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ABSTRACT
I find that the highly regarded investor and manager sentiment indices demonstrate both cyclical and persistent variations. The presence of cyclicality in the orthogonalized indices suggests the existence of feedback loops connecting sentiment with economic or market outcomes. For example, optimistic sentiment can stimulate increased consumer spending and investment, thereby fostering economic growth and further boosting sentiment. These feedback loops have the potential to amplify cyclical sentiment trends and increase the volatility of economic and market cycles, leading to persistent cycles driven by feedback mechanisms. Importantly, my results remain robust against potential mean reversion resulting from heuristic behaviors such as herding and overreaction, as well as against random behavior arising from intermittent bubbles characterized by near-rational learning and potential overextrapolation bias.

KEYWORDS
Animal spirit; Business cycles; Heuristic; Herding; Shifts in expectations

1. Introduction

The investor sentiment indices proposed by Baker and Wurgler (2006) and Huang et al. (2015), as well as the manager sentiment index introduced by Jiang et al. (2019), undergo orthogonalization with respect to macroeconomic factors. This process ensures that these indices are free from any inherent fundamental components and are solely driven by behavioral factors. Specifically, the sentiment indices are made orthogonal to various economic indicators, including the industrial production index, consumer durables and nondurables, services, employment figures, and a dummy variable representing the National Bureau of Economic Research (NBER) recessions. Furthermore, the manager sentiment index is orthogonalized with respect to 14 macro factors outlined in Welch and Goyal's (2008) review.[1]

However, the impact of pure sentiment factors on cyclical patterns varies depending on their characteristics. In his renowned work, the *General Theory*, Keynes (1936) emphasized the importance of shifts in expectations, which he coined as "animal spirits," distinct from rational probabilistic calculations. Keynes proposed that the animal spirits of entrepreneurs, which influence their investment decisions, serve as a key driver of economic fluctuations. Similarly, Pigou ([1927]; 2016) attributed business cycles mainly to expectations, highlighting entrepreneurs' oscillations between optimism and pessimism as pivotal factors in shaping real economic activity. Recent research by Lagerborg, Pappa, and Ravn (2023) has shown that sentiment shocks have significant implications. A negative sentiment shock tends to precipitate a recessionary scenario, initiating a prolonged decline in consumer confidence, resulting in contractions across industrial production, private sector consumption, and the labor market.

Ultimately, cyclical sentiment can be reinforced by feedback loops that interconnect sentiment with economic or market outcomes. For instance, optimistic sentiment can fuel increased consumer spending and investment, thus fostering economic growth and further uplifting sentiment. Conversely, pessimistic sentiment can lead to reduced spending and investment, potentially exacerbating economic downturns. These feedback loops have the capacity to amplify cyclical sentiment trends and heighten the volatility of economic and market cycles, resulting in persistent cycles driven by feedback mechanisms. As mentioned by Gardini et al. (2023), the bidirectional feedback loop between national income and investor sentiment can generate endogenous business cycles that evolve alongside alternating waves of optimism and pessimism.

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In this article, I aim to assess the cyclical and persistent nature of esteemed investor and manager sentiment indices, contrasting them with two distinct alternative hypotheses. My hypothesis asserts that sentiment exhibits both persistence and cyclicality, influenced by shifts in expectations that may not adhere to rational probabilistic calculations—a concept akin to Keynes' "animal spirits" from 1936. This behavioral phenomenon can stem from a spectrum of emotions, including confidence, fear, and optimism. I propose that manager and investor sentiments are both cyclical and persistent. If this is the case, the adjustment mechanism will be long and delayed, as suggested by Lagerborg, Pappa, and Ravn (2023).

Conversely, the first competing hypothesis suggests that sentiment follows a random walk pattern, characterized by persistence but lacking cyclicality. This notion aligns with the concept of near-rational learning, which can lead to the emergence of rational bubbles, as demonstrated by Lansing (2010). Furthermore, the hypothesis of cyclical and persistent sentiment is contrasted with the second competing hypothesis, suggesting that sentiment is influenced by herding behavior, wherein investors emulate the actions of others rather than making independent decisions based on their own analysis or information. This behavior entails mimicking the actions of a larger group, often driven by a desire for safety or a fear of missing out on potential gains. Herding can lead to the formation and continuation of trends in asset prices, as individuals join the crowd in buying or selling securities. This mean reversion pattern is associated with trends and fads in investor attitudes, as proposed by De Long et al. (1990), among others, or possibly by overreactions, as suggested by De Bondt and Thaler (1985). Such overreactions and fads result in mean reversion behavior that lacks cyclicality. López-Salido, Stein, and Zakrajšek (2017) provided evidence showing that elevated credit market sentiment leads to predictable mean reversion in credit market conditions. Evans, Honkapohja, and Mitra (2022) found that a significant shock to pessimistic expectations has the potential to ensnare the economy in a state of stagnation characterized by a persistent low-level equilibrium, accompanied by declining inflation and output. Claus and Nguyen (2023) provided evidence that prior to events, an overabundance of optimism motivates consumers to reduce saving and increase borrowing, thereby fostering an increase in consumption growth. However, following events, if family finances exhibit sustained improvement less than anticipated, consumers curtail borrowing and increase saving, leading to a decline in consumption growth.

I find that the orthogonalized sentiment indices exhibit nonrandom behavior. Their persistent nature likely stems from potential cyclicality resulting from shifts in expectations, which may not adhere to rational probabilistic calculations. This conclusion is supported by the ability of these tests to isolate the component associated with overextrapolation bias. If the persistence of the indices is driven by overextrapolation, investors and managers believe that recent high returns are more likely to be followed by high returns, regardless of variations in business cycles, leading to noncyclical behavior. However, my results reject noncyclicality in favor of cyclical indices.

In contrast to Tham (2023), I find no evidence of mean reversion in sentiment indices and reject the overreaction and fads hypotheses. Instead, sentiment indices demonstrate persistence and cyclical patterns. These results suggest the influence of standard business cycle variables, aligning with Bernanke and Gertler (1989) and Chordia and Shivakumar (2002), who attributed momentum strategies to business cycles. Additionally, López-Salido, Stein, and Zakrajšek (2017) found that investors' predictions about future credit defaults are overly influenced by economic fundamentals. Our results support the non–market clearing approach.

Unlike Gardini et al. (2023), we conclude that sentiment effects are permanent and the market economy's adjustment mechanism is slow. Supporting Lagerborg, Pappa, and Ravn (2023), I find that a negative sentiment shock can precipitate a recessionary scenario, which may lead to a prolonged decline in economic activity. This underscores the need for government interventions following significant sentiment shocks, as suggested by the Keynesian school, to address the slow adjustment mechanism in the economy resulting from possible price rigidities.

Sentiment data often exhibit transient features—temporary patterns that do not persist over time. If these features are not properly accounted for, they can significantly distort analysis and interpretation. Examples include sudden spikes or outliers in investor optimism following significant events like elections or major policy announcements, which cause sharp, temporary changes in the index. Additionally, random short-term fluctuations or noise, such as measurement errors or minor index variations due to daily news events, can momentarily influence investor and manager sentiment without lasting impact. To counter these problems, I conduct several robustness tests based on wavelet analysis. My results demonstrate resilience against these transient features of the data. Consistent with Birru and Young (2022), I find that when uncertainty is relatively high, such as during economic downturns, the effects of sentiment become more pronounced. I conclude that sentiment exhibits a cyclical and persistent nature under these conditions.

The rest of the article is structured as follows. Section 2 develops the hypotheses. Section 3 describes the data. Section 4 develops the methodologies and reviews the results. Finally, Section 5 concludes.

2. Hypothesis

2.1. Hypothesis 1: Cyclical and persistent sentiment vs. random walk sentiment

I follow Barsky and Sims (2012) and define sentiment as the optimistic or pessimistic tone of expectations, able to alter economic variables, without basis on economic fundamentals. In this case, when the sentiment is not aligned with the facts, the expectations turn out to be erroneous. Hence, sentiment could have both rational and irrational components (Barsky and Sims 2012; Nowzohour and Stracca 2020; Verma and Soydemir 2009).

Accordingly, I hypothesize that orthogonalized sentiment indices are random. This is consistent with the near-rational learning that generates rational bubbles. Lansing (2010) suggested a geometric random walk without drift process to model asset prices with near-rational equilibrium.[2]

The above hypothesis is contrasted with the null hypothesis positing that sentiment exhibits both persistence and cyclicality, driven by shifts in expectations that may not adhere to rational probabilistic calculations (Keynes 1936; Pigou [1927]; 2016). Mertens et al. (2020) further contributed to this understanding by investigating the influence of monetary policy news on household consumer sentiment, which mirrored the prevailing economic conditions during the survey period. Their study revealed that a positive shock in monetary policy elicits adverse effects on economic sentiment, supporting the notion of cyclicality in sentiments. Similarly, Lamla and Vinogradov (2021) explored the repercussions of Bank of England announcements on inflation expectations and perceptions, corroborating the findings of Mertens et al. (2020). Anastasiou, Kapopoulos, and Zekente (2023) provided additional insights by demonstrating that fluctuations in house prices are driven by sentimental shocks, even in the absence of significant changes in overall fundamentals. Gregory (2021) found evidence that investor and managerial sentiments are influenced by macroeconomic fundamentals. Furthermore, Lagerborg, Pappa, and Ravn (2023) provided evidence indicating the sentimental nature of sentiment shocks. Consequently, these findings lead to my first hypothesis:

Hypothesis 1_0. Orthogonalized sentiment indices are persistent and procyclical.

Against the alternative hypothesis:

Hypothesis 1_A. Orthogonalized sentiment indices follow a geometric random walk without drift.

2.2. Hypothesis 2: Mean-reverting sentiment vs. cyclical and persistent sentiment

The concept of fashions and fads in investor attitudes (De Long et al. 1990, among others) along with the overreaction hypothesis (De Bondt and Thaler 1985) suggests the possibility of sentiment reversals from previous periods, leading to mean reversion behavior characterized by cyclical patterns. López-Salido, Stein, and Zakrajšek (2017) offered evidence indicating that elevated credit market sentiment tends to result in predictable mean reversion in credit market conditions. Al-Zoubi et al. (2023) presented findings suggesting that positive sentiment can prompt some CEOs to issue fewer stocks than advisable, with excessive debt financing in prior months increasing the likelihood of CEOs resorting to equity financing in subsequent periods. López-Salido, Stein, and Zakrajšek (2017) also demonstrated that optimistic sentiment in the credit market correlates with a decline in economic activity over the subsequent 2 years, implying foreseeable mean reversion in credit market conditions.

Furthermore, Bernanke and Kuttner (2005) delved into the impact of surprise policy actions on stock prices, revealing that the stock market's response to monetary policy is mainly influenced by unexpected changes in the fed funds target rate and their effect on the equity risk premium. They proposed that the significant impact of monetary shocks on anticipated excess returns could be attributed to monetary policy's impact on stock riskiness or investor risk aversion. Nonetheless, they acknowledged that their findings align with the possibility of investor overreaction or excessive sensitivity of stock prices to monetary shocks. In essence, investor psychology may play a pivotal role in shaping the response of equity investors to monetary news, potentially leading to mean reversion in sentiments as predicted by the overreaction and fads hypotheses. This conclusion leads to my second hypothesis:

Hypothesis 2_0. Orthogonalized sentiment indices exhibit mean reversion.

Against the alternative hypothesis:

Hypothesis 2_A. Orthogonalized sentiment indices are persistent and procyclical.

3. Data

I collected monthly sentiment data sourced from Guofu Zhou's personal website, accessible at http://apps.olin.wustl.edu/faculty/zhou/. Guofu Zhou served as a coauthor of the Jiang et al. (2019) publication. My data set comprised three common sentiment indices found in the literature: the investor sentiment index of Baker and Wurgler (2006) covering the period from July 1965 to December 2014, Huang et al.'s (2015) index covering the period from July 1965 to December 2023, and the manager sentiment index of Jiang et al. (2019) spanning from January 2003 to December 2017. To ensure the accuracy of these indices in measuring sentiment, I employed the orthogonalized versions, which are orthogonalized to the growth of industrial production, durable consumption, nondurable consumption, service consumption, employment growth, and a dummy variable for NBER recessions. The manager sentiment index is orthogonalized to 14 macroeconomic variables as reviewed in Welch and Goyal (2008). The index BWO is the orthogonalized version of BW from Baker and Wurgler (2006). The index PLSO is the orthogonalized version of PLS from Huang et al. (2015), and MS is the orthogonalized manager sentiment index from Jiang et al. (2019).

Figure 1 illustrates the three sentiment indices across the two sample periods. My sample period encompasses seven business cycles with troughs in 1970, 1975, 1980, 1982, 1991, 2001, and 2009. Additionally, it includes five financial crashes and crises, such as Black Monday (1987), Black Wednesday (1992–1993), the Mexican debt crisis (1994–1995), the Russian financial crises (1998 and 2014), and the financial crises of 2007–2008. The sentiment indices demonstrate a pronounced cyclicality as they decline with each U.S. economic contraction. Notably, there is a significant shift in sentiment due to the global bond market collapse in 1994 triggered by rising short-term interest rates. Following Black Wednesday in 1993, the Federal Reserve commenced raising interest rates in February 1994 as the U.S. economy recovered from the 1993 recession. The escalating short-term interest rates led to declines in the prices of long-term bonds, resulting in a substantial loss in the bond market value of $600 billion domestically and approximately $1.5 trillion globally.[3]

To draw conclusions regarding the cyclicality of sentiment indices, I compare the cycle periods of the orthogonalized sentiment indices with those from the NBER. Table 1 presents U.S. business cycle expansions and contractions during the period from July 1965 to February 2020, detailing cycle durations (trough-to-trough and peak-to-peak) in months.

4. Methodology

In this section, I introduce two robust methodologies to detect and test cyclical variations in manager and investor sentiment indices. The first methodology utilizes the periodogram of sentiment data. Following Bierens (2001), I test for persistent cyclicality against two competing hypotheses: mean reversion and random walk. Periodogram analysis offers significant advantages, such as providing a clear representation of the strength of periodic components in the frequency domain and identifying dominant cycles in the data. However, it has drawbacks, particularly with persistent data. It may suffer from fixed resolution in the frequency domain, making it challenging to distinguish closely spaced frequencies. Additionally, spectral leakage can occur if the data are not properly windowed, leading to spurious peaks. Despite these limitations, it remains an efficient method for testing cyclicality.

To address these issues, I also conducted an extensive wavelet analysis. Wavelet analysis excels by offering both time and frequency localization, making it highly suitable for nonstationary data. It can analyze data at various scales, capturing both short-term and long-term features. More important, wavelet analysis is adept at identifying transient features and changes in frequency over time. This capability is crucial because sentiment data often exhibit temporary patterns that do not persist over time.

4.1. Periodogram analysis and specification tests

To investigate whether the explanatory power of sentiment indices is influenced by business cycles, I adhere to Bierens' (2001) approach and define the following standardized periodogram:

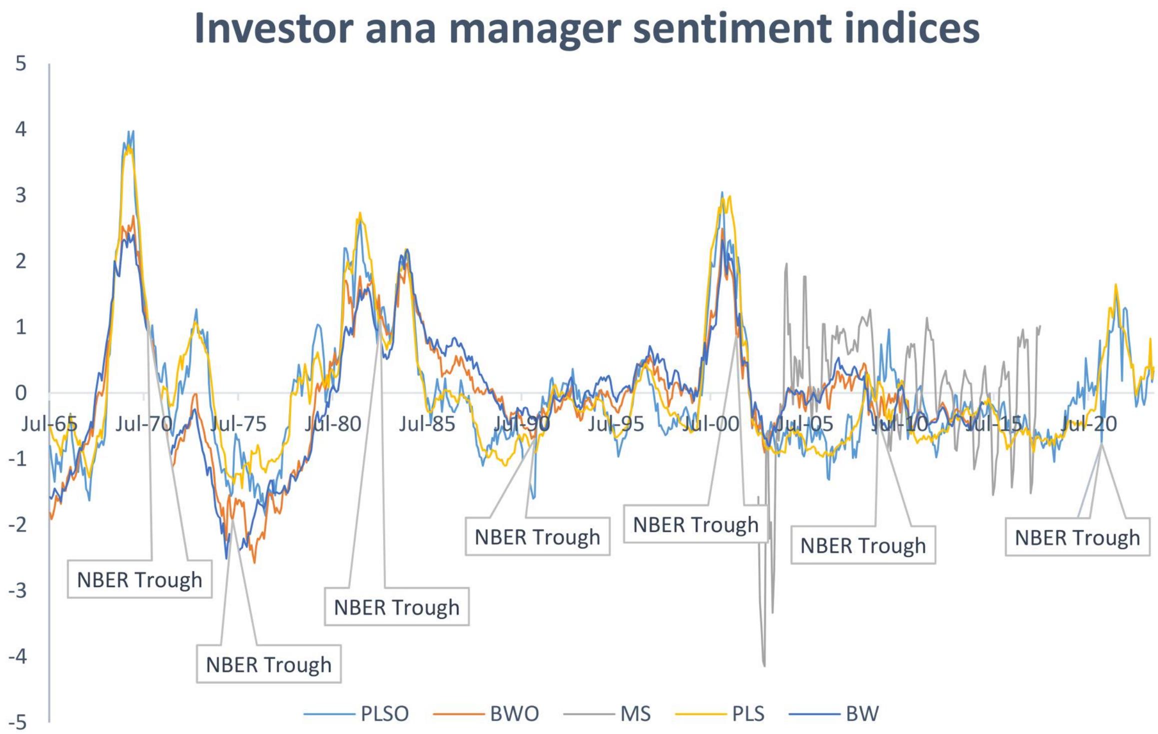

Figure 1. Monthly orthogonalized and unorthogonalized sentiment indices: The PLSO index (blue line), the BWO index (orange line), the MS index (gray line), the unorthogonalized PLS index (yellow line), and the BW index (dark blue line). I used data for the period starting in July 1965 through December 2014 for the BW and aligned indices and for the period starting in January 2003 through December 2014 for the MS index. The period includes seven business cycles with troughs in 1970, 1975, 1980, 1982, 1991, 2001, and 2009. My sample period also contains five financial crashes and crises including Black Monday (1987), Black Wednesday (1992–1993), the Mexican debt crisis (1994–1995), the Russian financial crises (1998 and 2014), the financial crises of 2007–2008, the Crimea crises (2014), and the Ukraine war (2022–present).

Table 1. U.S. business cycle expansions and contractions during the period from July 1965 to December 2023.

Peak	Trough	Peak-to-peak (months)	Trough-to-trough (months)
December 1969	November 1970	116	117
November 1973	March 1975	47	52
January 1980	July 1980	74	64
July 1981	November 1982	18	28
July 1990	March 1991	108	100
March 2001	November 2001	128	128
December 2007	June 2009	8	91
February 2020	April 2020	130	146

$$\rho(\xi) = \frac{2}{n\sigma_y^2}\left(\left(\sum\nolimits_{t=1}^{n} y_t \cos(\varepsilon_t)\right)^2 + \left(\sum\nolimits_{t=1}^{n} y_t \sin(\varepsilon_t)\right)^2\right),$$

where $t = 1, 2, \ldots n, \varepsilon_t$ is an independent and identically distributed (iid) $(0, 1)$ error term, σ_y^2 is the variance, and ξ is a random function with boundaries $(0, \pi)$ given as $\frac{2\pi}{k}, k = 2, \ldots, n,$ where k is the feasible cycle phase.

I hypothesize that sentiment indices, $SENT$, exhibit multiple peaks in cycle frequencies and test the null hypothesis that the indices are complex unit roots[4]:

$$\begin{aligned} SENT_t &= \sum\nolimits_{j=0}^{k} SENT_{j,t} \\ &= \prod\nolimits_{j=1}^{k}\left(1 - 2\cos\left(\emptyset_{k+1+j}\right)L + L^2\right) rp_t \\ &= \mu_j + \eta_j(L)\varepsilon_{j,t}, \end{aligned} \tag{1}$$

where $\emptyset_j \in (0, 2\pi) - \{\pi\}, \eta_j(L)$ is the lag polynomial with roots out of the complex unit circle, and the ε_t is an iid $(0, 1)$ with $E\left(\left|\varepsilon_{j,t}\right|^{2+\gamma}\right) < 0$ for some $\gamma < 0$.

To develop the alternative hypothesis of random walk sentiment indices, I draw motivation from the behavioral finance literature on sentiment. Following Chhaochharia et al. (2019) and Hirshleifer, Jiang, and DiGiovanni (2020), I define sentiment as the emotional states of investors and managers that are orthogonal to the economic measurable fundamentals. Accordingly, I hypothesize that sentiment indices are random. This is consistent with near-rational learning, in which investors and managers update their beliefs about the current state of the economy using Bayes' rule but make random miscalculations. Lansing (2010) suggested a geometric random walk without drift process to model asset prices with near-rational equilibrium.

The first hypothesis, which proposes persistent cyclical sentiment against the alternative of random walk sentiment (where sentiment is defined as the optimistic or pessimistic tone of expectations, capable of influencing economic variables without basis on economic fundamentals), can be examined using the test statistic described in Equation 1. This statistic follows the distribution outlined below:

$$\max_{j=1,\dots k}\left\{\frac{\rho(\emptyset_j)}{n} \geq B_k\right\},$$

where

$$B(k) = \left(\sum_{m=1}^{k} \frac{\int_0^1 w_{1,m}(x)^2 dx + \int_0^1 w_{2,m}(x)^2 dx}{\left(\int_0^1 w_{1,m}(x) dx\right)^2 + \left(\int_0^1 w_{2,m}(x) dx\right)^2}\right),$$

and $(w_{1,m}, w_{2,m})$ are two independent standard Brownian motions.

Next, I examine my second hypothesis, which proposes that the sentiment index demonstrates stationarity (defined as the tendency for investor attitudes, influenced by fashions, fads or overreaction, to revert to the mean) as opposed to the alternative persistent cyclicality, by substituting the variance σ_ε^2 and the lag polynomials by their ordinary least squares equivalents, σ^2 and $\hat{\theta}_p$. The resulting test statistic is

$$\widehat{A_{k,p}} = \hat{\sigma}^{-2} \sum_{j=1}^{k} \left|\hat{\theta}_p\left(\exp(i\emptyset_j)\right)\right|^2 \rho(\theta_j)$$

with a χ^2_{2k} distribution under the null hypothesis of stationary process.

4.2. Wavelet analysis and significance testing

I adopt the definitions of the continuous wavelet transform from Percival and Walden (2000) and Serroukh, Walden, and Percival (2000) to analyze a time series of the sentiment index ($SENT_t$) defined as

$$W_{x(a,b)} = \int_{-\infty}^{\infty} SENT(t)\ \Psi^*\left(\frac{t-b}{a}\right) dt,$$

where Ψ is mother wavelet, a is the scaling parameter, controlling the width of the wavelet. b is the translation parameter, controlling the location of the wavelet, and denotes the complex conjugate. The continuous wavelet transform provides a measure of the correlation between the wavelet at different scales and the time series at different times.

To detect and test for cycles in the sentiment indices, we use the wavelet power spectrum (WPS), which is given by:

$$P_{SENT(a,b)} = \left|W_{SENT)}(a,b)\right|^2.$$

The average wavelet power spectrum (AWPS) over a range of scales a can be defined as

$$\overline{P_{SENT(a)}} = \frac{1}{T} \sum\nolimits_b P_{SENT(a,b)}.$$

The null hypothesis of no significant periodicity is tested against the alternative hypothesis of cyclicality in sentiments by comparing the calculated AWPS from the observed data with a null distribution of AWPS values generated through simulation.

3. Empirical results

3.1. Cycle durations

Utilizing the methodology outlined by Bierens (2001), we initially analyze the periodograms for the sentiment indices: BWO index, PLSO index, and MS index. These periodograms, depicted in Figure 2, enable us to identify frequencies associated with the highest peaks (K). For the BWO sentiment index, the most prominent and statistically significant peak is observed at a cycle duration of 190 months, with other notable peaks detected at cycle durations of 117, 75, and 231 months. For the PLSO index, cycle durations of 186, 116, and 94 months are of significance. Similarly, for the manager sentiment index, the highest peaks align with cycle durations of 85 and 38 months.

4.2. Persistent–cyclical sentiment indices null vs. random sentiment indices alternative

In Table 2, I provide cycle periods and the maximum max $\hat{\rho}(\varphi_{0,j})/n$ statistics for the 6 highest peaks for each sentiment index. I conduct a test for cyclicality using the $B(k)$ test, where the joint hypothesis of 6 cycles is tested against the alternative of a random walk. The results show that all sentiment indices exhibit cyclical and persistent behavior. The hypothesis of random sentiment behavior is rejected. These findings hold not only statistically but also

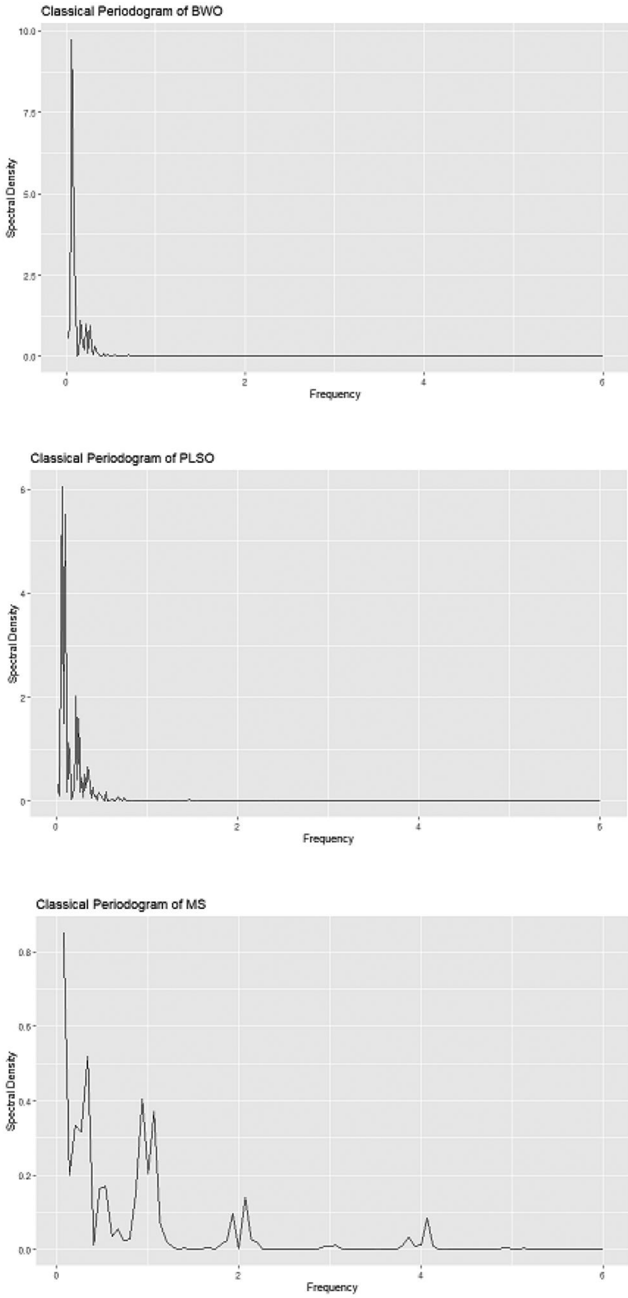

Figure 2. Classical periodograms of the BWO index, aligned index, and manager index, respectively.

economically significant implications. Specifically, the cycle durations of 190 months for the BWO index, 118 and 94 months for the aligned index, and 85 and 38 months for the MS index indicate the presence of complex unit cycles at the 5% and 10% significance levels. It is noteworthy that the cycle duration of 118 months for both the BWO and aligned sentiment indices, as well as the 75-month cycle duration for the BWO index, the 79-month cycle duration for the aligned index, and the 85-month cycle duration for the MS index, align with the NBER business cycles of November 1970 and June 1980, respectively. Similarly, the aligned index with a 94-month cycle duration and the MS index with an 85-month cycle duration correspond to the NBER business cycle of June 2009.

Table 2. The null complex unit root $B(k)$ test against unit root alternative for the BWO sentiment index for the period from January 1965 to December 2023, aligned investor sentiment index for the period from January 1965 to December 2023, and the MS manager sentiment index for the periods from January 2003 to December 2017.

J	$\varphi_{0,1}$	Cycle period	$\hat{\rho}(\varphi_{0,j})/n$
BWO			
1	0.01244	231	0.06801
2	0.03307	190	0.30581**
3	0.0537	117	0.11546
4	0.08378	75	0.06534
5	0.09973	63	0.05796
6	0.11424	55	0.04945
PLSO			
1	0.03653	186	0.19883*
2	0.05325	116	0.17832*
3	0.06684	94	0.07612
4	0.07953	79	0.05499
5	0.11424	55	0.07101
6	0.1309	47	0.08936
MS			
1	0.07402	85	0.36347**
2	0.16501	38	0.34001**
3	0.26310	24	0.11727
4	0.34313	17	0.05101
5	0.48332	13	0.02210
6	0.70031	9	0.01958

The max $\hat{\rho}(\varphi_{0,j})/n$ and p value for BWO, aligned, and MS sentiment indices are (0.30581, 1), (0.19883, 1), and (0.36339, 1), respectively.
Joint test: 10% and 5% critical regions = (0.0331, 0.0199).
Individual tests: 10% and 5% critical regions = (0.1403, 0.2411).
*Significant at 10% level.
**Significant at 5% level.

Table 3. The null stationary $\hat{A}_{k,p}$ test against the cyclical alternative for the BWO sentiment index (1965–2014), the aligned investor sentiment index (1965–2023), and the MS manager sentiment index (2003–2017).

p	BWO	PLSO	MS
1	397.65	406.85	124.61
2	57.93	60.71	39.41
3	58.93	82.43	49.87
4	59.08	86.63	49.97
5	59.64	88.74	58.12
6	61.28	89.71	60.33
7	61.86	87.29	57.82
8	62.76	90.28	61.75
12	65.88	110.55	72.37
18	65.17	113.44	74.16
24	71.03	115.03	79.77
36	70.03	129.74	91.81
48	68.99	129.51	101.06

10% and 5% Critical regions = (18.55, 21.03).

I conclude that the orthogonalized sentiment indices cannot be random. The persistent behavior of sentiment is likely due to possible cyclicality resulting from shifts in expectations that may not adhere to rational probabilistic calculations. This conclusion holds validity because these tests can isolate the component related to the bias of overextrapolations. If the persistence of the

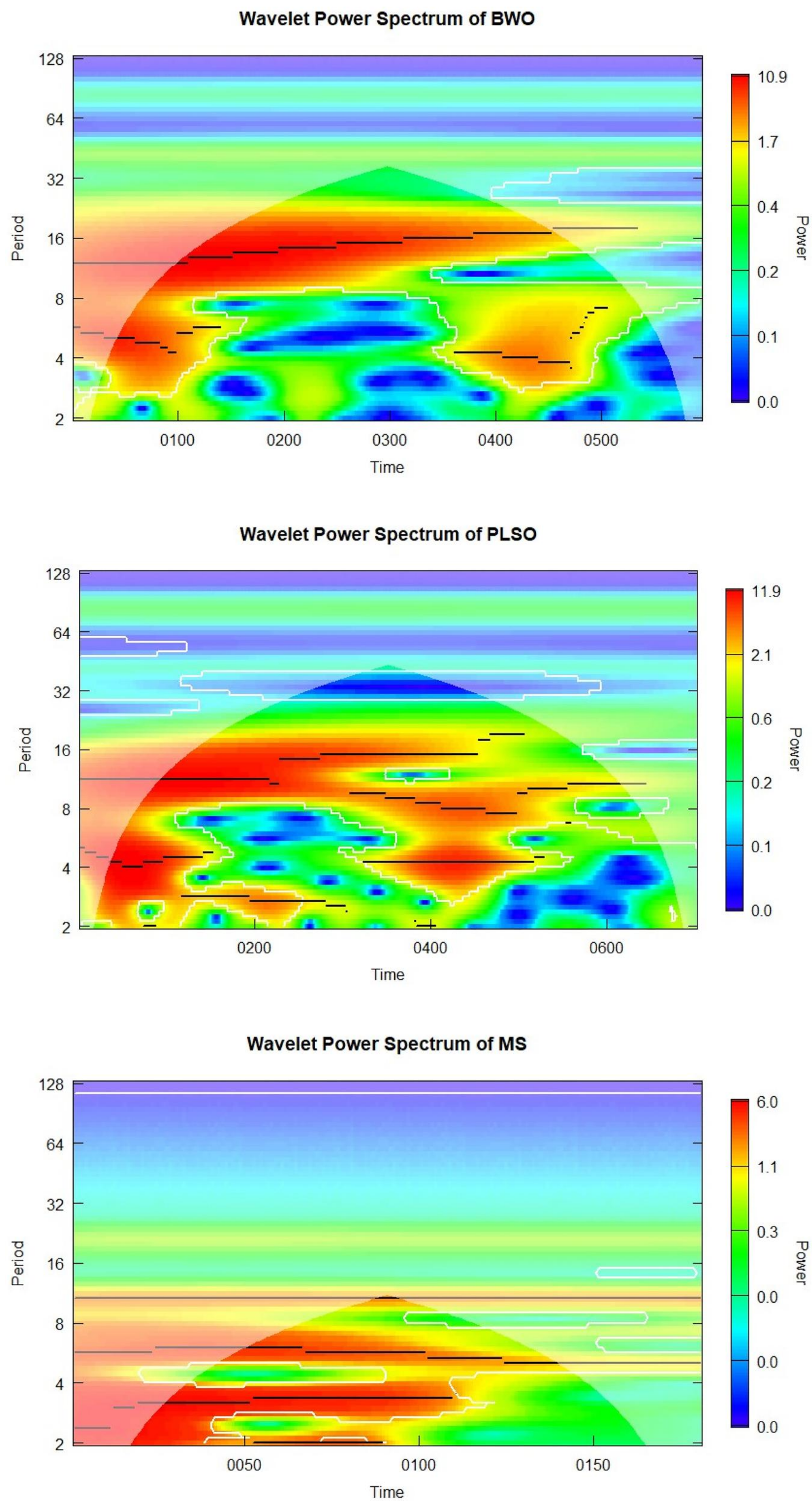

Figure 3. Wavelet power spectrum of the BWO index, aligned index, and manager index, respectively.

indices is driven by overextrapolation, investors and managers do not respond immediately to changes in business cycles. Instead, an extrapolative agent believes that recent high returns are more likely to be followed by high returns and, similarly, recent low returns are more likely to be followed by low returns, regardless of

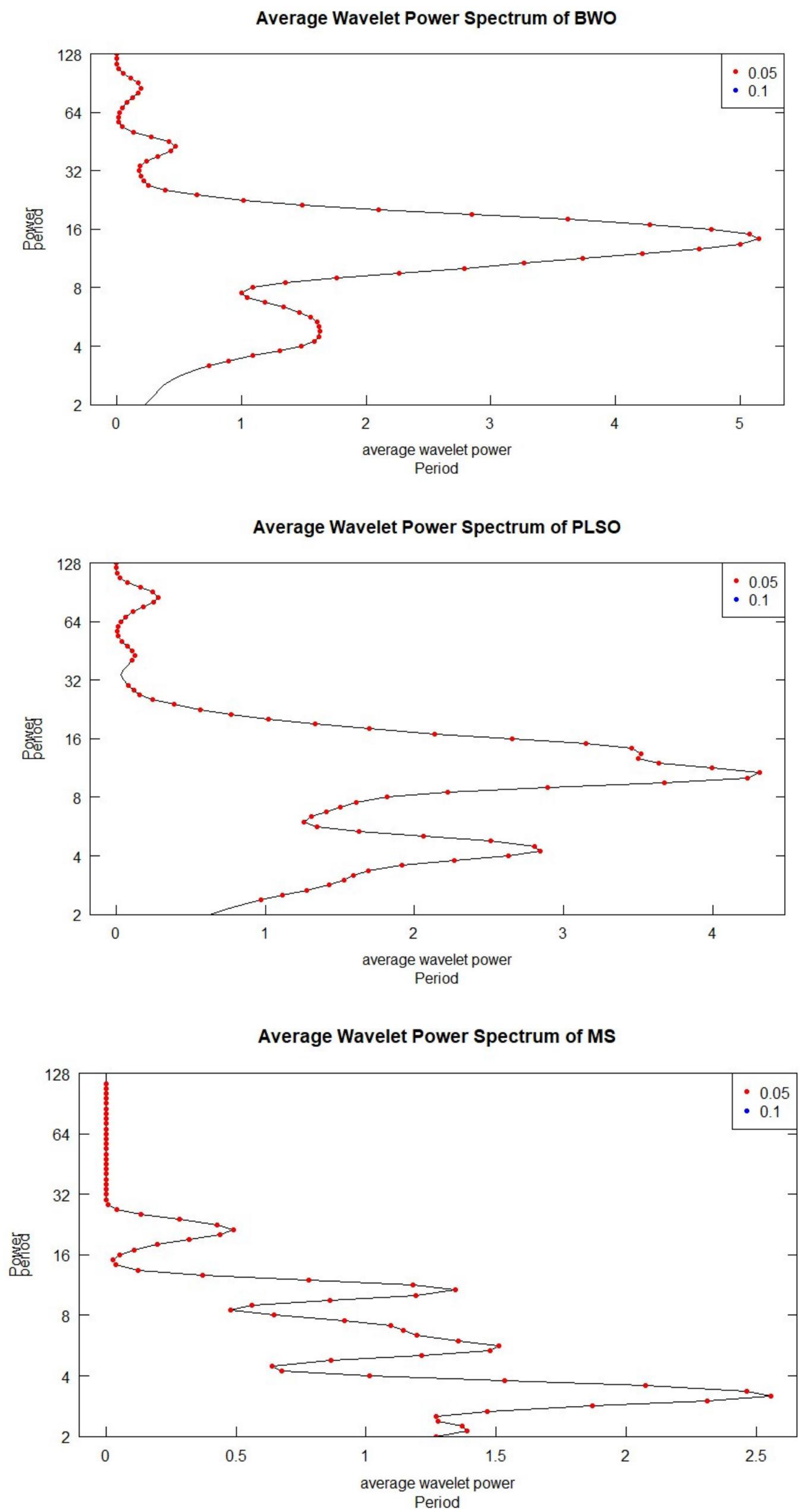

Figure 4. Average wavelet power spectrum of the BWO index, PLSO index, and MS index, respectively. Red dots indicate *p* values at the 5% significance level, and blue dots indicate *p* values at the 1% significance level.

the variation in business cycles. Such behavior would result in noncyclical behavior. My results reject noncyclicality in favor of cyclical indices.

4.3. Mean-reverting sentiment indices null vs. persistent–cyclical sentiment indices alternative

In Table 3, I report the $\hat{A}_{k.p}$ stationary tests and their p values against the cyclical and persistent alternatives for the three sentiment indices. In contrast to overreaction and fads hypotheses, sentiment indices are shown to be persistent and cyclical. My interpretation of the results is that the behavior of sentiment indices is attributable to standard business cycle variables. This is consistent with the work of Bernanke and Gertler (1989) and Chordia and Shivakumar (2002), who found that momentum strategies are attributable to business cycles. López-Salido, Stein, and Zakrajšek (2017) found evidence that investors' predictions about future credit defaults are excessively affected by economic fundamentals, so that when there is positive sentiment about the current state of the economy, investors become overly optimistic, credit spreads shrink, the loans expand, and real activity speeds up. My results are robust to possible misspecifications in autoregressive lags with a wide range of lag polynomials (up to 48 months are examined).

4.4. Robustness test

In this section, I present the results of several robustness tests to determine how sensitive the findings are to transient features in the data and the econometric procedures used. The tests are divided into 2 categories. First, I examine whether the results are influenced by the construction of the sentiment index, particularly considering sudden spikes or outliers due to manager and investor optimism. Second, I explore the potential impact of noise in the data structure caused by daily news events that can momentarily affect sentiment without a lasting effect.

I employ wavelet analysis to detect and analyze cycles in the sentiment indices, following the methodologies outlined by Percival and Walden (2000). Wavelet analysis is chosen for its flexibility and robustness to noise, allowing one to capture transient features such as spikes and trends in the data.

Figure 3 illustrates the wavelet power spectrum for each sentiment index, where warmer colors like red and yellow denote higher power, contrasting with cooler shades of blue and white indicating lower power. Cooler tones, such as blue and green, suggest a lack of cyclicality in those regions of the spectrum. The plot reveals prominent high-power areas spanning from 8 to 20 months. Specifically, from 1970 to 2005, both the BWO and PLSO investor sentiment indices exhibit distinct cyclical patterns with periods ranging from 8 to 16 months. The cycles align with the NBER peak-to-peak cycles during the 1981–1982 oil shock and the 2007–2009 financial crisis. The manager sentiment index shows cycles occurring approximately every 3 to 5 months. Another notable cycle with periods of 8 to 10 months is observed around 2009, marked at the apex of the spectrum's cone. Importantly, these cycles are situated within the cone of influence, indicating their statistical significance.

Once significant power regions—highlighted by peaks or clusters in the WPS—are identified, I calculate the average period corresponding to these regions. This average period provides crucial insights into the predominant frequency or cycle length within the data set. As illustrated in Figure 4, the average power wavelet period for investor sentiment indices spans approximately 4 to 5 months, surpassing that of the manager sentiment index. Specifically, the manager sentiment index shows an average power period of about 2.5 months.

5. Conclusion

I derive implications from the models of Barsky and Sims (2012), De Long et al. (1990), and De Bondt and Thaler (1985) and conduct specification tests using investor and manager sentiment to examine whether these indices exhibit cyclical and persistent behavior against 2 competing hypotheses, namely, mean reversion and random walk. I find that these indices display cyclical and fundamental variations that align with the durations of NBER cycles. Based on this analysis, I conclude that orthogonalized sentiment index variables are both persistent and cyclical, supporting the hypothesis that shifts in expectations, distinct from rational probabilistic calculations, serve as key drivers of economic fluctuations, resulting in a loop in sentiment.

Notes

1. Welch and Goyal (2008) considered 14 macro factors. These factors are dividend–price ratio, dividend yield, dividend–payout ratio, earnings–price ratio, term spreads, net equity expansion, book-to-market ratio, Treasury Bill rate, long-term yield, long-term return,

default yield spread, default return spread, stock volatility, and inflation.
2. In a near-rational learning model, investors and managers update their beliefs about the current state of the economy using Bayes' rule, but they make random miscalculations.
3. Al-Zoubi (2019, 2024) demonstrated the permanent effect of monetary policy changes on bond markets.
4. To mitigate the risk of overextrapolation and the presence of any single unit root, I follow Al-Zoubi (2017) and Al-Zoubi, O'Sullivan, and Alwathnani (2018) and compute changes in the sentiment index (ΔSENT) as the yearly differences after seasonal adjustment. The rationale behind this approach is that when there is a possibility of overextrapolation, the index tends to be asymptotically nonstationary. If investors overextrapolate past returns, they believe that recent firm profitability, whether high or low, is more likely to persist in the future. In other words, they perceive good or bad news to be more persistent than it actually is. This tendency is consistent with the "law of small numbers" proposed by Tversky and Kahneman (1971), as well as the "hot-hand fallacy" identified by Gilovich, Vallone, and Tversky (1985), wherein investors rely excessively on the most recent observations about the state of the economy.

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