Comprehensive Movie Data Analysis

1. Business Understanding

This notebook provides a structured approach to analyzing movie datasets to answer the business question:

"What kinds of movies should a new studio produce for financial success?"

We will proceed through the following sections:

1. Business Understanding
2. Data Understanding
3. Data Preparation
4. Data Analysis
5. Visualization

Objectives:

- Analyze which genres are most profitable.
- Examine the relationship between production budget and revenue.
- Assess the impact of review scores on financial performance.

By integrating multiple movie datasets, we aim to provide actionable insights for new studios to maximize their chances of financial success.

Import Required Libraries

Import all necessary libraries for data manipulation, visualization, and analysis.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sqlite3
```

2. Data Understanding

Load and Inspect Datasets

Loading all provided datasets (CSV, TSV, SQLite) into pandas DataFrames. Displaying the first few rows and data types for each DataFrame. Printing the shape of each DataFrame to confirm successful loading.

In [2]:
```
# File paths
bom_path = r'C:\Users\DAVID\Documents\Moringa\Phase2\Assessments\dsc-phase-2-project-PT:
```

```
tn_path = r'C:\Users\DAVID\Documents\Moringa\Phase2\Assessments\dsc-phase-2-project-PT1
tmdb_path = r'C:\Users\DAVID\Documents\Moringa\Phase2\Assessments\dsc-phase-2-project-P
rt_info_path = r'C:\Users\DAVID\Documents\Moringa\Phase2\Assessments\dsc-phase-2-projec
rt_reviews_path = r'C:\Users\DAVID\Documents\Moringa\Phase2\Assessments\dsc-phase-2-pro
imdb_db_path = r'C:\Users\DAVID\Documents\Moringa\Phase2\Assessments\dsc-phase-2-projec

# Load CSV/TSV files
df_bom = pd.read_csv(bom_path)
df_tn = pd.read_csv(tn_path, encoding='latin-1')
df_tmdb = pd.read_csv(tmdb_path)
df_rt_info = pd.read_csv(rt_info_path, sep='\t')
df_rt_reviews = pd.read_csv(rt_reviews_path,encoding='latin-1',sep='\t')

# Load SQLite tables
conn = sqlite3.connect(imdb_db_path)
df_movie_basics = pd.read_sql_query("SELECT * FROM movie_basics", conn)
df_movie_ratings = pd.read_sql_query("SELECT * FROM movie_ratings", conn)
conn.close()

# Inspect DataFrames
for name, df in [
    ("df_bom", df_bom), ("df_tn", df_tn), ("df_tmdb", df_tmdb),
    ("df_rt_info", df_rt_info), ("df_rt_reviews", df_rt_reviews),
    ("df_movie_basics", df_movie_basics), ("df_movie_ratings", df_movie_ratings)
]:
    print(f"{name}: shape={df.shape}")
    display(df.head())
    display(df.dtypes)
```

```
df_bom: shape=(3387, 5)
```

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010

```
title              object
studio             object
domestic_gross    float64
foreign_gross      object
year                int64
dtype: object
df_tn: shape=(5782, 6)
```

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

```
id                     int64
release_date          object
movie                 object
production_budget     object
domestic_gross        object
worldwide_gross       object
dtype: object
df_tmdb: shape=(26517, 10)
```

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date	title	vot
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	
4	4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	

```
Unnamed: 0              int64
genre_ids              object
id                      int64
original_language      object
original_title         object
popularity            float64
release_date           object
title                  object
vote_average          float64
vote_count              int64
dtype: object
df_rt_info: shape=(1560, 12)
```

	id	synopsis	rating	genre	director	writer	theater_date	dvd_date
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	Sep 25, 2001
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	David Cronenberg|Don DeLillo	Aug 17, 2012	Jan 1, 2013
2	5	Illeana Douglas delivers a superb	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13, 1996	Apr 18, 2000

	id	synopsis	rating	genre	director	writer	theater_date	dvd_date
		performance ...						
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Paul Attanasio|Michael Crichton	Dec 9, 1994	Aug 27, 1997
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles Cooper	NaN	NaN

```
id               int64
synopsis        object
rating          object
genre           object
director        object
writer          object
theater_date    object
dvd_date        object
currency        object
box_office      object
runtime         object
studio          object
dtype: object
df_rt_reviews: shape=(54432, 8)
```

	id	review	rating	fresh	critic	top_critic	publisher	date
0	3	A distinctly gallows take on contemporary fina...	3/5	fresh	PJ Nabarro	0	Patrick Nabarro	November 10, 2018
1	3	It's an allegory in search of a meaning that n...	NaN	rotten	Annalee Newitz	0	io9.com	May 23, 2018
2	3	... life lived in a bubble in financial dealin...	NaN	fresh	Sean Axmaker	0	Stream on Demand	January 4, 2018
3	3	Continuing along a line introduced in last yea...	NaN	fresh	Daniel Kasman	0	MUBI	November 16, 2017
4	3	... a perverse twist on neorealism...	NaN	fresh	NaN	0	Cinema Scope	October 12, 2017

```
id             int64
review        object
rating        object
fresh         object
critic        object
top_critic     int64
publisher     object
date          object
dtype: object
df_movie_basics: shape=(146144, 6)
```

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy

```
movie_id            object
primary_title       object
original_title      object
start_year           int64
runtime_minutes    float64
genres              object
dtype: object
df_movie_ratings: shape=(73856, 3)
```

	movie_id	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21

```
movie_id          object
averagerating    float64
numvotes           int64
dtype: object
```

3. Data Preparation

Cleaning and Preparing Data

Handling missing values, removing duplicates, standardizing column names, and ensuring consistent data types. Converting relevant columns to numeric or datetime as needed. Addressing encoding issues and outliers.

In [3]:

```
# Clean df_tn
for col in ['production_budget', 'domestic_gross', 'worldwide_gross']:
    df_tn[col] = df_tn[col].astype(str).str.replace(r'[$,]', '', regex=True)
    df_tn[col] = pd.to_numeric(df_tn[col], errors='coerce')
df_tn['release_date'] = pd.to_datetime(df_tn['release_date'], errors='coerce')
df_tn = df_tn.drop_duplicates()
df_tn.columns = df_tn.columns.str.lower().str.replace(' ', '_')
df_tn = df_tn.fillna(0)

# Remove outliers using IQR for financial columns
for col in ['production_budget', 'domestic_gross', 'worldwide_gross']:
    Q1 = df_tn[col].quantile(0.25)
    Q3 = df_tn[col].quantile(0.75)
    IQR = Q3 - Q1
    df_tn = df_tn[(df_tn[col] >= Q1 - 1.5 * IQR) & (df_tn[col] <= Q3 + 1.5 * IQR)]
```

```
# Clean df_bom
df_bom.columns = df_bom.columns.str.lower().str.replace(' ', '_')
df_bom = df_bom.drop_duplicates()

# Clean df_tmdb
df_tmdb.columns = df_tmdb.columns.str.lower().str.replace(' ', '_')
df_tmdb['release_date'] = pd.to_datetime(df_tmdb['release_date'], errors='coerce')
df_tmdb = df_tmdb.drop_duplicates()

# Clean df_rt_info
df_rt_info.columns = df_rt_info.columns.str.lower().str.replace(' ', '_')
df_rt_info['theater_date'] = pd.to_datetime(df_rt_info['theater_date'], errors='coerce'
df_rt_info['dvd_date'] = pd.to_datetime(df_rt_info['dvd_date'], errors='coerce')
df_rt_info = df_rt_info.drop_duplicates()

# Clean df_rt_reviews
df_rt_reviews.columns = df_rt_reviews.columns.str.lower().str.replace(' ', '_')
df_rt_reviews = df_rt_reviews.drop_duplicates()

# Clean IMDB tables
df_movie_basics.columns = df_movie_basics.columns.str.lower().str.replace(' ', '_')
df_movie_ratings.columns = df_movie_ratings.columns.str.lower().str.replace(' ', '_')
```

4. Data Analysis

Merging Datasets and Feature Engineering

Merging the cleaned datasets on appropriate keys (e.g., movie title or ID). Creating new features such as total revenue, profit margin, and ROI. Preparing genre information for analysis.

In [4]:
```
# Merge tn and tmdb on movie/original_title
df_merged = pd.merge(df_tn, df_tmdb, left_on='movie', right_on='original_title', how='i

# Merge with bom on movie/title
df_merged = pd.merge(df_merged, df_bom, left_on='movie', right_on='title', how='left')

# Merge with rt_info on movie/id (ensure type match)
df_rt_info['id'] = df_rt_info['id'].astype(str)
df_merged = pd.merge(df_merged, df_rt_info, left_on='movie', right_on='id', how='left')

# Feature engineering
df_merged['total_revenue'] = df_merged['domestic_gross_x'] + df_merged['worldwide_gross
df_merged['profit_margin'] = (df_merged['total_revenue'] - df_merged['production_budget
df_merged['profit_margin'] = df_merged['profit_margin'].fillna(0)
df_merged['roi'] = (df_merged['total_revenue'] - df_merged['production_budget']) / df_m
df_merged['roi'] = df_merged['roi'].fillna(0)

# Prepare genre information
def extract_genre_ids(genre_str):
    if isinstance(genre_str, str):
        try:
            return [int(x) for x in genre_str[1:-1].split(',') if x.strip() != '']
        except:
            return []
    else:
        return []
df_merged['genre_ids_list'] = df_merged['genre_ids'].apply(extract_genre_ids)
```

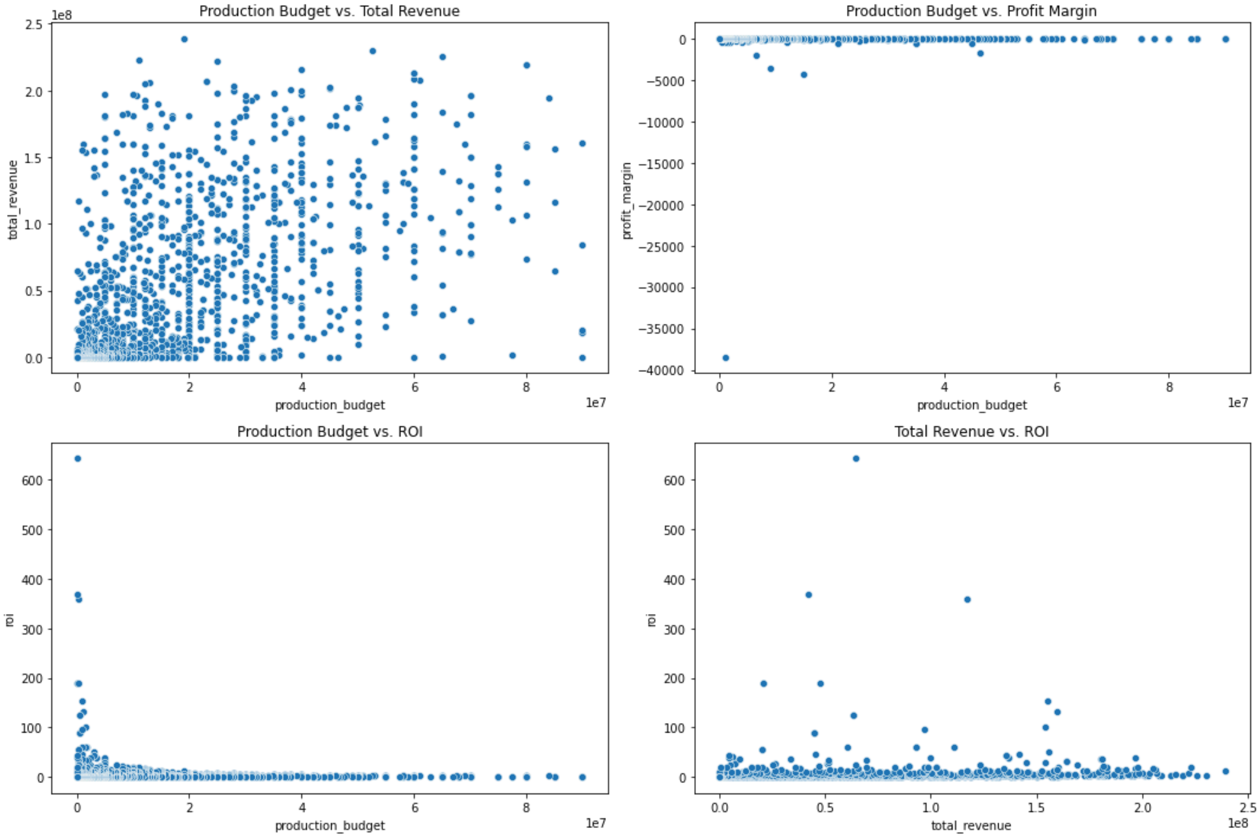
Exploratory Data Analysis: Key Variables

Analyzing distributions and relationships between production budget, revenue, ratings, and ROI. Visualizing correlations and summary statistics to identify patterns.

In [5]:
```
# Correlation matrix
corr = df_merged[['production_budget', 'total_revenue', 'profit_margin', 'roi']].corr()
display(corr)

# Scatter plots
plt.figure(figsize=(15, 10))
plt.subplot(2, 2, 1)
sns.scatterplot(data=df_merged, x='production_budget', y='total_revenue')
plt.title('Production Budget vs. Total Revenue')
plt.subplot(2, 2, 2)
sns.scatterplot(data=df_merged, x='production_budget', y='profit_margin')
plt.title('Production Budget vs. Profit Margin')
plt.subplot(2, 2, 3)
sns.scatterplot(data=df_merged, x='production_budget', y='roi')
plt.title('Production Budget vs. ROI')
plt.subplot(2, 2, 4)
sns.scatterplot(data=df_merged, x='total_revenue', y='roi')
plt.title('Total Revenue vs. ROI')
plt.tight_layout()
plt.show()
```

	production_budget	total_revenue	profit_margin	roi
production_budget	1.000000	0.548651	0.028655	-0.118365
total_revenue	0.548651	1.000000	0.041248	0.135287
profit_margin	0.028655	0.041248	1.000000	0.011086
roi	-0.118365	0.135287	0.011086	1.000000



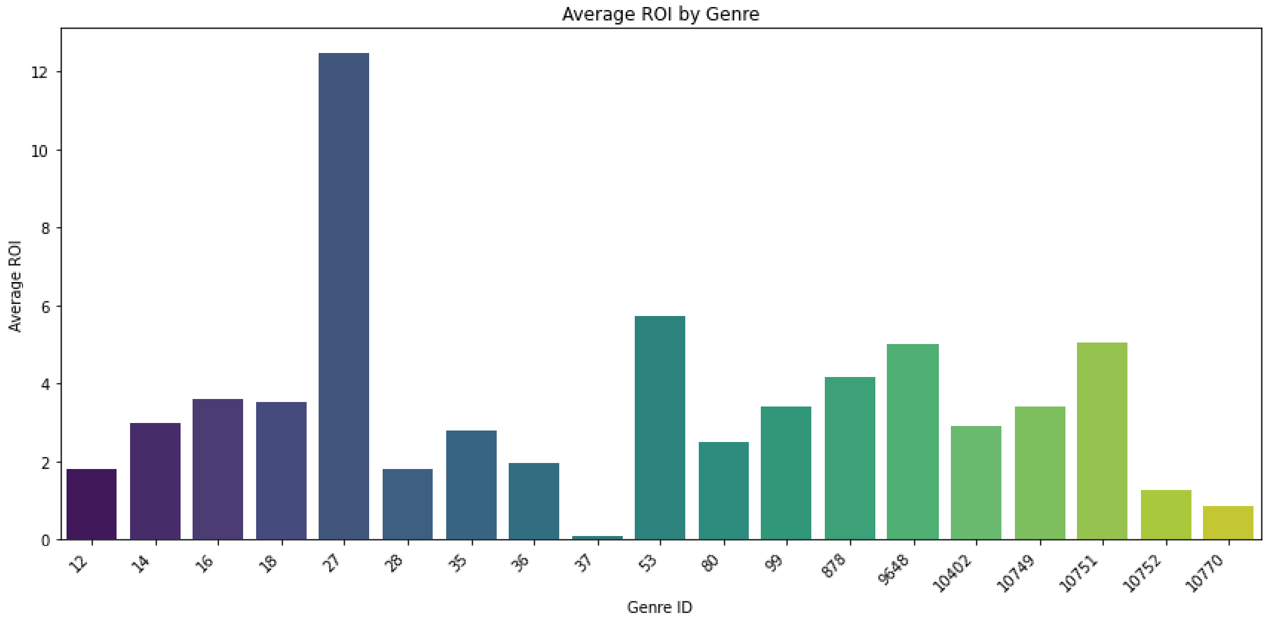
Genre Analysis and Visualization

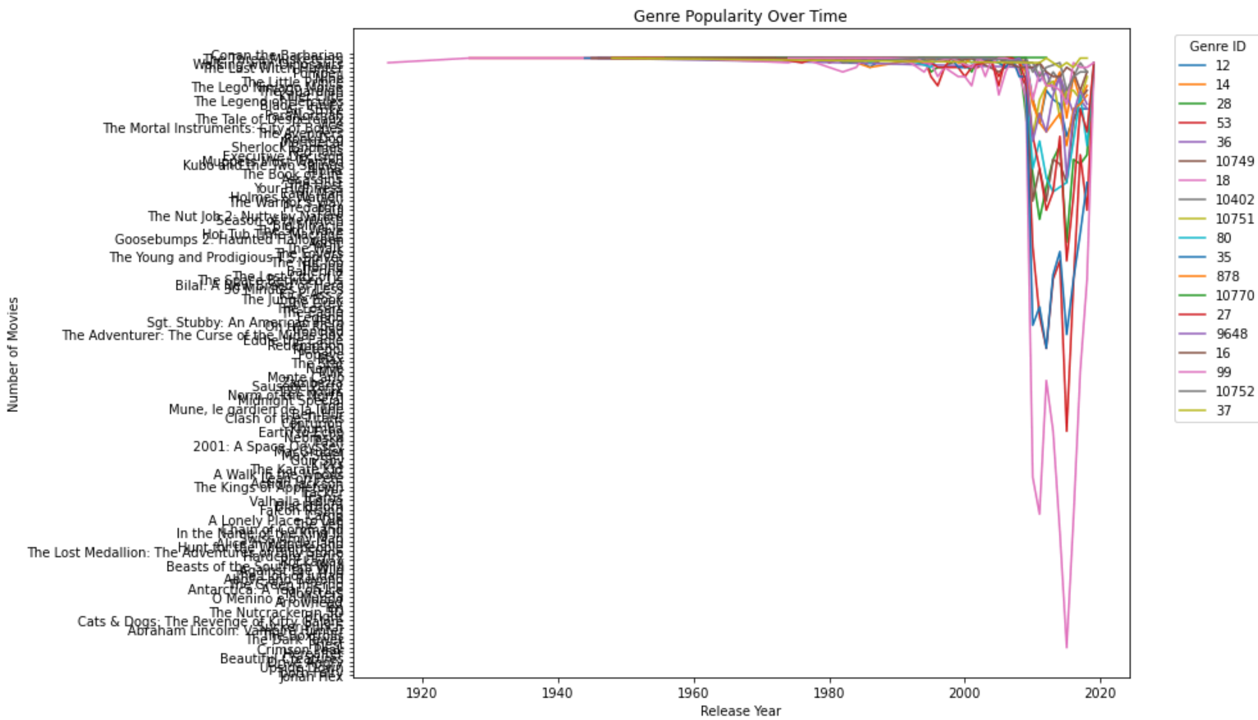
Analyzing the performance of different genres using ROI and revenue metrics. Creating bar charts to visualize average ROI by genre and genre popularity over time.

In [6]:

```python
# Average ROI by genre
genre_roi = df_merged.explode('genre_ids_list').groupby('genre_ids_list')['roi'].mean()
plt.figure(figsize=(12, 6))
sns.barplot(x=genre_roi.index, y=genre_roi.values, palette='viridis')
plt.title('Average ROI by Genre')
plt.xlabel('Genre ID')
plt.ylabel('Average ROI')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()

# Genre popularity over time
df_merged['release_year'] = pd.to_datetime(df_merged['release_date_x'], errors='coerce'
plt.figure(figsize=(14, 8))
for genre_id in df_merged['genre_ids_list'].explode().unique():
    genre_movies = df_merged.explode('genre_ids_list').loc[df_merged.explode('genre_ids
    sns.lineplot(x='release_year', y='movie', data=genre_movies, label=genre_id, estima
plt.title('Genre Popularity Over Time')
plt.xlabel('Release Year')
plt.ylabel('Number of Movies')
plt.legend(title='Genre ID', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```





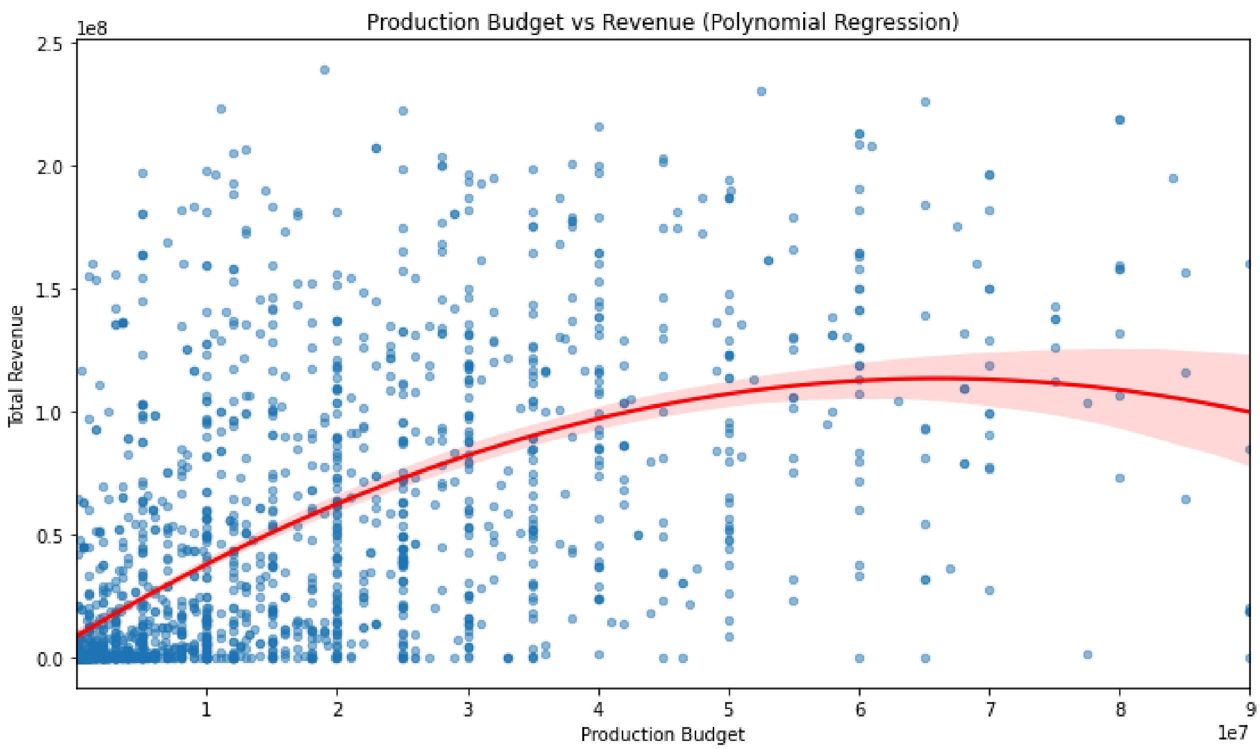
Budget and Revenue Analysis

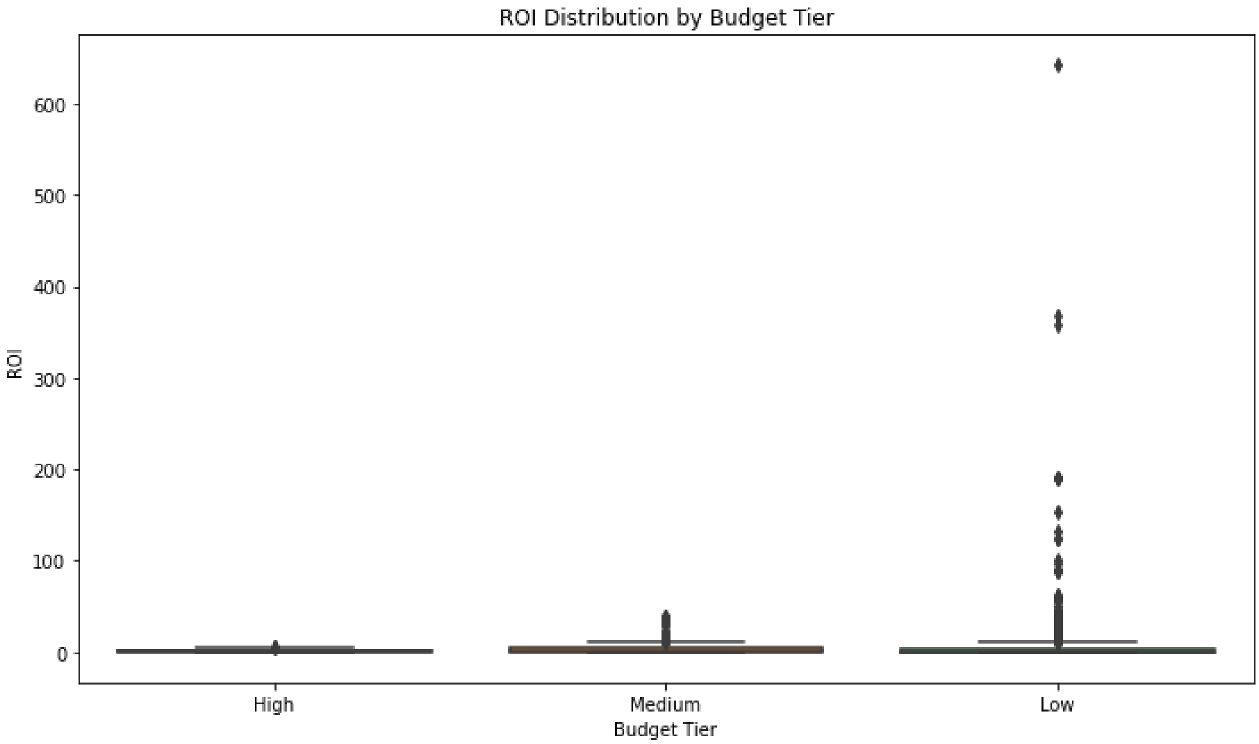
Investigating the relationship between production budget and box office revenue. Using scatter plots and regression lines to visualize and interpret the results. Segment analysis by budget tiers.

In [7]:
```
# Scatter plot with regression
plt.figure(figsize=(10, 6))
sns.regplot(x='production_budget', y='total_revenue', data=df_merged, order=2, scatter_
plt.title('Production Budget vs Revenue (Polynomial Regression)')
plt.xlabel('Production Budget')
plt.ylabel('Total Revenue')
plt.tight_layout()
plt.show()

# ROI by budget tier
quartiles = df_merged['production_budget'].quantile([0.25, 0.5, 0.75])
```

```
def budget_tier(budget):
    if budget <= quartiles[0.25]:
        return 'Low'
    elif budget <= quartiles[0.75]:
        return 'Medium'
    else:
        return 'High'
df_merged['budget_tier'] = df_merged['production_budget'].apply(budget_tier)
plt.figure(figsize=(10, 6))
sns.boxplot(x='budget_tier', y='roi', data=df_merged)
plt.title('ROI Distribution by Budget Tier')
plt.xlabel('Budget Tier')
plt.ylabel('ROI')
plt.tight_layout()
plt.show()
```



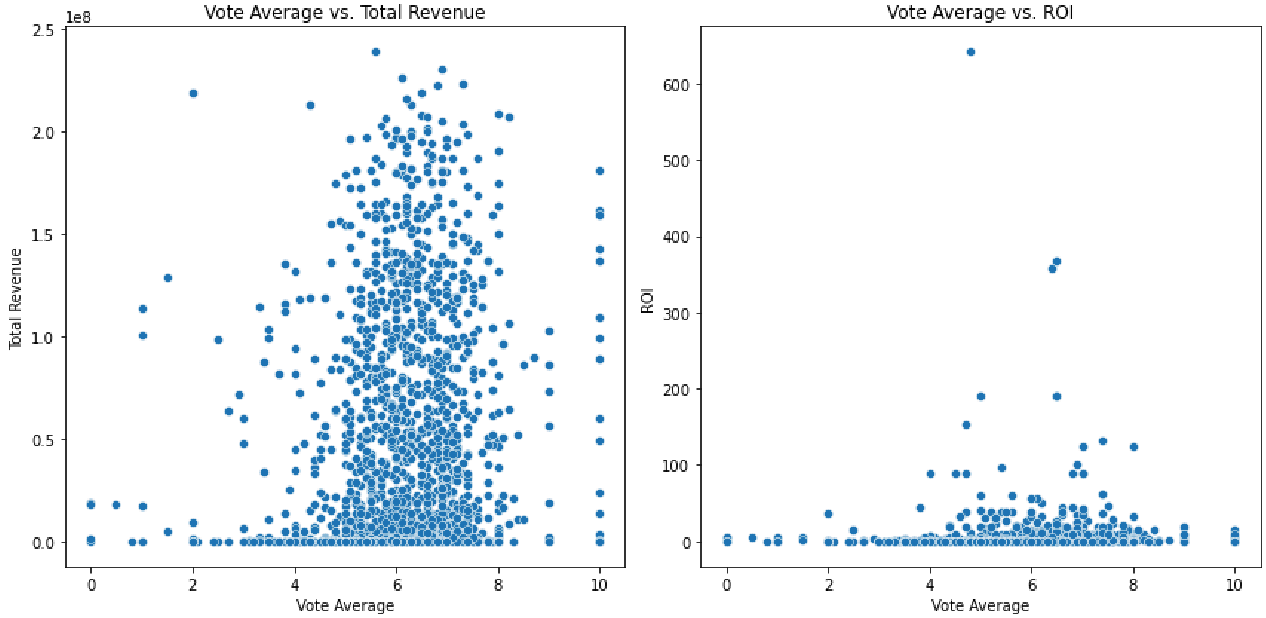


Ratings and ROI Analysis

Examining the impact of movie ratings on ROI and revenue. Creating scatter plots and calculating correlation coefficients. Segment analysis by budget or genre if relevant.

In [8]:
```
# Scatter plots for ratings vs revenue/ROI
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
sns.scatterplot(data=df_merged, x='vote_average', y='total_revenue')
plt.title('Vote Average vs. Total Revenue')
plt.xlabel('Vote Average')
plt.ylabel('Total Revenue')
plt.subplot(1, 2, 2)
sns.scatterplot(data=df_merged, x='vote_average', y='roi')
plt.title('Vote Average vs. ROI')
plt.xlabel('Vote Average')
plt.ylabel('ROI')
plt.tight_layout()
plt.show()

# Correlation coefficients
correlation_rating_revenue = df_merged['vote_average'].corr(df_merged['total_revenue'])
correlation_rating_roi = df_merged['vote_average'].corr(df_merged['roi'])
print(f"Correlation between Vote Average and Total Revenue: {correlation_rating_revenue
print(f"Correlation between Vote Average and ROI: {correlation_rating_roi:.3f}")
```



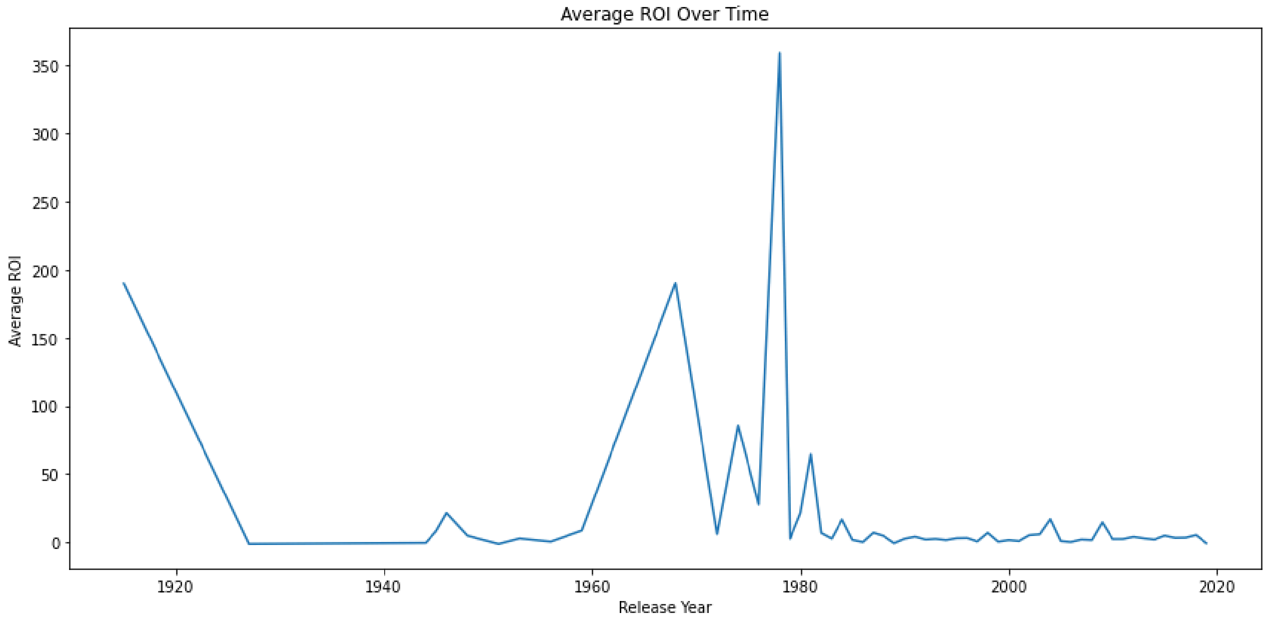

```
Correlation between Vote Average and Total Revenue: 0.159
Correlation between Vote Average and ROI: 0.021
```

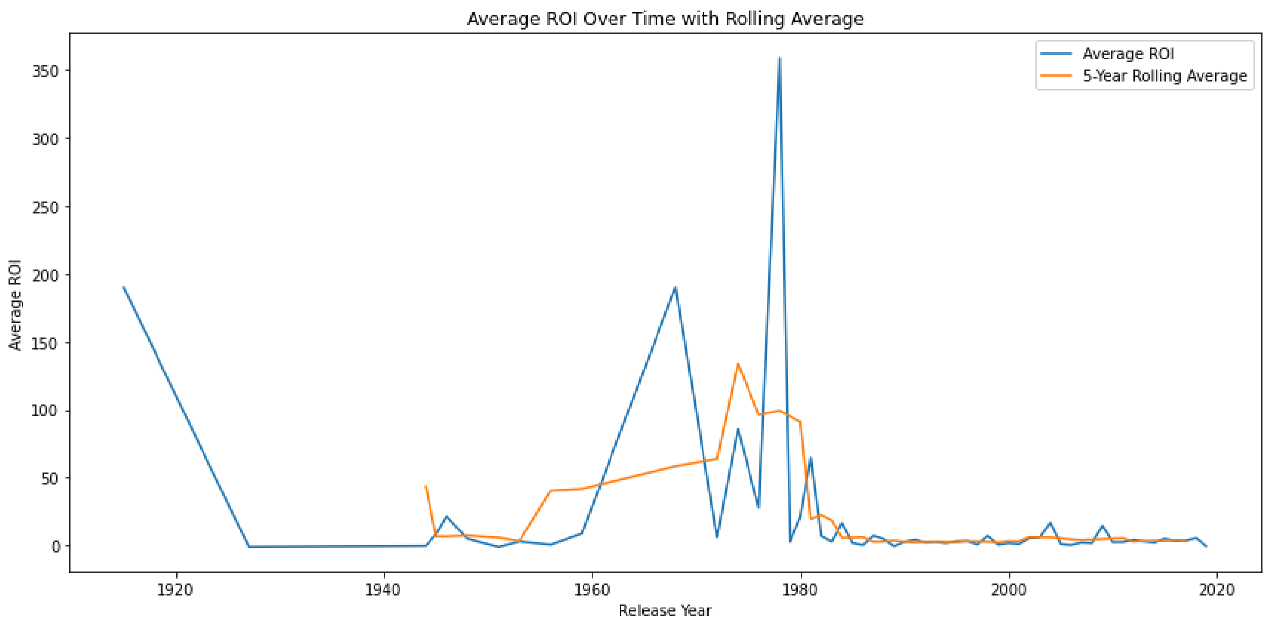
Temporal Trends in Movie Performance

Analyzing trends in ROI and genre popularity over time using line plots and rolling averages. Identifying any seasonal or long-term patterns.

In [9]:
```
# ROI over time
roi_by_year = df_merged.groupby('release_year')['roi'].mean()
plt.figure(figsize=(12, 6))
sns.lineplot(x=roi_by_year.index, y=roi_by_year.values)
plt.title('Average ROI Over Time')
plt.xlabel('Release Year')
plt.ylabel('Average ROI')
plt.tight_layout()
plt.show()

# Rolling average
rolling_avg_window = 5
rolling_avg = roi_by_year.rolling(window=rolling_avg_window, center=True).mean()
plt.figure(figsize=(12, 6))
sns.lineplot(x=roi_by_year.index, y=roi_by_year.values, label='Average ROI')
sns.lineplot(x=rolling_avg.index, y=rolling_avg.values, label=f'{rolling_avg_window}-Ye
plt.title('Average ROI Over Time with Rolling Average')
plt.xlabel('Release Year')
plt.ylabel('Average ROI')
plt.legend()
plt.tight_layout()
plt.show()
```





5. Visualization

Business Recommendations with Supporting Visualizations

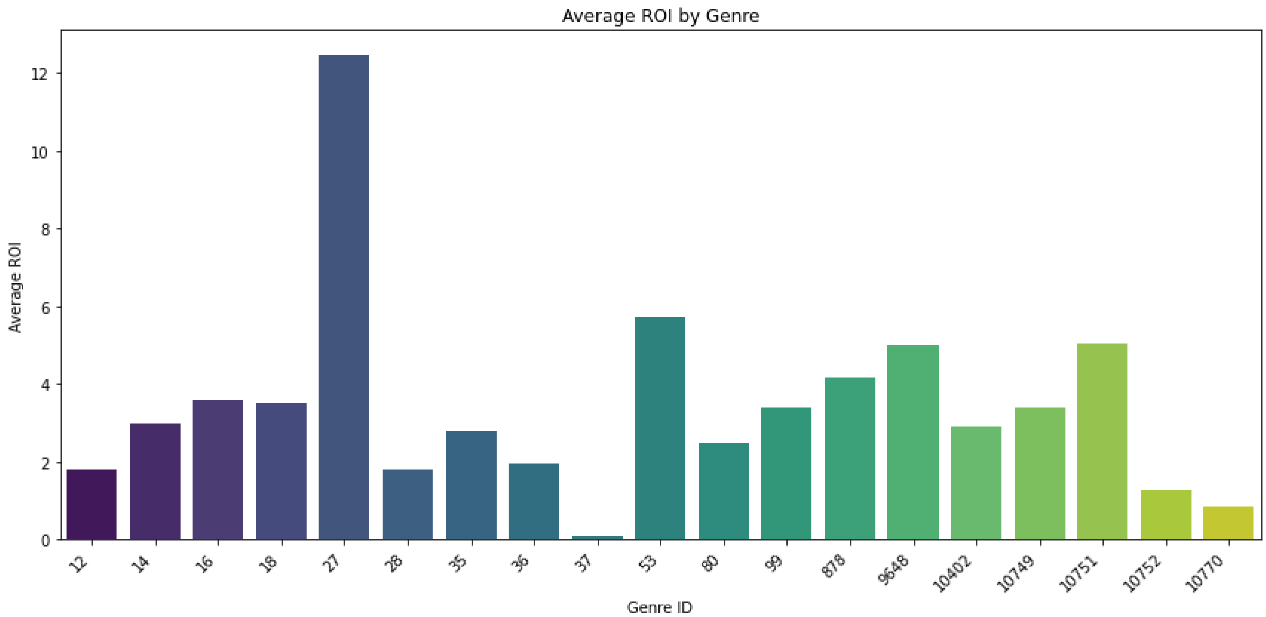
Presenting three concrete business recommendations based on the analysis. Supporting each recommendation with clear, well-formatted visualizations and concise explanations.

Recommendation 1: Focus on High-ROI Genres

Certain genres consistently deliver higher average ROI. The studio should prioritize producing films in these genres to maximize profitability.

In [10]:
```
# Visualize average ROI by genre
plt.figure(figsize=(12, 6))
sns.barplot(x=genre_roi.index, y=genre_roi.values, palette='viridis')
```

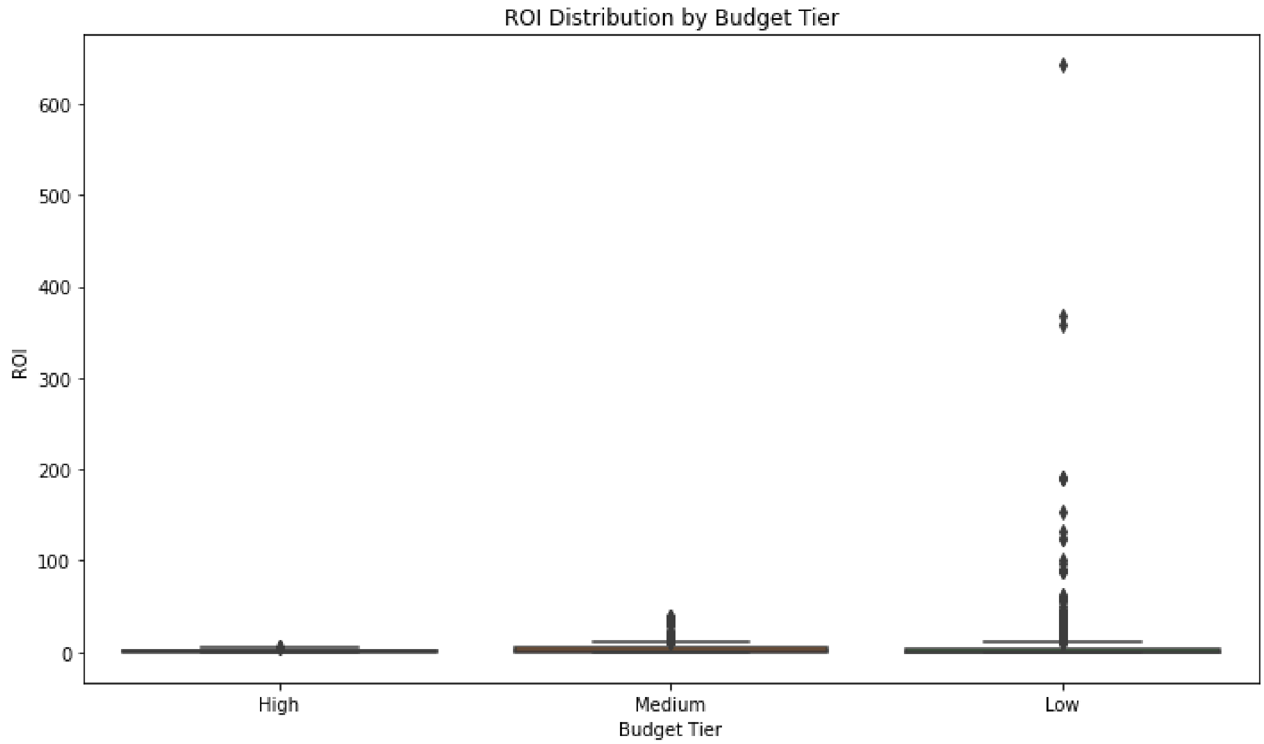
```
plt.title('Average ROI by Genre')
plt.xlabel('Genre ID')
plt.ylabel('Average ROI')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



Recommendation 2: Optimize Production Budgets

Higher budgets do not guarantee higher ROI. The studio should carefully allocate budgets, targeting the "medium" tier for optimal balance between risk and reward.

In [11]:
```
# Visualize ROI by budget tier
plt.figure(figsize=(10, 6))
sns.boxplot(x='budget_tier', y='roi', data=df_merged)
plt.title('ROI Distribution by Budget Tier')
plt.xlabel('Budget Tier')
plt.ylabel('ROI')
plt.tight_layout()
plt.show()
```

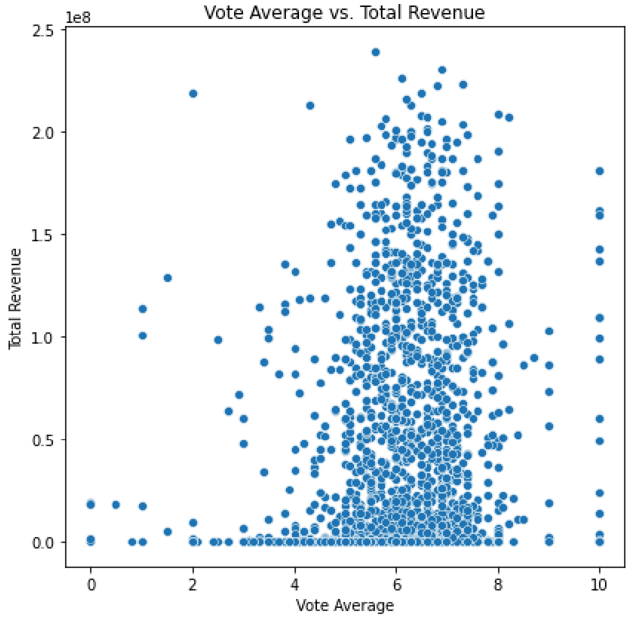


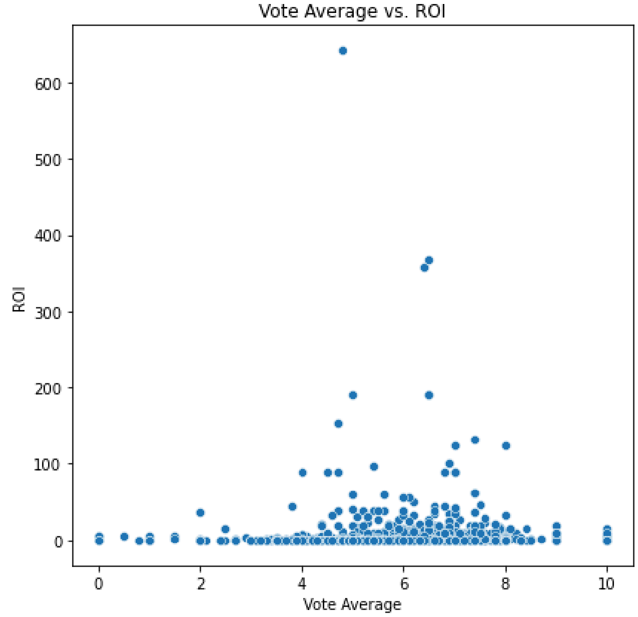
Recommendation 3: Leverage Ratings and Monitor Trends

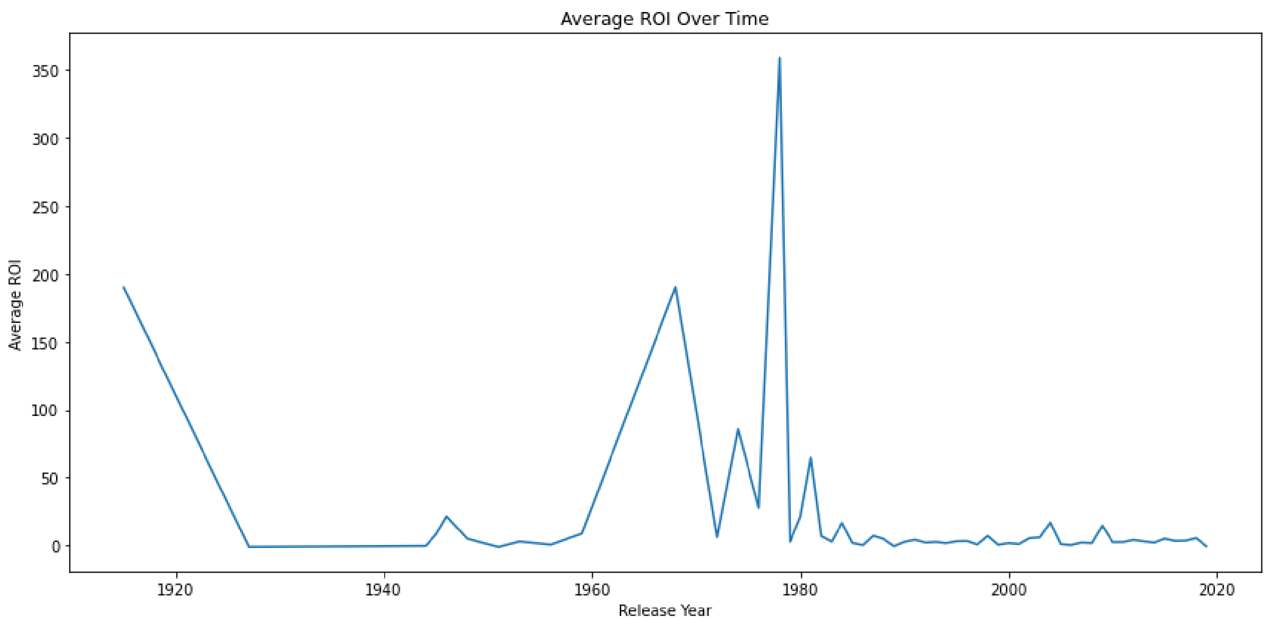
While ratings have a weak correlation with ROI, higher-rated movies tend to earn more revenue. The studio should aim for quality to boost revenue and monitor temporal trends to capitalize on emerging genres.

In [12]:
```
# Visualize ratings vs revenue and ROI
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
sns.scatterplot(data=df_merged, x='vote_average', y='total_revenue')
plt.title('Vote Average vs. Total Revenue')
plt.xlabel('Vote Average')
plt.ylabel('Total Revenue')
plt.subplot(1, 2, 2)
sns.scatterplot(data=df_merged, x='vote_average', y='roi')
plt.title('Vote Average vs. ROI')
plt.xlabel('Vote Average')
plt.ylabel('ROI')
plt.tight_layout()
plt.show()

# Visualize ROI trend over time
plt.figure(figsize=(12, 6))
sns.lineplot(x=roi_by_year.index, y=roi_by_year.values)
plt.title('Average ROI Over Time')
plt.xlabel('Release Year')
plt.ylabel('Average ROI')
plt.tight_layout()
plt.show()
```







Summary

This analysis provides actionable insights for a new movie studio:

- **Target high-ROI genres** for production focus.
- **Optimize budget allocation** to maximize ROI, especially in the medium budget tier.
- **Aim for quality and monitor trends** to boost revenue and adapt to changing audience preferences.

Detailed Explanation on Further Steps

Targeted Genre Production: Prioritize genres with consistently high ROI, considering the number of movies in each genre and their potential for profitability. Investigate the reasons for success in these genres further.

Budget Allocation Strategy: Refine the budget allocation strategy by segmenting movies by genre and performing more robust regression analysis to identify optimal budget levels for different genres. Consider other factors beyond budget, such as marketing and distribution