CS418: Rising Cost of Homes and Unaffordability — Progress Report

📄 **GitHub Repository Link:**
Home Ownership Project Report 11/13 - Big Data Dunces Team

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```
from google.colab import drive
drive.mount('/content/drive')
%cd /content/drive/My Drive/Colab Notebooks/418BigDataDunces
```

```
Mounted at /content/drive
/content/drive/My Drive/Colab Notebooks/418BigDataDunces
```

1. Introduction

For our data science project we are analyzing why owning a home in the United States has become more unattainable. Is this due to lower financial literacy? Is this due to housing prices shooting up? Does this have something to do with income not rising at the same rate? We are investigating these questions.

Our project, **"Rising Cost of Homes and Unaffordability**," investigates how housing affordability in the United States has evolved over time, with a focus on generational and economic factors that make homeownership increasingly unattainable; particularly for Millennials and Gen Z.

We are analyzing multiple datasets that together provide a comprehensive view of the housing market and its socioeconomic drivers:

California Housing Dataset – includes variables such as median income, median house value, population, and geographic coordinates, allowing us to explore spatial trends in affordability.

NFCS State Data – captures demographic and financial behavior at the state level, including living arrangements, marital status, and financial well-being indicators.

Household Income Regression Dataset – contains detailed individual-level attributes such as age, education level, occupation, income, employment status, and homeownership, which we use to identify patterns between personal characteristics and homeownership likelihood.

New York Housing Dataset – provides detailed listing-level data for New York, enabling localized analysis of property prices and market variations.

Median U.S. Household Income and Median Home Price (1984–2024) – two time-series datasets that help us analyze the long-term divergence between household earnings and home prices.

2. Any Changes

Some changes in our scope are that we are investigating overall data but not specifically focusing on a concrete conclusion. The housing crisis has been widely debated and is influenced by many complex factors. In our project, we have switched to focusing on a subset of these factors to explore whether they may have contributed significantly to the broader issue. Simply speaking, originally we wanted to focus on how much each factor contributed to the crisis, instead we shifted to how each of the factors changed over time and whether or not they were significant factors.

Since our initial proposal, our project scope and direction have evolved significantly. We only had a general idea of our theme and no finalized datasets or analysis plan. We have since added several complementary datasets covering income distribution, demographic variation, and national housing trends (1984–2024). This expansion allows for a more complete, multi-dimensional understanding of affordability.

3. Cleaning Datasets

Money Management and Financial Literacy

https://catalog.data.gov/dataset/money-management-and-financial-literacy

```
import pandas as pd
import numpy as np

df = pd.read_csv("Money_Management_and_Financial_Literacy.csv")

df_clean = df.drop(columns=[
    'X', 'Y', 'MAR_MATCHADDRESS', 'MAR_XCOORD', 'MAR_YCOORD',
    'MAR_ERROR', 'MAR_IGNORE', 'MAR_SOURCEOPERATION'
])


df_clean.columns = df_clean.columns.str.lower().str.replace(' ', '_')

print(df_clean.info)
display(df_clean.head())
df_clean.to_csv('/content/Money_Management_and_Financial_Literacy_clean.csv', index=False)
```

```
<bound method DataFrame.info of    objectid          categories_of_service  \
0     14087  Bill Pay and Money Management
1     14088    Planning for Long Term Care
2     14089    Planning for Long Term Care

                                     organization  \
0  East River Family Strengthening Collaborative ...
1      Seabury Resources for Aging - Care Management
```

2024 National Financial Capability Study

https://finrafoundation.org/nfcs-data-and-downloads

```
import pandas as pd # Loads and normalizes the column names
import numpy as np
import re

df = pd.read_csv("NFCS 2024 State Data 250623.csv")

normalized_cols = []
i = 0
while i < len(df.columns):
    name = str(df.columns[i])
    name = name.strip()
    name = re.sub(r"[^0-9a-zA-Z]+", "_", name)
    name = re.sub(r"_+", "_", name).strip("_").lower()
    normalized_cols.append(name)
    i = i + 1

df.columns = normalized_cols
print(df.shape)
df.head(3)
```

```
(25539, 133)
```

	nfcsid	stateq	censusdiv	censusreg	a50a	a3ar_w	a50b	a4a_new_w	a5_2015	a6	...	m6	m7	m8	m31	m50	m9	m10	wgt_
0	2024010001	36	3	2	2	3	9	1	6	1	...	1	3	98	98	98	1	2	1.1535
1	2024010002	48	9	4	1	6	6	1	5	5	...	1	3	98	3	3	1	2	1.3986
2	2024010003	38	9	4	1	6	6	1	4	1	...	1	3	1	98	98	2	2	1.3986

3 rows × 133 columns

```
# Turns the survey missing codes into NaN (98, 99, 999)
col_index = 0 # Replaces the survey missing codes with NaN
while col_index < len(df.columns):
    col = df.columns[col_index]

    if pd.api.types.is_numeric_dtype(df[col]):
        df[col] = df[col].replace(98, np.nan)
        df[col] = df[col].replace(99, np.nan)
        df[col] = df[col].replace(999, np.nan)
    else:
        df[col] = df[col].replace("98", np.nan)
        df[col] = df[col].replace("99", np.nan)
        df[col] = df[col].replace("999", np.nan)
    col_index = col_index + 1

# Drops the fully empty columns after replacement
empty_cols = []
j = 0
while j < len(df.columns):
    col = df.columns[j]
    if df[col].isna().all():
        empty_cols.append(col)
    j = j + 1

if len(empty_cols) > 0:
    df = df.drop(columns=empty_cols).reset_index(drop=True)

print("Dropped empty columns:", empty_cols)
```

```
Dropped empty columns: ['MAR_ERROR', 'MAR_IGNORE']
```

```
# Added actually human readable labels for key variables
# Pre created columns as the object dtype because I was getting dtype warnings
```

```
    if "stateq" in df.columns:
        df["state_label"] = pd.Series([None]*len(df), dtype="object")

    if "censusreg" in df.columns:
        df["region_label"] = pd.Series([None]*len(df), dtype="object")

    if "a50a" in df.columns:
        df.rename(columns={"a50a": "gender_code"}, inplace=True)

    if "a3ar_w" in df.columns:
        df.rename(columns={"a3ar_w": "age_group_code"}, inplace=True)

    if "m9" in df.columns:
        df.rename(columns={"m9": "mortgage_knowledge_code"}, inplace=True)

    if "m10" in df.columns:
        df.rename(columns={"m10": "investment_knowledge_code"}, inplace=True)

    if "stateq" in df.columns: # Stateq to stateq_label
        df.loc[df["stateq"] == 1, "stateq_label"] = "Alabama"
        df.loc[df["stateq"] == 2, "stateq_label"] = "Alaska"
        df.loc[df["stateq"] == 3, "stateq_label"] = "Arizona"
        df.loc[df["stateq"] == 4, "stateq_label"] = "Arkansas"
        df.loc[df["stateq"] == 5, "stateq_label"] = "California"
        df.loc[df["stateq"] == 6, "stateq_label"] = "Colorado"
        df.loc[df["stateq"] == 7, "stateq_label"] = "Connecticut"
        df.loc[df["stateq"] == 8, "stateq_label"] = "Delaware"
        df.loc[df["stateq"] == 9, "stateq_label"] = "District of Columbia"
        df.loc[df["stateq"] == 10, "stateq_label"] = "Florida"

        df.loc[df["stateq"] == 11, "stateq_label"] = "Georgia"
        df.loc[df["stateq"] == 12, "stateq_label"] = "Hawaii"
        df.loc[df["stateq"] == 13, "stateq_label"] = "Idaho"
        df.loc[df["stateq"] == 14, "stateq_label"] = "Illinois"
        df.loc[df["stateq"] == 15, "stateq_label"] = "Indiana"
        df.loc[df["stateq"] == 16, "stateq_label"] = "Iowa"
        df.loc[df["stateq"] == 17, "stateq_label"] = "Kansas"
        df.loc[df["stateq"] == 18, "stateq_label"] = "Kentucky"
        df.loc[df["stateq"] == 19, "stateq_label"] = "Louisiana"
        df.loc[df["stateq"] == 20, "stateq_label"] = "Maine"

        df.loc[df["stateq"] == 21, "stateq_label"] = "Maryland"
        df.loc[df["stateq"] == 22, "stateq_label"] = "Massachusetts"
        df.loc[df["stateq"] == 23, "stateq_label"] = "Michigan"
        df.loc[df["stateq"] == 24, "stateq_label"] = "Minnesota"
        df.loc[df["stateq"] == 25, "stateq_label"] = "Mississippi"
        df.loc[df["stateq"] == 26, "stateq_label"] = "Missouri"
        df.loc[df["stateq"] == 27, "stateq_label"] = "Montana"
        df.loc[df["stateq"] == 28, "stateq_label"] = "Nebraska"
        df.loc[df["stateq"] == 29, "stateq_label"] = "Nevada"
        df.loc[df["stateq"] == 30, "stateq_label"] = "New Hampshire"

        df.loc[df["stateq"] == 31, "stateq_label"] = "New Jersey"
        df.loc[df["stateq"] == 32, "stateq_label"] = "New Mexico"
        df.loc[df["stateq"] == 33, "stateq_label"] = "New York"
        df.loc[df["stateq"] == 34, "stateq_label"] = "North Carolina"
        df.loc[df["stateq"] == 35, "stateq_label"] = "North Dakota"
        df.loc[df["stateq"] == 36, "stateq_label"] = "Ohio"
        df.loc[df["stateq"] == 37, "stateq_label"] = "Oklahoma"
        df.loc[df["stateq"] == 38, "stateq_label"] = "Oregon"
        df.loc[df["stateq"] == 39, "stateq_label"] = "Pennsylvania"
        df.loc[df["stateq"] == 40, "stateq_label"] = "Rhode Island"

        df.loc[df["stateq"] == 41, "stateq_label"] = "South Carolina"
        df.loc[df["stateq"] == 42, "stateq_label"] = "South Dakota"
        df.loc[df["stateq"] == 43, "stateq_label"] = "Tennessee"
        df.loc[df["stateq"] == 44, "stateq_label"] = "Texas"
        df.loc[df["stateq"] == 45, "stateq_label"] = "Utah"
        df.loc[df["stateq"] == 46, "stateq_label"] = "Vermont"
        df.loc[df["stateq"] == 47, "stateq_label"] = "Virginia"
        df.loc[df["stateq"] == 48, "stateq_label"] = "Washington"
        df.loc[df["stateq"] == 49, "stateq_label"] = "West Virginia"
        df.loc[df["stateq"] == 50, "stateq_label"] = "Wisconsin"
        df.loc[df["stateq"] == 51, "stateq_label"] = "Wyoming"

    if "censusreg" in df.columns: # Census region, censusreg to censusreg_label
        df.loc[df["censusreg"] == 1, "censusreg_label"] = "Northeast"
```

```
    df.loc[df["censusreg"] == 2, "censusreg_label"] = "Midwest"
    df.loc[df["censusreg"] == 3, "censusreg_label"] = "South"
    df.loc[df["censusreg"] == 4, "censusreg_label"] = "West"

if "a50a" in df.columns: # Gender, a50a to gender_label
    df.loc[df["a50a"] == 1, "gender_label"] = "Male"
    df.loc[df["a50a"] == 2, "gender_label"] = "Female"

if "a3ar_w" in df.columns: # Age group a3ar_w to age_group_label
    df.loc[df["a3ar_w"] == 1, "age_group_label"] = "18–24"
    df.loc[df["a3ar_w"] == 2, "age_group_label"] = "25–34"
    df.loc[df["a3ar_w"] == 3, "age_group_label"] = "35–44"
    df.loc[df["a3ar_w"] == 4, "age_group_label"] = "45–54"
    df.loc[df["a3ar_w"] == 5, "age_group_label"] = "55–64"
    df.loc[df["a3ar_w"] == 6, "age_group_label"] = "65+"

# Financial knowledge items
if "m9" in df.columns: # 15-year vs 30-year mortgage (1=True, 2=False)
    df.loc[df["m9"] == 1, "m9_label"] = "True"
    df.loc[df["m9"] == 2, "m9_label"] = "False"
    df["m9_question_text"] = (
        "Question M9: 'A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, "
        "but the total interest paid over the life of the loan will be less.' "
        "(Codes: 1=True, 2=False, 98=Don't know, 99=Prefer not to say — this is a knowledge question, not your mortgage type.)"
    )

if "m10" in df.columns: # Single stock vs mutual fund (1=True, 2=False)
    df.loc[df["m10"] == 1, "m10_label"] = "True"
    df.loc[df["m10"] == 2, "m10_label"] = "False"
    df["m10_question_text"] = (
        "Question M10: 'Buying a single company's stock usually provides a safer return than a stock mutual fund.' "
        "(Codes: 1=True, 2=False, 98=Don't know, 99=Prefer not to say — a knowledge question; correct answer is 2=False.)"
    )

df = df.copy()

print("Added *_label columns where available.") # Keep weights as they are (wgt_n2, wgt_d2, wgt_s3) for analysis
df.filter(regex="^(stateq|censusreg|a50a|a3ar_w|m9|m10)|(_label)$").head(8)
```

```
Added *_label columns where available.
```

0
1
2

```
import pandas as pd # Fixes the problem where these columns are none (state_label   region_label    mortgage_knowledge_label
import numpy as np

if "state_label" not in df.columns:
    df["state_label"] = pd.Series([None]*len(df), dtype="object")
else:
    df["state_label"] = df["state_label"].astype("object")

if "region_label" not in df.columns:
    df["region_label"] = pd.Series([None]*len(df), dtype="object")
else:
    df["region_label"] = df["region_label"].astype("object")

if "mortgage_knowledge_label" not in df.columns:
    df["mortgage_knowledge_label"] = pd.Series([None]*len(df), dtype="object")
else:
    df["mortgage_knowledge_label"] = df["mortgage_knowledge_label"].astype("object")

if "investment_knowledge_label" not in df.columns:
    df["investment_knowledge_label"] = pd.Series([None]*len(df), dtype="object")
else:
    df["investment_knowledge_label"] = df["investment_knowledge_label"].astype("object")

row = 0
while row < len(df):
    if "stateq_label" in df.columns:
        val = df.at[row, "stateq_label"] if "stateq_label" in df.columns else None
        if pd.notna(val) and (pd.isna(df.at[row, "state_label"]) or df.at[row, "state_label"] in [None, ""]):
            df.at[row, "state_label"] = val
```

```
    if "censusreg_label" in df.columns:
        val = df.at[row, "censusreg_label"] if "censusreg_label" in df.columns else None
        if pd.notna(val) and (pd.isna(df.at[row, "region_label"]) or df.at[row, "region_label"] in [None, ""]):
            df.at[row, "region_label"] = val

    val_m9 = None
    if "m9_label" in df.columns:
        val_m9 = df.at[row, "m9_label"]
    if pd.notna(val_m9) and (pd.isna(df.at[row, "mortgage_knowledge_label"]) or df.at[row, "mortgage_knowledge_label"] in [None
        df.at[row, "mortgage_knowledge_label"] = val_m9
    else:
        if "mortgage_knowledge_code" in df.columns:
            code = df.at[row, "mortgage_knowledge_code"]
            if pd.notna(code):
                if code == 1 and (pd.isna(df.at[row, "mortgage_knowledge_label"]) or df.at[row, "mortgage_knowledge_label"] in
                    df.at[row, "mortgage_knowledge_label"] = "True"
                if code == 2 and (pd.isna(df.at[row, "mortgage_knowledge_label"]) or df.at[row, "mortgage_knowledge_label"] in
                    df.at[row, "mortgage_knowledge_label"] = "False"

    val_m10 = None
    if "m10_label" in df.columns:
        val_m10 = df.at[row, "m10_label"]
    if pd.notna(val_m10) and (pd.isna(df.at[row, "investment_knowledge_label"]) or df.at[row, "investment_knowledge_label"] in
        df.at[row, "investment_knowledge_label"] = val_m10
    else:
        if "investment_knowledge_code" in df.columns:
            code2 = df.at[row, "investment_knowledge_code"]
            if pd.notna(code2):
                if code2 == 1 and (pd.isna(df.at[row, "investment_knowledge_label"]) or df.at[row, "investment_knowledge_label"
                    df.at[row, "investment_knowledge_label"] = "True"
                if code2 == 2 and (pd.isna(df.at[row, "investment_knowledge_label"]) or df.at[row, "investment_knowledge_label"
                    df.at[row, "investment_knowledge_label"] = "False"

    row = row + 1

print(df[["state_label","region_label","mortgage_knowledge_label","investment_knowledge_label"]].head(8))
```

```
  state_label region_label mortgage_knowledge_label investment_knowledge_label
0        None         None                     None                       None
1        None         None                     None                       None
2        None         None                     None                       None
```

```
import pandas as pd
import numpy as np

# drops the almost empty and near constant columns, keeping the ids/weights
rows_count = len(df)

keep_always = []
if "nfcsid" in df.columns:
    keep_always.append("nfcsid")
if "wgt_n2" in df.columns:
    keep_always.append("wgt_n2")
if "wgt_d2" in df.columns:
    keep_always.append("wgt_d2")
if "wgt_s3" in df.columns:
    keep_always.append("wgt_s3")

mostly_missing = []
i = 0
while i < len(df.columns):
    col = df.columns[i]
    if col not in keep_always:
        n_missing = int(df[col].isna().sum())
        if n_missing > 0.95 * rows_count:
            mostly_missing.append(col)
    i = i + 1

near_constant = []
j = 0
while j < len(df.columns):
    col = df.columns[j]
    if col not in keep_always:
        unique_nonnull = df[col].dropna().unique()
        if len(unique_nonnull) == 1:
            near_constant.append(col)
```

```
        j = j + 1

    drop_list = []
    k = 0
    while k < len(mostly_missing):
        drop_list.append(mostly_missing[k])
        k = k + 1

    m = 0
    while m < len(near_constant):
        if near_constant[m] not in drop_list:
            drop_list.append(near_constant[m])
        m = m + 1

    if len(drop_list) > 0:
        df = df.drop(columns=drop_list)

    print("Dropped (mostly missing):", mostly_missing[:10], " ... total:", len(mostly_missing))
    print("Dropped (near constant):", near_constant[:10], " ... total:", len(near_constant))
    print("Shape after drop:", df.shape)

    # adds human readable labels for major NFCS variables
    if "a5" in df.columns and "education_label" not in df.columns:
        df["education_label"] = pd.Series([None]*len(df), dtype="object")
    if "a6" in df.columns and "marital_status_label" not in df.columns:
        df["marital_status_label"] = pd.Series([None]*len(df), dtype="object")
    if "a7" in df.columns and "living_arrangement_label" not in df.columns:
        df["living_arrangement_label"] = pd.Series([None]*len(df), dtype="object")
    if "a7a" in df.columns and "marital_net_label" not in df.columns:
        df["marital_net_label"] = pd.Series([None]*len(df), dtype="object")
    if "a4a" in df.columns and "ethnicity_net_label" not in df.columns:
        df["ethnicity_net_label"] = pd.Series([None]*len(df), dtype="object")
    if "a50b" in df.columns and "gender_age_net_label" not in df.columns:
        df["gender_age_net_label"] = pd.Series([None]*len(df), dtype="object")

    # Education
    if "a5" in df.columns:
        df.loc[df["a5"] == 1, "education_label"] = "Did not complete high school"
        df.loc[df["a5"] == 2, "education_label"] = "High school diploma"
        df.loc[df["a5"] == 3, "education_label"] = "GED/alternative credential"
        df.loc[df["a5"] == 4, "education_label"] = "Some college, no degree"
        df.loc[df["a5"] == 5, "education_label"] = "Associate’s degree"
        df.loc[df["a5"] == 6, "education_label"] = "Bachelor’s degree"
        df.loc[df["a5"] == 7, "education_label"] = "Post-graduate degree"

    # Marital status
    if "a6" in df.columns:
        df.loc[df["a6"] == 1, "marital_status_label"] = "Married"
        df.loc[df["a6"] == 2, "marital_status_label"] = "Single"
        df.loc[df["a6"] == 3, "marital_status_label"] = "Separated"
        df.loc[df["a6"] == 4, "marital_status_label"] = "Divorced"
        df.loc[df["a6"] == 5, "marital_status_label"] = "Widowed/widower"

    # Living arrangement
    if "a7" in df.columns:
        df.loc[df["a7"] == 1, "living_arrangement_label"] = "Only adult in household"
        df.loc[df["a7"] == 2, "living_arrangement_label"] = "Live with spouse/partner"
        df.loc[df["a7"] == 3, "living_arrangement_label"] = "Live in parents’ home"
        df.loc[df["a7"] == 4, "living_arrangement_label"] = "Live with family/friends/roommates"

    # Marital net
    if "a7a" in df.columns:
        df.loc[df["a7a"] == 1, "marital_net_label"] = "Married"
        df.loc[df["a7a"] == 2, "marital_net_label"] = "Living with partner"
        df.loc[df["a7a"] == 3, "marital_net_label"] = "Single"

    # Ethnicity net
    if "a4a" in df.columns:
        df.loc[df["a4a"] == 1, "ethnicity_net_label"] = "White non-Hispanic"
        df.loc[df["a4a"] == 2, "ethnicity_net_label"] = "Black non-Hispanic"
        df.loc[df["a4a"] == 3, "ethnicity_net_label"] = "Hispanic (alone or in combination)"
        df.loc[df["a4a"] == 4, "ethnicity_net_label"] = "Asian/Pacific Islander non-Hispanic"
        df.loc[df["a4a"] == 5, "ethnicity_net_label"] = "Other non-Hispanic"

    # Gender times Age net
    if "a50b" in df.columns:
        df.loc[df["a50b"] == 1,  "gender_age_net_label"] = "Male 18–24"
```

```
    df.loc[df["a50b"] == 2,  "gender_age_net_label"] = "Male 25–34"
    df.loc[df["a50b"] == 3,  "gender_age_net_label"] = "Male 35–44"
    df.loc[df["a50b"] == 4,  "gender_age_net_label"] = "Male 45–54"
    df.loc[df["a50b"] == 5,  "gender_age_net_label"] = "Male 55–64"
    df.loc[df["a50b"] == 6,  "gender_age_net_label"] = "Male 65+"
    df.loc[df["a50b"] == 7,  "gender_age_net_label"] = "Female 18–24"
    df.loc[df["a50b"] == 8,  "gender_age_net_label"] = "Female 25–34"
    df.loc[df["a50b"] == 9,  "gender_age_net_label"] = "Female 35–44"
    df.loc[df["a50b"] == 10, "gender_age_net_label"] = "Female 45–54"
    df.loc[df["a50b"] == 11, "gender_age_net_label"] = "Female 55–64"
    df.loc[df["a50b"] == 12, "gender_age_net_label"] = "Female 65+"

# adds Census Division labels if available
target_div_col = None
probe_div_cols = ["censusdiv", "census_div", "division"]
p = 0
while p < len(probe_div_cols):
    name = probe_div_cols[p]
    if name in df.columns:
        target_div_col = name
        break
    p = p + 1

if target_div_col is not None and "census_division_label" not in df.columns:
    df["census_division_label"] = pd.Series([None]*len(df), dtype="object")
    df.loc[df[target_div_col] == 1, "census_division_label"] = "New England"
    df.loc[df[target_div_col] == 2, "census_division_label"] = "Middle Atlantic"
    df.loc[df[target_div_col] == 3, "census_division_label"] = "East North Central"
    df.loc[df[target_div_col] == 4, "census_division_label"] = "West North Central"
    df.loc[df[target_div_col] == 5, "census_division_label"] = "South Atlantic"
    df.loc[df[target_div_col] == 6, "census_division_label"] = "East South Central"
    df.loc[df[target_div_col] == 7, "census_division_label"] = "West South Central"
    df.loc[df[target_div_col] == 8, "census_division_label"] = "Mountain"
    df.loc[df[target_div_col] == 9, "census_division_label"] = "Pacific"

# Creates readable labels for leftover 1/2-coded binary variables
skip_cols = []
if "nfcsid" in df.columns:
    skip_cols.append("nfcsid")
if "wgt_n2" in df.columns:
    skip_cols.append("wgt_n2")
if "wgt_d2" in df.columns:
    skip_cols.append("wgt_d2")
if "wgt_s3" in df.columns:
    skip_cols.append("wgt_s3")

q = 0
while q < len(df.columns):
    col = df.columns[q]
    if col.endswith("_label"):
        skip_cols.append(col)
    q = q + 1

r = 0
while r < len(df.columns):
    col = df.columns[r]
    if col not in skip_cols:
        if pd.api.types.is_numeric_dtype(df[col]):
            non_null_vals = df[col].dropna().unique()
            is_subset = True
            s = 0
            while s < len(non_null_vals):
                v = non_null_vals[s]
                if v not in [1, 2]:
                    is_subset = False
                s = s + 1
            if is_subset:
                new_col = col + "_label"
                if new_col not in df.columns:
                    df[new_col] = pd.Series([None]*len(df), dtype="object")
                idx2 = 0
                while idx2 < len(df):
                    val = df.at[idx2, col]
                    if pd.notna(val):
                        if val == 1:
                            df.at[idx2, new_col] = "Yes/True"
                        if val == 2:
```

```
                        df.at[idx2, new_col] = "No/False"
                idx2 = idx2 + 1
    r = r + 1

print("Finished generic 1/2 labeling for remaining binary items.")

# Renames key confusing columns into descriptive names
rename_map = {}
if "m9_label" in df.columns:
    rename_map["m9_label"] = "mortgage_knowledge_label_(15yr_vs_30yr)"
if "m10_label" in df.columns:
    rename_map["m10_label"] = "investment_knowledge_label_(stock_vs_mutualfund)"
if "wgt_n2" in df.columns:
    rename_map["wgt_n2"] = "national_weight"
if "wgt_d2" in df.columns:
    rename_map["wgt_d2"] = "census_division_weight"
if "wgt_s3" in df.columns:
    rename_map["wgt_s3"] = "state_weight"

if len(rename_map) > 0:
    df = df.rename(columns=rename_map)

print("Renamed columns:")
for old, new in rename_map.items():
    print(f"{old} → {new}")

# Saves and preview
final_name = "NFCS_2024_State_Data.cleaned_labeled.csv"
df.to_csv(final_name, index=False)
print("Saved final version with readable column names:", final_name)

show_cols = []
probe = ["state_label","region_label","census_division_label","gender_label","age_group_label",
         "education_label","marital_status_label","living_arrangement_label","marital_net_label",
         "ethnicity_net_label","gender_age_net_label",
         "mortgage_knowledge_label_(15yr_vs_30yr)","investment_knowledge_label_(stock_vs_mutualfund)",
         "m9_correct","m10_correct","national_weight","census_division_weight","state_weight"]
i = 0
while i < len(probe):
    if probe[i] in df.columns:
        show_cols.append(probe[i])
    i = i + 1

print(show_cols)
df[show_cols].head(12)
```

```
Dropped (mostly missing): ['state_label', 'region_label', 'mortgage_knowledge_label', 'investment_knowledge_label']  ... total:
Dropped (near constant): ['SERVICE_AVAILABLE_TO', 'ADDITIONAL_SERVICES_MAYINCLUDE', 'MAR_SCORE', 'MAR_SOURCEOPERATION']  ... tot
Shape after drop: (3, 20)
Finished generic 1/2 labeling for remaining binary items.
Renamed columns:
Saved final version with readable column names: NFCS_2024_State_Data.cleaned_labeled.csv
[]
```

0
1
2

```
# Makes the entire CSV file look like the output above

desired = ["state_label",
           "region_label",
           "census_division_label",
           "marital_status_label",
           "living_arrangement_label",
           "marital_net_label",
           "gender_age_net_label",
           "national_weight",
           "census_division_weight",
           "state_weight"]

export_cols = []
i = 0
while i < len(desired):
```

```
        name = desired[i]
        if name in df.columns:
            export_cols.append(name)
        i = i + 1

    if len(export_cols) != len(desired):
        print("Warning: some expected columns are missing from df:")
        missing_list = []
        j = 0
        while j < len(desired):
            if desired[j] not in df.columns:
                missing_list.append(desired[j])
            j = j + 1
        print("Missing:", missing_list)

    # Creates the exact view with ALL ROWS
    df_out = df[export_cols].copy()

    k = 0
    while k < len(export_cols):
        col = export_cols[k]
        if ("weight" in col) and (col in df_out.columns):
            if pd.api.types.is_numeric_dtype(df_out[col]):
                df_out[col] = df_out[col].round(6)
        k = k + 1

    # USE THIS DATASET CALLED PRESENTATION VIEW for NFCS state Date !!

    final_subset_name = "NFCS_2024_State_Data.PRESENTATION_VIEW.csv"
    df_out.to_csv(final_subset_name, index=False)

    print("Saved:", final_subset_name)
    print("Rows (should match df):", len(df_out), "  Columns:", len(df_out.columns))
    print(df_out.head(12))
```

```
Warning: some expected columns are missing from df:
Missing: ['state_label', 'region_label', 'census_division_label', 'marital_status_label', 'living_arrangement_label', 'marital_n
Saved: NFCS_2024_State_Data.PRESENTATION_VIEW.csv
Rows (should match df): 3   Columns: 0
Empty DataFrame
Columns: []
Index: [0, 1, 2]
```

New York Housing Market

https://www.kaggle.com/datasets/nelgiriyewithana/new-york-housing-market

```
import pandas as pd
import numpy as np
import re

df = pd.read_csv("NY-House-Dataset.csv")

cleaned_names = [] # normalizes the column names
i = 0
while i < len(df.columns):
    name = df.columns[i]
    name = name.strip()
    name = re.sub(r'[^0-9a-zA-Z]+', '_', name)
    name = re.sub(r'_+', '_', name).strip('_').lower()
    cleaned_names.append(name)
    i = i + 1
df.columns = cleaned_names

j = 0 # Trims the whitespace in the text columns
while j < len(df.columns):
    col = df.columns[j]
    if df[col].dtype == object:
        df[col] = df[col].astype(str).str.strip()
    j = j + 1

if "latitude" in df.columns:
    df["latitude"] = df["latitude"].clip(-90, 90)
if "longitude" in df.columns:
    df["longitude"] = df["longitude"].clip(-180, 180)
```

```
if "price" in df.columns and "propertysqft" in df.columns:
    df["price_per_sqft"] = df["price"] / df["propertysqft"]

df.to_csv("NY-House-Dataset.cleaned.csv", index=False)
```

California Housing Prices

https://www.kaggle.com/datasets/camnugent/california-housing-prices?resource=download

```
import pandas as pd
import numpy as np

df = pd.read_csv('housing.csv')

df.fillna({'total_bedrooms': df['total_bedrooms'].median()}, inplace=True)

df = df.drop_duplicates()

df.columns = df.columns.str.lower().str.replace(' ', '_')

display(df.head())

df.to_csv('/content/housing_clean.csv', index=False)
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_valu
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200

Regression Dataset for Household Income Analysis

https://www.kaggle.com/datasets/stealthtechnologies/regression-dataset-for-household-income-analysis

```
import pandas as pd
import numpy as np
import re

df = pd.read_csv("Regression-Dataset-For-Household-Income-Analysis.csv") # Loads the file

cleaned_columns = [] # Normalizes the column names, makes them into lowercase and makes them snake_case
i = 0
while i < len(df.columns):
    name = str(df.columns[i])
    name = name.strip()
    name = re.sub(r"[^0-9a-zA-Z]+", "_", name)
    name = re.sub(r"_+", "_", name)
    name = name.strip("_").lower()
    cleaned_columns.append(name)
    i = i + 1
df.columns = cleaned_columns

j = 0 # Trims the whitespace in the string columns
while j < len(df.columns):
    col = df.columns[j]
    if df[col].dtype == object:
        df[col] = df[col].astype(str).str.strip()
    j = j + 1

k = 0 # Changes clearly numeric text columns like income or age into numeric columns
while k < len(df.columns):
    col = df.columns[k]
    if df[col].dtype == object:
        col_lower = col.lower()
        if "income" in col_lower or "age" in col_lower or "year" in col_lower or "salary" in col_lower:
```

```
            cleaned = df[col].astype(str)
            cleaned = cleaned.str.replace(r"[\$,€£,%]", "", regex=True)
            cleaned = cleaned.str.replace(",", "", regex=True)
            cleaned = cleaned.str.replace(r"[^\d\.\-eE]", "", regex=True)
            df[col] = pd.to_numeric(cleaned, errors="coerce")
    k = k + 1

df = df.drop_duplicates().reset_index(drop=True) # Deduplication if it is needed

if "income" in df.columns: # Creates log_income if the income column exists and it is numeric
    if pd.api.types.is_numeric_dtype(df["income"]):
        df["income"] = df["income"].clip(lower=0)
        df["log_income"] = np.log1p(df["income"])

df.to_csv("Regression-Dataset-For-Household-Income-Analysis.cleaned.csv", index=False) # Saves the cleaned copy of the dataset

print("Saved cleaned dataset as Regression-Dataset-For-Household-Income-Analysis.cleaned.csv")
print(df.shape)
print(df.head(3))
```

```
Saved cleaned dataset as Regression-Dataset-For-Household-Income-Analysis.cleaned.csv
(10000, 15)
   age education_level  occupation  number_of_dependents location  \
0   56        Master's  Technology                     5    Urban
1   69     High School     Finance                     0    Urban
2   46      Bachelor's  Technology                     1    Urban

   work_experience marital_status employment_status  household_size  \
0               21        Married         Full-time               7
1                4         Single         Full-time               7
2                1         Single         Full-time               7

  homeownership_status     type_of_housing  gender  \
0                  Own           Apartment    Male
1                  Own           Apartment    Male
2                  Own  Single-family home  Female

  primary_mode_of_transportation  income  log_income
0                 Public transit   72510   11.191494
1                         Biking   75462   11.231398
2                            Car   71748   11.180929
```

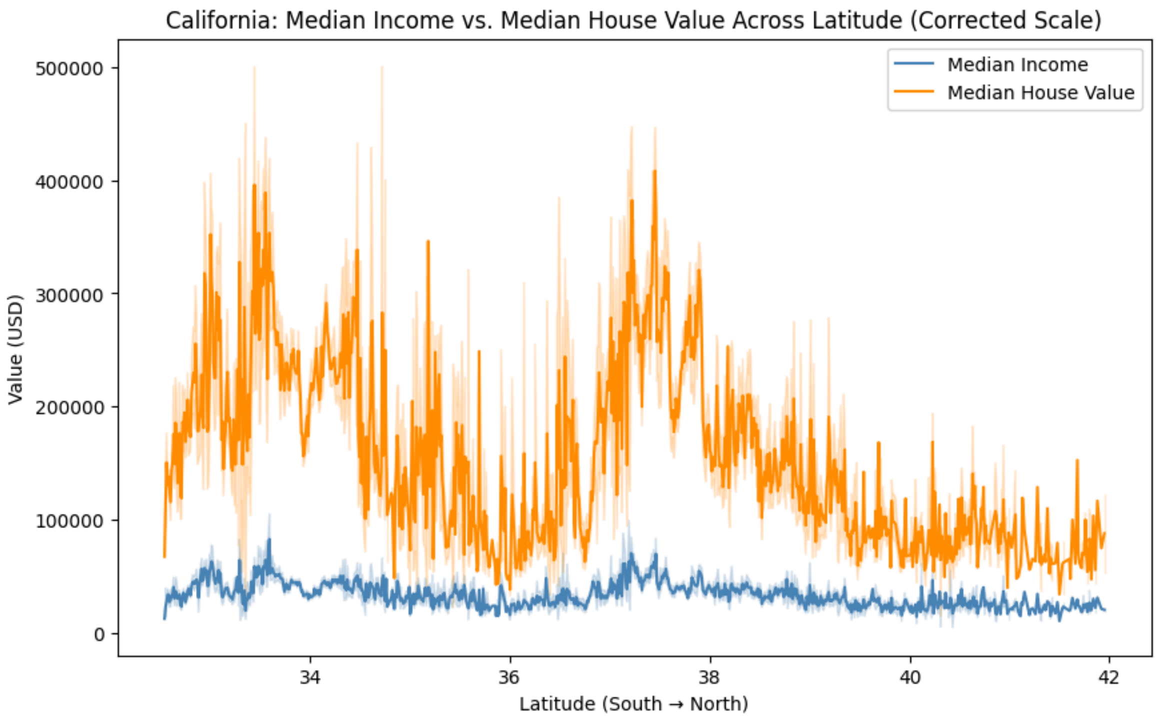
4. Exploratory Data Analysis

Details about the columns, rows, and data values in each dataset are above. Next, we'll explore some findings in our data.

```
# --- Imports ---
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# --- Load datasets ---
housing = pd.read_csv("housing_clean.csv")
ny_house = pd.read_csv("NY-House-Dataset.cleaned.csv")
regression = pd.read_csv("Regression-Dataset-For-Household-Income-Analysis.cleaned.csv")

# --- Basic info ---
datasets = {
    "Housing": housing,
    "NY_House": ny_house,
    "Regression": regression
}

# We'll perform EDA on these 3 main data sets that offer the most insights
```

```
housing = pd.read_csv("housing_clean.csv")

# Scale median_income to represent actual yearly salaries (in dollars)
housing_fixed = housing.copy()
housing_fixed['median_income'] = housing_fixed['median_income'] * 10000  # Convert tens of thousands to actual dollars

# Sort by latitude for smooth line plot
housing_sorted = housing_fixed.sort_values(by="latitude")
```

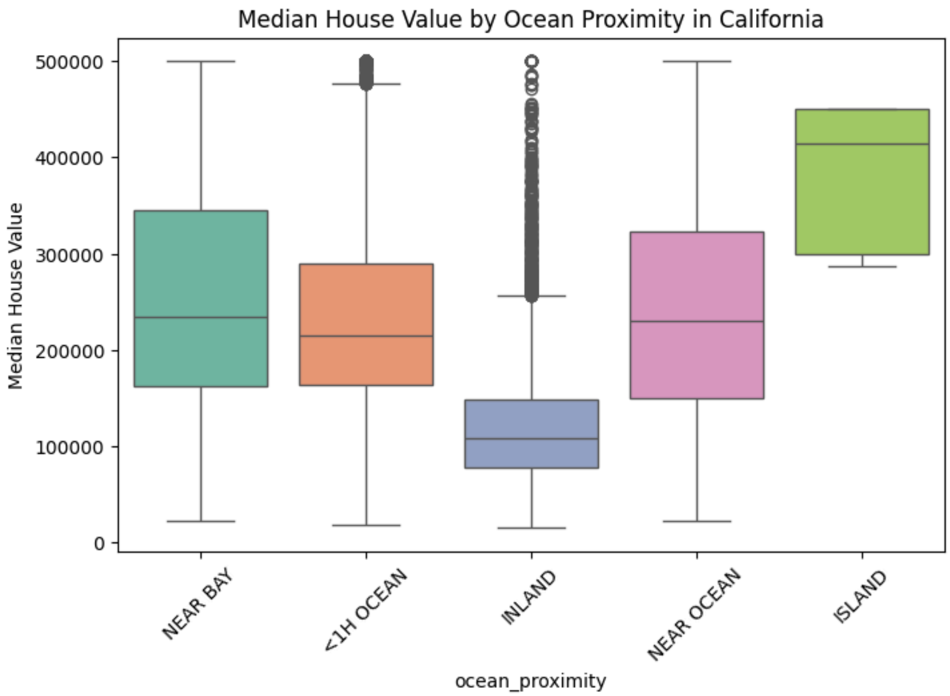
```
# Plot
plt.figure(figsize=(10,6))
sns.lineplot(x="latitude", y="median_income", data=housing_sorted, label="Median Income", color="steelblue")
sns.lineplot(x="latitude", y="median_house_value", data=housing_sorted, label="Median House Value", color="darkorange")
plt.title("California: Median Income vs. Median House Value Across Latitude (Corrected Scale)")
plt.xlabel("Latitude (South → North)")
plt.ylabel("Value (USD)")
plt.legend()
plt.show()
```



Plot Insight

The line chart shows that while both median income and median house value vary with latitude, house values rise much more steeply in certain southern and coastal regions. Median income increases only slightly, indicating a widening affordability gap where housing prices outpace income growth across California.

```
plt.figure(figsize=(8,5))
sns.boxplot(x="ocean_proximity", y="median_house_value", data=housing, hue = 'ocean_proximity', palette="Set2", legend = False)
plt.title("Median House Value by Ocean Proximity in California")
plt.xticks(rotation=45)
plt.ylabel("Median House Value")
plt.show()
```



Plot Insight

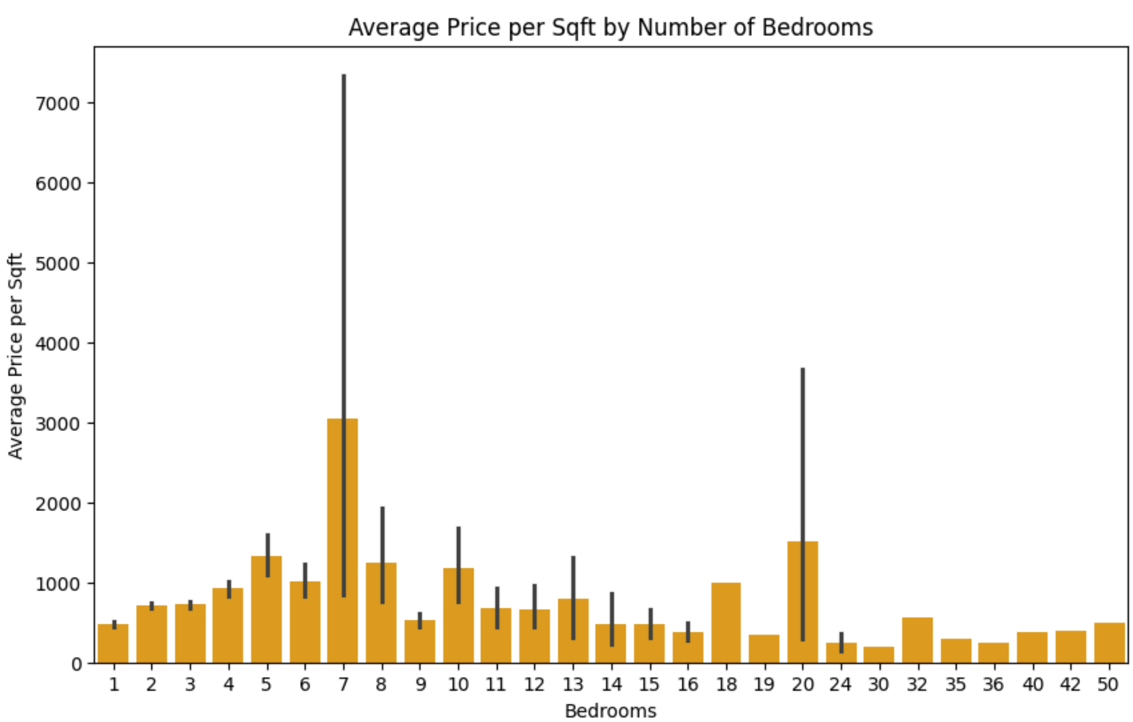
Properties closer to the water have substantially higher median values and wider variability. Inland areas show lower, more compact price distributions, highlighting a strong coastal premium in California housing.

```
# Load dataset
ny_house = pd.read_csv("NY-House-Dataset.cleaned.csv")

# Remove top 1% of prices to eliminate extreme outliers
ny_no_outliers = ny_house[ny_house['price'] < ny_house['price'].quantile(0.99)]

# Plot scatter plot
plt.figure(figsize=(8,6))
sns.scatterplot(x="propertysqft", y="price", data=ny_no_outliers, alpha=0.5, color="seagreen")
plt.title("New York: Property Size vs. Price (Outliers Removed)")
plt.xlabel("Property Size (sq ft)")
plt.ylabel("Price (USD)")
plt.show()
```

Plot Insight

Most listings cluster under 5,000 sq ft, showing that larger homes typically cost more, but price growth slows beyond mid-range sizes. This suggests location and neighborhood effects influence prices more than just size.

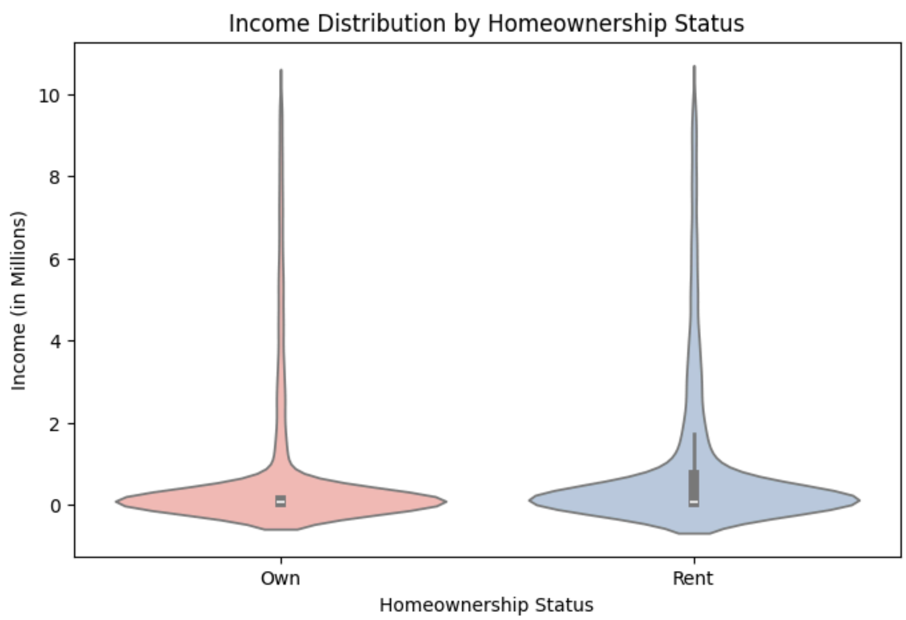
```
plt.figure(figsize=(10,6))
sns.barplot(x="beds", y="price_per_sqft", data=ny_house, color = 'orange')
plt.title("Average Price per Sqft by Number of Bedrooms")
plt.xlabel("Bedrooms")
plt.ylabel("Average Price per Sqft")
plt.show()
```



Plot Insight

The average price per square foot generally decreases/ stays steady as the number of bedrooms increases. Smaller units with fewer bedrooms tend to be more expensive per square foot, which aligns with high-density, urban apartment trends where compact living spaces command premium rates. It is not necessary that more bedrooms means more expensive in NY

```
regression = pd.read_csv("Regression-Dataset-For-Household-Income-Analysis.cleaned.csv")

# Convert income to millions for a clearer y-axis
regression_fixed = regression.copy()
regression_fixed['income_millions'] = regression_fixed['income'] / 1_000_000

# Plot violin plot
plt.figure(figsize=(8,5))
sns.violinplot(x="homeownership_status", y="income_millions", data=regression_fixed, hue="homeownership_status", palette="Paste
plt.title("Income Distribution by Homeownership Status")
plt.xlabel("Homeownership Status")
plt.ylabel("Income (in Millions)")
plt.yticks([0, 2, 4, 6, 8, 10])
plt.show()
```



Plot Insight

Homeowners typically report higher incomes than renters, but the violin plot shows notable overlap between the two distributions. This implies that income alone doesn't fully determine homeownership. Other factors like debt, credit, or savings likely play important roles.

Cross-Dataset Insights and Preliminary EDA Conclusions

After exploring the three major datasets: California Housing, New York Housing, and the Regression (Income) dataset, some consistent themes emerge.

1. Regional Affordability Gaps

- Housing costs in both California and New York show strong right-skewed distributions.
- Coastal or urban proximity is a key price driver: homes near the coast in California and central locations in New York command disproportionately higher prices.
- Even after scaling income correctly, the average household income is far below the mean home value, indicating affordability pressure in both states.

2. Socio-economic Patterns

- In the income dataset, homeownership correlates with higher income levels, yet the overlap between renters and owners suggests income alone doesn't fully explain ownership.
- Surprisingly, the education-to-income pattern is reversed in this sample: individuals with only a high school education earn slightly more on average than those with advanced degrees, possibly due to higher work experience or labor-market differences. Or it could

be that people who didn't go to college didn't take up common, ordinary professions and instead tried businesses/occupations that pay off the risks they take.

3. Market Behavior

- In New York, property size and the number of rooms influence total price but not price per square foot, implying that dense urban housing markets value compact units more highly.
- In California, both income and house values increase toward specific latitudes, suggesting spatial clustering of wealth and property prices.

5. Hypothesis Visualizations

Loading Datasets

Financial Data (State, Age, Marital, Living Arrangement)

```
import pandas as pd # Loads and normalizes the column names
import numpy as np

FinancialData = pd.read_csv("NFCS_2024_State_Data.PRESENTATION_VIEW.csv")

print(FinancialData.shape)
FinancialData.head(3)
```

```
(25539, 10)
```

	state_label	region_label	census_division_label	marital_status_label	living_arrangement_label	marital_net_label	gender_a
0	Ohio	Midwest	East North Central	Married	Live with spouse/partner	Married	
1	Washington	West	Pacific	Widowed/widower	Only adult in household	Single	
2	Oregon	West	Pacific	Married	Live with spouse/partner	Married	

Next steps: Generate code with `FinancialData` New interactive sheet

Housing Data (Location, Age, Rooms, Median House Value, Ocean)

```
HousingData = pd.read_csv("housing_clean.csv")

print(HousingData.shape)
HousingData.head(3)
```

```
(20640, 10)
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_valu
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100

Next steps: Generate code with `HousingData` New interactive sheet

Houeshold Income Data (Person Info: Education, Number Dependant, Marital, Mode of transport, Own/Rent, Income)

```
HouseholdIncomeData = pd.read_csv("Regression-Dataset-For-Household-Income-Analysis.cleaned.csv")

print(HouseholdIncomeData.shape)
HouseholdIncomeData.head(3)
```

(10000, 15)

	age	education_level	occupation	number_of_dependents	location	work_experience	marital_status	employment_status	househol
0	56	Master's	Technology	5	Urban	21	Married	Full-time	
1	69	High School	Finance	0	Urban	4	Single	Full-time	
2	46	Bachelor's	Technology	1	Urban	1	Single	Full-time	

Next steps: Generate code with HouseholdIncomeData New interactive sheet

NY House Data

```
NYHouseData = pd.read_csv("NY-House-Dataset.cleaned.csv")

print(NYHouseData.shape)
NYHouseData.head(3)
```

(4801, 18)

	brokertitle	type	price	beds	bath	propertysqft	address	state	main_address	administrative_area_level_2	localit
0	Brokered by Douglas Elliman -111 Fifth Ave	Condo for sale	315000	2	2.0	1400.0	2 E 55th St Unit 803	New York, NY 10022	2 E 55th St Unit 803New York, NY 10022	New York County	New Yo
1	Brokered by Serhant	Condo for sale	195000000	7	10.0	17545.0	Central Park Tower Penthouse-217 W 57th New Yo...	New York, NY 10019	Central Park Tower Penthouse-217 W 57th New Yo...	United States	New Yo
2	Brokered by Sowae Corp	House for sale	260000	4	2.0	2015.0	620 Sinclair Ave	Staten Island, NY 10312	620 Sinclair AveStaten Island, NY 10312	United States	New Yo

Next steps: Generate code with NYHouseData New interactive sheet

Preparing Data

```
def assign_age_cohort(age):
    """Categorize ages into generational cohorts."""
    if pd.isna(age):
        return np.nan
    age = int(age)
    if 18 <= age <= 27:
        return "Gen Z (18-27)"
    elif 28 <= age <= 43:
        return "Millennial (28-43)"
    elif 44 <= age <= 59:
        return "Gen X (44-59)"
    elif age >= 60:
        return "Boomer+ (60+)"
    else:
        return "Under 18"

# Apply to household income dataset (which contains age info)
HouseholdIncomeData["age_cohort"] = HouseholdIncomeData["age"].apply(assign_age_cohort)
```

```
def calc_price_to_income(df, income_col, price_col):
    """
    Compute price-to-income ratio.
    Note: In HousingData, median_income is in units of 10,000 dollars.
    """
    df = df.copy()
    df["price_to_income_ratio"] = df[price_col] / (df[income_col] * 10000)
    # Clean up extreme outliers
    df = df[df["price_to_income_ratio"].between(df["price_to_income_ratio"].quantile(0.01),
                                                df["price_to_income_ratio"].quantile(0.99))]
```

```
    return df

# Apply to housing dataset
HousingData = calc_price_to_income(HousingData, "median_income", "median_house_value")
```

```
# Check the new columns
print(HouseholdIncomeData["age_cohort"].value_counts(dropna=False))
print(HousingData[["median_income", "median_house_value", "price_to_income_ratio"]].head())
```

```
age_cohort
Millennial (28–43)    3129
Gen X (44–59)         2984
Boomer+ (60+)         2060
Gen Z (18–27)         1827
Name: count, dtype: int64
   median_income  median_house_value  price_to_income_ratio
0         8.3252            452600.0               5.436506
1         8.3014            358500.0               4.318549
2         7.2574            352100.0               4.851600
3         5.6431            341300.0               6.048094
4         3.8462            342200.0               8.897093
```

```
!pip install plotly
```

```
Requirement already satisfied: plotly in /usr/local/lib/python3.12/dist-packages (5.24.1)
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.12/dist-packages (from plotly) (8.5.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.12/dist-packages (from plotly) (25.0)
```

Hypothesis/Claim 1: California Price-to-Income ratio

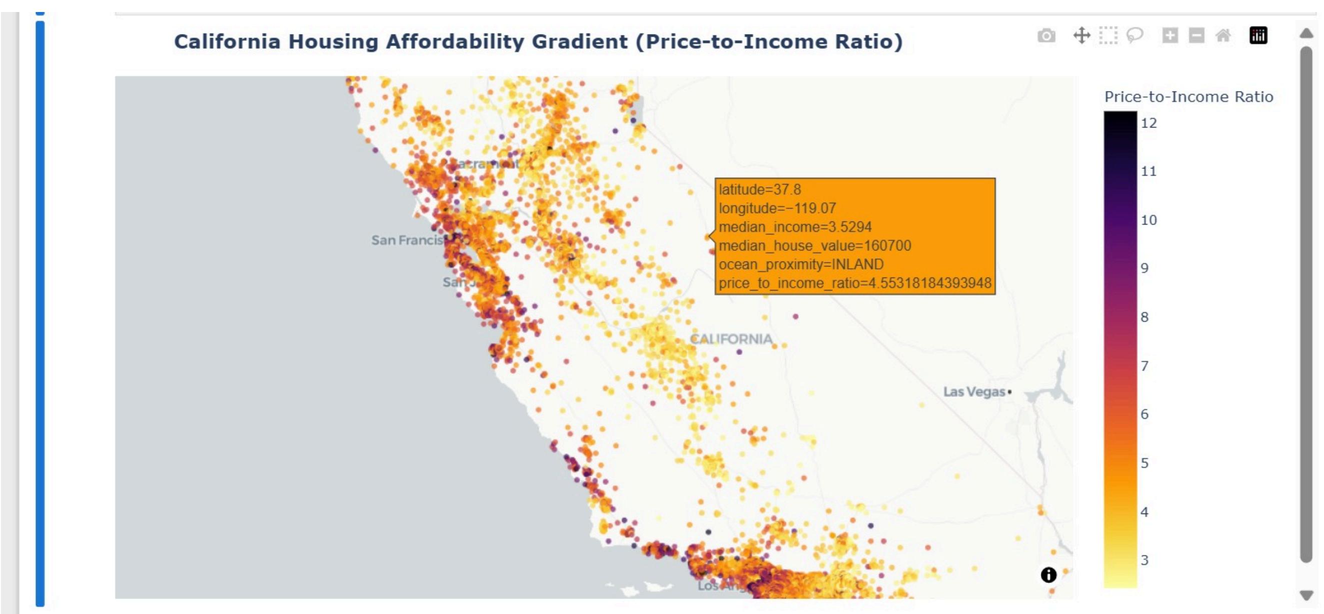
The closer a home is to California's coast, the higher its price-to-income ratio is; indicating that homes near coastal areas have become increasingly unaffordable relative to all income levels.

I thought this hypothesis is interesting because coastal regions like Los Angeles, San Francisco, and San Diego have been economic and cultural hubs with dense job markets, lifestyle amenities, and limited housing supply. However, these advantages come with a steep affordability cost. By comparing median house value to median household income across thousands of tracts, the price-to-income ratio reveals where housing costs most exceed what residents can reasonably afford.

```
import plotly.express as px
import plotly.io as pio
pio.renderers.default = "colab"
import matplotlib.pyplot as plt
%matplotlib inline

# Check price_to_income_ratio exists, if not create
if "price_to_income_ratio" not in HousingData.columns:
    HousingData["price_to_income_ratio"] = HousingData["median_house_value"] / (HousingData["median_income"] * 10000)

# Removing outliers (1st–99th percentile)
q_low, q_high = HousingData["price_to_income_ratio"].quantile([0.01, 0.99])
HousingData = HousingData.query("@q_low <= price_to_income_ratio <= @q_high")

# Plotly
fig1 = px.scatter_map(
    HousingData,
    lat="latitude",
    lon="longitude",
    color="price_to_income_ratio",
    color_continuous_scale=px.colors.sequential.Inferno[::-1],
    zoom=5,
    opacity=0.7,
    hover_data=["median_income", "median_house_value", "ocean_proximity"],
    title="California Housing Affordability Gradient (Price-to-Income Ratio)",
)

# --- Map style
fig1.update_layout(
    map_style="carto-positron",   # clean base map with light coastlines
```

```
        map_center={"lat": 36.5, "lon": -119.5},
        margin={"r":0,"t":50,"l":0,"b":0},
        title_font=dict(size=18, weight='bold'),
        coloraxis_colorbar=dict(title="Price-to-Income Ratio")
    )

    # Display in Notebook
    fig1.show("notebook_connected")
```

The visualization plot is working well in Jupyter Notebooks. There seems to be an issue displaying the same visualization here in Google Colab notebook. Could be some version difference between Colab and Jupyter Notebooks. I have attached a screenshot of the visualization from my Jupyter Notebook below.



Hypothesis/Claim 2: House prices Outpaced Income growth over 40 years (U.S.)

Median household income in the United States has not kept pace with rising median home prices over the past 40 years, making homeownership increasingly unaffordable for the average household

Understanding this is important as it connects to other trends: slowing wage growth, generational wealth inequality, and regional housing crises. Investigating this relationship helps quantify why homeownership, once considered a hallmark of the American middle class, has become out of reach for many families today despite overall economic growth.

```
import pandas as pd
import plotly.graph_objects as go
import plotly.io as pio
pio.renderers.default = "colab"
import matplotlib.pyplot as plt
%matplotlib inline

# --- Load datasets ---
income = pd.read_csv("Median HH Income Dataset.csv")
price = pd.read_csv("Median House Price Dataset.csv")

# --- Clean and prepare the Year column ---
income["Year"] = pd.to_datetime(income["Year"]).dt.year
price["Year"] = pd.to_datetime(price["Year"]).dt.year

# --- Merge the two datasets on Year ---
merged = pd.merge(income, price, on="Year", how="inner")

# --- Rename columns for readability ---
merged.rename(columns={
    "Median HH Income": "Median Household Income ($)",
    "Median House Price": "Median House Price ($)"
}, inplace=True)
```

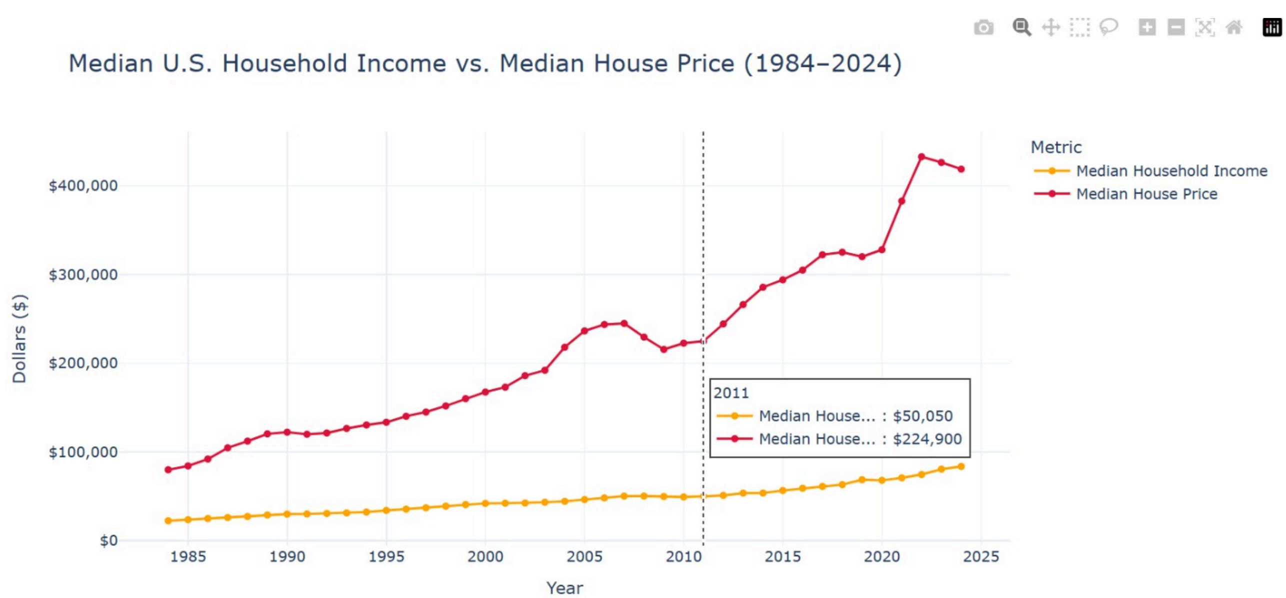
```
print(income.columns.tolist())
print(price.columns.tolist())
```

```
['Year', 'Median HH Income']
['Year', 'Median House Price ']
```

```
# --- Create the figure ---
fig = go.Figure()

# Line 1: Median Household Income
fig.add_trace(go.Scatter(
    x=merged["Year"],
    y=merged["Median Household Income ($)"],
    mode="lines+markers",
    name="Median Household Income",
    line=dict(color="orange", width=2),
    marker=dict(size=6)
))

# Line 2: Median House Price
fig.add_trace(go.Scatter(
    x=merged["Year"],
    y=merged["Median House Price "],
    mode="lines+markers",
    name="Median House Price ",
    line=dict(color="crimson", width=2),
    marker=dict(size=6)
))

# --- Layout customization ---
fig.update_layout(
    title="Median U.S. Household Income vs. Median House Price (1984–2024)",
    xaxis_title="Year",
    yaxis_title="Dollars ($)",
    yaxis=dict(
        tickformat="$,",
        tick0=0,
        dtick=100000  # increments of $100K
    ),
    legend_title="Metric",
```

```
    template="plotly_white",
    hovermode="x unified",
    title_font=dict(size=20)
)

# --- Display chart ---
fig.show("notebook_connected")
```

The visualization plot is working well in Jupyter Notebooks. There seems to be an issue displaying the same visualization here in Google Colab notebook. Could be some version difference between Colab and Jupyter Notebooks. I have attached a screenshot of the visualization from my Jupyter Notebook below.



6. ML Analysis

ML Analysis: Logistic regression with class weighting achieved 63.2% accuracy, improving over the 59.6% majority baseline. Class performance is asymmetric: the model identifies owners well (precision = 0.67, recall = 0.77), but under-detects renters (precision = 0.55, recall = 0.42). This indicates useful signal in the features, but also a bias toward the majority class. Next, we will address renter recall via threshold tuning, additional affordability features (e.g., regional price levels), and non-linear models. Adding engineered income features did not increase accuracy, suggesting that affordability is influenced by unobserved variables such as regional housing costs or credit constraints. The model could be extended with geographic housing-price data.

```
import numpy as np
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report

# --- engineer porentially relevant features
df["log_income"] = np.log1p(df["income"])
df["income_per_person"] = df["income"] / df["household_size"].replace(0, np.nan)

# --- feature / target setup
features = ["age","education_level","marital_status","work_experience",
            "household_size","income","log_income","income_per_person","location"]
target = "homeownership_status"
X = df[features].dropna()
y = df.loc[X.index, target].map({"Own":1,"Rent":0})

# --- preprocessing
categorical = ["education_level","marital_status","location"]
numeric = ["age","work_experience","household_size","income","log_income","income_per_person"]
preprocess = ColumnTransformer([
    ("cat", OneHotEncoder(handle_unknown="ignore"), categorical),
    ("num", StandardScaler(), numeric)
])

# --- model
pipe = Pipeline([
    ("prep", preprocess),
    ("clf", LogisticRegression(max_iter=1000, class_weight="balanced"))
])

# --- split / train / evaluate
X_tr, X_te, y_tr, y_te = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)
pipe.fit(X_tr, y_tr)
pred = pipe.predict(X_te)
print("Accuracy:", accuracy_score(y_te, pred))
print(classification_report(y_te, pred, target_names=["Rent","Own"]))
```

```
Accuracy: 0.632
              precision    recall  f1-score   support

        Rent       0.55      0.42      0.48       796
         Own       0.67      0.77      0.72      1204

    accuracy                           0.63      2000
   macro avg       0.61      0.60      0.60      2000
weighted avg       0.62      0.63      0.62      2000
```

```
from sklearn.dummy import DummyClassifier

dummy = DummyClassifier(strategy="most_frequent")
dummy.fit(X_train, y_train)
baseline_preds = dummy.predict(X_test)

baseline_acc = accuracy_score(y_test, baseline_preds)
print("Baseline accuracy:", baseline_acc)
```

```
Baseline accuracy: 0.5955
```

7. Reflection

- The hardest part of the project so far has been working with multiple datasets that differ in scale, structure, and purpose. Aligning income data, housing markets, and demographic attributes into a coherent analysis required careful cleaning and interpretation.

Even within EDA, it was challenging to compare variables that use different units or represent different geographic contexts.

- Our initial insights show consistent patterns of housing unaffordability in both California and New York. Median house values rise much faster than median incomes, particularly in coastal or urban regions. We also observed unexpected demographic patterns—such as the non-linear relationship between education and income—which suggests deeper structural factors at play.
- At this point, we do have concrete results from our EDA: clear visual trends, geographic patterns, and evidence of affordability gaps. Our current findings mainly establish the groundwork for the predictive and statistical analysis to come.
- Going forward, the biggest challenges will be selecting meaningful target variables for affordability, engineering features that connect datasets conceptually, and designing models that produce interpretable results. We also need to ensure that our visualizations communicate trends clearly without overwhelming the viewer.
- Overall, we believe we are on track. The datasets are clean, the EDA is complete, and the main themes of our project are now well-defined. If anything, we will need to allocate more time to the ML component and to crafting clear visual storytelling for the final report and presentation.
- Based on the exploration so far, it is absolutely worth continuing with this project. The data reveal strong, interpretable signals about housing affordability and financial well-being, and there is clear potential for meaningful analysis in the next milestone.

8. Next Steps

Over the next month, our focus will shift from exploration to building, evaluating, and clearly communicating our final solution. The remaining work aligns with the two upcoming milestones: the project presentation (December 2) and the final report (December 11).

1. Model Development and Statistical Analysis

- Implement **at least two ML/statistical techniques** on our affordability-related targets (e.g., predicting house values, affordability scores, or homeownership likelihood).
    - Examples: linear or regularized regression, tree-based models, clustering of regions by affordability, or logistic regression for classification.
- Add **at least one extra analysis** beyond the minimum requirement (e.g., an additional model or a more advanced interpretability method like feature importance).
- Compare all models against a **simple baseline** (e.g., mean predictor, dummy classifier) to determine whether our methods meaningfully improve performance.
- Document our modeling choices, feature engineering (e.g., affordability ratios, price-per-sqft, income-per-dependent), and evaluation metrics.

2. Visualization and Storytelling

- Design **at least two distinct visualizations** for the final results (not just EDA), such as:
    - A visualization that explains model predictions versus actual values.
    - A visualization that compares affordability across regions or demographic groups.
- Add **at least one extra visualization or refinement** (e.g., an interactive figure, map-style plot, or a composite chart linking income and housing).
- Ensure each visualization clearly answers a specific question and includes readable labels, legends, and short textual explanations.

3. Presentation Preparation (Due Dec 2)

- Create a **slide deck** organized around the four core components:
    1. Project name and team members
    2. Problem and motivation (housing affordability and financial well-being)
    3. Data (sources, cleaning, and key features)
    4. Solution (EDA, models, main findings, and takeaways)
- Prepare a **short demo** (if that works best) that shows either:
    - Key visualizations and model results, or
    - A simple workflow of how we move from raw data → cleaned data → analysis → conclusions.
- Decide whether we will submit a **recorded video** or **present live**, and rehearse to ensure we can present within the time limit while leaving room for Q&A.

- Use the presentation as an opportunity to collect feedback on clarity, missing angles, or additional analysis worth adding before the final report.

4. Final Report Assembly (Due Dec 11)

- Organize and submit:
  - Our **cleaned datasets**, or links plus cleaning scripts where the data are large.
  - All **analysis code** (EDA, ML, visualization) in a clean, reproducible structure (e.g., notebooks + helper scripts).
- Write the full report sections:
  - Data and preprocessing (what we actually did, not just planned).
  - ML/Stats methods (at least two techniques + one extra) and how we evaluated them.
  - Visualization section (at least two distinct techniques + one extra deliverable).
  - Results and inferences: what we learned about affordability, inequality, and demographics.
  - Limitations and future work.
- Include a **GenAI Guidance** section that reflects on:
  - Which AI-generated suggestions we used (e.g., feature engineering, visualization ideas, modeling directions).
  - Which suggestions we chose not to use, and why.

5. How We Will Evaluate Success

We will consider the project successful if:

- **Technical requirements are met or exceeded**:
  - At least two ML/statistical techniques plus one extra.
  - At least two distinct visualizations plus one extra.
  - Cleaned data and code are well-documented and runnable.
- **Models perform better than simple baselines** and their behavior is interpretable (we can explain which features matter and how).
- **Visualizations clearly communicate affordability patterns** and are understandable without extra explanation.
- The presentation and final report **tell a coherent story**: starting from our problem and data and ending with concrete, data-backed insights about housing affordability and financial standing.
- We can point to **specific questions from our proposal** and show that we either answered them or learned something meaningful from trying.

These steps will guide our work from this progress report through the December 2 presentation and the final report due on December 11.

9. Generative AI Sugesstions

To gather external feedback and generate high-level ideas for improving our project, we used OpenAI's ChatGPT (GPT-5.1 model). We provided the model with excerpts from our exploratory data analysis, including some visualizations, a description of our project goal (evaluating home affordability, people's financial situations, demographics, etc), and asked for suggestions on improving our analysis and next steps.

Model - **ChatGPT (GPT-5.1)**

Here are the prompts we used and the suggestions it provided:

1. What are high-level suggestions to improve our analysis?

Here are targeted improvements based on the EDA you performed:

- Consolidate affordability metrics instead of looking at income and house values separately. For example: price-to-income ratio, monthly mortgage estimate, or residual income after housing costs.
- Stratify your analysis by key demographic categories (homeownership status, education, employment status) to reveal subgroup differences.

2. How can we better connect our housing data with income and demographic data?

You can connect the datasets more meaningfully by:

- Mapping demographic groups to affordability levels:
  - Which education levels have the lowest/highest price-to-income ratio?
  - Which employment statuses are most likely to afford coastal CA homes or NY apartments?

- Creating derived socioeconomic indicators, such as:
  - income per household member
  - income per bedroom needed

3. What would make our visualizations more meaningful or interpretable?

For your specific visuals, improvements could include:

- Annotating major trends directly on the plots (e.g., "Coastal spike in prices begins here").
- Combining multiple visuals (side-by-side heatmap + bar chart) to reinforce interpretations.
- Highlighting extreme conditions (e.g., top 5% most expensive counties) to help the viewer understand financial pressure points.

These improvements turn raw visuals into clear storytelling elements.