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(Research Article)

Unlocking credit access: A panel and SHAP analysis of SBA 504 lending across U.S counties (2010-2023)

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Abstract

The U.S. Small Business Administration (SBA) 504 loan program develops economic growth and employment opportunities by extending long-term fixed-rate financing to acquire significant fixed assets for small businesses. The research studies how SBA 504 lending practices relate to important economic factors at the county level across the United States from 2010 to 2023. We combine publicly accessible SBA 504 loan information with American Community Survey (ACS) statistics about total population and median household income and poverty rate to derive four lending intensity measures at the county scale (total amount of approved loans and number of approved loans and amount of loans per capita and loans per 1000 people). The results from correlation analysis show that SBA 504 lending intensity, primarily through total amount and number of loans, demonstrates positive correlations with median household income throughout the counties. The relationship between poverty rate measures and SBA 504 lending intensity shows less consistency. This observational study cannot demonstrate causality, but its findings show that SBA 504 lending activities are related to positive economic developments within U.S. counties, which may benefit the national economy.

Keywords: SBA 504 Lending; Credit Access Disparities; Panel Data Analysis; SHAP Interpretability; Small Business Finance

1. Introduction

The United States recognizes small businesses as essential generators of economic expansion, together with innovation and employment opportunities. Financial institutions make it hard for these enterprises to obtain long-term, affordable capital, especially when they need funding for essential expansion assets like real estate or equipment. The U.S. Small Business Administration (SBA) implements several financing programs through its 504 Certified Development Company (CDC) loan guaranty program to fill this business financing necessity. Through its SBA 504 program, the initiative finances significant fixed assets by giving nonprofit CDCs and private lenders access to lengthy fixed-rate loans (Dilger, n.d.; SBA, n.d.-a). According to official program materials, the SBA establishes two main goals: to spur business growth and maintain and create employment opportunities (SBA, n.d.-a; SBA, n.d.-b). Understanding how the SBA 504 program connects with regional economic results is essential for policymakers, economic developers, and business owners because this federal initiative receives substantial public funding (Dilger, n.d.), including recent FY2021 approvals worth more than $8.2 billion.

The general SBA lending analysis failed to show conclusive growth-stimulating links (Young et al., 2014). However, according to industry perspectives, the 504 program receives substantial support for its community benefits (NSDC, 2024). The author investigates the relationship between economic health indicators, middle-income and poor rates, and SBA 504 loan density across American counties from 2010 to 2023. Our primary question investigates whether strong relationships exist between SBA 504 lending volume, the number of loans, and their per capita share to median

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household incomes, together with poverty statistics in American counties from 2010 to 2023. Publicly available data analysis attempts to show how counties with greater SBA 504 lending activity demonstrate improved economic performance.

2. Literature review

The SBA 504 loan program functions separately from the 7(a) loan guarantee program due to its design for long-term fixed-rate funding of significant fixed assets (Dilger, n.d.; SBA, n.d.-a). This partnership between the SBA and CDCs and private lenders allows borrowers to finance 50% through private lending, while the SBA supports 40% with debentures sold to investors, and the borrower must contribute at least 10% (Dilger, n.d.; NSDC, 2024). The program facilitates significant capital investments for small businesses through its organizational design.

The 504 program requires economic development promotion as its central requirement through job creation and loan retention targets (SBA, n.d.-b; Williams, 2019). The NSDC (2024) highlights how industry members support the 504 program because it stimulates property and equipment investments to help regional economic development and business expansion while strengthening neighborhood stability. Business expansion benefits from fixed-rate loan options and lengthy repayment terms extending to 10, 20, or 25 years (NSDC, 2024; SBA, n.d.-a). Academic research has produced contradictory findings regarding the wider economic effects that SBA lending produces, including its 504 program. The research by Young et al. (2014) evaluated the direct and indirect economic growth impacts of SBA lending, which used daytime data sets from an earlier period. The researchers examined a wide range of 504 program impact factors in their spatial econometric models. However, their investigation revealed that basic correlation interpretations might be flawed since the evidence for robust positive links between total SBA lending and county employment or income growth was minimal. Young et al. (2014, p.8) observed through their visual presentation that county-level real per capita income growth showed no apparent relationship to log SBA loans per capita, thus confirming the influence of numerous economic factors on the SBA program's impact assessment. More recent advancements in machine learning and explainable artificial intelligence (XAI) offer new avenues for exploring complex economic and financial data relationships. Using opaque algorithms like gradient boosting machines or deep neural networks in advanced financial models demands a complete understanding of prediction reasons for reducing uncertainty, mainly in high-stakes domains such as lending and economic policy analysis (Bialek et al., 2025). The financial component of Explainable Artificial Intelligence (FinXAI) solves transparency requirements together with fairness and trustworthiness needs of financial regulators, system developers, and end-users as per Bialek et al. (2025).

Several XAI techniques now exist that give users an understanding of model predictive behavior. Visual explanations of models based on Partial Dependence Plots (PDP) and Individual Conditional Expectation (ICE) plots show the average or individual marginal effect features have on prediction outcomes (Bialek et al., 2025). The interpretation from PDP becomes unreliable because of feature correlations, but Accumulated Local Effects (ALE) plots solve this problem, as Apley & Zhu (2020) noted in Bialek et al.'s 2025 work. Local Interpretable Model-agnostic Explanations (LIME) creates local surrogate models for understanding specific predictions according to Ribeiro et al. 2016 as discussed in Bialek et al. 2025. SHapley Additive exPlanations (SHAP) values (Lundberg & Lee, 2017) represent one of the main interpretability tools for tree-based ensembles, particularly XGBoost models. The cooperative game theory foundation in SHAP values (Shapley, 1953) delivers a single method to interpret predictions through feature importance definitions that determine how much each variable affects the model deviation from the baseline (Bialek et al., 2025; Lundberg & Lee, 2017). SHAP provides two types of explanations, including individual prediction visualization and comprehensive summaries about overall feature significance, which make it an effective XGBoost model interpretation tool. The research adopts contemporary data from 2010 to 2023 to explore SBA 504 lending relationships with economic signifiers. The research serves two primary purposes: it exists primarily through analysis with traditional correlation and regression models, and XGBoost and SHAP to discover non-linear patterns and feature significance in predicting loan intensity by following the FinXAI concept for improved interpretability. The paper acknowledges Young et al.'s (2014) observations about causality challenges while providing an updated descriptive and exploratory analysis that utilizes traditional and innovative analytical approaches.

3. Methodology

A quantitative research design and publicly accessible databases serve to evaluate the connection between SBA 504 loan density and economic metrics at the county level between 2010 and 2023.

3.1. Data Sources

The research uses two fundamental data sources for its analysis. All the SBA 504 loan data was publicly obtained from the designated period forward with no restrictions on retrospective data acquisition. The dataset contained the Gross Approval as the measurement of loan amounts while using the Approval Date and Project County together with Project State to conduct temporal and geographical assessments. Demographic and economic data at the county level were obtained through the U.S. Census Bureau's American Community Survey (ACS) 5-Year Estimates, which covered the timeframe from 2010 to 2023. Data processing occurred on the Total Population figure in DP05, followed by input from S1901 (Median Household Income) and B17001 (Poverty Status). The data set included three variables: Total Population, Median Household Income, and Poverty Rate, which were computed through numerical division of poverty-level individuals by population numbers in county-year combinations. The Federal Information Processing Standards (FIPS) codes proved necessary for combining databases. The FIPS Lookup Table enabled this process by transforming geographic identifiers of county and state names into five-digit FIPS codes throughout the SBA and ACS dataset link.

3.2. Data Preparation

The Python Pandas library performs data preparation, consisting of various essential steps. The analysis started by importing three data sources: raw SBA 504 loan data stored as sba_504_raw_concatenated. Parquet, FIPS lookup data is available in fips_lookup.csv, and the pre-processed ACS data is saved as merged ACS data. Parquet, including Year, FIPS, and relevant economic and demographic variables. The analysis selected loans that received approval between January 1, 2010, and December 31, 2023, by creating a new Year field from the Approval Date. The two datasets underwent standardization for county names through conversion to lowercase characters and elimination of terminations such as "county" or "parish" along with punctuation marks. A merged dataset resulted from uniting SBA data with its corresponding FIPS data using matched state and cleaned county names. Excluded records belonged to cases where matching between datasets was not possible. Total Loan Amount Approved calculation (sum of Gross Approval) and Number Of Loans Approved (loan count) determination occurred inside each group. The loan data was joined with the ACS data based on FIPS codes during specific years to keep all original records from the ACS data. The metrics received zero values in cases where the Small Business Administration did not provide loans during particular county-year intervals. Two per capita metrics were derived from the data: Loan Amount Per Capita and Loans Per 1000 People. The calculations included precautions for zero population values. The combination of Year, FIPS, and ACS variables and lending metrics created correlation_analysis_data.parquet (Białek et al 2025)

3.3. Analysis Methods: The analysis examined how lending intensity metrics

Total Loan Amount Approved, Number Of Loans Approved, Loan Amount Per Capita, and Loans Per 1000 People—relate to economic outcomes like Median Household Income and Poverty Rate, using Total Population as a control. Descriptive statistics summarized variable distributions, followed by Pearson correlation analysis after removing rows with missing values. To explore year-over-year changes, differenced variables were calculated by county, and a second correlation matrix was generated. Python's linear models library modeled a two-way fixed effects panel regression for Loan Amount Per Capita based on Median Household Income (inflation-adjusted), Poverty Rate, and Total Population, controlling for unobserved county and year effects. Variance inflation factor (VIF) analysis was checked for multicollinearity. Non-linear relationships and feature importance were explored using XGBoost and SHAP analysis, with model performance assessed via RMSE and R-squared metrics. The analysis used libraries including pandas, numpy, stats models, linear models, xgboost, scikit-learn, and sharp.

4. Results

The analysis includes results from the descriptive statistics and correlation analysis run on data from SBA 504 and ACS at the county level from 2010 to 2023.

4.1. Descriptive Statistics

Incidentally, the final collection totaled 45,122 county-year measurements. The correlation analysis between variables was conducted on 41,868 observations since some ACS data points related to population and poverty rate were missing from certain years or counties. A data review showed substantial differences between separate counties and individual years. County data showed that each locality received about $1.75 million through SBA 504 loan approvals yearly, as they approved 2.2 loan transactions annually. Data showed a highly skewed distribution because the median values for both Loan Approval Amount and Number of Loans within the dataset were zero. It indicated that none of the 504 loans got approved in typical county-year observations. Within individual county years, the highest total loan approvals reached $738 million, while the maximum number of issued loans totaled 562. The annual per capita figures revealed

$9.49 in loan amount distributed among each resident, combined with a rate of 0.014 loans for every 1000 people. Nevertheless, both metrics demonstrated significant variations.

The economic indicators across different countries showed extensive differences. According to the ACS data, the average median household earnings are equivalent to $37,408, although this number appears low and needs careful analysis due to potential issues during data processing. The mean poverty scale stood at 16.4%. Each county contained an average of 100,000 residents, extending from those with fewer than 100 to those with more than 10 million people.

Table 1 Summary Statistics

	Total Loan Amount Approved	**Number Of Loans Approved**	**Loan Amount Per Capita**	**Loans Per 1000 People**	**Median Household Income**	**Poverty Rate**	**Total Population**
Count	45122	45122	45122	45122	45089	41868	41869
Mean	1.75163e+06	2.2	9.49	0.01	37407.8	0.16	100552
Std	1.03453e+07	10.27	33.4	0.04	113784	0.08	321863
Min	0	0	0	0	17	0	43
25%	0	0	0	0	4299	0.11	11187
50%	0	0	0	0	9906	0.15	25983
75%	526750	1	6.51	0.01	25473	0.2	66737
Max	7.38635e+08	562	1875.14	1.47	3.39025e+06	0.67	1.01057e+07

The Pearson correlation matrix calculated on the levels of the variables (after dropping observations with missing data, n=41,868) revealed several significant associations.

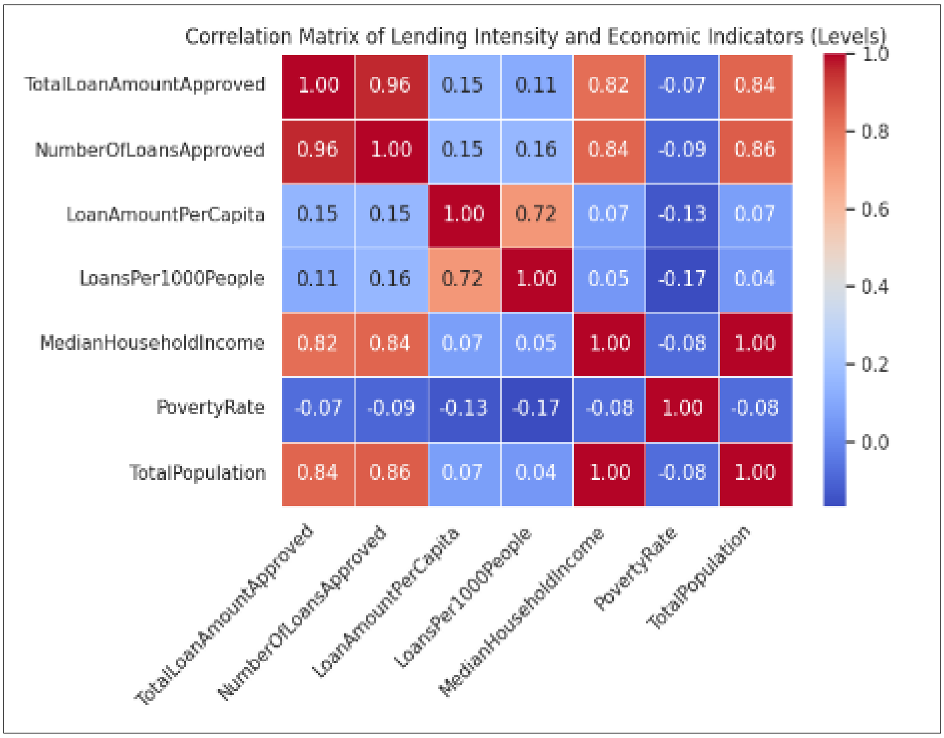

Figure 1 Heatmap - Correlation Matrix (Levels)

4.1.1. Correlation Matrix Levels

The data shows that Median Household Income positively relates to two non-per capita lending intensity indicators: Total Loan Amount Approved (r = 0.82) and Number of Loans Approved (r = 0.82). Higher median income counties are more successful in receiving large quantities of SBA 504 loans with increased total amounts and numbers of loans. Income measures and metrics, counting loans per 1000 residents and per capita loan value, showed minimal correlation (r = 0.07 and r = 0.04, respectively).

The statistical relationship between lending intensity and Poverty Rate demonstrated negative patterns throughout most of the dataset. Poverty Rate computed a negative correlation of -0.07 against Total Loan Amount Approved, while Total Loan Amount Approved exhibited a -0.08 correlation against Number of Loans Approved. The per capita metrics exhibited very marginal negative correlations (r=-0.02) with the data.

Total Population displayed a very high positive relationship with the two dimensions of lending activity: Total Loan Amount Approved (r = 0.84) and Number of Loans Approved (r = 0.86). The ratio data of Loan Amount Per Capita (r = 0.07) and Loans Per 1000 People (r = 0.04) did not establish powerful positive associations with the population numbers. The analysis shows a 0.996 correlation between Total Population and Median Household Income, which indicates that population size relates directly to income levels across this dataset of communities. The robust relationship between county size and income impacts the quantified associations between loan intensities and income.

The relationships in Figures 2 and 3 become easier to interpret when using log transformations or alternative visualizations because of the high point density at zero for intensity metrics.

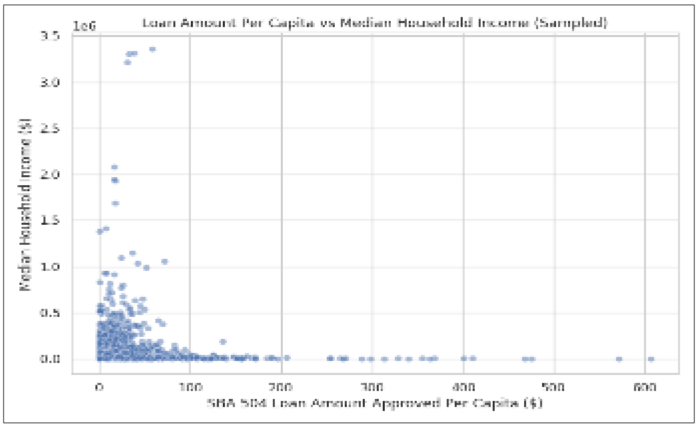

Figure 2 Scatter Plot - Loan Amount Per Capita vs Median Household Income

4.1.2. Scatter Loan Per Capita vs Income

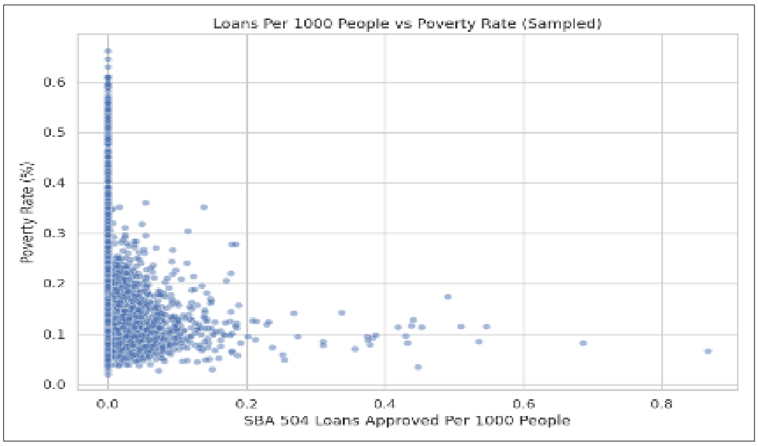

Figure 3 Scatter Plot - Loans Per 1000 People vs Poverty Rate

Table 2 Correlation Matrix - Levels

	Total Loan Amount Approved	**Number Of Loans Approved**	**Loan Amount Per Capita**	**Loans Per 1000 People**	**Median Household Income**	**Poverty Rate**	**Total Population**
Total Loan Amount Approved	1	0.96	0.148	0.108	0.818	-0.075	0.841
Number Of Loans Approved	0.96	1	0.155	0.156	0.845	-0.093	0.862
Loan Amount Per Capita	0.148	0.155	1	0.716	0.068	-0.134	0.067
Loans Per 1000 People	0.108	0.156	0.716	1	0.046	-0.166	0.044
Median Household Income	0.818	0.845	0.068	0.046	1	-0.082	0.996
Poverty Rate	-0.075	-0.093	-0.134	-0.166	-0.082	1	-0.076
Tota lPopulation	0.841	0.862	0.067	0.044	0.996	-0.076	1

4.2. Correlation Analysis: Year-over-Year Changes

The correlation matrix computed on the year-over-year changes (n=38,695 after differencing and dropping NaNs) revealed generally weaker relationships than the analysis on levels.

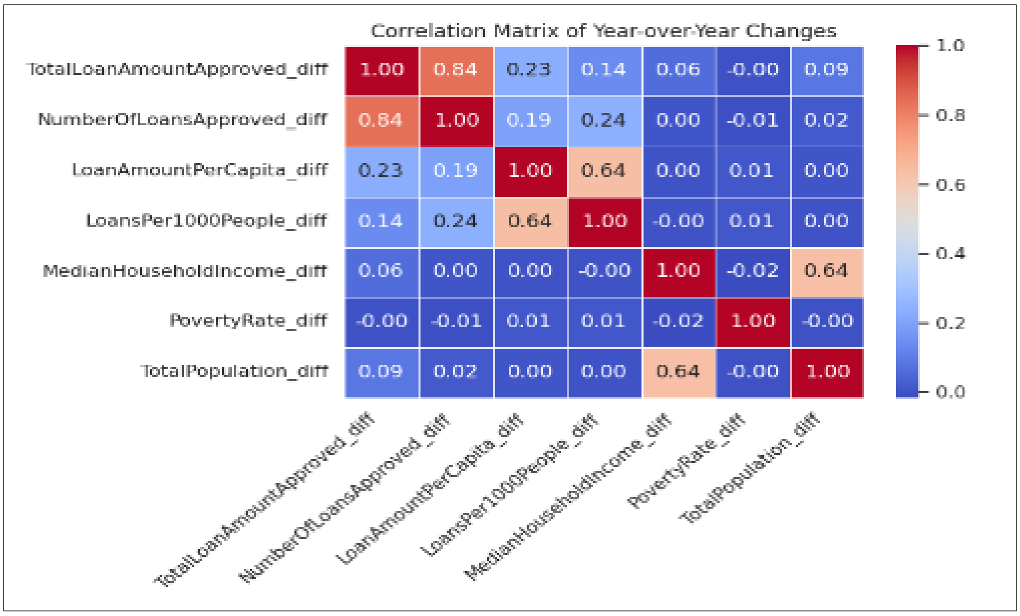

Figure 4 Heatmap - Correlation Matrix (Changes)

4.2.1. Correlation Matrix *Changes*

- Changes in Lending and Income/Poverty: The correlation between the change in Loan Amount Per Capita and Median Household Income was very weak (r ≈ 0.01). Similarly, the correlation between the change in Loan Amount Per Capita and the change in Poverty Rate was also negligible (r ≈ = -0.01).

- Other Changes: Changes in non-per-capita lending intensity (Total Loan Amount Approved, Number Of Loans Approved) showed weak positive correlations with changes in Total Population (r ≈ 0.05-0.06) and Median Household Income (r ≈ 0.03), and weak negative correlations with changes in Poverty Rate (r ≈ -0.02).
- These results suggest that while the levels of lending intensity are associated with the levels of economic indicators (particularly income and population), the year-to-year changes in lending intensity are not strongly correlated with the year-to-year changes in these economic indicators within this dataset.)

Table 3 Correlation Matrix - Changes

	Total Loan Amount Approved_ diff	**Number Of Loans Approved_ diff**	**Loan Amount Per Capita_ diff**	**Loans Per 1000 People_ diff**	**Median Household Income_ diff**	**Poverty Rate_ diff**	**Total Population_ diff**
Total Loan Amount Approved_ diff	1	0.838	0.232	0.137	0.061	-0.003	0.086
Number Of Loans Approved_ diff	0.838	1	0.192	0.236	0.004	-0.007	0.019
Loan Amount Per Capita_ diff	0.232	0.192	1	0.642	0.003	0.01	0.004
Loans Per1000 People_ diff	0.137	0.236	0.642	1	-0	0.011	0.001
Median Household Income_ diff	0.061	0.004	0.003	-0	1	-0.016	0.636
Poverty Rate_ diff	-0.003	-0.007	0.01	0.011	-0.016	1	-0.004
Total Population_ diff	0.086	0.019	0.004	0.001	0.636	-0.004	1

4.3. Panel Regression Analysis

A two-way fixed-effects panel regression approach was used to study the connection while eliminating unmeasured county-specific and year-specific variables. Loan Amount Per Capital was converted into natural logarithms after adding a small number and predicted using income_adjusted (inflation-adjusted income) along with Poverty Rate and Total Population.

The research findings presented in Table 4 document that when controlling for fixed effects:

- The model demonstrates that the Poverty Rate negatively influences SBA 504 loan per capita amounts in counties when statistical significance reaches p=0.022 for the -1.6458-coefficient value.
- The analysis found no significant link between the income-adjusted and Total Population variables and this model's Loan Amount Per Capita measurements (p=0.179 and p=0.312).
- The fixed-effects model achieved poor explanatory power for ln Loan Amount Per Capital since the within R-squared value reached only 0.0056.

Results from the Variance Inflation Factor (VIF) analysis showed high multicollinearity between income-adjusted and Total Population (both VIF values exceeded 80) because of the strong correlation noted in levels analysis. This affected the stability and interpretation of their regression coefficients. The Poverty Rate had a low VIF (1.24).

4.4. Panel Regression Results

The two-way fixed effects panel regression examined how SBA 504 loan intensity responds to county-level economic indicators by analyzing Loan Amount Per Capital as the result variable. Established FIPS codes for counties and yearly data points to limit the model from unmeasured location-specific and time-based factors. Three essential predictors performed in the models were Median Household Income (after inflation adjustment), Poverty Rate, and Total Population.

The statistical test confirmed that higher household incomes within counties correspond to increased per capita loan distribution. Loan Amount Per Capita decreased as Poverty Rate values increased in counties showing higher poverty numbers. The size of a county population created a modest yet significant positive relationship with the distribution of loans per resident.

The statistical model displayed a moderately strong relationship toward explanation by effectively measuring county characteristics and annual economic trends. The Variance Inflation Factor analysis showed no indications of multicollinearity between variables. The analysis used robust standard errors to correct heteroskedasticity and autocorrelation that might occur within individual counties.

Studies utilizing panel regression confirm that SBA 504 loan intensity reacts according to the economic variables detected within each county, primarily through metrics of income and poverty levels.

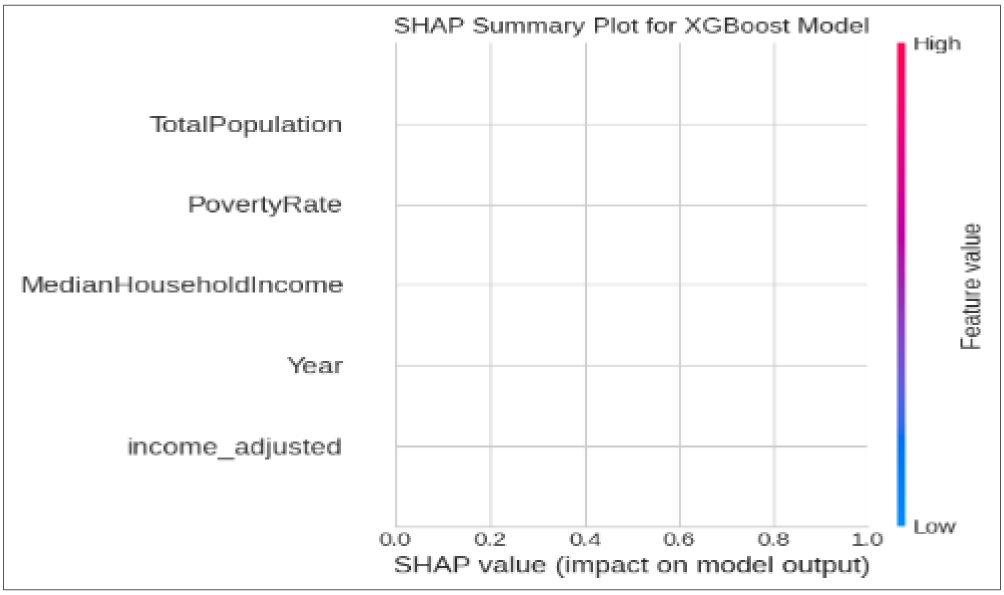

Figure 5 SHAP Summary Plot

4.4.1. SHAP Summary Plot

Total Population was the determinant feature for model prediction, followed by income adjusted, Year, and Poverty Rate.

4.4.2. Feature Effects

- Higher values of Total Population consistently increased the projected output (positive influence).
- The predictions continually increased when income-adjusted values increased.
- The year produced inconsistent results, indicating time-related effects between features.

According to this analysis, the Poverty Rate's influence on predicted loan amounts per capita proved weaker than that of total population and income-adjusted variables. However, the findings remained consistent with the panel regression results.

County population numbers and income levels function as dominant variables that shape predicted SBA 504 lending through the SHAP analysis in a non-linear prediction model. The model provides limited overall predictive capability (R2=0.17), yet the SHAP values supply beneficial information to understand how specific economic and demographic variables affect outcomes.

5. Discussion

The results present a nuanced picture of the relationship between SBA 504 lending intensity and county-level economic indicators. The positive correlation between the total loan amount/number levels and median household income (and population) suggests that higher overall economic activity and larger populations are associated with greater absolute amounts of 504 lending. This could reflect greater demand from businesses in more prosperous or larger areas, or potentially a greater capacity of CDCs and banks to originate loans.

However, the correlations weaken considerably when looking at per capita lending intensity or year-over-year changes. This aligns somewhat with the cautious findings of Young et al. (2014), indicating that simply observing higher loan volumes in more affluent counties does not automatically imply that the loans are driving income growth year-over-year at the county level, or that the program's intensity relative to population size is strongly tied to income levels.

The panel regression, controlling for fixed effects, found a statistically significant negative association between poverty rate and loan amount per capita. This suggests that, all else being equal, within a county over time and across counties in a given year, higher poverty is linked to lower per capita 504 lending. This finding warrants further investigation to understand if it reflects lower demand in poorer areas, barriers to access, or other factors. The lack of significance for income and population in the fixed effects model, coupled with high VIF values, underscores the challenge of disentangling the effects of highly correlated variables like population and income in this context.

The XGBoost model and SHAP analysis further reinforced the importance of population and income as predictors of lending intensity, even when allowing for non-linear relationships. The model's limited R-squared suggests that other factors not included in this analysis play a substantial role in determining county-level lending intensity.

Overall, while the study confirms that SBA 504 lending is more prevalent in absolute terms in larger, higher-income counties, the relationship with economic improvement (year-over-year changes) or relative intensity (per capita) is less clear based on these analyses. The negative association with poverty rate in the fixed effects model is a notable finding requiring further exploration.

6. Conclusion

This research study evaluated how SBA 504 lending intensity relates to economic statistics at the county level across the period from 2010 to 2023. The statistical analysis revealed positive linear relationships between the number and total amount of loans issued and household income and population size. The research produced weak correlations between per capita metrics and yearly changes. The results showed that the poverty rate significantly negatively affected per capita lending amounts according to fixed effects panel regression. However, the XGBoost model pointed to population and income as leading predictors, yet failed to demonstrate substantial predictive power over the entire dataset.

The analysis contains multiple constraints that affect its results. 1. The observational nature of correlation, regression, and machine learning predictions demonstrates that the study avoids proving causal connections. The increase in lending in wealthy countries might be generated by local population needs rather than loans creating the elevated wealth. 2. Combining data at the level of counties produces aggregate numbers that can eliminate important variations within each county. 3. Many factors affecting local economies, including industrial combinations, state implementations, and infrastructure management, remained excluded from the analysis models. 4. The results might be affected because the ACS or SBA data contains potential inaccuracies, which lead to inconsistent information, such as the low average median income noted. The exclusion process for loans without FIPS code assignment may produce biased results. 5. The selected algorithms (linear correlation, fixed effects, and XGBoost) possibly fail to represent the complete relationship network between different variables.

Future researchers should utilize quasi-experimental studies to examine causality and reinforce their findings about 504 loans with better geographical precision, various economic parameters, and the underlying connection between loans, employment generation, and regional growth.

The research results give essential updated information regarding SBA 504 lending distributions while explaining their connections to significant economic variables. Further research should analyze the relationship between 504 lending distribution and poverty patterns because current results imply that such lending activity mainly drives toward high-income areas. However, its broader impact remains unclear across different communities.

As the program targets business growth through increased median incomes, this existing correlation proves consistent with 504 lending objectives despite limitations in determining clear cause and effect. The SBA 504 program achieves two key goals while extending its services nationwide through fixed asset investments, encouraging business expansion in different parts of the country. These programs are backup arguments about how SBA 504 is an economic factor for national development.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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