

Loading Packages

```
import pandas as pd
from utils import custom_info
import numpy as np
import seaborn as sns
from scipy import stats
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
```

Part A: Load the endline data.

```
endline_df = pd.read_stata('endline.dta')
```

We can observe totformalborrow_24, totinformalborrow_24, hhinc parameters have Null Values

```
custom_info(endline_df)
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 4160 entries, 0 to 4159
```

```
Data columns (total 7 columns):
```

	Non-Null Count	Null Count	Unique Values	Dtype
Column				
hhid	4160	0	4160	float64
group_id	4160	0	101	float32
totformalborrow_24	2939	1221	413	object
totinformalborrow_24	2621	1539	346	object
hhinc	3916	244	802	object
hhnomembers	4160	0	14	int8
survey_round	4160	0	3	object
Total Rows	4160			

```
memory usage: 187328 bytes
```

```
endline_df
```

	hhid	group_id	totformalborrow_24	totinformalborrow_24
hhinc \				
0	86.0	3.0	120000	69000
NaN				
1	147.0	96.0	NaN	300000
10700				
2	179.0	4.0	50000	96000
4300				
3	192.0	76.0	140000	NaN
NaN				
4	261.0	14.0	NaN	NaN
60000				
...

```

.
4155  185874.0      30.0      6000      NaN
10750
4156  185875.0      44.0      NaN      NaN
7000
4157  185876.0      32.0      NaN      NaN
NaN
4158  185877.0     142.0      NaN      NaN
1000
4159  185878.0     152.0      NaN      NaN
500

      hhnomembers  survey_round
0              4  Endline II
1              4  Endline II
2              5  Endline II
3              2  Endline II
4              7  Endline I
...
4155          3  Endline III
4156          4  Endline III
4157          3  Endline III
4158          2  Endline III
4159          1  Endline III

[4160 rows x 7 columns]

```

Part B: Recode household debt and income variables as numeric values instead of strings, and replace "None" with Zero

```

cols_to_convert = ['totformalborrow_24', 'totinformalborrow_24',
'hhinc']

for col in cols_to_convert:
    endline_df[col] = pd.to_numeric(endline_df[col], errors='coerce')
    endline_df[col] = endline_df[col].fillna(0).astype(int)

endline_df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4160 entries, 0 to 4159
Data columns (total 7 columns):
#   Column              Non-Null Count  Dtype
---  -
0   hhid                4160 non-null   float64

```

```

1  group_id          4160 non-null float32
2  totformalborrow_24 4160 non-null int64
3  totinformalborrow_24 4160 non-null int64
4  hhinc             4160 non-null int64
5  hhnomembers        4160 non-null int8
6  survey_round       4160 non-null object
dtypes: float32(1), float64(1), int64(3), int8(1), object(1)
memory usage: 182.9+ KB

```

We can see hhinc, totformalborrow_24, totalinformalborrow_24 follow skewed distribution, hence replacing with median is the best option, and also adding a column called hhinc_24 for 24 months income of the family (Assuming per month (30 days = 1 month) remains constant for 24 months

```

endline_df['hhinc_24'] = endline_df['hhinc'].fillna(0) * 24
endline_df

```

	hhid	group_id	totformalborrow_24	totinformalborrow_24
hhinc \				
0	86.0	3.0	120000	69000
0				
1	147.0	96.0	0	300000
10700				
2	179.0	4.0	50000	96000
4300				
3	192.0	76.0	140000	0
0				
4	261.0	14.0	0	0
60000				
...
...				
4155	185874.0	30.0	6000	0
10750				
4156	185875.0	44.0	0	0
7000				
4157	185876.0	32.0	0	0
0				
4158	185877.0	142.0	0	0
1000				
4159	185878.0	152.0	0	0
500				

	hhnomembers	survey_round	hhinc_24
0	4	Endline II	0
1	4	Endline II	256800
2	5	Endline II	103200

3	2	Endline II	0
4	7	Endline I	1440000
...
4155	3	Endline III	258000
4156	4	Endline III	168000
4157	3	Endline III	0
4158	2	Endline III	24000
4159	1	Endline III	12000

[4160 rows x 8 columns]

```

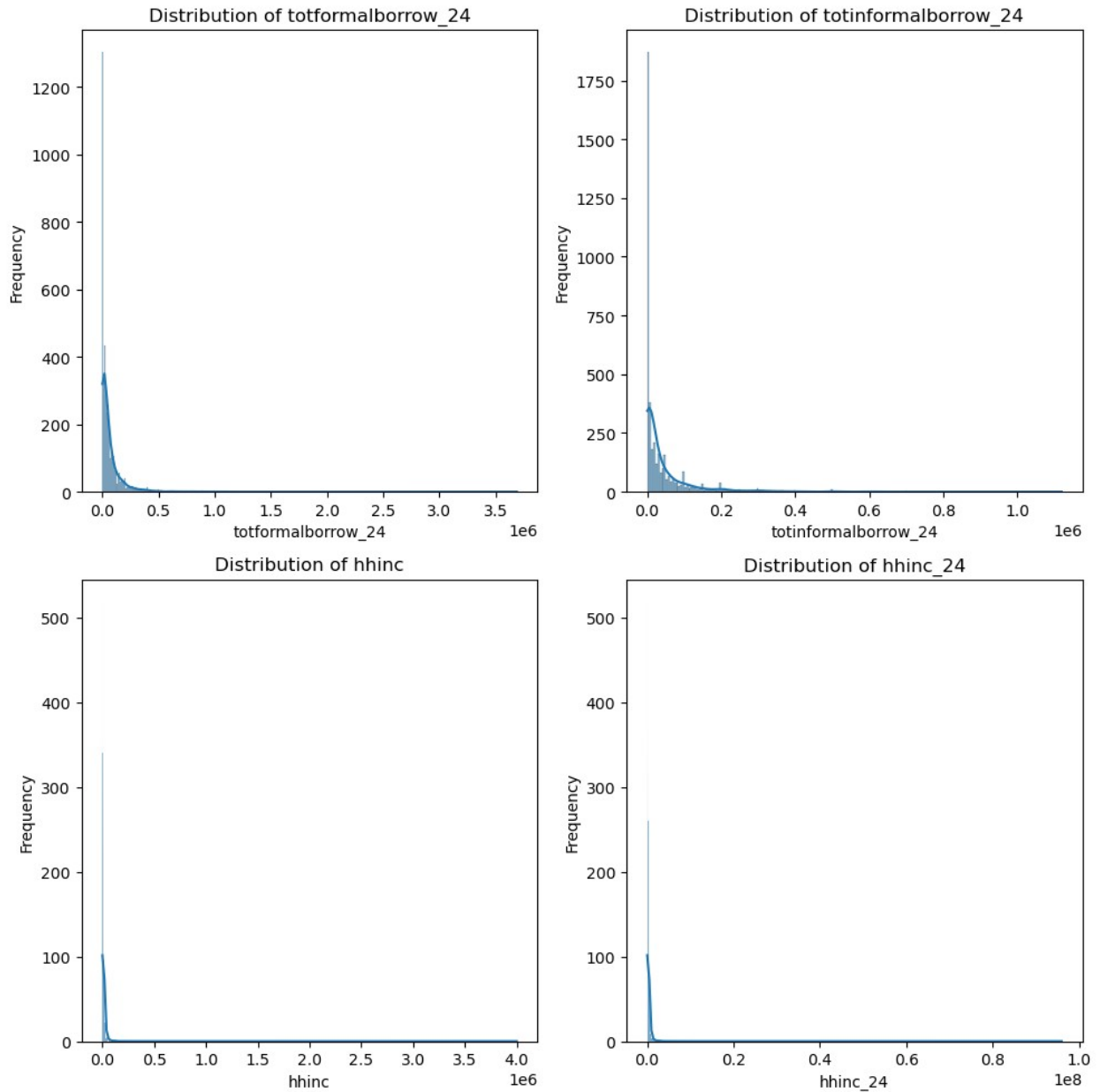
numeric_features = ['totformalborrow_24', 'totinformalborrow_24',
                    'hhinc', 'hhinc_24']
num_rows = 2
num_cols = 2
fig, axes = plt.subplots(num_rows, num_cols, figsize=(10, 10))

axes = axes.flatten()

for i, feature in enumerate(numeric_features):
    sns.histplot(endline_df[feature], kde=True, ax=axes[i])
    axes[i].set_title(f'Distribution of {feature}')
    axes[i].set_xlabel(feature)
    axes[i].set_ylabel('Frequency')

plt.tight_layout()
plt.show()

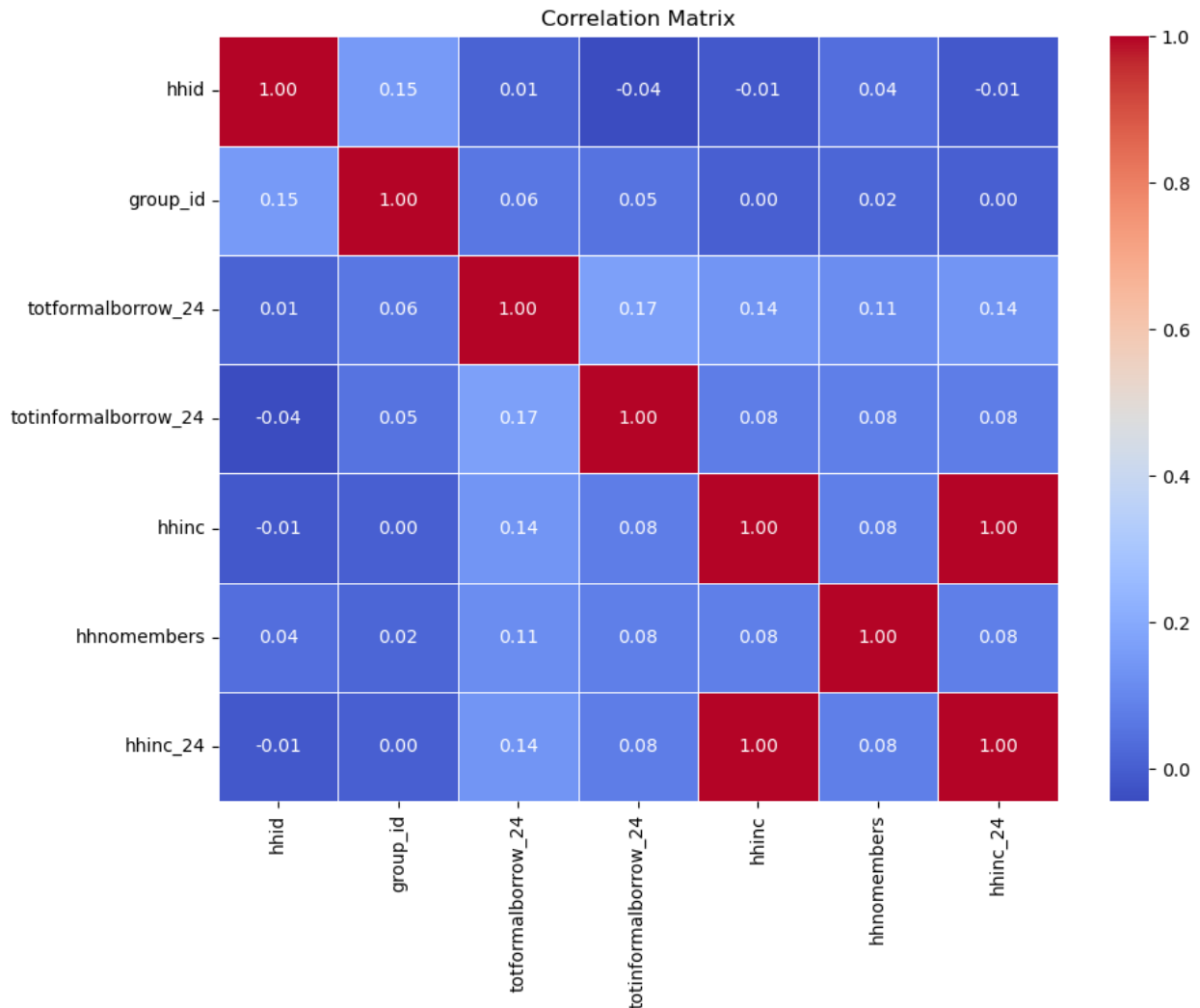
```



```
# Select only the numeric columns
numeric_cols = endline_df.select_dtypes(include=[np.number]).columns

# Create a new DataFrame with only the numeric columns
numeric_df = endline_df[numeric_cols]

plt.figure(figsize=(10, 8))
sns.heatmap(numeric_df.corr(), annot=True, cmap='coolwarm', fmt=".2f",
            linewidths=0.5)
plt.title('Correlation Matrix')
plt.tight_layout()
plt.show()
```



Now we have dataset which has imputation with the median and extra column hhinc_24

```

endline_df = pd.read_stata('endline.dta')

# Columns to convert and handle missing values
cols_to_convert = ['totformalborrow_24', 'totinformalborrow_24',
'hhinc']

# Convert columns to numeric and replace missing values with the
median
for col in cols_to_convert:
    endline_df[col] = pd.to_numeric(endline_df[col], errors='coerce')
    median_value = endline_df[col].median()
    endline_df[col] = endline_df[col].fillna(median_value).astype(int)

# Create a new column 'hhinc_24' by multiplying 'hhinc' by 24
endline_df['hhinc_24'] = endline_df['hhinc'] * 24

```

```
custom_info(endline_df)
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 4160 entries, 0 to 4159
```

```
Data columns (total 8 columns):
```

	Non-Null Count	Null Count	Unique Values	Dtype
Column				
hhid	4160	0	4160	float64
group_id	4160	0	101	float32
totformalborrow_24	4160	0	412	int64
totinformalborrow_24	4160	0	345	int64
hhinc	4160	0	801	int64
hhnomembers	4160	0	14	int8
survey_round	4160	0	3	object
hhinc_24	4160	0	801	int64
Total Rows	4160			

```
memory usage: 220608 bytes
```

```
endline_df.describe()
```

	hhid	group_id	totformalborrow_24
count	4160.000000	4160.000000	4.160000e+03
mean	105520.079087	113.227402	7.904370e+04
std	47127.152425	53.617245	1.219337e+05
min	86.000000	1.000000	2.000000e+03
25%	78535.250000	76.000000	3.487500e+04
50%	114347.500000	133.000000	5.000000e+04
75%	125841.000000	159.000000	7.500000e+04
max	185878.000000	183.000000	3.690000e+06

	hhinc	hhnomembers	hhinc_24
count	4.160000e+03	4160.000000	4.160000e+03
mean	1.219746e+04	4.514423	2.927390e+05
std	6.737758e+04	1.855772	1.617062e+06
min	3.000000e+01	1.000000	7.200000e+02
25%	3.400000e+03	3.000000	8.160000e+04
50%	6.700000e+03	4.000000	1.608000e+05
75%	1.100000e+04	6.000000	2.640000e+05
max	4.000000e+06	16.000000	9.600000e+07

Part 3: Browse the variables in this dataset, and write a few sentences about the financial status of households in this sample, supported by this data. Feel free to use a table or figure to support your argument.

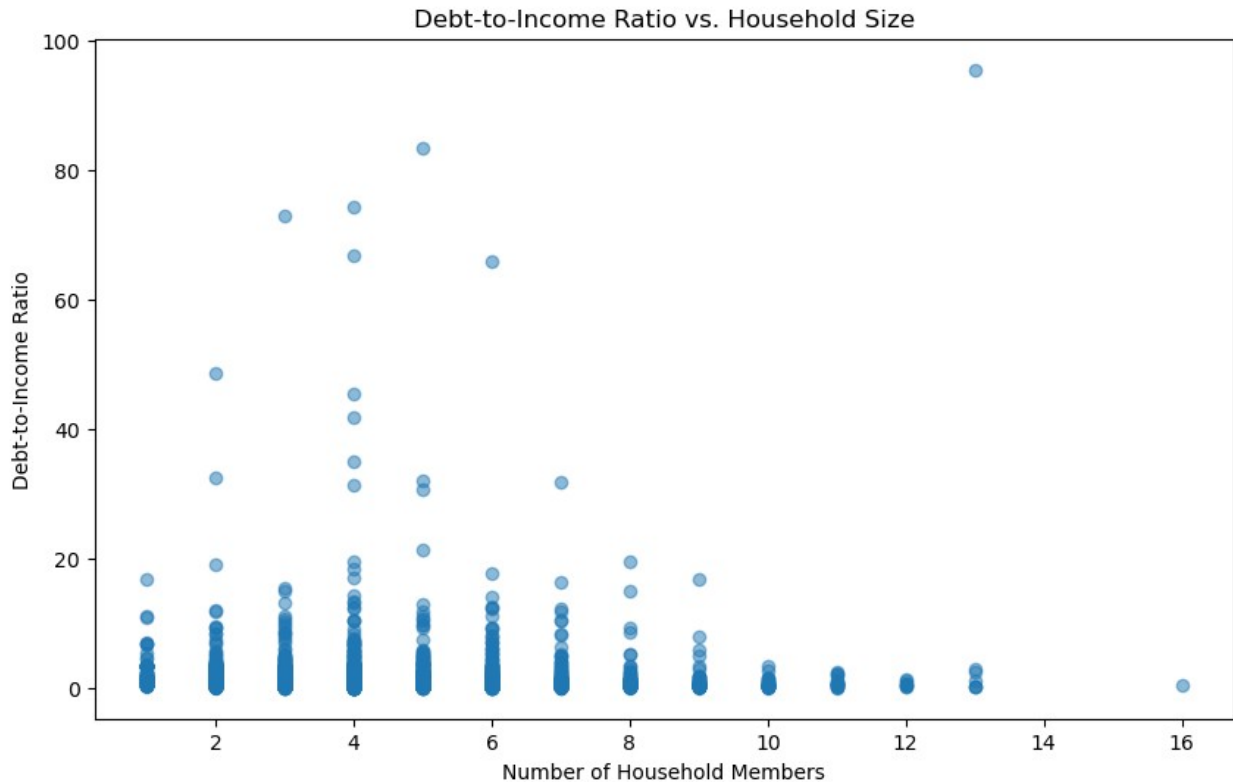
All households have a debt-to-income ratio greater than 1, indicating that their total borrowing over the past 24 months exceeds their total income over the same period. This suggests a high level of indebtedness relative to income, which could imply financial stress.

```
endline_df1 = endline_df.copy()

# Calculate total borrowed amount and normalize income to 24 months
endline_df1['total_borrowed'] = endline_df1['totformalborrow_24'] +
endline_df1['totinformalborrow_24']
endline_df1['normalized_income'] = endline_df1['hhinc_24']

# Calculate debt-to-income ratio
endline_df1['debt_to_income_ratio'] = endline_df1['total_borrowed'] /
endline_df1['normalized_income']

# Create a scatter plot of debt-to-income ratio vs. number of
household members
plt.figure(figsize=(10, 6))
plt.scatter(endline_df1['hhnomembers'],
endline_df1['debt_to_income_ratio'], alpha=0.5)
plt.xlabel('Number of Household Members')
plt.ylabel('Debt-to-Income Ratio')
plt.title('Debt-to-Income Ratio vs. Household Size')
plt.show()
```

The scatter plot provided illustrates the relationship between household size and the debt-to-income ratio for a sample of households. From the plot, we can observe several trends and points of interest:

1. **Decreasing Debt-to-Income Ratio with Larger Household Size:** There is a general trend where larger households, particularly those with 10 or more members, tend to have lower debt-to-income ratios. This could indicate that as households grow in size, they may benefit from economies of scale or have more potential income earners, which helps in managing and reducing relative debt levels.
2. **Variability in Smaller Households:** Smaller households, especially those with 2 to 6 members, display a wide range of debt-to-income ratios, with some households experiencing very high ratios, well above 20. This variability suggests that financial health in smaller households is less consistent and possibly more vulnerable to fluctuations in income or unexpected expenses.
3. **Presence of High Debt-to-Income Ratios:** There are several outliers with extremely high debt-to-income ratios across different household sizes. These outliers indicate that some households, regardless of size, may be facing significant financial stress, with debt levels that are disproportionately high compared to their income.
4. **Overall Financial Health:** While larger households appear to have a more favorable financial status based on their lower debt-to-income ratios, the presence

of households with high ratios across all sizes indicates that financial challenges are not exclusive to any particular household size. It is important to consider that the debt-to-income ratio is just one aspect of financial health and other factors such as savings, assets, and expenses would also play a critical role in a comprehensive assessment.

```
def analyze_financial_status(df):
    df['totformalborrow_24'] = pd.to_numeric(df['totformalborrow_24'],
errors='coerce')
    df['totinformalborrow_24'] =
pd.to_numeric(df['totinformalborrow_24'], errors='coerce')
    df['hhinc_24'] = pd.to_numeric(df['hhinc_24'], errors='coerce')

    # Calculate total borrowed and adjust income for 24 months
    df['total_borrowed'] = df['totformalborrow_24'].fillna(0) +
df['totinformalborrow_24'].fillna(0)
    df['adjusted_income'] = df['hhinc_24'].fillna(0) * 24

    # Calculate debt-to-income ratio
    df['debt_to_income_ratio'] = df['total_borrowed'] /
df['adjusted_income'].replace(0, np.nan)

    num_ignored = df['debt_to_income_ratio'].isnull().sum()
    print(f"Number of values ignored while calculating debt-to-income
ratio: {num_ignored}")

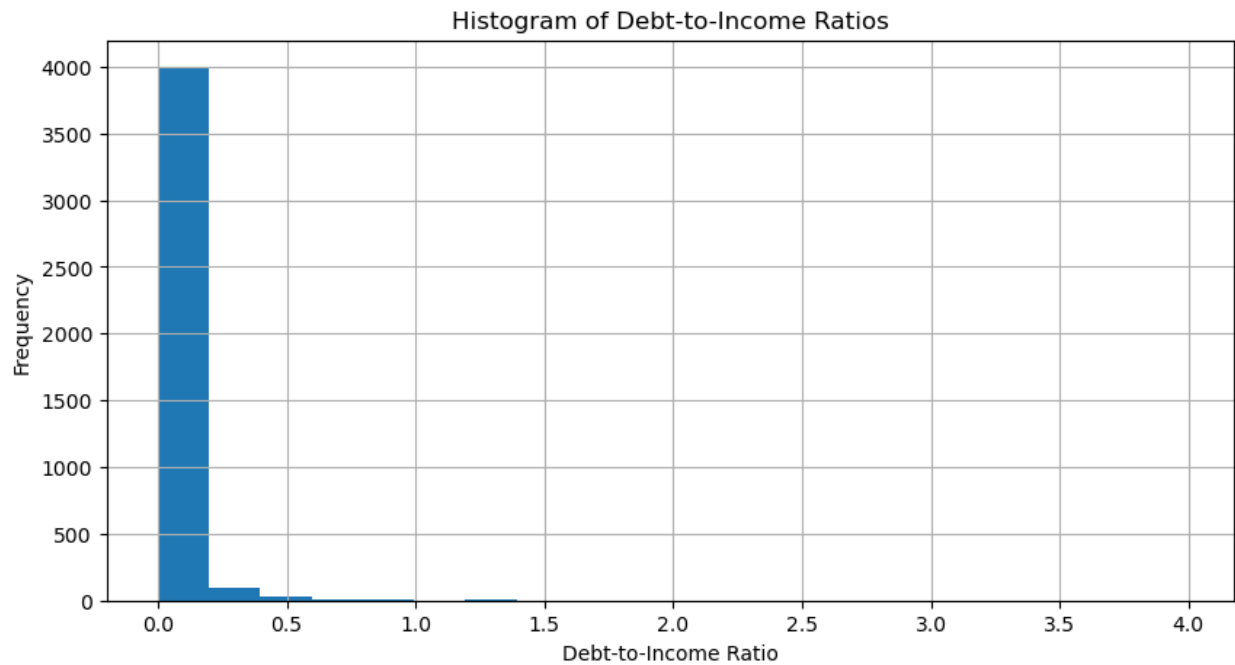
    # Summary statistics
    summary_stats = df[['debt_to_income_ratio',
'hhnomembers']].describe()

    # Plotting
    plt.figure(figsize=(10, 5))
    df['debt_to_income_ratio'].hist(bins=20)
    plt.title('Histogram of Debt-to-Income Ratios')
    plt.xlabel('Debt-to-Income Ratio')
    plt.ylabel('Frequency')
    plt.show()

    return summary_stats
```

```
analyze_financial_status(endline_df1)
```

```
Number of values ignored while calculating debt-to-income ratio: 0
```



	debt_to_income_ratio	hhnomembers
count	4160.000000	4160.000000
mean	0.056169	4.514423
std	0.157901	1.855772
min	0.000100	1.000000
25%	0.012770	3.000000
50%	0.024034	4.000000
75%	0.052083	6.000000
max	3.975694	16.000000

The mean debt-to-income ratio is approximately 0.056, which suggests that, on average, households have a debt amount that is just 5.6% of their income. This indicates a relatively low level of indebtedness across the sample as a whole.

However, the standard deviation is about 0.158, which points to substantial variability in the financial burden among households. Some households have much higher debt-to-income ratios, which could signal financial stress.

The minimum debt-to-income ratio is very close to zero, showing that some households have negligible debt. In contrast, the maximum ratio is nearly 4, indicating that at least one household has debt that is nearly four times its income, which is a sign of high financial distress.

The median household size is 4 members, with half of the households having between 3 and 6 members. This suggests that the sample includes many medium-sized households.

```
median_income = endline_dfl['normalized_income'].median()
endline_dfl['income_class'] =
endline_dfl['normalized_income'].apply(lambda x: 'Above Median or
equal' if x >= median_income else 'Below Median')

num_rows = 2
num_cols = 1
fig, axes = plt.subplots(num_rows, num_cols, figsize=(12, 12))

axes = axes.flatten()

for i, income_class in enumerate(['Above Median or equal', 'Below
Median']):
    subset = endline_dfl[endline_dfl['income_class'] == income_class]
    axes[i].scatter(subset['hhnomembers'],
```

```

subset['debt_to_income_ratio'], alpha=0.5)
    axes[i].set_title(f'Debt-to-Income Ratio vs. Household Size:
{income_class}')
    axes[i].set_xlabel('Number of Household Members')
    axes[i].set_ylabel('Debt-to-Income Ratio')
    summary_stats = subset[['debt_to_income_ratio',
'hhnomembers']].describe()
    print(f"Summary Statistics for {income_class}:")
    print(summary_stats)
    print(f"Total number of households in {income_class}:
{len(subset)}\n")

plt.tight_layout()
plt.show()

```

Summary Statistics for Above Median or equal:

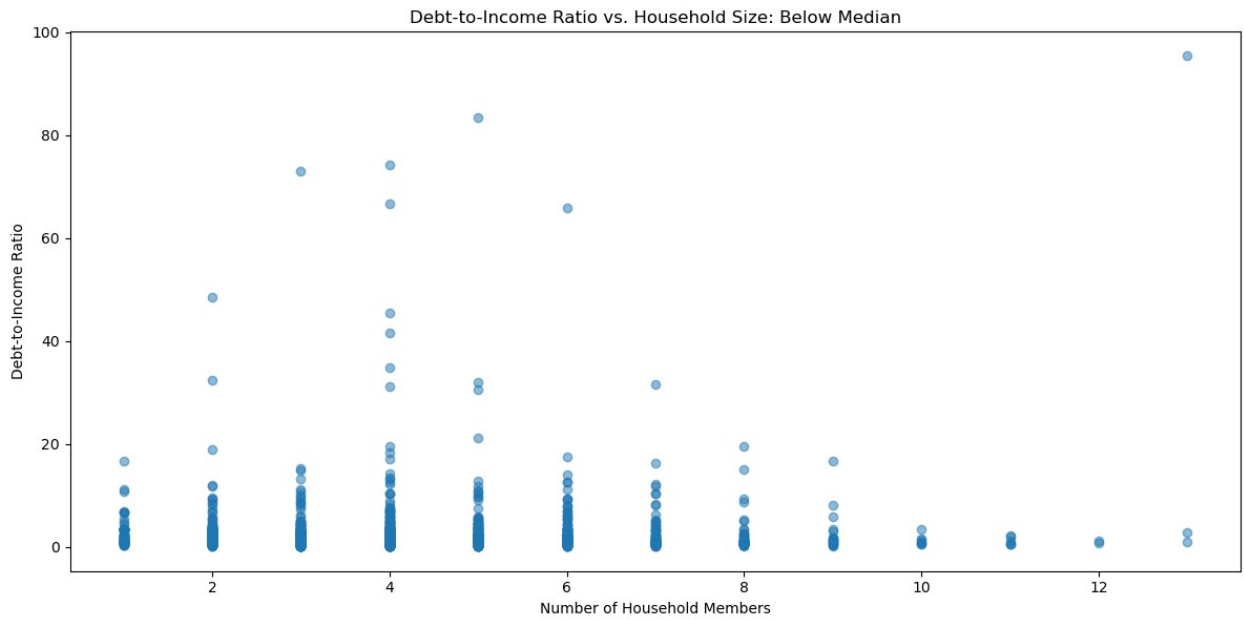
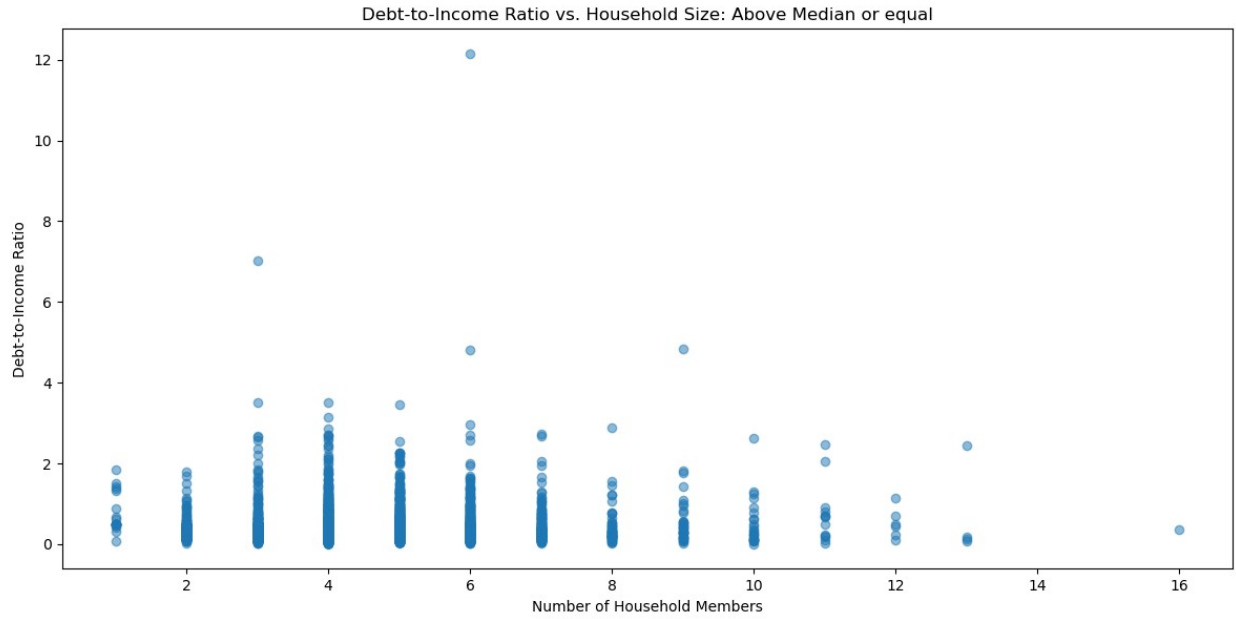
	debt_to_income_ratio	hhnomembers
count	2205.000000	2205.000000
mean	0.502004	4.798186
std	0.557768	1.818337
min	0.002396	1.000000
25%	0.204352	4.000000
50%	0.354167	5.000000
75%	0.588235	6.000000
max	12.157960	16.000000

Total number of households in Above Median or equal: 2205

Summary Statistics for Below Median:

	debt_to_income_ratio	hhnomembers
count	1955.000000	1955.000000
mean	2.302306	4.194373
std	5.338313	1.845925
min	0.057471	1.000000
25%	0.625000	3.000000
50%	1.111111	4.000000
75%	2.301136	5.000000
max	95.416667	13.000000

Total number of households in Below Median: 1955



For households above or equal to the median size, the average debt-to-income ratio is 0.502, which suggests that on average, the debt is approximately half of the income. This group has a relatively lower mean debt-to-income ratio and a standard deviation of 0.558, indicating moderate variability in financial burden among these households. The median household size is 5 members, and the range extends up to 16 members, which is the largest household size observed in the sample.

In contrast, households below the median size have a significantly higher mean debt-to-income ratio of 2.302, indicating that on average, their debt is more than twice their income. This group exhibits a much higher standard deviation of 5.338, reflecting a greater disparity in the financial status among these households. The median household size is 4 members, with the range going up to 13 members.

The scatter plots reinforce these findings, showing that households above or equal to the median size tend to have a cluster of lower debt-to-income ratios, whereas households below the median size display a wider spread of ratios, including some extreme values.

larger households tend to have a more favorable financial status with lower debt relative to their income. In contrast, smaller households appear to face greater financial strain, with higher debt-to-income ratios indicating potential challenges in managing debt and maintaining financial stability.

Part 4 and 5: Top code household debt and income variables, replacing all values greater than three standard deviations above the mean with a value that is equal to three standard deviations and Label the new top-coded variables.

This process helps to manage outliers in my data that can skew analysis.

```
# Variables to top code
columns_to_top_code = ['totformalborrow_24', 'totinformalborrow_24',
                        'hhinc', 'hhinc_24']

for column in columns_to_top_code:
    mean = endline_df[column].mean()
    std_dev = endline_df[column].std()
    cutoff = mean + 3 * std_dev
    top_coded_label = column + '_top_coded'
    endline_df[top_coded_label] = np.where(endline_df[column] >
    cutoff, cutoff, endline_df[column])
```

endline_df

	hhid	group_id	totformalborrow_24	totinformalborrow_24
hhinc \				
0	86.0	3.0	120000	69000
6700				
1	147.0	96.0	50000	300000
10700				
2	179.0	4.0	50000	96000
4300				
3	192.0	76.0	140000	30000
6700				
4	261.0	14.0	50000	30000
60000				
...
...				
4155	185874.0	30.0	6000	30000
10750				
4156	185875.0	44.0	50000	30000

7000				
4157	185876.0	32.0	50000	30000
6700				
4158	185877.0	142.0	50000	30000
1000				
4159	185878.0	152.0	50000	30000
500				

	hhnomembers	survey_round	hhinc_24	totformalborrow_24_top_coded
\				
0	4	Endline II	160800	120000.0
1	4	Endline II	256800	50000.0
2	5	Endline II	103200	50000.0
3	2	Endline II	160800	140000.0
4	7	Endline I	1440000	50000.0
...
4155	3	Endline III	258000	6000.0
4156	4	Endline III	168000	50000.0
4157	3	Endline III	160800	50000.0
4158	2	Endline III	24000	50000.0
4159	1	Endline III	12000	50000.0

	totinformalborrow_24_top_coded	hhinc_top_coded
hhinc_24_top_coded		
0	69000.000000	6700.0
160800.0		
1	293642.188493	10700.0
256800.0		
2	96000.000000	4300.0
103200.0		
3	30000.000000	6700.0
160800.0		
4	30000.000000	60000.0
1440000.0		
...
...		
4155	30000.000000	10750.0
258000.0		
4156	30000.000000	7000.0

168000.0		
4157	30000.000000	6700.0
160800.0		
4158	30000.000000	1000.0
24000.0		
4159	30000.000000	500.0
12000.0		

[4160 rows x 12 columns]

Usually z-score = 3 is considered as a cut-off value to set the limit. Therefore, any z-score greater than +3 or less than -3 is considered as outlier

```
numeric_features = ['totformalborrow_24', 'totinformalborrow_24',
                    'hhinc', 'hhinc_24',
                    'totformalborrow_24_top_coded',
                    'totinformalborrow_24_top_coded',
                    'hhinc_top_coded', 'hhinc_24_top_coded']
```

```
for feature in numeric_features:
    z_scores = stats.zscore(endline_df[feature])

    outliers = endline_df[(z_scores < -3) | (z_scores >= 3)]
    num_outliers = len(outliers)

    # Print the feature name and the number of outliers
    print(f"Feature: {feature}")
    print(f"Number of outliers: {num_outliers}")
    print("---")
```

```
Feature: totformalborrow_24
Number of outliers: 55
---
Feature: totinformalborrow_24
Number of outliers: 95
---
Feature: hhinc
Number of outliers: 9
---
Feature: hhinc_24
Number of outliers: 9
---
Feature: totformalborrow_24_top_coded
Number of outliers: 133
---
Feature: totinformalborrow_24_top_coded
Number of outliers: 145
---
```

```
Feature: hhinc_top_coded
Number of outliers: 69
---
Feature: hhinc_24_top_coded
Number of outliers: 69
---
```

Part H: Write a few sentences about why we might want to top code these types of survey responses from households, and give an example of another data quality or cleaning check

1. **Check for Outliers:**

- Identify outliers in numeric features using statistical methods (e.g., IQR, Z-score).
- Decide on the appropriate treatment for outliers:
 - Remove outliers if they are deemed erroneous or influential.
 - Transform outliers using techniques like log transformation if they are not errors but affect model performance.

Reducing the impact of outliers: Extreme values, such as unusually high income or debt figures, can significantly skew statistical measures like the mean and standard deviation. By top coding these outliers, we can mitigate their influence on the overall analysis and obtain more representative results.

```
numeric_features = ['totformalborrow_24', 'totinformalborrow_24',
                    'hhinc', 'hhinc_24', 'totformalborrow_24_top_coded',
                    'totinformalborrow_24_top_coded', 'hhinc_top_coded',
                    'hhinc_24_top_coded']

num_rows = (len(numeric_features) + 1) // 2
num_cols = 2

fig, axes = plt.subplots(num_rows, num_cols, figsize=(20, 30))
axes = axes.flatten()

def format_tick_labels(x, pos):
    if x >= 1e6:
        return f'{x / 1e6:.1f}M'
    elif x >= 1e3:
        return f'{x / 1e3:.1f}K'
    else:
```

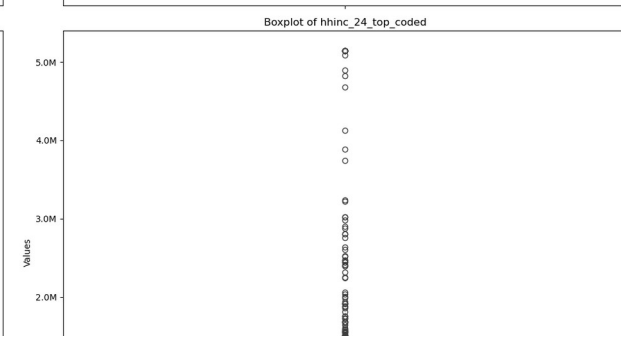
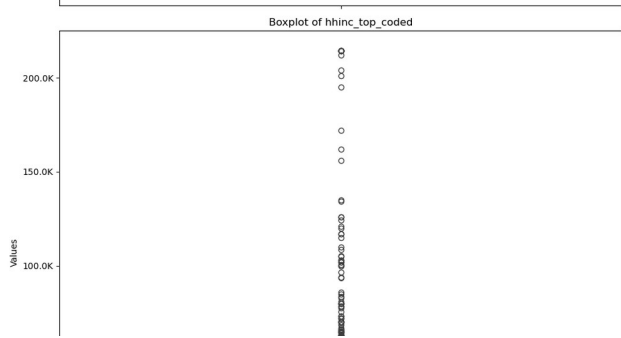
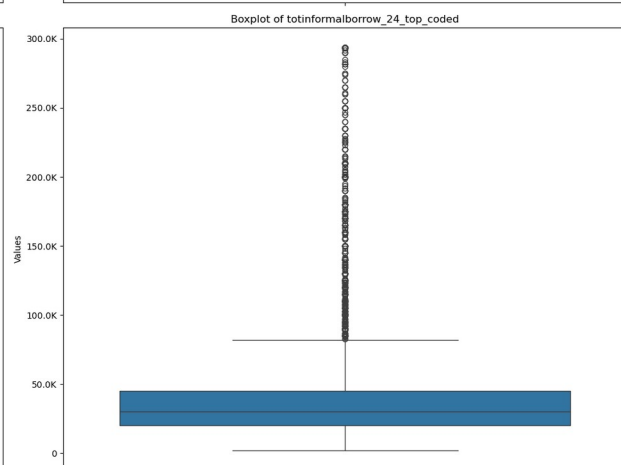
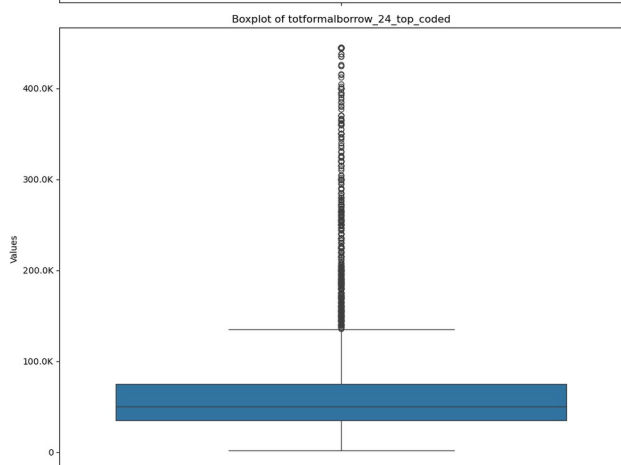
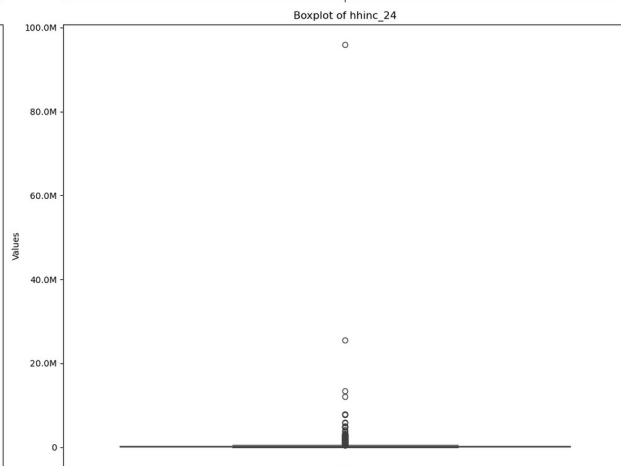
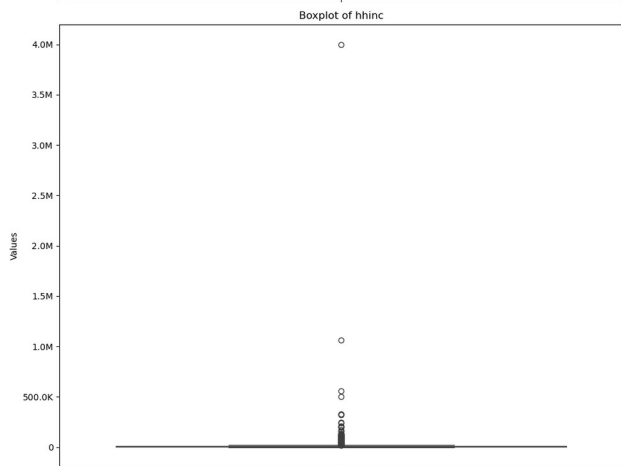
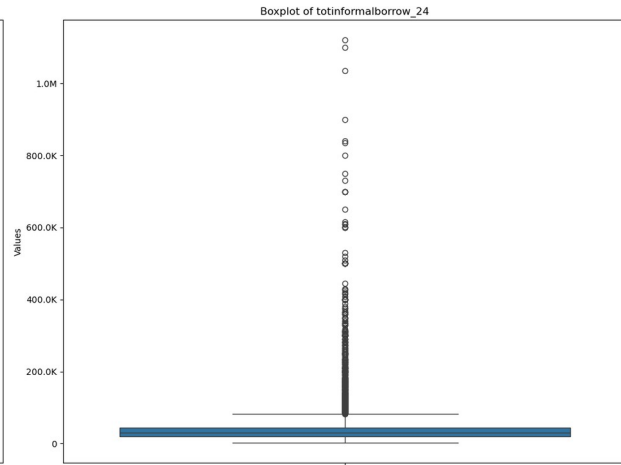
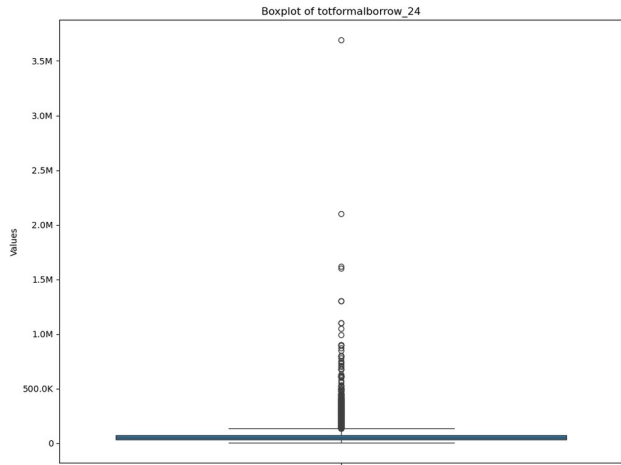
```
        return f'{x:.0f}'

for i, feature in enumerate(numeric_features):
    sns.boxplot(data=endline_df[feature], ax=axes[i])
    axes[i].set_title(f'Boxplot of {feature}')
    axes[i].set_ylabel('Values')

axes[i].yaxis.set_major_formatter(ticker.FuncFormatter(format_tick_labels))

if len(numeric_features) % 2 != 0:
    fig.delaxes(axes[-1])

plt.tight_layout()
plt.show()
```



```

# Function to remove outliers based on IQR-score
def remove_outliers_iqr(data, numeric_features):
    outliers_indices = []
    for feature in numeric_features:
        Q1 = np.percentile(data[feature], 25)
        Q3 = np.percentile(data[feature], 75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        outliers = data[(data[feature] < lower_bound) | (data[feature]
> upper_bound)]
        outliers_indices.extend(outliers.index)

    outliers_indices = list(set(outliers_indices))
    data_cleaned = data.drop(outliers_indices)
    return data_cleaned

```

```

data_cleaned = remove_outliers_iqr(endline_df.copy(),
numeric_features)

```

data_cleaned

	hhid	group_id	totformalborrow_24	totinformalborrow_24
hhinc \ 0	86.0	3.0	120000	69000
6700				
8	450.0	76.0	15000	10000
1500				
9	500.0	134.0	25000	30000
8940				
10	554.0	122.0	15000	30000
10000				
12	1129.0	57.0	16000	26450
7000				
...
...				

4155	185874.0	30.0	6000	30000
10750				
4156	185875.0	44.0	50000	30000
7000				
4157	185876.0	32.0	50000	30000
6700				
4158	185877.0	142.0	50000	30000
1000				
4159	185878.0	152.0	50000	30000
500				

	hhnomembers	survey_round	hhinc_24	totformalborrow_24_top_coded
\ 0	4	Endline II	160800	120000.0

8	6	Endline II	36000	15000.0
9	6	Endline II	214560	25000.0
10	5	Endline I	240000	15000.0
12	3	Endline II	168000	16000.0
...
4155	3	Endline III	258000	6000.0
4156	4	Endline III	168000	50000.0
4157	3	Endline III	160800	50000.0
4158	2	Endline III	24000	50000.0
4159	1	Endline III	12000	50000.0

totinformalborrow_24_top_coded		hhinc_top_coded
hhinc_24_top_coded		
0	69000.0	6700.0
160800.0		
8	10000.0	1500.0
36000.0		
9	30000.0	8940.0
214560.0		
10	30000.0	10000.0
240000.0		
12	26450.0	7000.0
168000.0		
...
...		
4155	30000.0	10750.0
258000.0		
4156	30000.0	7000.0
168000.0		
4157	30000.0	6700.0
160800.0		
4158	30000.0	1000.0
24000.0		
4159	30000.0	500.0
12000.0		

[2969 rows x 12 columns]

PartG: Create a total borrowed amount variable that equals the sum of formal and informal borrowed amounts.

```
endline_df['total_borrowed_amount'] = endline_df['totformalborrow_24']
+ endline_df['totinformalborrow_24']
```

endline_df

	hhid	group_id	totformalborrow_24	totinformalborrow_24
hhinc \				
0	86.0	3.0	120000	69000
6700				
1	147.0	96.0	50000	300000
10700				
2	179.0	4.0	50000	96000
4300				
3	192.0	76.0	140000	30000
6700				
4	261.0	14.0	50000	30000
60000				

...
...				
4155	185874.0	30.0	6000	30000
10750				
4156	185875.0	44.0	50000	30000
7000				
4157	185876.0	32.0	50000	30000
6700				
4158	185877.0	142.0	50000	30000
1000				
4159	185878.0	152.0	50000	30000
500				

	hhnomembers	survey_round	hhinc_24	totformalborrow_24_top_coded
\				
0	4	Endline II	160800	120000.0
1	4	Endline II	256800	50000.0
2	5	Endline II	103200	50000.0
3	2	Endline II	160800	140000.0
4	7	Endline I	1440000	50000.0
...

4155	3	Endline III	258000	6000.0
4156	4	Endline III	168000	50000.0
4157	3	Endline III	160800	50000.0
4158	2	Endline III	24000	50000.0
4159	1	Endline III	12000	50000.0

totinformalborrow_24_top_coded		hhinc_top_coded
hhinc_24_top_coded \		
0	69000.000000	6700.0
160800.0		
1	293642.188493	10700.0
256800.0		
2	96000.000000	4300.0
103200.0		
3	30000.000000	6700.0
160800.0		
4	30000.000000	60000.0
1440000.0		
...
...		
4155	30000.000000	10750.0
258000.0		
4156	30000.000000	7000.0
168000.0		
4157	30000.000000	6700.0
160800.0		
4158	30000.000000	1000.0
24000.0		
4159	30000.000000	500.0
12000.0		

total_borrowed_amount	
0	189000
1	350000
2	146000
3	170000
4	80000
...	...
4155	36000
4156	80000
4157	80000
4158	80000
4159	80000

[4160 rows x 13 columns]

Part H: Merge the endline data with the treatment_status dataset to assign a treatment status for each household

```
# Read the treatment_status dataset
treatment_status_df = pd.read_csv("treatment_status.csv")

# Merge the endline DataFrame with the treatment_status DataFrame
merge_df = pd.merge(endline_df, treatment_status_df, on="group_id",
                    how="left")
```

merge_df

	hhid	group_id	totformalborrow_24	totinformalborrow_24
hhinc \ 0	86.0	3.0	120000	69000
6700				
1	147.0	96.0	50000	300000
10700				
2	179.0	4.0	50000	96000
4300				
3	192.0	76.0	140000	30000
6700				
4	261.0	14.0	50000	30000
60000				
...
...				
4155	185874.0	30.0	6000	30000
10750				
4156	185875.0	44.0	50000	30000
7000				
4157	185876.0	32.0	50000	30000
6700				
4158	185877.0	142.0	50000	30000
1000				
4159	185878.0	152.0	50000	30000
500				

	hhnomembers	survey_round	hhinc_24	totformalborrow_24_top_coded
\ 0	4	Endline II	160800	120000.0
1	4	Endline II	256800	50000.0
2	5	Endline II	103200	50000.0
3	2	Endline II	160800	140000.0

4	7	Endline I	1440000	50000.0
...
4155	3	Endline III	258000	6000.0
4156	4	Endline III	168000	50000.0
4157	3	Endline III	160800	50000.0
4158	2	Endline III	24000	50000.0
4159	1	Endline III	12000	50000.0
<div> <div>totinformalborrow_24_top_coded</div> <div>hhinc_top_coded</div> <div>hhinc_24_top_coded \</div> <div>0</div> <div>69000.000000</div> <div>6700.0</div> <div>160800.0</div> <div>1</div> <div>293642.188493</div> <div>10700.0</div> <div>256800.0</div> <div>2</div> <div>96000.000000</div> <div>4300.0</div> <div>103200.0</div> <div>3</div> <div>30000.000000</div> <div>6700.0</div> <div>160800.0</div> <div>4</div> <div>30000.000000</div> <div>60000.0</div> <div>1440000.0</div> <div>...</div> <div>...</div> <div>...</div> <div>4155</div> <div>30000.000000</div> <div>10750.0</div> <div>258000.0</div> <div>4156</div> <div>30000.000000</div> <div>7000.0</div> <div>168000.0</div> <div>4157</div> <div>30000.000000</div> <div>6700.0</div> <div>160800.0</div> <div>4158</div> <div>30000.000000</div> <div>1000.0</div> <div>24000.0</div> <div>4159</div> <div>30000.000000</div> <div>500.0</div> <div>12000.0</div> </div>				
<div> <div>total_borrowed_amount</div> <div>pair_id</div> <div>treated</div> <div>0</div> <div>189000</div> <div>31</div> <div>1</div> <div>1</div> <div>350000</div> <div>14</div> <div>0</div> <div>2</div> <div>146000</div> <div>31</div> <div>0</div> <div>3</div> <div>170000</div> <div>5</div> <div>0</div> <div>4</div> <div>80000</div> <div>1</div> <div>0</div> <div>...</div> <div>...</div> <div>...</div> <div>...</div> <div>4155</div> <div>36000</div> <div>28</div> <div>1</div> <div>4156</div> <div>80000</div> <div>28</div> <div>0</div> <div>4157</div> <div>80000</div> <div>32</div> <div>1</div> </div>				

4158	80000	36	0
4159	80000	36	1

[4160 rows x 15 columns]

Part i: Create a dummy variable for households that are below the poverty line using a daily per capita poverty line of 26.995 INR (which was equivalent to 1.90 USD at the time of data collection). Use the endline top coded “hhinc” variable, which contains self-reported household income over the past 30 days, in order to do this

```
poverty_line_per_day_per_person = 26.995

# Calculate daily household income from 'hhinc_top_coded' and divide
# by 'hhnomembers' to get per capita income
merge_df['daily_per_capita_income'] = (merge_df['hhinc_top_coded'] /
30) / merge_df['hhnomembers']

# Create a dummy variable for households below the poverty line # 0 -
# below poverty, 1 - above poverty
merge_df['below_poverty_line'] = (merge_df['daily_per_capita_income']
>= poverty_line_per_day_per_person).astype(int)
```

merge_df

	hhid	group_id	totformalborrow_24	totinformalborrow_24
hhinc \				
0	86.0	3.0	120000	69000
6700				
1	147.0	96.0	50000	300000
10700				
2	179.0	4.0	50000	96000
4300				
3	192.0	76.0	140000	30000
6700				
4	261.0	14.0	50000	30000
60000				
...

```

...
4155 185874.0      30.0      6000      30000
10750
4156 185875.0      44.0      50000      30000
7000
4157 185876.0      32.0      50000      30000
6700
4158 185877.0     142.0      50000      30000
1000
4159 185878.0     152.0      50000      30000
500

```

```

      hhnomembers survey_round  hhinc_24  totformalborrow_24_top_coded
\
0      4  Endline II    160800      120000.0
1      4  Endline II    256800      50000.0
2      5  Endline II    103200      50000.0
3      2  Endline II    160800      140000.0
4      7  Endline I     1440000      50000.0
...      ...      ...      ...      ...
4155      3  Endline III    258000      6000.0
4156      4  Endline III    168000      50000.0
4157      3  Endline III    160800      50000.0
4158      2  Endline III     24000      50000.0
4159      1  Endline III     12000      50000.0

```

```

      totinformalborrow_24_top_coded  hhinc_top_coded
hhinc_24_top_coded \
0      69000.000000      6700.0
160800.0
1      293642.188493      10700.0
256800.0
2      96000.000000      4300.0
103200.0
3      30000.000000      6700.0
160800.0
4      30000.000000      60000.0
1440000.0
...      ...      ...

```

```

...
4155          30000.000000          10750.0
258000.0
4156          30000.000000          7000.0
168000.0
4157          30000.000000          6700.0
160800.0
4158          30000.000000          1000.0
24000.0
4159          30000.000000          500.0
12000.0

```

```

      total_borrowed_amount  pair_id  treated  daily_per_capita_income
\
0          189000           31         1          55.833333
1          350000           14         0          89.166667
2          146000           31         0          28.666667
3          170000            5         0         111.666667
4           80000            1         0         285.714286
...
4155          36000           28         1         119.444444
4156          80000           28         0          58.333333
4157          80000           32         1          74.444444
4158          80000           36         0          16.666667
4159          80000           36         1          16.666667

```

```

      below_poverty_line
0              1
1              1
2              1
3              1
4              1
...
4155          1
4156          1
4157          1
4158          0
4159          0

```

```
[4160 rows x 17 columns]
```

Part J: Write a few sentences about the strengths and limitations of using the dummy you created to assess a household's poverty status. If you were able to collect more data from these households, what types of additional questions might you ask?

Strengths of Using the Poverty Line Dummy Variable

The dummy variable for poverty status based on a daily per capita income threshold simplifies the analysis by converting a continuous income measure into a binary indicator, which is easy to interpret and use in statistical models. Using a standardized poverty line allows for comparisons across different studies and geographical areas. This can be particularly useful in policy analysis and international development research. The dummy variable directly addresses economic vulnerability and can be immediately useful for targeting and evaluating poverty alleviation programs. It helps in identifying the households most in need of support.

Limitations of Using the Poverty Line Dummy Variable

The dummy variable does not capture the depth or severity of poverty. Households significantly below the poverty line are treated the same as those just below it. It can be the case a rich household can be under huge debt whereas a poor household in very less debt.

Additional Data Collection Suggestions

1. **Expenditure Details:** What are the major areas of household expenditure? Understanding where money is spent can provide insights into household priorities and needs.
2. **Asset Ownership:** What assets (e.g., land, livestock, vehicles, appliances) does the household own? Assets are a critical component of household wealth and can provide a buffer against economic shocks which can tell their net worth.
3. **Access to Services:** Does the household have access to essential services such as clean water, sanitation, electricity, healthcare, and education? These factors are crucial for understanding living standards and well-being.

4. **Employment and Labor Information:** What types of employment do household members engage in? Are these jobs stable or seasonal? Information about employment can help assess economic stability and vulnerability.
5. **Education Levels:** What are the education levels of household members? Education is a key factor in long-term economic prospects and social mobility.

Part K: Merge your working data with the baseline controls dataset, and save the merged data. If you need to make decisions about dropping mismatched values, please justify them in notes.

```
baseline_df = pd.read_stata('baseline_controls.dta')
```

```
baseline_df
```

	hhid	group_id	hhnomembers	gender_hoh	age_hoh	\
0	73.0	35.0	5	Female (0)	30.0	
1	86.0	3.0	4	Male (1)	55.0	
2	179.0	4.0	5	Male (1)	51.0	
3	192.0	76.0	2	Male (1)	57.0	
4	261.0	14.0	7	Male (1)	46.0	
...	
4061	185362.0	120.0	4	Male (1)	39.0	
4062	185417.0	120.0	4	Female (0)	45.0	
4063	185436.0	120.0	4	Female (0)	34.0	
4064	185452.0	120.0	5	Female (0)	51.0	
4065	185460.0	120.0	5	Female (0)	50.0	
	educyears_hoh		readwrite_hoh	noclasspassed_hoh		\
0	10 years		1.0	0.0		
1	10 years		1.0	0.0		
2	8 years		1.0	0.0		
3	12 years		1.0	0.0		
4	19+ years (Post-graduate)		1.0	0.0		
...		
4061	3-7 years (Classes 1-5)		1.0	0.0		
4062	0 years		0.0	1.0		
4063	14 years (Class 12/HSC)		1.0	0.0		
4064	0 years		0.0	1.0		
4065	0 years		0.0	1.0		
	higheduc_hoh	hhnomembers_above18	hhnomembers_below18			

hhreg_muslim \			
0	0.0	2.0	3.0
0.0			
1	0.0	4.0	0.0
0.0			
2	0.0	5.0	0.0
0.0			
3	0.0	2.0	0.0
0.0			
4	1.0	4.0	3.0
0.0			
...
...			
4061	0.0	2.0	2.0
0.0			
4062	0.0	2.0	2.0
0.0			
4063	0.0	2.0	2.0
0.0			
4064	0.0	5.0	0.0
0.0			
4065	0.0	3.0	2.0
0.0			

	hhreg_christian	hhcaste_fc	hhcaste_bc	hhcaste_mbc
hhcaste_sc_st				
0	0.0	0.0	0.0	1.0
0.0				
1	0.0	0.0	1.0	0.0
0.0				
2	0.0	0.0	0.0	0.0
1.0				
3	0.0	0.0	1.0	0.0
0.0				
4	0.0	0.0	0.0	0.0
1.0				
...
...				
4061	0.0	0.0	0.0	1.0
0.0				
4062	0.0	0.0	0.0	1.0
0.0				
4063	0.0	0.0	1.0	0.0
0.0				
4064	0.0	0.0	0.0	1.0
0.0				
4065	0.0	0.0	0.0	1.0
0.0				

```
[4066 rows x 17 columns]

common_columns = merge_df.columns.intersection(baseline_df.columns)
print("Common Columns:", common_columns)

Common Columns: Index(['hhid', 'group_id', 'hhnomembers'],
dtype='object')

merged_data_inner = pd.merge(merge_df, baseline_df , on='hhid',
how='inner')
```

The inner join (how='inner') will keep only the rows that have matching 'hhid' values in both datasets. This means that if there are any 'hhid' values present in one dataset but not in the other, those rows will be excluded from the merged result. The common attribute between them is hhid

```
merged_data_inner
```

	hhid	group_id_x	totformalborrow_24	totinformalborrow_24
hhinc \				
0	86.0	3.0	120000	69000
6700				
1	179.0	4.0	50000	96000
4300				
2	192.0	76.0	140000	30000
6700				
3	261.0	14.0	50000	30000
60000				
4	268.0	96.0	120000	30000
26000				
...
...				
3797	185314.0	120.0	3500	30000
1500				
3798	185362.0	120.0	20000	4000
20000				
3799	185417.0	120.0	90000	200000
10000				
3800	185452.0	120.0	60000	370000
4000				
3801	185460.0	120.0	50000	30000
13500				
	hhnomembers_x	survey_round	hhinc_24	
totformalborrow_24_top_coded \				
0	4	Endline II	160800	
120000.0				

1	5	Endline II	103200	
50000.0				
2	2	Endline II	160800	
140000.0				
3	7	Endline I	1440000	
50000.0				
4	5	Endline II	624000	
120000.0				
...
..				
3797	4	Endline III	36000	
3500.0				
3798	4	Endline III	480000	
20000.0				
3799	4	Endline III	240000	
90000.0				
3800	5	Endline III	96000	
60000.0				
3801	5	Endline III	324000	
50000.0				
totinformalborrow_24_top_coded ... noclasspassed_hoh				
higheduc_hoh \				
0	69000.000000	...		0.0
0.0				
1	96000.000000	...		0.0
0.0				
2	30000.000000	...		0.0
0.0				
3	30000.000000	...		0.0
1.0				
4	30000.000000	...		1.0
0.0				
...
...				
3797	30000.000000	...		0.0
0.0				
3798	4000.000000	...		0.0
0.0				
3799	200000.000000	...		1.0
0.0				
3800	293642.188493	...		1.0
0.0				
3801	30000.000000	...		1.0
0.0				
hhnomembers_above18 hhnomembers_below18 hhreg_muslim				
hhreg_christian \				
0	4.0	0.0		0.0

0.0			
1	5.0	0.0	0.0
0.0			
2	2.0	0.0	0.0
0.0			
3	4.0	3.0	0.0
0.0			
4	5.0	0.0	0.0
0.0			
...
...			
3797	2.0	2.0	0.0
0.0			
3798	2.0	2.0	0.0
0.0			
3799	2.0	2.0	0.0
0.0			
3800	5.0	0.0	0.0
0.0			
3801	3.0	2.0	0.0
0.0			

	hhcaste_fc	hhcaste_bc	hhcaste_mbc	hhcaste_sc_st
0	0.0	1.0	0.0	0.0
1	0.0	0.0	0.0	1.0
2	0.0	1.0	0.0	0.0
3	0.0	0.0	0.0	1.0
4	0.0	0.0	1.0	0.0
...
3797	0.0	1.0	0.0	0.0
3798	0.0	0.0	1.0	0.0
3799	0.0	0.0	1.0	0.0
3800	0.0	0.0	1.0	0.0
3801	0.0	0.0	1.0	0.0

[3802 rows x 33 columns]

As the inner join was performed on hhid, I checked if there were any mismatched on the other common columns - group_id and hhnomembers, I dropped rows if any mismatches were there

```
mismatch_mask = merged_data_inner['group_id_x'] !=
merged_data_inner['group_id_y']

# Count the number of mismatches
mismatch_count = mismatch_mask.sum()

# Print the number of mismatches
if mismatch_count > 0:
```

```

    print(f"There are {mismatch_count} mismatches between 'group_id_x'
and 'group_id_y'.")
else:
    print("The values in 'group_id_x' and 'group_id_y' are always
equal for all rows.")

```

Optional: Display rows where mismatches occur

```

if mismatch_count > 0:
    print("Displaying rows with mismatches:")
    ff = merged_data_inner[mismatch_mask]
    print(ff[['hhid', "group_id_x", "group_id_y"]])

```

There are 2 mismatches between 'group_id_x' and 'group_id_y'.

Displaying rows with mismatches:

	hhid	group_id_x	group_id_y
1577	106131.0	148.0	152.0
1601	106360.0	148.0	152.0

```

mismatch_mask = merged_data_inner['hhnomembers_x'] !=
merged_data_inner['hhnomembers_y']

```

Count the number of mismatches

```

mismatch_count = mismatch_mask.sum()

```

Print the number of mismatches

```

if mismatch_count > 0:
    print(f"There are {mismatch_count} mismatches between 'group_id_x'
and 'group_id_y'.")
else:
    print("The values in 'hhnomembers_x' and 'hhnomembers_y' are
always equal for all rows.")

```

Optional: Display rows where mismatches occur

```

if mismatch_count > 0:
    print("Displaying rows with mismatches:")
    ff = merged_data_inner[mismatch_mask]
    print(ff[['hhid', "hhnomembers_x", "hhnomembers_y"]])

```

The values in 'hhnomembers_x' and 'hhnomembers_y' are always equal for all rows.

```

hhids_to_drop = [106131.0, 106360.0]

```

Find the index of rows with these hhids

```

indexes_to_drop =
merged_data_inner[merged_data_inner['hhid'].isin(hhids_to_drop)].index

```

Drop these rows

```

merged_data_inner.drop(indexes_to_drop, inplace=True)

```

```
merged_data_inner =
merged_data_inner.drop(['group_id_y', 'hhnomembers_y'], axis=1)
```

```
merged_data_inner
```

hhinc \	hhid	group_id_x	totformalborrow_24	totinformalborrow_24
0	86.0	3.0	120000	69000
6700				
1	179.0	4.0	50000	96000
4300				
2	192.0	76.0	140000	30000
6700				
3	261.0	14.0	50000	30000
60000				
4	268.0	96.0	120000	30000
26000				
...
...				
3797	185314.0	120.0	3500	30000
1500				
3798	185362.0	120.0	20000	4000
20000				
3799	185417.0	120.0	90000	200000
10000				
3800	185452.0	120.0	60000	370000
4000				
3801	185460.0	120.0	50000	30000
13500				

hhnomembers_x	survey_round	hhinc_24
totformalborrow_24_top_coded \		
0	4 Endline II	160800
120000.0		
1	5 Endline II	103200
50000.0		
2	2 Endline II	160800
140000.0		
3	7 Endline I	1440000
50000.0		
4	5 Endline II	624000
120000.0		
...
...		
3797	4 Endline III	36000
3500.0		
3798	4 Endline III	480000
20000.0		
3799	4 Endline III	240000
90000.0		

3800	5	Endline III	96000
60000.0			
3801	5	Endline III	324000
50000.0			

	totinformalborrow_24_top_coded	...	noclasspassed_hoh
higheduc_hoh \			
0	69000.000000	...	0.0
0.0			
1	96000.000000	...	0.0
0.0			
2	30000.000000	...	0.0
0.0			
3	30000.000000	...	0.0
1.0			
4	30000.000000	...	1.0
0.0			
...
...			
3797	30000.000000	...	0.0
0.0			
3798	4000.000000	...	0.0
0.0			
3799	200000.000000	...	1.0
0.0			
3800	293642.188493	...	1.0
0.0			
3801	30000.000000	...	1.0
0.0			

	hnomembers_above18	hnomembers_below18	hhreg_muslim
hhreg_christian \			
0	4.0	0.0	0.0
0.0			
1	5.0	0.0	0.0
0.0			
2	2.0	0.0	0.0
0.0			
3	4.0	3.0	0.0
0.0			
4	5.0	0.0	0.0
0.0			
...
...			
3797	2.0	2.0	0.0
0.0			
3798	2.0	2.0	0.0
0.0			
3799	2.0	2.0	0.0

```

0.0
3800          5.0          0.0          0.0
0.0
3801          3.0          2.0          0.0
0.0

```

```

      hhcaste_fc hhcaste_bc hhcaste_mbc hhcaste_sc_st
0            0.0          1.0          0.0          0.0
1            0.0          0.0          0.0          1.0
2            0.0          1.0          0.0          0.0
3            0.0          0.0          0.0          1.0
4            0.0          0.0          1.0          0.0
...
3797         0.0          1.0          0.0          0.0
3798         0.0          0.0          1.0          0.0
3799         0.0          0.0          1.0          0.0
3800         0.0          0.0          1.0          0.0
3801         0.0          0.0          1.0          0.0

```

```
[3800 rows x 31 columns]
```

```
custom_info(merged_data_inner)
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 3800 entries, 0 to 3799
```

```
Data columns (total 31 columns):
```

```

                                     Non-Null Count  Null Count Unique
Values \
Column
hhid          3800          0
3800
group_id_x    3800          0
101
totformalborrow_24    3800          0
400
totinformalborrow_24    3800          0
330
hhinc          3800          0
760
hhnomembers_x    3800          0
14
survey_round    3800          0
3
hhinc_24        3800          0
760
totformalborrow_24_top_coded    3800          0
360
totinformalborrow_24_top_coded    3800          0
283

```


hhinc_top_coded	3800	0
753		
hhinc_24_top_coded	3800	0
753		
total_borrowed_amount	3800	0
612		
pair_id	3800	0
50		
treated	3800	0
2		
daily_per_capita_income	3800	0
1139		
below_poverty_line	3800	0
2		
gender_hoh	3800	0
2		
age_hoh	3800	0
72		
educyears_hoh	3800	0
12		
readwrite_hoh	3800	0
2		
noclasspassed_hoh	3800	0
2		
higheduc_hoh	3800	0
2		
hhnomembers_above18	3800	0
13		
hhnomembers_below18	3800	0
9		
hhreg_muslim	3798	2
2		
hhreg_christian	3798	2
2		
hhcaste_fc	3799	1
2		
hhcaste_bc	3799	1
2		
hhcaste_mbc	3799	1
2		
hhcaste_sc_st	3799	1
2		
Total Rows	3800	

Dtype	
Column	
hhid	object
group_id_x	float32

totformalborrow_24	int64
totinformalborrow_24	int64
hhinc	int64
hhnomembers_x	int8
survey_round	object
hhinc_24	int64
totformalborrow_24_top_coded	float64
totinformalborrow_24_top_coded	float64
hhinc_top_coded	float64
hhinc_24_top_coded	float64
total_borrowed_amount	int64
pair_id	int64
treated	int64
daily_per_capita_income	float64
below_poverty_line	int64
gender_hoh	category
age_hoh	category
educyears_hoh	category
readwrite_hoh	float32
noclasspassed_hoh	float32
higheduc_hoh	float32
hhnomembers_above18	float32
hhnomembers_below18	float32
hhreg_muslim	float32
hhreg_christian	float32
hhcaste_fc	float32
hhcaste_bc	float32
hhcaste_mbc	float32
hhcaste_sc_st	float32
Total Rows	
memory usage: 687200 bytes	
merged_data_inner.to_csv("Merge.csv")	