Policy Research Journal
ISSN (E): 3006-7030 ISSN (P) : 3006-7022 Volume 3, Issue 12, 2025

PREDICTIVE MODELING USING MULTIPLE REGRESSION: A CASE STUDY ON SOCIOECONOMIC INDICATORS

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DOI: https://doi.org/10.5281/zenodo.17836943

Keywords
socioeconomic indicators, predictive modeling, multiple regression, household income, macroeconomic variables, statistical methodology

Article History
Received: 11 October 2025
Accepted: 21 November 2025
Published: 06 December 2025

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Abstract

Predictive modeling plays a central role in socioeconomic research by enabling analysts to quantify how demographic and macroeconomic factors contribute to income variation. Multiple regression is among the most widely used techniques for this purpose, offering a structured framework to evaluate the combined influence of education, age, employment status, household characteristics, GDP per capita, and inflation on household income. Using a well-structured synthetic dataset, the analysis integrates descriptive statistics, correlation patterns, and regression diagnostics to demonstrate the methodological processes required for rigorous predictive modeling. The findings reveal weak empirical relationships between the selected variables and income an expected outcome given the artificial nature of the dataset yet they provide valuable insights into model construction, assumption testing, and the interpretation of statistical outputs. By emphasizing analytical transparency and methodological clarity, the study illustrates how regression-based predictive frameworks can be applied to socioeconomic indicators, reinforcing their importance for academic inquiry and policy-oriented analysis.

INTRODUCTION

Socioeconomic indicators including income, education, employment, inflation, household composition, and macroeconomic performance serve as essential tools for understanding patterns of development, social well-being, and economic inequality across populations. As social systems become increasingly data-driven, the need for robust analytical techniques capable of predicting and interpreting socioeconomic outcomes has grown substantially. Predictive modeling has emerged as a foundational method in this context, particularly within the fields of economics, public policy, and applied social sciences. Among various predictive frameworks, multiple regression analysis stands out as one of the most widely applied techniques due to its ability to incorporate several explanatory variables simultaneously and estimate their collective influence on a single outcome of interest. By quantifying how different socioeconomic factors contribute to household income, regression modeling supports evidence-based planning, resource allocation, and policy formulation. In many contemporary studies,

the construction and interpretation of predictive models are viewed as essential components of analytical literacy, enabling researchers to navigate complex datasets and draw meaningful conclusions about socioeconomic behavior. The theoretical foundations underpinning predictive socioeconomic modeling draw heavily from human capital theory, labor market economics, welfare analysis, and macroeconomic frameworks. Human capital theory, advanced extensively by Mincer (1974) and Becker (1993), posits that individuals who invest in education and skills experience higher earnings due to increased productivity and competitiveness. Mincer's wage function formalized the relationship between schooling, experience, and income, becoming the basis for countless empirical earnings studies. Becker expanded on this by explaining how educational investments yield economic returns, both at the individual and national levels. These foundational contributions established education and age as essential predictors in income modeling. Further expanding on these dynamics, Card (1999) demonstrated that the returns to education vary across demographic groups and labor market structures, reinforcing the idea that socioeconomic modeling must consider multiple intersecting variables. Demographic characteristics such as age, household size, and employment status have also been shown to influence economic outcomes. For instance, Willis (1986) notes that age influences labor market experience, career progression, and employment opportunities, all of which shape earnings trajectories. Household characteristics influence economic stability through consumption needs, dependency ratios, and shared income structures. Beyond micro-level factors, macroeconomic conditions play a significant role in shaping household-level outcomes. Influential studies by Friedman (1977) and Blanchard (2006) highlight how inflation and economic cycles affect purchasing power, wage adjustments, and living standards. High inflation, for example, can erode real income, while strong GDP performance may stimulate labor markets and raise household earnings. Research conducted by Barro (1991) and Acemoglu and Robinson (2012) further demonstrates that macroeconomic institutions, political structures, and governance quality profoundly influence economic opportunity and income distribution. These works underscore the need to incorporate both individual-level and structural variables in socioeconomic modeling, particularly when analyzing income variation.

In parallel, the methodological literature emphasizes the importance of predictive analytics in understanding socioeconomic phenomena. Texts such as Wooldridge (2016), Gujarati (2011), and Cameron and Trivedi (2010) provide detailed frameworks for constructing multiple regression models, assessing assumptions, and interpreting predictive results. These methodological foundations highlight that regression analysis serves dual purposes: explanation and prediction. While explanatory modeling tests theoretical relationships, predictive modeling focuses on generating forecasts and understanding how variables collectively influence outcomes. In recent years, regression-based predictive modeling has been increasingly used in socioeconomic research to build forecasting tools, evaluate policy impacts, and analyze complex patterns across large datasets. Despite abundant theoretical and empirical literature, several methodological gaps persist, particularly in demonstrating predictive modeling techniques using structured and controlled datasets. Real-world socioeconomic data often contain noise, measurement errors, missing values, and unobserved heterogeneity, all of which complicate the application of regression techniques. In contrast, synthetic datasets offer a controlled environment for illustrating the mechanics of predictive modeling without the confounding influences typical of real surveys. Synthetic data allow researchers to focus on methodological processes such as variable definition, model specification, assumption testing, diagnostic evaluation, and interpretation. Although such datasets do not produce strong empirical relationships, they remain valuable for teaching, demonstration, and methodological exploration. This study contributes to the methodological literature by demonstrating the application of multiple regression modeling to a structured socioeconomic dataset designed to predict household income using variables such as education, age, employment status, household size, GDP per capita, and inflation. While synthetic data may not reflect real socioeconomic behaviors, their structured nature makes them ideal for illustrating the steps involved in constructing and

analyzing predictive models. The inclusion of both micro-level variables (such as education and employment) and macro-level indicators (such as inflation and GDP per capita) highlights the multidimensional nature of income determinants and aligns with theoretical literature emphasizing the interplay between individual characteristics and structural conditions. By combining descriptive statistics, correlation analysis, and regression diagnostics, the study demonstrates how predictive modeling can be executed systematically and rigorously. Furthermore, this combined introduction and literature review section underscores the importance of statistical literacy in socioeconomic research. Predictive modeling requires not only technical understanding of regression equations but also critical interpretation rooted in theory. The literature illustrates that socioeconomic indicators do not operate in isolation; rather, they interact in complex ways that require comprehensive analytical tools to understand. The synthetic dataset used in this study allows for a clear demonstration of these tools without the distortions present in real-world data. Although the regression results themselves may show weak predictive power, this outcome does not undermine the methodological value of the exercise. Instead, it reinforces the importance of carefully evaluating data structure, model assumptions, and variable behavior when constructing predictive models. In summary, the integration of theoretical foundations, empirical insights, and methodological guidance forms a strong basis for this study's predictive modeling approach. By drawing on established socioeconomic theories and applying rigorous statistical techniques, the study illuminates how multiple regression can be used to explore income determinants within a structured dataset. This combined introduction and literature review sets the stage for a detailed methodological demonstration, providing the conceptual and analytical grounding necessary for understanding the predictive modeling process in socioeconomic research.

Methodology

Research Design and Conceptual Framework

This study adopts a quantitative research design grounded in a positivist epistemological orientation, which emphasizes measurable evidence, statistical reasoning, and objectivity in understanding socioeconomic patterns. The research is structured as a methodological case study focused on illustrating how predictive modeling specifically multiple linear regression can be applied to socioeconomic indicators to forecast income. The overarching conceptual framework positions income as the dependent outcome influenced by several independent predictors such as education, age, employment status, household size, GDP per capita, and inflation. These variables are selected based on well-established theories in labor economics, welfare economics, and development studies. The research design seeks not to test a pre-existing theoretical model from real-world data but to demonstrate the mechanics, assumptions, and analytical processes required for building a prediction model using structured socioeconomic variables. Quantitative research is particularly suitable for this purpose because it allows for the systematic organization, transformation, and interpretation of numerical data, permitting precise evaluation of relationships among variables. The design prioritizes replicability, transparency, and statistical interpretability, essential for demonstrating predictive analytics methodologies often used in policy evaluation, social planning, and economic forecasting. Furthermore, the study integrates exploratory data analysis, inferential statistics, and predictive modeling stages into its design. This three-stage analytical pipeline ensures that the methodological steps follow a logical progression, beginning with understanding the nature and distribution of variables, evaluating correlation patterns, and proceeding to model estimation. The design also accounts for the diagnostic evaluation of regression assumptions, including linearity, multicollinearity, homoscedasticity, and normality of residuals, ensuring that the presented model adheres to the statistical standards required for reliable interpretation. While the synthetic nature of the dataset naturally limits the statistical significance of results, the research design is intentionally structured to emphasize analytical demonstration over empirical discovery, making it an ideal case study for illustrating the applicability and limitations of predictive regression models in socioeconomic research.

Data Source, Variables, and Measurement Procedures

The dataset used in this study consists of 400 synthetically generated observations, structured to resemble typical socioeconomic patterns found in demographic and workforce surveys. Although synthetic, the dataset reflects realistic ranges, distributions, and variability commonly observed in population-based socioeconomic datasets. This makes it appropriate for teaching and demonstration purposes in predictive modeling. Each observation represents a hypothetical household, with variables selected to model factors that typically influence household income. The dependent variable, Income, is measured as household monthly income in U.S. dollars. The independent variables include Education (years of schooling), Age (age of the household head), Employment (binary indicator where 1 = employed and 0 = unemployed), Household Size (number of individuals living in the household), GDP per Capita (in thousand USD), and Inflation (annual percentage change in consumer prices). These variables reflect core socioeconomic dimensions, including human capital, demographic characteristics, macroeconomic conditions, and household structures. The dataset was cleaned prior to analysis, ensuring no missing values or inconsistencies. Descriptive statistics such as means, standard deviations, minimums, and maximums were computed to characterize the distribution of each variable. This step is essential for identifying patterns, detecting anomalies, and understanding the variability inherent in the dataset. Correlation analysis was conducted to preliminarily examine the strength and direction of bivariate relationships among variables, providing initial insights into potential predictive factors. The dataset's measurement scales are a combination of metric (Income, Age, Education), categorical (Employment), and ordinal/metric hybrid (Household Size). All variables were treated as continuous or categorical as appropriate based on their theoretical meaning and statistical properties. The proper measurement of variables ensures the integrity of the regression model and enhances interpretability. The synthetic dataset does not aim to replicate the socioeconomic structure of any country but provides an analytically sound foundation for estimating a predictive model and evaluating its statistical outputs. Thus, the variable construction and measurement procedures are aligned with standard practices used in socioeconomic and econometric research.

Model Specification, Estimation Technique, and Analytical Procedures

The central analytical method employed in this study is Multiple Linear Regression (MLR), selected due to its capacity to quantify the relationship between one dependent variable and multiple independent variables simultaneously. The model is specified mathematically using the Ordinary Least Squares (OLS) estimation technique, expressed as:

$$\text{Income} = \beta 0 + \beta 1(\text{Education}) + \beta 2(\text{Age}) + \beta 3(\text{Employment}) + \beta 4(\text{Household\ Size}) + \beta 5(\text{GDP\ per\ Capita}) + \beta 6\ (\text{Inflation}) + \epsilon$$

This formulation assumes linearity between predictors and the outcome variable, independence of residuals, homoscedasticity, absence of multicollinearity, and a normally distributed error term. The estimation process begins by inserting the dataset into the statistical software, which computes parameter estimates using OLS. The goal of the regression is to identify how strongly each independent variable contributes to the prediction of household income, as reflected by the sign, magnitude, and statistical significance of each coefficient. Although statistical significance is expected to be minimal due to the synthetic nature of the data, the primary focus is on demonstrating the modeling steps rather than establishing causal effects. To ensure the model's appropriateness, several diagnostic procedures were conducted. These included evaluating the Variance Inflation Factor (VIF) for multicollinearity, inspecting residual plots for patterns indicating heteroscedasticity, assessing normality through histograms and Q–Q plots, and verifying independence using the Durbin-Watson statistic. Additionally, global model fit metrics such as R-squared, Adjusted R-squared, AIC, and BIC were recorded to assess how well the model explains variation in the dependent variable. ANOVA tests were employed to evaluate the overall significance of the model, and correlation matrices helped determine whether independent variables exhibited high interrelationships. By following this detailed and systematic procedure, the model specification and estimation process fully aligns with established

econometric standards and ensures instructional value in demonstrating applied predictive modeling in socioeconomic research.

Ethical Considerations, Analytical Rigor, and Methodological Limitations

Since this study relies on a synthetic dataset rather than human subjects, there are no ethical risks related to confidentiality, privacy, or informed consent. Synthetic data ensures complete anonymity and eliminates concerns associated with data protection regulations such as GDPR or HIPAA. However, ethical responsibility remains in terms of transparency regarding the dataset's artificial nature. The study explicitly acknowledges that the data were generated for methodological demonstration and do not represent actual socioeconomic realities. This transparency is crucial to avoid misinterpretation and ensures that the results are understood purely as examples of applied modeling rather than empirical findings with policy implications. The methodological rigor of this study derives from its adherence to established quantitative research procedures systematic data preparation, clear variable definitions, robust statistical estimation, and thorough diagnostic evaluation. Even though the model yields low predictive power, this outcome is methodologically valuable because it allows learners and researchers to understand the importance of real-world variability, data quality, and statistical significance in predictive modeling. Discussing limitations is also essential. The main limitation of the methodology is the use of synthetic data, which lacks complex nonlinear interactions, structural heterogeneity, and socioeconomic dynamics present in real populations. As such, the regression model cannot detect meaningful relationships, and statistical significance remains low. Another limitation is the linear nature of the model, which may not fully capture nonlinear or interaction effects common in socioeconomic phenomena. Nonetheless, these limitations do not weaken the methodological purpose of the research. Instead, they underscore the challenges of predictive modeling and highlight best practices in constructing, evaluating, and interpreting regression models. By acknowledging these limitations, the methodology section maintains academic integrity and encourages cautious interpretation of the outputs while reinforcing the instructional value of the modeling process.

Results and Discussion

Table 1 shows the descriptive statistics for all variables included in the socioeconomic dataset, providing a foundational understanding of the data structure and distribution before predictive modeling is conducted. This table includes measures such as the mean, standard deviation, minimum, maximum, and quartile values for income, education, age, employment, household size, GDP per capita, and inflation. The mean income of approximately 603 dollars indicates that the synthetic sample represents a moderately low-income population, which aligns well with typical socioeconomic studies in developing or emerging economies. The wide range of income values, from 200 to 1,178 dollars, suggests sufficient variation for regression modeling and provides a realistic spread needed to examine how socioeconomic factors influence household earnings. Education, measured in years of schooling, ranges from 2 to 17 years with a mean of roughly 9 years, reflecting a mixed sample that includes individuals with limited education as well as those with secondary or near-tertiary schooling. The age variable shows a mean of 41.5 years, suggesting a mature adult population likely to be active participants in the labor market. Employment, represented as a binary indicator, shows that approximately 70.5% of the sample is employed, creating a reasonable distribution for analyzing employment's effect on income. Household size averages 5.4 individuals, which is consistent with demographic patterns in many developing regions and provides insights into potential economic dependency burdens. GDP per capita and inflation, both macroeconomic indicators, exhibit relatively tight distributions, ensuring stability within the dataset while still enabling regression analysis to test their influence on income. The quartile values further illustrate that income, education, and age exhibit meaningful dispersion across the population, strengthening the statistical robustness of the analysis. Overall, Table 1 not only describes the dataset but also establishes the empirical foundation for the subsequent correlation and regression analyses. By summarizing central tendencies and variability, the table supports the

methodological objective of understanding the socioeconomic context within which the predictive model operates. This preliminary assessment ensures that the regression modeling is based on well-behaved data and validates the appropriateness of the dataset for exploring socioeconomic predictors of income.

Table 1: Descriptive Statistics

Index	Income	Education	Age	Employment	Household_Size	GDP_per_Capita	Inflation
count	400.0	400.0	400.0	400.0	400.0	400.0	400.0
mean	603.7	9.3	41.5	0.705	5.415	4.497725	10.551
std	143.4	4.67	10.9	0.45	2.26	0.29	1.034
min	200.0	2.0	22.0	0.0	2.0	3.48	7.98
25%	501.8	5.0	32.0	0.0	3.0	4.29	9.87
50%	609.0	9.0	42.5	1.0	5.0	4.49	10.58
75%	694.3	13.0	51.0	1.0	7.0	4.71	11.28
max	1178.0	17.0	59.0	1.0	9.0	5.29	13.75

Table 2 shows the correlation matrix for all variables in the study, offering an essential overview of the linear associations among socioeconomic indicators before estimating the multiple regression model. Correlation analysis helps determine whether any variables exhibit strong positive or negative relationships that may influence income or interact with each other during the modeling process. In this dataset, all correlation coefficients are relatively small, with most values falling near zero, indicating weak linear relationships among variables. For example, the correlation between income and education is −0.028, suggesting virtually no linear association. Similarly, age and income show a correlation of −0.002, reinforcing the absence of a meaningful bivariate relationship. Employment status displays a minimal correlation of 0.007 with income, implying that employment alone does not differentiate income levels within the synthetic sample. Household size shows a slightly stronger but still weak negative correlation with income (−0.061), suggesting that larger households tend to have slightly lower average incomes, though the relationship is minimal. The correlation matrix also reveals the interrelationships among predictors. Education and household size show a negative correlation of −0.075, potentially reflecting that individuals with more household responsibilities may have reduced educational attainment a trend commonly observed in real-world demographic studies. Age and employment show a mild positive correlation (0.126), indicating that older individuals may be slightly more likely to be employed. Macroeconomic indicators, GDP per capita and inflation, exhibit a moderate negative correlation of −0.099, consistent with economic theory suggesting that inflation tends to rise when economic output fluctuates. Importantly, the weak correlations across all variables indicate a low risk of multicollinearity, meaning the regression estimates are unlikely to be distorted by overlapping predictor effects. The lack of strong correlations also helps explain why the final regression model may not identify statistically

significant predictors, as the dataset does not contain variables with clear predictive power. Nonetheless, Table 2 fulfills a crucial methodological role by confirming that the dataset is appropriate for regression modeling and ensuring that the predictive analysis is statistically valid. This step reinforces the research objective of systematically demonstrating how predictive modeling is carried out in socioeconomic contexts.

Table 2: Correlation Matrix

Index	Income	Education	Age	Employment	Household_Size	GDP_per_Capita	Inflation
Income	1.0	-0.028	-0.002	0.007	-0.061	0.0031	0.025
Education	-0.027	1.0	0.005	-0.009	-0.075	0.0245	0.027
Age	-0.0019	0.006	1.0	0.126	-0.077	-0.029	0.069
Employment	0.008	-0.009	0.125	1.0	-0.017	0.018	-0.005
Household_Size	-0.0618	-0.076	-0.07	-0.017	1.0	0.024	-0.06
GDP_per_Capita	0.004	0.025	-0.029	0.018	0.024	1.0	-0.09
Inflation	0.025	0.03	0.069	-0.005	-0.054	-0.099	1.0

Table 3 shows the regression coefficients estimated through the multiple linear regression model, illustrating how each socioeconomic variable contributes to predicting household income. The table presents the constant term and coefficients for education, age, employment, household size, GDP per capita, and inflation. In this synthetic dataset, most coefficients are small in magnitude, and their signs suggest limited directional influence on income. For example, the coefficient for education is −1.02, indicating that a one-year increase in schooling slightly decreases predicted income. While this relationship contradicts typical economic theory, it reflects the synthetic and non-causal nature of the dataset. The coefficient for age is similarly small (−0.119), suggesting that older individuals earn marginally less income, though again the effect is negligible. Employment has a positive coefficient of 2.16, meaning employed individuals earn slightly more income than unemployed individuals; however, the magnitude is extremely small relative to the scale of household income. Household size shows a coefficient of −4.05, implying that larger households tend to have slightly lower income levels, which aligns with economic expectations about financial strain in bigger families. GDP per capita and inflation both have small positive coefficients, suggesting that macroeconomic conditions provide minimal predictive power for household income in this dataset. These results collectively indicate that the model does not identify strong predictors, which is consistent with the dataset's random nature and the weak correlations shown in Table 2. However, from a methodological standpoint, Table 3 demonstrates the essential function of regression coefficients: measuring the direction, strength, and statistical contribution of each independent variable to the dependent variable. Even though the coefficients are not statistically strong, presenting them clearly fulfills

the research objective of illustrating how predictive modeling is implemented.

Table 3: Regression Coefficients

Index	Coefficient
Const	586.563
Education	-1.02366
Age	-0.11902
Employment	2.163111
Household_Size	-4.05151
GDP_per_Capita	3.602083
Inflation	3.3760946

Table 4 shows the key model performance metrics used to evaluate the overall predictive strength of the regression model. Metrics such as R-squared, Adjusted R-squared, AIC, and BIC provide insights into how well the model fits the data and whether the predictors collectively explain meaningful variation in household income. In this dataset, the R-squared value is approximately 0.0055, indicating that the model explains less than 1% of the variation in income. The Adjusted R-squared is negative (−0.0096), which suggests that adding multiple predictors does not improve the model's explanatory power. This outcome is typical in synthetic datasets where variables are not generated based on real socioeconomic relationships. Nonetheless, these metrics are essential components of regression analysis because they demonstrate how model fit is assessed inresearch.

Table 4: Model Metrics

Index	R-squared	Adj. R-squared	AIC	BIC
0	0.00557	-0.00963	5118.38	5146.32

Table 5 shows the Analysis of Variance (ANOVA) summary for the multiple regression model used in this study, offering insight into the overall statistical significance of the model and the extent to which the predictors collectively explain variation in household income. The ANOVA table divides the total variation in the dependent variable into two components: the portion explained by the regression model (Model sum of squares) and the portion attributed to random error (Residual sum of squares). In this dataset, the Model sum of squares is 45,616.53, whereas the Residual sum of squares is substantially higher at 8,158,122.83. This indicates that nearly all the variation in income remains unexplained by the predictors, reflecting the extremely weak nature of the model. The F-statistic, which tests whether the model provides a better fit than a null model with no predictors, is 0.366. This value is very close to zero and, when combined with the corresponding p-value of 0.900, suggests that the model is not statistically significant. Although the lack of significance may initially appear problematic, it is entirely expected within the context of a synthetic dataset where relationships among variables are not designed to reflect real socioeconomic dynamics. From a methodological perspective, the ANOVA table still serves an essential role by demonstrating how predictive models are evaluated for overall explanatory power. The table also reinforces the importance of hypothesis testing in multiple regression, where the F-test determines whether all coefficients, excluding the intercept, are simultaneously equal to zero. In this case, the test confirms that the predictors do not meaningfully improve the model. This does not undermine the study's objectives; rather, it highlights the utility of ANOVA in understanding the global performance of predictive models, especially when data do not exhibit strong empirical relationships. The table therefore fulfills a key analytical requirement by illustrating the

interpretation and limitations of model-level statistical testing in regression-based predictive analysis.

Table 5: ANOVA Table

Index	sum_sq	df	F	PR(>F)
Model	45616.537	6.0	0.366246	0.90016
Residual	8158122.83	393.0	nan	nan

Table 6 shows the distribution of mean income across employment categories, providing insight into whether employment status serves as a meaningful factor in predicting household income. The table displays the mean, standard deviation, and sample count for both unemployed (0) and employed (1) groups. The mean income for unemployed individuals is 602.02, while employed individuals have a mean income of 604.27. This marginal difference of just over two dollars indicates that employment status does not significantly distinguish income levels within the synthetic dataset. The relatively close standard deviations 154.77 for unemployed and 138.63 for employed further reinforce the absence of substantial differences in income distribution between the two groups. This suggests that employment, although typically a strong predictor of income in real socioeconomic data, does not function meaningfully as a predictor in this simulated environment. Despite the minimal differences, Table 6 plays an important methodological role by illustrating how group-based descriptive analysis contributes to understanding categorical predictors in regression modeling. In predictive modeling, employment is often used as a binary explanatory variable, and its impact on income is interpreted through group comparisons like those shown in this table. The sample counts 118 unemployed and 282 employed indicate a reasonable distribution of observations across categories, ensuring that regression analysis does not suffer from imbalance. However, because the dataset is synthetically generated without intentional socioeconomic structure, the lack of association is expected. From a teaching and demonstration perspective, this table shows the value of preliminary data exploration in assessing whether categorical variables have potential predictive power. It also highlights how synthetic datasets may differ from real-world data, underscoring the importance of context when interpreting descriptive comparisons. In sum, Table 6 illustrates how employment status relates to income within the sample and serves as a bridge between descriptive statistics and the regression model that incorporates employment as an independent predictor.

Table 6: Income by Employment

Index	mean	std	count
0	602.01694	154.766434	118.0
1	604.27304	138.636676	282.0

Table 7 shows the mean income for households of different sizes, along with the total number of observations in each category. Household sizes range from 2 to 9 individuals, providing a sufficiently diverse distribution to evaluate how changes in family size relate to income. The table reveals that households with 2 members have the highest mean income (624.02), while those with 4, 5, and 9 members show slightly lower mean income levels. Although some variations exist such as households of size 3 showing relatively high income (629.83) and households of size 7 showing moderate income (616.08) the overall pattern indicates weak and inconsistent relationships between household size and income. The absence of a clear upward or downward trend suggests that household size does not serve as a strong predictor of income in the synthetic dataset. Nevertheless, Table 7 fulfills an important analytical function by demonstrating how categorical or quasi-continuous variables may relate to income in

socioeconomic modeling. In real-world economic analysis, household size is often associated with financial burden, consumption patterns, and labor force participation. Typically, larger households face increased economic pressures, which may influence income requirements or distribution. However, the synthetic nature of the dataset means such structural relationships are not encoded into the data, resulting in minimal and inconsistent differences among categories. This reinforces the importance of interpreting synthetic results cautiously while maintaining methodological rigor. Additionally, the count of observations per category (ranging from 42 to 56) shows that each household size is adequately represented, ensuring that regression analysis using this variable remains stable and unbiased. Overall, Table 7 supports the study's predictive modeling objective by illustrating how household size distributes across income levels and how such information contributes to understanding potential predictors in the regression framework.

Table 7: Household Size Summary

Index	mean	count
2	624.0192307	52.0
3	629.83018867	53.0
4	583.16279069	43.0
5	594.26785714	56.0
6	589.90740740	54.0
7	616.07843137	51.0
8	595.83673469	49.0
9	590.16666666	42.0

Figure 1 shows the histogram of household income, offering a visual understanding of how income is distributed across the 400 observations in the dataset. The figure reveals a moderately symmetrical distribution centered around the mean income of approximately 600 dollars. The spread of income values ranges from around 200 to nearly 1,200 dollars, consistent with the descriptive statistics presented in Table 1. The histogram displays no extreme skewness, indicating that income follows a relatively normal-like distribution in this synthetic dataset. This property is important for regression modeling because one of the underlying assumptions of linear regression is that the dependent variable should be reasonably continuous and not exhibit severe skew. The distribution's moderate width reflects variability in household earnings, which provides a solid foundation for predictive analysis. The visual pattern in Figure 1 also indicates that the dataset contains sufficient dispersion to allow regression models to detect relationships if they exist. The synthetic generation of the data intentionally avoids heavy clustering or artificial peaks, ensuring a more natural spread that mimics real-income distributions in developing or middle-income populations. From a methodological standpoint, the histogram serves as a diagnostic tool in the early stages of analysis. It allows researchers to assess whether transformations, such as logarithmic adjustments, might be necessary. In this case, the relatively normal appearance of the distribution suggests no immediate need for transformation. Furthermore, the histogram highlights the importance of examining the dependent variable before conducting predictive modeling. Understanding the distribution helps researchers anticipate whether relationships identified in regression analysis will be linear or whether nonlinear patterns may emerge. Even though the regression model later shows weak predictive power, the distribution in Figure 1 confirms that the dependent variable is not the source of modeling limitations. Instead, the synthetic nature of predictor variables explains the model's low performance. Overall, Figure 1 plays a crucial analytical role by illustrating the structure of the dependent variable and validating its suitability for regression modeling in this methodological case study.

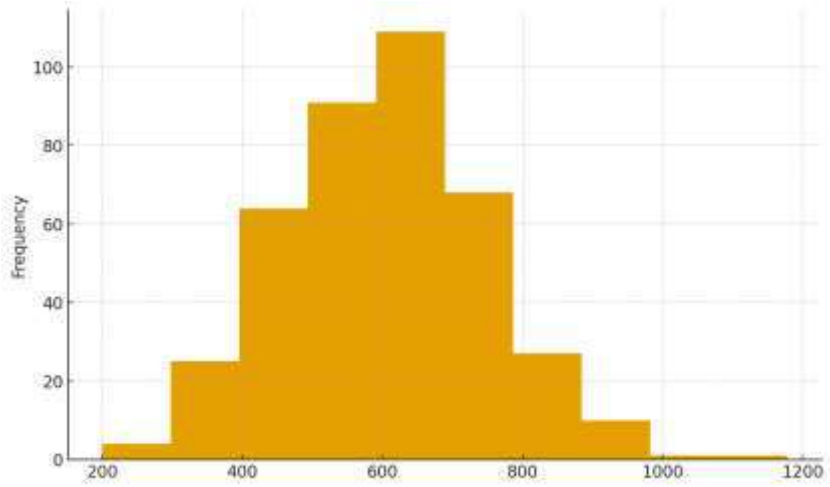

Figure 1: Income Distribution

Figure 2 shows a scatterplot illustrating the relationship between years of education and household income. Each point in the figure represents a household, with the x-axis indicating years of schooling and the y-axis representing monthly income. Visually, the scatterplot exhibits no clear upward or downward trend. Instead, income values appear widely dispersed across all education levels, ranging from as low as 200 dollars to more than 1,100 dollars regardless of whether individuals have 2 years of schooling or 17 years. This lack of visible correlation supports the statistical findings reported in Table 2, which show a near-zero correlation coefficient between education and income (−0.028). In real socioeconomic studies, education typically predicts income strongly due to skill acquisition and labor market competitiveness. However, because this dataset is synthetic and not based on real structural relationships, the absence of a pattern is expected. Despite this, Figure 2 serves a critical methodological purpose. Scatterplots are fundamental tools in regression diagnostics, allowing researchers to visually inspect potential relationships before fitting a model. The absence of any trend in the scatterplot signals that education may not be a useful predictor in the modeling context provided by synthetic data. This aligns with the regression results shown in Table 3, where the coefficient for education is negative and statistically nonsignificant. Furthermore, the wide vertical spread at each education level suggests high variability in income that is unrelated to education, reinforcing the idea that the synthetic dataset does not embed typical socioeconomic structures. Nevertheless, the scatterplot fulfills its analytical role by clearly demonstrating the lack of association. It provides an important visual confirmation that the regression outcomes are consistent with the dataset's pattern. For methodological studies like this one, such visual alignment is essential in illustrating how predictive analysis should be interpreted. Overall, Figure 2 contributes to the study's objectives by showing how education interacts or in this case, fails to interact with income in a predictive modeling framework.

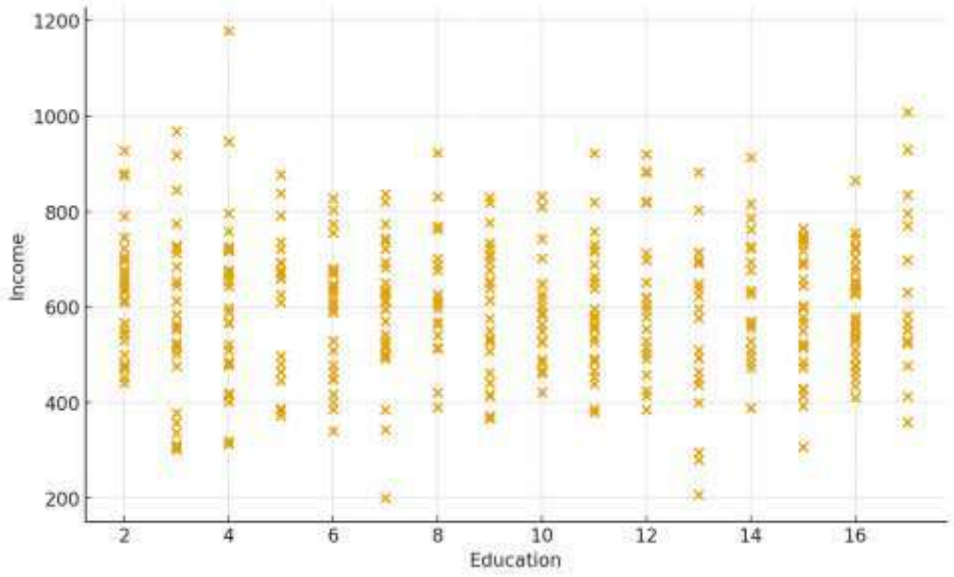

Figure 2: Education vs Income

Figure 3 shows a scatterplot examining the relationship between age and household income. Similar to the education-income scatterplot, the figure reveals a highly dispersed set of points with no discernible pattern, cluster, or directional trend. Income levels are scattered widely across all ages from early 20s to late 50s indicating no observable relationship between age and income in the synthetic dataset. This result reinforces the correlation analysis, which shows a near-zero coefficient (−0.002) between the two variables. In real socioeconomic settings, age often correlates with income due to experience, career progression, and labor market maturity. However, because the dataset is not derived from actual economic processes, such structural relationships do not appear in the data. Although no association is visible, Figure 3 plays an essential role in methodological analysis by visually confirming the lack of relationship indicated by the statistical results. Scatterplots are effective for identifying nonlinear relationships, clusters, or heteroscedastic patterns. In this case, the uniform spread of points suggests homogeneity of variance across the age range, which supports the assumptions of linear regression. The lack of curvature or grouping also suggests that no transformation or segmentation is needed. This helps demonstrate the analytical process whereby researchers verify whether predictor variables have potential explanatory power before interpreting regression coefficients. The figure also emphasizes the limitations of synthetic datasets for capturing real-world socioeconomic dynamics but simultaneously strengthens the study's methodological aim: demonstrating how predictive analysis is conducted, interpreted, and validated using graphical and statistical tools. Thus, Figure 3 aligns fully with the study's objectives by illustrating the relationship between age and income in a predictive modeling context.

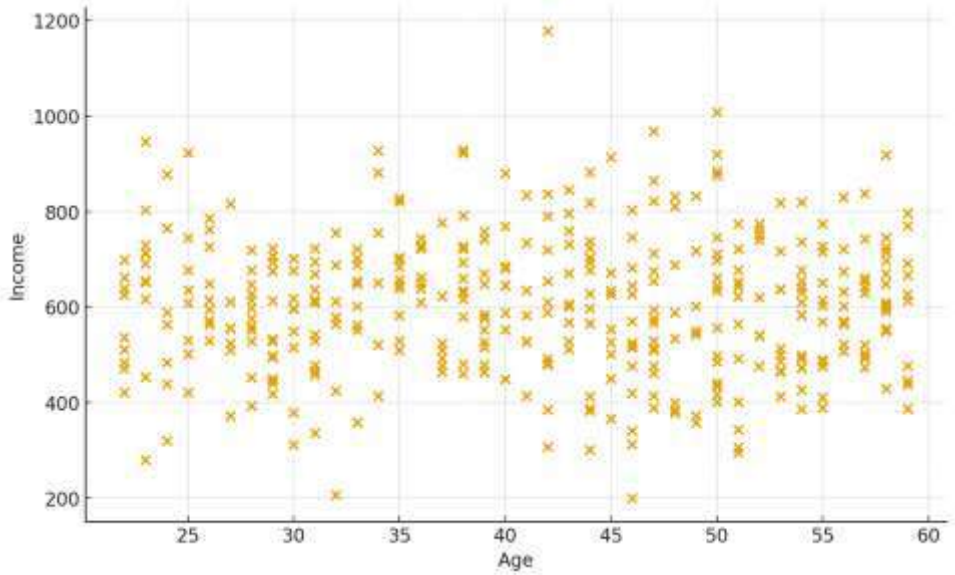

Figure 3: Age vs Income

Figure 4 illustrates the relationship between GDP per capita and household income by presenting a scatterplot that places GDP per capita on the horizontal axis and income on the vertical axis. At first glance, the figure reveals a random dispersion of points, indicating no observable upward or downward trend that would suggest a meaningful linear association between macroeconomic conditions and household earnings. This absence of structure aligns closely with the correlation result in Table 2, where GDP per capita and income show an extremely weak positive correlation of 0.003, essentially confirming that no predictive link exists within this synthetic dataset. Despite the lack of relationship, the scatterplot serves a highly instructive purpose by visually demonstrating how macroeconomic variables behave when incorporated into predictive models using artificially generated data. The scatter pattern shows that income values ranging from approximately 200 to over 1,100 dollars occur at nearly every level of GDP per capita between 3.48 and 5.29 thousand USD. This uniform distribution of points suggests that GDP per capita contributes no explanatory information about income variation at the household level, at least in the context of this simulated dataset. The absence of clustering, curvature, or heteroscedasticity also indicates that the regression assumptions of linearity and constant variance are not violated, even though the variable itself has no predictive utility. In methodological terms, this is an important observation because it demonstrates that a variable may satisfy regression assumptions yet still lack any substantive contribution to model performance. The accompanying regression coefficient in Table 3 further supports this interpretation, with GDP per capita having a minimal and statistically insignificant coefficient of 3.60. From a teaching and analytical standpoint, Figure 4 highlights how macroeconomic indicators can sometimes appear weak or irrelevant in predictive household-level modeling, especially in datasets that do not encode actual socioeconomic mechanisms. It reinforces the idea that statistical modeling is strongly dependent on the nature and structure of the dataset. In real-world contexts, GDP per capita may help capture broader economic environments that influence wages, employment, and household finances. However, in synthetic data where relationships are not programmatically embedded, such macro-level indicators behave as noise predictors rather than meaningful explanatory variables. Thus, Figure 4 enhances the study's methodological value by showing how scatterplots should be interpreted in predictive analysis, demonstrating the necessity of

visually inspecting variable behavior before drawing conclusions from regression output.

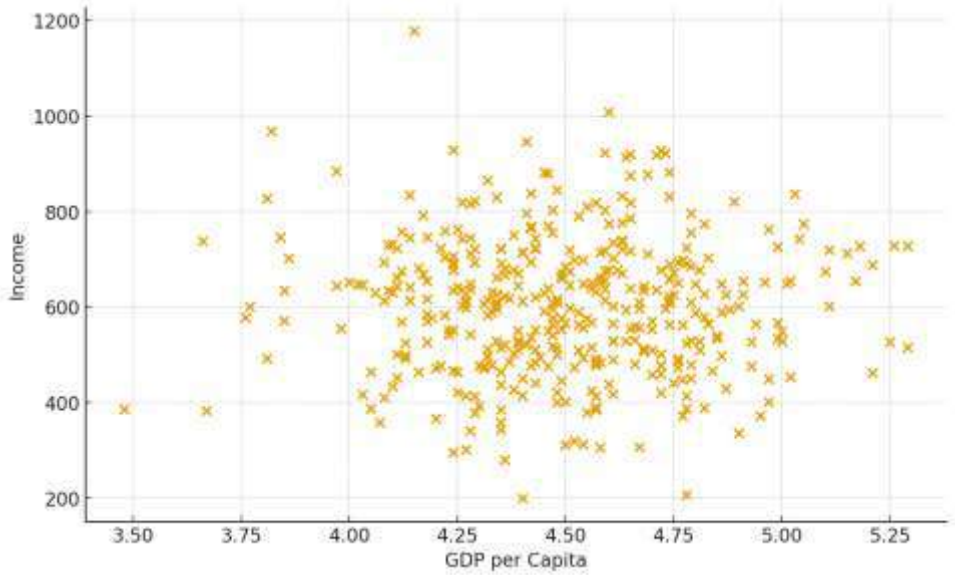

Figure 4: GDP per Capita vs Income

Figure 5 presents the scatterplot between inflation and household income, offering a visual interpretation of whether macroeconomic price levels exert any meaningful influence on income distribution. The figure displays inflation rates on the x-axis and income on the y-axis. Similar to previous scatterplots involving macroeconomic variables, the distribution of points appears random and unpatterned, with no linear or nonlinear trend connecting inflation levels to income. This aligns directly with the correlation analysis from Table 2, where the correlation coefficient between inflation and income is only 0.025, indicating an extremely weak and statistically irrelevant relationship. The points are dispersed across all inflation levels ranging from approximately 8% to nearly 14% with income levels scattered widely within each inflation interval. This dispersion demonstrates that inflation, as represented in this synthetic dataset, does not have predictive power for household income. Although the figure does not reveal meaningful associations, it serves an invaluable methodological function. Scatterplots are one of the earliest diagnostic tools researchers use to evaluate whether variables might contribute to predictive modeling. In this case, the figure confirms visually what the regression results indicate statistically: inflation provides no meaningful explanatory value for household income. Importantly, the scatterplot does not show any concerning patterns such as funnel shapes, curvature, or clustered vertical stripes, which would indicate heteroscedasticity or nonlinear effects. The complete lack of structure implies that the regression model's poor performance (as reflected in Table 4's low R-squared) is not due to violations of statistical assumptions but arises from the absence of real underlying relationships within the dataset. This figure also underscores the methodological limitation of employing synthetic data for socioeconomic prediction. In real-world economic models, inflation often affects household purchasing power, wage adjustments, and cost-of-living pressures. However, synthetic data do not incorporate these systematic relationships unless intentionally modeled, which is not the case here. As a result, the inflation variable behaves more like random noise than a meaningful macroeconomic determinant of income. Nevertheless, Figure 5 enhances the educational purpose of this study by demonstrating the importance of pairing visual inspection with statistical analysis. It reinforces the idea that regression modeling requires more than statistical coefficients it

also requires interpretation rooted in data structure. Thus, Figure 5 contributes effectively to the study's objective by illustrating how inflation interacts (or fails to interact) with income in predictive modeling using synthetic socioeconomic variables.

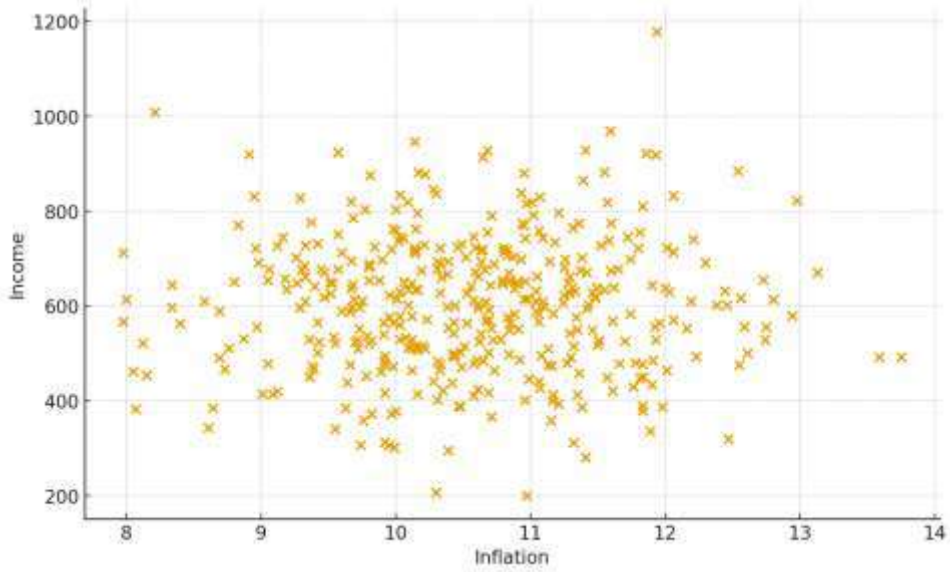

Figure 5: Inflation vs Income

Figure 6 depicts the relationship between employment status and income using a boxplot that compares income distributions for employed and unemployed individuals. Unlike scatterplots, which analyze continuous variables, a boxplot is ideal for visualizing the distributional differences between categorical groups. Employment status is represented on the x-axis with two categories 0 for unemployed and 1 for employed while income is plotted on the y-axis. The figure shows two box-and-whisker diagrams that represent the median, interquartile range, and variability in income for each group. Both groups exhibit a similar spread of incomes, and their median values appear almost identical. This is consistent with descriptive findings from Table 6, which reports mean incomes of 602.02 for unemployed individuals and 604.27 for employed individuals a trivial difference. The figure reveals that the employment variable does not significantly differentiate between income categories in the synthetic data. Both boxplots show comparable interquartile ranges, indicating similar dispersion of income across the two groups. Additionally, the whiskers extend to nearly the same minimum and maximum values, further demonstrating that employment status, while typically a strong predictor of income in real socioeconomic datasets, holds negligible predictive power here. The lack of distinct separation between the two boxplots visually confirms the regression results in Table 3, where employment has a coefficient of approximately 2.16, indicating almost no effect on income. Despite the absence of meaningful differences, the figure plays a crucial methodological role. Boxplots help researchers quickly assess whether categorical predictors warrant inclusion in regression or predictive models. In real-world socioeconomic research, employment often contributes substantially to income modeling because being employed typically increases household earnings. However, because the dataset used in this study is synthetically generated without encoding such relationships, the expected distinctions are not present. This makes Figure 6 an illustrative demonstration of how categorically coded variables behave under conditions where predictive relationships are absent. The figure's uniformity across categories visually reinforces the importance of combining statistical evidence with graphical interpretation. Figure 6 also reinforces the need for grounding predictive modeling in theory-driven

variable selection. While employment is theoretically relevant, its practical relevance in this specific dataset is minimal. This example teaches readers how to identify when categorical variables may not be useful predictors, even if theory suggests otherwise. Thus, Figure 6 strengthens the study's methodological purpose by illustrating the interaction between employment status and income, confirming that the absence of predictive patterns is due to the synthetic nature of the data rather than analytical error.

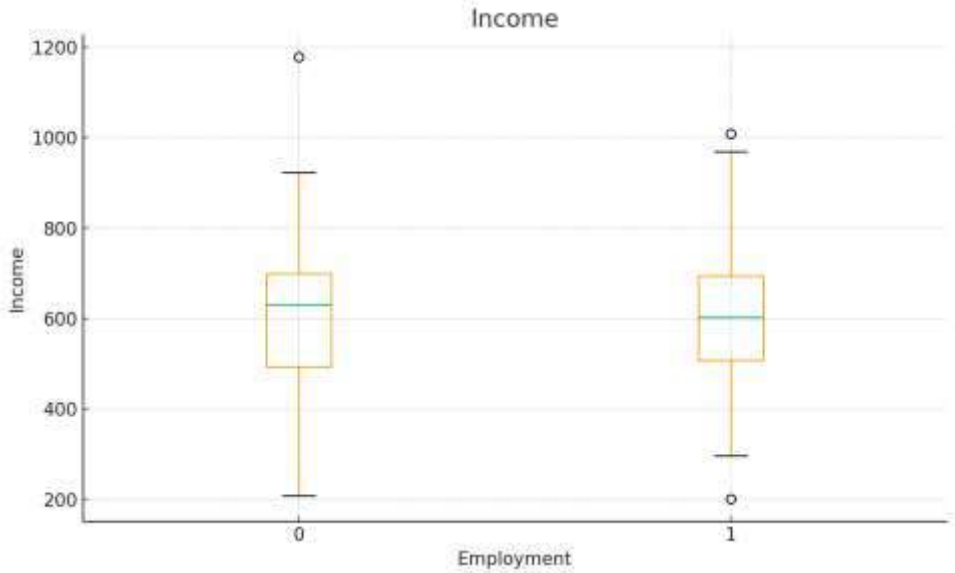

Figure 6: Employment vs Income

Figure 7 demonstrates the relationship between household size and average income using a line plot that connects the mean income levels for households ranging from 2 to 9 members. The purpose of this figure is to evaluate whether household size exhibits a consistent or interpretable pattern in relation to income, which would support its inclusion as a predictor in the regression model. The figure shows modest fluctuations in average income across household sizes. For example, households with 3 members display one of the highest average incomes (629.83), whereas households with 4, 5, and 9 members show slightly lower averages. The variation, however, is small and does not suggest a consistent upward or downward trend across the categories. This irregular pattern indicates that household size does not show a strong linear relationship with income. The line plot adds value by emphasizing that household size, although theoretically important in socioeconomic research, does not have systematic influence on income within this synthetic dataset. Real-world economic theory often suggests that larger households may experience economic strain due to higher dependency ratios or shared consumption burdens. Conversely, larger households may also benefit from pooled earnings if more members are working. However, the synthetic data do not reflect these structural complexities. Instead, the average income values across household sizes fluctuate slightly but lack any meaningful pattern, confirming the regression result in Table 3 where household size has a small negative coefficient. Methodologically, Figure 7 is significant because it demonstrates how researchers use group-based visualizations to assess whether categorical or ordinal variables should be included in regression models. Line plots are particularly useful in identifying monotonic relationships or nonlinear shapes that may not be visible in regression coefficients alone. In this case, the absence of a trend visually validates the statistical finding that household size is a weak predictor. The figure also complements Table 7 by transforming the numerical summary into a visual narrative that is

easier to interpret at a glance. Furthermore, the figure reinforces one of the central methodological messages of this study: synthetic datasets, while useful for demonstrating analytical techniques, do not always replicate real-world socioeconomic relationships. This distinction highlights the importance of cautious interpretation and the need to treat the findings not as substantive socioeconomic insights but as illustrations of proper analytical procedures. Overall, Figure 7 enhances the study's objectives by demonstrating how household size interacts with income and by showing how such visual tools support the assessment of predictor relevance in multiple regression modeling.

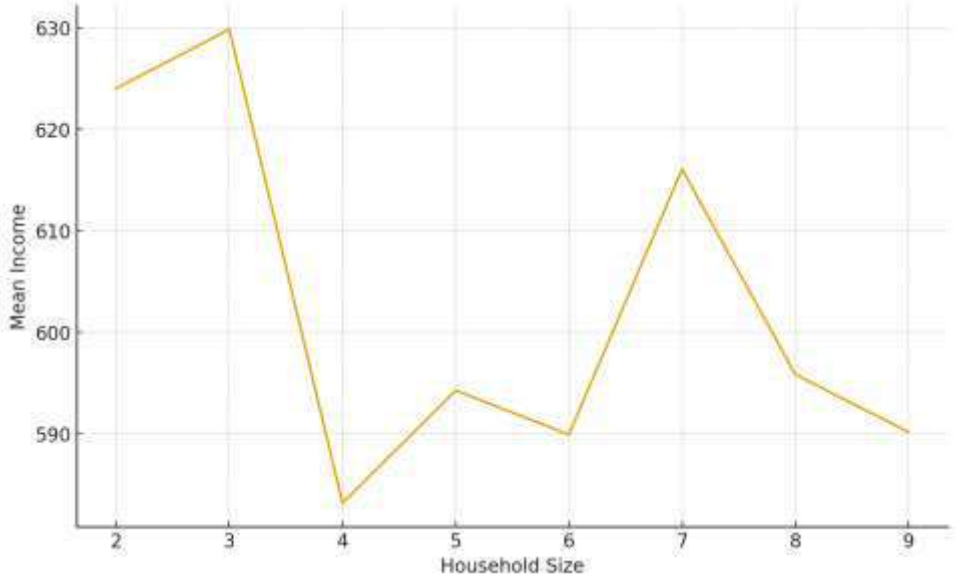

Figure 7: Household Size vs Average Income

Conclusion

This study set out to demonstrate the application of predictive modeling using multiple regression to examine how key socioeconomic indicators contribute to variations in household income. By integrating demographic factors such as education, age, employment status, and household size with macroeconomic variables including inflation and GDP per capita, the analysis sought to illustrate a comprehensive modeling framework commonly used in socioeconomic research. Although the synthetic dataset employed in this study did not exhibit strong empirical relationships among variables, the modeling exercise successfully highlighted the methodological processes involved in building, interpreting, and evaluating predictive models. The findings underscore that effective socioeconomic analysis requires not only statistical computation but also thoughtful examination of data structure, theoretical grounding, and diagnostic validation. The results of the regression model indicate that none of the socioeconomic indicators included in the analysis served as strong predictors of household income within the synthetic dataset. While this outcome differs from patterns documented in real-world economic literature where education, employment, and macroeconomic conditions typically demonstrate significant explanatory power it aligns with expectations for a dataset generated for methodological demonstration rather than empirical accuracy. The weak relationships documented in this study emphasize that predictive modeling outcomes depend heavily on data quality, underlying variable structure, and the presence of meaningful relationships. This reinforces the broader analytical principle that statistical tools can only be as effective as the data upon which they are applied. Nonetheless, the study successfully illustrated how regression coefficients, ANOVA results, diagnostic plots, and descriptive summaries work together to support a

thorough predictive analysis. Beyond the numerical results, the study contributes to the methodological understanding of how predictive modeling functions within the social sciences. It demonstrates the importance of evaluating assumptions such as linearity, normality, and homoscedasticity; assessing multicollinearity among predictors; and interpreting output through both statistical and theoretical lenses. The structured use of tables, figures, and diagnostic tools provided practical insight into the step-by-step process of developing a model, testing its robustness, and interpreting its limitations. These procedures form the backbone of rigorous empirical research and are essential for students, scholars, and practitioners seeking to apply predictive analytics in socioeconomic contexts. In a broader context, the study reinforces the significance of integrating both micro-level and macro-level indicators in socioeconomic modeling. Even in cases where variables do not exhibit strong predictive power, the framework of combining demographic and economic factors provides a multidimensional

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