DS_PROJ_py

July 8, 2022

1 Introduction

The interaction between commercial bank activity and financial markets has been a hot topic of discussion since the Global Financial Crisis (GFC). The risk-taking activities of commercial banks was brought under tight scrutiny after the GFC. The effect of bank activity on financial stability has become a large focus of Central Banks all around the world. The focus of this paper is to investigate the interaction between the balance sheets of the major banks in SA and the stock market. Specifically, the major aggregated components of these commercial banks are pooled together, to develop a model for their interaction with the index for the total value of South African shares. The data spans over the months starting from January 1993 up to April 2022 observed over monthly periods.

```
The data is gathered from two different sources. The `BA900` dataset includes all the balance s

The total value for monthly share prices is obtained from FRED (2022).
```

```
[ ]:
```

```
[ ]:
```

```
[ ]:
```

2 Setup (Only for Replication)

2.1 Check Python version

```
[2]: from platform import  python_version
```

```
[3]: python_version()
```

```
[3]: '3.10.5'
```

2.2 Install/Download necessary packages

```
[4]: import sys
```

```
[5]: # # Uncomment these if any packages are not installed in your current jupyter␣
     ↪env
```

```
# # Installing a pip package in the current kernel
# # Pandas also installs the numpy package
# !{sys.executable} -m pip install pandas
# !{sys.executable} -m pip install requests
# !{sys.executable} -m pip install matplotlib
# !{sys.executable} -m pip install sklearn
# !{sys.executable} -m pip install featuretools
# !{sys.executable} -m pip install seaborn
# !{sys.executable} -m pip install jupyterlab-citation-manager
```

[6]:
```
# import the required packages (more imported in the model section)
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import os
import datetime as dt
import featuretools as ft
from featuretools.selection import selection
from IPython.core.interactiveshell import InteractiveShell
from IPython.display import Image
import inspect
from functools import reduce
```

[7]:
```
# import warnings
# warnings.filterwarnings('ignore')
```

2.3 Functions

[8]:
```
def view_files():
    path = os.getcwd()
    path = f"{path}\data"
    return(os.listdir(path))

def check_file(file):
    #grab the file path from which to import the dataset
    path = os.getcwd()
    path = f"{path}\data"
    path = f"{path}\{file}"
    return(path)

def import_data(path):
    # read the csv file as a dataframe and remove unnecessary columns
    df = pd.read_csv(filepath_or_buffer=path)
    return(df)
```

3 Importing and Preprocessing the Data

[9]:
```
view_files()
```

[9]:
```
['absa2.csv',
 'absa_jup.csv',
 'AllShares_growth.csv',
 'banks_data.csv',
 'capitec.csv',
 'feature_imp_select.csv',
 'fnb.csv',
 'household_financial_assets-currency_and_deposits.csv',
 'investec.csv',
 'investment_Qgrowth.csv',
 'inv_by_assets_intellectual.csv',
 'nedbank.csv',
 'share_prices.csv',
 'standard_bank.csv']
```

3.1 Importing and Cleaning

[10]:
```
check_file("absa.csv")
```

[10]:
```
'C:\\GitHub\\DS_PROJ\\data\\absa.csv'
```

[11]:
```
absa = import_data(check_file("absa2.csv"))
absa.head(1)
```

[11]:
```
                      Bank                         Unit  \
0  B_34118: Absa Bank Ltd  U_RT: R'000 (thousands)

                                  Table        Time series code  \
0  T_T01: Table 1: LIABILITIES AT MONTH-END  RBD-B_34118-T_T01-U_RT

   D_M_1993M01: 1993M01  D_M_1993M02: 1993M02  D_M_1993M03: 1993M03  \
0                   NaN                   NaN                   NaN

   D_M_1993M04: 1993M04  D_M_1993M05: 1993M05  D_M_1993M06: 1993M06  …  \
0                   NaN                   NaN                   NaN  …

   D_M_2021M07: 2021M07  D_M_2021M08: 2021M08  D_M_2021M09: 2021M09  \
0                   NaN                   NaN                   NaN

   D_M_2021M10: 2021M10  D_M_2021M11: 2021M11  D_M_2021M12: 2021M12  \
0                   NaN                   NaN                   NaN

   D_M_2022M01: 2022M01  D_M_2022M02: 2022M02  D_M_2022M03: 2022M03  \
```

```
0                    NaN                    NaN                    NaN

   D_M_2022M04: 2022M04
0                    NaN

[1 rows x 356 columns]
```

The data is not stored in the format typically useful for the pandas framework.

First, the unnecessary variables/indicators such as `Units` and `Time series code"`

is be removed or transformed and the excessive variable naming trimmed.

[12]:
```python
def clean_names1(df, bank_prefix="B_34118: "):
    df = df.drop(["Unit", "Time series code"], axis="columns")

    # Remove ugly string labels of columns
    df.columns = df.columns.str.replace(pat="D_M_[0-9]{4}M[0-9]{2}:", repl="",␣
 ↪regex=True)
    df["Bank"] = df["Bank"].str.replace(pat=bank_prefix, repl="", regex=True)
    df["Bank"] = df["Bank"].str.replace(pat = " ", repl = "_")
    return(df)
```

[13]:
```python
absa = clean_names1(absa)
```

[14]:
```python
absa.head(1)
```

[14]:
```
            Bank                                    Table   1993M01  \
0  Absa_Bank_Ltd  T_T01: Table 1: LIABILITIES AT MONTH-END       NaN

   1993M02  1993M03  1993M04  1993M05  1993M06  1993M07  1993M08  …  \
0      NaN      NaN      NaN      NaN      NaN      NaN      NaN  …

   2021M07  2021M08  2021M09  2021M10  2021M11  2021M12  2022M01  \
0      NaN      NaN      NaN      NaN      NaN      NaN      NaN

   2022M02  2022M03  2022M04
0      NaN      NaN      NaN

[1 rows x 354 columns]
```

Below is a check to ensure that all the rows that have lable

`T_T[0-9]{2}R[0-9]{3}:` or `T_T[0-9]{2}R[0-9]{3}_A:` do not

contain any observations and can therefore be removed

[15]:
```python
InteractiveShell.ast_node_interactivity = "all"
```

[16]:
```
all(absa[absa["Table"].str.contains("T_T[0-9]{2}R[0-9]{3}:",
                                    regex = True)].isna().sum(axis=1,
                                                              skipna=False) ==␣
 ↪len(absa.columns) - 2);
all(absa[absa["Table"].str.contains("T_T[0-9]{2}R[0-9]{3}_A:",
                                    regex = True)].isna().sum(axis=1,
                                                              skipna=False) ==␣
 ↪len(absa.columns) - 2)
```

[16]:
```
True
```

[16]:
```
True
```

[17]:
```
InteractiveShell.ast_node_interactivity = "last"
```

Now, we can remove the rows that contain the labels

mentioned above

[18]:
```
def remove_empty(df):
    # Remove empty title rows
    df = df[~df["Table"].str.contains("T_T[0-9]{2}R[0-9]{3}:", regex = True)]
    df = df[~df["Table"].str.contains("T_T[0-9]{2}R[0-9]{3}_A:", regex = True)]

    return(df)
```

[19]:
```
absa = remove_empty(absa)
```

[20]:
```
absa.head(1)
```

[20]:
```
            Bank                                    Table   1993M01  \
0  Absa_Bank_Ltd  T_T01: Table 1: LIABILITIES AT MONTH-END       NaN

   1993M02   1993M03   1993M04   1993M05   1993M06   1993M07   1993M08  …  \
0      NaN       NaN       NaN       NaN       NaN       NaN       NaN  …

   2021M07   2021M08   2021M09   2021M10   2021M11   2021M12   2022M01  \
0      NaN       NaN       NaN       NaN       NaN       NaN       NaN

   2022M02   2022M03   2022M04
0      NaN       NaN       NaN

[1 rows x 354 columns]
```

[21]:
```
# absa.loc[absa["Table"].str.contains("T_T01R[0-9]{3}C[0-9]{2}:␣
 ↪T01R[0-9]{3}[A]{0,1}C[0-9]{2}: ",
#                                 regex=True), :].iloc[:,1:3].set_index("Table").
 ↪head(15)
```

```
absa.loc[absa["Table"].str.contains("T_T01R001|T_T01R002|T_T02R032",
                                    regex=True), :].iloc[:,1:3].set_index("Table")
```

[21]:

```
                                                              1993M01
Table
T_T01R001C01: T01R001C01: DEPOSITS (total of it…   9588342.0
T_T01R001C02: T01R001C02: DEPOSITS (total of it…   7800740.0
T_T01R001C03: T01R001C03: DEPOSITS (total of it…   8946659.0
T_T01R001C04: T01R001C04: DEPOSITS (total of it…   9417927.0
T_T01R001C05: T01R001C05: DEPOSITS (total of it…  21301640.0
T_T01R001C06: T01R001C06: DEPOSITS (total of it…   8981624.0
T_T01R001C07: T01R001C07: DEPOSITS (total of it…  66036932.0
T_T01R001C08: T01R001C08: DEPOSITS (total of it…         NaN
T_T01R002C01: T01R002C01: DEPOSITS DENOMINATED …   9588342.0
T_T01R002C02: T01R002C02: DEPOSITS DENOMINATED …   7800740.0
T_T01R002C03: T01R002C03: DEPOSITS DENOMINATED …   8946145.0
T_T01R002C04: T01R002C04: DEPOSITS DENOMINATED …   9417927.0
T_T01R002C05: T01R002C05: DEPOSITS DENOMINATED …  21299872.0
T_T01R002C06: T01R002C06: DEPOSITS DENOMINATED …   8981624.0
T_T01R002C07: T01R002C07: DEPOSITS DENOMINATED …  66034650.0
T_T01R002C08: T01R002C08: DEPOSITS DENOMINATED …         NaN
T_T02R032C01: T02R032C01: DEPOSITS DENOMINATED …         NaN
T_T02R032C02: T02R032C02: DEPOSITS DENOMINATED …         NaN
T_T02R032C03: T02R032C03: DEPOSITS DENOMINATED …       514.0
T_T02R032C04: T02R032C04: DEPOSITS DENOMINATED …         NaN
T_T02R032C05: T02R032C05: DEPOSITS DENOMINATED …      1768.0
T_T02R032C06: T02R032C06: DEPOSITS DENOMINATED …         NaN
T_T02R032C07: T02R032C07: DEPOSITS DENOMINATED …      2282.0
T_T02R032C09: T02R032C09: DEPOSITS DENOMINATED …         NaN
```

[22]:

```
66034650.0 + 2282.0 == 66036932.0

# i.e. what we have above is
r_001 = absa.loc[absa["Table"].str.contains("DEPOSITS [(]total of items 2 and␣
↪32[)]: TOTAL [(]7[)]"),
        :].iloc[:,3]
r_002 = absa.loc[absa["Table"].str.contains("DEPOSITS DENOMINATED IN RAND␣
↪[(]total of items 3, 6, 12, 13 and 29[)]: TOTAL [(]7[)]"),
          :].iloc[:,3]
r_032 = absa.loc[absa["Table"].str.contains("DEPOSITS DENOMINATED IN FOREIGN␣
↪CURRENCY [(]total of items 33 to 38[)]: TOTAL [(]7[)]"),
          :].iloc[:,3]
int(r_001) == int(r_002) + int(r_032)
```

[22]: True

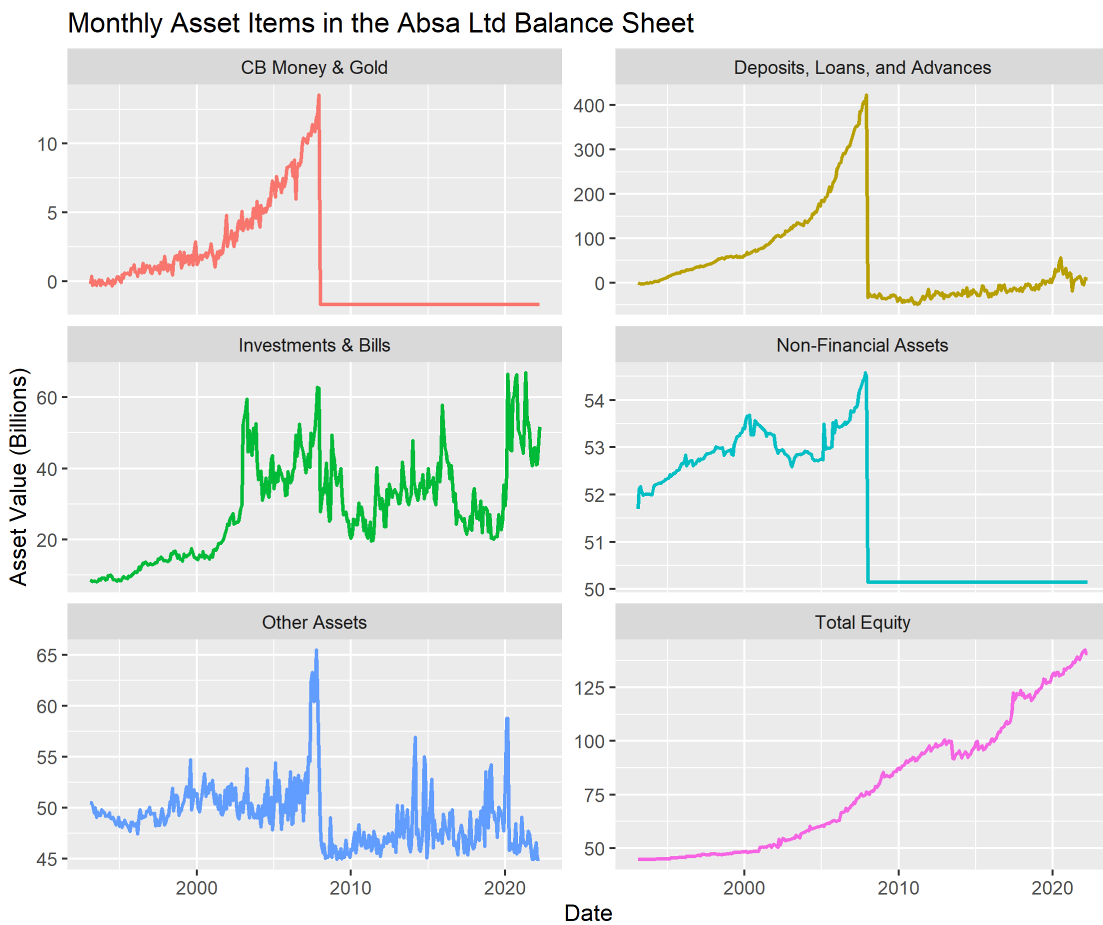
And finally, we can remove the ugly naming

[23]:
```python
def clean_names2(df):
    # Label the different tables withing the df, i.e liablities, assets, etc.
    df["Table"] = df["Table"].str.replace("T_T0[1-2](R[0-9]{3,4})C[0-9]{2}:␣
↪T0[1-2]R[0-9]{3}[A]{0,1}C[0-9]{2}: ",
                                          regex = True, repl=r"L_T1-2_\1_")
    df["Table"] = df["Table"].str.replace("T_T0[3-4](R[0-9]{3,4})C[0-9]{2}:␣
↪T0[3-4]R[0-9]{3}[A]{0,1}C[0-9]{2}: ",
                                          regex = True, repl=r"L_T3-4_\1_")
    df["Table"] = df["Table"].str.replace("T_T0[5](R[0-9]{3,4})C[0-9]{2}:␣
↪T0[5]R[0-9]{3}[A]{0,1}C[0-9]{2}: ",
                                      regex = True, repl=r"E_T5_\1_")
    df["Table"] = df["Table"].str.replace("T_T0[6-9](R[0-9]{3,4})C[0-9]{2}:␣
↪T0[6-9]R[0-9]{3}[A]{0,1}C[0-9]{2}: ",
                                          regex = True, repl=r"A_T6-13_\1_")
    df["Table"] = df["Table"].str.replace("T_T1[0-3](R[0-9]{3,4})C[0-9]{2}:␣
↪T1[0-3]R[0-9]{3}[A]{0,1}C[0-9]{2}: ",
                                          regex = True, repl=r"A_T6-13_\1_")
    df["Table"] = df["Table"].str.replace(",", "")
    # remove bracket explanations
#     df["Table"] = df["Table"].str.replace("[(][0-9a-z\s,]{2,}[)][:] ", regex␣
↪= True, repl="")
    return(df)
```

The lines below are only clear after completing the entire sequence of steps followed in this project and plotting the `Central bank money and gold` variable over time. The total column for this feature is empty from around 2005 and we need to specifically impute the missing values from its subcategory. Similar issues are also present for the `Deposits, Loans, and Advances` and `Non-financial Assets`

[24]:
```python
from IPython.display import Image
Image("./figures/missing_totals.png", width=700, height=700)
```

[24]:



[25]:
```
absa.loc[absa["Table"].str.contains("Central.{,3}Bank", regex=True,␣
↪case=False),][["Table",
                                                  " 2007M11", " 2007M12", "␣
↪2008M01", " 2008M02", " 2022M04"]]
```

[25]:
```
                                             Table     2007M11   \
758  T_T06R103C18: T06R103C18: CENTRAL BANK MONEY A…  13645297.0
759  T_T06R103C19: T06R103C19: CENTRAL BANK MONEY A…         NaN
760  T_T06R103C21: T06R103C21: CENTRAL BANK MONEY A…         0.0
761  T_T06R103C22: T06R103C22: CENTRAL BANK MONEY A…         NaN
762  T_T06R103C24: T06R103C24: CENTRAL BANK MONEY A…  13645297.0
763  T_T06R103C25: T06R103C25: CENTRAL BANK MONEY A…         0.0

        2007M12      2008M01      2008M02      2022M04
758  15190112.0   13758992.0   13315198.0   33454208.0
759         NaN          NaN          NaN          NaN
760         0.0          NaN          NaN          0.0
761         NaN          NaN          NaN          NaN
```

```
762  15190112.0         0.0         0.0         0.0
763         0.0         NaN         NaN         0.0
```

[26]:
```python
absa.loc[absa["Table"].str.contains("Deposits, loans",
                                    regex=True,
                                    case=False),]#[["Table", " 2007M11", "␣
↪2007M12", " 2008M01", " 2008M02"]]
```

[26]:
```
             Bank                                            Table  \
807  Absa_Bank_Ltd  T_T06R110C18: T06R110C18: DEPOSITS, LOANS AND …
808  Absa_Bank_Ltd  T_T06R110C19: T06R110C19: DEPOSITS, LOANS AND …
809  Absa_Bank_Ltd  T_T06R110C21: T06R110C21: DEPOSITS, LOANS AND …
810  Absa_Bank_Ltd  T_T06R110C22: T06R110C22: DEPOSITS, LOANS AND …
811  Absa_Bank_Ltd  T_T06R110C24: T06R110C24: DEPOSITS, LOANS AND …
812  Absa_Bank_Ltd  T_T06R110C25: T06R110C25: DEPOSITS, LOANS AND …

        1993M01     1993M02     1993M03     1993M04     1993M05     1993M06  \
807  64047968.0  65947855.0  64696818.0  63307284.0  63139892.0  63178459.0
808         NaN         NaN         NaN         NaN         NaN         NaN
809    937381.0    838561.0    811696.0    504127.0    949588.0    814481.0
810         NaN         NaN         NaN         NaN         NaN         NaN
811  64985349.0  66786416.0  65508514.0  63811411.0  64089480.0  63992940.0
812         NaN         NaN         NaN     51000.0         NaN     67000.0

        1993M07     1993M08  …      2021M07      2021M08      2021M09  \
807  64254248.0  65044752.0  …  900001589.0  912977212.0  926291034.0
808         NaN         NaN  …          NaN          NaN          NaN
809    408669.0    369640.0  …   51067949.0   52016315.0   52100644.0
810         NaN         NaN  …          NaN          NaN          NaN
811  64662917.0  65414392.0  …   74529667.0   77663925.0   78899748.0
812     76000.0     81000.0  …   57435201.0   60076132.0   59485984.0

         2021M10      2021M11      2021M12      2022M01      2022M02  \
807  930239471.0  973512169.0  956047585.0  938001855.0  941540133.0
808          NaN          NaN          NaN          NaN          NaN
809   52745582.0   53468243.0   52749188.0   52977051.0   53516247.0
810          NaN          NaN          NaN          NaN          NaN
811   81178798.0   74540284.0   64701459.0   62134502.0   76409017.0
812   58404757.0   65695050.0   51309794.0   48540893.0   59137706.0

         2022M03      2022M04
807  942356062.0  952401151.0
808          NaN          NaN
809   51851753.0   53561665.0
810          NaN          NaN
811   75906076.0   75427581.0
812   58564677.0   58874042.0
```

```
[6 rows x 354 columns]
```

[27]:
```
absa.loc[absa["Table"].str.contains("NON-FINANCIAL",
                                    regex=True),][["Table",
                                                   " 2007M11", " 2007M12", "␣
 ↪2008M01", " 2008M02"]]
```

[27]:
```
                                                      Table     2007M11     2007M12  \
1948  T_T13R258C18: T13R258C18: NON-FINANCIAL ASSETS…  4425493.0  4360173.0
1949  T_T13R258C20: T13R258C20: NON-FINANCIAL ASSETS…        NaN        NaN
1950  T_T13R258C21: T13R258C21: NON-FINANCIAL ASSETS…        0.0        0.0
1951  T_T13R258C23: T13R258C23: NON-FINANCIAL ASSETS…        NaN        NaN
1952  T_T13R258C24: T13R258C24: NON-FINANCIAL ASSETS…  4425493.0  4360173.0
1953  T_T13R258C25: T13R258C25: NON-FINANCIAL ASSETS…        NaN        NaN

        2008M01     2008M02
1948  4346590.0   4354713.0
1949        NaN         NaN
1950        NaN         NaN
1951        NaN         NaN
1952        0.0         0.0
1953        NaN         NaN
```

[28]:
```
absa.loc[absa["Table"].str.contains("OTHER ASSETS",
                                    regex=True),][["Table",
                                                   " 2007M11", " 2007M12", "␣
 ↪2008M01", " 2008M02"]]
```

[28]:
```
                                                      Table      2007M11  \
2011  T_T13R267C18: T13R267C18: OTHER ASSETS (total …  16799115.0
2012  T_T13R267C20: T13R267C20: OTHER ASSETS (total …         NaN
2013  T_T13R267C21: T13R267C21: OTHER ASSETS (total …         0.0
2014  T_T13R267C23: T13R267C23: OTHER ASSETS (total …         NaN
2015  T_T13R267C24: T13R267C24: OTHER ASSETS (total …  16799115.0
2016  T_T13R267C25: T13R267C25: OTHER ASSETS (total …         NaN

         2007M12      2008M01      2008M02
2011  10121892.0   19805087.0   13059691.0
2012         NaN          NaN          NaN
2013         0.0          NaN          NaN
2014         NaN          NaN          NaN
2015  10121892.0    3112576.0    1314520.0
2016         NaN          NaN          NaN
```

[29]:
```
test1 = absa.loc[absa["Table"].str.contains("OTHER ASSETS",
```

```
                                        regex=True),].loc[2011," 1993M01" : "␣
↪2007M12"].fillna(0)
test2 = absa.loc[absa["Table"].str.contains("OTHER ASSETS",
                                        regex=True),].loc[2015," 1993M01" : "␣
↪2007M12"].fillna(0)
#sum(test1 == test2), len(test1)
test1[test1 != test2], test2[test1 != test2]
```

[29]:
```
( 1994M04    4219413.0
 Name: 2011, dtype: float64,
  1994M04    4219944.0
 Name: 2015, dtype: float64)
```

[30]:
```
def fill_totals(df):
    # CB money
    repl1 = df["Table"].str.contains("T_T06R103C24: T06R103C24:", regex=True,␣
↪case=False)
    with1 = df["Table"].str.contains("T_T06R103C18: T06R103C18:", regex=True,␣
↪case=False)

    df.loc[repl1,:] = df.loc[repl1,:].replace(list(df.loc[repl1,:].iloc[0,2:]),␣
↪1)
    df.loc[repl1, " 1993M01":] = df.loc[repl1, " 1993M01":].cumsum(axis=1)

    df.loc[repl1,:] = df.loc[repl1,:].replace(list(df.loc[repl1,:].iloc[0,2:]),
                                              list(df.loc[with1,:].iloc[0,2:
↪]))
    # Deposits
    repl2 = df["Table"].str.contains("T_T06R110C24: T06R110C24:", regex=True,␣
↪case=False)
    with2 = df["Table"].str.contains("T_T06R110C18: T06R110C18:", regex=True,␣
↪case=False)
    joint1 = df.loc[with2,:].iloc[0,2:].add(df.loc[repl2,:].iloc[0,2:])["␣
↪2008M01":]
    with2b = list(df.loc[repl2,:].iloc[0,2:][:" 2007M12"].append(joint1))

    df.loc[repl2,:] = df.loc[repl2,:].replace(list(df.loc[repl2,:].iloc[0,2:]),
                                              list(with2b))

    # NON-FINANCIAL ASSETS
    repl3 = df["Table"].str.contains("T_T13R258C24: T13R258C24:", regex=True,␣
↪case=False)
    with3 = df["Table"].str.contains("T_T13R258C18: T13R258C18:", regex=True,␣
↪case=False)
```

```
    df.loc[repl3,:] = df.loc[repl3,:].replace(list(df.loc[repl3,:].iloc[0,2:]),␣
↪1)
    df.loc[repl3, " 1993M01":] = df.loc[repl3, " 1993M01":].cumsum(axis=1)

    df.loc[repl3,:] = df.loc[repl3,:].replace(list(df.loc[repl3,:].iloc[0,2:]),
                                              list(df.loc[with3,:].iloc[0,2:]))

    # OTHER ASSETS
    repl4 = df["Table"].str.contains("T_T13R267C24: T13R267C24:", regex=True,␣
↪case=False)
    with4a = df["Table"].str.contains("T_T13R267C21: T13R267C21:", regex=True,␣
↪case=False)
    with4b = df["Table"].str.contains("T_T13R267C18: T13R267C18:", regex=True,␣
↪case=False)
    joint2 = df.loc[with4a,:].fillna(0).iloc[0,2:].add(df.loc[with4b,:].
↪fillna(0).iloc[0,2:])

    df.loc[repl4,:] = df.loc[repl4,:].replace(list(df.loc[repl4,:].iloc[0,2:]),
                                              list(joint2))

    return(df)
```

[31]:
```
absa = fill_totals(absa)
```

```
C:\Users\gerar\AppData\Local\Temp\ipykernel_9792\3008019174.py:15:
FutureWarning: The series.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  with2b = list(df.loc[repl2,:].iloc[0,2:][:" 2007M12"].append(joint1))
```

[32]:
```
absa = clean_names2(absa)
```

[33]:
```
absa.head(1)
```

[33]:
```
             Bank                                      Table   1993M01  \
0  Absa_Bank_Ltd  T_T01: Table 1: LIABILITIES AT MONTH-END       NaN

    1993M02   1993M03   1993M04   1993M05   1993M06   1993M07   1993M08  …  \
0       NaN       NaN       NaN       NaN       NaN       NaN       NaN  …

    2021M07   2021M08   2021M09   2021M10   2021M11   2021M12   2022M01  \
0       NaN       NaN       NaN       NaN       NaN       NaN       NaN

    2022M02   2022M03   2022M04
0       NaN       NaN       NaN

[1 rows x 354 columns]
```

[34]:
```
list(absa["Table"])[:6]
```

[34]:
```
['T_T01: Table 1: LIABILITIES AT MONTH-END',
 'L_T1-2_R001_DEPOSITS (total of items 2 and 32): Cheque (1)',
 'L_T1-2_R001_DEPOSITS (total of items 2 and 32): Savings (2)',
 'L_T1-2_R001_DEPOSITS (total of items 2 and 32): Up to 1 day (3)',
 'L_T1-2_R001_DEPOSITS (total of items 2 and 32): More than 1 day to 1 month
(4)',
 'L_T1-2_R001_DEPOSITS (total of items 2 and 32): More than 1 month to 6 months
(5)']
```

[35]:
```
list(absa[absa["Table"].str.contains("total", case=False)]["Table"])[:6]
```

[35]:
```
['L_T1-2_R001_DEPOSITS (total of items 2 and 32): Cheque (1)',
 'L_T1-2_R001_DEPOSITS (total of items 2 and 32): Savings (2)',
 'L_T1-2_R001_DEPOSITS (total of items 2 and 32): Up to 1 day (3)',
 'L_T1-2_R001_DEPOSITS (total of items 2 and 32): More than 1 day to 1 month
(4)',
 'L_T1-2_R001_DEPOSITS (total of items 2 and 32): More than 1 month to 6 months
(5)',
 'L_T1-2_R001_DEPOSITS (total of items 2 and 32): More than 6 months (6)']
```

So we want to exclude several types of columns. That is,

Those not containing the uppercase label `TOTAL`

First, to make things easier, the data is split into the three

major components of the Balance Sheet. That is, liabilities, assets, and equity

The dataframe must frist be transposed to ensure it is in the correct form for the model from the start

[36]:
```
list(absa.loc[absa["Table"].str.contains("TOTAL"),:]["Table"])[:6]
```

[36]:
```
['L_T1-2_R001_DEPOSITS (total of items 2 and 32): TOTAL (7)',
 'L_T1-2_R002_DEPOSITS DENOMINATED IN RAND (total of items 3 6 12 13 and 29):
TOTAL (7)',
 'L_T1-2_R003_SA banksb (total of items 4 and 5): TOTAL (7)',
 'L_T1-2_R004_NCDs/PNsi: TOTAL (7)',
 'L_T1-2_R005_Other deposits: TOTAL (7)',
 'L_T1-2_R006_Central and provincial government sector depositsc (total of items
7 10 and 11): TOTAL (7)']
```

It is clear from the above that the columns containing enough

aggregated information are tagged with `(total of items ...)`

so this can be filtered

[37]:
```
def filter_totals(df):
    df = df.loc[df["Table"].str.contains("TOTAL"),:]
    df = df.loc[df["Table"].str.contains("[(]total of items ", regex=True), :]
    dups = df["Table"].str.replace(".*(R[0-9]{3}).*", regex=True, repl=r"\1").
 ↪duplicated()
    df = df.loc[~dups,:]
    return(df)
```

[38]:
```
absa = filter_totals(absa)
```

[39]:
```
InteractiveShell.ast_node_interactivity = "all"
```

[40]:
```
absa.head(1)
absa.info()
```

[40]:
```
              Bank                                               Table  \
8   Absa_Bank_Ltd  L_T1-2_R001_DEPOSITS (total of items 2 and 32)…

      1993M01      1993M02      1993M03      1993M04      1993M05      1993M06  \
8  66036932.0  65948319.0  66446620.0  64813147.0  64317315.0  65148147.0

      1993M07      1993M08  …       2021M07       2021M08       2021M09  \
8  64450271.0  66006474.0  …  987428308.0  978982466.0  990882087.0

        2021M10        2021M11        2021M12      2022M01        2022M02  \
8  1.002621e+09  1.026975e+09  1.025364e+09  997923770.0  1.011085e+09

        2022M03        2022M04
8  1.022591e+09  1.048495e+09

[1 rows x 354 columns]

<class 'pandas.core.frame.DataFrame'>
Int64Index: 67 entries, 8 to 2081
Columns: 354 entries, Bank to  2022M04
dtypes: float64(352), object(2)
memory usage: 185.8+ KB
```

[41]:
```
InteractiveShell.ast_node_interactivity = "last"
```

[42]:
```
def reformat(df):
    df = df.drop("Bank", axis=1)
    df = df.set_index("Table").T
    df.columns.name = None
    df.index.name = "Date"
    df.index = pd.to_datetime(df.index, format=" %YM%m")
    df.columns = df.columns.str.replace(pat=" ", repl="_")
    df.columns = df.columns.str.replace(pat="total_of_items", repl="tot")
```

```
    df = df.apply(pd.to_numeric)

    return(df)
```

[43]:
```
absa = reformat(absa)
```

[44]:
```
def liabilities(df):
    df = df.iloc[:,df.columns.str.startswith(("L_"))]
    return(df)

def equity(df):
    df = df.iloc[:,df.columns.str.startswith(("E_"))]
    return(df)

def assets(df):
    df = df.iloc[:,df.columns.str.startswith(("A_"))]
    return(df)
```

[45]:
```
absa_l = liabilities(absa)
absa_e = equity(absa)
absa_a = assets(absa)
```

[46]:
```
list(absa_l.iloc[:,
                absa_l.columns.str.
 ↪contains("L_T[13]-[24]_R[0-9]{3}_[A-Z]{3,}")].columns[1:-1])
```

[46]:
```
['L_T1-2_R002_DEPOSITS_DENOMINATED_IN_RAND_(tot_3_6_12_13_and_29):_TOTAL_(7)',
 'L_T1-
2_R032_DEPOSITS_DENOMINATED_IN_FOREIGN_CURRENCY_(tot_33_to_38):_TOTAL_(7)',
 'L_T3-4_R041_OTHER_BORROWED_FUNDS_(tot_42_51_and_57):_TOTAL_(4)',
 'L_T3-4_R058_FOREIGN_CURRENCY_FUNDING_(tot_59_to_63_and_66):_TOTAL_(4)',
 'L_T3-4_R067_OTHER_LIABILITIES_TO_THE_PUBLIC_(tot_68_73_74_and_77):_TOTAL_(4)',
 'L_T3-4_R078_TOTAL_LIABILITIES_TO_THE_PUBLIC_(tot_1_41_58_and_67):_Short-
term_(1)',
 'L_T3-4_R080_OTHER_LIABILITIES_(tot_81_85_86_90_91_and_94):_TOTAL_(4)']
```

[47]:
```
list(absa_e.columns[:-2])
```

[47]:
```
['E_T5_R096_TOTAL_EQUITY_(tot_97_and_101):_TOTAL_(1)']
```

[48]:
```
absa_a.iloc[:,absa_a.columns.str.contains("A_T6-13_R[0-9]{3}_[A-Z-]{4,}")].
 ↪columns[:-1]
```

[48]:
```
Index(['A_T6-
13_R103_CENTRAL_BANK_MONEY_AND_GOLD_(tot_104_to_106):_TOTAL_ASSETS_(Col_1_plus_c
ol_3)_(5)',
       'A_T6-
13_R110_DEPOSITS_LOANS_AND_ADVANCES_(tot_111_117_118_126_135_139_150_166_171_and
```

```
_180_less_item_194):_TOTAL_ASSETS_(Col_1_plus_col_3)_(5)',
       'A_T6-
13_R195_INVESTMENTS_AND_BILLS_including_trading_portfolio_assets_(tot_196_207_21
3_217_221_225_229_233_237_241_and_246_less_item_245):_TOTAL_ASSETS_(Col_1_plus_c
ol_3)_(5)',
       'A_T6-13_R258_NON-
FINANCIAL_ASSETS_(tot_259_and_264):_TOTAL_ASSETS_(Col_1_plus_col_3)_(5)',
       'A_T6-
13_R267_OTHER_ASSETS_(tot_268_to_272_and_276):_TOTAL_ASSETS_(Col_1_plus_col_3)_(
5)'],
      dtype='object')
```

The columns referring to `RXXX` indexes prior to its own

will be removed, and the the `tot_XXX` columns referred to in the

brackets above will be used to include more information

[49]:
```python
def clean_liab(df):
    keep = list(df.iloc[:,
                            df.columns.str.
 ↪contains("L_T[13]-[24]_R[0-9]{3}_[A-Z]{3,}")].columns[1:-1])
    del keep[-2]
    df = df[keep]
    df.columns = df.columns.str.replace("T[13]-[24]_R[0-9]{3}_", "", regex=True)
    df.columns = df.columns.str.replace("_[(].*[)]:", "", regex=True)
    df.columns = df.columns.str.replace("_[(][0-9][)]", "", regex=True)
    return(df)

def clean_assets(df):
    keep = list(df.iloc[:,
                            df.columns.str.
 ↪contains("A_T6-13_R[0-9]{3}_[A-Z-]{4,}")].columns[:-1])
    df = df[keep]
    df.columns = df.columns.str.replace("T6-13_R[0-9]{3}_", "", regex=True)
    df.columns = df.columns.str.replace("_[(].*[)]:", "", regex=True)
    df.columns = df.columns.str.replace("_[(][0-9][)]", "", regex=True)
    df.columns = df.columns.str.replace("_[(].*[)]", "", regex=True)
    return(df)

def clean_equity(df):
    keep = list(df.columns[:-2])
    df = df[keep]
    df.columns = df.columns.str.replace("T5_R[0-9]{3}_", "", regex=True)
    df.columns = df.columns.str.replace("_[(].*[)]:", "", regex=True)
    df.columns = df.columns.str.replace("_[(][0-9][)]", "", regex=True)
    return(df)
```

[50]:
```python
absa_l = clean_liab(absa_l)
absa_e = clean_equity(absa_e)
absa_a = clean_assets(absa_a)
```

[51]:
```python
def join_diff(liab, ass, eq, bank="ABSA"):
    df = pd.concat([liab, ass, eq], axis = 1)
#     df = df.replace(0, 1)
#     df = df.fillna(1)
    df = df.fillna(0)
#     df = np.log(df)
    df = df.diff()
    df = df.iloc[1:,:]
    df.insert(0, "Bank", bank)
    return(df)
```

[52]:
```python
absa = join_diff(absa_l, absa_a, absa_e)
```

[53]:
```python
check_file("absa2.csv")
```

[53]:
```
'C:\\GitHub\\DS_PROJ\\data\\absa2.csv'
```

[54]:
```python
# Call the following to see a clear picture of the sequence of
# steps to clean each of the banks' datasets.
[ f for f in globals().values() if inspect.isfunction(f) ]
```

[54]:
```
[<function platform.python_version()>,
 <function __main__.view_files()>,
 <function __main__.check_file(file)>,
 <function __main__.import_data(path)>,
 <function __main__.clean_names1(df, bank_prefix='B_34118: ')>,
 <function __main__.remove_empty(df)>,
 <function __main__.clean_names2(df)>,
 <function __main__.fill_totals(df)>,
 <function __main__.filter_totals(df)>,
 <function __main__.reformat(df)>,
 <function __main__.liabilities(df)>,
 <function __main__.equity(df)>,
 <function __main__.assets(df)>,
 <function __main__.clean_liab(df)>,
 <function __main__.clean_assets(df)>,
 <function __main__.clean_equity(df)>,
 <function __main__.join_diff(liab, ass, eq, bank='ABSA')>]
```

[55]:
```python
view_files()
```

[55]:
```
['absa2.csv',
 'absa_jup.csv',
 'AllShares_growth.csv',
```

```
 'banks_data.csv',
 'capitec.csv',
 'feature_imp_select.csv',
 'fnb.csv',
 'household_financial_assets-currency_and_deposits.csv',
 'investec.csv',
 'investment_Qgrowth.csv',
 'inv_by_assets_intellectual.csv',
 'nedbank.csv',
 'share_prices.csv',
 'standard_bank.csv']
```

[56]:
```
check_file("standard_bank.csv")
```

[56]:
```
'C:\\GitHub\\DS_PROJ\\data\\standard_bank.csv'
```

[57]:
```
absa.to_csv("C:/GitHub/DS_PROJ/data/absa_jup.csv")
```

[58]:
```
standard_bank = reformat(filter_totals(clean_names2(fill_totals(
    remove_empty(clean_names1(import_data(check_file("standard_bank.csv")),
                                                                         ␣
 ↪bank_prefix="B_416061: "))))))
standard_bank
l_std = clean_liab(liabilities(standard_bank))
e_std = clean_equity(equity(standard_bank))
a_std = clean_assets(assets(standard_bank))

standard_bank = join_diff(l_std, e_std, a_std, bank="STANDARD_BANK")
standard_bank.head(1)
```

```
C:\Users\gerar\AppData\Local\Temp\ipykernel_9792\3008019174.py:15:
FutureWarning: The series.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  with2b = list(df.loc[repl2,:].iloc[0,2:][:" 2007M12"].append(joint1))
```

[58]:
```
                     Bank  L_DEPOSITS_DENOMINATED_IN_RAND_TOTAL  \
Date
1993-02-01  STANDARD_BANK                             -420910.0

            L_DEPOSITS_DENOMINATED_IN_FOREIGN_CURRENCY_TOTAL  \
Date
1993-02-01                                           -3967.0

            L_OTHER_BORROWED_FUNDS_TOTAL  L_FOREIGN_CURRENCY_FUNDING_TOTAL  \
Date
1993-02-01                     -314590.0                          -58478.0

            L_OTHER_LIABILITIES_TO_THE_PUBLIC_TOTAL  \
```

```
Date
1993-02-01                                   113171.0

            L_OTHER_LIABILITIES_TOTAL  E_TOTAL_EQUITY_TOTAL  \
Date
1993-02-01                    87232.0              152636.0

            A_CENTRAL_BANK_MONEY_AND_GOLD_TOTAL_ASSETS  \
Date
1993-02-01                                    -89264.0

            A_DEPOSITS_LOANS_AND_ADVANCES_TOTAL_ASSETS  \
Date
1993-02-01                                   -899615.0

A_INVESTMENTS_AND_BILLS_including_trading_portfolio_assets_TOTAL_ASSETS  \
Date
1993-02-01                                           173511.0

            A_NON-FINANCIAL_ASSETS_TOTAL_ASSETS  A_OTHER_ASSETS_TOTAL_ASSETS
Date
1993-02-01                               -394.0                     160439.0
```

[59]:

```
fnb = reformat(filter_totals(clean_names2(fill_totals(
    remove_empty(clean_names1(import_data(check_file("fnb.csv")),
                                        bank_prefix=""))))))
fnb
l = clean_liab(liabilities(fnb))
e = clean_equity(equity(fnb))
a = clean_assets(assets(fnb))

fnb = join_diff(l, e, a, bank="FNB")
fnb.head(1)
```

```
C:\Users\gerar\AppData\Local\Temp\ipykernel_9792\3008019174.py:15:
FutureWarning: The series.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  with2b = list(df.loc[repl2,:].iloc[0,2:][:" 2007M12"].append(joint1))
```

[59]:

```
           Bank  L_DEPOSITS_DENOMINATED_IN_RAND_TOTAL  \
Date
1993-02-01  FNB                             1325346.0

            L_DEPOSITS_DENOMINATED_IN_FOREIGN_CURRENCY_TOTAL  \
Date
1993-02-01                                          128151.0

            L_OTHER_BORROWED_FUNDS_TOTAL  L_FOREIGN_CURRENCY_FUNDING_TOTAL  \
```

```
Date
1993-02-01                      27282.0                              -252496.0

            L_OTHER_LIABILITIES_TO_THE_PUBLIC_TOTAL  \
Date
1993-02-01                                -1150666.0

            L_OTHER_LIABILITIES_TOTAL  E_TOTAL_EQUITY_TOTAL  \
Date
1993-02-01                  -105941.0                 239.0

            A_CENTRAL_BANK_MONEY_AND_GOLD_TOTAL_ASSETS  \
Date
1993-02-01                                   -104879.0

            A_DEPOSITS_LOANS_AND_ADVANCES_TOTAL_ASSETS  \
Date
1993-02-01                                    315014.0

A_INVESTMENTS_AND_BILLS_including_trading_portfolio_assets_TOTAL_ASSETS  \
Date
1993-02-01                                          -185054.0

            A_NON-FINANCIAL_ASSETS_TOTAL_ASSETS  A_OTHER_ASSETS_TOTAL_ASSETS
Date
1993-02-01                              37124.0                    -130543.0
```

[60]:
```
nedbank = reformat(filter_totals(clean_names2(fill_totals(
    remove_empty(clean_names1(import_data(check_file("nedbank.csv")),
 ␣
  ↪bank_prefix=""))))))
nedbank
l = clean_liab(liabilities(nedbank))
e = clean_equity(equity(nedbank))
a = clean_assets(assets(nedbank))

nedbank = join_diff(l, e, a, bank="NEDBANK")
nedbank.head(1)
```

```
C:\Users\gerar\AppData\Local\Temp\ipykernel_9792\3008019174.py:15:
FutureWarning: The series.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  with2b = list(df.loc[repl2,:].iloc[0,2:][:" 2007M12"].append(joint1))
```

[60]:
```
               Bank  L_DEPOSITS_DENOMINATED_IN_RAND_TOTAL  \
Date
1993-02-01  NEDBANK                             -353276.0
```

```
            L_DEPOSITS_DENOMINATED_IN_FOREIGN_CURRENCY_TOTAL  \
Date
1993-02-01                                           -59594.0

            L_OTHER_BORROWED_FUNDS_TOTAL  L_FOREIGN_CURRENCY_FUNDING_TOTAL  \
Date
1993-02-01                      -38339.0                          -21189.0

            L_OTHER_LIABILITIES_TO_THE_PUBLIC_TOTAL  \
Date
1993-02-01                                  73316.0

            L_OTHER_LIABILITIES_TOTAL  E_TOTAL_EQUITY_TOTAL  \
Date
1993-02-01                    24800.0              -21486.0

            A_CENTRAL_BANK_MONEY_AND_GOLD_TOTAL_ASSETS  \
Date
1993-02-01                                     51383.0

            A_DEPOSITS_LOANS_AND_ADVANCES_TOTAL_ASSETS  \
Date
1993-02-01                                    222317.0

A_INVESTMENTS_AND_BILLS_including_trading_portfolio_assets_TOTAL_ASSETS  \
Date
1993-02-01                                          -491901.0

            A_NON-FINANCIAL_ASSETS_TOTAL_ASSETS  A_OTHER_ASSETS_TOTAL_ASSETS
Date
1993-02-01                              43588.0                    -196910.0
```

[61]:

```
investec = reformat(filter_totals(clean_names2(fill_totals(
    remove_empty(clean_names1(import_data(check_file("investec.csv")),
 
  ↪bank_prefix=""))))))
investec
l = clean_liab(liabilities(investec))
e = clean_equity(equity(investec))
a = clean_assets(assets(investec))

investec = join_diff(l, e, a, bank="INVESTEC")
investec.head(1)
```

```
C:\Users\gerar\AppData\Local\Temp\ipykernel_9792\3008019174.py:15:
FutureWarning: The series.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  with2b = list(df.loc[repl2,:].iloc[0,2:][:" 2007M12"].append(joint1))
```

[61]:
```
                Bank  L_DEPOSITS_DENOMINATED_IN_RAND_TOTAL  \
Date
1993-02-01  INVESTEC                               96785.0

            L_DEPOSITS_DENOMINATED_IN_FOREIGN_CURRENCY_TOTAL  \
Date
1993-02-01                                               0.0

            L_OTHER_BORROWED_FUNDS_TOTAL  L_FOREIGN_CURRENCY_FUNDING_TOTAL  \
Date
1993-02-01                        4125.0                            -877.0

            L_OTHER_LIABILITIES_TO_THE_PUBLIC_TOTAL  \
Date
1993-02-01                                   3866.0

            L_OTHER_LIABILITIES_TOTAL  E_TOTAL_EQUITY_TOTAL  \
Date
1993-02-01                        0.0                5918.0

            A_CENTRAL_BANK_MONEY_AND_GOLD_TOTAL_ASSETS  \
Date
1993-02-01                                      -926.0

            A_DEPOSITS_LOANS_AND_ADVANCES_TOTAL_ASSETS  \
Date
1993-02-01                                    129179.0

A_INVESTMENTS_AND_BILLS_including_trading_portfolio_assets_TOTAL_ASSETS  \
Date
1993-02-01                                            -4823.0

            A_NON-FINANCIAL_ASSETS_TOTAL_ASSETS  A_OTHER_ASSETS_TOTAL_ASSETS
Date
1993-02-01                                853.0                      -2350.0
```

[62]:
```
capitec = reformat(filter_totals(clean_names2(fill_totals(
    remove_empty(clean_names1(import_data(check_file("capitec.csv")),
                                                                              ␣
  ↪bank_prefix=""))))))
capitec
l = clean_liab(liabilities(capitec))
e = clean_equity(equity(capitec))
a = clean_assets(assets(capitec))

capitec = join_diff(l, e, a, bank="CAPITEC")
capitec.head(1)
```

```
C:\Users\gerar\AppData\Local\Temp\ipykernel_9792\3008019174.py:15:
FutureWarning: The series.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  with2b = list(df.loc[repl2,:].iloc[0,2:][:" 2007M12"].append(joint1))
```

[62]:
```
                 Bank  L_DEPOSITS_DENOMINATED_IN_RAND_TOTAL  \
Date
1993-02-01  CAPITEC                                   0.0

            L_DEPOSITS_DENOMINATED_IN_FOREIGN_CURRENCY_TOTAL  \
Date
1993-02-01                                               0.0

            L_OTHER_BORROWED_FUNDS_TOTAL  L_FOREIGN_CURRENCY_FUNDING_TOTAL  \
Date
1993-02-01                           0.0                               0.0

            L_OTHER_LIABILITIES_TO_THE_PUBLIC_TOTAL  \
Date
1993-02-01                                      0.0

            L_OTHER_LIABILITIES_TOTAL  E_TOTAL_EQUITY_TOTAL  \
Date
1993-02-01                        0.0                   0.0

            A_CENTRAL_BANK_MONEY_AND_GOLD_TOTAL_ASSETS  \
Date
1993-02-01                                         0.0

            A_DEPOSITS_LOANS_AND_ADVANCES_TOTAL_ASSETS  \
Date
1993-02-01                                         0.0

A_INVESTMENTS_AND_BILLS_including_trading_portfolio_assets_TOTAL_ASSETS  \
Date
1993-02-01                                                0.0

            A_NON-FINANCIAL_ASSETS_TOTAL_ASSETS  A_OTHER_ASSETS_TOTAL_ASSETS
Date
1993-02-01                                  0.0                          0.0
```

4 Aggregating the Banks Together

[63]:
```
def join_banks(df1, df2, df3, df4, df5, df6):
    df = reduce(lambda a, b: a.add(b, fill_value=0), [df1, df2, df3, df4, df5,
 ↪df6])
    df = df.drop("Bank", axis=1)
```

```python
    return(df)
```

[64]:
```python
banks = join_banks(absa, standard_bank, nedbank, fnb, capitec, investec)
```

[65]:
```python
banks.head(1)
```

[65]:
```
            A_CENTRAL_BANK_MONEY_AND_GOLD_TOTAL_ASSETS  \
Date
1993-02-01                                   -327647.0

            A_DEPOSITS_LOANS_AND_ADVANCES_TOTAL_ASSETS  \
Date
1993-02-01                                   1567962.0

A_INVESTMENTS_AND_BILLS_including_trading_portfolio_assets_TOTAL_ASSETS  \
Date
1993-02-01                                          -629455.0

            A_NON-FINANCIAL_ASSETS_TOTAL_ASSETS  A_OTHER_ASSETS_TOTAL_ASSETS  \
Date
1993-02-01                              83391.0                     143264.0

            E_TOTAL_EQUITY_TOTAL  \
Date
1993-02-01              137307.0

            L_DEPOSITS_DENOMINATED_IN_FOREIGN_CURRENCY_TOTAL  \
Date
1993-02-01                                           64119.0

            L_DEPOSITS_DENOMINATED_IN_RAND_TOTAL  \
Date
1993-02-01                              559803.0

            L_FOREIGN_CURRENCY_FUNDING_TOTAL  L_OTHER_BORROWED_FUNDS_TOTAL  \
Date
1993-02-01                         -236352.0                     1071988.0

            L_OTHER_LIABILITIES_TOTAL  L_OTHER_LIABILITIES_TO_THE_PUBLIC_TOTAL
Date
1993-02-01                   367124.0                                -687740.0
```

[66]:
```python
banks.to_csv("./data/banks_data.csv")
```

5 Shares

[67]:
```python
shares = pd.read_csv("./data/share_prices.csv")
shares.head(1)
```

[67]:
```
  LOCATION INDICATOR SUBJECT  MEASURE FREQUENCY     TIME     Value  Flag Codes
0      ZAF   SHPRICE     TOT  IDX2015         M  1960-01  0.367696         NaN
```

[68]:
```python
def wrangle_shares(df):
    df = shares[["TIME", "Value"]]
    df = df.set_index("TIME")
    df.index = pd.to_datetime(df.index, format="%Y-%m")
    df = df.diff()
    df = df.loc["1993-02-01":"2022-04-01"]
    return(df)
```

[69]:
```python
shares = wrangle_shares(shares)
```

[70]:
```python
InteractiveShell.ast_node_interactivity = "all"
```

[71]:
```python
shares.head(1)
banks.head(1)
```

[71]:
```
               Value
TIME
1993-02-01  0.161575
```

[71]:
```
            A_CENTRAL_BANK_MONEY_AND_GOLD_TOTAL_ASSETS  \
Date
1993-02-01                                   -327647.0

            A_DEPOSITS_LOANS_AND_ADVANCES_TOTAL_ASSETS  \
Date
1993-02-01                                   1567962.0

A_INVESTMENTS_AND_BILLS_including_trading_portfolio_assets_TOTAL_ASSETS  \
Date
1993-02-01                                          -629455.0

            A_NON-FINANCIAL_ASSETS_TOTAL_ASSETS  A_OTHER_ASSETS_TOTAL_ASSETS  \
Date
1993-02-01                              83391.0                     143264.0

            E_TOTAL_EQUITY_TOTAL  \
Date
1993-02-01              137307.0

            L_DEPOSITS_DENOMINATED_IN_FOREIGN_CURRENCY_TOTAL  \
```

```
Date
1993-02-01                                           64119.0

            L_DEPOSITS_DENOMINATED_IN_RAND_TOTAL  \
Date
1993-02-01                              559803.0

            L_FOREIGN_CURRENCY_FUNDING_TOTAL  L_OTHER_BORROWED_FUNDS_TOTAL  \
Date
1993-02-01                         -236352.0                     1071988.0

            L_OTHER_LIABILITIES_TOTAL  L_OTHER_LIABILITIES_TO_THE_PUBLIC_TOTAL
Date
1993-02-01                   367124.0                                -687740.0
```

[72]:
```
shares.describe()
banks.describe()
```

[72]:
```
            Value
count  351.000000
mean     0.383069
std      2.417176
min    -21.702500
25%     -0.475430
50%      0.378450
75%      1.437770
max      7.425600
```

[72]:
```
       A_CENTRAL_BANK_MONEY_AND_GOLD_TOTAL_ASSETS  \
count                                3.510000e+02
mean                                 4.522916e+05
std                                  4.388543e+06
min                                 -3.286008e+07
25%                                 -9.751130e+05
50%                                  3.522990e+05
75%                                  1.695969e+06
max                                  3.266915e+07

       A_DEPOSITS_LOANS_AND_ADVANCES_TOTAL_ASSETS  \
count                                3.510000e+02
mean                                 1.216169e+07
std                                  2.469413e+07
min                                 -6.296183e+07
25%                                  1.065199e+06
50%                                  6.731999e+06
75%                                  2.046875e+07
max                                  1.617355e+08
```

	A_INVESTMENTS_AND_BILLS_including_trading_portfolio_assets_TOTAL_ASSETS \
count	3.510000e+02
mean	7.703279e+05
std	1.943875e+07
min	-1.915898e+08
25%	-5.354569e+06
50%	4.978690e+05
75%	4.663307e+06
max	1.112526e+08

	A_NON-FINANCIAL_ASSETS_TOTAL_ASSETS	A_OTHER_ASSETS_TOTAL_ASSETS \
count	3.510000e+02	3.510000e+02
mean	2.380714e+05	2.597255e+05
std	7.220150e+05	6.272783e+06
min	-3.097381e+06	-2.992281e+07
25%	-1.842232e+04	-2.282324e+06
50%	9.156500e+04	1.432640e+05
75%	4.029994e+05	2.710220e+06
max	9.287935e+06	2.450820e+07

	E_TOTAL_EQUITY_TOTAL	L_DEPOSITS_DENOMINATED_IN_FOREIGN_CURRENCY_TOTAL \
count	3.510000e+02	3.510000e+02
mean	1.251278e+06	6.527960e+05
std	2.918968e+06	5.364917e+06
min	-1.038261e+07	-2.428134e+07
25%	2.306700e+04	-9.084105e+05
50%	7.013292e+05	1.480770e+05
75%	2.390600e+06	1.976295e+06
max	1.501661e+07	3.276245e+07

	L_DEPOSITS_DENOMINATED_IN_RAND_TOTAL	L_FOREIGN_CURRENCY_FUNDING_TOTAL \
count	3.510000e+02	3.510000e+02
mean	1.210421e+07	2.923482e+05
std	2.252057e+07	8.627608e+06
min	-8.141831e+07	-4.037649e+07
25%	4.027476e+05	-2.348286e+06
50%	6.593286e+06	1.650020e+05
75%	2.406895e+07	3.190577e+06
max	1.102514e+08	4.316232e+07

	L_OTHER_BORROWED_FUNDS_TOTAL	L_OTHER_LIABILITIES_TOTAL \
count	3.510000e+02	3.510000e+02
mean	5.795071e+05	1.438985e+06
std	8.963922e+06	2.793051e+07
min	-3.680302e+07	-6.614101e+07

```
25%                     -2.627997e+06            -9.501097e+06
50%                      2.978050e+05             2.458900e+04
75%                      3.645654e+06             6.042989e+06
max                      3.045689e+07             2.447002e+08

       L_OTHER_LIABILITIES_TO_THE_PUBLIC_TOTAL
count                             3.510000e+02
mean                              1.168575e+06
std                               4.931576e+06
min                              -1.316763e+07
25%                              -8.986175e+05
50%                               4.196943e+05
75%                               2.304931e+06
max                               5.659738e+07
```

[73]:
```
InteractiveShell.ast_node_interactivity = "last"
```

6 Correlation Analysis

[74]:
```
share_corr = shares.join(banks).corr()[["Value"]]
plot_names = share_corr[share_corr["Value"]<0.10].index.to_list()
share_corr.sort_values("Value", key=abs, ascending=False)
```

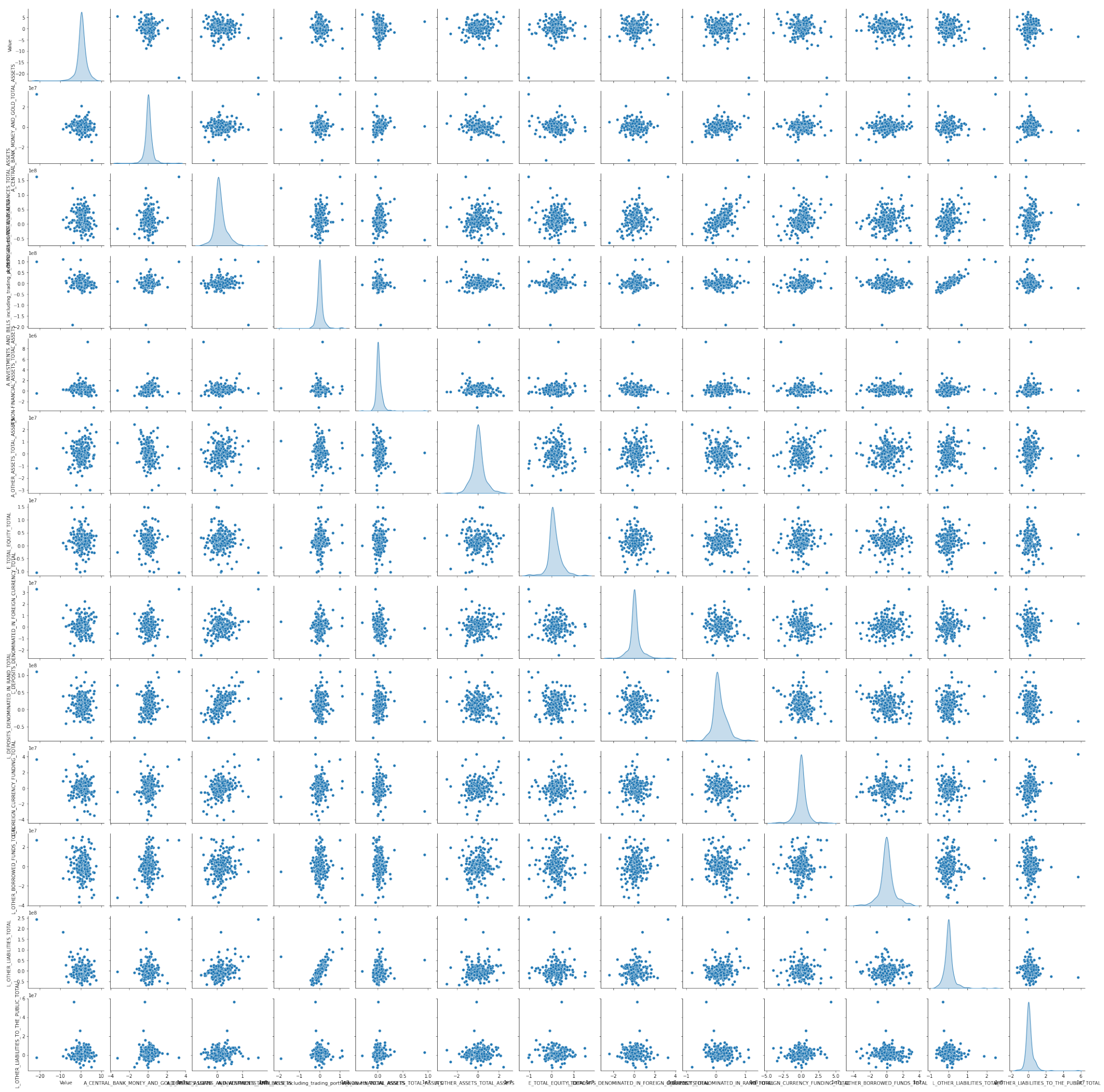
[74]:
```
                                                        Value
Value                                                1.000000
L_OTHER_LIABILITIES_TOTAL                           -0.366697
A_CENTRAL_BANK_MONEY_AND_GOLD_TOTAL_ASSETS          -0.300625
L_FOREIGN_CURRENCY_FUNDING_TOTAL                    -0.224657
A_DEPOSITS_LOANS_AND_ADVANCES_TOTAL_ASSETS          -0.204616
A_INVESTMENTS_AND_BILLS_including_trading_portf… -0.201991
L_OTHER_BORROWED_FUNDS_TOTAL                        -0.170269
A_OTHER_ASSETS_TOTAL_ASSETS                          0.155158
L_DEPOSITS_DENOMINATED_IN_FOREIGN_CURRENCY_TOTAL    -0.119003
L_DEPOSITS_DENOMINATED_IN_RAND_TOTAL                -0.114247
E_TOTAL_EQUITY_TOTAL                                 0.089638
A_NON-FINANCIAL_ASSETS_TOTAL_ASSETS                 -0.042484
L_OTHER_LIABILITIES_TO_THE_PUBLIC_TOTAL             -0.026856
```

[ ]:
```

```

[75]:
```
import seaborn as sns

sns.pairplot(shares.join(banks), diag_kind="kde")
plt.show()
```



```
[76]: def quarter_delay(banks_df, shares_df):
          banks_df = banks_df.shift(-3, "MS")
          joined_df = shares_df.join(banks_df, how="inner")
          shares_df = joined_df[["Value"]]
          banks_df = joined_df.iloc[:,1:]
          return(banks_df, shares_df)
```

```
[77]: def month_delay(banks_df, shares_df):
          banks_df = banks_df.shift(-1, "MS")
          joined_df = shares_df.join(banks_df, how="inner")
          shares_df = joined_df[["Value"]]
          banks_df = joined_df.iloc[:,1:]
          return(banks_df, shares_df)
```

[78]:
```
qbanks, qshares = quarter_delay(banks, shares)
```

[79]:
```
mbanks, mshares = month_delay(banks, shares)
```

[80]:
```
def compare_corr():
    share_corr = shares.join(banks).corr()[["Value"]]
    mshare_corr = mshares.join(mbanks).corr()[["Value"]]
    qshare_corr = qshares.join(qbanks).corr()[["Value"]]
    plot_names = share_corr[share_corr["Value"]<0.10].index.to_list()
    corrSTD = share_corr.sort_values("Value", key=abs, ascending=False)
    corrM = mshare_corr.sort_values("Value", key=abs)
    corrQ = qshare_corr.sort_values("Value", key=abs)
    corrjoin1 = corrSTD.join(corrM, lsuffix="_STD", rsuffix="_M")
    corrjoin1 = corrjoin1.join(corrQ, rsuffix="_Q")
    corrjoin1["M > Q"] = abs(corrjoin1["Value_M"]) > abs(corrjoin1["Value"])
    corrjoin1.loc["Total"] = corrjoin1.sum()
    return(corrjoin1)

compare_corr()
```

[80]:
```
                                                     Value_STD   Value_M  \
Value                                                 1.000000  1.000000
L_OTHER_LIABILITIES_TOTAL                            -0.366697 -0.162764
A_CENTRAL_BANK_MONEY_AND_GOLD_TOTAL_ASSETS           -0.300625  0.267213
L_FOREIGN_CURRENCY_FUNDING_TOTAL                     -0.224657 -0.006258
A_DEPOSITS_LOANS_AND_ADVANCES_TOTAL_ASSETS           -0.204616  0.029271
A_INVESTMENTS_AND_BILLS_including_trading_portf…  -0.201991 -0.088938
L_OTHER_BORROWED_FUNDS_TOTAL                         -0.170269  0.148842
A_OTHER_ASSETS_TOTAL_ASSETS                           0.155158 -0.000785
L_DEPOSITS_DENOMINATED_IN_FOREIGN_CURRENCY_TOTAL     -0.119003 -0.079976
L_DEPOSITS_DENOMINATED_IN_RAND_TOTAL                 -0.114247  0.020994
E_TOTAL_EQUITY_TOTAL                                  0.089638  0.163713
A_NON-FINANCIAL_ASSETS_TOTAL_ASSETS                  -0.042484 -0.095868
L_OTHER_LIABILITIES_TO_THE_PUBLIC_TOTAL              -0.026856 -0.082753
Total                                                -0.526648  1.112691

                                                        Value  M > Q
Value                                                1.000000  False
L_OTHER_LIABILITIES_TOTAL                           -0.093664   True
A_CENTRAL_BANK_MONEY_AND_GOLD_TOTAL_ASSETS          -0.017780   True
L_FOREIGN_CURRENCY_FUNDING_TOTAL                     0.029655  False
A_DEPOSITS_LOANS_AND_ADVANCES_TOTAL_ASSETS           0.021923   True
A_INVESTMENTS_AND_BILLS_including_trading_portf… -0.118528  False
L_OTHER_BORROWED_FUNDS_TOTAL                         0.161640  False
A_OTHER_ASSETS_TOTAL_ASSETS                          0.078833  False
L_DEPOSITS_DENOMINATED_IN_FOREIGN_CURRENCY_TOTAL     0.032351   True
L_DEPOSITS_DENOMINATED_IN_RAND_TOTAL                -0.091561  False
```

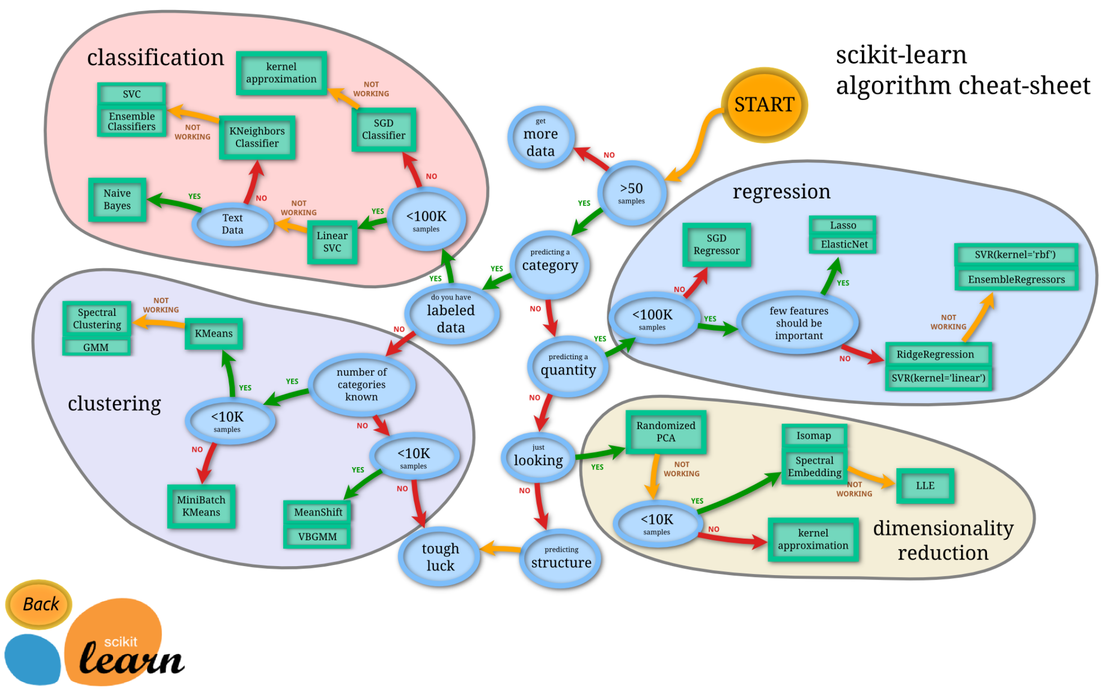
E_TOTAL_EQUITY_TOTAL	0.023564	True
A_NON-FINANCIAL_ASSETS_TOTAL_ASSETS	-0.050095	True
L_OTHER_LIABILITIES_TO_THE_PUBLIC_TOTAL	0.025663	True
Total	1.002002	7.0

7 Model

Base on the scikit-learn estimator roadmap shown below, the ideal estimator to start with will be the `Ridge` regression estimator

[81]:
```
url='https://scikit-learn.org/stable/_static/ml_map.png'
Image(url, width=700, height=700)
```

[81]:



7.1 Base Model - LASSO Regression

[82]:
```
from sklearn.linear_model import Ridge
from sklearn.preprocessing import Normalizer
from sklearn.model_selection import TimeSeriesSplit

X = np.array(banks)
y = np.array(shares["Value"])

scaler = Normalizer()
X = scaler.fit_transform(X)
```

```
tss = TimeSeriesSplit()

ridge = Ridge()
ridge.fit(X, y)
```

[82]: Ridge()

[83]:
```
def coeff_exaplained(df, coeff):
    features_coeff = pd.DataFrame(columns=["Feature_Coeff"])
    features = df.columns.to_list()
    j = 0
    for i in coeff:
        #print(f"{features[j]}: {i}")
        features_coeff.loc[f"{features[j]}"] = [i]
        j+=1
    features_coeff.sort_values("Feature_Coeff", ascending=False, inplace=True,␣
 ↪key=abs)
    return(features_coeff)
```

[84]:
```
coeff_exaplained(banks, ridge.coef_)
```

[84]:

	Feature_Coeff
L_FOREIGN_CURRENCY_FUNDING_TOTAL	-1.827367
A_OTHER_ASSETS_TOTAL_ASSETS	1.552313
L_OTHER_BORROWED_FUNDS_TOTAL	-1.266400
L_OTHER_LIABILITIES_TOTAL	-1.066132
L_OTHER_LIABILITIES_TO_THE_PUBLIC_TOTAL	-0.717617
A_INVESTMENTS_AND_BILLS_including_trading_portf…	0.518765
A_CENTRAL_BANK_MONEY_AND_GOLD_TOTAL_ASSETS	-0.518271
L_DEPOSITS_DENOMINATED_IN_RAND_TOTAL	-0.420953
A_DEPOSITS_LOANS_AND_ADVANCES_TOTAL_ASSETS	0.273966
A_NON-FINANCIAL_ASSETS_TOTAL_ASSETS	-0.174446
E_TOTAL_EQUITY_TOTAL	-0.109360
L_DEPOSITS_DENOMINATED_IN_FOREIGN_CURRENCY_TOTAL	0.017474

[85]:
```
from sklearn.model_selection import cross_val_score
def scores(X, y, model):
    '''Returns a dataframe containing the MSE &
       R-Squared metrics of the given model, based
       on Time Series Data.'''
    tss_cv = tss.split(X)
    r_2 = cross_val_score(model, X, y, cv=tss_cv, scoring="r2")
    tss_cv = tss.split(X)
    mse = -cross_val_score(model, X, y, cv=tss_cv,␣
 ↪scoring="neg_mean_squared_error")
    df = pd.DataFrame({ "Mean Squared Error": mse,
```

```
                            "R-Squared": r_2})
    df.loc["Avg:"] = df.mean()
    return(df)
```

[86]:
```
scores(X, y, ridge)
```

[86]:

	Mean Squared Error	R-Squared
0	0.848074	0.018859
1	1.964489	-0.329888
2	5.703828	-0.032767
3	6.526641	-0.002001
4	19.535861	0.033194
Avg:	6.915779	-0.062521

7.2 Alternative Model - Random Forest Regressor

[87]:
```
from sklearn.ensemble import RandomForestRegressor
```

[88]:
```
forest = RandomForestRegressor(oob_score=True)
forest.fit(X, y)
```

[88]:
```
RandomForestRegressor(oob_score=True)
```

[89]:
```
forest.feature_importances_
```

[89]:
```
array([0.05984626, 0.08017426, 0.06340859, 0.06495621, 0.05294885,
       0.08120496, 0.12015906, 0.0641982 , 0.09889953, 0.07086676,
       0.19857139, 0.04476592])
```

[90]:
```
def features_exaplained(df, imp):
    features_imp = pd.DataFrame(columns=["Feature_Importance"])
    features = df.columns.to_list()
    j = 0
    for i in imp:
        #print(f"{features[j]}: {i}")
        features_imp.loc[f"{features[j]}"] = [i]
        j+=1
    features_imp.sort_values("Feature_Importance", ascending=False,␣
 ↪inplace=True)
    features_imp.loc["Total"] = features_imp.sum()
    features_imp.loc["(The Out of Bag Score Returns: )"] = [forest.oob_score_]
    return(features_imp)
```

[91]:
```
features_exaplained(df=banks, imp=forest.feature_importances_)
```

[91]:

	Feature_Importance
L_OTHER_LIABILITIES_TOTAL	0.198571

```
L_DEPOSITS_DENOMINATED_IN_FOREIGN_CURRENCY_TOTAL              0.120159
L_FOREIGN_CURRENCY_FUNDING_TOTAL                              0.098900
E_TOTAL_EQUITY_TOTAL                                          0.081205
A_DEPOSITS_LOANS_AND_ADVANCES_TOTAL_ASSETS                    0.080174
L_OTHER_BORROWED_FUNDS_TOTAL                                  0.070867
A_NON-FINANCIAL_ASSETS_TOTAL_ASSETS                           0.064956
L_DEPOSITS_DENOMINATED_IN_RAND_TOTAL                          0.064198
A_INVESTMENTS_AND_BILLS_including_trading_portf…            0.063409
A_CENTRAL_BANK_MONEY_AND_GOLD_TOTAL_ASSETS                    0.059846
A_OTHER_ASSETS_TOTAL_ASSETS                                   0.052949
L_OTHER_LIABILITIES_TO_THE_PUBLIC_TOTAL                       0.044766
Total                                                         1.000000
(The Out of Bag Score Returns: )                             -0.157248
```

The feature importances displayed above illustrate the relative importance of each of the features relative to each other. As the total column suggests, the sum of all the feature importances is 1. To more critically analyse whether all the features are in fact necessary in the model, an interative fitting method is displayed below.

[92]:
```python
scores(X, y, forest)
```

[92]:
```
      Mean Squared Error  R-Squared
0               0.888627  -0.050829
1               1.721340  -0.176072
2               6.053595  -0.101952
3               6.837149  -0.062880
4              19.898954   0.012255
Avg:            7.079933  -0.075896
```

Below we apply an iterative method of cloning the original model characteristics and retrain it multiple times by excluding each of the features in turn.
This gives a more direct picture of which variables decrease the performance of the model instead of aiding performance.

[93]:
```python
from sklearn.base import clone

def imp_df(column_names, importances):
    data = {
        'Feature': column_names,
        'Importance': importances,
    }
    df = pd.DataFrame(data) \
        .set_index('Feature') \
        .sort_values('Importance', ascending=False)
```

```
    return(df)

def feat_eval_iter(model, X, y, random_state = 42):

    # clone the model to have the exact same specification as the one initially␣
 ↪trained
    forest_clone = clone(model)
    # set random_state for comparability
    forest_clone.random_state = random_state
    # training and scoring the benchmark model
    forest_clone.fit(X, y)
    benchmark_score = forest_clone.score(X, y)
    # list for storing feature importances
    importances = []

    # iterating over all columns and storing feature importance (difference␣
 ↪between benchmark and new model)
    for col in X.columns:
        forest_clone = clone(model)
        forest_clone.random_state = random_state
        forest_clone.fit(X.drop(col, axis = 1), y)
        drop_col_score = forest_clone.score(X.drop(col, axis = 1), y)
        importances.append(benchmark_score - drop_col_score)

    importances_df = imp_df(X.columns, importances)



    return(importances_df)
```

[94]:
```
df_imp = feat_eval_iter(forest, banks, y)
```

[95]:
```
df_imp.to_csv("./data/feature_imp_select.csv")
df_imp
```

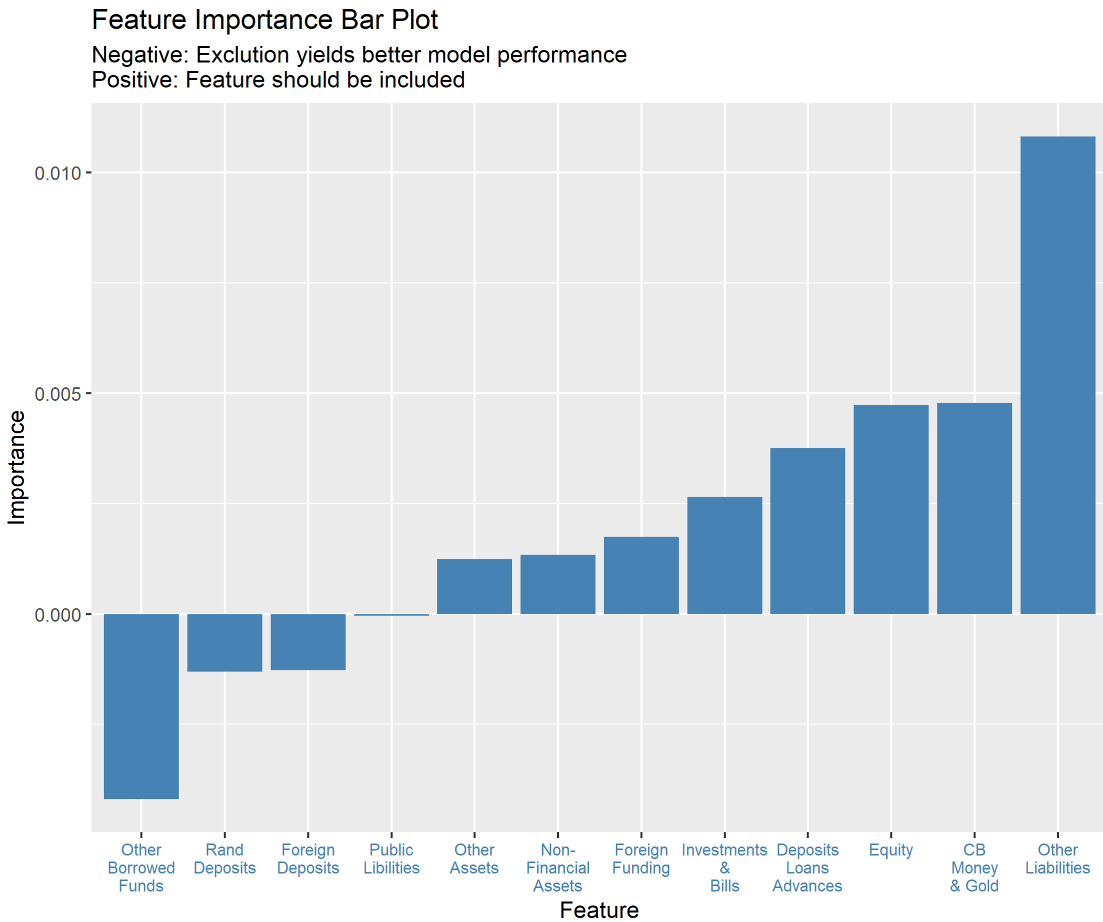
[95]:

Feature	Importance
L_OTHER_LIABILITIES_TOTAL	0.010823
A_CENTRAL_BANK_MONEY_AND_GOLD_TOTAL_ASSETS	0.004781
E_TOTAL_EQUITY_TOTAL	0.004743
A_DEPOSITS_LOANS_AND_ADVANCES_TOTAL_ASSETS	0.003751
A_INVESTMENTS_AND_BILLS_including_trading_portf…	0.002659
L_FOREIGN_CURRENCY_FUNDING_TOTAL	0.001756
A_NON-FINANCIAL_ASSETS_TOTAL_ASSETS	0.001339
A_OTHER_ASSETS_TOTAL_ASSETS	0.001244
L_OTHER_LIABILITIES_TO_THE_PUBLIC_TOTAL	-0.000045

```
L_DEPOSITS_DENOMINATED_IN_FOREIGN_CURRENCY_TOTAL     -0.001270
L_DEPOSITS_DENOMINATED_IN_RAND_TOTAL                 -0.001313
L_OTHER_BORROWED_FUNDS_TOTAL                         -0.004194
```

[96]:
```python
Image("./figures/Feature_imp_plot.png", width=700, height=700)
```

[96]:



7.2.1 Towards Improving the Model

Removing the features that decrease the model performance as the graph above displays yields the following

[97]:
```python
def reduce_banks(df):
    df1 = df_imp[df_imp["Importance"]>0]
    df1 = df1.reset_index()
    df1 = df[df1["Feature"].to_list()]
    return(df1)
```

[98]:
```python
reduced_banks = reduce_banks(banks)
```

[99]:
```
forest_reduced = RandomForestRegressor(oob_score=True)
X_reduced = np.array(reduce_banks(banks))
forest_reduced.fit(X_reduced, y)
```

[99]: RandomForestRegressor(oob_score=True)

[100]:
```
features_exaplained(df=reduced_banks, imp=forest_reduced.feature_importances_)
```

[100]:

	Feature_Importance
L_OTHER_LIABILITIES_TOTAL	0.175076
L_FOREIGN_CURRENCY_FUNDING_TOTAL	0.155034
A_DEPOSITS_LOANS_AND_ADVANCES_TOTAL_ASSETS	0.136907
A_CENTRAL_BANK_MONEY_AND_GOLD_TOTAL_ASSETS	0.123522
E_TOTAL_EQUITY_TOTAL	0.119472
A_OTHER_ASSETS_TOTAL_ASSETS	0.110416
A_INVESTMENTS_AND_BILLS_including_trading_portf…	0.093093
A_NON-FINANCIAL_ASSETS_TOTAL_ASSETS	0.086479
Total	1.000000
(The Out of Bag Score Returns:)	-0.157248

The feature importances displayed above illustrate the relative importance of each of the features relative to each other. As the total column suggests, the sum of all the feature importances is 1. To more critically analyse whether all the features are in fact necessary in the model, an interative fitting method is displayed below.

[101]:
```
scores(X_reduced, y, forest_reduced)
```

[101]:

	Mean Squared Error	R-Squared
0	0.954470	-0.119340
1	2.089539	-0.407280
2	6.060686	-0.128165
3	6.786227	-0.057014
4	17.560501	0.122520
Avg:	6.690284	-0.117856

Below we apply an iterative method of cloning the original model characteristics and retrain it multiple times by excluding each of the features in turn. This gives a more direct picture of which variables decrease the performance of the model instead of aiding performance.

7.3 Month Shift

[102]:
```
X_m = reduce_banks(mbanks)
y_m = np.array(mshares["Value"])

forest_m = RandomForestRegressor(oob_score=True)
forest_m.fit(X_m, y_m)
```

[102]:
```
RandomForestRegressor(oob_score=True)
```

[103]:
```
features_exaplained(df=X_m, imp=forest_m.feature_importances_)
```

[103]:
```
                                                     Feature_Importance
A_CENTRAL_BANK_MONEY_AND_GOLD_TOTAL_ASSETS                     0.269460
A_NON-FINANCIAL_ASSETS_TOTAL_ASSETS                            0.137883
E_TOTAL_EQUITY_TOTAL                                           0.121886
L_OTHER_LIABILITIES_TOTAL                                      0.113371
A_DEPOSITS_LOANS_AND_ADVANCES_TOTAL_ASSETS                     0.102531
L_FOREIGN_CURRENCY_FUNDING_TOTAL                               0.098938
A_OTHER_ASSETS_TOTAL_ASSETS                                    0.090666
A_INVESTMENTS_AND_BILLS_including_trading_portf…             0.065266
Total                                                          1.000000
(The Out of Bag Score Returns: )                              -0.157248
```

[104]:
```
scores(X_m, y_m, forest_m)
```

[104]:
```
      Mean Squared Error  R-Squared
0               0.908224   0.004505
1               1.511875  -0.191778
2               5.510136   0.024081
3               7.415195  -0.158952
4              22.066023  -0.055495
Avg:            7.482291  -0.075528
```

A possible next step would be to consider a more aggregated dataset such as converting the monthly data to quarterly. However, a lot of information is lost during the process of removing overlapping columns. This is due to some total columns originating from more than one collection of individual columns summed together. i.e. a total column `A` can be obtained from summing together a set of individual columns `x1`, or a different set `x2`. By removing these individual columns, a lot of information is lost. A different model can be used to select individual columns more systematically, such that we are left with columns explaining more of the variance in the shares output variable. The anaylsis provided in this paper provides some insight regarding the most important features withing the balance sheet of the largest banks in South Africa. Using these as a part of a more comprehensive model for the movements in the share market for South Africa can provide more insight into whether they add to the explanatory power of such a model.

The results from each of the models up to now suggest that there is very little power in the balance sheets of the top 6 banks in SA for explaining movements in the stock market for South Africa. There seems to be some significant consistency across the models that `Other Liabilities` tends to be the most siginficant relationship with south african share prices. Additionally, the `Central Bank Money & Gold` is also regarded in the same light, however, not in as many of the models.

These two variables are also the variables with the highest correlation with share prices in South Africa.

8 References

```
[ ]:
```