

# ECBERT: Fine-Tuning ModernBERT for Monetary Policy Sentiment Analysis

**Exploiting Textual Data for Inflation Forecasting** 



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### The (Modern)BERT Architecture

#### **ECBERT**

- BERT was Introduced by Google in 2018, and still one of the most widely-used NLP models
- It is an Encoder-only Transformer (focuses on understanding input text rather than generating text)
- Ideal for tasks such as text classification (e.g. sentiment analysis), information retrieval, and entity extraction



- ModernBERT was introduced in December 2024 by Answer.Al and LightOn (1)
- Supports longer sequence lengths up to 8k tokens (vs. 512 in original BERT)
- Incorporates advances learned from large-scale transformer models (e.g., smarter architecture design, larger training data, code inclusion
- Achieves faster processing and better accuracy across multiple tasks

#### The Task

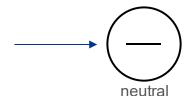
#### **ECBERT**

- Monetary policy sentiment analysis allows to quantify central bank communications
- By automating sentiment analysis, stakeholders can rapidly gauge how markets might interpret a shift in language tone, without sifting through long documents
- By analyzing overall trends and sentiment changes, we get a comprehensive picture of the likely economic impacts (e.g., inflation targeting, interest rate adjustments).
- This broad perspective helps economists, investors, and policymakers spot longer-term implications and align strategies across multiple sectors of the economy.

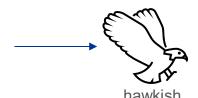
The Committee judges that, on balance, the risk of inflation becoming undesirably low remains the predominant concern for the foreseeable future.



In light of the increasing economic slack here and abroad, the Committee expects that inflation will remain subdued.

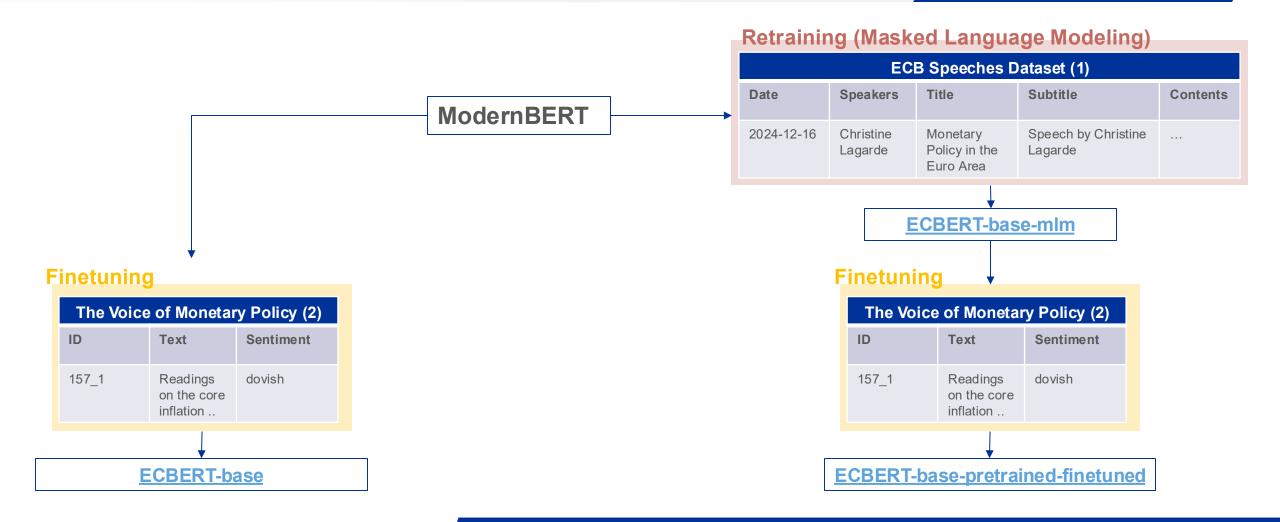


The experience of the last several years has reinforced the conviction that low inflation is essential to realizing the economy's fullest growth potential.



#### The Data and the Models

#### **ECBERT**

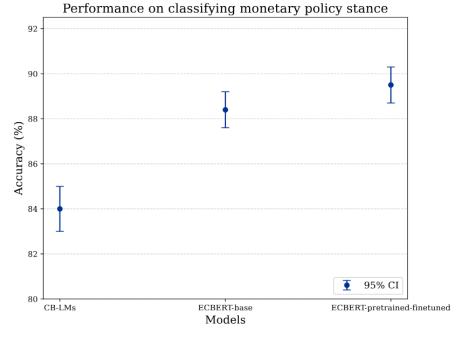


<sup>(1)</sup> European Central Bank. (25 October 2019). Speeches dataset. Retrieved from: https://www.ecb.europa.eu/press/key/html/downloads.en.html

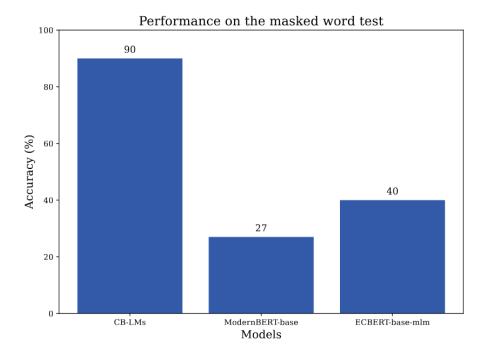
<sup>(2)</sup> Gorodnichenko, Y., Pham, T., & Talavera, O. (2023). The Voice of Monetary Policy (Version v1) [Dataset]. https://doi.org/10.3886/E178302V1

#### Performances and Results

#### **ECBERT**



- ECBERT outperforms
   the state-of-the-art
   Central Banking
   Language Models (CB-LMs (1)) created by the
   Bank for International
   Settlements for the task
   of monetary policy
   sentiment analysis.
- It underperforms in the task of Masked Language Modeling if compared to the CB-LMs.



# Working with Inflation Forecasting

#### **ECBERT** in Action

• A **time-decaying sentiment** measure helps capture the intuition that recent policy communications have a stronger, more immediate effect on inflation expectations, while older statements gradually lose their influence until the next official statement.

### **Extract Sentiment from Policy Statements**

- Apply ECBERT model on central bank statements
- Classify each statement as Hawkish (+1), Neutral (0), or Dovish (-1)

### Introduce Time-Decay Between Statements

• After a statement at time  $T_k$ , its sentiment  $S_{T_k}$  decays to  $\alpha^{\tau} \times S_{T_k}$  for each week (or day)  $\tau$  until the next statement

#### **Incorporate into Inflation Forecasting**

- Optimize  $\alpha$  using historical data (e.g., RMSE or MAE minimization)
- Align statement-based sentiment (weekly/daily) with monthly or quarterly inflation data
- Test alternative decay forms (linear, stepwise) and different classification thresholds

# Thank you!

## Any questions?