Customer Sales Data EDA Analysis

Import python libraries

In [4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
pd.options.display.float_format = '{:,.2f}'.format
warnings.filterwarnings("ignore")
```

Dataset Loading

In [5]:
```
df=pd.read_csv("/content/Customer_sales_dataset.csv")
```

In [6]:
```
# show fisrt 5 rows
df.head()
```

Out[6]:

	order_id	order_date	region	country	customer_segment	product_categor
0	ORD204623	2021-01-01	North	UK	Consumer	Electronic
1	ORD213244	2021-01-01	North	Australia	Home Office	Office Supplie
2	ORD200353	2021-01-01	East	UK	Corporate	Electronic
3	ORD204552	2021-01-01	North	Australia	Consumer	Electronic
4	ORD210506	2021-01-01	Central	India	Consumer	Furnitur

In [7]:
```
# show last five rows
df.tail()
```

Out[7]:

	order_id	order_date	region	country	customer_segment	product_cat
14995	ORD214919	2024-12-30	South	UK	Consumer	Elec
14996	ORD203260	2024-12-30	North	Australia	Home Office	Fu
14997	ORD202671	2024-12-30	East	Australia	Home Office	Office S
14998	ORD202805	2024-12-30	North	India	Corporate	Elec
14999	ORD200137	2024-12-30	West	Australia	Home Office	Office S

In [10]:
```
#shape of dataset
```

```
df.shape
```

Out[10]:
```
(15000, 12)
```

In [11]:
```
#Check all the cloumns in dataset
df.columns
```

Out[11]:
```
Index(['order_id', 'order_date', 'region', 'country', 'customer_segment',
       'product_category', 'product_name', 'quantity', 'unit_price', 'sales',
       'discount', 'profit'],
      dtype='object')
```

In [12]:
```
#check datatype of dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15000 entries, 0 to 14999
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   order_id          15000 non-null  object 
 1   order_date        15000 non-null  object 
 2   region            15000 non-null  object 
 3   country           15000 non-null  object 
 4   customer_segment  15000 non-null  object 
 5   product_category  15000 non-null  object 
 6   product_name      15000 non-null  object 
 7   quantity          15000 non-null  int64  
 8   unit_price        15000 non-null  float64
 9   sales             15000 non-null  float64
 10  discount          15000 non-null  float64
 11  profit            15000 non-null  float64
dtypes: float64(4), int64(1), object(7)
memory usage: 1.4+ MB
```

Data Cleaning and Preprocessing

In [13]:
```
# identify Missing values
df.isnull().sum()
```

Out[13]:

	0
order_id	0
order_date	0
region	0
country	0
customer_segment	0
product_category	0
product_name	0
quantity	0
unit_price	0
sales	0
discount	0
profit	0

dtype: int64

Insights -- There is no anykind of missing value and no need to handle them.

In [15]:
```
df.duplicated().sum()
```

Out[15]:
```
np.int64(0)
```

Insights -- I have been observed that there is no duplicate value and it is good for analysis

In [16]:
```
df.dtypes
```

Out[16]:

	0
order_id	object
order_date	object
region	object
country	object
customer_segment	object
product_category	object
product_name	object
quantity	int64
unit_price	float64
sales	float64
discount	float64
profit	float64

dtype: object

Insights -- As per my analysis all the data types are correct and no need to change them

In [17]:

```
#Standardtize text
df.columns = df.columns.str.title().str.replace(' ', '_')
```

In [18]:

```
df.head()
```

Out[18]:

	Order_Id	Order_Date	Region	Country	Customer_Segment	Product_Categ
0	ORD204623	2021-01-01	North	UK	Consumer	Electror
1	ORD213244	2021-01-01	North	Australia	Home Office	Office Supp
2	ORD200353	2021-01-01	East	UK	Corporate	Electror
3	ORD204552	2021-01-01	North	Australia	Consumer	Electror
4	ORD210506	2021-01-01	Central	India	Consumer	Furnit

Exploratory Data Analysis

In [19]:

```
# summary Statistics
df.describe()
```

Out[19]:

	Quantity	Unit_Price	Sales	Discount	Profit
count	15,000.00	15,000.00	15,000.00	15,000.00	15,000.00
mean	5.47	1,019.65	5,582.70	0.15	133.73
std	2.87	564.00	4,547.63	0.09	810.15
min	1.00	50.16	50.16	0.00	-3,889.18
25%	3.00	524.12	1,805.56	0.08	-167.92
50%	5.00	1,015.83	4,288.35	0.15	52.10
75%	8.00	1,506.81	8,393.08	0.22	401.33
max	10.00	1,999.81	19,969.80	0.30	5,186.82

Insights -- Sales and profit values show high variability, indicating a mix of low and high-value orders.

In [22]:

```
#categorial columns value count
df['Region'].value_counts()
```

Out[22]:

Region	count
Central	3086
West	3067
North	2956
East	2952
South	2939

dtype: int64

In [23]:

```
df['Product_Category'].value_counts()
```

Out[23]:

Product_Category	count
Furniture	5038
Electronics	4994
Office Supplies	4968

dtype: int64

Insights --

central Region is th most frequently sold.

Electronics is the most frequently sold category.

In [24]:
```
#groupby analysis
df.groupby("Product_Category")['Sales'].sum().sort_values(ascending=False)
```

Out[24]:

	Sales
Product_Category	
Furniture	28,790,718.64
Electronics	27,620,653.96
Office Supplies	27,329,149.28

dtype: float64

In [25]:
```
#Avg profit
df.groupby("Customer_Segment")["Profit"].mean()
```

Out[25]:

	Profit
Customer_Segment	
Consumer	123.84
Corporate	131.56
Home Office	146.01

dtype: float64

Insights --

Furniture generates the highest revenue, driven by higher unit prices.

Home office customers generate the highest average profit per order.

In [28]:
```
#top 10 product by sale
df.groupby("Product_Name")["Sales"].sum().sort_values(ascending=False).head(10
```

Out[28]:

Product_Name	Sales
Desk	10,881,070.68
Printer	10,701,074.38
Monitor	10,669,238.72
Chair	10,390,661.19
Mobile	10,375,226.67
Mouse	10,294,780.40
Keyboard	10,221,058.38
Laptop	10,207,411.46

dtype: float64

In [29]:

```
df.sort_values('Profit').head(10)
```

Out[29]:

	Order_Id	Order_Date	Region	Country	Customer_Segment	Product_C
12719	ORD201357	2024-05-15	North	Australia	Consumer	
783	ORD210279	2021-03-17	East	USA	Consumer	El
12593	ORD206533	2024-05-01	West	India	Corporate	
5343	ORD202131	2022-06-01	Central	USA	Home Office	
8189	ORD209361	2023-03-06	North	Germany	Home Office	El
1683	ORD201724	2021-06-12	South	Germany	Home Office	
14996	ORD203260	2024-12-30	North	Australia	Home Office	
14226	ORD201285	2024-10-14	North	USA	Corporate	El
3276	ORD213831	2021-11-12	South	Australia	Consumer	
1700	ORD206985	2021-06-13	South	India	Corporate	El

Insighta --

High-priced items like Desks and Printers dominate sales revenue.

Some orders show negative profit, mainly due to high discounts.

In [30]:

```
#correlation Between Numerical colums
df[["Quantity",'Unit_Price','Sales','Discount','Profit']].corr()
```

Out[30]:

	Quantity	Unit_Price	Sales	Discount	Profit
Quantity	1.00	0.00	0.65	0.01	0.08
Unit_Price	0.00	1.00	0.68	-0.01	0.10
Sales	0.65	0.68	1.00	-0.00	0.14
Discount	0.01	-0.01	-0.00	1.00	-0.59
Profit	0.08	0.10	0.14	-0.59	1.00

Insights --

Sales and profit are strongly positively correlated.

Discount has a negative correlation with profit, confirming margin erosion.

Data Visuallization

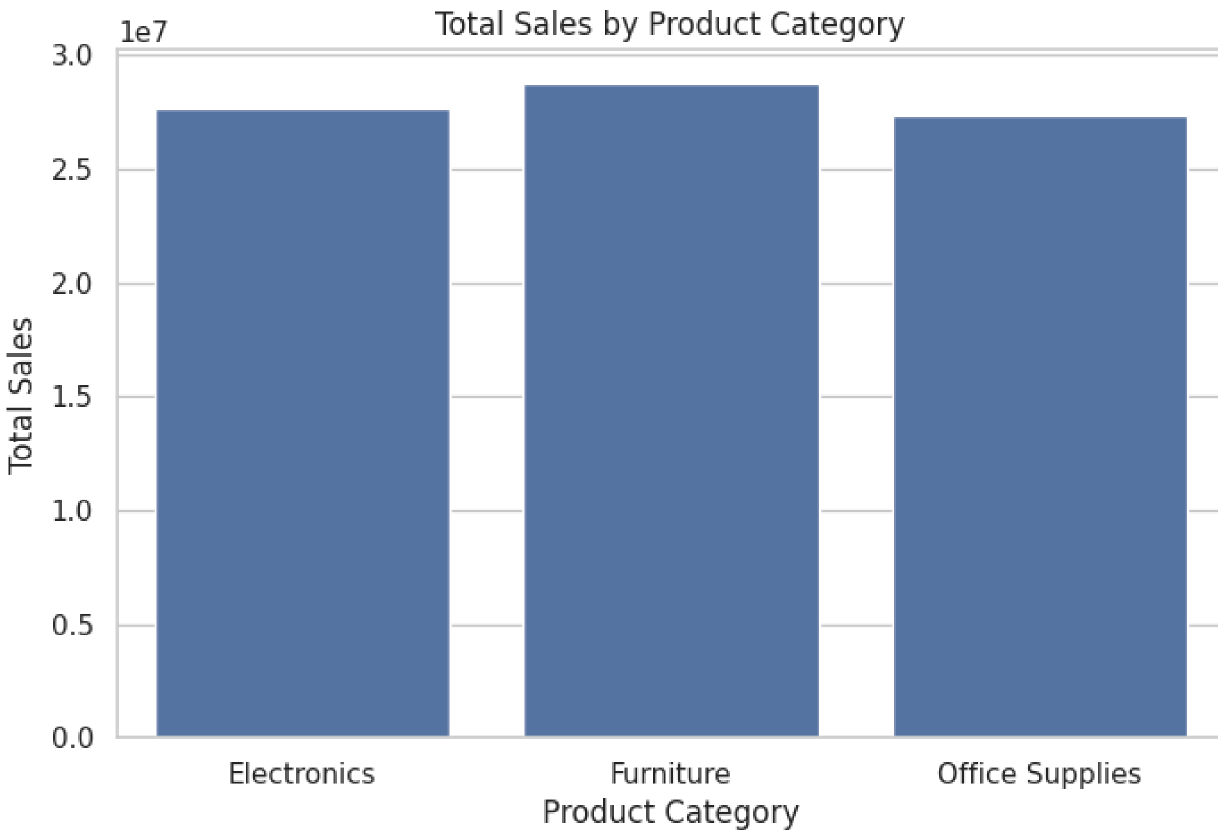
In [31]:

```
import matplotlib.pyplot as plt
import seaborn as sns

sns.set(style="whitegrid")
```

In [33]:

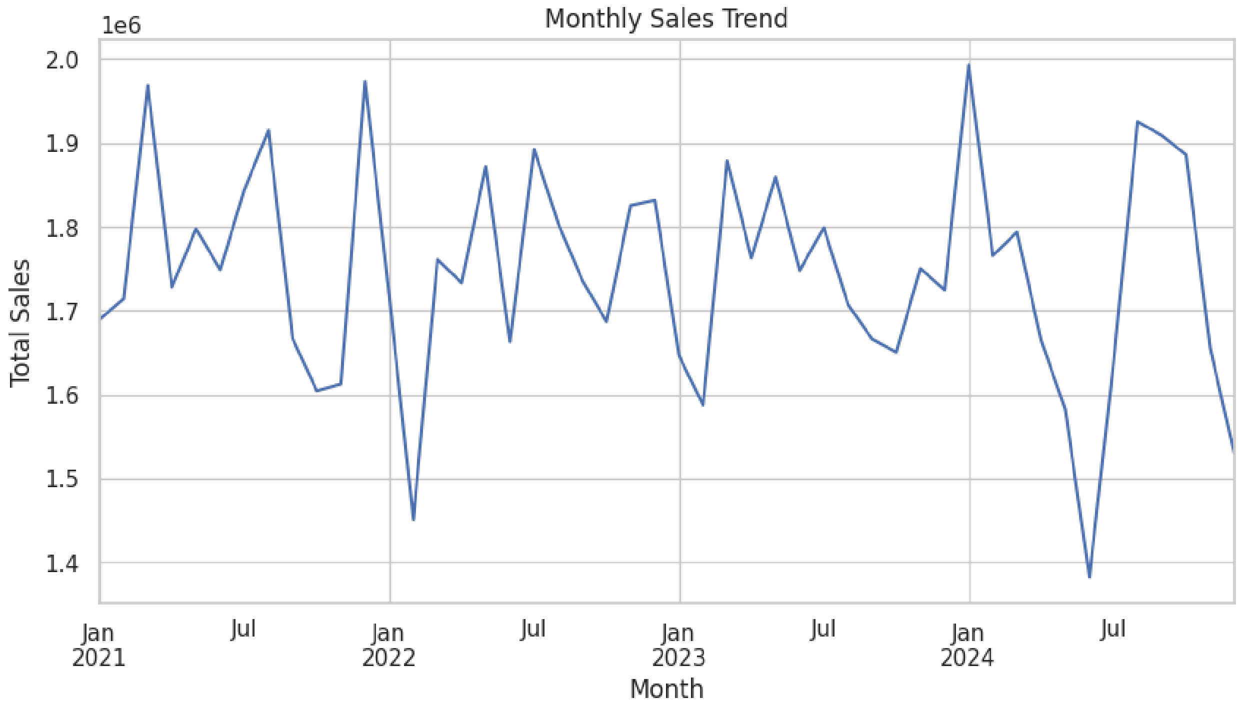
```
# Categorical Sales comparison
plt.figure(figsize=(8,5))
sns.barplot(
    x=df.groupby("Product_Category")["Sales"].sum().index,
    y=df.groupby("Product_Category")["Sales"].sum().values
)
plt.title("Total Sales by Product Category")
plt.xlabel("Product Category")
plt.ylabel("Total Sales")
plt.show()
```



Insights -- Furniture is the top revenue-generating category

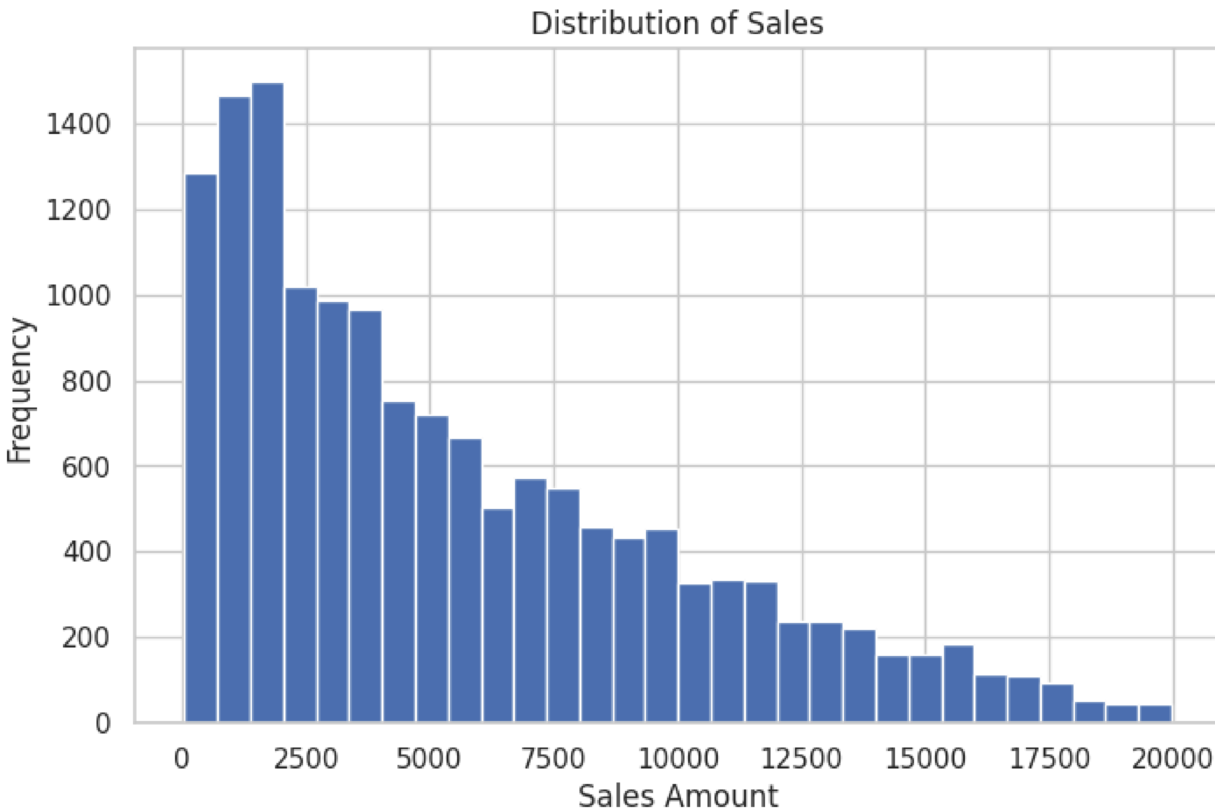
In [34]:
```
#Trend analysis over time
df["Order_Date"] = pd.to_datetime(df["Order_Date"])
monthly_sales = df.groupby(df["Order_Date"].dt.to_period("M"))["Sales"].sum()

plt.figure(figsize=(10,5))
monthly_sales.plot()
plt.title("Monthly Sales Trend")
plt.xlabel("Month")
plt.ylabel("Total Sales")
plt.show()
```



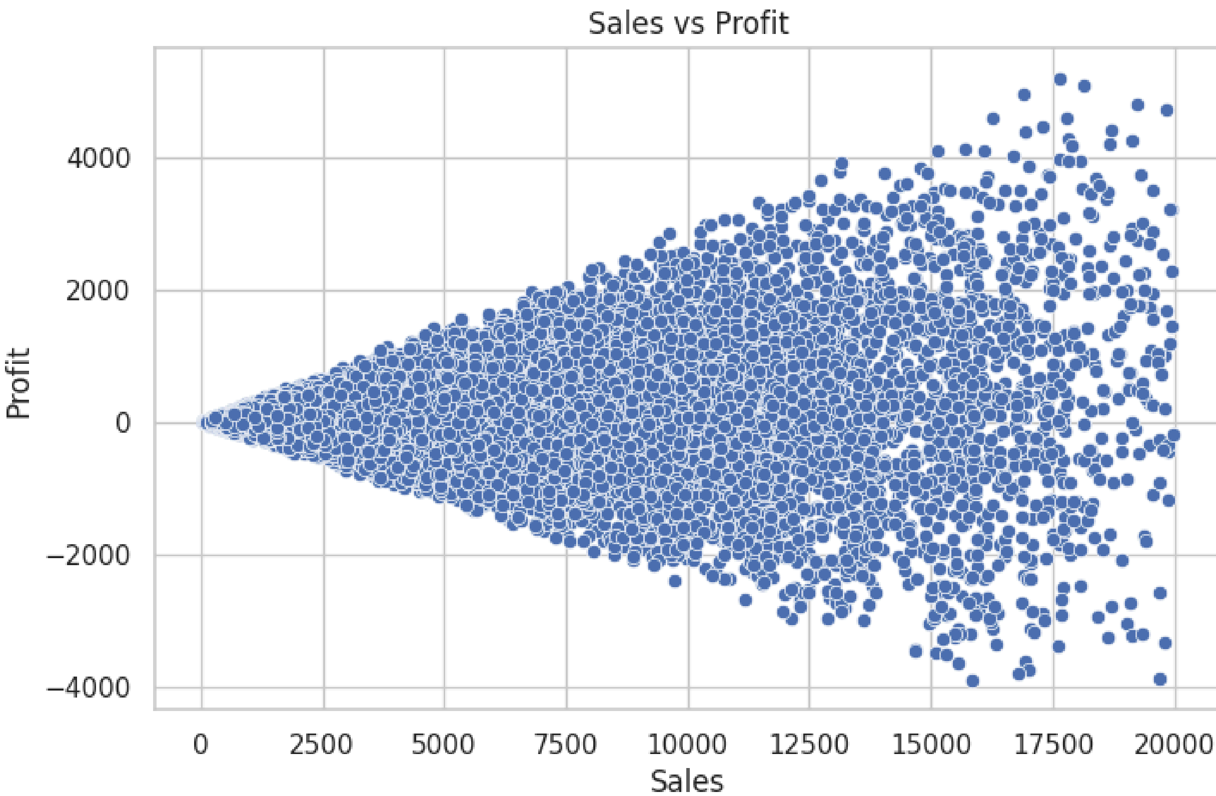
Insights -- Certain months experience spikes, indicating seasonal demand.

In [35]:
```
# sales Distribution
plt.figure(figsize=(8,5))
plt.hist(df["Sales"], bins=30)
plt.title("Distribution of Sales")
plt.xlabel("Sales Amount")
plt.ylabel("Frequency")
plt.show()
```



Insights -- Few high-value transactions significantly impact total revenue.

In [36]:
```
#Show sales vs profit
plt.figure(figsize=(8,5))
sns.scatterplot(x="Sales", y="Profit", data=df)
plt.title("Sales vs Profit")
plt.xlabel("Sales")
plt.ylabel("Profit")
plt.show()
```

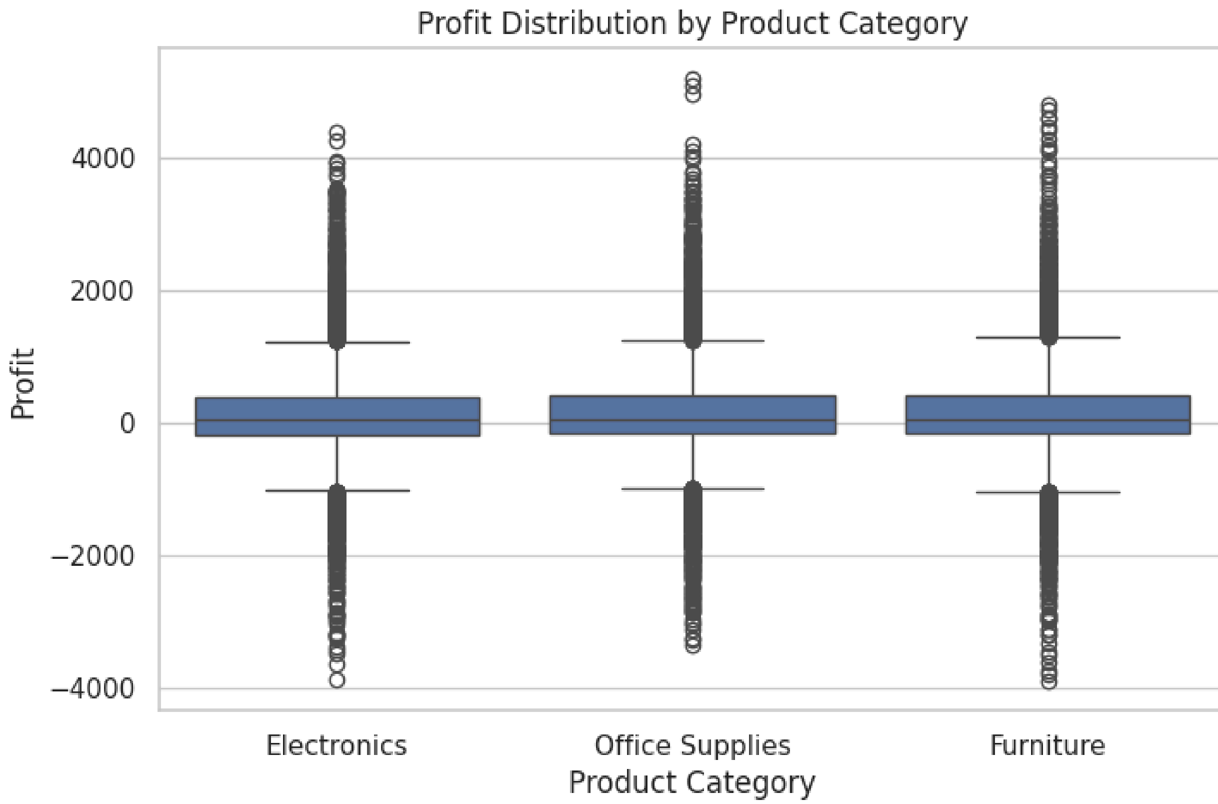


insights -- Higher sales generally lead to higher profit.

In [39]:
```
#shows correlation between numerical columns
plt.figure(figsize=(8,6))
sns.heatmap(
    df[["Quantity", "Unit_Price", "Sales", "Discount", "Profit"]].corr(),
    annot=True,
    cmap="coolwarm"
)
plt.title("Correlation Heatmap")
plt.show()
```

Strong positive correlation between sales and profit.

In [38]:
```
#indentify the outliers
plt.figure(figsize=(8,5))
sns.boxplot(x="Product_Category", y="Profit", data=df)
plt.title("Profit Distribution by Product Category")
plt.xlabel("Product Category")
plt.ylabel("Profit")
plt.show()
```



Insights -- Electronics shows higher profit spread and outliers.

1.Revenue Concentration in Few Products

What the data shows: The analysis reveals that a small number of high-priced products—mainly in the Furniture category—contribute a disproportionately large share of total sales revenue. Most orders are low-value, but a few high-value transactions significantly impact overall sales.

Why it matters: This indicates revenue dependency on key products. While profitable, it increases business risk if demand for these products declines. Diversifying revenue sources can improve long-term stability.

2.Relationship Between Sales and Profit

What the data shows: Sales and profit have a strong positive relationship, meaning higher sales generally lead to higher profit. However, this relationship is inconsistent, as some high-sales orders generate low or even negative profit.

Why it matters: This shows that revenue growth alone does not guarantee profitability. Profit-focused strategies are needed alongside sales expansion to ensure sustainable growth.

3.Impact of Discounts on Profitability

What the data shows: Discount levels vary across orders, and higher discounts are clearly associated with lower profit margins. Some heavily discounted orders result in losses despite high sales values.

Why it matters: Discounting must be carefully controlled. Unplanned or excessive discounts directly reduce profit, making pricing strategy a critical business decision.

4.Product Category Performance

What the data shows: Electronics dominates in both sales and profit due to higher unit prices. Office Supplies shows high order volume but low revenue and profit per order. Furniture falls between the two, with moderate performance.

Why it matters: Understanding category-level performance helps allocate resources efficiently. High-margin categories should receive priority, while low-margin categories need cost optimization or pricing review.

5.Customer Segment Behavior

What the data shows: Corporate customers generate higher average profit per order compared to Consumer and Home Office segments. Consumers place more orders but contribute lower profit per transaction.

Why it matters: Targeting high-value customer segments improves overall profitability. Marketing and sales efforts should be aligned with segments that offer better returns.

6.Regional and Country-Level Distribution

What the data shows: Sales are evenly distributed across regions, with India and the USA emerging as top revenue-generating countries. No single region dominates overall sales.

Why it matters: This geographic diversification reduces business risk. It also highlights markets with growth potential where focused expansion can increase revenue.

7.Sales Trends Over Time

What the data shows: Monthly sales trends show steady growth with noticeable seasonal fluctuations. Certain periods record spikes in sales, likely due to promotions or seasonal demand.

Why it matters: Identifying trends helps in better demand forecasting, inventory planning, and timing promotional campaigns to maximize impact.

8.Variability, Outliers, and Business Risk

What the data shows: Sales and profit distributions are right-skewed, with several outliers showing extremely high or low profit. Electronics category shows the highest variability.

Why it matters: Outliers can distort overall performance metrics. Monitoring these cases helps identify high-risk transactions and exceptional opportunities, leading to better decision-making.

In [39]:

```
```