# Investor Sentiment and Credit Cycles: A Threshold Bayesian VAR Model

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Feb 15, 2025

**Abstract**

This paper examines the role of investor sentiment in shaping credit market dynamics through a threshold Bayesian vector autoregression (TBVAR) model. By identifying sentiment shocks and accounting for regime-dependent non-linearities, I demonstrate that sentiment shocks exert asymmetric effects, with greater persistence and amplification during periods of credit market stress. Incorporating information rigidity as an alternative mechanism, the results show that delayed adjustments in expectations intensify the propagation of sentiment shocks, particularly under adverse credit conditions. The structural identification of sentiment shocks disentangles their contributions from broader macroeconomic disturbances, highlighting the need for policies that align expectations to mitigate sentiment-driven disruptions.

**Keywords:** Investor Sentiment, Credit Cycles, Macroeconomic Fluctuations, Financial Instability
**JEL Codes:** E32, E44, G01, G02, G12

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# Acknowledge

This research is a self-funded research, and all errors are on my own.

# 1 Introduction

Do credit booms lead to recessions? The COVID-19 pandemic financial crisis spawns a resurgence in the popularity of sentiment-driven credit booms as a source of recurrent crises. To understand the mechanism of sentiment-driven financial instability, this paper uses a dynamic causal inference approach to explore the role of sentiment in shaping credit market dynamics and the underlying economic fluctuations. This approach aims to disentangle the macroeconomic mechanism through a micro-level phenomenon.

While recent empirical studies highlight that corporate bond credit spreads often precede sentiment fluctuations, the converse relationship, specifically, the extent to which sentiment shocks influence credit spreads, remains comparatively underexplored. To understand the identification issue, I demonstrate that measures of investor sentiment, such as the Baker Wurgler Sentiment Index, negatively correlate with future values of the corporate bond spread identified by Gilchrist and Zakrajšek (2012) and the default spread between BAA and AAA bonds. Potential explanations for this reverse predictive correlation include: a causal influence of market sentiment's condition on credit markets, such as the VIX index; the persistence of credit spreads combined with a causal effect of credit markets on market sentiment conditions; and the possibility that a common factor, such as information frictions or agents' expectations, influences both macroeconomic activity and credit spreads. To overcome this identification issue, I employ sentiment shocks as instruments to test whether market sentiment conditions structurally drive fluctuations in credit spreads. The unexpected change in the Baker-Wurgler Sentiment Index measures the sentiment shocks. The index is constructed using a combination of market-based and behavioral indicators that reflect investor risk appetite shifts and optimism and isolate changes in underlying economic conditions. Therefore, the effect of these shocks on credit markets can be interpreted as a result of their influence on market sentiment conditions.

Using the local linear projection method developed by Jordà (2005), I find that unexpected increases in investor sentiment lead to a pronounced and prolonged decline in credit

spreads. For example, six quarters following a positive two-standard deviation sentiment shock, the Gilchrist and Zakrajšek (GZ) spread decreases by 40 basis points (bps) below its mean, representing approximately 42% of its unconditional standard deviation. Besides, the impulse response of credit spreads is of similar magnitude but opposite in direction to the response of macroeconomic activity. Additionally, credit spreads reach their lowest point either simultaneously with or after macroeconomic activity peaks. The fact that the responses of credit spreads and macroeconomic activity are nearly mirror images confirms the countercyclical behavior of credit spreads and macroeconomic activities in response to sentiment shocks.

My initial finding is that these sentiment shocks are key drivers of fluctuations in both credit spreads and real economic activity. By employing forecast error variance decompositions (FEVD) adapted for local projections (as detailed by Gorodnichenko and Lee (2020) and Plagborg-Møller and Wolf (2022)), I demonstrate that the sentiment shocks account for 30% of the unpredictable variation in credit spreads and approximately 40% of the unpredictable variation in macroeconomic activity at horizons exceeding one year. The diversity of these shocks in terms of their origins, motivations, and sample periods provides strong validation for my identification strategy and underscores the robustness of my findings.

My findings raise important issues regarding the nature of investor sentiment: asymmetries and nonlinearities. I solve these issues by employing a comprehensive model that combines Bayesian theory and regime-dependent behaviors. To this end, I adopt a threshold Bayesian vector autoregressive (TBVAR) model. This methodology extends the standard Bayesian VAR framework by incorporating threshold effects, allowing for regime shifts in the dynamic relationships between variables based on the state of the credit cycle. This method is well-suited to understanding how sentiment shocks propagate differently during periods of credit expansion versus contraction. The results emphasize the asymmetric propagation of sentiment shocks across credit market regimes. During normal credit conditions, sentiment shocks significantly alleviate credit spreads and risk premiums, fostering improved bor-

rowing conditions. However, during stressed periods, the effectiveness of sentiment shocks is constrained, likely due to structural impediments such as impaired intermediation and heightened uncertainty. This regime-dependent behavior highlights the need for tailored policy interventions to stabilize credit markets during stress, as traditional sentiment-driven mechanisms may be insufficient under such conditions.

One concerning phenomenon from my findings is that the responses of credit spreads and macroeconomic activities are delayed and prolonged. This raises an important question about what may cause the delayed and prolonged responses and the potential mechanism behind the fluctuations. I deal with this criticism by incorporating the information rigidity theory by Coibion and Gorodnichenko (2012). I test whether there is information rigidity in forming investors' expectations and how they transform into investor sentiment and influence the credit market and macroeconomic activities. The results show information rigidity plays a pronounced role in shaping credit market dynamics, which highlights the agents' expectations explanation in operating the credit cycle. Moreover, the two potential explanations are not contradictory, they provide a more robust account of the countercyclical response of credit spreads.

This paper contributes to the body of research on the credit cycle and macroeconomic fluctuations, which has identified various credit boom indicators that predict market sentiment performance—a causal relationship that is well established. In contrast, my focus is on examining the reverse causality, using exogenous sentiment shocks to represent investors' perspective fluctuations. Due to their exogenous nature, sentiment shocks are unlikely to correlate with factors such as financial frictions, time-variation in sentiment, reaching-for-yield behavior, or credit supply expansions, though they may influence the future values of these variables. My findings reveal that positive sentiment shocks impact credit markets by improving investment prospects, ultimately lowering expected bond returns. This aligns with the evidence presented by Fama and French (1989) and more recent work by Gomes et al. (2019). I contribute to this literature by directly identifying time variation in investment

opportunities through the lens of sentiment shocks.

This paper provides several key contributions to the existing literature on the interplay between credit market sentiment and macroeconomic dynamics. Compared to recent studies, my work advances the discourse in the three directions. First, I focus on credit market sentiment in a non-linear framework. While prior research such as Gilchrist and Zakrajšek (2012) and Greenwood and Hanson (2013) focuses on the predictive power of credit spreads and issuance, my paper explicitly identifies and models sentiment shocks within credit markets using a threshold Bayesian VAR (TBVAR) framework. This approach allows us to examine how the impact of sentiment shocks varies across regimes characterized by high and low credit-market stress, capturing non-linear dynamics often overlooked in linear VAR models. By explicitly considering the regime-dependent nature of sentiment propagation, we contribute to the literature on non-linear economic adjustments, complementing linear models that dominate the field.

Second, I extend the existing literature by introducing information rigidity as a key economic mechanism in credit markets. Unlike traditional models that focus solely on financial frictions or behavioral biases, our framework highlights the role of delayed adjustments in expectations. This focus on expectation variables (e.g., expected GDP growth, expected credit spreads) enriches the understanding of how credit-market sentiment propagates under different regimes, advancing the work of Bordalo et al. (2018) and others who emphasize behavioral biases.

One particular contribution is that I take policy-relevant insights into regime-specific dynamics. By examining regime-specific responses to sentiment shocks, our paper offers nuanced policy implications. For example, we show that in high-stress regimes (e.g., during periods of elevated default spreads), sentiment shocks have more persistent and destabilizing effects due to higher information rigidity. This finding is relevant for policymakers aiming to stabilize credit markets during crises. Our results emphasize the importance of targeted interventions, such as improving transparency, promoting financial literacy, or enhancing

central bank communication to reduce the persistence of sentiment-driven disruptions.

The remainder of the paper is organized as follows. I begin in Section 2 by providing a measurement for investor sentiment as the exogenous variable. In Section 3, I establish the basic results describing the fundamental framework. In Section 4, I introduce a threshold Bayesian VAR model (TBVAR) and present the regime-dependent results. In Section 5, I provide an alternative economic mechanism that incorporates information rigidity into the TBVAR model. Section 6 concludes.

# 2 Measuring the Sentiment

To quantify investor sentiment, this paper employs the Baker-Wurgler sentiment index, a comprehensive measure aggregating multiple investor sentiment proxies. The index is constructed using a combination of market-based and behavioral indicators that reflect investor risk appetite shifts and optimism. It provides a robust representation of sentiment-driven dynamics in financial markets, making it an ideal choice for studying credit market behavior.

The Baker-Wurgler sentiment index is based on six key components: IPO volume, share of equity in new issuance, dividend premium, closed-end fund discount, trading volume, and volatility metrics. To isolate sentiment-driven effects, the index adjusts these components for macroeconomic fundamentals using principal component analysis (PCA). This ensures that the index reflects shifts in sentiment rather than changes in underlying economic conditions. To capture time-varying investor sentiment, this index represents a significant advancement over the traditional measure based on the closed-end fund premium (Lee, Shleifer, and Thaler, 1991). It has inspired extensive research on the impact of investor sentiment on asset prices and corporate decision-making.

The Baker-Wurgler sentiment index is particularly suitable for analyzing the credit cycles because: it captures broad-based sentiment across multiple market dimensions, including equity issuance, trading behavior, and risk pricing; it provides a long historical time series,

enabling robust analysis of credit market dynamics over extended periods; its construction ensures that sentiment is measured independently of macroeconomic variables, addressing endogeneity concerns.

The sentiment data ranges from 1965 Q1 to 2023 Q4. Sentiment shocks are defined as unexpected changes in the Baker-Wurgler sentiment index. Figure 1 illustrates the evolution of investor sentiment, measured by the Baker-Wurgler Index, over time, with shaded regions representing NBER-defined recession periods[1]. The sentiment index exhibits pronounced cyclical behavior, with notable peaks preceding economic downturns and declines occurring around recessions. This pattern suggests that investor sentiment tends to rise during economic expansions, reaching euphoric levels before experiencing sharp contractions as financial conditions deteriorate. The sentiment index also displays significant volatility, reflecting shifts in market optimism and risk appetite. The most recent observations indicate a resurgence in sentiment post-2020, following the pandemic-induced recession. This visualization underscores the role of investor sentiment in credit market dynamics and its potential predictive power in anticipating economic fluctuations. The plotted relationship between investor sentiment and NBER recessions motivates analyzing the sentiment-led credit cycles.

[1]The National Bureau of Economic Research (NBER) defines recessions as significant declines in economic activity spread across the economy, lasting more than a few months, and visible in real GDP, real income, employment, industrial production, and wholesale-retail sales. The official recession dates are determined by the NBER Business Cycle Dating Committee. For more details, visit https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions.

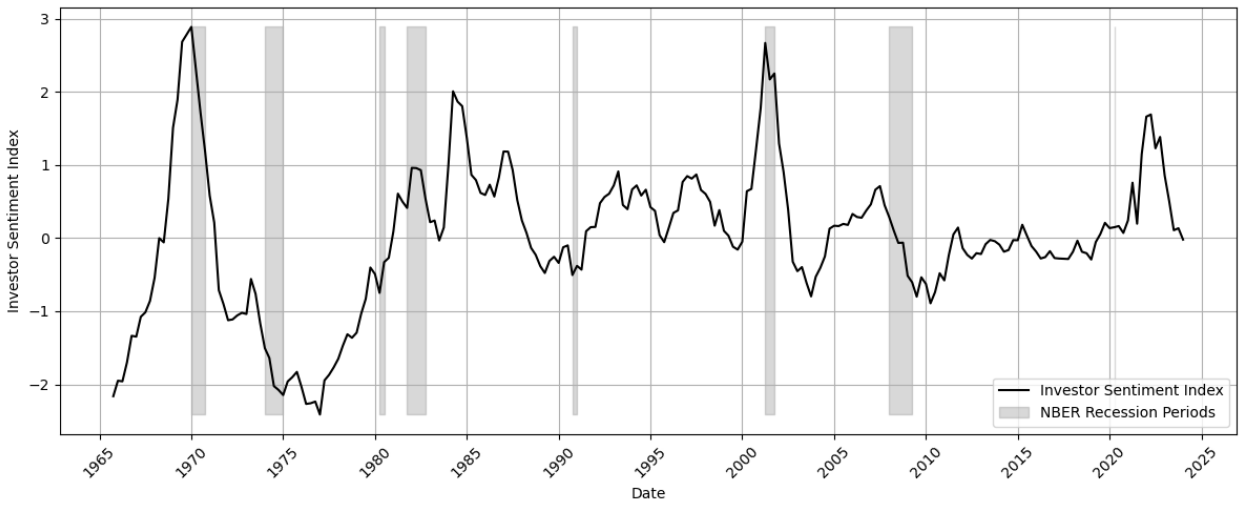



Figure 1: **Investor Sentiment with NBER Recessions.** This figure plots the Baker-Wurgler investor sentiment index over time, with NBER recession periods shaded in gray. The sentiment index captures fluctuations in investor optimism and risk appetite, exhibiting cyclical patterns with peaks generally preceding economic downturns and declines coinciding with recessions. The data highlights the interaction between investor sentiment and macroeconomic conditions, emphasizing its role in credit market fluctuations. Sources: Baker and Wurgler (2006), NBER.

To explain the mechanism of the credit cycle, I introduce three credit market variables: Gilchrist and Zakrajšek spreads (GZ), default spreads (DS), and excess bond premiums (EBP), and three macroeconomic variables: real GDP per capita (GDP), Chicago Fed National Activity Index (CFNAI), and Consumer Price Inflation Index (CPI).

To be specific, GZ spreads (Gilchrist and Zakrajšek (2012)) are credit spread metrics that reflect the premium investors demand for holding corporate bonds relative to risk-free Treasury securities. It is calculated by decomposing corporate bond spreads into two components: the default risk component and the excess bond premium component. The spread is constructed as the yield spread between corporate bonds and risk-free Treasury securities, adjusted for firm-specific default probabilities and bond characteristics. Default spreads (DS) are a measure of credit risk in financial markets. It represents the difference between the yields of corporate bonds with varying levels of default risk and those of risk-free government securities, such as U.S. Treasury bonds. Typically, the default spread is calculated as the yields on risky corporate bonds minus the yields on risk-free Treasury securities. Excess bond premium (EBP) is derived by regressing corporate bond spreads on a set of firm-level default risk characteristics and extracting the residual. The Chicago Fed National Activity Index (CFNAI) is a monthly economic indicator designed to gauge overall economic activity and related inflationary pressures in the United States. It is a composite index derived from a weighted average of 85 individual economic indicators that cover four broad categories: production, employment, consumption, and sales. It is particularly useful for identifying turning points in the business cycle. The CFNAI is expressed as a single value, with zero representing the historical trend of economic activity. Deviations from zero indicate the economy's position relative to its historical trend. This means the positive value represents the above-trend growth, potentially indicating increasing inflationary pressures, and the negative value represents the below-trend growth, signaling weaker economic activity. For consistency, all the data on credit market variables and macroeconomic variables ranges from 1965 Q1 to 2023 Q4.

# 3 Does Sentiment Drive Credit Market Dynamics?

This section begins with a structural VAR framework that relies on relatively strong identification assumptions regarding the contemporaneous relationships between credit market variables and investor sentiment. I then transition to an approach with weaker identification assumptions employing exogenous sentiment shocks.

## 3.1 A Structural VAR Model

This section examines the dynamic interactions between sentiment shocks and key credit market variables within a structural VAR framework. My study focuses on sentiment shocks as the primary driver of fluctuations in credit markets. Sentiment shocks are constructed from unanticipated changes in the Baker-Wurgler sentiment index, which captures shifts in investor risk appetite and optimism.

I employ a structural VAR framework to identify the contemporaneous and dynamic relationships between sentiment shocks ($S_{t+1}$) and credit market variables ($C_{t+1}$), represented as:

$$\begin{bmatrix} C_{t+1} \\ S_{t+1} \end{bmatrix} = \begin{bmatrix} 0 & b_{12} \\ b_{21} & 0 \end{bmatrix} \begin{bmatrix} C_{t+1} \\ S_{t+1} \end{bmatrix} + \Phi' Q_t + \varepsilon_{t+1}$$

where the structural shocks are $\varepsilon_{t+1} = [\varepsilon_{C,t+1}, \varepsilon_{S,t+1}]'$, with $\mathbb{E}(\varepsilon_{t+1}) = 0$ and $\mathbb{E}(\varepsilon_{t+1}\varepsilon'_{t+1}) = D$, where $D$ is a diagonal matrix, and $\mathbb{E}(\varepsilon_t \varepsilon'_s) = 0$ for $t \neq s$. This can be written more concisely as:

$$Q_{t+1} = B_0 Q_{t+1} + \Phi' Q_t + \varepsilon_{t+1}$$

where $Q_t = \left[ Q'_t, Q'_{t-1}, \ldots, Q'_{t-p} \right]'$, with $Q_{t+1} = [C_{t+1}, S_{t+1}]'$, and $\Phi'$ is a matrix of autoregressive coefficients, capturing lagged effects from $Q_t$.

The contemporaneous structural relationship between $C_{t+1}$ and $S_{t+1}$ is captured by the parameters in $B_0$. To identify $B_0$, I make two assumptions. The first is that sentiment ($S_{t+1}$) responds contemporaneously to changes in credit market variables ($b_{21} \neq 0$). The

second is that credit market variables ($C_{t+1}$) respond to sentiment only with a lag ($b_{12} = 0$). These identification assumptions are motivated by the forward-looking nature of sentiment, which tends to react immediately to new information, while credit market adjustments often require time to materialize.

To impose the recursive identification, I apply a Cholesky decomposition (Sims (1980)) to the covariance matrix of the residuals from the reduced-form VAR:

$$Q_{t+1} = \tilde{\Phi}' Q_t + u_{t+1}$$

where $\tilde{\Phi}$ is a matrix of autoregressive coefficients, $u_{t+1} = [u_{C,t+1}, u_{S,t+1}]'$ are the reduced-form residuals, and $\mathbb{E}(u_{t+1}u'_{t+1}) = \Sigma$.

The relation between the reduced-form residuals and the structural shocks is given by:

$$\varepsilon_{t+1} = (I - B_0)^{-1} u_{t+1}$$

where $\Sigma$ is decomposed into $B_0$ and the variance of the shocks $D$. I choose the optimal lag length $p$ for the reduced-form VAR using the Bayesian Information Criterion (BIC). To facilitate interpretation, sentiment and credit market variables are standardized for a unit standard deviation.

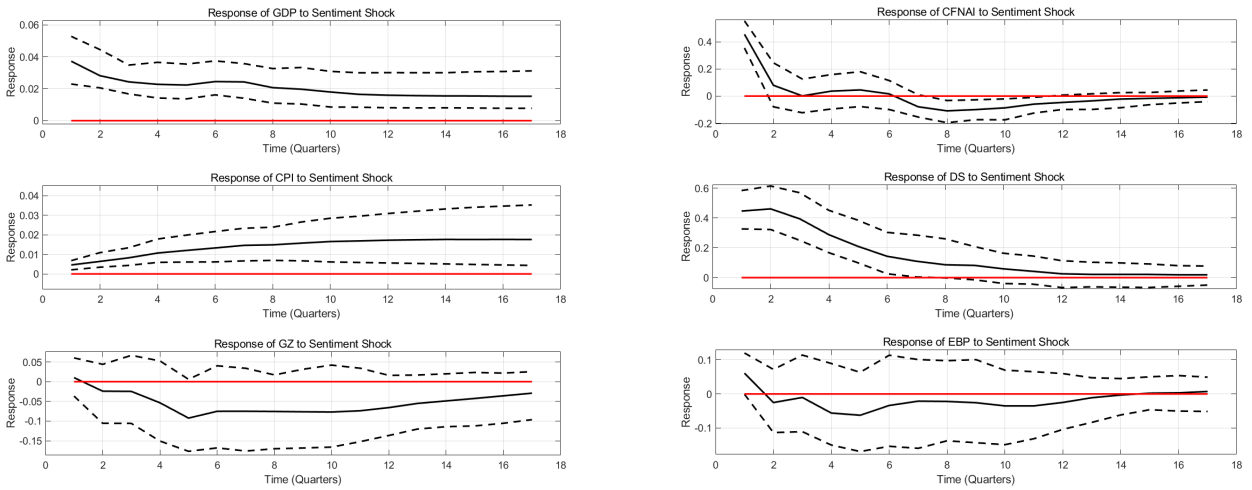



Figure 2: **Impulse Responses of Credit Spreads and Macroeconomic Activities to Structural Sentiment Shocks.** This figure presents the impulse response functions (IRFs) of selected credit market variables (GZ spreads (GZ), default spreads (DS), excess bond premiums (EBP)) and macroeconomic activity variables (real GDP per capita (GDP), consumer price index (CPI), Chicago Fed National Activity Index (CFNAI)) to structural sentiment shocks. The solid black line represents the estimated response, while the dashed black lines indicate the 90% confidence intervals derived from bootstrap simulations. The red line represents the baseline level. The responses are reported over a horizon of 16 quarters. The IRFs are estimated using a structural VAR method with controls for macroeconomic conditions and lagged variables. The results suggest a significant relationship between sentiment shocks and the evolution of key credit market and macroeconomic activity indicators, with varying degrees of persistence across different variables.

Figure 2 plots the impulse response function of how a sentiment shock propagates through the economy, affecting macroeconomic variables and credit market indicators over time. Each subplot captures the evolution of the variable's response over a 16-quarter horizon, along with 90% confidence intervals (dashed lines). These IRFs provide insight into how sentiment-driven shocks propagate through the economy and financial markets, capturing both immediate and persistent effects.

Regarding the macroeconomic variables, the IRF shows a positive but moderate response of real GDP per capita to sentiment shocks, peaking in the early quarters before gradually tapering off. This indicates that improved sentiment leads to short-term economic growth, potentially through increased investment and consumption spurred by optimism. CFNAI responds strongly initially, quickly reversing toward equilibrium. This suggests that sentiment-driven shocks might influence aggregate economic activity through immediate but transitory adjustments in economic indicators. Regarding price stability, the response of CPI exhibits a gradual upward trend following a sentiment shock, implying that sentiment influences demand-side pressures, potentially leading to mild inflationary effects over a longer horizon. The reaction of DS highlights a decline following a sentiment shock, reflecting improved credit conditions and a reduced risk of default. This could indicate that sentiment-driven optimism encourages risk-taking and reduces perceived credit risks in the short run. Regarding credit market dynamics, the reaction of default spreads highlights a decline following a sentiment shock, reflecting improved credit conditions and a reduced risk of default. This could indicate that sentiment-driven optimism encourages risk-taking and reduces perceived credit risks in the short run. GZ spreads exhibit a hump-shaped response, with an initial decline followed by gradual normalization. This pattern points to easing credit market conditions in the immediate aftermath of a positive sentiment shock. EBP similarly demonstrates a strong and persistent decline, underscoring the role of sentiment in reducing non-default-related risk premia in financial markets. This suggests that sentiment affects investor risk appetite and liquidity conditions.

To summarize, this section collectively suggests that sentiment shocks act as a critical driver of credit market dynamics, influencing both spreads and premiums while also spilling over to real economic activity. The immediate and significant responses of credit spreads, combined with their persistence, underline the pivotal role of sentiment in shaping the credit cycle. Moreover, the macroeconomic responses indicate that sentiment operates not just through financial channels but also by directly influencing investment and consumption decisions. These results highlight the importance of sentiment as a driver of economic and financial fluctuations, with distinct transmission mechanisms affecting credit markets and broader macroeconomic variables. This analysis underscores the interconnectedness of credit dynamics and sentiment-driven shocks, offering insights into the mechanisms that amplify economic cycles. In the next section, I make weaker identification assumptions using exogenous sentiment shocks.

## 3.2 Impulse Responses

To analyze the dynamic responses of credit market variables to sentiment shocks, we employ the local projection methodology introduced by Jordà (2005). This approach is well-suited for our analysis as it allows for flexible estimation of impulse response functions (IRFs) without imposing stringent parametric restrictions on the underlying data-generating process. Moreover, local projections offer a robust alternative to VAR models, particularly in scenarios where variables exhibit non-linear responses or the structural shocks are external instruments.

I conduct a local projection framework to estimate the dynamic responses to sentiment shocks (Jordà (2005)):

$$Y_{t+k} = \alpha_k + \beta_k S_t + \gamma_k(L) Z_{t-1} + \epsilon_{t+k}$$

where $Y_{t+k}$ represents the outcome variables at horizon $k$ (credit market variables such as GZ spreads, default spreads, or macroeconomic indicators like GDP or CPI ), $S_t$ represents the

external sentiment shocks (unexpected changes in BW sentiment), $Z_{t-1}$ represents a vector of lagged controls that includes the sentiment shock $S_t$, the response variable $Y_t$ , $\gamma_k(L)$ is a polynomial of lag operators to account for autocorrelation and control for serial dependence and $\varepsilon_{t+k}$ represents the error term with $\epsilon_{t+k} \sim N(0, \Sigma)$.

The impulse response function (IRF) is derived from the sequence of estimated coefficients $\beta_k$ across horizons $k = 0, 1, ..., h$. These coefficients capture the marginal effect of a one-unit shock to sentiment on the response variable.

To identify the sentiment shock, I normalize $S_t$ to have a unit standard deviation to facilitate interpretation. Following the literature, I assume that the sentiment shock is exogenous to contemporaneous credit market conditions, ensuring a causal interpretation of the IRFs. The external shock $S_t$ is constructed using the orthogonalized component of the Baker-Wurgler sentiment index. I then estimate the local projections using ordinary least squares (OLS). Confidence intervals for the IRFs are constructed using robust standard errors corrected for heteroskedasticity and autocorrelation. Additionally, I implement Newey-West standard errors to address potential issues of overlapping data in the IRF estimation.

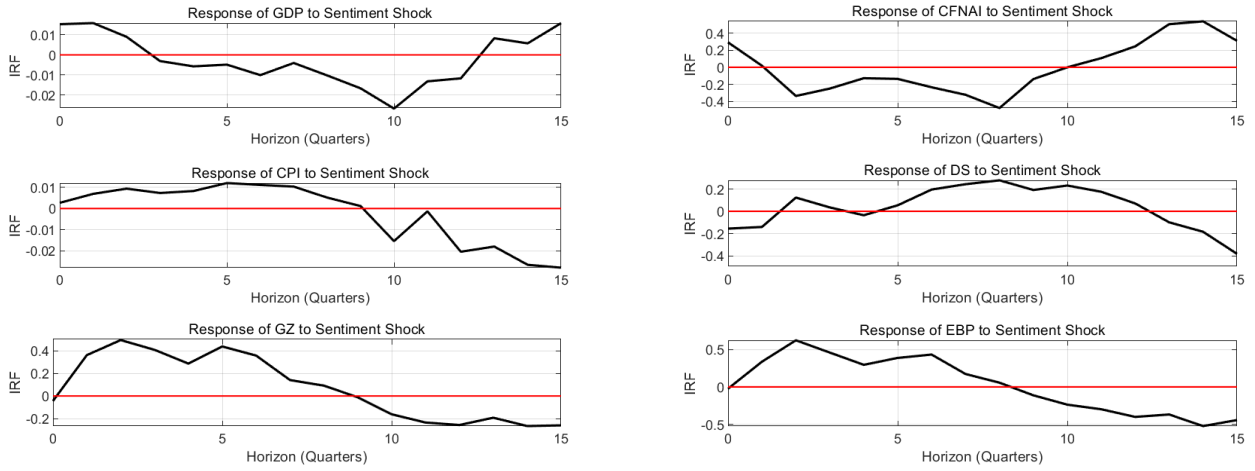



Figure 3: **Impulse Responses of Credit Spreads and Macroeconomic Activities to External Sentiment Shocks.** This figure displays the impulse response functions (IRFs) of credit market variables (GZ spreads (GZ), default spreads (DS), excess bond premiums (EBP)) and macroeconomic activity variables (real GDP per capita (GDP), consumer price index (CPI), Chicago Fed National Activity Index (CFNAI)) to external sentiment shocks over a 15-quarter horizon. The solid black line represents the estimated response, while the red horizontal line denotes the baseline level. The results are derived using a local projection method, controlling for macroeconomic fundamentals and lagged variables. The responses exhibit heterogeneous dynamics across variables, with credit spreads (GZ and EBP) demonstrating a more pronounced and persistent reaction compared to macroeconomic indicators such as GDP and CPI. The findings highlight the role of sentiment-driven fluctuations in influencing credit market conditions and economic activity.

The impulse response functions (IRFs) presented in Figure 3 illustrate the dynamic responses of macroeconomic and credit market variables to a one-unit sentiment shock over a 15-quarter horizon. These IRFs provide insight into how sentiment-driven shocks propagate through the economy and financial markets, capturing both immediate and persistent effects.

For the macroeconomic variables, the initial positive response of GDP reflects an immediate boost to economic activity, likely driven by increased optimism leading to higher investment and consumption. However, this effect reverses after a few quarters, potentially due to overvaluation or a correction in expectations, which dampens long-term economic output. This pattern illustrates that while sentiment shocks can serve as a short-term stimulant, their persistence is limited and may even introduce volatility into economic growth over time. CFNAI, which captures overall economic activity, shows a sharp initial positive response that declines and becomes negative. This suggests that sentiment-driven improvements in aggregate economic indicators are short-lived and may overshoot initially, necessitating a subsequent correction. The recovery toward equilibrium highlights the economy's resilience to such shocks, with transient effects dominating over the medium term. The response of CPI is relatively subdued, with minimal changes over the horizon. This suggests that sentiment-driven shocks do not create significant demand-pull inflation pressures, perhaps because they are not strongly tied to fundamental changes in aggregate demand or supply-side constraints. The modest decline at later horizons could reflect slower consumption or investment after initial optimism fades.

For the credit market variables, the initial decline in DS indicates that sentiment improves credit conditions, reducing perceived credit risk. However, the subsequent rise suggests that such improvements may be short-lived as fundamentals reassert their influence and risk pricing adjusts accordingly. This underscores the temporary nature of sentiment-driven credit easing. The GZ spreads (a measure of credit market stress) also display a hump-shaped response. The decline in the early quarters points to reduced financial stress and improved borrowing conditions, likely due to heightened investor optimism. The eventual reversal to-

ward equilibrium reflects the fading influence of sentiment shocks as market conditions normalize. The most pronounced and persistent response is observed in EBP, which represents non-default-related risk premia. The significant and sustained decline suggests that sentiment plays a crucial role in shaping investor risk appetite, liquidity conditions, and broader financial market sentiment. This finding highlights the critical role sentiment shocks play in moderating credit market dynamics over longer horizons.

To summarize, this section reveals that sentiment shocks exert both immediate and lagged effects, with macroeconomic variables showing shorter-lived responses compared to more persistent effects on credit markets. The stronger and more prolonged impact on financial variables underscores the importance of sentiment as a driver of credit cycles, potentially amplifying booms and busts in financial markets. Moreover, the contrasting responses between macroeconomic activity and credit conditions suggest that sentiment shocks primarily propagate through financial channels, influencing borrowing costs, investor confidence, and risk premia before affecting real economic outcomes. These findings provide valuable insights into the mechanisms of sentiment shocks, emphasizing their ability to influence both short-term economic dynamics and medium-term credit market conditions. The analysis also underscores the interconnectedness between financial markets and macroeconomic stability, with sentiment serving as a key transmission channel. Such insights can inform policymakers and market participants about the potential amplification effects of sentiment-driven fluctuations in the economy.

## 3.3 Variance Decomposition

To quantify the relative importance of sentiment shocks in explaining the variability of key economic and financial variables, I utilize the forecast error variance decomposition (FEVD) approach tailored for local projections, as proposed by Gorodnichenko and Lee (2020) and Plagborg-Møller and Wolf (2022). This methodology is particularly suited for identifying the contribution of structural shocks in the context of local projections.

The FEVD is implemented in two steps: I first regress future realizations of the variables of interest—real GDP, CFNAI, CPI inflation, GZ spreads, default spreads (DS), and excess bond premium (EBP)—on a set of control variables (lags of the variables themselves) while excluding contemporaneous shocks. This step estimates the forecast error variance attributable to residuals. Then, I regress the residuals from the first step on contemporaneous and future sentiment shocks. The $R^2$ from these regressions provide the share of forecast error variance at different horizons explained by the sentiment shock. Bias-corrected confidence intervals are computed using a bootstrap procedure, following Gorodnichenko and Lee (2020).

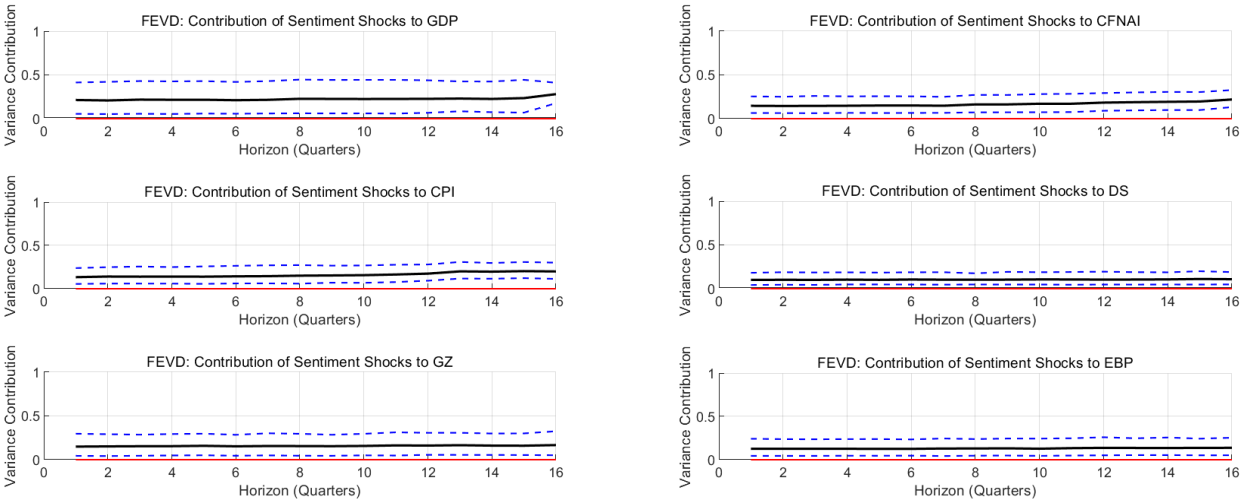



Figure 4: **Forecast Error Variance Decompositions of and Credit Spreads and Macroeconomic Activities.** This figure presents the forecast error variance decomposition (FEVD) of credit market variables (GZ spreads (GZ), default spreads (DS), excess bond premiums (EBP)) and macroeconomic activity variables (real GDP per capita (GDP), consumer price index (CPI), Chicago Fed National Activity Index (CFNAI)) in response to sentiment shocks over a 16-quarter horizon. The solid black line represents the estimated variance contribution, while the blue dashed lines indicate the 90% confidence intervals. The red horizontal line denotes the baseline level. The results suggest that sentiment shocks account for a relatively small but gradually increasing share of the forecast error variance in macroeconomic indicators (GDP, CFNAI, CPI) and credit spreads (DS, GZ, EBP). This highlights the limited but non-negligible role of sentiment fluctuations in driving economic and financial dynamics over time.

The Forecast Error Variance Decomposition (FEVD) presented in Figure 4 provides a detailed view of the contribution of sentiment shocks to the forecast error variance of key economic and credit market variables over a 16-quarter horizon. The solid black lines represent the point estimates of the FEVD, while the dashed blue lines indicate the 90% confidence intervals.

For GDP per capita, sentiment shocks contribute modestly to forecast error variance, with contributions increasing slightly over time. The confidence intervals suggest that while the contribution is statistically significant, it remains relatively low throughout the horizon. This indicates that other factors beyond sentiment are the primary drivers of GDP dynamics. CFNAI, which captures aggregate economic activity, shows a similar pattern, with a small but consistent contribution from sentiment shocks. The increasing trend at longer horizons suggests that sentiment-driven effects on overall economic activity may accumulate over time, albeit modestly. The CPI inflation exhibits limited sensitivity to sentiment shocks, as evidenced by the flat FEVD and narrow confidence intervals. This suggests that inflation is primarily driven by factors unrelated to sentiment, such as supply and demand imbalances or monetary policy.

For the credit market variables, sentiment shocks explain a more substantial portion of the variance for credit market indicators such as default spreads (DS), GZ spreads, and excess bond premiums (EBP). While the contributions are not overwhelming, they are consistently higher compared to macroeconomic variables. This highlights the role of sentiment as a key driver of financial conditions, particularly through its influence on credit risk and investor confidence. The confidence intervals for these variables remain relatively wide, reflecting uncertainty in the exact magnitude of the sentiment shock's influence. However, the positive contributions are evident across all horizons, underscoring the relevance of sentiment in shaping credit market dynamics.

To summarize, these findings illustrate that sentiment shocks play a more significant role in financial markets than in macroeconomic outcomes. The modest yet consistent contribu-

tions to macroeconomic variables highlight the indirect transmission of sentiment through financial channels. The wider confidence intervals for credit market variables suggest that sentiment-induced volatility may depend on specific market conditions, reinforcing the need to further explore the mechanisms linking sentiment and credit markets.

# 4 A Threshold Bayesian VAR Model of Credit Cycle

The analysis of credit market dynamics requires a framework capable of capturing potential nonlinearities and regime-dependent behavior. To this end, I adopt a thresholdhold Bayesian vector autoregressive (TBVAR) model. This methodology extends the standard Bayesian VAR framework by incorporating threshold effects, allowing for regime shifts in the dynamic relationships between variables based on the state of the credit cycle. This method is well-suited to understanding how sentiment shocks propagate differently during periods of credit expansion versus contraction.

The TBVAR model can be specified as:

$$\mathbf{Y}_t = \begin{cases} \Phi_0^{(1)} + \sum_{l=1}^{p} \Phi_l^{(1)} \mathbf{Y}_{t-l} + \mathbf{u}_t^{(1)}, & \text{if } Q_{t-d} \leq \gamma, \\ \Phi_0^{(2)} + \sum_{l=1}^{p} \Phi_l^{(2)} \mathbf{Y}_{t-l} + \mathbf{u}_t^{(2)}, & \text{if } Q_{t-d} > \gamma, \end{cases}$$

where $Y_t$ represents the vector of endogenous variables, including GZ spreads, Default spreads (DS), Excess bond premium (EBP), Real GDP per capita (GDP), CPI inflation, and CFNAI; $\Phi_0^{(1)}$ and $\Phi_l^{(2)}$ represent the regime-specific intercepts and lag coefficient matrices, respectively, for regime $r = \{1, 2\}$; $p$ is the lag length; $\mathbf{u}_t^{(r)} \sim \mathcal{N}(\mathbf{0}, \Sigma^{(r)})$ represents the regime-specific error terms; $Q_{t-d}$ represents the threshold variable (e.g., lagged credit growth or a composite credit condition index). $\gamma$ represents the threshold level separating the two regimes; $d$ is the delay parameter that determines how far back the threshold variable influences regime determination.

The TBVAR structure allows us to distinguish between two distinct regimes: a "normal

regime" ($Q_{t-d} \leq \gamma$) and a "stressed regime" ($Q_{t-d} > \gamma$). This threshold captures the state of the credit cycle, enabling a richer characterization of the dynamics underlying credit markets and macroeconomic variables.

Sentiment shocks are identified within the TBVAR framework using sign restrictions. First, a positive sentiment shock is assumed to reduce GZ spreads, default spreads (DS), and excess bond premiums (EBP) contemporaneously. Second, the shock is also assumed to increase real GDP and CFNAI while leaving CPI inflation unchanged on impact. These restrictions are implemented by sampling from the posterior distribution of structural shocks that satisfy the sign conditions.

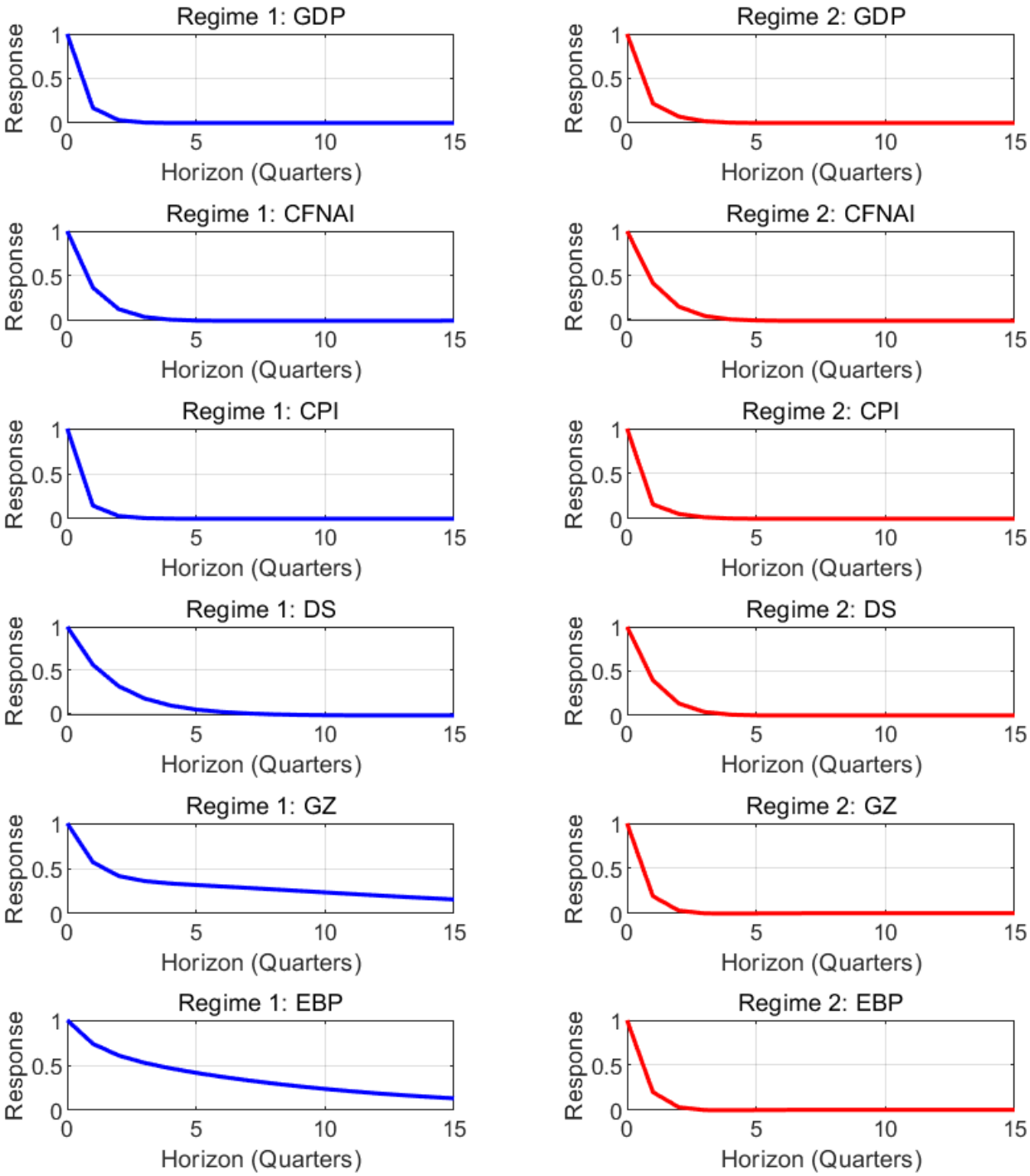



Figure 5: **TBVAR: Impulse Responses of Credit Spreads and Macroeconomic Activities to Sentiment Shocks.** This figure presents the impulse response functions (IRFs) estimated from a threshold Bayesian vector autoregression (TBVAR) model, depicting the dynamic effects of sentiment shocks on credit spreads and macroeconomic variables across two distinct regimes. The left column (blue) corresponds to Regime 1, characterized by economic expansions, while the right column (red) represents Regime 2, associated with economic downturns. The results suggest that the magnitude and persistence of sentiment shock effects vary significantly between regimes, with stronger and more persistent impacts in contractionary periods (Regime 2). These findings highlight the non-linear nature of sentiment transmission in credit market systems.

The impulse response functions (IRFs) shown in Figure 5 illustrate the regime-dependent dynamics of macroeconomic variables (GDP, CFNAI, and CPI) in response to sentiment shocks under two regimes identified in the threshold Bayesian VAR model. The two regimes correspond to distinct phases of the credit cycle: Regime 1 (blue lines) represents periods of normal credit conditions, while Regime 2 (red lines) represents stressed credit market conditions.

In Regime 1, sentiment shocks have a significant and immediate positive impact on GDP, with the response peaking in the first quarter and gradually dissipating over the subsequent quarters. This highlights the role of sentiment in driving economic activity during stable credit conditions, likely through improved investment and consumption. In Regime 2, the response of GDP is noticeably muted, with a smaller initial peak and faster dissipation. This suggests that the effectiveness of sentiment shocks in stimulating economic activity is constrained under stressed credit conditions, potentially due to tighter financial constraints and reduced risk-taking.

Similar to GDP, the CFNAI response in Regime 1 exhibits a sharp initial increase following a sentiment shock, reflecting a broad-based improvement in economic activity. The effect persists for several quarters before stabilizing. Under Regime 2, the CFNAI response is significantly weaker, underscoring the limited capacity of sentiment shocks to influence overall economic activity during periods of financial stress.

In both regimes, the response of CPI inflation is subdued compared to GDP and CFNAI. This indicates that sentiment shocks primarily affect real economic activity rather than price levels. The slightly stronger response in Regime 1 suggests a more active transmission of demand-side pressures to inflation during stable credit conditions.

The results highlight the asymmetric impact of sentiment shocks across different credit cycle regimes. During periods of normal credit conditions (Regime 1), sentiment shocks propagate effectively, supporting economic growth and activity. However, during stressed periods (Regime 2), the transmission of sentiment shocks is dampened, reflecting the constraints im-

posed by tighter financial conditions and heightened risk aversion. This underscores the importance of considering regime-dependent dynamics in understanding sentiment shocks' macroeconomic and financial effects.

The impulse response functions (IRFs) depicted in Figure **??** focus on the regime-dependent effects of sentiment shocks on key credit market variables, including default spreads (DS), GZ spreads, and excess bond premiums (EBP). These responses highlight the nonlinear dynamics of the credit market across two regimes: Regime 1 (blue lines) represents periods of normal credit conditions. In contrast, Regime 2 (red lines) corresponds to stressed credit market environments.

In Regime 1, sentiment shocks lead to a sharp decline in default spreads, with the response peaking negatively in the first quarter and gradually dissipating over subsequent quarters. This indicates that sentiment improves credit risk perceptions during periods of stability, lowering the cost of borrowing. In Regime 2, the effect on DS is significantly muted, with a smaller and shorter-lived reduction. This implies that sentiment shocks are less effective under stressed conditions in altering credit risk dynamics, likely due to heightened risk aversion and structural constraints in financial markets.

The GZ spreads, which measure overall credit market conditions, exhibit similar patterns across regimes. In Regime 1, the response to sentiment shocks is more pronounced and persistent, reflecting an improvement in broader credit market conditions during stable periods. In Regime 2, the response is dampened and short-lived, suggesting that credit markets remain constrained under stress, regardless of shifts in sentiment. This underscores the asymmetry in sentiment transmission across different phases of the credit cycle.

For EBP, sentiment shocks lead to a significant and persistent decline in Regime 1, highlighting the role of sentiment in reducing the non-default risk component of corporate bond spreads during normal conditions. Conversely, in Regime 2, the impact on EBP is minimal, reflecting the limited ability of sentiment to influence financial conditions when risk premia are already elevated due to systemic stress.

These findings emphasize the asymmetric propagation of sentiment shocks across credit market regimes. During normal credit conditions, sentiment shocks significantly alleviate credit spreads and risk premiums, fostering improved borrowing conditions. However, during stressed periods, the effectiveness of sentiment shocks is constrained, likely due to structural impediments such as impaired intermediation and heightened uncertainty. This regime-dependent behavior highlights the need for tailored policy interventions to stabilize credit markets during stress, as traditional sentiment-driven mechanisms may be insufficient under such conditions.

# 5 Exploring the Economic Mechanisms

To understand the economic mechanisms through which sentiment shocks influence credit market dynamics and the broader economy, I explore the underlying economic mechanisms driving the observed regime-dependent responses in an alternative explanation. In the previous section, I demonstrated that elevated levels of credit-market sentiment are unfavorable for future economic activity. My central hypothesis is that high sentiment is more likely to reverse within the following few years, leading to a widening of credit spreads, which reflects a reduction in credit supply and subsequently affects the real economy. However, an alternative interpretation of our findings exists that does not rely on reversals in credit supply. As suggested by López-Salido et al. (2017), credit booms may be characterized by widespread optimism that drives overinvestment in certain sectors. This inefficient investment can render the economy susceptible to future downturns, even without a subsequent contraction in credit supply. In other words, our sentiment proxies might be capturing predictions not about future credit supply but rather future credit demand. I test this alternative explanation with information rigidity in forming expectations (Coibion and Gorodnichenko (2012) Coibion and Gorodnichenko (2015)) where sentiment shocks lead to persistent over- or underreaction in macroeconomic and credit market variables, driven by delayed revisions in

agents' expectations, and positive sentiment shocks result in prolonged credit expansion and lower risk spreads, as agents fail to recognize the full extent of credit risks.

## 5.1 Information Rigidity in Forming Expectations

Information rigidity in forming expectations refers to the delayed or incomplete adjustment of agents' expectations to new information. In this section, I explore how information rigidity interacts with sentiment shocks to influence macroeconomic and financial variables across different regimes of the credit cycle. Information rigidity implies that agents, such as households, firms, and financial intermediaries, do not instantly update their expectations in response to new information. Instead, expectations adjust gradually, leading to persistent effects of shocks over time.

In the context of sentiment shocks, optimistic sentiment may result in delayed recognition of worsening credit conditions, amplifying risk-taking, and credit expansion during periods of stability. Conversely, pessimistic sentiment may exacerbate credit constraints during stressed periods, as agents overreact to negative information or fail to incorporate offsetting improvements. By incorporating information rigidity into the TBVAR framework, I aim to capture the delayed adjustment of macroeconomic and credit market variables to sentiment shocks and investigate how this mechanism varies across regimes.

I extend the TBVAR model to account for information rigidity by including expectations data and interaction terms that reflect agents' responsiveness to sentiment shocks:

$$Y_t = \begin{cases} \Phi_0^{(1)} + \sum_{l=1}^{p} \Phi_l^{(1)} Y_{t-l} + \lambda^{(1)} E_t + u_t^{(1)}, & \text{if } Q_{t-d} \leq \gamma, \\ \Phi_0^{(2)} + \sum_{l=1}^{p} \Phi_l^{(2)} Y_{t-l} + \lambda^{(2)} E_t + u_t^{(2)}, & \text{if } Q_{t-d} > \gamma, \end{cases}$$

where $Y_t$ is the vector of endogenous variables: GZ spreads, Default spreads (DS), Excess bond premium (EBP), Real GDP per capita (GDP), CPI inflation, and CFNAI; $E_t$ represents expectations data (e.g., forecasted GDP growth, inflation expectations, or credit risk

perceptions); $\lambda^{(r)}$ captures the effect of expectations rigidity in regime $r$; other terms are defined as in the baseline TBVAR model.

The expectation data ($E_t$) is crucial for quantifying information rigidity. For this analysis, I incorporate the Blue Chip Economic Indicators[2] for expectations of real GDP per capita and GZ credit spreads. I also extend the Bayesian framework by introducing priors on $\lambda^{(r)}$, the information rigidity parameter. Priors on $\lambda^{(r)}$ is centered around zero, reflecting the assumption of limited prior knowledge about the magnitude of information rigidity. The posterior distribution incorporates the likelihood of observed data under the specified TBVAR structure. The TBVAR model separately estimates the role of information rigidity $\lambda^{(r)}$ in each regime. This allows us to test the hypothesis that information rigidity amplifies the effects of sentiment shocks during periods of stability (Regime 1) and dampens them during stress (Regime 2). To account for the interplay between sentiment shocks and information rigidity, we include interaction terms between $E_t$ and sentiment, where $InteractionTerm = E_t * Sentiment_t$.

Figure 6 reports the output, which sheds light on how different regimes, characterized by varying levels of sentiment and credit dynamics, exhibit markedly distinct responses to sentiment shocks. These differences not only highlight the presence of asymmetric behaviors across economic conditions but also provide evidence of how information rigidity shapes credit and macroeconomic outcomes.

In Regime 1, the sharp and rapid responses of GDP and GZ spreads to sentiment shocks suggest an environment where information flows efficiently, allowing economic agents to adjust their expectations and actions swiftly. This regime likely corresponds to periods of higher economic confidence or stability, where market participants possess clearer signals

[2]Blue Chip Economic Indicators: a widely respected monthly publication that compiles economic forecasts from leading economists, industry experts, and financial institutions. Established in 1976, it provides consensus forecasts for key macroeconomic indicators, including GDP growth, inflation, interest rates, and industrial production, covering both short-term and long-term horizons. The forecasts represent an aggregation of expert opinions, making it a reliable benchmark for assessing economic conditions and trends. Due to its comprehensive and forward-looking nature, the publication is frequently used in academic research, policy analysis, and financial decision-making. More information is available at Blue Chip Economic Indicators.

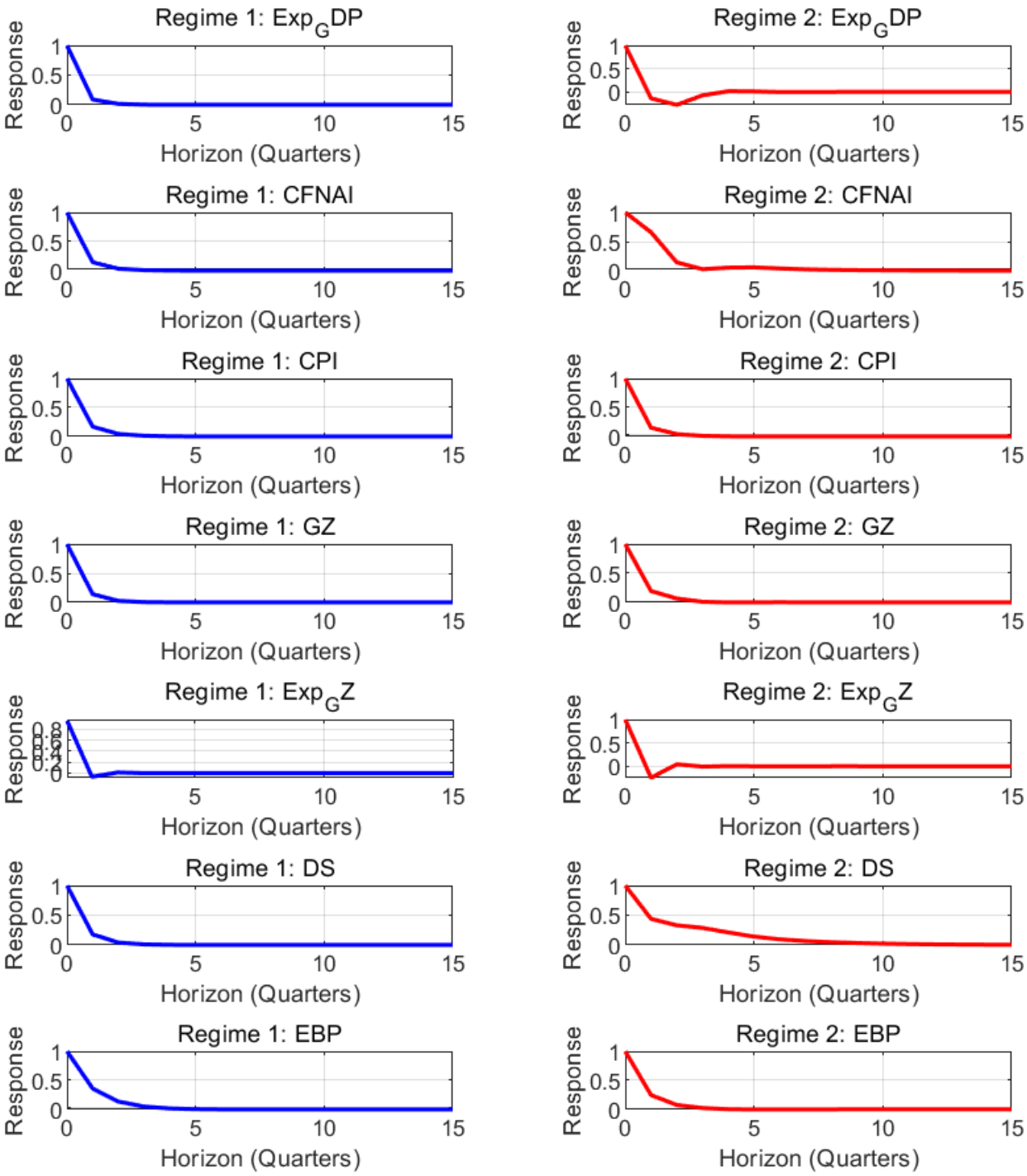



Figure 6: **Information Rigidity: Forecast Error Variance Decompositions of and Credit Spreads and Macroeconomic Activities.** This figure presents the forecast error variance decomposition (FEVD) results from the threshold Bayesian VAR (TBVAR) model under the existing of information rigidity, illustrating the contribution of sentiment shocks to the forecast variability of credit spreads and macroeconomic variables under the existing of information rigidity across different regimes. The left column (blue) corresponds to Regime 1, indicative of normal economic conditions, while the right column (red) represents Regime 2, characterized by economic downturns. The inclusion of expectation variables ($Exp_{GDP}$ and $ExpGZ$) allows for an assessment of information rigidity, highlighting how agents incorporate sentiment-driven signals into their forecasts. The results demonstrate that the predictive power of sentiment varies between regimes, with stronger informational effects observed in contractionary periods. These findings underscore the asymmetric role of sentiment in shaping economic expectations and credit conditions.

regarding future economic conditions. The behavior of the expectation variables, such as expected GDP growth and expected GZ spreads, further supports this interpretation: these variables show a quick alignment with actual variables, implying a well-functioning feedback mechanism between realized outcomes and expectations. This alignment reduces the persistence of sentiment shocks, ensuring that economic disruptions dissipate relatively quickly. Such behavior aligns with theories of rational expectations in efficient markets, where the adjustment process minimizes the amplification of initial shocks.

Conversely, Regime 2 displays sluggish and prolonged responses to sentiment shocks, indicative of heightened information rigidity. This regime may represent periods of elevated economic uncertainty, higher default spreads, or financial stress. In this context, the muted adjustment of both actual and expected variables suggests that economic agents struggle to process new information effectively. This rigidity can arise from factors such as uncertainty-induced inertia, reliance on outdated information, or limited access to credible signals. The prolonged persistence of sentiment shocks under this regime has significant policy implications, as it implies that uncertainty can amplify and extend economic downturns by delaying the adjustment of expectations and actions. Notably, the divergence between actual and expected variables in this regime underscores the breakdown of the expectation-formation process, further exacerbating the rigidity and persistence of shocks.

An important observation across both regimes is the critical role played by expectation variables in mediating the dynamics of sentiment shocks. The differential behavior of expected GDP growth and GZ spreads highlights the significance of expectation-formation mechanisms in amplifying or dampening the effects of shocks. In Regime 1, the expectation variables quickly converge with actual outcomes, stabilizing the system, while in Regime 2, the lag in expectations contributes to the persistence of deviations, signaling a feedback loop that prolongs the effects of shocks. This finding aligns with models of imperfect information, such as sticky information or rational inattention theories, where the speed of information updating is influenced by economic conditions.

The results also emphasize the critical policy implications of information rigidity. For example, in regimes with high rigidity (Regime 2), monetary or fiscal policy interventions may need to be more aggressive to counteract the slow adjustment of expectations. Moreover, improving the quality and dissemination of economic data could help reduce uncertainty and enhance the responsiveness of economic agents. In contrast, during periods of low rigidity (Regime 1), policy interventions may focus more on preventing over-adjustments or excessive volatility, as information flows efficiently in this environment.

In summary, the findings underscore the importance of regime-dependent dynamics in understanding the interplay between sentiment shocks, information rigidity, and macro-financial variables. By explicitly modeling these dynamics through a threshold Bayesian VAR (TBVAR) framework, this study provides novel insights into how economic regimes shape the propagation and persistence of shocks. These insights are invaluable for designing effective policy responses that account for the asymmetric nature of economic adjustments across different states of the economy.

# 6 Conclusion

This paper provides a comprehensive analysis of the role of credit market sentiment in driving credit market dynamics, utilizing a threshold Bayesian VAR (TBVAR) model to account for the regime-dependent and non-linear nature of sentiment propagation. By incorporating sentiment shocks and their interactions with key macro-financial variables, such as GDP, credit spreads, and expectations, my study offers novel insights into the complex mechanisms underlying credit cycles.

My findings highlight three key contributions to the literature. First, I show that credit market sentiment shocks have asymmetrical effects across regimes, with more persistent and pronounced impacts during periods of heightened credit market stress. This underscores the importance of accounting for non-linearities in the transmission of sentiment-driven fluctua-

tions. Second, I integrate information rigidity into the analysis, demonstrating that delayed adjustments in expectations amplify the persistence of sentiment shocks, particularly in stressed regimes. This perspective enriches the existing understanding of credit cycles by emphasizing the role of forward-looking variables and behavioral dynamics. Third, my structural identification of sentiment shocks allows us to disentangle their effects from broader macroeconomic shocks, providing clearer causal insights into the mechanisms at play.

The results carry significant implications for policymakers. In regimes characterized by high credit market stress, interventions aimed at improving the flow of information, reducing uncertainty, and aligning expectations with economic fundamentals could mitigate the persistence of sentiment-driven disruptions. Furthermore, by fostering transparency and promoting financial literacy, policymakers can enhance the resilience of credit markets to adverse sentiment shocks, thereby stabilizing the broader economy.

Overall, this paper contributes to the growing body of literature on the interplay between sentiment, credit markets, and macroeconomic outcomes. By bridging the gap between traditional financial friction models and behavioral finance, our framework offers a nuanced perspective on the dynamics of credit cycles. Future research could build on these findings by exploring cross-country applications, incorporating global credit sentiment measures, or examining the interaction between sentiment shocks and monetary policy. Such extensions would further enhance our understanding of the pivotal role of credit markets in shaping economic stability.

# References


Bordalo, P., Gennaioli, N., and Shleifer, A. (2018). Diagnostic expectations and credit cycles. *The Journal of Finance*, 73(1):199–227.

Coibion, O. and Gorodnichenko, Y. (2012). What can survey forecasts tell us about information rigidities? *Journal of Political Economy*, 120(1):116–159.

Coibion, O. and Gorodnichenko, Y. (2015). Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review*, 105(8):2644–2678.

Fama, E. F. and French, K. R. (1989). Business conditions and expected returns on stocks and bonds. *Journal of financial economics*, 25(1):23–49.

Gilchrist, S. and Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American economic review*, 102(4):1692–1720.

Gomes, J. F., Grotteria, M., and Wachter, J. A. (2019). Cyclical dispersion in expected defaults. *The Review of Financial Studies*, 32(4):1275–1308.

Gorodnichenko, Y. and Lee, B. (2020). Forecast error variance decompositions with local projections. *Journal of Business & Economic Statistics*, 38(4):921–933.

Greenwood, R. and Hanson, S. G. (2013). Issuer quality and corporate bond returns. *The Review of Financial Studies*, 26(6):1483–1525.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American economic review*, 95(1):161–182.

López-Salido, D., Stein, J. C., and Zakrajšek, E. (2017). Credit-market sentiment and the business cycle. *The Quarterly Journal of Economics*, 132(3):1373–1426.

Plagborg-Møller, M. and Wolf, C. K. (2022). Instrumental variable identification of dynamic variance decompositions. *Journal of Political Economy*, 130(8):2164–2202.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: journal of the Econometric Society*, pages 1–48.