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Artificial Intelligence and Employment Sentiment in Europe: Time Trends and Persistence

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Abstract

This paper studies how developments in artificial intelligence (AI) affect employment sentiment in Europe. Using monthly data, we analyze the dynamic relationship between an employment sentiment indicator and a market-based AI index, explicitly accounting for persistence and long-memory behavior. We find that employment sentiment exhibits strong persistence and adjusts only gradually over time. AI-related developments systematically precede changes in employment sentiment, whereas the reverse relationship is not supported by the data. The interaction is concentrated at short- and medium-term horizons, indicating rapid expectation adjustments. Overall, the results suggest that AI influences labor market perceptions through expectation-driven channels with persistent effects.

Keywords: *Artificial Intelligence; Employment Sentiment; Labor Market Expectations; Persistence; Europe.*

JEL Classification*: C00; C22; E24; J24; O33.*

Introduction

Artificial intelligence (AI) represents one of the most profound technological transformations affecting labor markets in modern economic history. Beyond its direct effects on productivity, task allocation, and wage structures, AI has increasingly reshaped workers' expectations, perceptions, and confidence regarding future employment prospects. These subjective dimensions are not merely ancillary. A large body of economic research has established that expectations and sentiment influence job search behavior, human capital investment, consumption decisions, and aggregate labor market dynamics. Understanding how AI affects employment sentiment is therefore essential for a comprehensive assessment of its economic consequences.

This question is particularly salient in Europe. European labor markets are characterized by strong employment protection, extensive social insurance systems, and institutional arrangements that amplify the role of expectations in shaping adjustment processes. In such environments, shocks to perceptions may persist long after the initial economic impulse has faded, affecting labor supply decisions and the transmission of policy interventions. Recent crises, including the global financial crisis, the sovereign debt crisis, and the COVID-19 pandemic, have reinforced the view that labor market perceptions in Europe adjust slowly and exhibit substantial persistence.

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A long-standing literature in labor economics emphasizes the persistence of labor market outcomes and expectations. Classical contributions on unemployment dynamics, ranging from NAIRU-based frameworks (Friedman 1968; Phelps 1967, 1968) to hysteresis theories (Blanchard and Summers 1986, 1987; Barro 1988) and structuralist approaches (Phelps 1994; Pissarides 2000), highlight that shocks to labor markets can generate long-lasting effects. Empirical work has repeatedly documented that labor market variables often display strong persistence, challenging the assumption of rapid mean reversion. This insight has been extended to expectations and sentiment indicators, which are increasingly recognized as forward-looking measures with predictive content for macroeconomic fluctuations.

Recent empirical evidence confirms that employment sentiment in Europe exhibits long-memory behavior, with shocks that dissipate slowly over time and differ markedly across economic episodes. Using fractional integration techniques, prior research has shown that employment sentiment reacts persistently to recessions and can act as both a leading and lagging indicator of economic downturns, with causal relationships that vary across time horizons (see Luna Kanematsu et al., 2026a). These findings suggest that labor market perceptions are not short-lived responses to news, but rather evolve through cumulative adjustment processes shaped by institutional settings and past experiences.

Parallel research has examined how objective economic conditions interact with subjective labor market perceptions. While rising income per capita is often assumed to improve workers' confidence, evidence indicates that this relationship is neither immediate nor linear. Employment sentiment appears to be more persistent than income itself, and causality between the two variables is bidirectional, where income growth may boost sentiment in the short run, but sentiment exerts a more durable influence on future economic performance (see Luna Kanematsu et al. 2026b). This asymmetry underscores the importance of expectations as an autonomous driver of labor market dynamics rather than a passive reflection of economic fundamentals.

Against this backdrop, the rapid diffusion of AI introduces a new and potentially powerful source of expectation shocks. Unlike conventional business-cycle disturbances, AI adoption unfolds gradually, is highly visible in public discourse, and is frequently framed in terms of long-term job displacement, skill obsolescence, and structural change. A growing literature using sentiment and text-based methods documents that workers' perceptions of AI are deeply ambivalent, combining optimism about productivity gains with fears about employment security. Importantly, these perceptions vary across occupations, regions, and over time, and appear to evolve in a persistent manner rather than as short-lived reactions to technological announcements.

Despite these advances, two key gaps remain. First, most studies analyzing AI and employment sentiment rely on cross-sectional or short-horizon designs, which are ill-suited to capture persistence, long-memory behavior, and slow adjustment dynamics. Second, the interaction between AI-related developments and employment sentiment has rarely been analyzed within a unified time-series framework capable of distinguishing short-, medium-, and long-term effects. As a result, existing evidence provides limited guidance on whether AI shocks generate temporary fluctuations in sentiment or induce durable shifts in labor market confidence.

This paper addresses these gaps by examining the dynamic relationship between artificial intelligence and employment sentiment in Europe through a long-memory and time–frequency perspective. We build on the insight that employment sentiment exhibits persistent dynamics and extend it to the context of technological change. Our central hypothesis is that AI-related developments Granger-cause employment sentiment in a persistent and frequency-dependent manner, reflecting the gradual diffusion of technology and the slow adjustment of expectations. To test this hypothesis, we employ a comprehensive empirical strategy that combines fractional integration (ARFIMA models), Granger causality analysis, wavelet coherence, and fractional cointegration techniques. This approach allows us to (i) characterize the persistence of both employment sentiment and AI-related indicators, (ii) identify the direction of causality between them, and (iii) assess how their interaction varies across time horizons. By doing so, we move beyond static correlations and provide a richer depiction of how technological change interacts with labor market perceptions.

This analysis is significant for several reasons. First, it allows us to determine whether employment sentiment in Europe exhibits short- or long-memory behavior in response to technological change, which has direct implications for the persistence of perception shocks and the reliability of sentiment indicators for economic analysis and policy design. If AI-related developments generate highly persistent effects on workers' expectations, conventional approaches that assume rapid adjustment may substantially underestimate their long-run impact. Second, by explicitly modeling fractional integration, the analysis provides a more accurate characterization of the stochastic properties of employment sentiment and AI-related indicators. This framework enables us to distinguish between transitory fluctuations and deeply rooted shifts in labor market perceptions, offering a more nuanced understanding of how expectations evolve in the presence of structural technological change.

Third, the multivariate approach adopted in this paper enhances our understanding of the dynamic interaction between artificial intelligence and employment sentiment. By combining time-domain Granger causality, frequency-domain causality, wavelet coherence, and fractional cointegration techniques, the analysis identifies not only whether a causal relationship exists, but also the horizons over which this relationship operates. This distinction is crucial in the context of AI adoption, which is unlikely to affect workers' perceptions uniformly across short-, medium-, and long-term horizons.

From an economic perspective, this approach sheds light on whether AI-induced changes in employment sentiment reflect short-lived reactions to technological news or whether they embody persistent adjustments in expectations that may influence labor market behavior over extended periods. From a policy standpoint, the results can inform the design of labor market and training policies by clarifying whether restoring confidence requires temporary interventions or sustained, long-term strategies aimed at managing technological transitions.

The remainder of the paper is structured as follows. Section 2 describes the data employed in the analysis about the employment sentiment and artificial intelligence indicators. Section 3 presents the econometric methodology, detailing the fractional integration and cointegration framework, causality tests, and wavelet-based techniques. Section 4 reports and discusses the empirical results. Finally, Section 5 concludes the paper and highlights the main implications for economic theory and policy.

Data

Employment sentiment is measured using the Employment Expectations Indicator from Eurostat's Business and Consumer Survey. The series is forward-looking, available at monthly frequency, and widely used as a proxy for labor market confidence in Europe. Its long historical availability and high temporal resolution make it particularly suitable for analyzing persistence, long-memory behavior, and dynamic interactions with other macroeconomic indicators.

To proxy developments in artificial intelligence, we use the S&P Kensho Artificial Intelligence Enablers & Adopters Index, provided by S&P Dow Jones Indices. The index tracks publicly listed firms that either develop core AI technologies or systematically adopt AI in their business models.

As a market-based indicator, the index captures expectations, investment dynamics, and the diffusion of AI technologies across sectors. It therefore provides a forward-looking measure of the AI environment faced by firms and workers. Monthly index values are used to ensure consistency with the employment sentiment data and to facilitate time-series and time–frequency analysis.

The empirical analysis is conducted using monthly data over the common sample period determined by data availability. All variables are analyzed in levels. No pre-filtering or detrending is applied, as the econometric framework explicitly accommodates non-stationarity and fractional integration.

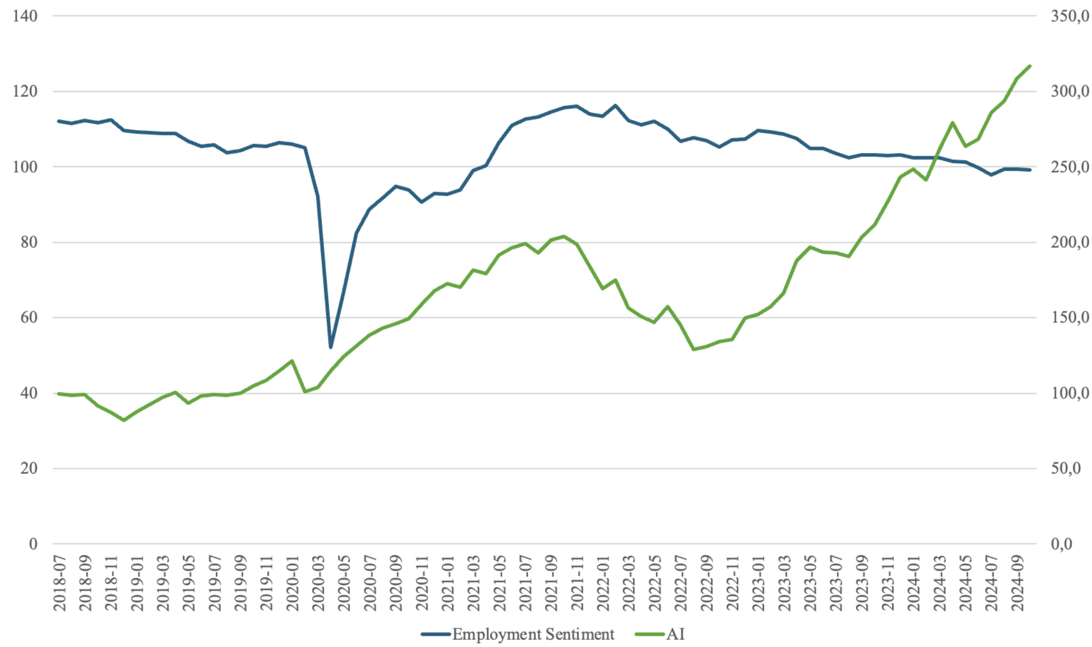

Figure 1 plots the monthly evolution of employment sentiment in Europe and the artificial intelligence index over the sample period. Both series display pronounced persistence, albeit with markedly different dynamics. Employment sentiment exhibits relatively smooth fluctuations punctuated by sharp declines during episodes of heightened uncertainty, most notably during the COVID-19 shock in early 2020, followed by a gradual and incomplete recovery. This pattern is consistent with the forward-looking and expectation-based nature of the indicator.

In contrast, the artificial intelligence index shows a strong upward trend over the sample period, reflecting the rapid diffusion and increasing economic relevance of AI technologies, interspersed with episodes of heightened volatility. While the two series occasionally move in opposite directions, particularly during periods of macroeconomic stress, the figure suggests that changes in AI-related developments are not immediately mirrored by contemporaneous movements in employment sentiment. Instead, the visual evidence points to potentially delayed and persistent interactions, motivating a formal analysis of long-memory behavior and dynamic dependence in the subsequent sections.

Methodology

Unit Roots

In both statistical and econometric analysis, time series models, whether based on univariate or multivariate regression structures, are commonly employed to study the behavior of variables and the relationships among them (Box and Jenkins, 1970). However, a critical preliminary step before model implementation is understanding the fundamental characteristics of the time series in question.

One of the most important aspects is identifying whether a series is stationary, classified as I(0), indicating the absence of a unit root, or non-stationary, labeled as I(1), which implies that a unit root is present (Nelson and Plosser, 1982). To determine the integration order of each variable, conventional unit root tests are applied. The Dickey-Fuller test (Dickey and Fuller, 1979) is among the most frequently used for this purpose. When the basic model's error terms display autocorrelation, the augmented version (ADF) is used to ensure more reliable results (Dickey and Fuller, 1981).

Additionally, several alternative approaches have been introduced to increase the tests' robustness and power. Notably, Phillips (1987) and Phillips and Perron (1988) developed procedures using non-parametric methods to estimate the spectral density at the zero frequency. Another approach, proposed by Kwiatkowski et al. (1992), shifts the focus by testing for the existence of a deterministic trend, serving as a useful counterpart to traditional unit root tests.

ARFIMA (p, d, q) Model

After establishing the integration order of each series through standard unit root tests, we advance to a more sophisticated analytical method. Building on foundational work by Adenstedt (1974), Granger and Joyeux (1980), Granger (1980, 1981), and Hosking (1981), we apply the concept of fractional integration, represented as I(d). Unlike traditional models that restrict the differencing parameter to integers, this approach allows dd to take on any real value, thereby achieving stationarity under more flexible conditions.

Fractional differencing provides a way to render non-stationary series stationary while also capturing long-range dependencies more effectively than conventional differencing methods. Its enhanced statistical power makes it particularly suitable when the data-generating process is characterized by fractional integration, as demonstrated in studies by Diebold and Rudebusch (1991), Hassler and Wolters (1994), and Lee and Schmidt (1996).

One of the key advantages of I(d) models lies in their ability to detect persistence, defined as the continued correlation of data points over time, even when those points are widely spaced.

For this analysis, we apply the ARFIMA (p, d, q) model, an extension of the traditional ARIMA framework that incorporates fractional differencing to better represent the long-memory characteristics inherent in the data. The formal representation of this model is as follows:

$$(1-L)^d x_t = u_t, t = 1, 2, \tag{1}$$

Equation (1) defines a time series that follows a process of fractional integration of order d, denoted as $x_t \sim I(d)$, where d can be any real number. In this formulation, L is the lag operator, such that $Lx_t = x_{t-1}$, and $u_t \sim I(0)$ refers to a stationary process with finite and positive spectral density at zero frequency, implying weak dependence over time. When u_t follows an ARMA(p, q) process, the resulting series x_t is said to follow an ARFIMA(p, d, q) model.

The term $(1-L)^d$, derived through a binomial expansion, allows for fractional differencing. Unlike standard differencing techniques, this approach implies that each observation in the series is influenced by a potentially infinite history of past values. As the value of d increases, so too does the persistence of the series, indicating a stronger long-range dependency.

The value of the differencing parameter d determines several key properties of the time series. When $d = 0$, the series exhibits short memory, meaning that correlations decay quickly over time. For $d > 0$, the series displays long memory, where correlations persist even at long lags. If $d < 0.5$, the series remains covariance stationary, while values of $d \geq 0.5$ indicate non-stationarity. Furthermore, if $d < 1$, the series tends to revert to a long-term mean, but when $d \geq 1$, , this mean-reverting property is lost, and shocks to the series have permanent effects.

To estimate the degree of long memory and identify the fractional order of integration, several methodologies can be applied. Among the most recognized are those developed by Geweke and Porter-Hudak (1983), Sowell (1992), Robinson (1994, 1995a, 1995b), and Phillips (1999, 2007). In selecting the most appropriate ARFIMA specification, we use information criteria such as the Akaike Information Criterion (AIC) (Akaike, 1973) and the Bayesian Information Criterion (BIC) (Akaike, 1979), which help optimize the trade-off between model fit and complexity.

Granger Causality Test

After estimating the VAR model, the Granger causality test is run to determine the direction of causation between two stationary series, x_t and y_t. The vector autoregressive representation (VAR) used in the Granger test is made up of the following two series:

$$x_t = a_1 + \sum_{i=1}^{k} a_i x_{t-i} + \sum_{i=1}^{k} \beta_i y_{t-i} + \epsilon_{1t}$$

$$y_t = a_2 + \sum_{i=1}^{k} \gamma_i x_{t-i} + \sum_{i=1}^{k} \delta_i y_{t-i} + \epsilon_{2t}$$

K represents the lag length of the variables x_t and y_t. The null hypothesis can be tested "x is not a consequence of y", which can be described as $H_0^1 = \gamma_1 = \cdots = \gamma_k = 0$. The result reflects that the causality goes from y_t to x_t when the null value is rejected; in the same way as in the second case $H_0^2 = a_1 = \cdots = a_k = 0$ the causality from x_t to y_t occurs when the null value is rejected. Both hypotheses can be rejected. The Chi-square distribution has been chosen to perform the statistical tests.

Wavelet Analysis

Wavelet methodology allows time series to be analysed in the time-frequency domain. Thus, for this research article we use two tools named wavelet coherency and wavelet phase difference, because the requirement of stationarity is not necessary and studying the interaction in time and frequency domain of the time series reveals evidence of potential changes (structural changes).

Furthermore, the most important information is hidden in the frequency content of the signal. So, as we know, we can define the time series as an aggregation of components operating on different frequencies.

Finally, if we follow the research carried out by Zhou (2008), Podobnik and Stanley (2008), Gu and Zhou (2010) and Jiang and Zhou (2011) we can conclude that misleading results will be found if we apply a typical cross-correlation to study statistical relationships between two multifractal time series.

The wavelet coherency plot represents the correlation of time series and helps us to identify hidden patterns and/or information in the time-frequency domain. The wavelet transform, represented by $WT_x(a, \tau)$, of a time series $x(t)$ obtained by projecting a mother wavelet ψ, is defined as:

$$WT_x(a,\tau) = \int_{-\infty}^{+\infty} x(t)\frac{1}{\sqrt{a}}\psi^*\left(\frac{t-\tau}{a}\right)dt,$$

where the wavelet coefficients of $x(t)$ are represented by $WT_x(a,\tau)$ and provide information on time and frequency by mapping the original time series onto a function of τ and a. Following Aguiar-Conraria and Soares (2014) we choose the Morlet wavelet as the mother wavelet because it is a complex sine wave within a Gaussian envelope, so we will be able to measure the synchronism between time series.

Wavelet coherence helps us understand how one time series interacts with another. We can define this term as:

$$WCO_{xy} = \frac{SO(WT_x(a,\tau)WT_y(a,\tau)^*)}{\sqrt{SO(|WT_x(a,\tau)|^2)SO\left(\left|WT_y(a,\tau)\right|^2\right)}},$$

Where the smoothing operator in time and scale is represented with the parameter *SO*. This operator is important because without it, the wavelet coherency is always one for all times and scales (Aguiar-Conraria et al., 2008). In Aguiar-Conraria's website[4] we can find the Matlab codes for the CWT resolution.

FCVAR Model

To analyze the long-run relationship between the variables, we apply the Fractional Cointegrated Vector Autoregressive (FCVAR) model, as introduced by Johansen and Nielsen (2012). The specification of the model is given by the following expression:

$$\Delta^d X_t = \alpha\beta' L_b \Delta^{d-b} X_t + \sum_{i=1}^{k} \Gamma_i\, \Delta^b L_b^i Y_t + \varepsilon_t \qquad (5)$$

In this formulation, α and β are $p \times r$ matrices, where $0 \leq r \leq p$. The term ε_t represents a p-dimensional error term with zero mean and a variance-covariance matrix Ω, assumed to be independently and identically distributed.

The matrix β captures the long-term cointegration structure of the system, indicating stable relationships among variables. The matrices Γ_i govern the short-run dynamics, adjusting for temporary fluctuations. Finally, α determines how deviations from the long-run equilibrium are corrected over time, reflecting the speed of adjustment back to equilibrium.

Empirical Results

Table 1 reports the results of standard unit root tests applied to the Employment Sentiment Index and the Artificial Intelligence Index. We present both Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests under alternative specifications: (i) without deterministic components, (ii) including an intercept, and (iii) including both an intercept and a linear time trend.

[4] https://sites.google.com/site/aguiarconraria/joanasoares-wavelets

Table 1. Unit roots results

	ADF			PP		
	(i)	(ii)	(iii)		(ii)	(iii)
Original Data						
Employment Sentiment Index	–0.4877	–3.1103*	–3.0941		–2.6938	–2.6777
IA Index	2.4133	0.9898	–0.7645		1.2344	–0.6723

For the Employment Sentiment Index, the evidence is mixed. The ADF test rejects the null hypothesis of a unit root when an intercept is included, while the null cannot be rejected under alternative specifications or according to the PP test. This pattern suggests that employment sentiment displays a high degree of persistence and may lie close to the boundary between stationarity and non-stationarity.

In contrast, the Artificial Intelligence Index shows no evidence of stationarity under any specification. Both ADF and PP tests fail to reject the unit root null across all cases, indicating that the series is non-stationary in levels.

Overall, the unit root results point to heterogeneous stochastic properties across the two variables and suggest that conventional unit root tests may lack sufficient power to characterize their persistence accurately. In particular, the borderline behavior of employment sentiment motivates the use of fractional integration techniques, which allow for intermediate degrees of persistence between stationarity and unit-root non-stationarity. Accordingly, the analysis proceeds with ARFIMA-based long-memory estimation.

Given the mixed evidence from conventional unit root tests, we proceed by estimating ARFIMA (p, d, q) models to assess the degree of persistence in both series. This framework allows the order of integration to take fractional values, thereby accommodating intermediate cases between stationarity and unit-root non-stationarity.

Table 2 reports the estimates of the models for the Employment Sentiment Index and the Artificial Intelligence Index. Model selection is based on standard information criteria, and the fractional parameter d is estimated using maximum likelihood methods.

Table 2. Long memory results

Data analyzed	**Sample size (month)**	**Model Selected**	**d**	**Std. Error**	**Interval**	**I(d)**
Original Data						
Employment Sentiment Index	76	ARFIMA (0, d, 0)	0.93	0.123	[0.73, 1.14]	I(d), I(1)

IA Index	76	ARFIMA (1, d, 2)	1.26	0.208	[0.92, 1.60]	I(1)

For the Employment Sentiment Index, the estimated value of d is 0.93, with a 95 percent confidence interval of [0.73, 1.14]. This result indicates strong long-memory behavior and places employment sentiment close to the boundary between stationary long-memory and unit-root processes. Shocks to employment sentiment therefore decay slowly and may exert persistent effects over extended periods, although gradual mean reversion cannot be ruled out.

The Artificial Intelligence Index exhibits even stronger persistence. The estimated fractional differencing parameter is 1.26, with a confidence interval of [0.92, 1.60], indicating non-stationary long-memory dynamics. This behavior is consistent with the cumulative and trend-driven nature of AI-related developments, reflecting sustained investment, diffusion, and evolving expectations rather than short-lived fluctuations.

Overall, the ARFIMA results confirm that both variables are characterized by substantial persistence and cannot be adequately described by short-memory processes. The degree of persistence is notably higher for the Artificial Intelligence Index than for employment sentiment, suggesting asymmetries in adjustment dynamics. These findings reinforce the appropriateness of employing econometric methods that explicitly account for long-memory behavior when analyzing the interaction between artificial intelligence and labor market perceptions.

To examine the direction of dynamic interactions between artificial intelligence and employment sentiment, we conduct Granger causality tests within a vector autoregressive framework. The tests assess whether past values of one variable contain predictive information about the other beyond that already embedded in its own history. Lag length selection is based on standard information criteria.

Table 3. Results of Granger causality test

Direction of Causality	Lags[5]	Prob.	Decision	Outcome
AI → ESI	1	0.003	Reject Null	Artificial Intelligence is causing behavior in Employment sentiment in Europe.
ESI → AI	1	0.525	Not Reject Null	Employment sentiment is not causing any behavior in Artificial Intelligence

The results in Table 3 indicate a unidirectional Granger causal relationship running from the Artificial Intelligence Index to the Employment Sentiment Index. The null hypothesis that AI does not Granger-cause employment sentiment is rejected at conventional significance levels, whereas the reverse hypothesis cannot be rejected. This finding suggests that developments in artificial intelligence systematically precede changes in employment sentiment in Europe.

From an economic perspective, this result is consistent with the view that AI-related developments act as a driver of labor market perceptions rather than a passive response to them. Importantly, the Granger causality evidence should be interpreted as predictive rather than

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

structural causality. It indicates temporal precedence and informational content, not a direct causal mechanism.
Taken together with the long-memory results, the Granger causality findings suggest that AI-related shocks may generate persistent changes in employment sentiment. In the next section, we explore whether this predictive relationship varies across time horizons by adopting a time–frequency approach.
To assess whether artificial intelligence and employment sentiment share a stable long-run relationship in the presence of fractional integration, we estimate a Fractionally Cointegrated Vector Autoregressive (FCVAR) model. This framework allows for cointegration between variables that exhibit different orders of fractional integration, thereby extending conventional cointegration analysis to long-memory processes.

Table 4: Results of the FCVAR model

	$d \neq b$	Cointegrating equation beta	
		AI	**ESI**
AI vs ESI	$d = 1.318\ (0.146)$ $b = 1.191\ (0.204)$	1.000	0.016
	$\Delta^d\left(\begin{bmatrix} CCC \\ Stock\ Prices \end{bmatrix} - \begin{bmatrix} 108.745 \\ 99.791 \end{bmatrix}\right) = L_d \begin{bmatrix} -0.209 \\ -0.304 \end{bmatrix} \nu_t + \sum_{i=1}^{2} \hat{\Gamma}_i \Delta^d L_d^i (X_t - \mu) + \varepsilon_t$		

Table 4 reports the FCVAR estimates for the bivariate system comprising the Artificial Intelligence Index and the Employment Sentiment Index. The estimated order of integration of the system is $d = 1.318$ (standard error 0.146), while the order of fractional cointegration is $b = 1.191$ (standard error 0.204), implying $d \neq b$. This result confirms that the two series exhibit heterogeneous persistence dynamics but remain linked through a fractional cointegrating relationship.
The estimated cointegrating vector assigns a normalized coefficient of 1.000 to the Artificial Intelligence Index and a coefficient of 0.016 to the Employment Sentiment Index. Although the magnitude of the latter coefficient is small, its presence indicates that deviations from the long-run equilibrium between artificial intelligence and employment sentiment are systematically corrected over time. The associated adjustment coefficients are negative, implying a gradual convergence toward the long-run relationship following shocks.
From an economic perspective, these results suggest that artificial intelligence and employment sentiment are connected not only through short- and medium-term predictive dynamics, as shown in the Granger causality and wavelet analyses, but also through a stable long-run relationship characterized by slow adjustment. The FCVAR evidence therefore reinforces the view that AI-related developments exert persistent effects on labor market perceptions, with deviations from equilibrium dissipating only gradually due to the long-memory nature of employment sentiment.
While the FCVAR framework establishes the existence of a long-run equilibrium relationship between artificial intelligence and employment sentiment in the presence of long memory, it does not provide information on how this relationship unfolds across different time horizons. Given that AI adoption is a gradual and non-linear process, we complement the FCVAR analysis with wavelet coherence techniques to examine whether the interaction between AI and employment

sentiment is concentrated in specific frequency bands and whether it varies over time.

Table 5: Wavelet analysis

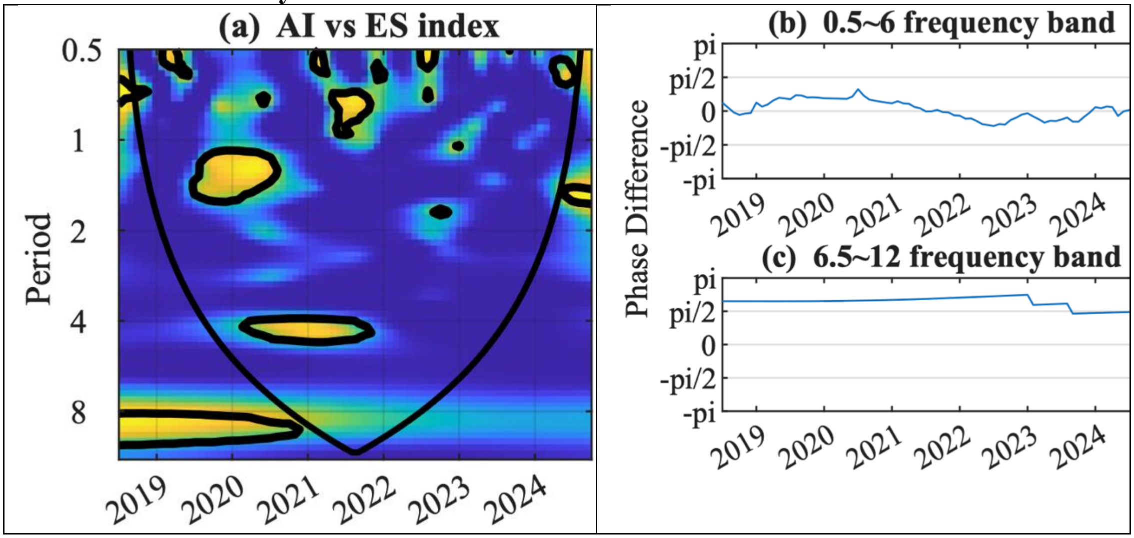

Figure 5 presents the wavelet coherence analysis between the Artificial Intelligence Index and the Employment Sentiment Index, allowing the dynamic interaction between the two series to be examined simultaneously in the time and frequency domains.

Panel (a) displays the wavelet coherence surface. Coherence is predominantly concentrated at higher frequencies, corresponding to short- and medium-term horizons. In particular, recurrent and sustained coherence is observed at periodicities between approximately 0.5 and 6 months, indicating that the interaction between artificial intelligence and employment sentiment is most pronounced over short- and medium-term horizons.

This pattern is further clarified in panel (b), which reports the phase-difference dynamics for the 0.5–6 month frequency band. Phase differences in this range are relatively stable over time and remain predominantly positive, implying that movements in the Artificial Intelligence Index tend to precede changes in employment sentiment within this horizon. This lead–lag structure suggests that developments related to artificial intelligence are followed by adjustments in labor market perceptions with a short to medium delay.

From an economic perspective, these findings are consistent with the view that AI-related information, such as investment announcements, technological breakthroughs, or adoption signals, affects workers' expectations relatively quickly. Rather than operating through slow-moving structural adjustments alone, artificial intelligence appears to influence employment sentiment through expectation-driven channels that respond within months. This short- and medium-term transmission mechanism aligns with the forward-looking nature of employment sentiment indicators and highlights the role of information diffusion and anticipatory behavior in shaping labor market perceptions.

Importantly, the concentration of coherence in this frequency band suggests that the impact of artificial intelligence on employment sentiment is not purely a long-run phenomenon but also manifests through recurrent adjustments at business-cycle-relevant horizons. This complements the long-memory and FCVAR evidence by showing that, even in the presence of persistent dynamics, AI-related shocks generate economically meaningful responses in sentiment over relatively short time frames.

Concluding Remarks

This paper has examined the relationship between artificial intelligence and employment sentiment in Europe, focusing on the dynamic, persistent, and horizon-dependent nature of workers' perceptions. While much of the existing literature has emphasized the effects of AI on employment levels, wages, and productivity, our analysis highlights the importance of expectations and sentiment as key channels through which technological change affects labor markets.

The empirical results point to three main conclusions. First, employment sentiment in Europe exhibits strong persistence, adjusting only gradually to new information. This finding underscores that labor market perceptions are not short-lived reactions but reflect slow-moving expectation formation processes shaped by past experiences and institutional settings. Second, developments in artificial intelligence systematically precede changes in employment sentiment, indicating that AI acts as a driver of labor market perceptions rather than a passive outcome of them. Third, the interaction between AI and employment sentiment is concentrated at short- and medium-term horizons, suggesting that AI-related information is incorporated into workers' expectations relatively quickly, even though its effects remain persistent over time.

Taken together, these findings reconcile two seemingly opposing views. On the one hand, workers respond rapidly to AI-related signals, such as investment announcements or technological breakthroughs. On the other hand, the resulting shifts in sentiment display long memory, implying that expectation adjustments triggered by AI can have lasting consequences for labor market confidence. This combination of rapid information processing and persistent adjustment highlights the need to consider both time horizons and memory when assessing the labor market implications of technological change.

From a broader economic perspective, the results have implications for how technological transitions are managed. If AI-related developments generate persistent shifts in employment sentiment, policies aimed at supporting labor markets should not focus exclusively on short-term outcomes. Communication strategies, reskilling initiatives, and institutional frameworks that shape expectations may play a critical role in moderating the long-run effects of technological change on workers' perceptions and behavior.

Several limitations of the analysis suggest avenues for future research. First, the use of aggregate indicators masks potential heterogeneity across countries, sectors, and occupational groups. Future work could exploit disaggregated or micro-level data to examine how AI affects employment sentiment across different segments of the labor market. Second, while the market-based AI index captures expectations and diffusion dynamics, alternative measures, such as firm-level adoption data or task-based exposure indicators, could provide complementary insights. Finally, extending the analysis to a cross-country or panel framework could shed light on the role of institutions and policy regimes in shaping the interaction between artificial intelligence and labor market perceptions.

Overall, this paper contributes to the understanding of how artificial intelligence influences labor markets by emphasizing the role of expectations, persistence, and time horizons. Accounting for these dimensions is essential for a comprehensive assessment of technological change and for designing policies that foster both economic efficiency and sustained labor market confidence.

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