

Payoff of Credibility and Communication Strategy of Central Banks on Inflation Expectations

Latin America Case Study: Text Mining and Neural Networks

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Motivation and research question

MOTIVATION

- **Methodological gap:** Central Banks' communication is a monetary policy tool, but how do we measure its effectiveness systematically?
- **Policy relevance:** Expectations are a key transmission mechanism. Rate decisions, exchange rate, wages, and prices all respond to how agents form expectations.
- **Need for Alternative Methods:** In Latin America, high-frequency expectation data is scarce and generic NLP dictionaries (Harvard-IV, Loughran-McDonald) are not tailored to regional Central Banks discourse.

Objective: quantify the alignment between Central Bank tone and public inflation expectations for Chile, Colombia, Peru & Dominican Republic.

KEY CONCEPT

Expectations Entropy

$$S = E(\pi^*) - E(\pi)$$

$E(\pi^*)$ Simulated expectations from CB tone

$E(\pi)$ Observed expectations (surveys)

Higher S

→ Greater de-anchoring risk

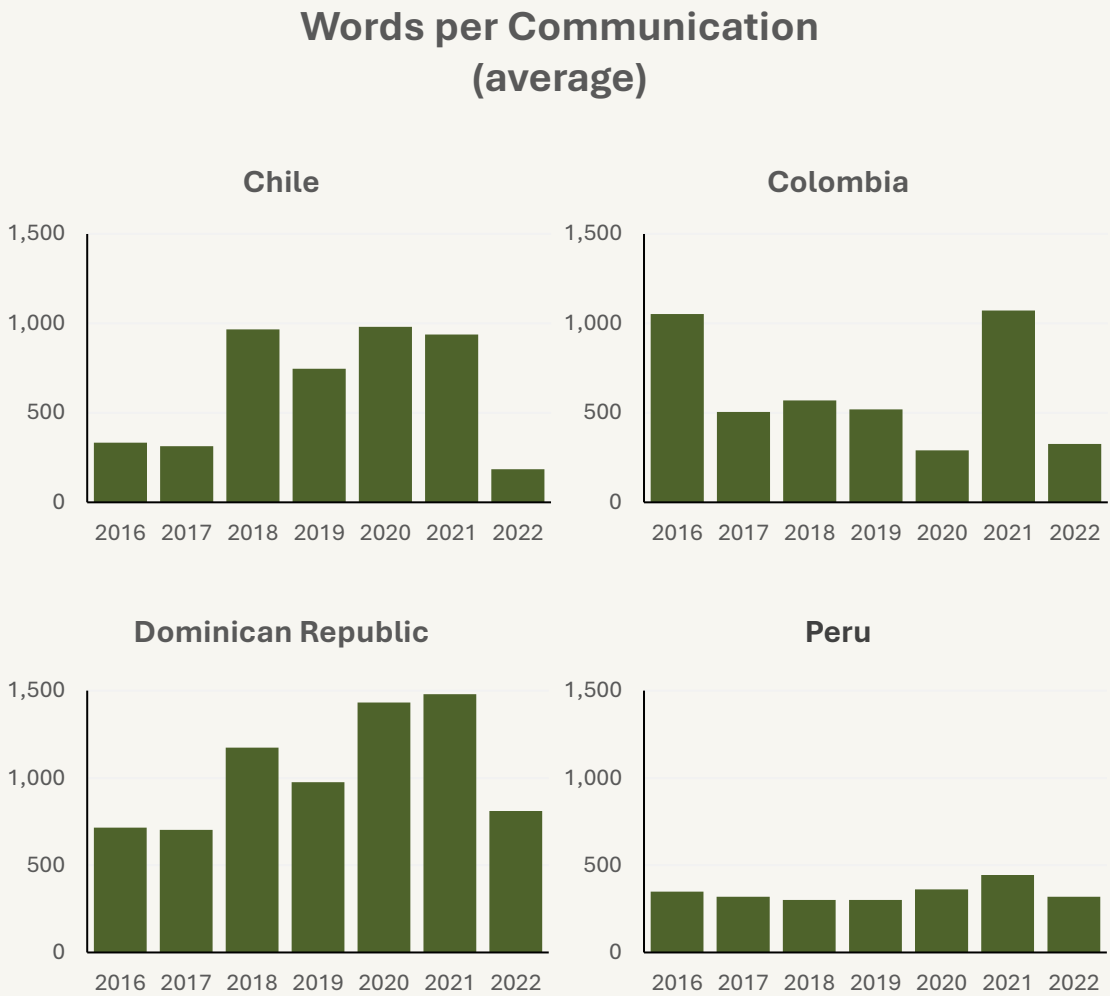
→ More monetary policy effort required

Data

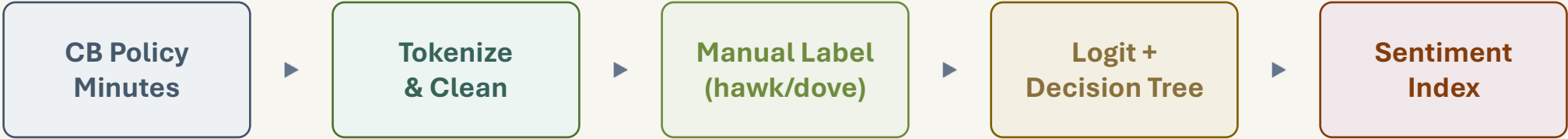
Country	Period	Source
Dominican Republic	Jan 2016 – May. 2022	BCRD
Peru	Jan 2016 – May. 2022	BCRP
Colombia	Jan 2016 – May. 2022	BanRep
Chile	Jan 2016 – May. 2022	BCCh

Variables: Monetary policy minutes; CPI inflation; Inflation expectations (surveys); Policy rate.

- The four countries issued longer and more detailed statements following the post-2020 pandemic, consistent with greater *forward guidance* from central banks amid high uncertainty.
- The Dominican Republic produces the longest minutes among the four countries.



Methodology I: Country-Specific Sentiment Indices



Tokens: Unigrams & Bigrams | **Split:** 70% train / 30% test | Per-country models

Classifier Performance — Best F1-Score by Country

Country	Best F1	Best Model	Remark
Dominican Republic	0.583	Decision Tree / Bigrams	Most consistent metrics across models
Peru	0.642	Decision Tree / Bigrams	Uniform across models
Colombia	0.648	Decision Tree / Bigrams	Best overall F1
Chile	0.532	Decision Tree / Unigrams	Non-monthly comms. → interpolated*

Benchmark

Own indices outperform Harvard-IV, Loughran-McDonald, Henry & QDAP on correlation with expectations

→ **Country-specific dictionaries are important**

*Chile's lower F1 reflects its non-monthly publication frequency; interpolation was applied to homogenize the series.

Methodology II: Neural Network for Simulating Inflation Expectations

Input

Sentiment index

tone at t
tone at $t - 1$
tone at $t - 2$

Observed inflation

CPI at t
CPI at $t - 1$

MLP Model

Architecture

Multilayer Perceptron
1–2 hidden layers
Sigmoid activation

Training

70% train / 30% test
Min-max normalization
Models per country

Output

Simulated expectations

$E(\pi^*)$ en $t + 12$

What agents would expect
if guided solely by Central
Banks' tone

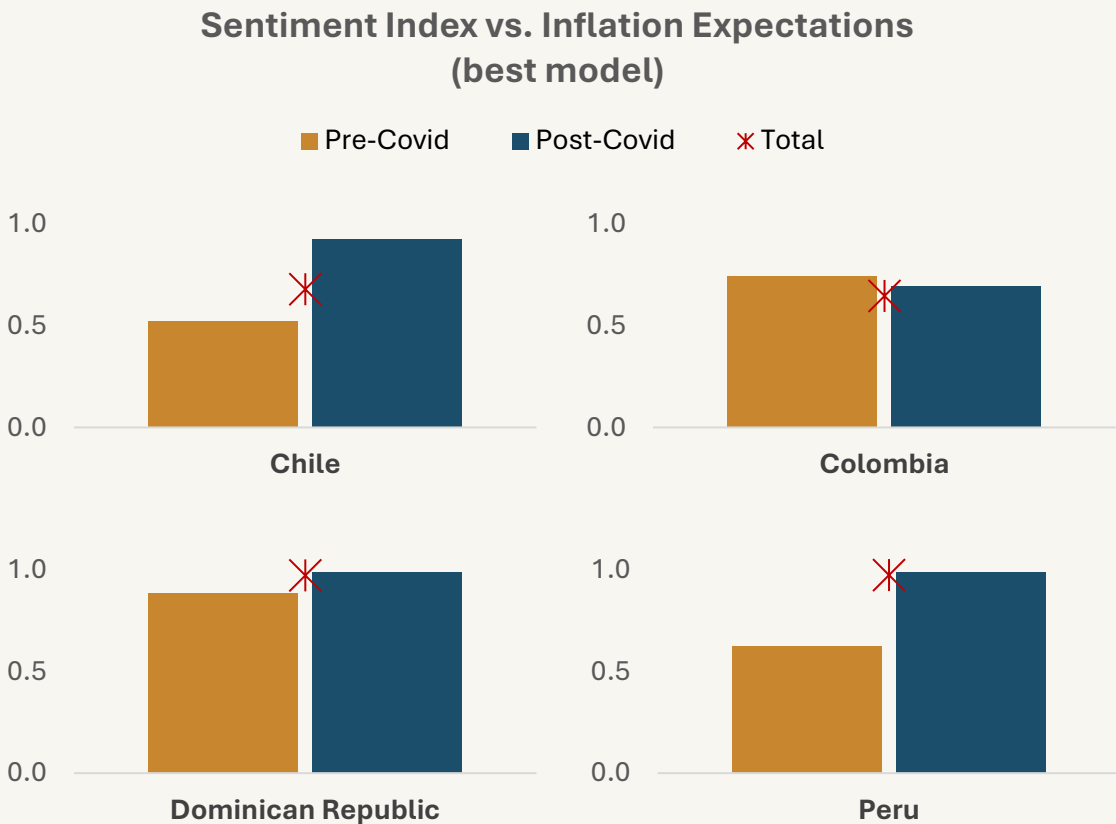
Entropy

$$S = E(\pi^*) - E(\pi)$$

Divergence between
Central Banks' discourse
and public
expectations

Interpretation: $S \approx 0 \rightarrow$ expectations align with the central bank's tone (credibility). High $S \rightarrow$ the tone has lost traction, or expectations are anchored by external factors (e.g., COVID). Entropy is a monitoring metric, not a structural causal estimate.

Results I: Sentiment Indices and Country Heterogeneity



Benchmark: Country-specific indices outperform Harvard-IV, Loughran-McDonald, Henry & QDAP across all four countries

Country-specific dictionaries matter

Generic dictionaries consistently underestimate the signal. Latin American Central Banks’ discourse requires local calibration.

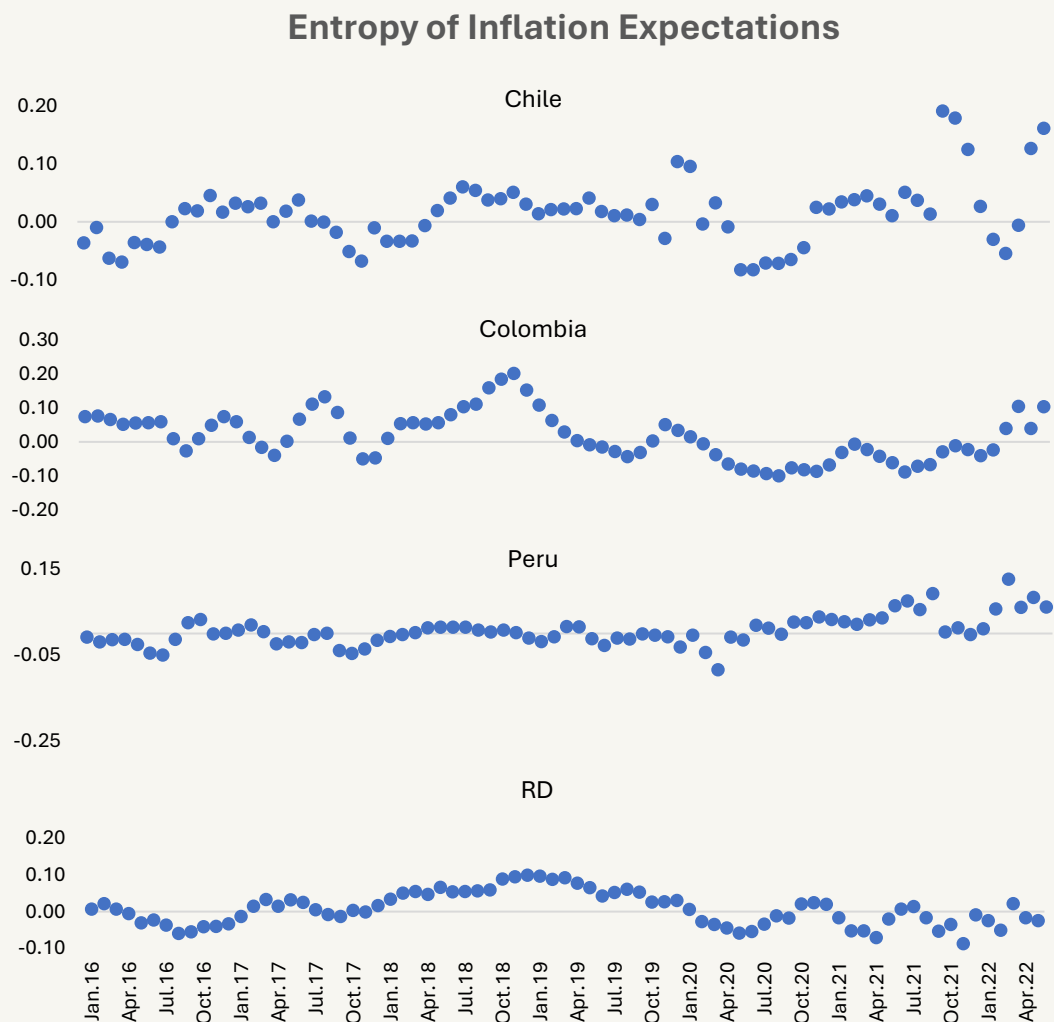
Post-COVID convergence

Greater alignment between the Central Bank's tone and public expectations after 2020. Market participants relied more heavily on forward guidance amid high uncertainty.

Granger causality: mixed results

Significant for Colombia and Chile. For DR and Peru, COVID shocks likely explain expectation formation outside CB discourse.

Results II: Expectations Entropy and Policy Implications



Policy Implications

01

Credibility reduces adjustment costs

Lower entropy → fewer or smaller MPR moves needed to keep inflation within target.

02

Forward guidance amplifies slack

Central Banks with credible communication can implement counter-cyclical policy more freely.

03

Replicable monitoring tool

Entropy can be computed in near real-time by any CB in the region using this pipeline.

Lower S → higher CB credibility → less MPR effort needed to anchor expectations.

Conclusions

Main Findings

- 1. Country-specific indices outperform standard dictionaries for Latin American CB communications**
- 2. Significant heterogeneity in tone-expectation alignment across countries: no universal solution**
- 3. Post-COVID convergence: forward guidance gained traction when uncertainty was highest**
- 4. Peru and Dominican Republic show the lowest expectations entropy, consistent with greater CB credibility during the study period**

Future Extensions

- From stemmed tokens to full-form text.** Stemming aids classification in small corpora but discards nuance. Contextual embeddings capture similarity between word forms without destroying them.
- From token counts to sentence-level meaning.** Transformers with full attention relate every word to every other across the sentence: negations, syntax, and distant tone-defining words are all considered.
- From manual to LLM-assisted labeling.** Hand-labeling a sample of communiqués caps the training set. LLM-generated sentence-level labels, validated by economists, expand it at negligible cost.
- Compute implicit MPR path consistent with entropy trajectory**



Documenting inflation-targeting frameworks: an experimental cross-country data set

Victor Gonçalves, **Cristina Leonte**, Jitong Xu (BIS)

20 August 2026

The views expressed here are those of the authors and do not necessarily reflect those of the Bank for International Settlements (BIS), Central Bank of Brazil, Irving Fisher Committee on Central Bank Statistics (IFC) or any of those institutions mentioned.

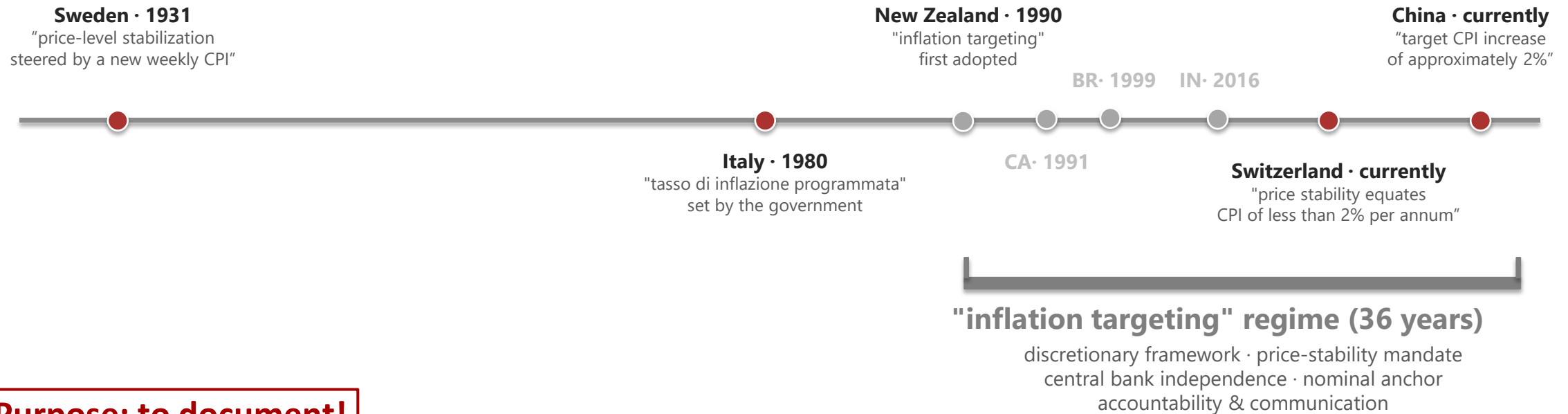
Motivation: **inflation objective** is broader than **inflation targeting (IT)**

Inflation targeting has become "the de facto global monetary standard"

Borio (2024), "Whither inflation targeting as a global monetary standard?", BIS Working Papers no 1230

Borio & Chavaz (2025), "Moving targets? Inflation targeting frameworks, 1990–2025", BIS Quarterly Review

- explicit "IT" adoption
- inflation objective without the "IT" label



Purpose: to document!

The **inflation objective** is the organizing concept:
explicit inflation targeting regime (legal mandate or self-recognition) vs **implicit regime** (inflation objective defined)

Experimental data set: four statistical **challenges**, one **design**

- **Four statistical challenges**

- **Numerical objective:** the same number can carry different meanings
eg ECB 2%: from “below, but close to, 2%” (2003) to explicitly symmetric (2021)
- **Heterogeneity:** legal acts, reports, policy decisions, speeches, IT website sections
- **Multidimensionality:** institutional arrangements are meaningful
eg the commitment horizon, underlying price index, the treatment of the breaches
- **Timing:** announcement date and effective date do not always coincide

- **The design: disentangling the concept from its measures**

- An inflation objective is one statistical concept with multiple measures embedded in the institutional arrangements
- The objective steers policy, distinct from a forecast or expectations

Experimental data set: examples of **classification** by operational commitment

1

*"the operational target for monetary policy remains an inflation rate of **2 per cent**, measured by the 12-month increase in the **Consumer Prices Index**. ... The target **applies at all times**. ... If inflation moves away from the target by **more than 1 percentage point** ... I shall expect you to send an **open letter** to me ..."*
United Kingdom (HM Treasury, remit for the Monetary Policy Committee)

Regime explicit	Numerical objective midpoint 2; lower 1; upper 3	Midpoint classification point target	Band classification trigger	Underlying price index headline
Commitment horizon continuous	Communication channel report; press	Accountability instrument open letter; parliamentary hearings; report	Accountability setting government	Escape / exoneration no

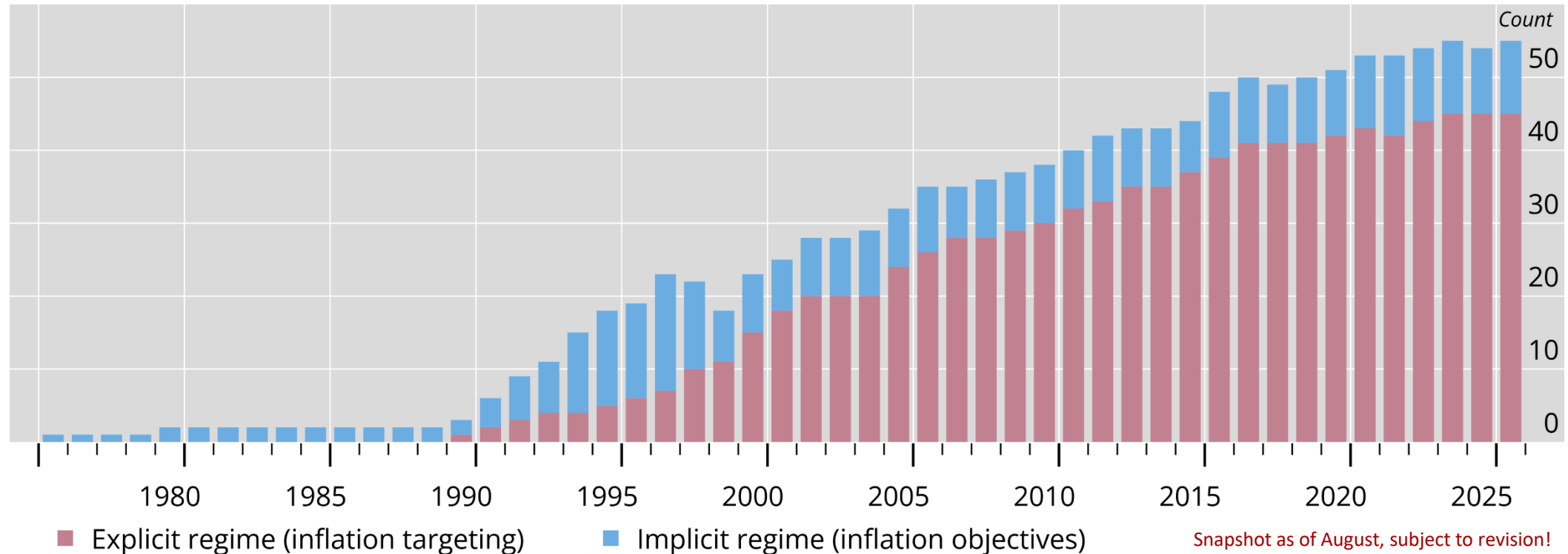
2

*"price stability is best maintained by aiming for **a symmetric 2% inflation target** over the **medium term**"*
Euro Area (ECB Governing Council, strategy statement, 8 July 2021)

Regime explicit from Jul 2021 ("target" adopted)	Numerical objective midpoint 2; lower 2; upper 2	Midpoint classification point target	Band classification derived	Underlying price index hicp
Commitment horizon medium term	Communication channel report; press; website	Accountability instrument parliamentary hearings; report	Accountability setting central bank	Escape / exoneration no

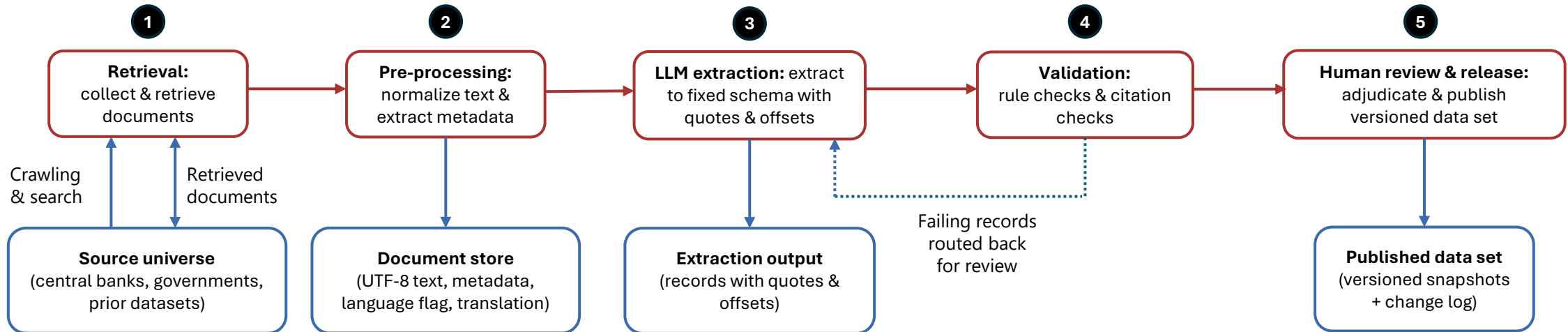
The same 2% has different operational commitments: what a breach triggers, the discretion the horizon grants, whether an explanation is owed (accountability) or offered (practice)

Experimental data set: **inflation objective** as the organizing concept



- More than **70 jurisdictions** (**euro area** recorded as continuity, not exit)
- **Monthly panel**, recorded when a change takes effect, not when announced
- **Implicit objectives** can exist before the introduction of formal IT frameworks

Experimental data set: **compilation pipeline** leveraging **AI**



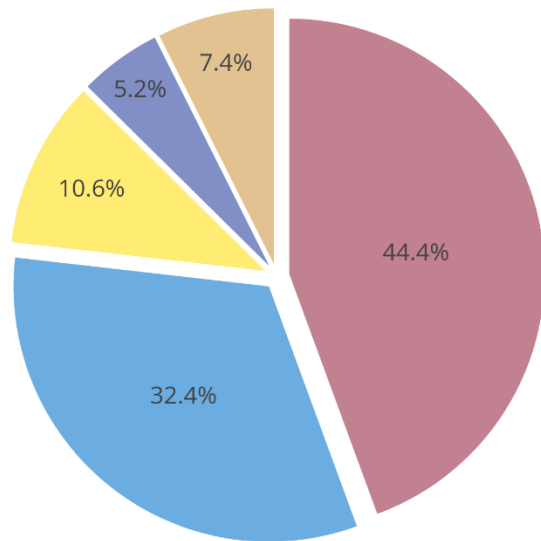
- **AI is the enabler:**

- **Auditable:** every value is traced to authoritative references
- **Reproducible:** schema and prompt fixed and versioned
- **Conservative:** absence of evidence yields a gap, failing records flagged for review
- **Rule-bound:** applies a classification framework

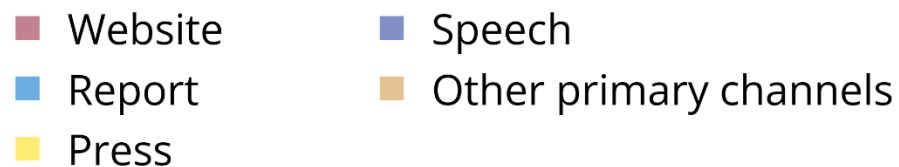
- Cross-source checks and benchmarking: divergence investigated by **expert judgement**, made explicable

The pipeline scales and complements statistical domain knowledge

Preliminary insights: records grounded mainly in **primary sources**

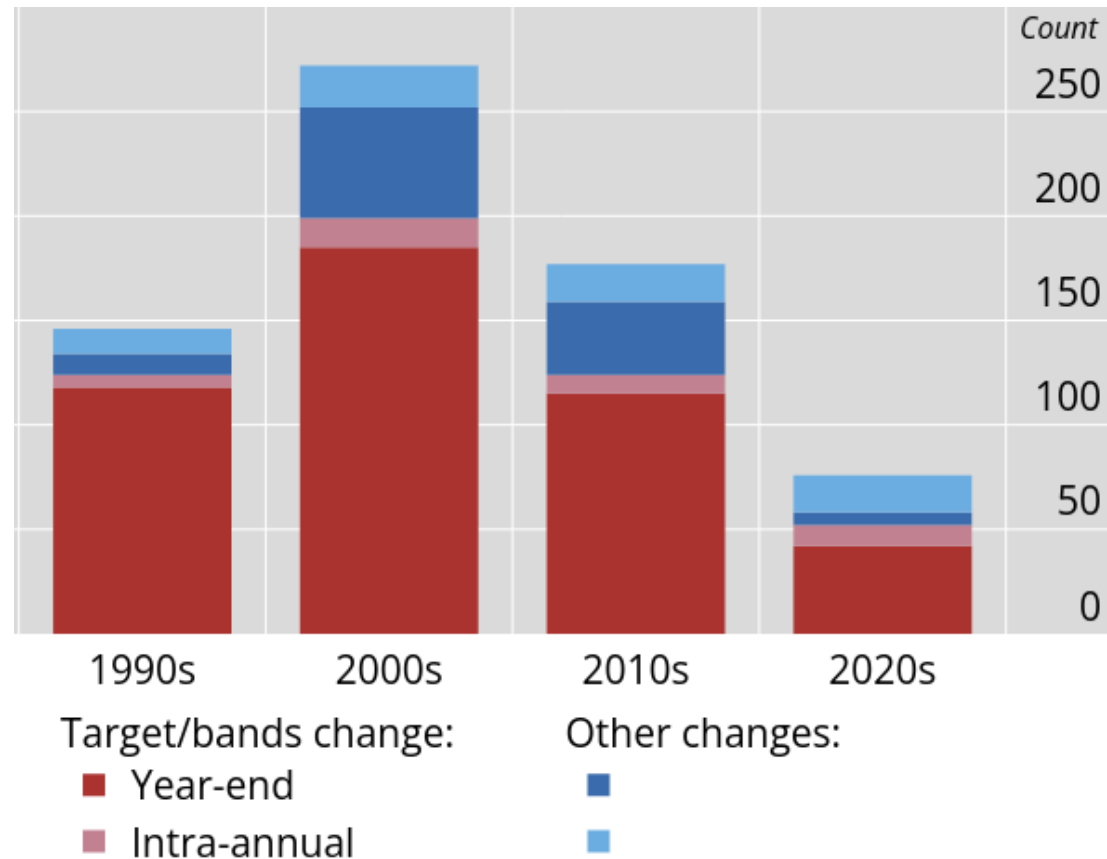


Breakdown of primary channels:



- ~**130 thousand** sourced observations across the nine dimensions
- ~ **90% is from primary sources** (mainly central bank and government material)
- Remainder excluded: secondary and tertiary sources are IMF, BIS, OECD, EU reports and academic papers or specialist compilations

Preliminary insights: changes **beyond the target** and **beyond the year-end**



- Changes mainly driven by **disinflation** and **adoption of inflation targeting**
- Changes go **beyond the target**, and **beyond the year-end**
- **Institutional arrangements evolved**: longer horizons, headline CPI, escape and exoneration clauses codified

Open questions and **way forward**

- **Consolidation**

- Confirmation of gaps and conflicts, translation and residual ambiguity directly with the competent authorities

- **Extension**

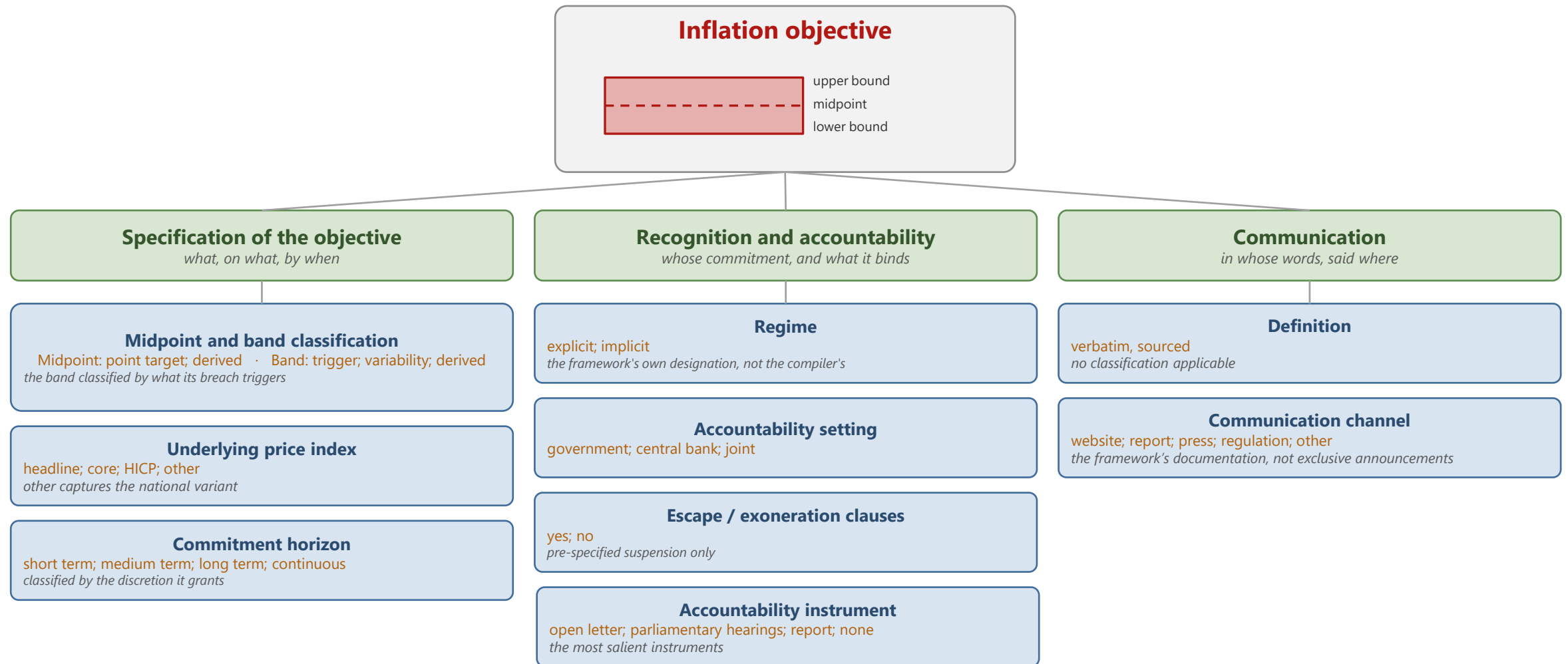
- Accountability (routine vs breach reporting, clause categories), communication vehicle and frequency, announcement date
- Multiple and interim targets, confirmations and review cadence, statutory mandate, exchange rate arrangement
- Collection effort vs accuracy of the information gained



Thank you!

Comments and feedback welcome: [**cristina.leonte@bis.org**](mailto:cristina.leonte@bis.org)

Experimental data set: **classification** by operational meaning



Bridging the Data Gap: An LLM-Powered Market Price Index for High-Frequency Inflation Monitoring

Data Governance and Statistics Department

Mustafa Tanyer
Kerem Hulusi Gkalp

20 August 2026

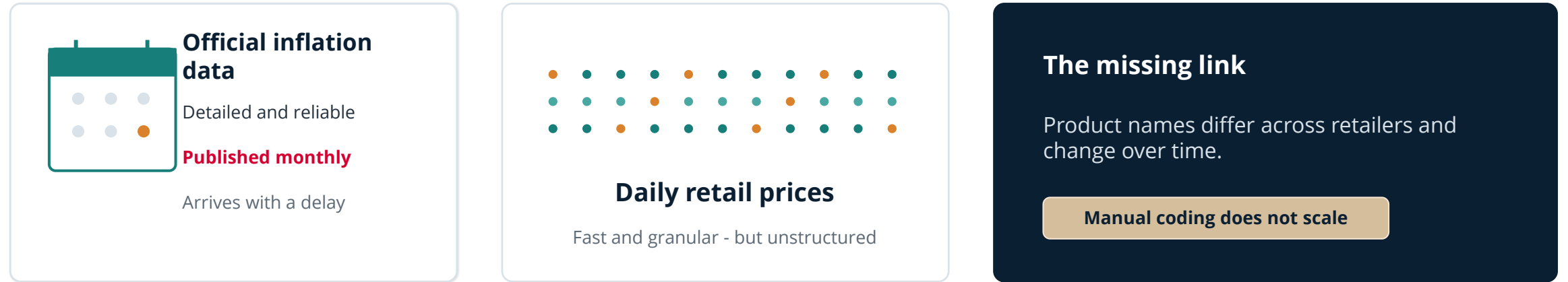
Basel



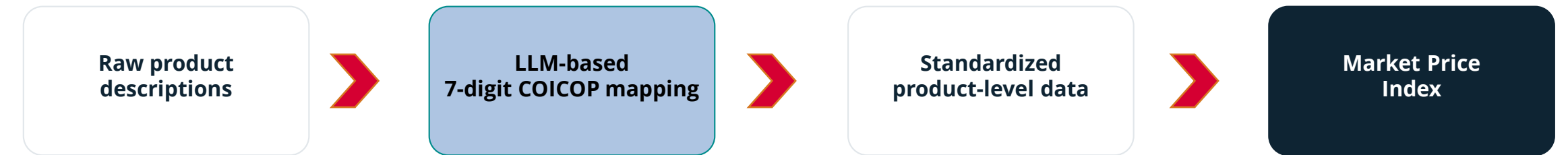
Why We Need Faster Inflation Signals

The key challenge is not only data collection; it is turning raw product names into standard categories.

THE POLICY NEED



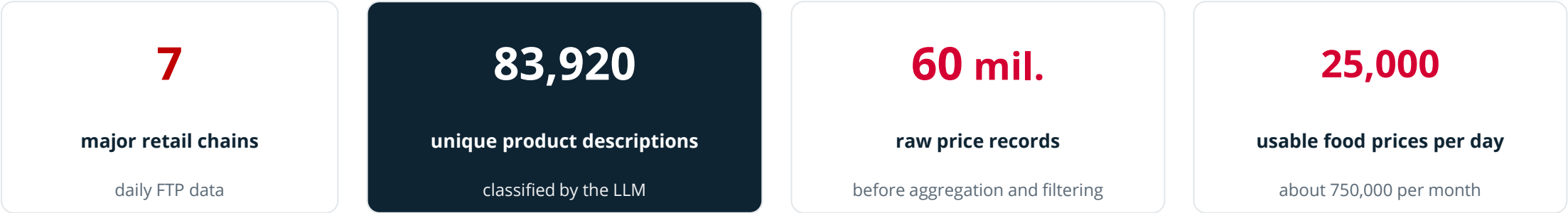
OUR CONTRIBUTION



LLM mapping turns unstructured daily prices into a usable high-frequency indicator.

The Data: Large, Daily, and Noisy

The scale explains why manual classification is not practical.



FROM RAW RECORDS TO INDEX INPUT



Coverage

June 2024 - June 2026
COICOP 01: Food and Non-Alcoholic Beverages

End-use data

After classification and filtering, about 25,000 observations per day enter the MPI calculation.

Automation must be accurate, fast, stable, and inexpensive enough to run again as new product descriptions arrive.

How We Used the LLM

The model turns raw product descriptions into seven-digit COICOP codes or an out-of-scope label.

Gemini API: gemini-3-flash-preview

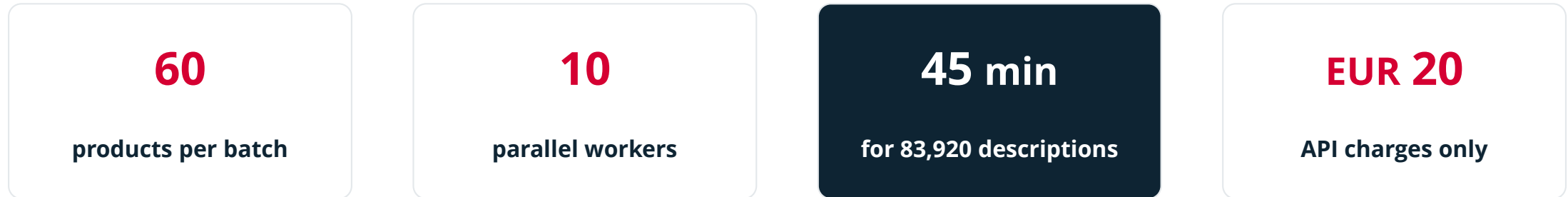
temperature = 0.2 to reduce variation

stateless API calls

CLASSIFICATION PIPELINE



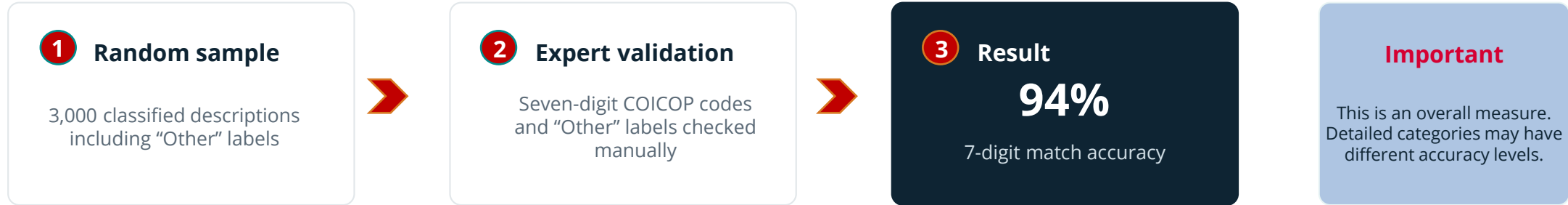
OPERATIONAL DESIGN



The method is fast and inexpensive enough for repeated statistical production.

Validation: Is the Classification Reliable?

Speed and cost matter only if the classification quality is strong.



WHAT THIS SHOWS

- ▶ The main classification bottleneck can be solved at scale.
- ▶ The process combines strong overall accuracy with very low API cost.

Next: data cleaning, weighting, and MPI calculation

My co-presenter will continue from the standardized product-level dataset.

Data Cleaning & Quality Assurance

■ Product-Level Filtering

- Keyword Filtering:
 - Exclude niche & specialty items
 - Focus: standard, representative products
- Examples Excluded:
 - Imported specialty teas
 - Premium/organic variants
 - Quail eggs, luxury cheeses

■ Outlier Detection

- Price (P): Median Price
- Extreme Price Changes:
 - Remove $\% \Delta P > 200\%$
- Tukey's Hinges Method:
 - By 7 digit COICOP group & retailer
 - $3IQR_{g,r,t}$

Date	Retailer	Title	Coicop_name	Coicop_number	Price Change %
2026-05-31	a101	Kebir Tel Peynir 500 Gr	Local cheeses	0114505	0.0
2026-05-31	carrefour	Pınar Aç Bitir Macar Salam Büyük Dilim 50 Gr	Beef salami	0112312	6.4
2026-05-31	migros	Sarelle Şeker İlavesiz Kakaolu Fındık Ezmesi 350 Gr	Chocolate spread	0118593	-2.8
2026-05-31	hakmar	Crax Chili Lime Kraker 50 Gr	Crackers	0111394	0.8
2026-05-31	bim	Superfresh Slimmo King Dondurulmuş Pizza 600 Gr	Frozen and ready pizzas	0119145	7.3
2026-05-31	a101	Lezita Dondurulmuş Piliç Çıtır Kova 850 Gr	Prepared poultry dishes	0112590	-5.2
2026-05-31	sok	Aytaç Tavuk Dürüm Döner 170 Gr	Prepared poultry dishes	0112590	0.0
2026-05-31	hakmar	Sprite Limon Aromalı Gazoz 330 Ml	Soft drinks	0126002	2.0
2026-05-31	tarım_kredi	Koska Üzüm Pekmezi 380 Gr	Molasses (grape molasses)	0118397	4.2
2026-05-31	migros	Mila Su 330 Ml	Bottled water	0125001	9.9
2026-05-31	carrefour	Pakmaya Karamelli Puding 84 Gr	Instant dessert powders	0119904	-3.1

Index Calculation & Weighting

■ Price Change Calculation:

$$\bullet \quad \% \Delta P = \left(\frac{P_t^{(n)}}{P_{t-1}} - 1 \right) \times 100$$

$P_t^{(n)}$: Average of N Daily Median Price in Current Month

P_{t-1} : Average Median Price in Previous Month

■ Stage 1: Retailer-Level Weighting

Price changes at the product and retailer levels.

Weight by retailer turnover share (t-2)

COICOP 7-digit level indices

Retailer	COICOP	COICOP Name	Price Change	Market Weight	Weighted Results		
					COICOP	COICOP Name	Price Change
A101	0111121	Rice	-0.8%	20.3%	0111121	Rice	2.1%
BİM	0111121	Rice	0.0%	33.2%			
Carrefour	0111121	Rice	6.1%	5.2%			
Hakmar	0111121	Rice	0.0%	1.3%			
Migros	0111121	Rice	6.5%	23.0%			
Şok	0111121	Rice	1.9%	13.4%			
Tarım Kredi	0111121	Rice	5.1%	3.6%			

Index Calculation & Weighting

■ Product-Level Filtering

7-digit level

0111121 Rice (63.0%)
0111192 Bulgur (cracked wheat) (37.0%)

5-digit level

01111 Cereals (10.5%)

4-digit level

0111 Cereals and Cereal Products (20.1%)

3-digit level

011 Food (90.4%) 012 Non-alcoholic Beverages (9.6%)

2-digit level

01 Food and Non-alcoholic Beverages

Value in parentheses represent COICOP component weights at each level

Hierarchical Weighting

7-digit → 5-digit → 4-digit
→ 3-digit → 2-digit levels

Using TURKSTAT official weights at each breakdown level (Except for 7 digit)

↑ Hierarchical Aggregation Formula

$$R_j = \sum_i W_{i,j} \times R_i$$

R_j : higher-level price change rate

R_i : lower-level price change rate

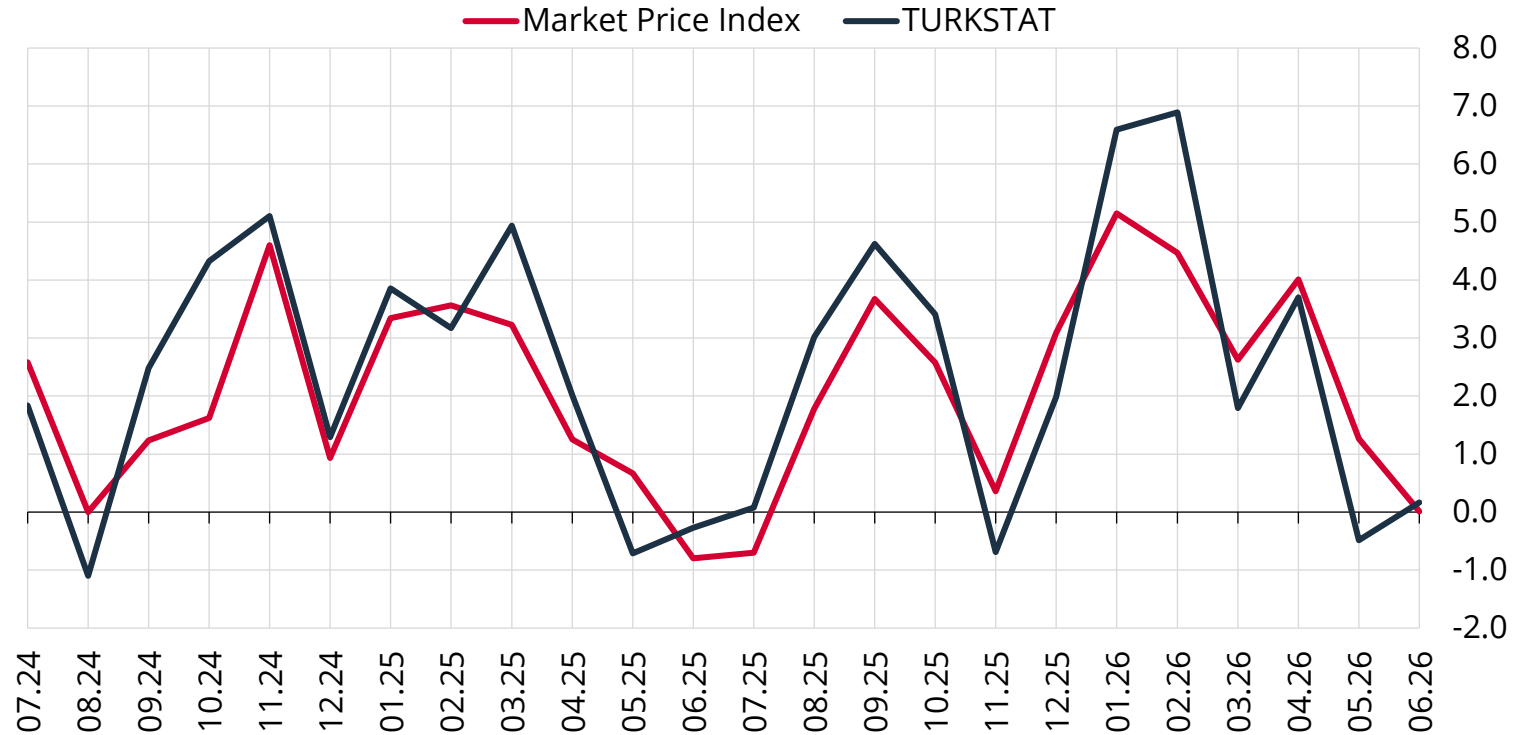
W_{ij} : weight of component i in aggregate j

Comparison with Official Inflation Measure

MPI and TURKSTAT indices track each other through inflation cycles; both indices accelerate/decelerate together. In June 2026, the Market Price Index remained unchanged, while the TURKSTAT Food and Non-Alcoholic Beverages Index increased by 0.2%.

Indices also can be monitored daily by senior management through the IPPA dashboards.

Food and Non-alcoholic Beverages Indices (Monthly, Percentage Change)





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