John Padworski Week 1 Micro Project #1

Problem statement

We aim to understand which demographic and work-related factors are associated with higher income in the Adult Income dataset. Specifically, we will explore how variables such as age, education, occupation, work hours, marital status, and capital gains/losses relate to the probability that an individual's annual income exceeds $50K.

Hypothesis

- H1 (Education): Individuals with higher education-num have a higher probability of income == >50K than those with lower education-num.
  - H0: Mean high-income rate is equal across education levels.
  - HA: Mean high-income rate increases with education level.
- H2 (Work hours): hours-per-week is positively associated with >50K income.
  - H0: Mean hours are equal between <=50K and >50K.
  - HA: Mean hours are higher in the >50K group.
- H3 (Marital status): Being married (e.g., Married-civ-spouse) is associated with a higher >50K rate compared with non-married categories.
  - H0: High-income rate is independent of marital status.
  - HA: High-income rate differs by marital status (expected higher for married).
- H4 (Occupation): occupation groups differ in high-income rates.
  - H0: High-income rate is equal across occupations.
  - HA: At least one occupation has a different high-income rate.
- H5 (Capital gains): Positive capital-gain is associated with higher odds of >50K.
  - H0: High-income rate is independent of having any capital gains.
  - HA: High-income rate is higher when capital-gain > 0.

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
Pandas: 2.3.0
```

In [4]:
```
CSV_PATH = r"adult_income.csv"
df = pd.read_csv(CSV_PATH)
```

```python
print("Shape:", df.shape)
df.head()
```

```
Shape: (32561, 15)
```

Out[4]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	cap
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	

In [ ]:

```python
df.info()

#Numeric summary
df.describe(include=[np.number])

#Categorical peek: top categories for a few columns
cat_cols = df.select_dtypes(include=["object"]).columns.tolist()
{c: df[c].value_counts().head(5) for c in cat_cols[:8]}
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int64 
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64 
 3   education       32561 non-null  object
 4   education-num   32561 non-null  int64 
 5   marital-status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital-gain    32561 non-null  int64 
 11  capital-loss    32561 non-null  int64 
 12  hours-per-week  32561 non-null  int64 
 13  native-country  32561 non-null  object
 14  income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

Out[ ]:
```
{'workclass': workclass
 Private             22696
 Self-emp-not-inc     2541
 Local-gov            2093
 ?                    1836
 State-gov            1298
 Name: count, dtype: int64,
 'education': education
 HS-grad         10501
 Some-college     7291
 Bachelors        5355
 Masters          1723
 Assoc-voc        1382
 Name: count, dtype: int64,
 'marital-status': marital-status
 Married-civ-spouse    14976
 Never-married         10683
 Divorced               4443
 Separated              1025
 Widowed                 993
 Name: count, dtype: int64,
 'occupation': occupation
 Prof-specialty     4140
 Craft-repair       4099
 Exec-managerial    4066
 Adm-clerical       3770
 Sales              3650
 Name: count, dtype: int64,
 'relationship': relationship
 Husband          13193
 Not-in-family     8305
 Own-child         5068
 Unmarried         3446
 Wife              1568
 Name: count, dtype: int64,
 'race': race
 White                 27816
 Black                  3124
 Asian-Pac-Islander     1039
 Amer-Indian-Eskimo      311
 Other                   271
 Name: count, dtype: int64,
 'sex': sex
 Male      21790
 Female    10771
 Name: count, dtype: int64,
 'native-country': native-country
 United-States    29170
 Mexico             643
 ?                  583
 Philippines        198
 Germany            137
 Name: count, dtype: int64}
```

In [ ]:
```python
#Replace '?' with NaN in object columns
df_clean = df.replace('?', np.nan).copy()

#Basic missingness overview
df_clean.isna().sum().sort_values(ascending=False).head(15)
```

```
Out[ ]: occupation        1843
        workclass         1836
        native-country     583
        age                  0
                          ...
        capital-gain         0
        capital-loss         0
        hours-per-week       0
        income               0
        Length: 15, dtype: int64
```

```
In [8]: #Simple imputation strategy:
        #Categorical: fill missing with mode
        #Numeric: fill missing with median
        for c in df_clean.columns:
            if pd.api.types.is_numeric_dtype(df_clean[c]):
                if df_clean[c].isna().any():
                    df_clean[c] = df_clean[c].fillna(df_clean[c].median())
            else:
                mode_val = df_clean[c].mode(dropna=True)
                if not mode_val.empty:
                    df_clean[c] = df_clean[c].fillna(mode_val.iloc[0])
                else:
                    df_clean[c] = df_clean[c].fillna("Missing")

        df_clean.isna().sum().sort_values(ascending=False).head(10)
```

```
Out[8]: age               0
        workclass         0
        fnlwgt            0
        education         0
                         ..
        occupation        0
        relationship      0
        race              0
        sex               0
        Length: 10, dtype: int64
```

```
In [9]: #Drop exact duplicate rows
        before = len(df_clean)
        df_clean = df_clean.drop_duplicates()
        after = len(df_clean)
        print(f"Removed {before - after} duplicate rows. New shape: {df_clean.shape}")
```

```
Removed 24 duplicate rows. New shape: (32537, 15)
```

```
In [10]: #Target: high_income (1 if >50K else 0)
         df_feat = df_clean.copy()
         df_feat["high_income"] = (df_feat["income"].str.strip() == ">50K").astype(int)

         #Binary flags useful for analysis
         df_feat["any_capital_gain"] = (df_feat["capital-gain"] > 0).astype(int)
         df_feat["any_capital_loss"] = (df_feat["capital-loss"] > 0).astype(int)

         #An example of grouping education levels via education-num (already numeric years-of-education pr
         #Also create a tidy label for plotting
         df_feat["education_num_label"] = df_feat["education-num"].astype(int).astype(str)

         df_feat[["education","education-num","hours-per-week","income","high_income","any_capital_gain"]
```

Out[10]:

	education	education-num	hours-per-week	income	high_income	any_capital_gain
0	Bachelors	13	40	<=50K	0	1
1	Bachelors	13	13	<=50K	0	0
2	HS-grad	9	40	<=50K	0	0
3	11th	7	40	<=50K	0	0
4	Bachelors	13	40	<=50K	0	0

In [11]:

```
#IQR capping for highly skewed numerics (capital-gain, capital-loss, hours-per-week)
def iqr_cap(series):
    q1, q3 = series.quantile([0.25, 0.75])
    iqr = q3 - q1
    low, high = q1 - 1.5*iqr, q3 + 1.5*iqr
    return series.clip(lower=low, upper=high)

for col in ["capital-gain", "capital-loss", "hours-per-week"]:
    if col in df_feat.columns and pd.api.types.is_numeric_dtype(df_feat[col]):
        df_feat[col + "_capped"] = iqr_cap(df_feat[col])

caps = [c for c in df_feat.columns if c.endswith("_capped")]
df_feat[caps].describe() if caps else "No caps created."
```

Out[11]:

	capital-gain_capped	capital-loss_capped	hours-per-week_capped
count	32537.0	32537.0	32537.000000
mean	0.0	0.0	41.203246
std	0.0	0.0	6.187352
min	0.0	0.0	32.500000
25%	0.0	0.0	40.000000
50%	0.0	0.0	40.000000
75%	0.0	0.0	45.000000
max	0.0	0.0	52.500000

In [12]:

```
#High-income rate by education level
edu_rate = (df_feat.groupby("education-num")["high_income"]
            .mean()
            .sort_index())
edu_rate.head(10), edu_rate.tail(10)
```

Out[12]:
```
(education-num
 1     0.000000
 2     0.036145
 3     0.048193
 4     0.062016
         ...
 7     0.051064
 8     0.076212
 9     0.159520
 10    0.190332
 Name: high_income, Length: 10, dtype: float64,
 education-num
 7     0.051064
 8     0.076212
 9     0.159520
 10    0.190332
         ...
 13    0.414908
 14    0.556911
 15    0.734375
 16    0.740920
 Name: high_income, Length: 10, dtype: float64)
```

In [13]:
```
#High-income rate by marital status
ms_rate = df_feat.groupby("marital-status")["high_income"].mean().sort_values(ascending=False)
ms_rate.head(10)
```

Out[13]:
```
marital-status
Married-civ-spouse       0.446894
Married-AF-spouse        0.434783
Divorced                 0.104256
Widowed                  0.085599
Married-spouse-absent    0.081340
Separated                0.064390
Never-married            0.046030
Name: high_income, dtype: float64
```

In [14]:
```
#High-income rate by occupation
occ_rate = df_feat.groupby("occupation")["high_income"].mean().sort_values(ascending=False)
occ_rate.head(10)
```

Out[14]:
```
occupation
Exec-managerial      0.484133
Prof-specialty       0.342699
Protective-serv      0.325116
Tech-support         0.305286
                       ...
Transport-moving     0.200376
Adm-clerical         0.134554
Machine-op-inspct    0.124500
Farming-fishing      0.115927
Name: high_income, Length: 10, dtype: float64
```

In [15]:
```
#Average hours-per-week by income group
df_feat.groupby("income")["hours-per-week"].mean().sort_values(ascending=False)
```

Out[15]:
```
income
>50K     45.473402
<=50K    38.842862
Name: hours-per-week, dtype: float64
```

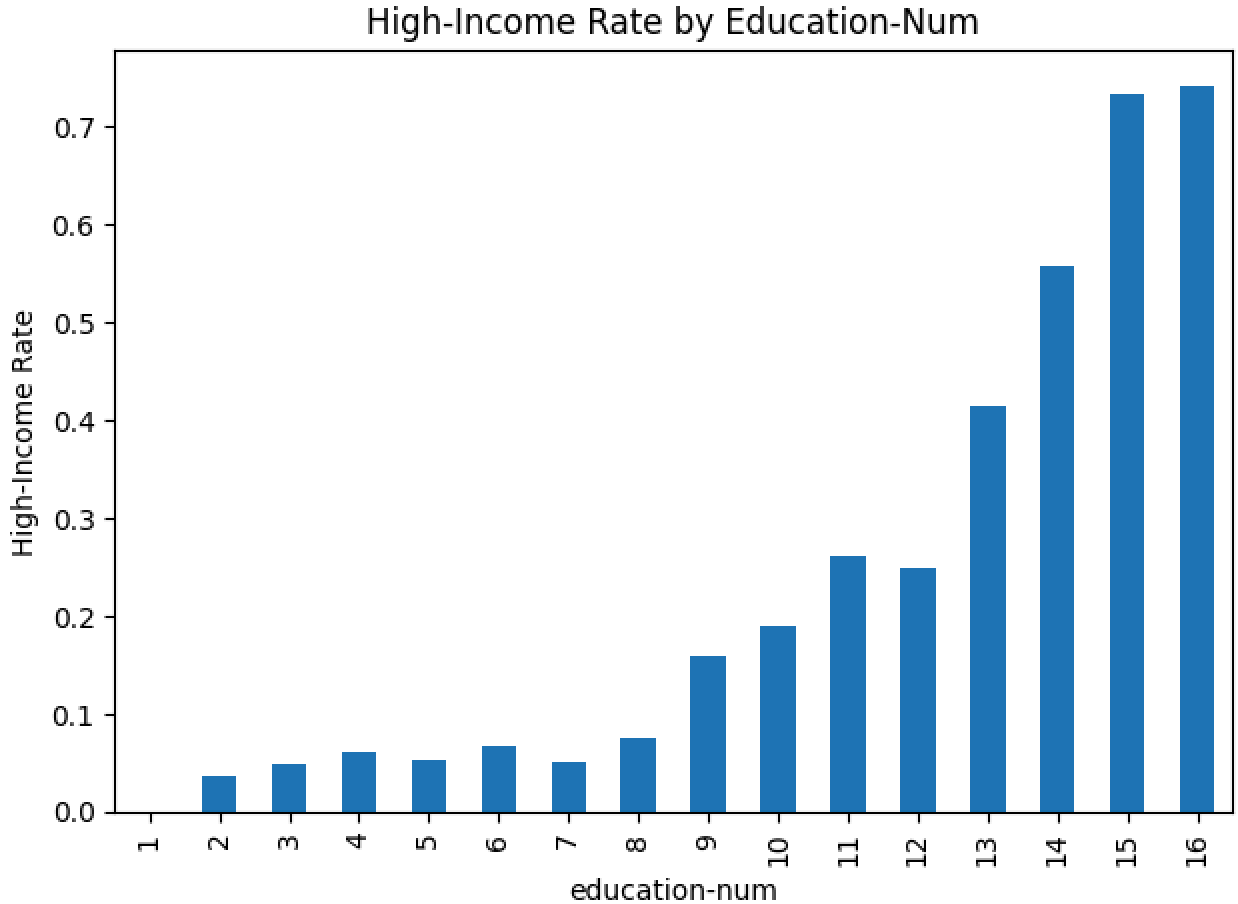
In [16]:
```
#Cross-tab: occupation × (high_income rate)
pivot_occ_edu = pd.pivot_table(
    df_feat,
    values="high_income",
    index="occupation",
    columns="education",
    aggfunc="mean"
)
pivot_occ_edu.round(3).head(10)
```

Out[16]:

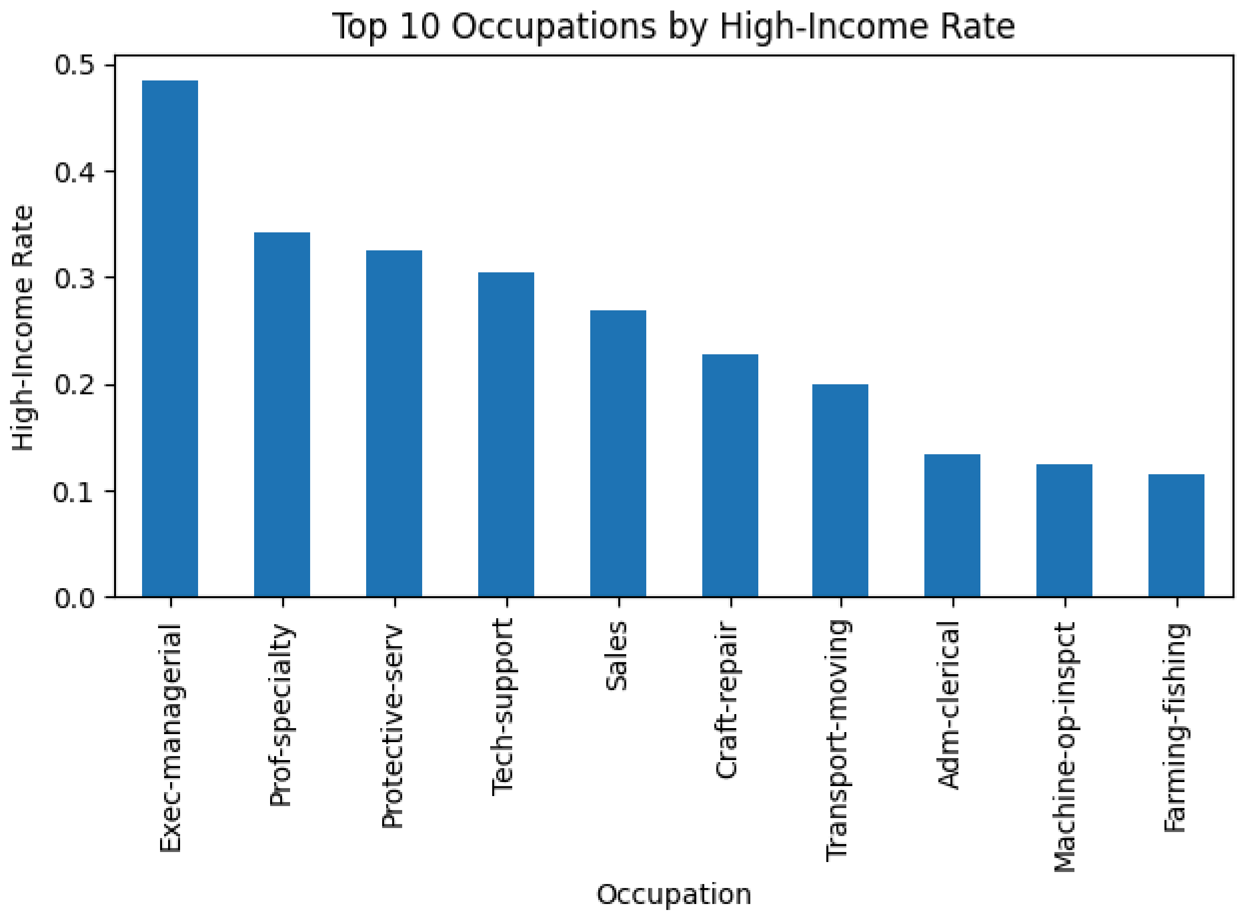
education occupation	10th	11th	12th	1st-4th	5th-6th	7th-8th	9th	Assoc-acdm	Assoc-voc	Bachelors	Doctorate	HS-grad	I
Adm-clerical	0.000	0.045	0.026	NaN	0.000	0.091	0.071	0.155	0.108	0.235	0.400	0.119	
Armed-Forces	NaN	NaN	0.000	NaN	NaN	NaN	NaN	NaN	NaN	0.000	NaN	0.000	
Craft-repair	0.112	0.103	0.155	0.087	0.070	0.070	0.073	0.278	0.321	0.391	0.500	0.211	
Exec-managerial	0.250	0.206	0.154	0.500	1.000	0.316	0.154	0.455	0.427	0.569	0.909	0.323	
...	...	...	...	...	...	...	...	...	...	...	...	...	
Machine-op-inspct	0.059	0.030	0.029	0.043	0.054	0.065	0.039	0.273	0.222	0.261	1.000	0.136	
Other-service	0.005	0.025	0.012	0.000	0.000	0.010	0.020	0.077	0.078	0.160	1.000	0.041	
Priv-house-serv	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.143	NaN	0.000	
Prof-specialty	0.045	0.014	0.080	0.000	0.065	0.024	0.019	0.232	0.312	0.374	0.726	0.138	

10 rows × 16 columns

In [17]:
```
#High-income rate by education-num (ordered)
plt.figure()
edu_rate.plot(kind="bar", title="High-Income Rate by Education-Num")
plt.xlabel("education-num")
plt.ylabel("High-Income Rate")
plt.tight_layout()
plt.show()
```

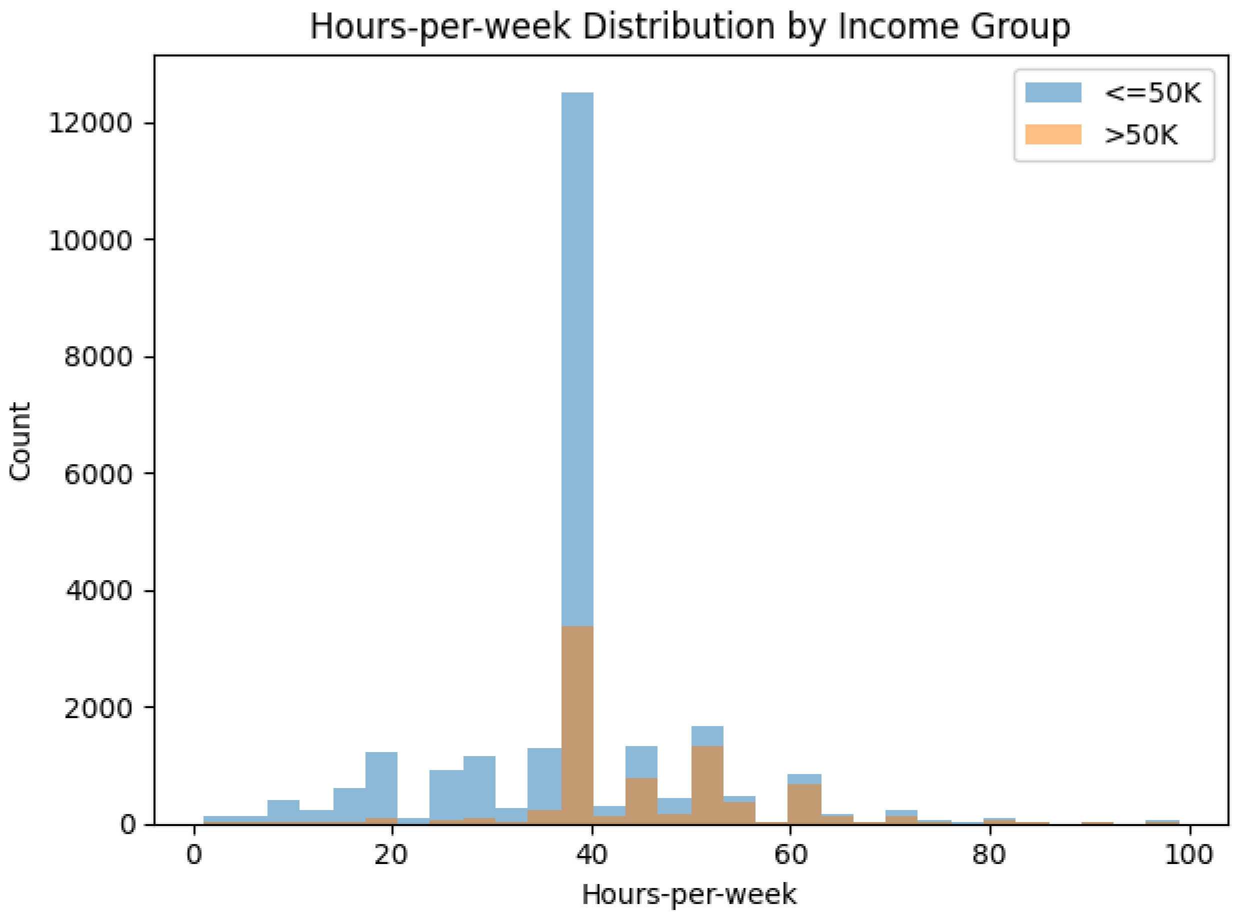


In [19]:
```
#Top 10 occupations by high-income rate (drop NaNs)
top_occ = occ_rate.dropna().head(10)
plt.figure()
top_occ.plot(kind="bar", title="Top 10 Occupations by High-Income Rate")
plt.xlabel("Occupation")
plt.ylabel("High-Income Rate")
plt.tight_layout()
plt.show()
```



In [20]:

```
#Hours-per-week distribution by income group (simple overlaid histograms)
plt.figure()
for label, g in df_feat.groupby("income"):
    g["hours-per-week"].plot(kind="hist", alpha=0.5, bins=30, label=label)
plt.title("Hours-per-week Distribution by Income Group")
plt.xlabel("Hours-per-week")
plt.ylabel("Count")
plt.legend()
plt.tight_layout()
plt.show()
```



In [21]:
```
from scipy import stats

#H2: t-test on hours-per-week between <=50K and >50K
g0 = df_feat.loc[df_feat["high_income"] == 0, "hours-per-week"].dropna()
g1 = df_feat.loc[df_feat["high_income"] == 1, "hours-per-week"].dropna()

tstat, pval = stats.ttest_ind(g1, g0, equal_var=False)
print(f"H2 t-test (hours-per-week): t={tstat:.3f}, p={pval:.3g} (n>50K={len(g1)}, n<=50K={len(g0
```

```
H2 t-test (hours-per-week): t=45.095, p=0 (n>50K=7839, n<=50K=24698)
```

In [22]:
```
#H3: Chi-square test of independence for marital-status vs high_income
ct_ms = pd.crosstab(df_feat["marital-status"], df_feat["high_income"])
chi2, p, dof, exp = stats.chi2_contingency(ct_ms)
print("H3 Chi-square (marital-status ~ high_income):")
print(f"chi2={chi2:.3f}, dof={dof}, p={p:.3g}")
ct_ms.head()
```

```
H3 Chi-square (marital-status ~ high_income):
chi2=6510.332, dof=6, p=0
```

Out[22]:

high_income	0	1
marital-status		
Divorced	3978	463
Married-AF-spouse	13	10
Married-civ-spouse	8280	6690
Married-spouse-absent	384	34
Never-married	10176	491

In [23]:
```python
#H4: Chi-square test for occupation vs high_income
ct_occ = pd.crosstab(df_feat["occupation"], df_feat["high_income"])
chi2, p, dof, exp = stats.chi2_contingency(ct_occ)
print("H4 Chi-square (occupation ~ high_income):")
print(f"chi2={chi2:.3f}, dof={dof}, p={p:.3g}")
ct_occ.head()
```

```
H4 Chi-square (occupation ~ high_income):
chi2=3197.613, dof=13, p=0
```

Out[23]:

high_income	0	1
occupation		
Adm-clerical	3261	507
Armed-Forces	8	1
Craft-repair	3165	929
Exec-managerial	2097	1968
Farming-fishing	877	115

In [24]:
```python
#H5: Chi-square for any capital gain vs high_income
ct_gain = pd.crosstab(df_feat["any_capital_gain"], df_feat["high_income"])
chi2, p, dof, exp = stats.chi2_contingency(ct_gain)
print("H5 Chi-square (any_capital_gain ~ high_income):")
print(f"chi2={chi2:.3f}, dof={dof}, p={p:.3g}")
ct_gain
```

```
H5 Chi-square (any_capital_gain ~ high_income):
chi2=2302.418, dof=1, p=0
```

Out[24]:

high_income	0	1
any_capital_gain		
0	23663	6162
1	1035	1677