Final Project

By: Thomas Nash & Daniel Mehta

Problem Statement:

A comparative analysis of value and performance between two Airbnb rental types across the five boroughs of New York City.

In [33]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.ensemble import ExtraTreesRegressor
```

In [34]:
```
df = pd.read_csv("Airbnb_Open_Data_cleansed.csv")
```

```
/var/folders/xb/2tg9ddl94wl284px7ngj8hn40000gn/T/ipykernel_25259/1262225521.py:1: DtypeWarning: Columns (11,25) have mi
xed types. Specify dtype option on import or set low_memory=False.
  df = pd.read_csv("Airbnb_Open_Data_cleansed.csv")
```

In [35]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 102599 entries, 0 to 102598
Data columns (total 26 columns):
 #   Column                          Non-Null Count   Dtype  
---  ------                          --------------   -----  
 0   id                              102599 non-null  int64  
 1   NAME                            102349 non-null  object 
 2   host id                         102599 non-null  int64  
 3   host_identity_verified          102310 non-null  object 
 4   host name                       102193 non-null  object 
 5   neighbourhood group             102570 non-null  object 
 6   neighbourhood                   102583 non-null  object 
 7   lat                             102591 non-null  float64
 8   long                            102591 non-null  float64
 9   country                         102599 non-null  object 
 10  country code                    102599 non-null  object 
 11  instant_bookable                102494 non-null  object 
 12  cancellation_policy             102523 non-null  object 
 13  room type                       102599 non-null  object 
 14  Construction year               102385 non-null  float64
 15  price                           102352 non-null  object 
 16  service fee                     102326 non-null  object 
 17  minimum nights                  102190 non-null  float64
 18  number of reviews               102416 non-null  float64
 19  last review                     86706 non-null   object 
 20  reviews per month               86720 non-null   float64
 21  review rate number              102273 non-null  float64
 22  calculated host listings count  102280 non-null  float64
 23  availability 365                102151 non-null  float64
 24  house_rules                     50468 non-null   object 
 25  license                         2 non-null       object 
dtypes: float64(9), int64(2), object(15)
memory usage: 20.4+ MB
```

Cleaning and Preprocessng

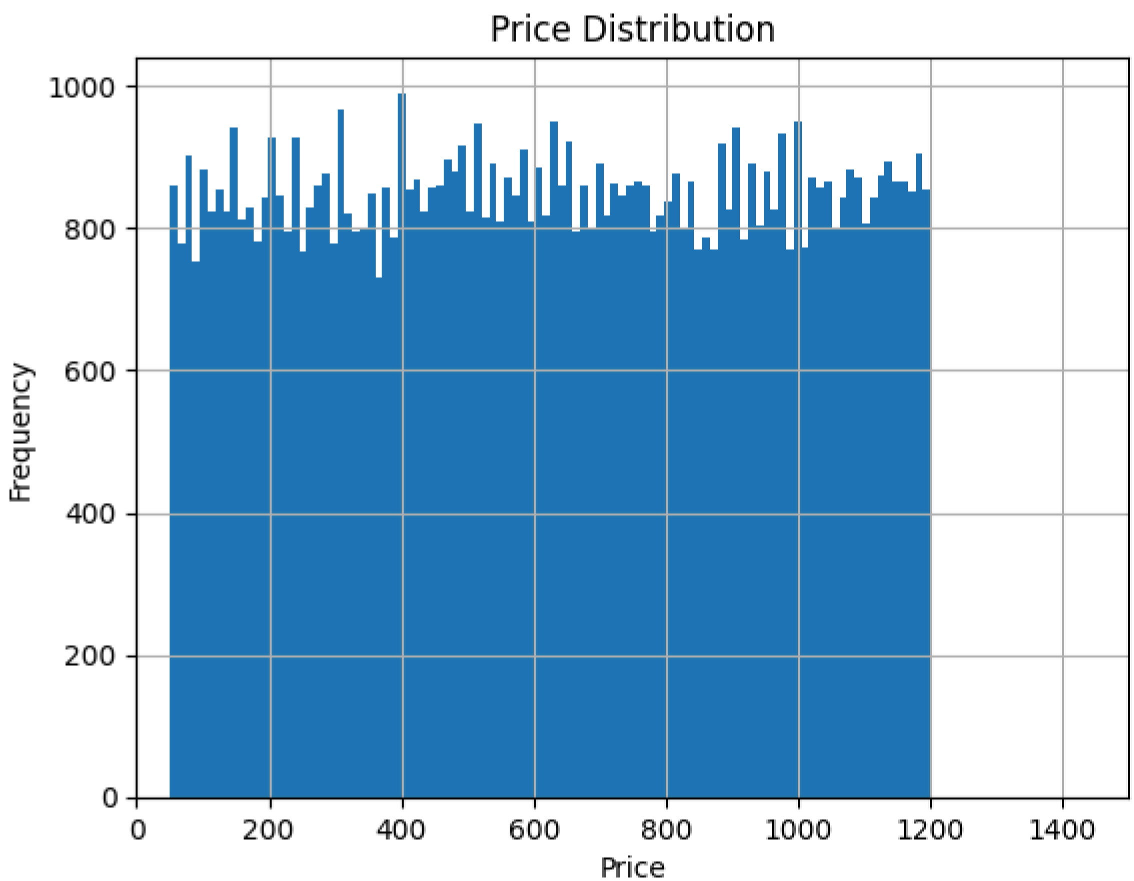
In [36]:
```
df_clean = df.copy()
df_vis = df.copy()
```

In [37]:
```
#Dropping Unneeded Columns
columns_to_drop = [
    'id', 'NAME', 'host id', 'host name', 'country', 'country code',
    'last review', 'house_rules', 'license', 'lat', 'long'
]
df_clean.drop(columns=columns_to_drop, inplace=True)
```

```
In [38]: #Drop Columns where price column is missing
df_clean = df_clean[df_clean['price'].notnull()]
```

```
In [39]: #Remove $ and commas from price and service fee columns then convert to float
df_clean['price'] = df_clean['price'].replace('[\$,]', '', regex=True).astype(float)
df_clean['service fee'] = df_clean['service fee'].replace('[\$,]', '', regex=True).astype(float)
```

```
In [62]: #Used this graph to determine if there is any unrealistic prices in the dataset, I came into the conclution that all th
df_clean['price'].hist(bins=100)
plt.xlim(0, 1500)
plt.title('Price Distribution')
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.show()
```




```
In [41]: #Dropping rows with missing values in important columns
df_clean = df_clean.dropna(subset=[
    'neighbourhood group', 'host_identity_verified', 'instant_bookable',
    'cancellation_policy', 'room type', 'Construction year',
```

```
    'minimum nights', 'number of reviews', 'reviews per month',
    'review rate number', 'calculated host listings count',
    'availability 365'
])
```

In [42]:
```
#Encode categorical features using get_dummies (one-hot encoding)
categorical_cols = [
    'neighbourhood group', 'host_identity_verified', 'instant_bookable',
    'cancellation_policy', 'room type'
]
df_encoded = pd.get_dummies(df_clean, columns=categorical_cols, drop_first=True)
```

In [43]:
```
#Feature engineering (Adding Total Cost and price per night)
df_encoded['total cost'] = df_encoded['price'] + df_encoded['service fee']
df_encoded['price_per_night'] = df_encoded['price'] / df_encoded['minimum nights']
df_encoded['price_per_night'].replace([np.inf, -np.inf], np.nan, inplace=True)
df_encoded['price_per_night'].fillna(0, inplace=True)
```

In [44]:
```
#Resting the index
df_encoded.reset_index(drop=True, inplace=True)
```

In [45]:
```
print("Final shape:", df_encoded.shape)
df_encoded.head()
```

```
Final shape: (85029, 23)
```

Out[45]:

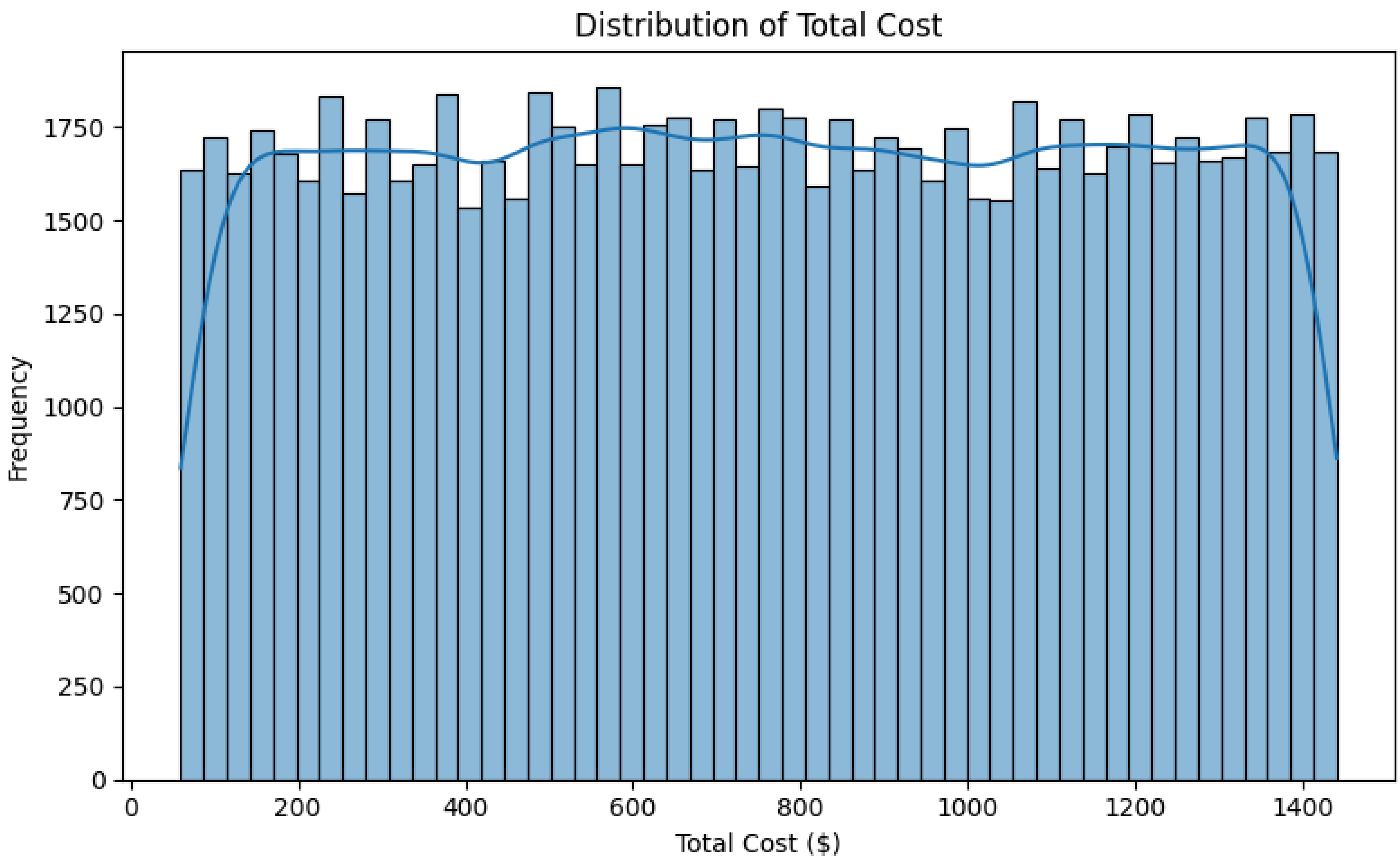
	neighbourhood	Construction year	price	service fee	minimum nights	number of reviews	reviews per month	review rate number	calculated host listings count	availability 365	...	neighbourhood group_Staten Island	host
0	Kingsbridge	2009.0	55.0	11.0	30.0	4.0	0.35	5.0	2.0	315.0	...	False	
1	Woodlawn	2010.0	811.0	162.0	1.0	197.0	2.49	5.0	1.0	132.0	...	False	
2	Spuyten Duyvil	2016.0	344.0	69.0	2.0	47.0	1.22	1.0	1.0	28.0	...	False	
3	Longwood	2022.0	719.0	144.0	5.0	82.0	0.96	3.0	1.0	268.0	...	False	
4	Concourse	2006.0	665.0	133.0	3.0	119.0	1.41	1.0	1.0	70.0	...	False	

5 rows × 23 columns

Data Vis

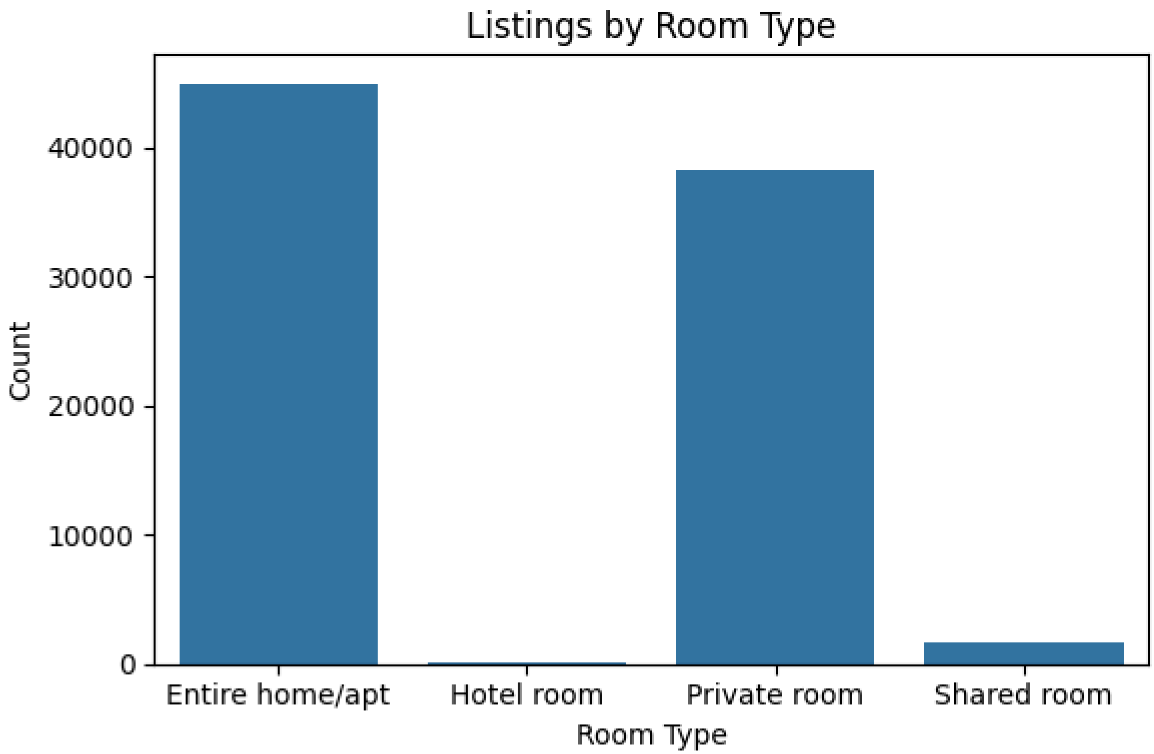
In [46]:
```python
df_vis['price'] = df_vis['price'].replace('[\$,]', '', regex=True).astype(float)
df_vis['service fee'] = df_vis['service fee'].replace('[\$,]', '', regex=True).astype(float)

df_vis['total cost'] = df_vis['price'] + df_vis['service fee']
```

In [47]:
```python
plt.figure(figsize=(8, 5))
sns.histplot(df_encoded['total cost'], bins=50, kde=True)
plt.title("Distribution of Total Cost")
plt.xlabel("Total Cost ($)")
plt.ylabel("Frequency")
plt.tight_layout()
plt.show()
```



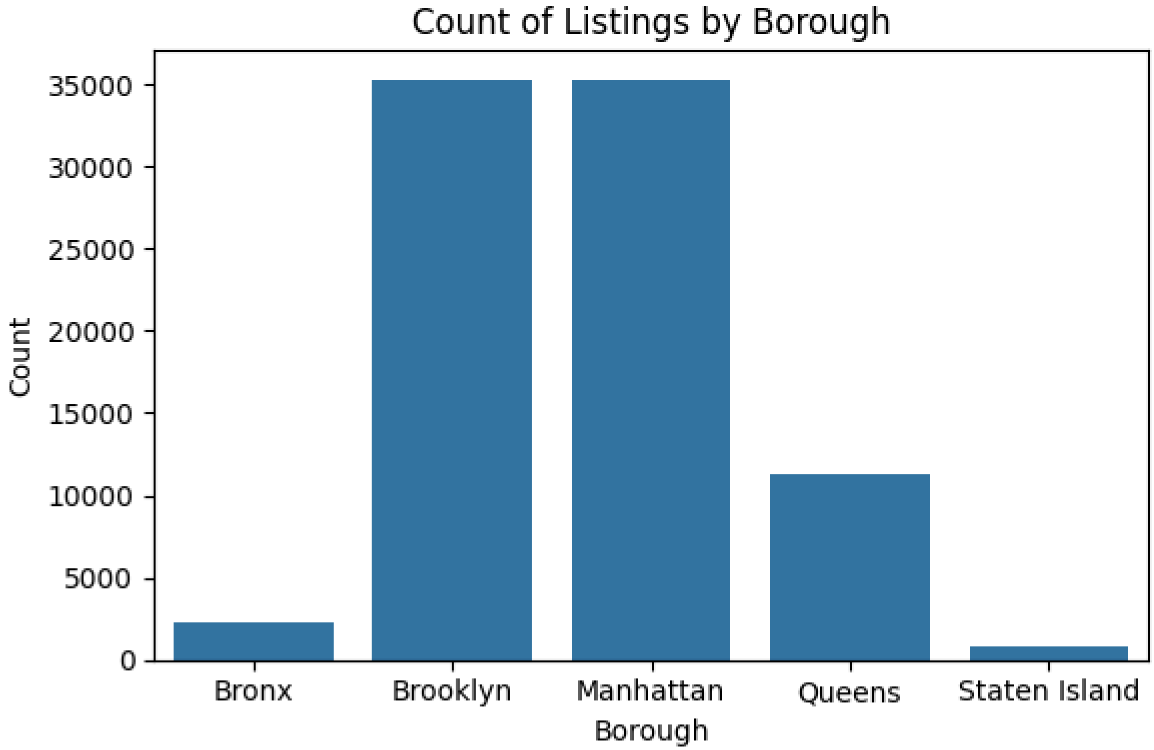
In [48]:
```python
plt.figure(figsize=(6, 4))
sns.countplot(data=df_clean, x='room type')
plt.title("Listings by Room Type")
plt.xlabel("Room Type")
```

```
plt.ylabel("Count")
plt.tight_layout()
plt.show()
```

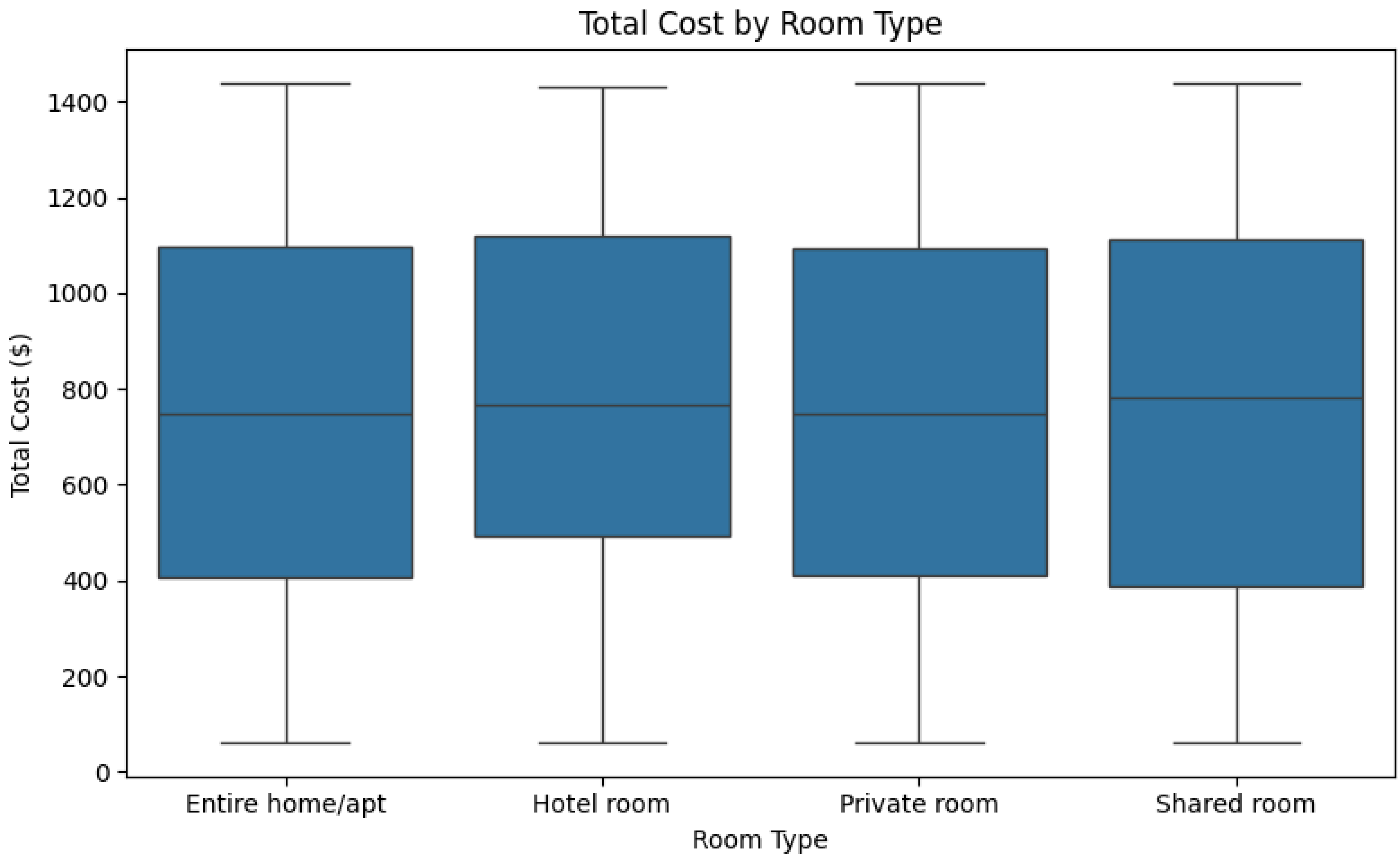


In [49]:

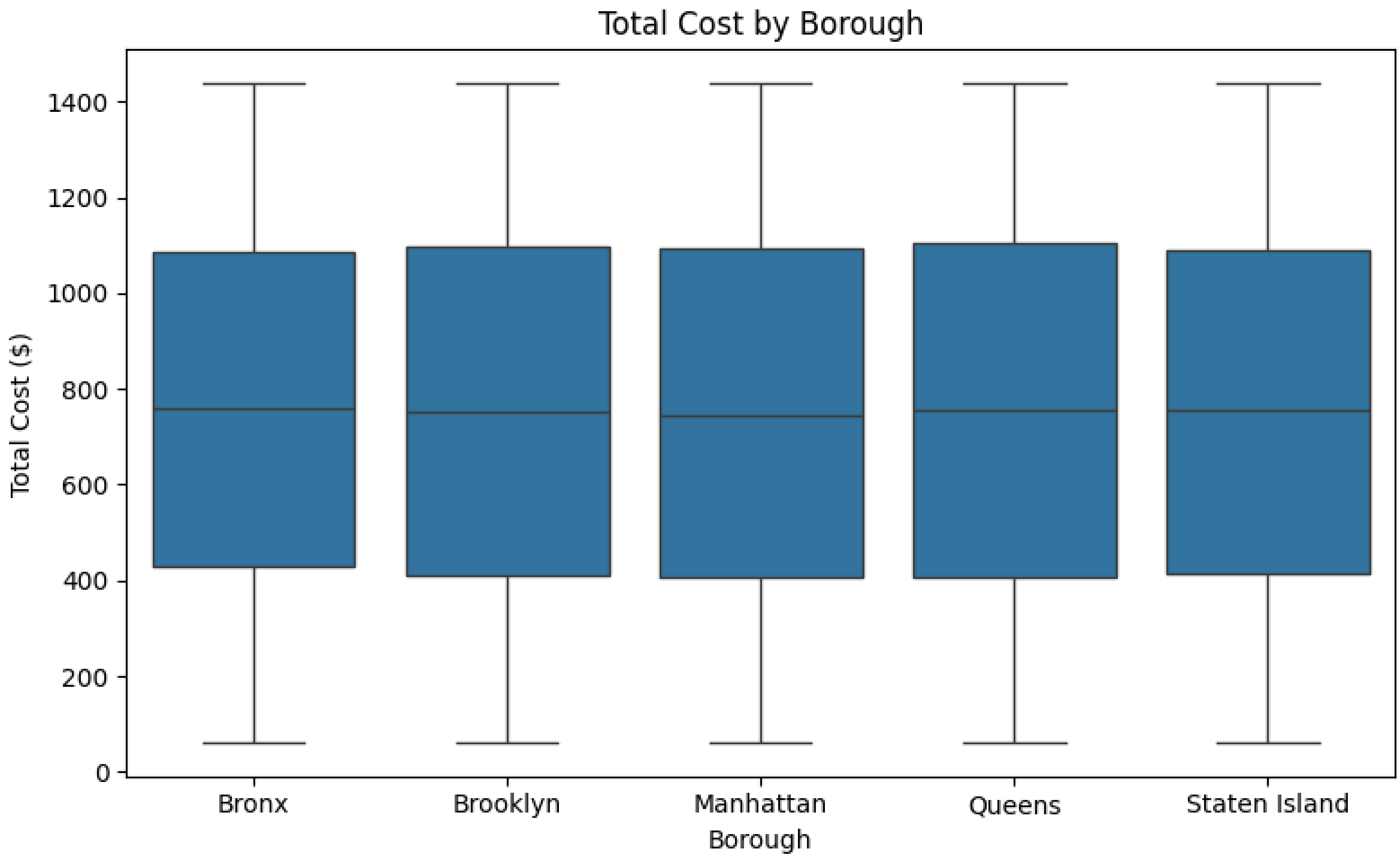
```
plt.figure(figsize=(6, 4))
sns.countplot(data=df_clean, x='neighbourhood group')
plt.title("Count of Listings by Borough")
plt.xlabel("Borough")
plt.ylabel("Count")
plt.tight_layout()
plt.show()
```



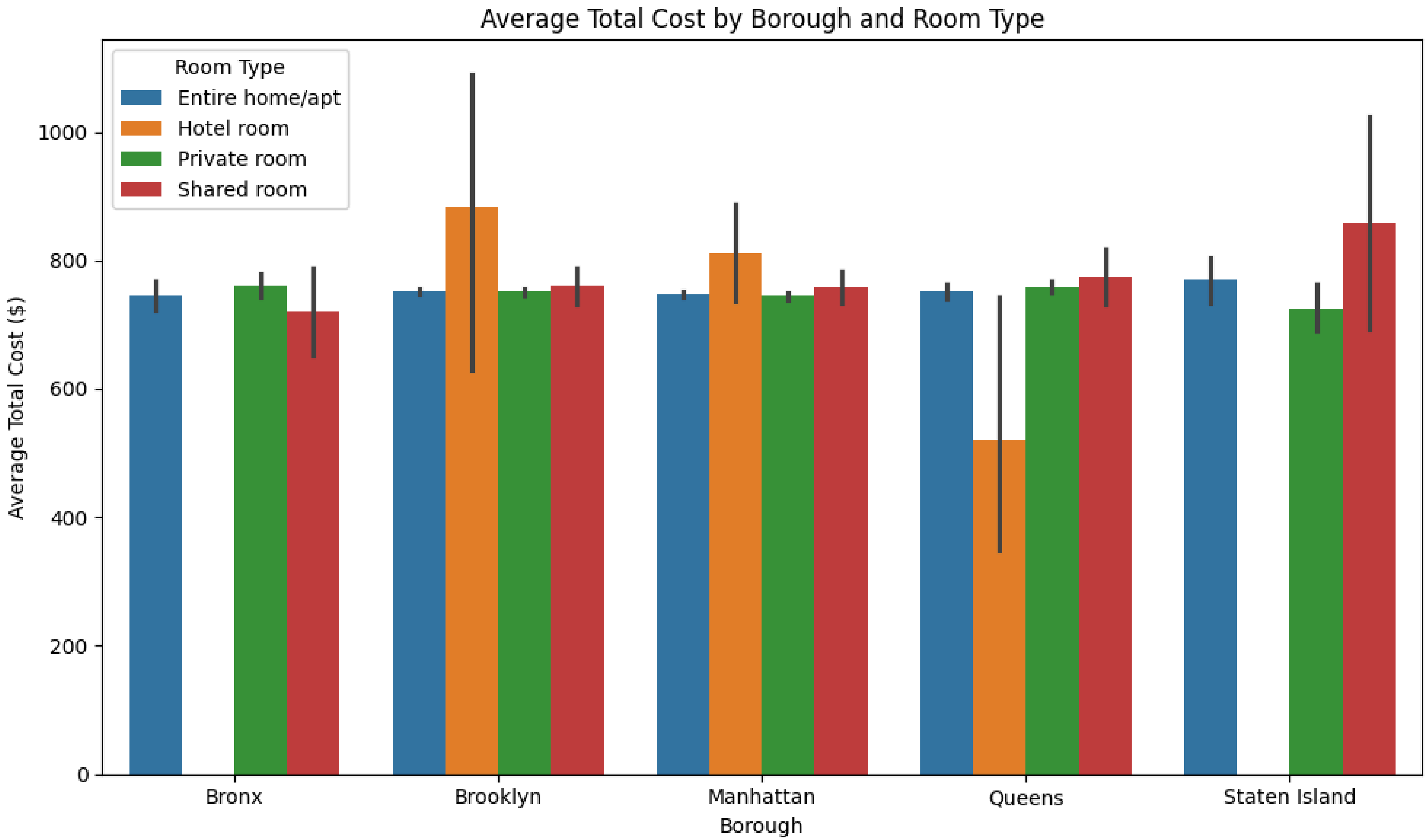
In [50]:
```
plt.figure(figsize=(8, 5))
sns.boxplot(data=df_vis, x='room type', y='total cost')
plt.title("Total Cost by Room Type")
plt.xlabel("Room Type")
plt.ylabel("Total Cost ($)")
plt.tight_layout()
plt.show()
```



In [51]:
```
plt.figure(figsize=(8, 5))
sns.boxplot(data=df_vis, x='neighbourhood group', y='total cost')
plt.title("Total Cost by Borough")
plt.xlabel("Borough")
plt.ylabel("Total Cost ($)")
plt.tight_layout()
plt.show()
```

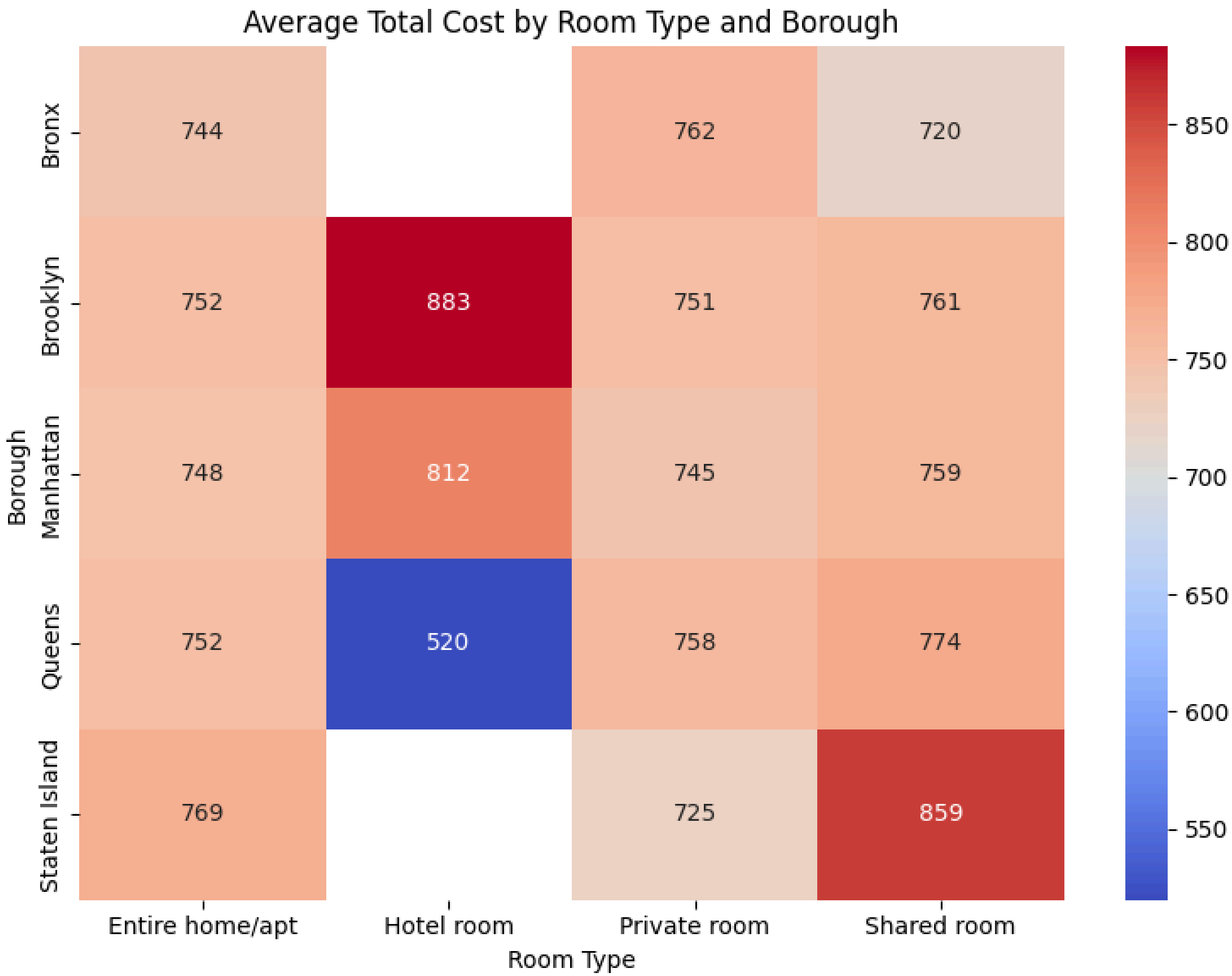


In [52]:
```
plt.figure(figsize=(10, 6))
sns.barplot(data=df_vis, x='neighbourhood group', y='total cost', hue='room type', estimator=np.mean)
plt.title("Average Total Cost by Borough and Room Type")
plt.xlabel("Borough")
plt.ylabel("Average Total Cost ($)")
plt.legend(title="Room Type")
plt.tight_layout()
plt.show()
```



In [53]:

```
heatmap_data = df_vis.groupby(['neighbourhood group', 'room type'])['total cost'].mean().unstack()
plt.figure(figsize=(8, 6))
sns.heatmap(heatmap_data, annot=True, fmt=".0f", cmap="coolwarm")
plt.title("Average Total Cost by Room Type and Borough")
plt.xlabel("Room Type")
plt.ylabel("Borough")
plt.tight_layout()
plt.show()
```



Model (ExtraTreesRegressor)

In [54]:

```
# Data Splitting

X = df_encoded.drop(columns=['price', 'service fee', 'total cost', 'price_per_night'])
y = df_encoded['total cost']
X = X.select_dtypes(include=[np.number])

# Combine and drop rows with any NaNs
model_data = pd.concat([X, y], axis=1).dropna()
```

```python
# Resplit X and y after dropping NaNs
X = model_data.drop(columns=['total cost'])
y = model_data['total cost']

#80/20 split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [55]:

```python
'''
model = RandomForestRegressor(
    n_estimators=100,
    random_state=42,
    n_jobs=-1
)
'''
model = ExtraTreesRegressor(
    n_estimators=100,
    random_state=42,
    n_jobs=-1
)

#train
model.fit(X_train, y_train)

#predict
y_pred = model.predict(X_test)
```

In [56]:

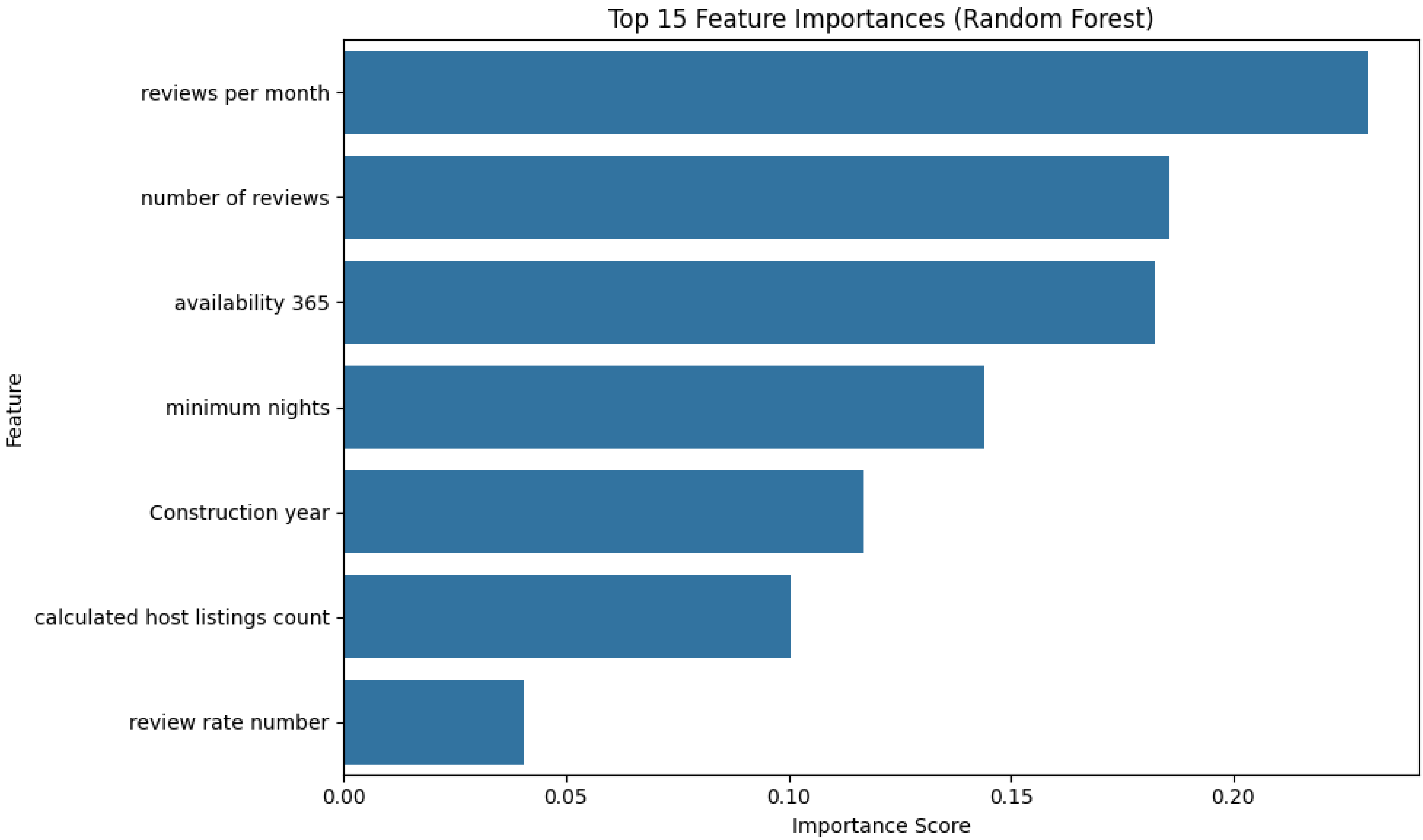
```python
# Evaluation metrics
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)

print(f"MAE: ${mae:.2f}")
print(f"RMSE: ${rmse:.2f}")
print(f"R2 Score: {r2:.4f}")
```

```
MAE: $200.22
RMSE: $311.63
R2 Score: 0.3839
```

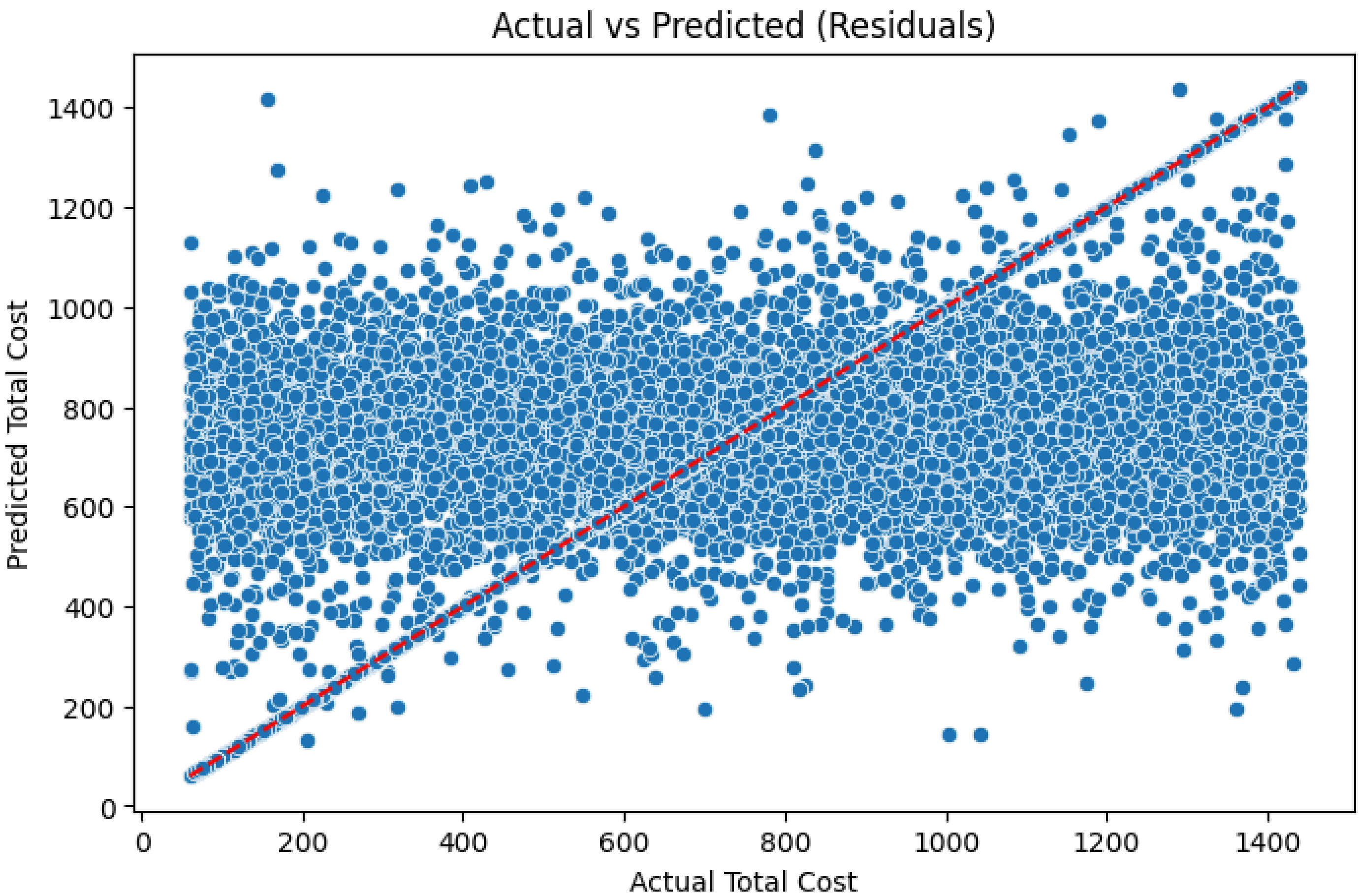
In [57]:

```python
importances = model.feature_importances_
features = X_train.columns
indices = np.argsort(importances)[::-1]

plt.figure(figsize=(10, 6))
sns.barplot(x=importances[indices][:15], y=features[indices][:15])
plt.title('Top 15 Feature Importances (Random Forest)')
```

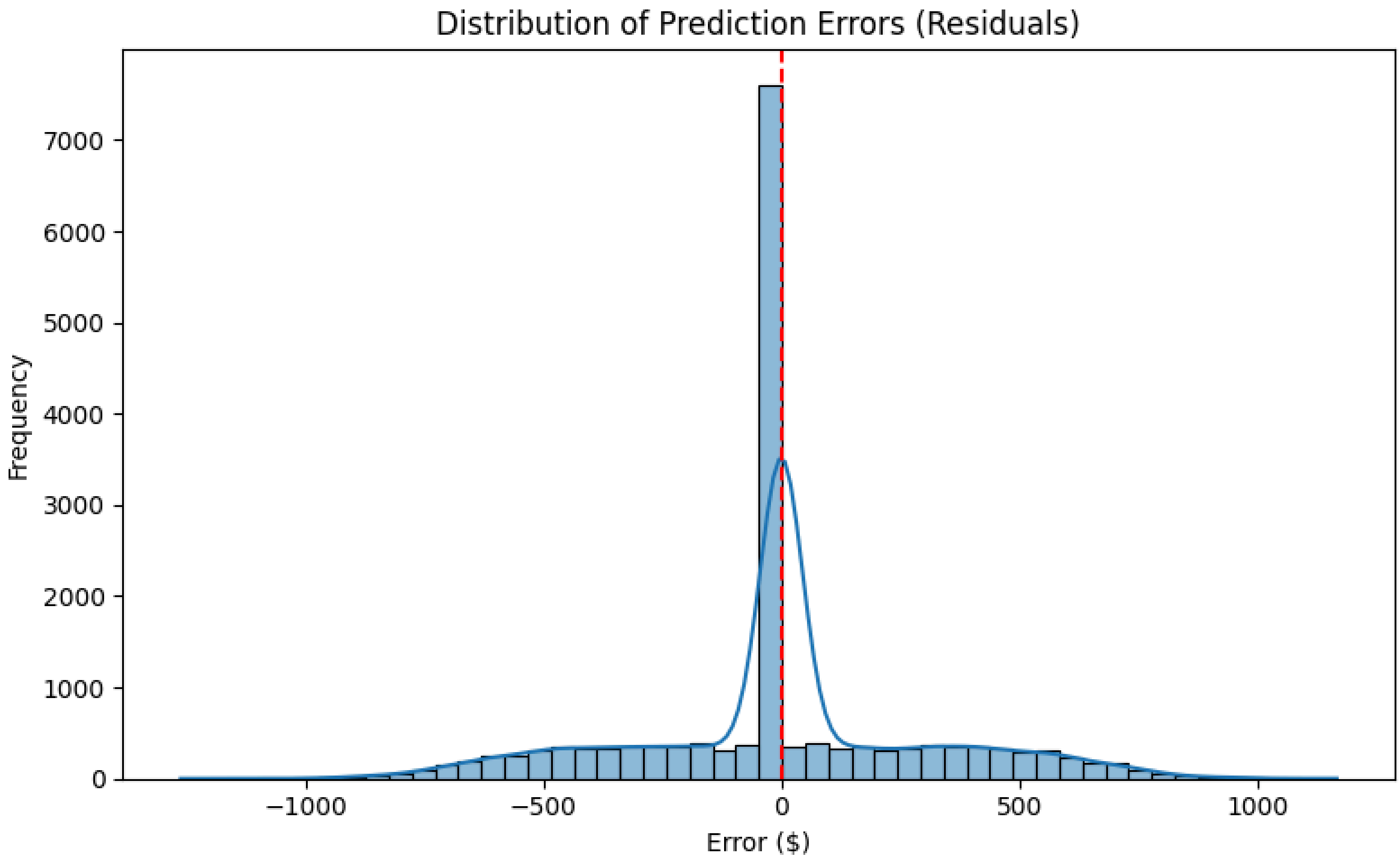
```python
plt.xlabel('Importance Score')
plt.ylabel('Feature')
plt.tight_layout()
plt.show()
```



In [58]:
```python
plt.figure(figsize=(8,5))
sns.scatterplot(x=y_test, y=y_pred)
plt.xlabel("Actual Total Cost")
plt.ylabel("Predicted Total Cost")
plt.title("Actual vs Predicted (Residuals)")
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')  # 45-degree line
plt.show()
```

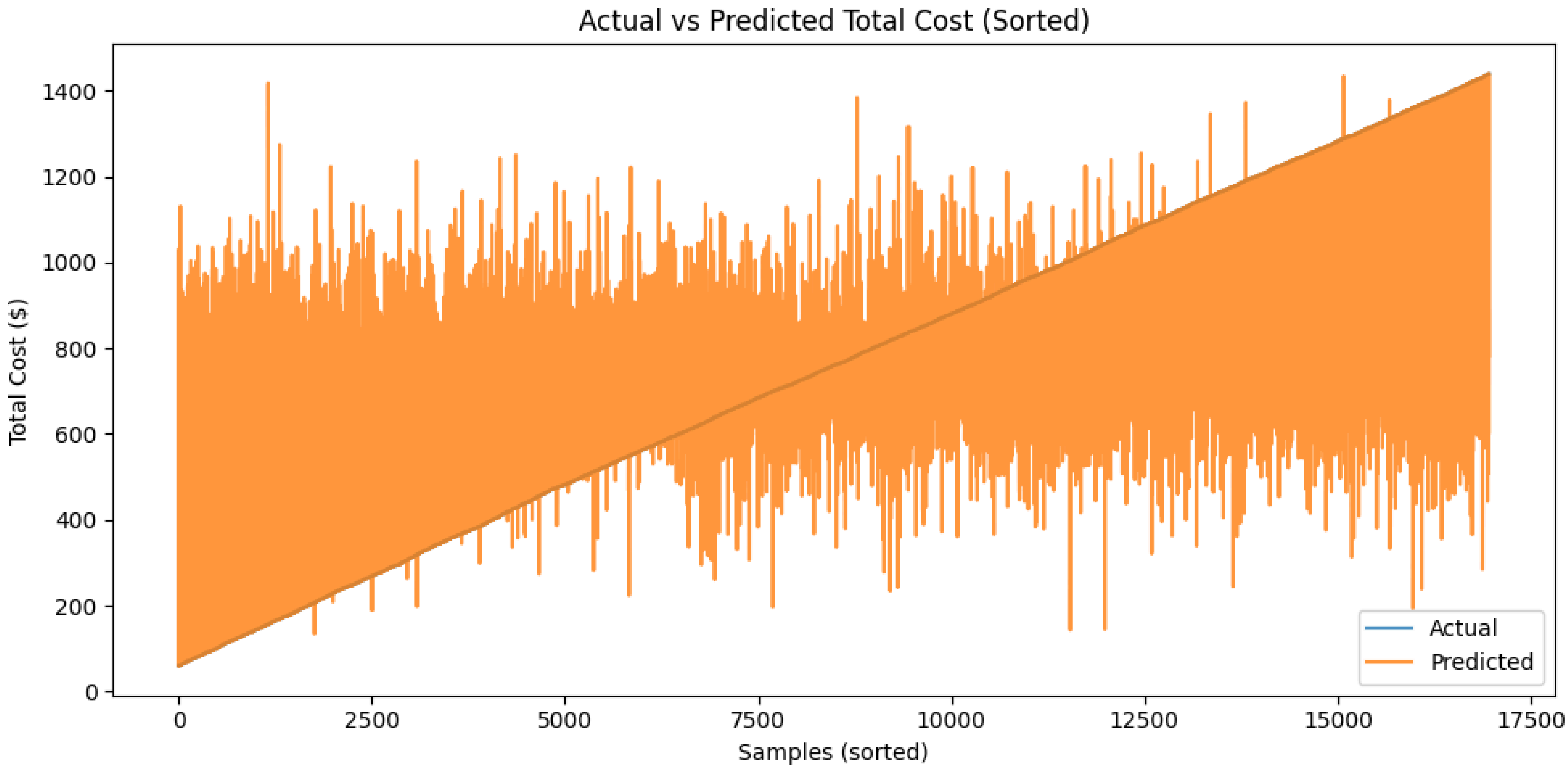


In [59]:
```
errors = y_test - y_pred

plt.figure(figsize=(8, 5))
sns.histplot(errors, bins=50, kde=True)
plt.title("Distribution of Prediction Errors (Residuals)")
plt.xlabel("Error ($)")
plt.ylabel("Frequency")
plt.axvline(0, color='red', linestyle='--')
plt.tight_layout()
plt.show()
```

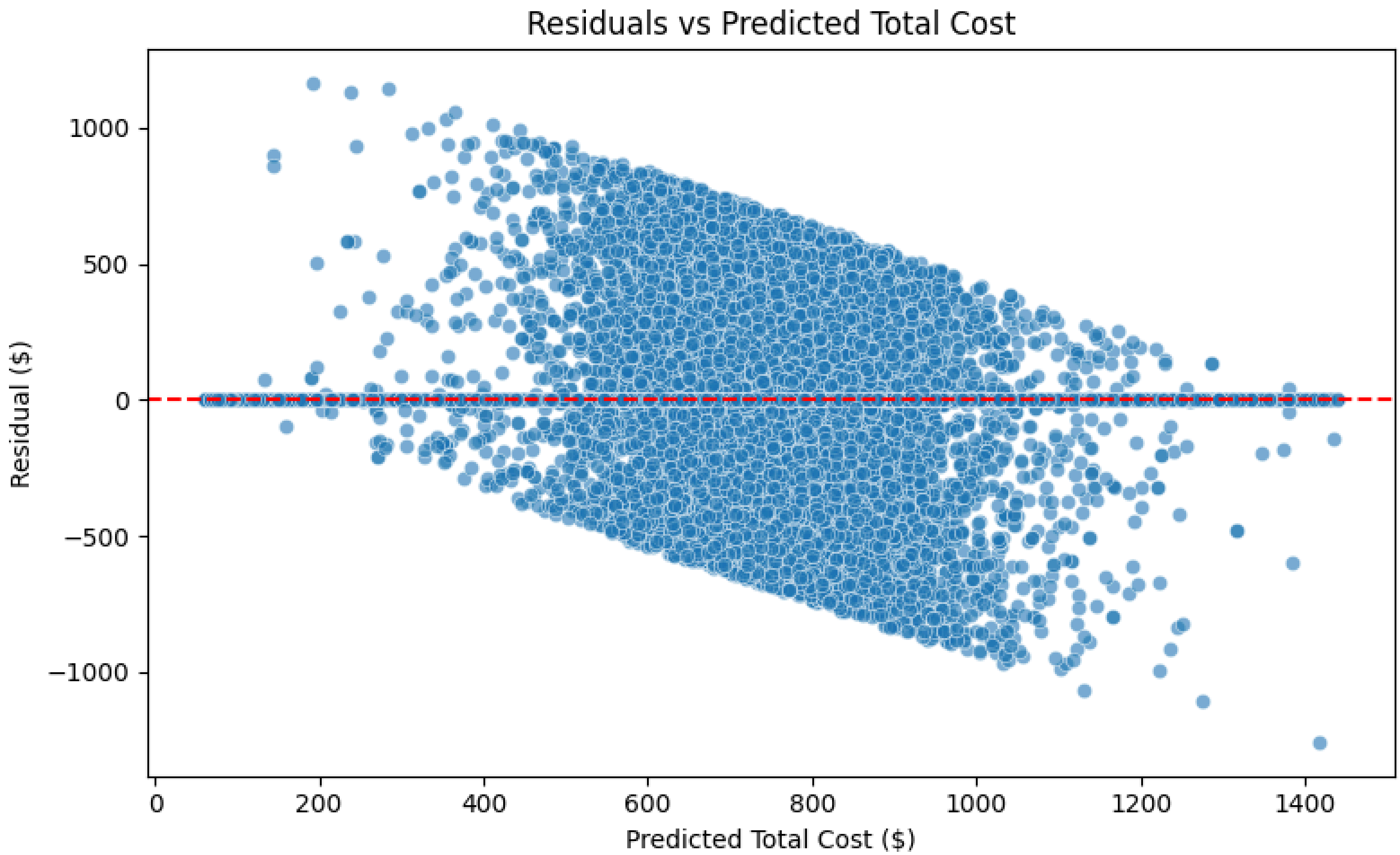


In [67]:

```
#Get back to Tom on it

plt.figure(figsize=(10, 5))
sorted_idx = np.argsort(y_test.values)
plt.plot(y_test.values[sorted_idx], label='Actual', alpha=0.8)
plt.plot(y_pred[sorted_idx], label='Predicted', alpha=0.8)
plt.title("Actual vs Predicted Total Cost (Sorted)")
plt.xlabel("Samples (sorted)")
plt.ylabel("Total Cost ($)")
plt.legend()
plt.tight_layout()
plt.show()
```



In [61]:
```
residuals = y_test - y_pred
plt.figure(figsize=(8, 5))
sns.scatterplot(x=y_pred, y=residuals, alpha=0.6)
plt.axhline(0, color='red', linestyle='--')
plt.title("Residuals vs Predicted Total Cost")
plt.xlabel("Predicted Total Cost ($)")
plt.ylabel("Residual ($)")
plt.tight_layout()
plt.show()
```



Results

I compared multiple models including Linear Regression, XGBoost, Random Forest, and ExtraTrees. ExtraTrees performed the best

Strengths

- Model performs well overall – it captures general patterns in total cost across listings
- Prediction errors are centered around 0 with no major bias in over or under-prediction
- Most predictions are accurate within $200

Weaknesses

- Model struggles with very expensive listings – tends to underpredict the high end

- Guest activity features (reviews, availability) are more important than location
- Some predictions are too "average" – doesn’t always capture extreme cases

```
In [ ]:
```