The similarity of ECB's communication

Replication & Extensions

(Amaya & Filbien, 2015)

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I Introduction

Central bank communication is an integral part of monetary policy. For financial markets, ECB press conferences are moments when expectations can shift, not only because of the policy decision itself, but because the accompanying statement reveals how policymakers assess risks and how they may respond going forward. Interpreting these statements, however, is not mechanical: investors must translate words into beliefs about the central bank's reaction function, and that task may become easier as communication becomes more structured, combining text-based measures of similarity and tone with event-study evidence on market responses.

Amaya and Filbien (2015), in "The similarity of ECB's communication", build precisely on this idea. They argue that ECB press-conference statements become increasingly similar across meetings and that this standardization reduces market reactions, as investors learn how to interpret the ECB's wording. They test this mechanism around press-conference dates, predicting that similarity should mitigate the price impact of pessimism.

Our project follows the same agenda in two steps. First, we replicate the main empirical results of Amaya and Filbien (2015) using a reproducible pipeline that reconstructs their core textual indicators and market-reaction measures over the original sample window. Second, we extend the analysis by expanding the set of text-based measures and robustness exercises implemented in our codebase and by extending the observation period through 2025. This allows us to assess how sensitive the learning narrative is to alternative ways of measuring similarity and communication content, and whether the paper's patterns persist in more recent years.

II Paper Replication

The replication follows four major stages: collecting the data, preparing the texts, constructing the key variables (similarity, pessimism, and market reaction), and estimating the paper's main regressions.

Data collection: ECB texts and market inputs

We begin by reconstructing the full set of ECB monetary-policy press conferences. Because the ECB index page loads items dynamically, we automate scrolling to retrieve all statement links, then visit each page to extract its publication date. This yields a clean mapping from date to URL.

Next, we download each statement page and extract the transcript content, separating the introductory statement from the Q&A using a mix of HTML structure cues and simple text markers. We also remove recurrent webpage boilerplate (navigation prompts, transcript links, separators), recording failures explicitly rather than dropping them. In parallel, we import Euro Stoxx 50 prices and the macroeconomic and monetary series used as controls.

Cleaning and preprocessing the corpus

The raw scrape still contains documents that are not comparable to standard monetary-policy press conferences (special events, seminars, one-off briefings). Before any text measurement, we therefore apply a targeted filtering step that removes these outliers using transparent rules based on titles and, in a few cases, specific date–title pairs.

We then preprocess the remaining transcripts to obtain a consistent text representation for measurement.

Focusing on the introductory statement, we normalize the text (whitespace, punctuation variants), tokenize it into words, remove English stopwords, and apply Porter stemming. The output is a standardized corpus where each meeting is represented by cleaned tokens and their stemmed counterparts.

Constructing the key variables: similarity, tone, and market reaction

With a clean statement corpus in hand, we build the three core meeting-level variables used in the replication.

(i) Standardization: consecutive similarity (Jaccard on bigrams). For each meeting i, we compare the statement to the previous one $i-1$. We form stemmed bigrams B_i and compute Jaccard similarity as:

$$JS(S_i, S_{i-1}) = \frac{|B_i \cap B_{i-1}|}{|B_i \cup B_{i-1}|}.$$

(ii) Tone: dictionary-based pessimism (Loughran–McDonald). We quantify tone using the finance-specific Loughran–McDonald dictionary. For each statement, we count negative and positive words and define:

$$Pessimism_i = \frac{Neg_i - Pos_i}{TotalWords_i}.$$

(iii) Market response: event-study CAR. We measure market reactions around each ECB event using a constant-mean return event study based on Euro Stoxx 50 returns. For each press-conference date, we align the event to the nearest trading day, estimate the average daily return over a pre-event estimation window $[-250, -50]$, and compute cumulative abnormal returns (CAR) over the event window $[-5, +5]$:

$$CAR_i = \sum_{t=-5}^{+5} (r_{i,t} - \hat{r}_i), \qquad \hat{r}_i = \frac{1}{200} \sum_{t=-250}^{-50} r_{i,t}.$$

Following the paper, the main outcome variable is |CAR|, which we merge back to the meeting-level text measures.

Regressions

In the final step, we merge the text measures (similarity and pessimism) with the event-study market reaction CAR. We first estimate:

$$\log(Similarity_i) = \alpha_0 + \alpha_1 \log(Time_i) + \gamma' Controls_i + \varepsilon_i.$$

Second, we test the learning mechanism via the interaction between tone and similarity:

$$|\mathrm{CAR}_i| = \beta_0 + \beta_1 (Pessimism_i \times \log(Similarity_i)) + \delta' Controls_i + u_i.$$

Results

The regressions over 1999–2013 confirm the paper's main patterns. In the similarity equations, the time trend in $\log(Similarity)$ is positive and highly significant across specifications, indicating a clear rise in standardization. In the $|CAR|$ regressions, pessimism is positively related to market reactions in the baseline model, while the key interaction term $Pessimism \times \log(Similarity)$ is negative and significant in the parsimonious specification, consistent with the learning mechanism. With controls included, the interaction remains negative but is estimated less precisely, suggesting sensitivity in magnitude rather than in sign.

III Paper Extensions

To advance the analysis beyond replication, we extend the sample period through 2025 and broaden the text-based measurement strategy. Specifically, we complement the paper's Jaccard bigram similarity with an alternative standardization metric based on TF–IDF cosine similarity, and we go beyond the baseline LM pessimism index by adding an LM uncertainty measure. We also examine asymmetries by separating good-news from bad-news communication. We then re-estimate the core interaction framework using these extensions to assess robustness to alternative definitions of similarity and communication content, and to evaluate whether the paper's patterns persist in more recent ECB communication regimes.

Extension 1: Time period

1999–2025. Over the full horizon, ECB statements exhibit a strong long-run rise in standardization: the time trend in $\log(Similarity)$ is positive and highly significant. At the same time, the learning channel is weaker than in 1999–2013: the interaction $Pessimism \times \log(Similarity)$ is negative in parsimonious specifications but becomes less precisely estimated once controls are added.

2014–2025. Focusing on the post-2013 regime yields a different within-period dynamic. The time trend in $\log(Similarity)$ turns negative, indicating that consecutive statements become less similar over time within this later sample. The interaction effect on $|CAR|$ remains negative but is no longer precisely estimated, pointing to a looser and more context-dependent link between statement wording and market reactions. This regime shift is consistent with communication being shaped by policy regime change and unconventional tools, a crisis-dominated macro environment, and more heterogeneous market-moving content within press conferences, where nuances and QA may matter relatively more than the introductory statement alone.

Extension 2: Cosine-based similarity (Counts vs. TF–IDF)

To relax the paper's Jaccard-bigram construction, we compute an alternative measure of communication standardisation based on consecutive cosine similarity in an n-gram vector space. Using the preprocessed statements, we build unigram–bigram features ($n \in \{1, 2\}$) and represent each statement i by a vector v_i. Consecutive similarity is then defined as:

$$Similarity_i^{\cos} = \frac{v_i \cdot v_{i-1}}{\|v_i\| \, \|v_{i-1}\|}.$$

We implement this metric under two representations built on the same corpus and feature set: raw n-gram counts and TF–IDF weights. In the TF–IDF case, each n-gram t in statement i receives weight

$$w_{i,t} = tf_{i,t} \cdot idf(t), \qquad idf(t) = \log\left(\frac{1+N}{1+df(t)}\right) + 1,$$

where $tf_{i,t}$ is the raw frequency of t, $df(t)$ is the number of statements containing t, and N is the total number of statements. This weighting scheme down-weights ubiquitous expressions and assigns relatively more importance to distinctive wording, providing a more conservative notion of textual reuse than the count-based cosine similarity.

We plot the two consecutive cosine similarity series over time. Both measures display strong co-movement, indicating that they capture the same underlying communication dynamics, while differing in levels for mechanical reasons, as TF–IDF similarity is lower by construction. The series also highlights episodic breaks, with sharp drops around 2020–2021 followed by a recovery, consistent with periods in which the ECB's language and framing shift abruptly before converging again toward a more stable template.

TF–IDF cosine similarity on the original sample window (1999–2013) leaves the paper's first result intact: log(similarity) still rises significantly over time, confirming a clear increase in standardisation. Regarding the learning channel, the interaction between pessimism and TF–IDF similarity remains *negative*: it is statistically significant in the parsimonious specification, but becomes smaller and no longer significant once macro controls are included. Overall, TF–IDF cosine similarity does not overturn the qualitative "dampening" pattern, but the evidence is less robust across specifications than with the baseline Jaccard-bigram measure.

Extension 3: Uncertainty measure (dictionary-based)

To complement the paper's tone measure (pessimism), we construct an alternative indicator based on linguistic uncertainty using the *Uncertainty* category of the Loughran–McDonald dictionary. For each press-conference statement i, we count the number of uncertainty-related words and scale by the total number of words in the statement:

$$Uncertainty_i = \frac{Unc_i}{TotalWords_i} \times 100.$$

We then merge this meeting-level uncertainty measure with the event-study outcome $|\mathrm{CAR}_i|$ and re-estimate the specifications corresponding to Table 4 of the original paper. In these regressions, pessimism is replaced by uncertainty, and we include its interaction with communication standardisation, measured by $\log(Similarity_i)$ based on Jaccard bigrams.

Results (1999–2013). Uncertainty does not behave like pessimism in the original paper. The coefficient on uncertainty is positive but not statistically significant. The interaction term Uncertainty $\times$ log(Similarity) is close to zero and not significant in the parsimonious specification, but it becomes negative and marginally significant once macro controls are included. Overall, this points to weak and specification-dependent evidence that standardisation dampens the market response to uncertainty-related language.

Results (1999–2025). Over the extended sample, the main effect of Uncertainty remains imprecisely estimated. The interaction term Uncertainty $\times$ log(Similarity) is negative and becomes marginally significant once macro controls are included. Overall, this suggests that any dampening effect of communication standardisation on the market response to uncertainty-related language is modest and specification-dependent.

Extension 4: Asymmetric effects of "bad news" vs. "good news"

To examine whether market reactions differ depending on the sign of ECB communication, we decompose the Loughran–McDonald tone signal into two distinct components based on dictionary word counts. For each press-conference meeting i, we construct measures of *bad news* and *good news* as the shares of LM-negative and LM-positive words in the introductory statement, respectively, expressed in percent.

Rather than estimating level effects of tone components, we focus on how communication standardisation moderates their impact on market reactions. Specifically, we interact each tone component with consecutive textual similarity, measured using Jaccard similarity on stemmed bigrams. Because similarity lies in the interval $(0, 1)$ and its logarithm is negative, we use a centered version of log-similarity to reduce collinearity in interaction terms:

$$\log(\widehat{Similarity_i}) = \log(Similarity_i) - \overline{\log(Similarity)}.$$

The estimated specifications are interaction-only models of the form:

$$|CAR_i| = \alpha + \gamma_b \big(BadNews_i \times \log(\widehat{Similarity_i})\big) + \gamma_g \big(GoodNews_i \times \log(\widehat{Similarity_i})\big) + \delta' Controls_i + \varepsilon_i,$$

where controls include the output gap, inflation, and changes in the main refinancing operations rate (ΔMRO). All regressions are estimated by OLS with HC1 heteroskedasticity-robust standard errors.

In addition to joint specifications including both interaction terms, we estimate separate regressions focusing exclusively on bad-news interactions and good-news interactions, with and without macroeconomic controls. This allows us to assess whether similarity moderates negative and positive communication asymmetrically, without imposing restrictions on their relative importance.

As a robustness check, we replicate the same interaction-only framework using an alternative decomposition of tone based on the positive and negative components of the pessimism index $(Neg - Pos)/Total$. The qualitative conclusions regarding asymmetry remain unchanged.

Over 1999–2013, the joint model indicates clear asymmetry in level effects: the Wald test rejects equality of bad- and good-news coefficients, with good-news intensity estimated as negative in the interacted specification, while bad-news intensity is positive but less precisely estimated. By contrast, we do not find robust asymmetry in the interaction channel: equality of interaction coefficients cannot be rejected. Overall, this extension suggests that equity responses in the original sample are more sensitive to the type of news conveyed than to a strongly differential "learning-by-standardisation" mechanism across positive vs negative content.

Extension 5: Information structure in ECB statements

To assess whether market reactions depend not only on what the ECB says (tone) or how repetitive its language is (similarity), but also on how information is organised within statements, we construct a set of information-structure proxies at the level of each introductory statement and examine whether they help explain the magnitude of equity market responses. The underlying idea is that two statements may be equally similar in aggregate wording yet differ in how concentrated, varied, or "novel" their content is features that may affect how quickly markets extract the relevant policy signal.

We proxy information structure using four complementary measures computed for each statement i.

First, we compute *lexical entropy*,

$$H_i = -\sum_w p_i(w) \, \log p_i(w),$$

where $p_i(w)$ denotes the empirical frequency of token w in statement i. Lexical entropy captures the dispersion of attention across words, with higher values indicating more diffuse wording.

Second, we consider a *normalised entropy* measure,

$$H_i^{\text{norm}} = \frac{H_i}{\log V_i},$$

where V_i is the number of distinct tokens in statement i. This adjustment isolates dispersion relative to vocabulary size.

Third, we capture phrase-level structure through the *bigram uniqueness ratio* which measures how template-like the statement is at the two-word level.

$$BigramUniqueRatio_i = \frac{\text{number of unique bigrams in } i}{\text{total number of bigrams in } i},$$

Finally, we construct a forward-looking *novelty proxy* defined as the *new-token ratio*,

$$NewTokenRatio_i = \frac{|S_i \setminus S_{i-1}|}{|S_i|},$$

where S_i denotes the set of token types in statement i. This measure captures the share of vocabulary newly introduced relative to the previous meeting.

We then re-estimate the Table 4 regressions with $|CAR_i|$ as the dependent variable, augmenting the baseline specification with each information-structure proxy while controlling for communication similarity. In richer specifications, we additionally include tone and the standard macroeconomic controls. Because novelty measures may be sensitive to extreme observations, we perform a robustness exercise that winsorises the new-token ratio at the 1st and 99th percentiles and re-estimate the key regressions. We also estimate an alternative "full" specification substituting the bigram uniqueness ratio for novelty to verify that results are not driven by a single proxy.

Results (1999–2013). Across baseline specifications, entropy-based measures, both raw and normalised, do not display robust explanatory power for $|CAR|$. In contrast, structure captured at the phrase level proves more informative. The bigram uniqueness ratio enters with a negative and statistically significant coefficient in the parsimonious model and remains economically meaningful and significant in the full specification including controls and tone.

This pattern suggests that more template-like phrasing (lower bigram uniqueness) is associated with larger market reactions, whereas more idiosyncratic statement structure is associated with smaller responses. A plausible interpretation is that repeated and recognisable phrasing facilitates faster extraction of policy-relevant information, thereby concentrating immediate repricing. Novelty, as measured by the new-token ratio, is not robust once controls and tone are included, and its winsorised versions confirm that the lack of significance is not driven by outliers. Overall, this extension indicates that how information is packaged matters primarily through phrase-level repetition and variety rather than through broad token dispersion, and that these structure effects are not fully subsumed by the similarity and tone channels emphasised in Amaya and Filbien (2015).

IV Conclusion

Our project replicates Amaya Filbien (2015) with a reproducible pipeline and then tests how robust the standardisation and learning story is to alternative measures and a longer sample. In the original window (1999–2013), we recover the paper's core fact: ECB introductory statements become increasingly standardised over time, with a strong positive trend in log similarity. The interaction results are broadly consistent with the learning intuition: tone matters for market reactions and similarity can mitigate it, although the interaction is less precisely estimated once macro controls are included.

The extensions show that the narrative is not invariant. Extending the sample to 2025 preserves the long-run rise in standardisation but weakens the learning channel, consistent with post-2013 regime shifts and crisis/unconventional-policy communication. Switching from Jaccard bigrams to TF–IDF cosine similarity preserves the time-trend result and yields a similarly negative interaction in parsimonious specifications, but the effect becomes less robust once macro controls are included, suggesting the learning mechanism depends on what "similarity" captures. An LM uncertainty indicator does not replicate the pessimism channel: any dampening effect of standardisation on the market response to uncertainty-related wording is modest and specification-dependent. Moreover, "good vs bad news" interaction-only specifications provide little evidence that similarity differentially moderates negative versus positive wording, as the interaction terms are not precisely estimated. Finally, information-structure proxies indicate that bigram-level variety is more informative for $|CAR|$ than entropy or lexical novelty, and the main pattern survives basic robustness checks.

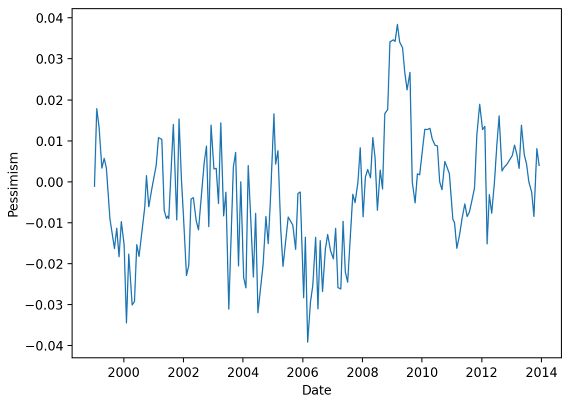
Overall, standardisation is robust, while the learning-by-standardisation mechanism is sensitive to measurement choices and to the post-2013 communication regime.

Citations

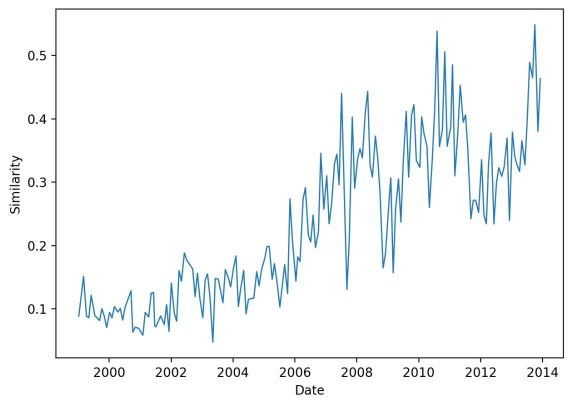
Amaya, D., & Filbien, J.-Y. (2015). *The similarity of ECB's communication.* Finance Research Letters, 13, 234–242.

Appendix

Appendix A. Figures

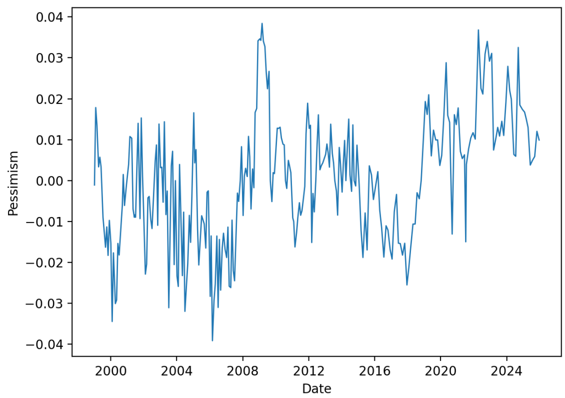


(a) ECB pessimism (Loughran–McDonald)

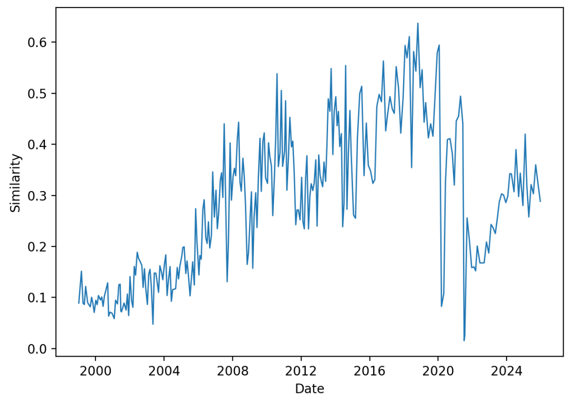


(b) ECB text similarity (Jaccard bigrams)

Figure 1: **Replication (1999–2013).** Evolution of ECB communication tone and textual similarity.

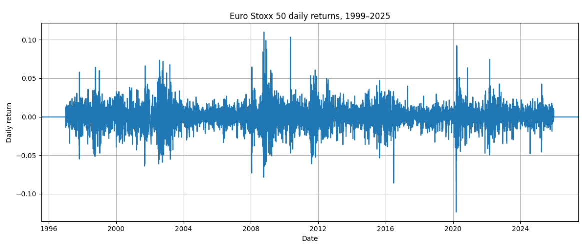


(a) ECB pessimism (Loughran–McDonald)



(b) ECB text similarity (Jaccard bigrams)

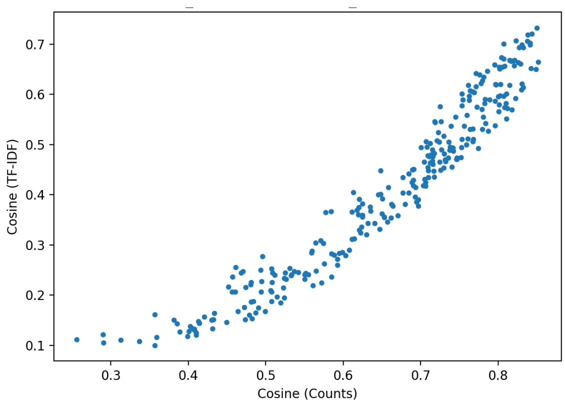
Figure 2: **Extension (1999–2025).** Evolution of ECB communication tone and textual similarity.



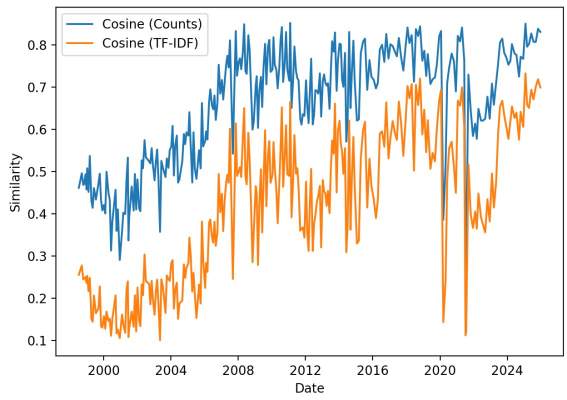
(a) Daily returns

(b) Index level (closing price)

Figure 3: **Euro Stoxx 50 market dynamics (1999–2025).**



(a) TF–IDF vs count-based cosine similarity



(b) Time-series evolution

Figure 4: **Extension 2: Cosine-based similarity measures.**

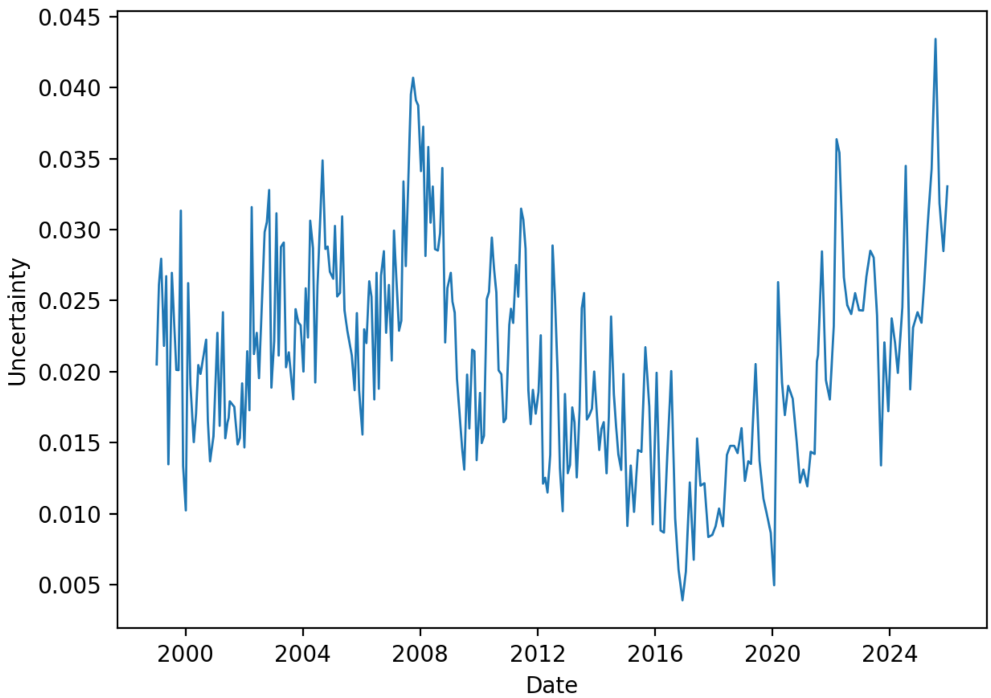


Figure 5: **ECB uncertainty (Loughran–McDonald), 1999–2025**.

Appendix B. Tables

Table 1: Summary statistics (1999-2013)

Variable	Mean	Std. dev.	Min	Q1	Median	Q3	Max
CAR	-0.05	4.59	-21.37	-2.42	0.30	2.85	13.17
$\|CAR\|$	3.43	3.04	0.02	1.44	2.54	4.59	21.37
Pessimism	-0.27	1.49	-3.91	-1.17	-0.25	0.65	3.84
Similarity	0.23	0.12	0.05	0.12	0.21	0.33	0.55
Output gap	-0.13	1.98	-3.57	-2.12	0.14	1.58	2.64
Inflation	2.03	0.79	-0.65	1.72	2.12	2.46	4.06
Δ MRO	-0.01	0.17	-0.75	0.00	0.00	0.00	0.50

Notes: The sample consists of ECB monetary policy announcements.

Table 2: Explaining similarity with time: Jaccard bigrams (1999–2013)

Variable	(1)	(2)	(3)	(4)
Intercept	-2.051***	-4.768***	-4.809***	-3.506***
Time		0.415***	0.429***	
Time (count)				0.480***
Output gap	-0.200***		-0.050**	-0.035
Inflation	0.208***		-0.040	-0.054
Δ MRO	0.251		0.288**	0.295**
Adjusted R^2	33.44%	53.03%	60.50%	63.33%

Notes: The dependent variable is log(Similarity), where similarity is measured using consecutive Jaccard similarity on stemmed bigrams. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Explaining absolute cumulative abnormal returns using Jaccard Bigrams (1999-2013)

Variable	(1)	(2)	(3)	(4)
Intercept	3.558***	2.341***	3.579***	2.461***
Pessimism	0.489***			
Pessimism × Similarity			-0.244***	-0.157
Output gap		-0.217*		-0.148
Inflation		0.509		0.510
Δ MRO		-3.264*		-2.141
Adjusted R^2	5.19%	3.81%	3.62%	4.33%

Notes: The dependent variable is the absolute cumulative abnormal return ($|CAR|$). Pessimism is measured using the Loughran–McDonald dictionary. Similarity is measured using consecutive Jaccard similarity on stemmed bigrams. OLS estimates with HC1 heteroskedasticity-robust standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Explaining similarity with time: Jaccard bigrams (1999–2025)

Variable	(1)	(2)	(3)	(4)
Intercept	-1.405***	-4.575***	-4.905***	-3.478***
Time		0.389***	0.462***	
Time (count)				0.503***
Output gap	-0.106***		0.016	0.024
Inflation	-0.028*		-0.125***	-0.126***
Δ MRO	0.157		0.280***	0.282***
Adjusted R^2	12.65%	41.37%	50.64%	52.89%

Notes: The dependent variable is log(Similarity), where similarity is measured using consecutive Jaccard similarity on stemmed bigrams. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Explaining $|CAR|$ with pessimism and TF–IDF similarity (1999–2013)

Variable	(1)	(2)	(3)	(4)
Intercept	3.558***	2.341***	3.601***	2.460***
Pessimism	0.489***			
Pessimism × similarity			-0.295**	-0.164
Output gap		-0.217*		-0.162
Inflation		0.509		0.502
Δ MRO		-3.264*		-2.400
Adjusted R^2	5.19%	3.81%	3.05%	3.96%

Notes: Dependent variable is $|CAR|$. HC1 robust standard errors. ***, **, * denote significance at 1%, 5%, and 10% levels.

Table 7: Explaining $|CAR|$ with uncertainty (1999–2013)

Variable	(1)	(2)	(3)	(4)
Intercept	2.741***	2.341***	3.366***	1.210
Uncertainty	0.302			
Uncertainty × log(Similarity)			-0.017	-0.258*
Output gap		-0.217*		-0.348**
Inflation		0.509		0.598*
Δ MRO		-3.264*		-3.201*
Adjusted R^2	-0.18%	3.81%	-0.58%	4.42%

Notes: Dependent variable is $|CAR|$. HC1 robust standard errors. ***, **, * denote significance at 1%, 5%, and 10% levels.

Table 8: Explaining $|CAR|$ with uncertainty (1999–2025)

Variable	(1)	(2)	(3)	(4)
Intercept	2.287***	2.674***	2.500***	1.557**
Uncertainty	0.434			
Uncertainty $\times$ log(Similarity)			-0.227	-0.410*
Output gap		-0.292		-0.409*
Inflation		0.198		0.105
Δ MRO		-2.580		-2.354
Adjusted R^2	0.53%	2.95%	1.03%	6.31%

Notes: Dependent variable is $|CAR|$. HC1 robust standard errors.

Table 9: Asymmetric effects of bad vs. good news: interaction-only specifications (1999–2013)

	(1) Int only	(2) Int + Ctls	(3) Bad only	(4) Bad + Ctls	(5) Good only	(6) Good + Ctls
Intercept	3.354***	2.146***	3.414***	2.295***	3.426***	2.196***
Bad news $\times$ similarity	0.391	0.368	0.074	-0.072		
Good news $\times$ similarity	-0.314	-0.416			0.009	-0.140
Output gap		-0.229		-0.254		-0.285**
Inflation		0.567*		0.535		0.574*
Δ MRO		-3.472*		-3.182		-3.191
Adjusted R^2	-0.49%	3.67%	-0.44%	3.33%	-0.59%	3.74%

Notes: The dependent variable is the absolute cumulative abnormal return ($|CAR|$). Bad and good news are measured as shares of Loughran–McDonald negative and positive words, respectively. Similarity is measured using consecutive Jaccard similarity on stemmed bigrams and is centered before interaction. All regressions are estimated by OLS with HC1 heteroskedasticity-robust standard errors. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Descriptive statistics of information-structure measures (1999-2013)

Variable	Mean	Std. dev.	Min	Q1	Median	Q3	Max
Number of tokens (n_tokens)	846.95	249.78	371	691.75	806.50	987.25	3042
Vocabulary size (v_types)	439.18	80.80	249	388.75	431.00	476.25	1137
Type–token ratio (TTR)	0.532	0.059	0.300	0.487	0.533	0.573	0.680
Herdan's C	0.905	0.014	0.843	0.896	0.906	0.915	0.939
Lexical entropy	5.751	0.141	5.308	5.666	5.743	5.834	6.592
Normalised entropy	0.948	0.009	0.913	0.943	0.949	0.953	0.966
Bigram uniqueness ratio	0.857	0.053	0.553	0.821	0.867	0.895	0.954
New-type ratio	0.043	0.091	0.000	0.010	0.041	0.019	1.000
New-token ratio	0.028	0.075	0.000	0.005	0.027	0.011	1.000

Notes: This table reports descriptive statistics for the information-structure measures computed from ECB introductory statements. The sample consists of 280 press-conference statements over 1999–2025. Entropy and bigram-based measures capture lexical dispersion and phrase-level structure, while new-type and new-token ratios proxy for linguistic novelty.

Table 11: Information structure and market reactions (1999-2013)

	(1) Entropy + Sim.	(2) Entropy (norm) + Sim.	(3) Bigram uniq. + Sim.	(4) New-token + Sim.	(5) Full (NT)	(6) Full (BU)	(7) NT (wins.) + Sim.	(8) Full (wins.)
Intercept	1.141	42.834	17.019***	3.855***	1.834**	13.139**	3.849***	1.833**
Entropy	0.438							
Entropy (normalised)		-41.469						
Bigram uniqueness ratio			-17.418**			-15.158*		
New-token ratio				6.266	15.509			
New-token ratio (winsorised)							6.050	15.422
Similarity (log)	0.147	0.007	-0.895*	0.360	0.038	-1.310**	0.353	0.033
Pessimism					0.393**	0.276		0.393**
Output gap					-0.192	-0.207		-0.192
Inflation					0.672**	0.645**		0.670**
Δ MRO					-1.689	-1.805		-1.689
Observations	172	172	172	172	171	171	172	171
Adjusted R^2	-1.04%	-0.29%	4.72%	-0.97%	5.43%	9.05%	-0.98%	5.41%

Notes: The dependent variable is the absolute cumulative abnormal return ($|CAR|$). Similarity is measured as the log of consecutive Jaccard similarity on stemmed bigrams. Entropy and entropy (normalised) capture lexical dispersion. The bigram uniqueness ratio measures phrase-level template repetition. The new-token ratio captures lexical novelty relative to the previous statement. Columns (5), (6), and (8) include macroeconomic controls (output gap, inflation, ΔMRO) and tone (pessimism). All regressions are estimated by OLS with HC1 heteroskedasticity-robust standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.