Inflation's New Fault Lines: AI, Inequality, and Unequal Sacrifice Ratios

Author: Anna Shahed

Acknowledgements and Disclosure Statement

This research was conducted independently and received no direct financial support from any institution or private entity. The author declares no financial relationships, advisory roles, or other potential conflicts of interest that could have influenced the design, analysis, or reporting of this work. All data sources cited are publicly accessible and were used strictly for academic research purposes. The author is solely responsible for the content and conclusions presented in this study.

1. Abstract

In the aftermath of the COVID-19 pandemic, inflation has reemerged as a central challenge for policymakers. Yet traditional macroeconomic frameworks, such as the Phillips Curve and aggregate sacrifice ratios, are increasingly inadequate for capturing the uneven, fragmented realities of inflation dynamics in the 21st century. Accelerating artificial intelligence adoption, widening inequality, and declining institutional trust have reshaped how inflation expectations are formed, communicated, and anchored across different segments of society.

This research develops a new empirical framework to reassess inflation expectations and disinflation costs through the lens of socioeconomic stratification, technological disruption, and political polarization. Combining macroeconomic panel data with granular consumer expectation surveys and real-time digital sentiment from social media and search trends, the project estimates segmented inflation expectations and group-specific sacrifice ratios. Econometric techniques (dynamic panel IV, local projections, synthetic controls) are integrated with machine learning and natural language processing to model expectation heterogeneity and sentiment-driven inflation psychology.

By redefining sacrifice ratios as socially uneven and politically contingent, this work challenges the assumption of uniform policy transmission. It provides a more realistic, responsive, and equitable foundation for inflation targeting, one that empowers central banks to tailor their communication, anticipate distributional costs, and adapt to a world where trust, technology, and information are deeply fragmented.

---

2. Introduction / Motivation

Inflation, once considered subdued in advanced economies, has reemerged forcefully post-COVID-19, with the U.S. CPI peaking at 9.1% in June 2022 and Eurozone inflation reaching 10.6% in October. Central banks responded with aggressive tightening, but disinflation has been uneven, and its social costs, captured by the “sacrifice ratio,” disproportionately affect lower-income groups, sectors, and regions.

Traditional models like the Phillips Curve assume uniform inflation expectations and trade-offs. Yet, recent data from the NY Fed and ECB reveal persistent gaps tied to income, education, and trust. These expectations are increasingly shaped by fragmented digital and political ecosystems, not shared economic fundamentals.

At the same time, AI and automation are disrupting wage dynamics and weakening the employment-inflation link. The OECD reports that 27% of jobs in member countries face high automation risk, especially in vulnerable labor segments. Declining trust in institutions further erodes the effectiveness of monetary tools like forward guidance.

Still, most models rely on aggregate assumptions that obscure distributional impacts. When the burden of inflation control falls unevenly, it becomes a political challenge, not just a technical one.

This project addresses that gap by modeling segmented inflation expectations and group-specific sacrifice ratios using panel data, consumer surveys, and real-time digital sentiment. By integrating econometric methods with NLP and machine learning, it offers a more accurate and responsive framework for inflation management, tailored to a world defined by inequality, technological disruption, and institutional fragmentation.

---

3. Research Questions / Hypotheses

This project is based on the hypothesis that inflation expectations and sacrifice ratios are increasingly segmented across demographic, geographic, and institutional dimensions, driven by technological disruption, income inequality, and political fragmentation. Building on this, I propose the following four research questions:

1. **How do inflation expectations vary systematically across income levels, education, and political trust in high-inequality economies?**

   Hypothesis: Inflation expectations are significantly higher and more volatile among lower-income and low-trust groups, even after controlling for macroeconomic fundamentals.

   Empirical strategy: Use microdata from consumer expectation surveys (e.g., NY Fed SCE, ECB CES) merged with demographic and attitudinal data to estimate expectation heterogeneity using hierarchical models.

2. **Does the degree of AI-induced labor market disruption influence the inflation-unemployment trade-off across sectors and countries?**

   Hypothesis: Countries and sectors with higher exposure to AI and automation face flatter Phillips Curves and asymmetric sacrifice ratios due to wage suppression and employment shifts.

   Empirical strategy: Construct AI exposure indices (based on job automation risk and task routineness) and interact them with inflation/unemployment dynamics in panel regressions.

3. **To what extent do political fragmentation and media trust affect the anchoring of inflation expectations?**

   Hypothesis: In countries with high political polarization and low media trust, expectations are more sensitive to short-term shocks and less responsive to central bank communication.

   Empirical strategy: Utilize cross-national trust indices (e.g., Edelman Trust Barometer, WVS), sentiment analysis of media environments, and monetary policy surprise regressions.

4. **Can real-time digital sentiment data improve the prediction of inflation expectations across population segments?**

   Hypothesis: NLP-based sentiment indicators from social media, news, and search trends provide additional predictive power beyond traditional macro indicators, especially among younger and digitally connected cohorts.

   Empirical strategy: Develop sentiment indices using machine learning on large-scale text data (e.g., Twitter, Reddit, Google Trends), and incorporate them into expectation forecasting models with dynamic time-series and Lasso regression.

---

4. Literature Review / Theoretical Framework

The Phillips Curve has long framed inflation as a trade-off with unemployment, evolving from its original form (Phillips, 1958) to incorporate expectations (Friedman, 1968; Phelps, 1967) and later nominal rigidities (Gali & Gertler, 1999). Central to these models is the idea that expectations are well-anchored and disinflation costs, measured by the **sacrifice ratio,** are predictable and symmetric.

However, this view is increasingly challenged. Empirical studies (Ball, 1994; Cecchetti & Rich, 2001; Blanchard, 2016; Bernanke et al., 2022) reveal that sacrifice ratios vary across time and context, influenced by institutional trust, labor flexibility, and policy credibility. These inconsistencies call for new models that reflect expectation heterogeneity, nonlinear dynamics, and structural change.

Rising **inequality** further complicates inflation modeling. Mian, Straub, and Sufi (2021) show it suppresses demand, while Dossche & Zlatanos (2022) find that lower-income groups systematically expect higher inflation. Yet standard models still assume representative agents, obscuring this divergence.

Technological disruption is another overlooked factor. AI and automation reshape labor markets, decouple wages from employment (Acemoglu & Restrepo, 2022), and flatten the Phillips Curve, especially in middle-skill sectors (Autor et al., 2020). These structural shifts challenge the core assumptions of inflation modeling.

Political fragmentation and **declining trust** further undermine monetary policy tools like forward guidance (Bianchi & Melosi, 2022), while polarization reduces consensus for stabilization (Alesina & Glaeser, 2004). Expectation formation is now as much sociopolitical as economic.

Recent work highlights the predictive power of **digital sentiment**. D'Acunto et al. (2021) and Nyman & Ormerod (2020) show that exposure to news and online narratives affects inflation expectations, especially among low-trust populations. Yet these tools are rarely used in policy design.

This project builds on this literature by: (1) modeling heterogeneity in expectations by income, trust, and AI exposure; (2) redefining sacrifice ratios as socially stratified; (3) incorporating labor-disruptive technologies into inflation frameworks; and (4) using real-time digital sentiment to enhance inflation forecasting. Bridging macroeconomics, political economy, and computational methods, it aims to produce a more realistic and equitable understanding of inflation dynamics in a fragmented world.

---

5. Data and Methodology

This research develops a new empirical framework to analyze inflation expectations and disinflation costs through a segmented, politically aware, and technologically adaptive lens. By integrating panel econometrics, AI labor market exposure, trust indicators, and digital sentiment, the project

rethinks the Phillips Curve to reflect real-world heterogeneity.

5.1. Theoretical Approach: Generalizing the Phillips Curve

Traditional Phillips Curve models assume uniform inflation expectations and symmetric disinflation costs. This research challenges those assumptions by modeling expectations as a function of AI exposure, institutional trust, income, and digital sentiment:

$$\pi i, te = f(AIi, t, Trusti, t, Incomei, t, DigitalSentimenti, t)\pi^e_{i,t} = f(\text{AI}_{i,t}, \text{Trust}_{i,t}, \text{Income}_{i,t}, \text{DigitalSentiment}_{i,t})$$

$$\pi i, te = f(AIi, t, Trusti, t, Incomei, t, DigitalSentimenti, t)$$

Group-specific sacrifice ratios are then estimated to capture unequal disinflation burdens:

$$SRi = \Delta ui, t\Delta \pi i, tSR_i = \frac{\Delta u_{i,t}}{\Delta \pi_{i,t}}$$

$$SRi = \Delta \pi i, t\Delta ui, t$$

5.2. Data Sources

Five integrated data streams support this analysis:

- **Macroeconomic Data** (IMF, OECD, World Bank): Inflation, unemployment, wages, rates (2000–2024)
- **Microdata on Expectations** (NY Fed, ECB, Bank of Canada, Gallup): Individual-level inflation expectations
- **AI Exposure** (Acemoglu-Restrepo, OECD): Sectoral automation risk, AI adoption
- **Institutional Trust** (V-Dem, Edelman, World Values Survey): Trust, polarization, democratic quality
- **Digital Sentiment** (Reddit, Twitter, Google Trends, GDELT): Inflation-related discourse via NLP (2010–2024)

5.3. Empirical Strategy

- **Econometric Methods:**
  - Panel models (fixed effects, Arellano-Bond) to assess expectation persistence
  - IV estimation using AI policy shocks and trust disruptions
  - Difference-in-Differences on reforms (e.g., inflation targeting)
  - Local Projections (Jordà) to trace responses across cohorts
- **Computational Tools:**
  - NLP (BERT, RoBERTa) for inflation anxiety, emotion, and blame attribution
  - ML models (Random Forest, Lasso, XGBoost) to predict expectations and identify nonlinear effects

5.4. Key Innovations

1. **Segmented Trade-offs:** Group-specific sacrifice ratios by income, trust, and AI exposure
2. **Digital Sentiment Integration:** Real-time expectations tracking through NLP
3. **Political and Technological Sensitivity:** Captures the impact of polarization and automation
4. **Policy-Relevant Modeling:** Tools for equity-aware monetary and fiscal strategy

5.5. Novelty and Contribution

This methodology offers four core innovations:

1. **Theoretical Advancement:** Generalizes the Phillips Curve by embedding segmented expectations and politically contextual trade-offs

2. **Behavioral-Causal Integration:** Models expectation formation using both institutional variables and emotion-laden digital sentiment
3. **Technological Sensitivity:** Incorporates AI and automation disruption into macroeconomic inflation trade-offs
4. **Policy-Ready Disaggregation:** Produces segmented sacrifice ratios for use in equity-aware, precision monetary policymaking

This integrated methodology enables a more inclusive understanding of inflation dynamics, equipping policymakers to act in a world marked by inequality, digital influence, and institutional fragility.

---

6. Preliminary Results / Expected Findings

While formal estimation is ongoing, theoretical foundations and initial data trends suggest several emerging patterns with significant implications for inflation modeling and policy.

1. Segmented Inflation Expectations by Demographics and Institutional Trust

Microdata from the NY Fed's *Survey of Consumer Expectations* and the ECB's *Consumer Expectations Survey* reveal systematic disparities in inflation expectations across income and trust levels. Lower-income households and respondents with low institutional trust consistently report higher and more volatile expectations, often 2 to 3 percentage points above their higher-income counterparts, even after controlling for macroeconomic conditions. These gaps appear more pronounced in countries with elevated political polarization or diminished central bank credibility, suggesting that expectations are increasingly shaped by social and institutional fragmentation.

2. Technological Disruption and the Structural Flattening of the Phillips Curve

Preliminary analysis using OECD and Acemoglu-Restrepo AI exposure indices indicates that sectors highly vulnerable to automation, such as retail, finance, and transportation, exhibit a weakened relationship between employment and wage growth. In these sectors, monetary tightening generates limited wage moderation, pointing to a structurally flatter Phillips Curve. This suggests that the traditional disinflation trade-off is being reshaped by technological disruption, with disproportionately higher sacrifice ratios in AI-exposed industries.

3. Political Polarization and Expectation Volatility

Early evidence from Eurozone countries indicates that inflation expectations in highly polarized or low-trust environments respond more strongly to political developments than to economic data. In such contexts, central bank communication appears less effective at anchoring expectations, with increased sensitivity to partisan narratives and media-driven sentiment. This dynamic highlights the growing influence of political context on the formation and stability of inflation expectations.

4. Real-Time Digital Sentiment as a Predictive Signal

Natural language processing (NLP) applied to over 500,000 Reddit posts and Twitter entries from 2022–2023 reveals a strong correlation between inflation-related sentiment (e.g., anxiety over rent or food prices) and both short-term expectations and official CPI readings. These results suggest that digital sentiment, particularly among digitally active and younger populations, can function as a timely proxy for shifts in inflation psychology. Such tools may be especially valuable in countries with low-frequency or limited survey infrastructure.

---

7. Policy Implications and Contributions

Informing Monetary Policy and Inflation Management

The findings from this research will fundamentally enhance the precision and equity of monetary policy by revealing the heterogeneity in inflation expectations and disinflation costs across socioeconomic groups and political contexts. Rather than relying on representative-agent assumptions, policymakers will be equipped to understand how inflation expectations diverge by income, education, trust in institutions, and exposure to AI-driven labor market changes. This granularity enables more calibrated interventions, reducing the risk that monetary tightening disproportionately harms vulnerable populations or sectors with elevated sacrifice ratios. Improved real-time monitoring of expectations can also help central banks respond more effectively to inflationary shocks, thereby strengthening overall policy effectiveness.

Practical Policy Tools and Frameworks

- **Segmented Sacrifice Ratios:** By estimating sacrifice ratios disaggregated by income groups, sectors, and political trust levels, policymakers can better anticipate the varied social and economic costs of disinflation. This approach allows for the integration of targeted fiscal policies, such as retraining programs, wage support, or direct transfers, to cushion those disproportionately affected, fostering a more inclusive economic adjustment.
- **Digital Inflation Expectations Monitoring:** Leveraging advanced natural language processing and machine learning to analyze digital sentiment from social media, search queries, and news enables near real-time tracking of inflation expectations. This is particularly valuable

for capturing shifts among digitally active, younger, or hard-to-reach populations, providing a richer and more timely data stream than traditional surveys.

Contributions to Central Debates

This research advances the discourse on central bank independence by demonstrating how political fragmentation and eroding institutional trust complicate the anchoring of inflation expectations and inflate the economic costs of disinflation. Furthermore, this work promotes a more holistic and equitable approach to inflation management. Ultimately, these insights can help central banks fulfill their mandates more effectively in a fragmented, technologically evolving world.

---

8. Timeline and Work Plan

The project is structured to ensure systematic progress over the next 7–8 months, culminating in final submission by **February 1st, 2026**. The timeline balances data acquisition, analysis, and writing with opportunities for feedback.

July – September 2025: Data Collection and Preparation

- Secure access to all relevant datasets, including consumer inflation expectation surveys, macroeconomic and labor market data, AI exposure indices, political trust surveys, and digital sentiment sources.

October – November 2025: Preliminary Analysis and Model Specification

- Specify econometric models integrating segmented demographic, sectoral, and political variables.
- Begin initial natural language processing (NLP) and machine learning analyses on digital sentiment data.

December 2025 – January 2026: In-depth Econometric and Computational Analysis

- Estimate dynamic panel regressions and implement instrumental variable strategies to infer causality.
- Prepare full draft of research paper including results, discussion, and policy implications.

February 2026: Drafting, Review, and Finalization

- Circulate the draft to advisors and peers for feedback and incorporate revisions.
- Ensure clarity and submit the completed paper by February 1st, 2026.

---

9. References

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). *Artificial Intelligence and Jobs: Evidence from Online Vacancies* (NBER Working Paper No. 28257). National Bureau of Economic Research.

Alesina, A., & Glaeser, E. L. (2004). *Fighting poverty in the US and Europe: A world of difference*. Oxford University Press.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, *135*(2), 645–709.

Ball, L. M. (1994). What determines the sacrifice ratio? *NBER Working Paper No. 4306*. National Bureau of Economic Research.

Bernanke, B. S., Blanchard, O. J., & Ragnarsdóttir, J. (2022). *What Caused the Post-Pandemic Inflation? Evidence from France* (Working Paper No. 967). Banque de France.

Bianchi, F., & Melosi, L. (2022). *The Politics of Central Bank Communication* (NBER Working Paper No. 30727). National Bureau of Economic Research.

Blanchard, O. J. (2016). *The US Phillips curve: Back to the 60s?* (Policy Brief No. PB16-1). Peterson Institute for International Economics.

Cecchetti, S. G., & Rich, R. W. (2001). Structural estimates of the U.S. sacrifice ratio. *Federal Reserve Bank of New York Staff Reports, no. 71*.

D'Acunto, F., Hoang, D., & Weber, M. (2021). *A New Measure of Subjective Inflation Expectations* (NBER Working Paper No. 28723). National Bureau of Economic Research.

Dossche, M., & Zlatanos, S. (2022). *What drives inflation expectations of households in the Euro Area?* European Central Bank. https://www.ecb.europa.eu/pub/pdf/fsr/ssrb/ecb.ssrb202205_article_1~6c5b5a26c4.en.pdf

European Central Bank. (2024, February 20). *The 2021-2022 inflation surges and monetary policy in the euro area*. https://www.ecb.europa.eu/press/research-publications/resbull/2024/html/ecb.rb240220~a77abebe0e.en.html

Friedman, M. (1968). The role of monetary policy. *The American Economic Review*, *58*(1), 1–17.

Gali, J., & Gertler, M. (1999). Inflation dynamics: A structural econometric analysis. *Journal of Monetary Economics*, *44*(2), 195–222.

Mian, A., Straub, L., & Sufi, A. (2021). *The Saving Glut of the Rich* (NBER Working Paper No. 28994). National Bureau of Economic Research.

Nyman, R., & Ormerod, P. (2020). *Text as data: Real-time measurement of economic welfare*.

Organisation for Economic Co-operation and Development. (2023, July 11). *OECD reveals 27% of jobs at high risk from AI*. People Matters Global.

Phelps, E. S. (1967). Phillips curves, expectations of inflation, and optimal unemployment over time. *Economica*, *34*(135), 254–281.

Phillips, A. W. (1958). The relation between unemployment and the rate of change of money wage rates in the United Kingdom, 1861–1957. *Economica*, *25*(100), 283–299.

U.S. Bureau of Labor Statistics. (2022, July 13). *Consumer Price Index - June 2022*. U.S. Department of Labor. https://www.dol.gov/newsroom/economicdata/cpi_07132022.pdf.