\*\*Are-poor-cities-cheap-for-everyone\*\*

This study investigates micro-level evidence indicating that high-income households prioritize high-quality products and exhibit lower price sensitivity when controlling for this preference. To address the complexity introduced by dual non-homotheticity considerations, the study employs GMM-BIC model selection. Results highlight that a model incorporating non-homothetic demand for quality, excluding price, consistently outperforms alternatives, emphasizing the significance of quality preferences in grocery consumption.

Consequently, the study narrows its focus to price indexes accounting for non-homothetic demand for quality. This strategic decision is rooted in the understanding that differences in relative price indexes across income levels primarily reflect variations in the availability and prices of high-quality products across diverse markets.

In summary, the study underscores the prominence of non-homothetic demand for quality in grocery consumption, guiding subsequent analysis on how grocery costs vary for consumers at different income levels, with a specific emphasis on high-quality product preferences.

\*\*Geographic living-cost differentials in US\*\*

This study acknowledges the inherent limitations in living-cost data, emphasizing their potential crudeness and imprecision. The observed trends suggest that costs are inversely related to population size, holding other factors constant, while they tend to increase with population density. However, it's pragmatically noted that population size and density are highly correlated, challenging the assumption of ceteris paribus.

In practice, the interrelation between population size and density complicates the analysis, as indicated by a strong zero-order correlation coefficient (+.83). This challenges the a priori assumption of ceteris paribus conditions. Moreover, the study recognizes the need to consider additional relationships among independent variables, such as the likely interrelation between tax levels and population variables.

Given the observed challenges and interdependencies, the study concludes that the empirical results in the subsequent sections may not be entirely conclusive. The author highlights the importance of further refining the living-cost data and making necessary adjustments to enhance the robustness of the analysis. Consequently, the study calls for ongoing refinements in data quality and methodological approaches for a more comprehensive understanding of the dynamics involved in living-cost analysis.

\*\*Income and cost of living(Poverty, inequality)\*\*

Between 1966 and 1982, the Bureau of Labor Statistics produced a cost-of-living index for large metropolitan areas, spurring extensive research on regional cost variations. This resulted in a multitude of regression-based analyses, addressing the estimation of living costs, factors influencing them, and their responses to external variables and policy contexts.

While various cost-of-living measures exist, the Council for Community and Economic Research (C2ER) produces a widely used Cost-of-Living Index (COLI) since 1968. Early regression-based studies, such as those by Haworth and Rasmussen (1973) and McMahon & Melton (1978), incorporated demand-side factors like population, income, and population density. These studies aimed to understand the impact of economic, demographic, and institutional factors on living costs.

Natural amenities and tax burden also entered these models, reflecting their assumed influence on living costs. Unionization and a state’s "right-to-work" (RTW) status emerged as standard components, with RTW typically associated with lower living costs. However, empirical consistency varies, with state-level analyses consistently showing a negative association between RTW and living costs, while metropolitan-level studies exhibit more variability.

Despite the inclusion of RTW in standard cost-of-living models, empirical results have been inconclusive. The decline in union membership and the changing landscape of RTW states add complexity to the relationship between labor market structures and living costs. This dynamic context necessitates ongoing empirical scrutiny and refinement in understanding the intricate factors influencing the cost of living at both state and metropolitan levels.

\*\*Inflation and the cost of living\*\*

While the Consumer Price Index (CPI) is meticulously constructed using extensive survey data on price movements and item weights, research internationally, including Australia, suggests that individuals may perceive economic changes differently. Individuals, being somewhat 'loss averse,' tend to assign greater importance to prices that have risen rather than fallen, often preferring stability over offsetting changes. This psychological bias is reflected in the inclination to favor no change in prices over two offsetting price changes, whether in the same item over time or in different items simultaneously.

Moreover, consumers tend to place higher weight on larger price changes, particularly those occurring periodically rather than smoothly throughout the year. Items subject to infrequent but significant adjustments, such as utilities, education, and pharmaceuticals, draw more attention during these quarterly adjustments. These periodic changes often contribute to larger magnitude fluctuations than those observed in prices spread more evenly throughout the year. Notably, administered prices, including these periodic adjustments, have experienced higher inflation rates than the overall CPI in recent years.

Additionally, consumers tend to prioritize prices for frequently purchased items, such as food and fuel, which exhibit volatile price movements. In contrast, less frequently purchased consumer durables like computers and motor vehicles have shown price declines over the past decade, influenced by improvements in quality.

Over time, individuals may not only compare the cost of maintaining the same standard of living but also consider that of a 'reasonable' standard. Real consumption per person has increased, suggesting improved living standards, and likely, an evolving notion of what constitutes a reasonable standard of living. The perception of increasing living costs may be influenced by the desire to attain a higher standard of living, reflecting changing consumption patterns and preferences.

Furthermore, individuals' perceptions of wellbeing are shaped not solely in absolute terms but also by relative comparisons with peers, a phenomenon known as 'keeping up with the Joneses.' This comparative aspect adds a social dimension to individual assessments of their own economic circumstances, contributing to the nuanced understanding of how people gauge changes in their cost of living.

\*\*Living environment prediction \*\*

Existing literature on quality of life predominantly employs various methods and factors to calculate and assess individuals' well-being. However, the utilization of these calculated results has not been extensively explored. This study seeks to contribute by focusing on an under-discussed aspect of quality of life: its role in predicting a suitable living environment for individuals.

The proposed method, outlined in Fig. 1, involves gathering individuals' preferences on key city features like entertainment, social activity, and cultural life. Subsequently, quality of life indexes for desired cities are calculated and compared with existing city indexes. Individuals are then assigned to the most suitable cities based on their preferences and economic conditions. The study employs individual and ensemble machine learning (ML and EML) techniques to explore whether qualities of cities can be predicted solely from individuals' responses, without direct index calculations.

Machine learning methodologies, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and ensemble techniques like stacking and voting, are utilized to construct a living environment prediction model based on the quality of life index.

The dataset used in the study (Table 1) incorporates attribute values for predicting index values, with the last column representing the quality of life classes of desired cities. These cities are classified into five classes based on quality of life, ranging from the best (class value 1) to the worst (class value 5). The study leverages machine learning techniques to predict the quality of life classes, showcasing an innovative application of ML and EML in assessing and predicting suitable living environments based on individuals' quality of life preferences.