 2006 – April 27, 2023 full sample period (4130 observations)

Different levels of VIX may lead to varied behavior in credit spreads. For example, when the VIX reaches elevated levels, it indicates elevated amounts of fear and uncertainty in the capital markets. In this case, it is reasonable to anticipate different spread responses when testing at elevated, intermediate, and low levels of the VIX. Incremental changes in the VIX, when it is already at high levels can potentially have distinct effects on spreads, highlighting the importance of considering the VIX level in analyzing its influence on credit markets.

To examine this relationship, we conducted a similar threshold regression to identify the low, intermediate, and elevated levels of the VIX index. Interaction variables were generated using the same process as used with FEDL. Subsequently, an OLS regression was employed to estimate the coefficients in each zone and assess the varying dynamics across the different levels. Results are provided in Tables 10 and 11 in Section 3.

3. Empirical Results

3.1 The Relationship Between VIX and Bond Spreads

Considering the prevalent transmission of shocks from VIX to the bond market, we first use an OLS regression to explain this relationship across the entire sample. Prior studies have shown that the VIX is positively associated with bond spreads. Tables 2 and 3 display the results for investment-grade and high-yield bond spreads, respectively. Our estimation using Equation 1 confirms prior research, showing that increases in implied volatility are associated with increases in both investment-grade and high-yield bond spreads. The results show that both have positive coefficients with log changes in VIX exerting a more pronounced influence on changes in high yield spreads as compared to investment grade spreads. The consistent positive coefficients on log changes in VIX across both investment grade and high yield spread models validate the theoretical linkage between market volatility and borrowing costs. Essentially, swings in the "investor fear gauge" transmit into bond markets, driving spreads wider when uncertainty spikes and tighter when volatility subsides.

Table 2: Least Squares regression estimation of Eq.1 Changes in investment grade spreads (IG_SPR) as a function of log changes in VIX and a one-period lag of IG_SPR.

Variable	Coefficient	St Error
Log Δ VIX	0.073***	0.006
Δ IG_SPR (-1)	0.449***	0.014

Log Likelihood	8508.8
Akaike Information Criteria	-4.119
Adj R^2	0.221
N	4130

Notes: November 2, 2006 – April 27, 2023 full sample period (4130 observations)
*** denotes significance at 1%, ** at 5%, * at 10%.

Table 3: Least Squares regression estimation of Eq.1. Changes in high yield spreads (HY_SPR) as a function of log changes in VIX and a one-period lag of HY_SPR.

Variable	Coefficient	St Error
Log Δ VIX	0.587***	0.002
Δ HY_SPR (-1)	0.298***	0.020

Log Likelihood	3710.2
Akaike Information Criteria	-1.795
Adj R^2	0.235
N	4130

Notes: November 2, 2006 – April 27, 2023 full sample period (4130 observations)
*** denotes significance at 1%, ** at 5%, * at 10%.

3.2 Structural Breaks in the VIX-Spread Relationship

We find multiple structural breaks in the relationship between implied equity volatility and corporate bond spreads, offering new insights into the dynamics of this association over time. The relationship between volatility and investment grade bond spreads is further explored using the Bai & Perron (1998, 2003) multiple breakpoint regression. Results are presented in Table 4 and indicate two structural breaks found in this relationship. The first break occurred toward the end of the financial crisis in April 2009. Subsequently, another break occurred in February 2020, coinciding closely with the onset of the COVID-19 pandemic. Interestingly, no specific break was evident at the beginning of the regional banking crisis in mid-March 2023.

The coefficients of log changes in VIX on changes in investment grade spreads exhibited variations across the three distinct periods. Following the financial crisis, the magnitude of the association declined from 0.126 to 0.042. However, during the final period coinciding with the COVID-19 pandemic, it increased to 0.131. All coefficients were statistically significant throughout these periods. The findings suggest that, during periods of high market stress, investors can expect increased variability in investment grade spreads in response to changes in the VIX.

Using the same method, we tested the effect the VIX had on high yield bond spreads and found that the relationship has four discernible breaks. Like investment-grade spreads, high yield spreads have a positive, statistically significant relationship to changes in VIX. Two of the four resulting breaks surround the financial crisis and the COVID-19 pandemic. In both the financial crisis and the preceding period, we identified the most significant coefficient, reaching +0.878. However, after the financial crisis, the impact gradually declined until November 2018. Following this, the magnitude of the coefficient increased to +0.737, rebounding from a low of +0.266 observed during the period from April 2016 to November

2018. Results are presented in Table 5 and indicate how high-yield bonds can reprice rapidly when market volatility spikes, which is consistent with the characteristics of speculative grade investments. The subsequent decline in the coefficient over the next few years suggests some stabilization in the high yield market as the economy recovered from the financial crisis.

Table 4: Changes in investment grade spreads (IG_SPR) as a function of log changes in VIX. Bai and Perron multiple breakpoint regression estimation of Eq.1

Phases based on breakpoints	**Changes in IG_SPR as a function of log changes in VIX**	
	Coefficient B_1	**St Error**
Phase 1: 620 *obs.* *11/2/2006 –4/27/2009*	0.126***	0.016
Phase 2: 2714 *obs.* *4/28/2009 – 2/25/2020*	0.042***	0.007
Phase 3: 796 *obs.* *2/26/2020 – 4/27/2023*	0.131***	0.019
Diagnostic tests:	F-statistics = 208.300 Log likelihood = 8537.54 Akaike Information Criteria = -4.132 Schwartz Info. Criterion = -4.120 Durbin Watson stats. = 2.230	

Non-breaking Variable Δ IG_SPR (-1)

Notes: November 2, 2006 – April 27, 2023 full sample period (4130 observations);
*** denotes significance at 1%, ** at 5%, * at 10%.

Through the structural break analysis, we observed that the coefficient of VIX on high yield spreads varies through time and is tied to notable periods of volatility and tranquility. As such, the VIX has the strongest association with high yield spreads during times of turmoil while demonstrating a weaker association during periods of relative tranquility in the markets. We also notice that the structural break periods often surround periods when the Federal Reserve made changes to the Fed Funds policy rate.

In effect, the sensitivity of credit risk premiums to changes in volatility expectations may depend on the underlying rate backdrop set by central bank actions. Tighter policy not only directly raises borrowing costs via heightened rates, but serves an amplifying role - magnifying the impact of VIX shifts on spread levels during stress episodes.

Table 5: Changes in 5-year high yield spreads (HY_SPR) as a function of log changes in VIX. Bai and Perron multiple breakpoint regression estimation of Eq.1

Phases based on breakpoints	**Changes in HY_SPR as a function of log changes in VIX**	
	Coefficient B_1	**St Error**
Phase 1: 620 *obs.* *11/2/2006 –4/23/2009*	0.878***	0.075
Phase 2: 823 *obs.* *4/24/2009 – 8/1/2012*	0.581***	0.041
Phase 3: 926 *obs.* *8/2/2012 – 4/15/2016*	0.459***	0.031
Phase 4: 646 *obs.* *4/18/2016 – 11/8/2018*	0.266***	0.025
Phase 5: 1117 *obs.* *11/9/2018 – 4/27/2023*	0.737***	0.042
Diagnostic tests:	F-statistics = 142.191 Log likelihood = 3771.430 Akaike Information Criteria = -1.819 Schwartz Info. Criterion = -1,803 Durbin Watson stats. = 2.214	

Non-breaking Variable Δ HY_SPR(-1)

Notes: November 2, 2006 – April 27, 2023, full sample period (4130 observations);
*** denotes significance at 1%, ** at 5%, * at 10%.

3.3 FEDL Moderates VIX-Spread Association

We introduce the Federal Funds Effective Rate as a moderator of the VIX-spread relationship, and our findings emphasize that the level of FEDL plays a significant role in influencing the nature of this connection. Utilizing the SETAR threshold regressions, we identify elevated, intermediate, and low levels of the FEDL rate. These zones are presented in Table 6 below and are supported by low AIC and SIC of -2.436 and -2.431 respectively. With 2,249 low rate observations, 637 intermediate, and 1,244 high, the thresholds produce a reasonable distribution across rate levels.

Table 6: Fed Funds Estimated SETAR Zones

	Fed Funds Rate	Coefficient *B*
Zone 1: **Low Rates** No. Observations	FEDL < 0.230% 2249 obs	0.998***
Zone 2: **Intermediate Rates** No. Observations	0.230% <= FEDL < 1.410% 637 obs	0.981***
Zone 3: **Elevated Rates** No. Observations	1.410% <= FEDL 1244 obs	0.999***
Diagnostic tests:	R Squared = 0.998 Log likelihood = 5028.765 Mean = 1.071 St Deviation = 1.499 Akaike Information Criteria = -2.436 Schwartz Info. Criterion = -2.431 Durbin Watson stats. = 2.131	

Notes: November 2, 2006 – April 27, 2023 full sample period (4130 observations); from Eq (2)
*** denotes significance at 1%, ** at 5%, * at 10%.

During the years 2006 to 2023, the Federal Reserve employed various monetary policy tools to address financial market conditions. Expansionary monetary policy in a low-rate environment dominates most of the data in our analysis. The impact of VIX on investment grade spreads changes across interest rate levels, the changes are small in absolute terms but represent statistically significant changes in the relationship. Table 7 shows positive and statistically significant coefficients at each rate level. The impact of VIX on spreads during periods of intermediate interest rate levels is 0.069, and it is 0.030 lower and 0.074 higher during low and elevated rate environments respectively. The results confirm that the level of Federal interest rates are associated with the strength of the relationship between equity market volatility and investment grade credit spreads. Specifically, when rates are relatively low, volatility shifts have a more muted impact on spread variability. When rates are elevated, volatility shocks are more amplified into larger spread changes.

Table 7: Changes in 5-year investment grade spreads (IG_SPR) as a function of percent change in VIX regression estimation with interaction variables and one-period lag of IG_SPR, segmented by Fed Rate level (Eq3)

Interaction Variables	Range	Log Δ VIX Coef	Δ from Baseline	St Error
Low (FEDL_VIX)	< 0.23%	0.039**	-0.043***	0.015
Intermediate (FEDL_VIX)	0.23% - 1.41%	0.069***	-0.013	0.016
Elevated (FEDL_VIX)	> 1.41%	0.143**	0.067***	0.069

Log Likelihood	8043.2
Akaike Information Criteria	–3.893
Adj R^2	0.029
N	4130

Notes: November 2, 2006 – April 27, 2023 sample period (4130 observations); Lagged IG_SPR term removed as values were the same as the base regression.. *** denotes significance at 1%, *** at 5%, ** at 10%*.

When analyzing high yield spreads, we observe a consistently positive and statistically significant relationship between VIX and high yield spreads across all interest rate environments. However, this relationship appears to be less influenced by the level of interest rates. Notably, despite exhibiting stronger absolute changes, the coefficients across different rate-level zones lack statistical significance. For example, when interest rates transition from an intermediate to a higher level, the coefficient increases from 0.583 to 0.662. This indicates that while VIX has a stronger overall effect on high yield spreads, they are not very responsive to the level of FEDL rates on a relative basis. Results are presented in Table 8.

Overall, we find that high yield spreads are not significantly influenced by the level of FEDL. Conversely, investment grade spreads are more responsive to shifts in the FEDL on a relative basis. Regardless, investors need to recognize that both investment grade and high yield spreads will react more prominently when Federal Reserve rates are at higher levels.

3.4 VIX Level and Spread Relationship

Examining the low, intermediate, and elevated ranges of the VIX reveals changes to the strength of the VIX to bond spreads relationship. This underscores the importance for investors to consider the degree of implied volatility's influence on bond spreads. We used the same SETAR threshold model to identify zones of the VIX. Results are presented in Table 9.

The majority of observations occur in the intermediate zone when VIX is between 15.26 and 26.49.

Table 8: Changes in 5-year high yield (HY_SPR) as a function of percent change in VIX regression estimation with interaction variables and one-period lag of HY_SPR, segmented by Fed Funds rate (Eq3)

Interaction Variables	Range	Log Δ VIX Coef	Δ from Baseline	St Error
Low (FEDL_VIX)	< 0.23%	0.545**	-0.047	0.010
Intermediate (FEDL_VIX)	0.23% - 1.41%	0.583***	-0.040	0.062
Elevated (FEDL_VIX)	> 1.41%	0.662**	0.067	0.096

Log Likelihood	8519.9
Akaike Information Criteria	-4.123
Adj R^2	0.259
N	4130

Notes: November 2, 2006 – April 27, 2023 full sample period (4130 observations); Lagged HY_SPR term removed as values were the same as the base regression. *** denotes significance at 1%, ** at 5%, * at 10%.

We identify three significant market shocks within the sample period, including the financial crisis, COVID-19 pandemic, and the 2023 regional banking crisis. The observed volatility levels appeared to align with the prevailing market sentiment during these events. When we further analyze the VIX threshold levels, a significant pattern emerges during periods characterized by elevated implied volatility. During these periods, the relationship between VIX and both investment grade (Table 10) and high yield bond spreads (Table 11) is much stronger relative to the other levels. As the VIX, rises to elevated levels, changes in spreads exhibit greater sensitivity when compared to periods with lower VIX levels and more positive market sentiment. This observation holds significance for bond investors, as the volatility in their spread portfolios intensifies during high VIX levels and remains less reactive during tranquil phases characterized by low VIX levels.

Our analysis shows that while both investment grade and high yield spreads respond significantly to the VIX, the coefficient for high yield spreads is much stronger on an absolute basis when compared to investment grade spreads. The impact VIX has on both investment grade and high yield spreads is stronger during times of extreme volatility and weaker during times of lower expected volatility.

Table 9: VIX Estimated SETAR Zones

	VIX Index	Coefficient B
Zone 1: **Low Volatility** No. Observations	VIX < 15.260 1385 obs	1.009***
Zone 2: **Intermediate Volatility** No. Observations	15.260 <= VIX < 26.490 2093 obs	1.000***
Zone 3: **Elevated Volatility** No. Observations	26.490 <= VIX 652 obs	0.988***
Diagnostic tests:	R-squared = 0.953 Log likelihood = -8725.514 Mean = 20.196 St Deviation = 9.223 Akaike Information Criteria = 4.228 Schwartz Info. Criterion = 4.233 Durbin Watson stats. = 2.357	

Notes: November 2, 2006 – April 27, 2023 full sample period (4130 observations); from Eq(2);
*** denotes significance at 1%, ** at 5%, *

Table 10: Changes in 5-year investment grade (IG_SPR) spreads as a function of log changes in VIX regression estimation with interaction variables and the one-period lag of IG_SPR, segmented by VIX level (Eq3)

Interaction Variables	Range	Log Δ VIX Coef	Δ from Baseline	St Error
Low (VIX_VIX)	< 15.26%	0.013***	-0.063***	0.004
Intermediate (VIX_VIX)	15.26% - 26.49%	0.056***	-0.023	0.009
Elevated (VIX_VIX)	> 26.49%	0.140***	0.447***	0.045

Log Likelihood	8054.3
Akaike Information Criteria	-3.899
Adj R^2	0.034
N	4130

Notes: November 2, 2006 – April 27, 2023 full sample period (4130 observations); Lagged IG_SPR term removed as values were the same as the base regression.*** denotes significance at 1%, ** at 5%, * at 10%.

Table 11: Changes in 5-year high yield (HY_SPR) spreads as a function of log changes in VIX regression estimation with interaction variables and the one-period lag of HY_SPR, segmented by VIX level (Eq 3)

Interaction Variables	Range	Log Δ VIX Coef	Δ from Baseline	St Error
Low (VIX_VIX)	< 15.26%	0.241***	-0.167***	0.033
Intermediate (VIX_VIX)	15.26% - 26.49%	0.531***	-0.057	0.032
Elevated (VIX_VIX)	> 26.49%	0.901***	0.331***	0.144

Log Likelihood	3538.4
Akaike Information Criteria	-1.712
Adj R^2	0.168
N	4130

Notes: November 2, 2006 – April 27, 2023 full sample period (4130 observations); Lagged HY_SPR term removed as values were the same as the base regression.*** denotes significance at 1%, ** at 5%, * at 10%.

4. Conclusion

This study contributes to the existing literature in several ways. First, we demonstrate that there is a dynamic relationship between implied equity volatility and both investment grade and high yield corporate bond spreads by identifying several structural breaks in this relationship throughout the sample period. Investment grade spreads exhibit two significant breaks in the relationship, coinciding with the 2008/09 financial crisis and the 2020 COVID-19 pandemic. In contrast, high yield spreads had 4 breaks in the relationship. More structural breaks suggest that high yield spreads are more sensitive to changing market and economic conditions.

Second, our analysis shows a key distinction in the way the VIX impacts bond spreads across a range of credit qualities. The results show that high yield bond spreads exhibit a stronger and robust correlation with the VIX in comparison to investment grade spreads. This means that changes in the VIX have a stronger impact on high yield bond spreads, demonstrating a heightened sensitivity to market volatility. In contrast, the relationship between the VIX on investment grade spreads is less pronounced, indicating a milder responsiveness to changes in market sentiment. This suggests investors need to consider credit quality if making investment decisions based on changes in or absolute levels of the VIX. The magnitude of the coefficients for both investment grade and high yield spreads increase when the VIX is more elevated and decrease when VIX is relatively low.

Third, our study reveals how different levels of the Federal Funds Effective Rate play a significant role in influencing the relationship between the VIX and bond spreads. Our analysis highlights that the level of interest rates has measurable effects on this connection. Specifically, when the FEDL is higher, the impact of the VIX on bond spreads becomes more pronounced. This suggests interest rate levels can amplify the way market volatility affects credit spreads. Conversely, when the FEDL is lower, the influence of the VIX on spreads is smaller. This nuanced understanding emphasizes how economic factors and market sentiment work together, helping us comprehend how shifts in interest rates moderate the connection between the VIX and bond spreads.

This study has limitations that warrant acknowledgment, while also motivating future studies. First, subsequent studies could focus on more regional diversity. Expanding this framework into other global markets further adds more insight into this connection and could expose other relationship patterns that are unique to certain markets. Second, a comparative investigation could be conducted, contrasting the VIX against alternative market sentiment or volatility indicators like the EPU or historical volatility. Last, this dataset begins just before the financial crisis and could be expanded to include more periods of monetary policy interventions.

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