

The Dynamics Between Inflation and Unemployment: Empirical Evidence from U.S. Macroeconomic Data

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Section 1

Introduction

Introduction

- The inflation–unemployment relationship (Phillips curve) is **unstable** and varies across economic regimes.
- Recent evidence shows a **flattened and nonlinear** relationship, challenging conventional interpretations.
- Understanding inflation–unemployment dynamics requires identifying **underlying macroeconomic factors** and **regime shifts**.
- Machine learning methods offer useful tools for **classifying economic states**, though interpretability remains limited.

This Study

- Identify macroeconomic factors driving inflation and unemployment (via PCA)
- Detect regime shifts using clustering methods
- Evaluate regime identification using machine-learning classifiers (Naïve Bayes, Decision Trees, XGBoost)

Section 2

Related Literature

Related Literature

- Evidence on the inflation–unemployment relationship: trade-off, instability, and **flattening** over time
 - Phillips (1958); Samuelson and Solow (1960); Muth (1961); Lucas (1976); Mazumder and Ball (2011); Blanchard (2016)
- Phillips curve dynamics are **nonlinear and regime-dependent**
 - Hazell et al. (2022)
- Machine learning methods can help **identify economic states** and capture nonlinear patterns
 - Medeiros et al. (2021); Gogas, Papadimitriou, and Sofianos (2022)

Key Insight:

The inflation–unemployment relationship is **not stable**; it varies with economic regimes and underlying shocks.

Research Gap:

Existing studies address inflation, unemployment, regimes, or ML **separately**, but do not provide a **unified, reproducible framework** that

- jointly analyzes both variables,
- identifies economic regimes, and
- evaluates regime classification with ML.

Section 3

Data

Data

| Category | Variable | Freq. | Source | Code |
|------------------------|---------------------------|-------|-----------|------------|
| Inflation | Core PCE | M | FRED | PCEPILFE |
| Unemployment | Unemployment Rate | M | FRED | UNRATE |
| | Noncyclical Unemployment | Q | FRED | NROU |
| Regimes | Recession indicator | M | FRED | USREC |
| | Zero Lower Bound dummy | M | FRED | - |
| | COVID-19 period dummy | M | Created | - |
| Demand | Real GDP | Q | FRED | GDPC1 |
| | Real Potential GDP | Q | FRED | GDPPOT |
| | Industrial Production | M | FRED | INDPRO |
| | Retail Sales | M | FRED | RSAFS |
| Supply | Crude Oil Prices | M | FRED | MCOILWTICO |
| | Import Price Index | M | FRED | IR |
| | Labor Productivity | Q | FRED | OPHNFB |
| Labor Markets | Avg Hourly Earnings | M | FRED | CES050... |
| | Labor Force Participation | M | FRED | CIVPART |
| | Job Openings | M | FRED | JTSJOL |
| Monetary Policy | Fed Funds Rate | M | FRED | FEDFUNDS |
| | Money Supply M2 | M | FRED | M2SL |
| | Fed Total Assets | W | FRED | WALCL |
| Inflation Expectations | 5Y Breakeven | D | FRED | T5YIE |
| | 10Y Breakeven | D | FRED | T10YIE |
| | 1Y Exp. Inflation | M | UM Survey | PX_MD |
| | 5Y Exp. Inflation | M | UM Survey | PX5_MD |

Full list includes 23 series retrieved via FRED API or University of Michigan CSV downloads.

Section 4

Method

- **PCA (Principal Component Analysis)**

Reduce dimensionality and extract latent inflation and business-cycle factors.

- **K-Means & Hierarchical Clustering**

Identify macroeconomic regimes using unsupervised grouping.

- **Naïve Bayes**

Simple probabilistic classifier for high-inflation / high-unemployment regimes.

- **Decision Trees**

Nonlinear, interpretable classification based on threshold rules.

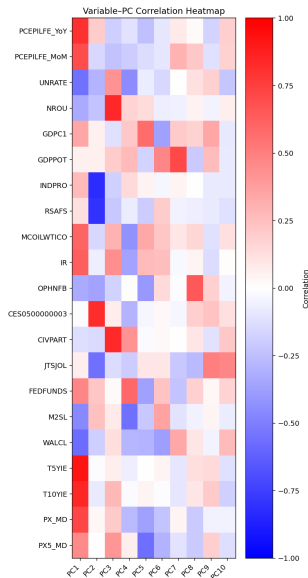
- **Boosting (XGBoost)**

Ensemble method capturing complex patterns and improving predictive accuracy.

Section 5

Results & Discussions

PCA Results: Macroeconomic Factor Structure

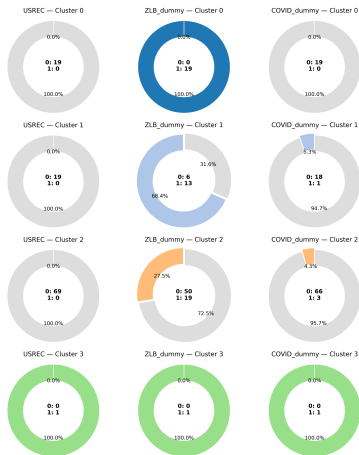


- **PC1: Inflation Factor** Strong link to Core PCE & expectations; negative with unemployment.
- **PC2–PC3: Business Cycle** Driven by production, sales, and labor-market indicators.
- **Policy Signals** Monetary Policy-related variables (FEDFUNDS, M2, and WALCL) spread across PCs.
- **Summary** PCA extracts **inflation** vs. **cycle** factors.

Regime Identification via Clustering (1/3)

K-Means (k = 12)

within shares of 0/1



Key Insight

- Many clusters show **near-pure 0/1 splits** for USREC, ZLB, or COVID dummies.
- Clusters align closely with well-known **macroeconomic regimes** (recession periods, ZLB episodes, COVID-19 shock).
- **Summary** Clearly identifies regimes such as high-inflation periods and recessions.

*Hierarchical clustering yields similar regime separation.

Regime Identification via Clustering (2/3)

K-Means (k = 12)

within shares of 0/1



Key Insight

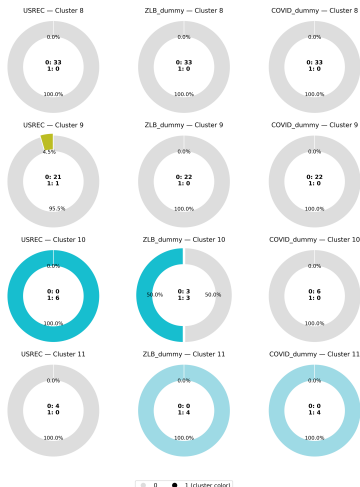
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Regime Identification via Clustering (3/3)

K-Means (k = 12)

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ML Model Comparison: Accuracy

| Task | Model | Accuracy |
|-----------------|---------------|----------|
| Unemployment | Naive Bayes | 0.86 |
| Unemployment | Decision Tree | 0.97 |
| Unemployment | XGBoost-A | 0.96 |
| Unemployment | XGBoost-B | 0.96 |
| Unemployment | XGBoost-C | 0.96 |
| Inflation (YoY) | Naive Bayes | 0.86 |
| Inflation (YoY) | Decision Tree | 0.93 |
| Inflation (YoY) | XGBoost-A | 0.84 |
| Inflation (YoY) | XGBoost-B | 0.83 |
| Inflation (YoY) | XGBoost-C | 0.86 |
| Inflation (MoM) | Naive Bayes | 0.71 |
| Inflation (MoM) | Decision Tree | 0.65 |
| Inflation (MoM) | XGBoost-A | 0.57 |
| Inflation (MoM) | XGBoost-B | 0.64 |
| Inflation (MoM) | XGBoost-C | 0.60 |

Notes: XGBoost-A is a baseline configuration with moderate depth and shrinkage. XGBoost-B has deeper trees and more estimators, optimized for capturing nonlinearities. XGBoost-C is shallow but high-learning-rate model emphasizing speed and simplicity. Please refer to the appendix for detailed parameters.

Key Insights

- Decision Tree and XGBoost achieve **very high accuracy** for unemployment classification.
- Inflation (YoY) is predicted well by all methods, with Decision Tree performing best.
- Inflation (MoM) remains the most challenging task across models.
- XGBoost parameter variations show clear trade-offs between model complexity and generalization.

Section 6

Conclusion

Conclusion, Implications, and Future Work

Conclusion

- PCA reveals distinct inflation and business-cycle factors.
- Clustering effectively identifies major macroeconomic regimes.
- ML models classify unemployment and YoY inflation well; MoM inflation is noisy.

Implications

- Macroeconomic dynamics are multi-factor and complex.
- ML can support rapid macro-state monitoring.
- Short-term inflation measures require cautious interpretation.

Future Work

- Add high-frequency data and extend models to other methods.
- Identify regime-specific shifts in inflation–unemployment dynamics.
- Comparison and integration with traditional macroeconomic models.

Thank you!

Appendix

XGBoost Parameter Summary

| Model | n_estimators | max_depth | learning_rate | subsample | colsample_bytree |
|-----------|--------------|-----------|---------------|-----------|------------------|
| XGBoost-A | 200 | 3 | 0.05 | 0.8 | 0.8 |
| XGBoost-B | 300 | 4 | 0.03 | 0.7 | 0.9 |
| XGBoost-C | 150 | 2 | 0.10 | 0.9 | 0.7 |

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