Project 3 - Share Market Data Analysis

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

Project Task - Week 1

1. Check the stock symbols of the companies in Nasdaq 100 Market cap.xlsx. Only the relevant files in the NASDAQ_DATA folder should be read.

2. Append all files (imported in the previous step) that contain no more than 10 years of data. For this, you may use your discretion.

In [2]:
```
market = pd.read_excel('Nasdaq 100 Market cap.xlsx')
```

In [3]:
```
market
```

Out[3]:

	Symbol	Name	Market Cap	Last Sale	Net Change	Percentage Change
0	AAPL	Apple Inc.	2625740143000	$151.45	$2.00	0.0134
1	ABNB	Airbnb, Inc.	69569944167	$116.65	$0.26	0.0022
2	ADBE	Adobe Inc.	149144569000	$320.81	$4.59	0.0145
3	ADI	Analog Devices, Inc.	75484763090	$146.76	$2.23	0.0154
4	ADP	Automatic Data Processing, Inc.	98332762096	$236.78	$0.13	-0.0005
...	...	...	...	...	...	...
97	WBA	Walgreens Boots Alliance, Inc.	30450068934	$35.21	$0.52	0.0150
98	WDAY	Workday, Inc.	39549440000	$154.49	$6.54	0.0442
99	XEL	Xcel Energy Inc.	34192428038	$62.51	$0.93	0.0151
100	ZM	Zoom Video Communications, Inc.	24659899766	$82.85	$2.24	0.0278
101	ZS	Zscaler, Inc.	22393436472	$156.54	$7.87	0.0529

102 rows × 6 columns

In [4]:
```
metrics = pd.read_excel('nasdaq100_metrics_ratios.xlsx')
```

In [5]:
```
metrics
```

Out[5]:

	symbol	company	sector	subsector	asset_turnover_2017	asset_turnover_2018	asset_turnover_2019	asset_turnover_2020	a
0	AAPL	Apple Inc.	Information Technology	Technology Hardware, Storage & Peripherals	0.66	0.72	0.74	0.83	
1	ABNB	Airbnb	Consumer Discretionary	Internet & Direct Marketing Retail	NaN	0.55	0.64	0.36	
2	ADBE	Adobe Inc.	Information Technology	Application Software	0.54	0.54	0.57	0.57	
3	ADI	Analog Devices	Information Technology	Semiconductors	0.36	0.30	0.29	0.26	
4	ADP	ADP	Information Technology	Data Processing & Outsourced Services	NaN	0.34	0.34	0.35	
...	...	...	...	...	...	...	...	...	
97	WBA	Walgreens Boots Alliance	Consumer Staples	Drug Retail	1.71	1.96	1.77	1.58	
98	WDAY	Workday, Inc.	Information Technology	Application Software	NaN	0.52	0.54	0.59	
99	XEL	Xcel Energy	Utilities	Multi-Utilities	0.27	0.26	0.24	0.22	
100	ZM	Zoom Video Communications	Information Technology	Application Software	NaN	0.70	1.16	0.76	
101	ZS	Zscaler	Information Technology	Application Software	NaN	0.60	0.58	0.35	

102 rows × 283 columns

In [6]:
```
metrics.rename(columns = {'symbol':'Symbol'},inplace=True)
```

In [7]:
```
df = pd.merge(market,metrics,on='Symbol',how='inner')
```

In [8]:
```
df
```

Out[8]:

	Symbol	Name	Market Cap	Last Sale	Net Change	Percentage Change	company	sector	subsector	asset_turnover_2017	..
0	AAPL	Apple Inc.	2625740143000	$151.45	$2.00	0.0134	Apple Inc.	Information Technology	Technology Hardware, Storage & Peripherals	0.66	..
1	ABNB	Airbnb, Inc.	69569944167	$116.65	$0.26	0.0022	Airbnb	Consumer Discretionary	Internet & Direct Marketing Retail	NaN	..
2	ADBE	Adobe Inc.	149144569000	$320.81	$4.59	0.0145	Adobe Inc.	Information Technology	Application Software	0.54	..
3	ADI	Analog Devices, Inc.	75484763090	$146.76	$2.23	0.0154	Analog Devices	Information Technology	Semiconductors	0.36	..
4	ADP	Automatic Data Processing, Inc.	98332762096	$236.78	$0.13	-0.0005	ADP	Information Technology	Data Processing & Outsourced Services	NaN	..
...	...	...	...	...	...	...	...	...	...	...	..
97	WBA	Walgreens Boots Alliance, Inc.	30450068934	$35.21	$0.52	0.0150	Walgreens Boots Alliance	Consumer Staples	Drug Retail	1.71	..
98	WDAY	Workday, Inc.	39549440000	$154.49	$6.54	0.0442	Workday, Inc.	Information Technology	Application Software	NaN	..
99	XEL	Xcel Energy Inc.	34192428038	$62.51	$0.93	0.0151	Xcel Energy	Utilities	Multi-Utilities	0.27	..
100	ZM	Zoom Video Communications, Inc.	24659899766	$82.85	$2.24	0.0278	Zoom Video Communications	Information Technology	Application Software	NaN	..
101	ZS	Zscaler, Inc.	22393436472	$156.54	$7.87	0.0529	Zscaler	Information Technology	Application Software	NaN	..

102 rows × 288 columns

In [9]:
```
variances = df.var()
```

```
C:\Users\Vinosh\AppData\Local\Temp\ipykernel_12216\529193874.py:1: FutureWarning: Dropping of nuisance columns in Da
taFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select
only valid columns before calling the reduction.
  variances = df.var()
```

In [10]:
```
less_var = variances < 0.005
```

In [11]:
```
less_va_col = variances.index[less_var]
```

In [12]:
```
less_va_col
```

Out[12]:
```
Index(['Percentage Change', 'capex_to_revenue_2022',
       'inventory_to_revenue_2017', 'inventory_to_revenue_2018',
       'inventory_to_revenue_2022'],
      dtype='object')
```

In [13]:
```
df.drop(less_va_col,axis=1,inplace=True)
```

In [14]:
```
df
```

Out[14]:

	Symbol	Name	Market Cap	Last Sale	Net Change	company	sector	subsector	asset_turnover_2017	asset_turnover
0	AAPL	Apple Inc.	2625740143000	$151.45	$2.00	Apple Inc.	Information Technology	Technology Hardware, Storage & Peripherals	0.66	
1	ABNB	Airbnb, Inc.	69569944167	$116.65	$0.26	Airbnb	Consumer Discretionary	Internet & Direct Marketing Retail	NaN	
2	ADBE	Adobe Inc.	149144569000	$320.81	$4.59	Adobe Inc.	Information Technology	Application Software	0.54	
3	ADI	Analog Devices, Inc.	75484763090	$146.76	$2.23	Analog Devices	Information Technology	Semiconductors	0.36	
4	ADP	Automatic Data Processing, Inc.	98332762096	$236.78	$0.13	ADP	Information Technology	Data Processing & Outsourced Services	NaN	
...	...	...	...	...	...	...	...	...	...	...
97	WBA	Walgreens Boots Alliance, Inc.	30450068934	$35.21	$0.52	Walgreens Boots Alliance	Consumer Staples	Drug Retail	1.71	
98	WDAY	Workday, Inc.	39549440000	$154.49	$6.54	Workday, Inc.	Information Technology	Application Software	NaN	
99	XEL	Xcel Energy Inc.	34192428038	$62.51	$0.93	Xcel Energy	Utilities	Multi-Utilities	0.27	
100	ZM	Zoom Video Communications, Inc.	24659899766	$82.85	$2.24	Zoom Video Communications	Information Technology	Application Software	NaN	
101	ZS	Zscaler, Inc.	22393436472	$156.54	$7.87	Zscaler	Information Technology	Application Software	NaN	

102 rows × 283 columns

In [15]:
```
missing_value = df.isnull().sum() / len(df) *100
```

In [16]:
```
missing_value_condition = missing_value > 30
```

In [17]:
```
missing_value_col = missing_value.index[missing_value_condition]
```

In [18]:
```
missing_value_col
```

Out[18]:
```
Index(['asset_turnover_2022', 'buyback_yield_2017', 'buyback_yield_2022',
       'cash_ratio_2022', 'cash_to_debt_2017', 'cash_to_debt_2022',
       'cogs_to_revenue_2022', 'mscore_2017', 'mscore_2022', 'zscore_2017',
       'zscore_2022', 'current_ratio_2022', 'days_inventory_2017',
       'days_inventory_2018', 'days_inventory_2019', 'days_inventory_2020',
       'days_inventory_2021', 'days_inventory_2022', 'debt_to_equity_2017',
       'debt_to_equity_2022', 'debt_to_assets_2017', 'debt_to_assets_2022',
       'debt_to_ebitda_2017', 'debt_to_ebitda_2022', 'debt_to_revenue_2017',
       'debt_to_revenue_2022', 'e10_2017', 'e10_2022',
       'effective_interest_rate_2017', 'effective_interest_rate_2022',
       'equity_to_assets_2022', 'enterprise_value_to_ebit_2017',
       'enterprise_value_to_ebit_2022', 'enterprise_value_to_ebitda_2017',
       'enterprise_value_to_ebitda_2022', 'enterprise_value_to_revenue_2017',
       'enterprise_value_to_revenue_2022', 'earning_yield_greenblatt_2017',
       'earning_yield_greenblatt_2022', 'fscore_2017', 'fscore_2022',
       'goodwill_to_asset_latest', 'gross_profit_to_assets_2022',
       'interest_coverage_2017', 'interest_coverage_2022',
       'inventory_turnover_2017', 'inventory_turnover_2018',
       'inventory_turnover_2019', 'inventory_turnover_2020',
       'inventory_turnover_2021', 'inventory_turnover_2022',
       'inventory_to_revenue_2019', 'inventory_to_revenue_2020',
       'inventory_to_revenue_2021', 'liabilities_to_assets_2022',
       'longterm_debt_to_assets_2017', 'longterm_debt_to_assets_2022',
       'price_to_book_ratio_2017', 'price_to_book_ratio_2022',
       'price_to_earnings_ratio_2017', 'price_to_earnings_ratio_2022',
       'price_to_earnings_ratio_nri_2017', 'price_to_earnings_ratio_nri_2022',
       'price_earnings_growth_ratio_2017', 'price_earnings_growth_ratio_2018',
       'price_earnings_growth_ratio_2019', 'price_earnings_growth_ratio_2020',
       'price_earnings_growth_ratio_2021', 'price_earnings_growth_ratio_2022',
       'price_to_free_cashflow_2017', 'price_to_free_cashflow_2022',
       'price_to_operating_cashflow_2017', 'price_to_operating_cashflow_2022',
       'rate_of_return_2017', 'rate_of_return_2022',
       'scaled_net_operating_assets_2022', 'yoy_ebitda_growth_2022',
       'yoy_eps_growth_2017', 'yoy_eps_growth_2022',
       'yoy_revenue_growth_2022'],
      dtype='object')
```

In [19]:
```
missing_value_col.shape
```

Out[19]:
```
(80,)
```

In [20]:
```
df.drop(missing_value_col,axis=1,inplace=True)
```

In [21]:
```
df
```

Out[21]:

	Symbol	Name	Market Cap	Last Sale	Net Change	company	sector	subsector	asset_turnover_2017	asset_turnover
0	AAPL	Apple Inc.	2625740143000	$151.45	$2.00	Apple Inc.	Information Technology	Technology Hardware, Storage & Peripherals	0.66	
1	ABNB	Airbnb, Inc.	69569944167	$116.65	$0.26	Airbnb	Consumer Discretionary	Internet & Direct Marketing Retail	NaN	
2	ADBE	Adobe Inc.	149144569000	$320.81	$4.59	Adobe Inc.	Information Technology	Application Software	0.54	
3	ADI	Analog Devices, Inc.	75484763090	$146.76	$2.23	Analog Devices	Information Technology	Semiconductors	0.36	
4	ADP	Automatic Data Processing, Inc.	98332762096	$236.78	$0.13	ADP	Information Technology	Data Processing & Outsourced Services	NaN	
...	...	...	...	...	...	...	...	...	...	...
97	WBA	Walgreens Boots Alliance, Inc.	30450068934	$35.21	$0.52	Walgreens Boots Alliance	Consumer Staples	Drug Retail	1.71	
98	WDAY	Workday, Inc.	39549440000	$154.49	$6.54	Workday, Inc.	Information Technology	Application Software	NaN	
99	XEL	Xcel Energy Inc.	34192428038	$62.51	$0.93	Xcel Energy	Utilities	Multi-Utilities	0.27	
100	ZM	Zoom Video Communications, Inc.	24659899766	$82.85	$2.24	Zoom Video Communications	Information Technology	Application Software	NaN	
101	ZS	Zscaler, Inc.	22393436472	$156.54	$7.87	Zscaler	Information Technology	Application Software	NaN	

102 rows × 203 columns

In [22]:
```
df.fillna(df.mean(),inplace=True)
```

```
C:\Users\Vinosh\AppData\Local\Temp\ipykernel_12216\2085774198.py:1: FutureWarning: Dropping of nuisance columns in D
ataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select
only valid columns before calling the reduction.
  df.fillna(df.mean(),inplace=True)
```

In [23]:
```
df
```

Out[23]:

	Symbol	Name	Market Cap	Last Sale	Net Change	company	sector	subsector	asset_turnover_2017	asset_turnover
0	AAPL	Apple Inc.	2625740143000	$151.45	$2.00	Apple Inc.	Information Technology	Technology Hardware, Storage & Peripherals	0.660000	
1	ABNB	Airbnb, Inc.	69569944167	$116.65	$0.26	Airbnb	Consumer Discretionary	Internet & Direct Marketing Retail	0.724932	
2	ADBE	Adobe Inc.	149144569000	$320.81	$4.59	Adobe Inc.	Information Technology	Application Software	0.540000	
3	ADI	Analog Devices, Inc.	75484763090	$146.76	$2.23	Analog Devices	Information Technology	Semiconductors	0.360000	
4	ADP	Automatic Data Processing, Inc.	98332762096	$236.78	$0.13	ADP	Information Technology	Data Processing & Outsourced Services	0.724932	
...	...	...	...	...	...	...	...	...	...	...
97	WBA	Walgreens Boots Alliance, Inc.	30450068934	$35.21	$0.52	Walgreens Boots Alliance	Consumer Staples	Drug Retail	1.710000	
98	WDAY	Workday, Inc.	39549440000	$154.49	$6.54	Workday, Inc.	Information Technology	Application Software	0.724932	
99	XEL	Xcel Energy Inc.	34192428038	$62.51	$0.93	Xcel Energy	Utilities	Multi-Utilities	0.270000	
100	ZM	Zoom Video Communications, Inc.	24659899766	$82.85	$2.24	Zoom Video Communications	Information Technology	Application Software	0.724932	
101	ZS	Zscaler, Inc.	22393436472	$156.54	$7.87	Zscaler	Information Technology	Application Software	0.724932	

102 rows × 203 columns

In [24]:
```
df.isnull().sum()
```

Out[24]:
```
Symbol                      0
Name                        0
Market Cap                  0
Last Sale                   0
Net Change                  0
                           ..
yoy_revenue_growth_2018     0
yoy_revenue_growth_2019     0
yoy_revenue_growth_2020     0
yoy_revenue_growth_2021     0
yoy_revenue_growth_latest   0
Length: 203, dtype: int64
```

In [25]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 102 entries, 0 to 101
Columns: 203 entries, Symbol to yoy_revenue_growth_latest
dtypes: float64(193), int64(3), object(7)
memory usage: 162.6+ KB
```

In [26]:
```
missing_value_corrected = df.isnull().sum() / len(df) *100
```

In [27]:
```
check_missing_after_remove = missing_value_corrected > 1
```

In [28]:
```
missing_value_col_corrected = missing_value_corrected.index[check_missing_after_remove]
```

In [29]:
```
missing_value_col_corrected
```

Out[29]:
```
Index([], dtype='object')
```

In [30]:
```
df.columns
```

Out[30]:
```
Index(['Symbol', 'Name', 'Market Cap', 'Last Sale', 'Net Change', 'company',
       'sector', 'subsector', 'asset_turnover_2017', 'asset_turnover_2018',
       ...
       'yoy_eps_growth_2019', 'yoy_eps_growth_2020', 'yoy_eps_growth_2021',
       'yoy_eps_growth_latest', 'yoy_revenue_growth_2017',
       'yoy_revenue_growth_2018', 'yoy_revenue_growth_2019',
       'yoy_revenue_growth_2020', 'yoy_revenue_growth_2021',
       'yoy_revenue_growth_latest'],
      dtype='object', length=203)
```

In [31]:
```
pd.set_option('display.max_columns', 250)
```

In [32]:
```
df
```

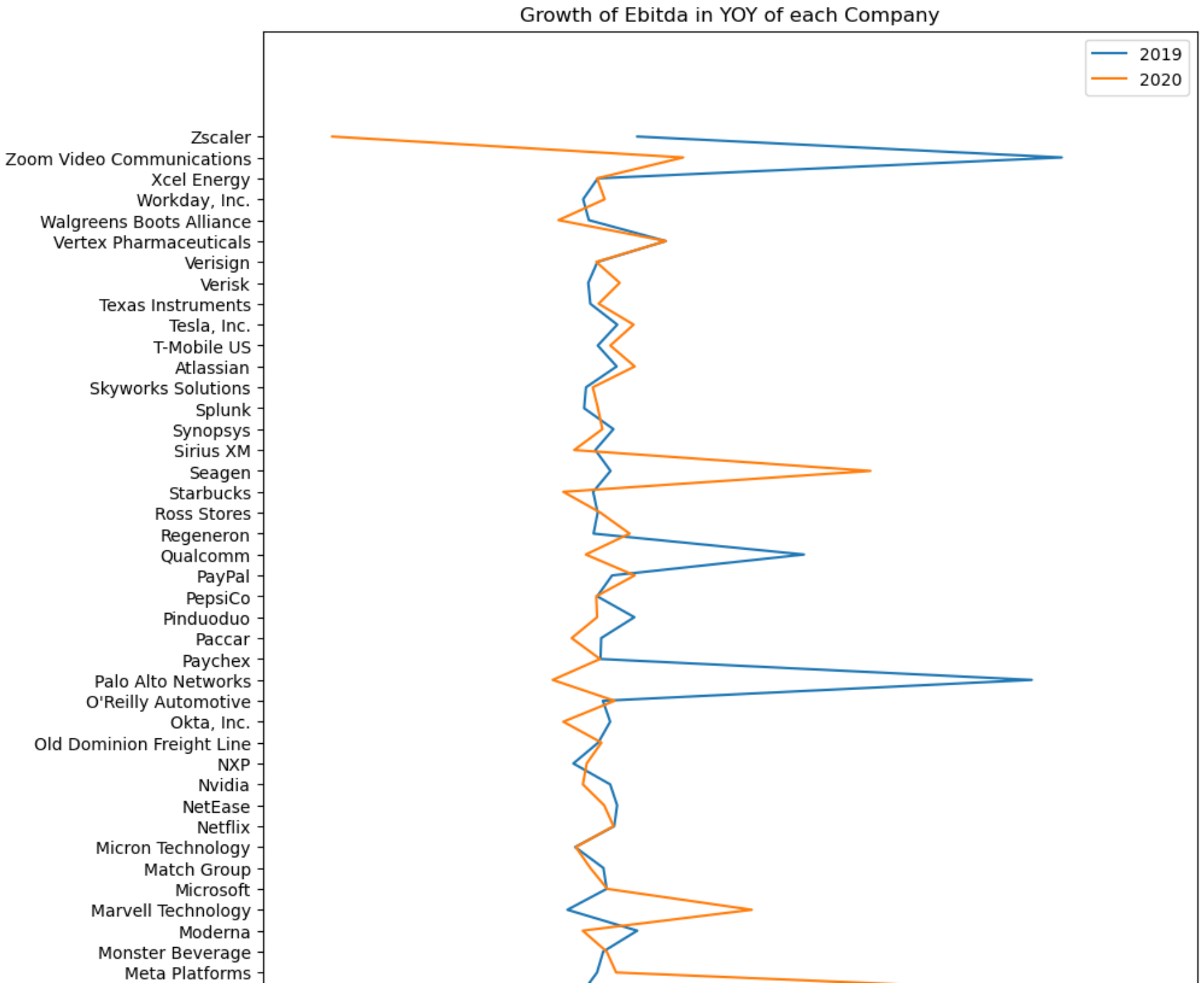
Out[32]:

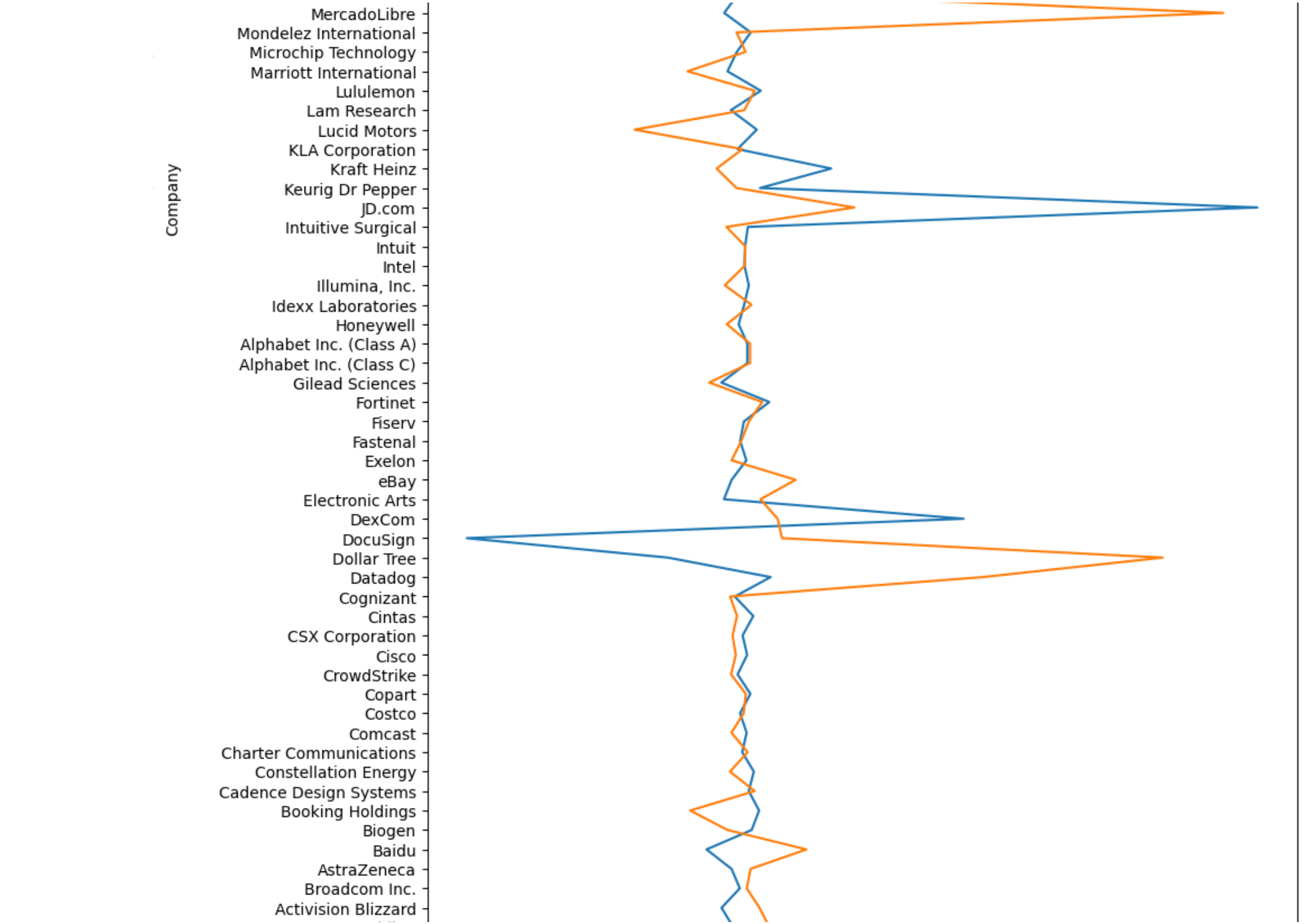
	Symbol	Name	Market Cap	Last Sale	Net Change	company	sector	subsector	asset_turnover_2017	asset_turnover
0	AAPL	Apple Inc.	2625740143000	$151.45	$2.00	Apple Inc.	Information Technology	Technology Hardware, Storage & Peripherals	0.660000	
1	ABNB	Airbnb, Inc.	69569944167	$116.65	$0.26	Airbnb	Consumer Discretionary	Internet & Direct Marketing Retail	0.724932	
2	ADBE	Adobe Inc.	149144569000	$320.81	$4.59	Adobe Inc.	Information Technology	Application Software	0.540000	
3	ADI	Analog Devices, Inc.	75484763090	$146.76	$2.23	Analog Devices	Information Technology	Semiconductors	0.360000	
4	ADP	Automatic Data Processing, Inc.	98332762096	$236.78	$0.13	ADP	Information Technology	Data Processing & Outsourced Services	0.724932	
...	...	...	...	...	...	...	...	...	...	...
97	WBA	Walgreens Boots Alliance, Inc.	30450068934	$35.21	$0.52	Walgreens Boots Alliance	Consumer Staples	Drug Retail	1.710000	
98	WDAY	Workday, Inc.	39549440000	$154.49	$6.54	Workday, Inc.	Information Technology	Application Software	0.724932	
99	XEL	Xcel Energy Inc.	34192428038	$62.51	$0.93	Xcel Energy	Utilities	Multi-Utilities	0.270000	
100	ZM	Zoom Video Communications, Inc.	24659899766	$82.85	$2.24	Zoom Video Communications	Information Technology	Application Software	0.724932	
101	ZS	Zscaler, Inc.	22393436472	$156.54	$7.87	Zscaler	Information Technology	Application Software	0.724932	

102 rows × 203 columns

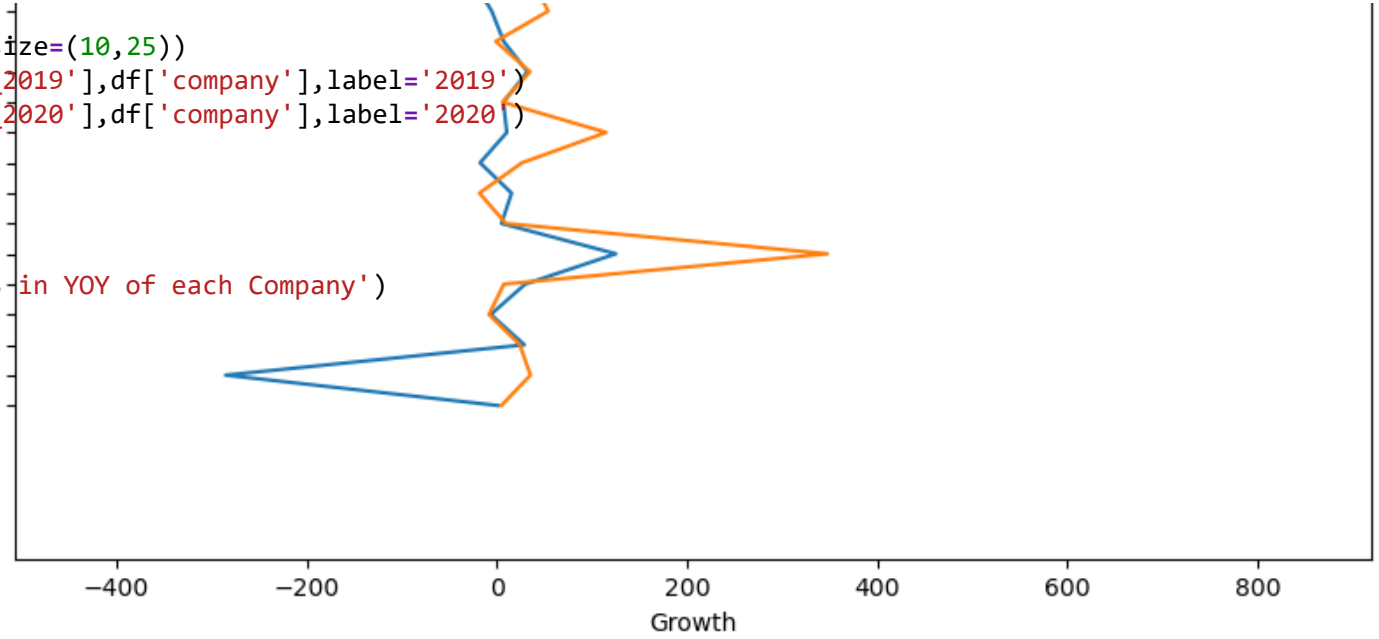
The impact of COVID has occurred during the year 2020

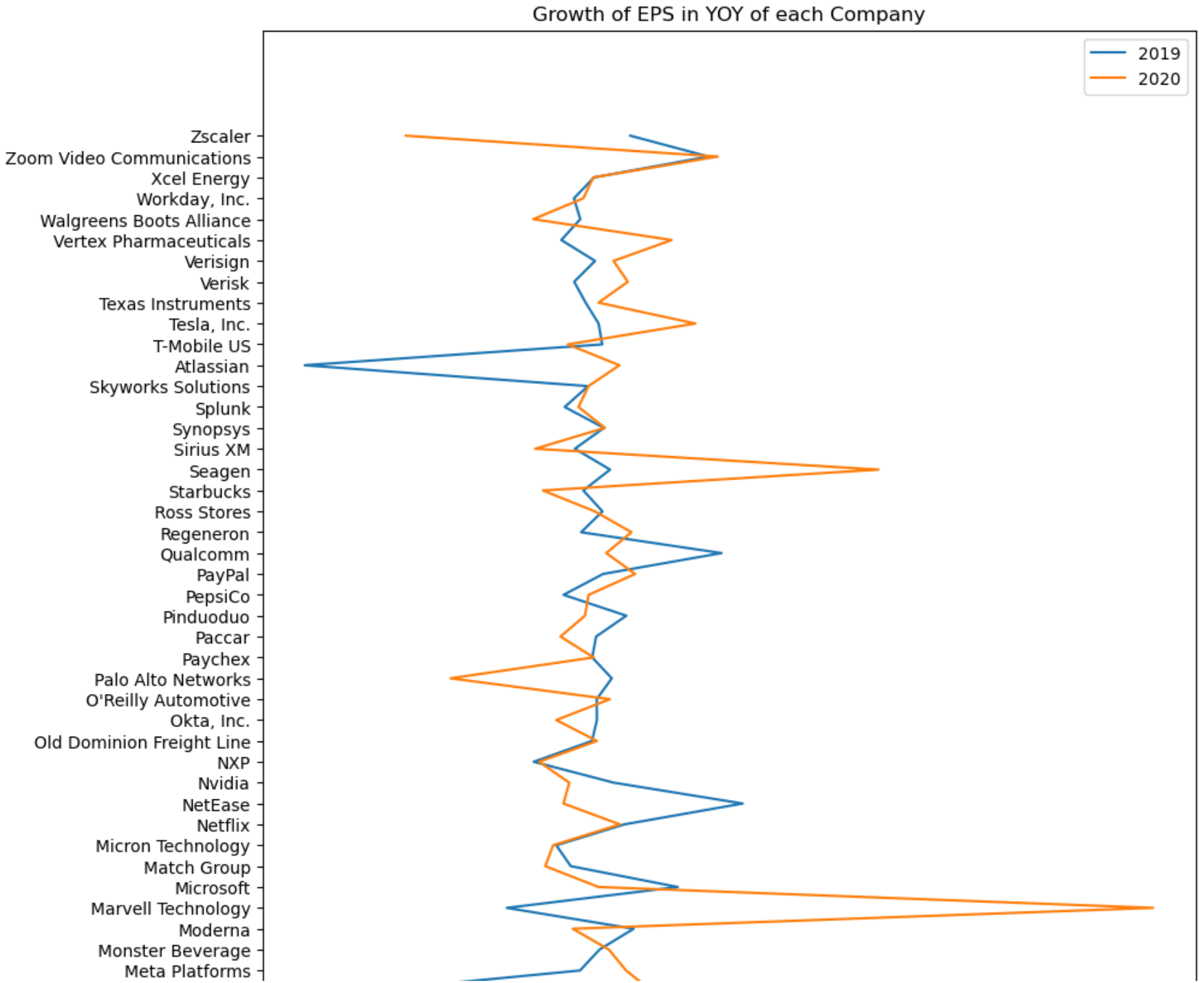
In [33]:
```
fig, ax = plt.subplots(figsize=(10,25))
ax.plot(df['yoy_ebitda_growth_2019'],df['company'],label='2019')
ax.plot(df['yoy_ebitda_growth_2020'],df['company'],label='2020')

ax.legend()
ax.set_xlabel('Growth')
ax.set_ylabel('Company')
ax.set_title('Growth of Ebitda in YOY of each Company')

plt.show()
```

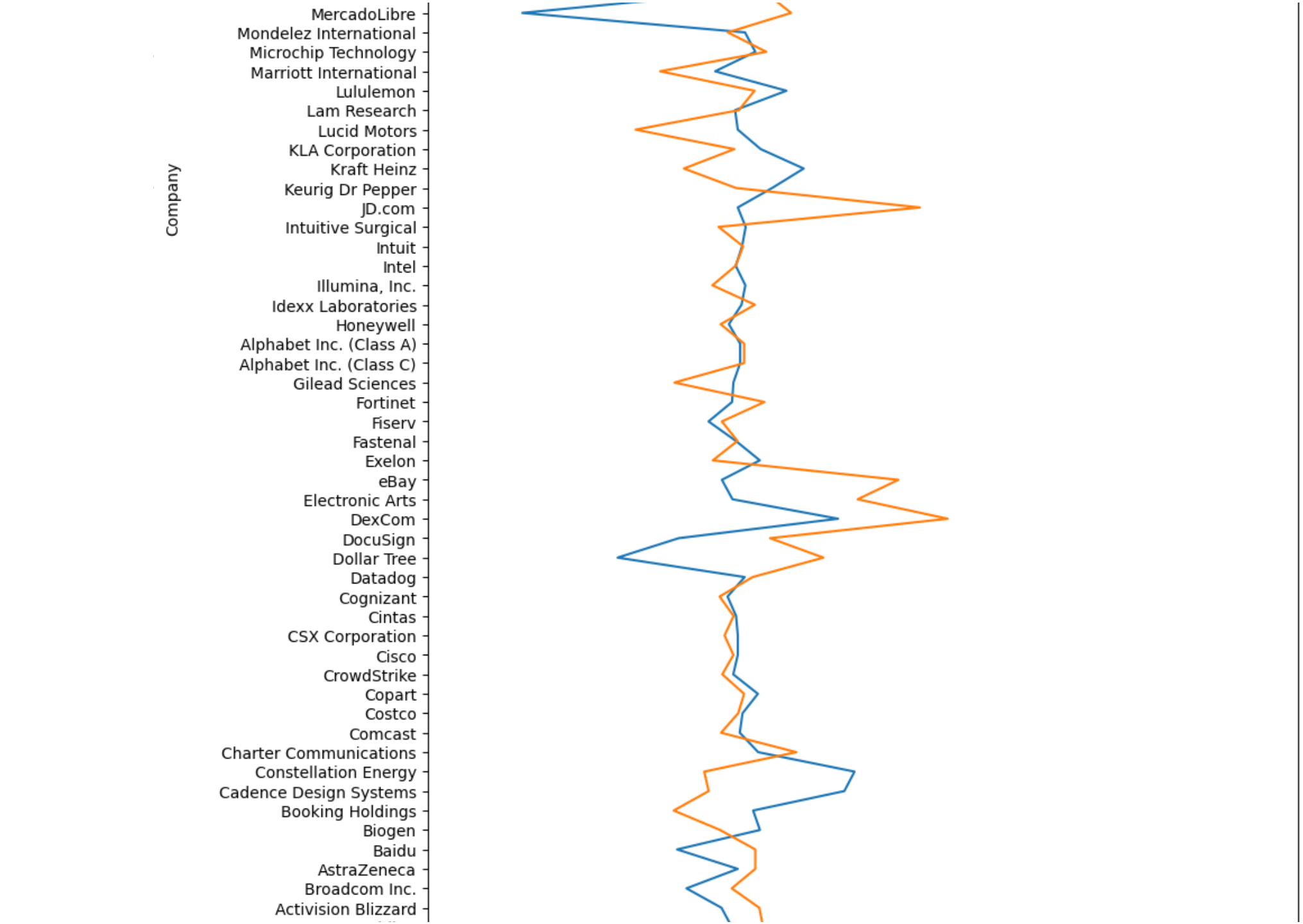

Growth of Ebitda in YOY of each Company
2019
2020
Zscaler
Zoom Video Communications
Xcel Energy
Workday, Inc.
Walgreens Boots Alliance
Vertex Pharmaceuticals
Verisign
Verisk
Texas Instruments
Tesla, Inc.
T-Mobile US
Atlassian
Skyworks Solutions
Splunk
Synopsys
Sirius XM
Seagen
Starbucks
Ross Stores
Regeneron
Qualcomm
PayPal
PepsiCo
Pinduoduo
Paccar
Paychex
Palo Alto Networks
O'Reilly Automotive
Okta, Inc.
Old Dominion Freight Line
NXP
Nvidia
NetEase
Netflix
Micron Technology
Match Group
Microsoft
Marvell Technology
Moderna
Monster Beverage
Meta Platforms


Company
MercadoLibre
Mondelez International
Microchip Technology
Marriott International
Lululemon
Lam Research
Lucid Motors
KLA Corporation
Kraft Heinz
Keurig Dr Pepper
JD.com
Intuitive Surgical
Intuit
Intel
Illumina, Inc.
Idexx Laboratories
Honeywell
Alphabet Inc. (Class A)
Alphabet Inc. (Class C)
Gilead Sciences
Fortinet
Fiserv
Fastenal
Exelon
eBay
Electronic Arts
DexCom
DocuSign
Dollar Tree
Datadog
Cognizant
Cintas
CSX Corporation
Cisco
CrowdStrike
Copart
Costco
Comcast
Charter Communications
Constellation Energy
Cadence Design Systems
Booking Holdings
Biogen
Baidu
AstraZeneca
Broadcom Inc.
Activision Blizzard

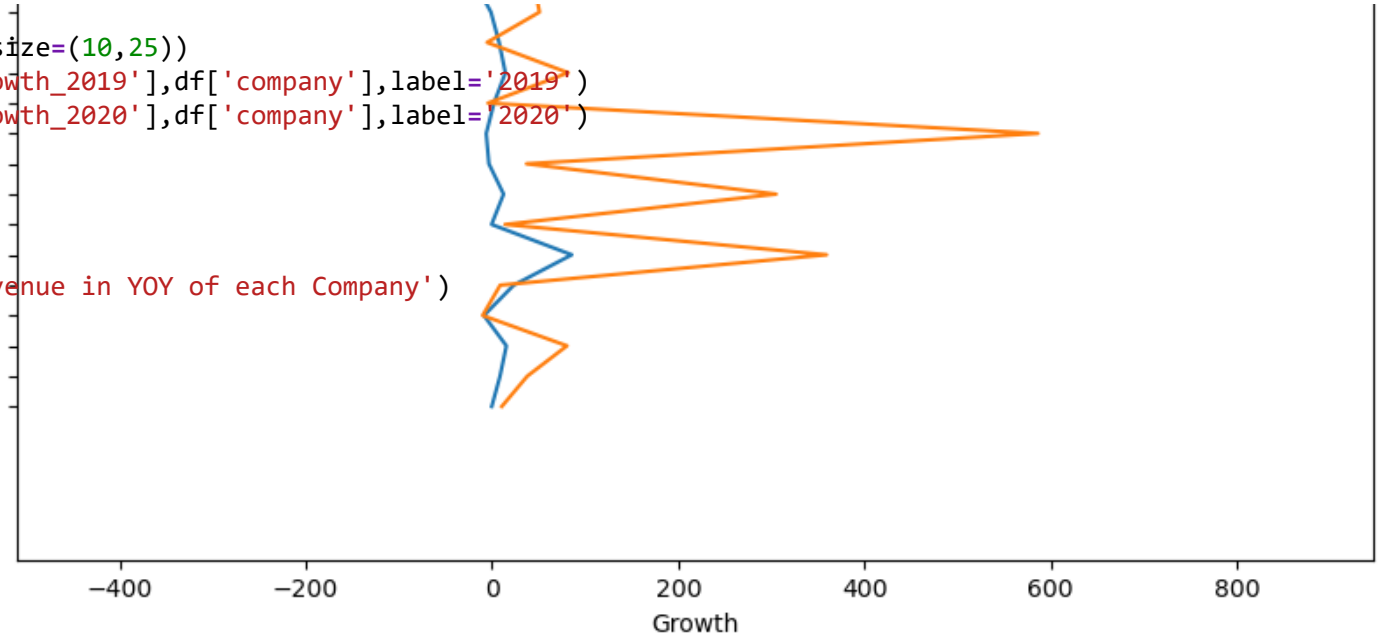
In [34]:
```
fig, ax = plt.subplots(figsize=(10,25))
ax.plot(df['yoy_eps_growth_2019'],df['company'],label='2019')
ax.plot(df['yoy_eps_growth_2020'],df['company'],label='2020')

ax.legend()
ax.set_xlabel('Growth')
ax.set_ylabel('Company')
ax.set_title('Growth of EPS in YOY of each Company')

plt.show()
```

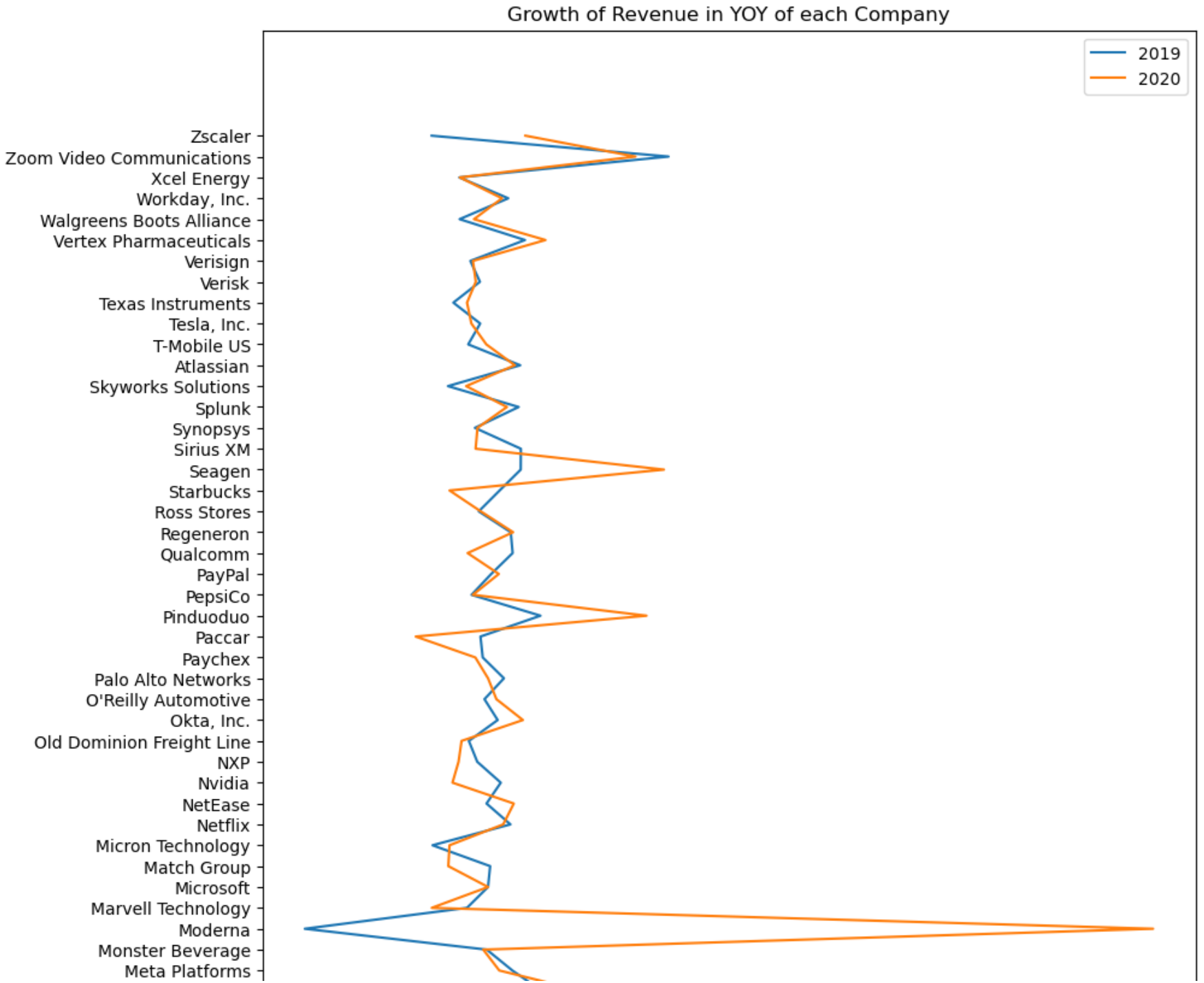


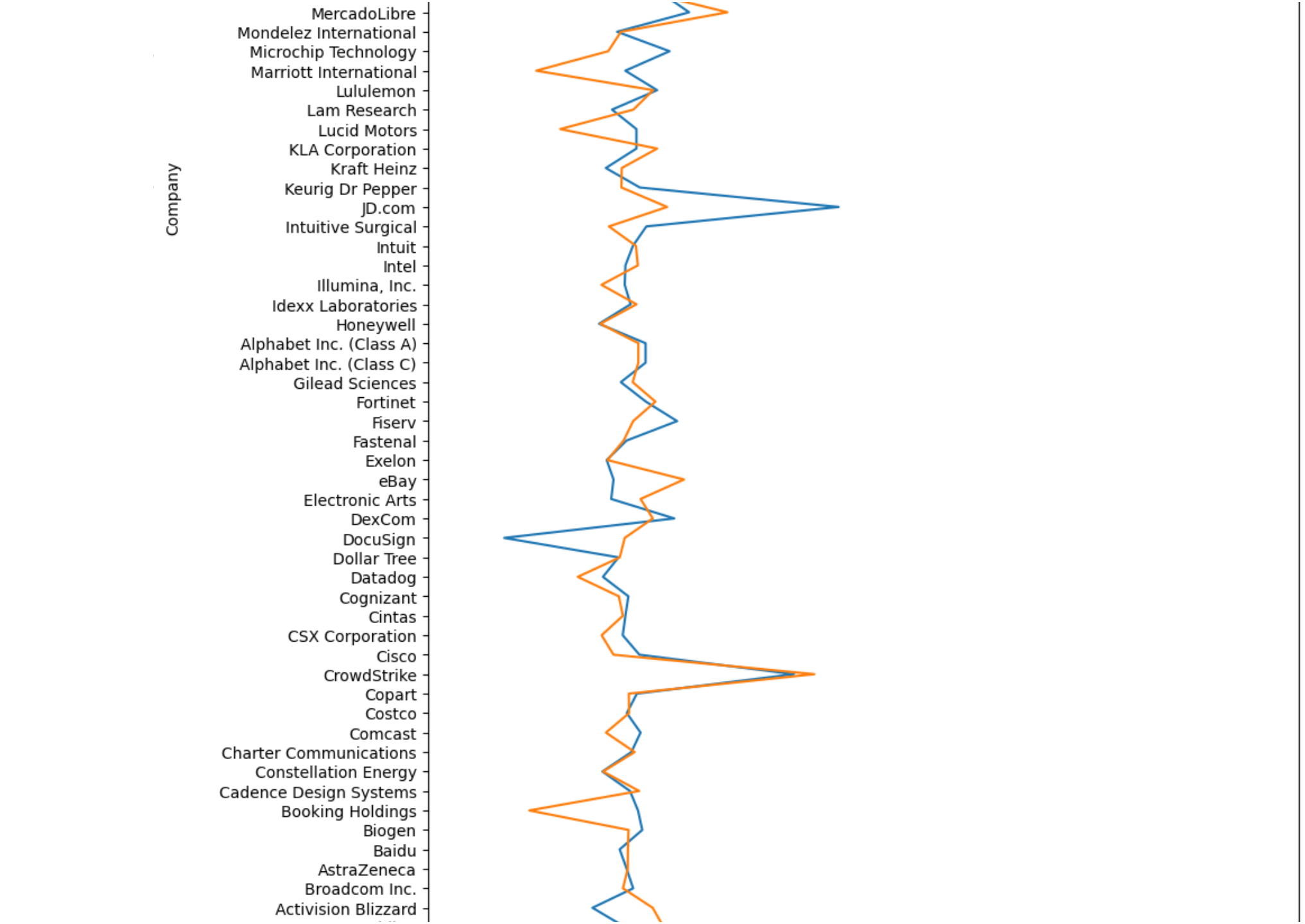

Growth of EPS in YOY of each Company
2019
2020
Zscaler
Zoom Video Communications
Xcel Energy
Workday, Inc.
Walgreens Boots Alliance
Vertex Pharmaceuticals
Verisign
Verisk
Texas Instruments
Tesla, Inc.
T-Mobile US
Atlassian
Skyworks Solutions
Splunk
Synopsys
Sirius XM
Seagen
Starbucks
Ross Stores
Regeneron
Qualcomm
PayPal
PepsiCo
Pinduoduo
Paccar
Paychex
Palo Alto Networks
O'Reilly Automotive
Okta, Inc.
Old Dominion Freight Line
NXP
Nvidia
NetEase
Netflix
Micron Technology
Match Group
Microsoft
Marvell Technology
Moderna
Monster Beverage
Meta Platforms


Company
MercadoLibre
Mondelez International
Microchip Technology
Marriott International
Lululemon
Lam Research
Lucid Motors
KLA Corporation
Kraft Heinz
Keurig Dr Pepper
JD.com
Intuitive Surgical
Intuit
Intel
Illumina, Inc.
Idexx Laboratories
Honeywell
Alphabet Inc. (Class A)
Alphabet Inc. (Class C)
Gilead Sciences
Fortinet
Fiserv
Fastenal
Exelon
eBay
Electronic Arts
DexCom
DocuSign
Dollar Tree
Datadog
Cognizant
Cintas
CSX Corporation
Cisco
CrowdStrike
Copart
Costco
Comcast
Charter Communications
Constellation Energy
Cadence Design Systems
Booking Holdings
Biogen
Baidu
AstraZeneca
Broadcom Inc.
Activision Blizzard

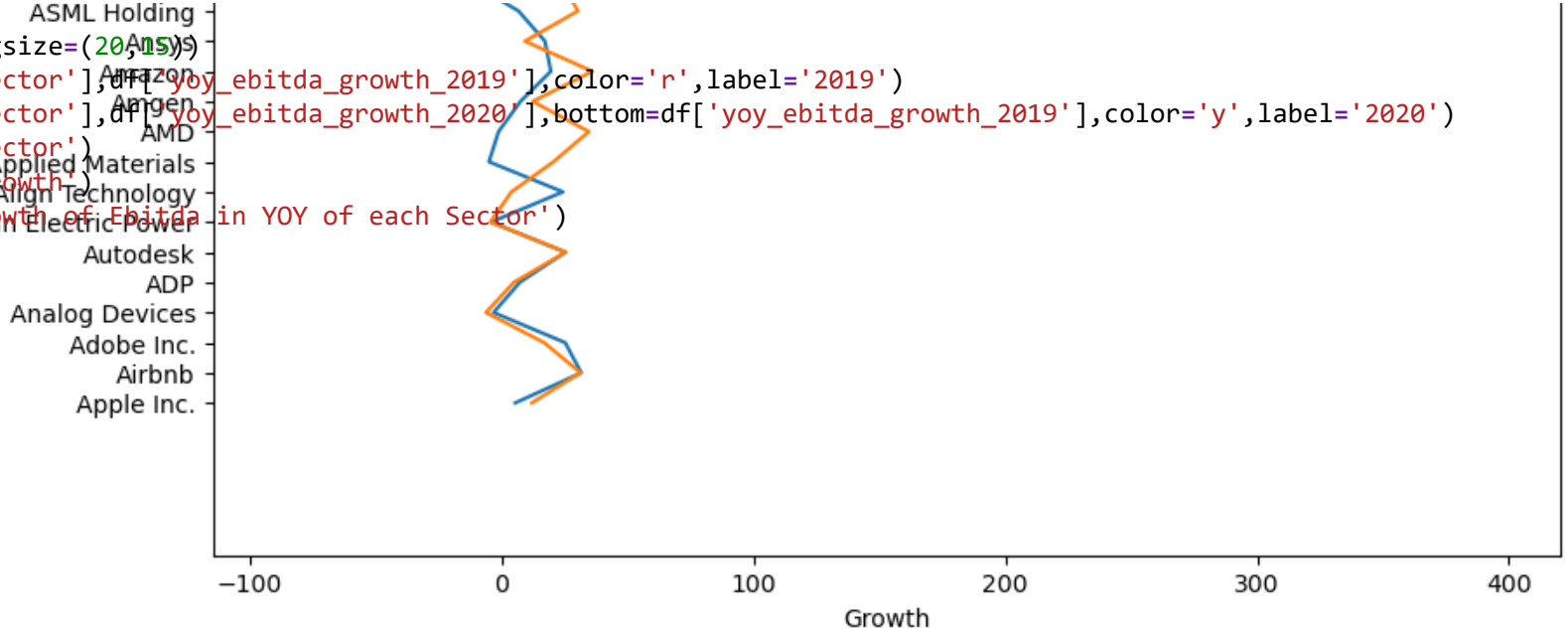
In [35]:
```
fig, ax = plt.subplots(figsize=(10,25))
ax.plot(df['yoy_revenue_growth_2019'],df['company'],label='2019')
ax.plot(df['yoy_revenue_growth_2020'],df['company'],label='2020')

ax.legend()
ax.set_xlabel('Growth')
ax.set_ylabel('Company')
ax.set_title('Growth of Revenue in YOY of each Company')

plt.show()
```

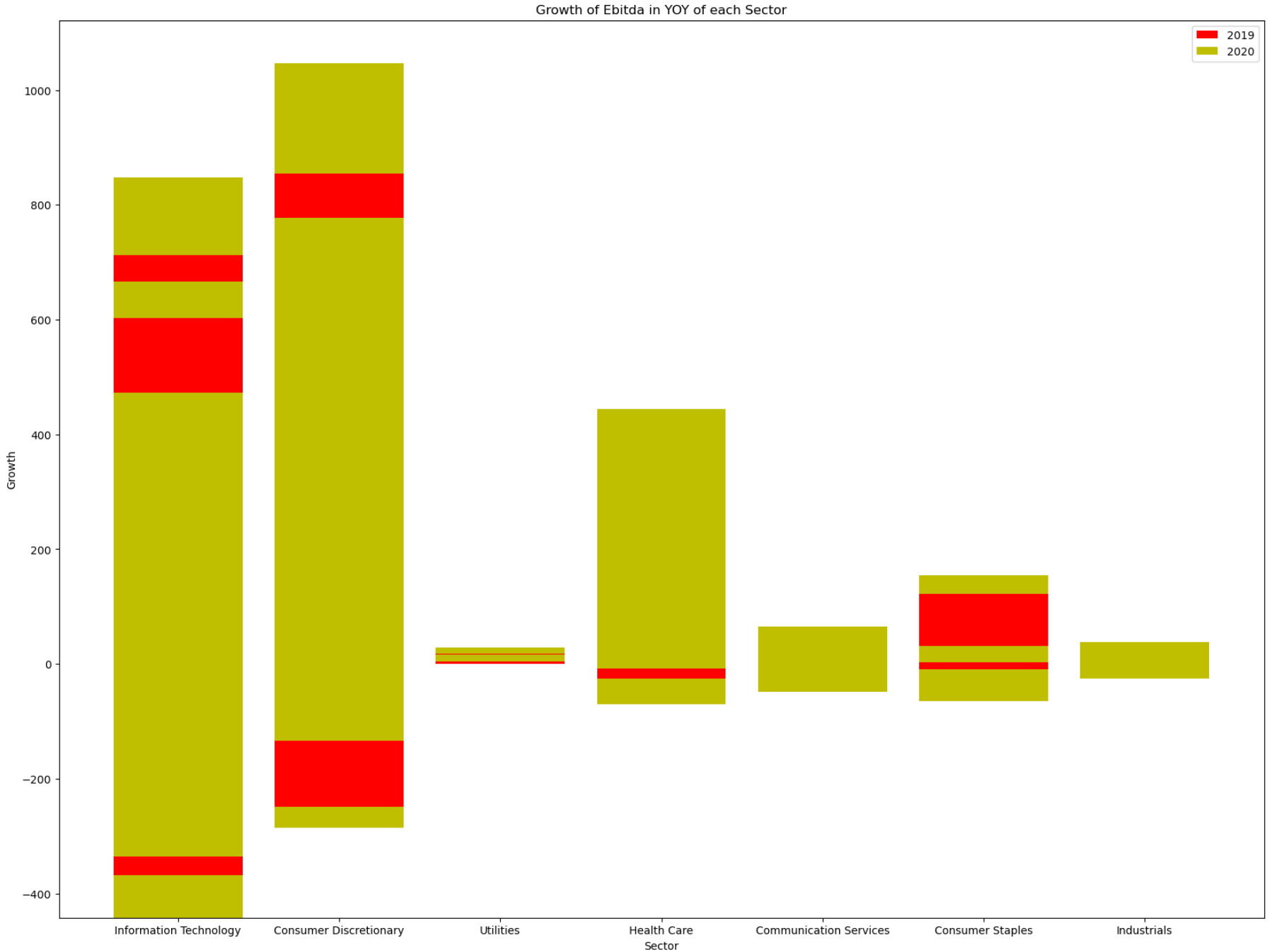



Growth of Revenue in YOY of each Company
2019
2020
Zscaler
Zoom Video Communications
Xcel Energy
Workday, Inc.
Walgreens Boots Alliance
Vertex Pharmaceuticals
Verisign
Verisk
Texas Instruments
Tesla, Inc.
T-Mobile US
Atlassian
Skyworks Solutions
Splunk
Synopsys
Sirius XM
Seagen
Starbucks
Ross Stores
Regeneron
Qualcomm
PayPal
PepsiCo
Pinduoduo
Paccar
Paychex
Palo Alto Networks
O'Reilly Automotive
Okta, Inc.
Old Dominion Freight Line
NXP
Nvidia
NetEase
Netflix
Micron Technology
Match Group
Microsoft
Marvell Technology
Moderna
Monster Beverage
Meta Platforms


Company
MercadoLibre
Mondelez International
Microchip Technology
Marriott International
Lululemon
Lam Research
Lucid Motors
KLA Corporation
Kraft Heinz
Keurig Dr Pepper
JD.com
Intuitive Surgical
Intuit
Intel
Illumina, Inc.
Idexx Laboratories
Honeywell
Alphabet Inc. (Class A)
Alphabet Inc. (Class C)
Gilead Sciences
Fortinet
Fiserv
Fastenal
Exelon
eBay
Electronic Arts
DexCom
DocuSign
Dollar Tree
Datadog
Cognizant
Cintas
CSX Corporation
Cisco
CrowdStrike
Copart
Costco
Comcast
Charter Communications
Constellation Energy
Cadence Design Systems
Booking Holdings
Biogen
Baidu
AstraZeneca
Broadcom Inc.
Activision Blizzard

In [36]:
```
plt.figure(figsize=(20,15))
plt.bar(df['sector'],df['yoy_ebitda_growth_2019'],color='r',label='2019')
plt.bar(df['sector'],df['yoy_ebitda_growth_2020'],bottom=df['yoy_ebitda_growth_2019'],color='y',label='2020')
plt.xlabel('Sector')
plt.ylabel('Growth')
plt.title('Growth of Ebitda in YOY of each Sector')
plt.legend()
plt.show()
```




Growth of Ebitda in YOY of each Sector
2019
2020
1000
800
600
400
200
0
−200
−400
Growth
Information Technology
Consumer Discretionary
Utilities
Health Care
Communication Services
Consumer Staples
Industrials
Sector

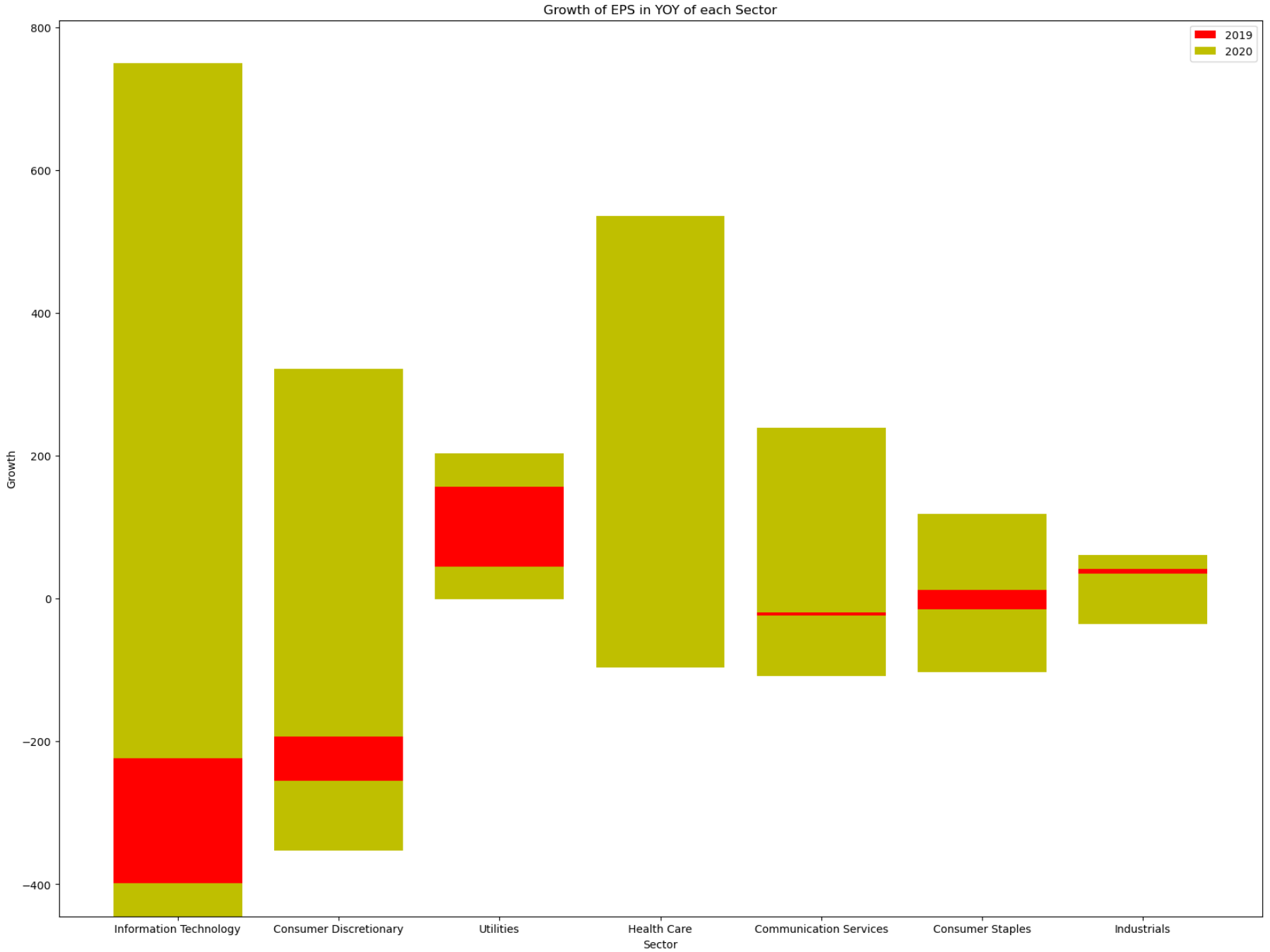
The greatest impact in Editda due to COVID occured for the Sector:

```
Information Technology, Consumer Disretionary
```

The Lowest impact in Editda due to COVID occured for the companies :

```
Utilities
```

In [37]:
```
plt.figure(figsize=(20,15))
plt.bar(df['sector'],df['yoy_eps_growth_2019'],color='r',label='2019')
plt.bar(df['sector'],df['yoy_eps_growth_2020'],bottom=df['yoy_eps_growth_2019'],color='y',label='2020')
plt.xlabel('Sector')
plt.ylabel('Growth')
plt.title('Growth of EPS in YOY of each Sector')
plt.legend()
plt.show()
```


Growth of EPS in YOY of each Sector
2019
2020
800
600
400
200
0
−200
−400
Growth
Information Technology
Consumer Discretionary
Utilities
Health Care
Communication Services
Consumer Staples
Industrials
Sector

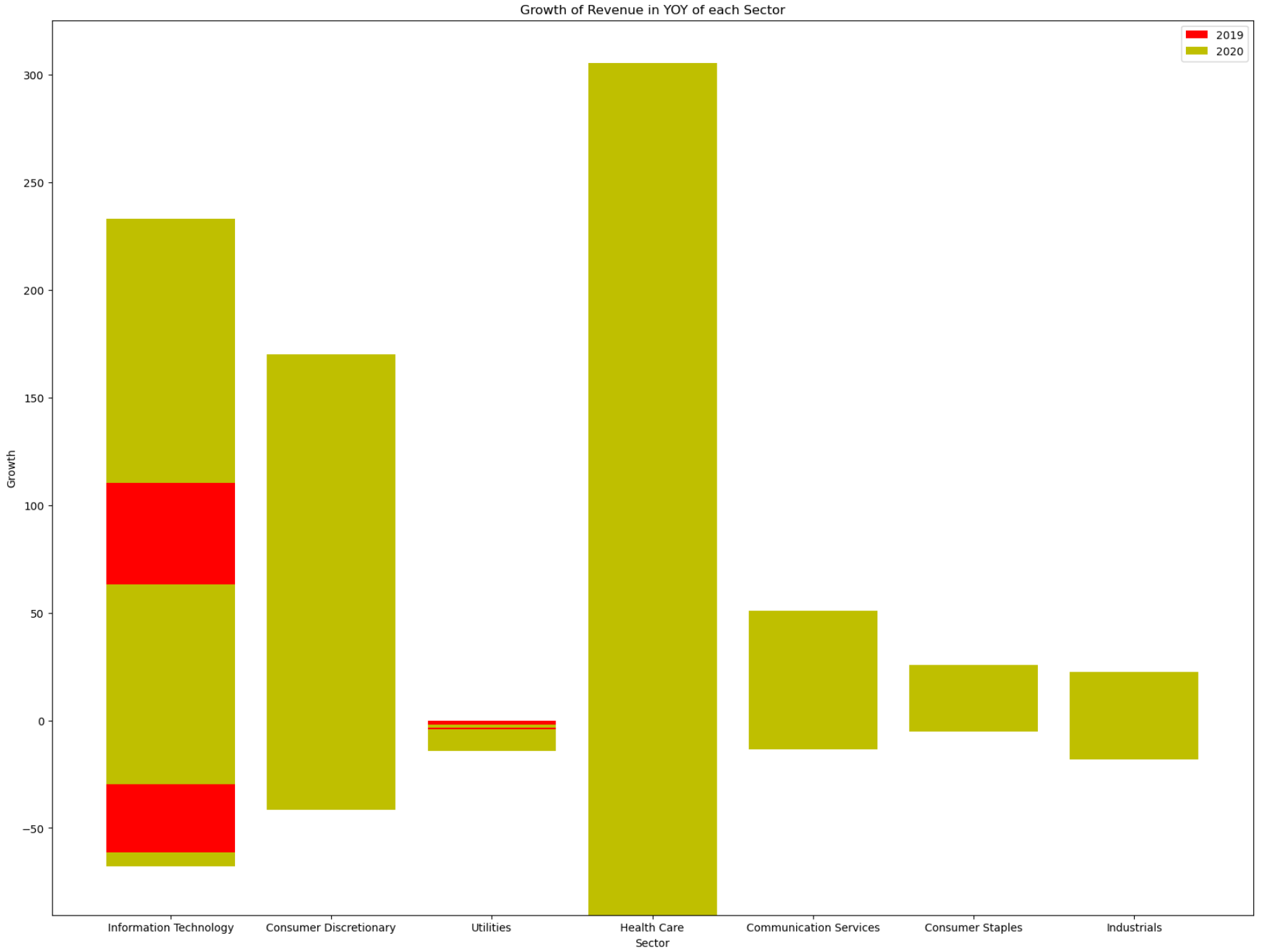
The greatest impact in EPS due to COVID occured for the Sector:

```
Information Technology, Consumer Disretionary
```

The lowest impact in EPS due to COVID occured for the Sector:

```
Industries, Utilities
```

In [38]:
```
plt.figure(figsize=(20,15))
plt.bar(df['sector'],df['yoy_revenue_growth_2019'],color='r',label='2019')
plt.bar(df['sector'],df['yoy_revenue_growth_2020'],bottom=df['yoy_revenue_growth_2019'],color='y',label='2020')
plt.xlabel('Sector')
plt.ylabel('Growth')
plt.title('Growth of Revenue in YOY of each Sector')
plt.legend()
plt.show()
```


Growth of Revenue in YOY of each Sector
2019
2020
Growth
300
250
200
150
100
50
0
−50
Information Technology
Consumer Discretionary
Utilities
Health Care
Communication Services
Consumer Staples
Industrials
Sector

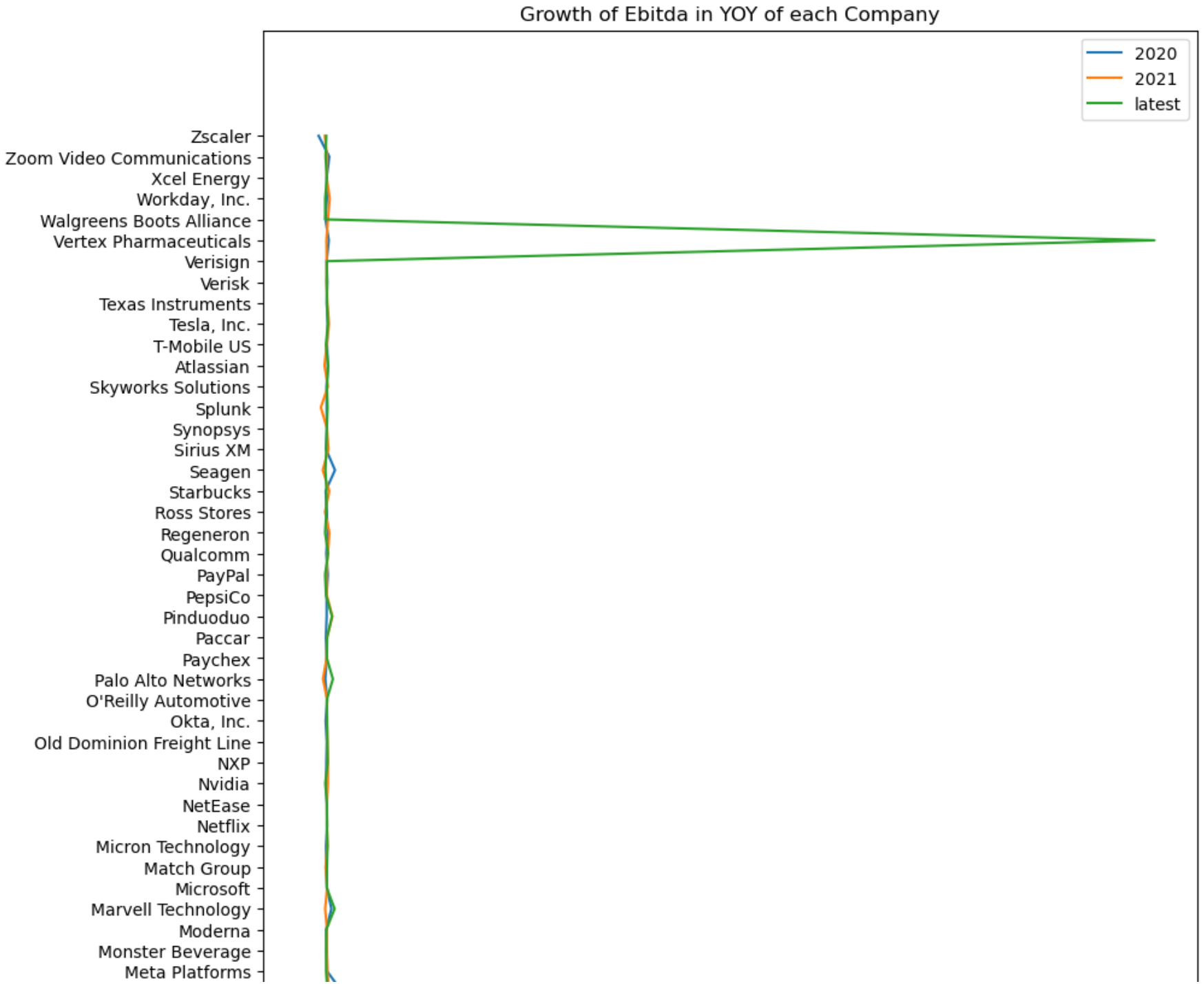
The greatest impact in Revenue due to COVID occured for the Sector:

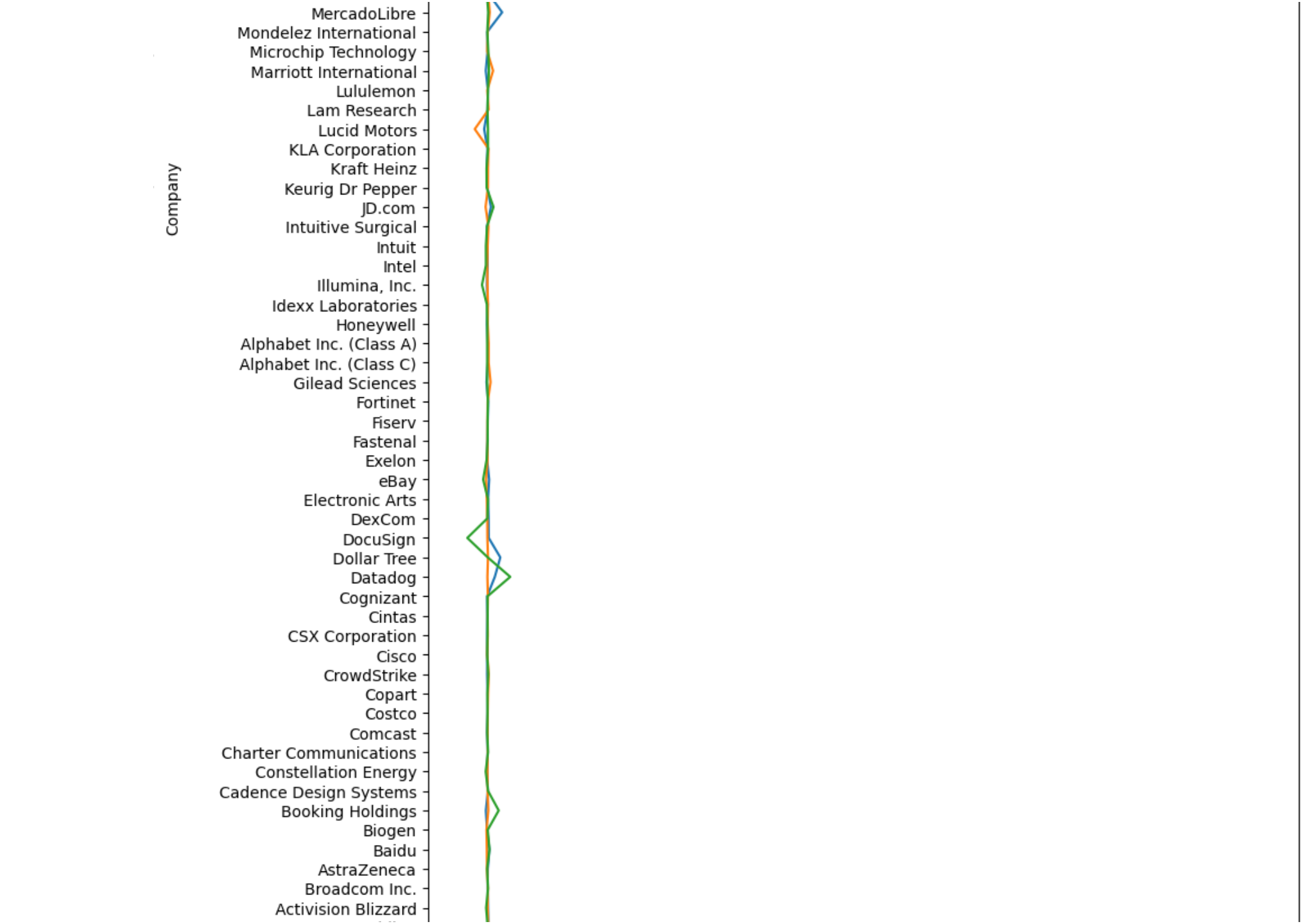
```
Information Technology
```

The lowest impact in Revenue due to COVID occured for the Sector:

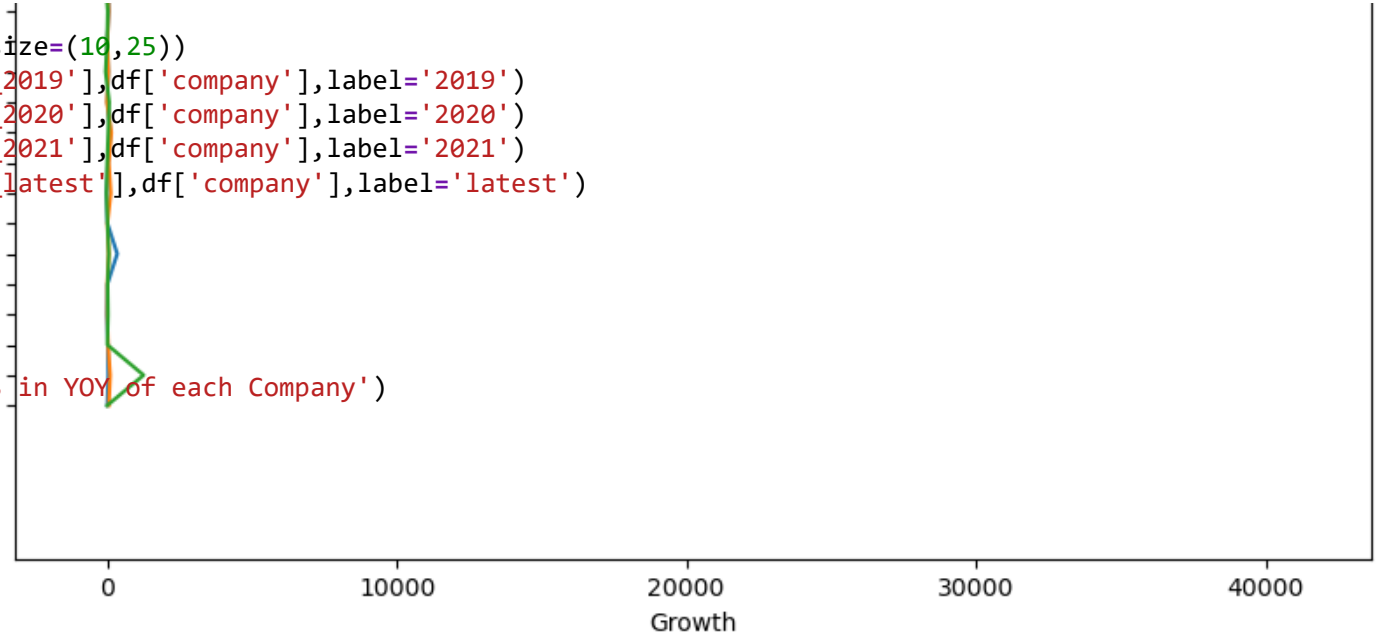
```
Utilities
```

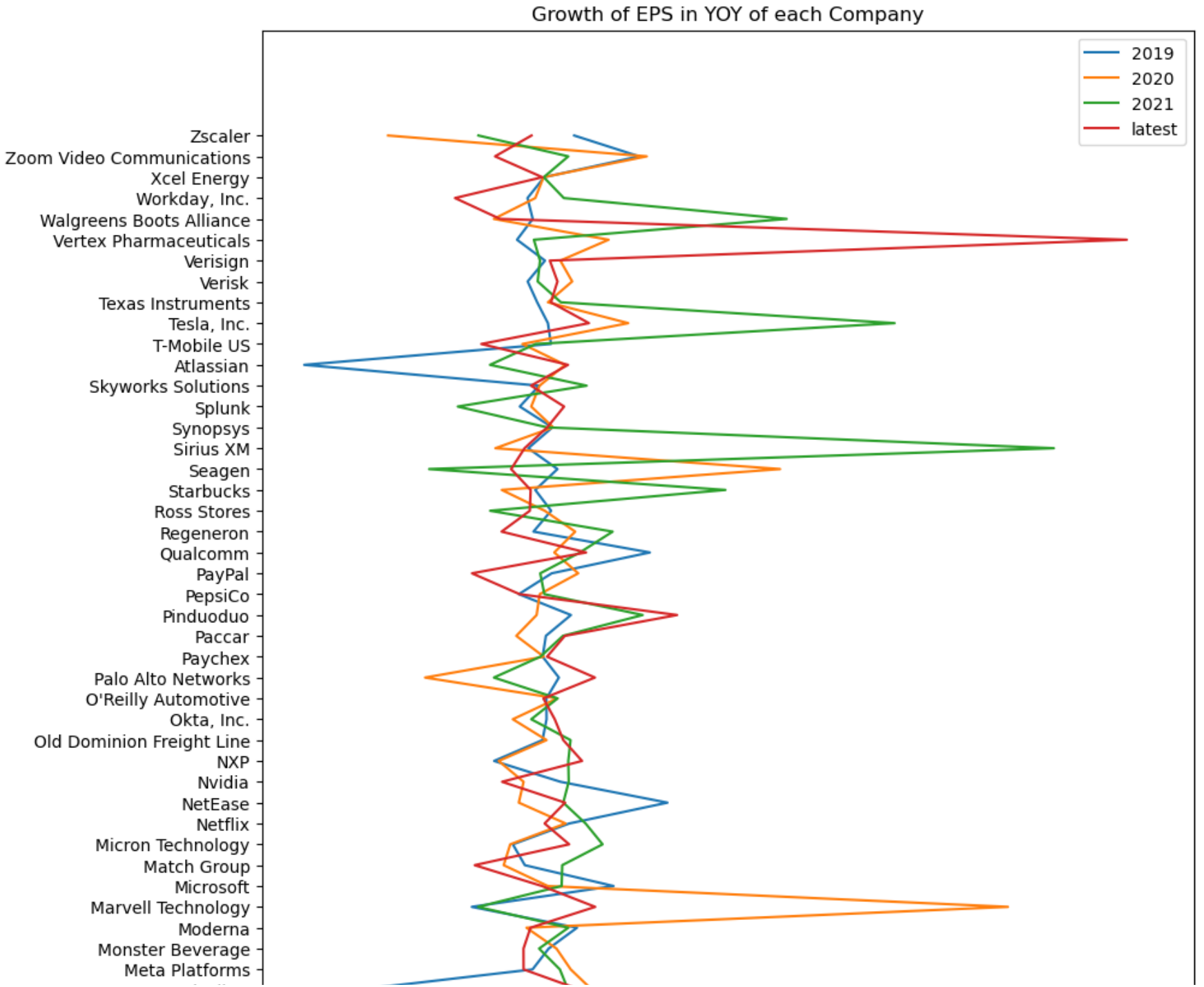
In [39]:
```
fig, ax = plt.subplots(figsize=(10,25))
ax.plot(df['yoy_ebitda_growth_2020'],df['company'],label='2020')
ax.plot(df['yoy_ebitda_growth_2021'],df['company'],label='2021')
ax.plot(df['yoy_ebitda_growth_latest'],df['company'],label='latest')


ax.legend()
ax.set_xlabel('Growth')
ax.set_ylabel('Company')
ax.set_title('Growth of Ebitda in YOY of each Company')

plt.show()
```

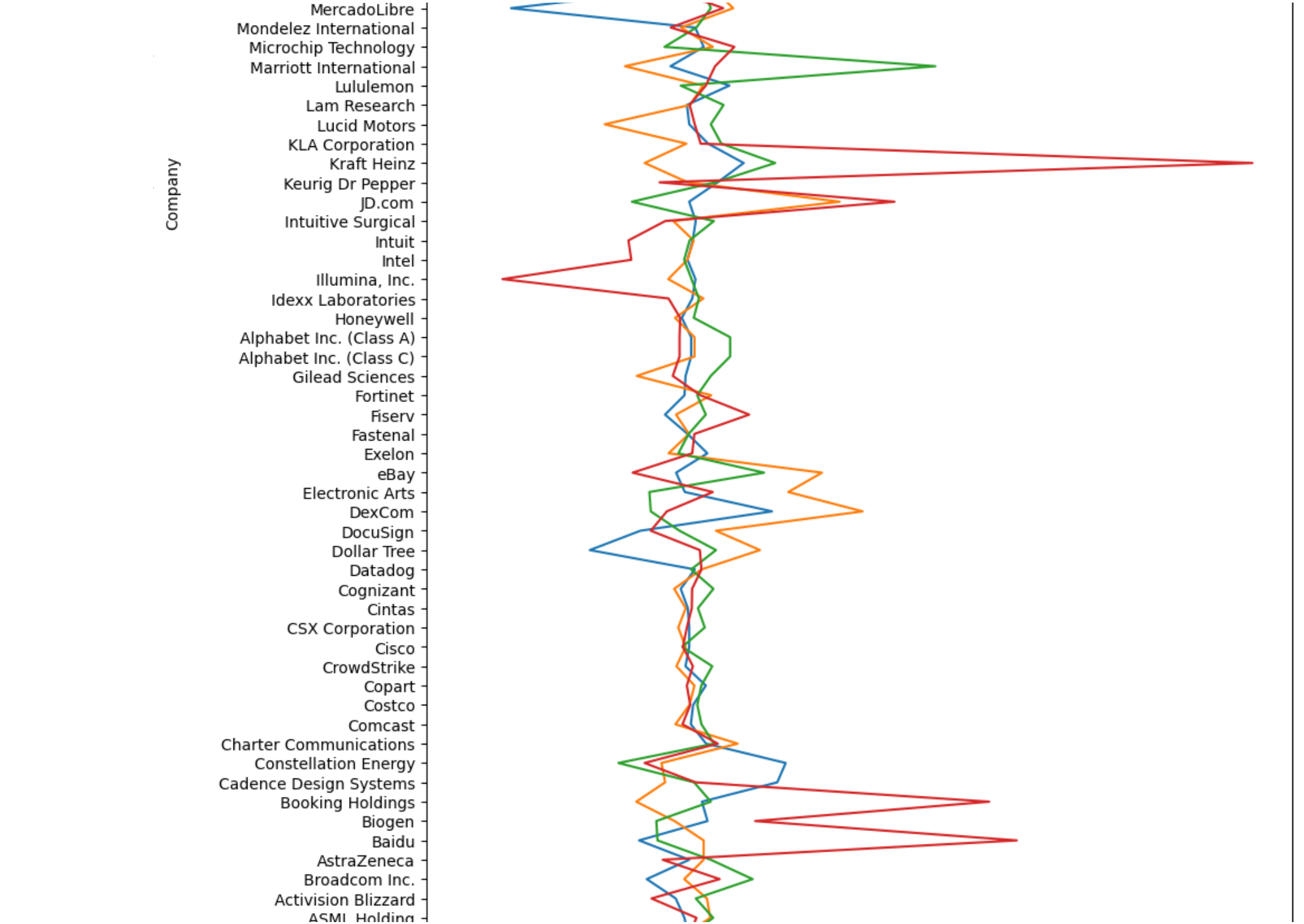

Growth of Ebitda in YOY of each Company
2020
2021
latest
Zscaler
Zoom Video Communications
Xcel Energy
Workday, Inc.
Walgreens Boots Alliance
Vertex Pharmaceuticals
Verisign
Verisk
Texas Instruments
Tesla, Inc.
T-Mobile US
Atlassian
Skyworks Solutions
Splunk
Synopsys
Sirius XM
Seagen
Starbucks
Ross Stores
Regeneron
Qualcomm
PayPal
PepsiCo
Pinduoduo
Paccar
Paychex
Palo Alto Networks
O'Reilly Automotive
Okta, Inc.
Old Dominion Freight Line
NXP
Nvidia
NetEase
Netflix
Micron Technology
Match Group
Microsoft
Marvell Technology
Moderna
Monster Beverage
Meta Platforms


Company
MercadoLibre
Mondelez International
Microchip Technology
Marriott International
Lululemon
Lam Research
Lucid Motors
KLA Corporation
Kraft Heinz
Keurig Dr Pepper
JD.com
Intuitive Surgical
Intuit
Intel
Illumina, Inc.
Idexx Laboratories
Honeywell
Alphabet Inc. (Class A)
Alphabet Inc. (Class C)
Gilead Sciences
Fortinet
Fiserv
Fastenal
Exelon
eBay
Electronic Arts
DexCom
DocuSign
Dollar Tree
Datadog
Cognizant
Cintas
CSX Corporation
Cisco
CrowdStrike
Copart
Costco
Comcast
Charter Communications
Constellation Energy
Cadence Design Systems
Booking Holdings
Biogen
Baidu
AstraZeneca
Broadcom Inc.
Activision Blizzard

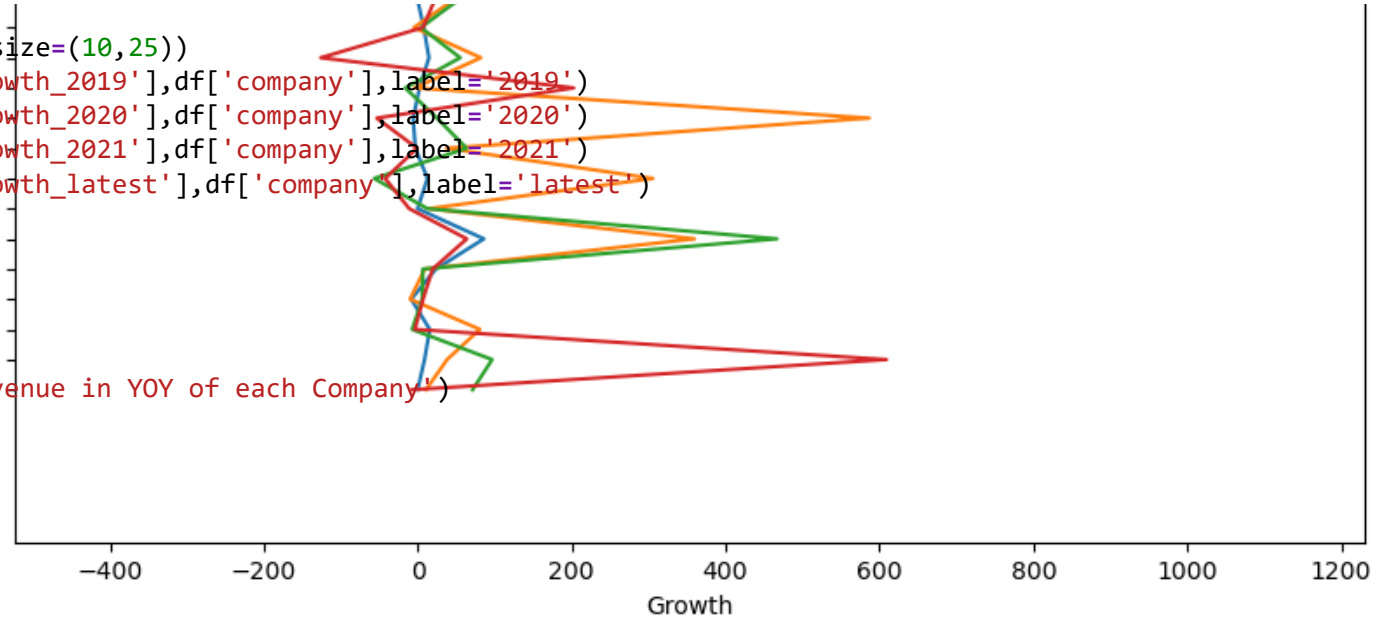
In [40]:
```
fig, ax = plt.subplots(figsize=(10,25))
ax.plot(df['yoy_eps_growth_2019'],df['company'],label='2019')
ax.plot(df['yoy_eps_growth_2020'],df['company'],label='2020')
ax.plot(df['yoy_eps_growth_2021'],df['company'],label='2021')
ax.plot(df['yoy_eps_growth_latest'],df['company'],label='latest')

ax.legend()
ax.set_xlabel('Growth')
ax.set_ylabel('Company')
ax.set_title('Growth of EPS in YOY of each Company')

plt.show()
```

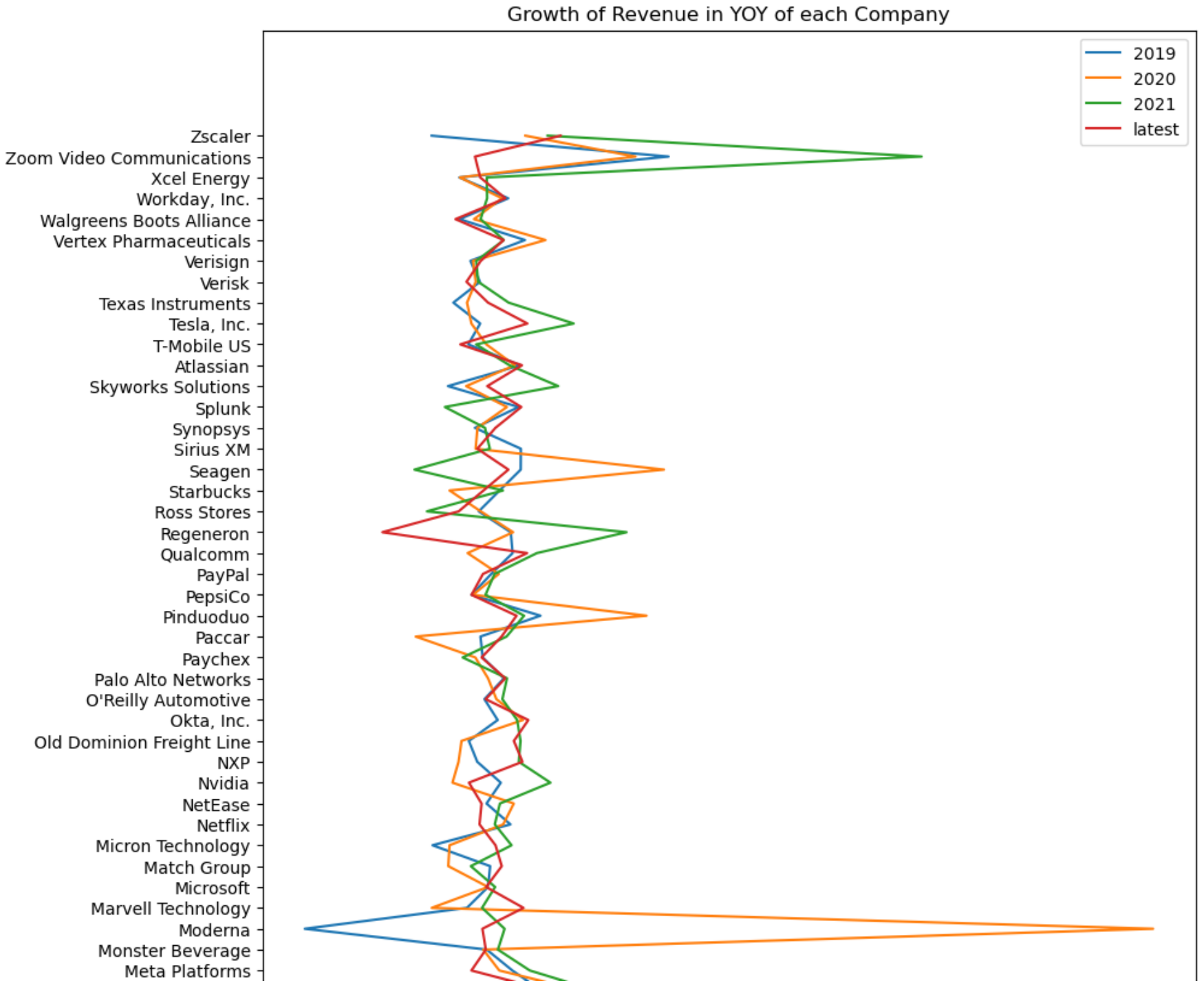


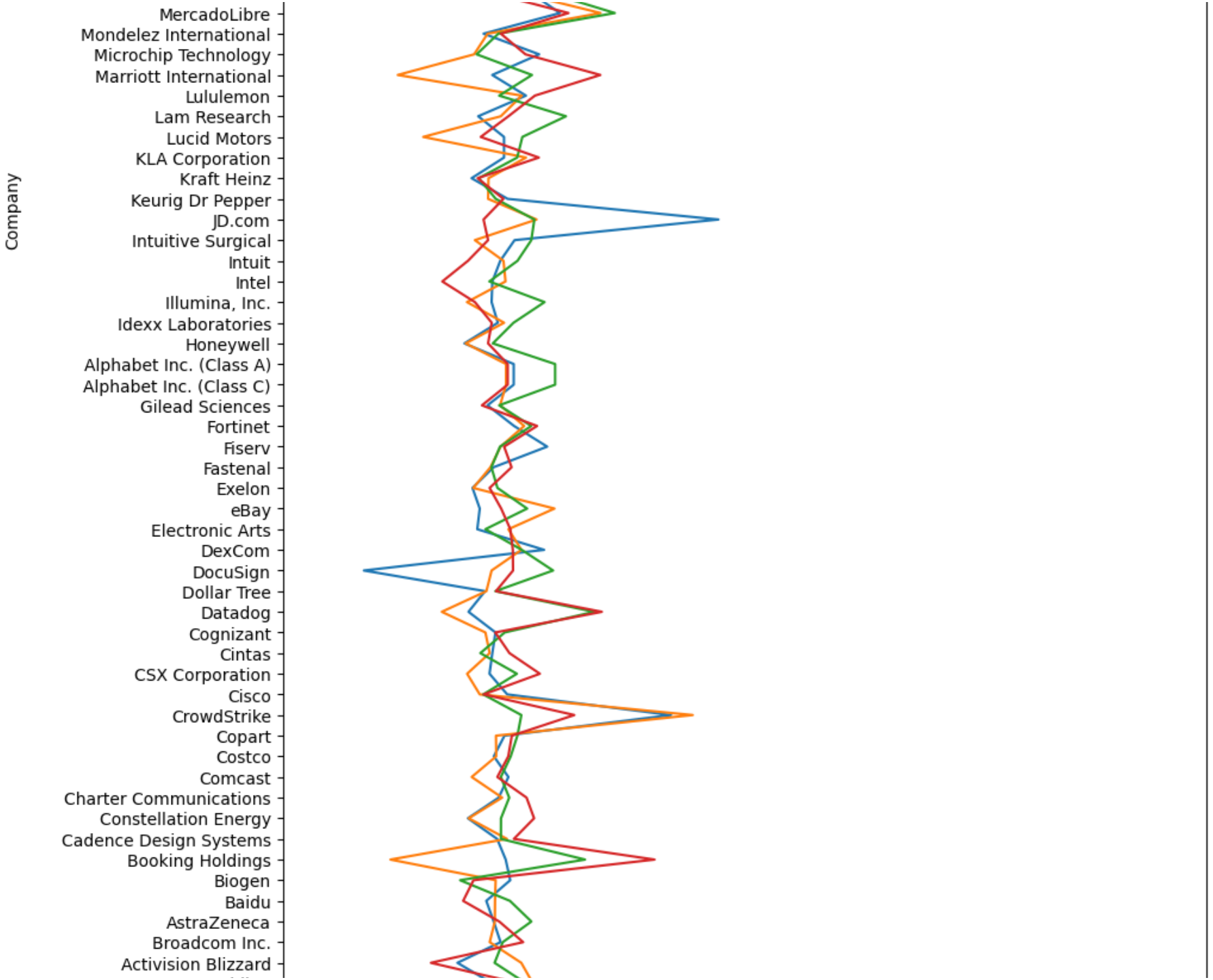

Growth of EPS in YOY of each Company
2019
2020
2021
latest
Zscaler
Zoom Video Communications
Xcel Energy
Workday, Inc.
Walgreens Boots Alliance
Vertex Pharmaceuticals
Verisign
Verisk
Texas Instruments
Tesla, Inc.
T-Mobile US
Atlassian
Skyworks Solutions
Splunk
Synopsys
Sirius XM
Seagen
Starbucks
Ross Stores
Regeneron
Qualcomm
PayPal
PepsiCo
Pinduoduo
Paccar
Paychex
Palo Alto Networks
O'Reilly Automotive
Okta, Inc.
Old Dominion Freight Line
NXP
Nvidia
NetEase
Netflix
Micron Technology
Match Group
Microsoft
Marvell Technology
Moderna
Monster Beverage
Meta Platforms


Company
MercadoLibre
Mondelez International
Microchip Technology
Marriott International
Lululemon
Lam Research
Lucid Motors
KLA Corporation
Kraft Heinz
Keurig Dr Pepper
JD.com
Intuitive Surgical
Intuit
Intel
Illumina, Inc.
Idexx Laboratories
Honeywell
Alphabet Inc. (Class A)
Alphabet Inc. (Class C)
Gilead Sciences
Fortinet
Fiserv
Fastenal
Exelon
eBay
Electronic Arts
DexCom
DocuSign
Dollar Tree
Datadog
Cognizant
Cintas
CSX Corporation
Cisco
CrowdStrike
Copart
Costco
Comcast
Charter Communications
Constellation Energy
Cadence Design Systems
Booking Holdings
Biogen
Baidu
AstraZeneca
Broadcom Inc.
Activision Blizzard
ASML Holding

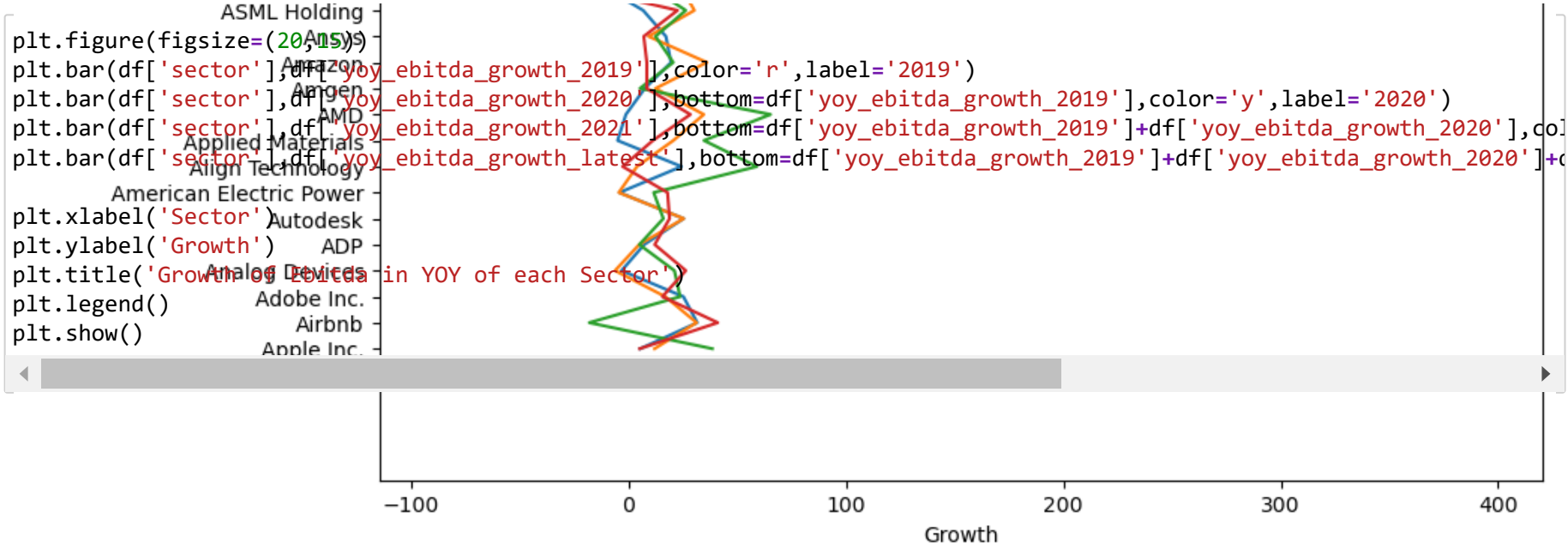
In [41]:
```
fig, ax = plt.subplots(figsize=(10,25))
ax.plot(df['yoy_revenue_growth_2019'],df['company'],label='2019')
ax.plot(df['yoy_revenue_growth_2020'],df['company'],label='2020')
ax.plot(df['yoy_revenue_growth_2021'],df['company'],label='2021')
ax.plot(df['yoy_revenue_growth_latest'],df['company'],label='latest')

ax.legend()
ax.set_xlabel('Growth')
ax.set_ylabel('Company')
ax.set_title('Growth of Revenue in YOY of each Company')

plt.show()
```

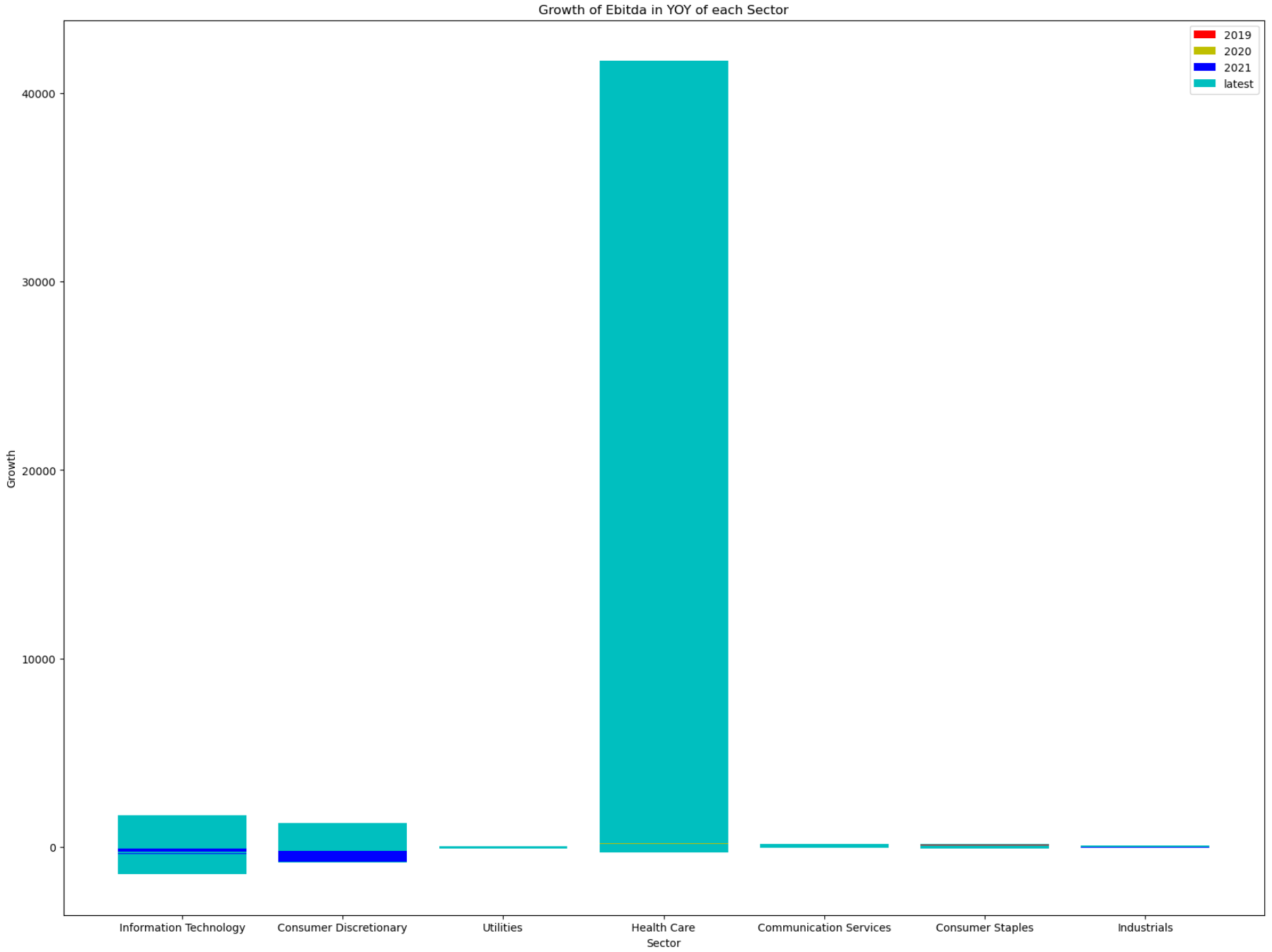



Growth of Revenue in YOY of each Company
2019
2020
2021
latest
Zscaler
Zoom Video Communications
Xcel Energy
Workday, Inc.
Walgreens Boots Alliance
Vertex Pharmaceuticals
Verisign
Verisk
Texas Instruments
Tesla, Inc.
T-Mobile US
Atlassian
Skyworks Solutions
Splunk
Synopsys
Sirius XM
Seagen
Starbucks
Ross Stores
Regeneron
Qualcomm
PayPal
PepsiCo
Pinduoduo
Paccar
Paychex
Palo Alto Networks
O'Reilly Automotive
Okta, Inc.
Old Dominion Freight Line
NXP
Nvidia
NetEase
Netflix
Micron Technology
Match Group
Microsoft
Marvell Technology
Moderna
Monster Beverage
Meta Platforms


Company
MercadoLibre
Mondelez International
Microchip Technology
Marriott International
Lululemon
Lam Research
Lucid Motors
KLA Corporation
Kraft Heinz
Keurig Dr Pepper
JD.com
Intuitive Surgical
Intuit
Intel
Illumina, Inc.
Idexx Laboratories
Honeywell
Alphabet Inc. (Class A)
Alphabet Inc. (Class C)
Gilead Sciences
Fortinet
Fiserv
Fastenal
Exelon
eBay
Electronic Arts
DexCom
DocuSign
Dollar Tree
Datadog
Cognizant
Cintas
CSX Corporation
Cisco
CrowdStrike
Copart
Costco
Comcast
Charter Communications
Constellation Energy
Cadence Design Systems
Booking Holdings
Biogen
Baidu
AstraZeneca
Broadcom Inc.
Activision Blizzard

In [42]:
```
plt.figure(figsize=(20,15))
plt.bar(df['sector'],df['yoy_ebitda_growth_2019'],color='r',label='2019')
plt.bar(df['sector'],df['yoy_ebitda_growth_2020'],bottom=df['yoy_ebitda_growth_2019'],color='y',label='2020')
plt.bar(df['sector'],df['yoy_ebitda_growth_2021'],bottom=df['yoy_ebitda_growth_2019']+df['yoy_ebitda_growth_2020'],col
plt.bar(df['sector'],df['yoy_ebitda_growth_latest'],bottom=df['yoy_ebitda_growth_2019']+df['yoy_ebitda_growth_2020']+d
plt.xlabel('Sector')
plt.ylabel('Growth')
plt.title('Growth of Ebitda in YOY of each Sector')
plt.legend()
plt.show()
```




Growth of Ebitda in YOY of each Sector
2019
2020
2021
latest
40000
30000
20000
10000
0
Growth
Information Technology
Consumer Discretionary
Utilities
Health Care
Communication Services
Consumer Staples
Industrials
Sector

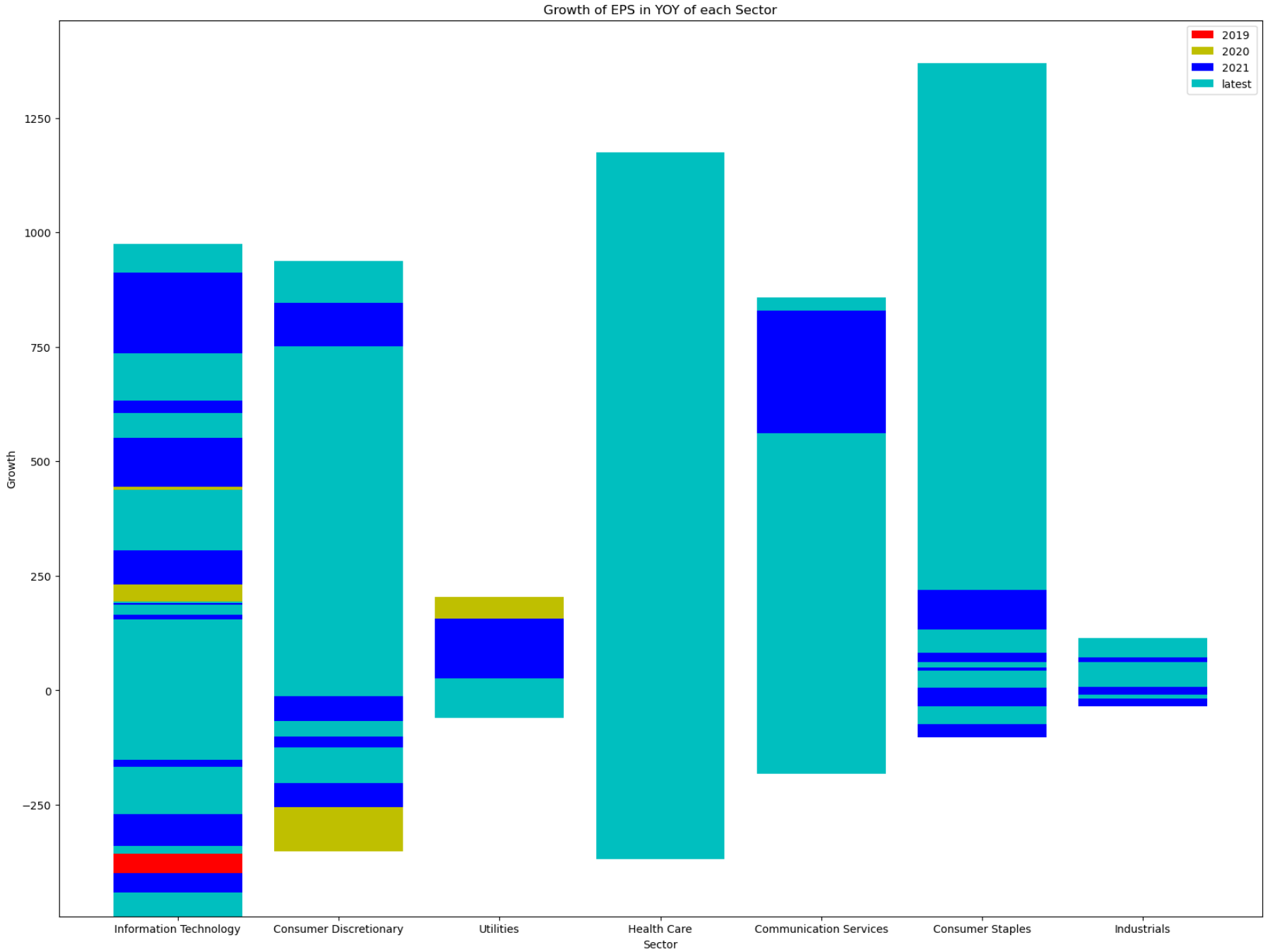
The Fastest recoveries Sector in Ebitda:

```
Health Care Sector
```

The Slowest recoveries Sector in Ebitda:

```
Consumer Staples, Communication Services
```

In [43]:
```
plt.figure(figsize=(20,15))
plt.bar(df['sector'],df['yoy_eps_growth_2019'],color='r',label='2019')
plt.bar(df['sector'],df['yoy_eps_growth_2020'],bottom=df['yoy_eps_growth_2019'],color='y',label='2020')
plt.bar(df['sector'],df['yoy_eps_growth_2021'],bottom=df['yoy_eps_growth_2019']+df['yoy_eps_growth_2020'],color='b',la
plt.bar(df['sector'],df['yoy_eps_growth_latest'],bottom=df['yoy_eps_growth_2019']+df['yoy_eps_growth_2020']+df['yoy_ep

plt.xlabel('Sector')
plt.ylabel('Growth')
plt.title('Growth of EPS in YOY of each Sector')
plt.legend()
plt.show()
```


Growth of EPS in YOY of each Sector
2019
2020
2021
latest
1250
1000
750
500
250
0
−250
Growth
Information Technology
Consumer Discretionary
Utilities
Health Care
Communication Services
Consumer Staples
Industrials
Sector

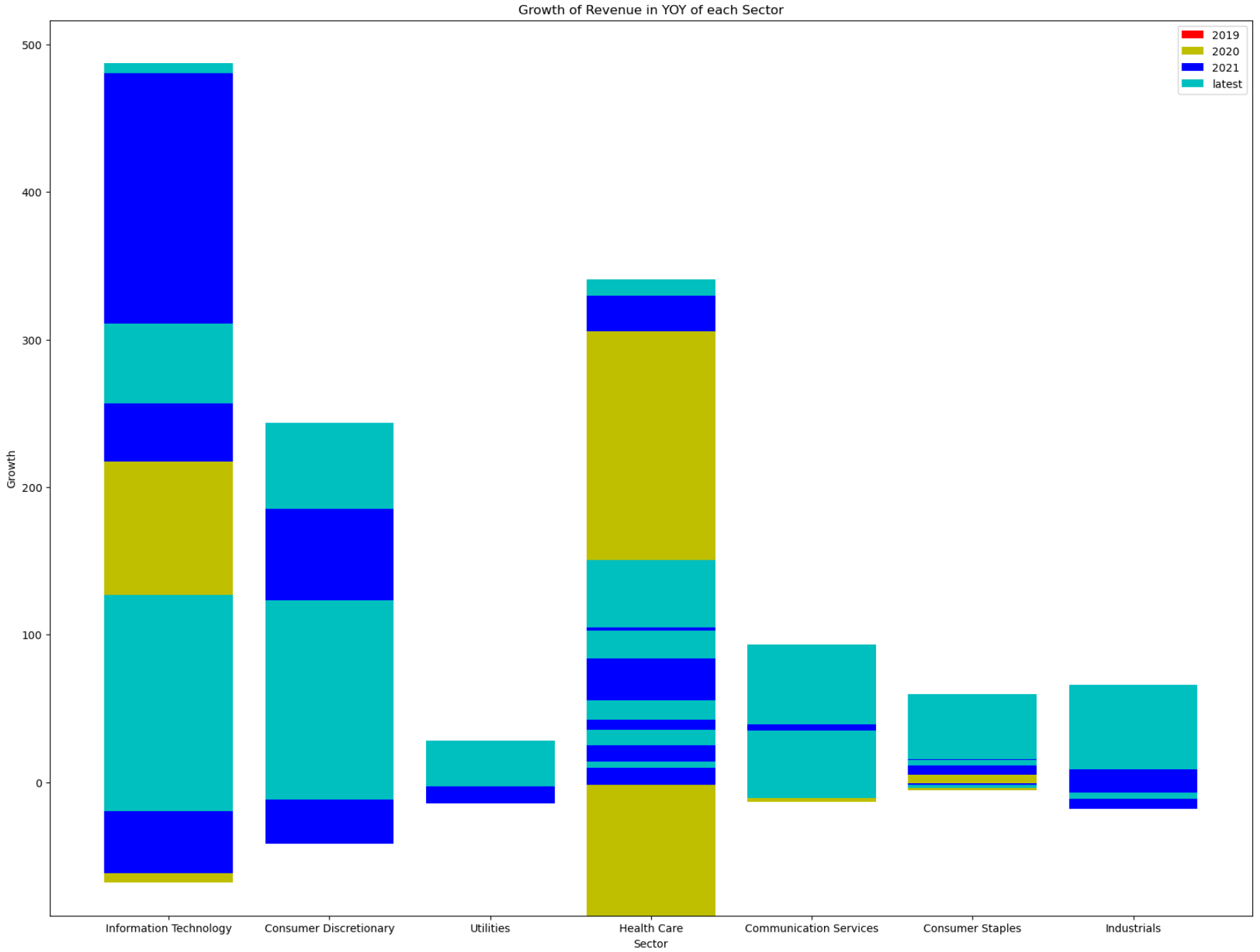
The Fastest recoveries Sector in EPS:

```
Consumer Discretionary
```

The Slowest recoveries Sector in EPS:

```
Industrials
```

In [44]:
```
plt.figure(figsize=(20,15))
plt.bar(df['sector'],df['yoy_revenue_growth_2019'],color='r',label='2019')
plt.bar(df['sector'],df['yoy_revenue_growth_2020'],bottom=df['yoy_revenue_growth_2019'],color='y',label='2020')
plt.bar(df['sector'],df['yoy_revenue_growth_2021'],bottom=df['yoy_revenue_growth_2019']+df['yoy_revenue_growth_2020'],
plt.bar(df['sector'],df['yoy_revenue_growth_latest'],bottom=df['yoy_revenue_growth_2019']+df['yoy_revenue_growth_2020'

plt.xlabel('Sector')
plt.ylabel('Growth')
plt.title('Growth of Revenue in YOY of each Sector')
plt.legend()
plt.show()
```


Growth of Revenue in YOY of each Sector
2019
2020
2021
latest
Growth
500
400
300
200
100
0
Information Technology
Consumer Discretionary
Utilities
Health Care
Communication Services
Consumer Staples
Industrials
Sector

The Fastest recoveries Sector in Revenue:

```
Information Technology, Health Care Sector
```

The Slowest recoveries Sector in Revenue:

```
Consumer Staples
```

Project Task - Week 2

1. Perform PCA to reduce the number of variables in the data

2. After PCA, perform cluster analysis to identify cohorts, define these cohorts (cluster profiling), and specify the insights found

3. Highlight companies from different sectors falling into the same cohort, and share your findings

4. Plot seasonality, trend, and irregular components over time for the historical stock price of Apple

In [45]:
```
df
```

Out[45]:

	Symbol	Name	Market Cap	Last Sale	Net Change	company	sector	subsector	asset_turnover_2017	asset_turnover
0	AAPL	Apple Inc.	2625740143000	$151.45	$2.00	Apple Inc.	Information Technology	Technology Hardware, Storage & Peripherals	0.660000	
1	ABNB	Airbnb, Inc.	69569944167	$116.65	$0.26	Airbnb	Consumer Discretionary	Internet & Direct Marketing Retail	0.724932	
2	ADBE	Adobe Inc.	149144569000	$320.81	$4.59	Adobe Inc.	Information Technology	Application Software	0.540000	
3	ADI	Analog Devices, Inc.	75484763090	$146.76	$2.23	Analog Devices	Information Technology	Semiconductors	0.360000	
4	ADP	Automatic Data Processing, Inc.	98332762096	$236.78	$0.13	ADP	Information Technology	Data Processing & Outsourced Services	0.724932	
...	...	...	...	...	...	...	...	...	...	...
97	WBA	Walgreens Boots Alliance, Inc.	30450068934	$35.21	$0.52	Walgreens Boots Alliance	Consumer Staples	Drug Retail	1.710000	
98	WDAY	Workday, Inc.	39549440000	$154.49	$6.54	Workday, Inc.	Information Technology	Application Software	0.724932	
99	XEL	Xcel Energy Inc.	34192428038	$62.51	$0.93	Xcel Energy	Utilities	Multi-Utilities	0.270000	
100	ZM	Zoom Video Communications, Inc.	24659899766	$82.85	$2.24	Zoom Video Communications	Information Technology	Application Software	0.724932	
101	ZS	Zscaler, Inc.	22393436472	$156.54	$7.87	Zscaler	Information Technology	Application Software	0.724932	

102 rows × 203 columns

In [46]:
```
df.to_csv('project 3.csv')
```

In [47]:
```
df_cat = df.select_dtypes(exclude=['int','float64'])
```

In [48]:
```
df_cat
```

Out[48]:

	Symbol	Name	Last Sale	Net Change	company	sector	subsector
0	AAPL	Apple Inc.	$151.45	$2.00	Apple Inc.	Information Technology	Technology Hardware, Storage & Peripherals
1	ABNB	Airbnb, Inc.	$116.65	$0.26	Airbnb	Consumer Discretionary	Internet & Direct Marketing Retail
2	ADBE	Adobe Inc.	$320.81	$4.59	Adobe Inc.	Information Technology	Application Software
3	ADI	Analog Devices, Inc.	$146.76	$2.23	Analog Devices	Information Technology	Semiconductors
4	ADP	Automatic Data Processing, Inc.	$236.78	$0.13	ADP	Information Technology	Data Processing & Outsourced Services
...	...	...	...	...	...	...	...
97	WBA	Walgreens Boots Alliance, Inc.	$35.21	$0.52	Walgreens Boots Alliance	Consumer Staples	Drug Retail
98	WDAY	Workday, Inc.	$154.49	$6.54	Workday, Inc.	Information Technology	Application Software
99	XEL	Xcel Energy Inc.	$62.51	$0.93	Xcel Energy	Utilities	Multi-Utilities
100	ZM	Zoom Video Communications, Inc.	$82.85	$2.24	Zoom Video Communications	Information Technology	Application Software
101	ZS	Zscaler, Inc.	$156.54	$7.87	Zscaler	Information Technology	Application Software

102 rows × 7 columns

In [49]:
```
df['Last Sale'] = df['Last Sale'].str.replace('$','')
```

```
C:\Users\Vinosh\AppData\Local\Temp\ipykernel_12216\4158779774.py:1: FutureWarning: The default value of regex will c
hange from True to False in a future version. In addition, single character regular expressions will *not* be treate
d as literal strings when regex=True.
  df['Last Sale'] = df['Last Sale'].str.replace('$','')
```

In [50]:
```
df['Last Sale'] = df['Last Sale'].str.replace(',','').astype(float)
```

In [51]:
```
df['Net Change'] = df['Net Change'].str.replace('$','')
```

```
C:\Users\Vinosh\AppData\Local\Temp\ipykernel_12216\907932616.py:1: FutureWarning: The default value of regex will ch
ange from True to False in a future version. In addition, single character regular expressions will *not* be treated
as literal strings when regex=True.
  df['Net Change'] = df['Net Change'].str.replace('$','')
```

In [52]:
```
df['Net Change'] = df['Net Change'].str.replace(',','').astype(float)
```

In [53]:
```
df.dtypes
```

Out[53]:
```
Symbol                    object
Name                      object
Market Cap                 int64
Last Sale                float64
Net Change               float64
                           ...
yoy_revenue_growth_2018  float64
yoy_revenue_growth_2019  float64
yoy_revenue_growth_2020  float64
yoy_revenue_growth_2021  float64
yoy_revenue_growth_latest float64
Length: 203, dtype: object
```

In [54]:
```
data = df.copy()
```

In [55]:
```
df = df.drop(['Symbol','Name'],axis=1)
```

In [56]:
```
df
```

Out[56]:

	Market Cap	Last Sale	Net Change	company	sector	subsector	asset_turnover_2017	asset_turnover_2018	asset_turnover_2019
0	2625740143000	151.45	2.00	Apple Inc.	Information Technology	Technology Hardware, Storage & Peripherals	0.660000	0.72	0.74
1	69569944167	116.65	0.26	Airbnb	Consumer Discretionary	Internet & Direct Marketing Retail	0.724932	0.55	0.64
2	149144569000	320.81	4.59	Adobe Inc.	Information Technology	Application Software	0.540000	0.54	0.57
3	75484763090	146.76	2.23	Analog Devices	Information Technology	Semiconductors	0.360000	0.30	0.29
4	98332762096	236.78	0.13	ADP	Information Technology	Data Processing & Outsourced Services	0.724932	0.34	0.34
...	...	...	...	...	...	...	...	...	...
97	30450068934	35.21	0.52	Walgreens Boots Alliance	Consumer Staples	Drug Retail	1.710000	1.96	1.77
98	39549440000	154.49	6.54	Workday, Inc.	Information Technology	Application Software	0.724932	0.52	0.54
99	34192428038	62.51	0.93	Xcel Energy	Utilities	Multi-Utilities	0.270000	0.26	0.24
100	24659899766	82.85	2.24	Zoom Video Communications	Information Technology	Application Software	0.724932	0.70	1.16
101	22393436472	156.54	7.87	Zscaler	Information Technology	Application Software	0.724932	0.60	0.58

102 rows × 201 columns

In [57]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

In [58]:
```
df['sector'] = le.fit_transform(df['sector'])
df['subsector'] = le.fit_transform(df['subsector'])
```

In [59]:
```
df = pd.get_dummies(df, columns = ['company'])
```

In [60]:
```
df
```

Out[60]:

	Market Cap	Last Sale	Net Change	sector	subsector	asset_turnover_2017	asset_turnover_2018	asset_turnover_2019	asset_turnover_2020	ass
0	2625740143000	151.45	2.00	5	38	0.660000	0.72	0.74	0.83	
1	69569944167	116.65	0.26	1	23	0.724932	0.55	0.64	0.36	
2	149144569000	320.81	4.59	5	2	0.540000	0.54	0.57	0.57	
3	75484763090	146.76	2.23	5	34	0.360000	0.30	0.29	0.26	
4	98332762096	236.78	0.13	5	10	0.724932	0.34	0.34	0.35	
...	...	...	...	...	...	...	...	...	...	
97	30450068934	35.21	0.52	2	12	1.710000	1.96	1.77	1.58	
98	39549440000	154.49	6.54	5	2	0.724932	0.52	0.54	0.59	
99	34192428038	62.51	0.93	6	27	0.270000	0.26	0.24	0.22	
100	24659899766	82.85	2.24	5	2	0.724932	0.70	1.16	0.76	
101	22393436472	156.54	7.87	5	2	0.724932	0.60	0.58	0.35	

102 rows × 302 columns

In [61]:
```
df.dtypes
```

Out[61]:
```
Market Cap                            int64
Last Sale                           float64
Net Change                          float64
sector                                int32
subsector                             int32
                                      ...
company_Workday, Inc.                 uint8
company_Xcel Energy                   uint8
company_Zoom Video Communications     uint8
company_Zscaler                       uint8
company_eBay                          uint8
Length: 302, dtype: object
```

In [62]:
```
df.columns
```

Out[62]:
```
Index(['Market Cap', 'Last Sale', 'Net Change', 'sector', 'subsector',
       'asset_turnover_2017', 'asset_turnover_2018', 'asset_turnover_2019',
       'asset_turnover_2020', 'asset_turnover_2021',
       ...
       'company_Texas Instruments', 'company_Verisign', 'company_Verisk',
       'company_Vertex Pharmaceuticals', 'company_Walgreens Boots Alliance',
       'company_Workday, Inc.', 'company_Xcel Energy',
       'company_Zoom Video Communications', 'company_Zscaler', 'company_eBay'],
      dtype='object', length=302)
```

The columns are converted to numerical data and its ready for modeling

Principal Component Analysis (PCA)

In [63]:
```
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
```

In [64]:
```
X = df.drop('Last Sale',axis=1)
```

In [65]:
```
y = df['Last Sale']
```

In [66]:
```
std = StandardScaler()
```

In [67]:
```
X_std = std.fit_transform(X)
```

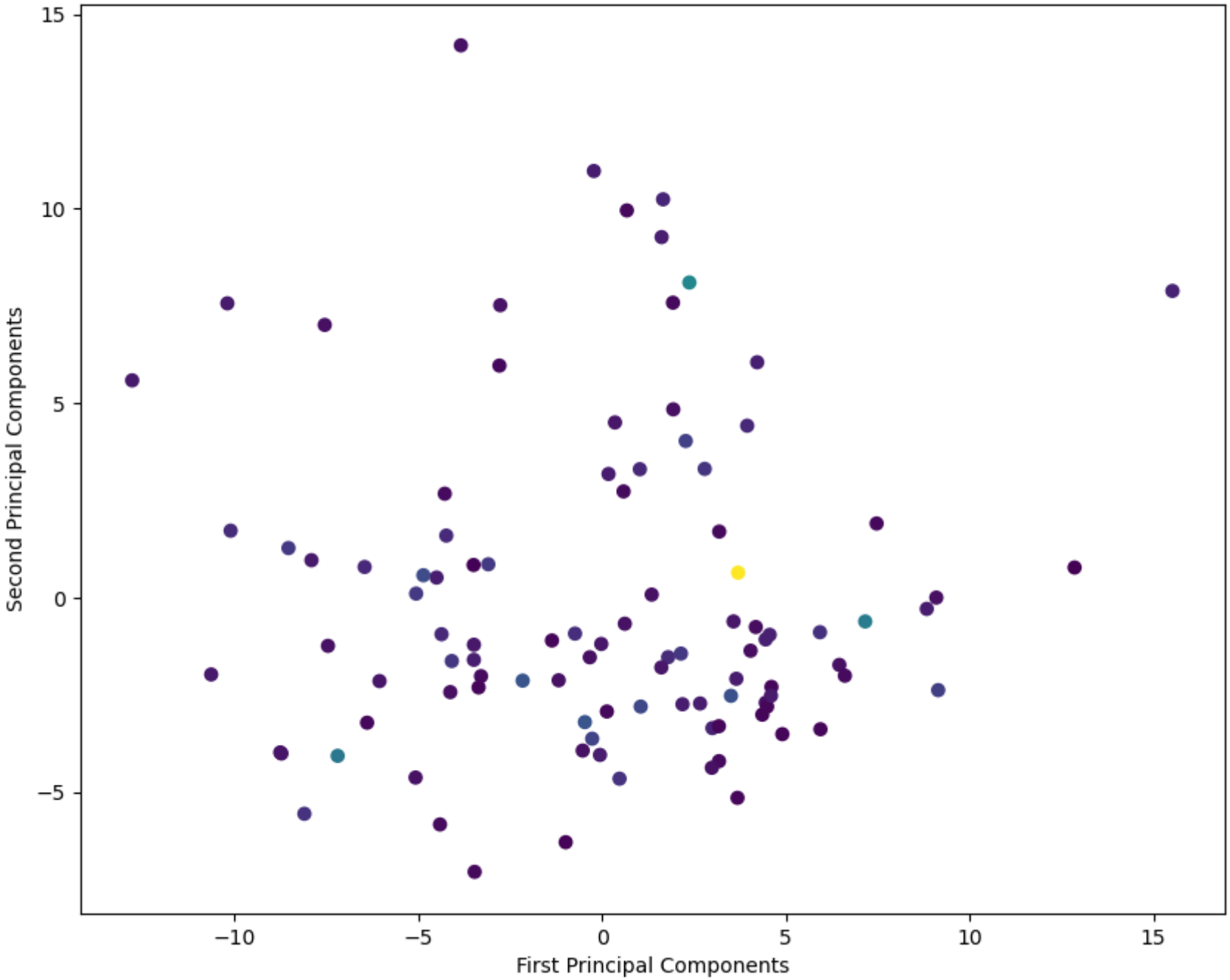
In [68]:
```
pca = PCA(n_components=0.9)
```

In [69]:
```
X_pca = pca.fit_transform(X_std)
```

In [70]:
```
X_pca.shape
```

Out[70]: (102, 73)

In [71]:
```
plt.figure(figsize=(10,8))
plt.scatter(X_pca[:,0],X_pca[:,1],c=y)
plt.xlabel('First Principal Components')
plt.ylabel('Second Principal Components')
plt.show()
```


15
10
5
0
−5
Second Principal Components
−10
−5
0
5
10
15
First Principal Components

In [72]:
```
pca.components_
```

Out[72]:
```
array([[-0.0168957 , -0.00649599, -0.00638135, ..., -0.02769942,
        -0.00080635,  0.01693557],
       [-0.03577938,  0.05660326,  0.02461218, ...,  0.03995057,
         0.06250352, -0.01308477],
       [-0.02202355, -0.03856795, -0.01964456, ..., -0.00644636,
         0.00911479, -0.0012068 ],
       ...,
       [-0.01743587, -0.06150392, -0.02043442, ...,  0.01421882,
         0.03464388, -0.08582917],
       [ 0.00949545,  0.06542478, -0.02726815, ...,  0.0006594 ,
        -0.07171743, -0.08376341],
       [-0.04744072, -0.01231   ,  0.00284727, ...,  0.02600811,
        -0.0262894 ,  0.00499303]])
```

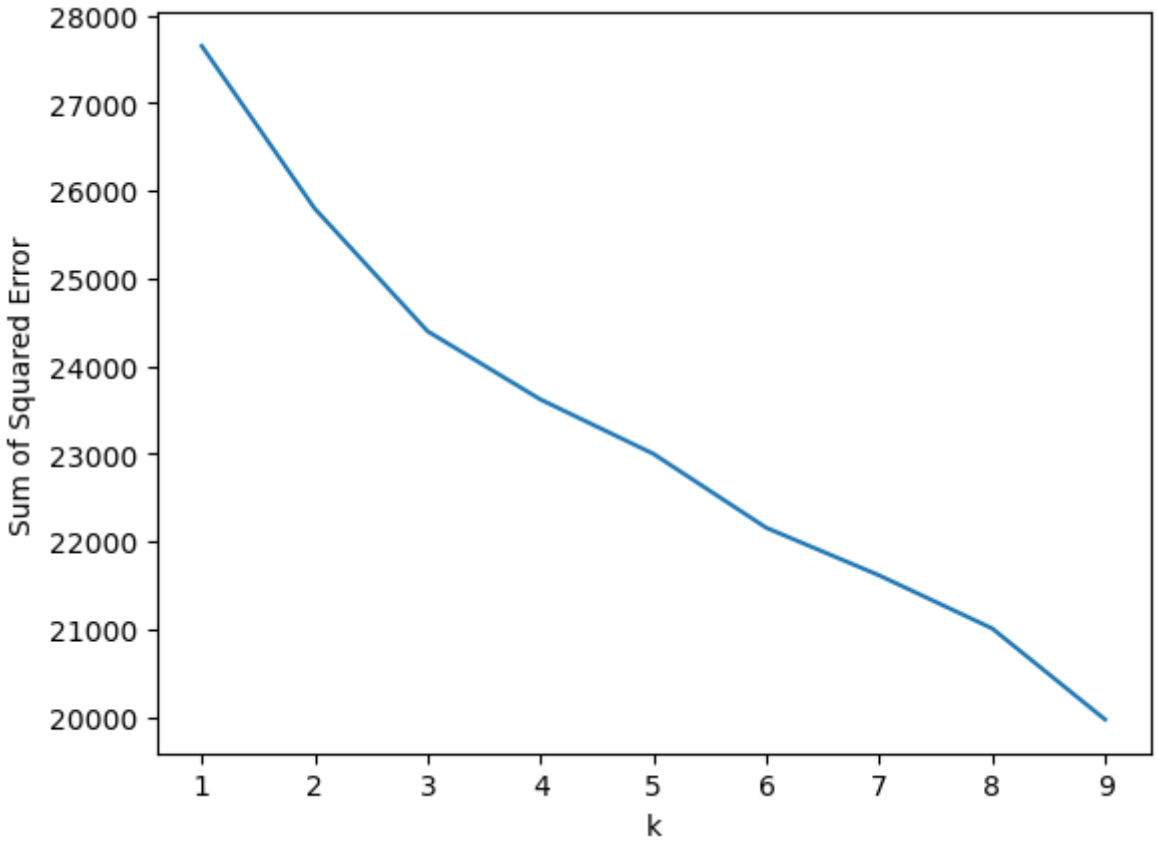
Clustering

In [73]:
```
from sklearn.cluster import KMeans
```

In [74]:
```
sse = []
k_range = range(1,10)
for k in k_range:
    km = KMeans(n_clusters=k)
    km.fit(X_pca)
    sse.append(km.inertia_)
```

```
C:\Users\Vinosh\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1036: UserWarning: KMeans is known to have a
memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the
environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

In [75]:
```
plt.plot(k_range,sse)
plt.xlabel('k')
plt.ylabel('Sum of Squared Error')
plt.show()
```



Here we take the K value - 3

In [76]:
```
kmeans = KMeans(n_clusters=3,random_state=42)
```

In [77]:
```
kmeans.fit(X_pca)
```

Out[77]:
```
KMeans(n_clusters=3, random_state=42)
```

In [78]:
```
labels = kmeans.labels_
```

In [79]:
```
data['cluster'] = labels
```

In [80]:
```
data['cluster'].value_counts()
```

Out[80]:
```
2    60
0    41
1     1
Name: cluster, dtype: int64
```

In [81]:
```
data
```

Out[81]:

	Symbol	Name	Market Cap	Last Sale	Net Change	company	sector	subsector	asset_turnover_2017	asset_turnover_
0	AAPL	Apple Inc.	2625740143000	151.45	2.00	Apple Inc.	Information Technology	Technology Hardware, Storage & Peripherals	0.660000	
1	ABNB	Airbnb, Inc.	69569944167	116.65	0.26	Airbnb	Consumer Discretionary	Internet & Direct Marketing Retail	0.724932	
2	ADBE	Adobe Inc.	149144569000	320.81	4.59	Adobe Inc.	Information Technology	Application Software	0.540000	
3	ADI	Analog Devices, Inc.	75484763090	146.76	2.23	Analog Devices	Information Technology	Semiconductors	0.360000	
4	ADP	Automatic Data Processing, Inc.	98332762096	236.78	0.13	ADP	Information Technology	Data Processing & Outsourced Services	0.724932	
...	...	...	...	...	...	...	...	...	...	...
97	WBA	Walgreens Boots Alliance, Inc.	30450068934	35.21	0.52	Walgreens Boots Alliance	Consumer Staples	Drug Retail	1.710000	
98	WDAY	Workday, Inc.	39549440000	154.49	6.54	Workday, Inc.	Information Technology	Application Software	0.724932	
99	XEL	Xcel Energy Inc.	34192428038	62.51	0.93	Xcel Energy	Utilities	Multi-Utilities	0.270000	
100	ZM	Zoom Video Communications, Inc.	24659899766	82.85	2.24	Zoom Video Communications	Information Technology	Application Software	0.724932	
101	ZS	Zscaler, Inc.	22393436472	156.54	7.87	Zscaler	Information Technology	Application Software	0.724932	

102 rows × 204 columns

In [82]:
```
centroid = kmeans.cluster_centers_
```

In [83]:
```
centroid
```

Out[83]:
```
array([[-4.91485934e+00, -6.36640897e-01,  1.64902224e-01,
        -1.10279230e+00,  2.14989774e-01, -2.01616520e-01,
        -2.14740247e-01,  6.91697674e-03,  3.70426441e-02,
         5.65681314e-02,  3.66665737e-01, -4.76257751e-02,
        -5.61761102e-02, -3.40590401e-01, -1.53953941e-01,
         4.12863389e-02, -6.58672611e-02, -8.89684964e-03,
        -5.74422960e-02,  6.04005043e-02,  1.21086493e-01,
        -1.13563871e-03, -8.09750267e-02, -1.10856245e-01,
         8.88021146e-02,  2.52051639e-01,  2.82430136e-01,
         9.18495712e-02,  3.49297458e-02,  5.55786420e-02,
         4.59098876e-02,  9.41411871e-02, -1.48122314e-01,
         1.37062026e-01, -9.79252679e-02,  1.63318877e-02,
        -1.64086808e-01, -1.79466611e-02, -2.52079835e-02,
        -2.61830317e-03, -1.06137167e-01,  5.47965243e-02,
        -8.37083008e-02, -3.69271195e-02, -8.26818082e-02,
        -7.79069554e-02,  6.13827367e-02,  1.31496955e-01,
         2.98158011e-02, -8.78043742e-02, -1.41678079e-01,
        -1.10980014e-01, -6.68155495e-02, -5.28022057e-02,
        -1.56813579e-01,  3.07078287e-02, -7.13277636e-02,
        -1.24792754e-02, -4.59419222e-03, -1.84185791e-01,
        -5.85131531e-02, -1.42004066e-02,  6.92824031e-02,
        -1.15641527e-01, -3.77111992e-03, -1.34702686e-01,
         2.68195301e-02, -1.28215916e-03, -1.29745247e-01,
         3.82516524e-02, -9.07928030e-02,  2.63653166e-02,
         1.99049906e-02],
       [-1.01886674e+01,  7.56545896e+00, -1.05908884e+00,
         2.12824028e+01, -1.18865042e+00,  1.65436477e+01,
        -9.94097034e+00,  1.17950110e+00, -1.01477694e+00,
        -2.92349669e+00, -2.07938546e+00, -6.33644800e-01,
        -4.07141821e+00, -1.21365635e+00,  1.24686776e+00,
        -2.41496987e+00, -1.47009661e+00, -4.55303735e-01,
        -1.08976382e+00, -8.12999700e-02,  3.22143123e-01,
        -1.43356060e-01, -1.55137994e-01,  6.17341929e-01,
        -6.85543614e-01, -1.80688013e+00, -9.32050401e-01,
         2.93811833e-01, -1.27104546e+00, -5.98789542e-02,
        -7.50198241e-03, -2.32364446e-01,  6.65196911e-01,
        -1.15912883e-01, -3.72736026e-01,  2.82403158e-01,
        -5.69504408e-01, -7.20694348e-01,  1.96013214e-01,
        -7.58272479e-01, -6.49415575e-01, -8.84184806e-01,
        -2.52946848e-02,  2.64914909e-01,  1.16537955e-01,
        -4.34654719e-01,  7.01343731e-02, -1.13559541e-01,
```

```
  2.38958363e-01, -1.41510707e-01,  5.09449394e-01,
 -1.30487471e-01,  3.45528595e-01,  2.64372997e-01,
 -1.89460952e-01,  7.05957339e-02,  6.87126358e-02,
  2.62651165e-01, -1.14163142e-01,  6.45417358e-01,
 -4.35227556e-01,  1.23765142e-01, -5.23814210e-02,
 -1.02287612e-01, -2.00535378e-01, -7.23474276e-03,
 -2.08321268e-01,  8.65709573e-02,  6.86687891e-02,
 -2.12509701e-01,  2.81371934e-01,  2.75618425e-02,
 -3.93539688e-02],
[ 3.52829834e+00,  3.08946964e-01, -9.50317058e-02,
  3.98868025e-01, -1.27098839e-01, -1.37956173e-01,
  3.12422008e-01, -2.43849525e-02, -8.39952442e-03,
  1.00700551e-02, -2.15898496e-01,  4.31050263e-02,
  1.06243979e-01,  2.52964380e-01,  8.44207305e-02,
  1.20371662e-02,  6.95109052e-02,  1.36679095e-02,
  5.74149659e-02, -3.99186784e-02, -8.81114887e-02,
  3.16528744e-03,  5.79185681e-02,  6.54627353e-02,
 -4.92557181e-02, -1.42120618e-01, -1.77459753e-01,
 -6.76607376e-02, -2.68456862e-03, -3.69807562e-02,
 -3.12467235e-02, -6.04570704e-02,  9.01302997e-02,
 -9.17271698e-02,  7.31278668e-02, -1.58668426e-02,
  1.21617726e-01,  2.42751242e-02,  1.39585685e-02,
  1.44270485e-02,  8.33506571e-02, -2.27078781e-02,
  5.76222503e-02,  2.08182832e-02,  5.45569363e-02,
  6.04806649e-02, -4.31137763e-02, -8.79635937e-02,
 -2.43567701e-02,  6.23581675e-02,  8.83225305e-02,
  7.80111341e-02,  3.98984822e-02,  3.16752906e-02,
  1.10313628e-01, -2.21602785e-02,  4.75954279e-02,
  4.14998544e-03,  5.04208371e-03,  1.15103334e-01,
  4.72377806e-02,  7.64085879e-03, -4.64699518e-02,
  8.07265034e-02,  5.91918824e-03,  9.21674143e-02,
 -1.48546578e-02, -5.66707198e-04,  8.75147724e-02,
 -2.25968008e-02,  5.73522165e-02, -1.84756637e-02,
 -1.29458441e-02]])
```

In [84]:
```
cluster_group = data.groupby('cluster').mean()
cluster_group
```

Out[84]:

cluster	Market Cap	Last Sale	Net Change	asset_turnover_2017	asset_turnover_2018	asset_turnover_2019	asset_turnover_2020	asset_turnover_2
0	1.392856e+11	177.393002	4.195685	0.849739	0.949668	0.901118	0.81936	0.802
1	5.351023e+10	136.785000	3.765000	0.140000	0.080000	0.030000	0.06000	1.110
2	1.689867e+11	192.815832	4.122332	0.649395	0.618607	0.600667	0.55050	0.582

In [85]:
```
data[['cluster','company']]
```

Out[85]:

	cluster	company
0	2	Apple Inc.
1	2	Airbnb
2	0	Adobe Inc.
3	2	Analog Devices
4	2	ADP
...	...	...
97	2	Walgreens Boots Alliance
98	2	Workday, Inc.
99	2	Xcel Energy
100	0	Zoom Video Communications
101	2	Zscaler

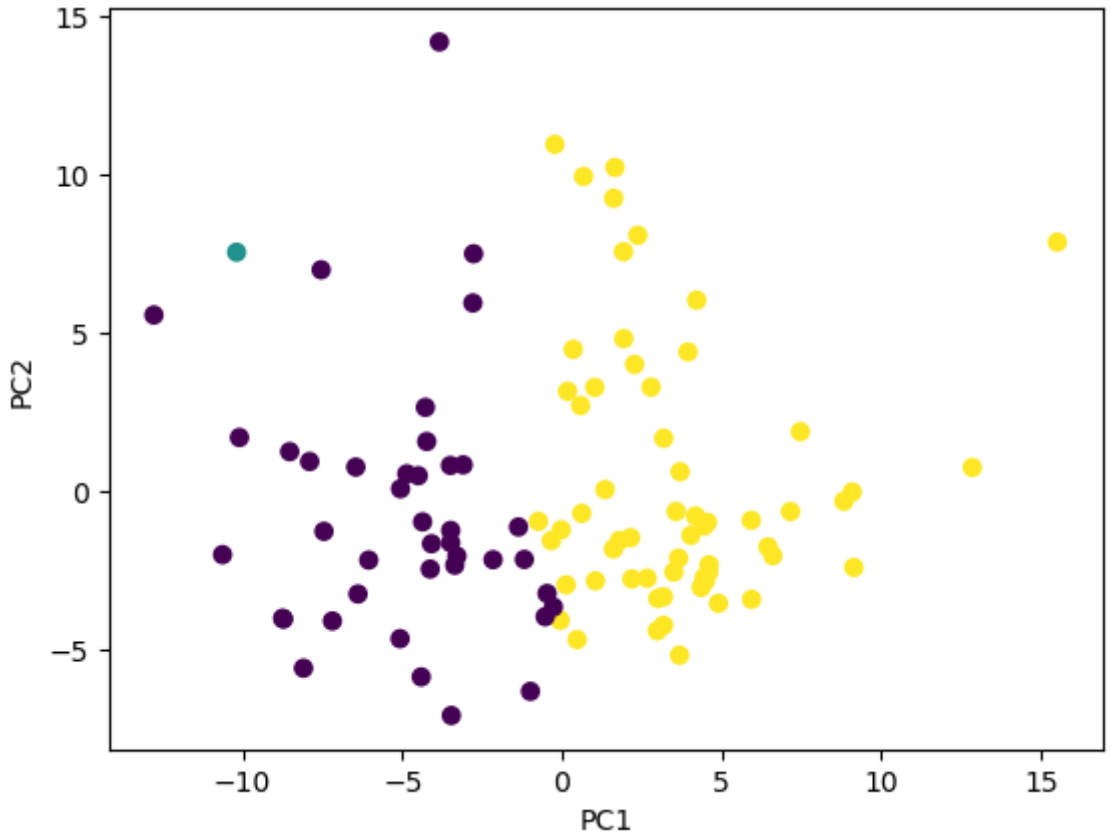
102 rows × 2 columns

In [86]:
```
cohort = data.groupby(['cluster','sector'])['company'].apply(list)
```

In [87]:
```
print(cohort)
```

```
cluster  sector
0        Communication Services    [Activision Blizzard, Electronic Arts, Alphabe...
         Consumer Discretionary    [JD.com, Lucid Motors, Lululemon, Pinduoduo, R...
         Consumer Staples                            [Costco, Monster Beverage]
         Health Care               [Align Technology, DexCom, Illumina, Inc., Int...
         Industrials                   [Copart, Fastenal, Old Dominion Freight Line]
         Information Technology    [Adobe Inc., Applied Materials, AMD, Ansys, AS...
1        Health Care                                                    [Moderna]
2        Communication Services    [Baidu, Charter Communications, Comcast, Match...
         Consumer Discretionary    [Airbnb, Amazon, Booking Holdings, Dollar Tree...
         Consumer Staples          [Keurig Dr Pepper, Kraft Heinz, Mondelez Inter...
         Health Care               [Amgen, AstraZeneca, Biogen, Gilead Sciences, ...
         Industrials               [CSX Corporation, Cintas, Honeywell, Paccar, V...
         Information Technology    [Apple Inc., Analog Devices, ADP, Autodesk, Br...
         Utilities                 [American Electric Power, Constellation Energy...
Name: company, dtype: object
```

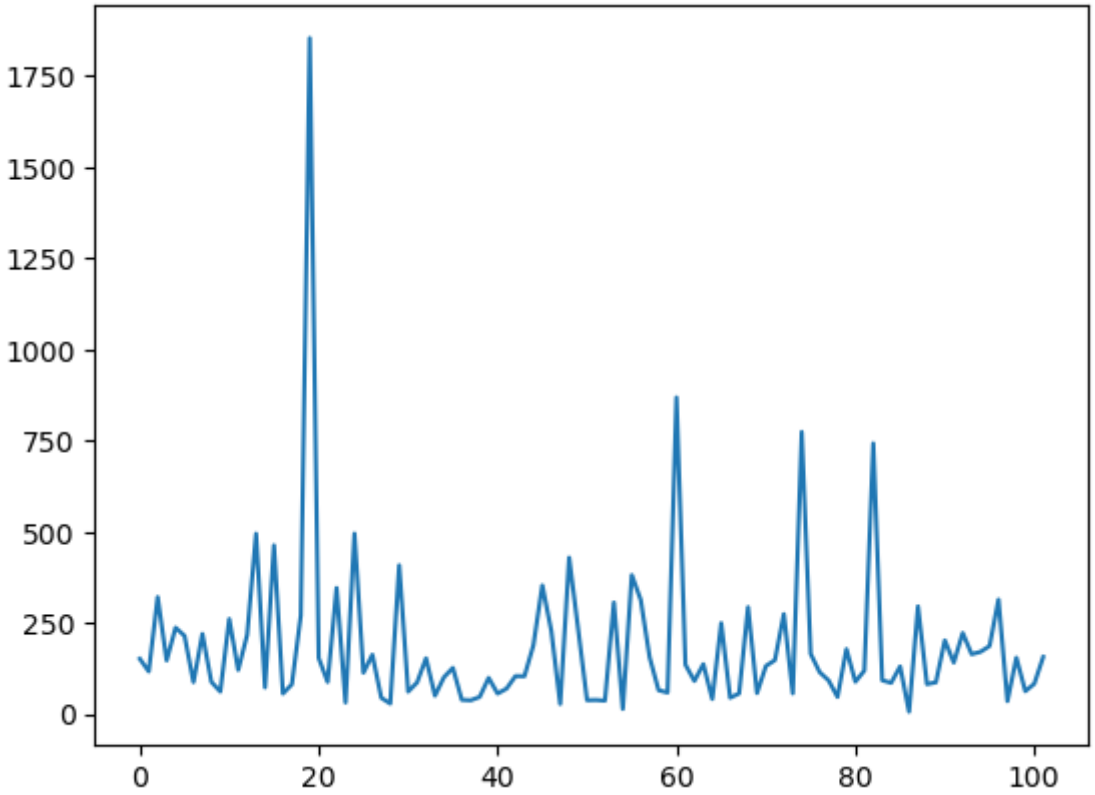
In [88]:
```
plt.scatter(X_pca[:,0],X_pca[:,1], c=data['cluster'])
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.show()
```



Seasonality, Trend, and Irregular Components

In [89]:
```
df['Last Sale'].plot()
```

Out[89]: <AxesSubplot:>

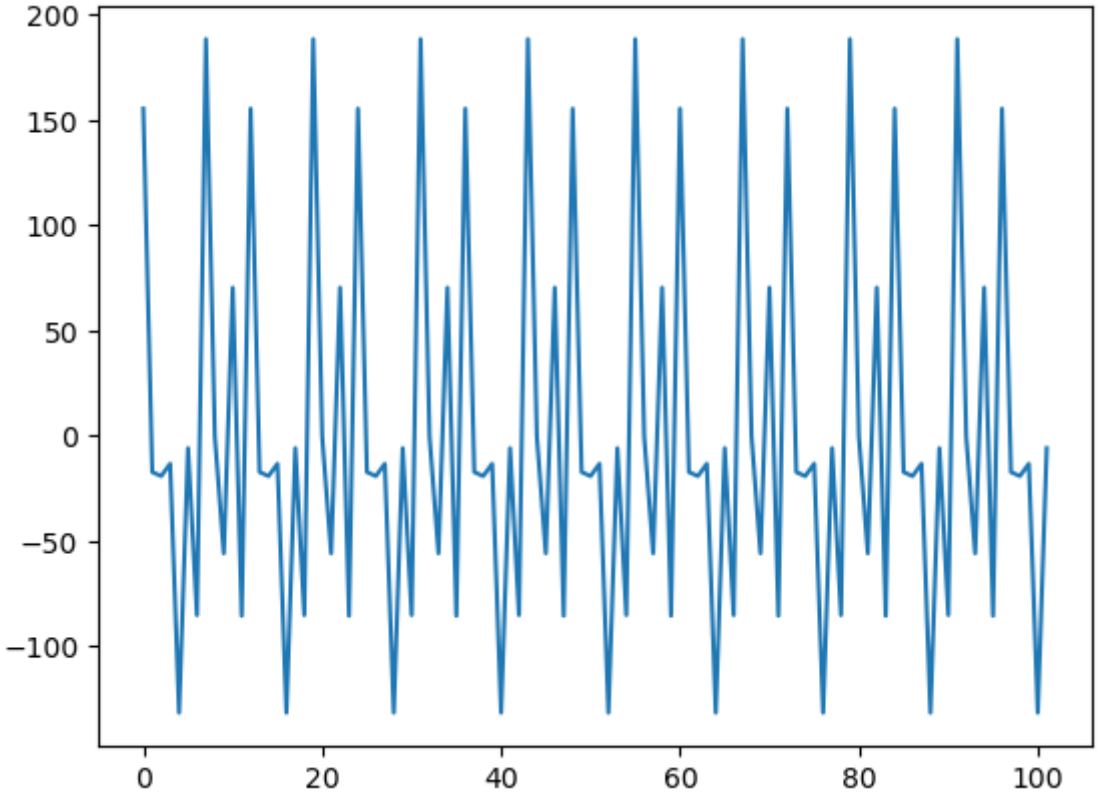


In [90]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
```

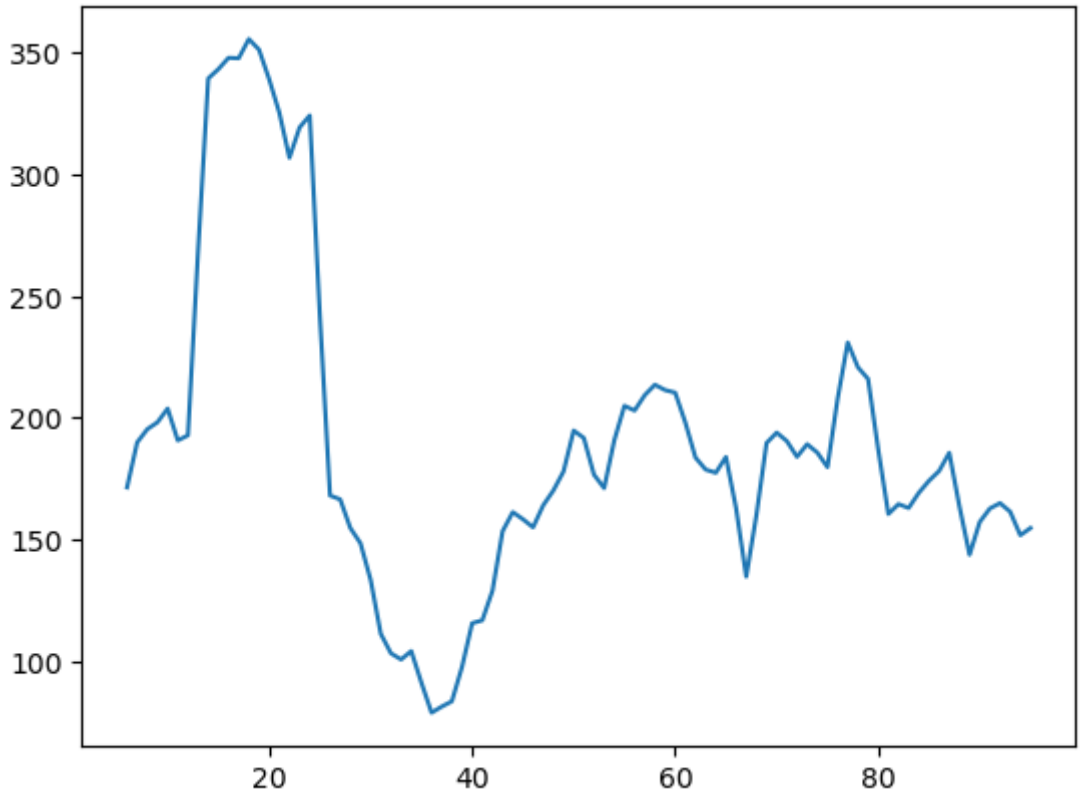
In [91]:
```
period = 12
```

In [92]:
```
result = seasonal_decompose(df['Last Sale'], model = 'additive',period=period)
```

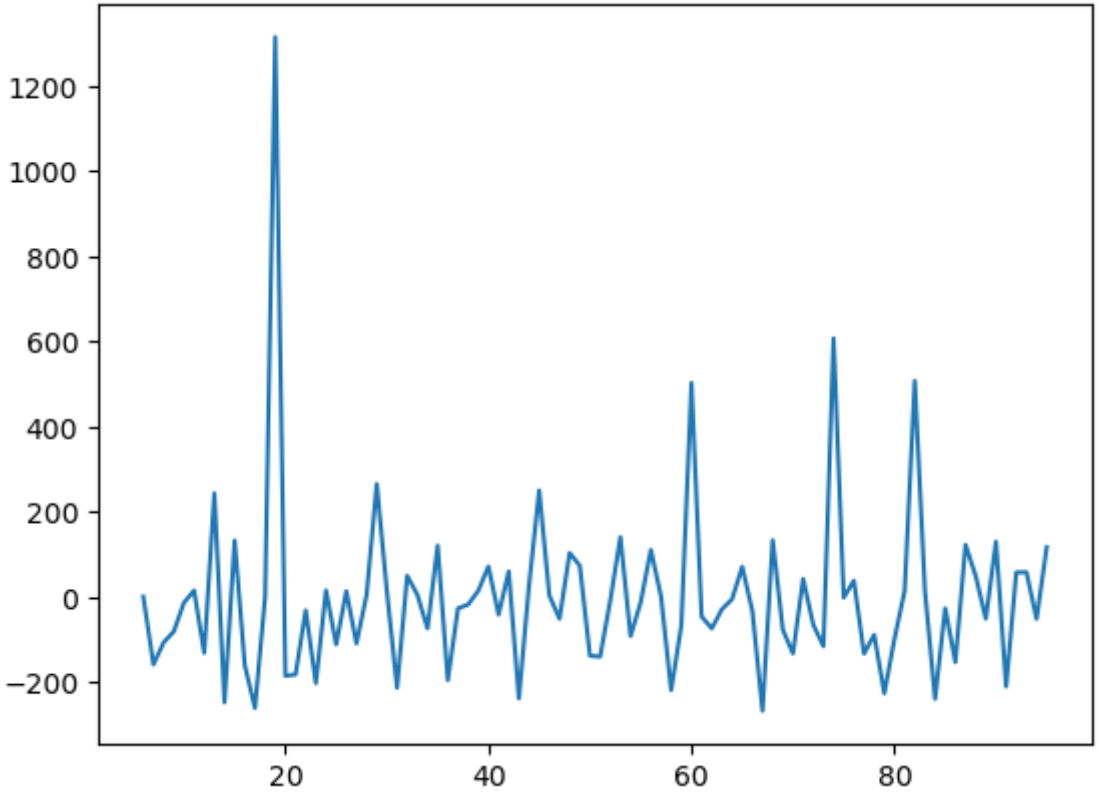
In [93]:
```
result.seasonal.plot()
plt.show()
```



In [94]:
```
result.trend.plot()
plt.show()
```



In [95]:
```
result.resid.plot()
plt.show()
```



In [96]:
```
from statsmodels.tsa.holtwinters import ExponentialSmoothing
```

In [97]:
```
train_data = df[:-20]['Last Sale']
test_data = df[-20:]['Last Sale']
```

In [98]:
```
train_data
```

Out[98]:
```
0     151.450
1     116.650
2     320.810
3     146.760
4     236.780
       ...
77     92.195
78     46.840
79    178.080
80     88.450
81    118.880
Name: Last Sale, Length: 82, dtype: float64
```

In [99]:
```
test_data
```

Out[99]:
```
82     742.475
83      92.430
84      85.450
85     130.470
86       6.275
87     295.265
88      81.850
89      86.850
90     202.030
91     141.110
92     222.250
93     164.000
94     170.630
95     186.500
96     313.930
97      35.210
98     154.490
99      62.510
100     82.850
101    156.540
Name: Last Sale, dtype: float64
```

In [100]:
```
model_exp = ExponentialSmoothing(train_data, seasonal='add', seasonal_periods=7*4)
```

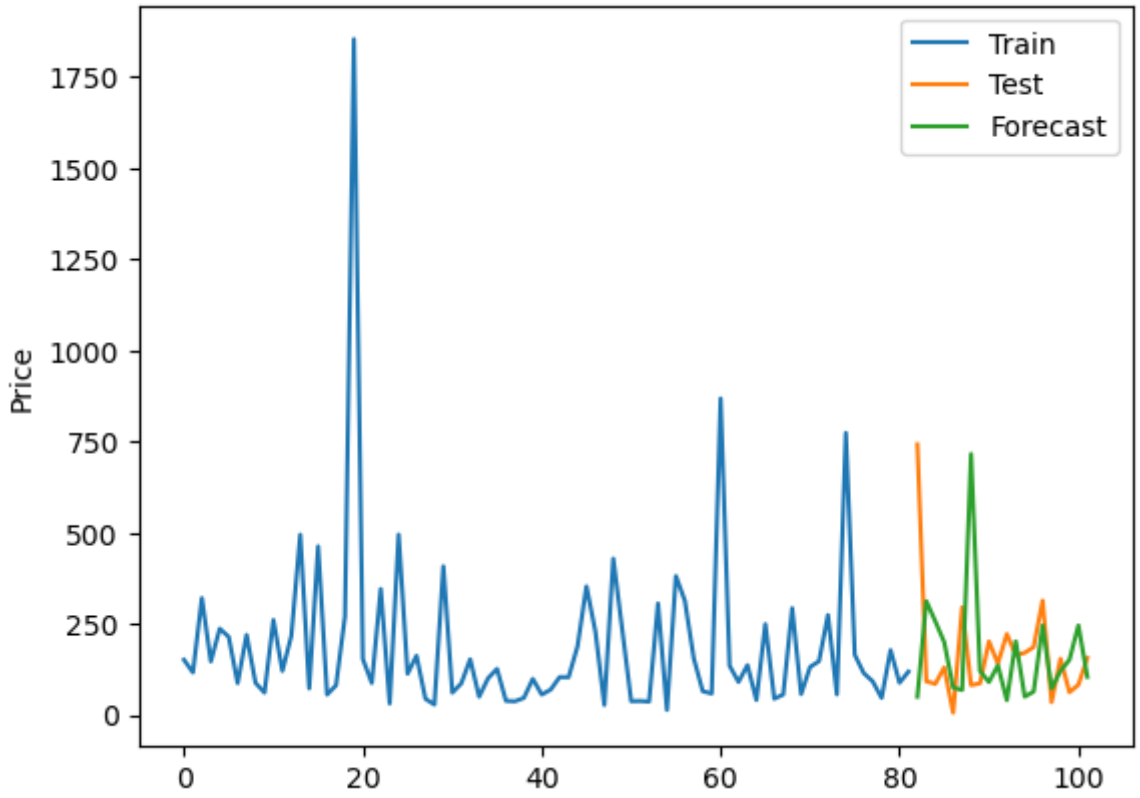
In [101]:
```
fit_exp = model_exp.fit()
```

In [102]:
```
exp_predictions = fit_exp.forecast(len(test_data))
```

In [103]:
```
print(exp_predictions)
```

```
82      50.097355
83     312.302831
84     257.117140
85     199.823242
86      75.218237
87      68.437841
88     716.134759
89     120.673449
90      90.352816
91     136.052409
92      40.471411
93     202.052728
94      50.332615
95      64.135432
96     245.176717
97      72.864656
98     120.676483
99     151.507547
100    245.863690
101    104.562837
dtype: float64
```

In [104]:
```
plt.plot(train_data.index, train_data, label='Train')
plt.plot(test_data.index, test_data, label='Test')
plt.plot(exp_predictions.index, exp_predictions, label='Forecast')
plt.legend(loc='best')
plt.ylabel('Price')
plt.show()
```



In [105]:
```
from statsmodels.tsa.stattools import adfuller
```

In [106]:
```
result_adfuller = adfuller(df['Last Sale'])
```

In [107]:
```
print('ADF Statistics :', result_adfuller[0])
```

```
ADF Statistics : -10.59343493822481
```

In [108]:
```
print('P-value :',result_adfuller[1])
```

```
P-value : 6.43970962377371e-19
```

In [109]:
```
print('Critical Values :')
for key, value in result_adfuller[4].items():
    print('\t%s : %.3f' % (key,value))
```

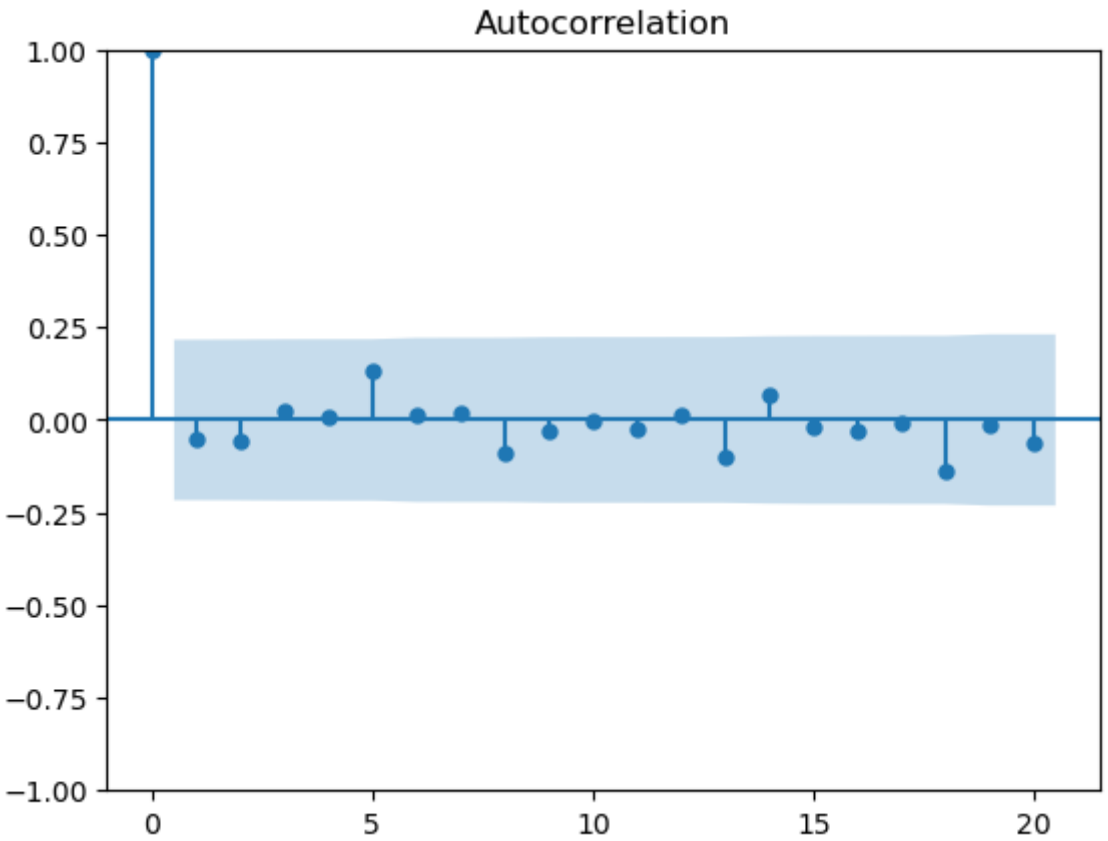
```
Critical Values :
        1% : -3.497
        5% : -2.891
        10% : -2.582
```

In [110]:
```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

In [111]:
```
train_data
```

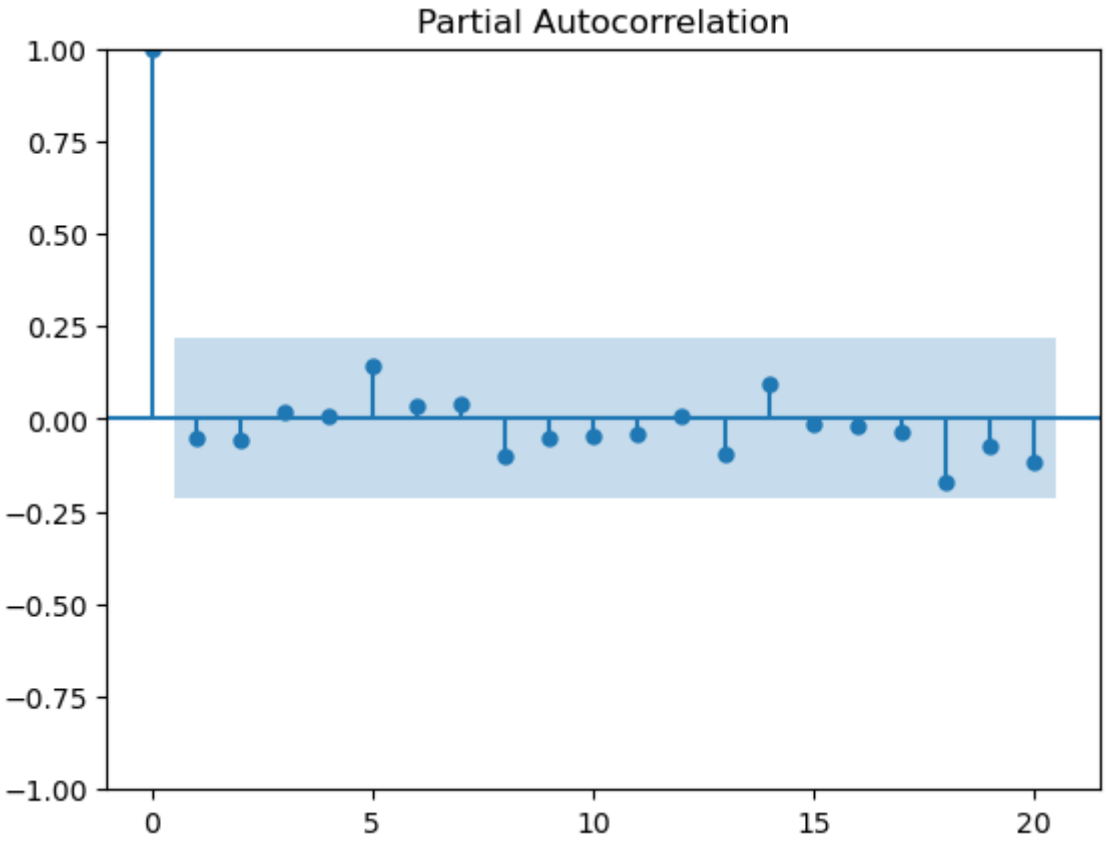
Out[111]:
```
0     151.450
1     116.650
2     320.810
3     146.760
4     236.780
       ...
77     92.195
78     46.840
79    178.080
80     88.450
81    118.880
Name: Last Sale, Length: 82, dtype: float64
```

In [112]:
```
acf = plot_acf(train_data)
```



In [113]:
```
pacf = plot_pacf(train_data)
```

```
C:\Users\Vinosh\anaconda3\lib\site-packages\statsmodels\graphics\tsaplots.py:348: FutureWarning: The default method
'yw' can produce PACF values outside of the [-1,1] interval. After 0.13, the default will change tounadjusted Yule-W
alker ('ywm'). You can use this method now by setting method='ywm'.
  warnings.warn(
```



In [114]:
```
from statsmodels.tsa.arima.model import ARIMA
```

In [115]:
```
model_arima = ARIMA(train_data,order=(2,1,0))
```

In [116]:
```
arima_fit = model_arima.fit()
```

In [117]:
```
print(arima_fit.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:              Last Sale   No. Observations:                   82
Model:                 ARIMA(2, 1, 0)   Log Likelihood                -572.440
Date:                Thu, 06 Apr 2023   AIC                           1150.881
Time:                        17:53:00   BIC                           1158.064
Sample:                             0   HQIC                          1153.763
                                  - 82
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.6822      0.068    -10.054      0.000      -0.815      -0.549
ar.L2         -0.3748      0.074     -5.053      0.000      -0.520      -0.229
sigma2      8.159e+04   4555.036     17.912      0.000    7.27e+04    9.05e+04
===================================================================================
Ljung-Box (L1) (Q):                   0.98   Jarque-Bera (JB):               946.86
Prob(Q):                              0.32   Prob(JB):                         0.00
Heteroskedasticity (H):               0.36   Skew:                             2.91
Prob(H) (two-sided):                  0.01   Kurtosis:                        18.71
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

In [118]:
```
arima_predictions = arima_fit.predict(start=len(train_data), end=len(train_data)+len(test_data)-1, dynamic=False)
```

In [119]:
```
arima_predictions
```

Out[119]:
```
82     131.710497
83     111.552761
84     120.496535
85     121.949357
86     117.606310
87     120.024806
88     120.002481
89     119.111326
90     119.727669
91     119.641160
92     119.469191
93     119.618935
94     119.581224
95     119.550832
96     119.585699
97     119.573302
98     119.568692
99     119.576483
100    119.572895
101    119.572423
Name: predicted_mean, dtype: float64
```

In [120]:
```
from sklearn.metrics import mean_absolute_percentage_error
```

In [121]:
```
mape = mean_absolute_percentage_error(test_data,arima_predictions)
```

In [122]:
```
print('MAPE :',mape)
```

```
MAPE : 1.373112630606639
```

In [123]:
```
data1 = data.copy()
```

In [124]:
```
grouped = data.groupby('sector')
```

In [125]:
```
top_companies = {}
```

In [126]:
```
for sector, data in grouped:
    sorted_data = data.sort_values('Market Cap',ascending=False)
    top_2 = sorted_data.iloc[:2]['company'].tolist()
    top_companies[sector] = top_2
```

In [127]:
```
for sector,companies in top_companies.items():
    print(f"{sector} : {',' .join(companies)}")
```

```
Communication Services : Alphabet Inc. (Class C),Alphabet Inc. (Class A)
Consumer Discretionary : Amazon,Tesla, Inc.
Consumer Staples : PepsiCo,Costco
Health Care : AstraZeneca,Amgen
Industrials : Honeywell,CSX Corporation
Information Technology : Apple Inc.,Microsoft
Utilities : American Electric Power,Exelon
```

In [128]:
```
data1
```

Out[128]:

	Symbol	Name	Market Cap	Last Sale	Net Change	company	sector	subsector	asset_turnover_2017	asset_turnover_
0	AAPL	Apple Inc.	2625740143000	151.45	2.00	Apple Inc.	Information Technology	Technology Hardware, Storage & Peripherals	0.660000	
1	ABNB	Airbnb, Inc.	69569944167	116.65	0.26	Airbnb	Consumer Discretionary	Internet & Direct Marketing Retail	0.724932	
2	ADBE	Adobe Inc.	149144569000	320.81	4.59	Adobe Inc.	Information Technology	Application Software	0.540000	
3	ADI	Analog Devices, Inc.	75484763090	146.76	2.23	Analog Devices	Information Technology	Semiconductors	0.360000	
4	ADP	Automatic Data Processing, Inc.	98332762096	236.78	0.13	ADP	Information Technology	Data Processing & Outsourced Services	0.724932	
...	...	...	...	...	...	...	...	...	...	...
97	WBA	Walgreens Boots Alliance, Inc.	30450068934	35.21	0.52	Walgreens Boots Alliance	Consumer Staples	Drug Retail	1.710000	
98	WDAY	Workday, Inc.	39549440000	154.49	6.54	Workday, Inc.	Information Technology	Application Software	0.724932	
99	XEL	Xcel Energy Inc.	34192428038	62.51	0.93	Xcel Energy	Utilities	Multi-Utilities	0.270000	
100	ZM	Zoom Video Communications, Inc.	24659899766	82.85	2.24	Zoom Video Communications	Information Technology	Application Software	0.724932	
101	ZS	Zscaler, Inc.	22393436472	156.54	7.87	Zscaler	Information Technology	Application Software	0.724932	

102 rows × 204 columns

In [129]:
```
data1['sector'].unique()
```

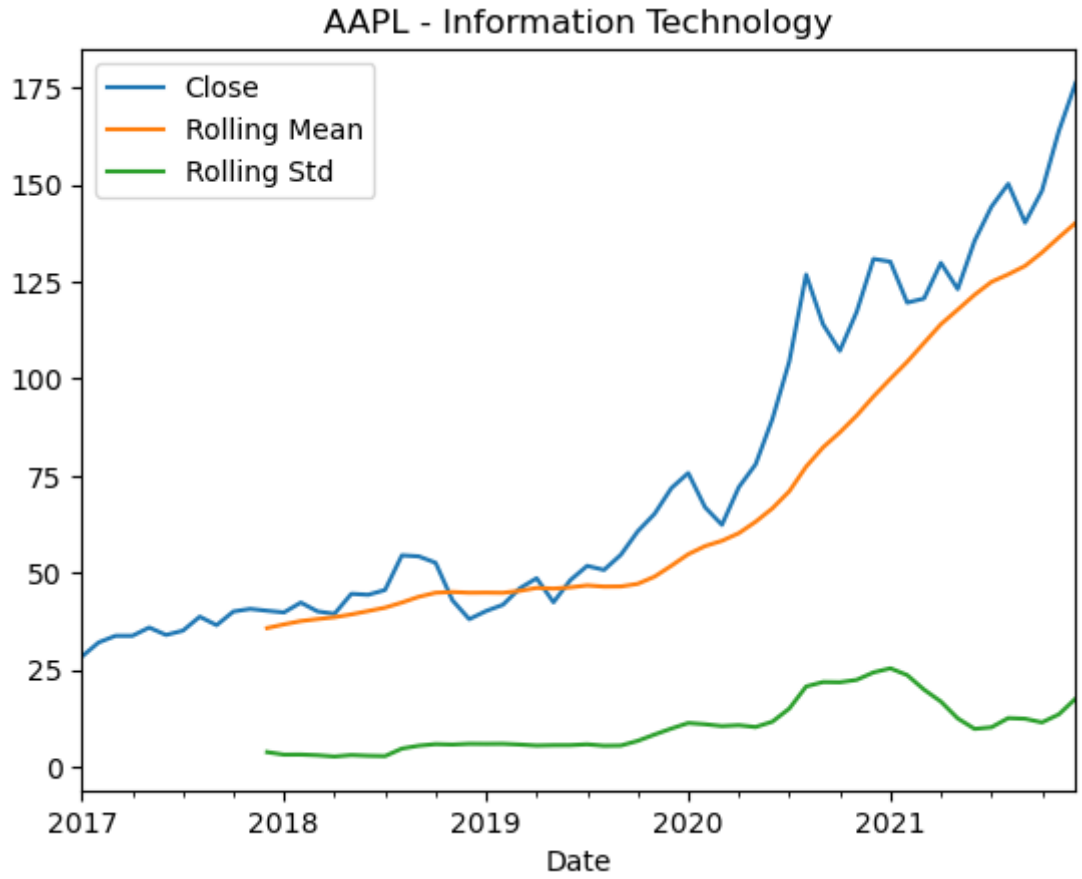
Out[129]:
```
array(['Information Technology', 'Consumer Discretionary', 'Utilities',
       'Health Care', 'Communication Services', 'Consumer Staples',
       'Industrials'], dtype=object)
```

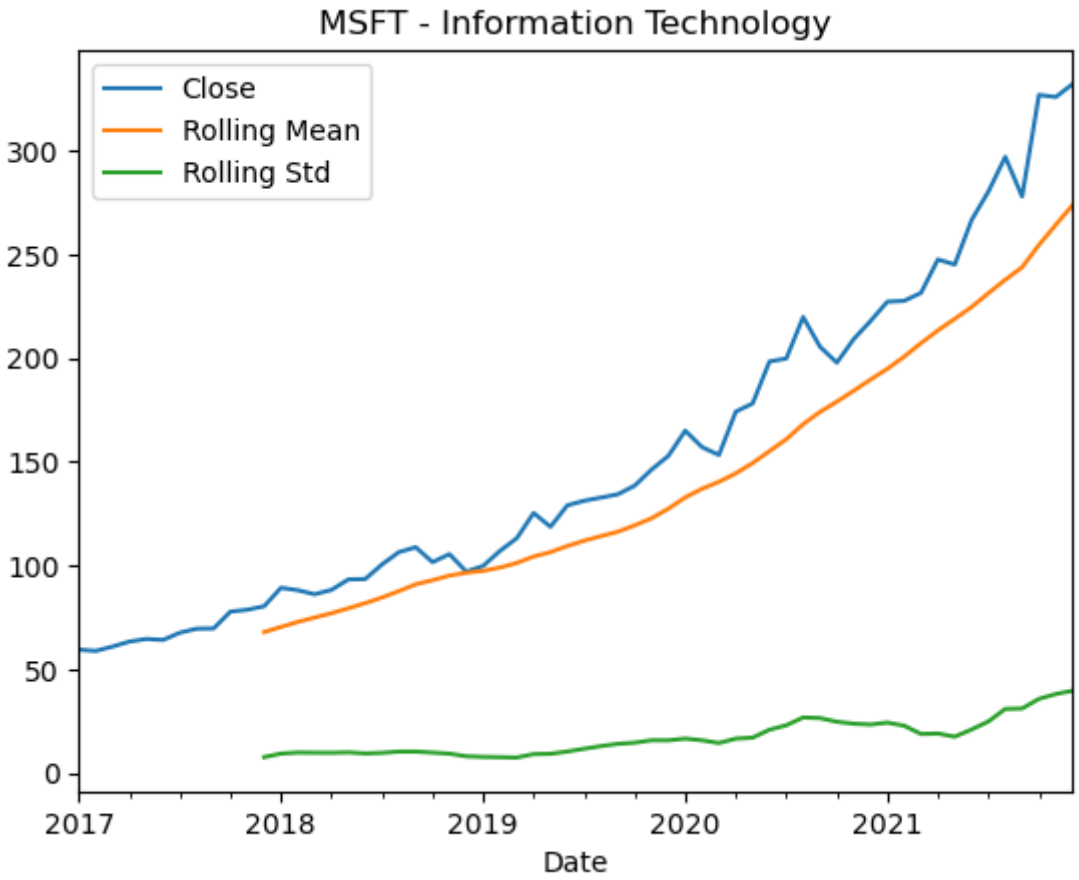
In [130]:
```
data1.set_index('Symbol',inplace=True)
```

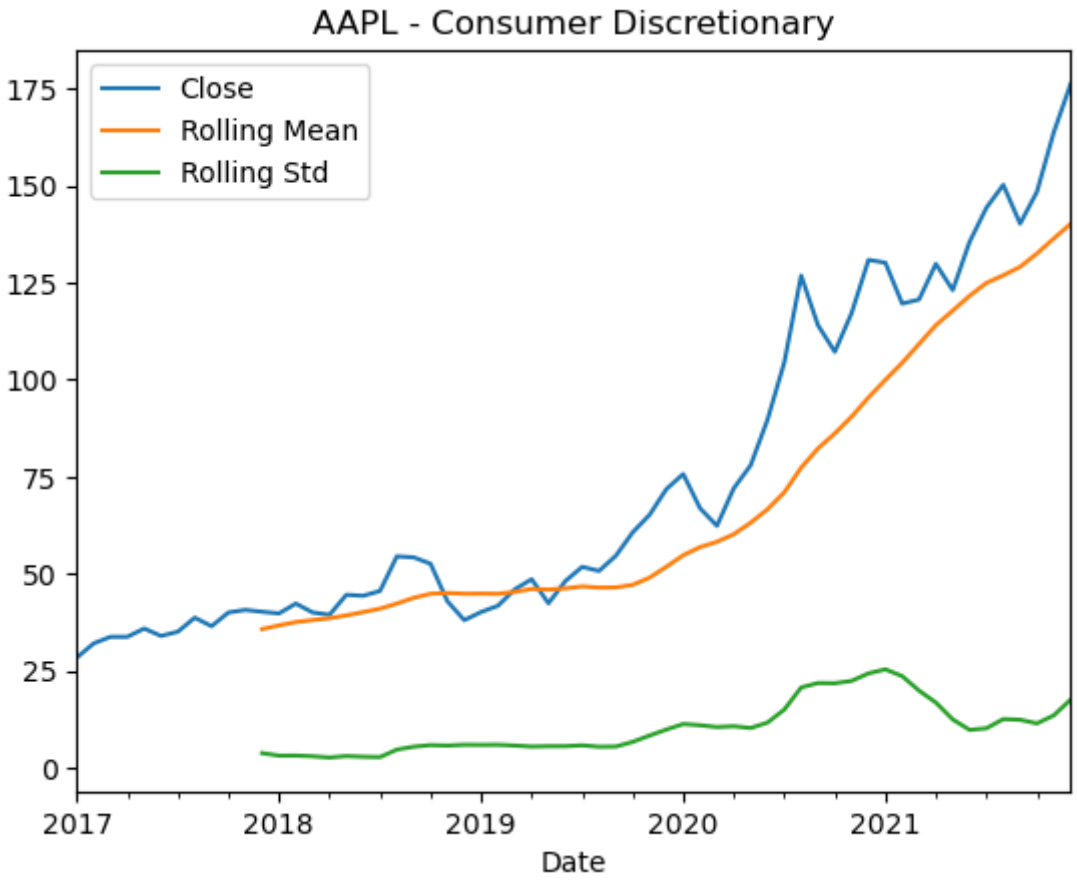
In [131]:
```
import yfinance as yf
```

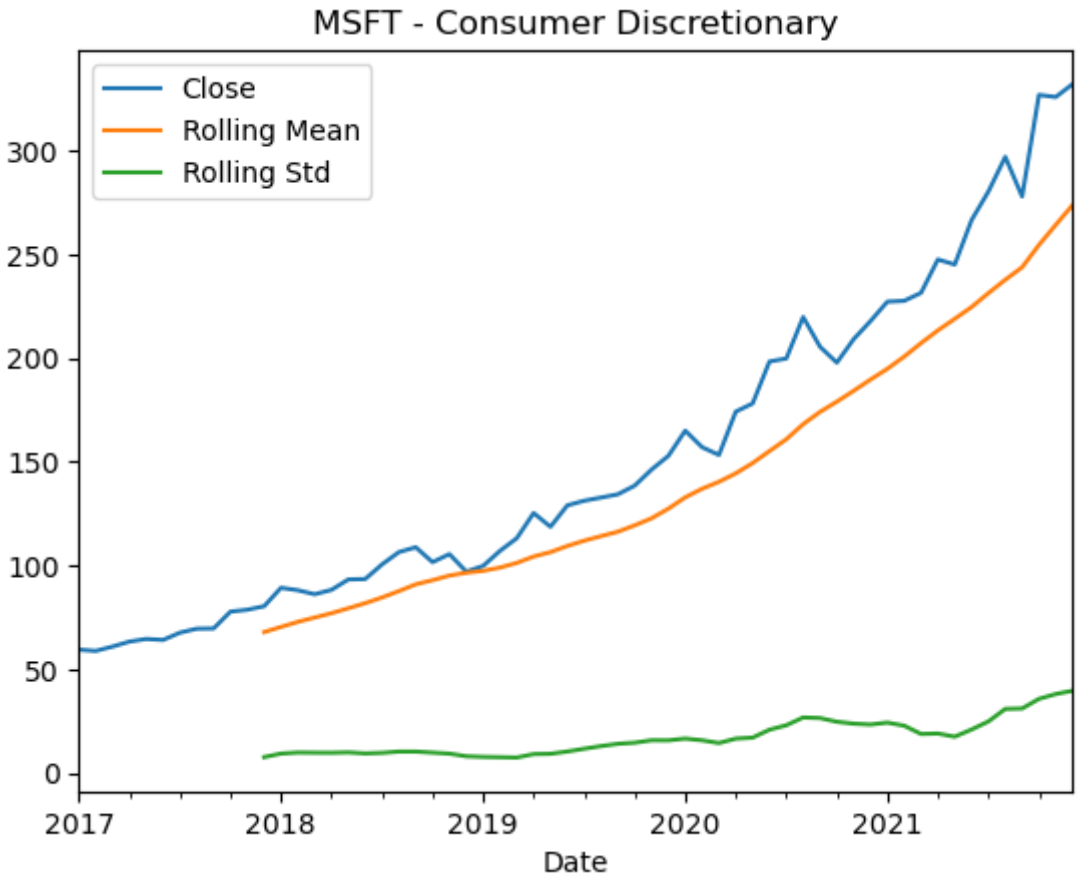
In [132]:
```
sectors = ['Information Technology', 'Consumer Discretionary', 'Utilities',
       'Health Care', 'Communication Services', 'Consumer Staples',
       'Industrials']
top_companies = {}

for sector in sectors:
    data1['Market Cap'] = data1['Market Cap'].apply(lambda x: float(x[:-1]) * 1000000000 if type(x) == str and x[-1] =
    top_companies[sector] = list(data1.nlargest(2, 'Market Cap').index)
```

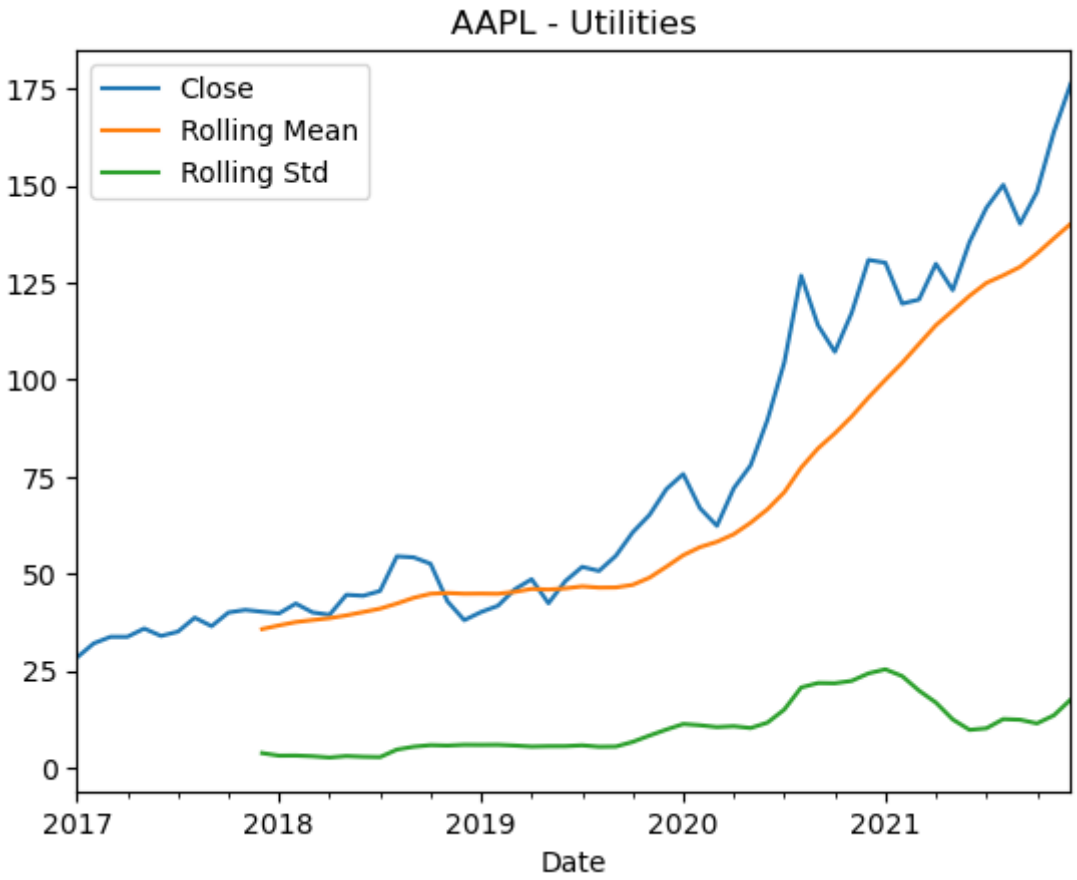
In [133]:
```
start_date = '2017-01-01'
end_date = '2022-01-01'
for sector in top_companies.keys():
    for company in top_companies[sector]:
        ticker = yf.Ticker(company)
        data1 = ticker.history(start=start_date, end=end_date, interval='1mo')
        data1['Rolling Mean'] = data1['Close'].rolling(window=12).mean()
        data1['Rolling Std'] = data1['Close'].rolling(window=12).std()
        data1.plot(y=['Close', 'Rolling Mean', 'Rolling Std'], title=f'{company} - {sector}')
```

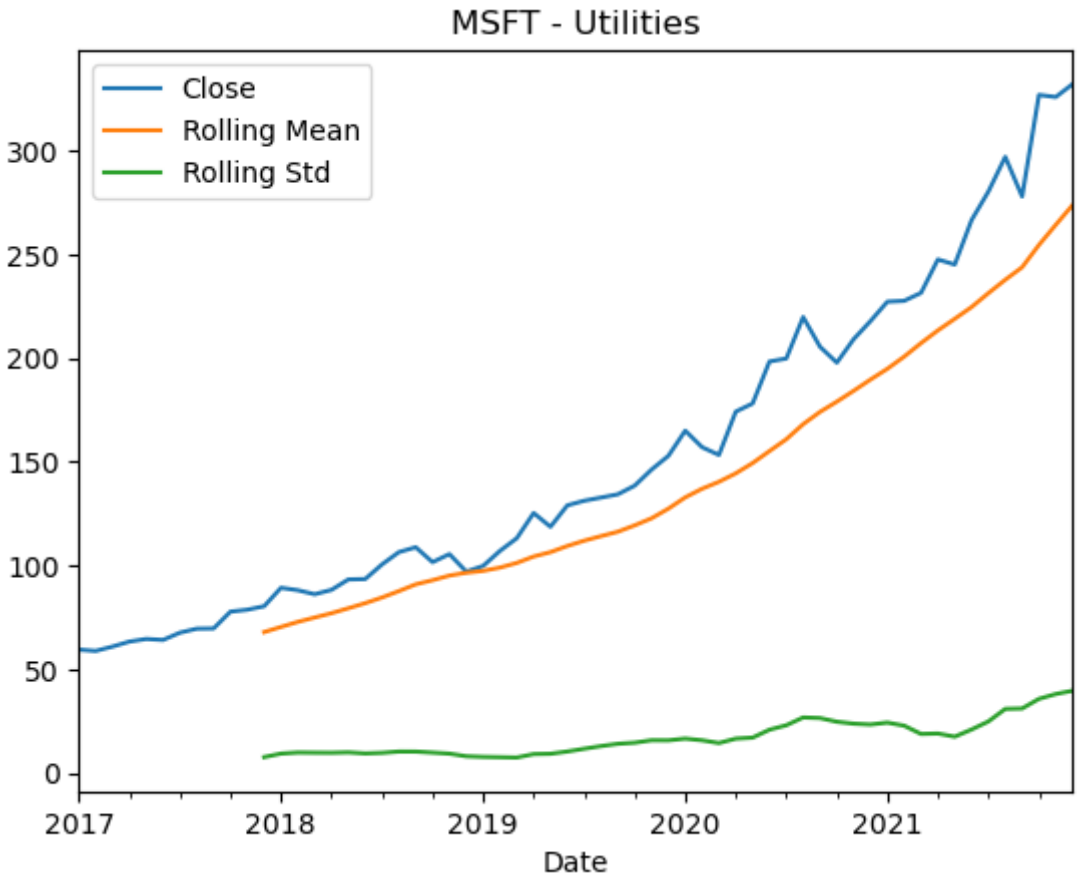


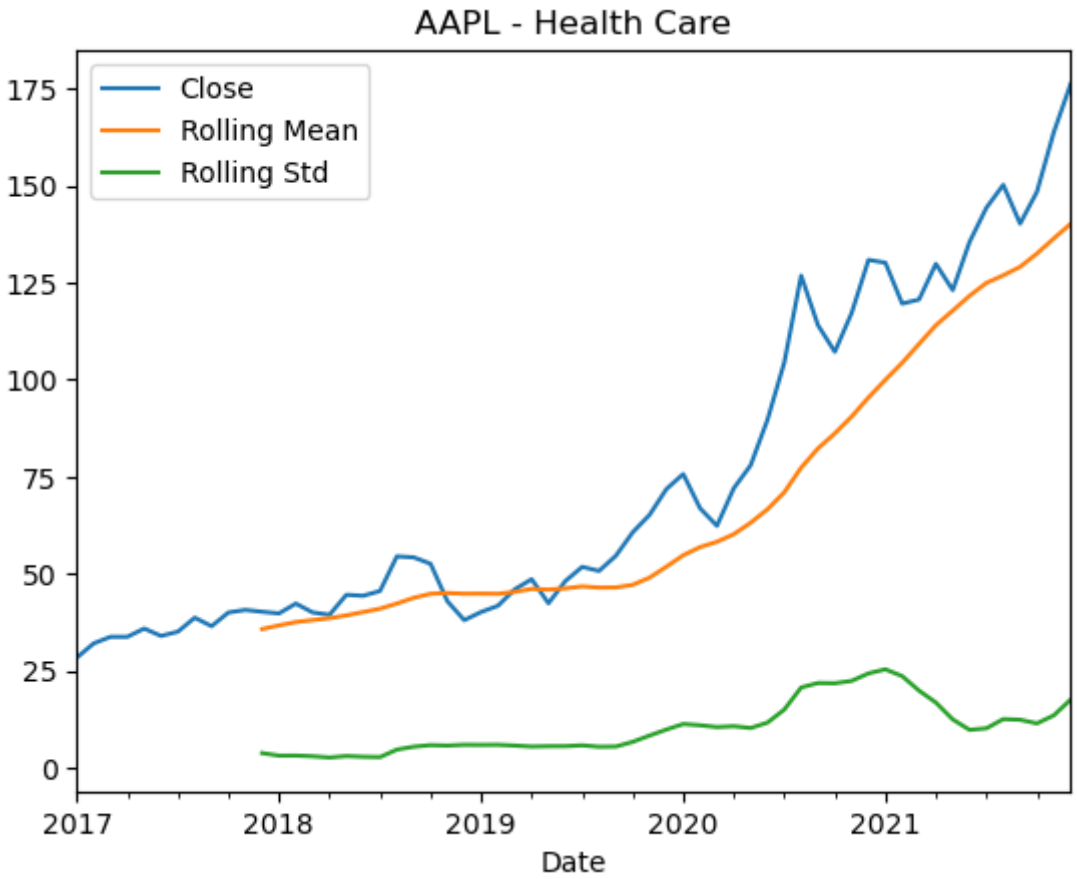

MSFT - Information Technology
Close
Rolling Mean
Rolling Std
300
250
200
150
100
50
0
2017
2018
2019
2020
2021
Date

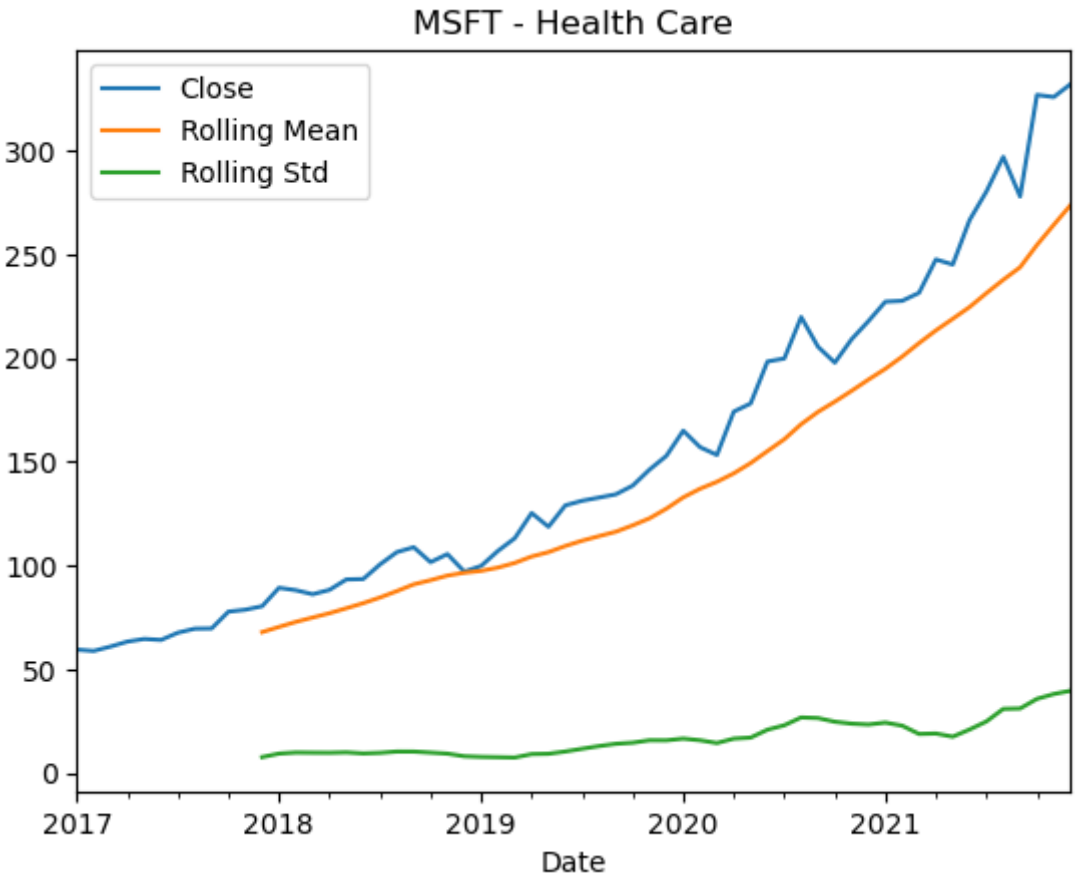

AAPL - Consumer Discretionary
Close
Rolling Mean
Rolling Std
175
150
125
100
75
50
25
0
2017
2018
2019
2020
2021
Date

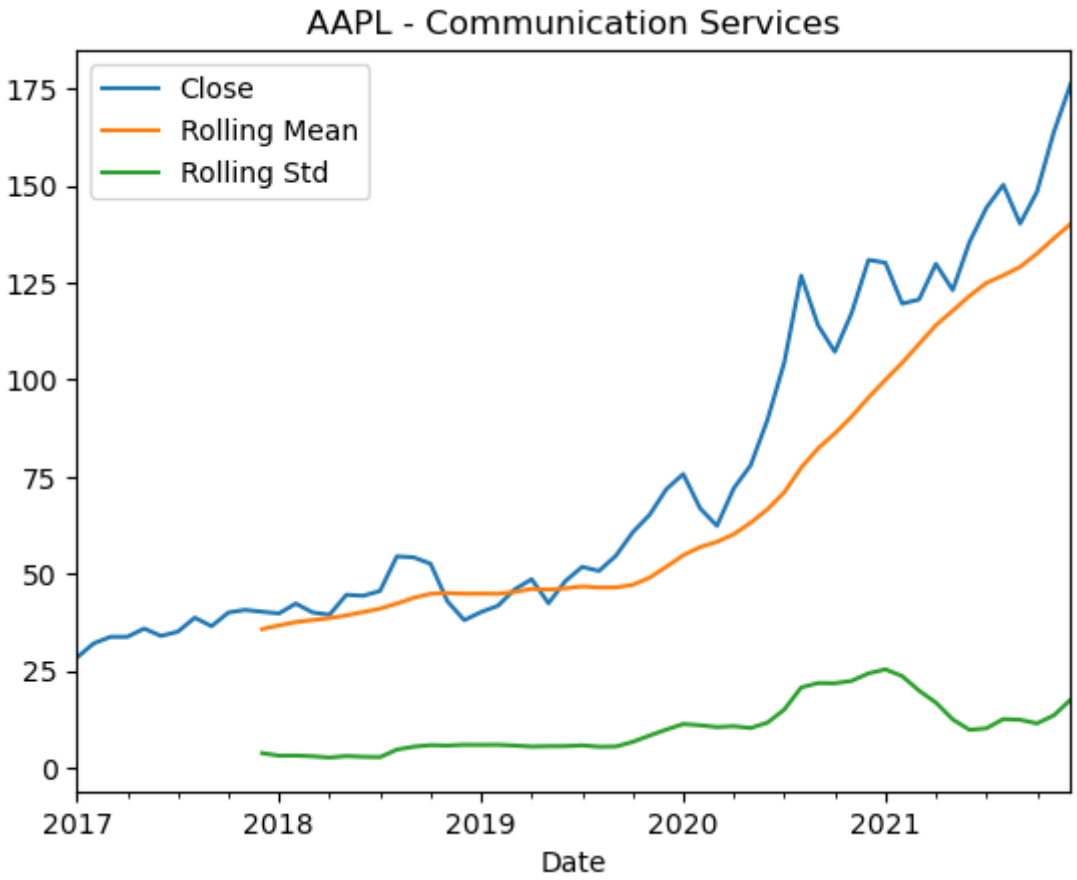

MSFT - Consumer Discretionary
Close
Rolling Mean
Rolling Std
300
250
200
150
100
50
0
2017
2018
2019
2020
2021
Date

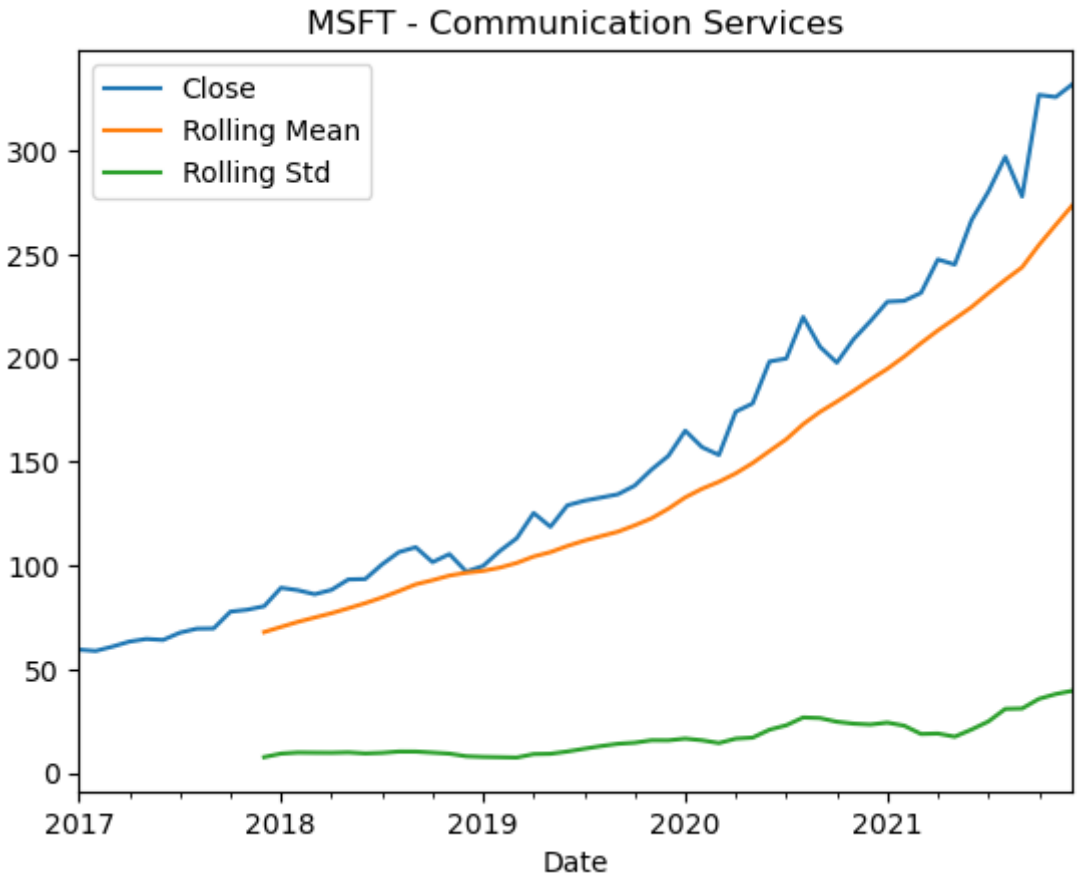

AAPL - Utilities
Close
Rolling Mean
Rolling Std
175
150
125
100
75
50
25
0
2017
2018
2019
2020
2021
Date

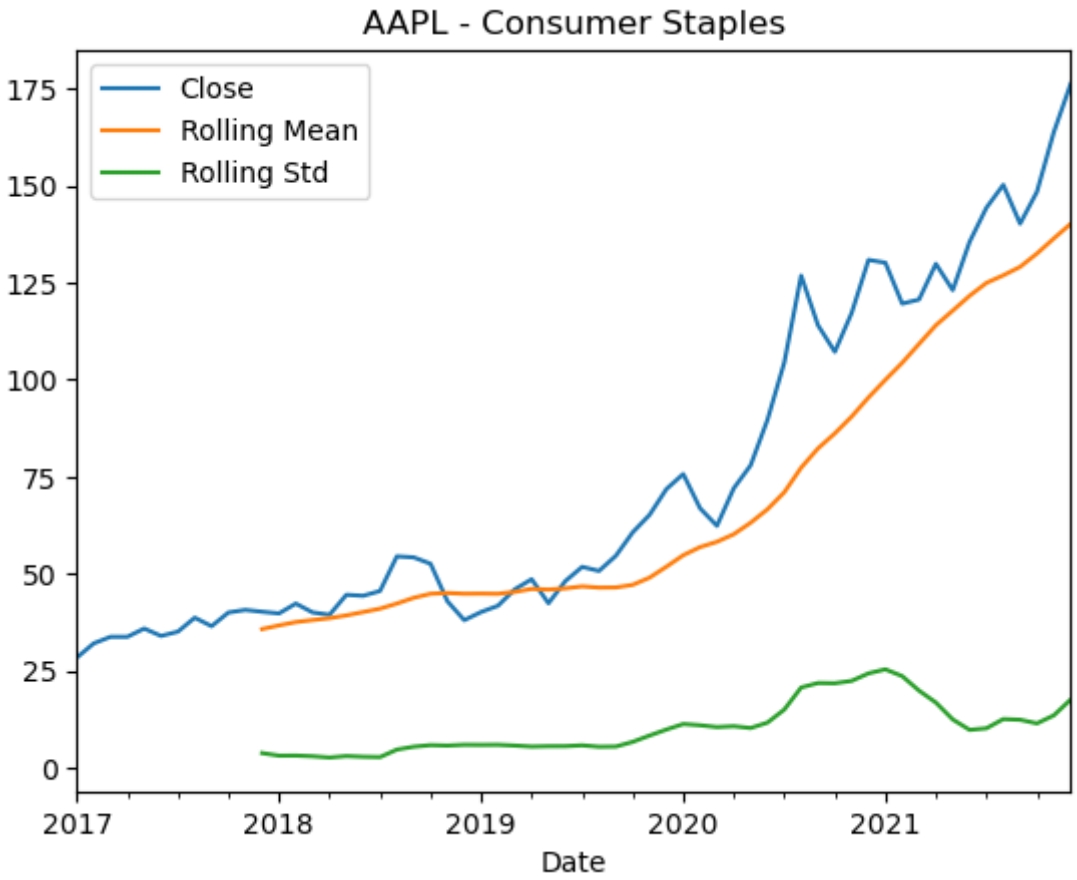

MSFT - Utilities
Close
Rolling Mean
Rolling Std
300
250
200
150
100
50
0
2017
2018
2019
2020
2021
Date

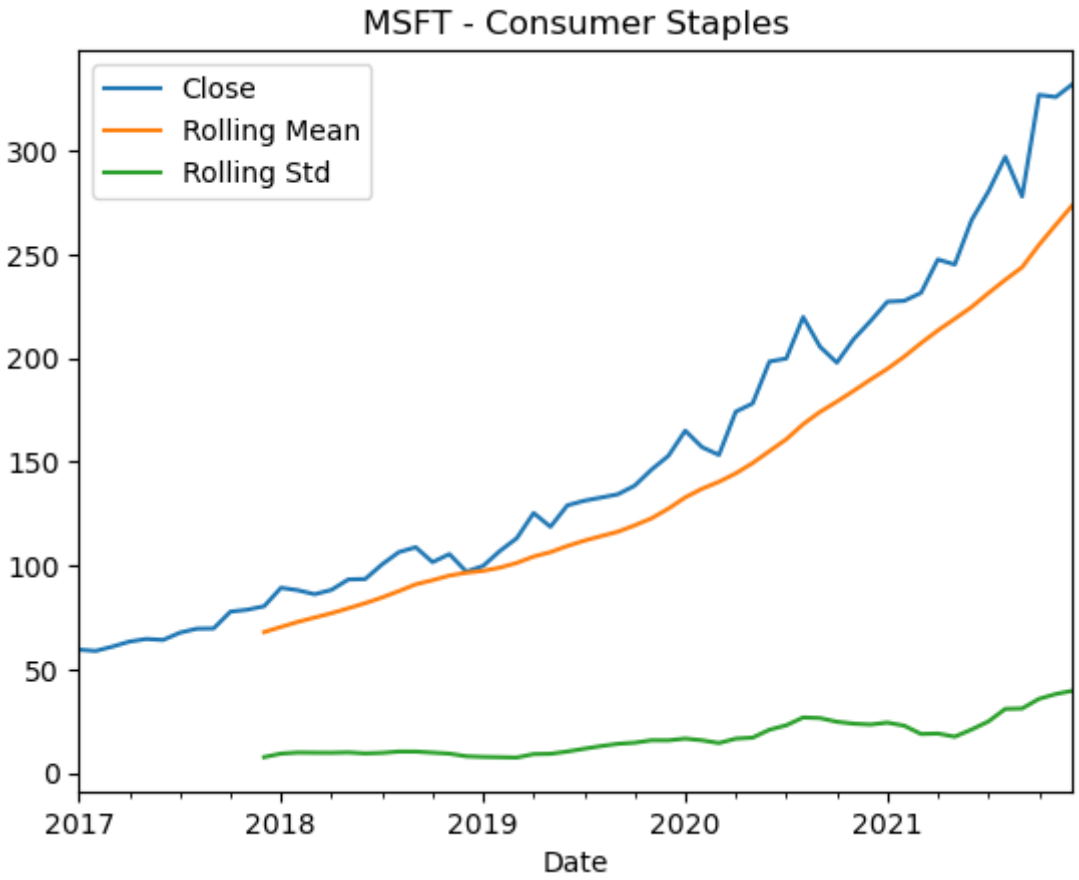

AAPL - Health Care
Close
Rolling Mean
Rolling Std
175
150
125
100
75
50
25
0
2017
2018
2019
2020
2021
Date

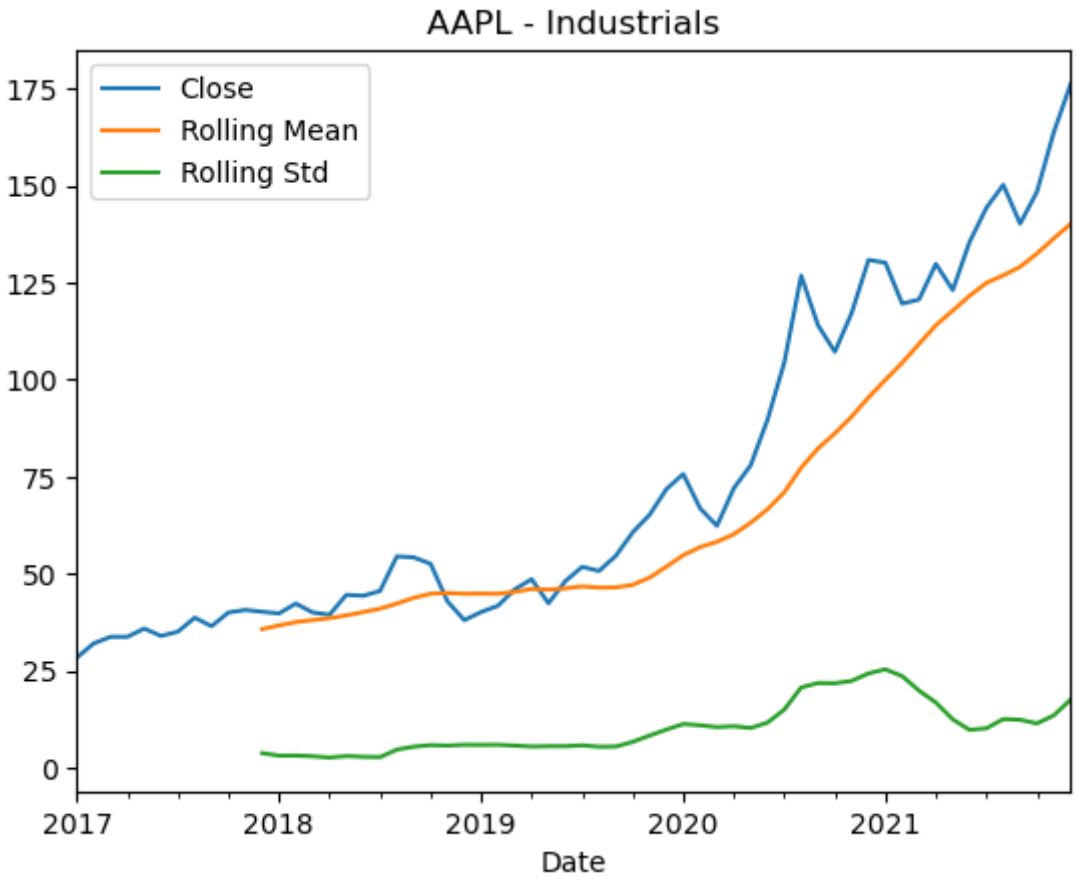

MSFT - Health Care
Close
Rolling Mean
Rolling Std
300
250
200
150
100
50
0
2017
2018
2019
2020
2021
Date

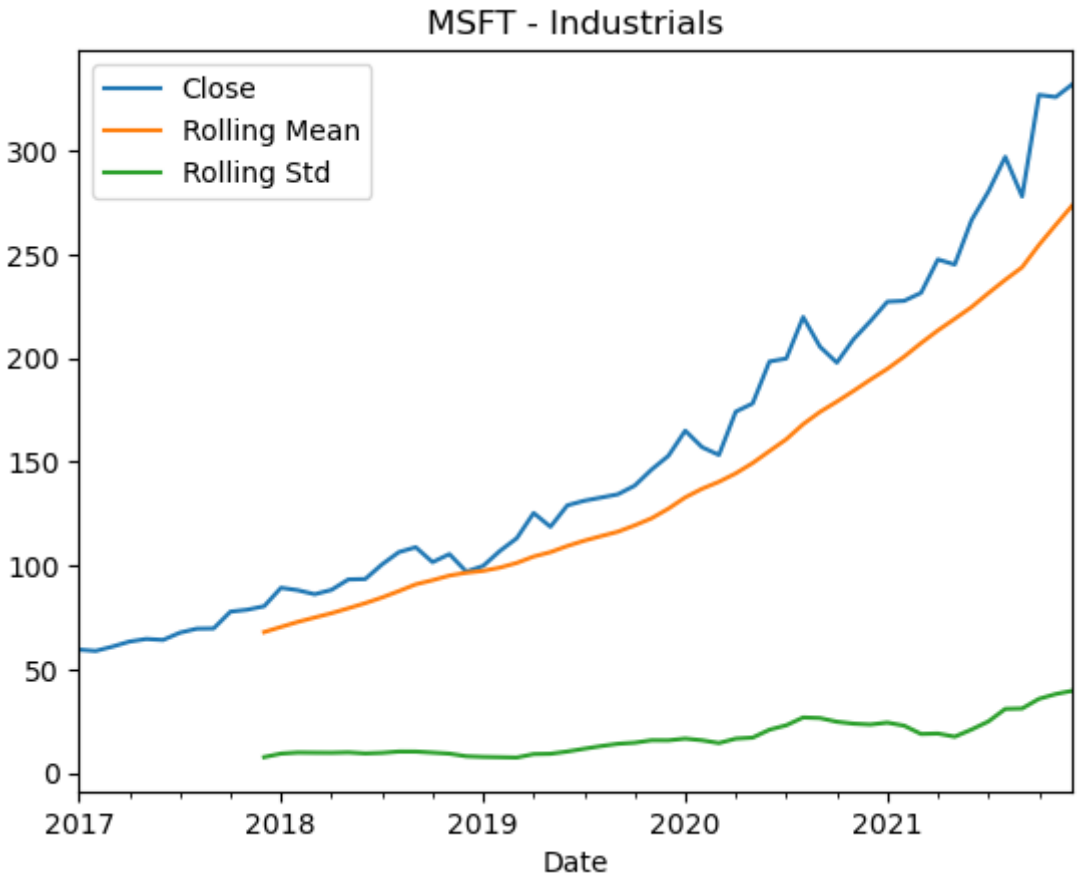

AAPL - Communication Services
Close
Rolling Mean
Rolling Std
175
150
125
100
75
50
25
0
2017
2018
2019
2020
2021
Date


MSFT - Communication Services
Close
Rolling Mean
Rolling Std
300
250
200
150
100
50
0
2017
2018
2019
2020
2021
Date


AAPL - Consumer Staples
Close
Rolling Mean
Rolling Std
175
150
125
100
75
50
25
0
2017
2018
2019
2020
2021
Date


MSFT - Consumer Staples
Close
Rolling Mean
Rolling Std
300
250
200
150
100
50
0
2017
2018
2019
2020
2021
Date


AAPL - Industrials
Close
Rolling Mean
Rolling Std
175
150
125
100
75
50
25
0
2017
2018
2019
2020
2021
Date


MSFT - Industrials
Close
Rolling Mean
Rolling Std
300
250
200
150
100
50
0
2017
2018
2019
2020
2021
Date

In [134]:
```
for sector in top_companies.keys():
    for company in top_companies[sector]:
        ticker = yf.Ticker(company)
        data = ticker.history(start=start_date, end=end_date, interval='1mo')
        result = adfuller(data['Close'])
        print(f'{company} - {sector}: ADF Statistic: {result[0]}, p-value: {result[1]}')
```

```
AAPL - Information Technology: ADF Statistic: 1.762568014599153, p-value: 0.998271814381589
MSFT - Information Technology: ADF Statistic: 3.0046896107884735, p-value: 1.0
AAPL - Consumer Discretionary: ADF Statistic: 1.762567686211993, p-value: 0.998271813677654
MSFT - Consumer Discretionary: ADF Statistic: 3.0046968205527285, p-value: 1.0
AAPL - Utilities: ADF Statistic: 1.7625682843224129, p-value: 0.9982718149597709
MSFT - Utilities: ADF Statistic: 3.0046949288131226, p-value: 1.0
AAPL - Health Care: ADF Statistic: 1.762568041004364, p-value: 0.9982718144381915
MSFT - Health Care: ADF Statistic: 3.0046968205527285, p-value: 1.0
AAPL - Communication Services: ADF Statistic: 1.7625682843224129, p-value: 0.9982718149597709
MSFT - Communication Services: ADF Statistic: 3.0046907598211776, p-value: 1.0
AAPL - Consumer Staples: ADF Statistic: 1.762568041004364, p-value: 0.9982718144381915
MSFT - Consumer Staples: ADF Statistic: 3.0046907598211776, p-value: 1.0
AAPL - Industrials: ADF Statistic: 1.762568041004364, p-value: 0.9982718144381915
MSFT - Industrials: ADF Statistic: 3.0046896107884735, p-value: 1.0
```

The p-value is greater than 0.05, so the time series is non-stationary.

In [135]:
```
import pmdarima as pm
```

In [136]:
```
auto_arima = pm.auto_arima(train_data,stepwise=False,seasonal=False)
```

In [137]:
```
auto_arima
```

Out[137]:
```
ARIMA(order=(1, 0, 3), scoring_args={}, suppress_warnings=True,
      with_intercept=False)
```

In [138]:
```
forecast_test_auto = auto_arima.predict(n_periods=len(test_data))
```

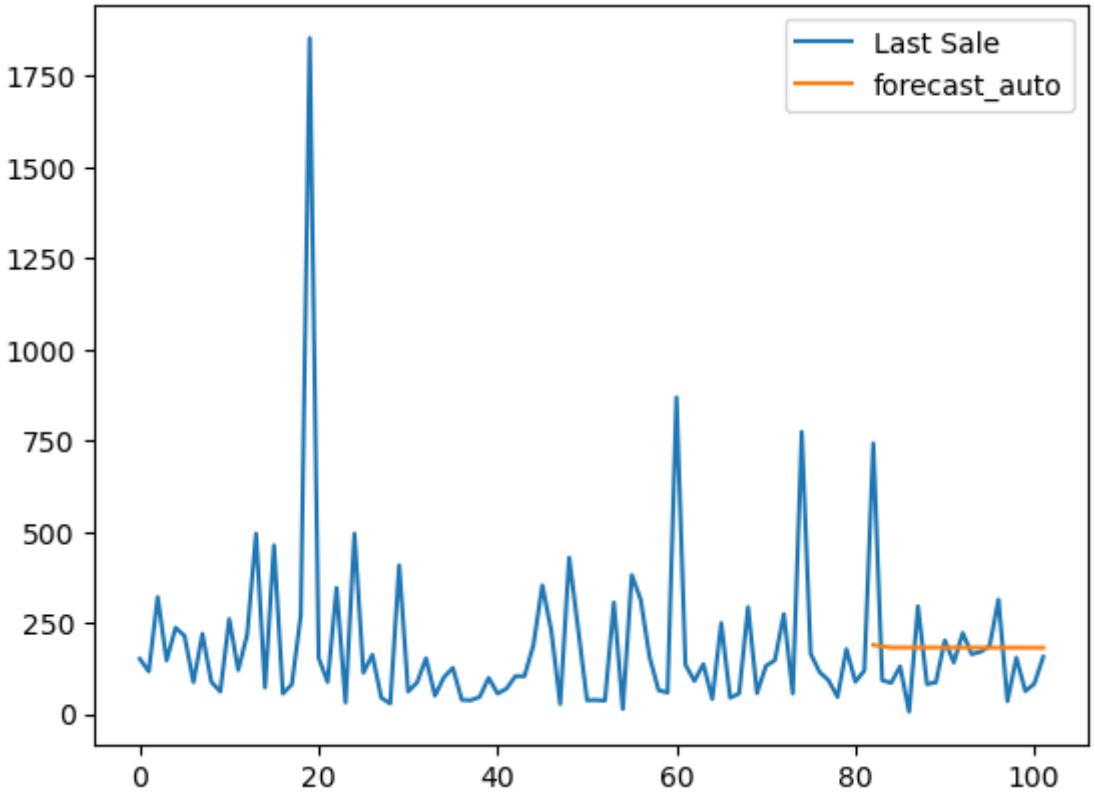
In [139]:
```
print(auto_arima.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                   82
Model:               SARIMAX(1, 0, 3)   Log Likelihood                -568.844
Date:                Thu, 06 Apr 2023   AIC                           1147.688
Time:                        17:53:25   BIC                           1159.722
Sample:                             0   HQIC                          1152.519
                                  - 82
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.9998      0.003    299.177      0.000       0.993       1.006
ma.L1         -1.0252      0.281     -3.653      0.000      -1.575      -0.475
ma.L2       3.349e-05      0.397   8.44e-05      1.000      -0.778       0.778
ma.L3          0.0396      0.223      0.177      0.859      -0.398       0.478
sigma2      5.957e+04   9509.893      6.264      0.000    4.09e+04    7.82e+04
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):              2062.07
Prob(Q):                              0.98   Prob(JB):                         0.00
Heteroskedasticity (H):               0.33   Skew:                             4.12
Prob(H) (two-sided):                  0.01   Kurtosis:                        26.14
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

In [140]:
```
df['forecast_auto'] = [None]*len(train_data) + list(forecast_test_auto)
```

In [141]:
```
df[['Last Sale','forecast_auto']].plot()
```

Out[141]: <AxesSubplot:>



In [142]:
```
from sklearn.metrics import mean_squared_error, mean_absolute_error
```

In [143]:
```
mae = mean_absolute_error(test_data,forecast_test_auto)
mape = mean_absolute_percentage_error(test_data,forecast_test_auto)
rmse = np.sqrt(mean_squared_error(test_data,forecast_test_auto))
```

In [144]:
```
print('MAE :',mae)
print('MAPE :',mape)
print('RMSE :',rmse)
```

```
MAE : 98.19368097347453
MAPE : 2.1414538674177597
RMSE : 151.35671702950643
```

In [ ]:
```

```