Decomposition of Consumer Sentiment and the Effects of its Cyclical Component*

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October 15, 2024

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Abstract

Conventional empirical models occasionally incorporate sentiment to explain business cycle movements but rarely distinguish consumer optimism or pessimism from overall sentiment level. In this paper, I decompose consumer sentiment into trends and cycles using various filtering methods, with the cycles representing consumer over-optimism or pessimism. To mitigate discrepancies arising from specific statistical methods, I construct an average cycle based on a suite of five distinct commonly used measures. Using the average cyclical sentiment, I analyze the impact of sentiment on inflation expectations and macroeconomic variables. When using monthly U.S. data from 1978 to 2023, I find that cyclical sentiment significantly impact inflation expectations, unemployment, and industrial production. However, the responses of core CPI inflation and CPI inflation to cyclical sentiment are ambiguous. I also incorporate several additional variables related to personal income, consumption, financial markets, and the labor market to examine their responses to cyclical sentiment. All these variables also exhibit short-lived but significant responses to cyclical sentiment movements.

JEL Classification Code: C32, E0, E32

Keywords: Consumer Sentiment, Business Cycles, Decomposition, Cyclical Sentiment, Local Projections, Impulse Responses

*I would like to thank Ryan Chahrour, Camilo Granados, Bernd Hayo, David Eagle, Irina Panovska, Srikanth Ramamurthy, Abu Bakkar Siddique, Victor Valcarcel, and participants at the 2024 WEAI, the 2024 CEA, the 2024 EEA, the 2024 WERI, and the UT Dallas Macroeconomics Brownbag Group for helpful comments and discussions.

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1 Introduction

Consumer sentiment plays a prominent role in household economic decisions, particularly regarding consumption and savings. Despite its influence on consumer behavior, the empirical importance of consumer sentiment in driving aggregate economic activity is still debated. In his *General Theory*, Keynes argued that individual positive decisions can be driven by 'animal spirits', which depends on spontaneous optimism rather than rational mathematical calculations (Keynes, 1936). Specifically, Keynes believed investors' animal spirits were an important source of economic fluctuations, whereas Pigou (1927) believed fluctuations in activity were driven by expectations. From a more recent perspective, Akerlof and Shiller (2010) defined animal spirits as a 'sense of confidence, of fairness, of good faith, of realistic valuations.' They reintroduced animal spirits as a key driver of the economy and argued they could be the main cause of the 2008-2009 recession. To contribute to this literature, I examine the effect of consumer sentiment on real economic activity by incorporating it into an empirical model of the economy.

Many conventional macroeconomic theories that rely on full information rational expectations do not incorporate consumer sentiment (in the broader sense described by Akerlof and Shiller (2010)) into the models. The exclusion of consumer sentiment can result in omitting potentially important information when forecasting economic crises and formulating policies to address them. To address this gap, Milani (2007, 2011, 2017) incorporated sentiment into DSGE models as a replacement for rational expectations. Milani (2017) and Milani (2011) identify the sources of U.S. business cycle fluctuations, and similar to Milani (2007), he defines expectational shocks as changes in agents' optimism and pessimism about the future economy. However, using a set of commonly applied trend-cycle decomposition methods, I capture consumer over-optimism or pessimism about the economy by extracting the cyclical component from the University of Michigan's Index of Consumer Sentiment, which reflects the overall confidence and outlook households have regarding their financial situation and the broader economy. I find that cyclical sentiment significantly affects inflation expectations, unemployment, industrial production, and various other macroeconomic variables.

Consumer sentiment and expectations have been extensively applied to analyze consumption behavior (Makridis, 2022; Gillitzer and Prasad, 2018; Carroll et al., 1994), fluctuations in business cycles (Angeletos and Lian, 2022; Angeletos et al., 2018; Angeletos and La'o, 2013; Akerlof and Shiller, 2010), stock returns (a meta-analysis by Gric et al. (2023)), and overall macroeconomic activity (Lagerborg et al., 2023; Benhabib and Spiegel, 2019; Barsky and Sims, 2012; Acemoglu and Scott, 1994).

Recent literature, such as Bhandari et al. (2024), Lagerborg et al. (2023), Gric et al. (2022), Shapiro et al. (2022), and Enders et al. (2021), defines consumer sentiment and confidence in various ways. Gric et al. (2022) decompose total sentiment into rational and irrational components by regressing it on the state of the economy, where the rational component reflects macroeconomic conditions, and the irrational component capturing excess optimism or pessimism. In contrast, Bhandari et al. (2024) estimate a time-varying measure of optimism and pessimism by comparing household survey expectations with statistical forecasts for inflation and unemployment. Belief shocks, which reflect current economic expectation shocks, are identified using the Survey of Professional Forecasters' output growth nowcast errors in Enders et al. (2021). Considering a different approach, Shapiro et al. (2022) construct a news sentiment index using text analysis based on economic and financial news, while Lagerborg et al. (2023) use fatalities in mass shootings as an instrument for consumer confidence. Following their respective definitions of sentiment and confidence, these studies apply sentiment and confidence shocks to analyze the responses of macroeconomic variables.

In this paper, I explore the role of sentiment by formally incorporating consumer sentiment into an empirical model of the economy. I capture over-optimism or pessimism about the economy from the University of Michigan's Index of Consumer Sentiment using a suite of trend-cycle decomposition models, and I construct an average measure of the cyclical component of sentiment based on five different approaches to avoid over-reliance on any single statistical method. The terms cyclical sentiment and average cyclical sentiment are used interchangeably throughout this analysis, representing consumer over-optimism or pessimism that cannot be fully explained by current or future economic fundamentals, including personal financial circumstances, the state of the economy, or the economic outlook. Finally, I analyze the impact of cyclical sentiment on inflation expectations and the U.S. economy using monthly data from 1978 to 2023.

To extract the cyclical portion of consumer sentiment, I decompose the index of consumer sentiment with decomposition methods such as the i) Hodrick and Prescott (1997), ii) Hamilton (2018), iii) Beveridge-Nelson decomposition following Kamber et al. (2018), vi) Unobserved Components Model with a nonzero correlation following Grant and Chan (2017) and Morley et al. (2003), and v) Multivariate Beveridge-Nelson decomposition as applied by Morley and Wong (2020).

Each of these decomposition methods is widely used in the literature, each with its own strengths and weaknesses. To avoid relying too much on the particular assumptions of any procedure, I take a model averaging approach. I make a simple average of cyclical sentiment extracted by five different approaches. Averaging has been shown to work well, assuming the models cover a wide enough range to capture the true cycle (see Arčabić et al. (2024), Donayre and Panovska (2021), Morley and Panovska (2020), and Morley and Piger (2012) for a model-averaged measure of the output gap). The averaged cyclical sentiment captures NBER recession dates. However, there are instances, such as from August to November 2005 and June to December 2011, where cyclical sentiment declines outside of recessionary periods, likely driven by factors other than economic downturns.

To explore the effects of cyclical sentiment on economic variables, I apply local linear projections following Jordà (2005) to compute impulse responses of macroeconomic variables to a one-unit positive shock, representing a one-unit increase in average cyclical sentiment. The macroeconomic variables included in the model are unemployment rate, Michigan one-year inflation expectations, core consumer price index (CPI) inflation, CPI inflation, and industrial production. The findings show that i) the various measures of cyclical sentiment do not respond significantly to most macroeconomic variables, ii) the average cyclical sentiment has a significant impact on unemployment, inflation expectations, and industrial production, and iii) responses of core CPI inflation and CPI inflation are mostly insignificant to average cyclical sentiment, which is consistent with Lagerborg et al. (2023).

As demonstrated in the literature, including Lagerborg et al. (2023), financial markets are responsive to consumer sentiment. To capture this dynamic, I extend the model by incorporating financial variables such as S&P 500 stock prices, the federal funds effective rate, and several additional variables in both smaller and extended models, one by one. These additional variables pertain to personal income, consumption, and the labor market. The findings indicate that a one-unit positive shock to cyclical sentiment significantly affects both financial and additional variables, but only for a few months. The sign and duration of the responses align with prior expectations for variables such as real personal income, labor force, employment, weekly hours, consumption, employees, and the stock market volatility index (VIX).

The findings of the paper have important macroeconomic policy implications, because the results indicate that temporary fluctuations in sentiment can have significant effects on real macroeconomic activity and on inflation expectations. Policymakers should incorporate consumer sentiment into macroeconomic models and monitor cyclical sentiment to better understand economic fluctuations while formulating policies. Given the significant impact of cyclical sentiment, policymakers might prioritize addressing unemployment, industrial production, and inflation expectations to stabilize the economy.

The paper is organized as follows. I discuss the data in Section 2, methods in Section

3, results in Section 4, robustness analysis in Section 5, and the conclusion in Section 6.

2 Data

I use the Index of Consumer Sentiment, constructed by the Michigan Surveys of Consumers, to extract the cyclical component of the sentiment. The one year ahead inflation expectations data is also from the same survey. The University of Michigan conducts Surveys of Consumers quarterly since 1946 and started collecting monthly data in 1978.

The macroeconomic variables include unemployment rate, core consumer price index (CPI) inflation, CPI inflation, and industrial production. In the larger model, I include financial variables such as the S&P 500 and the federal funds rate. The data are obtained from the Federal Reserve Economic Data (FRED), provided online by the Federal Reserve Bank of St. Louis. I also consider several additional variables from the FRED-MD monthly data base. These variables are real personal income, civilian labor force, civilian employment, average weekly hours: goods-producing, average weekly hours: manufacturing, all employees: total nonfarm, housing starts: total new privately owned, real personal consumption expenditures, durable goods consumption, nondurable goods consumption, services consumption, and the stock market volatility index (VIX). The data is monthly and spans the period from January 1978 to December 2023. The details of data sources and transformation are in Appendix B.

2.1 The Index of Consumer Sentiment

The Index of Consumer Sentiment (ICS) measures the consumers' confidence about the current and future economy. The ICS includes five questions related to personal and country financial, business, and economic conditions. The specific questions are as follows:

(a) "We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?"

(b) "Now looking ahead–do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?"

(c) "Now turning to business conditions in the country as a whole–do you think that during the next twelve months we'll have good times financially, or bad times, or what?"

(d) "Looking ahead, which would you say is more likely–that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?"

(e) "About the big things people buy for their homes–such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?"

The Index of Consumer Sentiment (ICS) takes the rounded relative scores for each of the five questions above by subtracting the percent of unfavorable responses from the favorable responses and adding 100. Then the sum of the scores is divided by the 1966 base value of 6.7558, with a constant of 2 added since December 1981. Prior to that date, a constant of 2.7 was added to correct for sample design changes, as detailed below:[1]

$$ICS = \frac{a + b + c + d + e}{6.7558} + 2$$

where the ICS denotes the index of consumer sentiment.

Figure 1 shows the ICS and the growth rates of various macroeconomic variables used in the smaller model for the U.S. from January 1978 to December 2023.

[1] The calculation process for the Index of Consumer Sentiment is available at https://data.sca.isr.umich.edu/fetchdoc.php?docid=75432.

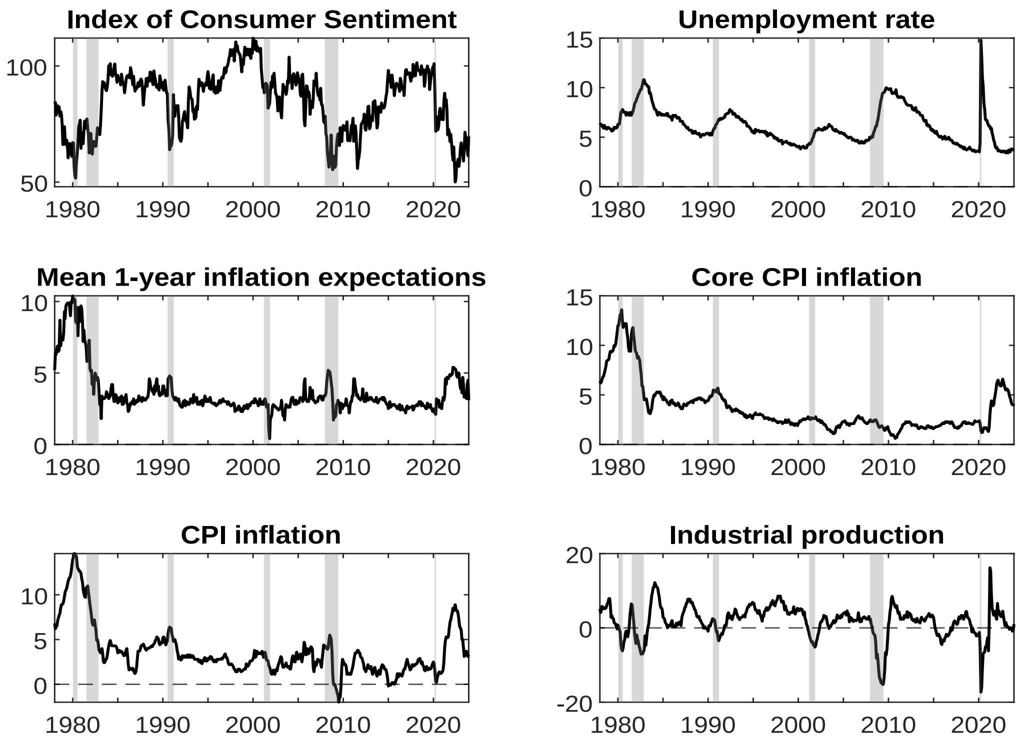

Figure 1: Monthly economic indicators from January 1978 to December 2023. The level of industrial production is converted to its growth rate. Shaded vertical regions denote NBER recession periods.

3 Methods

3.1 Decomposition of the Index of Consumer Sentiment

The trend-cycle decomposition of GDP and various economic aggregates has a rich tradition in macroeconomic fluctuations and business cycles study. To extract the cyclical portion of consumer sentiment, I apply five different trend-cycle decomposition methods such as Hodrick and Prescott (1997), Hamilton (2018), Beveridge-Nelson decomposition following Kamber et al. (2018), Unobserved Components Model with a nonzero correlation following Grant and Chan (2017) and Morley et al. (2003), and multivariate Beveridge-Nelson decomposition as applied by Morley and Wong (2020). Also, I make a simple average of cyclical sentiment extracted by five different approaches (see Arčabić et al. (2024), Donayre and Panovska (2021), Morley and Panovska (2020), and Morley and Piger (2012) for a model-averaged measure of the output gap) to avoid any discrepancy with a particular statistical decomposition method. I use the terms cyclical sentiment and average cyclical sentiment interchangeably throughout this analysis. The following decomposition methods are used to extract cyclical sentiment from the Index of Consumer Sentiment (ICS):

(i) Hodrick-Prescott (HP) Filter: Considering the time series y_t consists of a growth component (g_t) and a cyclical component (c_t), I minimize Equation 1 with the smoothing parameter $\lambda = 14400$ for monthly consumer sentiment data to obtain the trend, and subsequently the cycle.

$$\min_{g_t}\{\sum_{t=1}^{T}(y_t - g_t)^2 + \lambda\sum_{t=1}^{T}[(g_t - g_{t-1}) - (g_{t-1} - g_{t-2})]^2\} \tag{1}$$

The first term of the equation penalizes the cyclical component, while the second part penalizes the second difference of the growth component of ICS.

(ii) Hamilton Filter: In various circumstances, the Hodrick-Prescott (HP) filter generates spurious cycles, particularly when there are end-sample fluctuations. Therefore, I also consider the Hamilton (2018) filter, which is based on the Ordinary Least Squares (OLS) method. This method assumes that we can predict the trend using Equation 2 and derive the cycle from the residual ($\hat{\nu}_t$). The Hamilton filter employs an AR(4) model with an 8-quarter ahead forecast error for projection.

$$y_t = \beta_0 + \beta_1 y_{t-8} + \beta_2 y_{t-9} + \beta_3 y_{t-10} + \beta_4 y_{t-11} + \nu_t \tag{2}$$

(iii) Unobserved Components (UC) Model: The Hamilton filter allows for volatile trends, but does not handle nonlinearities and the volatile trends can be too volatile (Quast and Wolters, 2022). Hence, the UC model is another popular alternative. Morley et al. (2003) introduce a nonzero correlation between trend and cycle innovations, which improves the model's fit during expansions and outperforms various alternatives. Therefore, I consider the Unrestricted UC (UCUR) model following Morley et al. (2003) to extract cyclical sentiment. I apply the approach developed by Grant and Chan (2017) to estimate model parameters and to compute the cyclical component of the Index of Consumer Sentiment (ICS).[2]

The ICS consists of trend and cyclical components where the trend is long-term growth, and the cycle is the transitory deviation from the trend. In the present paper context, the cycle of ICS is the excess optimism or pessimism about the current and future economy.

The UC model can be represented with the following form:

$$y_t = \tau_t + c_t \tag{3}$$

$$\tau_t = \mu_1 + \tau_{t-1} + u_t^{\tau} \tag{4}$$

$$c_t = \phi_1 c_{t-1} + \phi_2 c_{t-2} + u_t^{c} \tag{5}$$

where y_t is the index of consumer sentiment series, τ_t is the trend of the series, c_t is the cycle of the series.

Here, trend τ_t is an AR (1) process with a drift, and the drift term is assumed to be close to zero. The cycle is an AR (2) process. The innovation of the trend u_t^{τ} and the

[2]The UCUR model assumes that the trend and cycle innovations are correlated ($\rho \neq 0$) and the prior for ρ is 0.5. The posterior value of ρ is not sensitive to the prior, which is around 0.75. I also use prior for the remaining 6 model parameters μ, τ, ϕ_1, ϕ_2, σ_{τ}^2, and σ_c^2. The prior for μ is close to zero which is for a trend without a drift of the index of consumer sentiment. The prior for τ is 80 and its variance is 70. The values of ϕ_1 and ϕ_2 are 1.3 and -0.7, respectively. The upper bounds of variances for both the trend and cycle are 5. The initial values for the Markov Chain for μ, ϕ_1, and ϕ_2 are zero, along with variances of trend σ_{τ}^2 and cycle σ_c^2 are 15 and 10, respectively. These priors and initial values are intuitive for accommodating the phenomenon related to the ICS. They also allow posteriors enough flexibility to be dominated by the data series by taking large prior variances of the parameters.

innovation of the cycle u_t^c are jointly normal with the following form as in Grant and Chan (2017):

$$\begin{pmatrix} u_t^c \\ u_t^\tau \end{pmatrix} \sim N\left(\mathbf{0}, \begin{pmatrix} \sigma_c^2 & \rho\sigma_c\sigma_\tau \\ \rho\sigma_c\sigma_\tau & \sigma_\tau^2 \end{pmatrix}\right) \tag{6}$$

where σ^2 denotes variance and ρ denotes the correlation between innovations of trend and cycle.

However, UC models can produce markedly different results in terms of trend and cycle estimation under some assumptions, as shown by Grant and Chan (2017); Basistha and Nelson (2007); Morley et al. (2003). The estimated cycle of the series can often be inconsistent with the belief about the behavior of the cyclical component of various series in downturns. This difference commonly arises due to different assumptions about the slope of trend or about the correlation between the trend and the cycle innovations.

(iv) Beveridge-Nelson (BN) decomposition: The BN decomposition consists of permanent (trend) and transitory (cycle) components of a time series. The trend is a long-horizon conditional forecast minus deterministic movements in the time series as follows:

$$\tau_t = \lim_{j\to\infty} E_t[y_{t+j} - jE[\Delta y]] \tag{7}$$

The seminal work of Beveridge and Nelson (1981) fits the data better (Morley and Panovska, 2020; Grant and Chan, 2017; Morley et al., 2017, 2003), but produce markedly different results in terms of GDP trend and cycle estimation due to a high signal-to-noise ratio while estimating parameters. The issue is addressed by Kamber et al. (2018) by modifying the BN decomposition and transforming the AR(P) model to impose a lower signal-to-noise ratio, $\delta \equiv \frac{\sigma^2_{\Delta\tau}}{\sigma^2_e}$. Here, the δ represents the ratio of the variance of trend shocks to the overall forecast error variance and is determined automatically with the full sample mean method for demeaning the series in the present paper.

(v) Multivariate BN decomposition: Although the univariate BN decomposition fits the data better than the HP and Hamilton filters, it can yield counterintuitive results for negative shocks (Morley and Wong, 2020). The multivariate BN approach improves this issue. Therefore, I use the multivariate BN decomposition based on vector autoregression to extract cyclical sentiment following Morley and Wong (2020).[3] The companion form for VAR(p) is as follows, where vector $\mathbf{\Delta x}_t$ stands for the first difference of the target variable y_t and $\mathbf{\Delta X}_t = \left\{\mathbf{\Delta x}'_t, \mathbf{\Delta x}'_{t-1}, \ldots, \mathbf{\Delta x}'_{t-p+1}\right\}'$.

$$(\mathbf{\Delta X}_t - \boldsymbol{\mu}) = \mathbf{F}(\mathbf{\Delta X}_{t-1} - \boldsymbol{\mu}) + \mathbf{H}\mathbf{e}_t \tag{8}$$

where $\mathbf{F}$ is the companion matrix, $\boldsymbol{\mu}$ is a vector of unconditional means, $\mathbf{H}$ maps the VAR forecast errors to the companion form, and $\mathbf{e}_t$ is a vector of serially uncorrelated forecast errors.

The trends ($\boldsymbol{\tau}_t$) and cycles ($\boldsymbol{c}_t$) can be decomposed with the following equations:

$$\boldsymbol{\tau}_t = \mathbf{X}_t + \mathbf{F}(\mathbf{I} - \mathbf{F})^{-1}(\mathbf{\Delta X}_t - \boldsymbol{\mu}) \tag{9}$$

$$\mathbf{c}_t = -\mathbf{F}(\mathbf{I} - \mathbf{F})^{-1}(\mathbf{\Delta X}_t - \boldsymbol{\mu}) \tag{10}$$

I apply the above five trend-cycle decomposition methods to extract the cyclical sentiment from the Index of Consumer Sentiment. I primarily consider univariate decompositions for a more focused and tractable analysis, while incorporating a multivariate method to capture the cycle by conditioning on additional variables. The Hodrick-Prescott filter provides a smooth trend but struggles with breaks, while Hamilton's forecast-based approach captures volatile trends but does not handle nonlinearities well. The univariate Beveridge-Nelson model fits the data well, though it may yield counterintuitive

[3] The multivariate BN decomposition of ICS is conditioned on five variables: unemployment rate, Michigan one-year inflation expectations, core CPI inflation, CPI inflation, and industrial production, using monthly data from 1978 to 2023.

results when faced with negative shocks. Multivariate approaches can improve on these limitations but may produce inaccurate estimates if relationships between variables are unstable. Each of these filters is widely used in the literature, each with its own strengths and weaknesses. To avoid any discrepancies from relying on a single decomposition method, I average them to obtain a more reliable measure of the cyclical component of sentiment, as explained in Section 3.2.

Figure 2 shows the cyclical sentiment estimated using the HP filter, Hamilton filter, BN decomposition, UCUR methods, multivariate BN, and the average cycle of the five consumer sentiment cycles. These cycles capture NBER recession dates. However, cyclical sentiment declines outside of recession periods, as observed from August to November 2005 and June to December 2011. These declines may be driven by factors unrelated to economic downturns.

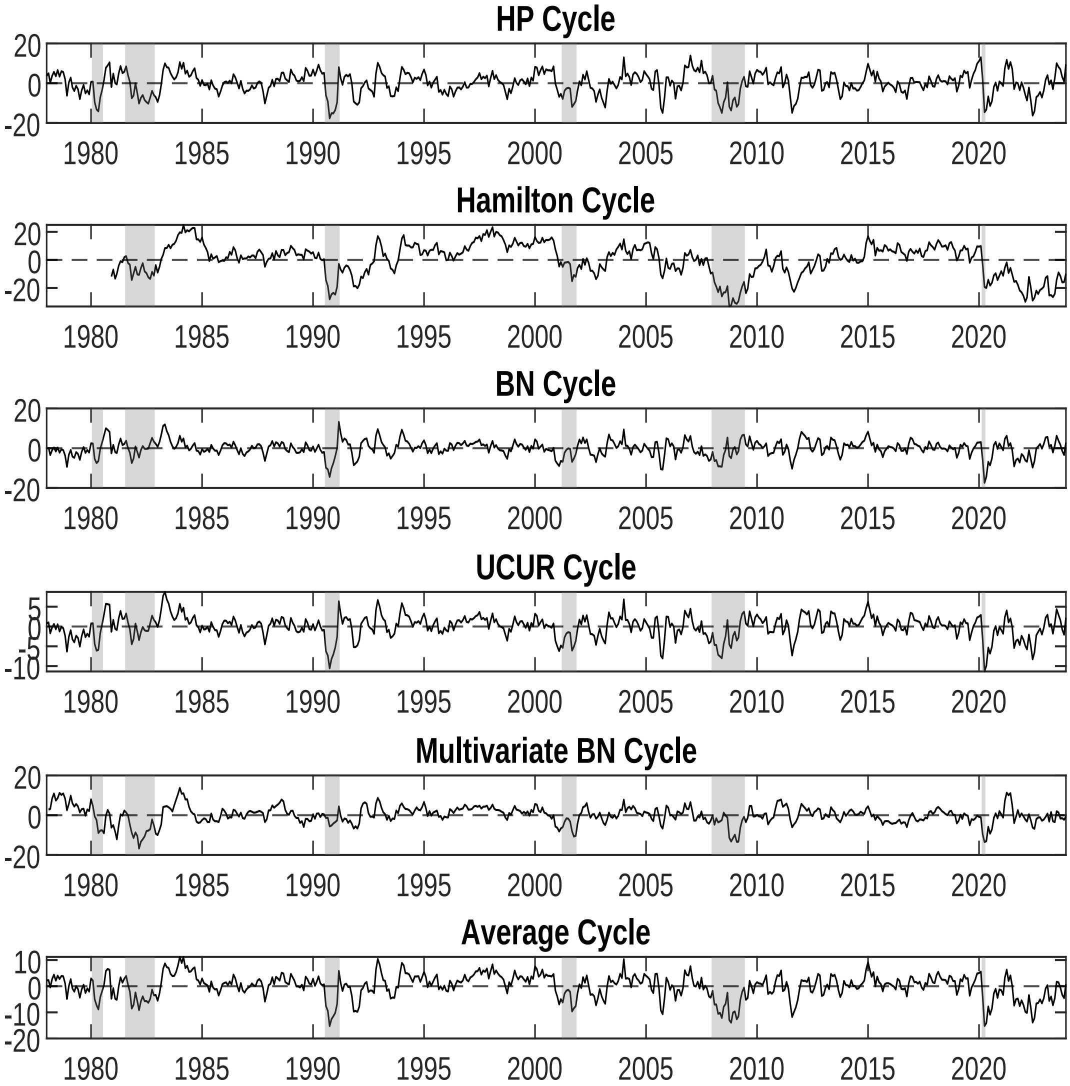

Figure 2: The cyclical component of the index of consumer sentiment estimated using the HP filter, Hamilton filter, BN decomposition, UCUR methods, multivariate BN, and the average cycle of the five consumer sentiment cycles. Shaded vertical regions denote NBER recession periods.

3.2 Averaging cyclical component of sentiment

I use five decomposition methods to extract cyclical sentiment, all of which are widely used in the literature and have their own strengths and weaknesses. For instance, the multivariate BN approach corrects counterintuitive results for negative shocks but may produce inaccurate estimates if the variable relationships are unstable, as it imposes an assumed relationship that might not exist (Donayre and Panovska, 2021; González-Astudillo, 2019; Panovska, 2017). To avoid any discrepancy with a particular decomposition method, I make a simple average of cyclical sentiment extracted by five different approaches. Averaging has been shown to work well, assuming the models cover a wide enough range to capture the true cycle (see Arčabić et al. (2024), Donayre and Panovska (2021), Morley and Panovska (2020), and Morley and Piger (2012) for a model-averaged measure of the output gap). The averaged cyclical sentiment captures the NBER recession dates, shown in Figure 2. However, there are instances, such as from August to November 2005 and June to December 2011, where cyclical sentiment across various measures declines outside of recessionary periods, likely driven by factors other than economic downturns.

3.3 Computing impulse responses of macroeconomic variables

I use the local linear projection method developed by Jordà (2005) to compute the responses of macroeconomic variables to cyclical sentiment.[4] The variable of interest, $\tilde{y}_t$, is the response variable projected onto a vector of controls ($\mathbf{Y}_t$) consisting of lags of both dependent and independent variables. The vector of controls in the smaller model is ordered as follows, with the average cyclical sentiment as the first variable.

$\mathbf{Y}_t = [cs_t, un_t, ie_t, ccpi_t, cpi_t, ip_t]$ and $\tilde{y}_t \in \mathbf{Y}_t$,

where cs_t is the average cyclical component of sentiment, un_t is the unemployment rate, ie_t represents the Michigan one-year inflation expectations, $ccpi_t$ is the core CPI

[4]The impulse responses of macroeconomic variables to cyclical sentiment, using the Cholesky Structural VAR model, are presented in Appendix C.

inflation, cpi_t is the CPI inflation, and ip_t is the growth rate of industrial production.

I impose a version of the timing restriction in the local projection model, assuming that cyclical sentiment occurs first, before other variables respond to it. The cyclical component responds with a delay, following standard practice in this field of research. An advantage of local projection is that it allows to estimate the responses equation by equation. Equation 11 is calculated through regressions for each horizon s and each variable individually.

$$\tilde{y}_{t+s} = \boldsymbol{\alpha}^s + \mathbf{B}_1^{s+1}\mathbf{Y}_{t-1} + \mathbf{B}_2^{s+1}\mathbf{Y}_{t-2} + ... + \mathbf{B}_p^{s+1}\mathbf{Y}_{t-p} + \mathbf{u}_{t+s}^s \tag{11}$$

where horizon $s = 0, 1, 2, ..., h$. Also, $\boldsymbol{\alpha}^s$ is a vector of constants and $\mathbf{B}_i^{s+1}$ as matrices of coefficients for each lag i and horizon $s+1$. The local projections are the collection of h regressions from the Equation 11. Therefore, the impulse responses (IR) are computed as follows, where $\hat{\mathbf{B}}_{1,11}^s$ represents the IR coefficients for the cyclical sentiment, and $\mathbf{d}_i$ corresponds to the i-th element in the vector of variables $\mathbf{Y}_t$. In my case, $\mathbf{d}_i$ represents the cyclical sentiment.

$$\hat{\mathbf{IR}}(t, s, \mathbf{d}_i) = \hat{\mathbf{B}}_{1,11}^s \mathbf{d}_i \tag{12}$$

There are several advantages of local projections, as shown by Jordà (2005). These include: i) they can be estimated by OLS, ii) they provide appropriate inference, and iii) they are robust to misspecification of the data-generating process. Furthermore, local projections and vector autoregressions yield identical impulse responses (Plagborg-Møller and Wolf, 2021), with local projections showing lower bias than VAR estimators (Li et al., 2024). Therefore, I use the local projection method to compute impulse responses of macroeconomic variables to cyclical sentiment.

4 Results

4.1 Impulse Response Functions

Initially, I begin by considering a smaller model to focus on key macroeconomic variables and analyze the impulse response functions of unemployment rate, Michigan one-year-ahead inflation expectations, core CPI inflation, CPI inflation, and industrial production over the 12 months following a shock, which represents a one-unit increase in the average cyclical component of sentiment.[5] As highlighted in the literature, including Lagerborg et al. (2023), financial markets respond to consumer sentiment. To capture this dynamic, I extend the model by incorporating financial variables into a larger model.

The graphs report the 95% confidence intervals. The number of lags for endogenous variables is 12. The responses of cyclical sentiment to its shocks have been normalized to 1 at horizon 1 and can be read as the responses to a one-unit positive shock. To make the data length similar for various decomposition methods, I exclude approximately the first three years of data when generating the impulse response functions.[6] The discarded data are from the volatile 1970s and 1980s, which could skew the results. I find that cyclical sentiment in various measures does not respond significantly to macroeconomic variables, except for unemployment.[7]

[5] I also compute the impulse responses of macroeconomic variables to a shock in cyclical sentiment separately, derived from each of the five decomposition methods, as detailed in Appendix A. The results show mostly consistent responses for unemployment, inflation expectations, and industrial production across the methods. However, the responses of core CPI and CPI inflation vary.

[6] The Hamilton filter discards data because it is regression-based, relying on both current and lagged values of a data series. Therefore, it requires a sufficient number of lagged observations (the sum of the horizon h and lags p, minus one), and in my case, $h = 24$ and $p = 12$.

[7] The response of cyclical sentiment to unemployment may occur due to high-frequency movements in unemployment. To address this, I extract the cycle at business cycle frequencies using the Baxter and King (1999) (BK) filter with higher frequency (2 to 96 months). This suggests that cyclical sentiment primarily responds to the unemployment rate at medium frequencies. The lower threshold of 2 months for the cycle may be too short, so I have excluded the BK filter with extreme thresholds from the averaging of cyclical sentiment.

4.2 Responses to average cyclical sentiment

Figure 3 illustrates the responses of macroeconomic variables to average cyclical sentiment within a smaller model. The left panel displays the response of cyclical sentiment and unemployment rate, while the middle panel shows the response of Michigan one-year inflation expectations and core CPI inflation. The right panel depicts the responses of CPI inflation and industrial production.

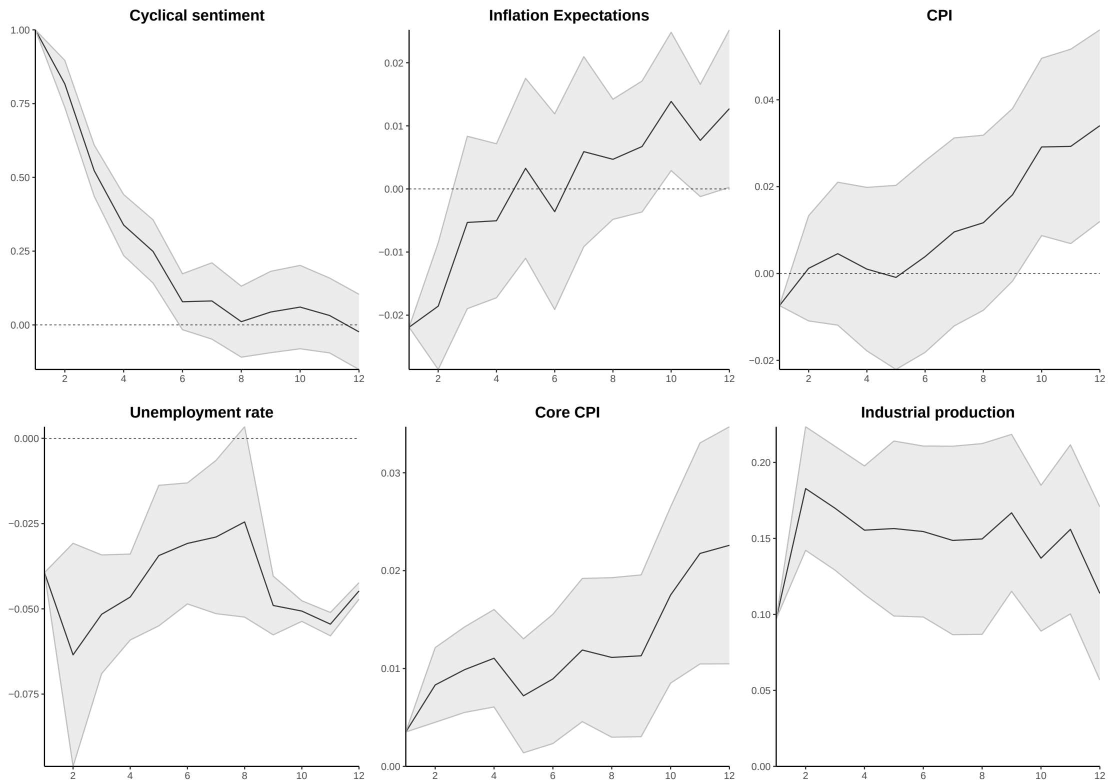

Figure 3: Impulse response functions of macroeconomic variables due to a positive cyclical sentiment (average of cycles) shock. Shaded regions denote a 95% confidence interval.

The response of cyclical sentiment starts at 1 and gradually declines over time following a one-unit positive shock to itself, remaining significant for 6 months within the 95% confidence interval. Cyclical sentiment shocks significantly reduce the unemployment rate, with the most substantial decline occurring at month 2. One-year-ahead inflation expectations initially decrease and become insignificant after the second month. The responses of core CPI inflation and CPI inflation increase gradually, but CPI inflation starts from a negative value and remains insignificant until month 9. Industrial production rises significantly in response to a positive cyclical sentiment shock. These responses align with economic intuition, as consumers' optimism about the economy leads to lower inflation expectations for a few months and increases consumer spending, generating demand for goods and services, and hence, production. Consequently, unemployment declines and industrial production increases. This should intuitively raise inflation. I find that the responses of core CPI inflation are rising, but CPI inflation is mostly insignificant, which is consistent with the findings in the literature. For example, Lagerborg et al. (2023) show that the response of CPI inflation to consumer confidence or sentiment, proxied by mass shooting fatalities, is mostly insignificant across various specifications, despite differing sample sizes. The ambiguity in inflation responses may stem from the state dependency of these responses, as analyzed by Cha (2024), who considers pessimism a shock, followed by Bhandari et al. (2024), and incorporates the good and bad economic states identified by NBER recession indicators.

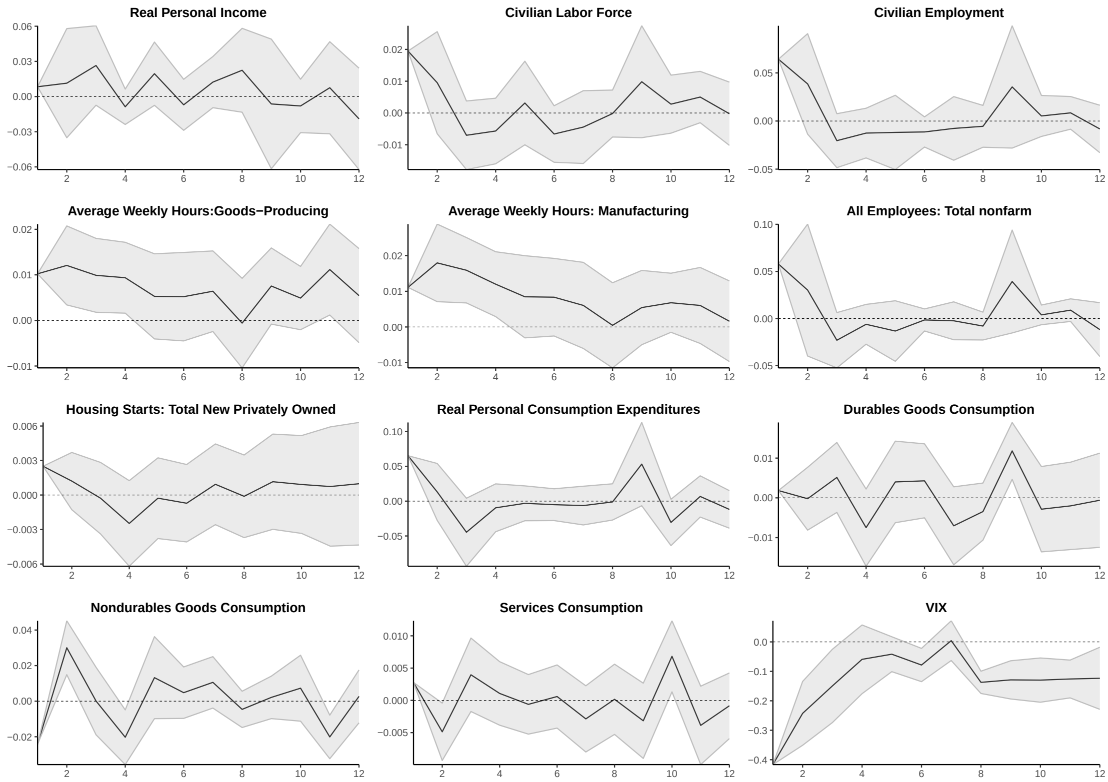

Figure 4: Impulse response functions of additional variables due to a positive cyclical sentiment (average of cycles) shock with the smaller model and calculated by adding one additional variable each time. Shaded regions denote a 95% confidence interval.

After analyzing the responses of key macroeconomic variables to cyclical sentiment, I expand the analysis to examine how cyclical sentiment impacts broader aspects of the economy. To capture the effects of cyclical sentiment shocks on these broader dimensions, I incorporate additional variables beyond the original, smaller model. These additional variables pertain to personal income, consumption, and the labor market. Each variable is added to the original model individually to assess its response to a one-unit positive cyclical sentiment shock. The results, as shown in Figure 4, reveal some interesting findings: (i) all additional variables respond positively and significantly at the 95% level in the beginning, except for the consumption of non-durable goods and the stock market volatility index (VIX) and (ii) these significant responses last for less than four months, and in most cases, less than two months. The impact of cyclical sentiment does not persist for an extended period.

4.3 Responses to cyclical sentiment including financial variables

To analyze the impulse responses of both macroeconomic and financial variables simultaneously, I incorporate the percentage change in stock prices, such as the S&P 500, and the federal funds effective rate (FFR) into the original model. In Figure 5, the response of cyclical sentiment to its own shock becomes significant up to month 5, whereas in the smaller model without financial variables, it remains significant for 6 months. Also, other variables included in the smaller model show similar response patterns to a positive cyclical sentiment shock as they do in the smaller model, except for core CPI inflation. The response of core CPI inflation is no longer increasing. The responses of the unemployment rate and industrial production become significant for fewer months compared to their responses in the smaller model. A positive cyclical sentiment shock results in an increase in FFR, remaining significant for nearly a year with a 95% confidence level. The increase in FFR to a positive cyclical sentiment shock may either due to a strong policy response to high inflation and overheating economy or to ensure financial stability and prevent asset bubbles. Initially, stock market prices rise before beginning to decline insignificantly from the second month following a positive shock.

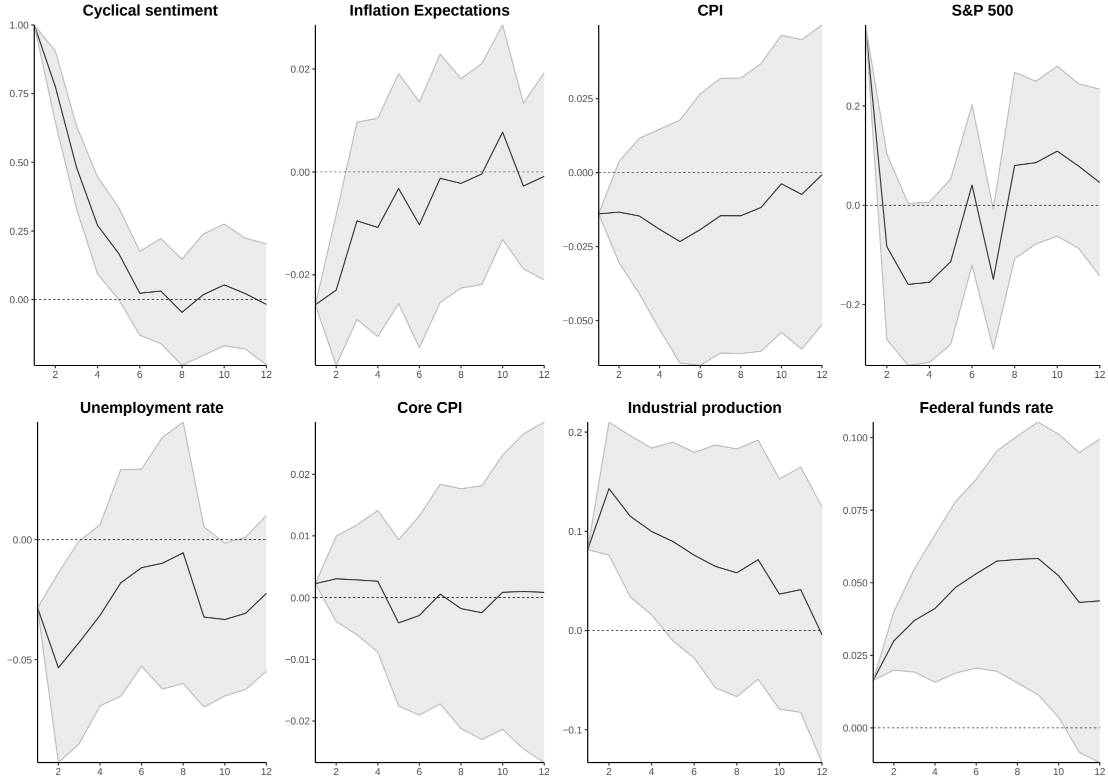

Figure 5: Impulse response functions of macroeconomic variables including financial variables due to a positive cyclical sentiment (average of cycles) shock. Shaded regions denote a 95% confidence interval.

Adding additional variables to the larger model with financial variables yields responses similar to those of the smaller model without financial variables. However, in the presence of financial variables, the responses of additional variables become insignificant even sooner for almost all variables compared to the smaller model, as shown in Figure 6.

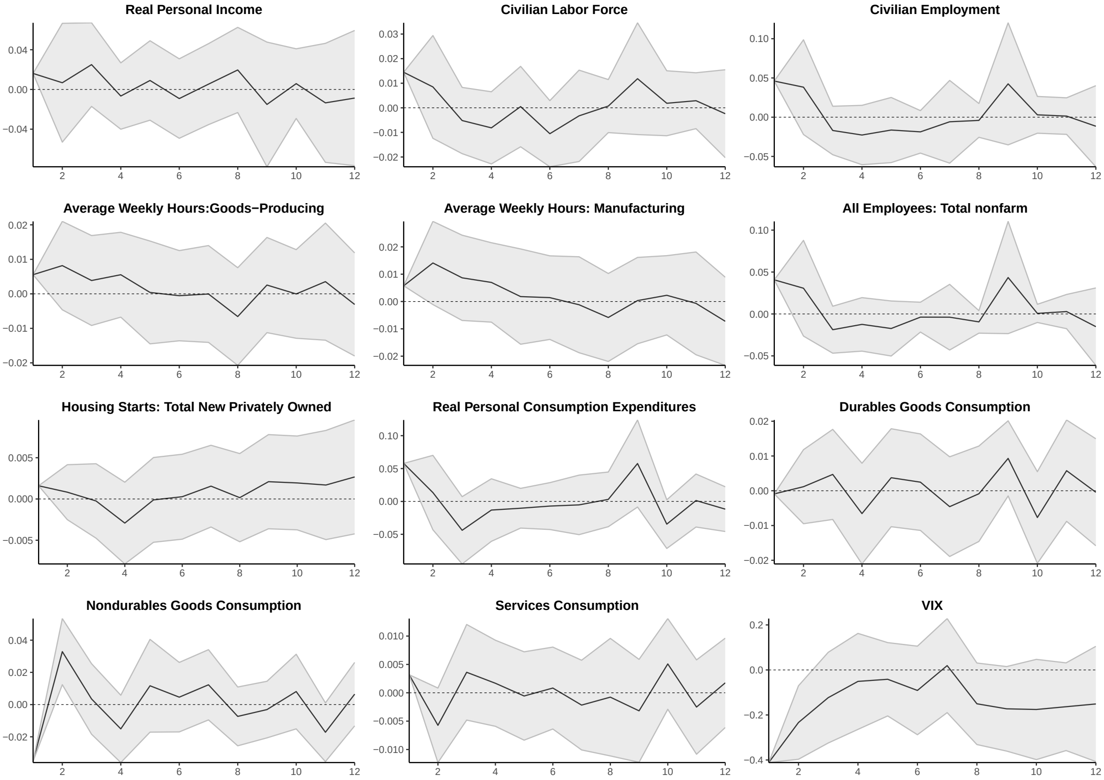

Figure 6: Impulse response functions of additional variables due to a positive cyclical sentiment (average of cycles) shock with larger model and calculated by adding one additional variable each time. Shaded regions denote a 95% confidence interval.

In summary, the responses of real variables, such as industrial production and unemployment rate, to a one-unit positive shock representing a one-unit increase in the average cyclical component of sentiment show consistent patterns across both the smaller and larger models. In the smaller model, these responses become significant over longer horizons, with a 95 percent confidence interval, compared to the larger model, which includes financial variables like the S&P 500 stock prices and the federal funds rate.

Furthermore, the response of industrial production to a positive cyclical sentiment shock ranges from approximately 0.10 to 0.18 in the smaller model, while it varies from -0.12 to -0.05 in the benchmark model used by Lagerborg et al. (2023) with a negative shock, which employs a mass shooting instrument as a proxy for sentiment, based on data from 1965 to 2007. In their benchmark model, they incorporate financial variables. When financial variables are included in my larger model, I find that the response of industrial production varies from 0.08 to 0.14 following a one-unit positive cyclical sentiment shock, remaining significant for five months at the 95 percent confidence level. When Lagerborg et al. (2023) extend their sample to 2018, the response of industrial production follows a similar pattern to their benchmark model but is no longer significant at the 90 percent confidence level. Thus, while the pattern of industrial production's response to cyclical sentiment is consistent with Lagerborg et al. (2023), the magnitude of the responses in this paper is stronger, despite differences in model specifications and sample periods.

Similarly, the response of the unemployment rate to a positive cyclical sentiment shock ranges from approximately -0.065 to -0.035 in the smaller model and from -0.055 to -0.03 in the larger model. In contrast, Lagerborg et al. (2023) find that the unemployment rate responds to a negative sentiment shock within a range of 0.01 to 0.03 in their benchmark model. The findings in this paper indicate that the unemployment rate's response to cyclical sentiment shocks is stronger than that reported by Lagerborg et al. (2023). In a different specification, Milani (2017) shows that sentiment accounts for approximately forty percent of output and consumption variability and nearly sixty percent of investment and inflation variability.

Turning to inflation, the responses of consumer inflation expectations and CPI inflation initially decline, while core CPI increases in response to a cyclical sentiment shock in both the smaller and larger models. However, the responses become insignificant more rapidly in the larger model. In contrast, Lagerborg et al. (2023) find that the CPI inflation responses are largely insignificant.

Moreover, the response of S&P 500 stock prices initially increases and remains significant for less than two months following a positive cyclical sentiment shock. In contrast, the federal funds rate response shows an increase and remains significant for over 10 months.

Adding additional variables individually to both the smaller and larger models reveals that an increase in cyclical sentiment leads to a positive response for most variables, including real personal income, labor force participation, employment, weekly hours, housing starts, real personal consumption expenditure, and services consumption. While the response of durable goods consumption is mostly insignificant, nondurable goods consumption and the volatility index (VIX) decrease initially.

Overall, an increase in cyclical sentiment leads to higher industrial production and improvements in various labor market indicators, including employment and hours worked, which in turn contribute to increased real personal consumption expenditures and services consumption. These relationships are consistent with demand shocks driven by cyclical sentiment, although nondurable goods consumption declines only in the first month following the shock, with a 95 percent confidence interval.

5 Robustness Analysis

In this section, I compute the impulse responses of macroeconomic and financial variables to overall sentiment, rather than cyclical sentiment. The specifications mirror those in Section 4, enabling a comparison between responses to overall and cyclical sentiment. These specifications involve a 12-month horizon for the impulse responses, a one-unit positive shock, a 95 percent confidence interval, and exclude approximately the first three years of data.

5.1 Responses to sentiment

In Figure 7, consumer sentiment responds to its own shock by rapidly declining to zero by the second month, and then becomes increasingly insignificant a few months later. The responses of inflation expectations and the unemployment rate follow a similar pattern as with cyclical sentiment but remain significant for a longer duration. The response of unemployment rate remains significant throughout the entire one-year period considered. Both CPI and core CPI inflation responses decline, with core CPI starting at a positive value and remaining insignificant for the first four months, except for an initial rise that is significant within the 95% confidence interval. In contrast to responses to cyclical sentiment shocks, CPI and core CPI inflation responses do not show the same upward trend. Overall, except for CPI and core CPI inflation, the responses of variables in the smaller model are similar to those with both sentiment and cyclical sentiment, with sentiment having a significant impact for a longer period.

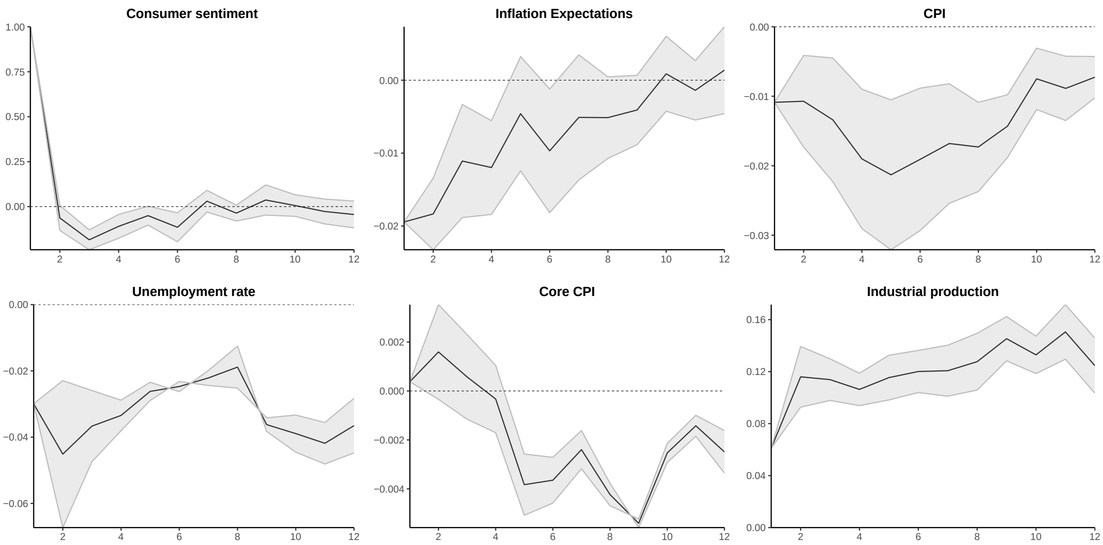

Figure 7: Impulse response functions of macroeconomic variables due to a positive sentiment shock. Shaded regions denote a 95% confidence interval.

5.2 Responses to sentiment including financial variables

After including financial variables in the model, the findings reveal a wider confidence interval and significance for fewer months compared to the responses to sentiment in the smaller model (Figure 8). However, when compared to responses to cyclical sentiment in the larger model, these responses become significant for a longer duration, particularly for the federal funds rate. Also, the response of the S&P 500 to both cyclical and sentiment shocks shows similar patterns.

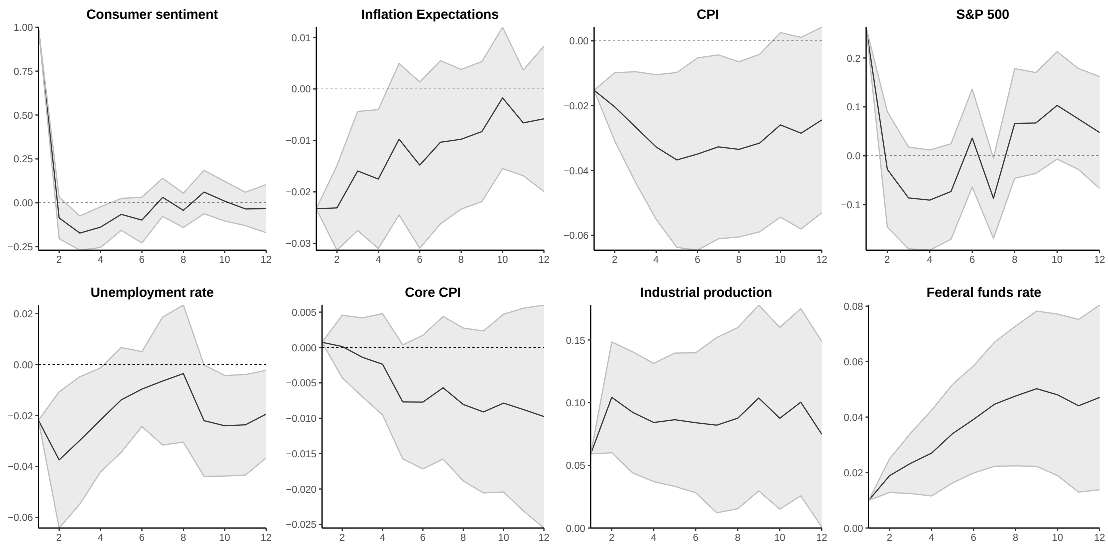

Figure 8: Impulse response functions of macroeconomic variables including financial variables due to a positive sentiment shock. Shaded regions denote a 95% confidence interval.

6 Conclusion

I decompose the University of Michigan's Index of Consumer Sentiment using a variety of methods, including the Hodrick-Prescott filter, Hamilton filter, correlated Unobserved Components model, Beveridge-Nelson decomposition, and Multivariate Beveridge-Nelson decomposition. Then, I compute an average of the cyclical components from these five methods and apply it as a shock to inflation expectations and real economic variables to analyze their responses. The results indicate that the cyclical component of sentiment consistently and significantly influences unemployment, inflation expectations, and industrial production. However, the responses of core CPI inflation and CPI inflation are ambiguous. These findings remain robust when financial variables and additional macroeconomic variables are incorporated into the model. The findings indicate that transitory movements in sentiment significantly influence real economic variables, highlighting crucial macroeconomic policy implications for effectively managing and communicating expectations. Future research could incorporate an instrumental variables approach to capture consumer over-optimism or pessimism, facilitating a comparison with this strand of literature.

Appendix

A Impulse responses to cyclical sentiment shocks from various decomposition methods

This section shows the impulse responses of inflation expectations and macroeconomic variables following a shock in the cyclical component of sentiment extracted by HP filter, Hamilton filter, UCUR, BN decomposition, and multivariate BN decomposition separately. I use the smaller model with six variables to observe their responses.

A.1 Responses to cyclical sentiment extracted by HP filter

The HP filter uses a smoothing parameter of $\lambda = 14400$ for monthly data with 12 lags. In Figure 9, the responses of various variables show similar patterns to those observed with an average cyclical sentiment shock. However, the responses of unemployment and industrial production remain significant for about a year, except for months 4 to 9 in the case of unemployment rate and around month 12 for industrial production.

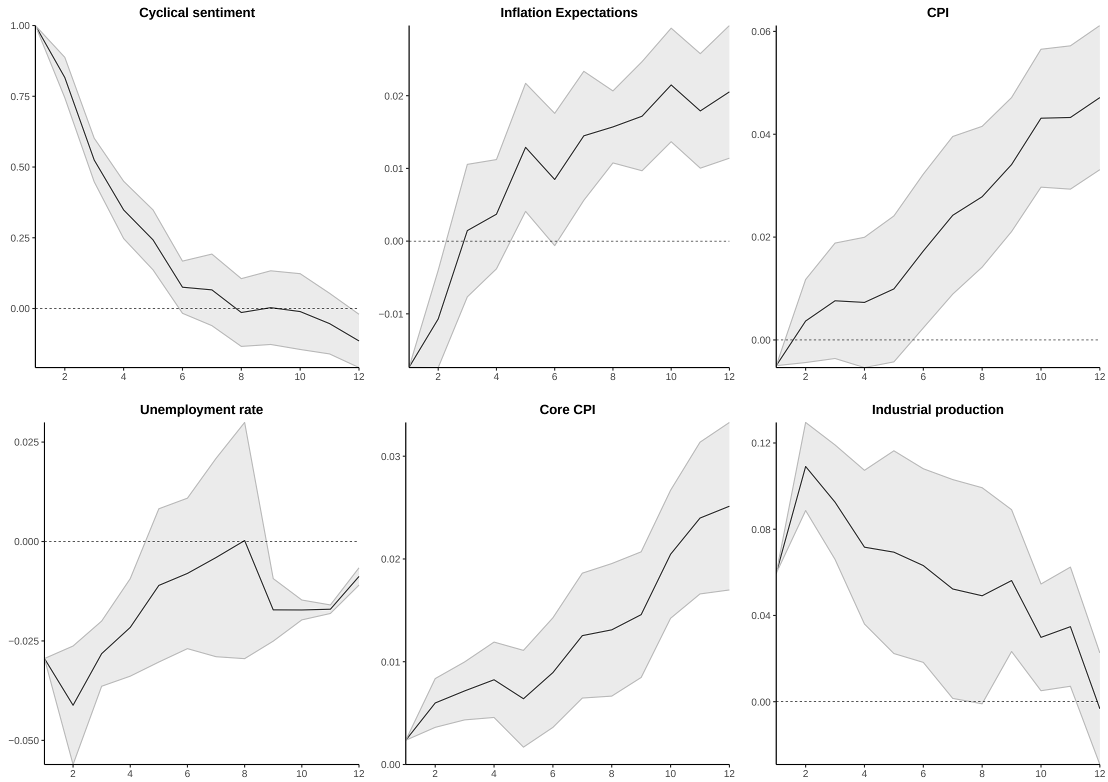

Figure 9: Impulse response functions of various variables from a one-unit positive shock to the cyclical component of sentiment extracted by the HP filter. Shaded regions denote a 95% confidence interval.

A.2 Responses to cyclical sentiment extracted by Hamilton filter

Figure 10 shows the responses of macroeconomic variables to cyclical sentiment extracted using the Hamilton filter. The responses of cyclical sentiment, unemployment rate, and industrial production to cyclical sentiment remain significant throughout the entire year, following the usual pattern observed in other measures. Core CPI inflation is significant for approximately half of the year at different intervals, while its response remains significant for the entire year with the HP cycle. The responses of inflation expectations and CPI inflation follow a similar pattern to the HP cycle but are significant for fewer months.

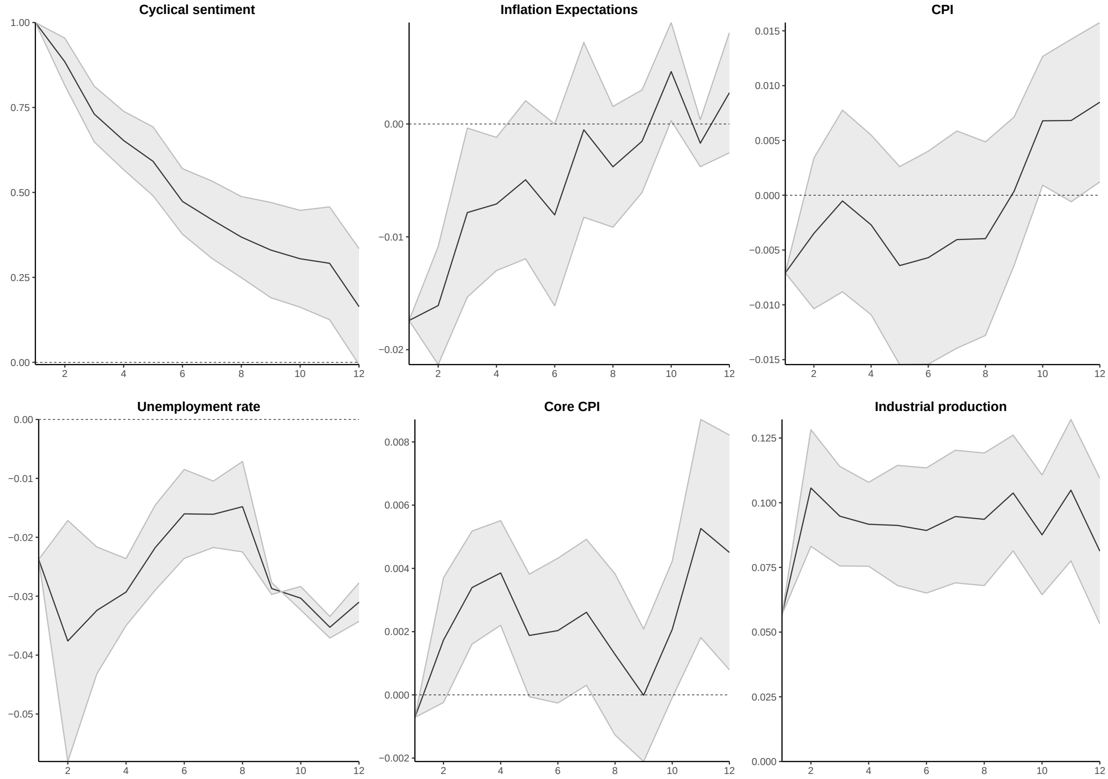

Figure 10: Impulse response functions of various variables from a one-unit positive shock to the cyclical component of sentiment extracted by Hamilton filter. Shaded regions denote a 95% confidence interval.

A.3 Responses to cyclical sentiment extracted by UCUR

In Figure 11, the responses of macroeconomic variables to the cyclical sentiment shock extracted by the UCUR model are similar to those observed with an average cyclical sentiment shock. However, the CPI inflation responses show a significant decline over a longer period, whereas core CPI initially increases and then declines.

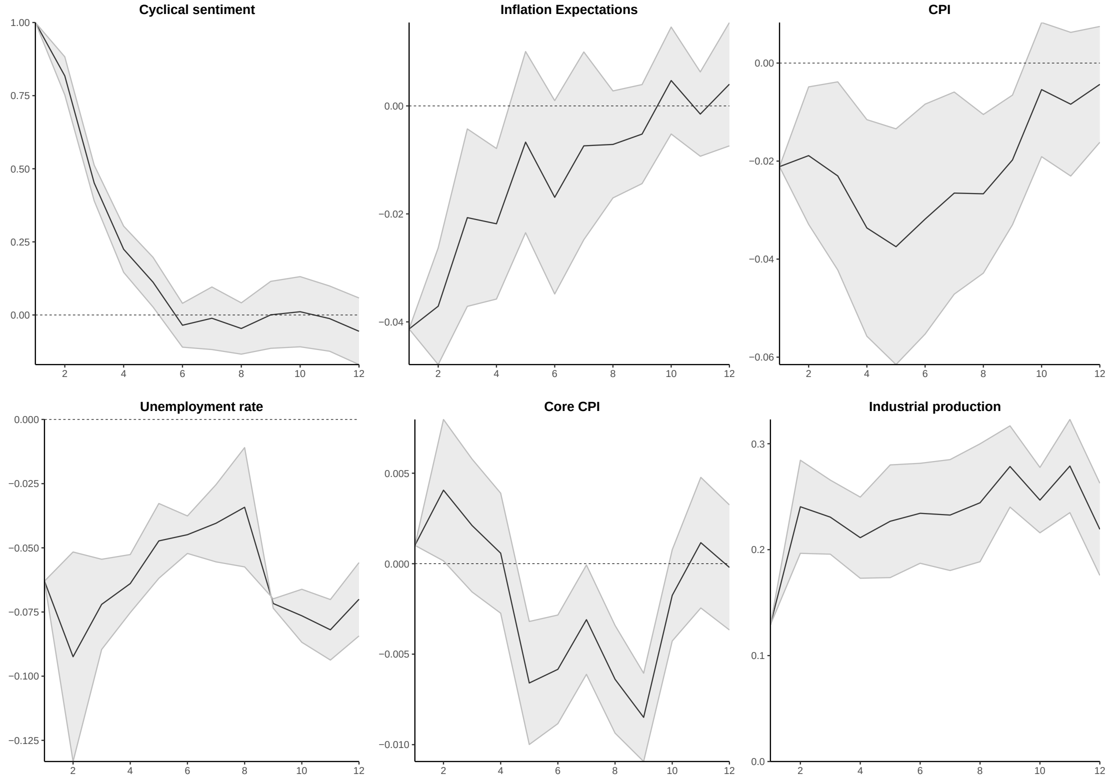

Figure 11: Impulse response functions of macroeconomic variables due to a positive cyclical sentiment shock extracted by UCUR. Shaded regions denote a 95% confidence interval.

A.4 Responses to cyclical sentiment extracted by BN decomposition

Figure 12 shows the responses of macroeconomic variables to cyclical sentiment shocks extracted by the BN decomposition, which are quite similar to the responses to a cyclical sentiment shock extracted by the UCUR model.

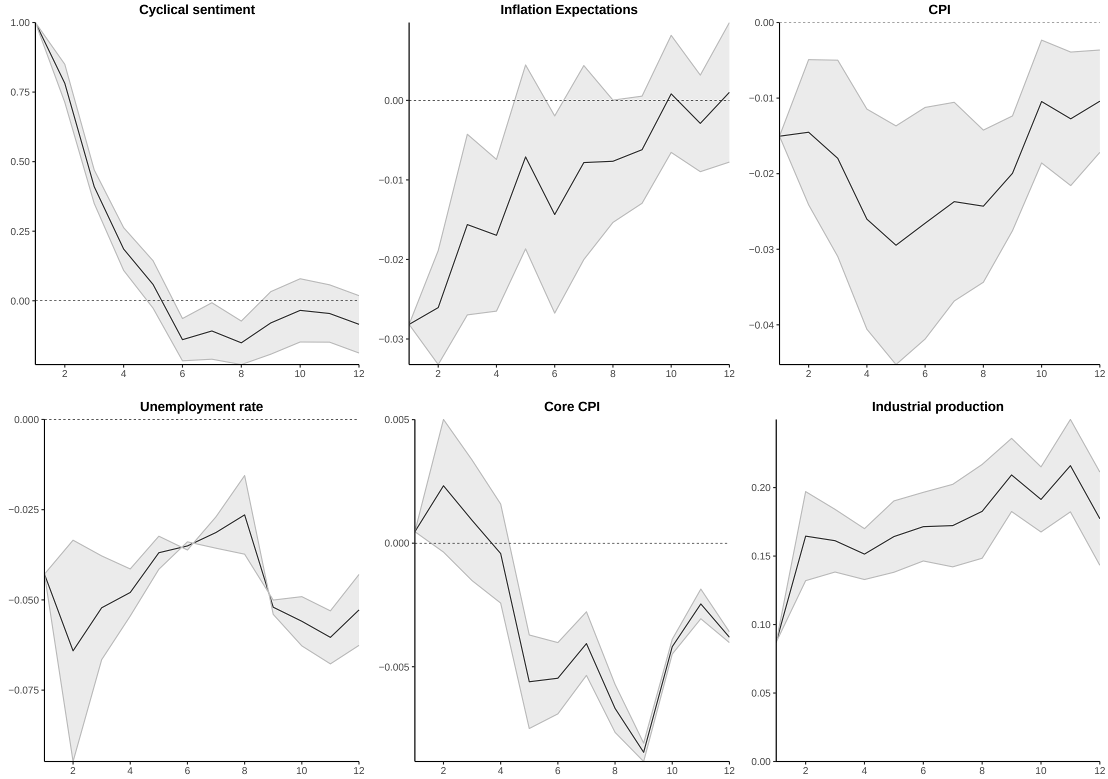

Figure 12: Impulse response functions of macroeconomic variables due to a positive cyclical sentiment shock extracted by BN decomposition. Shaded regions denote a 95% confidence interval.

A.5 Responses to cyclical sentiment extracted by multivariate BN

Figure 13 shows the responses of macroeconomic variables to a cyclical sentiment shock extracted using multivariate BN decomposition. The confidence intervals widen as additional variables are incorporated into the extraction of the cyclical component. The overall response pattern is similar to the responses to a cyclical sentiment shock, except for inflation expectations and CPI inflation, which initially increase.

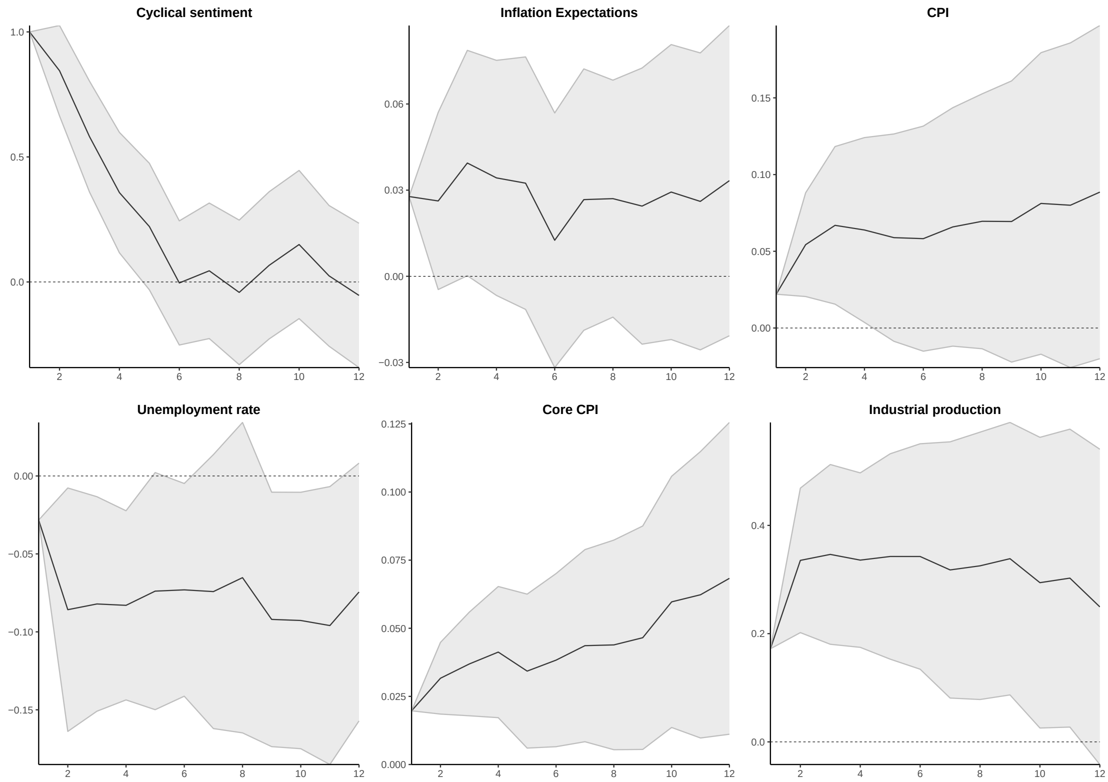

Figure 13: Impulse response functions of macroeconomic variables due to a positive cyclical sentiment shock extracted by multivariate BN. Shaded regions denote a 95% confidence interval.

The impulse responses of macroeconomic variables to cyclical sentiment shocks, extracted using different methods, indicate that the responses of unemployment, inflation expectations, and industrial production are mostly consistent across the various methods. However, the responses of core CPI inflation and CPI inflation vary.

B Data sources and transformation

In the smaller model, I use six variables: average cyclical sentiment, the unemployment rate, Michigan one-year inflation expectations, core CPI inflation, CPI inflation, and industrial production. The monthly data spans from January 1978 to December 2023. However, I consider the data from December 1980 to December 2023 for the impulse responses. In the extended model, I include the S&P 500 and the federal funds rate, along with 12 additional variables.

To compute cyclical sentiment, I use the Index of Consumer Sentiment (ICS) from the University of Michigan Surveys of Consumers. The ICS is constructed based on responses to five questions related to individual and national financial and business conditions, including current financial situation, future financial expectations, business conditions for the next year, long-term economic prospects, and timing for major purchases. Data for inflation expectations, CPI inflation, core CPI inflation, the unemployment rate, the growth rate of industrial production, and the federal funds effective rate are obtained from the Federal Reserve Economic Data (FRED), provided by the Federal Reserve Bank of St. Louis. Inflation expectations data are sourced from the University of Michigan Surveys of Consumers. CPI inflation, core CPI inflation, and unemployment rate data are produced by the Bureau of Labor Statistics, while data for industrial production and the federal funds effective rate are produced by the Board of Governors of the Federal Reserve System.

Other variables are also collected from FRED St. Louis FRED-MD monthly databases and transformed accordingly.[8] Some variables, such as real personal income, civilian labor force, civilian employment, total nonfarm employees, and real personal consumption expenditures, are transformed as the change in their logarithms. Average weekly hours for goods-producing and manufacturing industries are left unchanged. Housing starts for new privately owned homes are presented in logarithmic form. The second differences of the logarithms are used for durable goods, nondurable goods, and services consumption. The S&P 500 stock prices and the volatility index (VIX) are also from FRED-MD and are transformed as the percentage change in their logarithms.

[8] Here is the site for FRED-MD data: https://research.stlouisfed.org/econ/mccracken/fred-databases/

C Cholesky Structural VAR

In this section, I analyze the Cholesky Structural VAR to compute impulse response functions of macroeconomic variables to an average cyclical sentiment shock, in order to compare these responses with those obtained from local projections. The Cholesky structural VAR model incorporates average cyclical sentiment, the unemployment rate, inflation expectations, core CPI inflation, CPI inflation, and industrial production into a smaller model. This is extended to a larger model by adding the S&P 500 and the federal funds rate, with the variables ordered for Cholesky decomposition. For both models, I use monthly data from December 1980 to December 2023 to maintain consistency with impulse responses from local projection. The structural VAR follows an AB model framework as initiated by Bernanke (1986) and Sims (1986).

$$Ae_t = BZ_t, \quad \text{with} \quad E(Z_t Z_t') = I \tag{13}$$

where e_t is a reduced-form error and Z_t is a structural shock. Also,

$$E(e_t e_t') = A^{-1} B E(Z_t Z_t') B' (A^{-1})' = A^{-1} B B' (A^{-1})' = \Sigma \tag{14}$$

Equation 13 can be expressed with short-run exclusion restrictions on the parameters of the contemporaneous matrix A in a lower-order form, while the right-hand side features a diagonal identity matrix B. To identify the smaller model with 6 variables, 15 restrictions are required to estimate the remaining 21 parameters accurately, given that $\frac{K(K-1)}{2} = 15$ when $K = 6$. The Cholesky structural VAR model imposes 15 zero short-run restrictions on the contemporaneous matrix A in the left side of equation 13. These restrictions and the order of the variables in the structural VAR allow cyclical sentiment shocks to have a contemporaneous effect on other variables, while other shocks influence cyclical sentiment only with a delay through the lag polynomial.

The responses of macroeconomic variables are analyzed using Cholesky decomposition and compared with those from local projection. The specifications are generally similar between the two methods. However, while Cholesky decomposition uses a one-standard-deviation positive shock, local projection applies a one-unit positive shock to cyclical sentiment. The confidence interval is set at 95%, and bootstrapping is performed 1,000 times.

C.1 Responses to average cyclical sentiment with Cholesky SVAR

The responses of macroeconomic variables to a one-standard-deviation positive shock in average cyclical sentiment are similar to those obtained using local projection, with a scaling effect due to different units of measurement. However, the responses become insignificant earlier compared to those from local projection, with CPI and core CPI inflation responses becoming insignificant.

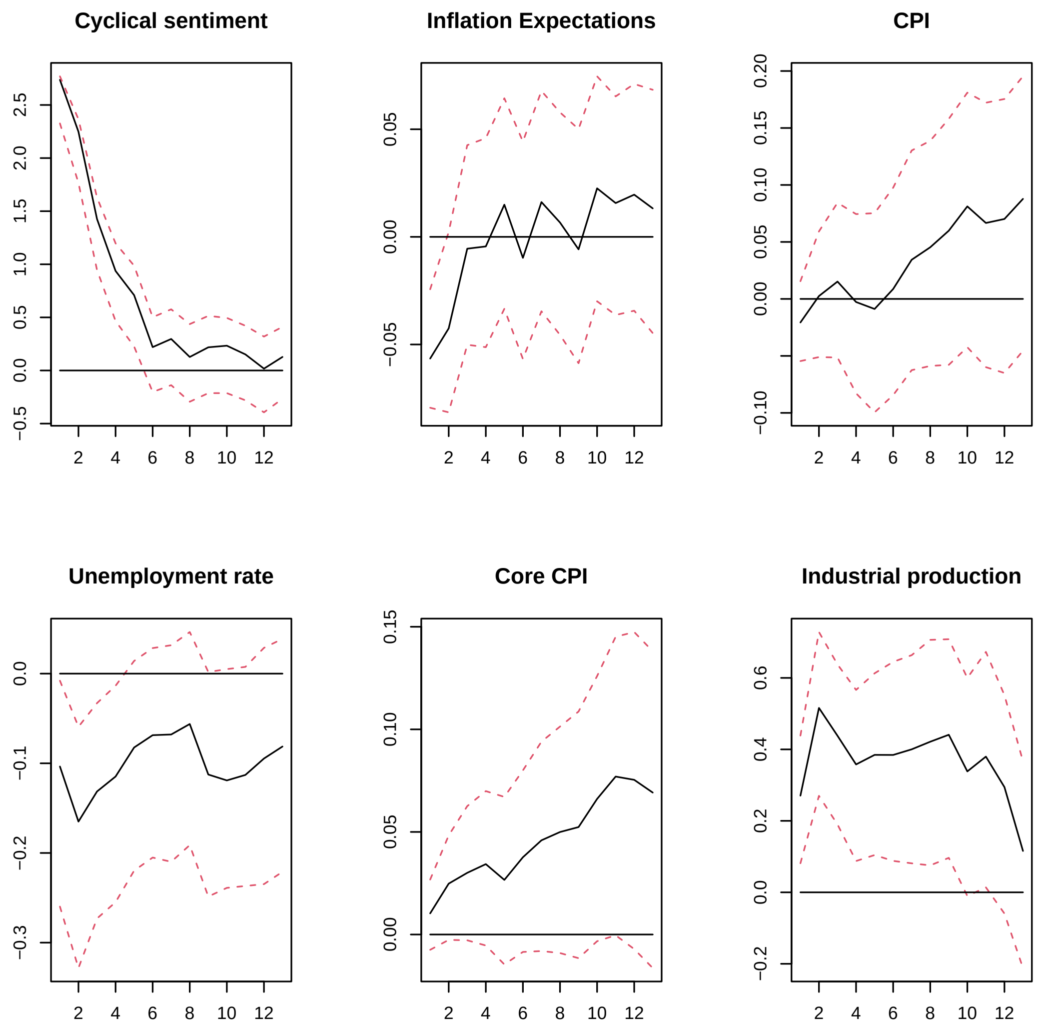

Figure 14: Impulse response functions of macroeconomic variables due to a one standard deviation cyclical sentiment (average of cycles) shock. Shaded regions denote a 95% confidence interval.

C.2 Responses to cyclical sentiment including financial variables with Cholesky SVAR

In a larger model that includes financial variables such as the S&P 500 and the federal funds rate, the responses of variables to average cyclical sentiment remain consistent with those obtained using local projection, after adjusting for scaling effects. However, the responses of CPI and core CPI inflation become insignificant, whereas they were significant for the first month in the local projection analysis.

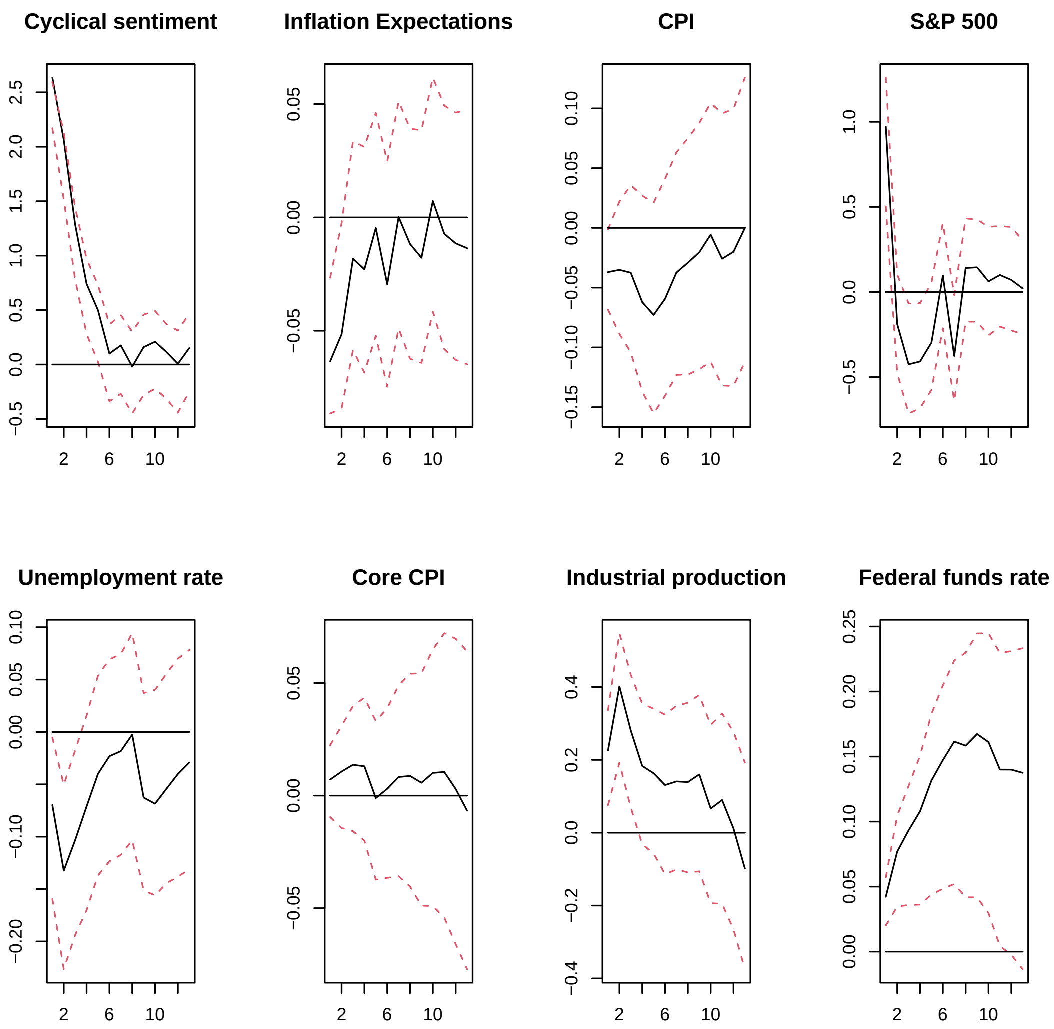

Figure 15: Impulse response functions of macroeconomic variables including financial variables due to a one standard deviation cyclical sentiment (average of cycles) shock. Shaded regions denote a 95% confidence interval.

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