Executive Summary

This project examined whether broader economic patterns could improve predictions of next-month inflation. Using multiple economic indicators, the analysis uncovered two major underlying forces that describe overall economic conditions. These discovered features were then added to several predictive models to determine whether they enhanced forecasting performance. While short-term inflation proved difficult to predict, integrating the broader economic themes led to small but consistent improvements. These findings suggest that understanding the economic environment provides valuable context for planning, even when precise forecasts are limited.

Feature Discovery

The analysis began by exploring all economic indicators using unsupervised learning. Instead of evaluating each indicator separately, the method combined related variables and revealed two meaningful economic forces. The first force represents general economic strength and is associated with movements in consumer spending, corporate profits, real estate activity, and retail sales. When this force rises, the overall economy tends to be more active. The second force reflects financial pressure and is linked to changes in exchange rates, gold prices, and other financial variables that signal uncertainty or tightening conditions.

Visualizations created in Phase One helped make these patterns clear. Time series graphs illustrated how economic indicators changed over time, while the PCA plots showed how the data clustered along the two discovered forces. These themes provided a more complete picture of the economic environment and served as new features for the predictive models. They matter because inflation is influenced by both the strength of the economy and the level of financial pressure, and these discovered forces summarize those influences more effectively than any individual indicator.

Predictive Models

The goal of Phase Two was to predict inflation one month ahead. Several models were created including linear regression and random forest models, both with and without the discovered economic features. Predicting next-month inflation proved challenging, which is common for

macroeconomic data that reacts to unexpected events and policy decisions. Despite this difficulty, adding the discovered economic features led to modest improvements in prediction accuracy.
A direct comparison of model performance is shown below.

Model Type	Raw Features Only (RMSE)	Raw + PCA Features (RMSE)	Improvement
Linear Regression	2.995	2.994	Slight improvement
Random Forest	3.023	3.021	Slight improvement

Models that relied only on the discovered features performed worse than those that combined them with the original indicators. This indicates that the broader economic forces are valuable when used as additional context, but not sufficient on their own. Overall, the findings show that the discovered features helped improve predictions, even if the improvement was small.

Business Recommendations

-Monitor the two broader economic forces—economic strength and financial pressure—on a monthly basis to better understand shifts in the economic environment.

-Treat short-term inflation forecasts cautiously and use ranges or scenario-based planning instead of relying on one precise prediction.

-Incorporate the discovered economic patterns into internal dashboards or financial planning tools, as they provide useful context even when predictive accuracy is limited.

-Focus on longer-term inflation trends (three to twelve months), which are typically more stable and easier to model than month-to-month changes.

-Strengthen risk management strategies to prepare for sudden inflation shifts, especially during periods of heightened financial pressure.

Limitations and Next Steps

The accuracy of the models was limited by the available dataset, which did not include several major drivers of inflation such as wage growth, energy costs, supply chain conditions, and policy announcements. Short-term inflation is also influenced by unexpected events, which makes monthly forecasting especially difficult. These limitations explain why the predictive models struggled to produce precise estimates.

Future improvements could include adding more detailed real-world data, such as labor market metrics or commodity prices, which are closely tied to inflation. Creating lagged versions of key variables or forecasting over longer time horizons would likely produce more stable and reliable results. Exploring alternative approaches, such as predicting whether inflation will rise or fall instead of estimating its exact level, may also enhance model performance. Even with these limitations, understanding the broader economic forces uncovered in this analysis can support more informed planning and better decision-making.