

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

In [2]: `fd=pd.read_excel("C:\\Users\\USER\\downloads\\projects\\VFI data.xlsx")
fd`

Out[2]:

	Sector	2000-01	2001-02	2002-03	2003-04	2004-05	2005-06	2006-07	2007-08	2008-09	2009-10	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17
0	METALLURGICAL INDUSTRIES	22.69	14.14	36.61	8.11	200.38	149.13	169.94	1175.75	959.94	419.88	1098.14	1786.14	1466.23	567.63	359.34	456.31	1440.18
1	MINING	1.32	6.52	10.06	23.48	9.92	7.40	6.62	444.36	34.16	174.40	79.51	142.65	57.89	12.73	684.39	520.67	55.75
2	POWER	89.42	757.44	59.11	27.09	43.37	72.69	157.15	988.68	907.66	1271.79	1271.77	1652.38	535.68	1066.08	707.04	868.80	1112.98
3	NON-CONVENTIONAL ENERGY	0.00	0.00	1.70	4.14	1.27	1.35	2.44	58.82	125.88	622.52	214.40	452.17	1106.52	414.25	615.95	776.51	783.57
4	COAL PRODUCTION	0.00	0.00	0.00	0.04	0.00	9.14	1.30	14.08	0.22	0.00	0.00	0.00	0.00	2.96	0.00	0.00	0.00
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
58	PRINTING OF BOOKS (INCLUDING LITHO PRINTING IN...	0.00	0.00	6.30	0.00	0.06	9.90	20.04	35.54	31.61	70.51	36.63	47.39	14.34	113.78	72.58	122.81	53.17
59	COIR	0.00	0.00	0.00	0.00	0.47	0.59	0.04	0.01	0.00	0.25	0.10	0.55	0.15	0.54	1.36	0.00	0.00
60	CONSTRUCTION (INFRASTRUCTURE) ACTIVITIES	0.00	0.00	0.00	0.00	0.00	0.93	64.06	182.92	172.70	324.56	675.07	386.28	283.89	485.37	870.25	4510.71	1860.73
61	CONSTRUCTION DEVELOPMENT: Townships, housing, ...	24.33	51.75	36.10	47.04	152.06	228.71	1392.95	3887.33	4657.51	5466.13	1663.03	3140.78	1332.49	1226.05	769.14	112.55	105.14
62	MISCELLANEOUS INDUSTRIES	832.07	221.37	218.76	235.48	121.83	164.76	304.87	528.42	1549.70	1147.56	1475.97	813.38	229.49	468.74	765.88	668.77	296.40

63 rows x 18 columns

In [3]: `fd.isna().any()`

Out[3]:

Sector	False
2000-01	False
2001-02	False
2002-03	False
2003-04	False
2004-05	False
2005-06	False
2006-07	False
2007-08	False
2008-09	False
2009-10	False
2010-11	False
2011-12	False
2012-13	False
2013-14	False
2014-15	False
2015-16	False
2016-17	False
dtype:	bool

In [4]: `fd.info()`

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 63 entries, 0 to 62
Data columns (total 18 columns):
 #   Column      Non-Null Count  Dtype
---  -
 0   Sector      63 non-null     object
 1   2000-01     63 non-null     float64
 2   2001-02     63 non-null     float64
 3   2002-03     63 non-null     float64
 4   2003-04     63 non-null     float64
 5   2004-05     63 non-null     float64
 6   2005-06     63 non-null     float64
 7   2006-07     63 non-null     float64
 8   2007-08     63 non-null     float64
 9   2008-09     63 non-null     float64
10  2009-10     63 non-null     float64
11  2010-11     63 non-null     float64
12  2011-12     63 non-null     float64
13  2012-13     63 non-null     float64
14  2013-14     63 non-null     float64
15  2014-15     63 non-null     float64
16  2015-16     63 non-null     float64
17  2016-17     63 non-null     float64
dtypes: float64(17), object(1)
memory usage: 9.0+ KB
```

In [5]: `fd.describe()`

Out[5]:

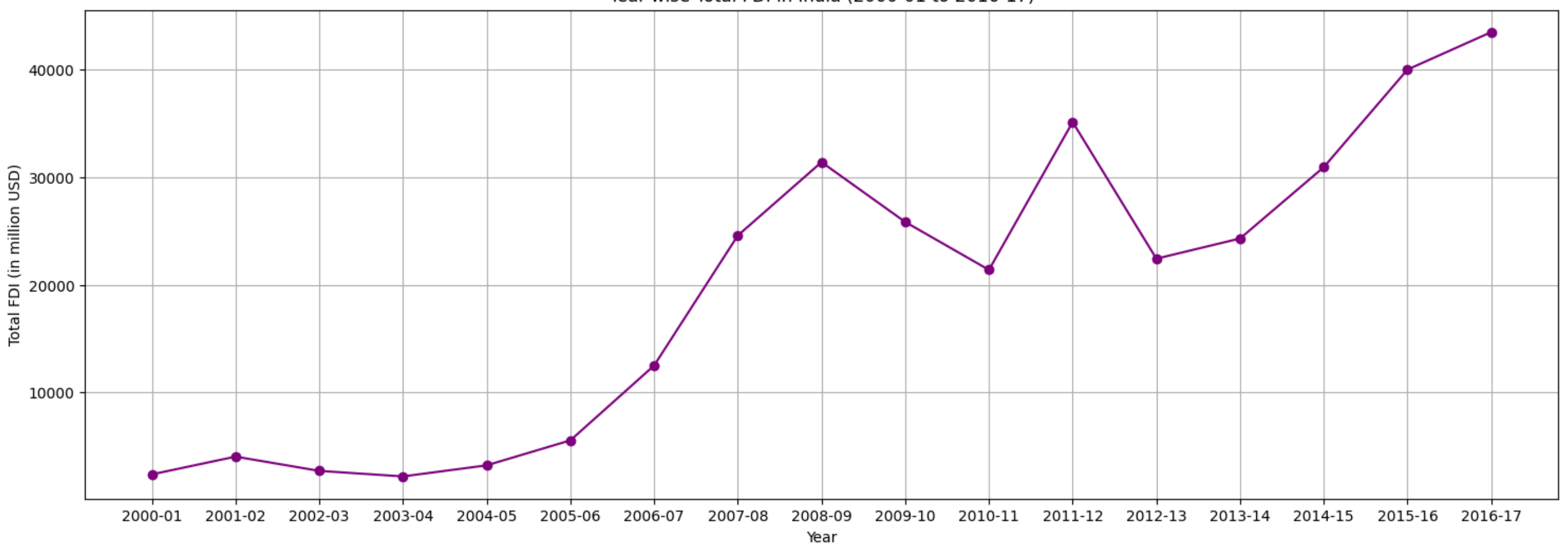
	2000-01	2001-02	2002-03	2003-04	2004-05	2005-06	2006-07	2007-08	2008-09	2009-10	2010-11	2011-12	2012-13	2013-14	2014
count	63.000000	63.000000	63.000000	63.000000	63.000000	63.000000	63.000000	63.000000	63.000000	63.000000	63.000000	63.000000	63.000000	63.000000	63.000000
mean	37.757302	63.931587	42.925714	34.727778	51.090317	87.932540	198.281905	390.085714	498.348571	410.069524	339.413810	557.472698	355.930000	385.703492	490.959800
std	112.227860	157.878737	86.606439	67.653735	101.934873	206.436967	686.783115	1026.249935	1134.649040	926.814626	627.141139	1031.474056	778.091368	658.429944	837.787000
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.200000	0.215000	0.715000	1.230000	4.160000	9.950000	11.950000	7.880000	8.430000	22.720000	15.115000	16.610000	33.800000
50%	4.030000	5.070000	11.010000	6.370000	9.090000	22.620000	25.820000	58.820000	84.880000	69.740000	58.070000	129.360000	95.410000	113.780000	177.220000
75%	23.510000	44.830000	36.555000	38.660000	43.205000	63.855000	108.325000	279.270000	383.320000	341.595000	304.280000	593.525000	288.025000	473.060000	595.390000
max	832.070000	873.230000	419.960000	368.320000	527.900000	1359.970000	4713.780000	6986.170000	6183.490000	5466.130000	3296.090000	5215.980000	4832.980000	3982.890000	4443.260000

In [9]: `print("Descriptive Statistics")
fd['Total_FDI'] = fd.iloc[:, 1:].sum(axis=1)
fd['Average_FDI'] = fd.iloc[:, 1:-1].mean(axis=1)
fd['StdDev_FDI'] = fd.iloc[:, 1:-1].std(axis=1)
print(fd[['Sector', 'Total_FDI', 'Average_FDI', 'StdDev_FDI']].sort_values(by='Total_FDI', ascending=False).head(10))`

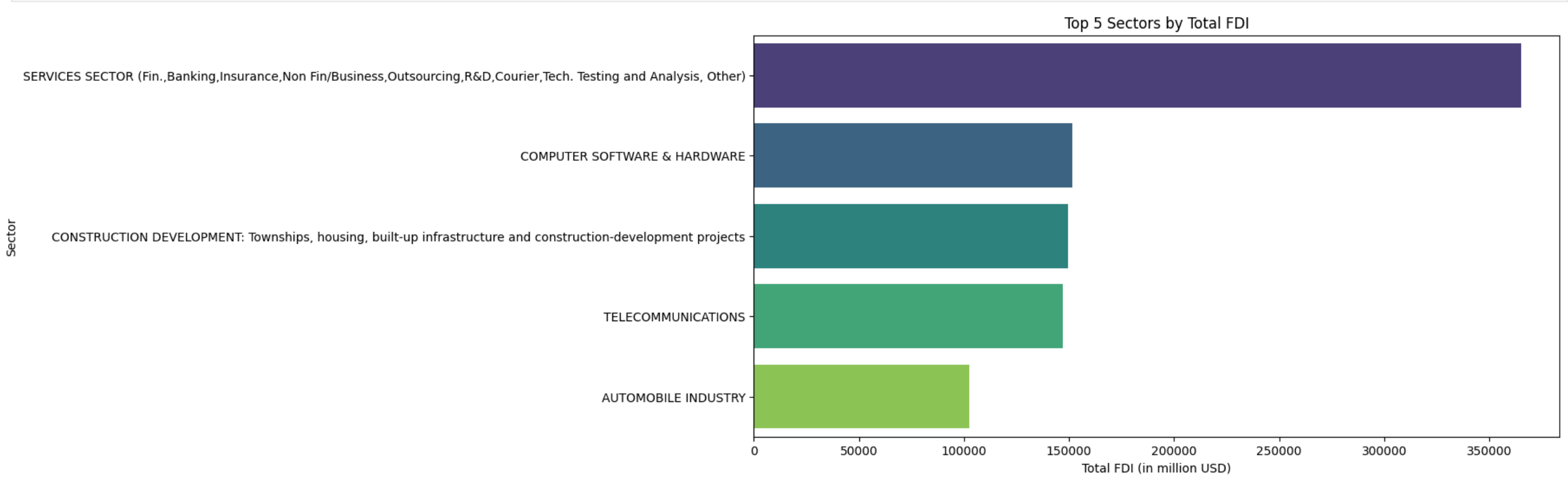
Descriptive Statistics

	Sector	Total_FDI	Average_FDI	StdDev_FDI
9	SERVICES SECTOR (Fin.,Banking,Insurance,Non Fi.,COMPUTER SOFTWARE & HARDWARE	365320.430690	151688.824472	151688.824472
61	CONSTRUCTION DEVELOPMENT: Townships, housing, built-up infrastructure and construction-development projects	149586.579479	149586.579479	149586.579479
11	TELECOMMUNICATIONS	147227.799272	147227.799272	147227.799272
13	AUTOMOBILE INDUSTRY	102431.437334	102431.437334	102431.437334
32	DRUGS & PHARMACEUTICALS	99643.813617	99643.813617	99643.813617
53	TRADING	87563.437554	87563.437554	87563.437554
29	CHEMICALS (OTHER THAN FERTILIZERS)	81912.225605	81912.225605	81912.225605
2	POWER	71170.756919	71170.756919	71170.756919
0	METALLURGICAL INDUSTRIES	63594.526579	63594.526579	63594.526579

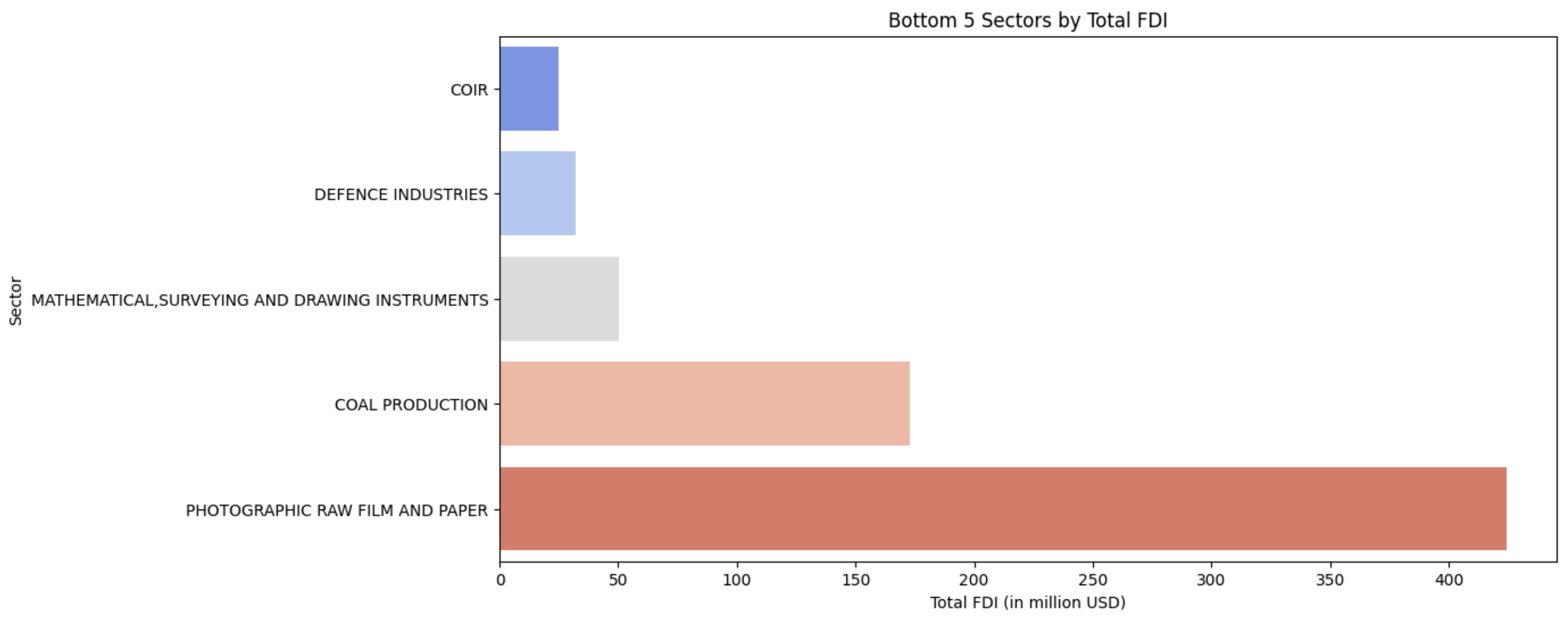
In [15]: `yearly_fdi = fd.iloc[:, 1:-1].sum(axis=0)
plt.figure(figsize=(18, 6))
plt.plot(yearly_fdi.index, yearly_fdi.values, marker='o', color="purple")
plt.title('Year-wise Total FDI in India (2000-01 to 2016-17)')
plt.xlabel('Year')
plt.ylabel('Total FDI (in million USD)')
plt.grid(True)`



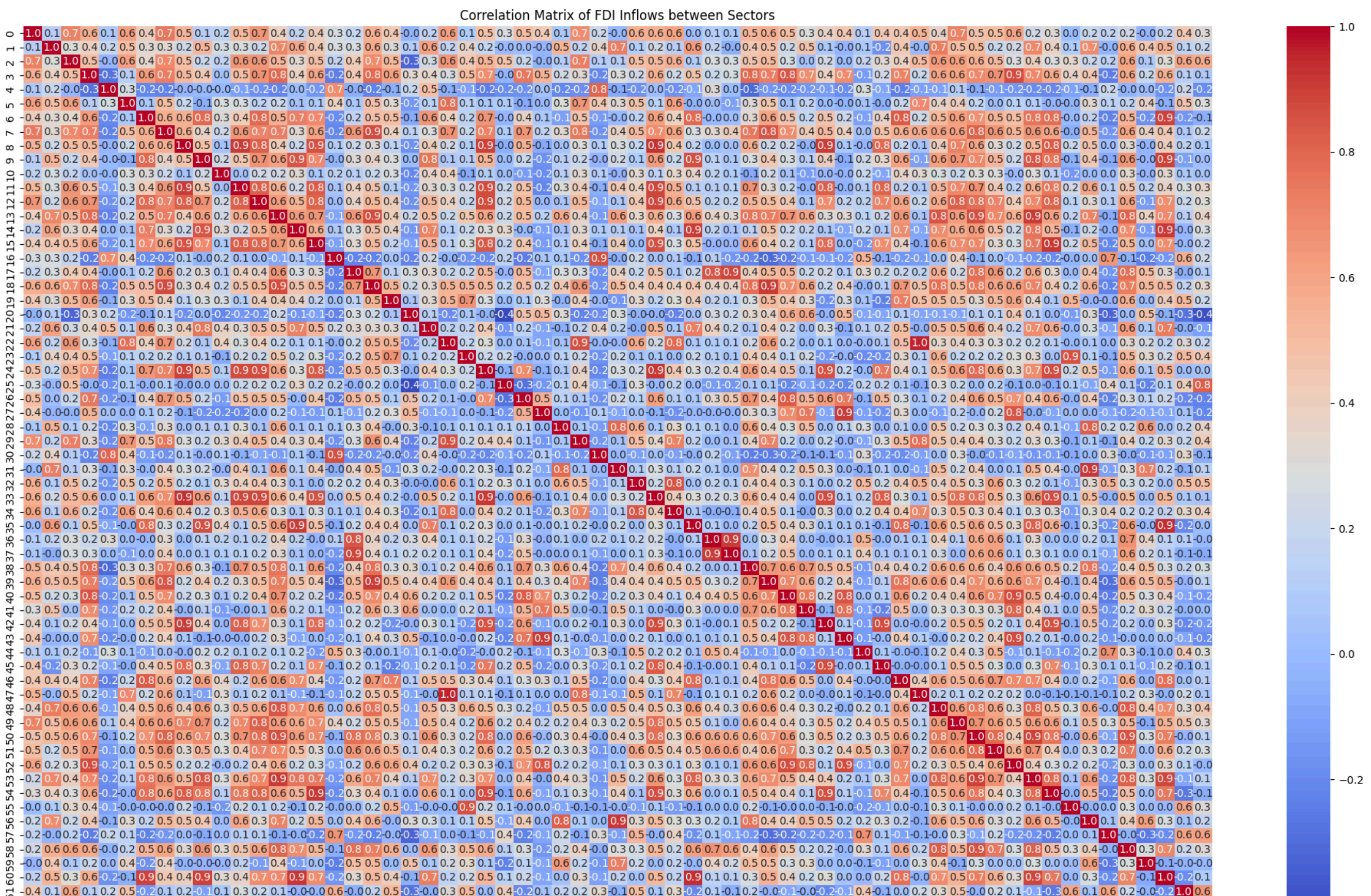
In [23]: `top_5_sectors = fd[['Sector', 'Total_FDI']].sort_values(by='Total_FDI', ascending=False).head(5)
plt.figure(figsize=(12, 6))
sns.barplot(data=top_5_sectors, x='Total_FDI', y='Sector', hue='Sector', palette="viridis")
plt.title('Top 5 Sectors by Total FDI')
plt.xlabel('Total FDI (in million USD)')
plt.ylabel('Sector')
plt.show()`



In [24]: `bottom_5_sectors = fd[['Sector', 'Total_FDI']].sort_values(by='Total_FDI', ascending=True).head(5)
plt.figure(figsize=(12, 6))
sns.barplot(data=bottom_5_sectors, x='Total_FDI', y='Sector', hue='Sector', palette="coolwarm")
plt.title('Bottom 5 Sectors by Total FDI')
plt.xlabel('Total FDI (in million USD)')
plt.ylabel('Sector')
plt.show()`



In [25]: `fdi_corr = fd.iloc[:, 1:-1].transpose().corr()
plt.figure(figsize=(25, 15))
sns.heatmap(fdi_corr, annot=True, cmap="coolwarm", fmt='.1f')
plt.title('Correlation Matrix of FDI Inflows between Sectors')
plt.show()`



In [ ]: