Import Library

In [21]:
```
%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt
import io, base64, os, json, re
import pandas as pd
import pandas_datareader.data as web
import datetime
import numpy as np

import numpy as np
import pandas as pd
import seaborn as sns
from scipy import stats
import matplotlib.pyplot as plt

import statsmodels.api as sm
from statsmodels.stats import diagnostic as diag
from statsmodels.stats.outliers_influence import variance_inflation_factor

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error

import matplotlib.transforms as mtransforms
import datetime
import math
```

Fred Data

In [2]:
```
def gather_data(data_codes, start,
                end = datetime.datetime.today(), freq = "M"):
    i = 0
    # dct.items() calls key and value that key points to
    for key, val in data_codes.items():
        if i == 0:
            # Create dataframe for first variable, then rename column
            df = web.DataReader(val, "fred", start, end).resample(freq).mean()
            df.rename(columns = {val:key}, inplace = True)
            # setting i to None will cause the next block of code to execute,
            # placing data within df instead of creating a new dataframe for
            # each variable
            i = None
        else:
            # If dataframe already exists, add new column
            df[key] = web.DataReader(val, "fred", start, end).resample(freq).mear

    return df
```

In [5]:
```
data_codes  = {"Base: Total ($ Mil)": "BOGMBASE",
               "Base: Currency in Circulation ($ Mil)": "WCURCIR",
               # Assets
               "Balance Sheet: Total Assets ($ Mil)": "WALCL",
               "Balance Sheet Securities, Prem-Disc, Repos, and Loans ($ Mil)": '
               "Balance Sheet: Securities Held Outright ($ Mil)": "WSHOSHO",
               ### breakdown of securities holdings ###
               "Balance Sheet: U.S. Treasuries Held Outright ($ Mil)":"WSHOTSL",
               "Balance Sheet: Federal Agency Debt Securities ($ Mil)" : "WSHOFAD
               "Balance Sheet: Mortgage-Backed Securities ($ Mil)": "WSHOMCB",
               # other forms of lending
               "Balance Sheet: Repos ($ Mil)": "WORAL",
               "Balance Sheet: Central Bank Liquidity Swaps ($ Mil)" : "SWPT",
               "Balance Sheet: Direct Lending ($ Mil)" : "WLCFLL",
               # unamortized value of securities held (due to changes in interest
               "Balance Sheet: Unamortized Security Premiums ($ Mil)": "WUPSHO",
               # Liabilities
               "Balance Sheet: Total Liabilities ($ Mil)" : "WLTLECL",
               "Balance Sheet: Federal Reserve Notes Outstanding ($ Mil)" : "WLFN
               "Balance Sheet: Reverse Repos ($ Mil)": "WLRRAL",
               ### Major share of deposits
               "Balance Sheet: Excess Reserves ($ Mil)": "EXCSRESNW",
               "Balance Sheet: Required Reserves ($ Mil)": "RESBALREQW",
               "Balance Sheet: Total Reserves ($ Mil)": "WRESBAL",
               "Balance Sheet: Deposits from Dep. Institutions ($ Mil)":"WLODLL",
               "Balance Sheet: U.S. Treasury General Account ($ Mil)": "WDTGAL",
               "Balance Sheet: Other Deposits ($ Mil)": "WOTHLB",
               "Balance Sheet: All Deposits ($ Mil)": "WLDLCL",
               # Interest Rates
               "Federal Funds Target (Pre-Crisis)": "DFEDTAR",
               "Federal Funds (Upper) Target":"DFEDTARU",
               "Effective Federal Funds Rate":"DFF",
               "Interest on Excess Reserves":"IOER",
               # Req Reserves and Vault Cash
               "Vault Cash ($ Mil)": "TLVAULTW",
               "Vault Cash Used as Req. ($ Mil)": "VAULT",
               }

# Select start and end dates
start = datetime.datetime(2000, 1, 1)
end = datetime.datetime.today()

# freq refers to data frequency. Choose "D", "W", "M", "Q", "A"
# a number may also be place in front of a letter. "2D" indicates
#       alternating days
fed_data = gather_data(data_codes = data_codes, start = start,
                   end = end, freq = "M")
```

In [6]:
```
fed_data
```

Out[6]:

DATE	Base: Total ($ Mil)	Base: Currency in Circulation ($ Mil)	Balance Sheet: Total Assets ($ Mil)	Balance Sheet Securities, Prem-Disc, Repos, and Loans ($ Mil)	Balance Sheet: Securities Held Outright ($ Mil)	Balance Sheet: U.S. Treasuries Held Outright ($ Mil)	Balance Sheet: Federal Agency Debt Securities ($ Mil)	Balan She Mortgag Back Securiti ($ M
2000-01-31	601900.0	594.67875	NaN	NaN	NaN	NaN	NaN	Na
2000-02-29	578000.0	566.14375	NaN	NaN	NaN	NaN	NaN	Na
2000-03-31	577100.0	563.70500	NaN	NaN	NaN	NaN	NaN	Na
2000-04-30	578600.0	564.73350	NaN	NaN	NaN	NaN	NaN	Na
2000-05-31	580600.0	565.83560	NaN	NaN	NaN	NaN	NaN	Na
...	...	...	...	...	...	...	...	
2021-06-30	6027000.0	2178.84320	8026555.20	7874851.20	7450341.40	5149903.00	2347.0	2298091.
2021-07-31	6130200.0	2186.11750	8190356.75	8042917.00	7617340.75	5232755.50	2347.0	2382238.
2021-08-31	6328700.0	2187.61075	8291893.25	8153497.75	7733453.75	5312788.25	2347.0	2418318.
2021-09-30	6388900.0	2194.88100	8418612.40	8289740.40	7881596.20	5394942.60	2347.0	2484306.
2021-10-31	6331000.0	2202.48475	8516524.50	8393472.00	8000350.50	5481949.25	2347.0	2516054.

262 rows × 28 columns

Load Data

In [51]:
```
data=pd.read_csv("data 1.csv")
```

In [52]:
```
data
```

Out[52]:

	Date	Base: Currency in Circulation ($ Mil)	Balance Sheet: Total Assets ($ Mil)	Effective Federal Funds Rate	Adj Close	Log Total Asset	Currency in Circulation/Total Asset	Log Stock Price
0	1/31/2000	594.68	0.00	5.45	1394.46	0.000000	0.000000	7.240263
1	2/29/2000	566.14	0.00	5.73	1366.42	0.000000	0.000000	7.219949
2	3/31/2000	563.71	0.00	5.85	1498.58	0.000000	0.000000	7.312273
3	4/30/2000	564.73	0.00	6.02	1452.43	0.000000	1.000000	7.280993
4	5/31/2000	565.84	0.00	6.27	1420.60	0.000000	0.000000	7.258835
...	...	...	...	...	...	...	...	...
257	6/30/2021	2178.84	8026555.20	0.08	4297.50	15.898266	0.000271	8.365789
258	7/31/2021	2186.13	8190356.75	0.10	4395.26	15.918468	0.000267	8.388282
259	8/31/2021	2187.63	8291893.25	0.09	4522.68	15.930789	0.000264	8.416860
260	9/30/2021	2194.90	8418612.40	0.08	4307.54	15.945956	0.000261	8.368122
261	10/31/2021	2202.51	8516524.50	0.08	4605.38	15.957519	0.000259	8.434980

262 rows × 9 columns

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

Out[53]:
```
Date                                      object
Base: Currency in Circulation ($ Mil)    float64
Balance Sheet: Total Assets ($ Mil)      float64
Effective Federal Funds Rate             float64
Adj Close                                float64
Log Total Asset                          float64
Currency in Circulation/Total Asset      float64
Log Stock Price                          float64
Unemployment Rate                        float64
dtype: object
```

In [54]:
```
data = data.set_index('Date')
```

In [55]:
```
data
```

Out[55]:

Date	Base: Currency in Circulation ($ Mil)	Balance Sheet: Total Assets ($ Mil)	Effective Federal Funds Rate	Adj Close	Log Total Asset	Currency in Circulation/Total Asset	Log Stock Price	Unem
1/31/2000	594.68	0.00	5.45	1394.46	0.000000	0.000000	7.240263	
2/29/2000	566.14	0.00	5.73	1366.42	0.000000	0.000000	7.219949	
3/31/2000	563.71	0.00	5.85	1498.58	0.000000	0.000000	7.312273	
4/30/2000	564.73	0.00	6.02	1452.43	0.000000	1.000000	7.280993	
5/31/2000	565.84	0.00	6.27	1420.60	0.000000	0.000000	7.258835	
...	...	...	...	...	...	...	...	
6/30/2021	2178.84	8026555.20	0.08	4297.50	15.898266	0.000271	8.365789	
7/31/2021	2186.13	8190356.75	0.10	4395.26	15.918468	0.000267	8.388282	
8/31/2021	2187.63	8291893.25	0.09	4522.68	15.930789	0.000264	8.416860	
9/30/2021	2194.90	8418612.40	0.08	4307.54	15.945956	0.000261	8.368122	
10/31/2021	2202.51	8516524.50	0.08	4605.38	15.957519	0.000259	8.434980	

262 rows × 8 columns

In [56]:
```
data_new = data.drop(['Base: Currency in Circulation ($ Mil)', 'Balance Sheet: To
```

In [57]:
```
data_new
```

Out[57]:

Date	Effective Federal Funds Rate	Log Total Asset	Currency in Circulation/Total Asset	Log Stock Price	Unemployment Rate
1/31/2000	5.45	0.000000	0.000000	7.240263	4.1
2/29/2000	5.73	0.000000	0.000000	7.219949	4.0
3/31/2000	5.85	0.000000	0.000000	7.312273	3.8
4/30/2000	6.02	0.000000	1.000000	7.280993	4.0
5/31/2000	6.27	0.000000	0.000000	7.258835	4.0
...	...	...	...	...	...
6/30/2021	0.08	15.898266	0.000271	8.365789	5.4
7/31/2021	0.10	15.918468	0.000267	8.388282	5.2
8/31/2021	0.09	15.930789	0.000264	8.416860	4.8
9/30/2021	0.08	15.945956	0.000261	8.368122	4.6
10/31/2021	0.08	15.957519	0.000259	8.434980	4.2

262 rows × 5 columns

In [58]:
```
data_new = data_new.loc['1/31/2009':'10/31/2021']
```

In [59]:
```
data_new
```

Out[59]:

Date	Effective Federal Funds Rate	Log Total Asset	Currency in Circulation/Total Asset	Log Stock Price	Unemployment Rate
1/31/2009	0.15	14.525435	0.000436	6.716449	8.3
2/28/2009	0.22	14.447648	0.000475	6.599993	8.7
3/31/2009	0.18	14.501045	0.000454	6.681946	9.0
4/30/2009	0.15	14.568579	0.000425	6.771718	9.4
5/31/2009	0.18	14.573726	0.000424	6.823438	9.5
...	...	...	...	...	...
6/30/2021	0.08	15.898266	0.000271	8.365789	5.4
7/31/2021	0.10	15.918468	0.000267	8.388282	5.2
8/31/2021	0.09	15.930789	0.000264	8.416860	4.8
9/30/2021	0.08	15.945956	0.000261	8.368122	4.6
10/31/2021	0.08	15.957519	0.000259	8.434980	4.2

154 rows × 5 columns

In [71]:
```
data_new.columns
```

Out[71]:
```
Index(['Effective Federal Funds Rate', 'Log Total Asset',
       'Currency in Circulation/Total Asset', 'Log Stock Price',
       'Unemployment Rate'],
      dtype='object')
```

In [61]:
```
data_new.diff()
```

Out[61]:

Date	Effective Federal Funds Rate	Log Total Asset	Currency in Circulation/Total Asset	Log Stock Price	Unemployment Rate
1/31/2009	NaN	NaN	NaN	NaN	NaN
2/28/2009	0.07	-0.077786	0.000039	-0.116457	0.4
3/31/2009	-0.04	0.053397	-0.000021	0.081953	0.3
4/30/2009	-0.03	0.067534	-0.000028	0.089772	0.4
5/31/2009	0.03	0.005147	-0.000001	0.051721	0.1
...	...	...	...	...	...
6/30/2021	0.02	0.020092	-0.000004	0.021971	-0.5
7/31/2021	0.02	0.020202	-0.000005	0.022493	-0.2
8/31/2021	-0.01	0.012321	-0.000003	0.028578	-0.4
9/30/2021	-0.01	0.015167	-0.000003	-0.048738	-0.2
10/31/2021	0.00	0.011563	-0.000002	0.066858	-0.4

154 rows × 5 columns

In [62]:
```
data_stock =  data_new.diff()
```

In [63]:
```
data_stock
```

Out[63]:

Date	Effective Federal Funds Rate	Log Total Asset	Currency in Circulation/Total Asset	Log Stock Price	Unemployment Rate
1/31/2009	NaN	NaN	NaN	NaN	NaN
2/28/2009	0.07	-0.077786	0.000039	-0.116457	0.4
3/31/2009	-0.04	0.053397	-0.000021	0.081953	0.3
4/30/2009	-0.03	0.067534	-0.000028	0.089772	0.4
5/31/2009	0.03	0.005147	-0.000001	0.051721	0.1
...	...	...	...	...	...
6/30/2021	0.02	0.020092	-0.000004	0.021971	-0.5
7/31/2021	0.02	0.020202	-0.000005	0.022493	-0.2
8/31/2021	-0.01	0.012321	-0.000003	0.028578	-0.4
9/30/2021	-0.01	0.015167	-0.000003	-0.048738	-0.2
10/31/2021	0.00	0.011563	-0.000002	0.066858	-0.4

154 rows × 5 columns

In [64]:
```
data_updated = data_stock.dropna()
```

In [65]:
```
data_updated
```

Out[65]:

Date	Effective Federal Funds Rate	Log Total Asset	Currency in Circulation/Total Asset	Log Stock Price	Unemployment Rate
2/28/2009	0.07	-0.077786	0.000039	-0.116457	0.4
3/31/2009	-0.04	0.053397	-0.000021	0.081953	0.3
4/30/2009	-0.03	0.067534	-0.000028	0.089772	0.4
5/31/2009	0.03	0.005147	-0.000001	0.051721	0.1
6/30/2009	0.03	-0.036956	0.000017	0.000196	0.0
...	...	...	...	...	...
6/30/2021	0.02	0.020092	-0.000004	0.021971	-0.5
7/31/2021	0.02	0.020202	-0.000005	0.022493	-0.2
8/31/2021	-0.01	0.012321	-0.000003	0.028578	-0.4
9/30/2021	-0.01	0.015167	-0.000003	-0.048738	-0.2
10/31/2021	0.00	0.011563	-0.000002	0.066858	-0.4

153 rows × 5 columns

In [70]:
```
data_updated.isnull().sum()
```

Out[70]:
```
index                                  0
Date                                   0
Effective Federal Funds Rate           0
Log Total Asset                        0
Currency in Circulation/Total Asset    0
Log Stock Price                        0
Unemployment Rate                      0
dtype: int64
```

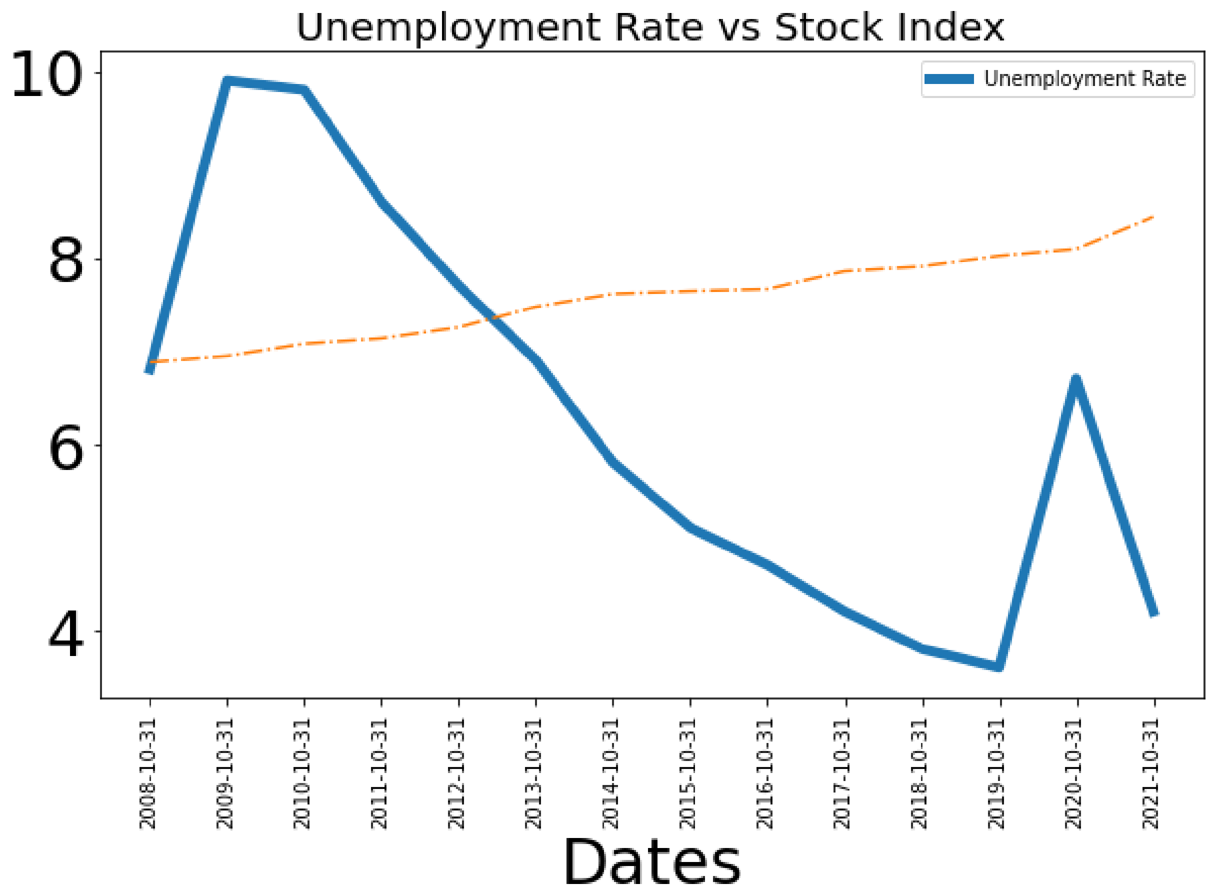
In [91]:
```
data_graph = pd.read_csv("data 3.csv")
```

In [92]:
```
data_graph
```

Out[92]:

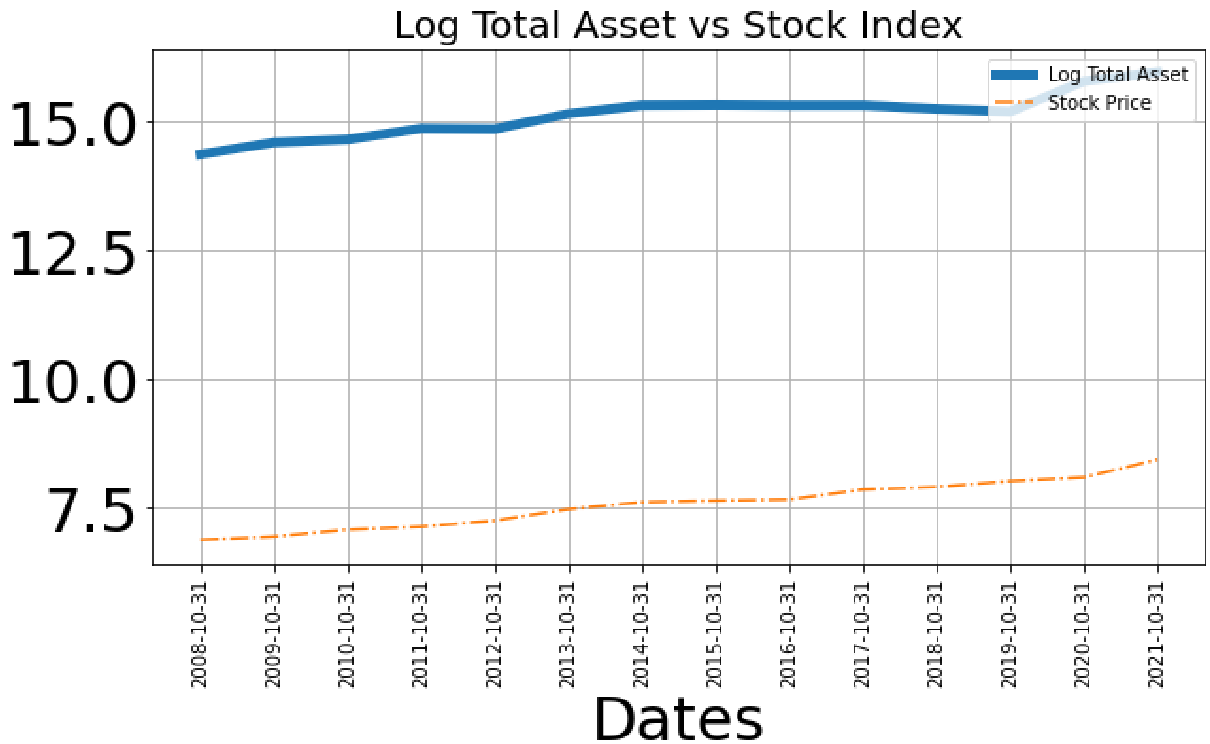
	Date	Base: Currency in Circulation ($ Mil)	Balance Sheet: Total Assets ($ Mil)	Effective Federal Funds Rate	Adj Close	Log Total Asset	Currency in Circulation/Total Asset	Log Stock Price	Unemp
0	2008-10-31	849.12	1727614.60	0.97	968.75	14.362252	0.000491	6.876007	
1	2009-10-31	915.32	2173382.25	0.12	1036.19	14.591795	0.000421	6.943306	
2	2010-10-31	960.37	2304649.00	0.19	1183.26	14.650439	0.000417	7.076029	
3	2011-10-31	1042.13	2854649.50	0.07	1253.30	14.864460	0.000365	7.133535	
4	2012-10-31	1134.62	2826231.20	0.16	1412.16	14.854455	0.000401	7.252876	
5	2013-10-31	1213.42	3800415.60	0.09	1756.54	15.150621	0.000319	7.471101	
6	2014-10-31	1294.04	4469678.60	0.09	2018.05	15.312827	0.000290	7.609887	
7	2015-10-31	1391.43	4495400.00	0.12	2079.36	15.318565	0.000310	7.639815	
8	2016-10-31	1475.81	4459703.25	0.40	2126.15	15.310593	0.000331	7.662068	
9	2017-10-31	1583.26	4462669.25	1.15	2575.26	15.311258	0.000355	7.853706	
10	2018-10-31	1690.13	4167971.40	2.19	2711.74	15.242940	0.000406	7.905346	
11	2019-10-31	1769.48	3970156.00	1.83	3037.56	15.194316	0.000446	8.018810	
12	2020-10-31	2040.20	7137411.50	0.09	3269.96	15.780861	0.000286	8.092533	
13	2021-10-31	2202.51	8516524.50	0.08	4605.38	15.957519	0.000259	8.434980	

In [135]:
```
plt.figure(figsize=(10,6))
plt.plot(data_graph["Unemployment Rate"], label="Unemployment Rate", linewidth=5.
plt.plot(data_graph["Log Stock Price"], linestyle = "-.")
plt.xticks(range(0,len(data_graph["Unemployment Rate"])), data_graph["Date"], rot
plt.title("Unemployment Rate vs Stock Index", fontsize = 20)
plt.legend(loc="upper right", fontsize=10)
plt.xlabel("Dates")
plt.show()
plt.savefig("Unemployment Rate vs Stock Index.jpg")
```



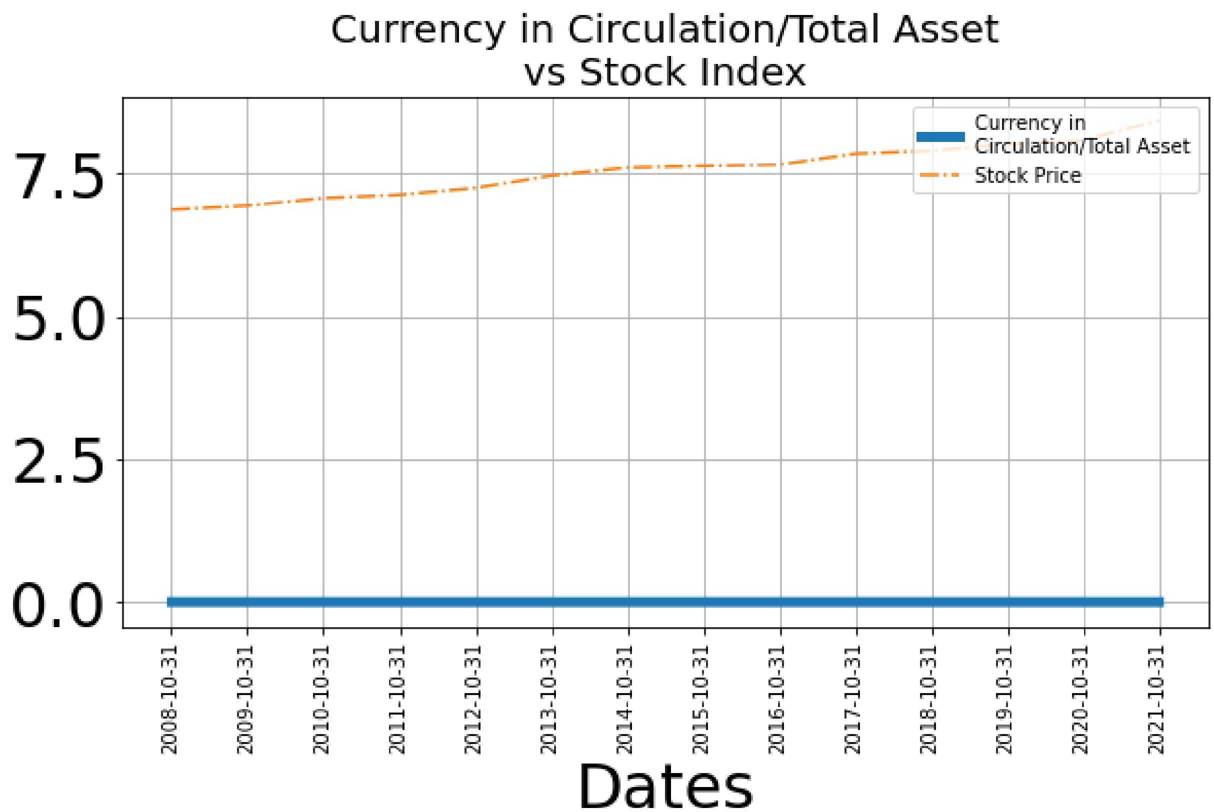

```
<Figure size 432x288 with 0 Axes>
```

In [137]:
```
plt.figure(figsize=(10,5))
plt.plot(data_graph["Log Total Asset"], label="Log Total Asset", linewidth=5.)
plt.plot(data_graph["Log Stock Price"],label="Stock Price", linestyle = "-.")
plt.xticks(range(0,len(data_graph["Log Total Asset"])), data_graph["Date"], rotat
plt.title("Log Total Asset vs Stock Index", fontsize = 20)
plt.legend(loc="upper right", fontsize=10)
plt.xlabel("Dates")
plt.grid(True)
plt.show()
plt.savefig("TA vs Stock Index.jpg")
```



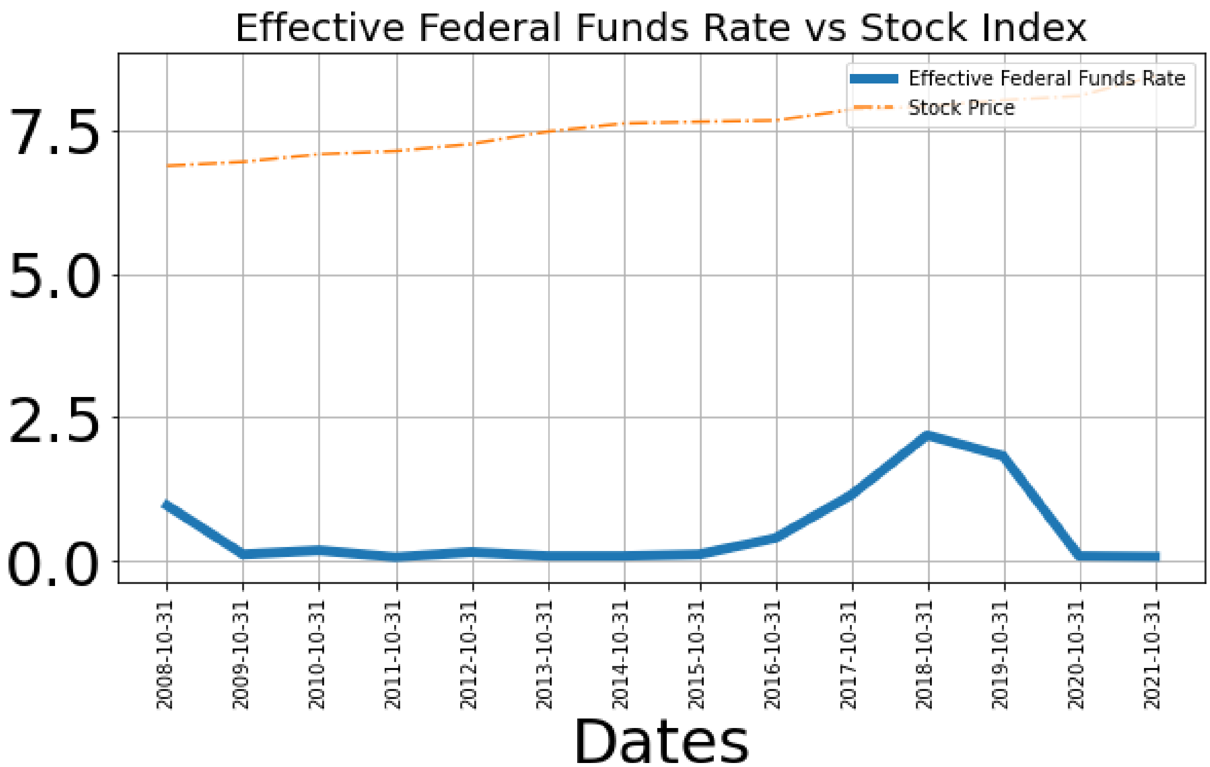

```
<Figure size 432x288 with 0 Axes>
```

In [138]:
```
plt.figure(figsize=(10,5))
plt.plot(data_graph["Currency in Circulation/Total Asset"], label="Currency in\nC
plt.plot(data_graph["Log Stock Price"],label="Stock Price", linestyle = "-.")
plt.xticks(range(0,len(data_graph["Currency in Circulation/Total Asset"])), data_
plt.title("Currency in Circulation/Total Asset\nvs Stock Index", fontsize = 20)
plt.legend(loc="upper right", fontsize=10)
plt.xlabel("Dates")
plt.grid(True)
plt.show()
plt.savefig("CA vs Stock Index.jpg")
```




```
<Figure size 432x288 with 0 Axes>
```

In [139]:
```
plt.figure(figsize=(10,5))
plt.plot(data_graph["Effective Federal Funds Rate"], label="Effective Federal Fur
plt.plot(data_graph["Log Stock Price"],label="Stock Price", linestyle = "-.")
plt.xticks(range(0,len(data_graph["Effective Federal Funds Rate"])), data_graph['
plt.title("Effective Federal Funds Rate vs Stock Index", fontsize = 20)
plt.legend(loc="upper right", fontsize=10)
plt.xlabel("Dates")
plt.grid(True)
plt.show()
plt.savefig("FFR vs Stock Index.jpg")
```




```
<Figure size 432x288 with 0 Axes>
```

In [ ]:
```
data_final = data_updated.drop(['Base: Currency in Circulation ($ Mil)', 'Balance
```

In [140]:
```
# get the summary
desc_df = data_updated.describe()

# add the standard deviation metric
desc_df.loc['+3_std'] = desc_df.loc['mean'] + (desc_df.loc['std'] * 3)
desc_df.loc['-3_std'] = desc_df.loc['mean'] - (desc_df.loc['std'] * 3)

# display it
desc_df
```

Out[140]:

	level_0	index	Effective Federal Funds Rate	Log Total Asset	Currency in Circulation/Total Asset	Log Stock Price	Unemployme Ra
count	153.000000	153.000000	153.000000	153.000000	1.530000e+02	153.000000	153.0000(
mean	76.000000	76.000000	-0.000458	0.009360	-1.157529e-06	0.011232	-0.0267(
std	44.311398	44.311398	0.107375	0.031180	1.068846e-05	0.041633	0.9084
min	0.000000	0.000000	-0.930000	-0.077786	-9.568000e-05	-0.133668	-2.2000(
25%	38.000000	38.000000	-0.010000	-0.001927	-3.443000e-06	-0.007526	-0.2000(
50%	76.000000	76.000000	0.000000	0.002383	8.780000e-07	0.017726	-0.1000(
75%	114.000000	114.000000	0.010000	0.016727	3.022000e-06	0.035100	0.1000(
max	152.000000	152.000000	0.240000	0.310113	3.948700e-05	0.119421	10.4000(
+3_std	208.934194	208.934194	0.321668	0.102900	3.090786e-05	0.136132	2.6985
-3_std	-56.934194	-56.934194	-0.322583	-0.084180	-3.322292e-05	-0.113667	-2.7521

Build Model

In [141]:
```
X = data_updated.drop('Log Stock Price', axis = 1)
Y = data_updated[['Log Stock Price']]

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.20, random_


regression_model = LinearRegression()


regression_model.fit(X_train, y_train)
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
C:\Users\PROMA~1.GUP\AppData\Local\Temp/ipykernel_6184/633723668.py in <modul
e>
      8
      9
---> 10 regression_model.fit(X_train, y_train)
     11 LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
     12          normalize=False)

~\Anaconda3\lib\site-packages\sklearn\linear_model\_base.py in fit(self, X,
 y, sample_weight)
    660         accept_sparse = False if self.positive else ["csr", "csc", "c
oo"]
    661
--> 662         X, y = self._validate_data(
    663             X, y, accept_sparse=accept_sparse, y_numeric=True, multi_
output=True
    664         )

~\Anaconda3\lib\site-packages\sklearn\base.py in _validate_data(self, X, y, r
eset, validate_separately, **check_params)
    574                 y = check_array(y, **check_y_params)
    575             else:
--> 576                 X, y = check_X_y(X, y, **check_params)
    577             out = X, y
    578

~\Anaconda3\lib\site-packages\sklearn\utils\validation.py in check_X_y(X, y,
 accept_sparse, accept_large_sparse, dtype, order, copy, force_all_finite, en
sure_2d, allow_nd, multi_output, ensure_min_samples, ensure_min_features, y_n
umeric, estimator)
    954         raise ValueError("y cannot be None")
    955
--> 956     X = check_array(
    957         X,
    958         accept_sparse=accept_sparse,

~\Anaconda3\lib\site-packages\sklearn\utils\validation.py in check_array(arra
y, accept_sparse, accept_large_sparse, dtype, order, copy, force_all_finite,
 ensure_2d, allow_nd, ensure_min_samples, ensure_min_features, estimator)
    736                     array = array.astype(dtype, casting="unsafe", cop
y=False)
    737                 else:
```

```
--> 738                 array = np.asarray(array, order=order, dtype=dtyp
e)
    739             except ComplexWarning as complex_warning:
    740                 raise ValueError(

~\Anaconda3\lib\site-packages\numpy\core\_asarray.py in asarray(a, dtype, ord
er, like)
    100         return _asarray_with_like(a, dtype=dtype, order=order, like=l
ike)
    101
--> 102     return array(a, dtype, copy=False, order=order)
    103
    104

~\Anaconda3\lib\site-packages\pandas\core\generic.py in __array__(self, dtyp
e)
   1991
   1992     def __array__(self, dtype: NpDtype | None = None) -> np.ndarray:
-> 1993         return np.asarray(self._values, dtype=dtype)
   1994
   1995     def __array_wrap__(

~\Anaconda3\lib\site-packages\numpy\core\_asarray.py in asarray(a, dtype, ord
er, like)
    100         return _asarray_with_like(a, dtype=dtype, order=order, like=l
ike)
    101
--> 102     return array(a, dtype, copy=False, order=order)
    103
    104

ValueError: could not convert string to float: '9/30/2010'
```

Exploring the Output

In [ ]:

```python
# Let's grab the coefficient of our model and the intercept
intercept = regression_model.intercept_[0]
coefficent = regression_model.coef_[0][0]

print("The intercept for our model is {:.4}".format(intercept))
print('-'*100)

# loop through the dictionary and print the data
for coef in zip(X.columns, regression_model.coef_[0]):
    print("The Coefficient for {} is {:.2}".format(coef[0],coef[1]))
```

Evaluating the Model

In [ ]:
```
# define our intput
X2 = sm.add_constant(X)

# create a OLS model
model = sm.OLS(Y, X2)

# fit the data
est = model.fit()
```

In [ ]:
```
# Get multiple predictions
y_predict = regression_model.predict(X_test)

# Show the first 5 predictions
y_predict[:5]
```

In [ ]:
```
# define our intput
X2 = sm.add_constant(X)

# create a OLS model
model = sm.OLS(Y, X2)

# fit the data
est = model.fit()
```

Checking for Heteroscedasticity

In [ ]:
```
_, pval, __, f_pval = diag.het_breuschpagan(est.resid, est.model.exog)
print(pval, f_pval)
print('-'*100)

# print the results of the test
if pval > 0.05:
    print("For the Breusch-Pagan's Test")
    print("The p-value was {:.4}".format(pval))
    print("We fail to reject the null hypthoesis, so there is no heterosecdastici

else:
    print("For the Breusch-Pagan's Test")
    print("The p-value was {:.4}".format(pval))
    print("We reject the null hypthoesis, so there is heterosecdasticity.")
```

Checking for Autocorrelation

In [ ]:
```
# test for autocorrelation
from statsmodels.stats.stattools import durbin_watson

# calculate the lag, optional
lag = min(10, (len(X)//5))
print('The number of lags will be {}'.format(lag))
print('-'*100)

# run the Ljung-Box test for no autocorrelation of residuals
# test_results = diag.acorr_breusch_godfrey(est, nlags = lag, store = True)
test_results = diag.acorr_ljungbox(est.resid, lags = lag)

# grab the p-values and the test statistics
ibvalue, p_val = test_results

# print the results of the test
if min(p_val) > 0.05:
    print("The lowest p-value found was {:.4}".format(min(p_val)))
    print("We fail to reject the null hypthoesis, so there is no autocorrelation.
    print('-'*100)
else:
    print("The lowest p-value found was {:.4}".format(min(p_val)))
    print("We reject the null hypthoesis, so there is autocorrelation.")
    print('-'*100)

# plot autocorrelation
sm.graphics.tsa.plot_acf(est.resid)
plt.show()
```

OLS

In [ ]:
```
y_var = ["Log Stock Price"]
x_vars = ["Log Total Asset",
          "Currency in Circulation/Total Asset",
          "Effective Federal Funds Rate",
          "Unemployment Rate"]
reg_vars = y_var + x_vars
reg_data = data[reg_vars].dropna()
reg_data
```

In [ ]:
```
reg_data.corr()
```

In [ ]:
```
from datlib.plots import *
corr_matrix_heatmap(reg_data.corr())
```

In [ ]:
```
reg_data.describe().round(2)
```

In [ ]:
```
y = reg_data[y_var]
X = reg_data[x_vars]
X["Constant"]=1
results = sm.OLS(y,X).fit()
results.summary()
```

In [ ]:
```
est.pvalues
```

In [ ]:
```
keys = ['Log Total Asset',
         'Currency in Circulation/Total Asset',
         'Effective Federal Funds Rate',
         'Unemployment Rate',
         'Log Stock Price']

keys = keys
reg_data = data_updated[keys].dropna()
```

In [ ]:
```
reg_data
```

In [ ]:
```
keys = ['Log Total Asset',
         'Currency in Circulation/Total Asset',
         'Effective Federal Funds Rate',
         'Unemployment Rate',
         'Log Stock Price']

keys = keys
reg_data = data_updated[keys].dropna()
```

In [ ]:
```
reg_data
```

Residuals

In [ ]:
```
import statsmodels.api as sm

residuals = {}
for y_var in reg_data.keys():
    X_vars = list(reg_data.keys())
    X_vars.remove(y_var)
    X = reg_data[X_vars]
    # Initial estimate should include constant
    #   This won't be the case we regress the errors
    X["Constant"] = 1
    # pass y_var as list for consistent structure
    y = reg_data[[y_var]]
    model = sm.OLS(y, X)
    results = model.fit()
    residuals[y_var] = results.resid
residuals = pd.DataFrame(residuals)
```

In [ ]:
```
residuals
```

In [ ]:
```
residuals.corr()[residuals.corr().abs() < 1].mul(-1).fillna(1).round(2)
```

In [ ]:
```
pcorr_pvalues = {}
for y, Y in residuals.items():
    pcorr_pvalues[y] = {}
    for x, X in residuals.items():
        if x != y:
            pcorr_pvalues[y][x] = sm.OLS(Y,X).fit().pvalues[x]

        else:
            pcorr_pvalues[y][x] = np.NaN
pd.DataFrame(pcorr_pvalues).round(2)
```

In [ ]:
```
import pingouin
from pgmpy.estimators import PC
c = PC(reg_data[keys].dropna())
max_cond_vars = len(keys) - 2

sig = 0.5
model = c.estimate(return_type = "dag", variant = "parallel",
                   significance_level = sig,
                   max_cond_vars = max_cond_vars, ci_test = "pearsonr")

edges = model.edges()
pcorr = reg_data.pcorr()
weights = {}
```

In [ ]:
```
from datlib.plots import *
corr_matrix_heatmap(data_updated.corr(),
                    save_fig = False,
                    pp = None,
                    title = "Correlation")
corr_matrix_heatmap(data_updated.pcorr(), save_fig = False, pp = None, title = "P
```

Using partial correlations to build a causal skeleton

In [ ]:
```
undirected_graph = {key:[] for key in reg_data.keys()}
for x in undirected_graph:
    remaining_vars = [y for y in reg_data.keys() if y != x]
    for y in remaining_vars:
        undirected_graph[x].append(y)

undirected_graph
```

In [ ]:
```
undirected_graph = {key:[] for key in reg_data.keys()}
for x in undirected_graph:
    remaining_vars = [y for y in reg_data.keys() if y != x]
    for y in remaining_vars:
        undirected_graph[x].append(y)

undirected_graph
```

In [ ]:
```
import copy
p_val = .01
def build_skeleton(reg_data, undirected_graph):
    def check_remaining_controls(control_vars, undirected_graph, x, y, controls_u
        for c_var in control_vars:
            # set c_used every time use cycle through a new control
            #  the program will then iterate through remaining controls
            #  until statistical significance is broken
            c_used = copy.copy(controls_used)
            if y in undirected_graph[x]:

                c_used.append(c_var)
                test = reg_data.partial_corr(x = x, y = y, covar=c_used,
                                      method = "pearson")
                if test["p-val"].values[0] > p_val:

                    undirected_graph[x].remove(y)
                    #breakout of the for
                    break
                else:
                    remaining_controls = copy.copy(control_vars)
                    remaining_controls.remove(c_var)
                    # recursive function that iterates through remaining variable
                    #  uses them as controls statistical significance holds witho
                    #  otherwise break
                    check_remaining_controls(remaining_controls, undirected_graph

    for x in reg_data.keys():
        ys = undirected_graph[x]
        for y in reg_data.keys():
            if x != y:
            # first check for correlation with no controls
                test = reg_data.partial_corr(x = x,
                                       y = y,
                                       covar = None,
                                       method = "pearson")
                if test["p-val"].values[0] > p_val:
                    undirected_graph[x].remove(y)
            # if correlated check for deseparation controlling for other variable
                else:
                    control_vars = [z for z in reg_data.keys() if z != y and z !=
                    check_remaining_controls(control_vars, undirected_graph, x, y
    return undirected_graph

undirected_graph = build_skeleton(reg_data, undirected_graph)
undirected_graph
```

In [ ]:
```
import matplotlib.pyplot as plt
import networkx as nx
def graph_DAG(undirected_graph, reg_data, title = "DAG Structure"):

    # generate partial correlation matrix to draw values from
    # for graph edges
    pcorr_matrix = reg_data.pcorr()
    graph = nx.Graph()
    edges = [['Effective Federal Funds Rate', 'Log Stock Price'], ['Log Stock Pri
    edge_labels = {}
    for key in undirected_graph:
        for key2 in undirected_graph[key]:
            if (key2, key) not in edges:
                edge = (key.replace(" ","\n"), key2[0].replace(" ","\n"))
                edges.append(edge)
                # edge label is partial correlation between
                # key and key2
                edge_labels[edge] = str(round(pcorr_matrix.loc[key][key2],2))

    # edge format: ("i", "j") --> from node i to node j
    graph.add_edges_from(edges)
    color_map = ["C0" for g in graph]

    fig, ax = plt.subplots(figsize = (20,12))
    graph.nodes()
    plt.tight_layout()
    pos = nx.spring_layout(graph)#, k = 5/(len(sig_corr.keys())**.5))

    plt.title(title, fontsize = 30)
    nx.draw_networkx(graph, pos, node_color=color_map,
                     node_size = 1000,
                     with_labels=True,  arrows=False,
                     font_size = 20, alpha = 1,
                     font_color = "white",
                     ax = ax)
    nx.draw_networkx_edge_labels(graph,pos,
                                 edge_labels=edge_labels,
                                 font_color='green',
                                 font_size=20)
    plt.show()
```

In [ ]:
```
graph_DAG(undirected_graph, reg_data, title = "Undirected Graph with Partial Corr
```

In [ ]:
```
import matplotlib.pyplot as plt
import networkx as nx
```

In [ ]:
```
import pingouin
from pgmpy.estimators import PC
c = PC(reg_data[keys].dropna())
max_cond_vars = len(keys) - 2

sig = 0.5
model = c.estimate(return_type = "dag", variant = "parallel",
                  significance_level = sig,
                  max_cond_vars = max_cond_vars, ci_test = "pearsonr")

edges = [['Effective Federal Funds Rate', 'Log Stock Price'], ['Log Stock Price',
G = nx.Graph()

edges = model.edges()
pcorr = reg_data.pcorr()
weights = {}
```

In [ ]:
```
from matplotlib.patches import ArrowStyle

def graph_DAG(edges, reg_data, title = ""):
    graph = nx.DiGraph()
    graph.add_edges_from(edges)
    color_map = ["C0" for g in graph]

    fig, ax = plt.subplots(figsize = (20,12))
    graph.nodes()
    plt.tight_layout()
    pos = nx.spring_layout(graph)#, k = 5/(len(sig_corr.keys())**.5))

    plt.title(title, fontsize = 30)
    nx.draw_networkx(graph, pos, node_color=color_map, node_size = 1200,
                     with_labels=True,  arrows=True,
                     font_color = "white",
                     font_size = 26, alpha = 1,
                     width = 1, edge_color = "C1",
                     arrowstyle=ArrowStyle("Fancy, head_length=3, head_width=1.5,

graph_DAG(edges, reg_data, title = "Directed Acyclic Graph")
edges
```

In [ ]:
```
from pgmpy.estimators import PC
c = PC(reg_data)
max_cond_vars = len(reg_data.keys()) - 2


model = c.estimate(return_type = "dag",variant= "parallel",#"orig", "stable"
                   significance_level = p_val,
                   max_cond_vars = max_cond_vars, ci_test = "pearsonr")
edges = model.edges()
```

In [ ]:
```
from matplotlib.patches import ArrowStyle

def graph_DAG(edges, reg_data, title = ""):
    graph = nx.DiGraph()
    graph.add_edges_from(edges)
    color_map = ["C0" for g in graph]

    fig, ax = plt.subplots(figsize = (20,12))
    graph.nodes()
    plt.tight_layout()
    pos = nx.spring_layout(graph)#, k = 5/(len(sig_corr.keys())**.5))

    plt.title(title, fontsize = 30)
    nx.draw_networkx(graph, pos, node_color=color_map, node_size = 1200,
                     with_labels=True,  arrows=True,
                     font_color = "white",
                     font_size = 26, alpha = 1,
                     width = 1, edge_color = "C1",
                     arrowstyle=ArrowStyle("Fancy, head_length=3, head_width=1.5,

graph_DAG(edges, reg_data, title = "Directed Acyclic Graph")
edges
```

In [ ]:
```
def graph_DAG(edges, df, title = ""):
    graph = nx.DiGraph()
    edge_labels = {}
    ############ Add ############
    for edge in edges:
        controls = [key for key in df.keys() if key not in edge]
        controls = list(set(controls))
        keep_controls = []
        for control in controls:
            control_edges = [ctrl_edge for ctrl_edge in edges if control == ctrl_
            if (control, edge[1]) in control_edges:
                print("keep control:", control)
                keep_controls.append(control)
        print(edge, keep_controls)
        pcorr = reg_data[[edge[0], edge[1]]+keep_controls].pcorr()
#          corr_matrix_heatmap(pcorr, save_fig = False, pp = None, title = "Partic
        edge_labels[edge] = str(round(pcorr[edge[0]].loc[edge[1]],2))
    graph.add_edges_from(edges)
    color_map = ["C0" for g in graph]

    fig, ax = plt.subplots(figsize = (20,12))
    graph.nodes()
    plt.tight_layout()
    pos = nx.spring_layout(graph)#, k = 5/(len(sig_corr.keys())**.5))

    plt.title(title, fontsize = 30)
    nx.draw_networkx(graph, pos, node_color=color_map, node_size = 1200,
                     with_labels=True,  arrows=True,
                     # turn text black for larger variable names in homework
                     font_color = "k",
                     font_size = 26, alpha = 1,
                     width = 1, edge_color = "C1",
                     arrowstyle=ArrowStyle("Fancy, head_length=3, head_width=1.5,
    ############ Add ############
    nx.draw_networkx_edge_labels(graph,pos,
                                 edge_labels=edge_labels,
                                 font_color='green',
                                 font_size=20)

graph_DAG(edges, reg_data, title = "Directed Acyclic Graph")
```

In [ ]:
```
here "Log stock price" is my dependent variable (Y)
```