Hackathon Project: Driving Strategic Import Reforms through Advanced Analytics

1. Introduction

This project addresses Nigeria's strategic goal of achieving **technological sovereignty and sustainable economic growth** by reforming its national import strategy—specifically focusing on **electrical machinery imports (HS Code 85)**. Leveraging historical import and tax data, this analysis aims to uncover patterns, risks, and opportunities that can inform **evidence-based government interventions** in areas such as **import substitution, taxation reform, innovation investment, and trade policy**.

Using a combination of **descriptive analytics, predictive modeling, and policy simulation**, the notebook is structured around the four core pillars of the hackathon challenge:

- **Strategic Import Dependency Analysis**
  Evaluates Nigeria's reliance on specific HS codes and supplier countries. It highlights dominant import partners, trends in import volume/value, and potential geopolitical or economic risks.

- **Taxation Optimization & Revenue Leakage**
  Investigates discrepancies between CIF values and collected taxes. This section identifies the tax gap, explores under-declaration risks, and recommends reforms to enhance customs efficiency and revenue generation.

- **Predictive Forecasting of Import Volume & Tax Revenue**
  Develops forecasting models to project future import volumes and tax revenues over the next 3–5 years. It simulates scenarios such as import reductions or shifts in supplier dominance to assess potential fiscal implications.

- **Policy Impact Modeling for Import Substitution & Innovation**
  Assesses the impact of substituting key imports with local alternatives. This section estimates the fiscal and industrial effects of 20–30% import reduction in strategic categories and offers data-driven guidance for allocating innovation funds.

By combining insights from these four areas, the analysis supports the formulation of **targeted policies** that reduce import dependency, strengthen local industry, and enhance Nigeria's fiscal resilience in a rapidly evolving global trade environment.

2. Exploratory Data Analysis

2.1 Data Overview

In [ ]:
```
# import neccessary libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import calendar
from pandas.api.types import CategoricalDtype
import matplotlib.cm as cm
import matplotlib.colors as mcolors
from scipy.stats import zscore
from sklearn.ensemble import IsolationForest
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
from sklearn.linear_model import LinearRegression

import logging
logging.getLogger('prophet').setLevel(logging.CRITICAL)
logging.getLogger('cmdstanpy').setLevel(logging.CRITICAL)
from prophet import Prophet

# mount google drive
from google.colab import drive
```

In [ ]:
```
# Load cleaned dataset
file_path = '/content/drive/MyDrive/ZTH_Hackathon/clean_data.xlsx'
data = pd.read_excel(file_path)
```

In [ ]:
```
print('Shape of the data', data.shape)
data.head()
```

```
Shape of the data (110369, 14)
```

Out[ ]:

	Custom_Office	Reg_Number	Reg_Date	Importer	Importer_Code	Item_Nb
0	PORT HARCOURT(3) ONNE	C33563	03/09/2019	0. C. CHRIS & CO	22228166-0001	1\
1	TIN CAN ISLAND	C102199	19/08/2019	08 EXPRESS SERVICES	22319106-0001	4\
2	TIN CAN ISLAND	C90075	24/07/2019	08 EXPRESS SERVICES	22319106-0001	4\
3	TIN CAN ISLAND	C33952	25/03/2019	08 EXPRESS SERVICES	22319106-0001	4\
4	APAPA PORT	C11025	18/02/2019	08 EXPRESS SERVICES	22319106-0001	4\

In [ ]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110369 entries, 0 to 110368
Data columns (total 14 columns):
 #   Column             Non-Null Count   Dtype 
---  ------             --------------   ----- 
 0   Custom_Office      110369 non-null  object
 1   Reg_Number         110369 non-null  object
 2   Reg_Date           110369 non-null  object
 3   Importer           110369 non-null  object
 4   Importer_Code      110369 non-null  object
 5   Item_Nbr           110369 non-null  object
 6   HS_Code            110369 non-null  int64 
 7   HS_Description     110369 non-null  object
 8   FOB_Value(N)       110369 non-null  int64 
 9   CIF_Value(N)       110369 non-null  int64 
 10  Total_Tax(N)       110369 non-null  int64 
 11  Mass(KG)           110369 non-null  int64 
 12  Country_of_Origin  110369 non-null  object
 13  Country_of_Supply  110369 non-null  object
dtypes: int64(5), object(9)
memory usage: 11.8+ MB
```

2.2 Data Cleaning

In [ ]:

```
# check for missing values
data.isnull().sum()
```

Out[ ]:

	0
Custom_Office	0
Reg_Number	0
Reg_Date	0
Importer	0
Importer_Code	0
Item_Nbr	0
HS_Code	0
HS_Description	0
FOB_Value(N)	0
CIF_Value(N)	0
Total_Tax(N)	0
Mass(KG)	0
Country_of_Origin	0
Country_of_Supply	0

dtype: int64

In [ ]:

```
# check for duplicates
data.duplicated().sum()
```

Out[ ]:

```
np.int64(0)
```

In [ ]:

```
# correct column data type
data['HS_Code'] = data['HS_Code'].astype(str)
# create month column
data['Reg_Date'] = pd.to_datetime(data['Reg_Date'], format='%d/%m/%Y')
data['Month'] = data['Reg_Date'].dt.month_name()
```

In [ ]:

```
# Drop irrelevant columns
data = data.drop(['Importer_Code', 'Mass(KG)'], axis=1)
```

2.3 Descriptive Statistics and Categorical Analysis

In [ ]:

```
# describe numerical columns
data.describe().T
```

Out[ ]:

	count	mean	min	25%	50%	
Reg_Date	110369	2019-06-28 16:44:36.229738240	2019-01-01 00:00:00	2019-04-01 00:00:00	2019-06-27 00:00:00	201 00:
FOB_Value(N)	110369.0	6566459.039332	3.0	100066.0	395422.0	2388
CIF_Value(N)	110369.0	7101979.306889	3.0	106117.0	473331.0	2860
Total_Tax(N)	110369.0	907528.219645	0.0	19182.0	69624.0	333

In [ ]:

```
cat_cols = ['Custom_Office', 'Importer', 'HS_Code', 'Country_of_Origin', 'Co

# Get unique counts for each categorical columns
for col in cat_cols:
    print(f"{col}: {data[col].nunique()} unique values")
```

```
Custom_Office: 17 unique values
Importer: 9910 unique values
HS_Code: 301 unique values
Country_of_Origin: 153 unique values
Country_of_Supply: 158 unique values
```

2.4 Exploratory Data Analysis (EDA) Summary

Dataset Overview

- **Records**: 110,369 transactions (1 year coverage)
- **Key Features**:
  - `Importer`, `HS_Code`, `CIF_Value(N)`, `Total_Tax(N)`
- **Data Quality**: Zero missing values/duplicates detected

Key Insights

1. Trade Diversity

- **Importers**: **9,910** unique entities (high fragmentation)
- **Products**: **301** unique HS Codes

2. Global Trade Network

- **Origins**: **153** source countries
- **Supply Routes**: **158** supplying countries
- **Top Trade Partners**:
  - China
  - India
  - UK

3. Financial Profile

Metric	Average Value
CIF Value	₦7.1M
Tax Paid	₦907K

(See Sections 3–6 for dependency, tax gap, and forecasting analysis.)

3. Strategic Import Dependency Analysis

3.1 Key Metric: Total Import Value

In [ ]:
```
# Calculate total Cost, Insurance and Frieght (CIF) Value
total_cif = data['CIF_Value(N)'].sum()
print(f"Total CIF Value of Imports: {total_cif:,.2f} Naira")
```

```
Total CIF Value of Imports: 783,838,354,122.00 Naira
```

3.2 Import Concentration by HS Code

In [ ]:
```
# Proportion of imports by HS codes

# By frequency
hs_freq = data.groupby(['HS_Code', 'HS_Description']).size().reset_index(nam
total_freq = hs_freq['Count'].sum()
hs_freq['percent'] = ((hs_freq['Count'] / total_freq) * 100).round(2)
print("Top HS Codes by Frequency of import:\n")
hs_freq.head()
```

```
Top HS Codes by Frequency of import:
```

Out[ ]:

	HS_Code	HS_Description	Count	percent
130	8517120000	Telephones For Cellular Networks Or For Other ...	13378	12.12
133	8517620000	Machines For Reception, Conversion And Transmi...	6154	5.58
49	8504409000	Other Static Converters Not Specified	5139	4.66
237	8537100000	Boards, Panels, Consoles For Electric Control/...	3316	3.00
232	8536500000	Other Electrical Switches	2914	2.64

In [ ]:
```
# By CIF value
hs_value = data.groupby(['HS_Code', 'HS_Description'])['CIF_Value(N)'].sum()

hs_value['%_of_Total_CIF'] = ((hs_value['CIF_Value'] / total_cif) * 100).rou
print("\nTop HS Codes by CIF Value:\n")
hs_value.head(10)
```

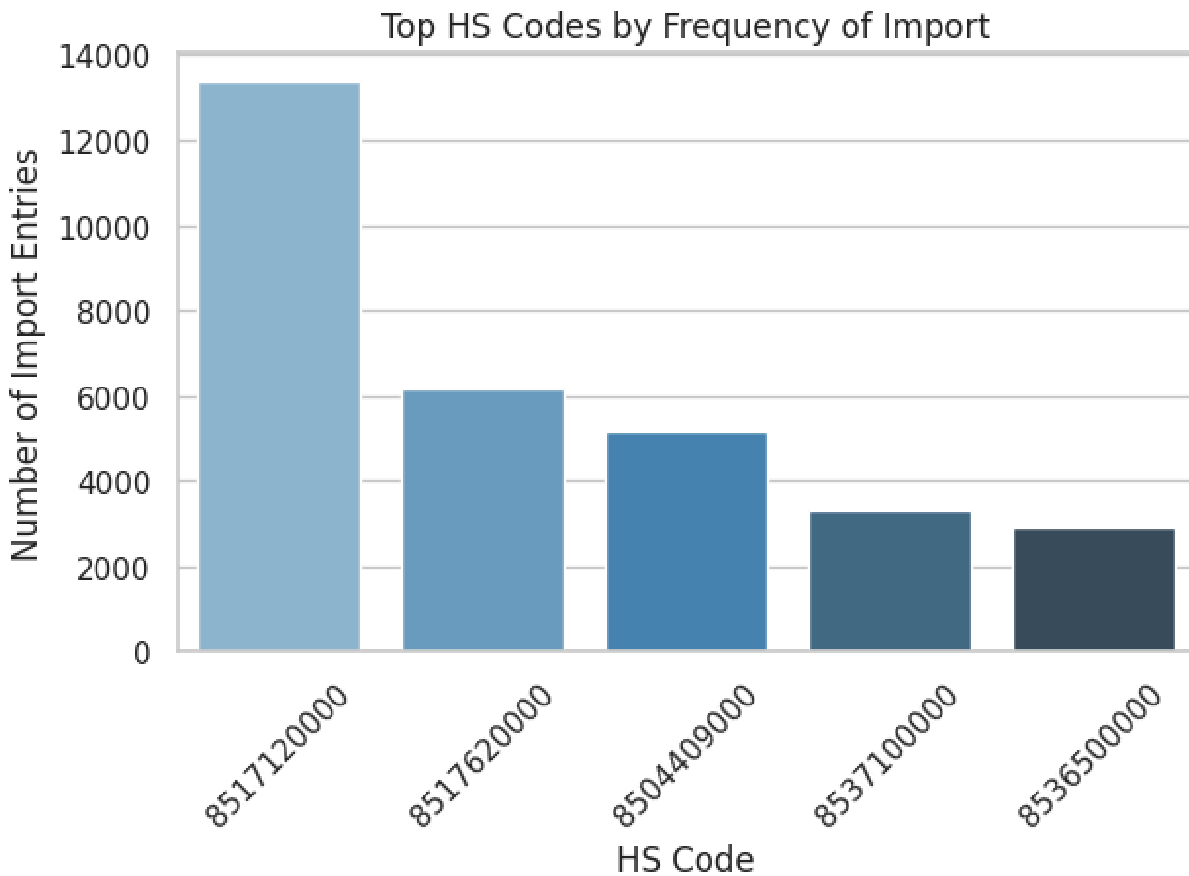
```
Top HS Codes by CIF Value:
```

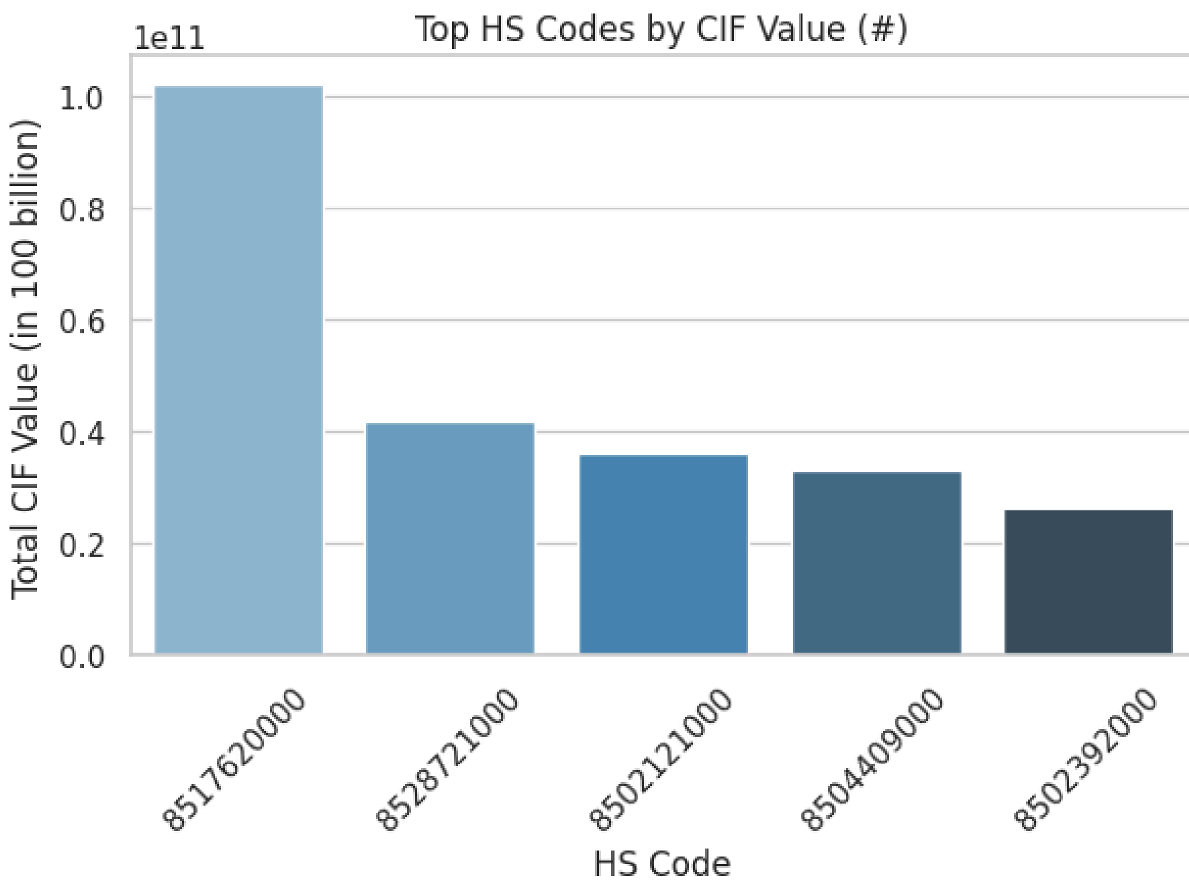
Out[ ]:

	HS_Code	HS_Description	CIF_Value	%_of_Total_CIF
133	8517620000	Machines For Reception, Conversion And Transmi...	102279539056	13.05
191	8528721000	Reception Apparatus For Television, Coloured, ...	41962385894	5.35
17	8502121000	Gen. Set, Diesel Or Semidiesel Engine, Output ...	36393600840	4.64
49	8504409000	Other Static Converters Not Specified	33122740574	4.23
34	8502392000	Gaspowered Generator	26380077578	3.37
268	8541401000	Solar Cells Whether Or Not In Modules Or Made ...	26094463458	3.33
237	8537100000	Boards, Panels, Consoles For Electric Control/...	22859138707	2.92
135	8517700000	Parts Of Article Of Heading 8517	20756282745	2.65
290	8544600000	Other Electric Conductors, For A Voltage Excee...	18173775432	2.32
131	8517180000	Other Telephone Sets Not Specified.	18034472021	2.30

In [ ]:

```
# Visualize top HS Codes
sns.set(style="whitegrid")

# by Frequency
top_hs_freq = hs_freq.head(5)
sns.barplot(x='HS_Code', y='Count', data=top_hs_freq, palette='Blues_d', hue
plt.title('Top HS Codes by Frequency of Import')
plt.xlabel('HS Code')
plt.ylabel('Number of Import Entries')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Top HS Codes by CIF (#) Value
top_hs_value = hs_value.head(5)
sns.barplot(x='HS_Code', y='CIF_Value', data=top_hs_value, hue='HS_Code', pa
plt.title('Top HS Codes by CIF Value (#)')
plt.xlabel('HS Code')
plt.ylabel('Total CIF Value (in 100 billion)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```





3.3 Import Concentration by Country of Origin

In [ ]:

```
# import proportion of source country

# by frequency
origin_freq = data['Country_of_Origin'].value_counts().reset_index()
origin_freq['%_of_Total'] = ((origin_freq['count'] / total_freq) * 100).rour

print("Top Countries of Origin by frequency:\n")
origin_freq.head()
```

```
Top Countries of Origin by frequency:
```

Out[ ]:

	Country_of_Origin	count	%_of_Total
0	China	34421	31.19
1	United States	23840	21.60
2	Germany	9765	8.85
3	United Kingdom	6733	6.10
4	Netherlands	4018	3.64

In [ ]:

```
# By CIF Value
origin_value = data.groupby('Country_of_Origin')['CIF_Value(N)'].sum().sort_
origin_value['%_of_Total_CIF'] = ((origin_value['CIF_Value(N)'] / total_cif)

print("Top Countries of Origin by CIF_Value:\n")
origin_value.head(10)
```

```
Top Countries of Origin by CIF_Value:
```

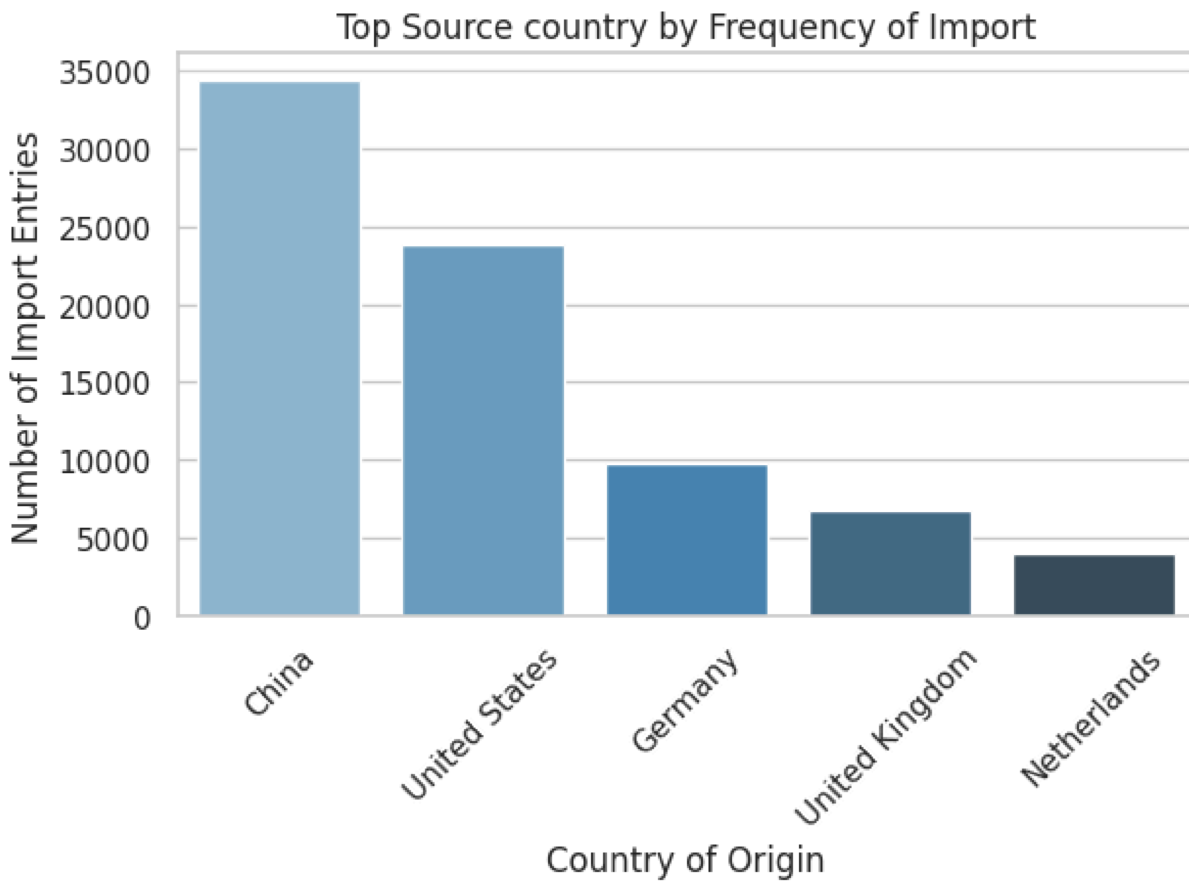
Out[ ]:

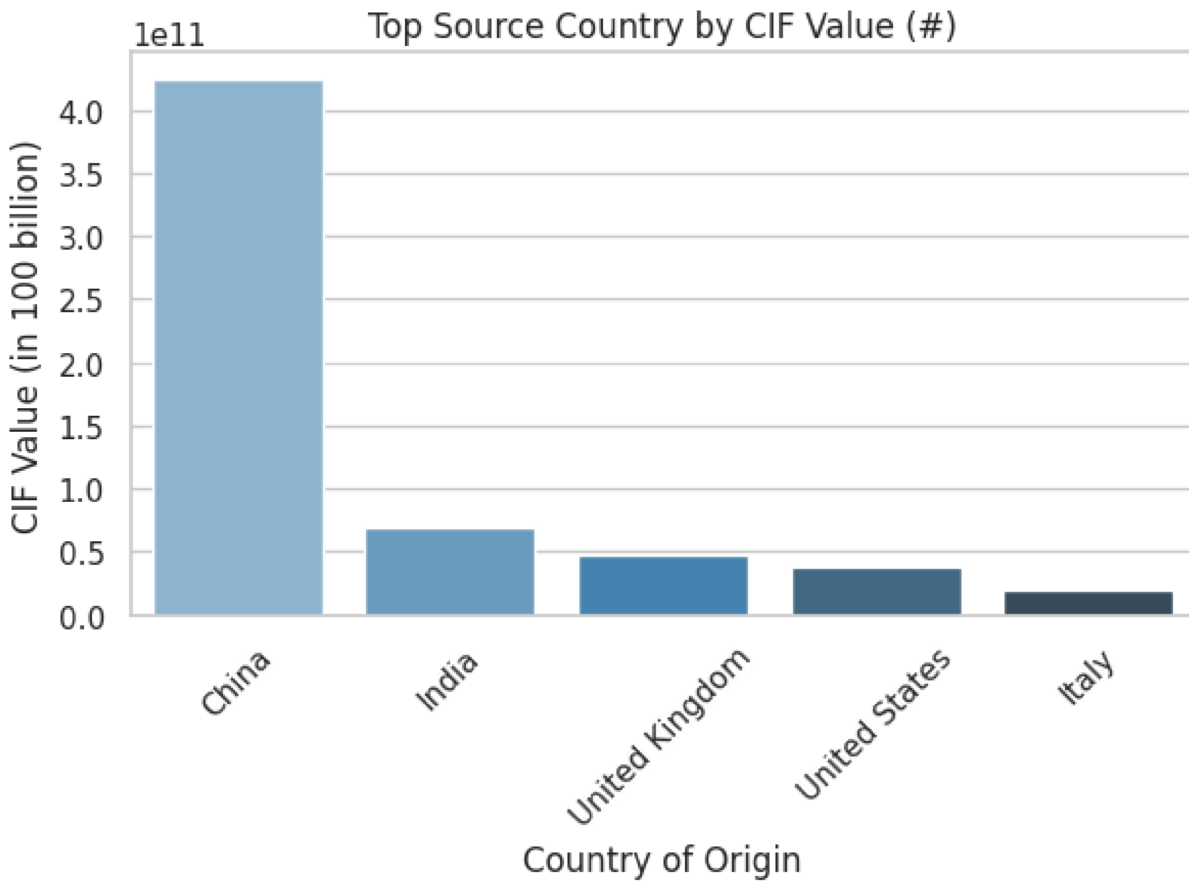
	Country_of_Origin	CIF_Value(N)	%_of_Total_CIF
0	China	424295637937	54.13
1	India	70097676199	8.94
2	United Kingdom	47445462065	6.05
3	United States	38758997642	4.94
4	Italy	19866446869	2.53
5	Germany	19123720341	2.44
6	South Korea	18657417091	2.38
7	Hong Kong	16502647771	2.11
8	Sweden	13896996689	1.77
9	France	13473972215	1.72

In [ ]:

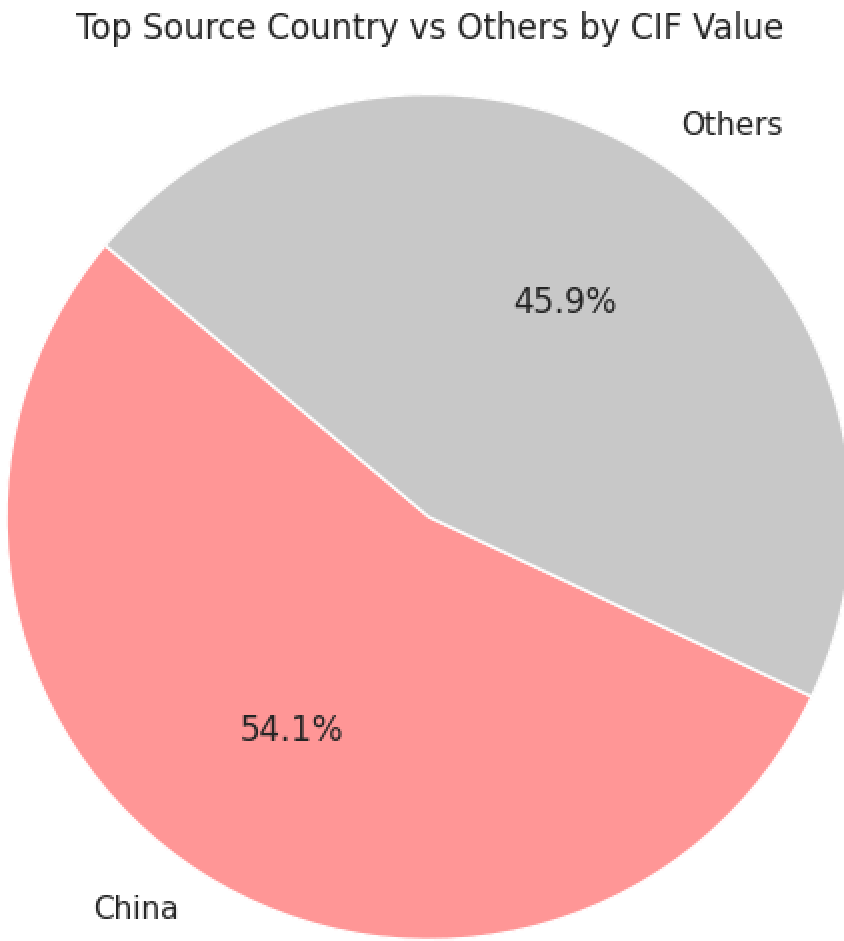
```
# Visualize Top Countries of Origin

# --- Top Countries by Frequency
```

```
top_origin_freq = origin_freq.head(5)
sns.barplot(x='Country_of_Origin', y='count', data=top_origin_freq, palette=
plt.title('Top Source country by Frequency of Import')
plt.xlabel('Country of Origin')
plt.ylabel('Number of Import Entries')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# --- Top Countries by CIF (#) Value
top_origin_value = origin_value.head(5)
sns.barplot(x='Country_of_Origin', y='CIF_Value(N)', data=top_origin_value,
plt.title('Top Source Country by CIF Value (#)')
plt.xlabel('Country of Origin')
plt.ylabel('CIF Value (in 100 billion)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```





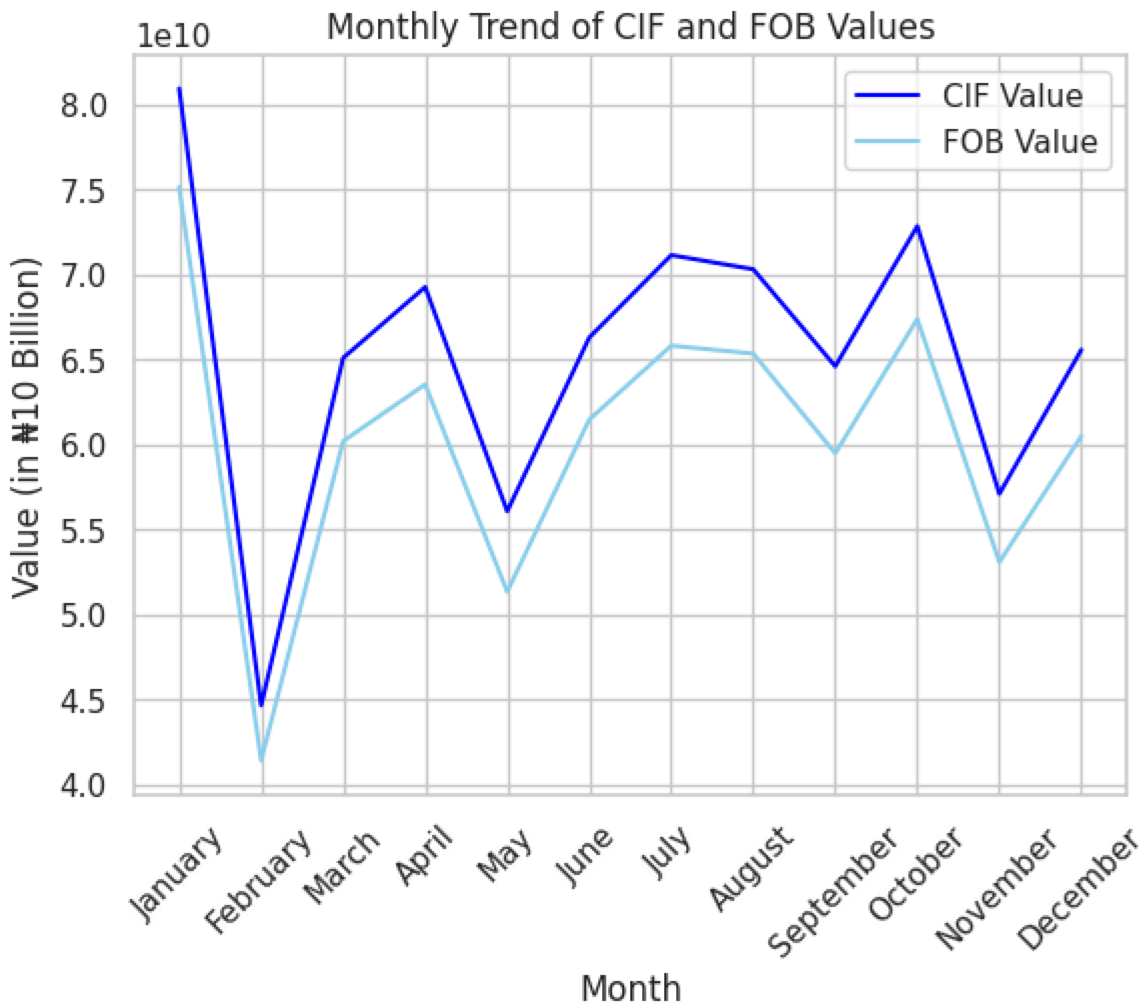
In [ ]:
```
# Visualize Top 1 Country Against others
top_country = origin_value.iloc[0]
others_cif = origin_value.iloc[1:]['CIF_Value(N)'].sum()

labels = [top_country['Country_of_Origin'], 'Others']
sizes = [top_country['CIF_Value(N)'], others_cif]
colors = ['#ff9999', '#cccccc']

# Step 4: Plot pie chart
plt.figure(figsize=(6, 6))
plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%', startangle=1
plt.title('Top Source Country vs Others by CIF Value')
plt.axis('equal')
plt.show()
```



3.4 Trends in Import Volume/Value Over Time

In [ ]:
```
month_order = list(calendar.month_name)[1:]

# Convert Month column to ordered categorical type
data['Month'] = pd.Categorical(data['Month'], categories=month_order, ordere

monthly_trend = data.groupby('Month')[['CIF_Value(N)', 'FOB_Value(N)']].sum(
```

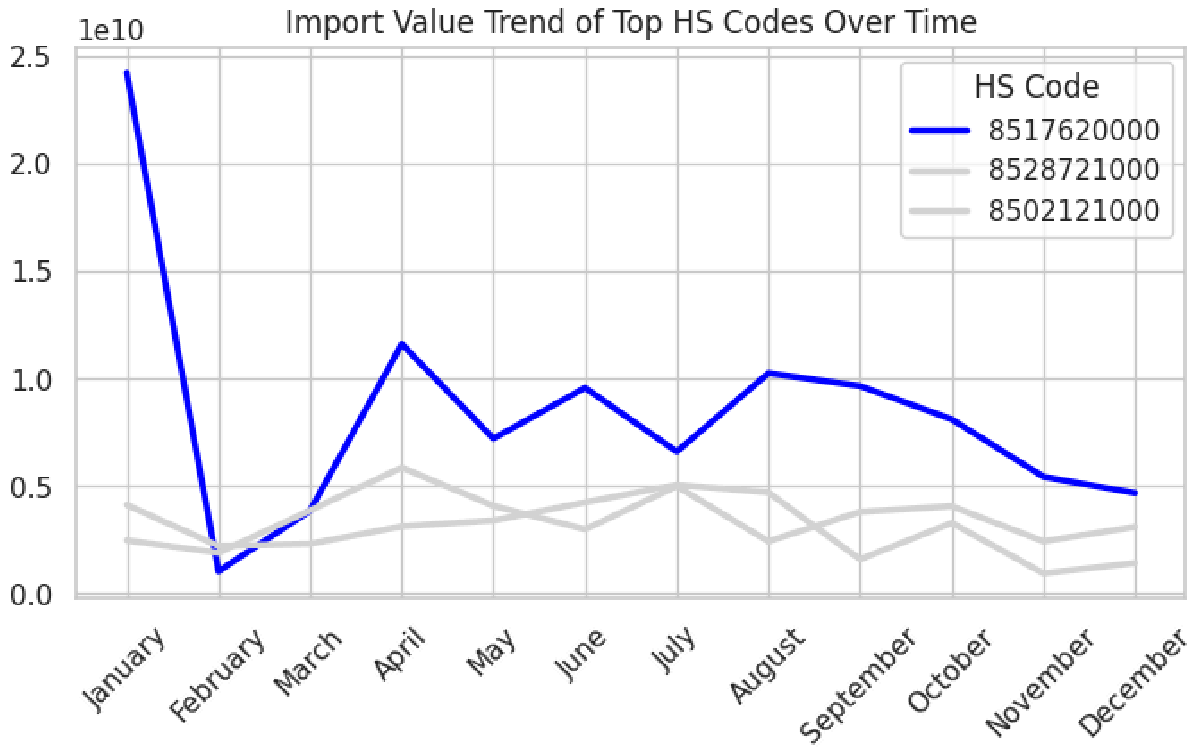
In [ ]:
```
# Visualize monthly trend of import value

sns.lineplot(data=monthly_trend, x='Month', y='CIF_Value(N)', label='CIF Val
sns.lineplot(data=monthly_trend, x='Month', y='FOB_Value(N)', label='FOB Val
plt.title("Monthly Trend of CIF and FOB Values")
plt.xlabel("Month")
plt.xticks(rotation=45)
plt.ylabel("Value (in ₦10 Billion)")
plt.legend()
plt.show()
```



In [ ]:

```
# Monthly Import Trend of Top 3 HS Codes

top3_hs_value = hs_value.head(3)['HS_Code']

# Filter for only top HS Codes
top_data = data[data['HS_Code'].isin(top3_hs_value)]

# Group by Month and HS Code
trend_data = top_data.groupby(['Month', 'HS_Code'])['CIF_Value(N)'].sum().re

top_1 = top3_hs_value.iloc[0]
plt.figure(figsize=(8,4))
colors = {}
for hs in top3_hs_value:
    if hs == top_1:
        colors[hs] = 'blue'
    else:
        colors[hs] = 'lightgray'

for hs_code in top3_hs_value:
    subset = trend_data[trend_data['HS_Code'] == hs_code]
    plt.plot(subset['Month'].astype(str), subset['CIF_Value(N)'], label=hs_c

plt.title('Import Value Trend of Top HS Codes Over Time')
```

```
plt.xticks(rotation=45)
plt.grid(True)
plt.legend(title='HS Code')
plt.show()
```



3.5 Countries Dominating Supply for Critical/Top HS Codes

In [ ]:
```
# Identify top 5 HS Code by import value
top5_hs_value = hs_value.head(5)['HS_Code']

critical_hs = data[data['HS_Code'].isin(top5_hs_value)]

# Group by HS Code and Country_of_Supply
critical_supply = critical_hs.groupby(['HS_Code', 'Country_of_Supply'])['CIF

# calculate total CIF per HS_Code
total_cif_per_code = critical_supply.groupby('HS_Code')['CIF_Value(N)'].sum(

# match each row's HS_Code to its total
critical_supply['%_of_Total_CIF'] = critical_supply.apply(
    lambda row: (row['CIF_Value(N)'] / total_cif_per_code[row['HS_Code']] *
    axis=1
)

# View top countries per HS Code
for hs in top5_hs_value:
    print(f"\nTop Countries Supplying HS Code {hs}:")
    display(critical_supply[critical_supply['HS_Code'] == hs].head(5))
```

```
Top Countries Supplying HS Code 8517620000:
```

	HS_Code	Country_of_Supply	CIF_Value(N)	%_of_Total_CIF
0	8517620000	China	66487351119	65.01
4	8517620000	Netherlands	13995227851	13.68
7	8517620000	Sweden	10903419584	10.66
15	8517620000	United Arab Emirates	2184041007	2.14
18	8517620000	France	1562393517	1.53

```
Top Countries Supplying HS Code 8528721000:
```

	HS_Code	Country_of_Supply	CIF_Value(N)	%_of_Total_CIF
1	8528721000	China	30145666839	71.84
6	8528721000	South Korea	11545614271	27.51
58	8528721000	United Arab Emirates	135226911	0.32
60	8528721000	Indonesia	111917430	0.27
93	8528721000	Taiwan, Province of China	16148247	0.04

```
Top Countries Supplying HS Code 8502121000:
```

	HS_Code	Country_of_Supply	CIF_Value(N)	%_of_Total_CIF
2	8502121000	United Kingdom	17353319243	47.68
5	8502121000	China	13275236257	36.48
14	8502121000	India	2311251562	6.35
22	8502121000	Lebanon	1022615313	2.81
28	8502121000	Belgium	741094510	2.04

```
Top Countries Supplying HS Code 8504409000:
```

	HS_Code	Country_of_Supply	CIF_Value(N)	%_of_Total_CIF
3	8504409000	China	15185385531	45.85
9	8504409000	India	6682596495	20.18
13	8504409000	Poland	2786203415	8.41
17	8504409000	Malaysia	1610277345	4.86
23	8504409000	Netherlands	897125016	2.71

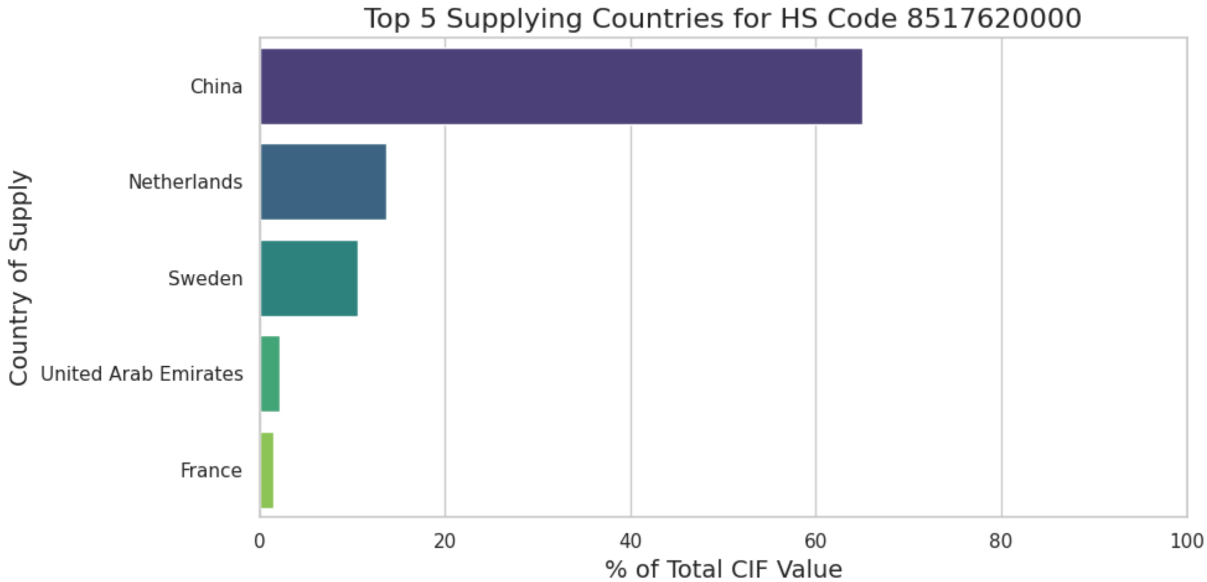
```
Top Countries Supplying HS Code 8502392000:
```

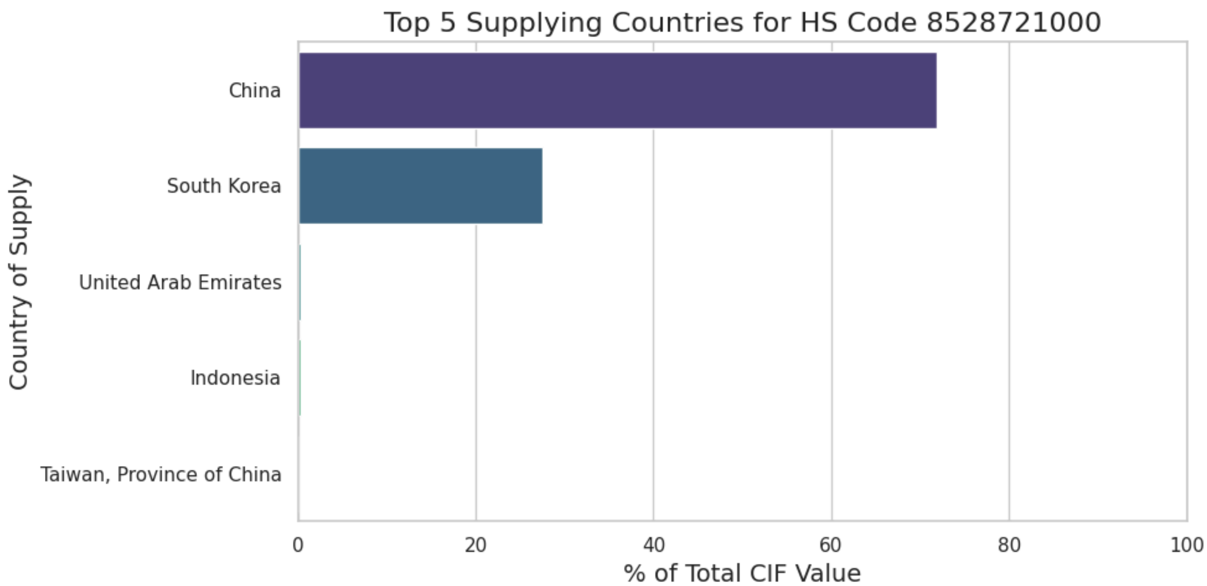
	HS_Code	Country_of_Supply	CIF_Value(N)	%_of_Total_CIF
8	8502392000	Belgium	6802876274	25.79
10	8502392000	Saudi Arabia	5922904443	22.45
11	8502392000	United Kingdom	3943426213	14.95
12	8502392000	United States	3529512152	13.38
16	8502392000	China	1962923999	7.44

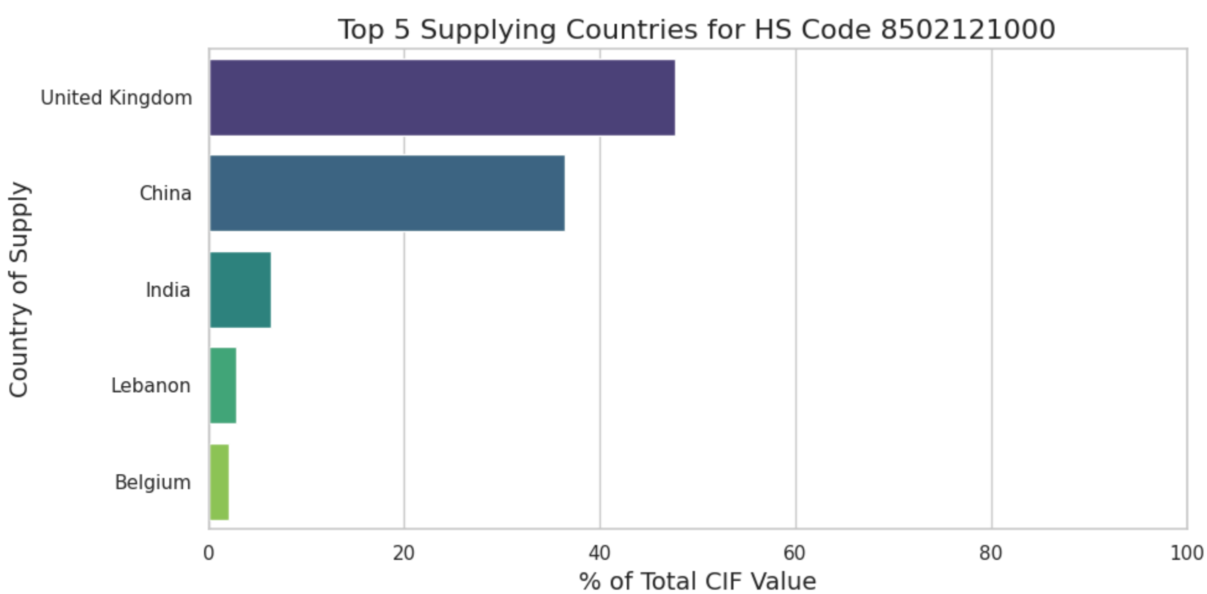
In [ ]:

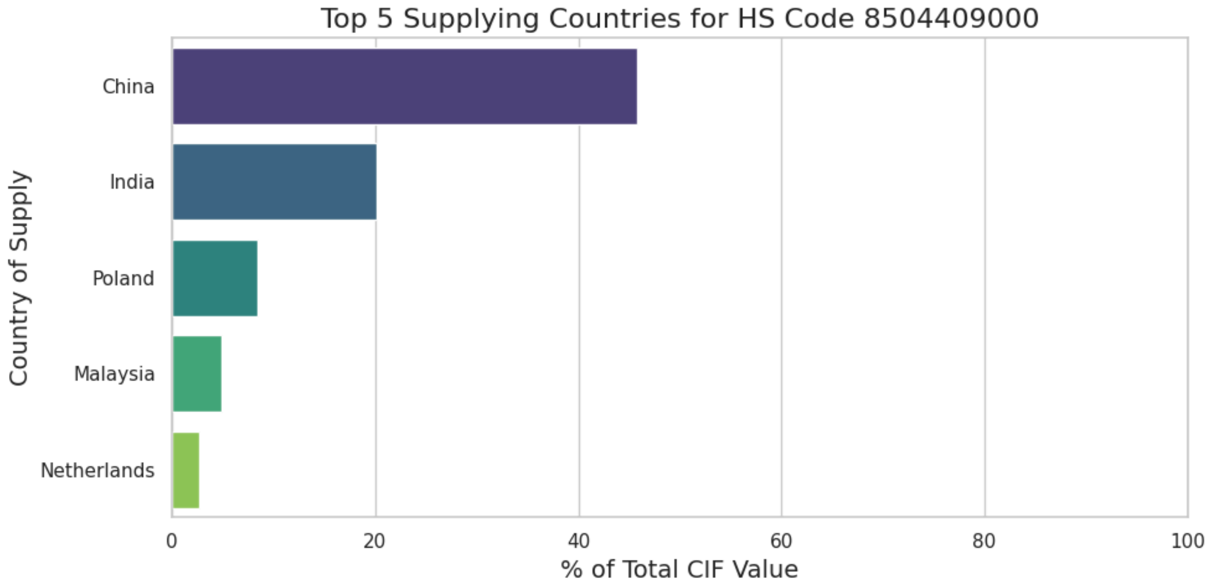
```
# Visualize Top countries supplying Critical HS Codes

# Set plot style
sns.set(style="whitegrid")
plt.figure(figsize=(8, 5))

# Plot for each HS_Code
for hs in top5_hs_value:
    subset = critical_supply[critical_supply['HS_Code'] == hs].sort_values('

    plt.figure(figsize=(10,5))
    sns.barplot(
        x='%_of_Total_CIF',
        y='Country_of_Supply',
        data=subset,
        palette='viridis',
        hue='Country_of_Supply'
    )

    plt.title(f"Top 5 Supplying Countries for HS Code {hs}", fontsize=16)
    plt.xlabel("% of Total CIF Value", fontsize=14)
    plt.ylabel("Country of Supply", fontsize=14)
    plt.xlim(0, 100)
    plt.tight_layout()
    plt.show()
```

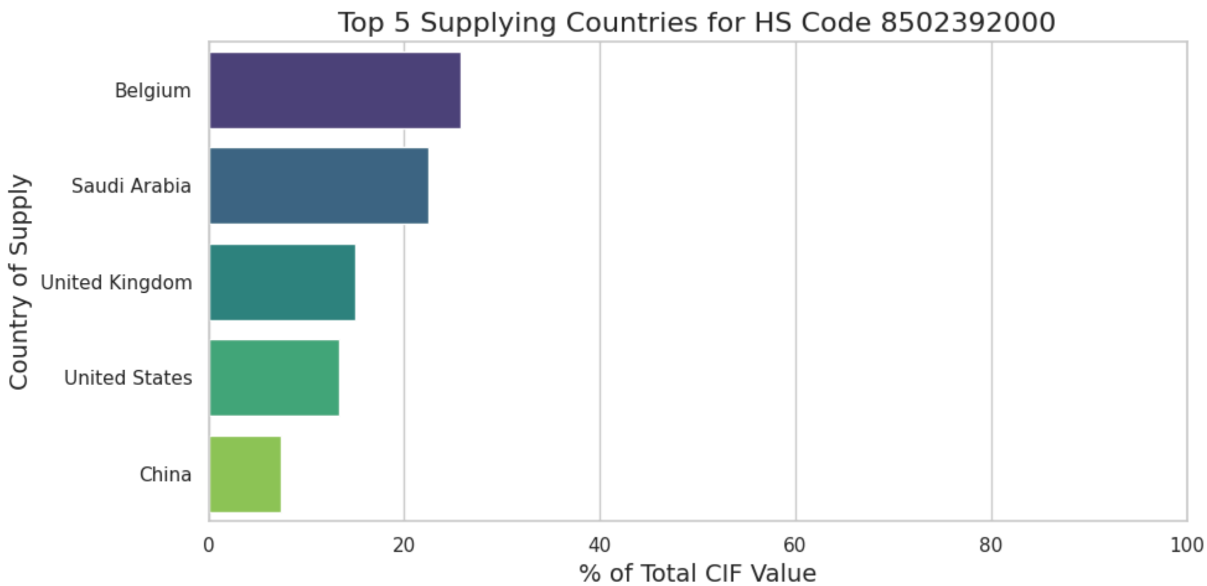
```
<Figure size 800x500 with 0 Axes>
```


Top 5 Supplying Countries for HS Code 8517620000
Country of Supply
China
Netherlands
Sweden
United Arab Emirates
France
0
20
40
60
80
100
% of Total CIF Value


Top 5 Supplying Countries for HS Code 8528721000
Country of Supply
China
South Korea
United Arab Emirates
Indonesia
Taiwan, Province of China
0
20
40
60
80
100
% of Total CIF Value


Top 5 Supplying Countries for HS Code 8502121000
Country of Supply
United Kingdom
China
India
Lebanon
Belgium
0
20
40
60
80
100
% of Total CIF Value

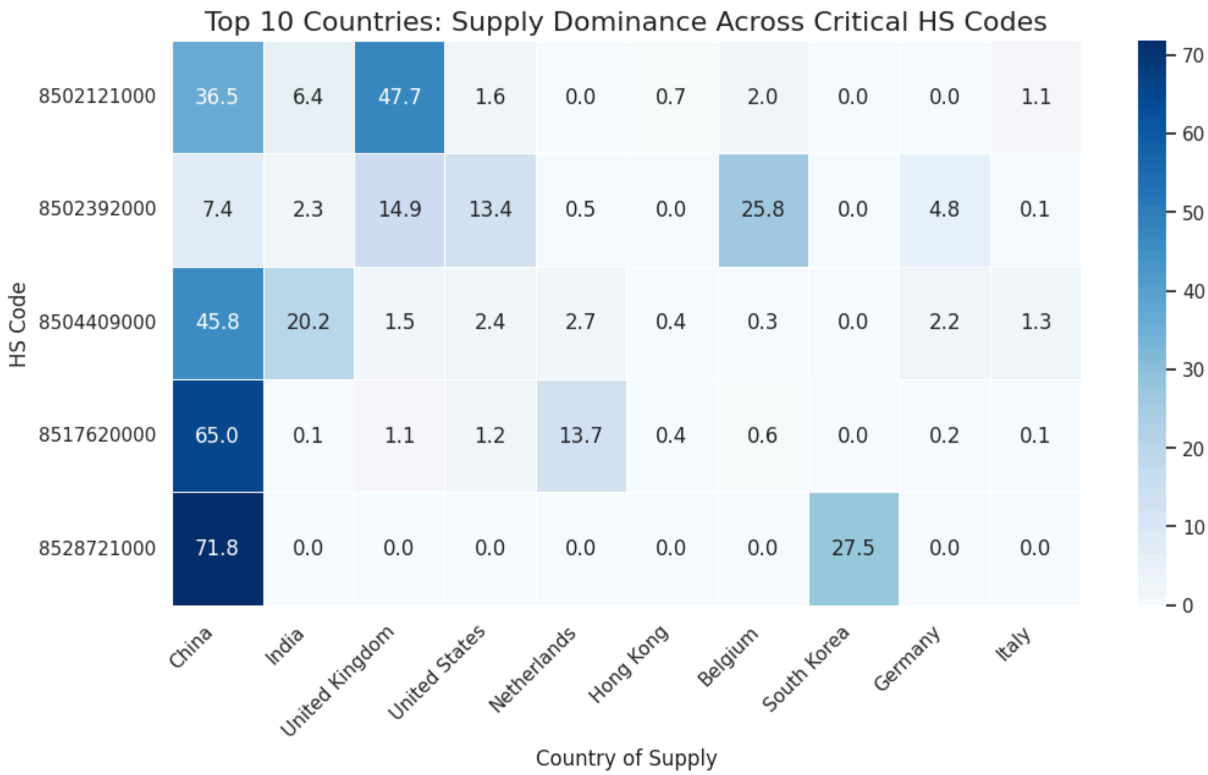




In [ ]:

```
pivot_table = critical_hs.pivot_table(
    index='HS_Code',
    columns='Country_of_Supply',
    values='CIF_Value(N)',
    aggfunc='sum',
    fill_value=0
)

# Normalize the pivot table row-wise
pivot_normalized = pivot_table.div(pivot_table.sum(axis=1), axis=0) * 100

# Select top 10 countries overall
top_countries = data.groupby('Country_of_Supply')['CIF_Value(N)'].sum().sort

# Filter pivot table
pivot_filtered = pivot_normalized[top_countries]

# Plot filtered heatmap
plt.figure(figsize=(12,6))
```

```
sns.heatmap(pivot_filtered, cmap="Blues", annot=True, fmt=".1f", linewidths=

plt.title('Top 10 Countries: Supply Dominance Across Critical HS Codes', for
plt.xlabel('Country of Supply')
plt.ylabel('HS Code')
plt.xticks(rotation=45, ha='right')
plt.show()
```



3.6 Conclusion: Strategic Import Dependency

Key Insights

- **Product Concentration**:
  - Top 5 HS codes ~ 30% of total import value
  - Peak items:
    - `8517120000` (Mobile phones) - **Most frequent import**
    - `8517620000` (Data transmission machines) - **Highest value (₦102.28B, 13.05%)**
- **Geographic Risks**:
  - **China dominates**: 54% of origin & 50% of supply value
  - Limited diversification (Next-largest origin: India 9%, UK 6%)
- **Seasonality**:
  - **January peak**: Highest import volumes
  - **February drop**: Sharp decline following January surge (seasonal pattern)

- **Mid-year dips**: Notable reductions in **May** and **November** suggesting demand volatility
- **Q4 fluctuation**: Moderate recovery after November dip

Recommendation

1. **Diversify Sources:**

- Implement **China+1** sourcing strategy for telecom/electronics to reduce geopolitical risk

2. **Boost Local Capacity**:
   - Target `8517620000` for SKD assembly tax incentives
3. **Dynamic Trade Policies**:
   - Tariff bands for over-concentrated HS codes
   - Real-time Herfindahl-Hirschman Index (HHI) dashboard for HS code concentration.

4. Taxation Optimization & Revenue Leakage

4.1 Key Metric: Total Tax Value (N)

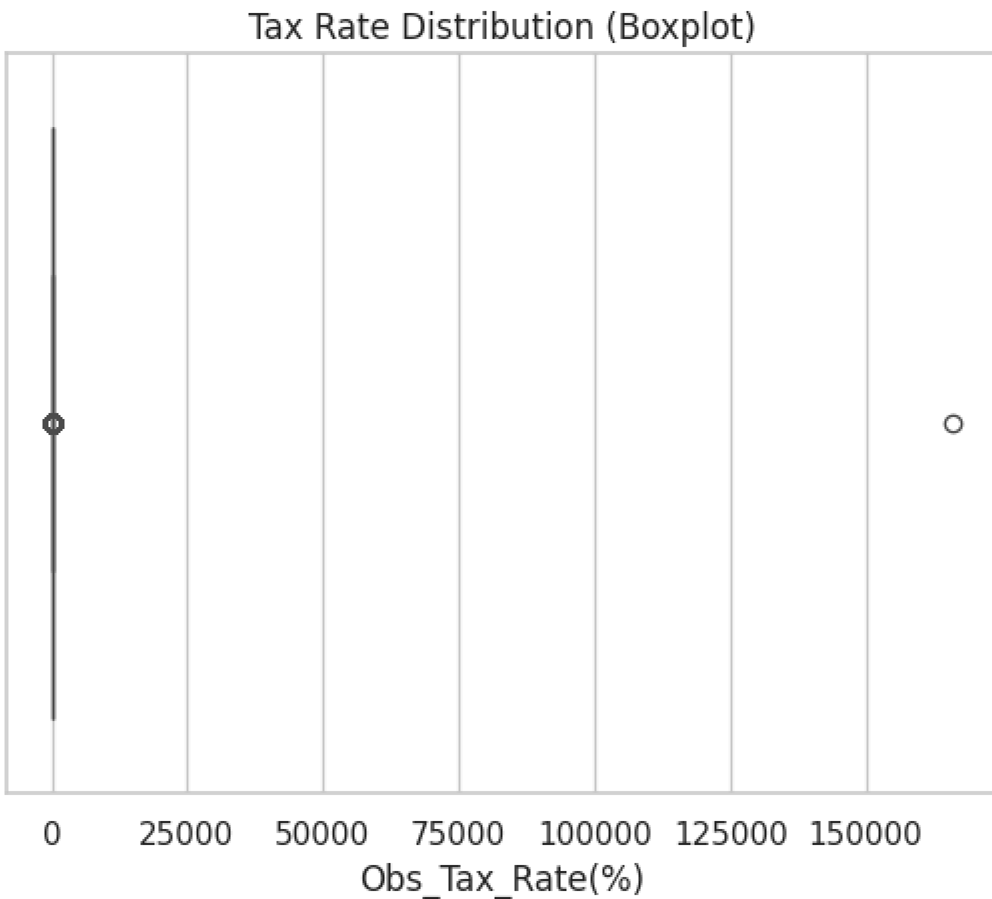
In [ ]:
```
# Calculate Total Tax Revenue
total_tax_rev = data['Total_Tax(N)'].sum()
print(f"Total Revenue From Tax: {total_tax_rev:,.2f} Naira")
```

```
Total Revenue From Tax: 100,162,982,074.00 Naira
```

4.2 Data Preparation & Tax Rate Computation

In [ ]:
```
#calculate observed tax rate
data['Obs_Tax_Rate(%)'] = ((data['Total_Tax(N)'] / data['CIF_Value(N)']) * 1
```

In [ ]:
```
# Distribution of tax rate to check for outliers
sns.boxplot(data=data, x='Obs_Tax_Rate(%)')
plt.title('Tax Rate Distribution (Boxplot)')
plt.show()
```



In [ ]:
```
# Check for outliers in Tax Rate column
data['Obs_Tax_Rate(%)'].quantile([0.95, 0.99, 0.999, 1])
```

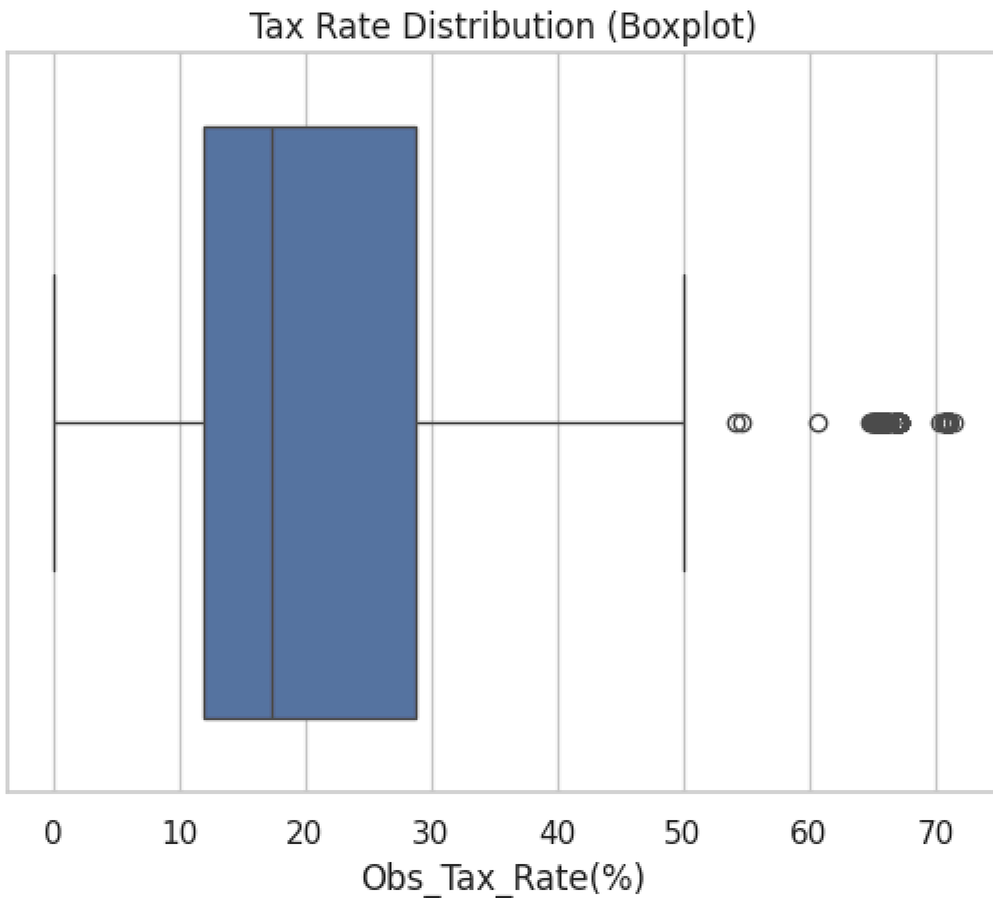
Out[ ]:

	Obs_Tax_Rate(%)
0.950	29.0
0.990	44.7
0.999	70.8
1.000	166163.1

dtype: float64

In [ ]:
```
# Remove Extreme Outliers
data = data[data['Obs_Tax_Rate(%)'] <= 100]

print(data['Obs_Tax_Rate(%)'].describe(), '\n')

# Distribution of tax rate
sns.boxplot(data=data, x='Obs_Tax_Rate(%)')
plt.title('Tax Rate Distribution (Boxplot)')
plt.show()
```

```
count    110366.000000
mean         17.138719
std           9.676227
min           0.000000
25%          12.000000
50%          17.400000
75%          28.700000
max          71.500000
Name: Obs_Tax_Rate(%), dtype: float64
```



In [ ]:
```
# load external datset containing Nigeria Custom Services (NCS) approved Rat
tax_data = pd.read_excel('/content/drive/MyDrive/ZTH_Hackathon/cet_tariff.xl
tax_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 350 entries, 0 to 349
Data columns (total 2 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   HS_Code       350 non-null    int64  
 1   Exp_Tax_Rate  350 non-null    float64
dtypes: float64(1), int64(1)
memory usage: 5.6 KB
```

In [ ]:
```
# Ensuring both datasets have HS_Code as string
tax_data['HS_Code'] = tax_data['HS_Code'].astype(str)

# rename expected rax rate
```

```python
tax_data = tax_data.rename(columns={'Exp_Tax_Rate': 'Exp_Tax_Rate(%)'})


# view dataset
tax_data.head()
```

Out[ ]:

	HS_Code	Exp_Tax_Rate(%)
0	8541420000	0.0
1	8541430000	0.0
2	8535900000	10.0
3	8517130000	22.5
4	8519811000	32.5

In [ ]:

```python
# merge both datasets on HS_Code
merged_data = data.merge(tax_data, on='HS_Code', how='left')
print(merged_data.shape)
merged_data.head()
```

```
(110366, 15)
```

Out[ ]:

	Custom_Office	Reg_Number	Reg_Date	Importer	Item_Nbr	HS_Code	I
0	PORT HARCOURT(3) ONNE	C33563	2019-09-03	0. C. CHRIS & CO	1\2	8513100000	
1	TIN CAN ISLAND	C102199	2019-08-19	08 EXPRESS SERVICES	4\4	8528739000	
2	TIN CAN ISLAND	C90075	2019-07-24	08 EXPRESS SERVICES	4\4	8528739000	
3	TIN CAN ISLAND	C33952	2019-03-25	08 EXPRESS SERVICES	4\4	8509800000	El
4	APAPA PORT	C11025	2019-02-18	08 EXPRESS SERVICES	4\4	8509800000	El

In [ ]:

```python
merged_data.isnull().sum()
```

Out[ ]:

	0
Custom_Office	0
Reg_Number	0
Reg_Date	0
Importer	0
Item_Nbr	0
HS_Code	0
HS_Description	0
FOB_Value(N)	0
CIF_Value(N)	0
Total_Tax(N)	0
Country_of_Origin	0
Country_of_Supply	0
Month	0
Obs_Tax_Rate(%)	0
Exp_Tax_Rate(%)	0

dtype: int64

In [ ]:

```
merged_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110366 entries, 0 to 110365
Data columns (total 15 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Custom_Office      110366 non-null  object
 1   Reg_Number         110366 non-null  object
 2   Reg_Date           110366 non-null  datetime64[ns]
 3   Importer           110366 non-null  object
 4   Item_Nbr           110366 non-null  object
 5   HS_Code            110366 non-null  object
 6   HS_Description     110366 non-null  object
 7   FOB_Value(N)       110366 non-null  int64
 8   CIF_Value(N)       110366 non-null  int64
 9   Total_Tax(N)       110366 non-null  int64
 10  Country_of_Origin  110366 non-null  object
 11  Country_of_Supply  110366 non-null  object
 12  Month              110366 non-null  category
 13  Obs_Tax_Rate(%)    110366 non-null  float64
 14  Exp_Tax_Rate(%)    110366 non-null  float64
dtypes: category(1), datetime64[ns](1), float64(2), int64(3), object(8)
memory usage: 11.9+ MB
```

```
In [ ]: # Calculate Expected Tax Amount
merged_data['Exp_Total_Tax(N)'] = ((merged_data['CIF_Value(N)'] * merged_dat

# Calculate Tax Gap
merged_data['Tax_Gap(N)'] = ((merged_data['Exp_Total_Tax(N)'] - merged_data[

# Difference in Rate
merged_data['Tax_Gap(%)'] = (merged_data['Exp_Tax_Rate(%)'] - merged_data['O

# print all computed values
print('Total Expected Tax (N):', "{:,.0f}".format(merged_data['Exp_Total_Tax
print('Total Observed Tax (N):', "{:,.0f}".format(merged_data['Total_Tax(N)'
print('Total Tax Gap(N):', "{:,.0f}".format(merged_data['Tax_Gap(N)'].sum())
print('Average Observed Tax Rate(%):', "{:.1f}".format(merged_data['Obs_Tax_
print('Average Expected Tax Rate(%):', "{:.1f}".format(merged_data['Exp_Tax_
print('Total Tax Gap:', "{:,.1f}".format(merged_data['Tax_Gap(N)'].sum()))
```

```
Total Expected Tax (N): 109,024,549,339
Total Observed Tax (N): 100,162,432,065
Total Tax Gap(N): 8,862,117,274
Average Observed Tax Rate(%): 17.1
Average Expected Tax Rate(%): 17.6
Total Tax Gap: 8,862,117,274.0
```

4.3 CIF vs. Tax Collected Across Customs Offices and Importers

4.3.1 By Custom Office

```
In [ ]: # CIF vs Tax: Group by Custom Office
customs_tax = merged_data.groupby('Custom_Office').agg({
    'CIF_Value(N)': 'sum',
    'Total_Tax(N)': 'sum',
    'Exp_Total_Tax(N)': 'sum'
})


# Calculate tax rates and gaps by Custom Office
customs_tax['Obs_Tax_Rate(%)'] = (customs_tax['Total_Tax(N)'] / customs_tax[
customs_tax['Exp_Tax_Rate(%)'] = customs_tax['Exp_Total_Tax(N)'] / customs_t
customs_tax['Tax_Gap(%)'] = customs_tax['Exp_Tax_Rate(%)'] - customs_tax['Ob
customs_tax['Tax_Gap(N)'] = customs_tax['Exp_Total_Tax(N)'] - customs_tax['T
customs_tax.sort_values(by='Tax_Gap(N)', ascending=False, inplace=True)
print('Custom Office Comparison \n')
customs_tax.reset_index()
```

```
Custom Office Comparison
```

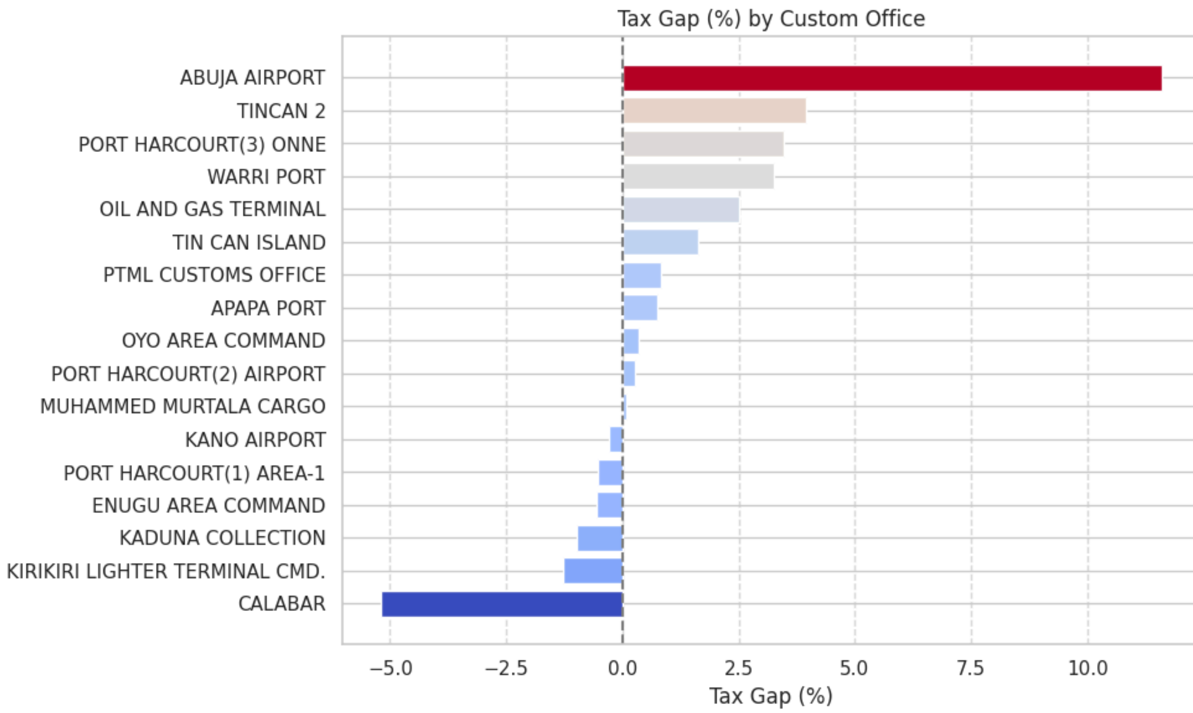
Out[ ]:

	Custom_Office	CIF_Value(N)	Total_Tax(N)	Exp_Total_Tax(N)	Obs_Tax_Rat
0	TIN CAN ISLAND	148431090541	20685755627	23109488464	13.93
1	APAPA PORT	304605868507	38002217935	40279439429	12.47
2	TINCAN 2	44538260000	5044545477	6808056084	11.32
3	PORT HARCOURT(3) ONNE	44929471514	4733552767	6294491500	10.53
4	ABUJA AIRPORT	3514813988	192224160	600465147	5.46
5	WARRI PORT	12165899024	574793525	969730931	4.72
6	PTML CUSTOMS OFFICE	26870381479	3784952821	4007355444	14.08
7	OIL AND GAS TERMINAL	4111224810	624871243	728021514	15.19
8	MUHAMMED MURTALA CARGO	139653556355	19756245370	19853896709	14.14
9	PORT HARCOURT(2) AIRPORT	12899368293	1853879725	1887955493	14.37
10	OYO AREA COMMAND	85210193	10367529	10662110	12.16
11	ENUGU AREA COMMAND	581728318	89595696	86324979	15.40
12	KADUNA COLLECTION	356770583	23963836	20430675	6.71
13	KANO AIRPORT	5994915727	871211404	853200166	14.53
14	CALABAR	451910415	79919524	56488792	17.68
15	PORT HARCOURT(1) AREA-1	8890899094	1148807845	1102774775	12.92
16	KIRIKIRI LIGHTER TERMINAL CMD.	25756984943	2685527581	2355767127	10.42

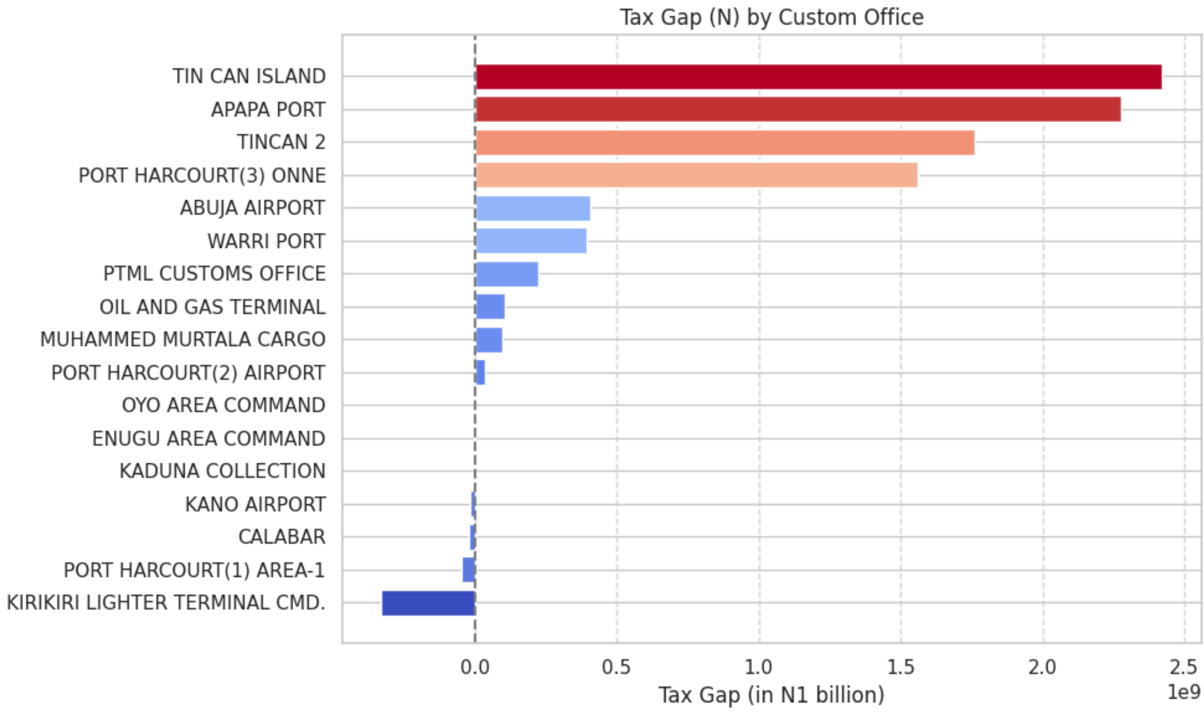
In [ ]:

```
# Visualize tax rates and gaps(%) by Custom Office
customs_tax_sorted = customs_tax.sort_values(by='Tax_Gap(%)', ascending=Fals

# Normalize and set colour
norm = mcolors.Normalize(vmin=customs_tax_sorted['Tax_Gap(%)'].min(), vmax=c
colors = cm.coolwarm(norm(customs_tax_sorted['Tax_Gap(%)'].values))

# Plotting
plt.figure(figsize=(10, 6))
```

```
plt.barh(customs_tax_sorted.index, customs_tax_sorted['Tax_Gap(%)'], color=c
plt.xlabel('Tax Gap (%)')
plt.title('Tax Gap (%) by Custom Office')
plt.axvline(0, color='gray', linestyle='--')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.grid(True, axis='x', linestyle='--', alpha=0.7)
plt.show()
```



In [ ]:
```
# Visualize tax rates and gaps value by Custom Office
# normalize and set colour
norm = mcolors.Normalize(vmin=customs_tax['Tax_Gap(N)'].min(), vmax=customs_
colors = cm.coolwarm(norm(customs_tax['Tax_Gap(N)'].values))

# Plotting
plt.figure(figsize=(10, 6))
plt.barh(customs_tax.index, customs_tax['Tax_Gap(N)'], color=colors)
plt.xlabel('Tax Gap (in N1 billion)')
plt.title('Tax Gap (N) by Custom Office')
plt.axvline(0, color='gray', linestyle='--')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.grid(True, axis='x', linestyle='--', alpha=0.7)
plt.show()
```



4.3.2 By Importer

In [ ]:

```
# CIF vs Tax: Group by Importer
importer_tax = merged_data.groupby('Importer').agg({
    'CIF_Value(N)': 'sum',
    'Total_Tax(N)': 'sum',
    'Exp_Total_Tax(N)': 'sum',
}).reset_index()


# Calculate tax rates and gaps for each Importer
importer_tax['Obs_Tax_Rate(%)'] = (importer_tax['Total_Tax(N)'] / importer_t
importer_tax['Exp_Tax_Rate(%)'] = importer_tax['Exp_Total_Tax(N)'] / importe
importer_tax['Tax_Gap(%)'] = importer_tax['Exp_Tax_Rate(%)'] - importer_tax[
importer_tax['Tax_Gap(N)'] = importer_tax['Exp_Total_Tax(N)'] - importer_tax

#sort importer by those with highest tax gaps
print('Top 10 Importers by Tax Gap (N)\n')
importer_tax.sort_values(by='Tax_Gap(N)', ascending=False).head(10)
```

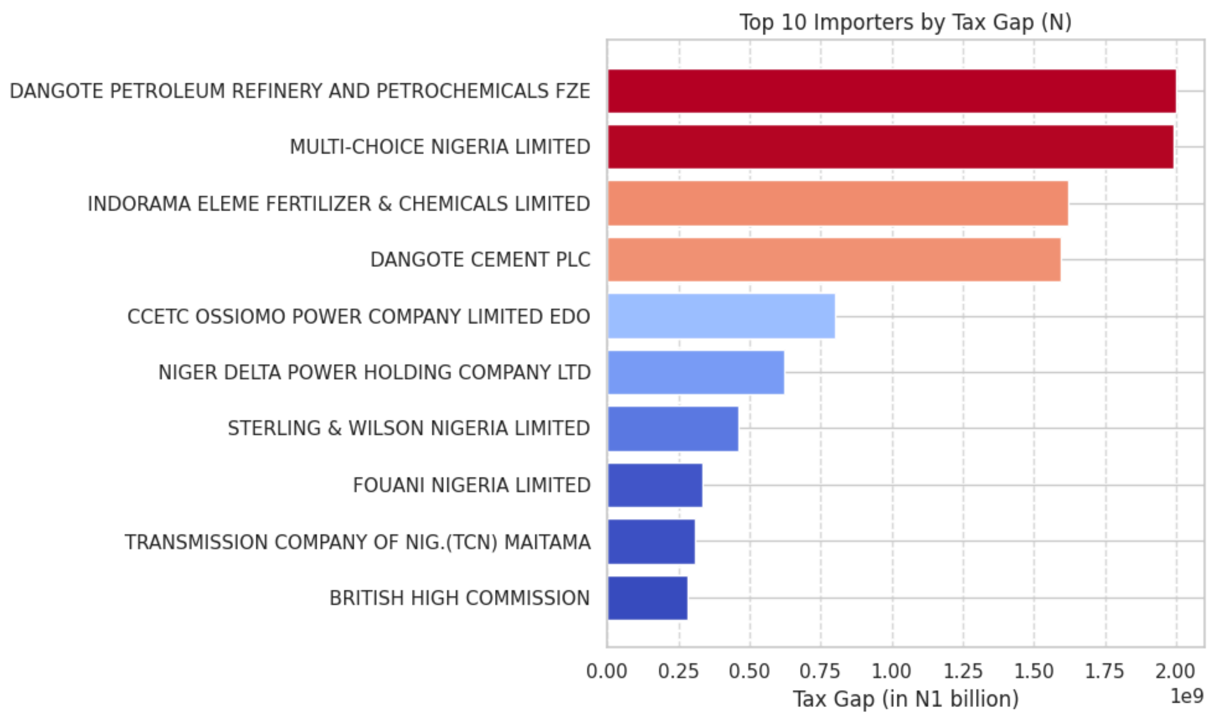
```
Top 10 Importers by Tax Gap (N)
```

Out[ ]:

	Importer	CIF_Value(N)	Total_Tax(N)	Exp_Total_Tax(N)	Obs_Tax_
2336	DANGOTE PETROLEUM REFINERY AND PETROCHEMICALS FZE	28892056425	3118935018	5119328094	10
6268	MULTI-CHOICE NIGERIA LIMITED	17260472048	4938158154	6929236328	28
4536	INDORAMA ELEME FERTILIZER & CHEMICALS LIMITED	10747088480	304788078	1924695778	2
2329	DANGOTE CEMENT PLC	11641746391	368621654	1961528828	3
1642	CCETC OSSIOMO POWER COMPANY LIMITED EDO	11560932097	206512616	1007193262	1
6497	NIGER DELTA POWER HOLDING COMPANY LTD	6913992026	170258330	792908531	2
8770	STERLING & WILSON NIGERIA LIMITED	2996962959	102025599	561270707	3
3613	FOUANI NIGERIA LIMITED	45754060112	6662698522	6997354221	14
9208	TRANSMISSION COMPANY OF NIG. (TCN) MAITAMA	3378480606	156846433	466779349	4
1462	BRITISH HIGH COMMISSION	1887393105	0	281755300	0

In [ ]:

```
# Visualize tax rates and gap value by Importer
top_importers_n = importer_tax.sort_values(by='Tax_Gap(N)', ascending=False)

# Normalize colors for Naira gap
norm_n = mcolors.Normalize(vmin=top_importers_n['Tax_Gap(N)'].min(), vmax=to
colors_n = cm.coolwarm(norm_n(top_importers_n['Tax_Gap(N)'].values))

plt.figure(figsize=(10, 6))

# Plot: Tax Gap (₦)
plt.barh(top_importers_n['Importer'], top_importers_n['Tax_Gap(N)'], color=c
plt.xlabel('Tax Gap (in N1 billion)')
plt.title('Top 10 Importers by Tax Gap (N)')
plt.gca().invert_yaxis()
plt.grid(True, axis='x', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



4.4 Estimated Tax Gap by HS Code

In [ ]:
```
# Group by HS Code
tax_gap_hs = merged_data.groupby(['HS_Code', 'HS_Description']).agg({
    'CIF_Value(N)': 'sum',
    'Exp_Total_Tax(N)': 'sum',
    'Total_Tax(N)': 'sum',
}).reset_index()

tax_gap_hs['Obs_Tax_Rate(%)'] = (tax_gap_hs['Total_Tax(N)'] / tax_gap_hs['CI
tax_gap_hs['Exp_Tax_Rate(%)'] = (tax_gap_hs['Exp_Total_Tax(N)'] / tax_gap_hs
tax_gap_hs['Tax_Gap(%)'] = tax_gap_hs['Exp_Tax_Rate(%)'] - tax_gap_hs['Obs_T
tax_gap_hs['Tax_Gap(N)'] = tax_gap_hs['Exp_Total_Tax(N)'] - tax_gap_hs['Tota

# View top HS Codes with highest gaps
print('HS Codes with the highest tax gaps \n')
tax_gap_hs.sort_values('Tax_Gap(N)', ascending=False).head(10)
```

```
HS Codes with the highest tax gaps
```

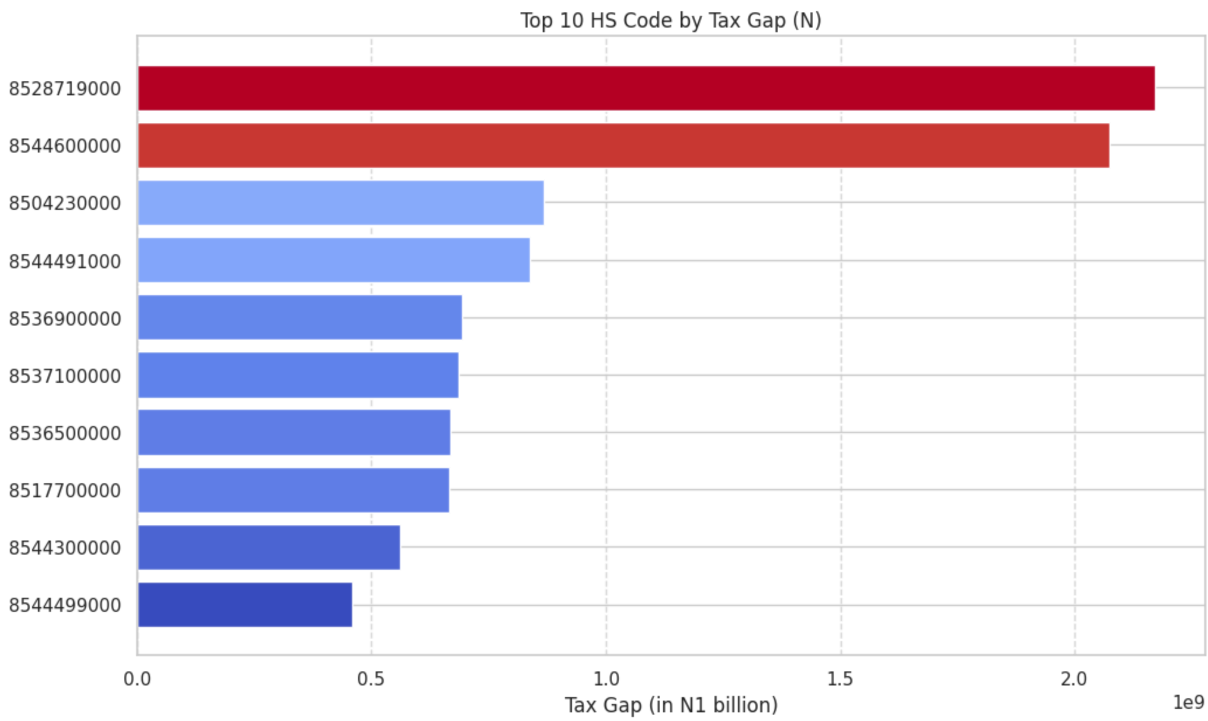
Out[ ]:

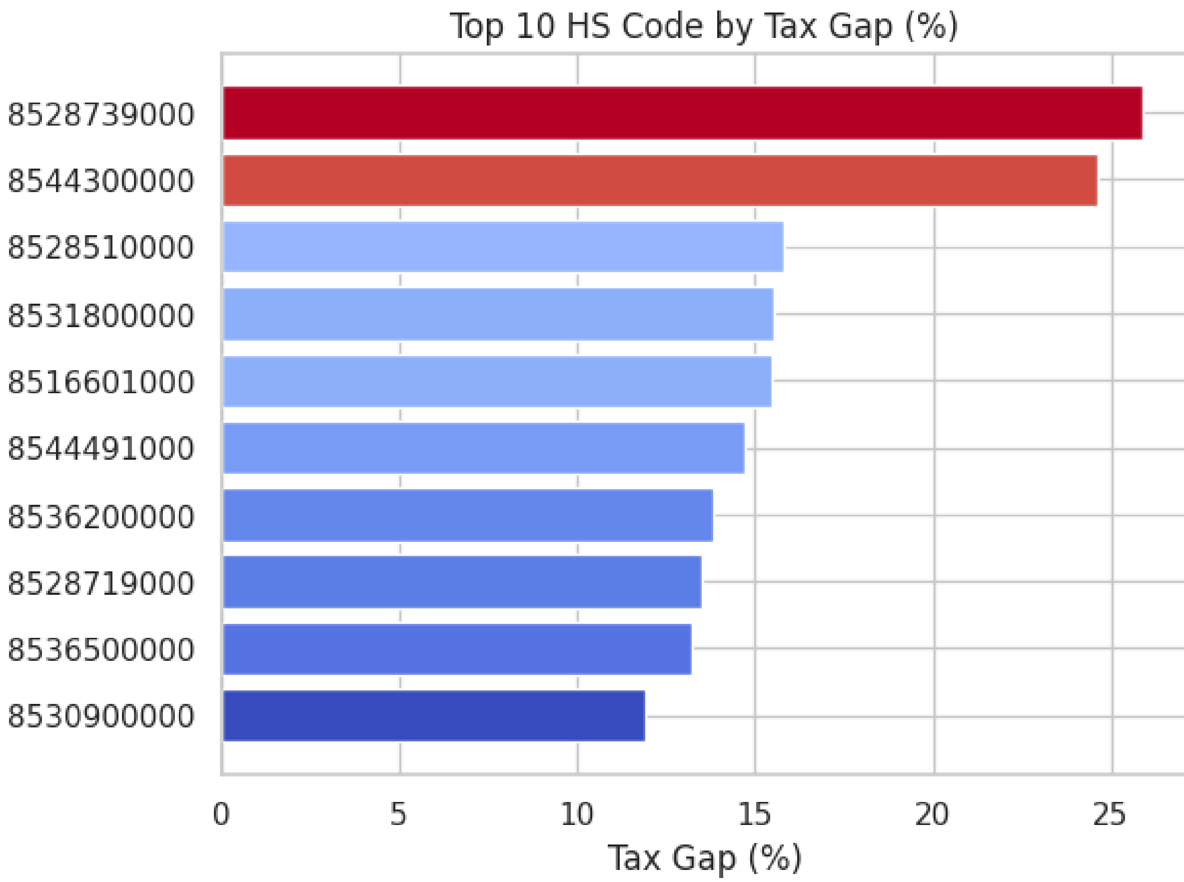
	HS_Code	HS_Description	CIF_Value(N)	Exp_Total_Tax(N)	Total_Tax(N)
190	8528719000	Reception Apparatus For Television, With No Vi...	16067707912	6828775141	4657944123
290	8544600000	Other Electric Conductors, For A Voltage Excee...	18173775432	3180410579	1106370987
42	8504230000	Liquid Dielectric Transformers, Having A Power...	8414210494	1051776271	184059829
288	8544491000	Almenec Insulated Cables, Metallic Part Made O...	5685176450	994905807	157604762
236	8536900000	Other Apparatus Of Heading 85.36 Not Specified	5939955765	1633487084	940024396
237	8537100000	Boards, Panels, Consoles For Electric Control/...	22859138372	2857390863	2172663173
232	8536500000	Other Electrical Switches	5049953736	1388735860	721246255
135	8517700000	Parts Of Article Of Heading 8517	20756282745	2075627026	1409074596
286	8544300000	Ignition Wiring Sets And Other Wiring Sets Of ...	2280459641	627126301	65971321
289	8544499000	Other Electric Conductors, For A Voltage Not E...	14104264697	3878672246	3419802485

In [ ]:

```
# Visualize HS Code with high tax gap
# Sort by Tax Gap (Naira) and select top 10
tax_gap_hs_n = tax_gap_hs.sort_values(by='Tax_Gap(N)', ascending=False).head

# Normalize colors for Naira gap
norm_n = mcolors.Normalize(vmin=tax_gap_hs_n['Tax_Gap(N)'].min(), vmax=tax_g
colors_n = cm.coolwarm(norm_n(tax_gap_hs_n['Tax_Gap(N)'].values))

# Plot: Tax Gap (N)
plt.figure(figsize=(10, 6))
plt.grid(True, axis='x', linestyle='--', alpha=0.7)
plt.tight_layout()

plt.barh(tax_gap_hs_n['HS_Code'], tax_gap_hs_n['Tax_Gap(N)'], color=colors_r
```

```
plt.xlabel('Tax Gap (in N1 billion)')
plt.title('Top 10 HS Code by Tax Gap (N)')
plt.gca().invert_yaxis()
plt.show()

# Sort by Tax Gap (%) and select top 10
tax_gap_hs_pct = tax_gap_hs.sort_values(by='Tax_Gap(%)', ascending=False).he

# Normalize colors for percentage gap
norm_pct = mcolors.Normalize(vmin=tax_gap_hs_pct['Tax_Gap(%)'].min(), vmax=t
colors_pct = cm.coolwarm(norm_pct(tax_gap_hs_pct['Tax_Gap(%)'].values))

# Plot: Tax Gap (%)
plt.barh(tax_gap_hs_pct['HS_Code'], tax_gap_hs_pct['Tax_Gap(%)'], color=colc
plt.xlabel('Tax Gap (%)')
plt.title('Top 10 HS Code by Tax Gap (%)')
plt.gca().invert_yaxis()
plt.show()
```





4.5 Risk Profiling: Low-Tax Goods & Importers

In [ ]:

```
# Threshold: large CIF but positive Tax Gap (paid less than expected)
low_tax_data = merged_data[(merged_data['Tax_Gap(N)'] > 10000000) & (merged_

# Group by Importer or HS Code for profiling
low_tax_profiles = low_tax_data.groupby('Importer')['Tax_Gap(N)'].sum().sort
low_tax_profiles
```

Out[ ]:

Importer	Tax_Gap(N)
DANGOTE PETROLEUM REFINERY AND PETROCHEMICALS FZE	2233763550
MULTI-CHOICE NIGERIA LIMITED	1981462301
INDORAMA ELEME FERTILIZER & CHEMICALS LIMITED	1505429808
DANGOTE CEMENT PLC	1489318513
CCETC OSSIOMO POWER COMPANY LIMITED EDO	768036906
NIGER DELTA POWER HOLDING COMPANY LTD	592438938
STERLING & WILSON NIGERIA LIMITED	433922874
TRANSMISSION COMPANY OF NIG.(TCN) MAITAMA	267983687
CNEEC NIGERIA LIMITED	260025454
DEFENCE INTELLIGENCE AGENCY	228379149

dtype: int64

In [ ]:

```
# Get list of top importers with high tax gaps
top_low_tax = low_tax_profiles.index.tolist()

top_low_tax = top_low_tax[0]
# Step 2: Filter low_tax_data to just those importers
top_importers_data = low_tax_data[low_tax_data['Importer'] == top_low_tax]

# Step 3: Group by Importer and HS_Code
importer_hscode_taxgap = top_importers_data.groupby(['Importer', 'HS_Code',
    'CIF_Value(N)': 'sum',
    'Total_Tax(N)': 'sum',
    'Tax_Gap(N)': 'sum'
}).sort_values('Tax_Gap(N)', ascending=False)

# View top HS codes per importer
print('HS Codes imported by Importer with the most Tax Gap(N)')
importer_hscode_taxgap.head()
```

```
HS Codes imported by Importer with the most Tax Gap(N)
```

Out[ ]:

Importer	HS_Code	HS_Description	CIF_Value(N)	Total_Tax(
DANGOTE PETROLEUM REFINERY AND PETROCHEMICALS FZE	**8544600000**	**Other Electric Conductors, For A Voltage Exceeding 1,000 V**	6917858889	
	8544491000	**Almenec Insulated Cables, Metallic Part Made Of 7 Strands Of Diameter 3.15Mm And 3.55Mm**	4748525399	
	8536900000	**Other Apparatus Of Heading 85.36 Not Specified**	1787784000	3184043
	8537100000	**Boards, Panels, Consoles For Electric Control/Distribution. For A Voltage < 1,000 V**	151280300	

In [ ]:

```
# Threshold: large CIF but positive Tax Gap (paid less than expected)
low_tax_data_p = merged_data[(merged_data['Tax_Gap(%)'] > 30) & (merged_data

# Group by Importer or HS Code for profiling
low_tax_profiles_p = low_tax_data_p.groupby('Importer')['Tax_Gap(%)'].mean()
low_tax_profiles_p
```

Out[ ]:

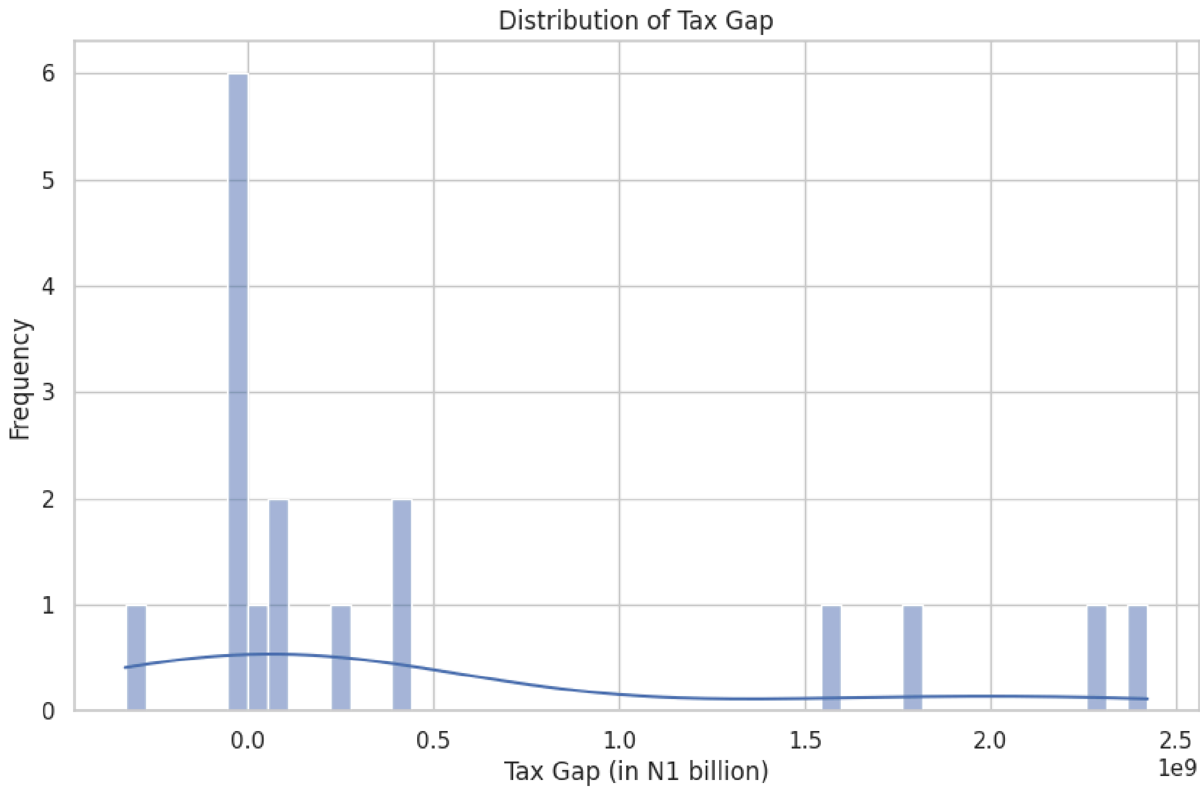
Importer	Tax_Gap(%)
UN WORLD FOOD PROGRAMME	62.500
BRITISH HIGH COMMISSION	51.875
BONNIM.SUNDAY MR.	42.500
BELLO OMOLARA ADUKE.	42.500
ALAOMA ONWUMERE OHO	42.500

dtype: float64

4.6 Anomaly Detection: Identifying Potential Under-Declarations and Tax Evasion

4.6.1 Tax Gap Distribution

```
In [ ]: # Check distribution of tax gap
plt.figure(figsize=(10,6))
sns.histplot(data=customs_tax, x='Tax_Gap(N)', bins=50, kde=True)
plt.title('Distribution of Tax Gap')
plt.xlabel('Tax Gap (in N1 billion)')
plt.ylabel('Frequency')
plt.show()
```



4.6.2 Anomaly detection using Z-score

```
In [ ]: # Subset of relevant numeric columns
cols_to_normalize = ['CIF_Value(N)', 'Total_Tax(N)', 'Tax_Gap(N)', 'Obs_Tax_
clean_data = merged_data[cols_to_normalize].copy()

# Drop rows with missing or infinite values
clean_data = clean_data.replace([float('inf'), -float('inf')], pd.NA).dropna

# Apply Z-score normalization
z_scores = clean_data.apply(zscore)

# flag extreme values in Tax_Gap(N)
z_scores['TaxGap_Z'] = z_scores['Tax_Gap(N)']

# Merge Z-scores back to the original data
merged_data_normalized = merged_data.loc[clean_data.index].copy()
merged_data_normalized['TaxGap_Z'] = z_scores['TaxGap_Z']

# Common threshold for outliers: |z| > 3
anomalies = merged_data_normalized[(merged_data_normalized['TaxGap_Z'].abs()
```

```
# Review top anomalies
anomalies[['Importer', 'HS_Code', 'CIF_Value(N)', 'Tax_Gap(N)', 'Obs_Tax_Rat
```

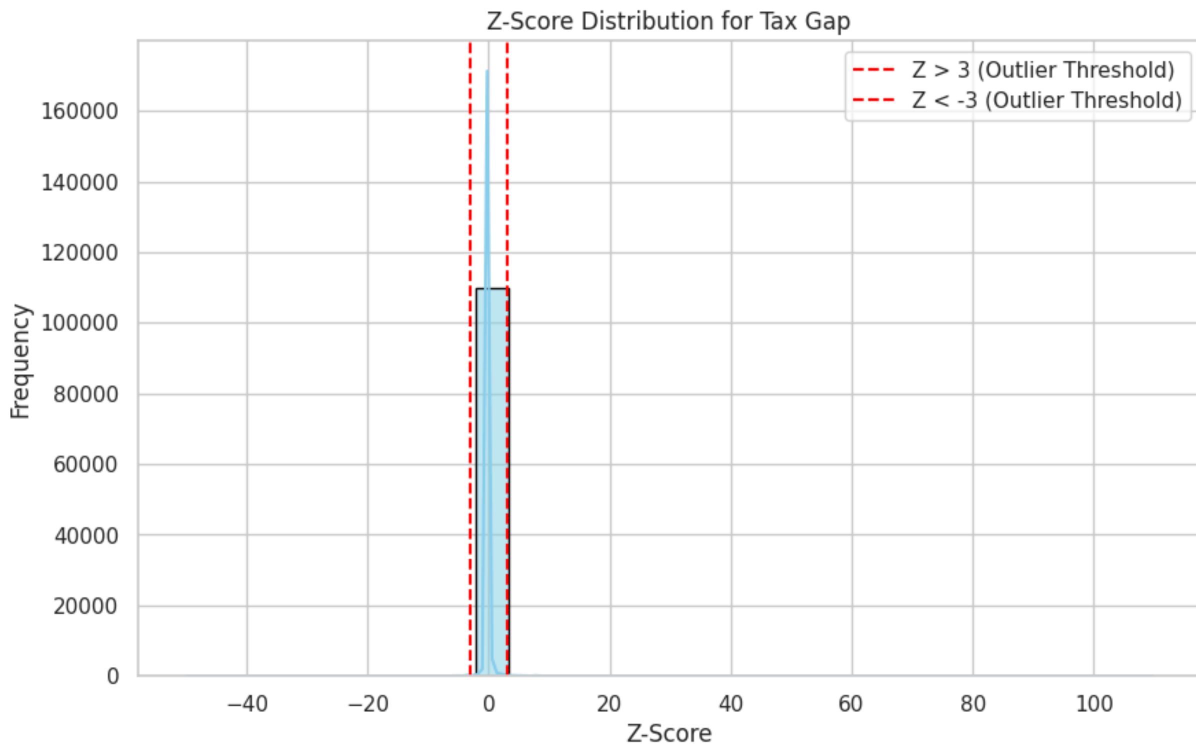
Out[ ]:

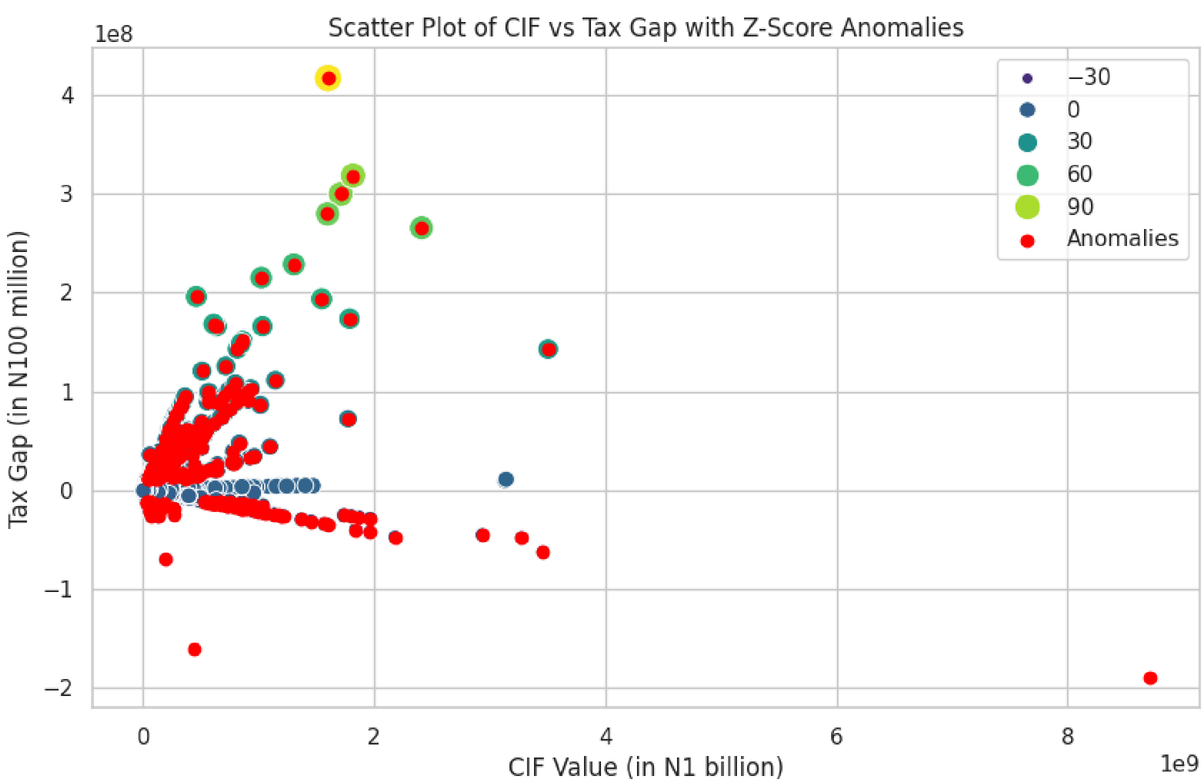
	Importer	HS_Code	CIF_Value(N)	Tax_Gap(N)	Obs_Tax_Rate(%)
0	DANGOTE CEMENT PLC	8544200000	1601010009	416668047	1.5
1	DANGOTE PETROLEUM REFINERY AND PETROCHEMICALS FZE	8544600000	1817555572	318072225	0.0
2	DANGOTE PETROLEUM REFINERY AND PETROCHEMICALS FZE	8544600000	1711089605	299440680	0.0
3	DANGOTE PETROLEUM REFINERY AND PETROCHEMICALS FZE	8544600000	1711089605	299440680	0.0
4	DANGOTE PETROLEUM REFINERY AND PETROCHEMICALS FZE	8544491000	1596406394	279371118	0.0
5	NIGER DELTA POWER HOLDING COMPANY LTD	8504230000	2410584206	265164260	1.5
6	DEFENCE INTELLIGENCE AGENCY	8531800000	1305023712	228379149	0.0
7	CCETC OSSIOMO POWER COMPANY LIMITED EDO	8544499000	1023440860	214758320	6.5
8	FASUYI CAXTON	8528739000	460425000	195680625	0.0
9	CNEEC NIGERIA LIMITED	8530900000	1546592151	193324018	0.0

In [ ]:

```
# Visualize Anomalies
plt.figure(figsize=(10, 6))
sns.histplot(z_scores['TaxGap_Z'], kde=True, bins=30, color='skyblue', edgec
plt.axvline(x=3, color='red', linestyle='--', label='Z > 3 (Outlier Threshol
plt.axvline(x=-3, color='red', linestyle='--', label='Z < -3 (Outlier Thresh
plt.title('Z-Score Distribution for Tax Gap')
plt.xlabel('Z-Score')
plt.ylabel('Frequency')
plt.legend()
plt.show()

# Scatter plot of anomalies
```

```
plt.figure(figsize=(10, 6))
sns.scatterplot(data=merged_data_normalized, x='CIF_Value(N)', y='Tax_Gap(N)
plt.scatter(anomalies['CIF_Value(N)'], anomalies['Tax_Gap(N)'], color='red',
plt.title('Scatter Plot of CIF vs Tax Gap with Z-Score Anomalies')
plt.xlabel('CIF Value (in N1 billion)')
plt.ylabel('Tax Gap (in N100 million)')
plt.legend()
plt.show()
```





4.6.3 Anomaly Detection Using Isolation Forest

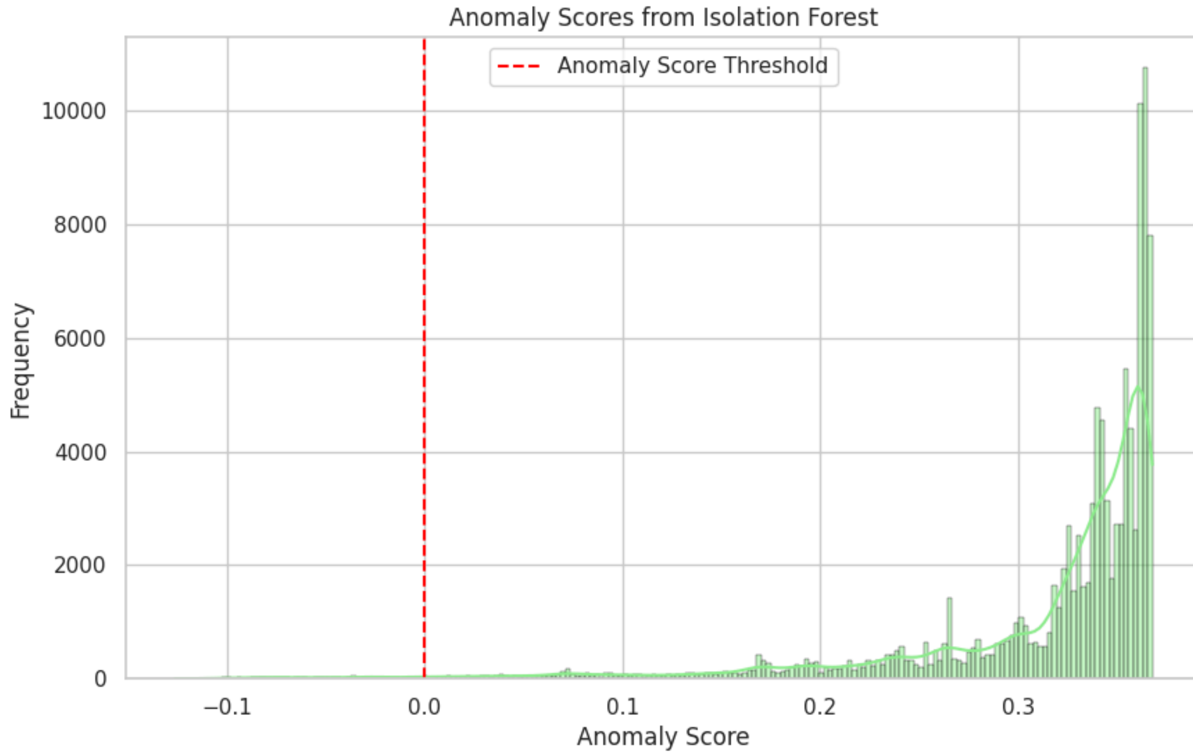
In [ ]:
```
# Prepare data
isf_data = clean_data.copy()

# Fit Isolation Forest
iso_forest = IsolationForest(n_estimators=100, contamination=0.01, random_st
isf_data['Anomaly_Score'] = iso_forest.fit_predict(isf_data)

# Interpret results: -1 = anomaly, 1 = normal
isf_data['Anomaly_Label'] = isf_data['Anomaly_Score'].map({-1: 'Anomaly', 1:

# Get anomaly scores (lower = more anomalous)
isf_data['Anomaly_Score_Value'] = iso_forest.decision_function(isf_data[clea

# Merge back to original data
merged_data_iforest = merged_data.loc[isf_data.index].copy()
merged_data_iforest['Anomaly_Label'] = isf_data['Anomaly_Label']
merged_data_iforest['Anomaly_Score_Value'] = isf_data['Anomaly_Score_Value']

# Filter and sort top anomalies
anomalies_iforest = merged_data_iforest[merged_data_iforest['Anomaly_Label']
anomalies_iforest = anomalies_iforest.sort_values(by='Anomaly_Score_Value')

# View top suspicious records
anomalies_iforest[['Importer', 'HS_Code', 'CIF_Value(N)', 'Tax_Gap(N)', 'Obs
```

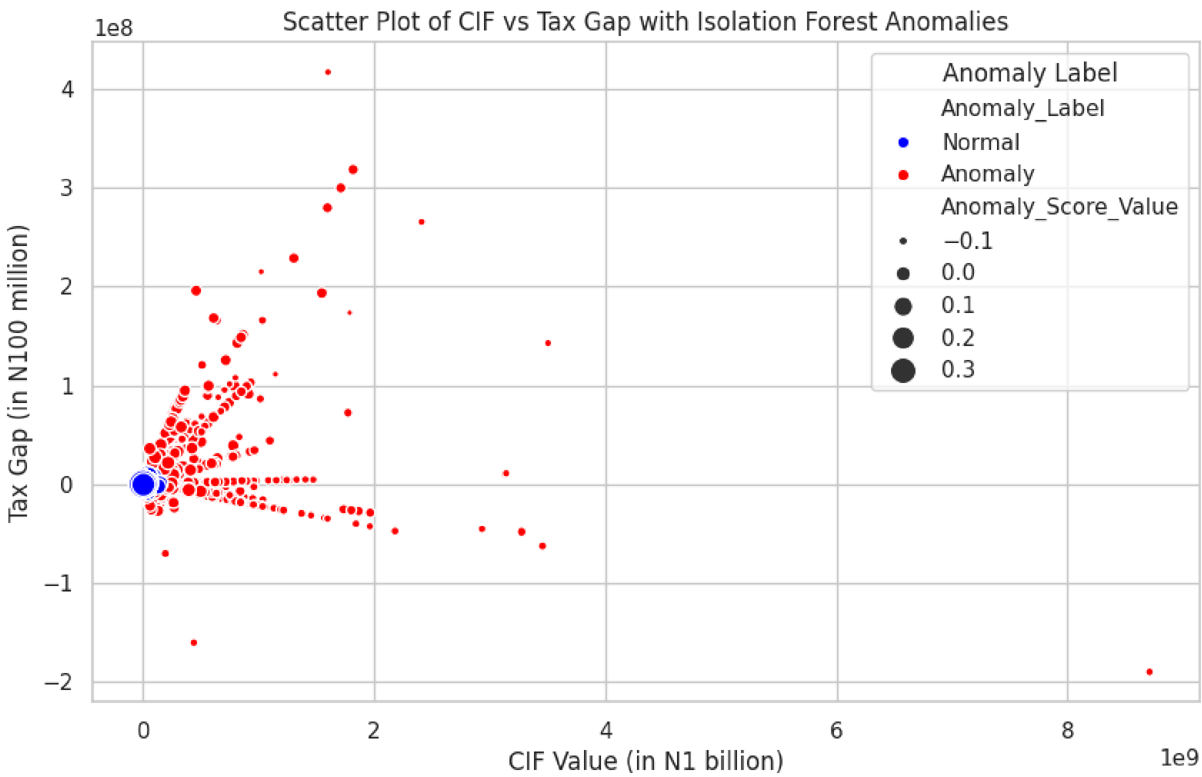
Out[ ]:

	Importer	HS_Code	CIF_Value(N)	Tax_Gap(N)	Obs_Tax_Rate(%)
0	DANGOTE PETROLEUM REFINERY AND PETROCHEMICALS FZE	8536900000	1787784000	173236269	17.8
1	MOBIL PRODUCING NIGERIA UNLIMITED	8536900000	1145206588	111164465	17.8
2	CCETC OSSIOMO POWER COMPANY LIMITED EDO	8544499000	1023440860	214758320	6.5
3	SIMTECKCARD PLANT LIMITED	8523520000	141801850	-4467079	65.7
4	MULTI-CHOICE NIGERIA LIMITED	8528719000	748481004	101161163	29.0
5	MULTI-CHOICE NIGERIA LIMITED	8528719000	798620020	107536715	29.0
6	NIGER DELTA POWER HOLDING COMPANY LTD	8504230000	2410584206	265164260	1.5
7	MULTI-CHOICE NIGERIA LIMITED	8528719000	704726505	95258951	29.0
8	CCETC OSSIOMO POWER COMPANY LIMITED EDO	8502392000	3505450646	142561102	0.9
9	DANGOTE CEMENT PLC	8544200000	1601010009	416668047	1.5

In [ ]:

```
# Plotting Isolation Forest anomaly scores
plt.figure(figsize=(10, 6))
sns.histplot(isf_data['Anomaly_Score_Value'], kde=True, color='lightgreen',
plt.axvline(x=0, color='red', linestyle='--', label='Anomaly Score Thresholc
plt.title('Anomaly Scores from Isolation Forest')
plt.xlabel('Anomaly Score')
plt.ylabel('Frequency')
plt.legend()
plt.show()

# Scatter plot of anomalies using Isolation Forest results
plt.figure(figsize=(10, 6))
sns.scatterplot(data=merged_data_iforest, x='CIF_Value(N)', y='Tax_Gap(N)',
plt.title('Scatter Plot of CIF vs Tax Gap with Isolation Forest Anomalies')
plt.xlabel('CIF Value (in N1 billion)')
plt.ylabel('Tax Gap (in N100 million)')
plt.legend(title='Anomaly Label')
plt.show()
```





4.7 Conclusion: Taxation Optimization & Revenue Leakage

Key Findings

- **₦8.86B Tax Gap** (Expected: ₦109.02B vs Collected: ₦100.16B)

    - Rate shortfall: 17.1% actual vs 17.6% expected
- **Top Leakage Points**:

Category	Specific Cases	Gap Amount
Customs Offices	Tin Can Island	₦2.42B
	Apapa Port	₦2.28B
	Tincan 2	₦1.76B
Importers	Dangote Petroleum Refinery	₦2.23B
	MultiChoice Nigeria	₦1.98B
HS Codes	8528719000 (Reception Apparatus)	₦2.17B
	8544600000 (HV Conductors)	₦2.07B

Anomalies Detected

- **Statistical Flags**:
    - Dangote Cement PLC (Z-Score/Isolation Forest outlier)
    - UN World Food Programme (>50% gap most likely due to exemptions)

Recommendations

1. **Audit Priority**:

    - Top 3 importers (₦5.71B combined gap)
    - HS 8528719000 & 8544600000 (₦4.24B gap)
2. **Port Controls**:

    - Real time CIF validation at Tin Can/Apapa
3. **Exemption Review**:

    - Verify UN/diplomatic claims

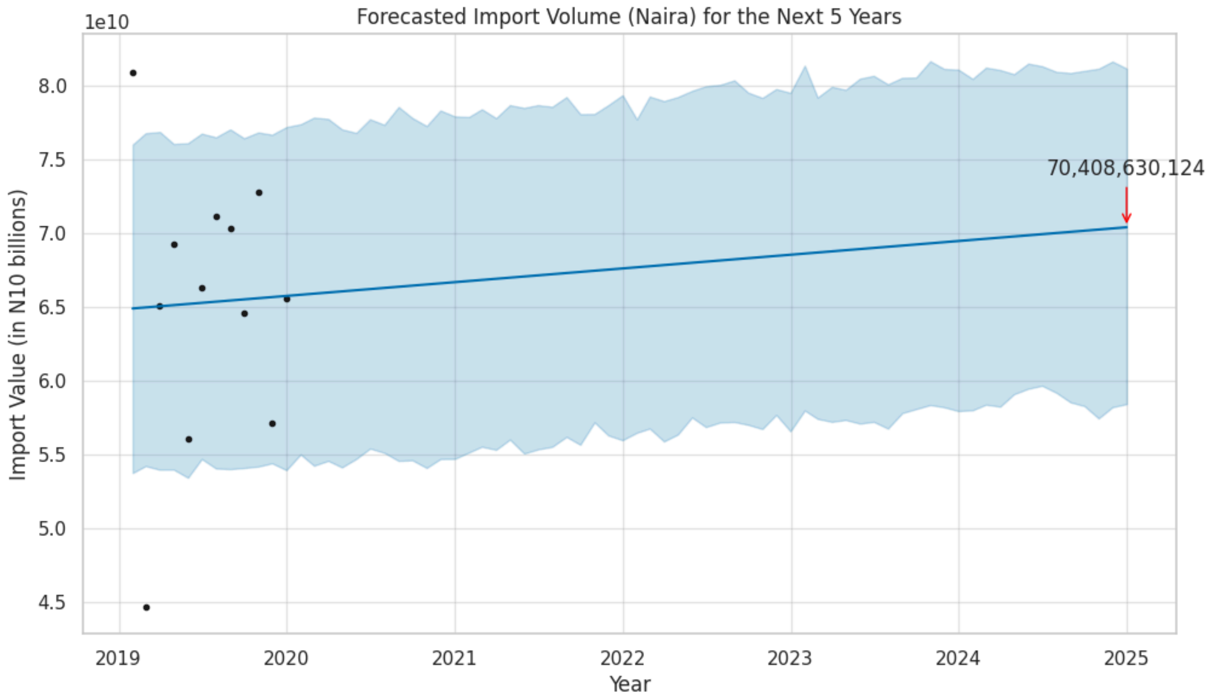
5. Predictive Forecasting of Import Volume & Tax Revenue

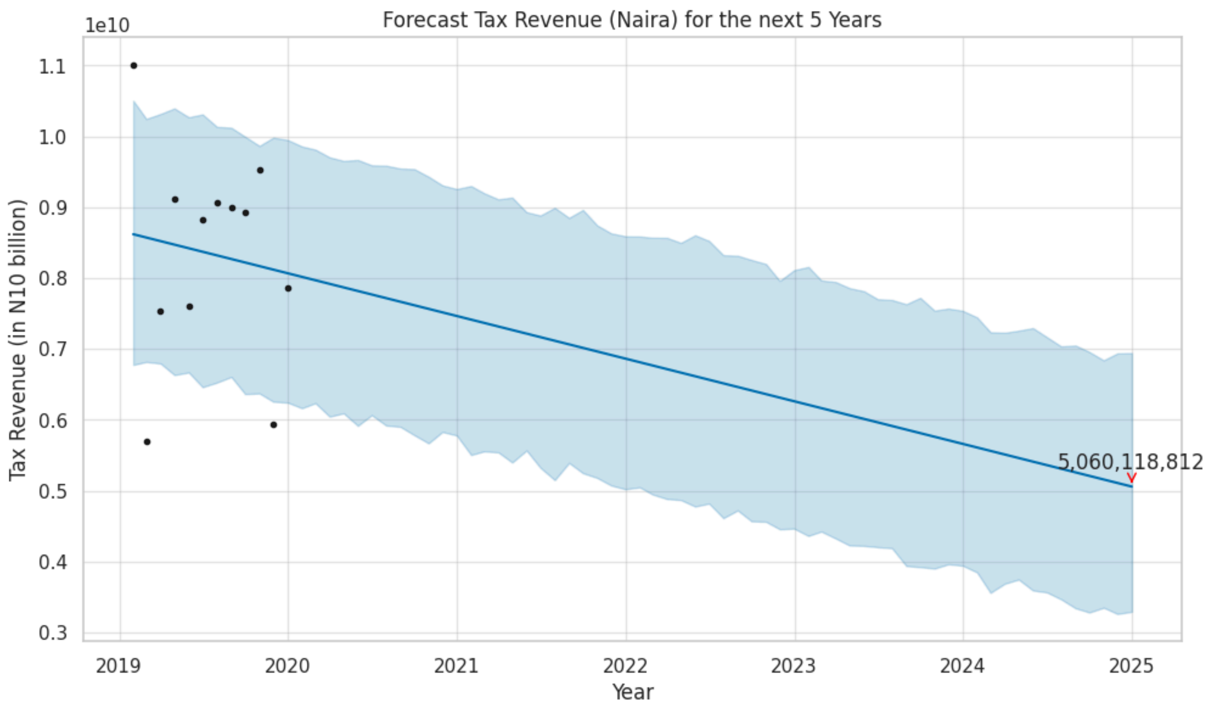
- Time Series Forecasting with Prophet (for extrapolation) -- We'll use Prophet for time series forecasting since it's user friendly and effective even with limited historical data. Prophet can handle seasonal patterns and trends, even with just one year of data.

5.1 Forecasting Import Value and Tax Revenue for the Next 5 Years (60 months) with Prophet

In [ ]:
```
# Use CIF_Value(N) as the target variable
forecast_data = merged_data[['Reg_Date', 'CIF_Value(N)', 'Total_Tax(N)', 'Ex

# Ensure Reg_Date is in datetime format
forecast_data['Reg_Date'] = pd.to_datetime(forecast_data['Reg_Date'])

# Resample to monthly data
forecast_data_monthly = forecast_data.resample('ME', on='Reg_Date').sum().re

# Forecasting Import Value for 5 years (60 months)
forecast_import = forecast_data_monthly.rename(columns={'Reg_Date': 'ds', 'C
import_model = Prophet()
import_model.fit(forecast_import)
future_import = import_model.make_future_dataframe(periods=60, freq='ME')
import_forecast = import_model.predict(future_import)

# Forecasting Tax Revenue for 60 months
forecast_tax = forecast_data_monthly.rename(columns={'Reg_Date': 'ds', 'Tota
tax_model = Prophet()
tax_model.fit(forecast_tax)
future_tax = tax_model.make_future_dataframe(periods=60, freq='ME')
tax_forecast = tax_model.predict(future_tax)

# Plot the import forecast
fig = import_model.plot(import_forecast)
plt.title('Forecasted Import Volume (Naira) for the Next 5 Years')
plt.xlabel("Year")
plt.ylabel("Import Value (in N10 billions)")

last_row = import_forecast.iloc[-1]
last_date = last_row['ds']
last_value = last_row['yhat']

# Annotate the last forecast value
plt.annotate(f"{last_value:,.0f}",
             xy=(last_date, last_value),
             xytext=(last_date, last_value + 0.05 * last_value),
             ha='center',
             arrowprops=dict(arrowstyle='->', color='red'))
plt.show()

# Plot tax forecast
fig2 = tax_model.plot(tax_forecast)
plt.title("Forecast Tax Revenue (Naira) for the next 5 Years")
plt.xlabel("Year")
plt.ylabel("Tax Revenue (in N10 billion)")
last_row_t = tax_forecast.iloc[-1]
last_date_t = last_row_t['ds']
last_value_t = last_row_t['yhat']

# Annotate the last forecast value
plt.annotate(f"{last_value_t:,.0f}",
             xy=(last_date_t, last_value_t),
             xytext=(last_date_t, last_value_t + 0.05 * last_value_t),
             ha='center',
```

```
                arrowprops=dict(arrowstyle='->', color='red'))

plt.show()
```



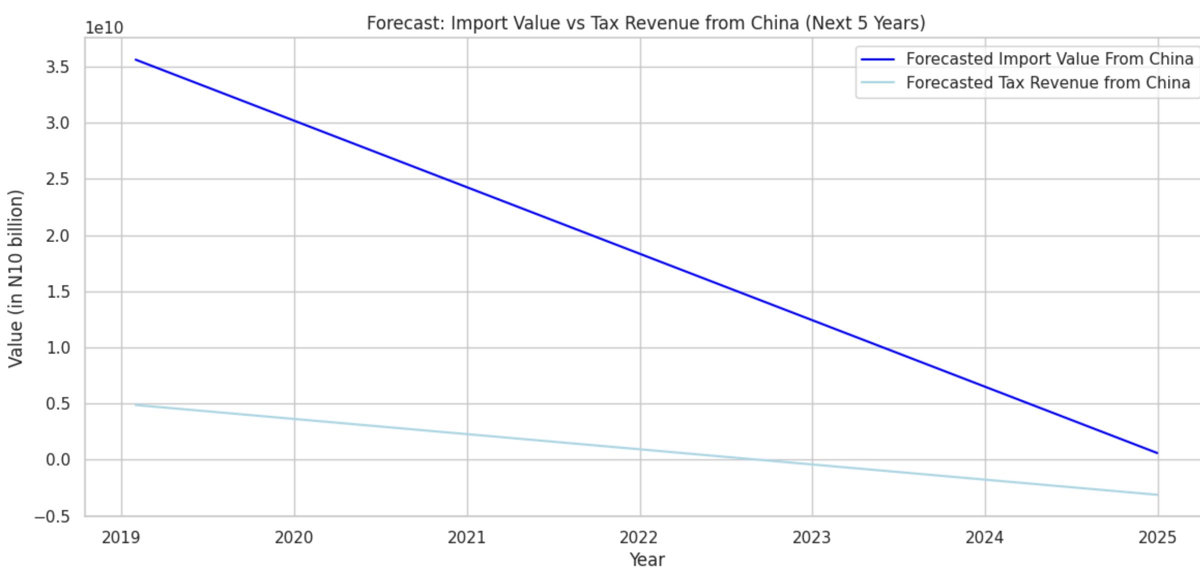


5.2 Forecasting Import Value and Tax Revenue for Top country of supply for the Next 5 Years (60 months) with Prophet

In [ ]:

```
# Filter data for China only
china_data = merged_data[merged_data['Country_of_Supply'] == 'China']
```

```python
# Monthly total CIF and tax
china_monthly = china_data.groupby(pd.Grouper(key='Reg_Date', freq='ME'))[['

# Forecast CIF_Value(N)
china_cif = china_monthly[['Reg_Date', 'CIF_Value(N)']].rename(columns={'Reg
china_model_cif = Prophet()
china_model_cif.fit(china_cif)
china_future_cif = china_model_cif.make_future_dataframe(periods=60, freq='M
china_forecast_cif = china_model_cif.predict(china_future_cif)

# Forecast Total_Tax(N)
china_tax = china_monthly[['Reg_Date', 'Total_Tax(N)']].rename(columns={'Reg
china_model_tax = Prophet()
china_model_tax.fit(china_tax)
china_future_tax = china_model_tax.make_future_dataframe(periods=60, freq='M
china_forecast_tax = china_model_tax.predict(china_future_tax)

# Visualize Forecast

plt.figure(figsize=(14, 6))
plt.plot(china_forecast_cif['ds'], china_forecast_cif['yhat'], label='Foreca
plt.plot(china_forecast_tax['ds'], china_forecast_tax['yhat'], label='Foreca
plt.xlabel('Year')
plt.ylabel('Value (in N10 billion)')
plt.title('Forecast: Import Value vs Tax Revenue from China (Next 5 Years)')
plt.legend()
plt.grid(True)
last_row_c = china_forecast_tax.iloc[-1]
last_date_c = last_row_c['ds']
last_value_c = last_row_c['yhat']
plt.show()
```



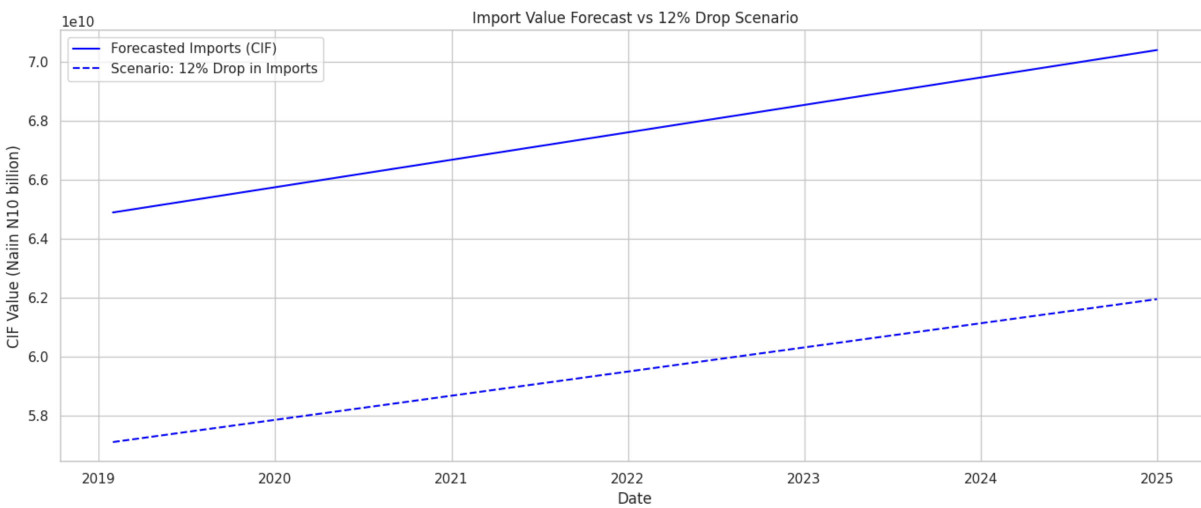
5.3 Scenario Forecasting/Modelling

- To simulate the impact of policy changes (e.g., tariffs or trade bans)

5.3.1 Scenario 12% Reduction in Import Volume

- Modelling the potential impact of a 12% reduction in forecasted import values, simulating the effect of successful import substitution, policy changes, or supply disruptions. This helps assess the fiscal implications of reduced import dependency and supports planning for strategic local production or innovation interventions.

In [ ]:
```
# Apply 12% drop to forecasted import values
import_forecast['yhat_adj'] = import_forecast['yhat'] * 0.88

# Plot Import Forecast vs 12% Drop Scenario
plt.figure(figsize=(14, 6))
plt.plot(import_forecast['ds'], import_forecast['yhat'], label='Forecasted I
plt.plot(import_forecast['ds'], import_forecast['yhat_adj'], label='Scenario
plt.title('Import Value Forecast vs 12% Drop Scenario')
plt.xlabel('Date')
plt.ylabel('CIF Value (Naiin N10 billion)')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

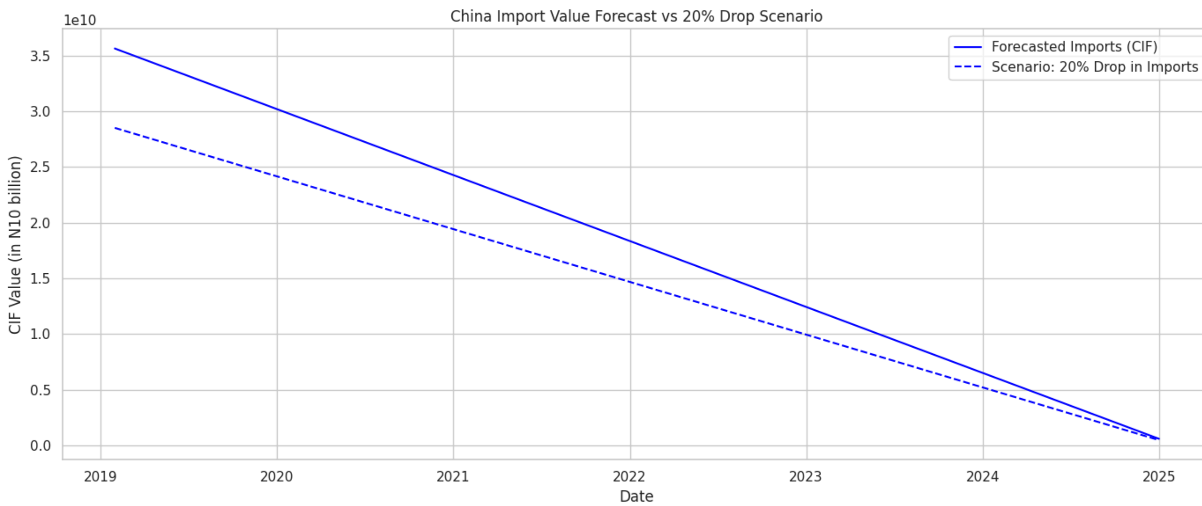


5.3.2 Scenario 20% Reduction in Import Volume for Top Country of supply

In [ ]:
```
# Apply 20% drop to China's forecasted import values
china_forecast_cif['yhat_adj'] = china_forecast_cif['yhat'] * 0.8

# Estimate tax revenue assuming same tax rate as historical average for Chir
historical_tax_rate_china = china_monthly['Total_Tax(N)'].sum() / china_mont
china_forecast_cif['Tax_Revenue_Estimated'] = china_forecast_cif['yhat_adj']
```

In [ ]:
```
# Plot China Import Forecast vs 20% Drop Scenario
plt.figure(figsize=(14, 6))
plt.plot(china_forecast_cif['ds'], china_forecast_cif['yhat'], label='Foreca
plt.plot(china_forecast_cif['ds'], china_forecast_cif['yhat_adj'], label='Sc
plt.title('China Import Value Forecast vs 20% Drop Scenario')
plt.xlabel('Date')
```

```
plt.ylabel('CIF Value (in N10 billion)')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



5.4 Identify Fast Growing Import Categories

In [ ]:

```
# Monthly import volume by HS codes
# Group by HS_Code and Month
monthly_hscode = (
    merged_data
    .groupby([pd.Grouper(key='Reg_Date', freq='M'), 'HS_Code'])['CIF_Value(N
    .sum()
    .reset_index()
)

# Pivot data to have months as columns
pivot = monthly_hscode.pivot(index='HS_Code', columns='Reg_Date', values='CI

# Calculate the growth rate for each HS_Code using linear regression
growth_rates = []
total_imports = []

for hs_code in pivot.index:
    y = pivot.loc[hs_code].values
    X = np.arange(len(y)).reshape(-1, 1)
    model = LinearRegression().fit(X, y)
    slope = model.coef_[0]
    growth_rates.append((hs_code, slope))

    # Calculate total import for each HS_Code (sum of CIF values)
    total_imports.append((hs_code, pivot.loc[hs_code].sum()))

# Create a DataFrame of HS_Code, their growth slopes, and total imports
hs_growth_df = pd.DataFrame(growth_rates, columns=['HS_Code', 'Growth_Slope'
hs_growth_df['Growth_Slope'] = hs_growth_df['Growth_Slope'].round(2)
total_imports_df = pd.DataFrame(total_imports, columns=['HS_Code', 'Total_Im
hs_growth_df = hs_growth_df.merge(total_imports_df, on='HS_Code', how='left'
```

```
hs_desc_df = merged_data[['HS_Code', 'HS_Description']].drop_duplicates()
hs_growth_df = hs_growth_df.merge(hs_desc_df, on='HS_Code', how='left').sort

fastest_growing = hs_growth_df[['HS_Code', 'HS_Description', 'Growth_Slope',
print('Top 10 Fast Growing Categories')
fastest_growing
```

Top 10 Fast Growing Categories

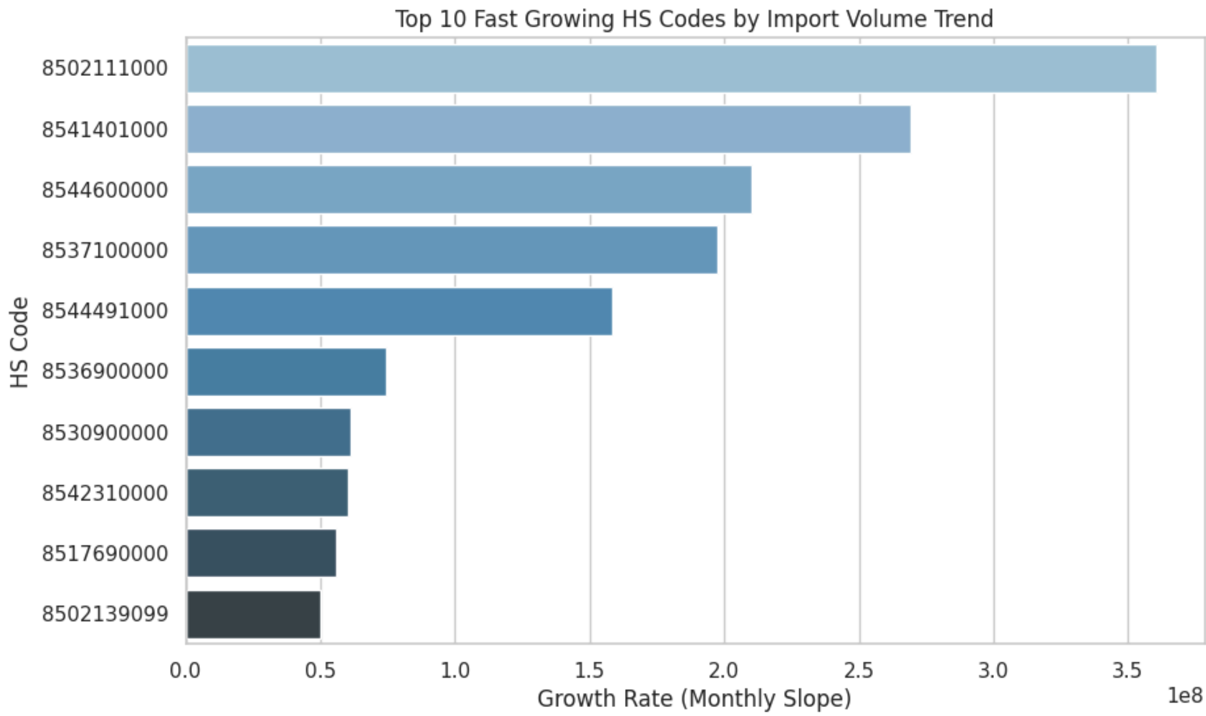
Out[ ]:

	HS_Code	HS_Description	Growth_Slope	Total_Import(N)
0	8502111000	Generating Sets, Diesel Or Semidiesel Engines,...	3.603721e+08	1.293321e+10
1	8541401000	Solar Cells Whether Or Not In Modules Or Made ...	2.694431e+08	2.609446e+10
2	8544600000	Other Electric Conductors, For A Voltage Excee...	2.102708e+08	1.817378e+10
3	8537100000	Boards, Panels, Consoles For Electric Control/...	1.976531e+08	2.285914e+10
4	8544491000	Almenec Insulated Cables, Metallic Part Made O...	1.585894e+08	5.685176e+09
5	8536900000	Other Apparatus Of Heading 85.36 Not Specified	7.463709e+07	5.939956e+09
6	8530900000	Parts Of Article Of Heading 85.30	6.110017e+07	1.626849e+09
7	8542310000	Processors And Controllers, Converters. Or Oth...	6.010500e+07	7.728600e+09
8	8517690000	Other Apparatus Of Subheading 8517.60 Not Spec...	5.592479e+07	4.003034e+09
9	8502139099	Of An Output Exceeding 1000Kva	5.021325e+07	1.165917e+10

In [ ]:

In [ ]:

```
# Visualize Top 10 Fast Growing HS Codes
plt.figure(figsize=(10, 6))
sns.barplot(data=fastest_growing, x='Growth_Slope', y='HS_Code', palette='Bl
plt.title('Top 10 Fast Growing HS Codes by Import Volume Trend')
plt.xlabel('Growth Rate (Monthly Slope)')
plt.ylabel('HS Code')
plt.show()
```



5.5 Conclusion: Predictive Forecasting of Import Volume & Tax Revenue

Key Projections

- **Import Value**:
  - 2019: ₦783B → 2024: ₦844B (7.8% growth)
- **Tax Revenue**:
  - 2019: ₦100B → 2024: ₦60B (40% decline)
  - Expected 2024: ₦112B (gap: ₦52B)
- **Top Supplier Risk**:
  - Projected fall: ₦420B (2019) → ₦7B (2024)
  - Tax revenue nears zero by 2024

Scenario Modeling

Scenario	Impact	Fiscal Shortfall
12% import drop (2020-2024)	Reduced trade volume	₦449B cumulative
20% drop from top supplier	Supply chain disruption	₦154B over 5 years

Fast-Growing HS Codes

1. `8502111000` : Diesel Generators (<75Kva)
2. `8541401000` : Solar Panels/Cells
3. `8544600000` : High-Voltage Conductors

Recommendations

1. **Tax Efficiency**: Close loopholes in fast growing categories
2. **Local Production**: Prioritize:
    - Solar panels (local assembly incentives)
    - HV conductors (tariff protections)
3. **Early Warning**: Monitor top supplier decline (₦420B→₦7B)

6. Policy Impact Modeling for Import Substitution & Innovation

6.1 Identifying HS Codes with Potential for Local Innovation or Production

`Approach: high import volume and growth potential.`

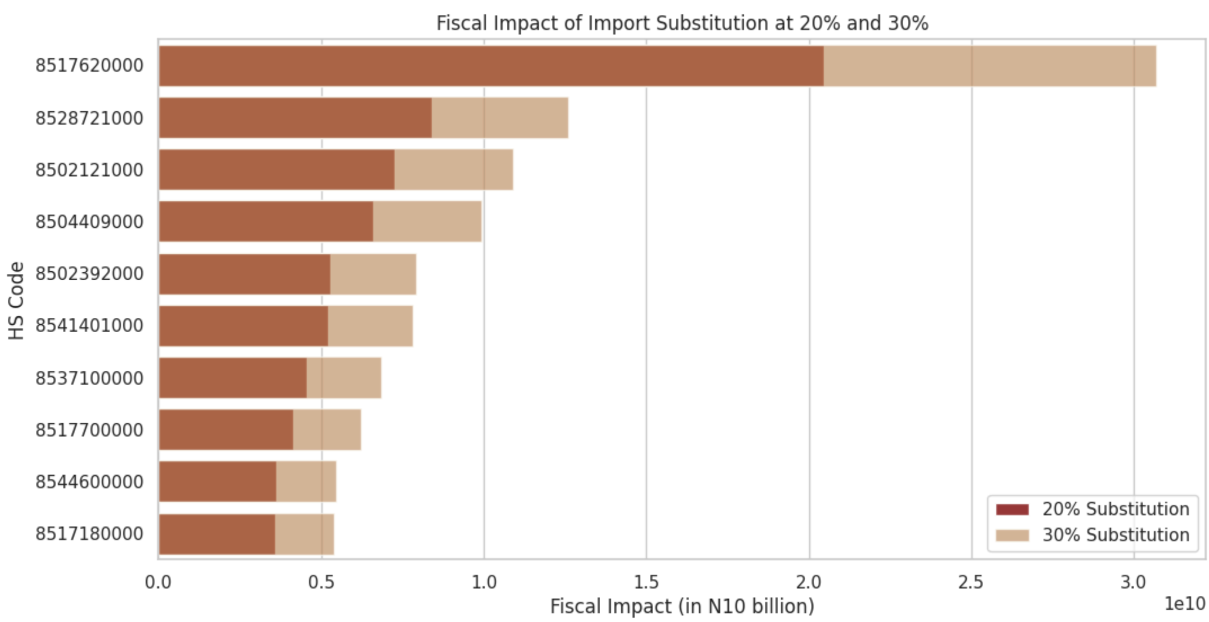
We identified the fastest growing HS codes from the previous analysis, highlighting sectors with high potential for local production or innovation. These categories are key for reducing import dependency and driving industrial growth in Nigeria.

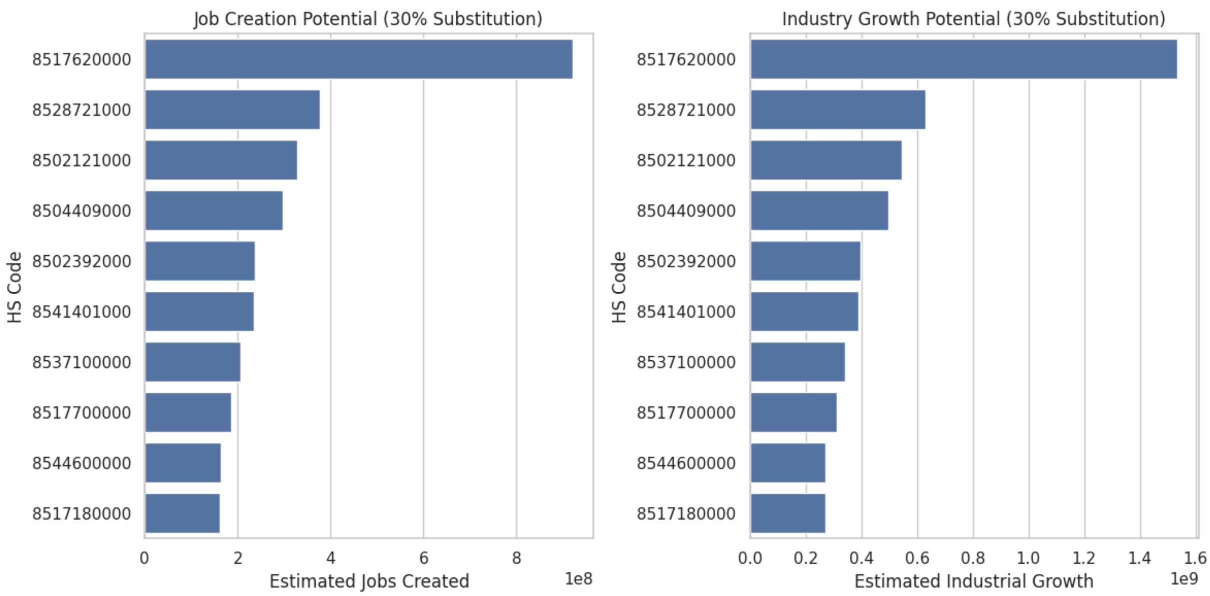
6.2 Estimating Fiscal and Industrial Impact of Substitution

`Approach: Potential impacts of substituting imports with local products.`

In [ ]:
```
# Estimate fiscal impact from import substitution for 20% and 30%
substitution_percentages = [0.2, 0.3]

# Calculate the fiscal impact (money saved from imports) for substitution
hs_growth_df['Fiscal_Impact_20'] = hs_growth_df['Total_Import(N)'] * substit
hs_growth_df['Fiscal_Impact_30'] = hs_growth_df['Total_Import(N)'] * substit
hs_growth_df = hs_growth_df.sort_values(by='Fiscal_Impact_30', ascending=Fal

# Visualize fiscal impact for substitution at 20% and 30%
plt.figure(figsize=(12, 6))
sns.barplot(x='Fiscal_Impact_20', y='HS_Code', data=hs_growth_df.head(10), c
sns.barplot(x='Fiscal_Impact_30', y='HS_Code', data=hs_growth_df.head(10), c
plt.title('Fiscal Impact of Import Substitution at 20% and 30%')
plt.xlabel('Fiscal Impact (in N10 billion)')
plt.ylabel('HS Code')
plt.legend()
plt.show()

# Estimate potential job creation and industry growth
hs_growth_df['Job_Creation_30%'] = hs_growth_df['Fiscal_Impact_30'] * 0.03
```

```
hs_growth_df['Industry_Growth_30%'] = hs_growth_df['Fiscal_Impact_30'] * 0.0

# Visualize job creation and industry growth
fig, axes = plt.subplots(1, 2, figsize=(12, 6))

# Job creation plot at 30% substitution
sns.barplot(x='Job_Creation_30%', y='HS_Code', data=hs_growth_df.head(10), a
axes[0].set_title('Job Creation Potential (30% Substitution)')
axes[0].set_xlabel('Estimated Jobs Created')
axes[0].set_ylabel('HS Code')

# Industry growth plot at 30% substitution
sns.barplot(x='Industry_Growth_30%', y='HS_Code', data=hs_growth_df.head(10)
axes[1].set_title('Industry Growth Potential (30% Substitution)')
axes[1].set_xlabel('Estimated Industrial Growth')
axes[1].set_ylabel('HS Code')

plt.tight_layout()
plt.show()

print('n Top 10 High Impact HS Codes \n')
hs_growth_df['Fiscal_Impact_30'].sum()
```






```
n Top 10 High Impact HS Codes
```

Out[ ]: np.float64(236333600609.7)

In [ ]:
```
total_savings_30 = hs_growth_df['Fiscal_Impact_30'].sum()
total_job_creation = hs_growth_df['Job_Creation_30%'].sum()
total_industry_growth = hs_growth_df['Industry_Growth_30%'].sum()

print(f"Estimated Total Fiscal Savings (30% Substitution): ₦{total_savings_3
print(f"Estimated Job Creation Activity: ₦{total_job_creation:,.0f}")
print(f"Estimated Industrial Growth: ₦{total_industry_growth:,.0f}")
```

```
Estimated Total Fiscal Savings (30% Substitution): ₦236,333,600,610
Estimated Job Creation Activity: ₦7,090,008,018
Estimated Industrial Growth: ₦11,816,680,030
```

6.3 Allocating Funds based on Import Sensitivity, Value, and National Piorities

The National Priority Score was calculated based on three factors:

- Gov. Initiative Score (0-5): Reflects alignment with national priorities.
- Employment Potential (0-5): Assesses the job creation potential of each product.
- Local Production Feasibility (0-5): Evaluates how feasible it is to produce the product locally.
- Scores are adjusted for non-clean energy sources, reducing their score by 0.3 points. The National Priority Score is the average of these three criteria.

HS Code	Description	Gov. Initiative	Employment Potential	Local Feasibility	National Priority Score
8541401000	Solar Cells Whether or Not in Modules or Made Up Into Panels	5	4	4	**4.33**
8504409000	Other Static Converters Not Specified (e.g., inverters, UPS)	4	4	3	**3.67**
8544600000	Other Electric Conductors, For A Voltage Exceeding 1,000 V	3	4	3	**3.33**
8537100000	Panels for Control/Distribution < 1,000 V	2	3	4	**3.00**
8502121000	Diesel Generator >75<375Kva, CKD for Assembly	3	3	3	**2.67**
8502392000	Gas-powered Generator	3	3	2	**2.67**
8517700000	Parts Of Articles Of Heading 8517 (e.g., telecom components)	2	3	3	**2.67**
8528721000	Reception Apparatus For Television, Coloured, CKD	2	3	3	**2.67**
8517180000	Other Telephone Sets Not Specified	2	3	3	**2.67**

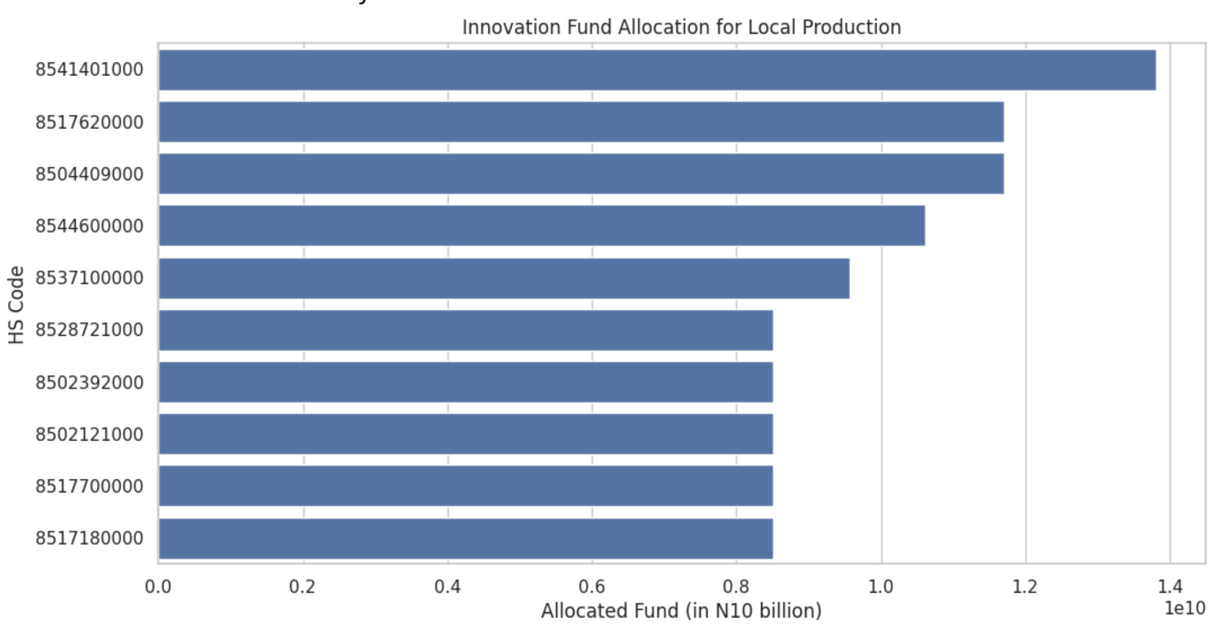
8517620000|Machines For Reception, Conversion And Transmission Of Voice, Images Or Data. | 5 | 4 | 2 | **3.67** |

In [ ]:

```python
# Get Top 10 high Impact HS Codes
top10_hs_growth_df = hs_growth_df.sort_values(by='Fiscal_Impact_30', ascendi
top10_hs_growth_df[['HS_Code', 'HS_Description']]

# Create DataFrame with HS codes and priority scores
priority_df = pd.DataFrame({
    'HS_Code': [
        '8517620000', '8528721000', '8502121000', '8504409000', '8502392000'
        '8541401000', '8537100000', '8517700000', '8544600000', '8517180000'
    ],
    'Priority_Score': [
        3.67, 2.67, 2.67, 3.67, 2.67,
        4.33, 3.00, 2.67, 3.33, 2.67
    ]
```

```python
})

#  Merge with top10 HS growth data
fund_df = top10_hs_growth_df.merge(priority_df, on='HS_Code', how='left')

#  Normalize scores
fund_df['Normalized_Score'] = fund_df['Priority_Score'] / fund_df['Priority_

#  Allocate funds (₦100 billion)
total_fund = 100000000000
fund_df['Allocated_Fund'] = (fund_df['Normalized_Score'] * total_fund).round

# Display key result columns
print('Fund Allocation for Key HS Codes')
fund_df = fund_df.sort_values(by='Allocated_Fund', ascending=False).reset_ir

# Visualize fund allocation
plt.figure(figsize=(12, 6))
sns.barplot(x='Allocated_Fund', y='HS_Code', data=fund_df)
plt.title('Innovation Fund Allocation for Local Production')
plt.xlabel('Allocated Fund (in N10 billion)')
plt.ylabel('HS Code')
plt.show()

print('Top 10 HS Codes for Fund Allocation')
fund_df[['HS_Code', 'HS_Description', 'Priority_Score', 'Fiscal_Impact_30',
```

```
Fund Allocation for Key HS Codes
```




```
Top 10 HS Codes for Fund Allocation
```

Out[ ]:

	HS_Code	HS_Description	Priority_Score	Fiscal_Impact_30	Allocated_Fur
0	8541401000	Solar Cells Whether Or Not In Modules Or Made ...	4.33	7.828339e+09	1.381180e+1
1	8517620000	Machines For Reception, Conversion And Transmi...	3.67	3.068386e+10	1.170654e+1
2	8504409000	Other Static Converters Not Specified	3.67	9.936822e+09	1.170654e+1
3	8544600000	Other Electric Conductors, For A Voltage Excee...	3.33	5.452133e+09	1.062201e+1
4	8537100000	Boards, Panels, Consoles For Electric Control/...	3.00	6.857742e+09	9.569378e+0
5	8528721000	Reception Apparatus For Television, Coloured, ...	2.67	1.258872e+10	8.516746e+0
6	8502392000	Gaspowered Generator	2.67	7.914023e+09	8.516746e+0
7	8502121000	Gen. Set, Diesel Or Semidiesel Engine, Output ...	2.67	1.091808e+10	8.516746e+0
8	8517700000	Parts Of Article Of Heading 8517	2.67	6.226885e+09	8.516746e+0
9	8517180000	Other Telephone Sets Not Specified.	2.67	5.410342e+09	8.516746e+0

6.4 Conclusion: Policy Impact Modeling for Import Substitution & Innovation

Key Insights

- **High-Growth HS Codes**:
  - Solar cells (`8541401000`)
  - Electric control panels (`8537109000`)
  - Diesel generators (`8502111000`)
- **Fiscal Impact (30% Substitution)**:

- Total savings: **₦236.33B**
- Top categories: Generators, solar tech

- **Economic Multipliers (30% Substitution)**:

  - Job creation: **₦7.09B**
  - Industrial growth: **₦11.82B**

Optimal ₦100B Fund Allocation

Priority Sector	Allocation (₦B)
Solar Cells	13.8
Data Transmission	11.7
Static Converters	11.7
Electric Conductors	10.6
Control Panels	9.6

Recommendations

1. **Local Production Push**:

   - Target: Solar tech + control systems
   - Leverage: ₦100B fund allocation
2. **Fiscal Incentives**:

   - Tax breaks for high impact HS code alternatives
3. **Industrial Clusters**

   - Energy tech hub (Solar/conductors)
   - Electronics hub (Control systems)
4. **Job Linkages**:

   - Tie 30% substitution to **₦7.09B** job creation target

In [ ]:

```
# Exporting the key dataframes to CSV

# Extract relevant columns from the import forecast

import_forecast_data = import_forecast[['ds', 'yhat', 'yhat_lower', 'yhat_up
    'ds': 'Date',
    'yhat': 'Forecasted_CIF_Value(N)',
    'yhat_lower': 'Confidence_Interval_Lower',
    'yhat_upper': 'Confidence_Interval_Upper',
    'yhat_adj': 'Forecasted_CIF_Value_Adjusted'
})
import_forecast_data['Year'] = import_forecast_data['Date'].dt.year
import_forecast_data['Month'] = import_forecast_data['Date'].dt.month

tax_forecast_data = tax_forecast[['ds', 'yhat', 'yhat_lower', 'yhat_upper']]
```

```
    'ds': 'Date',
    'yhat': 'Forecasted_Tax_Revenue(N)',
    'yhat_lower': 'Confidence_Interval_Lower',
    'yhat_upper': 'Confidence_Interval_Upper',
})

tax_forecast_data['Year'] = tax_forecast_data['Date'].dt.year
tax_forecast_data['Month'] = tax_forecast_data['Date'].dt.month

import_forecast_data.to_csv('forecasted_imports.csv', index=False)
tax_forecast_data.to_csv('forecasted_tax_revenue.csv', index=False)
merged_data.to_csv('merged_data.csv', index=False)
hs_growth_df.to_csv('hs_growth_df.csv', index=False)
fund_df.to_csv('fund_df.csv', index=False)

print("Forecast data for import volume and tax revenue has been successfully
```

```
Forecast data for import volume and tax revenue has been successfully export
ed!
```

7 Conclusion & Strategic Recommendations

Why This Matters

- **Critical Trends**:
  - Import growth (→ ₦844B by 2024) vs tax decline (→ ₦60B)
  - 12-20% import reductions risk ₦154-449B fiscal shortfalls
- **Urgent Opportunities**:
  - Fast-growing sectors: Solar cells (`8541401000`), HV conductors (`8544600000`)

Projected Impact *(30% Substitution Scenario)*

Metric	Value
Fiscal Savings	₦236.33 B
Job Creation	₦7.09 B
Industrial Growth	₦11.82 B

Action Plan

1. **Policy Infrastructure**:
   - Institutionalize data driven forecasting for trade decisions
   - Real-time tax gap monitoring (Current gap: ₦8.86B)
2. **Immediate Interventions**:
   - Target solar tech (₦13.8B allocation) and cable manufacturing

- Strengthen Tin Can/Apapa customs (₦6.46B leakage address)

3. **Long-term Shifts**:

   - Industrial clusters for:
     - Energy (Solar/conductors)
     - Electronics (Control systems)
   - Tie **₦100 B** innovation fund to measurable impact metrics (fiscal savings, jobs, local production)

Analysis note: Forecasts based on time-series trend analysis of 2019-2024 data

8. References and Links

GITHUB DRIVE POWERBI NOTEBOOK TRADE PORTAL