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Employment sentiment behavior during European economic crises: Time trends and persistence analysis

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ABSTRACT

This study analyzes employment sentiment dynamics in the Euro Area during recessions using long memory models and time–frequency causality tests. Results show strong persistence in expectations and evidence of bidirectional causality with recession indicators. Employment sentiment serves as a short- and medium-term predictor of recessions, while downturns have lasting effects on labor market perceptions. These findings highlight the relevance of sentiment indicators for macroeconomic forecasting and policy design.

1. Introduction

Labor markets within the European Union present a complex structure characterized by deep interconnections alongside marked national disparities. Investigating the evolution of employment-related sentiment during periods of economic stress is both relevant and necessary for understanding broader socio-economic dynamics. Recent empirical evidence suggests that, over the past thirty years, euro area (EA) countries have experienced economic downturns that are not only more frequent but also more severe compared to those observed in other advanced economies (Bluedorn et al., 2019).

In this context, the growing attention to leading indicators and their role in anticipating macroeconomic developments appears both justified and necessary (Rossi and Sekhposyan, 2017; Perić and Sorić, 2018). Considering that the most recent crisis has induced persistent effects on labor markets, commonly referred to as unemployment hysteresis (Kristic et al., 2018), the ability to accurately forecast unemployment trends become particularly critical for timely and effective policy responses.

Theoretical frameworks aimed at explaining unemployment dynamics are diverse and have received extensive empirical attention. Among the most influential are the NAIRU models (Friedman, 1997; Phelps, 1967, 1968), hysteresis theories (Blanchard and Summers, 1986, 1987; Barro, 1988), and structuralist approaches (Phelps, 1994; Pissarides, 2000; Blanchard, 1999; Phelps, 1999; Nickell, 1998; Nickell and Van Ours, 2000). These conceptual paradigms have been empirically evaluated primarily through unit root tests to assess

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the persistence of unemployment shocks, as demonstrated in early studies such as Blanchard and Summers (1986) and Alogoskoufis and Manning (1988). Further contributions—such as those by Gordon (1989), Lopez et al. (1996), and Wilkinson (1997)—explored the statistical underpinnings of the hysteresis hypothesis in greater detail. In response to concerns over structural changes in labor markets, subsequent studies incorporated the possibility of structural breaks in the analysis (e.g., Mitchell, 1993; Bianchi and Zoega, 1998; Papell et al., 2000). More recent research continues to report mixed evidence regarding the existence and magnitude of hysteresis effects across countries and time periods (Amable and Mayhew, 2011; Fosten and Ghoshray, 2011; Holl and Kunst, 2011; King and Morley, 2007; Srinivasan and Mitra, 2012).

Unemployment forecasting, on the other hand, has traditionally relied on the time-series characteristics of historical unemployment data, often supplemented by labor market indicators to enhance predictive accuracy (Barnichon and Nekarda, 2012; Claveria, 2019a, 2019b; Hutter and Weber, 2015). An alternative strand of the literature bases its forecasts on structural macroeconomic relationships—most notably Okun's law, which posits a systematic link between output fluctuations and changes in unemployment—providing a theoretically grounded basis for projection (Ball et al., 2015).

In this study, we introduce a novel approach that focuses exclusively on information derived from employment sentiment expectations. To the best of our knowledge, this is the first research effort to examine the behavior of employment sentiment during periods of economic recession through the lens of long memory methodologies. Specifically, we employ these techniques to investigate the statistical properties of sentiment dynamics, with particular emphasis on mean reversion and persistence.

This analysis is significant for several reasons. First, it enables us to determine whether the employment sentiment series exhibits short- or long-memory characteristics, which has direct implications for the persistence of shocks and the reliability of the series for forecasting purposes. Second, it allows for a more precise assessment of the stationarity properties of the data and facilitates the estimation of the degree of differencing required—within a fractional integration framework—to achieve statistical regularity over the period under study. Third, this approach enhances our understanding of how the series responds to exogenous shocks, offering insight into whether it exhibits mean-reverting behavior or whether policy intervention may be necessary to restore its original trend.

From a multivariate perspective, this study applies two complementary causality tests. First, we employ a Vector Autoregression (VAR)-based Granger causality test in the time domain, which allows us to evaluate whether a causal relationship exists between the variables of interest. Subsequently, we implement the frequency-domain test proposed by Breitung and Candelon (2006), which enables us to assess the statistical significance of this relationship across different time horizons (short-, medium-, and long-term dynamics).

The remainder of the paper is structured as follows. Section 2 describes the data employed in the analysis. Section 3 outlines the methodological framework. The empirical results are presented and discussed in Section 4. Finally, Section 5 concludes the study.

2. Data

This study uses monthly data for the Euro Area covering the period from January 1980 to January 2024. The main variable of interest is the Employment Sentiment Index, proxied by the Employment Expectations Indicator obtained from Eurostat's monthly business survey. This indicator reflects firms' expectations regarding employment developments over the subsequent three months and ranges approximately from −40 to 10, with lower values indicating more pessimistic perceptions about future employment conditions. As such, it provides timely information on labor market expectations and is widely regarded as a forward-looking indicator of economic activity.

Fig. 1 displays the evolution of the Employment Sentiment Index over the sample period. In the same figure, economic recessions are identified using the OECD-based Recession Indicator for the Euro Area provided by the Federal Reserve Bank of St. Louis.[1] This indicator is a monthly binary variable that takes the value one during recessionary episodes, defined as peak-to-trough periods, and zero otherwise. The recession periods highlighted in Fig. 1 coincide with well-documented episodes of economic downturn in the Euro Area, including the early 1980s recession, the European Monetary System crisis of 1992–1993, the dotcom downturn of the early 2000s, the global financial crisis of 2008–2009, the Eurozone sovereign debt crisis affecting the Euro Area during the first half of the 2010s, and the COVID-19 recession in 2020.

In the empirical analysis, the OECD-based recession indicator is not only used for graphical illustration but also to define the subperiods employed in the econometric analysis. Specifically, the analysis is conducted for the full sample and separately for eight post-recession subperiods. Each subperiod is defined as the interval following the end of a recession and ending at the onset of the subsequent recession, based on the OECD-based recession indicator for the Euro Area. These post-recession intervals capture distinct phases of economic recovery and expansion between successive downturns.

Based on this criterion, the eight post-recession subperiods considered in the analysis are defined as follows: (i) January 1980 to December 1990; (ii) February 1991 to January 1995; (iii) February 1995 to December 1997; (iv) January 1998 to December 2000; (v) January 2001 to December 2007; (vi) January 2008 to March 2011; (vii) April 2011 to October 2017; and (viii) October 2017 to October 2024. These post-recession subperiods are labeled as the first through the eighth periods in the empirical results.

[1] https://fred.stlouisfed.org/series/EURORECM.

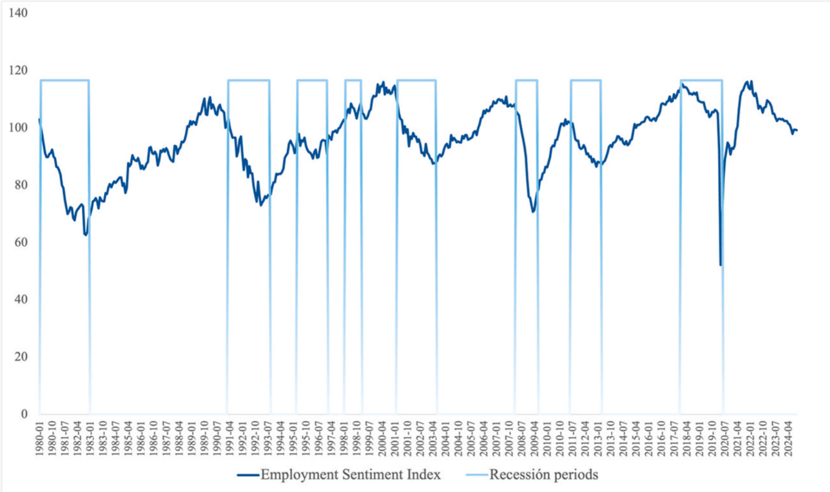

Fig. 1. Employment Sentiment Index time series.

3. Methodology

a. Unit roots

Tests for unit roots can be conducted in numerous ways. In this study, Dickey and Fuller's ADF test is employed (1979). Numerous alternative tests, like Phillips and Perron (1988), which employ a non-parametric estimation of the spectral density of u_t at the zero frequency, can be used to compute unit roots with higher powers. Additionally, we employ the methods based on Kwiatkowski et al. (1992) and Elliot et al. (1996), which yield nearly identical results when taking deterministic trends into account.

b. ARFIMA (p, d, q) model

Thanks to authors such as Lee and Schmidt (1996), Hassler and Wolters (1994), and Diebold and Rudebusch (1991), it is now widely accepted that conventional unit root tests have very low power when the true data-generating process is fractionally integrated or exhibits long-memory behavior. As a consequence, fractional orders of differentiation are allowed in the present analysis.

In this context, we employ the ARFIMA (p, d, q) model to analyze the persistence properties of the Employment Sentiment Index. The ARFIMA (p, d, q) model is formally defined as:

$$\phi(L)(1-L)^d y_t = \theta(L)\varepsilon_t \tag{1}$$

where $\phi(L) = 1 - \phi_1 L - \ldots - \phi_p L^p$ and $\theta(L) = 1 + \theta_1 L + \ldots + \theta_p L^q$ are the autoregressive (p) and moving average (q) lag polynomials, respectively. The parameters p and q therefore capture short-run dynamics, while the fractional differencing parameter d governs long-run persistence. The error term ε_t is assumed to be white noise.

According to equation (1), L denotes the lag operator, d is a real-valued parameter measuring the degree of fractional integration, and y_t represents the time series under analysis. When $d = 0$, the process is covariance stationary with short memory; when $0 < d < 1$, the series exhibits long-memory behavior with mean reversion; and when $d \geq 1$, the process becomes non-stationary.

The appropriate autoregressive and moving average orders p and q are selected using the Akaike Information Criterion (AIC) (Akaike, 1973) and the Bayesian Information Criterion (BIC) ((Akaike, 1979). For both the full sample and the post-recession sub-samples, the fractional differencing parameter d is estimated for all admissible combinations of p and q, and the corresponding 95 % confidence intervals are reported.

4. Empirical results

Table 1 summarizes the unit root test results for the Employment Sentiment Index, analyzing both the original dataset and eight distinct periods after the crisis. The tests employed include the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, which test for the null hypothesis of a unit root (non-stationarity), and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, which tests for stationarity as the null hypothesis. An asterisk (*) marks the rejection of the unit root null hypothesis (indicating stationarity) in the ADF and PP tests.

For the Employment Sentiment Index in its original form, evidence of stationarity is mixed. The ADF test detects stationarity under specifications (ii) and (iii) (test statistics: −3.2492* and −3.9136*, respectively), while specification (i) fails to reject the null hypothesis of a unit root (−0.3916). Similarly, the PP test indicates stationarity under specifications (ii) and (iii) (−3.039* and −3.7479*,

Table 1
Unit roots results.

	ADF			PP	
	(i)	(ii)	(iii)	(ii)	(iii)
Original Data					
Employment Sentiment Index	−0.3916	−3.2492*	−3.9136*	−3.039*	−3.7479*
After Recession Periods					
1st period: (01/1980–12/1990)	−0.0591	−0.9656	−3.5479*	−1.0463	−3.7938*
2nd period: (02/1991–01/1995)	−0.6868	−1.9779	−1.0862	−1.6263	−0.5899
3rd period: (02/1995–12/1997)	0.8561	−1.0016	−1.6473	−1.351	−2.0055
4th period: (01/1998–12/2000)	1.1785	−1.2674	−1.8665	−1.3774	−2.5543
5th period: (01/2001–12/2007)	−0.413	−1.4555	−4.4333*	−1.9757	−4.5258*
6th period: (01/2008–03/2011)	−0.5518	−1.9894	−2.2096	−1.4659	−1.4428
7th period: (04/2011–10/2017)	0.9598	0.4227	−3.2367	0.2718	−2.9444
8th period: (10/2017–10/2024)	−0.4997	−3.1*	−3.1063	−2.6868	−2.6952

respectively). This suggests that stationarity is more likely when incorporating deterministic terms like trends or longer lag lengths in the model.

The unit root test results for the periods following the crisis reveal a heterogeneous evolution in the stationarity of the Employment Sentiment Index. For the first period, stationarity is observed in models incorporating deterministic terms, such as trends (specification (iii)) in both the ADF and PP tests. This suggests that the index shows initial signs of stabilization in the immediate aftermath of the crisis. In the second period, All specifications of the ADF and PP tests indicate non-stationarity, reflecting persistent effects of the crisis or structural changes during this phase. Third and fourth periods exhibit consistent evidence of non-stationarity across all specifications, indicating that the underlying dynamics of the index remain unstable during these phases. In the fifth period a significant improvement in stationarity is observed, particularly in specification (iii) of the ADF and PP tests. This could signal a partial recovery or structural adjustment towards greater stability. Sixth and seventh periods revert to non-stationarity, suggesting that fluctuations in the index persist and may be influenced by external factors or additional shocks. Finally, in the eighth period, a recovery toward stationarity is detected in specifications (ii) and (iii), indicating greater stability towards the end of the analyzed periods.

Overall, the post-crisis behavior of the index is mixed, alternating between periods of non-stationarity and phases of increased stability. Notable progress toward stationarity is observed in the fifth and eighth periods, potentially reflecting adaptive processes or policy measures implemented to mitigate the crisis's impacts. These findings underscore the importance of analyzing each period individually to capture the nuances of the recovery.

Given the low power of the unit root methods under fractional alternatives[2] and in line with the aforementioned methodology, the ARFIMA (p,d,q) models are used in order to analyze the persistence of the time series that we are analyzing. To select the AR and MA orders in the models,[3] the AIC (Akaike, 1973) and BIC (Akaike, 1979) criteria have been used.

Table 2 shows the estimates of long memory test following Sowell (1992) and the maximum likelihood estimator for the three time series. Various ARFIMA specifications (p, d, q) have been considered with all combinations of $p, q \leq 2$ for each time series.

The behavior of employee sentiment following economic downturns provides key insights into resilience and lingering effects on job perceptions. The results obtained through the ARFIMA model highlight a combination of high long memory, moderate recovery indicators and significant heterogeneity between the different periods.

For the original dataset, the ARFIMA(2, d, 2) model estimates a fractional differencing parameter $d = 0.95$, with a standard error of 0.064 and a confidence interval of $[0.84, 1.06]$. The value of dd close to 1 indicates strong long-memory behavior, suggesting that the index exhibits persistent autocorrelation and mean-reverting properties, but only over very long horizons. The inferred level of integration I(d) confirms both stationary (I(d)) and non-stationary (I(1)) behaviors, depending on the specification.

The results for the post-crisis periods highlight a diverse range of long-memory behaviors in the Employment Sentiment Index, reflecting the varying economic dynamics and persistence of shocks during these phases.

Several periods, particularly the 1st, 2nd, 5th, 6th, and 7th periods, exhibit values of $d > 1$, indicating non-stationary long-memory behavior. In these periods, shocks to the index have persistent effects, failing to dissipate even over extended time horizons. This reflects a lack of mean reversion and suggests prolonged economic instability or structural changes during these phases.

The 8th period shows values of d close to or slightly below 1. Although this period shows some degree of mean reversion, the persistence of disturbances remains significant, although less pronounced than in the periods mentioned above. According to the confidence interval, an I(1) behavior of the analyzed series cannot be ruled out.

Notably, the 3rd and 4th periods show values of $d < 1$, indicative of stationary long-memory dynamics. These periods reflect stronger tendencies toward mean reversion, where the index stabilizes over time and shocks dissipate more effectively. The 4th period, with $d = 0.69$, demonstrates the strongest mean-reverting behavior among all periods.

[2] See Diebold and Rudebush (1991), Hassler and Wolters (1994) and Lee and Schmidt (1996).

[3] Note, however, that according to Hosking (1981) and Beran et al. (1998), the AIC and BIC criteria might not be the best criteria under the assumptions of fractional models.

Table 2
Long memory results.

Data analyzed	Sample size (month)	Model Selected	d	Std. Error	Interval	I(d)
Original Data						
Employment Sentiment Index	538	ARFIMA (2, d, 2)	0.95	0.064	[0.84, 1.06]	I(d), I(1)
After Recession Periods						
1st period: (01/1980–12/1990)	132	ARFIMA (2, d, 2)	1.11	0.186	[0.80, 1.42]	I(d), I(1)
2nd period: (02/1991–01/1995)	48	ARFIMA (1, d, 2)	1.28	0.207	[0.94, 1.62]	I(d), I(1)
3rd period: (02/1995–12/1997)	35	ARFIMA (2, d, 1)	0.86	0.439	[0.14, 1.58]	I(d), I(1)
4th period: (01/1998–12/2000)	36	ARFIMA (0, d, 0)	0.69	0.159	[0.43, 0.95]	I(d)
5th period: (01/2001–12/2007)	84	ARFIMA (0, d, 0)	1.01	0.075	[0.89, 1.14]	I(d), I(1)
6th period: (01/2008–03/2011)	39	ARFIMA (2, d, 2)	1.32	0.179	[1.03, 1.62]	I(1)
7th period: (04/2011–10/2017)	79	ARFIMA (2, d, 2)	1.30	0.152	[1.05, 1.55]	I(1)
8th period: (10/2017–10/2024)	85	ARFIMA (0, d, 0)	0.93	0.117	[0.74, 1.12]	I(d), I(1)

Since the recession indicator is a binary variable by construction, modeling long-memory dynamics through fractional integration is not appropriate, as the concept of persistent shocks in levels does not apply in this context. The univariate analysis therefore focuses on the Employment Sentiment Index, for which clear evidence of fractional integration is found. By contrast, the dynamic interaction between employment sentiment and recession episodes is examined using a VAR-based Granger causality framework, which allows us to assess predictive relationships without imposing identical integration properties on both variables. After completing the univariate analysis, we therefore turn to a bivariate framework to examine whether employment sentiment and recession episodes are dynamically related. Table 3 reports the results of the Granger causality tests based on a VAR model for the Employment Sentiment Index and the OECD-based recession indicator for the Euro Area.

The Granger causality test consist of a vector autoregressive representation (VAR) consisting of the two series:

$$ESI_t = \alpha_1 + \sum_{i=1}^{n} \beta_i RP_{t-i} + \sum_{j=1}^{m} \delta_j ESI_{t-j} + \epsilon_{ESI_t} \tag{2}$$

$$RP_t = \alpha_2 + \sum_{i=1}^{n} \theta_i RP_{t-i} + \sum_{j=1}^{m} \psi_j ESI_{t-j} + \epsilon_{RP_t} \tag{3}$$

Where *ESI* represents the Employment Sentiment Index and *RP* denotes the recession indicator. It is assumed that both ϵ_{ESI_t} and ϵ_{RP_t} are uncorrelated white noise error terms (see Asteriou and Hall, 2015). The letters m and n in equations (2) and (3) represent the maximum number of lags for each variables, selected according to standard information criteria.

The application of the VAR methodology is justified on the following grounds. First, the analysis does not impose identical integration properties on both variables. Fractional integration is established for the Employment Sentiment Index, while the recession indicator is a binary variable by construction. Second, the VAR framework allows the dynamic interactions between the variables to be examined without requiring the specification of long-run equilibrium relationships. Third, estimation is conducted using ordinary least squares, which is appropriate in this setting and widely adopted in the empirical literature.

The two Granger causality hypotheses that are tested in this study are as follows. The first hypothesis is $H_0 : \sum_{i=1}^{n} \beta_i = 0$ (employment sentiment does not influence recession indicator) and $H_1 : \sum_{i=1}^{n} \beta_i \neq 0$ (employment sentiment influences recession indicator) and the second hypothesis is $H_0 : \sum_{j=1}^{m} \psi_j = 0$ (recession indicator do not influence employment sentiment) and $H_1 : \sum_{j=1}^{m} \psi_j \neq 0$ (recession indicator influence employment sentiment) (see Asteriou and Hall, 2015).

The Granger causality test reveals a bidirectional causal relationship between the Employment Sentiment Index and Recession Periods, underscoring their interdependence. According to the Akaike criteria, we employ a lag structure of 3 periods.

If we put the focus on the employment sentiment direction with recession indicator, the test rejects the null hypothesis (Prob. = 0.0000) at the 1 % significance level. This result provides robust evidence that employment sentiment causes changes in recession indicators. This suggests that shifts in employment sentiment act as a leading indicator for recessionary dynamics, reflecting the sensitivity of labor market perceptions to underlying economic conditions. On the other hand, putting the focus on recession indicator direction with employment sentiment, the test rejects the null hypothesis (Prob. = 0.0004) at the 1 % significance level. The findings indicate that recession periods also cause changes in employment sentiment. This highlights the feedback effect where economic downturns directly influence labor market expectations and perceptions, exacerbating negative sentiments.

In order to complement the time-domain Granger causality analysis, we employ the frequency-domain causality test proposed by

Table 3
Results of Granger causality test.

Direction of Causality	Lags[a]	Prob.	Decision	Outcome
ESI → RP	3	0.0000	Reject Null	Employment sentiment in Europe is causing behavior in recession indicator.
RP → ESI	3	0.0004	Reject Null	Recession periods is causing behavior in employment sentiment.

[a] We have used Akaike Information Criterion to detect the number of lags.

Breitung and Candelon (2006). This approach allows the assessment of causal relationships at different frequencies, thereby distinguishing between short-, medium-, and long-term dynamics.

The test is based on the spectral representation of a VAR model and evaluates the null hypothesis that one variable does not Granger-cause another at a given frequency ω, where $\omega \in (0, \pi)$. Low frequencies (small values of ω) correspond to long-run fluctuations, medium frequencies capture business-cycle dynamics, and high frequencies (values of ω close to π) are associated with short-run movements.

The null hypothesis of no Granger causality at frequency ω is tested through linear restrictions on the coefficients of the VAR model, resulting in an F-statistic that follows a standard asymptotic distribution. Rejection of the null hypothesis at a given frequency indicates that past values of one variable contain predictive information for the other at the corresponding time horizon.

In the empirical analysis, frequencies are grouped into long-, medium-, and short-term bands following standard practice in the literature. The reported test statistics in Table 4 therefore reflect the presence or absence of Granger causality across different time horizons rather than at a single aggregate frequency.

The analysis confirms a bidirectional causality between employment sentiment and recession periods, emphasizing their interconnectedness. However, the nature of this relationship varies across time horizons. Employment sentiment is an effective leading indicator for recessionary dynamics in the short and medium terms. There is strong evidence of short $(p < 0.01)$ and medium-term causality $(p < 0.05)$ from employment sentiment to recession periods, respectively, as reflected by the statistically significant test statistic $(11.18^{***};\ 5.95^{**})$. This relationship indicates that employment sentiment is a strong leading indicator of short- and medium-term economic recessions. This suggests that immediate and intermediate changes in labor market perceptions and expectations are predictive of recessionary dynamics.

On the other hand, recessionary dynamics have a profound, cumulative effect on employment sentiment over longer periods, reflecting the deep-rooted impact of economic downturns on labor market confidence. Statistically, there is strong evidence of long-term causality $(p < 0.01)$ from recession indicator to employment sentiment, as reflected by the statistically significant test statistic (35.16^{***}). The strong long-term influence of recessionary conditions on sentiment suggests the need for sustained and robust economic recovery strategies to restore labor market confidence and prevent protracted negative perceptions.

5. Concluding remarks

This study provides novel empirical insights into the behavior of employment sentiment in the Euro Area during periods of economic recession, leveraging long memory methodologies and causality analyses. By focusing on the Employment Expectations Index, we contribute to a better understanding of labor market perceptions and their dynamic properties in response to macroeconomic shocks.

Our univariate analysis reveals that employment sentiment exhibits strong persistence, with evidence of long memory and mixed stationarity behavior across different post-crisis periods. These findings suggest that shocks to employment sentiment may have enduring effects, and that reversion to long-term trends is not immediate, particularly in the presence of structural breaks or protracted downturns. The ARFIMA-based estimations confirm that, in several instances, the series behaves as fractionally integrated, indicating a complex interplay between temporary disturbances and lasting shifts in expectations.

Furthermore, the bivariate causality framework uncovers a robust, bidirectional causal relationship between employment sentiment and recessionary dynamics. Granger causality tests in the time domain demonstrate that employment sentiment can serve as a leading indicator of recessions, while also being significantly influenced by downturns themselves. The frequency-domain analysis by Breitung and Candelon (2006) deepens this perspective by revealing that employment sentiment predicts recession periods in the short and medium term, whereas the impact of recessions on sentiment unfolds more substantially in the long term.

These findings carry important implications for both policymakers and forecasters. On the one hand, monitoring employment sentiment can enhance the timeliness and accuracy of recession forecasting, serving as an early warning indicator. On the other hand, the pronounced long-term impact of recessions on labor market confidence underscores the need for persistent and targeted policy responses to rebuild expectations and foster a sustainable recovery in employment sentiment.

Overall, this research underscores the relevance of sentiment-based indicators in macroeconomic analysis and policy design. It supports the integration of behavioral dimensions into conventional labor market assessments and opens new avenues for research on the role of expectations in economic fluctuations. A potential extension of this analysis would be to explore causality within a

Table 4
Breitung and candelon frequency domain causality test results.

Hypothesis	Long Term ($\omega = \mathbf{0.05}$)	Medium Term ($\omega = \mathbf{1.5}$)	Short Term ($\omega = \mathbf{2.5}$)
Original Time Series			
ESI → RP	3.90 (0.14)	5.95** (0.05)	11.18*** (0.00)
RP → ESI	35.16*** (0.00)	4.02 (0.14)	4.28 (0.12)

Notes: *, **, *** denote statistical significance at the 10 %, 5 % and 1 % levels, respectively. ω denotes the frequency at which the null hypothesis of no Granger causality is tested in the Breitung–Candelon framework. Low, medium and high frequencies correspond to long-, medium- and short-term dynamics, respectively. Values in parentheses are p-values associated with the F-statistics.

time–frequency framework, allowing causal relationships to vary not only across frequencies but also across specific time intervals. Such an approach could provide further insights into whether the short-run leading properties of employment sentiment differ across economic episodes, for instance during periods of heightened uncertainty such as the COVID-19 pandemic. Implementing this extension would require a substantially different methodological framework and is therefore left for future research.

CRediT authorship contribution statement

María Isabel Luna Kanematsu: Writing – review & editing, Writing – original draft, Visualization, Investigation, Formal analysis, Conceptualization. **Manuel Monge:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Juan Infante:** Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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