DYNAMIC RELATIONSHIP BETWEEN CONSUMER CONFIDENCE

AND FEDERAL FUNDS INTEREST RATES:

VECM AND TVECM ANALYSES

by

HOFNER DOYDORA RUSIANA

(Under the Direction of Ray (Shuyang) Bai)

ABSTRACT

This research investigates the relationship between the Federal Funds Rate (FEDFUNDS) and the University of Michigan Consumer Sentiment Index (UMCSENT). Employing Johansen cointegration tests, Vector Error Correction Models (VECM), and Threshold Vector Error Correction Models (TVECM), this study explores the existence of cointegration, short-term dynamics, and threshold effects between these macroeconomic indicators. Results show that there is cointegration between FEDFUNDS and UMCSENT. The findings also reveal a stable long-term relationship between FEDFUNDS and UMCSENT. Additionally, the VECM analysis demonstrates short-term adjustments in both variables, highlighting their interdependence. Further, the TVECM analysis identifies a threshold effect, indicating a shift in the relationship when FEDFUNDS crosses a specific threshold value.

INDEX WORDS: threshold cointegration, nonlinear relationship, monetary policy, VECM

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HOFNER DOYDORA RUSIANA

B.S., University of the Philippines, 2010

M.S., University of Georgia, 2015

M.A.B., University of Georgia, 2017

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HOFNER RUSIANA

Major Professor: Ray (Shuyang) Bai
Committee: Liang Liu
Cesar Escalante

Electronic Version Approved:

Ron Walcott
Vice Provost for Graduate Education and Dean of the Graduate School
The University of Georgia
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DEDICATION

Dedicated to my parents, Vicente and Evelia, for their love and support.

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To my major professor, Dr. Ray (Shuyang) Bai, and my committee members, Dr. Liang Liu and Dr. Cesar Escalante, I express my sincere gratitude for your guidance, support, and expertise in completing this research.

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CHAPTER 1

INTRODUCTION

Consumer sentiment is a pivotal indicator in economics, reflecting the psychological and economic state of the population and the stability of markets (Vuchelen, 2004). Understanding how this factor influences the decision-making processes of central banks, particularly the Federal Reserve, is crucial for economic stability and growth. Against rapidly changing global economic scenarios, investigating the intricate relationship between consumer sentiment and the Federal Reserve's responses becomes paramount.

The Federal Reserve, as the United States' central banking system, plays a vital role in steering the country's economy (Mester, 2017). However, the dynamics of how consumer sentiment changes influence the Fed's policies remain complex and multifaceted. Understanding the relationship between the Federal Reserve interest rate and consumer interest rates is crucial for consumers making financial decisions. When interest rates are high, it may be prudent to delay major purchases or refinance existing loans at lower rates. Conversely, when interest rates are low, it may be an opportune time to borrow money for investments or to consolidate debt.

Historically, economists have explored the linear relationships between monetary policy tools and consumer sentiment. However, the real-world dynamics governing these variables often defy linear models. The modern economic landscape is marked by complexities, including threshold effects, where the relationship between variables transforms at specific thresholds, and cointegration, signifying a long-term equilibrium between variables despite short-term fluctuations.

This thesis will employ the Vector Error Correction Model (VECM) and the Threshold Vector Error Correction Model (TVECM) to investigate the relationship between the federal funds rate (FEDFUNDS) and the University of Michigan Consumer Sentiment Index (UMCSENT). The VECM is utilized to analyze the dynamic interactions between these time-series variables. The TVECM, an extension of the VECM, incorporates the possibility of nonlinear adjustments to the long-run equilibrium relationship between the variables.

Using VECM aims to delineate the short and long-run dynamics between these time-series variables, while the TVECM will shed light on the long-run equilibrium relationship and the presence of threshold cointegration. These findings will have significant implications for policymakers and investors in understanding the interplay between monetary policy and consumer sentiment, ultimately influencing economic activity.

This study focuses exclusively on the United States, examining the Federal Reserve's responses within the national economic context. While it provides a comprehensive analysis of historical data, it is limited by the availability and reliability of the datasets used. Additionally, the Federal Reserve's decision-making processes are influenced by many factors, some of which need to be fully captured within the scope of this research.

The remainder of the thesis is organized as follows: Chapter 2 will review related literature. Chapter 3 describes the methodology and data used. Chapter 4 discussed the empirical results—and finally, Chapter 5 discussed conclusions and implications.

CHAPTER 2

LITERATURE REVIEW

2.1 Consumer Perceptions and Federal Reserve's Actions

The relationship between consumer sentiment and the Federal Reserve's decision-making process is deeply rooted in the theoretical frameworks of consumer behavior, monetary policy, and economic transmission mechanisms.

Consumer behavior theories provide a window into the formation and implications of consumer sentiment. With its emphasis on the relationship between consumption and disposable income, Keynesian economics highlights the role of consumer sentiment as a reflection of expectations about future income (Keynes, 1936).

Beyond Keynesian economics, other consumer behavior theories, such as the life-cycle hypothesis (LCH) and the permanent income hypothesis (PIH), provide further insights into the factors that shape consumer sentiment and its implications for economic activity (Modigliani & Brumberg, 1954). These theories propose that consumer spending decisions are not solely driven by current income but also by long-term expectations about future income and wealth.

The LCH suggests that individuals plan their consumption expenditures throughout their lifetimes, aiming to maintain a relatively stable level of consumption despite fluctuations in income over different life stages (Modigliani & Brumberg, 1954). According to the LCH, consumer sentiment is influenced by an individual's assessment of their current and expected future income relative to their desired consumption level. When consumers anticipate a decline in future income, they may tend to reduce their spending in the present, potentially dampening aggregate demand. Conversely, if consumers are optimistic about their future income prospects, they may be more willing to increase their current consumption, boosting aggregate demand.

The PIH, on the other hand, proposes that consumers distinguish between permanent income, which represents their long-term average income, and transitory income, which represents temporary fluctuations in income (Friedman, 1957). According to the PIH, consumers base their consumption decisions primarily on permanent income, smoothing out the impact of transitory income fluctuations. In this context, consumer sentiment is viewed as a reflection of an individual's assessment of their permanent income, influencing their consumption patterns over the longer term.

On the side of the Federal Reserve, the interest rate channel and expectations channel are two primary transmission mechanisms through which changes in monetary policy influence economic activity (Bernanke & Gertler, 1999; Woodford & Walsh, 2005). These channels operate through various economic linkages, affecting consumer spending, investment, and borrowing decisions.

The interest rate channel, a fundamental mechanism of monetary policy, works through the direct impact of interest rates on borrowing costs and investment decisions. When central banks lower interest rates, borrowing becomes more affordable for consumers and businesses, encouraging increased spending and investment. This surge in demand stimulates economic activity and can lead to faster economic growth.

On the other hand, when central banks raise interest rates, borrowing becomes more expensive, potentially discouraging spending and investment. This demand reduction can dampen economic activity and help to slow an overheating economy or combat inflationary pressures.

The expectations channel, another important mechanism of monetary policy, operates through the influence of monetary policy actions on economic expectations and beliefs (Woodford & Walsh, 2005). When central banks signal their intention to pursue expansionary monetary policy, such as by lowering interest rates, it can bolster consumer and business confidence, leading to increased spending and investment. This surge in demand, fueled by positive expectations, can stimulate economic growth.

2.2 Consumer Sentiment Index and Its Impact on Federal Reserve's Decision-Making

Consumer sentiment, as measured by various indices such as the University of Michigan Consumer Sentiment Index (UMCSENT) and the Conference Board Consumer Confidence Index (CCI), serves as a valuable barometer of public perception regarding the current and future economic outlook (Otoo, 1999). It represents the collective mood of consumers, encompassing their attitudes toward personal finances, employment prospects, and overall economic conditions. This information plays a critical role in shaping the decision-making processes of the Federal Reserve as it provides insights into the economic expectations and spending behavior of households, which are key drivers of aggregate demand and economic growth.

Numerous studies have examined the relationship between consumer sentiment and the Federal Reserve's monetary policy decisions, particularly those involving interest rate adjustments (Claus & Nguyen, 2020; Galariotis et al., 2018). These investigations have consistently demonstrated that consumer sentiment serves as a leading indicator of future economic activity, providing valuable insights into households' expectations and spending behavior, crucial drivers of aggregate demand and economic growth.

When consumer sentiment is high, reflecting optimism about personal finances, employment prospects, and overall economic conditions, individuals tend to be more confident in their spending decisions. This increased spending boosts aggregate demand, stimulating economic growth and potentially leading to higher inflation. Conversely, low consumer sentiment, characterized by pessimism and uncertainty about the economic outlook, can lead to declining consumer spending. This reduced demand can dampen aggregate economic activity and raise concerns about potential recessions.

The Federal Reserve closely monitors consumer sentiment indices, such as the University of Michigan's Consumer Sentiment Index and the Conference Board's Consumer Confidence Index, to assess the economy's overall health and gauge the potential impact of its policy decisions. Rising consumer sentiment is generally considered a positive sign, suggesting that households are more likely to engage in spending and investment activities, which can stimulate economic growth. Conversely, declining consumer sentiment may prompt the Federal Reserve to adopt a more accommodative monetary policy, such as lowering interest rates, to encourage borrowing and spending, thereby supporting economic expansion.

Empirical evidence supports the notion that consumer sentiment significantly influences the Federal Reserve's interest rate decisions. Studies have shown that changes in consumer sentiment have a measurable impact on future interest rate movements. For instance, a study by Howrey (2001) found that consumer sentiment is positively correlated with interest rate expectations, implying that when consumer sentiment is high, individuals expect higher interest rates. This suggests that the Federal Reserve considers consumer sentiment when setting interest rates, as it reflects the overall economic outlook and the potential impact of monetary policy on household behavior.

CHAPTER 3

DATA AND METHODOLOGY

3.1 Data

In this study, we utilize monthly data from January 1992 to May 2023, spanning over three decades. This period encompasses a wide range of economic conditions, including periods of economic growth, recession, and inflation. By using data from this extended period, we can gain a more comprehensive understanding of the relationship between consumer sentiment and interest rates.

The data we use in this study comes from the University of Michigan Survey of Consumers Research Center and the Federal Reserve. The University of Michigan Survey of Consumers Research Center collects monthly data on the Consumer Sentiment Index (UMCSENT), a measure of consumer confidence in the economy. The Federal Reserve collects monthly data on the Federal Funds Rate (FEDFUNDS), the interest rate banks lend to each other overnight. The data used in this study were retrieved from the St. Louis Fed FRED® database.

3.1.1 Consumer Sentiment Index (UMCSENT)

The Consumer Sentiment Index (UMCSENT) is a monthly survey conducted by the University of Michigan Survey of Consumers Research Center. The survey measures consumer confidence in the economy, personal financial situation, and buying conditions. The UMCSENT is a composite index of three sub-indices (Kellstedt et al., 2015):

Current Economic Conditions: This sub-index measures consumers' assessment of the current economic situation, such as the job market and inflation.

Expectations: This sub-index measures consumers' expectations for the future economic situation, such as personal income growth and job opportunities.

Buying Conditions: This sub-index measures consumers' assessment of the current buying conditions for durable goods, such as cars and homes.

The UMCSENT is a widely used indicator of consumer confidence and is closely watched by policymakers and investors. A high UMCSENT indicates that consumers are confident in the economy and are likely to spend more money. A low UMCSENT indicates that consumers are less confident in the economy and may be more likely to save money.

3.1.2 Federal Funds Rate (FEDFUNDS)

The Federal Funds Rate (FEDFUNDS) is the interest rate banks lend to each other overnight. The FEDFUNDS is set by the Federal Open Market Committee (FOMC), a Federal Reserve committee (Federal Reserve, 2007). The FOMC meets eight times yearly to discuss and set monetary policy, including the FEDFUNDS.

The FEDFUNDS is the most critical short-term interest rate in the United States and has a significant impact on the economy. A higher FEDFUNDS rate makes it more expensive for businesses to borrow money, which can slow economic growth. A lower FEDFUNDS rate makes it less expensive for businesses to borrow money, which can stimulate economic growth.

The decision to focus on only two variables, namely the University of Michigan Consumer Sentiment Index (UMCSENT) and the Federal Reserve's interest rate decisions, is a deliberate choice. The UMCSENT is a comprehensive measure that captures a wide range of consumer perceptions regarding the current and future economic outlook. It encompasses factors such as employment expectations, income prospects, and overall economic confidence, making it a holistic indicator of consumer sentiment. By employing a single comprehensive variable, we can avoid the potential pitfalls of introducing redundant or overlapping information from additional variables.

3.2 Empirical Model

We employ various time series econometric techniques to analyze the relationships between consumer sentiment (UMCSENT) and interest rates (FEDFUNDS).

Stationarity Test

Time series data represents a sequence of observations ordered chronologically. A unit root test, specifically the Augmented Dickey-Fuller (ADF) test, is employed on UMSCENT and FEDFUNDS to assess stationarity. In cases where the data is non-stationary, differencing is applied to transform it into a stationary form, as expressed by the equation:

$$\Delta Y_t = Y_t - Y_{t-1} \tag{1}$$

The ADF test involves estimating an equation that includes the lagged value of the dependent variable (Dickey & Fuller, 1981), denoted as ΔY_t, and is represented by:

$$\Delta Y_t = a_0 + \delta Y_{t-1} + \sum_{i=1}^{p} a_i \Delta Y_t + u_t \tag{2}$$

Here, u_t signifies the residual value of the ADF equation, and δ is the first lag parameter (Y_{t-1}). The null hypothesis (H_0) of the ADF test assumes non-stationarity, while the alternative hypothesis (H_1) suggests stationarity.

The test statistic, denoted as $\tau_{\text{statistic}}$, is calculated as:

$$\tau_{\text{statistic}} = \frac{\hat{\delta}}{SE(\hat{\delta})} \tag{3}$$

The decision rule involves comparing $\tau_{\text{statistic}}$ to critical values or assessing the p-value. If $\tau_{\text{statistic}} < \tau_{5\%}$ or the p-value is less than the significance level ($\alpha = 0.05$), the null hypothesis is rejected, indicating that the data is stationary.

3.3 Optimal Lag Length

Determining the appropriate lag length in constructing the VECM model is crucial as it significantly impacts the accuracy of accepting or rejecting the null hypothesis (H_0) and the precision of the resulting estimates. Selecting a lag that is too short may lead to an incomplete representation of the dynamic model, while an excessively long lag results in inefficient estimation due to a lack of degrees of freedom. The formulas for the criteria are outlined below:

$$AIC_p = -2T\left[\ln\left(\widehat{\sigma_p^2}\right)\right] + 2p \tag{4}$$

$$SIC_p = \ln\left(\widehat{\sigma_p^2}\right) + \frac{[p\ln(T)]}{T} \tag{5}$$

$$\mathrm{HQ_p} = \ln\left(\widehat{\sigma_\mathrm{p}^2}\right) + 2\,\frac{\ln(\ln(\mathrm{T}))}{\mathrm{T}} \tag{6}$$

where

p : length of the lag

$\widehat{\sigma_p^2}$: $(T-p-1)^{-1}\sum_{t=1}^{T}\varepsilon_t^2$

T : number of observations

According to Lütkepohl (2005), the lag length selection for a Vector Error Correction Model (VECM) can differ from that of a Vector Autoregressive (VAR) model, requiring a lag length of p-1. As such, this thesis follows this method and does lag length p-1 after running the lag selection criteria.

3.3 Cointegration Analysis

Following the initial differencing of the time series data, a secondary assessment is conducted to determine the presence of cointegration using Johansen Cointegration Test. This test determines whether a long-term relationship exists among the variables. If cointegration is confirmed, the subsequent model formed is the Vector Error Correction Model (VECM); otherwise, a Vector Autoregressive (VAR) model in first differences is established.

The Cointegration Test aims to determine long-run equilibrium within time series data and linear variables. Utilizing the Johansen cointegration method, the test formulates the following hypotheses:

H_0 : $rank\ cointegration \le k$ (there is cointegration at the rank k)

H_1 : $rank\ cointegration > k$ (there is no cointegration in the rank k)

The test statistics employ the trace statistic through the feature root test

$$\lambda_{\text{trace}}(r) = -T \sum_{i=r+1}^{k} \ln\left(1 - \widehat{\lambda_\iota}\right) \tag{7}$$

where
k : 2
T : number of observations
$\widehat{\lambda_\iota}$: estimated eigenvalues
r : rank cointegration, where the possible sum r is from $r = 0$ to $r = k - 1$.

The criteria for the test involve rejecting $\lambda_{\text{trace}}\,(r) > \lambda_{\text{trace. }5\%}$, indicating the presence of cointegration at the specified rank.

3.4 Vector Error Correction Models (VECM)

Employing the Vector Error Correction Model (VECM) for analyzing the relationship between FEDFUNDS and UMCSENT is grounded in its ability to effectively handle non-stationary variables and its suitability for examining both short-term and long-term dynamics. Unlike the Vector Autoregressive (VAR) model, the VECM does not require the variables to be stationary, a property that is often violated by economic time series data. Instead, it focuses on the cointegration relationship between the variables, allowing for the analysis of non-stationary variables that share a long-term equilibrium relationship (Engle & Granger, 1987). This characteristic makes the VECM particularly well-suited for investigating the dynamic interplay between FEDFUNDS and UMCSENT, as both variables may exhibit non-stationary behavior.

Furthermore, the VECM offers a comprehensive framework for analyzing short-term and long-term relationships. It incorporates an error correction term that captures the deviations from the long-term equilibrium, enabling the examination of how short-term adjustments contribute to the restoration of the long-term relationship between FEDFUNDS and UMCSENT. This feature provides a more complete picture of the dynamic interactions between the two variables, extending beyond the limitations of stationary models that focus solely on short-term dynamics.

In this stage, the Vector Error Correction Model (VECM) estimation is conducted in a stationary state. This estimation model is crucial in delineating the relationship between short-term and long-term dynamics. The VECM encompasses an equation for each variable, wherein the short-term dynamic relationship is influenced by deviations from the long-term equilibrium, termed the Error Correction Term (ECT), denoted as $W(\beta)$ in the form of the equation:

$$ECT_T = Y_{1t} - \beta_0 - \beta_1 Y_{2t} - \cdots - \beta_l Y_{lt} \quad (8)$$

The VECM model incorporates equations for each variable, capturing the changes in variables up to lag p. This is represented by the equation:

$$\begin{bmatrix} \Delta Y_{1t} \\ \Delta Y_{2t} \\ \vdots \\ \Delta Y_{lt} \end{bmatrix}_{l\times 1} = \begin{bmatrix} a_{10} & a_{y1} & a_{11,1} & \cdots & a_{1l,p} \\ a_{20} & a_{y2} & a_{21,1} & \cdots & a_{2l,p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{l0} & a_{yl} & a_{l1,1} & \cdots & a_{ll,p} \end{bmatrix} \begin{bmatrix} 1 \\ W_{t-1}(\beta) \\ \Delta Y_{1t-1} \\ \vdots \\ \Delta Y_{lt-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{y1,t} \\ \varepsilon_{y2,t} \\ \varepsilon_{y3,t} \\ \vdots \\ \varepsilon_{yl,t} \end{bmatrix} \quad (9)$$

$$\Delta y_t = A^T y_{t-1}(\beta) + u_t$$

where

Δy_t = $\left[\Delta Y_{\{1\ t\}} \Delta Y_{\{2\ t\}} \cdots \Delta Y_{\{l\ t\}}\right]^{\{T\}}$
$W_{t-1}(\beta)$ = ECT_{t-1} Is the ECT of the previous period.
$Y_{t-1}(\beta)$: $vector\ of\ size\ k \times 1$
A : $matrix\ of\ size\ k \times l$
k = $2 + lp$
u_t = $\left[\varepsilon_{y1,t} \cdots \varepsilon_{yl,t}\right]^{\{T\}}$

Alternatively, the model can be expressed as a system of equations:

$$\Delta Y_{1t} = a_{10} + a_{y1} W_{t-1} + \sum_{i=1}^{p} a_{11,i} \Delta Y_{1t-i} + \sum_{i=1}^{p} a_{12,i} \Delta Y_{2t-i} + \varepsilon_{1t} \quad (10)$$

$$\Delta Y_{2t} = a_{20} + a_{y2} W_{t-1} + \sum_{i=1}^{p} a_{21,i} \Delta Y_{1t-i} + \sum_{i=1}^{p} a_{22,i} \Delta Y_{2t-i} + \varepsilon_{2t} \quad (11)$$

The error terms are assumed to satisfy the conditions of no autocorrelation, homoscedasticity, and normality. These assumptions ensure that the estimated coefficients are unbiased and efficient. Violating these assumptions may lead to biased parameter estimates and affect the reliability of the model's inferences.

3.5 Threshold Vector Error Correction Model (TVECM)

To investigate the possibility of non-linearity in the long-run relationship between consumer sentiment and interest rates, we employ the TVECM. We estimate the TVECM and identify the threshold levels that divide the data into different regimes (Hansen, 1999). We then analyze the long-run equilibrium relationships within each regime to understand how the relationship between consumer sentiment and interest rates changes depending on the level of consumer sentiment.

Before examining the modeling of the Threshold Vector Error Correction Model (TVECM), it is important to perform a significance test to determine whether there is a presence of a threshold. The SupLagrange Multiplier (SupLM) Test is utilized for this goal, with p-values obtained through a fixed regressor bootstrap (Hansen & Seo, 2002). If the SupLM test indicates a statistically significant threshold effect, using the Threshold Vector Error Correction Model (TVECM) is considered appropriate. On the other hand, if the test indicates the absence of a significant threshold effect, the Vector Error Correction Model (VECM) is adequate for modeling.

To detect the presence of a threshold, the Lagrange Multiplier test is utilized with the following hypotheses:

H_0 : The model is a linear VECM

H_1 : Model is the threshold VECM

The p-value is determined through a fixed regressor bootstrap with 1000 replications using the RStudio package tsDyn. For the Lagrange Multiplier test, the test statistic LM(β,γ) is expressed as:

$$LM(\beta,\gamma) = \text{vec}\left(\widehat{\boldsymbol{A}}_{\mathbf{1}}(\beta,\gamma) - \widehat{\boldsymbol{A}}_{\mathbf{2}}(\beta,\gamma)\right)' \left(\widehat{\boldsymbol{V}}_{\mathbf{1}}(\beta,\gamma) + \widehat{\boldsymbol{V}}_{\mathbf{2}}(\beta,\gamma)\right)^{-1} \times \text{vec}\left(\widehat{\boldsymbol{A}}_{\mathbf{1}}(\beta,\gamma) - \widehat{\boldsymbol{A}}_{\mathbf{2}}(\beta,\gamma)\right) \tag{12}$$

In cases where (β,γ) is unknown, the test statistic cannot be utilized. An alternative approach involves the use of the SupLM statistic:

$$\text{SupLM} = \underset{\gamma_L \le \gamma \le \gamma_U}{\text{Sup}} \text{L}(\tilde{\beta},\gamma) \tag{13}$$

Here, γ represents the threshold, $\tilde{\beta}$ is an estimator of the linear VECM cointegration coefficient, γ_L is the π_0 percentile of ECT_{t-1}, and γ_U is the $1-\pi_0$ percentile of ECT_{t-1}. The optimization involves evaluating the grid $[\gamma_L, \gamma_U]$ with the cointegration vector β fixed at $\tilde{\beta}$ and using a fixed regressor bootstrap is determined as follows:

$$\text{SupLM}^* = \text{Sup}_{\gamma_L \le \gamma \le \gamma_U} \text{vec}\left(\widehat{\boldsymbol{A}}_{\mathbf{1}}(\gamma)_b - \widehat{\boldsymbol{A}}_{\mathbf{2}}(\gamma)_b\right)' \left(\widehat{\boldsymbol{V}}_{\mathbf{1}}(\gamma)_b - \widehat{\boldsymbol{V}}_{\mathbf{2}}(\gamma)_b\right)^{-1} \times \text{vec}\left(\widehat{\boldsymbol{A}}_{\mathbf{1}}(\gamma)_b - \widehat{\boldsymbol{A}}_{\mathbf{2}}(\gamma)_b\right) \tag{14}$$

where, $\widehat{A_1}(\gamma)_b$ and $\widehat{A_2}(\gamma)_b$ denote the coefficient matrix estimates, while $\widehat{V_1}(\gamma)_b$ and $\widehat{V_2}(\gamma)_b$ represent the Eicker-White covariance matrix estimator for vec$\widehat{A_1}(\gamma)_b$ and vec$\widehat{A_2}(\gamma)_b$, respectively.

As stated in Hansen & Seo (2002), the approximation derived from the distribution *Sup*M** yields valid results compared to the SupLM distribution. While this distribution remains unknown, it can be calculated using simulations to obtain the p-value. They propose a likelihood to estimate the values of β and the threshold γ_j, where $j = 1$ to $l - 1$, and l represents the number of TVECM model regimes with two variables:

(15)

$$L_n = -\frac{n}{2}\ln\left|\hat{\Sigma}(\beta, \gamma_j)\right| - \frac{2n}{2}$$

The general forms of TVECM with two regimes are presented as follows:

(16)

$$\Delta Y_{1t} = \begin{cases} \Delta Y_{1t} = a_{110} + a_{y11}W + \sum_{i=1}^{p} a_{111,i}\Delta Y_{1t-i} + \sum_{i=1}^{p} a_{112,i}\Delta Y_{2t-i} + \varepsilon_{11,t}, & \text{if } W \le \gamma \\ \Delta Y_{1t} = a_{210} + a_{y21}W + \sum_{i=1}^{p} a_{211,i}\Delta Y_{1t-i} + \sum_{i=1}^{p} a_{212,i}\Delta Y_{2t-i} + \varepsilon_{21,t}, & \text{if } W > \gamma \end{cases}$$
$$\Delta Y_{2t} = \begin{cases} \Delta Y_{2t} = a_{120} + a_{y12}W + \sum_{i=1}^{p} a_{121,i}\Delta Y_{1t-i} + \sum_{i=1}^{p} a_{122,i}\Delta Y_{2t-i} + \varepsilon_{12,t}, & \text{if } W \le \gamma \\ \Delta Y_{2t} = a_{220} + a_{y22}W + \sum_{i=1}^{p} a_{221,i}\Delta Y_{1t-i} + \sum_{i=1}^{p} a_{222,i}\Delta Y_{2t-i} + \varepsilon_{22,t}, & \text{if } W > \gamma \end{cases}$$

where W is the error correction term (ECT) , W_{t-1} (β).

CHAPTER 4

EMPIRICAL RESULTS

4.1 Stationarity test and Optimal Lag Length

Table 1. Stationarity Test Results

Variable	ADF Statistic	p-value
UMCSENT	-2.14831	0.514443
FEDFUNDS	-3.18482	0.090708

The ADF statistic for UMCSENT is -2.148309, and the p-value is 0.514443. Since the p-value is greater than 0.05, we fail to reject the null hypothesis that UMCSENT is non-stationary. Therefore, UMCSENT is likely non-stationary at the 5% significance level.

The ADF statistic for FEDFUNDS is -3.184817, and the p-value is 0.0907078. Since the p-value is still greater than 0.05, we fail to reject the null hypothesis. Therefore, we can conclude that FEDFUNDS is also likely non-stationary at the 5% significance level.

Since both UMCSENT and FEDFUNDS have been found to be non-stationary, we can proceed with testing for cointegration. If the two series are found to be cointegrated, then we can use a vector error correction model (VECM) to model the relationship between the two series. A VECM is a type of time series model that is specifically designed for modeling cointegrated variables.

The optimal lag length for the VECM was determined using the Hannan-Quinn (HQ) criterion. The HQ criterion indicated an optimal lag length of 2. However, Lutkepohl's (2005) method suggests using a lag length of p-1. We employed other lag length selection criteria to further investigate the optimal lag length and indicated the same or close value with HQ. Given the recommendation from the different lag length selection criteria, we decided to proceed with lag length 1 for further analysis.

4.2 Cointegration Test and VECM

The Johansen-Procedure was employed to explore the potential cointegration relationships between consumer sentiment (UMCSENT) and interest rates (FEDFUNDS). The results of the trace statistic test, with a linear trend, are detailed below:

Table 2. Johansen Cointegration Test Results

Test	Test Statistic	10% Critical Value	5% Critical Value	1% Critical Value
r <= 1	2.12	6.5	8.18	11.65
r = 0	20.6	15.66	17.95	23.52

Based on the results of the Johansen-Procedure test, it can be inferred that there is cointegration between the variables in the data because the test statistic (2.12) is less than the 5% critical value (8.18). This suggests that there is at least one cointegrating relationship among the variables. This suggests at least one cointegrating relationship exists between consumer sentiment and interest rates. The result concludes that consumer sentiment and federal interest rate have a cointegration or long-run equilibrium relationship.

Table 3. VECM Parameter Coefficient Estimation Results for FEDFUNDS and UMCSENT

FEDFUNDS		
Variables	Coefficient	SE
ECT	-0.0053	0.0037
Intercept	0.0007	0.0073
FEDFUNDS(-1)	0.6281	0.0412
UMCSENT(-1)	-6.80E-05	0.0018

UMCSENT		
Variables	Coefficient	SE
ECT	-0.0063	0.1057
Intercept	-0.0285	0.2102
UMCSENT(-1)	0.8576	1.1833
FEDFUNDS(-1)	-0.0332	0.0528

From the results, the VECM equation below are obtained:

$$\Delta\, FEDFUNDS = 0.0007 - 0.0053\, ECT_{t-1} + 0.6281 \Delta\, FEDFUNDS_{\,t-1} - (6.80\mathrm{E}-05)\, \Delta\, UMCSENT_{t-1} \tag{17}$$

$$\Delta\, UMCSENT = -0.0285 - 0.0063\, ECT_{t-1} + 0.8576\, \Delta\, UMCSENT_{t-1} - 0.0332\, \Delta\, FEDFUNDS_{\,t-1}$$

For the FEDFUNDS series, the ECT coefficient also indicates that the system converges to its long-run equilibrium at a rate of 0.53% per period.

The VECM also captures the short-run dynamics of the system. The results show that the FEDFUNDS series is positively correlated with its own lagged value and negatively correlated with the lagged value of the UMCSENT series. This suggests that interest rates are persistent in the short run and negatively affected by consumer sentiment.

The UMCSENT series is also positively correlated with its own lagged value, suggesting that consumer sentiment is persistent in the short run. However, there is no statistically significant relationship between the UMCSENT series and the lagged value of the FEDFUNDS series.

4.3 Threshold Cointegration Test and TVECM

In this section, we explore the Threshold Vector Error Correction Model (TVECM) outcomes and the subsequent threshold cointegration test. These analyses provide insights into the nonlinear interactions between consumer sentiment (UMCSENT) and interest rates (FEDFUNDS).

Table 4. Threshold Cointegration Test Results

Test Statistic	P-Value	0.90% Critical Value	0.95% Critical Value	0.99% Critical Value
18.31969	0.04	16.42296	18.50005	21.3445

The threshold cointegration test results suggest a threshold cointegrating relationship between the FEDFUNDS and UMCSENT series. This means the two series have a long-run equilibrium relationship but only above or below a certain threshold.

The p-value is 0.04, which suggests that the evidence for threshold cointegration is statistically significant at the 5% level but not at the 1% level.

Based on the grid search results, the estimated threshold value is 0.303.

Table 5. Summary of Parameter Coefficient Estimation Results TVECM 2-Regime

	Regime 1		Regime 2	
	FEDFUNDS	UMCSENT	FEDFUNDS	UMCSENT
ECT	-0.0257*	-0.2559	-0.0196	-0.1093
Intercept	0.0502	0.5559	-0.0273	-0.2472
FEDFUNDS(-1)	0.6361***	0.5891	0.6164***	1.4492
UMCSENT(-1)	0.002	-0.0086	-0.0019	-0.0559

(18)

$$\Delta\text{FEDFUNDS}_{1t} = \begin{cases} 0.0502 - 0.0257\ \text{ECT}_{t-1} + 0.6361\Delta\text{FEDFUNDS}_{t-1} + 0.002\Delta\text{UMCSENT}_{t-1}, & \text{if } W \leq 0.303 \\ -0.0273 - 0.0196\ \text{ECT}_{t-1} + 0.6164\Delta\text{FEDFUNDS}_{t-1} - 0.0019\Delta\text{UMCSENT}_{t-1}, & \text{if } W > 0.303 \end{cases}$$

$$\Delta\text{UMCSENT}_{2t} = \begin{cases} 0.5559 - 0.2559\ \text{ECT}_{t-1} + 0.5891\Delta\text{FEDFUNDS}_{t-1} - 0.0086\Delta\text{UMCSENT}_{t-1}, & \text{if } W \leq 0.303 \\ -0.2472 - 0.1093\ \text{ECT}_{t-1} + 1.4492\Delta\text{FEDFUNDS}_{t-1} - 0.0559\Delta\text{UMCSENT}_{t-1}, & \text{if } W > 0.303 \end{cases}$$

Up regime (Regime 1): The coefficient on the ECT term is -0.0257. This suggests that the system is converging to its long-run equilibrium at a rate of 2.57% per period. The coefficient on the FEDFUNDS(-1) term is 0.6362. This suggests that FEDFUNDS is persistent in the up regime.

Down regime (Regime 2): The coefficient on the ECT term is -0.0196. This suggests that the system is converging to its long-run equilibrium at a rate of 1.96% per period. The coefficient on the FEDFUNDS(-1) term is 0.6164. This suggests that FEDFUNDS is also persistent in the down regime.

The magnitude of the coefficient on the ECT term is more robust in the up regime than in the down regime. This suggests that the system converges to its long-run equilibrium more quickly in the up regime.

The coefficient on the UMCSENT(-1) term is negative in both regimes, but the magnitude of the coefficient is larger in the down regime. This suggests that UMCSENT is more responsive to FEDFUNDS in the down regime than in the up regime.

Overall, the results indicate that below the identified threshold, changes in both interest rates and consumer sentiment do not significantly correct back to their long-term equilibrium levels. However, above the threshold, changes in interest rates are corrected back to equilibrium, indicating a more stable relationship. Consumer sentiment, on the other hand, does not significantly affect the equilibrium in this regime.

These findings emphasize the asymmetric and nonlinear relationship between consumer sentiment and interest rates, revealing distinct behaviors in different market conditions.

CHAPTER 5

CONCLUSIONS

This paper investigates the complex relationship between consumer sentiment (UMCSENT) and interest rates (FEDFUNDS) using a threshold vector error correction model (TVECM). The results reveal nonlinear dynamics characterized by threshold effects. Below the threshold, neither FEDFUNDS nor UMCSENT significantly influences deviations from the long-term equilibrium. Above the threshold, changes in FEDFUNDS are significantly corrected back to equilibrium at a rate of -0.0258, while changes in UMCSENT do not significantly affect the equilibrium.

These findings suggest that the relationship between UMCSENT and FEDFUNDS is more stable and predictable above the threshold, providing valuable insights for policymakers and investors when making decisions in different market conditions.

While the historical dataset used in this study is comprehensive, it may only partially capture the nuances of rapidly evolving economic landscapes. Additionally, the complexity of the TVECM model challenges the straightforward interpretation of results. Future research should explore avenues to simplify these models and enhance their applicability and interpretability.

Overall, this thesis advances our understanding of the complex relationship between consumer sentiment and interest rates, shedding light on their nonlinear dynamics. The findings provide a solid foundation for policymakers, investors, and researchers, enriching our understanding of consumer sentiment and interest rate interactions and opening avenues for further exploration into nonlinear economic modeling.

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FIGURE 1. Consumer Sentiment Index and Interest Rates (1992-2023)

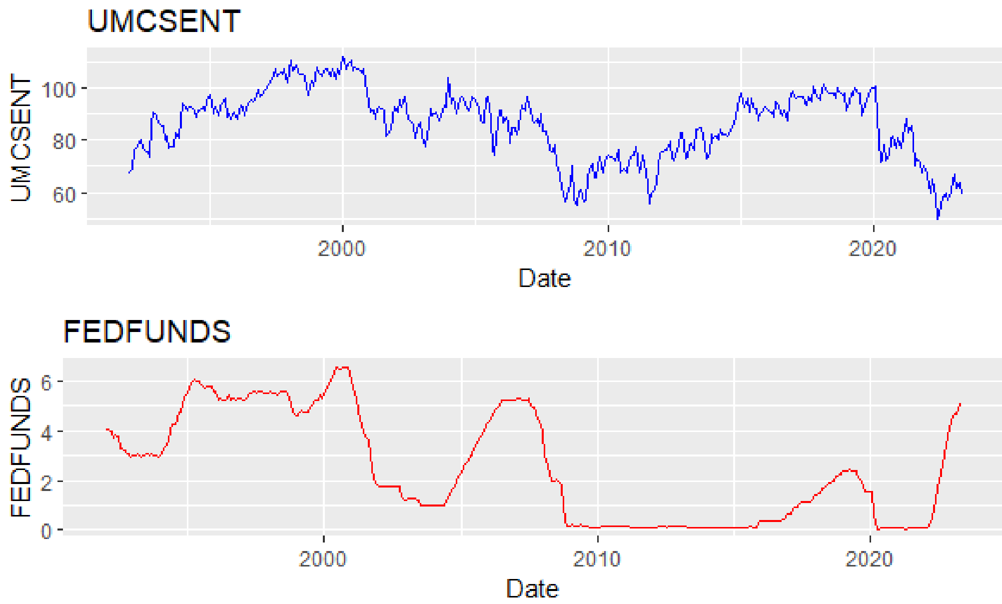

FIGURE 2. Linear vs. threshold cointegration plot

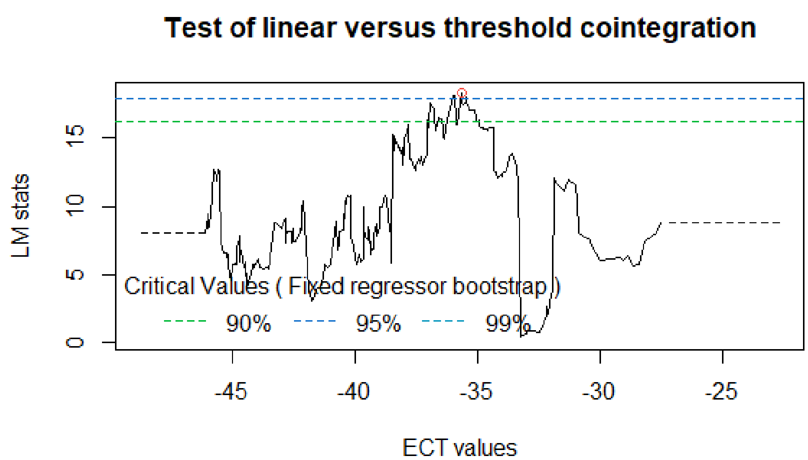

FIGURE 3. Density of bootstrap distribution

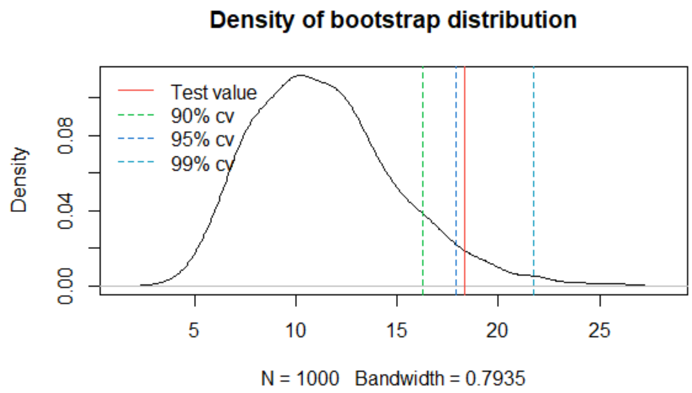

FIGURE 4. Threshold grid search plot