In [1]:
```
# Importing the libraries

import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns
sns.set()

import warnings
warnings.filterwarnings("ignore")

from sklearn.feature_selection import mutual_info_regression, f_regression
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.preprocessing import OneHotEncoder, LabelEncoder, StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error

from statsmodels.stats.outliers_influence import variance_inflation_factor

import scipy.stats as stats

from sklearn.linear_model import LinearRegression, Lasso, Ridge, ElasticNet

import statsmodels.api as sm
from statsmodels.formula.api import ols
import statsmodels.regression.linear_model as smf

from sklearn.tree import DecisionTreeRegressor

from sklearn.ensemble import RandomForestRegressor, AdaBoostRegressor

from sklearn.svm import SVR

from xgboost import XGBRegressor
```

In [2]:
```
# Reading and copying the train_data

train_data = pd.read_excel("Data_train.xlsx")
test_data = pd.read_excel("Test_set.xlsx")

df = train_data.copy()
```

Basic EDA

In [3]:
```
# Checking the first five records

df.head()
```

Out[3]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additio
0	IndiGo	24/03/2019	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	non-stop	
1	Air India	1/05/2019	Kolkata	Banglore	CCU → IXR → BBI → BLR	05:50	13:15	7h 25m	2 stops	
2	Jet Airways	9/06/2019	Delhi	Cochin	DEL → LKO → BOM → COK	09:25	04:25 10 Jun	19h	2 stops	
3	IndiGo	12/05/2019	Kolkata	Banglore	CCU → NAG → BLR	18:05	23:30	5h 25m	1 stop	
4	IndiGo	01/03/2019	Banglore	New Delhi	BLR → NAG → DEL	16:50	21:35	4h 45m	1 stop	

In [4]:
```
# Checking the last five records

df.tail()
```

Out[4]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Ad
10678	Air Asia	9/04/2019	Kolkata	Banglore	CCU → BLR	19:55	22:25	2h 30m	non-stop	
10679	Air India	27/04/2019	Kolkata	Banglore	CCU → BLR	20:45	23:20	2h 35m	non-stop	
10680	Jet Airways	27/04/2019	Banglore	Delhi	BLR → DEL	08:20	11:20	3h	non-stop	
10681	Vistara	01/03/2019	Banglore	New Delhi	BLR → DEL	11:30	14:10	2h 40m	non-stop	
10682	Air India	9/05/2019	Delhi	Cochin	DEL → GOI → BOM → COK	10:55	19:15	8h 20m	2 stops	

In [5]:
```
# Checking the random five records

df.sample(5)
```

Out[5]:

	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Ad
6172	Multiple carriers	27/03/2019	Delhi	Cochin	DEL → BOM → COK	10:20	18:50	8h 30m	1 stop	
2579	Air India	27/03/2019	Delhi	Cochin	DEL → HYD → BOM → COK	13:05	07:40 28 Mar	18h 35m	2 stops	
2357	IndiGo	21/06/2019	Banglore	Delhi	BLR → DEL	22:10	01:00 22 Jun	2h 50m	non-stop	
8458	Jet Airways	9/06/2019	Delhi	Cochin	DEL → BOM → COK	15:00	04:25 10 Jun	13h 25m	1 stop	
4038	Jet Airways	12/06/2019	Kolkata	Banglore	CCU → BOM → BLR	20:00	04:40 13 Jun	8h 40m	1 stop	

In [6]:
```
# Checking the shape of the data

print(f"No. of rows : {df.shape[0]}\nNo. of features : {df.shape[1]}")
```

```
No. of rows : 10683
No. of features : 11
```

In [7]:
```
# Checking the features

df.columns
```

Out[7]:
```
Index(['Airline', 'Date_of_Journey', 'Source', 'Destination', 'Route',
       'Dep_Time', 'Arrival_Time', 'Duration', 'Total_Stops',
       'Additional_Info', 'Price'],
      dtype='object')
```

In [8]:
```
# Checking the data types of the features

df.dtypes.sort_values()
```

Out[8]:
```
Price              int64
Airline           object
Date_of_Journey   object
Source            object
Destination       object
Route             object
Dep_Time          object
Arrival_Time      object
Duration          object
Total_Stops       object
Additional_Info   object
dtype: object
```

In [9]:
```
# Checking the metadata of the dataset

df.info(memory_usage = "deep")
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10683 entries, 0 to 10682
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Airline          10683 non-null  object
 1   Date_of_Journey  10683 non-null  object
 2   Source           10683 non-null  object
 3   Destination      10683 non-null  object
 4   Route            10682 non-null  object
 5   Dep_Time         10683 non-null  object
 6   Arrival_Time     10683 non-null  object
 7   Duration         10683 non-null  object
 8   Total_Stops      10682 non-null  object
 9   Additional_Info  10683 non-null  object
 10  Price            10683 non-null  int64
dtypes: int64(1), object(10)
memory usage: 7.1 MB
```

In [10]:
```
# Checking the number of null entries in the dataset

print('\033[1m' + f"The total number of null values in the dataset : {df.isna().sum().sum()}\n"

if df.isna().sum().sum() != 0:
    null_features = [col for col in df.columns if df[col].isna().sum() != 0]
    null_df = pd.DataFrame({
        "Feature" : [col for col in null_features],
        "Null_Count" : [df[col].isna().sum() for col in null_features],
        "Null_Percentage" : [str(np.round((df[col].isna().sum() / len(df)) * 100, 2)) + "%" for
        "Data_Type" : [df[col].dtype for col in null_features]
    }).set_index("Feature").sort_values("Null_Count")

else:
    pass

null_df
```

The total number of null values in the dataset : 2

Out[10]:

Feature	Null_Count	Null_Percentage	Data_Type
Route	1	0.01%	object
Total_Stops	1	0.01%	object

In [11]:
```
# Checking the statistical summary of the dataset

df.describe()
```

Out[11]:

	Price
count	10683.000000
mean	9087.064121
std	4611.359167
min	1759.000000
25%	5277.000000
50%	8372.000000
75%	12373.000000
max	79512.000000

In [12]:
```
# Checking the categorical summary of the dataset

df.describe(include = "O").T
```

Out[12]:

	count	unique	top	freq
Airline	10683	12	Jet Airways	3849
Date_of_Journey	10683	44	18/05/2019	504
Source	10683	5	Delhi	4537
Destination	10683	6	Cochin	4537
Route	10682	128	DEL → BOM → COK	2376
Dep_Time	10683	222	18:55	233
Arrival_Time	10683	1343	19:00	423
Duration	10683	368	2h 50m	550
Total_Stops	10682	5	1 stop	5625
Additional_Info	10683	10	No info	8345

In [13]:
```
# Checking the correlation

df.corr()
```

Out[13]:

	Price
Price	1.0

In [14]:
```
# Checking for duplicate records

print('\033[1m' + f"The total number of duplicate records in the dataset : {df.duplicated().sum(
```

```
The total number of duplicate records in the dataset : 220
```

In [15]:
```
# Checking the unique values in each of the features

# for col in df.columns:
#     print('\n\033[1m' + f"The {col} features consists of {df[col].nunique()} unique values, wh
```

```
#     for i in df[col].unique():
#         print(f"{i}")
```

Pre-Processing (I)

In [16]:

```
# Creating a function to perform data preprocessing

def pre_processing(data):

    # Transforming the data after EDA

    # Replacing the flight duration from 5 minutes to 4h 15min
    data.iloc[6474, 7] = "4h 15m"
    # Replacing the flight duration from "47h 40m" to "33h 15m"
    data.iloc[10456, 7] = "33h 15m"
    # Replacing "New Delhi" to "Delhi" in the "Destination" feature
    data["Destination"].replace("New Delhi", "Delhi", inplace = True)
    # Replacing "No Info" with "No info" in the "Additional Info" feature
    data["Additional_Info"].replace("No Info", "No info", inplace = True)

    # Creating a new categorical feature "In-flight_Meal"
    data["In-flight_Meal"] = np.where(data["Additional_Info"].str.contains("meal"), 0, 1)

    # Creating a new feature named "Next_day_Arrival" to store flights that arrived on next day
    data["Overnight_Flight"] = np.where(data["Arrival_Time"].str.split().str.len() != 1, 1, 0)

    # Stripping the date from the "Arrival_Time" feature
    data["Arrival_Time"] = data["Arrival_Time"].str.split(" ").str[0]

    # Preprocessing the "Duration" feature
    data["Duration"] = np.where(~data["Duration"].str.lower().str.contains("h"), "0h " + data["D
                                np.where(~data["Duration"].str.lower().str.contains("m"), data["

    # Converting the features "Date_of_Journey", "Dep_Time", "Arrival_Time" to datetime object
    for col in ["Date_of_Journey", "Dep_Time", "Arrival_Time"]:
        data[col] = pd.to_datetime(data[col])

    # Extracting the day, month and day_of_week from the 'Date_of_Journey' feature to create new
    data["Day"], data["Month"], data["Day_of_Week"] = data["Date_of_Journey"].dt.day, data["Date
    data["Day_of_Week"] += 1

    # Replacing "non-stop" with "0 stops" in the "Total_Stops" feature
    data["Total_Stops"].replace("non-stop", "0 stops", inplace = True)

    # Stripping "stop" / "stops" from the "Total_Stops" feature
    data["Total_Stops"] = data["Total_Stops"].str.split(" ").str[0]

    # Converting the "Total_Stops" feature to integer type
    data["Total_Stops"] = data["Total_Stops"].astype("int64", errors = "ignore")

    # Extracting "hours" and "minutes" from "Arrival_Time" and "Dep_Time" features, and storing
    data["Arrival_Time_Hour"], data["Arrival_Time_Minute"] = data["Arrival_Time"].dt.hour, data[
    data["Dep_Time_Hour"], data["Dep_Time_Minute"] = data["Dep_Time"].dt.hour, data["Dep_Time"].

    # Extracting hours and minutes from "Duration" features
    data["Duration_Hours"] = data["Duration"].str.split(" ").str[0].str[:-1].astype(int)
    data["Duration_Minutes"] = data["Duration"].str.split(" ").str[1].str[:-1].astype(int)

    # Calculation total duration a flight takes and storing it in "Total_Duration" feature
    data["Total_Duration"] = (data["Duration_Hours"] * 60) + (data["Duration_Minutes"] * 1)

    # Correcting the misspelled entry "Banglore" to "Bangalore" in both the "Source" and "Destin
```

```
    data["Source"].replace("Banglore", "Bangalore", inplace = True)
    data["Destination"].replace("Banglore", "Bangalore", inplace = True)

    # Dropping duplicate records
    data.drop_duplicates(inplace = True)

    # Dropping the missing data
    data.dropna(inplace = True)

    # Converting the "Total_Stops" feature to integer type
    data["Total_Stops"] = data["Total_Stops"].astype(int)

    # Dropping the features
    data.drop(columns = ["Date_of_Journey", "Arrival_Time", "Dep_Time", "Duration"], inplace = T

pre_processing(df)

df.head()
```

Out[16]:

	Airline	Source	Destination	Route	Total_Stops	Additional_Info	Price	In-flight_Meal	Overnight_Flight	Day
0	IndiGo	Bangalore	Delhi	BLR → DEL	0	No info	3897	1	1	24
1	Air India	Kolkata	Bangalore	CCU → IXR → BBI → BLR	2	No info	7662	1	0	5
2	Jet Airways	Delhi	Cochin	DEL → LKO → BOM → COK	2	No info	13882	1	1	6
3	IndiGo	Kolkata	Bangalore	CCU → NAG → BLR	1	No info	6218	1	0	5
4	IndiGo	Bangalore	Delhi	BLR → NAG → DEL	1	No info	13302	1	0	3

In [17]:

```
# Creating a copy of the pre-processed data

df_eda = df.copy()

# Creating a function to perform data preprocessing

def pre_processing_2(data):

    for col in ["Dep_Time_Hour", "Arrival_Time_Hour"]:

        data[col] = np.where(
            ((data[col] > 4) & (data[col] <= 8)), "Early Morning",
```

```
            np.where(((data[col] > 8) & (data[col] <= 12)), "Morning",
                    np.where(((data[col] > 12) & (data[col] <= 16)), "Afternoon",
                            np.where(((data[col] > 16) & (data[col] <= 20)), "Evening",
                                    np.where(((data[col] > 20) & (data[col] <= 24)), "Night", "L
        )

pre_processing_2(df_eda)

df_eda
```

Out[17]:

	Airline	Source	Destination	Route	Total_Stops	Additional_Info	Price	In-flight_Meal	Overnight_Flight
0	IndiGo	Bangalore	Delhi	BLR → DEL	0	No info	3897	1	1
1	Air India	Kolkata	Bangalore	CCU → IXR → BBI → BLR	2	No info	7662	1	0
2	Jet Airways	Delhi	Cochin	DEL → LKO → BOM → COK	2	No info	13882	1	1
3	IndiGo	Kolkata	Bangalore	CCU → NAG → BLR	1	No info	6218	1	0
4	IndiGo	Bangalore	Delhi	BLR → NAG → DEL	1	No info	13302	1	0
...	...	...	...	...	...	...	...	...	...
10678	Air Asia	Kolkata	Bangalore	CCU → BLR	0	No info	4107	1	0
10679	Air India	Kolkata	Bangalore	CCU → BLR	0	No info	4145	1	0
10680	Jet Airways	Bangalore	Delhi	BLR → DEL	0	No info	7229	1	0
10681	Vistara	Bangalore	Delhi	BLR → DEL	0	No info	12648	1	0
10682	Air India	Delhi	Cochin	DEL → GOI → BOM → COK	2	No info	11753	1	0

10460 rows × 19 columns

Exploratory Data Analysis (EDA)

Univairate Analysis (Numerical Features)

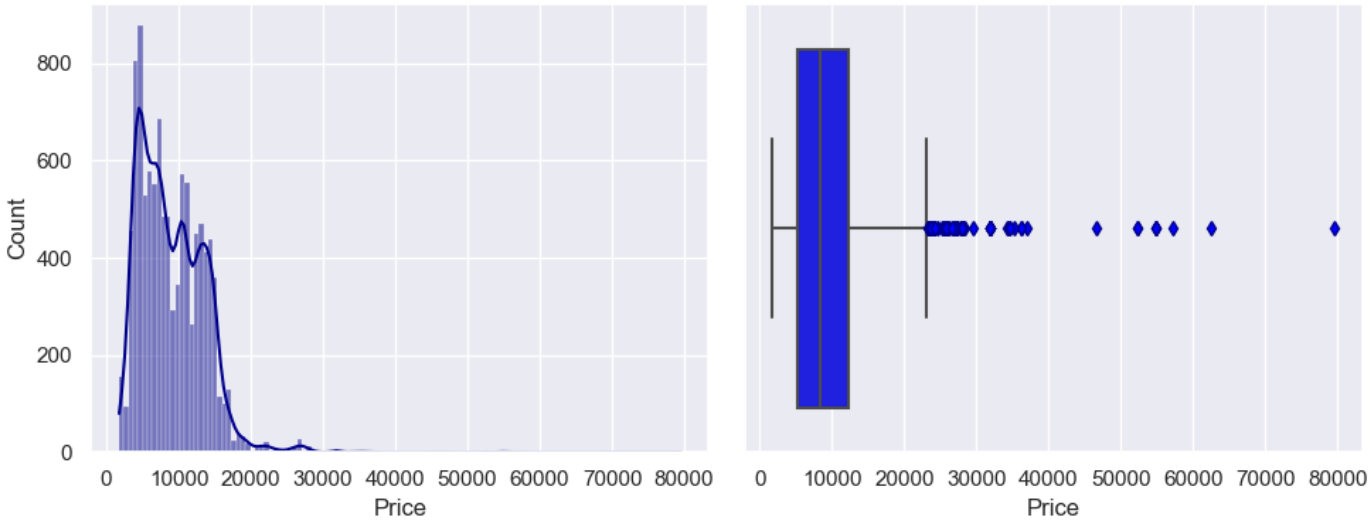
In [18]:
```
# Creating a function to perform Univariate Analysis on Numerical features

def univariate_eda_num(data, col):

    print('\033[1m' + f"\t\t\t\t\t\t\t{col}" + '\033[0m\n')

    # Checking the statistical summary of the feature
    print('\033[1m' + f"Statistical Summary" + '\033[0m\n')

    # Checking the skewness and outliers using IQR method
    skewness = np.round(data[col].skew(), 2)
    Q1, Q3 = data[col].quantile([0.25, 0.75])
    IQR = Q3 - Q1
    lower_bound, upper_bound = Q1 - (1.5 * IQR), Q3 + (1.5 * IQR)
    outlier_count = len(data[col][(data[col] < lower_bound) | (data[col] > upper_bound)])
    stats_sum = np.round(data[col].describe(), 2)
    stats_sum["skewness"] = skewness
    stats_sum["outliers"] = outlier_count
    print(f"{pd.DataFrame(stats_sum)}\n")

    # Plotting graphs to check the distribution and presence of outliers
    fig, axes = plt.subplots(1, 2, figsize = (10, 4))
    sns.histplot(x = data[col], color = "darkblue", ax = axes[0], kde = True)
    sns.boxplot(x = data[col], color = "blue", ax = axes[1], flierprops = {"markerfacecolor" : "
    plt.tight_layout()
```

In [19]:
```
# Exploring the Price feature

univariate_eda_num(df_eda, "Price")
```

Price

Statistical Summary

	Price
count	10460.00
mean	9027.36
std	4625.06
min	1759.00
25%	5224.00
50%	8266.00
75%	12346.25
max	79512.00
skewness	1.86
outliers	94.00



Insights

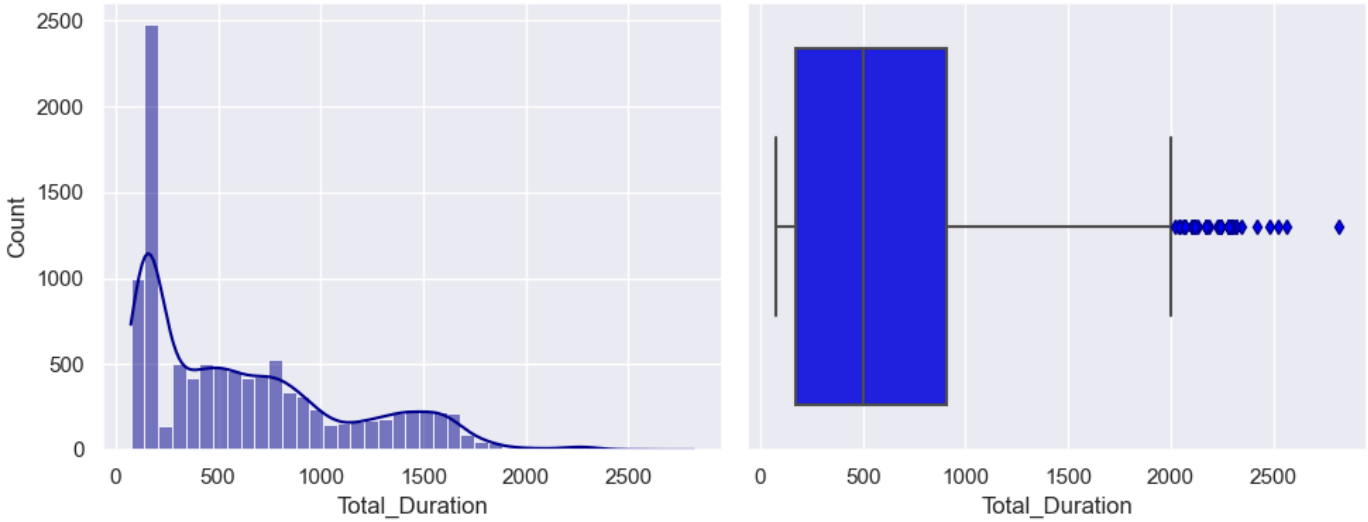
- There are four direct flights departing from Mumbai to Hyderabad with a **minimum flight fare** of **Rs. 1,759** in the dataset.
- There is a business class flight that departs from Bangalore, has a stopover in Bombay, and ultimately arrives in Delhi. This flight has a duration of 5 hours and 40 minutes and commands the **highest fare** of **Rs. 79,512**.
- The **average fare** is about **Rs. 9027.36**, and the **median fare** is **Rs. 8,266.00**.
- The **distribution** of the "Price" feature is **positively skewed**, with a **significant concentration of fares** found on the lower end, specifically **between Rs. 5,224.00 and Rs. 12,346.00**.
- There are outliers in the "Price" feature.

In [20]:
```
# Exploring the "Total_Duration" feature

univariate_eda_num(df_eda, "Total_Duration")
```

Total_Duration

Statistical Summary

	Total_Duration
count	10460.00
mean	629.81
std	500.39
min	75.00
25%	170.00
50%	505.00
75%	910.00
max	2820.00
skewness	0.90
outliers	74.00



Insights

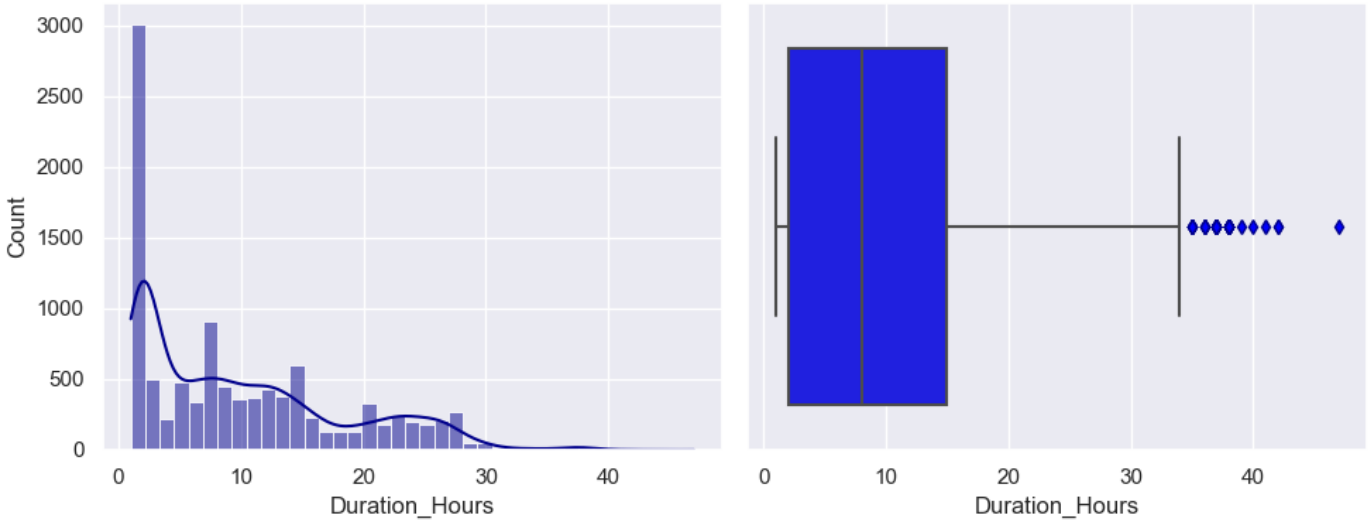
- The **minimum flight duration** is **75 minutes**, equivalent to **1 hour and 15 minutes**. These flights are evening flights departing from Mumbai to Hyderabad without any stops.
- The **longest flight** is **2,820 minutes**, which is equivalent to **47 hours**. This extensive duration is associated with a Jet Airways flight from Delhi to Cochin, which includes multiple stops during the journey.
- The **average flight duration** is approximately **629 minutes**, which is equivalent to **10 hours and 49 minutes**. The **median flight duration** is approximately **505 minutes**, equivalent to **8 hours and 41 minutes**.
- The **distribution** of the Total_Duration feature is **slightly positively skewed**, with a notable concentration of flight durations found at the lower end. This suggests that most of the flights had durations ranging from **170 minutes (equivalent to 2 hours and 50 minutes) to 910 minutes (equivalent to 15 hours and 17 minutes)**.
- There are outliers in the "Total_Duration" feature.

In [21]:
```
# Exploring the "Duration_Hours" feature

univariate_eda_num(df_eda, "Duration_Hours")
```

Duration_Hours

Statistical Summary

	Duration_Hours
count	10460.00
mean	10.03
std	8.37
min	1.00
25%	2.00
50%	8.00
75%	15.00
max	47.00
skewness	0.89
outliers	66.00



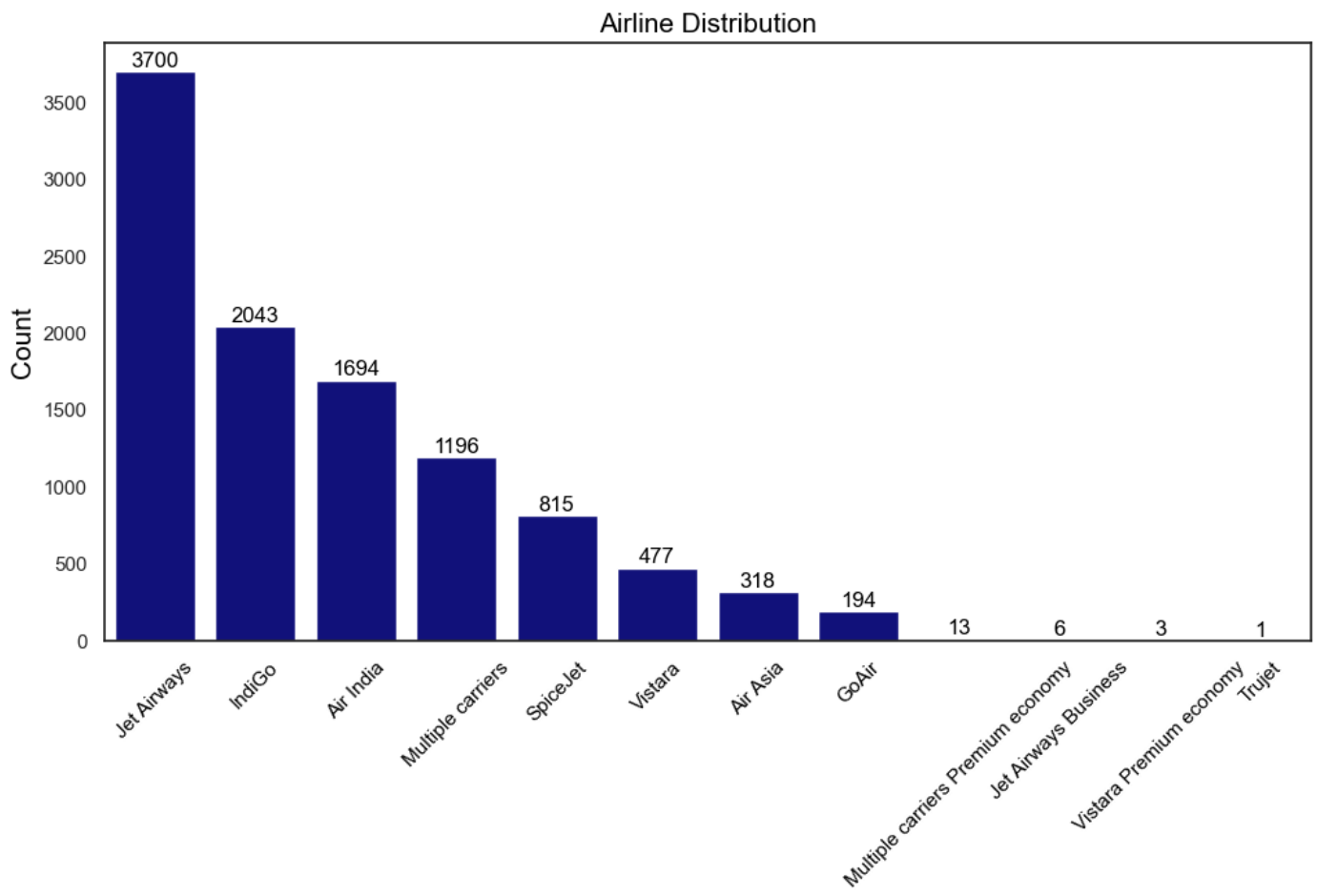
Insights

- The **shortest flight duration** is **1 hour**, departing from Mumbai and heading to Hyderabad.
- The **longest flight** from Delhi to Cochin with two stops, in Indore and Bombay, has a duration of **47 hours**.
- The **average flight duration** was about **10 hours**, and the **median flight duration** was **8 hours**.
- The **distribution** of the "Duration Hours" feature is **slightly positively skewed**, with the majority of observations found at the lower end. This indicates that most flights had a **duration** of **2 to 15 hours**.
- There are outliers in the "Duration_Hours" feature.

Univariate Analysis (Categorical Features)

In [22]:
```
# Creating a function to perform Univariate Analysis on the Categorical features

def univariate_cat_eda(data, col):

    # Plotting the distribution of categories
    plt.figure(figsize = (12, 6))
    sns.set(style = "white")
    sns.barplot(x = data[col].value_counts(ascending = False).index, y = data[col].value_counts(
    plt.title(f"{col} Distribution", color = "black", size = 15)
    plt.ylabel("Count", size = 15, color = "black")
    plt.xticks(rotation = 45, size = 11, color = "black")
    counts = data[col].value_counts(ascending = False)

    # Displaying the data above the bar
    for i in range(len(counts)):
        plt.text(x = i, y = counts[i] + 5, s = counts[i], ha = "center", va = "bottom", size = 1

    # plt.tight_layout()
    plt.show()
```

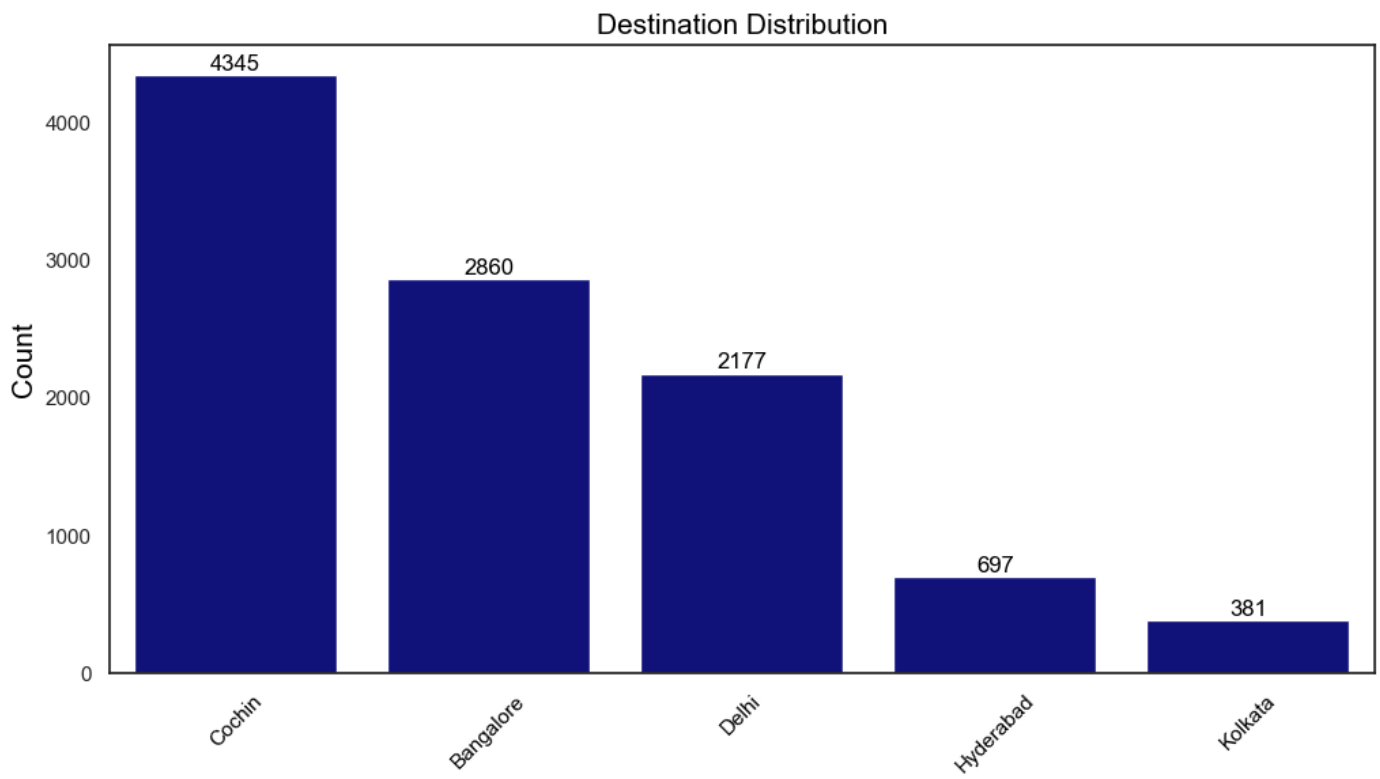
In [23]:
```
# Exploring the "Airline" feature

univariate_cat_eda(df_eda, "Airline")
```



Insights

- The **majority of flights** are operated by **Jet Airways Airline (3,700), followed by IndiGo Airlines (2,043) and Air India (1,694)**. This can be attributed to their **extensive route networks and larger fleets**.
- There are **very few flights** for **Jet Airways Business, Vistara Premium Economy, and Trujet**, each with counts of **less than 10**. This can be attributed to their **specialized nature**, **offering premium services**, **specific routes**, and **pricing** that play a significant role. These factors may limit their demand compared to economy class flights.

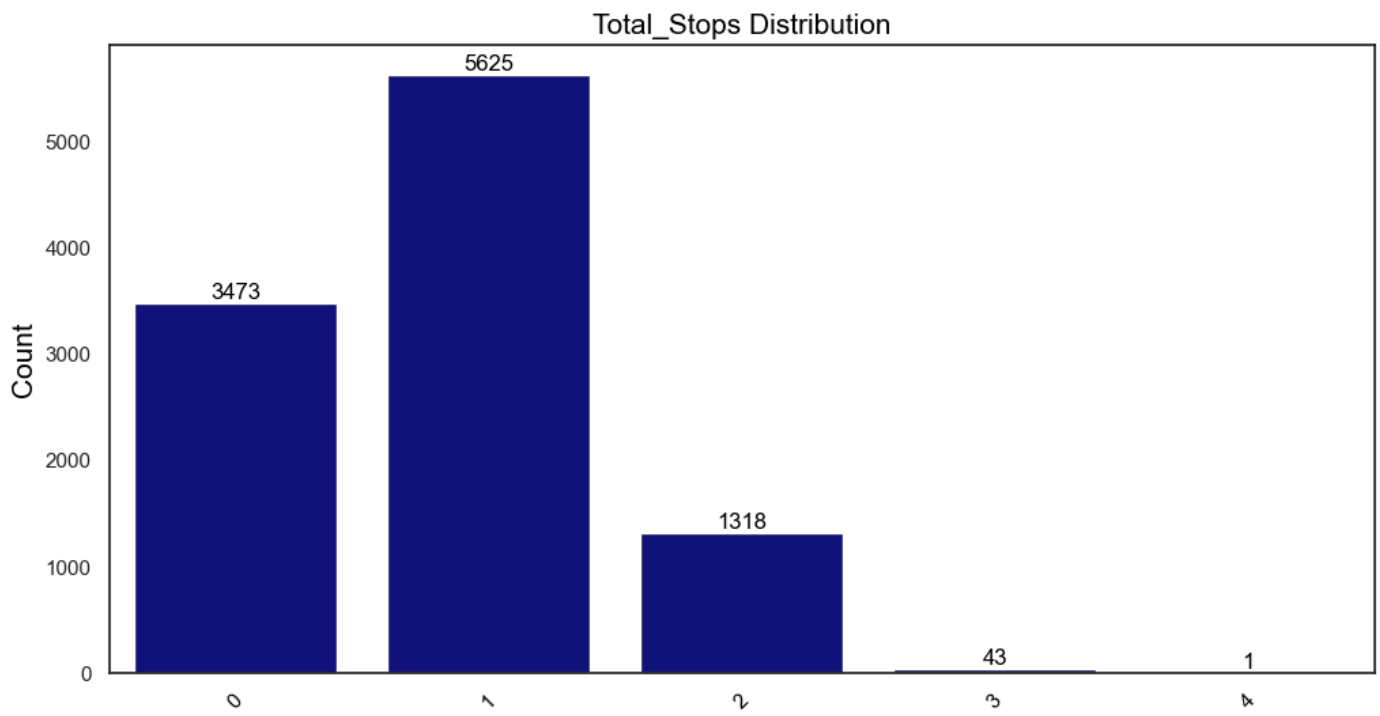
In [24]:
```
# Exploring the "Destination" feature

univariate_cat_eda(df_eda, "Destination")
```



Insights

- The **majority of passengers disembarked** in **Cochin (4,345)**, followed by **Bangalore (2,860)** and **Delhi (2,177)**. This can be attributed to their status as major **economic hubs, thriving business centers, and popular tourist destinations**. These cities host robust economic activities, with **Bangalore** serving as a **technology hub**, **Delhi** as the **national capital**, and **Cochin** attracting tourists with its **scenic beauty**.
- **Hyderabad (697)** and **Kolkata (381)** receive **fewer passengers** due to **differences in economic activity, international connectivity, and prominence in business and tourism** compared to other major Indian cities.

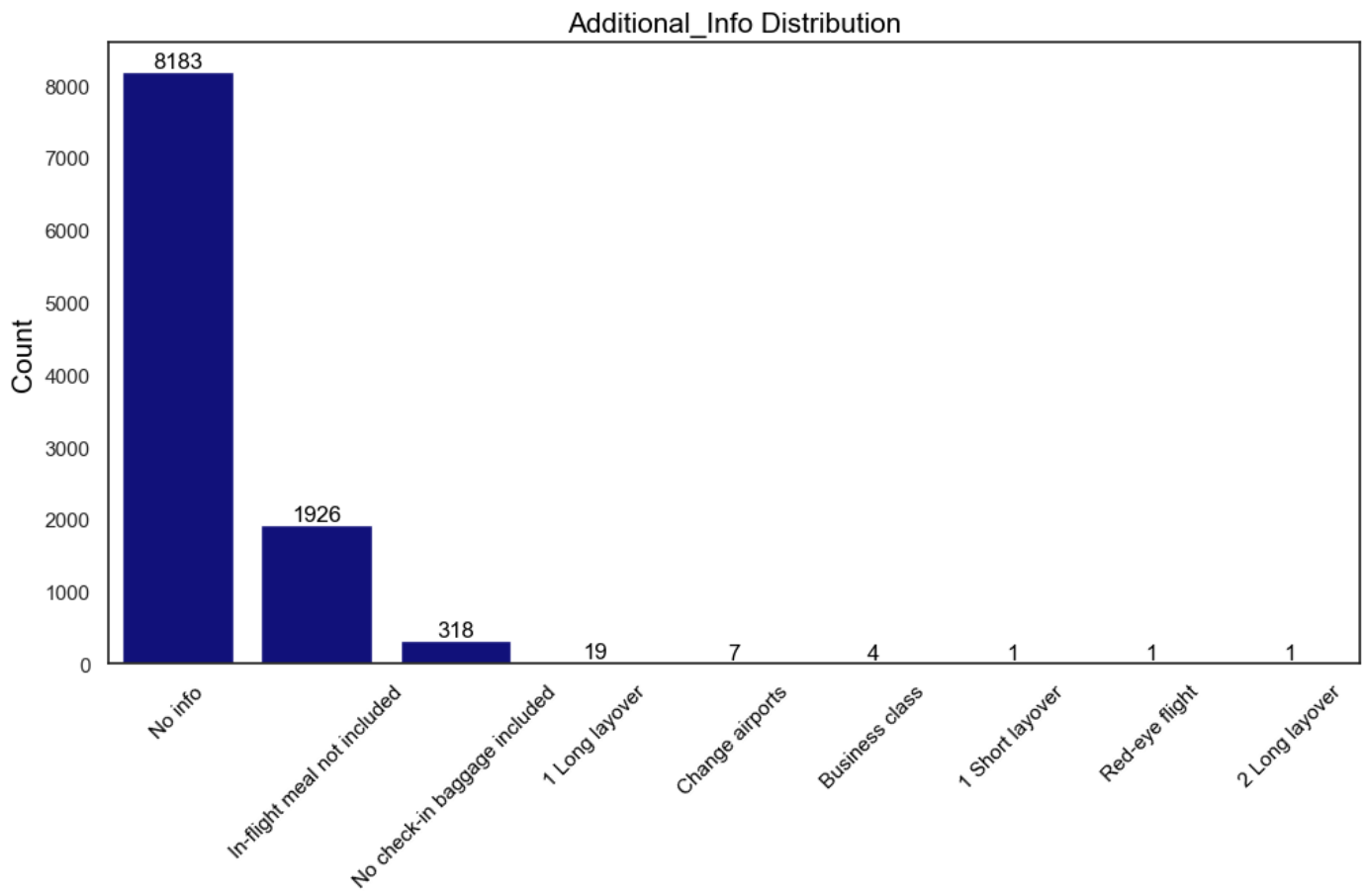
In [25]:
```
# Exploring the "Total_Stops" feature

univariate_cat_eda(df_eda, "Total_Stops")
```



Insights

- The **majority of passengers** featured in **one stop (5,625)**, providing themselves with **a single layover or connection to expand route options** . **Nonstop flights with no halts (3,473)** were preferred by passengers for **shorter routes, offering direct travel between departure and destination airports**. A smaller subset of flights **(1,318)** requires **two stops**, often used for **longer routes or specialized connections**.
- Multi-stop flights are infrequent, with **43 passengers** had **3 stops flights** and just **one passenger** with **4 stops**. These flights are usually designed for **unique itineraries, long-distance journeys, or passengers with specific travel needs.**

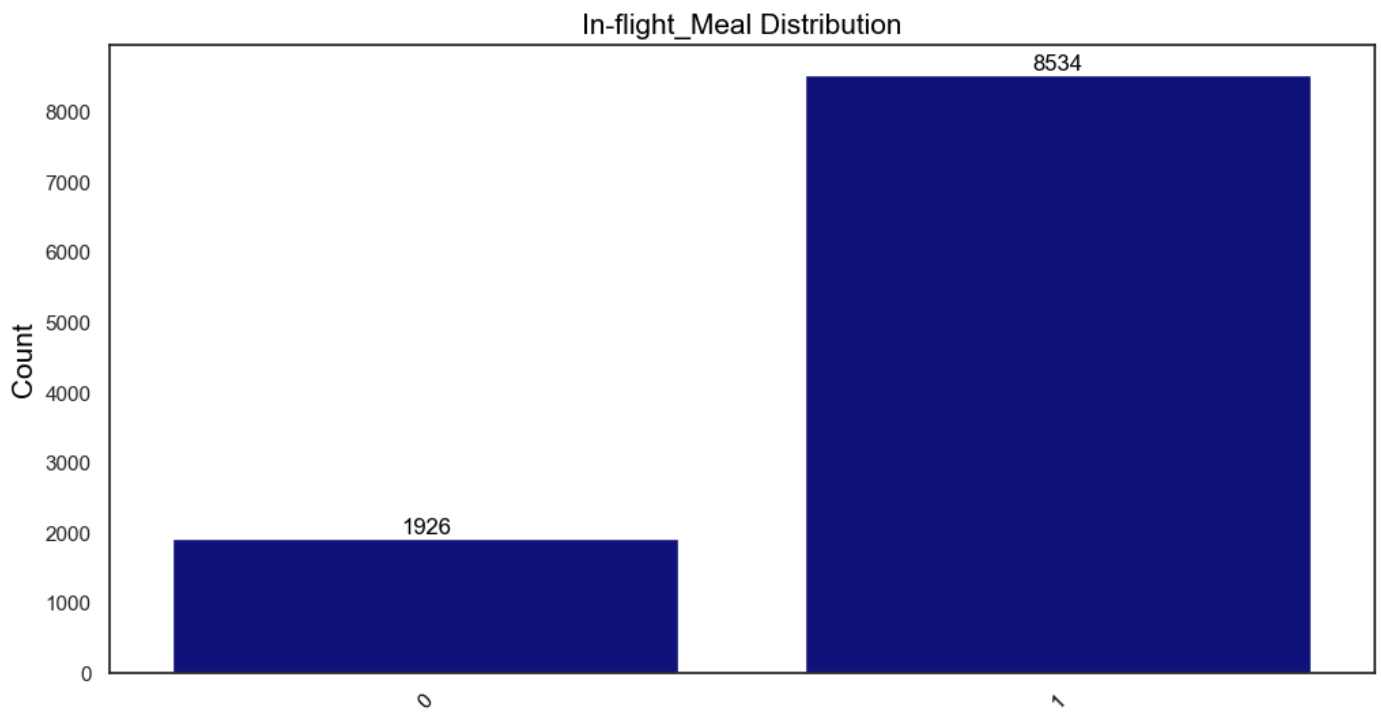
In [26]:
```
# Exploring the "Additional_Info" feature

univariate_cat_eda(df_eda, "Additional_Info")
```



Insights

- There are **8,183 passengers** with **no additional information / requirements**.
- **1,926 passengers do not have in-flight meals**, while **318** have **passengers with no check-in baggage**. These choices may result from **cost-conscious travelers** looking to **save on in-flight meal expenses or baggage fees**, as well as those who prefer the convenience of **traveling with hand luggage only**.
- Among the flights, there is **one flight** with a **1-short-layover**, denoting a **brief stopover**, and another categorized as a **1 Red-eye flight**, typically **operating overnight**. Additionally, **one flight** classified as **2-long-layover**, indicating **extended stopover times**, offering **diverse travel options** to accommodate different passenger needs and **scheduling preferences**.

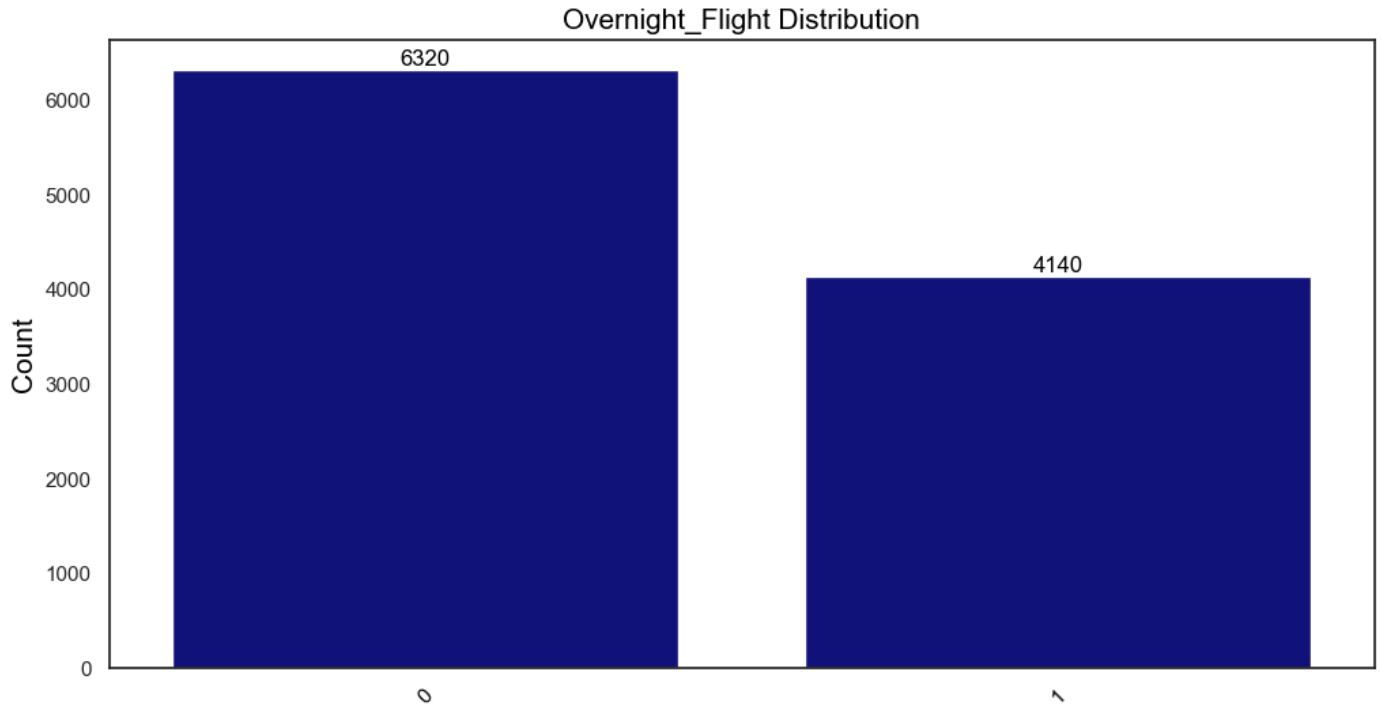
In [27]:
```
# Exploring the "In-flight_Meal" feature

univariate_cat_eda(df_eda, "In-flight_Meal")
```



Insights

- A total of **1,926 passengers opted not to have an in-flight meal**, while **8,534 passengers** chose to **enjoy a meal during their flight**.

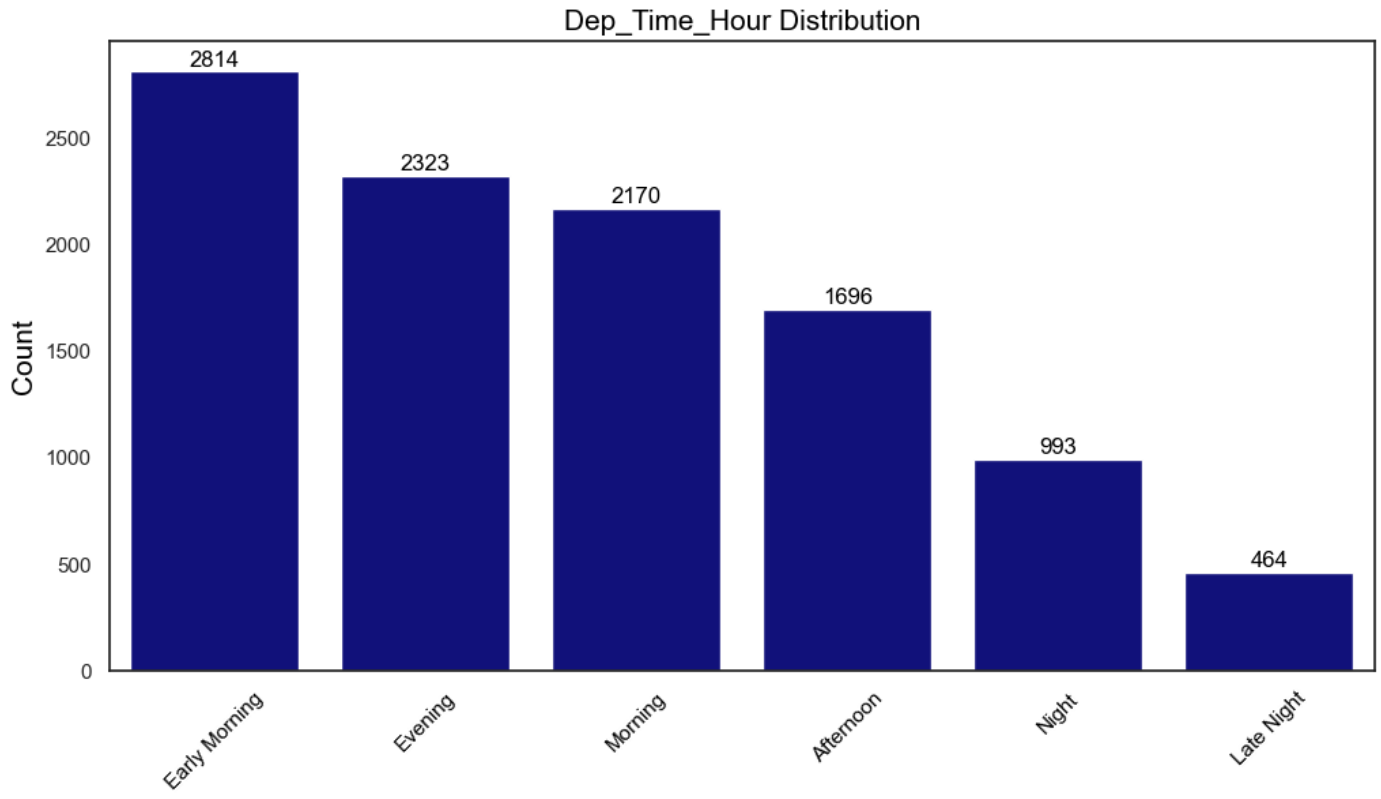
In [28]:
```
# Exploring the "Overnight_Flight" feature

univariate_cat_eda(df_eda, "Overnight_Flight")
```



Insights

- Among the passengers in the dataset, **4,140 traveled overnight**, likely on **red-eye flights** or during **nighttime hours**, while **6,320 did not experience overnight travel**, indicating **daytime or shorter duration flights**.

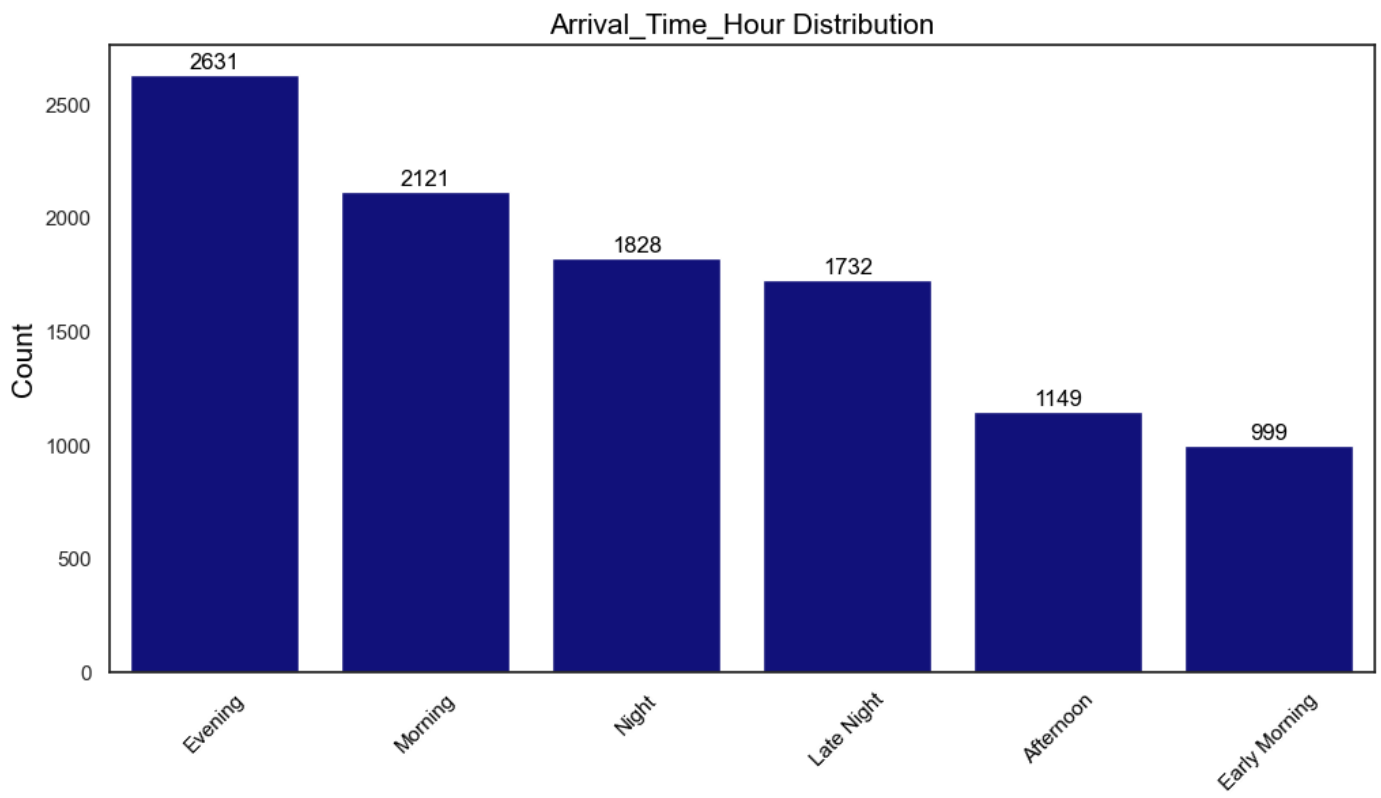
In [29]:
```
# Exploring the "Dep_Time_Hour" feature

univariate_cat_eda(df_eda, "Dep_Time_Hour")
```



Insights

- The **majority of passengers (2,814)** opted for **early morning flights**, typically departing between **4 am and 8 am** . Additionally, **2,323 passengers** chose **evening flights (between 4 pm and 8 pm)**, while **2,170 passengers** preferred **morning flights (between 8 am and 12 pm)**.
- A **smaller number of passengers (464)** took **late-night flights**, departing between **12 am and 4 am**, while **993 passengers** opted for **nighttime flights**, typically scheduled between **8 pm and 12 am**.

In [30]:
```
# Exploring the "Arrival_Time_Hour" feature

univariate_cat_eda(df_eda, "Arrival_Time_Hour")
```



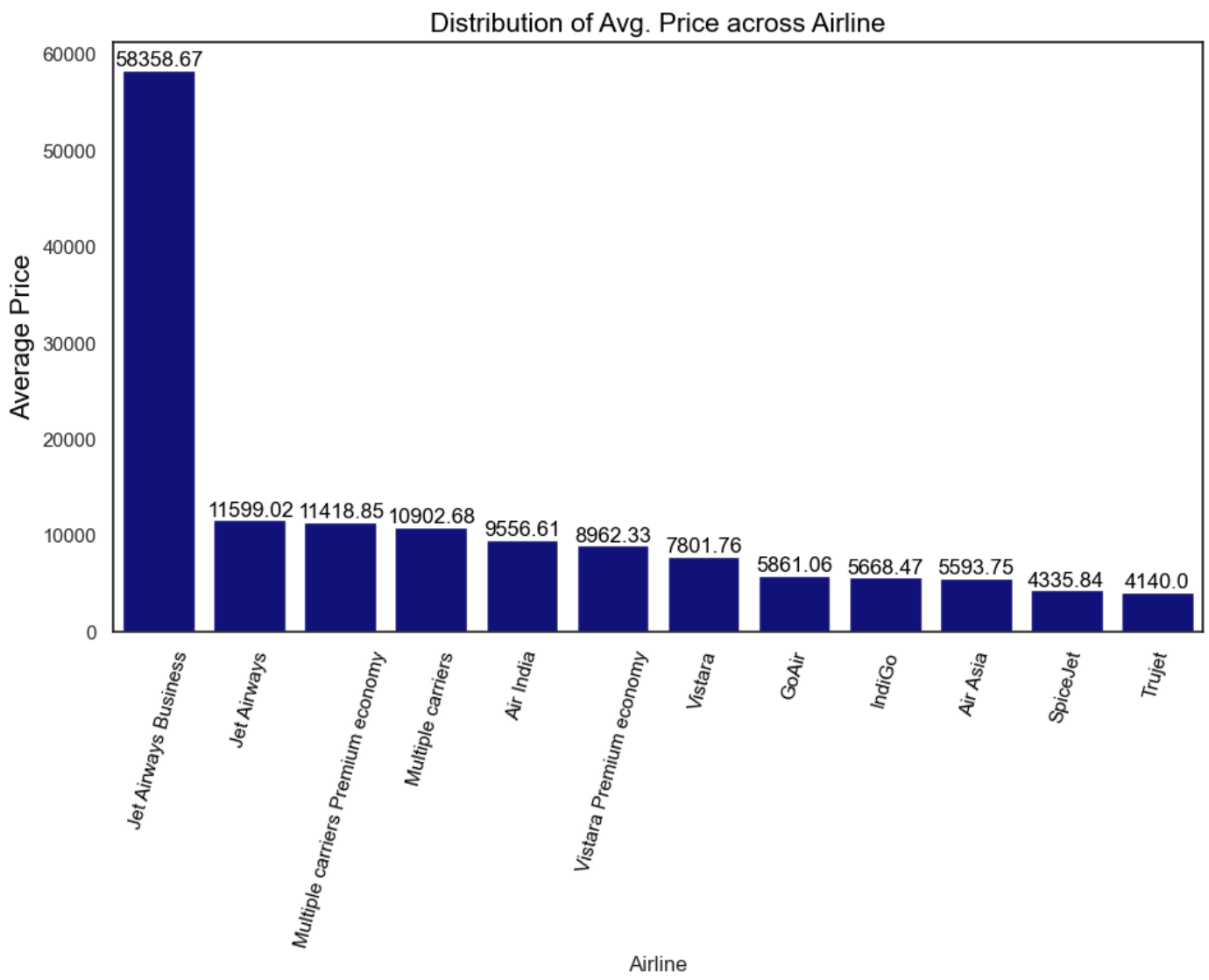
Insights

- The **largest number of passengers (2,631)** arrived in the **evening**, typically between **4 pm and 8 pm**. Additionally, **2,121 passengers** arrived in the **morning**, between **8 am and 12 pm**, while **1,828 passengers** arrived at **night**, between **8 pm and 12 am**.
- There were **999 passengers** who arrived in the **early morning (4 am to 8 am)** and **1,149 passengers** who arrived in the **afternoon (12 pm to 4 pm)**.

Bivariate Analysis (Categorical vs Numerical)

In [31]:
```
# Creating a function to perform Bivariate Analysis on Categorical vs Numerical features

def bivariate_cvn_eda(data, cat_col, num_col):

    plt.figure(figsize = (11, 6))
    sns.set(style = "white")

    # Plotting the Mean price distribution across different categories
    group = np.round(data.groupby(cat_col)[num_col].mean().sort_values(ascending = False), 2)
    sns.barplot(x = group.index, y = group.values, color = "darkblue")
    plt.title(f"Distribution of Avg. {num_col} across {cat_col}", color = "black", size = 15)
    plt.ylabel(f"Average {num_col}", size = 15, color = "black")
    plt.xticks(rotation = 75, size = 11, color = "black")

    # Displaying the data above the bar
    for i in range(len(group)):
        plt.text(x = i, y = group[i] + 5, s = group[i], ha = "center", va = "bottom", size = 12,
    plt.show()
```

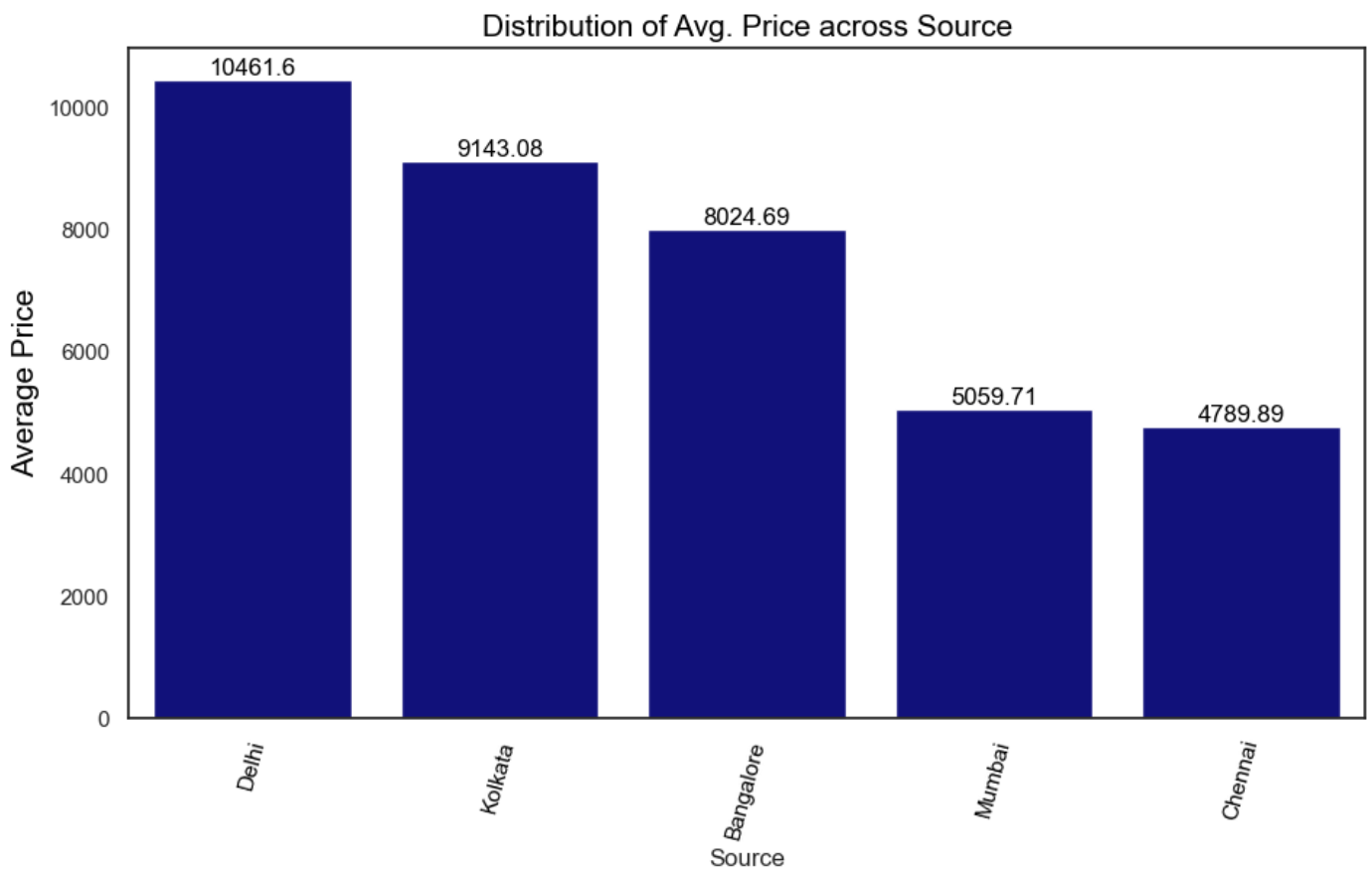
In [32]:
```
# Exploring the distribution of Avg. Price across Airline

bivariate_cvn_eda(df_eda, "Airline", "Price")
```



Insights

- The **higher mean price** of **Jet Airways Business class flights (Rs. 58,358)** compared to other airlines can be attributed to the **premium services and limited seating capacity** associated with business class offering **enhanced comfort, better in-flight amenities, and personalized service**, all of which contribute to the higher fare. In contrast, **Jet Airways (Rs. 11,599)** likely offers more **budget-friendly fares** in its **economy class**, attracting **cost-conscious travelers**. Multiple carriers Premium Economy (Rs. 11,418) strikes a **balance by offering a more comfortable experience than economy class at a relatively lower price point than business class**, making it an attractive option for travelers seeking added **comfort without the premium price tag**.
- Several passengers traveled on **Trujet airline** with a **fare** of **Rs. 4,140**, followed by **SpiceJet** at **Rs. 4,335**, and finally, **Air Asia** at **Rs. 5,593**.

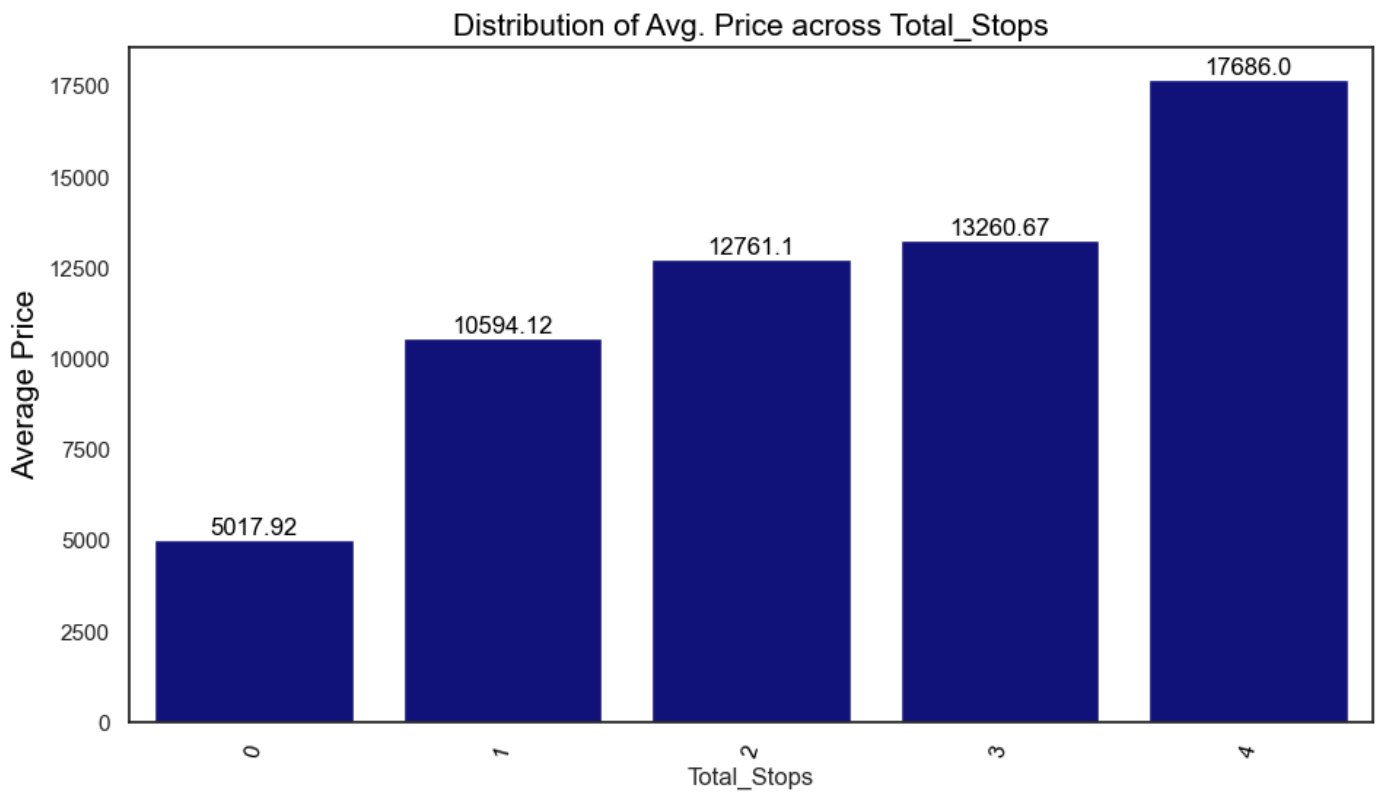
In [33]:
```
# Exploring the distribution of Avg. Price across Source

bivariate_cvn_eda(df_eda, "Source", "Price")
```



Insights

- The **highest average flight price** for flights **departing** from **Delhi (Rs. 10,461)** reflects the **city's status as a major aviation hub and its economic significance**. **Kolkata** follows with an **average fare** of **Rs. 9,143**, likely influenced by its **regional importance and passenger demand**. Flights from **Bangalore** have an **average cost** of **Rs. 8,024**, reflecting the **city's position as a major tech and business center**.
- The **flights boarded** from **Mumbai** have an **average fare** of **Rs. 5,059**, while those from **Chennai** have an **average fare** of **Rs. 4,789**.

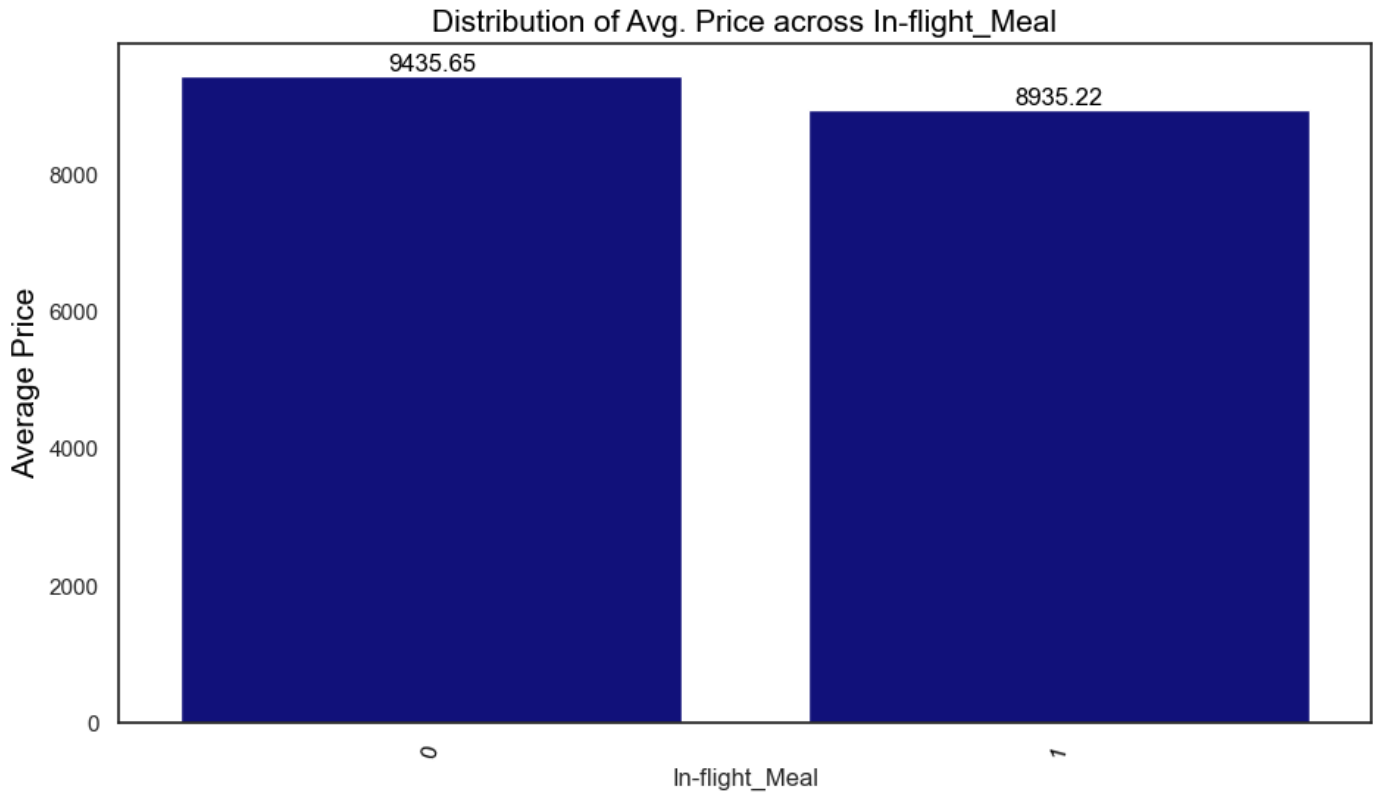
In [34]:
```
# Exploring the distribution Avg. Price across Destination

bivariate_cvn_eda(df_eda, "Total_Stops", "Price")
```



Insights

- As the **number of stops increases**, the **fare increases**.

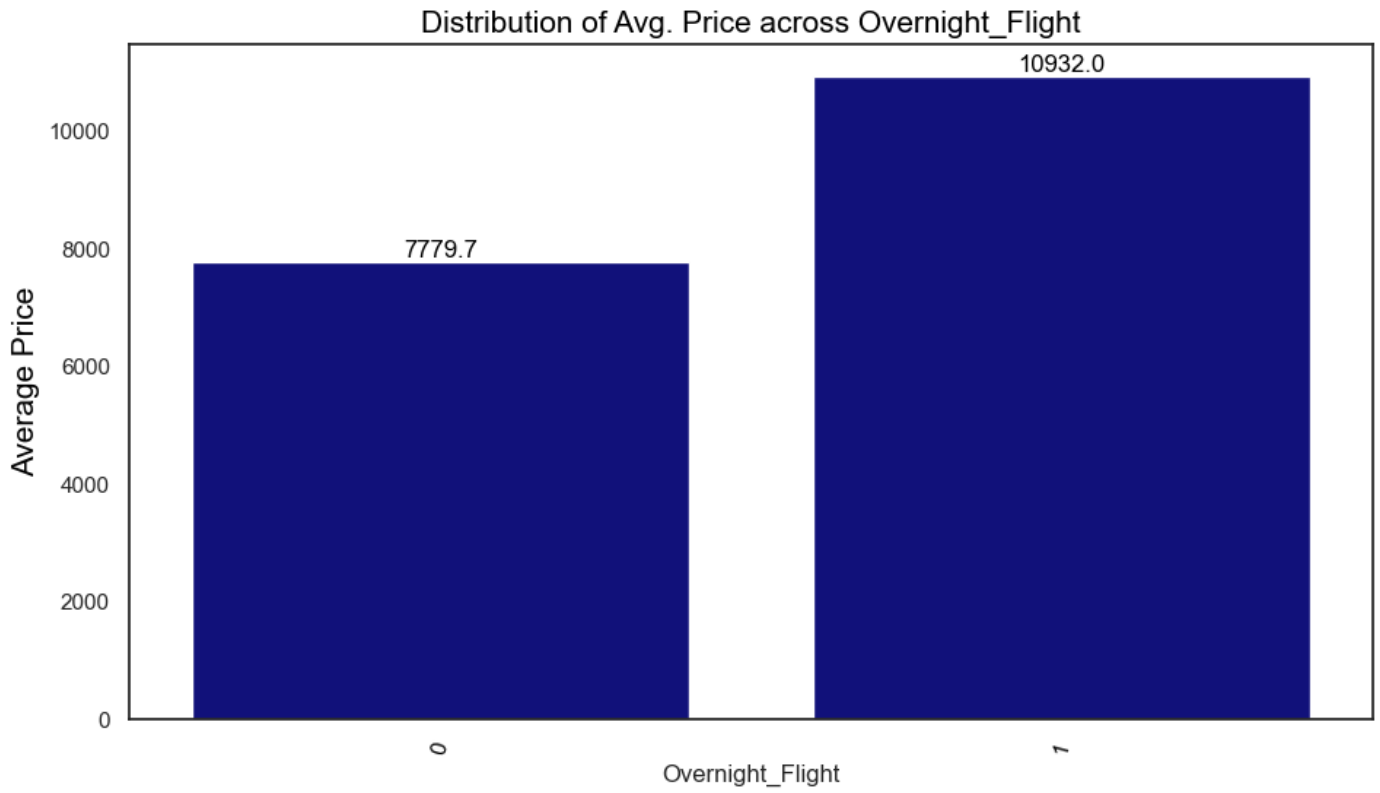
In [35]:
```
# Exploring the distribution of Avg. Price across In-flight_Meal

bivariate_cvn_eda(df_eda, "In-flight_Meal", "Price")
```



Insights

- The **flights** with a **high average price (Rs. 9,435)** are those where **passengers did not opt** for **In-flight meals**. In contrast, **flights offering meals** have **fewer passengers** who opted for in-flight meals.

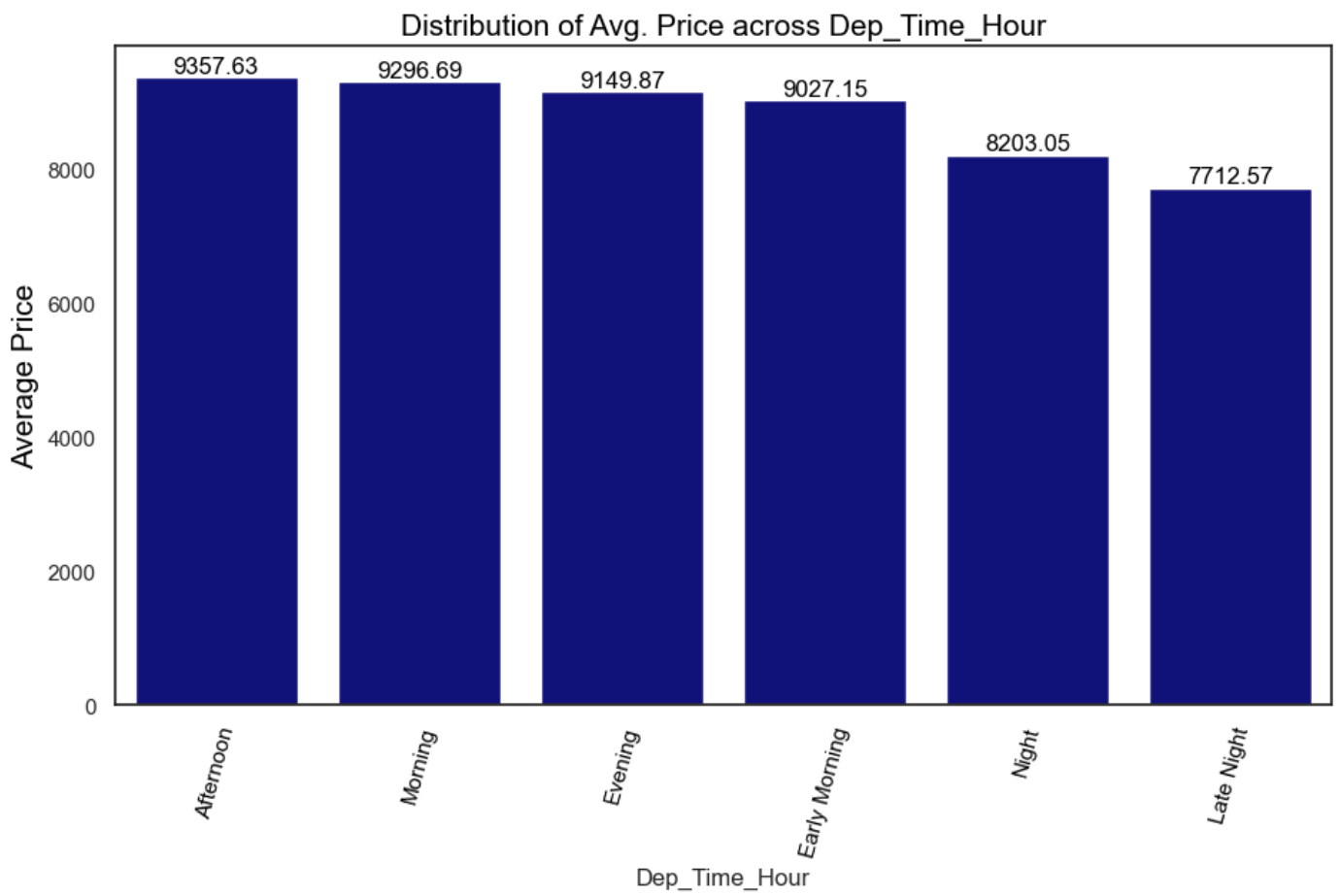
In [36]:
```
# Exploring the distribution of Avg. Price across "Overnight_Flight"

bivariate_cvn_eda(df_eda, "Overnight_Flight", "Price")
```



Insights

- **Overnight flights**, priced at an **average** of **Rs. 10,932**, tend to command a **higher cost** compared to **daytime flights (averaging Rs. 7,779)**. This **higher price** reflects the convenience of **traveling during nighttime hours**, which appeals to passengers **valuing time savings** and the ability to **arrive at their destination in the morning**. Additionally, **overnight flights** often incur **increased expenses** related to **crew accommodations, catering, and premium services**, contributing to their elevated pricing.

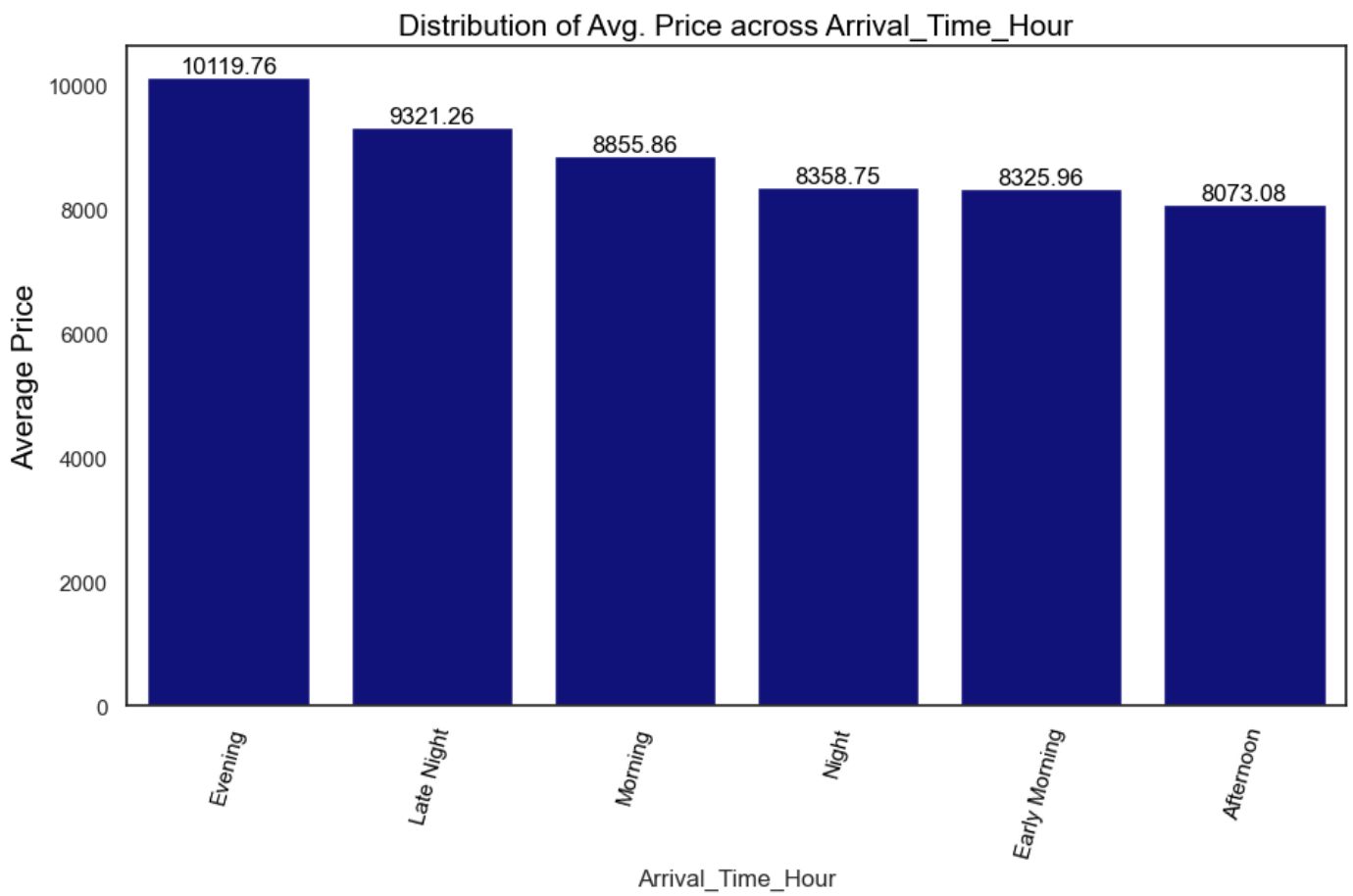
In [37]:
```
# Exploring the distribution of Avg. Price across "Dept_Time_Hour"

bivariate_cvn_eda(df_eda, "Dep_Time_Hour", "Price")
```



Insights

- **Flights** during **daytime hours (afternoon, morning, and evening)** often come with **higher fares** compared to night and late-night flights. This pricing difference is driven by the **convenience of daytime travel** and the **preferences of business travelers** who prioritize **schedule alignment**, while **night flights** tend to be **more affordable** due to their **less convenient travel times**.

In [38]:
```
# Exploring the distribution of Avg. Price across "Arrival_Time_Hour"

bivariate_cvn_eda(df_eda, "Arrival_Time_Hour", "Price")
```



Insights

- **Evening flights** are the **most expensive** at **Rs. 10,119**, followed by **late-night flights** at **Rs. 9,321** , and **morning flights** at **Rs. 8,855**. In contrast, **bafternoon flights** are the **least expensive** at **Rs. 8,073**, with **early morning flights** priced slightly higher at **Rs. 8,325**.

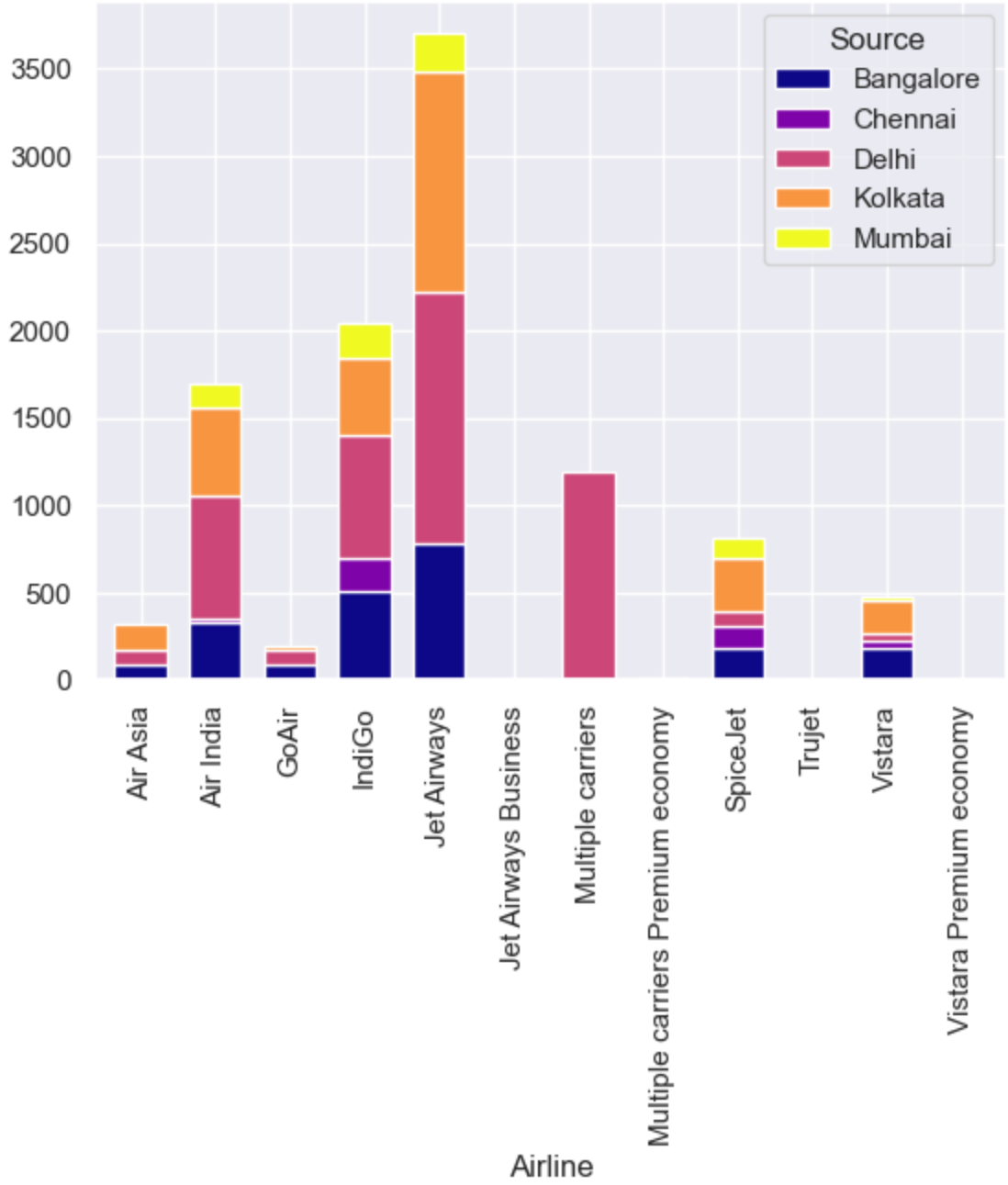
Bivariate Analysis (Categorical vs Categorical)

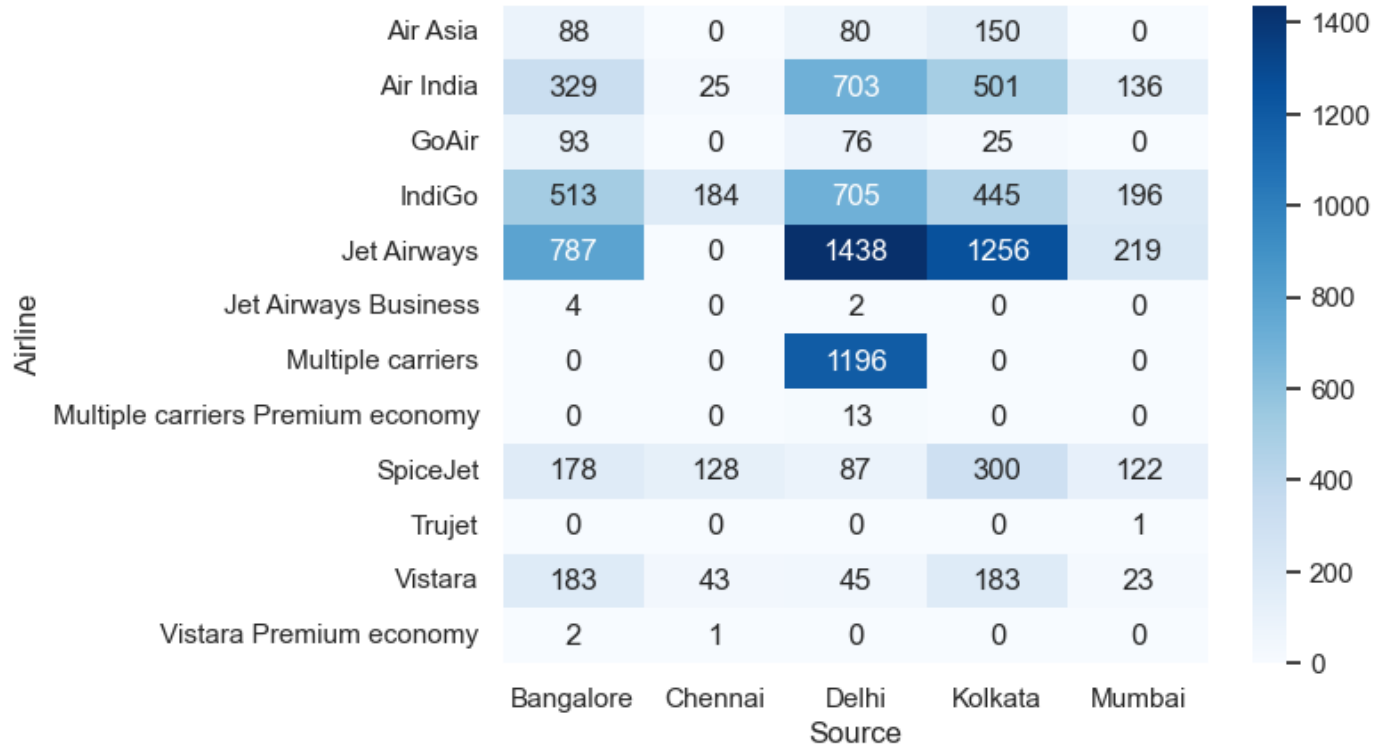
In [39]:
```
# Creating a function to perform Bivariate Analysis on Categorical vs Categorical features

def bivariate_cvc_eda(data, col1, col2):

    # Performing cross-tabulation on two categorical features
    cross_tab = pd.crosstab(data[col1], data[col2])
    print(f"{cross_tab}\n")

    # Plotting graphs to the distribution of categories
    plt.figure(figsize = (10, 6))
    sns.set()
    pd.crosstab(data[col1], df_eda[col2]).plot(kind = "bar", stacked = True, cmap = "plasma", wi
    plt.show()
    sns.heatmap(cross_tab, annot = True, cmap = "Blues", fmt = ".0f")
    plt.show()
```

In [40]:
```
# Exploring the distribution between "Airline" and "Source"

bivariate_cvc_eda(df_eda, "Airline", "Source")
```

Source	Bangalore	Chennai	Delhi	Kolkata	Mumbai
Airline					
Air Asia	88	0	80	150	0
Air India	329	25	703	501	136
GoAir	93	0	76	25	0
IndiGo	513	184	705	445	196
Jet Airways	787	0	1438	1256	219
Jet Airways Business	4	0	2	0	0
Multiple carriers	0	0	1196	0	0
Multiple carriers Premium economy	0	0	13	0	0
SpiceJet	178	128	87	300	122
Trujet	0	0	0	0	1
Vistara	183	43	45	183	23
Vistara Premium economy	2	1	0	0	0

<Figure size 1000x600 with 0 Axes>



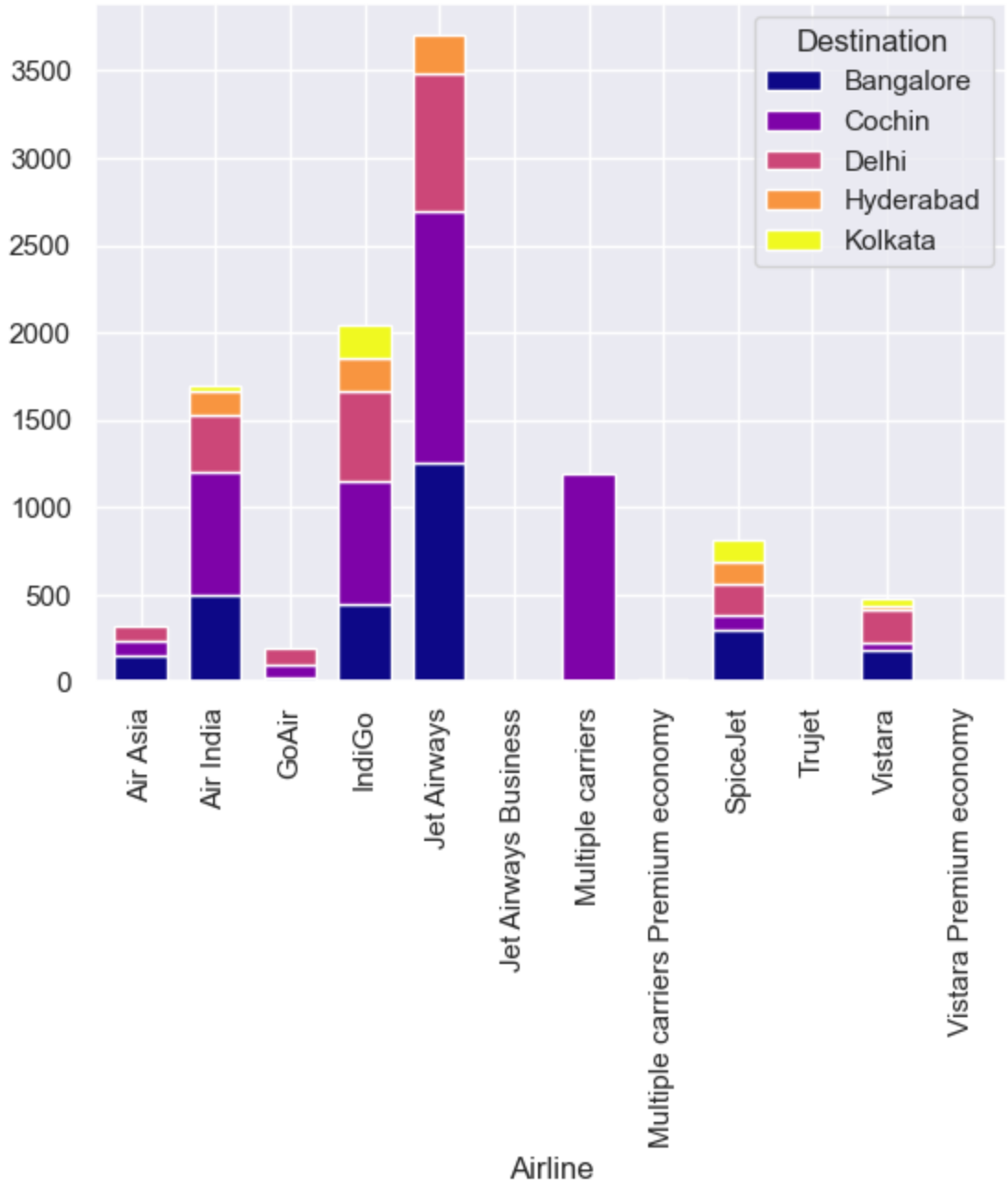


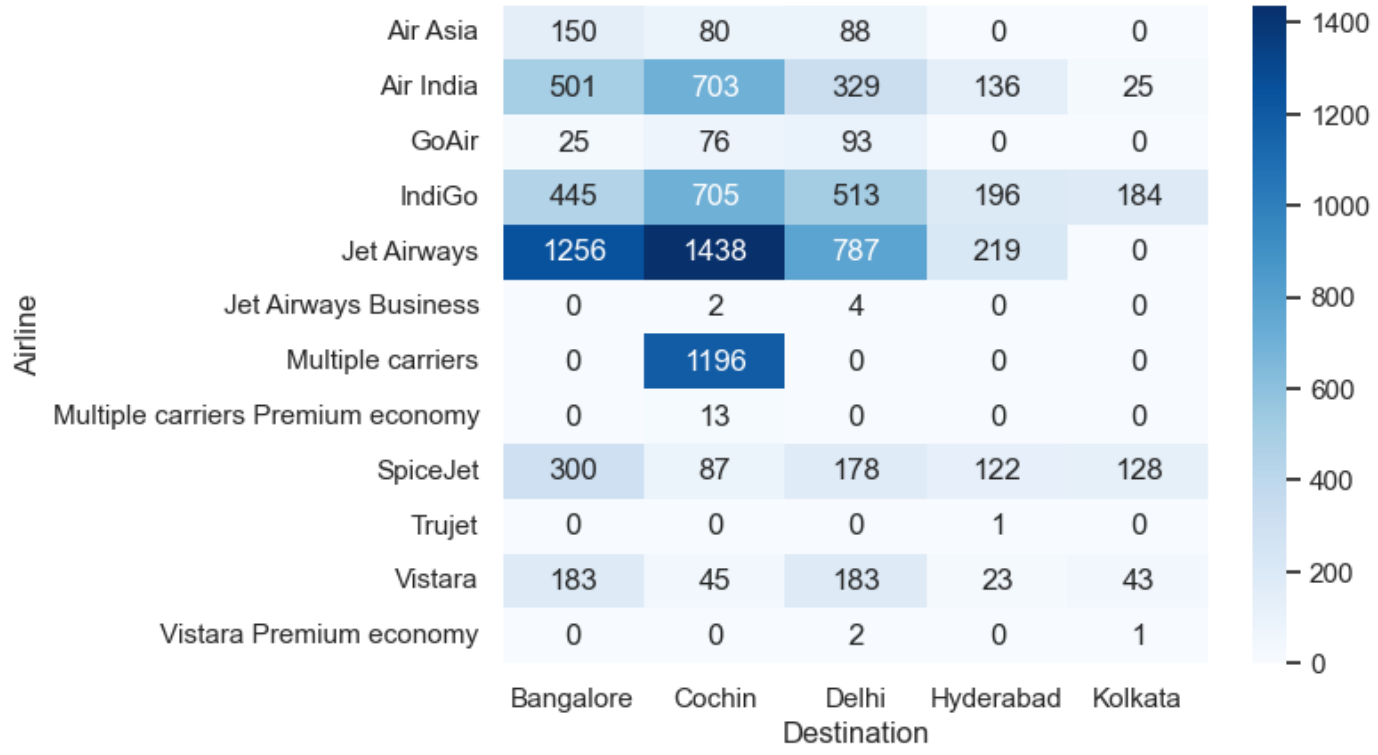
Insights

- **Jet Airways** has a significant **presence** in all the cities **expect for Chennai**, especially in **Delhi (1,438 passenegers)** and **Kolkata (1,256 passengers)**.
- **Flights** operated by **Multiple carriers** board **exclusively from Chennai**.
- **Flights** from **Vistara, SpiceJet, AirIndia and Indigo Airline** have **departed from all the cities**.

In [41]:
```
# Exploring the distribution between "Airline" and "Destination"

bivariate_cvc_eda(df_eda, "Airline", "Destination")
```

```
Destination                      Bangalore  Cochin  Delhi  Hyderabad  \
Airline
Air Asia                               150      80     88          0
Air India                              501     703    329        136
GoAir                                   25      76     93          0
IndiGo                                 445     705    513        196
Jet Airways                           1256    1438    787        219
Jet Airways Business                     0       2      4          0
Multiple carriers                        0    1196      0          0
Multiple carriers Premium economy        0      13      0          0
SpiceJet                               300      87    178        122
Trujet                                   0       0      0          1
Vistara                                183      45    183         23
Vistara Premium economy                  0       0      2          0

Destination                      Kolkata
Airline
Air Asia                               0
Air India                             25
GoAir                                  0
IndiGo                               184
Jet Airways                            0
Jet Airways Business                   0
Multiple carriers                      0
Multiple carriers Premium economy      0
SpiceJet                             128
Trujet                                 0
Vistara                               43
Vistara Premium economy                1

<Figure size 1000x600 with 0 Axes>
```


Destination
Bangalore
Cochin
Delhi
Hyderabad
Kolkata
3500
3000
2500
2000
1500
1000
500
0
Air Asia
Air India
GoAir
IndiGo
Jet Airways
Jet Airways Business
Multiple carriers
Multiple carriers Premium economy
SpiceJet
Trujet
Vistara
Vistara Premium economy
Airline

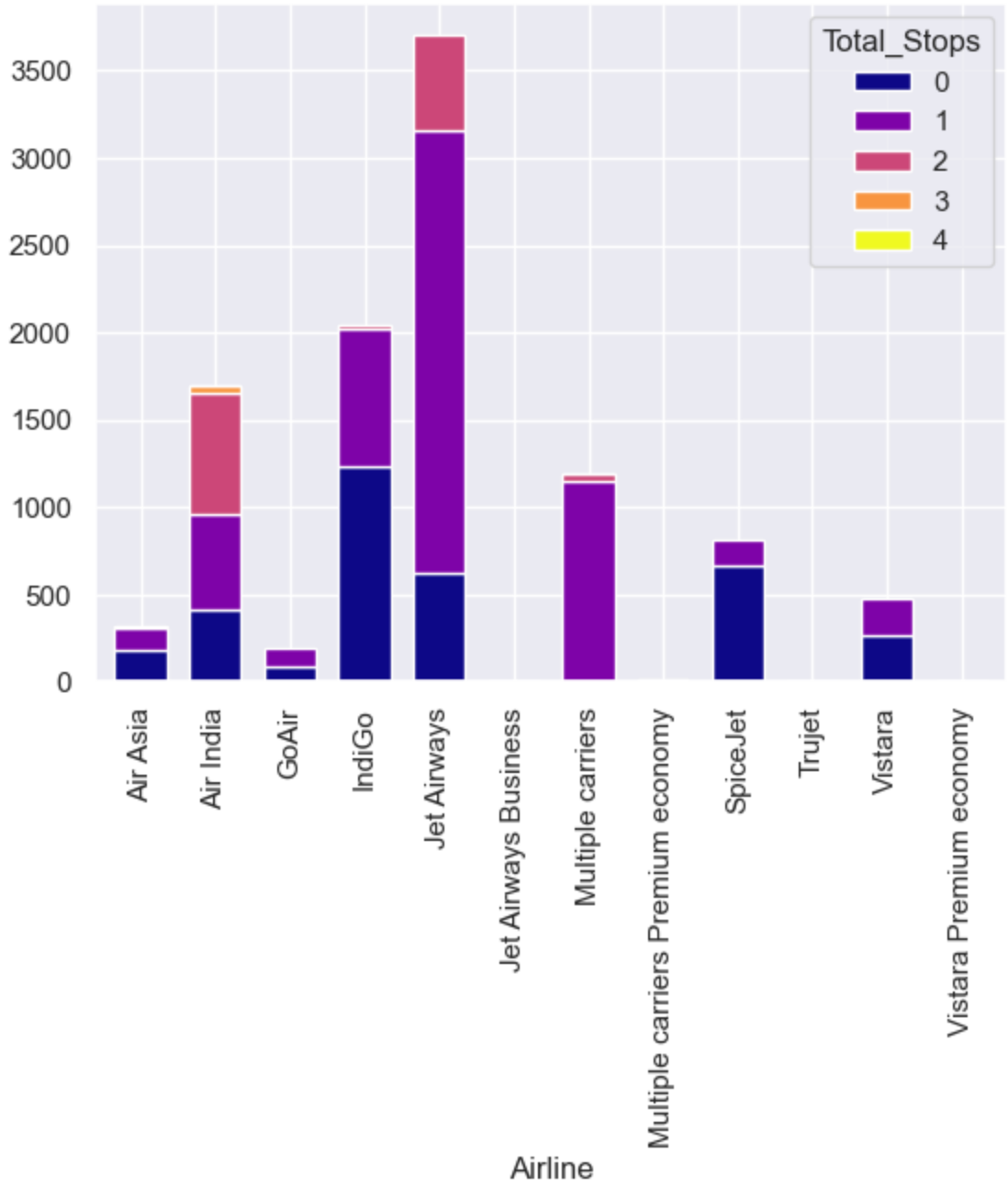


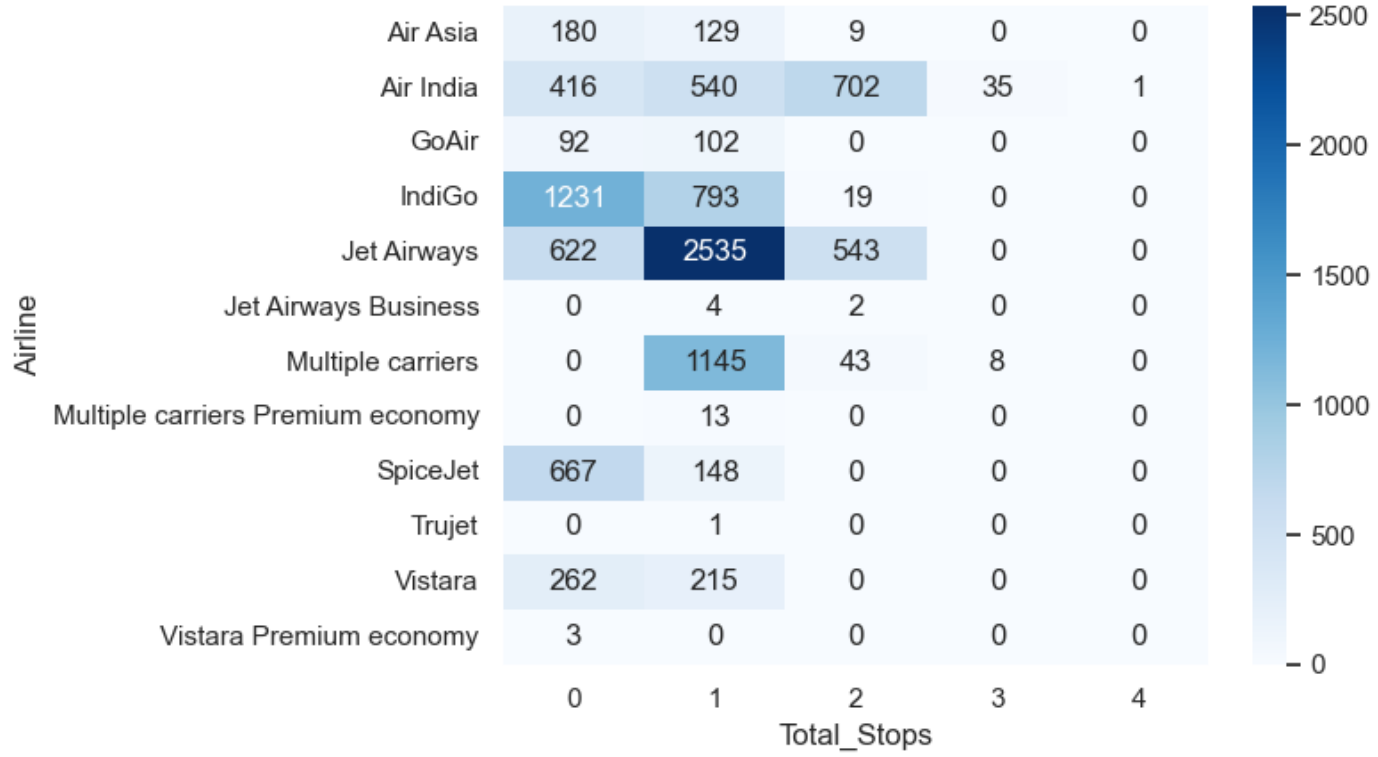
Insights

- **Flights** operated by **Multiple Carriers arrive exclusively at Cochin**, and these flights are **solely for travelling from Chennai to Cochin**.
- **Jet Airways Airlines flies** to **every city expect Chennai**.
- **Air India, IndiGo, Spice and Vistara Airline** provide **passenger service** to **every City**.

In [42]:
```
# Exploring the distribution between "Airline" and "Total_Stops"

bivariate_cvc_eda(df_eda, "Airline", "Total_Stops")
```

```
Total_Stops                       0     1    2   3  4
Airline
Air Asia                        180   129    9   0  0
Air India                       416   540  702  35  1
GoAir                            92   102    0   0  0
IndiGo                         1231   793   19   0  0
Jet Airways                     622  2535  543   0  0
Jet Airways Business              0     4    2   0  0
Multiple carriers                 0  1145   43   8  0
Multiple carriers Premium economy     0    13    0   0  0
SpiceJet                        667   148    0   0  0
Trujet                            0     1    0   0  0
Vistara                         262   215    0   0  0
Vistara Premium economy           3     0    0   0  0

<Figure size 1000x600 with 0 Axes>
```


Total_Stops
0
1
2
3
4
3500
3000
2500
2000
1500
1000
500
0
Air Asia
Air India
GoAir
IndiGo
Jet Airways
Jet Airways Business
Multiple carriers
Multiple carriers Premium economy
SpiceJet
Trujet
Vistara
Vistara Premium economy
Airline

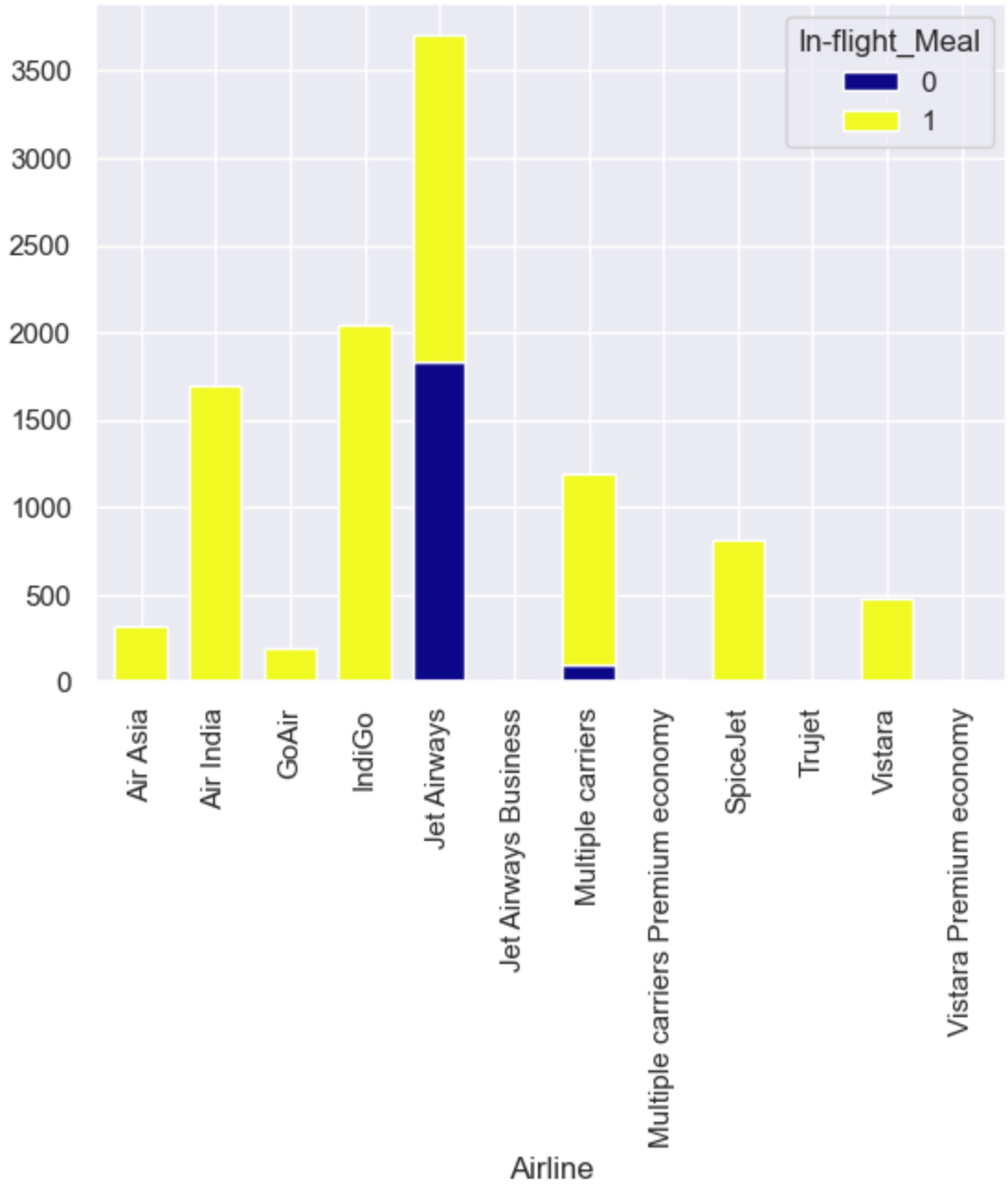


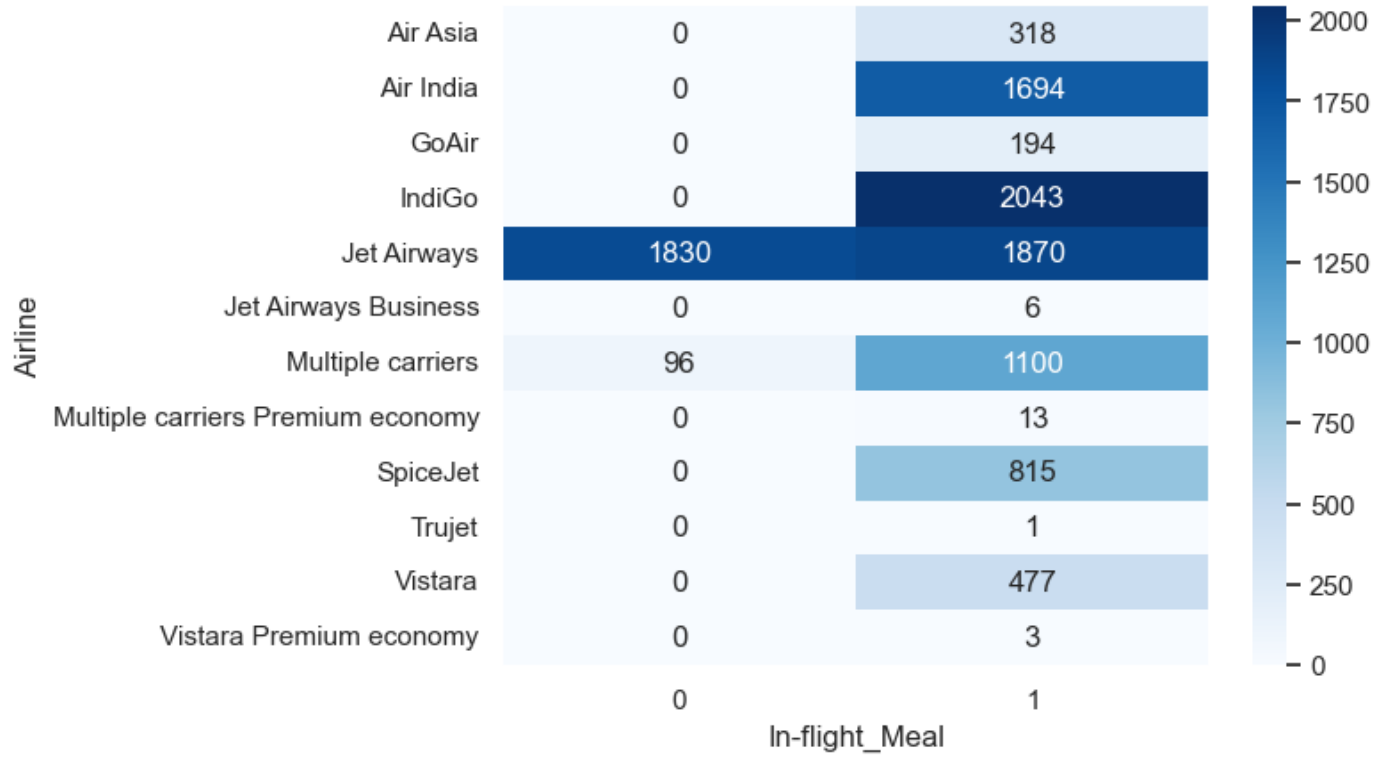
Insights

- **Jet Airway Airlines** often includes **multiple stops** in its flights, particularly **one-stop layovers**.
- **IndiGo Airlines** offer **non-stop flights (i.e with no layover)**.
- **A solitary passenger** flew from **Bangalore to Delhi** in **Air India Airlines**, included **four stopovers**.
- **Airline** that offers **flights** with **two or more stops** are **limited**.

In [43]:
```
# Exploring the distribution between "Airline" and "In-flight_Meal"

bivariate_cvc_eda(df_eda, "Airline", "In-flight_Meal")
```

```
In-flight_Meal                      0     1
Airline
Air Asia                            0   318
Air India                           0  1694
GoAir                               0   194
IndiGo                              0  2043
Jet Airways                      1830  1870
Jet Airways Business                0     6
Multiple carriers                  96  1100
Multiple carriers Premium economy   0    13
SpiceJet                            0   815
Trujet                              0     1
Vistara                             0   477
Vistara Premium economy             0     3

<Figure size 1000x600 with 0 Axes>
```


In-flight_Meal
0
1
3500
3000
2500
2000
1500
1000
500
0
Air Asia
Air India
GoAir
IndiGo
Jet Airways
Jet Airways Business
Multiple carriers
Multiple carriers Premium economy
SpiceJet
Trujet
Vistara
Vistara Premium economy
Airline

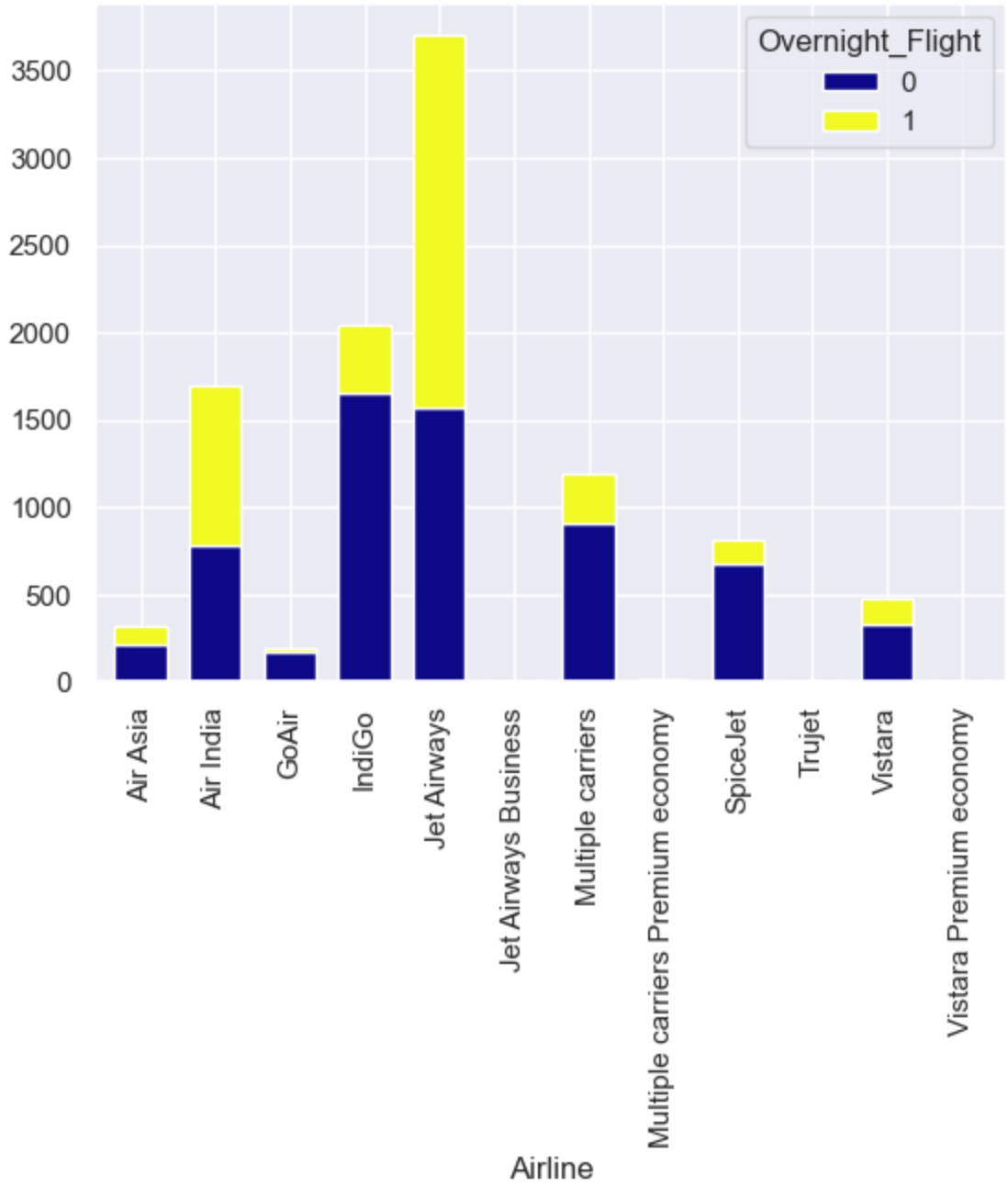


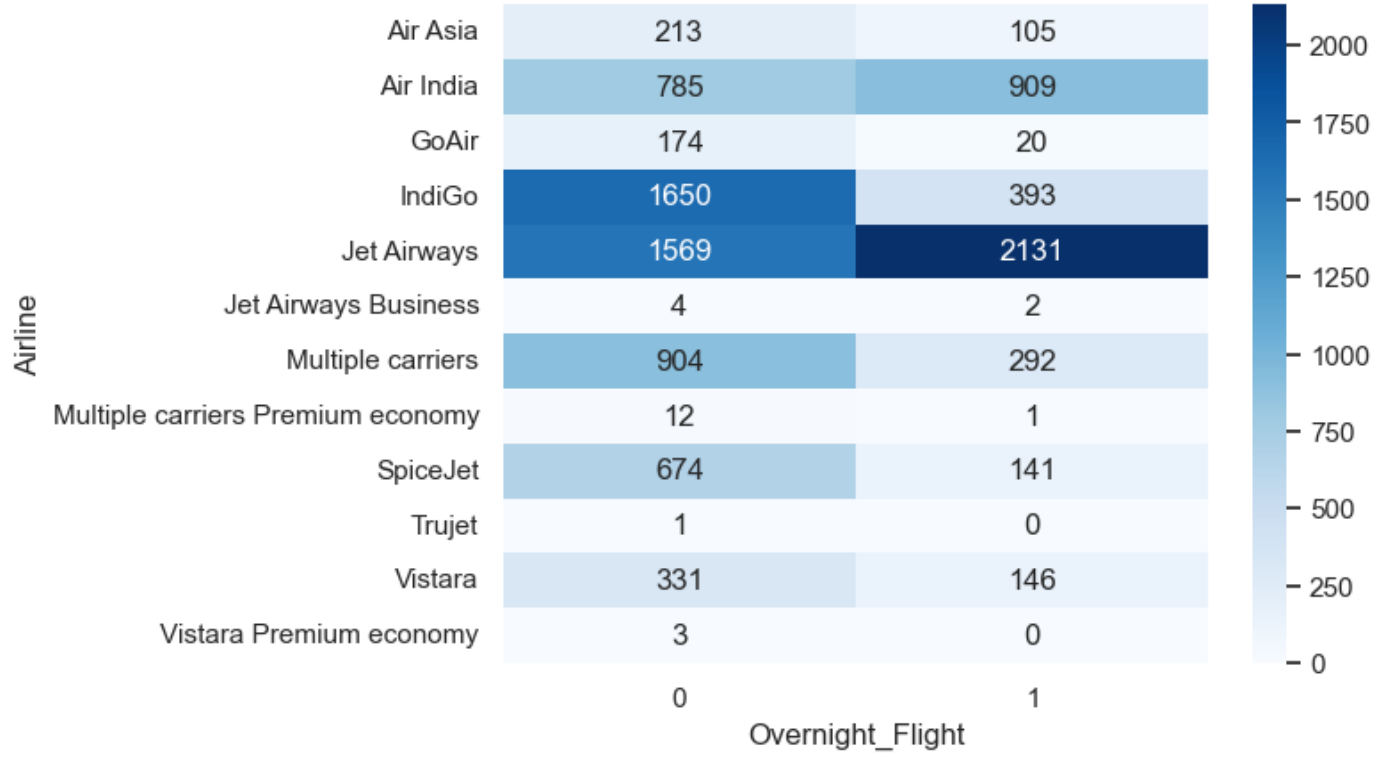
Insights

- **All the Airlines offered** their **passengers meals** during the journey, indicating they **prioritize offering meal services** to passengers.
- **IndiGO Airlines** offered **meals** to their **passengers the most**, followed by **Jet Airways** and **Air India**.
- **Airlines** like **Vistara, Trujet and Multiple carriers** have **limited in-flight meals** for passengers, potentially **catering** to those **seeking more budget-friendly options without meal services**.

In [44]:
```
# Exploring the distribution between "Airline" and "Overnight_Flight"

bivariate_cvc_eda(df_eda, "Airline", "Overnight_Flight")
```

```
Overnight_Flight                     0     1
Airline
Air Asia                           213   105
Air India                          785   909
GoAir                              174    20
IndiGo                            1650   393
Jet Airways                       1569  2131
Jet Airways Business                 4     2
Multiple carriers                  904   292
Multiple carriers Premium economy   12     1
SpiceJet                           674   141
Trujet                               1     0
Vistara                            331   146
Vistara Premium economy              3     0

<Figure size 1000x600 with 0 Axes>
```


Overnight_Flight
0
1
3500
3000
2500
2000
1500
1000
500
0
Air Asia
Air India
GoAir
IndiGo
Jet Airways
Jet Airways Business
Multiple carriers
Multiple carriers Premium economy
SpiceJet
Trujet
Vistara
Vistara Premium economy
Airline

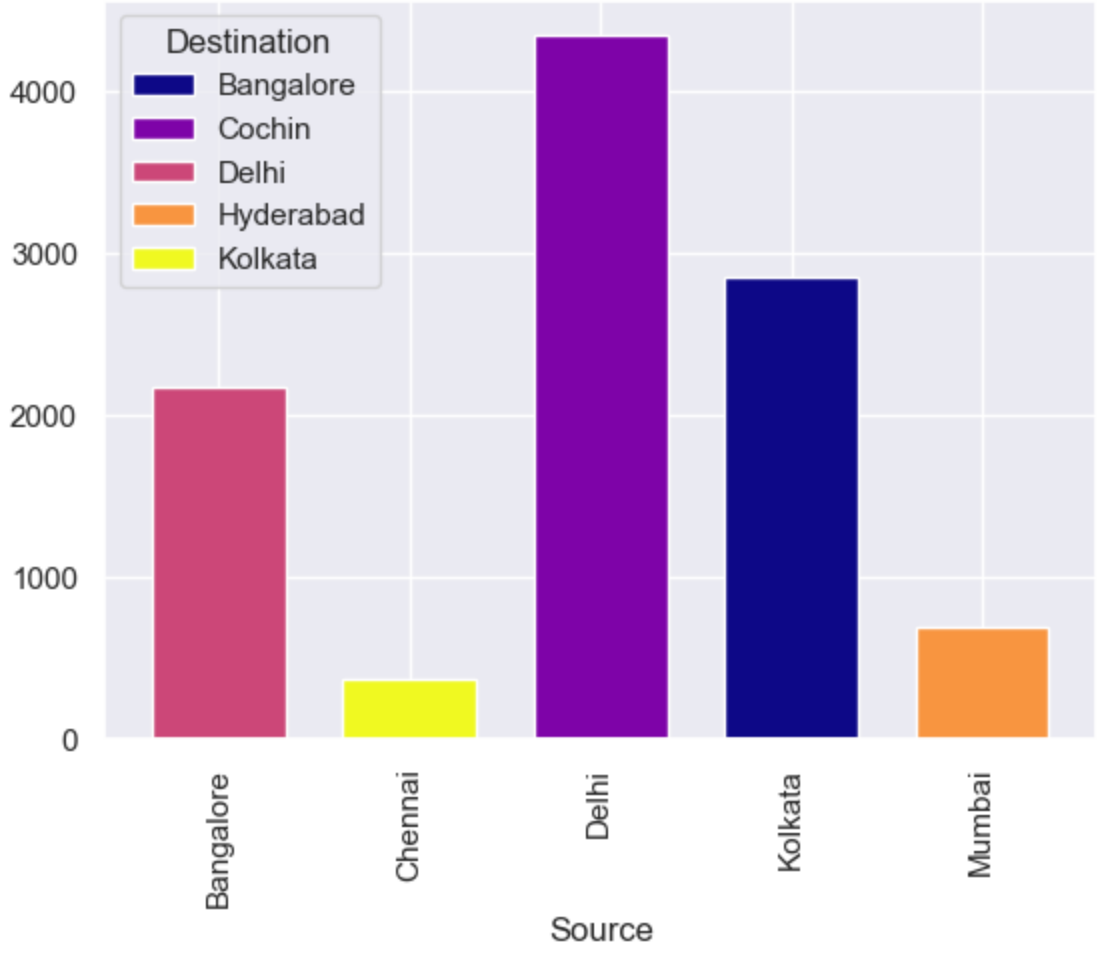


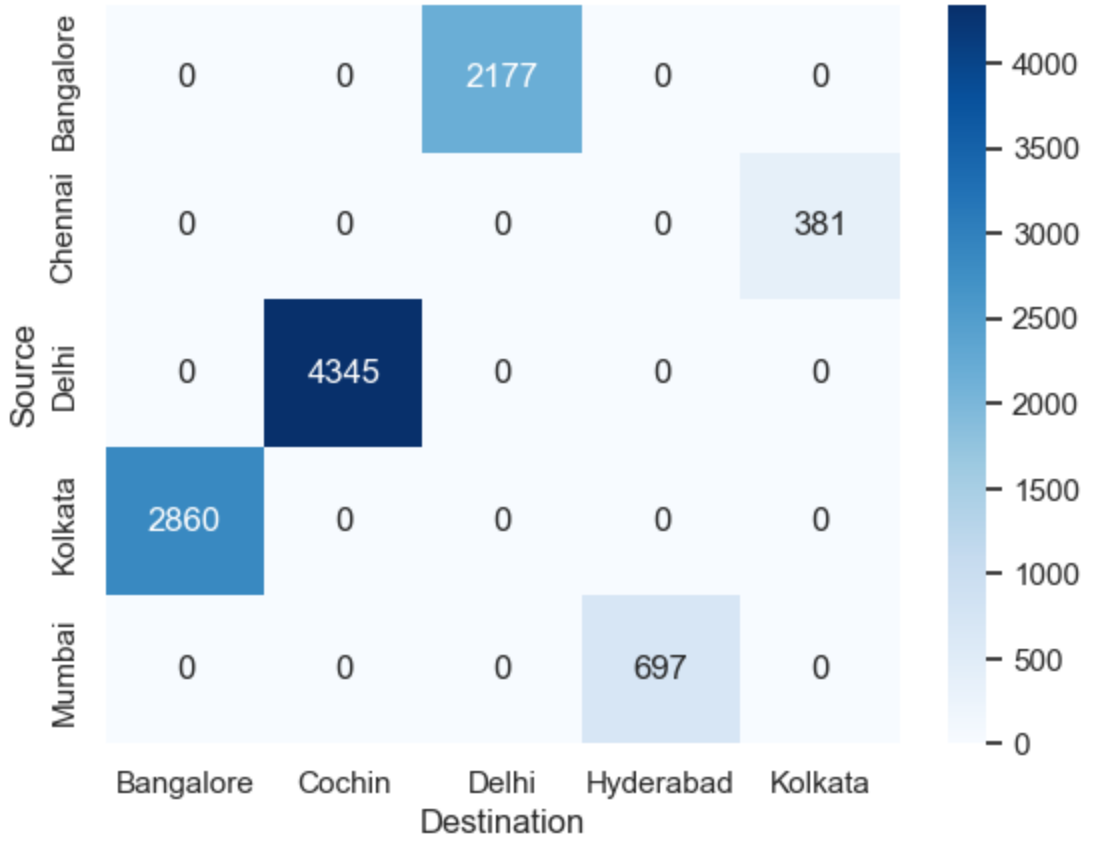
Insights

- **Except** for **Vistara Premium Economy** and **Trujet**, **all the airlines offer both day and overnight flights**.
- **Jet Airways** is the **preferred choice** for **passengers**, whether for **daytime or overnight flights**.
- **Jet Airways**, **Air India** and **IndiGo** are the **Airlines** that **majority of passengers choose for overnight flights**.

In [45]:
```
# Exploring the distribution between "Source" and "Destination"

bivariate_cvc_eda(df_eda, "Source", "Destination")
```

```
Destination  Bangalore  Cochin  Delhi  Hyderabad  Kolkata
Source
Bangalore            0       0   2177          0        0
Chennai              0       0      0          0      381
Delhi                0    4345      0          0        0
Kolkata           2860       0      0          0        0
Mumbai               0       0      0        697        0

<Figure size 1000x600 with 0 Axes>
```





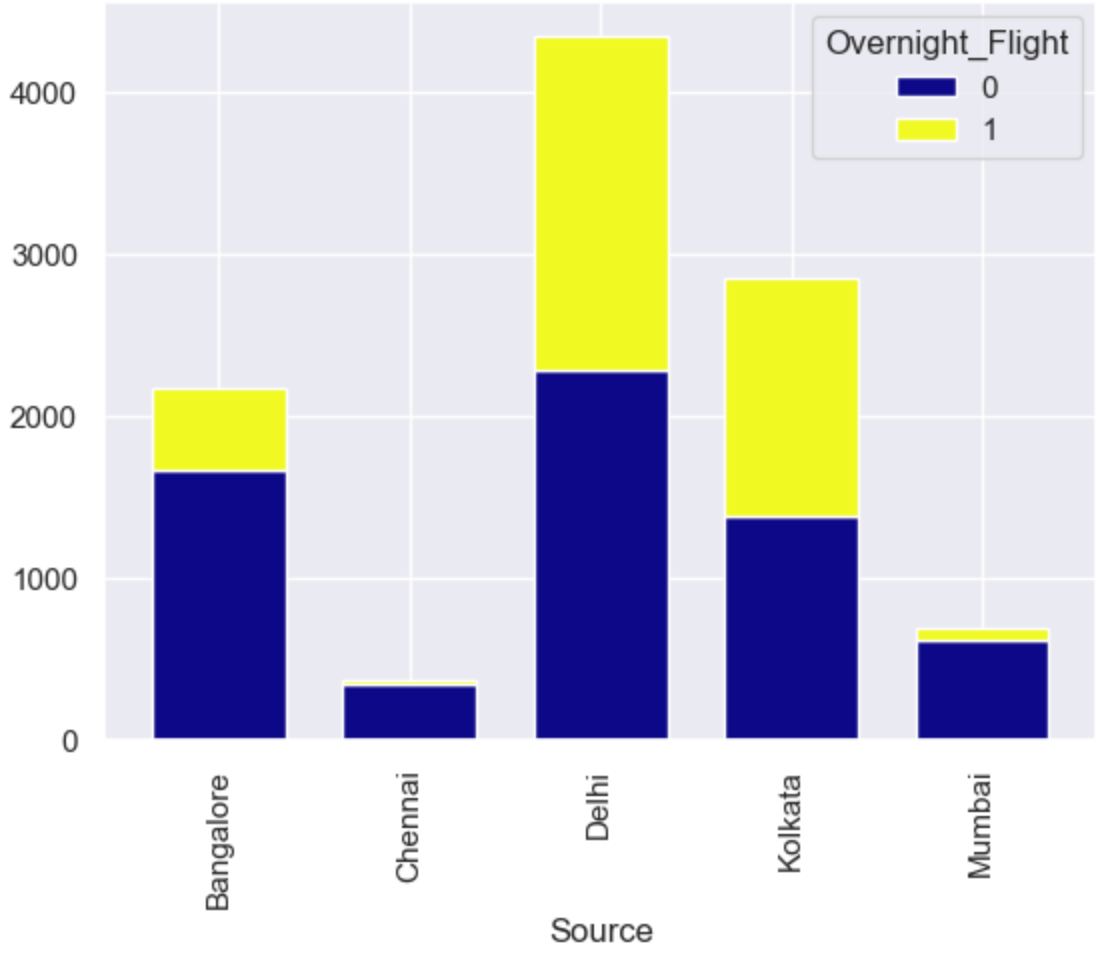
Insights

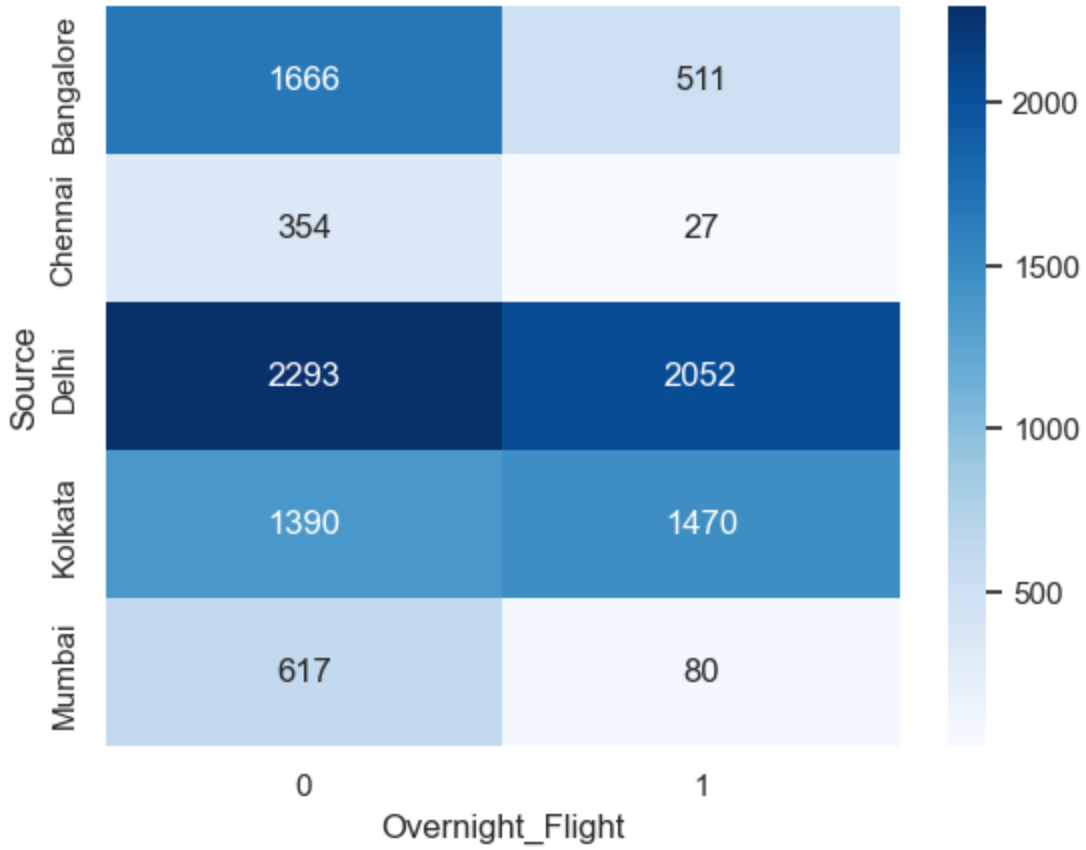
- The **majority** of the **passengers traveled** on the **Delhi to Cochin routes**, followed by the **Bangalore to Delhi** and **Kolkata to Bangalore routes**.

- The **fewest passengers** travelled between **Mumbai to Hyderabad**, as well as between **Chennai to Kolkata**.

In [46]:
```
# Exploring the distribution between "Source" and "Overnight_Flight"

bivariate_cvc_eda(df_eda, "Source", "Overnight_Flight")
```

```
Overnight_Flight     0     1
Source
Bangalore         1666   511
Chennai            354    27
Delhi             2293  2052
Kolkata           1390  1470
Mumbai             617    80

<Figure size 1000x600 with 0 Axes>
```



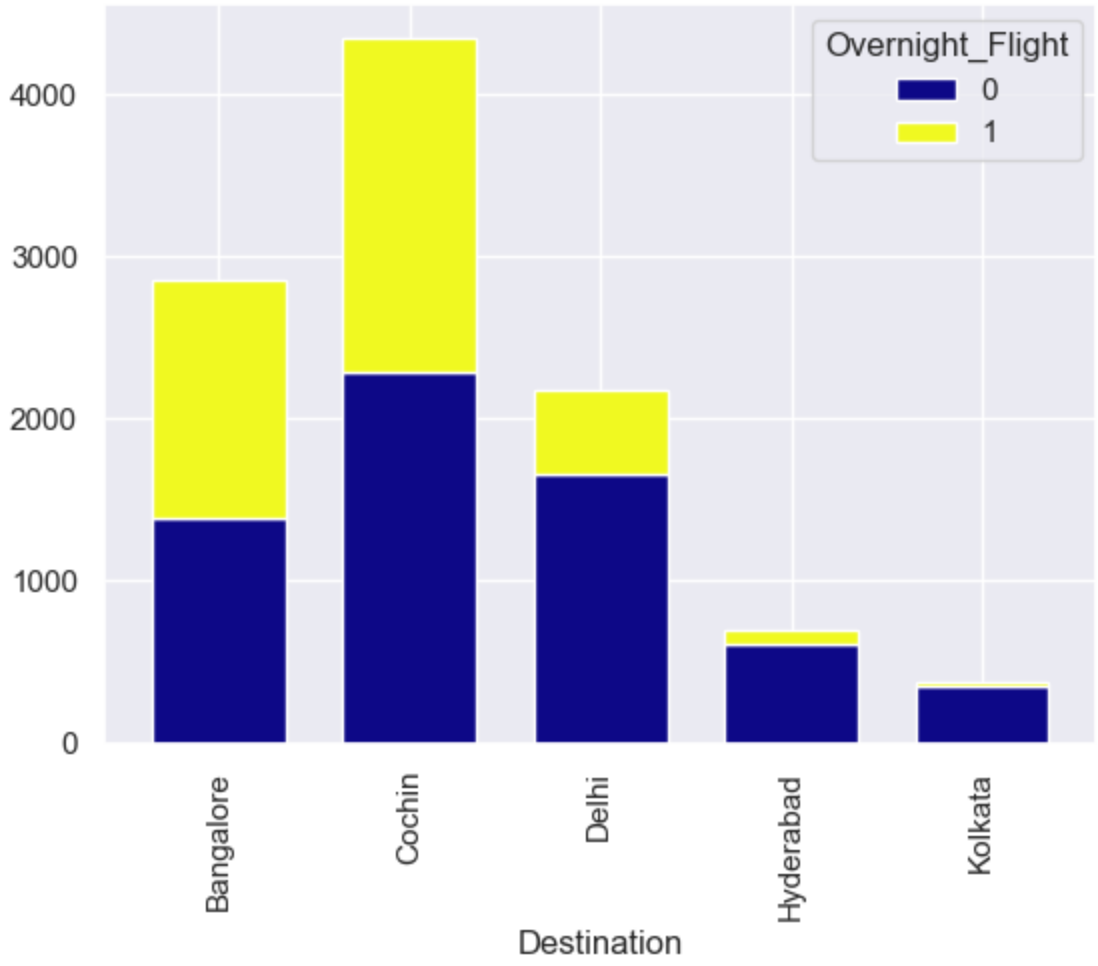


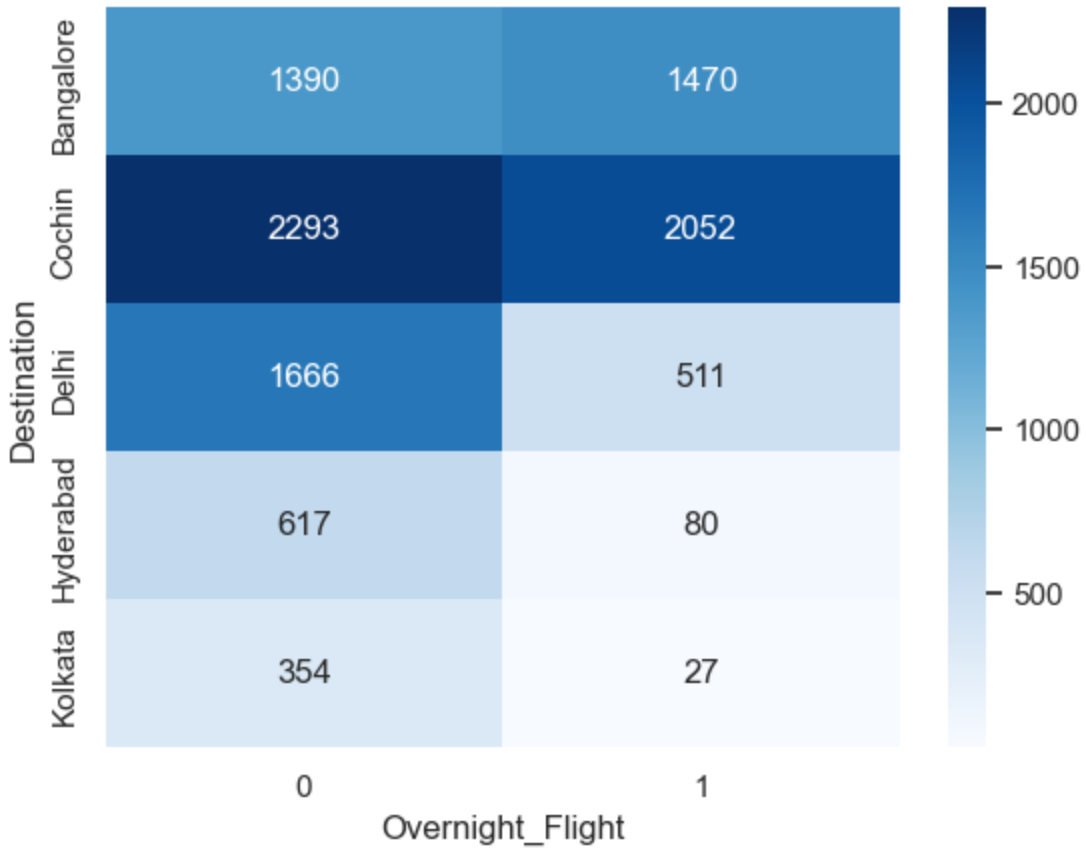
Insights

- The **majority** of the passengers travelling from **Delhi opted for Overnight travel**, followed by those from **Kolkata** and **Bangalore**.

In [47]:
```
# Exploring the distribution between "Destination" and "Overnight"

bivariate_cvc_eda(df_eda, "Destination", "Overnight_Flight")
```

```
Overnight_Flight     0     1
Destination
Bangalore         1390  1470
Cochin            2293  2052
Delhi             1666   511
Hyderabad          617    80
Kolkata            354    27

<Figure size 1000x600 with 0 Axes>
```





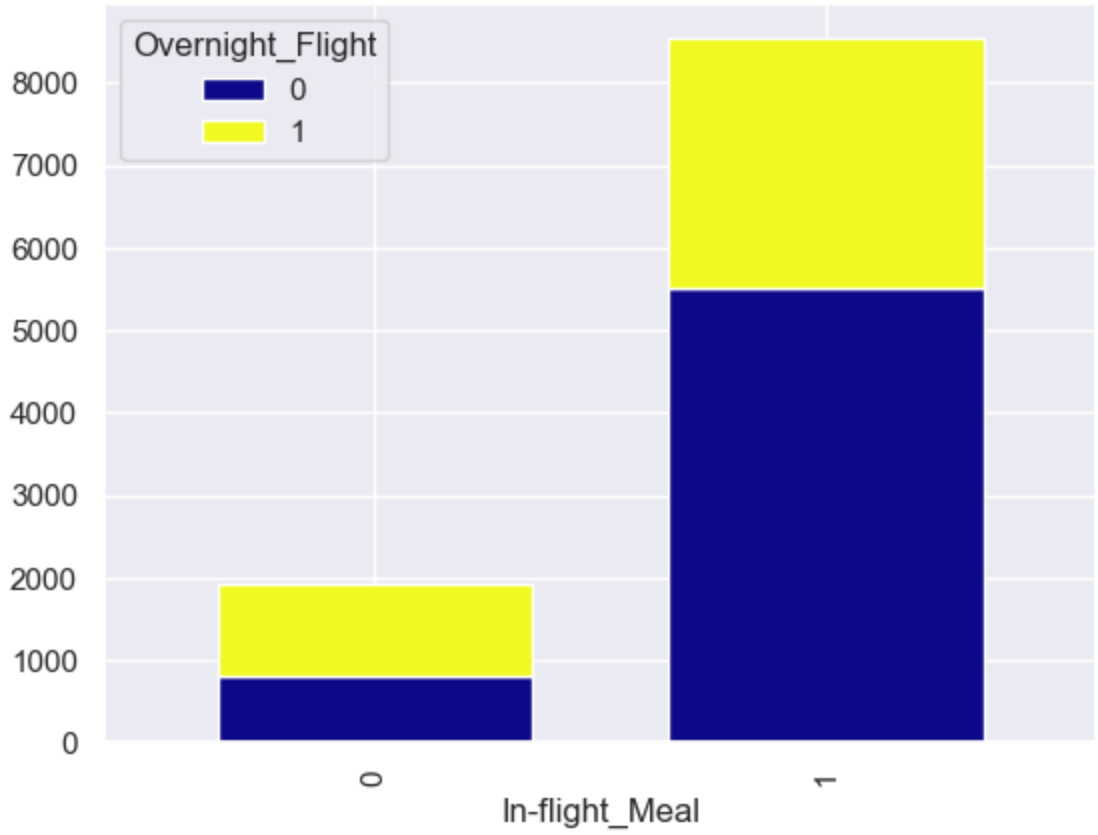
Insights

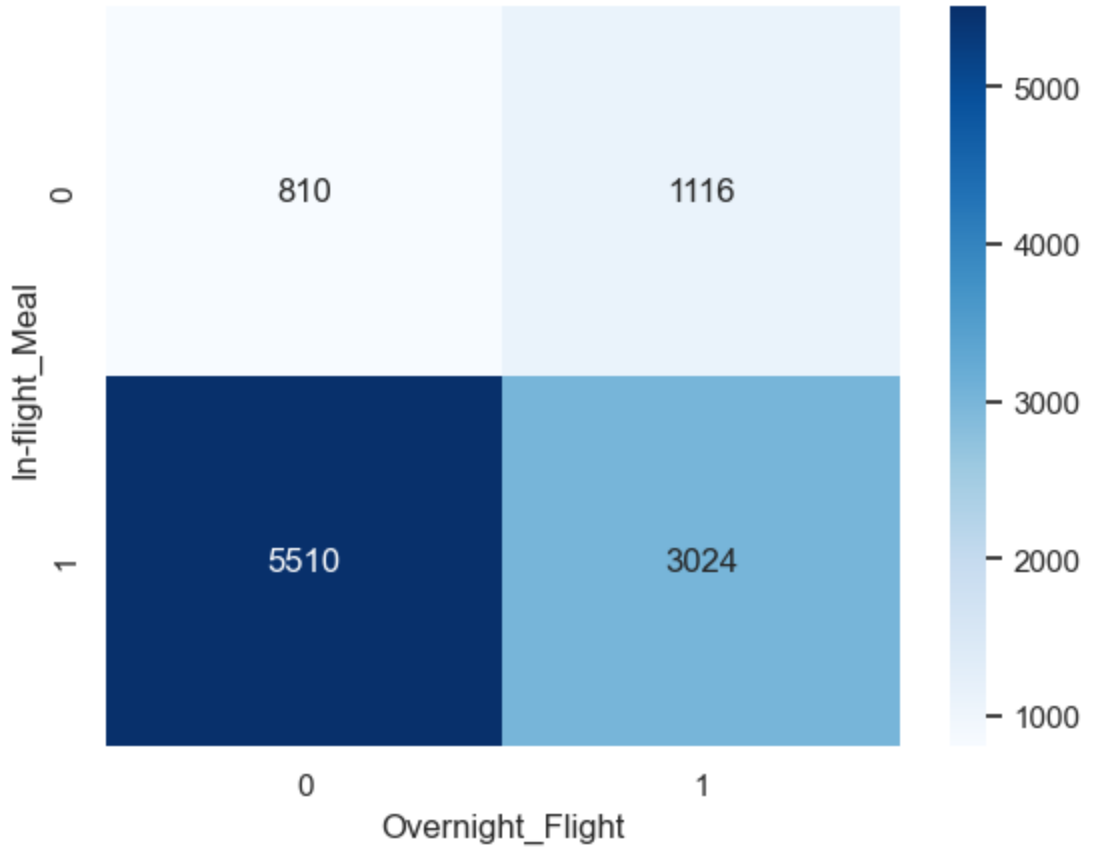
- The **majority** of passengers who **arrived** in **Delhi opted** for **Overnight flights**, followed by those in **Bangalore** and **Kolkata**.

In [48]:
```
# Exploring the distribution between "In-flight_Meal" and "Overnight_Flight"

bivariate_cvc_eda(df_eda, "In-flight_Meal", "Overnight_Flight")
```

```
Overnight_Flight     0     1
In-flight_Meal
0                  810  1116
1                 5510  3024
```

```
<Figure size 1000x600 with 0 Axes>
```





Insights

- The **majority** of the passengers who **travelled** during the **day opted for meals** compared to **overnight passengers**.

Pre-Processing (II)

In [49]:
```
# Creating a function to perform data preprocessing

# Creating a copy of the data

df_1 = df.copy()

def pre_processing_3(data):

    # Converting the features to object type
    to_int = ["Total_Stops", "In-flight_Meal", "Overnight_Flight"]
    for col in to_int:
        data[col] = data[col].astype("O")

    # Dropping irrelevant features
    data.drop(columns = ["Route", "Duration_Hours", "Duration_Minutes", "Additional_Info"], inpl

pre_processing_3(df_1)
```

Feature Engineering & Selection

In [50]:
```
print('\033[1m' + f"The total number of null values in the dataset : {df_1.isna().sum().sum()}"
```

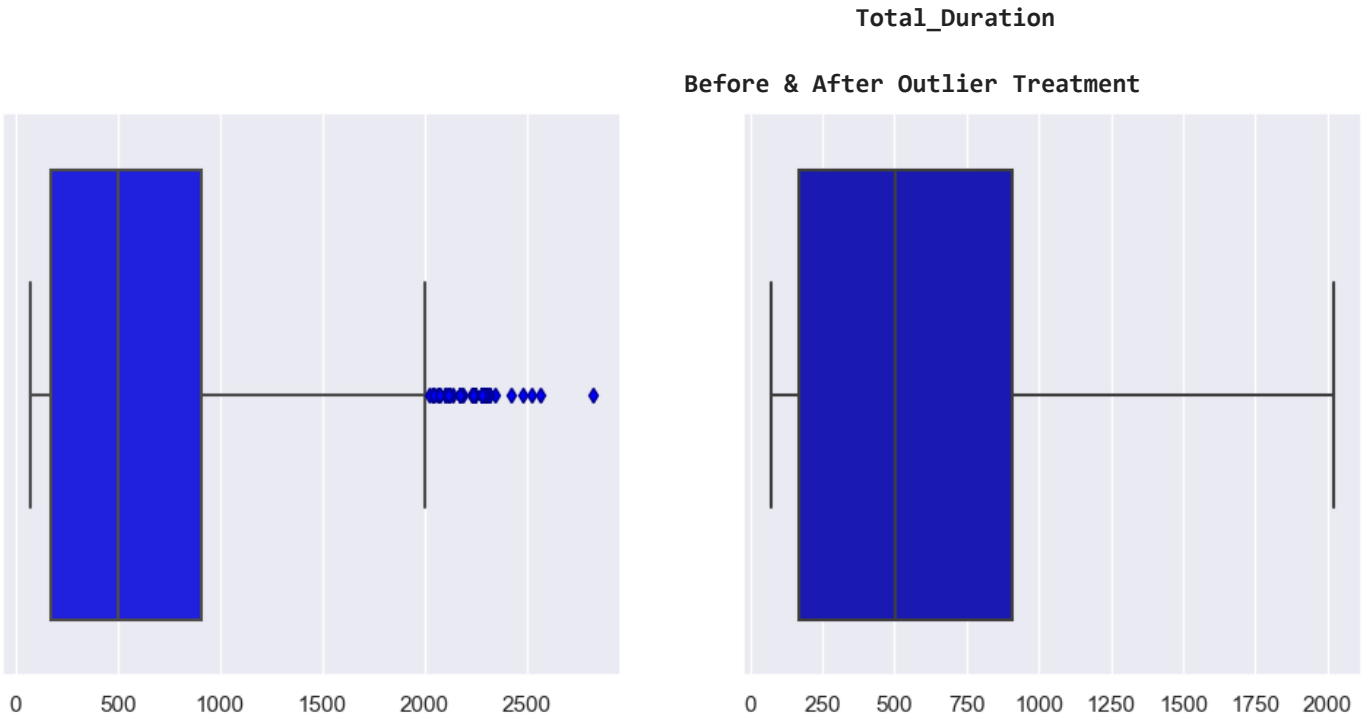
The total number of null values in the dataset : 0

Since the dataset does not contain any null values, NaN Imputation is not required.

Outlier Treatment

In [51]:
```
# Creating a function to handle outliers

def impute_outliers(data):

    for col in data.select_dtypes(include = [int, float]).drop(columns = ["Price", "Month"]).col

        # Checking for outliers in the feature
        Q1, Q3 = data[col].quantile([0.25, 0.75])
        IQR = Q3 - Q1
        lower_bound = Q1 - (1.5 * IQR)
        upper_bound = Q3 + (1.5 * IQR)
        outlier_count = len(data[col][(data[col] < lower_bound) | (data[col] > upper_bound)])

        # Replacing outliers with the lower and upper bound values of the feature
        if outlier_count != 0:
            print('\033[1m' + f"\t\t\t\t\t\t\t    {col}\n\n\t\t\t\t\t\t\tBefore & After Outlier Tr

            # Plotting the graphs to check the distribution of the features before and after imp
            fig, ax = plt.subplots(nrows = 1, ncols = 2, figsize = (12, 5))
            sns.boxplot(x = data[col], color = "blue", ax = ax[0], flierprops = {"markerfacecolo
            data[col] = np.where(data[col] < lower_bound, np.round(lower_bound, 2), np.where(dat
```

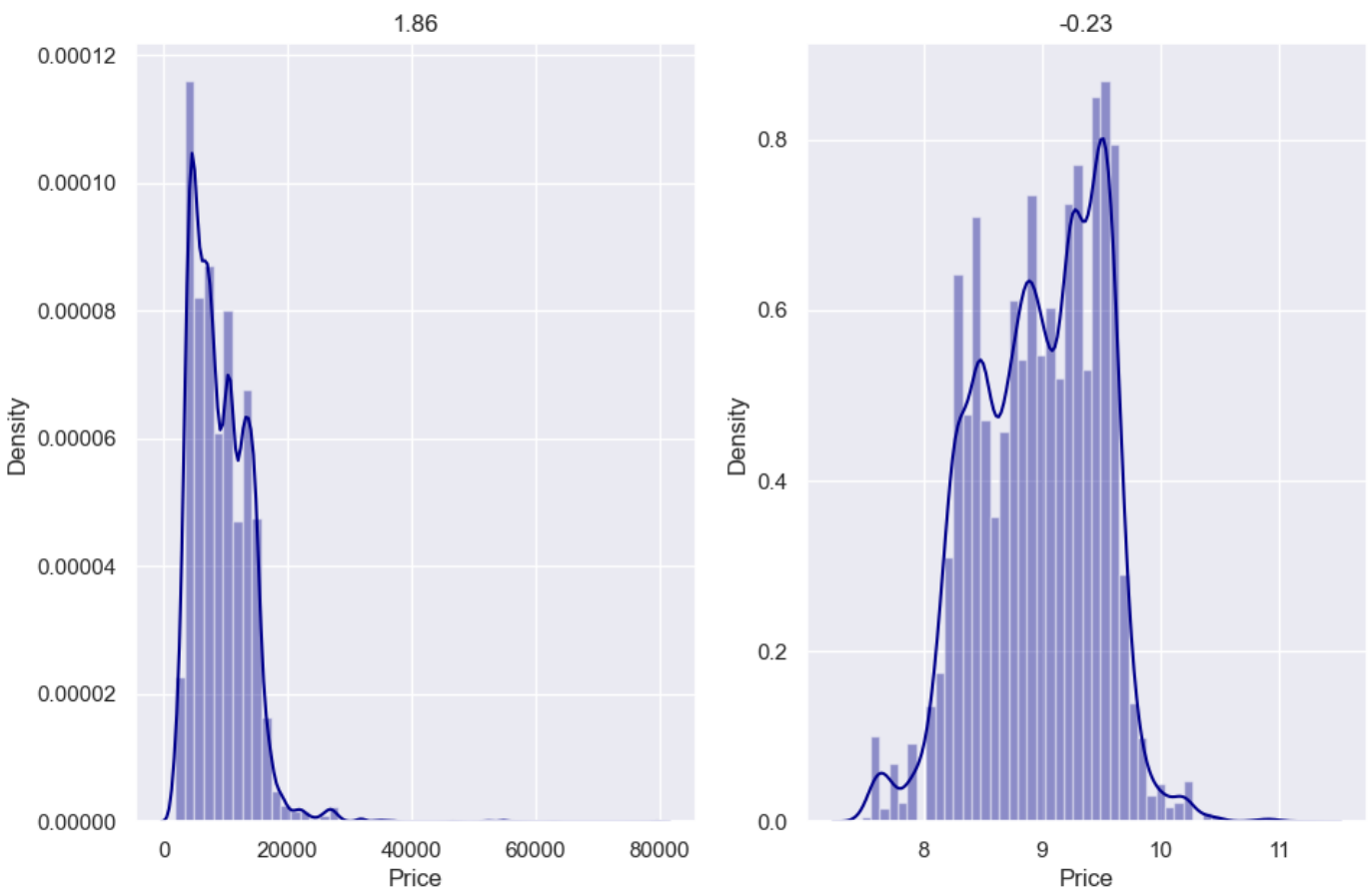
```
            sns.boxplot(x = data[col], color = "mediumblue", ax = ax[1], flierprops = {"markerfa
            ax[0].set_xlabel(" ")
            ax[1].set_xlabel(" ")
            plt.show()
        else:
            pass

impute_outliers(df_1)
```



Log Transformation

In [52]:
```
# Checking the distribution of the "Price" feature

plt.figure(figsize = (11, 7))

plt.subplot(1, 2, 1)
sns.distplot(df_1["Price"], color = "darkblue")
plt.title(np.round(df_1["Price"].skew(), 2))
print('\033[1m' + 'Since the "Price" feature is not normally distributed, there won\'t be a line

# Appling log transformation on the "Price" feature

plt.subplot(1, 2, 2)
df_1["Price"] = np.log1p(df_1["Price"])
sns.distplot(df_1["Price"], color = "darkblue")
plt.title(np.round(df_1["Price"].skew(), 2))
plt.show()
```

**Since the "Price" feature is not normally distributed, there won't be a linear relationship betw
een the dependent variables and "Price", which means the Linearity assumption won't be satisfie
d. However, applying a log transformation to the "Price" feature will make it normally distribut
ed and later take exponential to get the original predictions.**



Forward Elimination - I

In [53]:
```
# Creating a function to check statistical significance of the features

def feature_significance(data, target):

    X = data.drop(columns = "Price")
    y = data["Price"]

    for col in data.select_dtypes(exclude = [int, float]).columns:
        X[col] = LabelEncoder().fit_transform(X[col])

    p_values = pd.Series(np.round(f_regression(X, y)[1], 3), X.columns)
    non_significant_features = p_values[p_values > 0.05].to_dict()

    if len(non_significant_features) != 0:
        print('\033[1m' + f"Non-significant Features (p-value > 0.05)\n" + '\033[0m')
        for col, pval in non_significant_features.items():
            if pval > 0.05:
                print(f"{col} : {pval}")
            else:
                pass
    else:
        print('\033[1m' + "All features are statistically significant." + '\033[0m')

print('\033[1m' + "BEFORE DROPPING THE CORRELATED FEATURES\n" + '\033[0m')
feature_significance(df_1, "Price")

# Dropping the non-significant features

df_1.drop(columns = ["Source", "Day_of_Week", "Dep_Time_Hour"], inplace = True)

print('\033[1m' + "\nAFTER DROPPING THE CORRELATED FEATURES\n" + '\033[0m')
feature_significance(df_1, "Price")
```

BEFORE DROPPING THE CORRELATED FEATURES

Non-significant Features (p-value > 0.05)

Source : 0.118
Day_of_Week : 0.086
Dep_Time_Hour : 0.456

AFTER DROPPING THE CORRELATED FEATURES

All features are statistically significant.

Multicollinearity - I

In [54]:
```
def multicollinearity(data, col):

    X = data.drop(columns = [col])

    for col in data.select_dtypes(exclude = [int, float]).columns:
        X[col] = LabelEncoder().fit_transform(X[[col]])

    X_sc = StandardScaler().fit_transform(X)

    vif = pd.Series([np.round(variance_inflation_factor(X_sc, col), 3) for col in range(X_sc.sha

    high_vif = pd.Series()

    for col in vif.index:
        if vif[col] > 5:
            high_vif[col] = vif[col]
        else:
            pass

    high_vif.sort_values(ascending = False, inplace = True)

    if len(high_vif) != 0:
        print('\033[1m' + "Features (VIF > 5)\n" + '\033[0m')
        print(high_vif)
    else:
        print('\033[1m' + "There is no Multicollinearity." + '\033[0m')

multicollinearity(df_1, "Price")
```

There is no Multicollinearity.

Feature Encoding

In [55]:
```
# Creating a function to perform feature encoding on the data

df_2 = df_1.copy()

def feature_encoder(data):

    data["Index"] = list(range(len(data)))

    # Creating a dataframe to store the encoded data
    en_df = pd.DataFrame({"Index" : list(range(len(data)))})

    # Applying One hot encoding technique
    for col in data.select_dtypes("O").columns:
        data[col] = data[col].astype(str)
```

```
        # Creating an encoded dataframe contaning encoded values
        en_col = pd.DataFrame(OneHotEncoder(sparse = False, drop = [data[col].value_counts().ind
        en_df = pd.concat([en_df, en_col], axis = 1)
        data.drop(columns = [col], inplace = True)

    return en_df

df_2 = df_2.merge(feature_encoder(df_2),on = "Index").drop(columns = ["Index"])

df_2
```

Out[55]:

	Price	Day	Month	Arrival_Time_Hour	Arrival_Time_Minute	Dep_Time_Minute	Total_Duration	Airline_J Airwa
0	8.268219	24	3	1	10	20	170.0	
1	8.944159	5	1	13	15	50	445.0	
2	9.538420	6	9	4	25	25	1140.0	
3	8.735364	5	12	23	30	5	325.0	
4	9.495745	3	1	21	35	50	285.0	
...	...	...	...	...	...	...	...	
10455	8.320692	4	9	22	25	55	150.0	
10456	8.329899	27	4	23	20	45	155.0	
10457	8.885994	27	4	11	20	20	180.0	
10458	9.445333	3	1	14	10	30	160.0	
10459	9.371949	5	9	19	15	55	500.0	

10460 rows × 28 columns

Forward Elimination - II

In [56]:
```
print('\033[1m' + "BEFORE DROPPING THE CORRELATED FEATURES\n" + '\033[0m')
feature_significance(df_2, "Price")

print('\033[1m' + "\nAFTER DROPPING THE CORRELATED FEATURES\n" + '\033[0m')
df_2.drop(columns = ["Airline_Vistara Premium economy"], inplace = True)
feature_significance(df_2, "Price")

# # Dropping the non-significant features
# df_2.drop(columns = ["Airline_GoAir", "Airline_Vistara Premium economy", "Destination_Cochin"],
# feature_significance(df_2, "Price")
```

BEFORE DROPPING THE CORRELATED FEATURES

Non-significant Features (p-value > 0.05)

Airline_Vistara Premium economy : 0.784

AFTER DROPPING THE CORRELATED FEATURES

All features are statistically significant.

Multicollinearity - II

In [57]:
```
print('\033[1m' + "BEFORE DROPPING THE CORRELATED FEATURES\n" + '\033[0m')
multicollinearity(df_2, "Price")

# Dropping the correlated features with VIF > 5
df_2.drop(columns = ["Total_Stops_0"], inplace = True)
# multicollinearity(df_2, "Price")

df_2.drop(columns = ["Airline_SpiceJet"], inplace = True)
# multicollinearity(df_2, "Price")

df_2.drop(columns = ["Destination_Bangalore"], inplace = True)
# multicollinearity(df_2, "Price")

print('\033[1m' + "\nAFTER DROPPING THE CORRELATED FEATURES\n" + '\033[0m')
multicollinearity(df_2, "Price")
```

BEFORE DROPPING THE CORRELATED FEATURES

Features (VIF > 5)

```
Total_Stops_0                              2607.787
Total_Stops_1                              2329.560
Total_Stops_2                              1155.044
Airline_SpiceJet                            600.674
Airline_Multiple carriers                   412.606
Airline_IndiGo                              356.840
Airline_Air Asia                            266.767
Airline_Multiple carriers Premium economy   189.243
Airline_Jet Airways Business                114.993
Airline_Jet Airways                          78.384
Airline_Air India                            48.741
Total_Stops_3                                43.875
Destination_Bangalore                         9.626
Destination_Cochin                            7.402
Destination_Delhi                             5.703
dtype: float64
```

AFTER DROPPING THE CORRELATED FEATURES

There is no Multicollinearity.

Feature Importance

In [58]:
```
# Creating a function to select the significant features

def feature_selector(data):

    # Seperating the dependent and independent features
    X = data.drop(columns = ["Price"])
    y = data["Price"]

    # Splitting the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 11

    # Computing the importance of the features
    importance = mutual_info_regression(X_train, y_train)

    # Checking the feature importance
    feature_importance = pd.DataFrame({"Importance" : importance}, index = X.columns)
    print(feature_importance[feature_importance["Importance"] < 0.01].index)

feature_selector(df_2)
```

```
# df_2.drop(columns = ['Airline_Vistara'], inplace = True)
# df_2.drop(columns = ['Total_Stops_3'], inplace = True)

# feature_selector(df_2)
```

```
Index(['Airline_Vistara', 'Airline_GoAir', 'Total_Stops_3'], dtype='object')
```

Collinearity

In [59]:
```
# # Creating a function to check the correlation

# def collinearity(data):

#     plt.figure(figsize = (18, 8))
#     corr = np.round(abs(data.corr())[abs(data.corr()).iloc[1:, 1:] > 0.75].fillna({"Price" : d
#     mask = np.triu(np.ones_like(corr, dtype = bool))
#     sns.heatmap(corr, mask = mask, cmap = "Blues", annot = True, center = 0, square = True, li
#     sns.set(style = "darkgrid")
#     plt.show()

# #     return corr

# collinearity(df_2)
```

Feature Scaling

In [60]:
```
X = df_2.drop(columns = ["Price"])
y = df_2["Price"]

X_sc = StandardScaler().fit_transform(X)
```

Model Building and Evaluation

In [61]:
```
# Creating a function to build and evaluate a regression model

def regression_model(MODEL, train, test):

    print('\033[1m' + f"\t\t\t\t\tModel : {MODEL}" + '\033[0m\n')

    model = MODEL

    # Splitting the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(train, test, test_size = 0.2, random_sta

    metrics = []

    # Training the model
    model.fit(X_train, y_train)

    # Making predicitons on the training and testing data
    y_train_pred = model.predict(X_train)
    y_test_pred = model.predict(X_test)

    # Calculating the metrics of the model
    r2_train_score = np.round(r2_score(y_train, y_train_pred), 3)
    r2_test_score = np.round(r2_score(y_test, y_test_pred), 3)
    variance = str(np.round((r2_train_score * 100) - (r2_test_score * 100), 3)) + "%"
    adj_r2_train = np.round(1 - (1 - r2_score(y_train, y_train_pred)) * (len(y_train) - 1) / (le
```

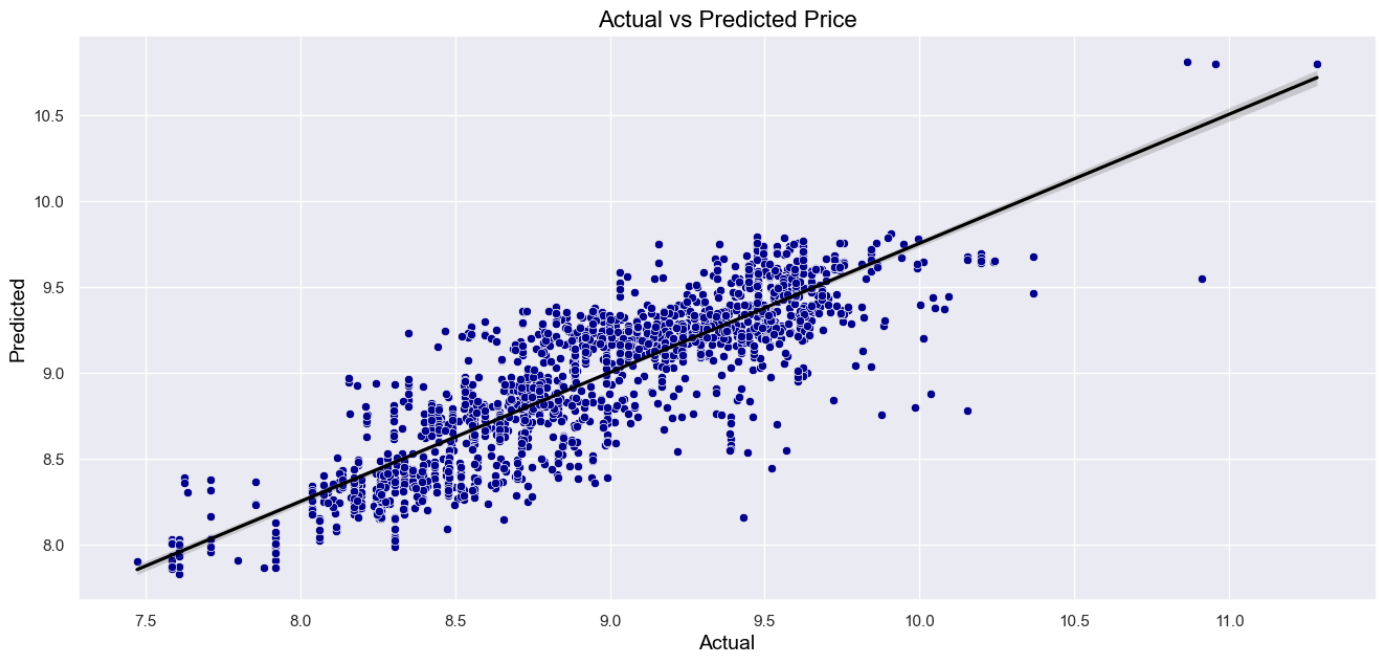
```
    adj_r2_test = np.round(1 - (1 - r2_score(y_test, y_test_pred)) * (len(y_test) - 1) / (len(y_
    mse = np.round(mean_squared_error(y_test, y_test_pred), 2)
    rmse = np.round(np.sqrt(mse), 2)
    mae = np.round(mean_squared_error(y_test, y_test_pred), 2)
    scores = cross_val_score(model, train, test, cv = 5, scoring = "neg_mean_squared_error").mea

    metrics.extend([r2_train_score, r2_test_score, variance, adj_r2_train, adj_r2_test, mse, rms
    print(pd.DataFrame(metrics,
                       index = ["r2_score (Train)", "r2_score (Test)", "Variance", "Adjusted_r2
                       columns = ["Metrics"]))

    # Plotting the actual vs predicted results
    plt.figure(figsize = (16, 7))
    sns.scatterplot(x = y_test, y = y_test_pred, color = "darkblue", edgecolor = "white")
    sns.regplot(x = y_test, y = y_test_pred, scatter = False, color = "black", line_kws = {"colo
    plt.xlabel("Actual", color = "black", size = 14)
    plt.ylabel("Predicted", color = "black", size = 14)
    plt.title(f"Actual vs Predicted Price", color = "black", size = 16)
    plt.show()
    print(f"\n\n")

    # Checking the normality of the residuals
    plt.figure(figsize = (16, 7))
    residuals = y_test - y_test_pred
    plt.subplot(1, 2, 1)
    sns.kdeplot(residuals, color = "darkblue")
    plt.subplot(1, 2, 2)
    stats.probplot(residuals, dist = "norm", plot = plt)
    plt.suptitle("Residuals Distribution", color = "black", size = 16)
    plt.show()
    print(f"\n\n")

    # Checking for homoscedasticity
    plt.figure(figsize = (16, 7))
    sns.scatterplot(x = y_test_pred, y = residuals, color = "darkblue")
    plt.axhline(y = 0, color = "red", linewidth = 2)
    plt.xlabel("Predictions", size = 14, color = "black")
    plt.ylabel("Residuals", size = 14, color = "black")
    plt.title("Predicted vs Residuals", color = "black", size = 16)
    plt.show()
    print(f"\n\n")

    return model, metrics
```

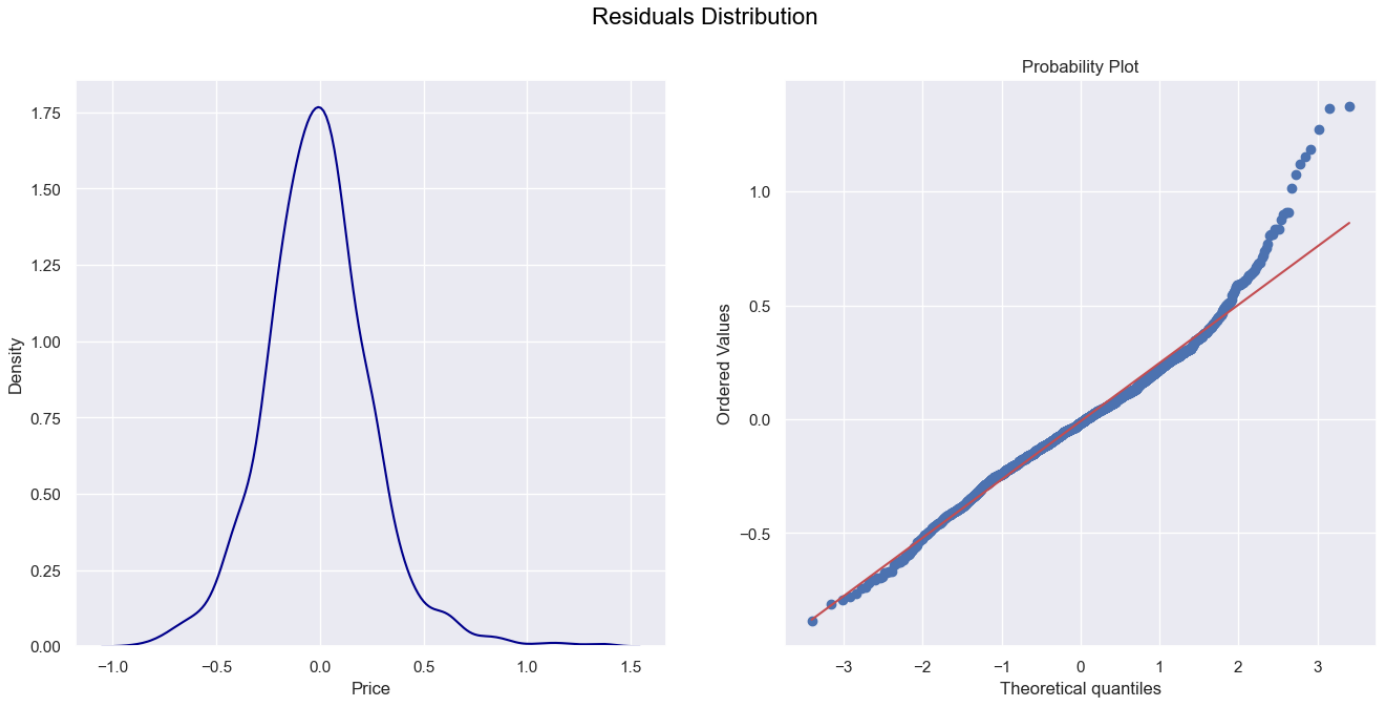
Linear Regression

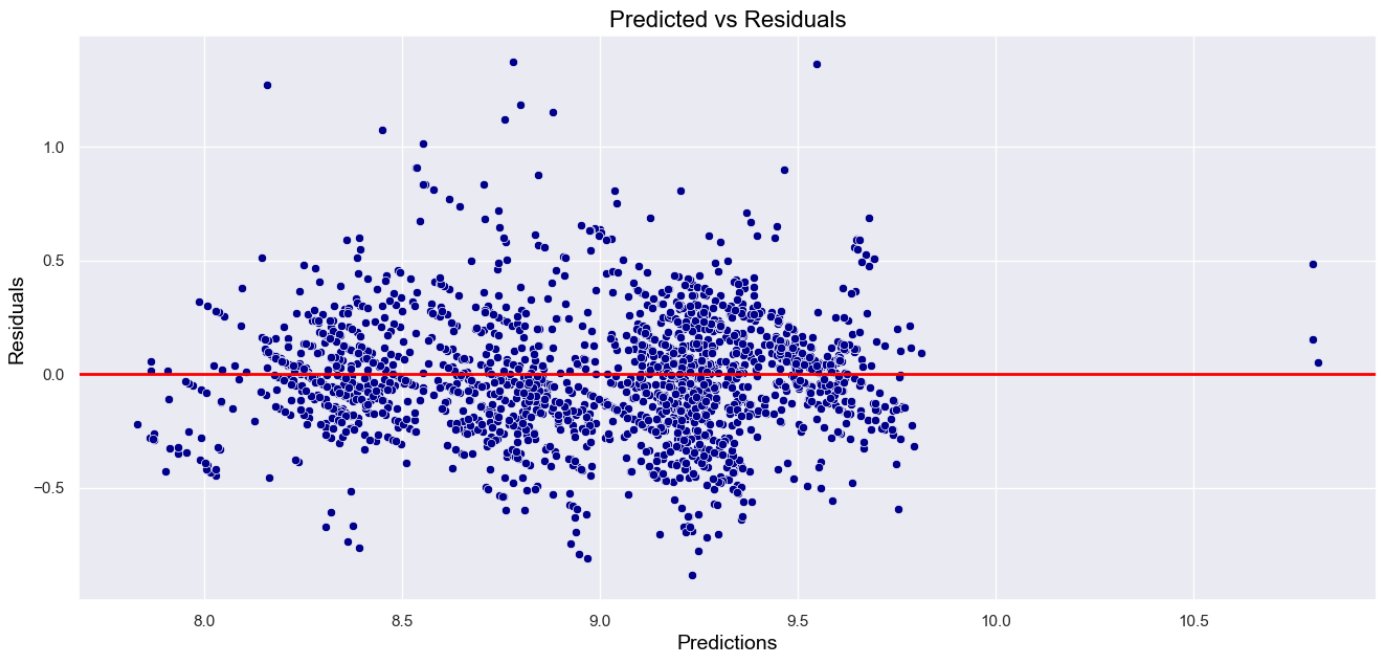
In [62]:
```
lr_base_model, lr_base_metrics = regression_model(LinearRegression(), X_sc, y)
```

Model : LinearRegression()

	Metrics
r2_score (Train)	0.758
r2_score (Test)	0.753
Variance	0.5%
Adjusted_r2 (Train)	0.757
Adjusted_r2 (Test)	0.75
MSE	0.07
RMSE	0.26
MAE	0.07
Cross_val_nmse (5-folds)	-0.064759


Actual vs Predicted Price
Predicted
Actual
10.5
10.0
9.5
9.0
8.5
8.0
7.5
8.0
8.5
9.0
9.5
10.0
10.5
11.0


Residuals Distribution
Density
Price
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
−1.0
−0.5
0.0
0.5
1.0
1.5
Probability Plot
Ordered Values
Theoretical quantiles
1.0
0.5
0.0
−0.5
−3
−2
−1
0
1
2
3



OLS

In [63]:
```
lr = LinearRegression()
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 11)
lr.fit(X_train, y_train)

reg_model = smf.OLS(endog = y_train, exog = X_train).fit()
reg_model.summary()
```

Out[63]:

OLS Regression Results

Dep. Variable:	Price	**R-squared (uncentered):**	0.970
Model:	OLS	**Adj. R-squared (uncentered):**	0.970
Method:	Least Squares	**F-statistic:**	1.181e+04
Date:	Tue, 10 Oct 2023	**Prob (F-statistic):**	0.00
Time:	20:19:13	**Log-Likelihood:**	-15559.
No. Observations:	8368	**AIC:**	3.116e+04
Df Residuals:	8345	**BIC:**	3.133e+04
Df Model:	23		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Day	0.0617	0.002	32.612	0.000	0.058	0.065
Month	0.2157	0.005	40.160	0.000	0.205	0.226
Arrival_Time_Hour	-0.0144	0.004	-3.663	0.000	-0.022	-0.007
Arrival_Time_Minute	0.0271	0.001	25.775	0.000	0.025	0.029
Dep_Time_Minute	0.0180	0.001	19.475	0.000	0.016	0.020
Total_Duration	0.0040	6.01e-05	65.747	0.000	0.004	0.004
Airline_Jet Airways	-0.5269	0.109	-4.846	0.000	-0.740	-0.314
Airline_IndiGo	-0.7182	0.061	-11.839	0.000	-0.837	-0.599
Airline_Air India	-0.5730	0.136	-4.201	0.000	-0.840	-0.306
Airline_Multiple carriers	0.0376	0.061	0.617	0.537	-0.082	0.157
Airline_Vistara	4.5946	0.900	5.106	0.000	2.831	6.358
Airline_Air Asia	0.8382	0.069	12.118	0.000	0.703	0.974
Airline_GoAir	0.4363	0.453	0.964	0.335	-0.451	1.324
Airline_Multiple carriers Premium economy	-0.2645	0.081	-3.271	0.001	-0.423	-0.106
Airline_Jet Airways Business	-0.7699	0.092	-8.331	0.000	-0.951	-0.589
Destination_Cochin	0.6914	0.046	15.097	0.000	0.602	0.781
Destination_Delhi	0.8707	0.055	15.817	0.000	0.763	0.979
Destination_Hyderabad	0.4583	0.081	5.659	0.000	0.300	0.617
Total_Stops_1	0.8699	0.058	14.896	0.000	0.755	0.984
Total_Stops_2	-0.2547	0.063	-4.055	0.000	-0.378	-0.132
Total_Stops_3	-1.3235	0.272	-4.861	0.000	-1.857	-0.790
In-flight_Meal_1	1.7620	0.053	33.321	0.000	1.658	1.866
Overnight_Flight_0	2.2417	0.069	32.663	0.000	2.107	2.376

Omnibus:	124.622	**Durbin-Watson:**	1.952
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	129.761
Skew:	0.302	**Prob(JB):**	6.65e-29

Kurtosis:	2.921	**Cond. No.**	4.26e+04

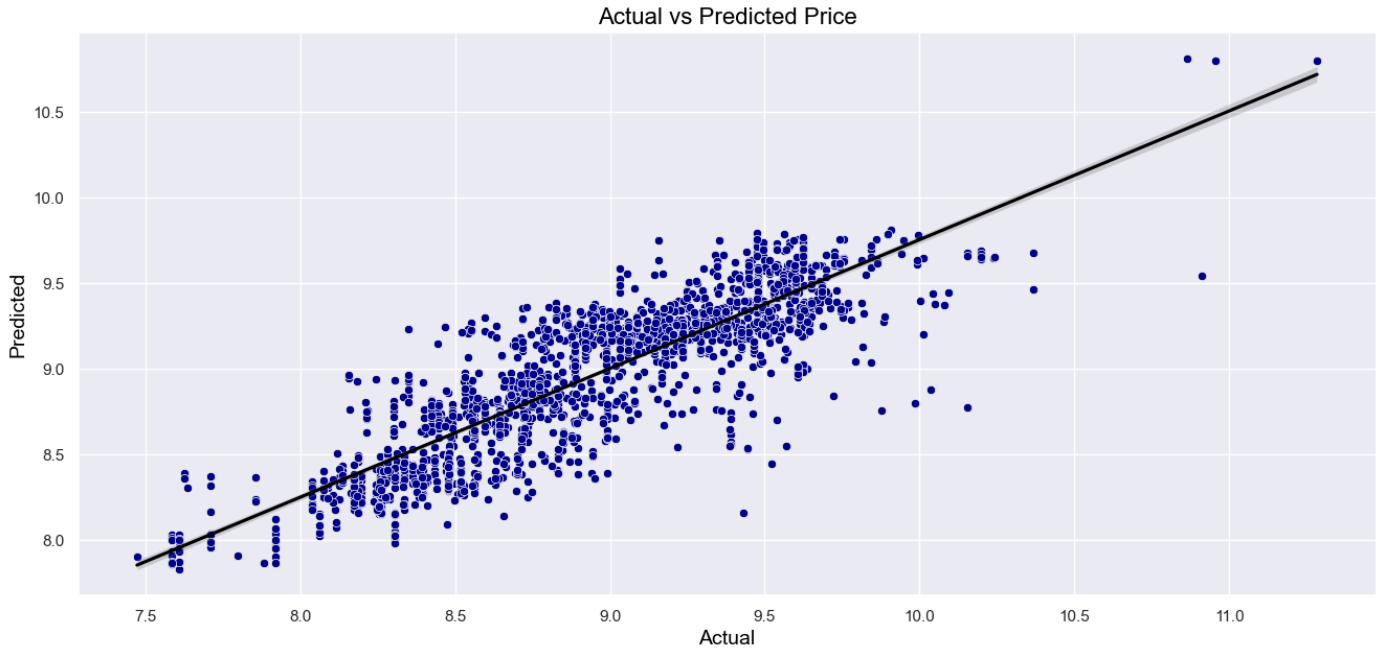
Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The condition number is large, 4.26e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

Linear / OLS Assumptions

Assumption 1 - Linearity

- A linear relationship exists between the independent and dependent features.
- The actual and predicted prices display a linear relationship.

In [64]:
```
# Verifying the linearity assumption

lr_base_model.fit(X_train, y_train)

# Making predicitons on the training and testing data
y_train_pred = lr_base_model.predict(X_train)
y_test_pred = lr_base_model.predict(X_test)

plt.figure(figsize = (16, 7))
sns.scatterplot(x = y_test, y = y_test_pred, color = "darkblue", edgecolor = "white")
sns.regplot(x = y_test, y = y_test_pred, scatter = False, color = "black", line_kws = {"color" :
plt.xlabel("Actual", color = "black", size = 14)
plt.ylabel("Predicted", color = "black", size = 14)
plt.title(f"Actual vs Predicted Price", color = "black", size = 16)
plt.show()
print(f"\n\n")
```



Assumption 2 - No Multicollinearity

- All the independent features have VIF < 5, which indicates the absence of multicollinearity among them.

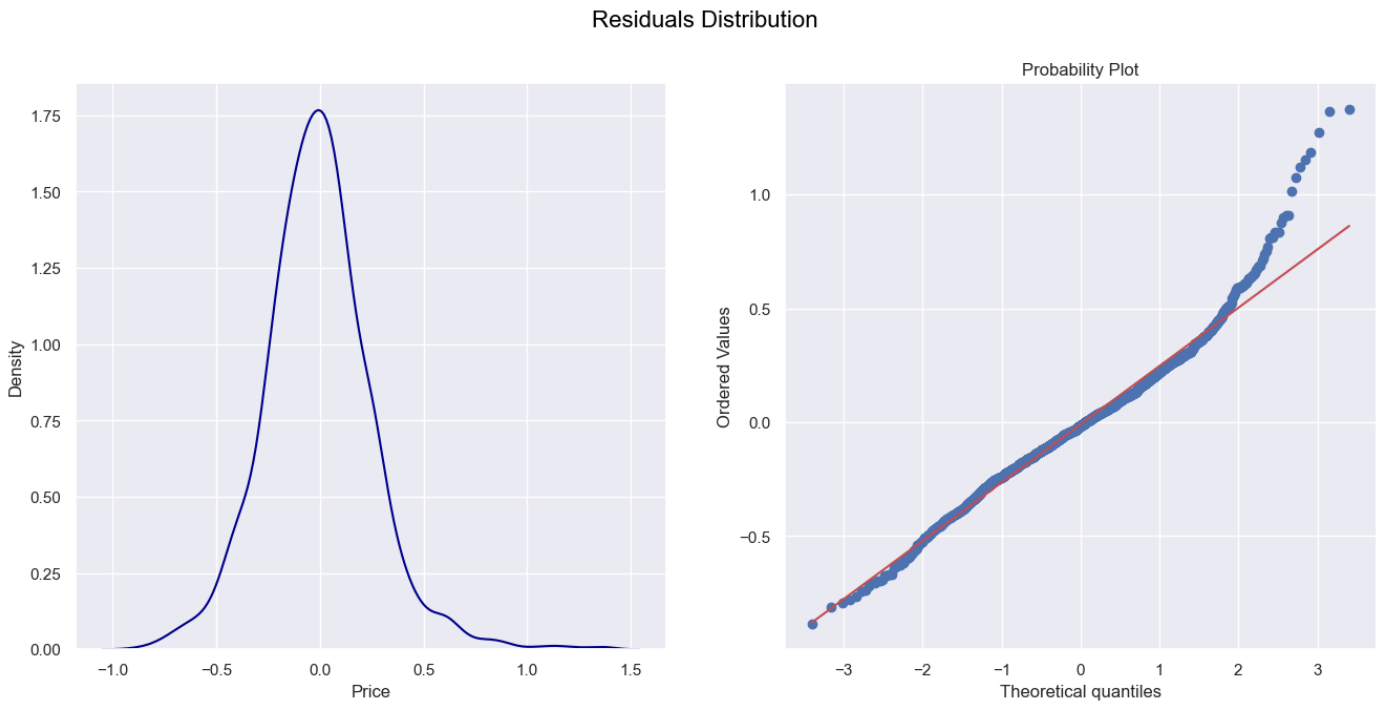
In [65]:
```
# Verifying the no multicollinearity assumption

vif = pd.Series([np.round(variance_inflation_factor(X_sc, col), 3) for col in range(X_sc.shape[1

high_vif = pd.Series()

for col in vif.index:
    if vif[col] > 5:
        high_vif[col] = vif[col]
    else:
        pass

high_vif.sort_values(ascending = False, inplace = True)

if len(high_vif) != 0:
    print('\033[1m' + "Features (VIF > 5)\n" + '\033[0m')
    print(high_vif)
else:
    print('\033[1m' + "There is no Multicollinearity." + '\033[0m')
```

There is no Multicollinearity.

Assumption 3 - Normality

- Residuals are normally distributed.

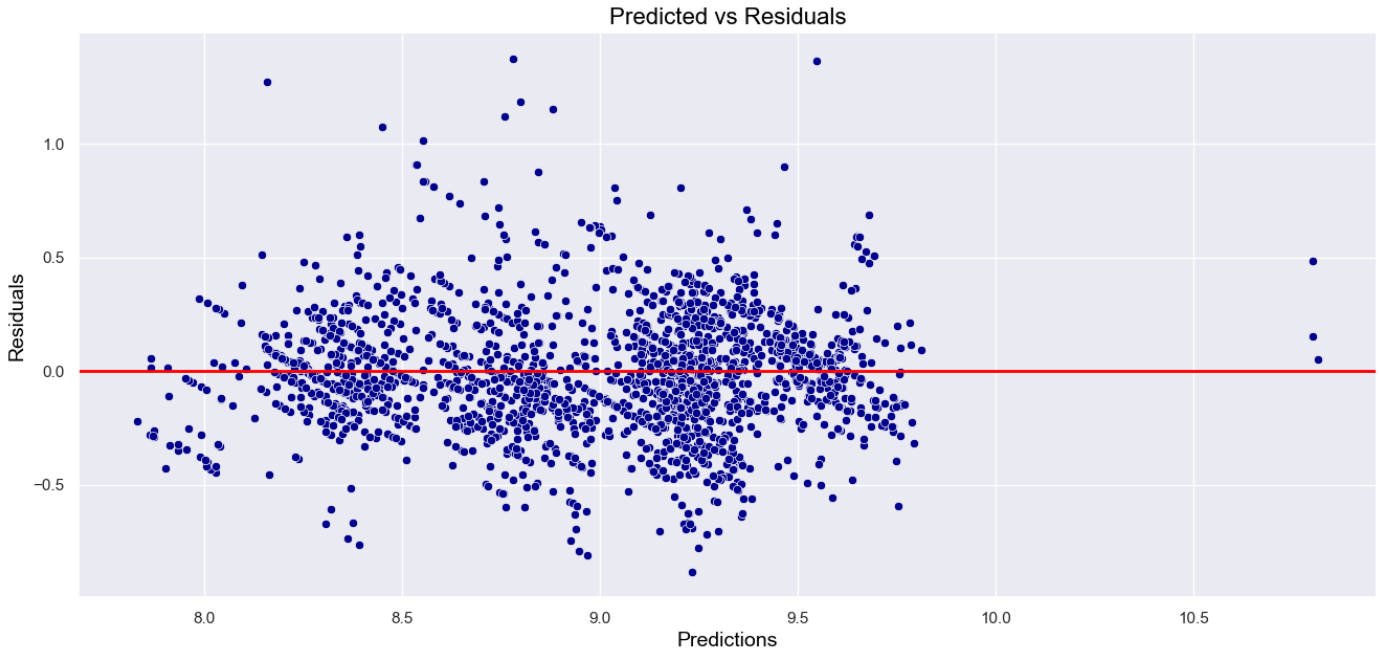
In [66]:
```
# Verifying the normality assumptions

plt.figure(figsize = (16, 7))
residuals = y_test - y_test_pred
plt.subplot(1, 2, 1)
sns.kdeplot(residuals, color = "darkblue")
plt.subplot(1, 2, 2)
stats.probplot(residuals, dist = "norm", plot = plt)
plt.suptitle("Residuals Distribution", color = "black", size = 16)
plt.show()
print(f"\n\n")
```



Assumption 4 - Homoscedasticity

- The residuals exhibit equal variance.

In [67]:
```
residuals = y_test - y_test_pred
plt.figure(figsize = (16, 7))
sns.scatterplot(x = y_test_pred, y = residuals, color = "darkblue")
plt.axhline(y = 0, color = "red", linewidth = 2)
plt.xlabel("Predictions", size = 14, color = "black")
plt.ylabel("Residuals", size = 14, color = "black")
plt.title("Predicted vs Residuals", color = "black", size = 16)
plt.show()
print(f"\n\n")
```



Assumption 5 - No Autocorrelation

- The Durbin-Watson statistic value is 1.95, which is nearly equal to 2, suggesting the absence of autocorrelation.

In [68]:
```
residuals = reg_model.resid
durbin_watson_statistic = sm.stats.stattools.durbin_watson(residuals)
print(f"Durbin Watson : {np.round(durbin_watson_statistic, 2)}")
```

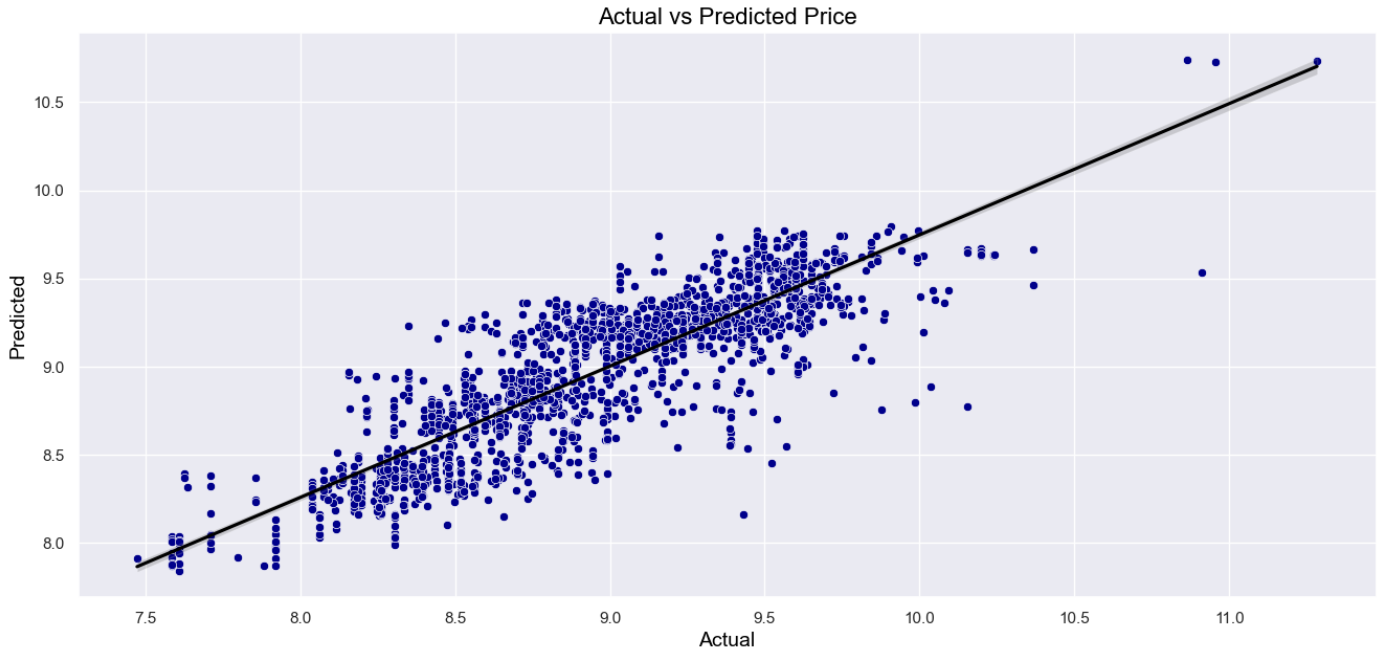
```
Durbin Watson : 1.95
```

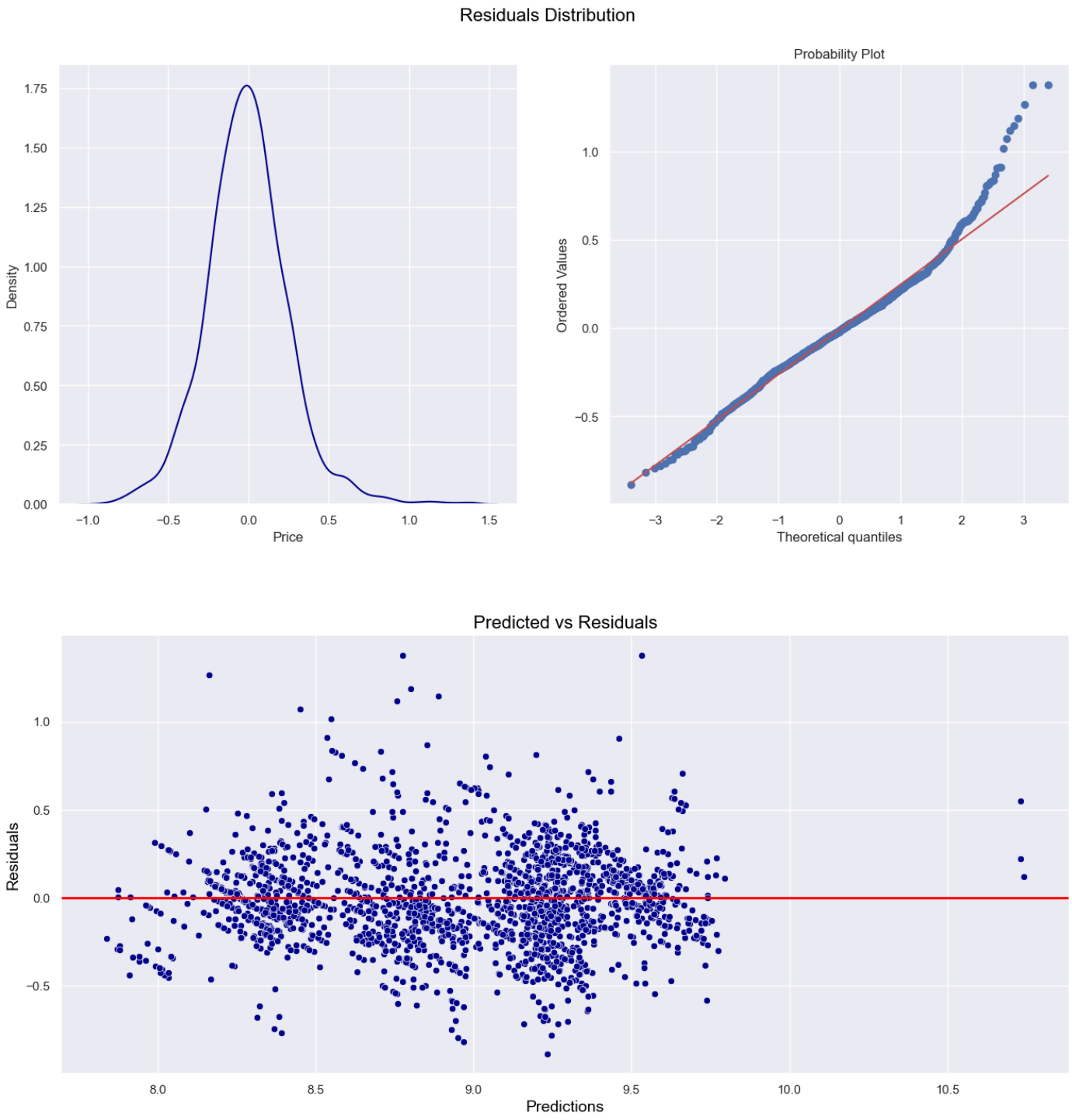
Lasso Regression (L1 Regularization)

In [69]:
```
# grid_model = GridSearchCV(Lasso(), param_grid = {"alpha" : [0.001, 0.01, 0.1, 1, 5]}, scoring =
# print(grid_model.best_params_)

lasso_model, lasso_metrics = regression_model(Lasso(0.001), X_sc, y)
```

Model : Lasso(alpha=0.001)

	Metrics
r2_score (Train)	0.758
r2_score (Test)	0.753
Variance	0.5%
Adjusted_r2 (Train)	0.757
Adjusted_r2 (Test)	0.75
MSE	0.07
RMSE	0.26
MAE	0.07
Cross_val_nmse (5-folds)	-0.064794



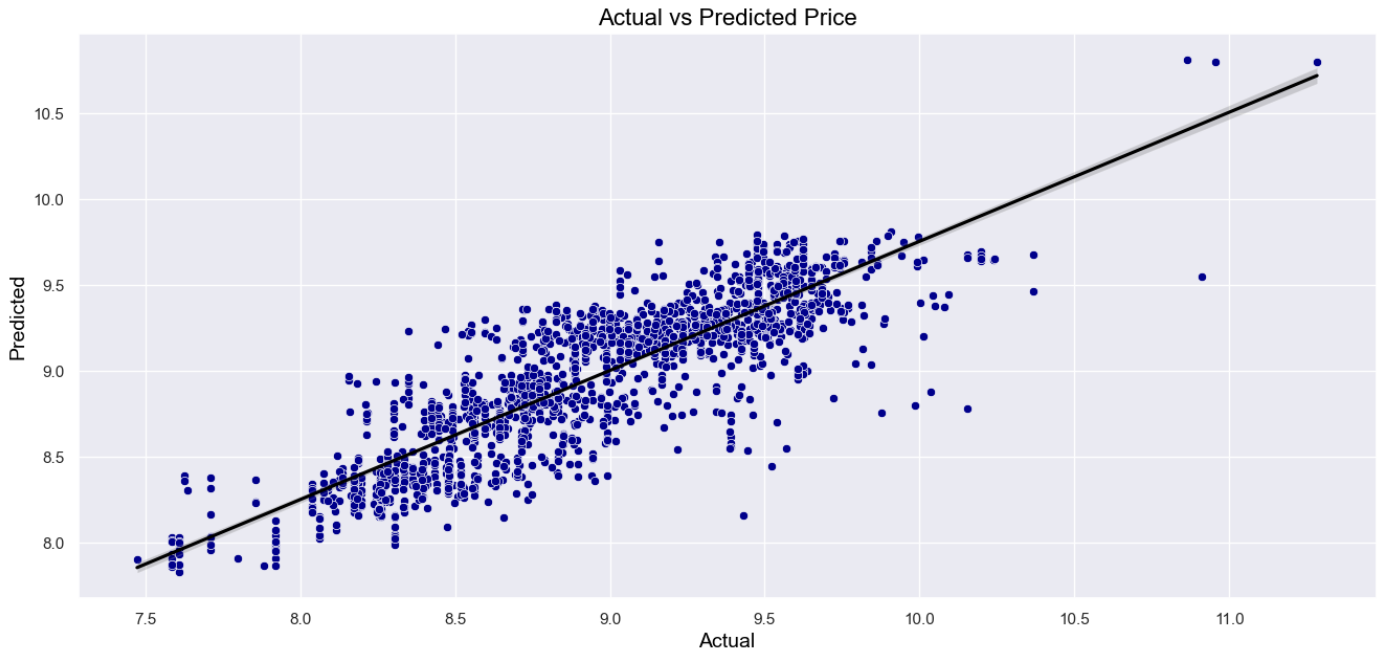


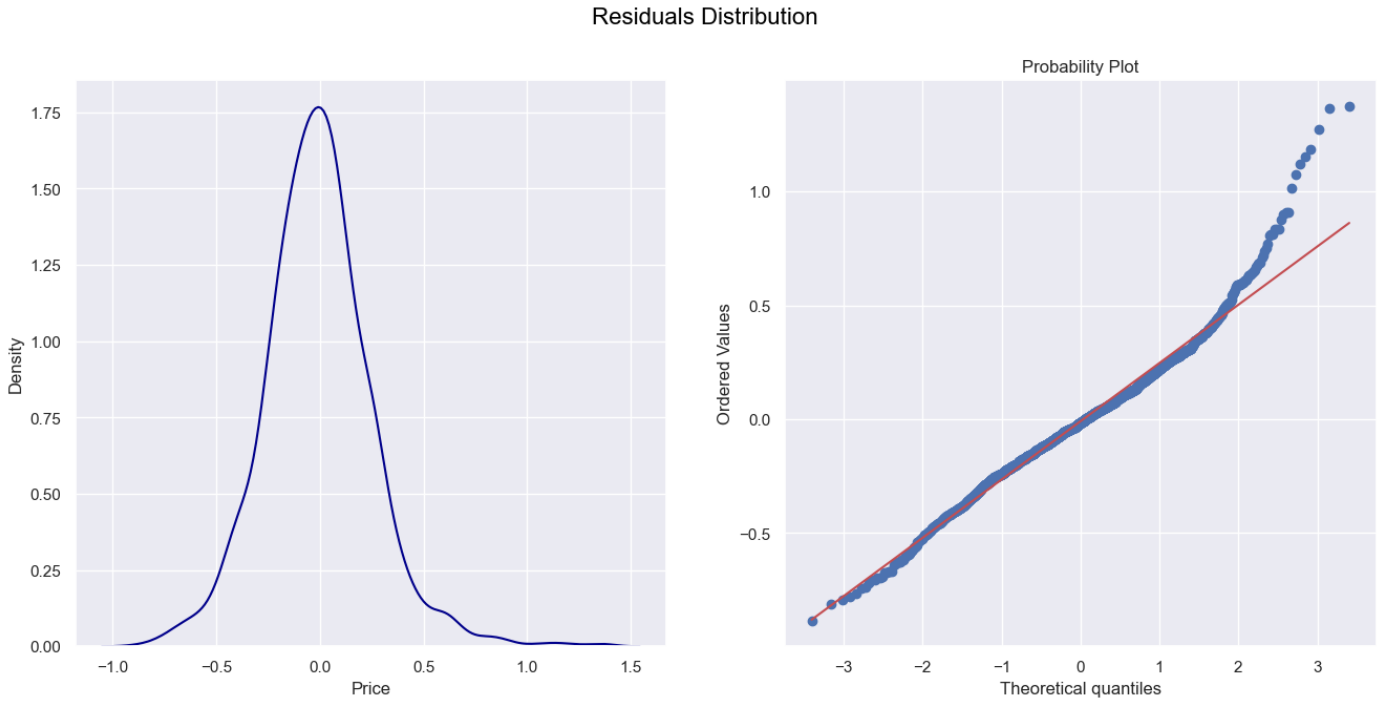
Ridge Regression (L2 Regularization)

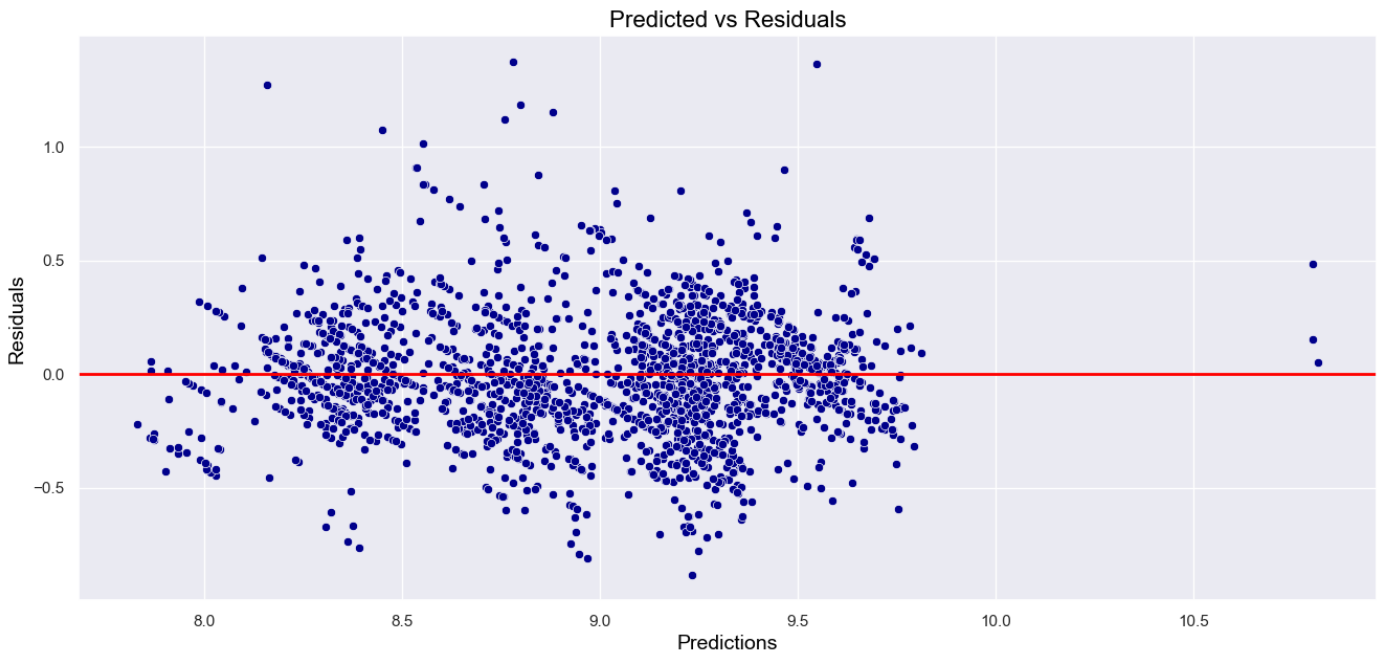
In [70]:
```
# grid_model = GridSearchCV(Ridge(), param_grid = {"alpha" : [0.001, 0.01, 0.1, 1, 5]}, scoring =
# print(grid_model.best_params_)

ridge_model, ridge_metrics = regression_model(Ridge(0.1), X_sc, y)
```

Model : Ridge(alpha=0.1)

	Metrics
r2_score (Train)	0.758
r2_score (Test)	0.753
Variance	0.5%
Adjusted_r2 (Train)	0.757
Adjusted_r2 (Test)	0.75
MSE	0.07
RMSE	0.26
MAE	0.07
Cross_val_nmse (5-folds)	-0.064759





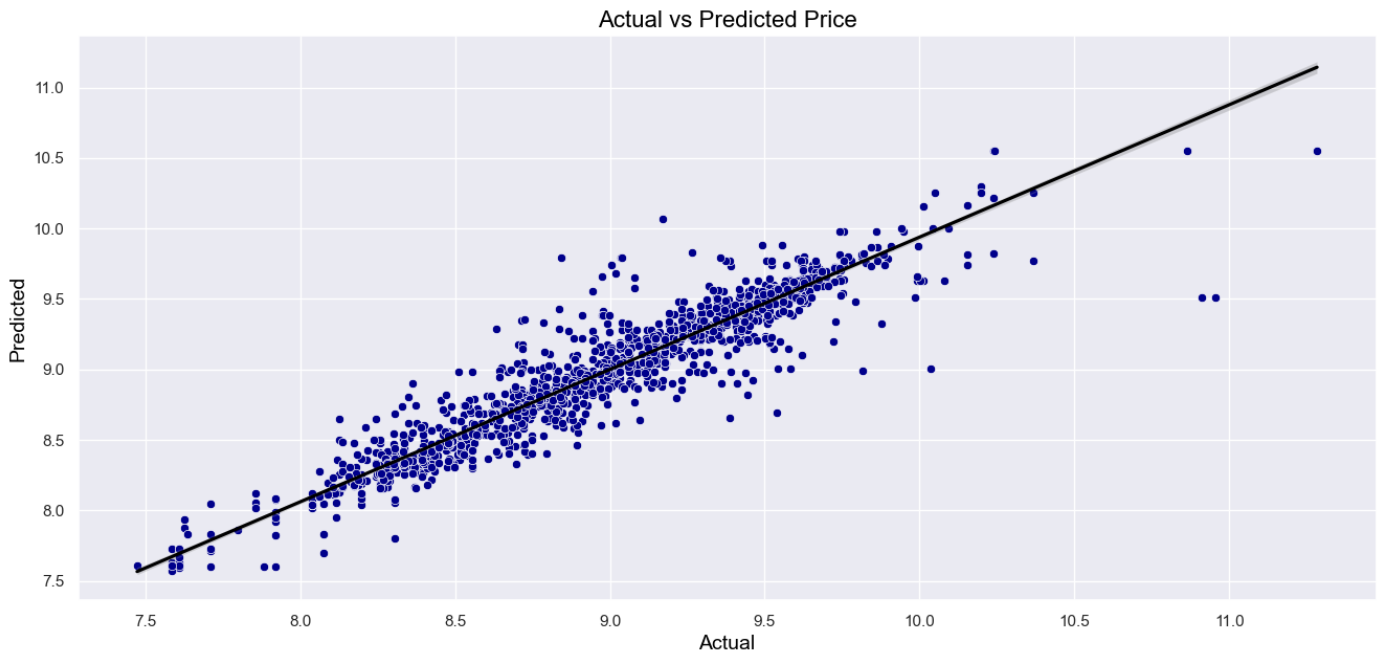


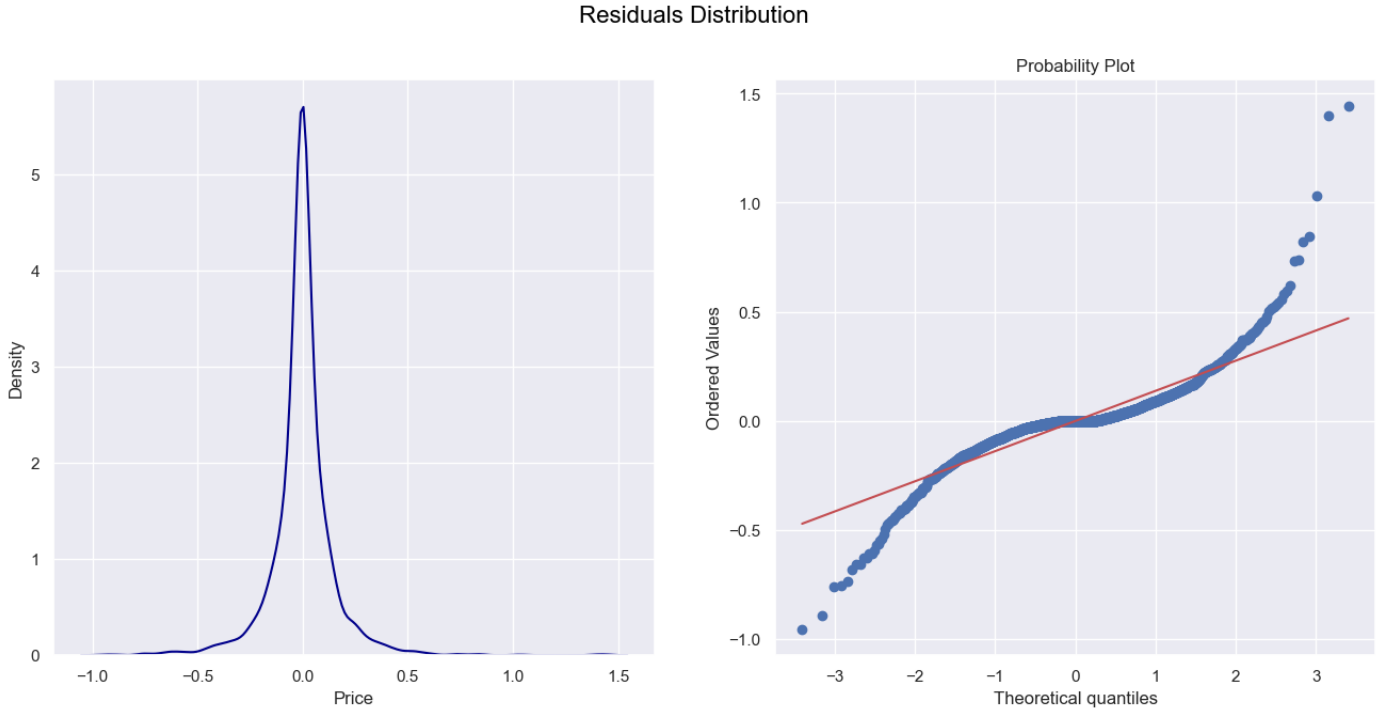
Decision Tree Regressor

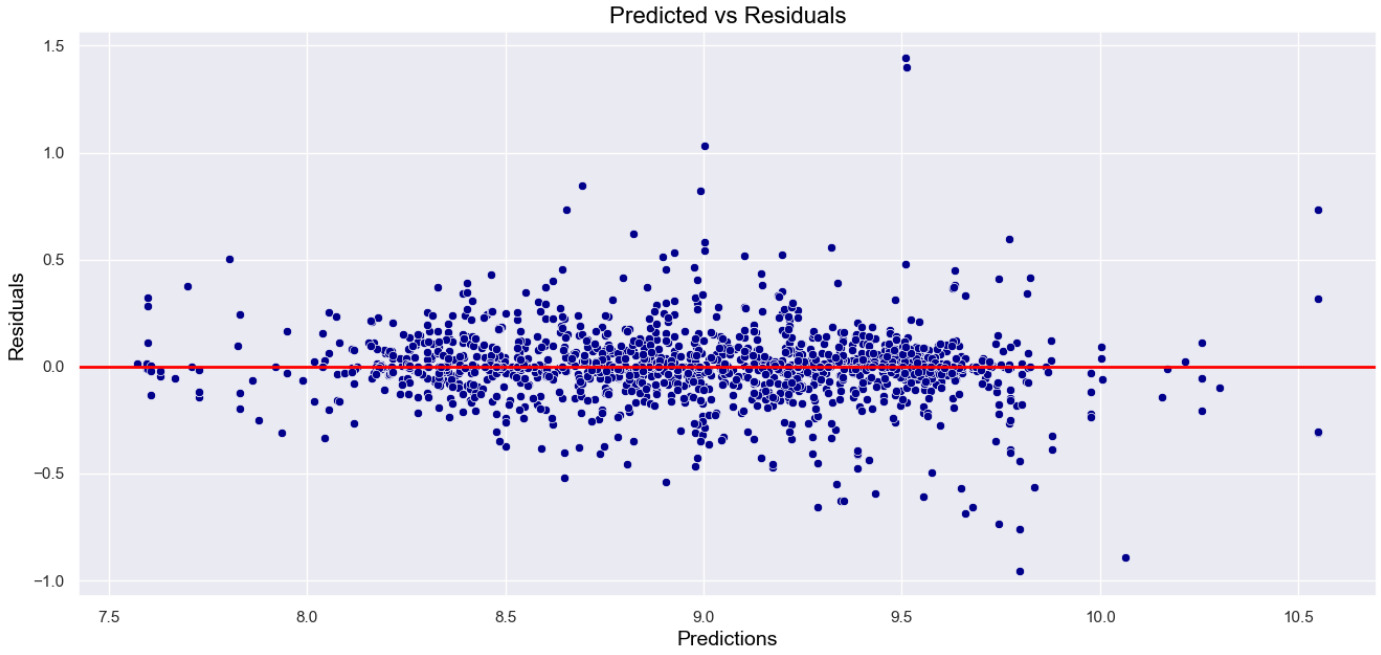
In [71]:
```
# param_grid = {
#     "max_depth" : [None, 1, 2, 3, 4, 5, 7, 10],
#     "min_samples_split" : [2, 5, 10, 20, 30],
#     "min_samples_leaf" : [1, 2, 3, 4, 5],
#     "max_features" : ['auto', 'sqrt', 'log2']
# }

# grid_model = GridSearchCV(DecisionTreeRegressor(), param_grid, scoring = "r2").fit(X_train, y_

# print(grid_model.best_params_)

dt_model, dt_metrics = regression_model(DecisionTreeRegressor(max_depth = None, max_features = "
```

**Model : DecisionTreeRegressor(max_features='auto', min_samples_leaf=3,
min_samples_split=10)**

	Metrics
r2_score (Train)	0.962
r2_score (Test)	0.914
Variance	4.8%
Adjusted_r2 (Train)	0.962
Adjusted_r2 (Test)	0.913
MSE	0.02
RMSE	0.14
MAE	0.02
Cross_val_nmse (5-folds)	-0.023099


Actual vs Predicted Price
Predicted
Actual
11.0
10.5
10.0
9.5
9.0
8.5
8.0
7.5
7.5
8.0
8.5
9.0
9.5
10.0
10.5
11.0


Residuals Distribution
Density
Price
5
4
3
2
1
0
−1.0
−0.5
0.0
0.5
1.0
1.5
Probability Plot
Ordered Values
Theoretical quantiles
1.5
1.0
0.5
0.0
−0.5
−1.0
−3
−2
−1
0
1
2
3

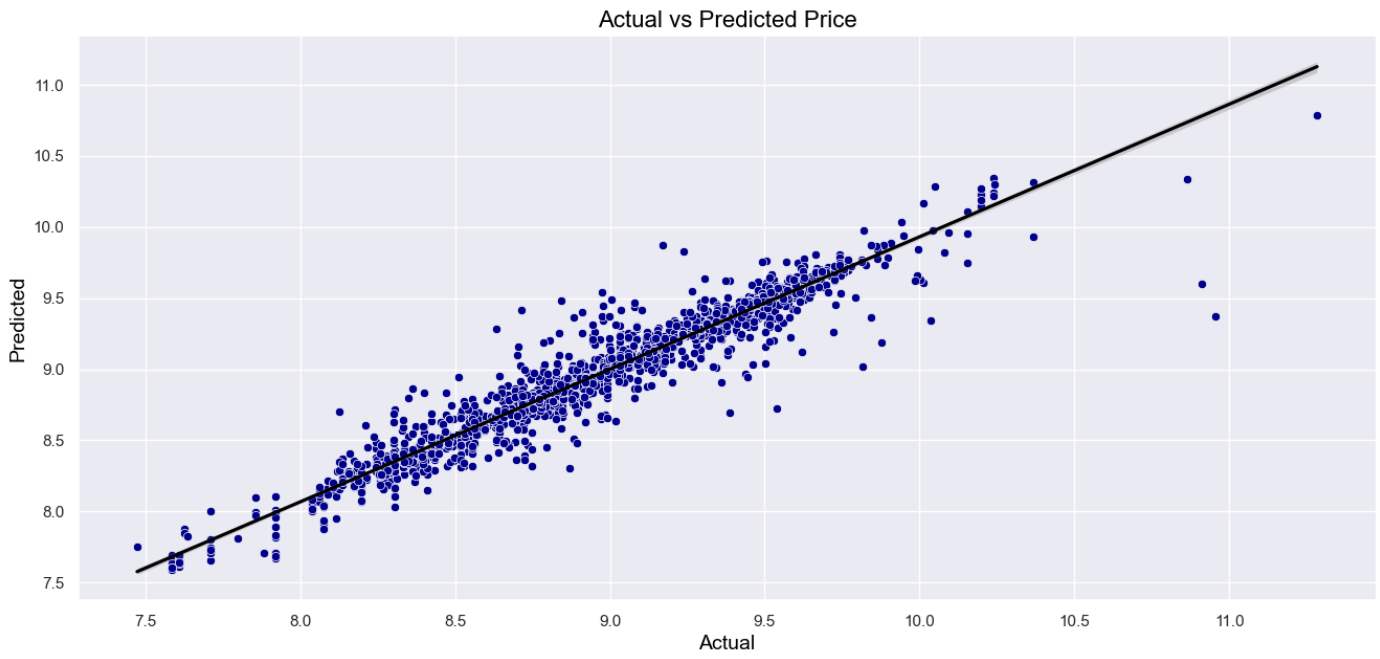


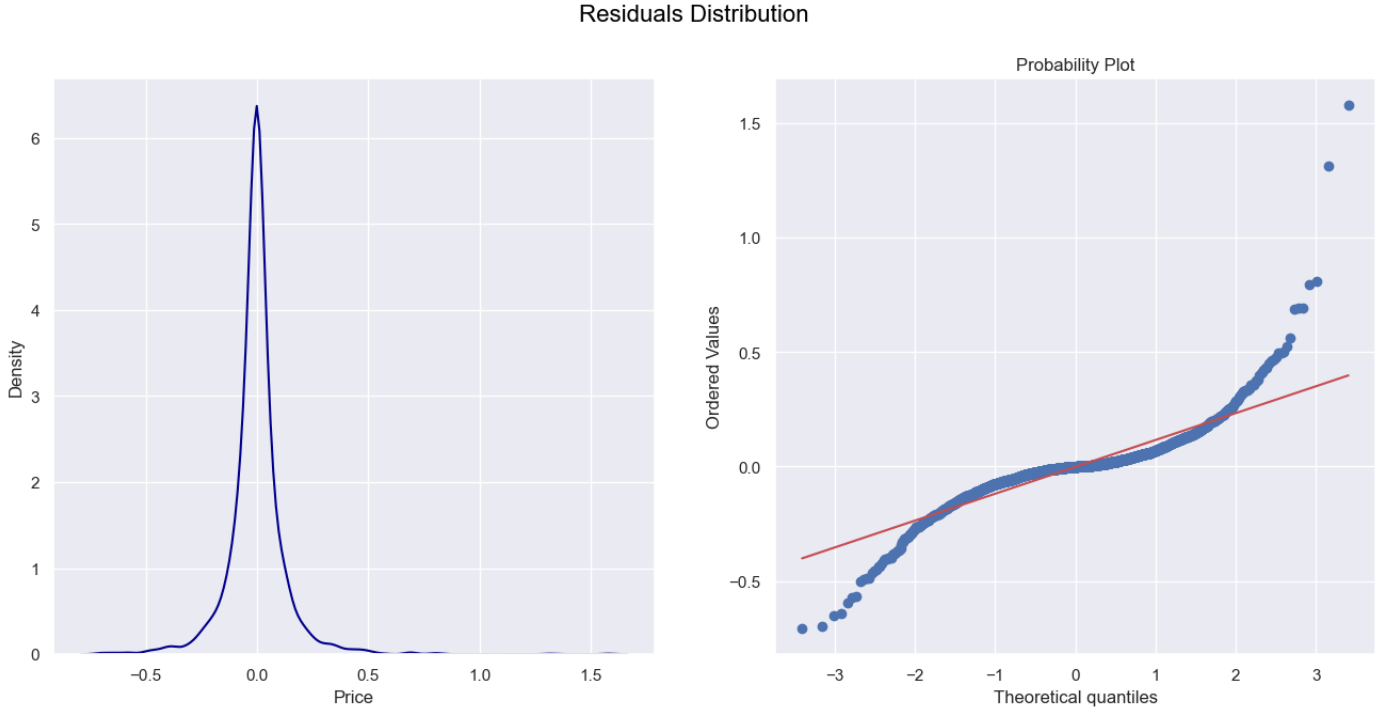
Random Forest Regressor

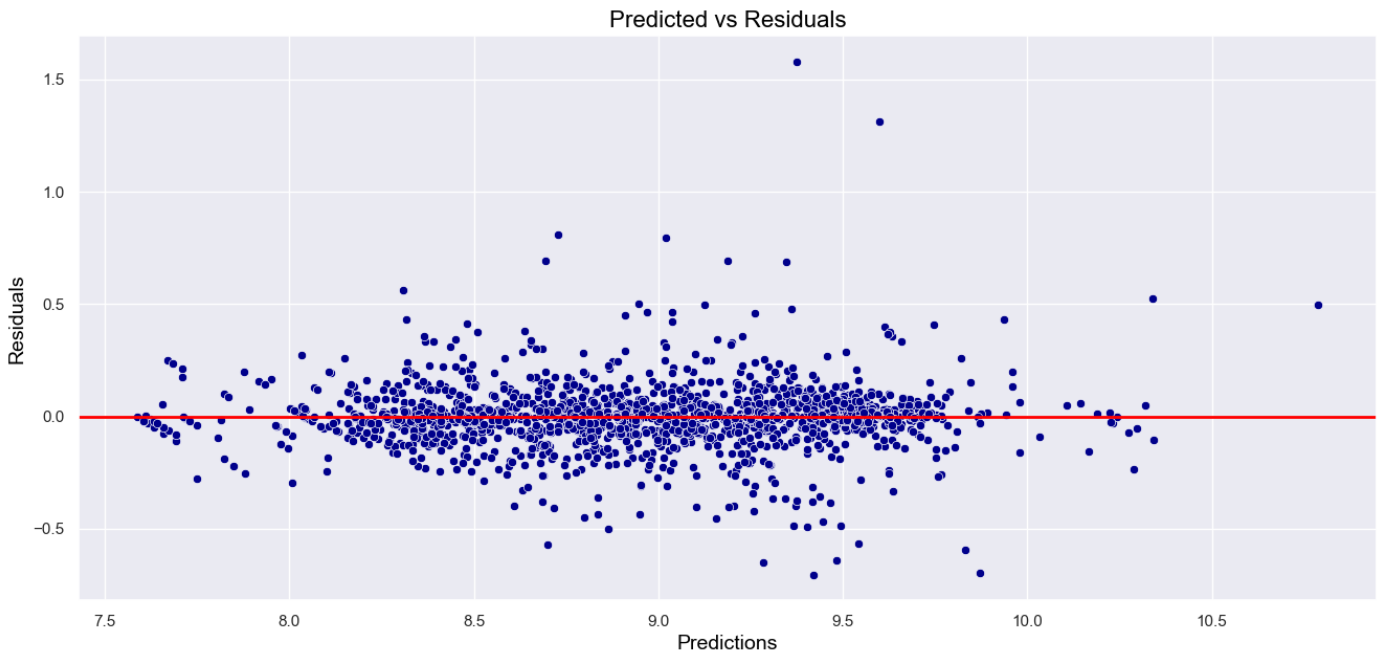
In [72]:
```
X_sc = StandardScaler().fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X_sc, y, test_size = 0.2, random_state = 11)

# param_grid = {"max_depth" : [None, 2, 3, 10],
#               "max_features" : ['auto', 'sqrt', 'log2'],
#               "min_samples_leaf" : [1, 2, 4],
#               "min_samples_split" : [2, 5, 10],
#               "n_estimators" :  [100, 200, 300]
#               }

# grid_model = GridSearchCV(RandomForestRegressor(bootstrap = True), param_grid, scoring = "r2")

# print(grid_model.best_params_)

rf_model, rf_metrics = regression_model(RandomForestRegressor(max_depth = None, max_features = "
```

**Model : RandomForestRegressor(max_features='auto', min_samples_split=5,
n_estimators=200)**

	Metrics
r2_score (Train)	0.979
r2_score (Test)	0.937
Variance	4.2%
Adjusted_r2 (Train)	0.979
Adjusted_r2 (Test)	0.936
MSE	0.02
RMSE	0.14
MAE	0.02
Cross_val_nmse (5-folds)	-0.017326


Actual vs Predicted Price
Predicted
Actual
11.0
10.5
10.0
9.5
9.0
8.5
8.0
7.5
7.5
8.0
8.5
9.0
9.5
10.0
10.5
11.0

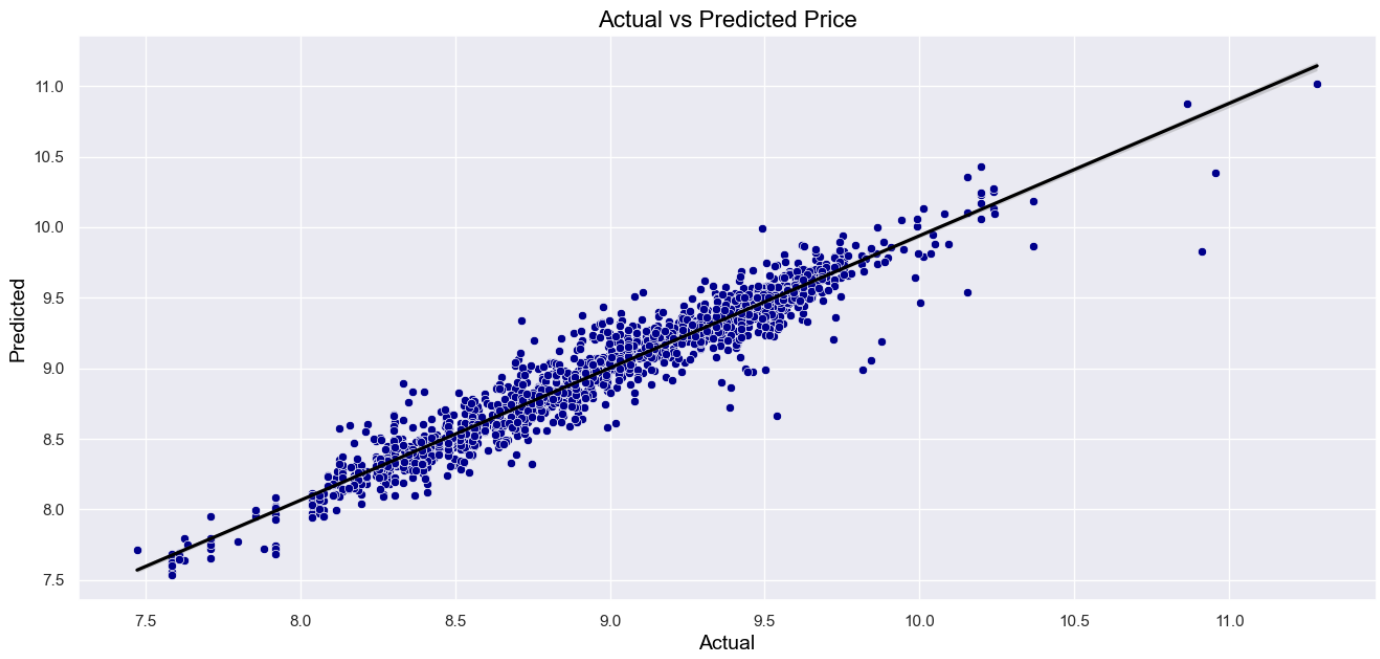

Residuals Distribution
Density
Price
6
5
4
3
2
1
0
−0.5
0.0
0.5
1.0
1.5
Probability Plot
Ordered Values
Theoretical quantiles
1.5
1.0
0.5
0.0
−0.5
−3
−2
−1
0
1
2
3

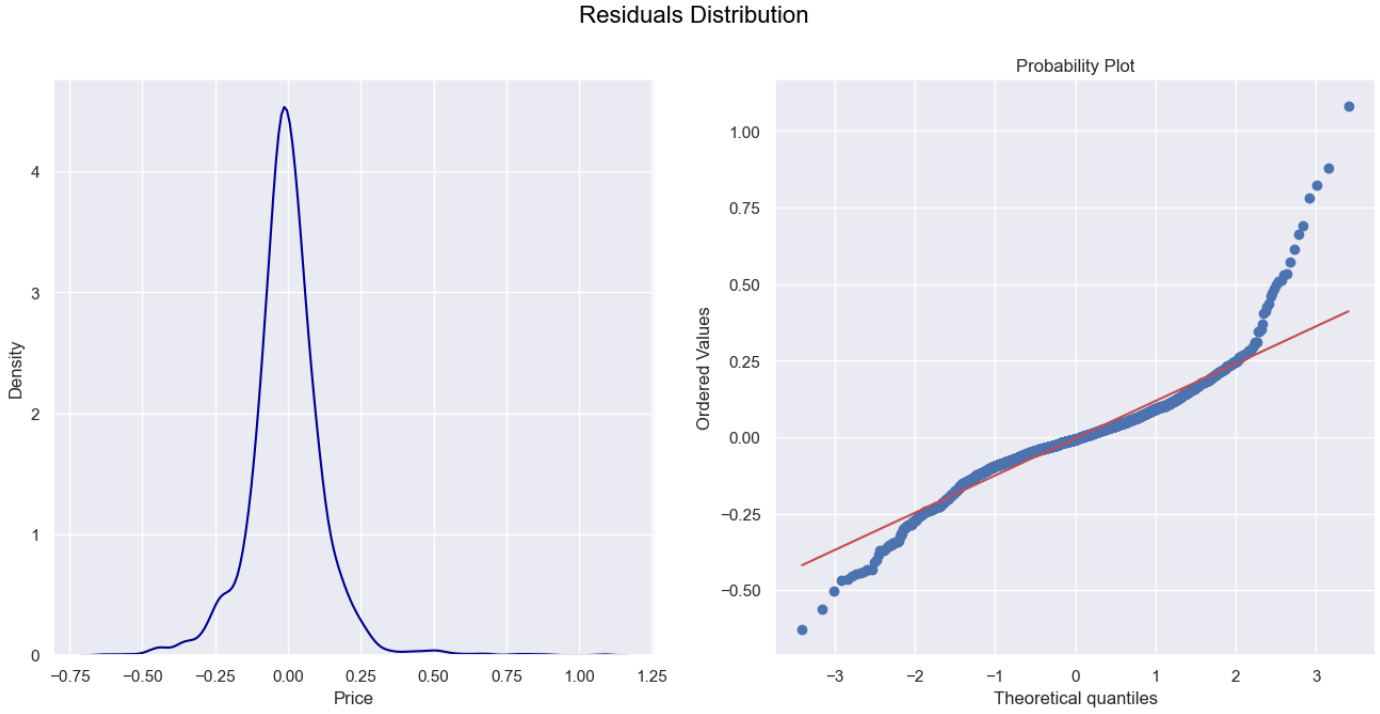


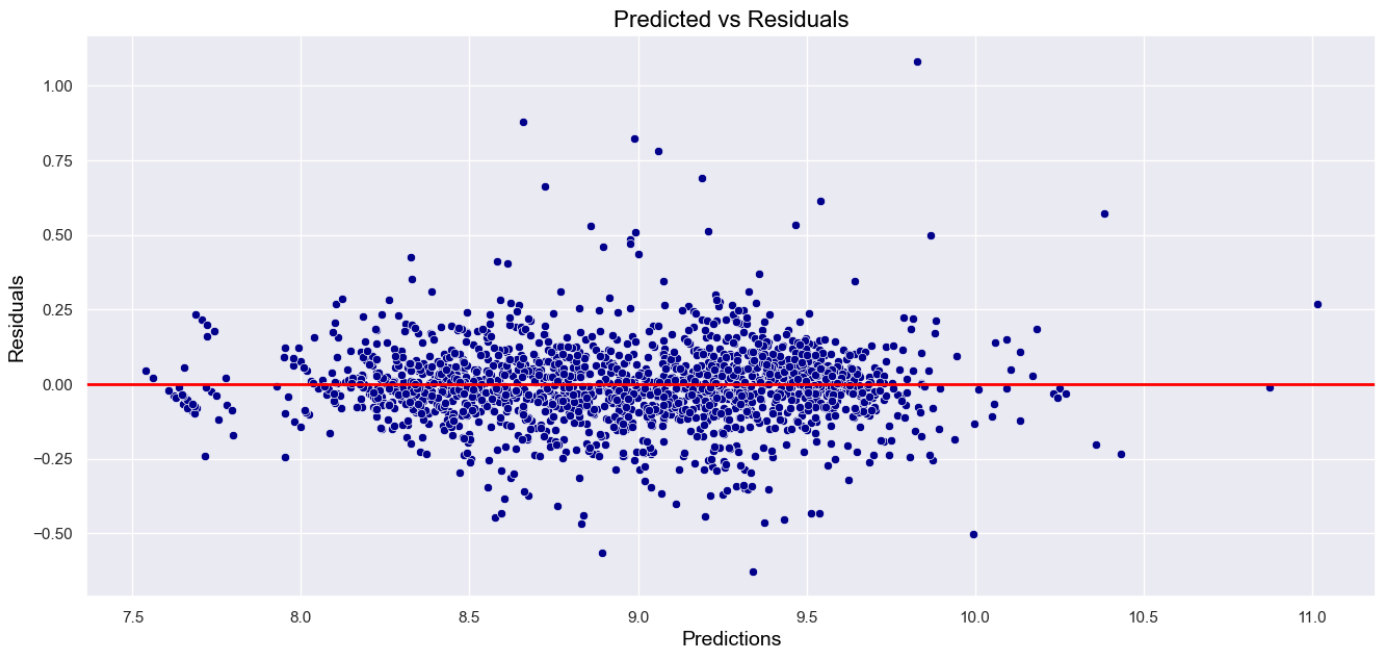
XGBoost Regressor

In [73]:
```
xgb_model, xgb_metrics = regression_model(XGBRegressor(), X_sc, y)
```

```
                                  Model : XGBRegressor(base_score=None, booster=None, call
backs=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             n_estimators=100, n_jobs=None, num_parallel_tree=None,
             predictor=None, random_state=None, ...)

                          Metrics
r2_score (Train)             0.97
r2_score (Test)              0.94
Variance                     3.0%
Adjusted_r2 (Train)         0.969
Adjusted_r2 (Test)          0.939
MSE                          0.02
RMSE                         0.14
MAE                          0.02
Cross_val_nmse (5-folds) -0.01637
```


Actual vs Predicted Price
Predicted
Actual
11.0
10.5
10.0
9.5
9.0
8.5
8.0
7.5
7.5
8.0
8.5
9.0
9.5
10.0
10.5
11.0


Residuals Distribution
Density
Price
4
3
2
1
0
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
1.25
Probability Plot
Ordered Values
Theoretical quantiles
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−3
−2
−1
0
1
2
3



Final Results

In [74]:
```
pd.DataFrame([lr_base_metrics, lasso_metrics, ridge_metrics, dt_metrics, rf_metrics, xgb_metrics
              index = ["Linear Regression", "Lasso Regression", "Ridge Regression", "Decision Tre
              columns = ["r2_score (train)", "r2_score (test)", "Varaince", "Adj_r2_score (train)
```

Out[74]:

	r2_score (train)	r2_score (test)	Varaince	Adj_r2_score (train)	Adj_r2_score (test)	MSE	RMSE	MAE	Cross_val_mse
Linear Regression	0.758	0.753	0.5%	0.757	0.750	0.07	0.26	0.07	-0.064759
Lasso Regression	0.758	0.753	0.5%	0.757	0.750	0.07	0.26	0.07	-0.064794
Ridge Regression	0.758	0.753	0.5%	0.757	0.750	0.07	0.26	0.07	-0.064759
Decision Tree Regressor	0.962	0.914	4.8%	0.962	0.913	0.02	0.14	0.02	-0.023099
Random Forest Regressor	0.979	0.937	4.2%	0.979	0.936	0.02	0.14	0.02	-0.017326
XGBoost Regressor	0.970	0.940	3.0%	0.969	0.939	0.02	0.14	0.02	-0.016370