Interpreting Economic Signals Using Rule-Based AI: An Analysis of PPI Relative Importance

Nathan Reid – University of Florida
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Introduction

The Producer Price Index (PPI) tracks changes in commodity values across the US economy. Because the PPI covers thousands of commodities across several unrelated sectors, it is wildly difficult for humans to interpret the changes in the commodity market, year-to-year, at scale.

This project beckons the question:
"Can AI help interpret large-scale PPI data by converting numerical variables into structured economic insights?"

We developed a rule-based natural language system that:
- Computes year-to-year changes in commodity relative importance
- Categorizes each change into qualitative buckets
- Generates short interpretive summaries for users

Contributions
- Curated 2900+ item 2023-2024 PPI Relative Importance dataset
- Classifier for qualitative economic labeling
- Natural-language generator producing easily readable interpretations of trends

Dataset

Source: Bureau of Labor Statistics – PPI Relative Importance Tables (2023 & 2024)
https://www.bls.gov/ppi/tables

Contents
- 2900+ commodities
- Values represent Relative Importance (e.g. contribution to PPI weighting)
- Sectors include agriculture, mining, manufacturing, food, metals, chemicals, etc.

Preprocessing
- Removed non-numeric rows and header columns
- Standardized column names
- Converted values to floats
- Filtered to commodities with 2023 & 2024 data
- Assigned a qualitative class to each item

Baseline

The baseline computes simple numerical percent-change using this formula:

$$PctChange = \frac{RI2024 - RI2023}{RI2023}$$

Limitations
- Fails on zeros
- Overinflates microscopic denominators
- Does not categorize results on its own
- Does not generate explanations for data

Methodology

Step 1 – Percent-Change Module
- Computes Raw Change using formula I = RI2024 – RI2023

Step 2 – Rule Based Classification
- change| < 1% = Stable
- 1% < change < 5% = Small Change
- 5% < change < 20% = Moderate Change
- change > 20% = Large Change

Step 3 – Natural-Language Generation
- Large Increase, Moderate Increase, Stable, or Decrease

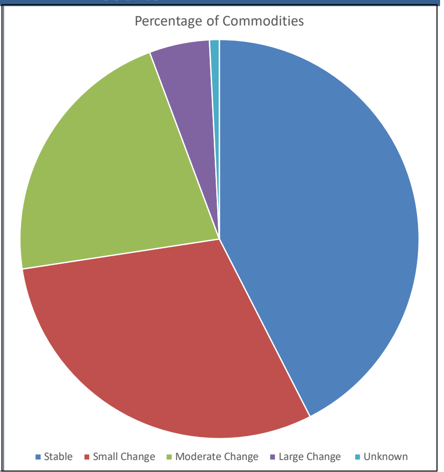
Commodity	ri_2023	ri_2024	pct_change	category	nlg output
blueberries	0.010	0.028	+180%	Large Change	"The relative importance of blueberries rose sharply by 180%, indicating a meaningful upward adjustment within its weighting in the PPI basket."
dry black beans	0.002	0.001	-50%	Large Change	"Dry black beans declined significantly by 50%, reflecting a reduced share in the overall PPI structure"

Table 1 – Example Input/Output Table

Results

Category Distribution
- Stable = 42.5%
- Small Change = 30.1%
- Moderate Change = 21.7%
- Large Change = 4.9%
- Unknown = 0.8%

Major Observations
- The median percent change is 0%, meaning year-to-year stability of the commodities market is strong
- The interquartile range is -1.29% to 2.31%, reinforcing that most PPI RI movements are small
- Large changes most often occur in small-weight agricultural commodities



Economic Interpretations

- High percent increases (e.g. blueberries +180%) arise from tiny denominators, not economic booms
- Agriculture occupies both the head and tail end of the data, possibly due to seasonal volatility and supply-chain fluctuations
- Most sectors have gradual structural shifts rather than extreme shocks (shown by the median and IQR)

Error Analysis

- Some errors occurred, such as division by zero which caused values to appear as infinite
- Tiny denominators can show massive percent increases, which the NLG helps contextualize
- Some items lie on thresholds between the rule based classifications, despite small nuances

Commodity	RI_2023	RI_2024	Pct_Change	Issue
Cotton linters	0.000	0.001	Inf	Division by 0
Rockfish	0.000	0.001	Inf	Division by 0
Pumpkin seeds	0.001	0.004	+300%	Small denominator

Table 2 – Examples of Errors

Conclusion + Future Works

A rule-based AI model can successfully process raw PPI data and turn it into structured, interpretable language that one can use to build economic insights. By combining percent-change calculations, qualitative classifications, and natural language model insights, the system provides accessible explanations of commodity trends.

Future works might
- Add filtering to remove low-weight commodities
- Analyze multiple years, not just two
- Filter by sector (agriculture, energy, mining, chemicals, etc.)
- Replace the NLG with more intelligent, contextual, narrative-driven language generator

Github QR Code

Contact

Nathan Reid
UF – Rinker School
mathan.reid@ufl.edu
https://github.com/NathRei2003/Economic-PPI-Health-Indicator

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