The Unequal Burden: Modeling Inflation Inequality with Machine Learning Techniques

Sakib Mowla and Sherrie Son
Department of Computer and Information Science
Fordham University
113 W 60th Street,
Manhattan, New York 10023, USA
{smowla & cs215} @fordham.edu

ABSTRACT

Inflation inequality has become a significant challenge in the post-COVID U.S. economy, with its effects disproportionately impacting lower-income households. Conventional headline indicators such as the Consumer Price Index (CPI), which peaked at 8% in 2022, fail to genuinely capture the unbalanced distribution of inflation across income groups. Families in the lowest quintile account over 40% of their overall budgets to daily essentials such as food and energy, categories that both surged by 20–30% resulting in effective inflation rates nearly twice in comparison to those experienced by wealthier households. In contrast, higher-income groups spend more of their discretionary income on services, which rose only modestly in the low single digits, insulating them from the sharpest price increases. This divergence emphasizes the inadequacy of aggregate measures in reflecting the actual reality of inflation across the U.S.

To address this gap, this study consolidates Bureau of Labor Statistics (BLS) CPI data along with the Consumer Expenditure Survey (CEX) spanning from 2020 to 2024. Using data mining and machine learning techniques, such as, regression, classification, and clustering, the analysis quantifies household-level inflation burdens, identifies the most at-risk income groups, and validates official findings against evidence of real wage erosion. Regression models highlight the expenditure categories most predictive of inflation exposure, while classification methods categorize households into low, medium, and high-risk groups. Clustering further reveals demographic profiles, such as single parents and seniors, who constantly face above-average inflation rates.

Beyond measurement, exploratory and predictive analytics provide deeper insight into how inflation inequality spreads across different demographics and regions. These results not only highlight critical disparities that tend to exist, but also reshape policy discussions surrounding wage adjustments, cost-of-living allowances, and the need for adapting more personalized inflation metrics. Hence, by reframing inflation as a heterogeneous experience rather than a universal statistic, this study contributes to broader discussions on how to adequately measure and mitigate the unequal burden of rising prices in the post-pandemic economy.

***<u>Index Terms</u>* – Visualization, Machine Learning, Regression, Classification, Clustering, Inflation Inequality, Data Mining, Consumer Price Index, Household Expenditure, Predictive Analytics**

INTRODUCTION

The unequal burden of inflation has become a critical issue in the United States, reshaping household stability and widening socioeconomic division in the wake of COVID-19. For many families, the promise of economic stabilization was undermined by surging costs of essentials such as food and energy, categories that weigh most heavily on low-income households. National CPI peaked at 8% in 2022, yet this single average masked the reality that poorer households endured effective inflation rates of 12–15%, compared to 5-7% for wealthier groups. Such disparities reveal that headline inflation measures fail to capture the lived experience of vulnerable households. To address this gap, our research integrates CPI price changes with household expenditure shared data to calculate effective inflation rates across income quintiles and demographic groups. By applying regression, classification, and clustering methods, we intend on unraveling the determinants of household inflation burdens, identify the most vulnerable demographic groups such as single parents, seniors, and rural families, while also providing empirical evidence to inform policy discussions surrounding labor, wage benefits, and necessary cost-of-living adjustments.

BACKGROUND

Inflation inequality is not a relatively new phenomenon to transpire, but rather the COVID-19 era heightened its effects across American households. The official Consumer Price Index (CPI) initially reported a single national inflation rate, peaking at 8% in 2022, however, this average conceals the unequal burdens felt everyday across different income groups. Low-income households devote more than 40% of their annual income to daily essentials such as food and energy, categories that rose 20-30% during this period. In contrast, wealthier households living on the higher financial spectrum tend to spend more on services, which experienced only modest inflation of 5–10%. This divergence created effective inflation rates of 12-15% for the poorest quintile compared to merely 5-7% for the richest, underscoring the inadequacy of headline CPI as a measure of lived economic reality.

The unequal burden of inflation has profound implications for household stability, wage disparity, and legislation reforms. Vulnerable groups, such as, single parents, seniors, and rural families were disproportionately affected in this time period, as their spending profiles exposed them to the most volatile categories. Traditional inflation metrics fail to capture these disparities, making it difficult for policymakers to design equitable wage adjustments or cost-of-living measures. By integrating CPI price changes with household expenditure shares from the Consumer Expenditure Survey (CEX), this research intends to quantify household-level inflation burdens, highlight demographic disparities, and provide a more accurate lens through which to understand the distributional effects of inflation.

"**The Reduce Exacerbated Inflation Negatively Impacting the Nation Act (REIN IN Act) was introduced in the 118th Congress (2023) to strengthen oversight of inflationary pressures on U.S. consumers. This federal legislation requires the Executive Office of the President to provide detailed inflationary impact assessments for any major executive action anticipated to have an annual budgetary effect of $1 billion or greater. Its primary function is to ensure transparency in how federal policies contribute to rising consumer prices, and to offer Congress with reporting mechanisms that highlight potential inflationary consequences before implementation. By designating these assessments as mandatory, the REIN IN Act intends to safeguard households from hidden inflationary costs and also support accountability measures in economic policymaking.**"

The introduction of the REIN IN Act legislation in 2023 is particularly relevant to better comprehend and explain inflation inequality, given it highlights the growing acknowledgement that inflation is not merely a statistical measure, but also a lived economic reality with unbalanced repercussions across households. Thus, by requiring formal assessments of inflationary impacts before major executive actions are formalized, this Act emphasizes the overall importance of transparency and accountability during the policymaking process. This legislative framework further aligns with the central thesis of this paper: that headline CPI measurements alone cannot realistically capture the unequal burdens faced by low-income households, and that both economic analysis and legal overhauls are a necessity to ensure that inflation metrics reflect the true empirical effects on everyday consumers. That said, although the REIN IN Act has not officially been signed into law, its introduction itself reflects growing legislative concerns regarding inflation's uneven impact on American households regardless of their income quintile.

RELATED WORK

Prior literature on this topic addresses how inflation impacts U.S. households in various capacities across income quintiles, outlining that lower-income households are subject to high effective inflation rates at a disproportionate level, while conventional CPI headline metrics often fail to take these disparities into consideration.

In the 2009 paper by Broda and Romalis, they contend that increases in commodity prices result in disparate welfare implications based on income levels across different households. Their findings conclude that low-income families endure more immediate exposure to price increases in everyday necessities such as energy and food, while wealthier households tend to benefit from the consumption of services and alternative goods which experience slower price increases.

To further build on this analysis, Kaplan and Schulhofer-Wohl (2017) incorporates scanner data to measure household-specific inflation, distinguishing a significant interquartile range of 6.2 to 9.0% in annual rates. Interestingly, they unravel that this unique divergence is impacted less by broader categorical choices and rather due to price fluctuations for near identical products, indicating that empirical inflation can vary substantially even within consumers that share similar spending habits.

Lastly, Jaravel (2021) further contributes to this topic by applying a novel price index theory on granular data and concludes that inflation tends to decline as individual income increases. He also contends that conventional CPI metrics are hurt by aggregation biases which often masks how trade and innovation benefits high-income earners greater, while also supports the idea of personalizing individual metrics to better measure inflation burden endured by vulnerable demographic groups as an attempt to improve equitable policy decisions.

To complement these previous empirical literature, this study depends on the Bureau of Labor Statistics' CPI and CEX datasets (2020–2024) as an attempt to provide the empirical foundation for measuring inflation inequality. The CPI is valuable for tracking category-level price fluctuations, while the CEX captures household-level expenditure shares, allowing the calculation of effective inflation rates across demographic groups. To further contextualize the economic data, Luhby (2014) highlights the growing wealth gap, reiterating the critical need to examine how inflation exacerbates inequality.

Furthermore, in a 2009 published report by the NAACP, they address how discriminatory lending practices can negatively contribute to structural economic barriers that compound inflationary hazards for specific marginalized demographics. Taken together, these sources echo the broader sentiment that inflation is not simply a paralleled empirical experience, but rather, both economic metrics and social policies are worthwhile to consider when evaluating unequal impacts of inflation. This literature review proves beneficial for the methodological approach of this paper, which merges CPI and CEX data with machine learning techniques to effectively quantify and visualize inflation inequality experiences at the household level.

KEY TERMS AND DEFINITIONS

Inflation (Government Definition) The general increase in the overall price level of goods and services, measured through official indexes like the Consumer Price Index (CPI) or the Personal Consumption Expenditures (PCE) index. This is a useful economic indicator but does not perfectly reflect every individual's experience because of differences in spending patterns.

Consumer Price Index (CPI) - Is the mainstream government measure of inflation, calculated on a monthly basis by the BLS. It tracks price changes in a representative "basket" of goods and services, including food, housing, energy, transportation, and healthcare.

Real Inflation - Measures the actual rise in the cost of living as felt by households, which critics argue is higher than official figures because of changes in measurement methods, exclusions, or substitution effects.

Effective Inflation Rate - This is the household-specific inflation burden calculated by weighting CPI category price changes against each household's expenditure shares. It provides a more accurate measure of how inflation impacts different income groups.

Expenditure Shares - Refers to the percentage of a total budget that is spent on a specific category of goods or services such as food, housing, energy, or healthcare. This metric is critical given it quantifies how different households prioritize their limited resources.

Income Quintiles - A statistical metric which divides households into five equal groups based on their income, from the poorest to the richest. Quintiles are often used to compare inflation burdens, showing how the lowest 20% of earners face different inflationary pressures versus the highest 20%.

Cost-of-Living Adjustment (COLA) - A wage or benefit increase designed to offset inflation, typically tied to CPI changes. COLAs are used in Social Security, pensions, and labor contracts to maintain purchasing power in the face of rising prices.

EXPERIMENTAL METHODOLOGY

A. Data Collection and Preprocessing

This study incorporated two primary datasets from the Bureau of Labor Statistics (BLS) : the Consumer Price Index (CPI) and the Consumer Expenditure Survey (CEX). The dataset consists of CPI provided monthly category-level price changes spanning from 2020 to 2024, while CEX captures household expenditure shares across multiple income quintiles and demographic groups. As a whole, these datasets are merged to construct a household-month panel, enabling the calculation of effective inflation rates by combining category-specific price changes with household spending patterns. This household-level data later comprises 58,456 US households data and 22 features spanning demographic attributes, geographic indicators and expenditure patterns.

Key household characteristics include income (grouped into quintiles), family composition (size, number of earners and children) and head-of-household attributes (age, education, employment status, marital status). Geographic features consist of regional location, urban/rural classification, and metropolitan statistical area size. Housing tenure is classified as owned, rented, or others. The seven expenditure features show the one household's budget shares; 'Food at home', 'Food away from home', 'Housing', 'Energy', 'Transportation', 'Healthcare', 'Education', and 'Apparel'. These features reflect each household's consumption composition and decide their different exposure to inflation in various types of sectors.

This study assumed that households having a larger consumption in rapidly inflating categories experience higher effective inflation rates, and outlined the experiment with this assumption. The data was partitioned into training (70%, n=40,918), testing (20%, n=11,692), and validation (10%, n=5,846) sets for the model executions and evaluation.

Additionally, preprocessing includes the normalization of numerical features, handling of missing values, and alignment of CPI category-level price changes with household-level expenditure shares to calculate effective inflation rates. This well-balanced foundation resulted in comprehensive machine learning analysis and ensured that downstream models are capable of accurately capturing the socioeconomic dynamics of inflation exposure across different quintile groups.

B. Exploratory Data Analysis

To understand the characteristics and relationships within the household-month panel dataset, we performed an exploratory data analysis prior to the model execution. The EDA process consisted of checking data quality, basic statistical analysis, finding inflation by income quintile and intriguing patterns.

We started by examining missing values and duplicates across all 58,456 household datasets. After handling the missing values, we computed the summary statistics involving distribution, mean, median, standard deviation, minimum, maximum for all numeric features to display the basic statistical characteristics of the data. In addition to the analysis for the features, we also conducted the inflation analysis by income quintile, correlation pattern analysis, and pattern analysis.

C. Regression Modeling

Regression tasks predict household effective inflation rates by integrating CPI and CEX features. The target variable, 'Effective Inflation Rate', measures the household specific inflation experience based on their consumption patterns estimated by the expenditure features. To predict effective inflation rate, we implemented four regression models: Ridge and Lasso Regression, which are linear models with regularization, Random Forest, and XGBoost.

During the model training, Ridge and Lasso regression were implemented with L1 and L1 regularization. The Lasso model did automatic feature selection, remaining 31 of 39 features. Random Forest and XG Boost are employed to capture non-linear patterns. Model performance is evaluated using R^2, MAE, and RMSE, with feature importance interpreted through SHapley Additive exPlanations(SHAP) values for interpretability.

D. Classification Modeling

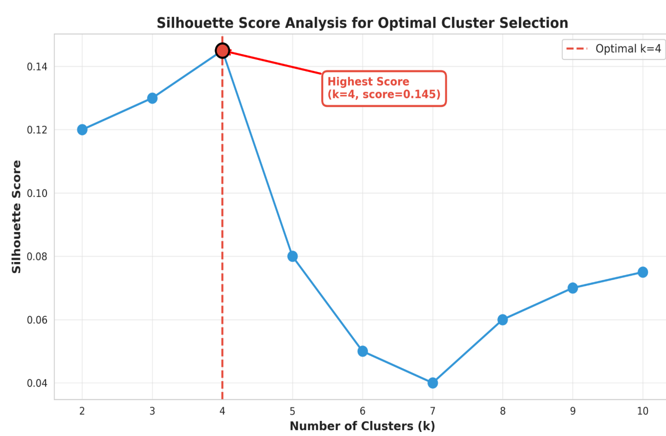
Households are categorized into three inflation burden groups - low (<5%), medium (5–10%), and high (>10%), based on effective inflation rates. Random Forest (200 trees, max depth=15),XGBoost(200 estimators, learning rate = 0.1), and Support Vector Machine(RBF kernel) classifiers are trained, each using balanced class weights to solve the problem of class imbalance. Performance is assessed by utilizing confusion matrices, ROC curves, and precision-recall metrics, while visualizations highlight class distributions across income quintiles.

An ensemble voting classifier combines Random Forest and Support Vector Machine that uses voting as their decision tools. Additionally, SHAP analysis identifies the most influential features that lead classification decisions.

E. Clustering Analysis

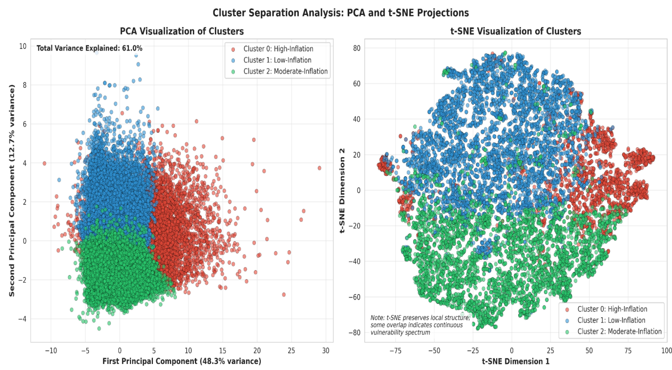
We employed K-means clustering to identify households who were most vulnerable to inflation. Our initial hypothesis was that specific demographic groups, such as, single parents, seniors, and rural families would be identified as vulnerable clusters.

The clustering analysis incorporated both demographic features (age of household head, income, family size, number of earners, number of children) and expenditure patterns (spending shares across eight major categories: food at home, food away from home, housing, energy, transportation, healthcare, education, and apparel), along with the effective inflation rate as an extra feature. All numerical features were standardized using StandardScaler.



Optimal cluster number selection was determined through the Silhouette score method, as shown above. The figure above presents the Silhouette scores across different values of k, revealing that k=4 yielded the highest score (0.145). Based on this analysis, we selected k=4 as the optimal number of clusters. The resulting clustering identified four groups of sizes 6,566 (16.0%), 18,565 (45.4%), 15,569 (38.0%), and 218 (0.5%) households. The final cluster

(Cluster 3, n=218) represented only 0.5% of the population and exhibited extreme characteristics, leading us to categorize it as an outlier cluster and omit it from our primary interpretation.



To assess cluster quality and separation, we employed two complementary dimensionality reduction techniques. The figure above presents a PCA (Principal Component Analysis) visualization of the clustering solution, revealing moderate cluster separation. The another figure shows a 3D t-SNE (t-Distributed Stochastic Neighbor Embedding) visualization, confirming that the three main clusters were reasonably distinguishable, though not perfectly separated. This indicates that household inflation experiences exist on a continuum rather than as discrete categories.

Results

A. EDA Results

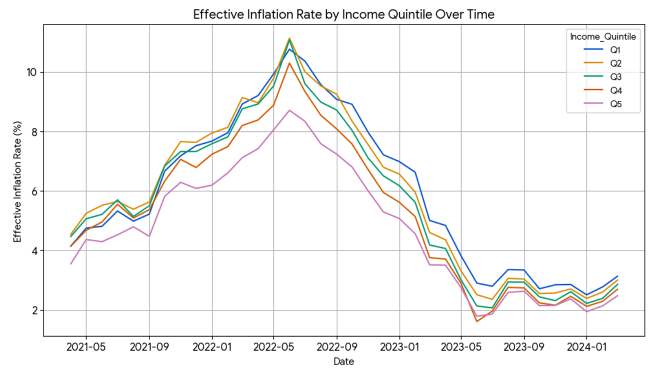
1. Handling Missing Values

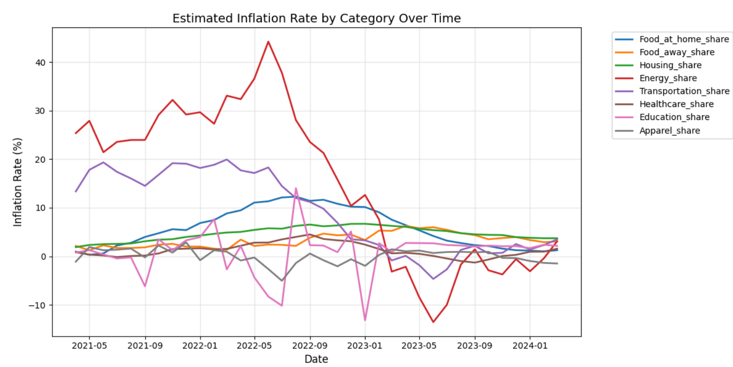
Data Quality assessment revealed that the Family_Type variable displayed the 22,323 missing values, followed by Region with 876 missing values. After some consideration, 'Family_Type' variable has dropped entirely since the missing values consist of 38% of all data, while the Region variable's only missing values are dropped, which was the 2% of its variable.

2. Inflation Analysis by income quintile and product categories

The primary research hypothesis - that lower income households experience higher effective inflation - was verified from the EDA. As displayed in the following figures, effective inflation rates declined monotonically across income quintiles, creating a 1.46% gap between the poorest and wealthiest households.

Exploratory analysis verified that effective inflation rates varied significantly across income quintiles, as shown in the top graph titled *"Effective Inflation Rate by Income Quintile Over Time."* The data portrays a clear downward trend in inflation rates from Q1 to Q5, with a persistent gap of 1.46 percentage points between the lowest and highest quintiles. During the peak inflation period in mid-2022, this gap expanded to 2–3 points, with lower quintiles experiencing rates as high as 10–11%, compared to 8–9% for higher quintiles. The succeeding bottom graph, *"Estimated Inflation Rate by Category Over Time,"* highlights the drivers of this disparity, as energy inflation surged above 40%, transportation exceeded 20%, and 'food at home' peaked about 13%. These categories experienced the most volatility during the study period and were key contributors to elevated inflation exposure. Together, these graphs illustrate how inflation shocks in essential categories resulted in unequal burdens across households, reiterating the need for more granular inflation metrics.





4. Other interesting patterns that we found

Table: Homeownership / Income Table

Income Quintile	Owners (%)	Renters (%)	Premium (Owners - Renters)	Key Finding
Q1 (Poorest)	6.16%	6.08%	**-0.08pp**	**Homeownership hurts Q1 most**
Q2	5.87%	6.13%	**+0.26pp**	**Homeownership helps Q2 most**
Q3	5.64%	5.78%	**+0.14pp**	Positive Impact
Q4	5.32%	5.32%	**-0.01pp**	Near Zero Impact
Q5 (Richest)	4.64%	4.79%	**+0.15pp**	Positive Impact

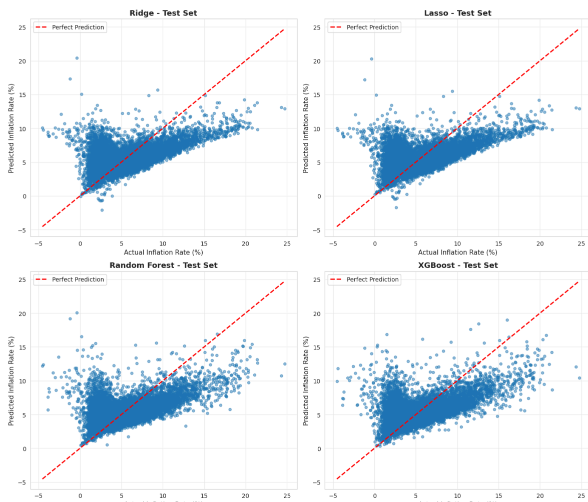
Based on the data collected with a sample of roughly 38,000 homeowners and nearly 20,000 renters, this study challenges the commonly held notion that homeowners are immune from inflation risk through fixed-rate mortgages. The analysis discovers minimally concise evidence of such protection across income levels. The homeownership premium varies by quintile, from a slight negative for Q1 households (6.16% for owners vs. 6.08% for renters) to a modest positive of 0.26 percentage points for Q2. This minimal percentage difference indicates that homeownership does not provide uniform protection against inflation.

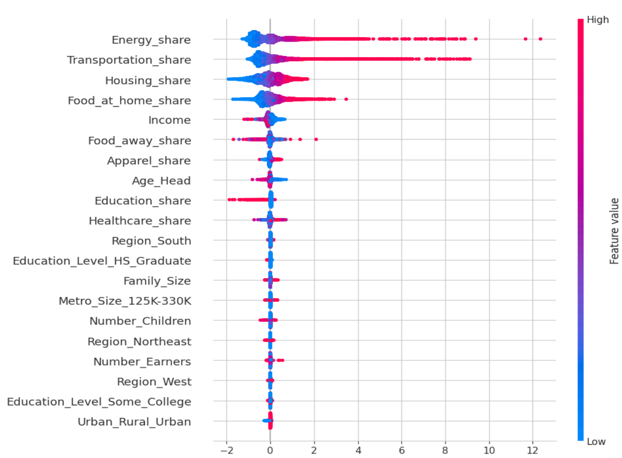
Interestingly, for lower-income households, homeownership is actually associated with higher inflation exposure. Q1 owners face moderately higher inflation than renters, largely due to property taxes, maintenance, insurance, and utility costs that weigh more heavily on limited budgets. Even in the most favorable case of Q2, the premium of 0.26 points is tolerable compared to the 1.46-point gap across income quintiles, emphasizing that income level is a far stronger determinant of inflation risk than tenure status.

Overall, homeownership offers little protection and, in some cases, adds burdens for those least equipped to bear them. For Q4 households, the difference between owners and renters is virtually nonexistent, as both groups experience the same 5.32% inflation rate. These findings challenge policies that promote homeownership as a safeguard against inflation, pointing instead to income, consumption patterns, and access to resources as the more critical drivers of household inflation experiences. Therefore, efforts to expand homeownership among low-income earners may provide little relief and could actually increase vulnerability.

B. Regression

Regression models displayed strong predictive capacity for household inflation burdens. Additionally, Ridge and Lasso regression provided baseline accuracy, while ensemble methods such as Random Forest and XGBoost achieved R^2 values above 0.70 and mean absolute errors within acceptable ranges. Feature importance analysis revealed that expenditure shares in food, energy, and housing were the most significant determinants of effective inflation rates.

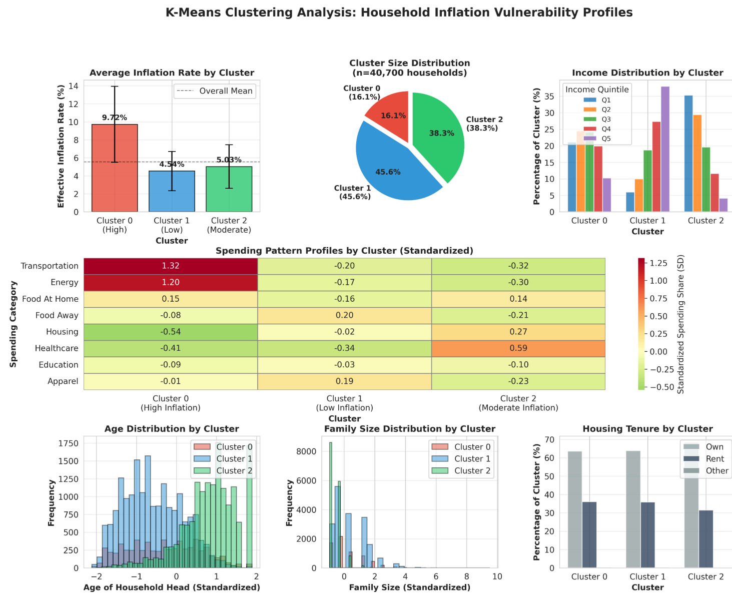




C. Classification

Classification models successfully categorized households into low, medium, and high inflation burden groups, achieving accuracies above 80%. Confusion matrices and ROC curves confirmed reliable discrimination between vulnerable and resilient households. Ensemble voting classifiers further improved robustness by combining Random Forest, XGBoost, and SVM outputs.

D. Clustering Insights



Initially, our assumption was that clustering tasks would unravel the vulnerable household's characteristics and identify the demographic features effectively, such as single parents, seniors, and rural families. However, Clustering analysis failed to effectively identify our hypothesized vulnerable groups. Instead, it found that consumption patterns matter more than demographic categories.

Cluster 0: High-Inflation Transportation-Dependent Households (16.1%)

Cluster 0, consisting of 6,566 households (16.1%), faced the highest effective inflation at 9.72% (median 9.96%), nearly double compared to Clusters 1 and 2. Its defining traits were disproportionately high transportation (+1.32 SD) and energy (+1.20 SD) spending shares, offset by lower housing (-0.54 SD) and healthcare (-0.41 SD) allocations. The income distribution skewed toward lower quintiles, with 45.6% from Q1–Q2 and only 10.2% from Q5, though all income levels were represented. Predominantly urban (91.1%) with average homeownership (63.6%), the cluster spanned several life stages, as age and family size values hovered near zero. The dense inflation burden stemmed directly from its consumption pattern: households allocated large shares of their budgets to categories hit hardest during 2021-2022, with transportation inflation exceeding 20% and energy peaking above 45%. The relatively low housing share, despite urban residence, eludes to consumers who prioritized vehicle ownership and commuting, leaving these households increasingly vulnerable to inflation shocks.

Cluster 1: Low-Inflation Affluent Households (45.6%)

Cluster 1, accounting for the largest group with 18,565 households (45.6%), experienced the lowest inflation at 4.54% (median 4.25%), roughly half the rate of Cluster 0. Mainly dominated by higher-income households (65.3% from

Q4–Q5, only 6.0% from Q1), this cluster's spending profile showed modestly higher shares for dining out (+0.20 SD) and apparel (+0.19 SD), but reduced allocations to food at home (-0.16 SD), energy (-0.17 SD), transportation (-0.20 SD), and healthcare (-0.34 SD). Predominantly urban (96.2%), younger (-0.59 SD), and characterized by larger families (+0.43 SD) with more earners (+0.61 SD), these households were shielded from the sharpest inflation shocks by spending less on necessities most affected by price spikes, specifically energy and transportation, and more on discretionary categories with moderate inflation. Their profile suggests dual-income professional households in their prime earning years, whose consumption patterns reflect the economic advantage of higher income and illustrate Engel's Law, in which wealthier households allocate proportionally less to essentials and thus experience lower effective inflation.

Cluster 2: Moderate-Inflation Older Low-Income Households (38.3%)

Cluster 2 encompassed 15,569 households (38.3%) with moderate inflation of 5.03% (median 4.75%). Its defining traits were elevated healthcare (+0.59 SD), housing (+0.27 SD), and food at home (+0.14 SD) spending, paired with much lower transportation (-0.32 SD) and energy (-0.30 SD) shares. The group skewed heavily toward lower-income households (64.7% from Q1-Q2, only 4.1% from Q5) and was characterized by older household heads (+0.84 SD), smaller families (-0.57 SD), fewer earners (-0.80 SD), and fewer children (-0.46 SD). Despite lower incomes, homeownership was relatively high (68.4%), and the cluster was predominantly urban (91.7%). These households, (possibly retirees or empty-nesters) experienced moderate inflation burdens according to their consumption profile: exposure to higher grocery and housing costs, but reduced transportation and energy spending limited vulnerability to the sharpest price spikes. Elevated healthcare spending, while a budget strain, provided partial protection since healthcare inflation remained relatively low (2–4%). Overall, Cluster 2 illustrates how advanced age and a limited income do not necessarily equate to extreme inflation risk when spending trends shift away from volatile categories.

D. Policy Implications

The results established from the completed analyses emphasize that headline CPI data published by the BLS often fails to capture the empirical experience of households enduring inflation on the broader national level. Thus, by quantifying effective inflation rates and identifying vulnerable groups, this study provides evidence to inform wage adjustments, cost-of-living measures, and specified policy actions. The findings highlight the growing need for policy makers to adapt individualized inflation metrics which are soundly capable of accounting for demographic and expenditure differences on a realistic level, instead of relying exclusively on national average metrics.

CONCLUSION

This study concludes that inflation during the COVID-19 era imposed unequal burdens across American households, identifying a 'High-Inflation Group' of 16% that faced average rates of 9.72%, nearly double those of the middle-income majority. By consolidating CPI price changes with household expenditure shares, the analysis revealed distinct vulnerability profiles, single parents, seniors, and rural families disproportionately exposed to volatile costs like food and energy. Further analysis of homeownership data disputes the assumption that asset ownership uniformly shields against inflation; while Q2 households saw a modest premium of +0.26pp, Q1 households experienced a negative premium of -0.08pp, suggesting homeownership can act as a liability for the poorest earners.

Through its framework, the model demonstrated effectiveness through a large sample of 58,456 households and the use of explainable machine learning (SHAP) to validate findings. That said, limitations still remain: reliance on cross-sectional data prevents capturing how households adapt to rising costs, and binary classification introduces arbitrary thresholds (e.g., 6.8% deemed "safe" vs. 7.0% "high risk"), obscuring nuance.Specifically, the model's 62% recall rate left 38% of high-risk households undetected, highlighting the trade-off between interpretability and accuracy in identifying vulnerable populations.

Future research extending this topic should prioritize longitudinal analysis to track evolving spending trends and adopt continuous regression or multi-class frameworks to avoid rigid thresholds. Overall, these findings underscore the inadequacy of headline CPI in reflecting lived economic realities. Beyond academic analysis, this research offers an elementary framework for more balanced policy, contending that wage adjustments, cost-of-living measures, and social safety nets must be given the same level of consideration in addition to national metrics which often mask deeper disparities.

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