College Major Selection and Shift Analysis

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Project Description: This project investigates how the most popular and lucrative college majors in the U.S. have changed from 2009–2023, with a special focus on whether wage growth predicts popularity.

Executive Summary

- Business Management and Administration, Psychology, and Accounting were the most popular U.S. majors from 2009–2023, with Accounting alone growing by 16.6% over the period, even as other business majors declined.
- Computer Engineering offered the highest median wage and saw a 40% pay increase over ten years; majors with the fastest wage growth also saw the greatest jumps in student interest.
- Students strongly favor majors with rising median earnings, suggesting that shifts in college major choice are closely linked to wage trends in those fields.

Research Question: How Distribution of college majors have changed over time and whether it is related to median earning after graduation

Business Questions:

- How have most popular college majors have change over time in US?
- Do changes in major popularity correspond to changes in the typical earnings for those majors?
- Can we prove that the corresponding shift is due to increased attractiveness in the terms of pay, or vice versa?

Years	Cohort
2009-2024	All graduates

In [1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:
```
# Using the only the columns that we need from the IPUMS USA dataset

usecols = [
```

```
    'YEAR', 'AGE', 'SEX', 'RACE', 'EDUC', 'EDUCD', 'DEGFIELD', 'DEGFIELDD',
    'EMPSTAT', 'CLASSWKR', 'INCWAGE', 'PERWT'
]
df_grad = pd.read_csv('./data/usa_00001.csv', usecols=usecols)
```

Understanding the data fields:

Field Name	Description	Typical Use in Analysis
YEAR	Census year / survey year	For time trends; critical for year-by-year analysis of majors and earnings.
PERWT	Person-level weight	Always used for population statistics - this makes our sample nationally representative!
SEX	Sex (1=male, 2=female)	For demographic analysis (gender splits, etc.).
AGE	Age in years	To define your analysis cohort (e.g., recent grads = ages 22–29).
RACE	General race code	For basic racial demographic splits/analysis.
EDUC	General education attainment	For simple cutoffs (e.g., high school/some college/bachelor's+).
EDUCD	Detailed education attainment	For precise cohort selection (e.g., exactly bachelor's, associate, advanced degrees).
DEGFIELD	General field of college major	For basic broad major groupings (e.g., "Engineering," "Business," etc.).
DEGFIELDD	Detailed field of degree	For fine-grained analysis (e.g., separates "Mechanical Engineering" from "Chemical Engineering").
EMPSTAT	Employment status	Filter for employed/unemployed/not-in-labor-force—crucial if you want only employed grads.
CLASSWKR	Class of worker (general)	Public/private/self-employed worker distinctions.
INCWAGE	Wage and salary income	Main variable for annual earnings; your "target" value for most of the pay analysis

This dataset is data courtesy of IPUMS USA, University of Minnesota, www.ipums.org.

Note: `My analyses exclude 2020 due to pandemic survey methodology changes as per Census recommendations.`

-> The ACS 2020 PUMS file uses experimental weights due to COVID-19 survey disruptions. For accurate historical comparisons, 2020 results should be interpreted with caution and are excluded from time trend analysis. For details, see Census Bureau's COVID-19 PUMS guidance.

In [3]:

```
# Let's take a look at our data

print(df_grad.head())
print(df_grad.info())
print(df_grad.isnull().sum())
print(df_grad['YEAR'].value_counts())
```

```
   YEAR  PERWT  SEX  AGE  RACE  EDUC  EDUCD  DEGFIELD  DEGFIELDD  EMPSTAT  \
0  2009    3.0    1   51     1     6     63         0          0        3
1  2009   22.0    2   64     1     7     71         0          0        1
2  2009   21.0    1   68     1     5     50         0          0        1
3  2009   30.0    2   61     2     6     63         0          0        1
4  2009   32.0    1   38     2     6     63         0          0        1

   CLASSWKR  INCWAGE
0         0        0
1         2    27100
2         2    22100
3         2     6000
4         2    14000
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 44562282 entries, 0 to 44562281
Data columns (total 12 columns):
 #   Column     Dtype
---  ------     -----
 0   YEAR       int64
 1   PERWT      float64
 2   SEX        int64
 3   AGE        int64
 4   RACE       int64
 5   EDUC       int64
 6   EDUCD      int64
 7   DEGFIELD   int64
 8   DEGFIELDD  int64
 9   EMPSTAT    int64
 10  CLASSWKR   int64
 11  INCWAGE    int64
dtypes: float64(1), int64(11)
memory usage: 4.0 GB
None
YEAR         0
PERWT        0
SEX          0
AGE          0
RACE         0
EDUC         0
EDUCD        0
DEGFIELD     0
DEGFIELDD    0
EMPSTAT      0
CLASSWKR     0
INCWAGE      0
dtype: int64
YEAR
2023    3405809
2022    3373378
2021    3252599
2019    3239553
2018    3214539
2017    3190040
2016    3156487
2015    3147005
2013    3132795
```

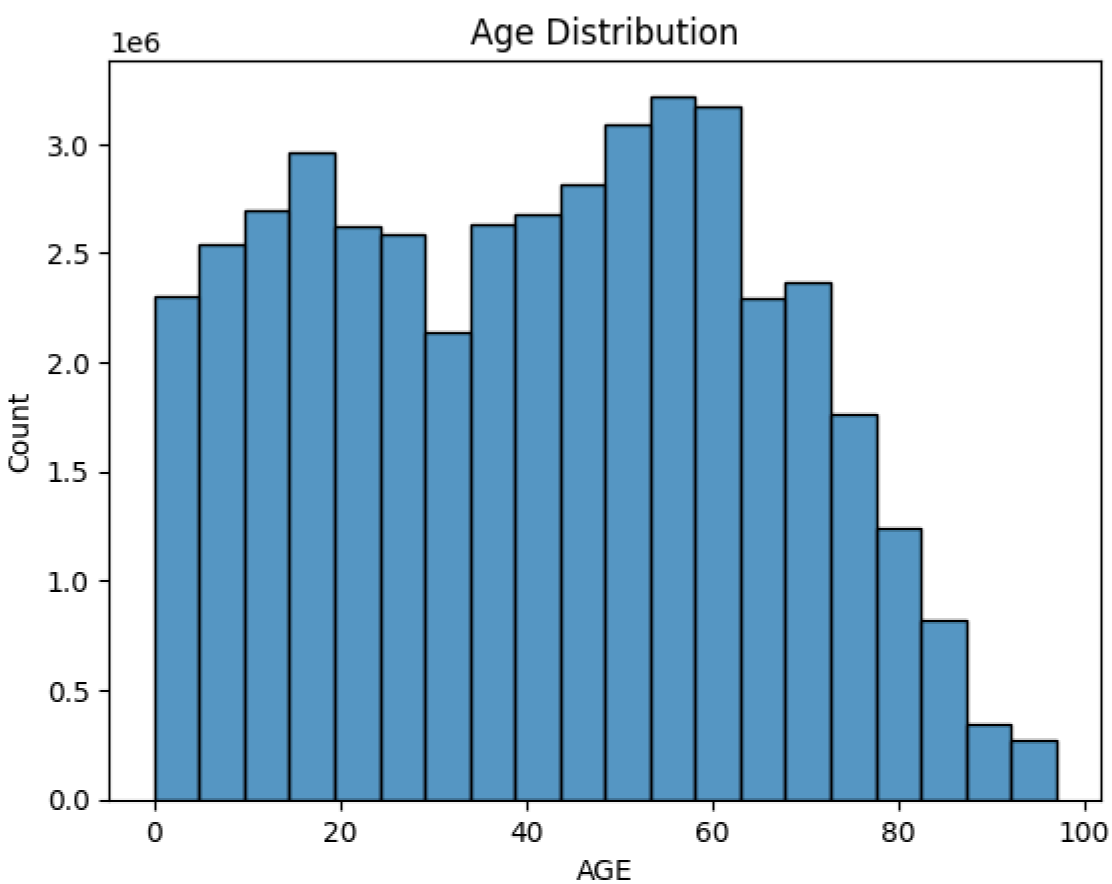
```
2014    3132610
2012    3113030
2011    3112017
2010    3061692
2009    3030728
Name: count, dtype: int64
```

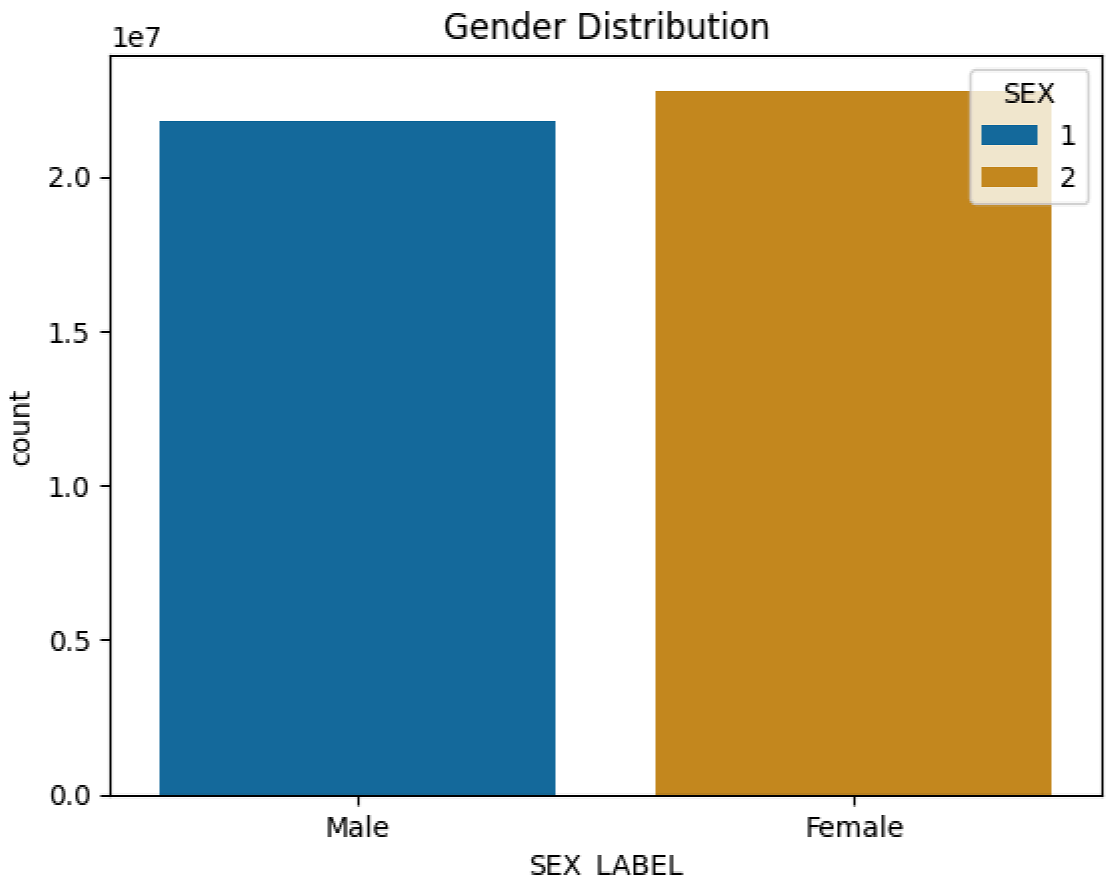
In [4]:
```python
# Let's take a look at the age and sex distribution

print(df_grad[['AGE', 'SEX']].describe())
sns.histplot(df_grad['AGE'], bins=20)
plt.title('Age Distribution')
plt.show()

sex_labels = {1: 'Male', 2: 'Female'}
df_grad['SEX_LABEL'] = df_grad['SEX'].map(sex_labels)
sns.countplot(x='SEX_LABEL', data=df_grad, palette='colorblind', hue='SEX')
plt.title('Gender Distribution')
plt.show()
```

```
                AGE           SEX
count  4.456228e+07  4.456228e+07
mean   4.126657e+01  1.511142e+00
std    2.366349e+01  4.998758e-01
min    0.000000e+00  1.000000e+00
25%    2.100000e+01  1.000000e+00
50%    4.200000e+01  2.000000e+00
75%    6.000000e+01  2.000000e+00
max    9.700000e+01  2.000000e+00
```





In [5]:
```
# Mapping the degree field codes to the degree field names, the original names can
from degfield_map import degfield_map
```

In [6]:
```
# Extracting the degree field names from the degree field codes
df_grad['major_str'] = df_grad['DEGFIELDD'].map(degfield_map)
```

In [7]:
```
# Filtering our the data to only include employed graduates with positive wages
data = df_grad[(df_grad['INCWAGE'] > 0) & (df_grad['EMPSTAT'] == 1)]
```

In [8]:
```
# Let's take a look at the major distribution now
print(data['major_str'].value_counts().head())
```

```
major_str
Business Management and Administration    442266
Psychology                                313573
Nursing                                   296810
General Business                          280951
Accounting                                265697
Name: count, dtype: int64
```

In [9]:
```
# Starting with EDA
# A. First, we will try to see the distribution of grads per major over time

major_year_ct = (
    data
    .groupby(['YEAR', 'major_str'], as_index=False)
    .agg({'PERWT': 'sum'})
```

```
    .rename(columns={'PERWT':'num_grads'})
)
```

In [10]:
```
print(major_year_ct.head())
```

```
   YEAR                         major_str  num_grads
0  2009                        Accounting  1633263.0
1  2009                 Actuarial Science    10347.0
2  2009  Advertising and Public Relations   159970.0
3  2009               Aerospace Engineering    91430.0
4  2009              Agricultural Economics    36652.0
```

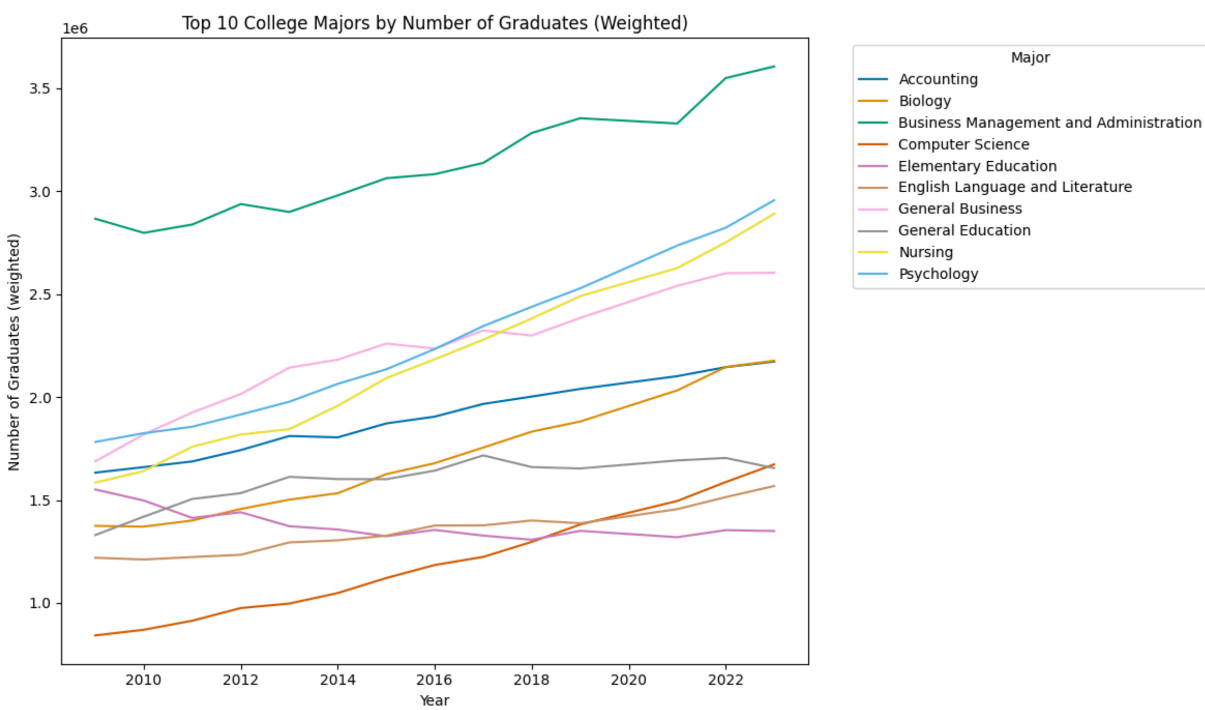
In [11]:
```
# Top 10 most popular majors over all years
top_majors = major_year_ct.groupby('major_str')['num_grads'].sum().sort_values(asce
```

In [12]:
```
print(top_majors)
```

```
['Business Management and Administration', 'Psychology', 'General Business', 'Nursin
g', 'Accounting', 'Biology', 'General Education', 'Elementary Education', 'English L
anguage and Literature', 'Computer Science']
```

In [13]:
```
# Let's plot the top 10 most popular majors over time

plt.figure(figsize=(12, 7))
sns.lineplot(data=major_year_ct[major_year_ct['major_str'].isin(top_majors)],
             x='YEAR', y='num_grads', palette='colorblind', hue='major_str')
plt.title('Top 10 College Majors by Number of Graduates (Weighted)')
plt.ylabel('Number of Graduates (weighted)')
plt.xlabel('Year')
plt.legend(title='Major', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```



EDA	The Story Behind the Plot
Accounting remained college major favourite, and even grew by 16.6% over 10 years.	Accounting shows a robust, counter-cyclical trend even as other business fields declined, like General Business Studies.
Computer Engineering, Biology and Psychology also saw steady growth in as college major favourites	The rise in Biology and Psychology can be understood due to increased awareness in healthcare, and mental wellbeing.

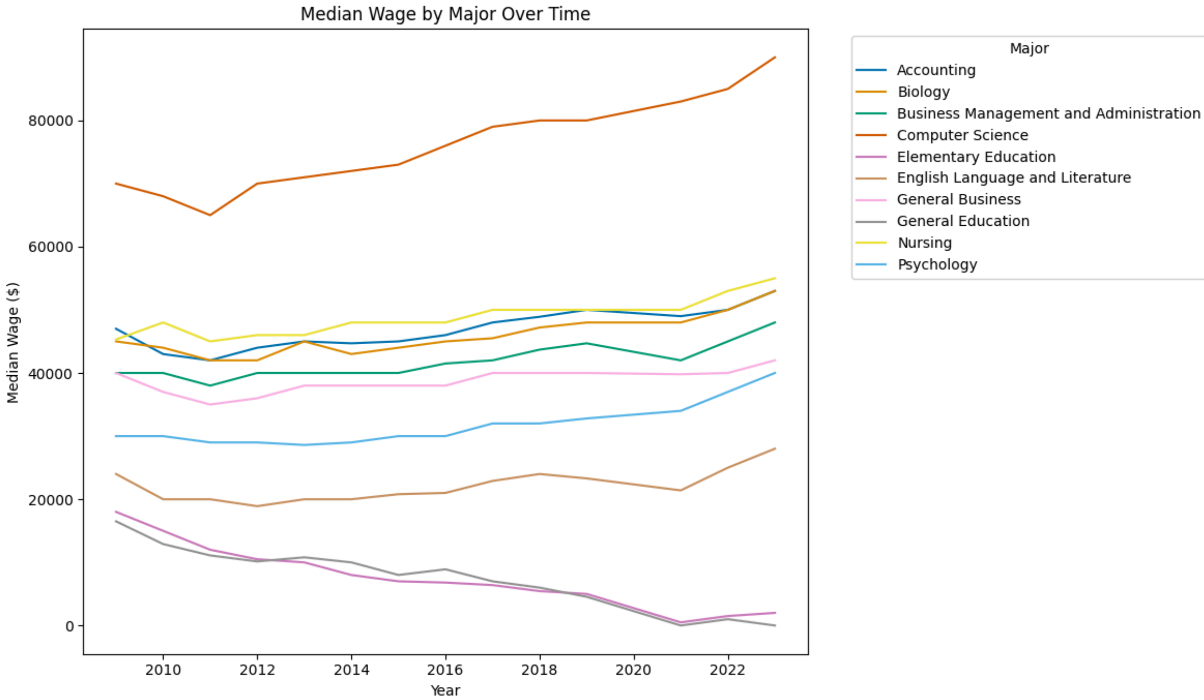
In [14]:
```
# b) Now, let's try to visualize the median Salary by Major and Year

wage_summary = (
    df_grad.groupby(['YEAR', 'major_str'], as_index=False)
    .agg(median_wage=('INCWAGE', 'median'))
    .reset_index()
    .rename(columns={0:'median_wage'})
)

print(wage_summary.head())
```

```
   index  YEAR                          major_str  median_wage
0      0  2009                         Accounting      47000.0
1      1  2009                 Actuarial Science      65000.0
2      2  2009  Advertising and Public Relations      35000.0
3      3  2009               Aerospace Engineering      67000.0
4      4  2009             Agricultural Economics      40000.0
```

In [15]:
```
plt.figure(figsize=(12, 7))
sns.lineplot(data=wage_summary[wage_summary['major_str'].isin(top_majors)], x = 'YE
plt.title('Median Wage by Major Over Time')
plt.ylabel('Median Wage ($)')
plt.xlabel('Year')
plt.legend(title='Major', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```



EDA	The Story Behind the Plot
Computer Engineering remained the highest paying job (median) for 10 years, and even increases by 40%.	This is a signal of persistent market demand.
Accounting, Biology, and Business Administration also remained competetively paid	This is a signal of persistent market demand.

Actionable Insights from the EDA:

- Universities may consider investing further in Computer Engineering and Accounting programs, as both student demand and wage outcomes remain high.
- The decline in General Business Studies suggests a possible shift in employer or student preferences toward more specialized degrees.

Limitations:

- Data excludes 2020 due to COVID-19 survey issues.
- Does not address lag effects or causality direction formally.
- Graduate degrees not separated from undergrad in this cut.

Next Steps:

- [ ] Explore causal tests, or lag effects
- [ ] Disaggregate by race, gender, or degree level.
- [ ] Compare outcomes for recent vs. older graduates.