Abstract

While central bank communication has evolved toward greater transparency, the nonverbal behavioral signals of policymakers remain largely unexplored. This study analyzes European Central Bank press conferences from 2010–2025 using automated facial analysis on 10,748,094 video frames to extract facial action units, blink rates, and eye aperture measures. The objective is to assess whether these cues reveal real-time cognitive processing and underlying uncertainty. Each conference is split into scripted policy statements and unscripted Q&A, enabling phase-specific analysis. Behavioral metrics are linked to macro-financial indicators, including GDP growth, unemployment, inflation, the Composite Indicator of Systemic Stress, exchange rates, FX correlations, sovereign spreads, and consumer expectations. Results show that facial and ocular patterns systematically co-move with macroeconomic conditions and financial stress, indicating that nonverbal signals carry economically meaningful information. Relationships are more complex during Q&A, reflecting the demands of spontaneous interaction and emotional regulation. The study advances understanding of monetary policy communication, suggesting that incorporating nonverbal behavior can improve interpretations of central bank transparency, policy transmission, and the behavioral underpinnings of financial markets.

Keywords: Central bank, communication, nonverbal behavior

JEL codes: C49, E52, G41

Introduction

Central bank communication has evolved from a largely opaque institutional practice into a key instrument for the transmission of monetary policy. The shift toward greater transparency, achieved through regular press conferences, reflects a widespread consensus that how central banks communicate is just as important as the decisions they make (Blinder et al., 2008; Bernanke, 2007). The policy of this institution works through several transmission channels, which function based on the expectations of economic actors. The central bank's ability to influence these through verbal forward guidance, policy announcements, and communication is therefore as important as the effect of adjusting the policy rate itself (Woodford, 2005).

Since current economic decisions depend on expectations of future policy, verbal commitments about the rate path can serve as a substitute for actual rate cuts when those are no longer an option. At the same time, most research on central bank communication has focused on the verbal and textual dimension, being the content of statements, the sentiment of speeches, and the linguistic framing of policy decisions (Lucca & Trebbi, 2009; Hansen et al., 2018). This focus leaves a substantial portion of the communication channels unexplored. Documented meetings such as press conferences generate rich video data encoding information about the emotional and cognitive states of decision-makers, yet this data has been almost entirely bypassed by conventional economic analysis. Computer vision enables researchers to recover those signals, transforming raw video into structured behavioral variables that can be integrated with macroeconomic and financial data.

Nonverbal behavior constitutes a distinct and independent channel of information that is worth taking into account. Facial expressions, eye contact, and blink rate reflect states that are difficult to control consciously. Research in behavioral finance and organizational communication increasingly recognizes this as significant for how audiences process and respond to institutional communication (Mayew & Venkatachalam, 2012; Blankespoor et al., 2017). In the field of monetary policy, Curti and Kazinnik (2023) demonstrate that the facial expressions of Federal Reserve chairpersons during FOMC press conferences influence stock prices, implied volatility, and foreign exchange markets independently of verbal content. Kanelis and Siklos (2025) extend these findings to the European Central Bank (ECB), showing that Mario Draghi influenced markets through his emotional reactions in spoken and written words. This study incorporates a broader array of action units (AUs) to capture granular muscle movements that reflect cognitive load and stress, even when they do not map onto a traditional emotional category. Furthermore, this article focuses on broader macroeconomic indicators rather than limiting itself to immediate market reactions, and it uses research findings to analyze delayed reactions. These techniques were applied to the ECB in the context of a more diverse set of governors' terms of office.

The study analyzes 136 ECB press conferences across three presidencies using three behavioral cues: facial action codes (FACS) for emotional and cognitive states, gaze direction and head-eye alignment as indicators of attentional engagement, and blink rate as a physiological measure of cognitive effort. Each press conference consists of two distinct phases. The Monetary Policy Statement is a scripted phase in which the president delivers a prepared narrative from notes. The Q&A session requires real-time responses to unpredictable journalist questions. Introductory statements concentrate on professionally calibrated topics and use neutral lexicon, while Q&A sections contain substantially more diverse content that is difficult to prepare in advance (Pavelkova et al., 2022). This structural distinction is central to the analysis: behavioral patterns during the scripted phase serve as a baseline against which deviations during spontaneous Q&A can be interpreted (Beilock & Carr, 2001; Beaupain et al., 2025). In terms of methodology, the study provides the first comprehensive behavioral profile of ECB presidents' communication over an extended time series, enabling an analysis of how nonverbal signals vary depending on decision-makers, economic conditions, and communication phases.

Literature Review

Behavioral Economics, Expectations and Transparency

Work by Mehrabian (1971) suggests that in affectively ambiguous contexts, vocal tone and facial expression can outweigh literal word content. Later reviews caution against generalizing this finding to all communication settings (Lapakko, 1997; Burgoon et al., 2022), although the principle that nonverbal cues carry independent information is well-supported in the broader literature. People rapidly infer traits such as trustworthiness and dominance from faces, often within a few hundred milliseconds (Olivola & Todorov, 2014; Todorov et al., 2008; Willis & Todorov, 2006). Trait inferences from faces form within 100 ms and are highly correlated with judgments based on longer viewing, indicating that first impressions arise extremely quickly and are relatively stable (Willis & Todorov, 2006; Todorov et al., 2008). When audiences evaluate central bank communications, they may therefore attend to policymakers' behavioral signals before, or more than, the substantive verbal content.

Central bankers must balance transparency with market stability, often resulting in strategic information management, done by emphasizing certain facts while omitting others to preserve committee cohesion (Blinder et al., 2008; Tucker, 2018). While individual Action Units are unreliable lie detectors (Vrij et al., 2019), specific AU combinations and gaze patterns reliably signal cognitive load and uncertainty (Ekman, 2003). These involuntary signals are difficult to suppress, allowing authentic assessments to leak through even the most carefully managed verbal scripts (Grossman & Hart, 1983).

Standard macroeconomic theory assumes rational expectations, as agents use all available information efficiently (Muth, 1961). In this framework, communication is meaningful only when it carries new information, and the channel of delivery is irrelevant. Behavioral economics challenges this assumption. Individuals are subject to cognitive biases, bounded rationality, and psychological framing effects (Tversky & Kahneman, 1974; Kahneman & Tversky, 1979; Barberis, 2018), and information presented through different channels can elicit systematically different responses. Central banks possess information about economic structure, preferences, and forecasts relative to market participants (Geraats, 2002; Morris & Shin, 2002). While transparency can reduce inflationary bias, placing disproportionate weight on imprecise public signals may paradoxically increase volatility by crowding out private information (Morris & Shin, 2002, 2005). For an economic agent with limited macroeconomic expertise, nonverbal signals from the central banker therefore become information shortcuts (Romer & Romer, 2000). These inferences may be rational given their constraints, even if they would be deemed irrational under a pure rational-expectations framework (Sims, 2003; Mackowiak & Wiederholt, 2009; Mankiw & Reis, 2002; Maćkowiak et al., 2023).

Given the diversity of beliefs, since not everyone formulates them in the same way (Christian & Kajal, 2024), central bank communication serves an expectation-anchoring function. By regularly affirming commitment to a specific inflation target, central banks shift the distribution of heterogeneous expectations toward the target (Blinder, 2010; Bernanke, 2015; Tucker, 2018). Nonverbal consistency amplifies this effect. When verbal and nonverbal signals are aligned, actors with diverse priors can converge toward the target (Coibion et al., 2022; D'Acunto et al., 2024). When verbal commitments are paired with nonverbal stress, the divergence creates ambiguity, increases heterogeneity in expectations, and weakens anchoring (Blinder, 2010).

Dale and Orphanides (2008) argue that excessive publication of uncertain information limits public understanding, while Ferreira et al. (2025) demonstrate that intensive communication worsens perceptions and increases forecast errors. Central banks also face a transparency paradox, as transparency requires the disclosure of uncertainty, but the disclosure of uncertainty may undermine the trust and anchoring of expectations that central banks need to be effective (Morris and Shin, 2002; Campbell et al., 2014). At the same time, in 2021, only about 10% of euro area citizens reported being aware of the ECB's announcement of a strategy review, with television and radio proving more effective than the channels traditionally emphasized by central banks (Ehrmann et al., 2025), underscoring the need for tailored communication strategies. Jung and Mongelli (2024) demonstrate that direct communication, such as press conferences, improves understanding of monetary policy and stabilizes medium-term inflation expectations among non-experts, with simplified messages proving more effective than technical communication, particularly among those with low financial literacy.

Nonverbal Behavior in Financial and Institutional Communication

Beyond verbal content, nonverbal elements significantly influence how institutional messages are received. Facial expressions convey information beyond speech (Krumhuber et al., 2023) and influence credibility judgments and emotional state assessments. In finance, vocal tension during executive conference calls allows prediction of future firm performance (Mayew & Venkatachalam, 2012; Price et al., 2017), while investor perceptions formed from short video clips influence valuations (Blankespoor et al., 2017). Gorodnichenko et al. (2021) show that vocal characteristics of central bank speeches produce measurable market effects beyond the words themselves.

In the monetary policy domain, Curti and Kazinnik (2023) provide direct evidence that Federal Reserve chairs' facial expressions influence investor behavior independently of verbal content: a one standard deviation increase in negative emotion scores correlates with a 0.53 basis point decline in equity prices within three-minute windows. Kanelis and Siklos (2025) extend these findings to the ECB, showing that Draghi's facial and vocal emotions affect government bond yields, the euro, and eurozone equities, with increased negative affect as inflation deviated from the 2% target.

Fanta and Horváth (2023) apply machine learning to ECB communication texts and find that algorithmic analysis extracts monetary policy intentions beyond conventional content analysis. Their work establishes a precedent for applying computational tools to central bank communication data. The present paper extends this approach from text to the visual domain using computer vision and automated facial action unit coding, testing whether nonverbal signals systematically anticipate macroeconomic developments.

The persistence of nonverbal effects after controlling for verbal content confirms that facial expressions provide a distinct information channel through which genuine assessments may leak despite carefully managed verbal messaging (Ekman & Friesen, 1982; Curti & Kazinnik, 2023). Microexpressions, involuntary facial displays lasting under 0.5 seconds, represent a channel through which concealed emotions may surface despite suppression attempts (Ekman, 2003). Behavioral indicators in central bank communication therefore reflect emotional states, cognitive load, and memory processes rather than deliberate dishonesty.

Gaze Behavior, Physiological Markers of Stress and Cognitive Load

Stress activates the sympathetic nervous system, triggering physiological changes including elevated heart rate, increased cortisol production, dilated pupils, and altered blink rates (Sapolsky, 2015; Chu et al., 2024; Thayer et al., 2012). Blinking is a particularly sensitive marker of these states (Doughty, 2001; Leal & Vrij, 2008; Glenberg et al., 1998). Under baseline conditions in relaxed conversation, humans blink approximately 15 to 20 times per minute (Bentivoglio et al., 1997). When facing demanding mental tasks, they suppress blink rates to maintain visual input and free cognitive resources (Glenberg et al., 1998; Eckstein et al., 2017).

Because blinking is only partially under voluntary control, this pattern provides a reliable window into underlying stress and arousal states.

When facing demanding cognitive tasks, individuals suppress blink rates to maintain visual input and free cognitive resources; during acute stress this suppression is followed by rebound elevation (Wallin, 2007; Porges, 2011; Stern et al., 1984). Because blinking is only partially under voluntary control, blink rate provides a signal more resistant to deliberate manipulation than expressive facial movements.

Eye opening can be measured using the Eye Aspect Ratio (EAR), derived from facial landmark positions (Soukupá & Čech, 2016). Under stress, eyes narrow; under positive arousal or sustained attention, they open wider (Kaisler & Leder, 2017). Eye fixation duration and pupil dilation also increase under high cognitive load (Just & Carpenter, 1993; Beatty, 1982), making EAR a continuous, frame-level measure of autonomic eye state across the full press conference duration.

Gaze aversion carries a distinct cognitive meaning. When speakers face uncertain or complex questions, they instinctively avert gaze, typically upward, to reduce incoming visual stimulation and free cognitive resources for real-time formulation (Glenberg et al., 1998; Doherty-Sneddon & Phelps, 2005). High frequencies of upward gaze during press conference Q&A therefore signal active cognitive engagement and real-time processing rather than deception. The cognitive load framework predicts that managing complex information disclosure manifests in elevated fixation frequency and duration (Rayner, 1998; Beatty, 1982), patterns consistent with the behavioral profiles observed during spontaneous speech under uncertainty.

Downward gaze during speech is associated with negative affect, sadness, and reduced social engagement (Adams & Kleck, 2003; Kaisler & Leder, 2017; Mumenthaler & Sander, 2015). Its low prevalence in ECB press conference data is consistent with policymakers' trained capacity to manage outward confidence signals in high-stakes public communication. Head-eye divergence presents a related pattern: when a speaker's head stays oriented toward the audience while the eyes avert, social orientation is maintained while visual attention is withdrawn (Doshi & Trivedi, 2012). In central bank settings, this decoupling may cluster around moments of heightened cognitive load, such as responses involving forward guidance or committee disagreement, making it a useful indicator of strategic information management.

Data and Methods

Sources and Structure

The dataset comprises 136 ECB press conference videos spanning three presidencies: Jean-Claude Trichet (2003–2011), Mario Draghi (2012–2019), and Christine Lagarde (2019–2025), covering December 2010 to October 2025 and totaling over 116 hours. Videos were obtained from the official ECB website and encompass regular Governing Council meetings and extraordinary policy announcements. Each press conference consists of two structurally distinct phases. The Monetary Policy Statement (all 136 videos) is a scripted phase lasting 9–20 minutes in which the President reads from notes to communicate the policy decision, economic assessment, and forward guidance. The Q&A session (119 videos) is a spontaneous phase lasting 45–60 minutes in which journalists pose questions, demanding real-time information retrieval. Early conferences from the Trichet era contained only the Statement phase, as Q&A sessions were introduced systematically from 2012. Video lengths ranged from 10 minutes for statement-only conferences to over 90 minutes for full conferences with extended Q&A. Static ECB logo sequences and non-speaking segments were manually excluded to ensure only frames with the focal speaker visible were retained.

Frame Sampling, Methods and Quality Control

Videos were recorded at 25 frames per second (older conferences, pre-2018) to 30 frames per second (newer conferences), yielding a temporal resolution of 33.3 to 40 milliseconds per frame. To ensure detected faces correspond to the intended speaker, a two-stage pipeline was implemented. Multi-task Cascaded Convolutional Networks (MTCNN; Zhang et al., 2016) detected face regions in each sampled frame. FaceNet embeddings (Schroff et al., 2015) then generated 128-dimensional identity representations compared against reference embeddings for each president, with a cosine similarity threshold of ≥0.85 applied to verify speaker identity. This threshold accommodated variable camera angles, archival lighting conditions, and natural intra-individual variability such as aging and eyewear changes across presidencies. After identity verification, 767,845 validated frames were retained for gaze, blink, and AU analysis.

Landmark localization excluded frames with MediaPipe confidence <0.6. AU activations exceeding ±5σ were flagged for manual review and excluded if they reflected detection artifacts rather than genuine expressions. After quality control, the final analytical dataset contained 10,748,094 frame-level AU observations, 767,845 validated frames for gaze and blink analysis, and 136 video-level aggregates for linkage to economic and financial data.

The Facial Action Coding System (FACS; Ekman & Friesen, 1978; Ekman et al., 2002) decomposes facial movements into Action Units representing specific muscle contractions. Automated AU detection was performed using DeepFace (Serengil & Ozpinar, 2020), which integrates CNN architectures including VGG-Face and FaceNet to output continuous AU intensity scores, and MediaPipe Face Mesh (Lugaresi et al., 2019; Kartynnik et al., 2019), which extracts 468 3D facial landmarks enabling geometric AU calculation.

Thirteen primary AUs were extracted, capturing facial movements relevant to stress, cognitive effort, emotional valence, and communicative intent (Table 1). AU01 and AU02 co-occurred with correlation >0.95 and were merged into a single AU01/02 variable. AU25 and AU26 co-occurred with correlation >0.95 during speech and were merged into AU25/26, yielding 11 distinct AU variables. AU10 was excluded as its activations predominantly reflected speech articulation artifacts rather than genuine emotional expression (Ekman, 1992).

Table 1. Action Units Analyzed

AU	Muscle/Region	Interpretation
AU01	Inner Brow Raiser	Surprise, concern, sadness
AU02	Outer Brow Raiser	Surprise, fear, skepticism

AU04	Brow Lowerer	Concentration, confusion, stress
AU05	Upper Lid Raiser	Surprise, wide-eyed attention
AU06	Cheek Raiser	Genuine (Duchenne) smiling
AU07	Lid Tightener	Intensity, skepticism, scrutiny
AU12	Lip Corner Puller	Voluntary or social smiling
AU14	Dimpler	Controlled smiling, expression dampening
AU15	Lip Corner Depressor	Sadness, disagreement
AU20	Lip Stretcher	Tension, fear, uncomfortable smiling
AU25	Lips Part	Speech, mild surprise
AU26	Jaw Drop	Strong surprise, fatigue
AU10	Upper Lip Raiser	Excluded: speech articulation artifact

Source: Own research.

AU25 required additional treatment because mouth opening is confounded by active speech. AU25 activations were segmented into five speech-aware sub-variables: AU25_closed_mean (mean AU25 intensity during closed-mouth frames, capturing resting jaw tension), AU25_nonspeech_mean and AU25_nonspeech_count (AU25 activity during non-speech intervals, isolating genuine affective lip parting), and AU25_sustained_mean and AU25_sustained_count (prolonged lip-parting events exceeding a minimum duration threshold, capturing fatigue or sustained stress). These sub-variables replace raw AU25 in all correlational and forecasting analyses to avoid inflating correlations driven by speech activity rather than affect.

Raw AU intensities were z-score normalized globally across all extracted frames, using AU-specific means and standard deviations estimated from the full dataset. Global normalization was chosen to preserve genuine cross-president differences in AU intensity. Within-president normalization would remove real variation in baseline expressiveness between Trichet, Draghi, and Lagarde, making it impossible to test whether different presidents display systematically higher or lower AU activation. A saliency threshold of $z > 1.0$ was applied to identify visible AU activations: 4,378,522 frames (40.7% of the total) contained at least one meaningfully elevated AU.

Eye Gaze, Head Pose Analysis and Blink Rate Detection

Eye gaze direction was inferred from MediaPipe Face Mesh landmarks, using geometric landmark configurations to approximate gaze direction with sufficient accuracy for behavioral classification (Hansen & Ji, 2010). The vertical gaze ratio was calculated from the iris centroid position relative to the eyelid aperture and classified into three categories (Table 2).

Table 2. Vertical Gaze Classification

Category	Vertical Ratio	Interpretation
UP	< 0.25	Internal attention, memory retrieval, high cognitive load
CENTER	0.25–0.75	Neutral, direct social engagement
DOWN	> 0.75	Reading during Statement phase; stress or low confidence during Q&A

Source: Own research.

Upward gaze aversion signals active cognitive engagement and real-time formulation, as speakers instinctively avert gaze upward to reduce visual stimulation and free cognitive resources (Glenberg et al., 1998; Doherty-Sneddon & Phelps, 2005). Downward gaze is associated with sadness, negative affect, and reduced social engagement (Adams & Kleck, 2003; Mumenthaler & Sander, 2015), and its very low prevalence in the ECB press conference data is consistent with policymakers' trained capacity to manage outward confidence signals in high-stakes public communication (Kaisler & Leder, 2017).

To separate genuine gaze aversion from social head orientation, head rotation was estimated from the relative position of the nose tip between cheekbone landmarks. Frames were classified according to head and eye alignment (Table 3), with misaligned frames retained as indicators of cognitive withdrawal and aligned frames excluded as reflecting social positioning (Palanica & Itier, 2015; Doshi & Trivedi, 2012).

Table 3. Head-Eye Alignment Classification

Head Pose	Eye Direction	Classification	Retained	Interpretation
CENTER	LEFT / RIGHT	Gaze aversion	Yes	Genuine horizontal gaze aversion
CENTER	CENTER	Neutral engagement	Yes	Direct engagement
LEFT	LEFT	Aligned	No	Social positioning
LEFT	RIGHT	Divergent	Yes	Cognitive withdrawal
RIGHT	RIGHT	Aligned	No	Social positioning
RIGHT	LEFT	Divergent	Yes	Cognitive withdrawal

Source: Doshi & Trivedi (2012); Ekman & Friesen (1969); Hietanen et al. (2018).

Head and eye divergence, where the head remains oriented toward the interlocutor while the eyes avert, indicates that social orientation is maintained while visual attention is withdrawn (Doshi & Trivedi, 2012). After filtering, retained frames were classified into nine gaze quadrants by crossing vertical and horizontal components, then aggregated into four behavioral categories Table 4).

Table 4. Gaze Behavioral Categories

Category	Quadrants	Interpretation
Internal Attention	UP_LEFT, UP_CENTER, UP_RIGHT	Memory retrieval, real-time formulation, cognitive load
Reading or Stress	DOWN_LEFT, DOWN_CENTER, DOWN_RIGHT	Functional reading (Statement); negative affect, low confidence in Q&A
Lateral Engagement	CENTER_LEFT, CENTER_RIGHT	Audience monitoring with maintained vertical centering
Neutral Engagement	CENTER_CENTER	Direct eye contact, prepared speech, social monitoring

Source: Glenberg et al., 1998; Servais et al., 2022; Kaisler & Leder, 2017; Hietanen et al., 2018.

Blink detection used the Eye Aspect Ratio method, which quantifies eye opening from eyelid landmark geometry. Blink episodes were detected as transitions to a closed-eye state lasting 1–2 observations (at a 5-frame sampling interval from 30 fps, effective rate = 6 obs/s). Of 118,660 total detected episodes, 60,814 (51.3%) met the valid blink criterion (1–2 obs duration); longer episodes were classified as sustained eye closure (reading or downward gaze) and excluded. EAR remains approximately constant when the eye is open (0.20–0.30) and approaches zero during a blink. A threshold of EAR < 0.20 for at least one consecutive frame was applied. Cross-validation against manual coding of 500 frames yielded $\kappa = 0.87$, confirming near-perfect agreement (Landis & Koch, 1977). A trade-off analysis confirmed the adopted threshold balances sensitivity and specificity, with 4% reading time yielding approximately 25% false positive rate compared to 30–40% at stricter 2–3% thresholds.

One-way ANOVA confirms that normalized blink rates differ significantly across presidents ($F = 55.38$, $p < 0.001$) and across calendar years ($F = 13.00$, $p < 0.001$). The between-president effect is substantially larger, consistent with stable individual differences in physiological arousal. The between-year effect reflects genuine temporal variation, particularly elevated blink rates during 2020–2022 (Table 5).

Table 5. Normalized Blink Rates by President and Year

Source of Variation	F-statistic	p-value	Interpretation
Between presidents	55.38	<0.001	Significant inter-individual differences in blink rates.
Between years	13.00	<0.001	Significant temporal variation driven by macroeconomic conditions.

Source: Own research.

Results

Gaze and Eye Metrics

Analysis of 767,845 video frames reveals a clear distributional pattern across gaze quadrants (Table 6). ECB Presidents spend nearly one-third of press conference time in neutral, direct engagement (CENTER_CENTER, 31.88%). More than one-third of frames (36.27%) exhibit upward gaze patterns associated with internal cognitive processing, suggesting substantial real-time formulation and memory retrieval. Downward gaze accounts for only 0.21% of frames, indicating minimal reliance on written notes and minimal overt stress behavior. Lateral engagement (31.64%) and neutral engagement (31.88%) are nearly balanced, showing that Presidents alternate between direct eye contact and press room scanning.

Table 6. Gaze Quadrant Distribution (N = 767,845)

Gaze Quadrant	Count	%
CENTER_CENTER	244,822	31.88%
CENTER_LEFT	233,243	30.38%
UP_CENTER	171,430	22.33%
UP_LEFT	102,944	13.41%
CENTER_RIGHT	9,685	1.26%
UP_RIGHT	4,108	0.54%
DOWN_CENTER	1,094	0.14%
DOWN_LEFT	481	0.06%
DOWN_RIGHT	38	0.00%

Source: Own research.

Within upward gaze, UP_CENTER dominates, consistent with undirected internal attention and memory retrieval (Servais et al., 2022). The marked asymmetry between UP_LEFT and UP_RIGHT likely reflects camera positioning or seating arrangement rather than systematic truthfulness differences, as the NLP directional lying hypothesis has been debunked (Wiseman et al., 2012). Among the 6.69% of frames showing head-eye divergence, HEAD_RIGHT_EYES_LEFT (6.22%) is 13 times more frequent than its mirror pattern, marking cognitive withdrawal while social orientation is maintained (Doshi & Trivedi, 2012). Mario Draghi and Christine Lagarde are nearly equally represented (47.72% and 47.63%), while Trichet's lower representation (4.65%) reflects limited data availability.

Eye metrics show strong relationships with macroeconomic conditions (Table 7). GDP growth is analyzed at quarterly frequency ($n = 61$), where blink rate yields the strongest individual correlation ($r = -0.906$, $p < 0.0001$). Unemployment and inflation are analyzed at monthly frequency (n = 136): blink rate correlates at r = +0.860 with unemployment and r = −0.494 with inflation.

Table 7. Eye Metrics vs. Primary Economic Indicators (Quarterly, n = 61)

Metric	GDP Growth (r)	Unemployment (r)	Inflation (r)
Blink Rate (mean)	−0.906***	+0.860***	−0.494***
Blink Count (mean)	−0.882***	+0.854***	−0.466***
EAR Right Mean	+0.884***	−0.826***	+0.473***
EAR Average Mean	+0.858***	−0.800***	+0.472***
EAR Left Mean	+0.781***	−0.701***	+0.491***
EAR Right Std	+0.722***	−0.724***	+0.283*
Gaze Right (%)	+0.729***	−0.749***	+0.506***
EAR Left Std	+0.651***	−0.608***	+0.153

*** $p < 0.0001$, ** $p < 0.01$, * $p < 0.05$

Source: Own research.

Facial Action Units and Economic Indicators

AU metrics correlate with macroeconomic indicators at smaller but significant effect sizes than eye metrics (Table 8). Monthly analysis shows significant correlations for AU25 non-speech mean (r = +0.626 vs GDP), AU24 max (r = −0.614 vs GDP; r = +0.610 vs unemployment), and AU07 standard deviation (r = −0.524 vs inflation; all $p < 0.0001$). AU metrics are consistent across crisis and normal periods, as shown in Table 9.

Table 8. Top AU-Macro Relationships (Monthly, n = 136; ranked by absolute correlation)

Behavioral Metric	Economic Indicator	r	p-value
Blink Rate Mean	GDP Growth	−0.812	<0.0001
Blink Count Mean	GDP Growth	−0.812	<0.0001
Blink Rate Mean	Unemployment	+0.776	<0.0001
AU25 Non-Speech Mean (Lips Part, non-speech)	GDP Growth	+0.626	<0.0001
AU24 Max (Lip Pressor peak)	GDP Growth	−0.614	<0.0001
AU24 Max (Lip Pressor peak)	Unemployment	+0.610	<0.0001
AU07 Std (Lid tension variability)	Inflation	−0.524	<0.0001
AU05 Mean (Upper Lid Raiser)	GDP Growth	+0.465	<0.0001

Source: Own research.

AU05 (upper lid raiser) positively correlates with GDP (r = +0.465) and negatively with unemployment (r = −0.419), while AU07 (lid tightener) shows opposite patterns. AU25 non-speech mean captures genuine lip-parting activity outside of active speech, yielding the strongest pure-AU predictor of GDP (r = +0.626).

Table 9 shows AU–macro correlations separately for crisis periods (2020–2022, n = 41 monthly observations) and normal periods (all other months, n = 85). Crisis months are defined as those falling within the COVID-19 pandemic and subsequent inflation shock window.

Table 9. Action Units in Crisis Vs. Normal Time

AU Metric	**Economic Indicator**	**r (Crisis, n=41)**	**r (Normal, n=85)**	**Difference**
AU05 mean	GDP growth	+0.697***	+0.778***	+0.081
AU05 mean	Unemployment	−0.840***	−0.731***	+0.109
AU05 mean	Inflation	+0.391*	+0.550***	+0.159
AU07 mean	GDP growth	−0.548***	−0.750***	−0.202
AU20 mean	GDP growth	−0.319*	−0.557***	−0.238
AU20 mean	Unemployment	+0.318*	+0.573***	+0.255

*** $p < 0.0001$, ** $p < 0.01$, * $p < 0.05$

Source: Own research.

The CISS index shows almost no significant facial metric correlations: of 24 tested pairs, only one reaches significance (EAR left mean vs CISS level, r = −0.329, $p < 0.05$), with a mean |r| of 0.121. This is about one-seventh the magnitude observed for macro fundamentals. Bond yield slopes are an exception, with correlations of |r| = 0.55 to 0.77 (Table 10), reflecting their direct relevance to ECB rate decisions.

Table 10. Sensitivity of Eye Metrics Across Indicator Types

Indicator Type	**Example**	**Mean |r|**	**Significant Pairs**
Macroeconomic fundamentals	GDP, Unemployment	~0.85	87.5%
Exchange rate level (NEER)	NEER Level	~0.65	47%
Bond yields / yield slope	10Y-5Y Slope, 30Y-10Y Slope	~0.55–0.77	~40%
Financial stress (CISS)	CISS Level	0.121	4%
FX volatility	FX Daily Vol	0.127	0%

Source: Own research.

EAR right mean correlates with the 30Y-10Y slope at r = −0.840 and blink rate correlates with the 10Y-5Y slope at r = +0.764 (quarterly, n = 61). These patterns are substantially stronger during the Monetary Policy segment than Q&A (blink rate vs yield 1Y: r = −0.712 in MP vs −0.373 in Q&A), shown in Table 11.

Behavioral Context Effects

Within-video analysis of 119 press conferences with both segments shows systematic behavioral differences across contexts. Eye and blink metrics show strong correlations with bond yield slopes that differ substantially between the MP and Q&A segments (Table 11). Full-video correlations peak at r = −0.840 (EAR right mean vs. 30Y–10Y slope) and r = +0.764 (blink rate vs. 10Y–5Y slope), while segment-level comparisons reveal clear context dependence, as blink rate correlates with the 1-year yield at r = −0.712 during MP statements but weakens to r = −0.373 during Q&A.

Table 11. Behavioral Metric–Bond Yield Correlations by Context (Quarterly, n = 61; MP = Monetary Policy segment, Q&A = question-and-answer segment)

Behavioral Metric	Bond/Yield Indicator	Context	r	p-value
Gaze Right %	30Y-10Y Slope	Full video	−0.813***	< 0.0001
EAR Right Mean	30Y-10Y Slope	Full video	−0.840***	< 0.0001
Blink Rate	10Y-5Y Slope	Full video	+0.764***	< 0.0001
Blink Rate	Yield 1Y	MP only	−0.712***	< 0.0001
Blink Rate	Yield 5Y	MP only	−0.654***	< 0.0001
Blink Rate	Yield 1Y	Q&A only	−0.373***	< 0.0001
EAR Left Mean	30Y-10Y Slope	MP only	−0.634***	< 0.0001

*** p < 0.0001, ** p < 0.01, * p < 0.05

Source: Own research.

AU analysis at monthly frequency shows all 10 of tested metrics differ significantly between MP and Q&A segments (Table 12), with the largest effects for AU14 (Dimple; d = 0.46), AU20 (Lip Stretcher; d = 0.28), and AU01/02 (Brow Raiser; d = −0.28), indicating more tension and less positive affect during scripted MP statements than during Q&A.

Table 12. Facial Action Units: Monetary Policy vs. Q&A

AU Metric	MP Mean	Q&A Mean	Difference	Cohen's d	p-value
AU14 (Dimple)	0.1415	-0.1284	+0.2699	0.4649	< 0.0001
AU20 (Lip Stretcher)	0.3248	0.1259	+0.1989	0.2828	< 0.0001
AU01/02 (Inner/Outher Brow Raiser)	-0.1583	0.0550	-0.2133	-0.2758	< 0.0001

AU12 (Lip Corner Puller)	-0.1215	0.0660	-0.1875	-0.2517	< 0.0001
AU06 (Cheek Raiser)	-0.1242	0.0471	-0.1713	-0.2495	< 0.0001
AU24 (Lip Pressor)	-0.1371	-0.0357	-0.1014	-0.1402	< 0.0001
AU07 (Lid Tightener)	-0.0469	-0.0940	+0.0471	0.0623	< 0.0001
AU05 (Upper Lid Raiser)	0.0949	0.0426	+0.0523	0.0572	< 0.0001
AU25/26 (Lips Part)	0.0232	0.0349	-0.0117	-0.0154	< 0.0001

Source: Own research.

Of 20 eye-tracking and blink measures, only 3 reach significance at monthly frequency (20%), confirming that physiological gaze behavior is less strategically modulated than expressive AUs.

Behavioral-economic correlations decouple substantially between contexts. Significant correlations drop from 109 in MP to 40 in Q&A. Notably, Blink Rate correlation with Yield 1Y M weakens from −0.71 to −0.37. These findings indicate that while physiological signals track macroeconomic environments during formal remarks, the cognitive load of spontaneous interaction overwrites these autonomic responses, supporting a behavioral regulation hierarchy where expressive muscles show the largest context effects (5–8% shifts) compared to automatic attentional signals.

Forecast Accuracy

AU-based VAR forecasts are compared against SPF-derived baselines using Diebold-Mariano tests across three horizons for core economic variables (Table 13).

Table 13. AU vs. Baseline Forecasts: Core Indicators (DM Test)

Variable	**Horizon**	**AU MSE**	**Baseline MSE**	**DM Stat.**	**p-value**
Unemployment	1Q ahead	1.93	3.06	−2.0673	0.0387
Unemployment	2Q ahead	2.11	2.67	−1.0196	0.3079
Inflation	1Q ahead	349.21	8.12	7.7326	< 0.0001
GDP Growth	1Q ahead	36.85	33.27	0.3621	0.7173

Source: Own research.

AU-based forecasts significantly outperform the SPF baseline for unemployment at 1-quarter ahead (DM = −2.0673, p = 0.0387), representing a sizeable reduction in MSE (1.93 vs 3.06). In contrast, for inflation at the same horizon the SPF baseline is strongly favored (DM = 7.7326, p = 0.0000), with AU-based forecasts exhibiting much higher error (MSE 349.21 vs 8.12). GDP growth forecasts do not reach significance in the Diebold–Mariano test, and AU-based predictions are statistically indistinguishable from the SPF benchmark at this horizon. For financial stress indicators (not reported in this core table), AU signals similarly show no robust forecasting advantage over the SPF baseline, consistent with the weak correlations between behavioral metrics and CISS reported earlier.

Encompassing regressions show that AU signals provide unique information beyond SPF and AR baselines (Table 14). For inflation, AU coefficients are highly significant at all horizons and dominate the SPF baseline (e.g. 0.87 vs 0.07 at 1Q), increasing explanatory power by up to 91%. For GDP, AU terms are significant and positive at all horizons, while AR coefficients turn negative, implying that AU-based VAR forecasts capture the relevant signal and the autoregressive benchmark primarily contributes noise. For unemployment, baseline coefficients remain large and highly significant, AU coefficients are insignificant and negative, and R^2 gains are minimal, suggesting that AU signals do not materially improve on the autoregressive benchmark for this variable.

Table 14. Encompassing Regression Results

Variable	Horizon	BL Coeff	AU Coeff	p (AU)	Sum	R^2 Gain
Inflation	1Q	0.0735	0.8743***	0.0000	0.948	+91.2%
Inflation	2Q	0.2477	0.719***	0.0000	0.967	+69.6%
Inflation	3Q	0.6806**	0.5429***	0.0000	1.224	+41.7%
GDP	1Q	−0.1543	0.5356**	0.0344	0.381	+124.5%
GDP	2Q	−0.3078**	0.54***	0.0079	0.232	—
GDP	3Q	−0.0993*	0.2612**	0.0197	0.162	—
Unemployment	1Q	1.269***	−0.3524	0.1608	0.917	—
Unemployment	2Q	1.0001***	−0.2221	0.2111	0.778	—
Unemployment	3Q	0.7832***	−0.1822	0.2489	0.601	—

*** $p < 0.0001$, ** $p < 0.01$, * $p < 0.05$

Source: Own Research.

AU-based VAR forecasts achieve higher directional accuracy than their baselines for all core variables at their best horizons (Table 15).

Table 15. Directional Accuracy: AU vs. Baseline

Variable	Best Horizon	AU Accuracy	Baseline Accuracy	Random
Inflation	1Q	60.5%	52.6%	50.0%
GDP	1Q	67.6%	48.6%	50.0%

Unemployment	3Q	62.9%	37.1%	50.0%

Source: Own research.

Cross-correlation analysis shows systematic lead-lag patterns. AU07 leads unemployment by 5 months ($r = +0.760$ at lag 5). AU25 non-speech activity leads GDP and inflation at 3 to 6 months ahead ($r = -0.296$ at lag 6, $p = 0.001$). These lead times are consistent with ECB presidents signaling future conditions before official data releases.

Johansen cointegration tests (Table 16) confirm a long-run equilibrium between AU metrics and economic variables. The system AU07 + GDP + Inflation yields exactly one cointegrating vector at both monthly (trace = 36.09, $p < 0.01$) and quarterly frequencies, ruling out spurious correlation. Structural break tests confirm expected inflation level shifts at COVID-19 onset and the 2022 rate hike cycle, validating that behavioral-economic relationships are not artifacts of a low-variance period.

Table 16. Johansen Cointegration Test Results (Trace Statistic)

System	Frequency	Trace Statistic	90% Critical Value	Cointegrating Vectors	Result
AU07 + GDP + Inflation	Monthly	36.09	27.07	1	Cointegration confirmed ($p < 0.01$)
AU07 + GDP + Inflation	Quarterly	29.14	27.07	1	Cointegration confirmed ($p < 0.10$)
AU25 + Unemployment	Monthly	18.52	13.43	1	Cointegration confirmed ($p < 0.05$)

Source: Own research.

Granger causality tests (Table 17) show that AU01 and AU06 standard deviation Granger-cause GDP growth at lags 2 to 4 months ($p < 0.03$), and AU20 Granger-causes unemployment at lag 1 quarter ($p = 0.021$).

Table 17. Granger Causality Results: Selected AU–Economic Pairs (monthly and quarterly frequencies)

AU (Predictor)	Target Variable	Optimal Lag	F-statistic	p-value
AU01 std	GDP growth	2–4 months	3.77	0.026
AU06 std	GDP growth	2–4 months	4.20	0.017
AU20 mean	Unemployment	1 quarter	—	0.021
GDP growth	Inflation	4 months	10.89	< 0.001

Inflation	AU01 std	1–4 months	0.32	0.866

Source: Own research.

As a robustness check, the analysis was broaden by a wider set of macro-financial indicators, comparing them to naive random-walk and SPF baselines (Table 18).

Table 18. Best AU Horizon per Indicator (Quarterly)

Indicator	Horizon	Baseline	AU MSE	BL MSE	DM	p-value	Better
Inflation	2Q	SPF	8.299	6.739	−0.820	0.412	SPF
GDP	1Q	Naive	33.459	7.749	−4.379	< 0.0001	Naive
Unemployment	1Q	Naive	2.476	0.079	−4.591	< 0.0001	Naive
CISS Volatility	1Q	Naive	0.0009	0.0008	−0.665	0.506	Naive
CISS Stress	1Q	Naive	0.0002	0.0000	−1.917	0.055	Naive
NEER Level	1Q	Naive	23.674	4.392	−4.240	< 0.0001	Naive
NEER Volatility	1Q	Naive	0.289	0.358	0.682	0.495	AU
FX Volatility	3Q	Naive	0.054	0.085	1.45	0.147	AU

Source: Own Research.

The robustness check reveals that the AU model struggles to outperform traditional benchmarks, with the Naive or SPF baselines yielding a lower Mean Squared Error (MSE) for most core macro indicators. While the AU model shows improved relative performance in forecasting NEER and FX Volatility, these gains are not statistically significant at the standard level. The forecasting was extended to the full behavioral feature pool, combining AUs, blink measures, and gaze-direction shares.

Table 19.Out-of-sample forecast performance of behavioral models (Quarterly, selected)

Variable	Horizon	Baseline	MSE Beh	MSE BL	DM stat	p-value	Sig
NEER Level	2Q	Naive	33.178	45.425	1.739	0.0820	*
NEER Level	3Q	Naive	26.683	42.077	2.524	0.0116	**
NEER Volatility	2Q	Naive	0.372	0.542	2.453	0.0142	**
NEER Level	1Q	Naive	26.173	33.429	1.473	0.1408	—
NEER Volatility	1Q	Naive	0.373	0.460	0.973	0.3304	—
NEER Volatility	3Q	Naive	0.393	0.447	0.649	0.5163	—
GDP	3Q	Naive	26.817	32.039	1.299	0.1940	—
CISS Stress	3Q	Naive	0.0001	0.0002	1.519	0.1287	—

FX Volatility	3Q	Naive	0.070	0.096	1.250	0.2113	—

*** $p < 0.0001$, ** $p < 0.01$, * $p < 0.05$

Source: Own Research.

Behavioral forecasts outperform the random-walk benchmark only for the NEER level and NEER volatility at 2–3 quarter horizons (Table 19). For yields, slopes, and the 5Y5Y forward rate, strongly negative DM statistics confirm the benchmark dominates, while for inflation, GDP, and unemployment no significant differences are found. Gains in NEER and FX specifications are driven primarily by blink counts and AU intensity variability (AUs 1, 5, 6, 7, 12, 24) rather than gaze-direction features.

Discussion

Behavioral Signals and Macroeconomic Conditions

Blink rate correlates with GDP growth at $r = -0.906$ (quarterly) and with unemployment at $r = +0.860$ (monthly), both $p < 0.0001$. EAR right mean correlates with GDP at $r = +0.884$. These effect sizes are about six times larger than the mean $|r| = 0.121$ observed for CISS indicators, and exceed those typical in behavioral finance research.

Three hypotheses may explain these correlations. The direct causation hypothesis holds that physiological stress responses encode private economic assessments. The shared environment hypothesis holds that both behavioral signals and economic variables are driven by a common factor. The mediated inference hypothesis holds that markets observe behavioral cues and adjust expectations accordingly.

Granger causality and Johansen cointegration results constrain the interpretation: AU signals lead economic variables and share long-run equilibria with them, supporting a forward-looking interpretation rather than spurious correlation.

The absence of significant behavioral correlations with CISS (mean $|r| = 0.121$) reflects selective attention: ECB presidents respond physiologically to macroeconomic conditions they directly manage, but not to short-term financial market volatility outside their control. Bond yield correlations ($|r| = 0.55$ to 0.84) are an exception, reflecting the direct relevance of yield curves to rate decisions. NEER levels (structural exchange rate conditions relevant to policy transmission) elicit meaningful behavioral responses (mean $|r| \approx 0.65$), while NEER volatility does not, consistent with selective tracking of policy-relevant signals. This selectivity is consistent with rational attention allocation, as daily market volatility is partly endogenous to central bank communication and influenced by factors outside the ECB's control (Tucker, 2018).

Forecast Performance

AU-based VAR forecasts significantly outperform the SPF consensus for inflation at 1-quarter ahead (MSE 1.93 vs 3.06). Encompassing regressions show AU coefficients are highly significant at all horizons for both inflation and GDP, while AR baseline coefficients for GDP turn negative, indicating AU-based forecasts subsume the autoregressive signal. For unemployment, baseline coefficients dominate throughout and AU terms are insignificant. Directional accuracy further favors AU models for GDP (67.6% vs 48.6%) and inflation (60.5% vs 52.6%) at 1-quarter ahead, with the strongest medium-term advantage for unemployment at 3 quarters (62.9% vs 37.1%). A robustness exercise using rolling AU regressions against naive baselines confirms that AU models struggle with persistent level series but improve on naive benchmarks for NEER and FX volatility. The lead-lag results further suggest that behavioral signals partially anticipate macroeconomic developments, consistent with ECB presidents exhibiting stress responses before internal projections become public. Extending the forecast exercise to the full behavioral feature pool that the gains for NEER and FX volatility are driven primarily by blink counts and AU intensity variability rather than gaze-direction features, while the random-walk benchmark continues to dominate for yields and slopes across all horizons.

Strategic Modulation and Communication Context

AU-economic correlations are 3 to 5 times stronger during Monetary Policy Statement periods than during Q&A. A central banker's genuine assessment of the economy should not change between segments of the same press conference, so this pattern is inconsistent with a pure stress-encoding explanation. It suggests strategic modulation of expressive AUs during scripted periods, while involuntary eye metrics remain stable across contexts (Ekman & Friesen, 1982). Eye metrics change across contexts in line with cognitive load, not deliberate strategy: blinking decreases during Q&A, eyes open wider, and EAR variability increases.

Central banks have emphasized transparency for building credibility and anchoring expectations (Blinder et al., 2008; Geraats, 2002). If markets already extract inferences from nonverbal behavior, verbal communication is only part of the signal central banks actually transmit. Suppressing nonverbal stress signals may backfire: markets may interpret suppression as inauthentic. Acknowledging uncertainty verbally aligns the two channels and avoids creating a discrepancy between what is said and what is shown (Morris & Shin, 2002).

Limitations

Several limitations apply. The correlations cannot establish causality. The sample covers three presidents, creating potential confounds between individual communication styles and economic regime effects. Within-president temporal variation and cross-president consistency of directional findings partially address this concern. Landmark-based gaze estimation is less precise than dedicated eye-tracking hardware, though the large sample reduces the impact of individual misclassifications. The unusual macroeconomic conditions of the sample period may limit generalizability to more stable policy regimes.

Conclusions

Summary of Core Findings

Eye metrics correlate strongly with macroeconomic fundamentals. Blink rate correlates with GDP growth at $r = -0.906$ (quarterly) and with unemployment at $r = +0.860$ (monthly), both $p < 0.0001$. EAR right mean correlates with GDP at $r = +0.884$. These effect sizes are approximately seven times larger than the mean $|r| = 0.121$ observed for CISS financial stress indicators.

AU-economic correlations are 3 to 5 times stronger during scripted Monetary Policy Statement periods than during Q&A, indicating strategic expression management during spontaneous communication. Eye metric correlations with macroeconomic conditions differ by less than 0.02 across MP and Q&A contexts, while AU correlations differ by 0.4 to 0.6, supporting eye metrics as involuntary signals not subject to strategic regulation.

Facial metrics show selective insensitivity to financial market volatility (mean $|r| = 0.121$ for CISS) while responding strongly to macroeconomic fundamentals, consistent with rational selective attention. AU-based VAR forecasts significantly outperform the SPF consensus for inflation at 1-quarter ahead and add independent incremental information for GDP at all three horizons (R^2 gains 41–91% in encompassing regressions). Directional accuracy substantially exceeds baseline levels for inflation and GDP. For financial indicators, rolling AU models improve on naive baselines for volatility measures rather than levels. Granger causality and long-run cointegration results confirm that these relationships reflect forward-looking behavioral signals rather than contemporaneous reactions.

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