# Il calcolo della perdita attesa secondo il principio IFRS9

Il principio contabile IFRS 9 “Strumenti Finanziari” ha introdotto significative novità in tema di riduzione di valore delle attività finanziarie, segnando il passaggio da un approccio retrospettivo basato sulle evidenze delle perdite incorse - "incurred loss approach" - , ad uno prospettico - Forward Looking Approach - finalizzato ad intercettare in anticipo eventuali possibili perdite di valore con lo scopo di rilevarne gli effetti nel conto economico senza dover attendere che le perdite stesse si realizzino. Secondo l’IFRS 9 per la rilevazione delle rettifiche di valore non si deve, quindi, attendere che l’evento di perdita si manifesti quanto piuttosto anticiparlo attraverso una stima della perdita attesa di valore (expected credit loss - ECL). La perdita attesa (ECL) corrisponderà alla perdita che si prevede di subire sull’attività finanziaria, ponderata per la probabilità che l’evento stesso di perdita si verifichi, ovvero:

ECL = (LGD*EAD) PD dove

ECL = Expected Credit Loss LGD*EAD = Loss Given deafult*Exposure at Default PD = Probabilità di default

Ai fini della determinazione della perdita attesa si dovrà fare riferimento: Ad un orizzonte temporale di 12 mesi nel caso in cui il rischio di credito dello strumento finanziario non abbia subito significativi incrementi rispetto alla rilevazione iniziale (perdita attesa ad 1 anno); A tutta la vita dell’attività, nel caso in cui il rischio di credito dello strumento finanziario sia significativamente aumentato (c.d. perdita attesa multiperiodale o life time).

Da tali disposizioni discende ancora una volta la necessità di una stretta comunicazione tra Bilancio e Risk Management in modo tale da garantire la coerenza tra i modelli di rischio e le rettifiche di valore sulle attività finanziarie così come rappresentate in bilancio.

In particolare, ai fini del calcolo della Expected Credit Loss (ECL) si rende necessario determinare l'influenza dei fattori sistemici o macroeconomici in modo tale da poterne misurare l'effetto nei diversi scenari. In tale contesto devono pertanto essere affrontate due questioni principali relative a come:

1) elaborare e definire prospetticamente degli scenari significativi e realistici riguardo l'evoluzione futura dei fattori che caratterizzano il quadro sistemico e quindi i valori dei parametri di rischio;

2) modellizzare la relazione di dipendenza rispetto al quadro sistemico e quindi stimare le sensitivities rispetto ai sopracitati fattori.

in relazione al secondo punto si riportano di seguito i risultati di alcune prove di analisi effettuate al fine di stimare un modello di regressione lineare tra il Credit Worhiness Y implicito nei tassi di decadimento trimestrali Bankit -TD - e un set di fattori macroeconomici quali il PIL, il tasso di disoccupazione, i tassi d'interesse bancari, il commercio estero, indici immobiliari, offerta di moneta M3, credito concesso ad imprese non finanziarie e famiglie consumatrici, inflazione ... Come modello di riferimento si è preso il Credit Portfolio View di Thomas Wilson che definisce la relazione di dipendenza esistente tra probabilità di default e fattori macroeconomici attraverso una funzione logistica. Il Credit Worthiness - CW - è stato estratto dai Tassi Decadimento trimestrali -TD - sulla base della relazione:

1) TD = 1/(1+EXP(-CW)) - Tasso di Decadimento -

2) CW = -log[(1-TD)/TD] - Credit Worthiness -

Le evidenze sembrano mostrare la presenza di una relazione significativa tra il Credit Worthiness - CW - estratto dai Tassi di Decadimento e il Credit To GDP Gap; quest'ultimo indicatore è anche la grandezza di riferimento in base alla quale il Comitato di Basilea prevede che sia determinato (con gli adattamenti previsti dalle singole autorità nazionali) il requisito patrimoniale relativo alla riserva di capitale anticiclica.

I tassi di decadimento sono reperibili sul sito della Banca d'Italia Tassi di decadimento trimestrali dei Residenti al netto delle Istituzioni Finanziarie - Numeri -

In [ ]:
```
#se si vuole eseguire in Google Colab occorre
#impostare la variabile colab a True - colab = True per installare le due librerie
colab = True
if colab:
    !pip install XlsxWriter
    !pip install pandasql
```

In [4]:
```
#Importazione delle librerie necessarie
# se non già presenti devono essere installate tramite !pip o conda
%matplotlib inline
import math
import numpy as np
import pandas as pd
import pandasql as pdsql
from pandasql import sqldf

import matplotlib.pyplot as plt
plt.rcParams.update({'figure.max_open_warning': 0})
import datetime
import seaborn as sb

from sklearn.preprocessing import StandardScaler # for standardizing the Data
#from sklearn.decomposition import PCA # for PCA calculation
#from sklearn.decomposition import FactorAnalysis
import statsmodels.api as sm
from statsmodels.tsa.stattools import adfuller
import openpyxl
import os
#import glob
#we set some print and visualization options
np.set_printoptions(precision=2)
pd.options.display.max_columns = None #to show all the columns
pd.set_option('display.float_format', lambda x: '%.3f' % x)
```

# Utility Functions

In [5]:
```
class CLS_Util(object):

    #we wrapp statsmodels adfullur just to get a nice result object
    @staticmethod
    def GM_ADF(series):
      from statsmodels.tsa.stattools import adfuller
      result = adfuller(series, autolag='AIC')
      out={'ADF Statistic':result[0],
          'P-values':result[1],
          'Lags':result[2], 'Critical Values':result[4]}
      return out

    #we iterate through all the variable in the input Data Frame
    @staticmethod
    def GM_ADF_ALL( df, filter = -1, export_file='' ):
      DictADF = dict()
      for ColName in df.columns:
        series = df[[str(ColName)]]
        DictADF[ColName]= CLS_Util.GM_ADF(series)
        OUT = pd.DataFrame(DictADF).T
```

```
    if (filter != -1) :
        OUT = OUT[OUT['P-values']>filter]
    OUT=OUT.sort_values(by=['P-values'], ascending=False)

    if export_file !='' :
        OUT.to_excel(export_file)
    return OUT

  @staticmethod
  def do_lag(df,N = 12 ):#we get a matrix with the original variable and the corresponding 8
    # df = input DataFrame to transform
    # N = number_of_lag
    # str(i) we put in each variable indicate the lag order
    Dates = df.index.values
    df_with_lag = df
    for i in np.arange(1,N +1):
      df_lag = pd.DataFrame(df.values[:-i,:], index = Dates[i:], columns = ["{}_".format(x) +
      df_with_lag = pd.concat([df_with_lag, df_lag], axis=1, join="inner")
    return df_with_lag


  @staticmethod
  def do_delta_perc(df,i = 12 ):#we get a matrix with the original variable and the correspon
    # df = input DataFrame to transform
    # N = number_of_lag
    # str(i) we put in each variable indicate the lag order
    Dates = df.index.values
    df_perc = pd.DataFrame((df.values[i:,:]-df.values[:-i,:])/df.values[:-i,:], index = Dates
                           columns = ["Perc_{}_".format(x) + str(i) for x in df.columns])
    #df_with_lag = pd.concat([df_with_lag, df_lag], axis=1, join="inner")
    return df_perc

  @staticmethod
  def TransformData(dt_in, TransformType= 0, normalize = 0):
    dt_out = np.empty_like(dt_in)

    if TransformType == 1:
      dt_out = dt_in.diff()
    elif TransformType == 2:
      dt_out = dt_in.pct_change()
    else:
      dt_out =  dt_in
    if normalize == 1:
      return (dt_out-dt_out.mean())/dt_out.std()
    else:
      return dt_out
    #sc = StandardScaler()
    #std_data = sc.fit_transform(data) #Numpy ndarray

  @staticmethod
  def is_locked(filepath):
     import os
     locked = None
     file_object = None
     if os.path.exists(filepath):
      try:
       buffer_size = 8
       file_object = open(filepath, 'a', buffer_size)
       if file_object:
        locked = False
      except IOError as message:
       locked = True
      finally:
       if file_object:
        file_object.close()
      return locked

  @staticmethod
```

```
    def wait_for_file(filepath):
       wait_time = 1
       while CLS_Util.is_locked(filepath):
         time.sleep(wait_time)

    @staticmethod
    def ALL_CHARTS(df, yvar ='CW'):
     for c in df.columns:
      if c not in ['CW', 'TD']:
        FileName = "{}.png".format(c)
        #FileName = "image.png"
        df[[yvar, c]].plot()
        plt.savefig(FileName , dpi = 120)
        plt.cla
     return

    @staticmethod
    def ALL_CHARTS_2(df, excelfile):
        wb = openpyxl.Workbook()
        wb.save(excelfile)
        wb = openpyxl.load_workbook(excelfile)
        ws = wb.active
        n=  1
        for c in df.columns:
          if c not in ['CW', 'TD']:
            FileName = "{}.png".format(c)
            img = openpyxl.drawing.image.Image(FileName)
            if n == 1 :
              ws.add_image(img,'A{}'.format(n) )
            else:
              ws.add_image(img,'A{}'.format((n-1)*25) )
            n += 1
        wb.save(excelfile)

    @staticmethod
    def Delete_Charts():
      import os
      import glob
      files = glob.glob('*.png')
      for f in files:
          os.remove(f)

    @staticmethod
    def ALL_CHARTS_TOT(df, excelfile):
      CLS_Util.ALL_CHARTS(df)
      CLS_Util.ALL_CHARTS_2(df, excelfile)
```

In [6]:

```
def Unireg_all(df, label):
  DictResults={}
  for var in df.columns :
   if var[:2] not in ['CW','TD']:
     YVAR = df.loc[:,['CW']]
     XVAR = df.loc[:,[var]]
     XVAR['CONST']= 1
     model = sm.OLS(YVAR, XVAR)
     results = model.fit()
     item = {'Data':label, 'Variable':var,'R':results.rsquared, 'PVAL':results.pvalues[0], 'PAR
     DictResults[var]=item

  uniregResults =pd.DataFrame(DictResults).T
  uniregResults = uniregResults.sort_values(by=['R'], ascending=False)
  uniregResults.to_excel('UNIREG_'+ label+'.xlsx')
  return uniregResults
```

# Data Import

In [7]:
```
#Importo i tassi di decadimento
path = r'https://github.com/GMISSAGLIA/GM_PyLab/blob/Main/TD_Bankit_regression_input_data_all.x

DF_CW = pd.read_excel(path, 'DF_CW', index_col=[0], parse_dates=[0])
DF_CW['TD']=DF_CW['TD']/100
DF_CW['CW']=-np.log((1-DF_CW['TD'])/DF_CW['TD'])

DF_CW_ALL= DF_CW.copy()
DF_CW_ALL['TD_1Y'] = (1- (1-DF_CW_ALL['TD']).rolling(4).apply(np.prod, raw = True))
DF_CW_ALL['CW_1Y']=-np.log((1-DF_CW_ALL['TD_1Y'])/DF_CW_ALL['TD_1Y'])

DF_CW_ALL['TD_AVG']=(1-DF_CW_ALL['TD']).rolling(4).apply(np.prod, raw = True).map(lambda x: 1-x
DF_CW_ALL=DF_CW_ALL.iloc[3:,:]
DF_CW_ALL['CW_AVG'] =-np.log((1-DF_CW_ALL['TD_AVG'])/DF_CW_ALL['TD_AVG'])

DF_CW_1Y = (1- (1-DF_CW).rolling(4).apply(np.prod, raw = True)).iloc[3:,:]
DF_CW_1Y['CW']=-np.log((1-DF_CW_1Y['TD'])/DF_CW_1Y['TD'])

DF_CW_AVG = pd.DataFrame((1-DF_CW['TD']).rolling(4).apply(np.prod, raw = True).map(lambda x: 1-
DF_CW_AVG['CW']=-np.log((1-DF_CW_AVG['TD'])/DF_CW_AVG['TD'])

TD = DF_CW_ALL[['TD','TD_1Y','TD_AVG']]
CW = DF_CW_ALL[['CW','CW_1Y','CW_AVG']]
```

In [8]:
```
DF_CW_ALL.head()
```

Out[8]:

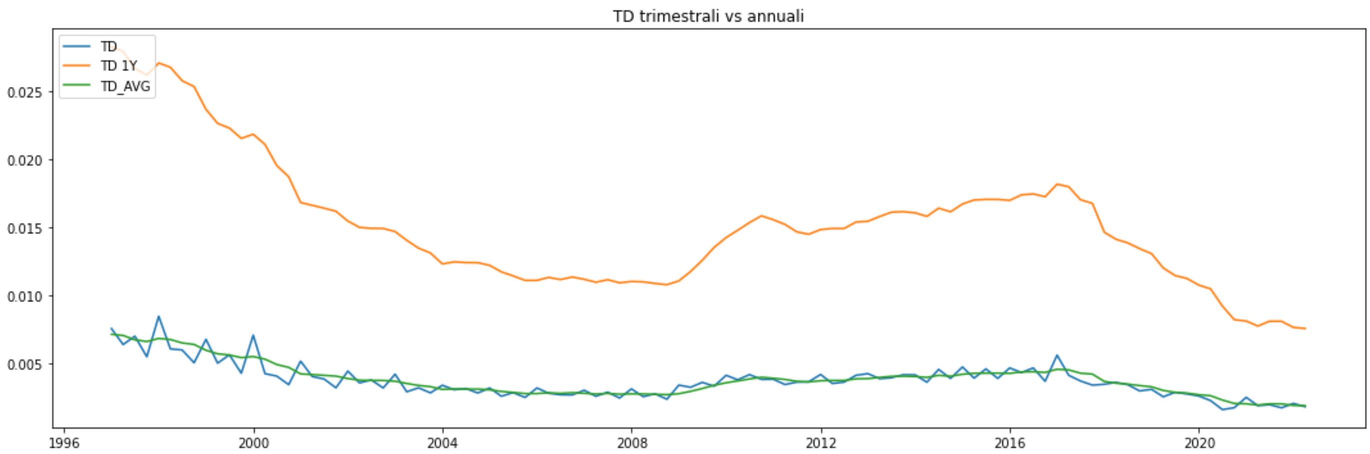
| DT | TD | CW | TD_1Y | CW_1Y | TD_AVG | CW_AVG |
|---|---|---|---|---|---|---|
| **1996-12-31** | 0.008 | -4.877 | 0.028 | -3.538 | 0.007 | -4.935 |
| **1997-03-31** | 0.006 | -5.047 | 0.028 | -3.550 | 0.007 | -4.947 |
| **1997-06-30** | 0.007 | -4.955 | 0.027 | -3.597 | 0.007 | -4.993 |
| **1997-09-30** | 0.005 | -5.199 | 0.026 | -3.616 | 0.007 | -5.012 |
| **1997-12-31** | 0.008 | -4.763 | 0.027 | -3.582 | 0.007 | -4.978 |

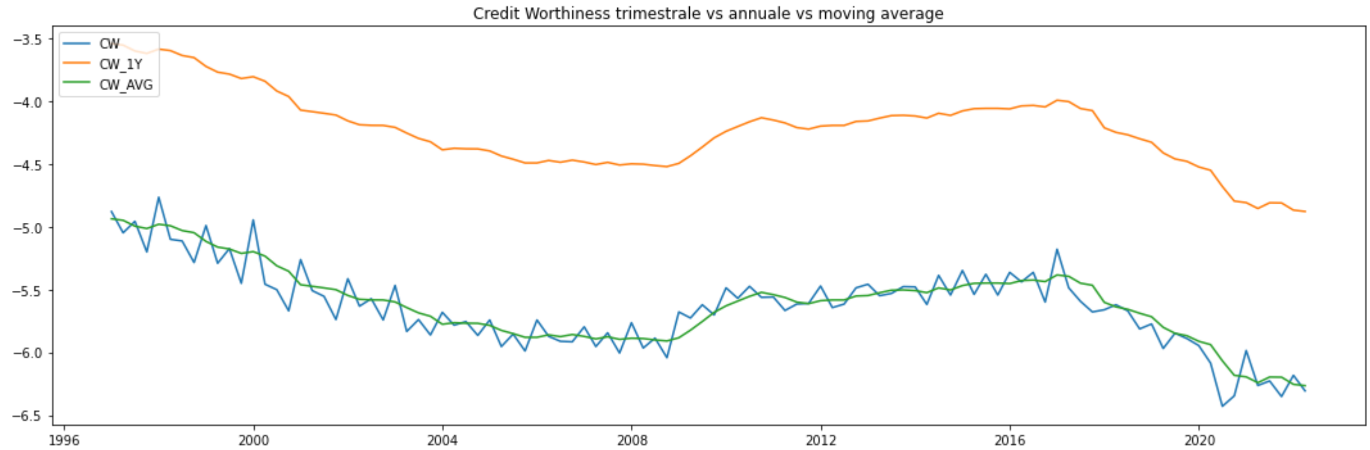
In [18]:
```
fig, axs = plt.subplots(2,1,figsize=(15, 10))

axs[0].plot(DF_CW_ALL['TD'], label =  'TD')
axs[0].plot(DF_CW_ALL['TD_1Y'], label =  'TD 1Y')
axs[0].plot(DF_CW_ALL['TD_AVG'], label =  'TD_AVG')
axs[0].set_title('TD trimestrali vs annuali')
axs[0].legend(loc='upper left')

axs[1].plot(DF_CW_ALL[['CW']], label = 'CW')
axs[1].plot(DF_CW_ALL[['CW_1Y']], label = 'CW_1Y')
axs[1].plot(DF_CW_ALL[['CW_AVG']], label = 'CW_AVG')
axs[1].set_title('Credit Worthiness trimestrale vs annuale vs moving average')
axs[1].legend(loc='upper left')

fig.tight_layout()
```




In [22]:

```
DF_YoY = pd.read_excel(path, 'DF_YoY', index_col=[0], parse_dates=[0])
DF_DECO = pd.read_excel(path, 'T_Deco_Var', index_col=[1])
DF_DECO
```

Out[22]:

| Variable | ID | Descrizione |
|---|---|---|
| **X_1** | 1 | Retail Sales (Real/Volume) |
| **X_2** | 2 | Harmonised Index of Consumer Prices |
| **X_3** | 3 | Producer Prices (Output Prices) |
| **X_4** | 4 | Disposable Personal Income Real |
| **X_5** | 5 | Eurostat Industrial Production Italy Wages & S... |
| **X_6** | 6 | House Prices SWDA |
| **X_7** | 7 | Property Price - Non-Residential Buildings |
| **X_8** | 8 | Property Price - Offices |
| **X_9** | 9 | Property Price - Residential Buildings |
| **X_10** | 10 | Property Price Commercial |
| **X_11** | 11 | Property Price - Industrial |
| **X_12** | 12 | Italy Real Effective Exchange Rate Broad |
| **X_13** | 13 | Italy Foreign Currency Reserve |
| **X_14** | 14 | Export NSA |
| **X_15** | 15 | Import NSA |
| **X_16** | 16 | Government Debt |
| **X_17** | 17 | Non Performing Loans |
| **X_18** | 18 | Italy Deposits of Resident Consumer Households |

| | ID | Descrizione |
|---|---|---|
| **Variable** | | |
| **X_19** | 19 | Deposits of Non-financial Corporations |
| **X_20** | 20 | Deposits of Producer Households |
| **X_21** | 21 | Italy Loans to Residents Non Financial Corpora... |
| **X_22** | 22 | Consumer Credit |
| **X_23** | 23 | Italy Loans to Residents > 5Y |
| **X_24** | 24 | Unemployement Rate |
| **X_25** | 25 | Capacity Utilization |
| **X_26** | 26 | EMMI EURO OverNight Index Aver |
| **X_27** | 27 | Italy Bank Interest Rates on Outstanding Euro ... |
| **X_28** | 28 | Minimum Rate on Short Term Loans to Non Financ... |
| **X_29** | 29 | Average Rate on Bonds - Outstanding Amounts |
| **X_30** | 30 | Mortgage Interest Rate NSA |
| **X_31** | 31 | Italy Bank Interest Rates on Mortgage |
| **X_32** | 32 | BIS Italy Credit to Private Non Financial Sect... |
| **X_33** | 33 | Real GDP (swda, yoy%) |
| **X_34** | 34 | EU Italy GDP Deflator (yoy %, sa) |
| **X_35** | 35 | Producer Price Index (yoy %) |
| **X_36** | 36 | Large Industry Employment (yoy %) |
| **X_37** | 37 | Unit Labor Costs (yoy %) |
| **X_38** | 38 | EU Italy Nominal Labour Costs (yoy %, wda) |
| **X_39** | 39 | Industrial Production (yoy %, wda) |
| **X_40** | 40 | Industrial Sales (yoy %) |
| **X_41** | 41 | New Car Registrations (yoy %) |
| **X_42** | 42 | OECD Italy Leading Indicator (yoy %) |
| **X_43** | 43 | Retail Sales (yoy %) |
| **X_44** | 44 | ECB M3 Money Supply (yoy %, sa) |

In [23]:

```
#from sklearn.preprocessing import MinMaxScaler
#from sklearn.preprocessing import StandardScaler
#scaler = StandardScaler()
#DF_YoY_STD = scaler.fit_transform(DF_YoY)
DF_CW_STD = (DF_CW - DF_CW.mean())/DF_CW.std()
DF_CW_1Y_STD = (DF_CW_1Y - DF_CW_1Y.mean())/DF_CW_1Y.std()
DF_CW_AVG_STD = (DF_CW_AVG - DF_CW_AVG.mean())/DF_CW_AVG.std()

DF_YoY_LAG = CLS_Util.do_lag(DF_YoY)
DF_YoY_STD = (DF_YoY - DF_YoY.mean())/DF_YoY.std()
DF_YoY_STD_LAG = CLS_Util.do_lag(DF_YoY_STD)


pd.DataFrame(DF_YoY_STD).describe()
```

Out[23]:

| | X_1 | X_2 | X_3 | X_4 | X_5 | X_6 | X_7 | X_8 | X_9 | X_10 | X_11 | X_12 | X_13 | X_1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

| | X_1 | X_2 | X_3 | X_4 | X_5 | X_6 | X_7 | X_8 | X_9 | X_10 | X_11 | X_12 | X_13 | X_1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 77.000 | 77.000 | 77.000 | 77.000 | 77.000 | 77.000 | 77.000 | 77.000 | 77.000 | 77.000 | 77.000 | 77.000 | 77.000 | 77.00 |
| **mean** | -0.000 | -0.000 | 0.000 | -0.000 | -0.000 | -0.000 | 0.000 | -0.000 | -0.000 | 0.000 | 0.000 | -0.000 | 0.000 | 0.00 |
| **std** | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.00 |
| **min** | -4.525 | -2.064 | -1.917 | -2.785 | -4.466 | -1.171 | -1.203 | -1.271 | -1.195 | -1.584 | -1.192 | -2.775 | -2.529 | -3.09 |
| **25%** | -0.480 | -0.859 | -0.776 | -0.456 | -0.146 | -0.614 | -0.760 | -0.727 | -0.573 | -0.723 | -0.680 | -0.655 | -0.580 | -0.40 |
| **50%** | -0.023 | -0.125 | 0.094 | 0.219 | 0.101 | -0.255 | -0.438 | -0.471 | -0.235 | -0.298 | -0.371 | 0.084 | -0.046 | 0.01 |
| **75%** | 0.365 | 0.693 | 0.441 | 0.608 | 0.362 | -0.085 | 0.951 | 0.679 | -0.058 | 0.744 | 0.507 | 0.620 | 0.603 | 0.59 |
| **max** | 5.196 | 2.013 | 5.150 | 3.165 | 4.600 | 3.074 | 2.375 | 2.606 | 3.067 | 3.054 | 3.482 | 2.580 | 3.209 | 1.99 |

In [24]:

```
ADF_YoY = CLS_Util.GM_ADF_ALL(DF_YoY)
ADF_YoY_STD = CLS_Util.GM_ADF_ALL(DF_YoY_STD)

ADF_CW = CLS_Util.GM_ADF_ALL(DF_CW)
ADF_CW_1Y = CLS_Util.GM_ADF_ALL(DF_CW_1Y)
ADF_CW_AVG = CLS_Util.GM_ADF_ALL(DF_CW_AVG)

ADF_CW_STD = CLS_Util.GM_ADF_ALL(DF_CW_STD)
ADF_CW_1Y_STD = CLS_Util.GM_ADF_ALL(DF_CW_1Y_STD)
ADF_CW_AVG_STD = CLS_Util.GM_ADF_ALL(DF_CW_AVG_STD)

with pd.ExcelWriter('00_Regression_Analysis_Input_data.xlsx') as writer:
 DF_CW.to_excel(writer, sheet_name='DF_CW')
 DF_CW_STD.to_excel(writer, sheet_name='DF_CW_STD')


 DF_CW_1Y.to_excel(writer, sheet_name='DF_CW_1Y')
 DF_CW_1Y_STD.to_excel(writer, sheet_name='DF_CW_1Y_STD')

 DF_CW_AVG.to_excel(writer, sheet_name='DF_CW_AVG')
 DF_CW_AVG_STD.to_excel(writer, sheet_name='DF_CW_AVG_STD')

 DF_YoY.to_excel(writer, sheet_name='DF_YoY')
 DF_YoY_LAG.to_excel(writer, sheet_name='DF_YoY_LAG')

 DF_YoY_STD.to_excel(writer, sheet_name='DF_YoY_STD')
 DF_YoY_STD_LAG.to_excel(writer, sheet_name='DF_YoY_STD_LAG')

 ADF_YoY.to_excel(writer, sheet_name='ADF_YoY')
 ADF_YoY_STD.to_excel(writer, sheet_name='ADF_YoY_STD')
 ADF_CW.to_excel(writer, sheet_name='ADF_CW')
 ADF_CW_STD.to_excel(writer, sheet_name='ADF_CW_STD')
 ADF_CW_1Y.to_excel(writer, sheet_name='ADF_CW_1Y')
 ADF_CW_1Y_STD.to_excel(writer, sheet_name='ADF_CW_1Y_STD')
 ADF_CW_AVG.to_excel(writer, sheet_name='ADF_CW_AVG')
 ADF_CW_AVG_STD.to_excel(writer, sheet_name='ADF_CW_AVG_STD')

 DF_DECO.to_excel(writer, sheet_name='DF_DECO')
```

# Credit Worthiness Univariate OLS Regression

In [25]:

```
#we get the total Dataframe containing the variable to Explain and all the possible explicative
df_all = pd.concat([DF_CW_1Y, DF_YoY_LAG], axis= 1, join='inner')
df_all_STD= pd.concat([DF_CW_1Y_STD, DF_YoY_STD_LAG], axis= 1, join='inner')
```

In [ ]:

```
CLS_Util.Delete_Charts()
CLS_Util.ALL_CHARTS_TOT(df_all_STD, 'ALL_CHARTS_YoY_STD.XLSX')
CLS_Util.Delete_Charts()
```

In [28]:

```
Unireg_all(df_all, 'CW Reg YoY')
```

Out[28]:

| | Data | Variable | R | PVAL | PARAMS |
|---|---|---|---|---|---|
| **X_32_3** | CW Reg YoY | X_32_3 | 0.741 | 0.000 | -0.049 |
| **X_32_2** | CW Reg YoY | X_32_2 | 0.733 | 0.000 | -0.048 |
| **X_32_4** | CW Reg YoY | X_32_4 | 0.673 | 0.000 | -0.049 |
| **X_32_1** | CW Reg YoY | X_32_1 | 0.664 | 0.000 | -0.046 |
| **X_17_9** | CW Reg YoY | X_17_9 | 0.618 | 0.000 | 0.900 |
| **...** | ... | ... | ... | ... | ... |
| **X_25_8** | CW Reg YoY | X_25_8 | 0.000 | 0.971 | -0.000 |
| **X_30_9** | CW Reg YoY | X_30_9 | 0.000 | 0.992 | 0.001 |
| **X_37_8** | CW Reg YoY | X_37_8 | 0.000 | 0.994 | -0.000 |
| **X_31_10** | CW Reg YoY | X_31_10 | 0.000 | 0.996 | -0.000 |
| **X_18_6** | CW Reg YoY | X_18_6 | 0.000 | 0.997 | 0.001 |

572 rows × 5 columns

In [69]:

```
# il modello stimato é:
# CW = b0 + b1*CreditToGDP_Gap_2 + b2*CreditToGDP_Gap_6+ b3*NPL_3+ b4*EXPORT_3+ e

df= df_all.loc[:,['CW','X_32_2','X_17_3','X_14_3']]
df.rename(columns={'X_32_2':'CreditToGDP_Gap_2',
                   'X_17_3':'NPL_3','X_14_3':'EXPORT_3'}, inplace=True)

YVAR = df.loc[:,'CW']
XVAR = df.loc[:,['CreditToGDP_Gap_2', 'NPL_3','EXPORT_3']]

CONST = pd.DataFrame(index=df.index)
CONST['CONST']= 1
XVAR_TOT = pd.concat([CONST,XVAR], axis=1, join='inner')
model = sm.OLS(YVAR, XVAR_TOT)
results = model.fit()
```

In [70]:

```
#le variabili esplicative risultano significative e con segno coerente con l'aspettattiva teori
results.summary()
```

Out[70]:

OLS Regression Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | CW | **R-squared:** | 0.871 |
| **Model:** | OLS | **Adj. R-squared:** | 0.864 |
| **Method:** | Least Squares | **F-statistic:** | 137.0 |
| **Date:** | Sat, 15 Oct 2022 | **Prob (F-statistic):** | 4.62e-27 |
| **Time:** | 19:05:07 | **Log-Likelihood:** | 67.469 |
| **No. Observations:** | 65 | **AIC:** | -126.9 |
| **Df Residuals:** | 61 | **BIC:** | -118.2 |

| | |
|---|---|
| **Df Model:** | 3 |
| **Covariance Type:** | nonrobust |

| | coef | std err | t | P>\|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **CONST** | -4.3349 | 0.012 | -367.911 | 0.000 | -4.358 | -4.311 |
| **CreditToGDP_Gap_2** | -0.0470 | 0.004 | -13.115 | 0.000 | -0.054 | -0.040 |
| **NPL_3** | 0.2334 | 0.063 | 3.693 | 0.000 | 0.107 | 0.360 |
| **EXPORT_3** | -0.8923 | 0.129 | -6.893 | 0.000 | -1.151 | -0.633 |

| | | | |
|---|---|---|---|
| **Omnibus:** | 1.020 | **Durbin-Watson:** | 0.784 |
| **Prob(Omnibus):** | 0.600 | **Jarque-Bera (JB):** | 0.427 |
| **Skew:** | -0.079 | **Prob(JB):** | 0.808 |
| **Kurtosis:** | 3.365 | **Cond. No.** | 51.0 |

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

# Matrice di correlazione e Condition Number

In [71]:

```
CORR_MAT = XVAR.corr()
CORR_MAT
```

Out[71]:

| | CreditToGDP_Gap_2 | NPL_3 | EXPORT_3 |
|---|---|---|---|
| **CreditToGDP_Gap_2** | 1.000 | -0.644 | -0.349 |
| **NPL_3** | -0.644 | 1.000 | 0.174 |
| **EXPORT_3** | -0.349 | 0.174 | 1.000 |

In [72]:

```
result =  np.linalg.cond(CORR_MAT)
result
```

Out[72]:

```
5.515205789156765
```

# Previsti vs Effettivi

In [73]:

```
def test(X, Y, results):
  CW_Predicted = results.predict(X)
  DF_CW_Predicted = pd.DataFrame(CW_Predicted,index=X.index)
  DF_CW_Predicted.columns = ['CW_Predicted']

  DF_CW_Compare = pd.concat([DF_CW_Predicted,Y, DF_CW_1Y['TD']],axis=1, join= 'inner')
  DF_CW_Compare['TD_Predicted']=DF_CW_Compare['CW_Predicted'].map(lambda x: 1/(1+math.exp(-x)))
  DF_CW_Compare['CW_Residuals']= DF_CW_Compare['CW']-DF_CW_Compare['CW_Predicted']
  DF_CW_Compare['TD_Residuals']= DF_CW_Compare['TD']-DF_CW_Compare['TD_Predicted']

  DF_CW_Compare[['TD_Residuals']].plot.kde()
  DF_CW_Compare[['CW_Residuals']].plot.kde()
  fig, axs = plt.subplots(5,1,figsize=(15, 10))
```

```python
    axs[0].plot(DF_CW_Compare[['TD']], label = 'TD')
    axs[0].plot(DF_CW_Compare[['TD_Predicted']], label =  'TD_Predicted')
    axs[0].set_title('TD effettivi vs Previsti')
    axs[0].legend(loc='upper left')

    axs[1].plot(DF_CW_Compare[['CW']], label = 'CW')
    axs[1].plot(DF_CW_Compare[['CW_Predicted']], label = 'CW Predicted')
    axs[1].set_title('Credit Worthiness effettivo vs Previsto')
    axs[1].legend(loc='upper left')

    axs[2].plot(df_all_STD[['CW']], label = 'CW')
    axs[2].plot(df_all_STD[['X_32_2']], label =  'Credit To GDP Lag 2')
    axs[2].set_title("Credit to GDP GAP - LAG 2")
    axs[2].legend(loc='upper left')

    axs[3].plot(df_all_STD[['CW','X_17_3']], label = 'CW')
    axs[3].plot(df_all_STD[['X_17_3']], label = 'NPL Lag 3')
    axs[3].set_title("Crediti Non Performing - LAG 3")
    axs[3].legend(loc='upper left')

    axs[4].plot(df_all_STD[['CW']], label = 'CW')
    axs[4].plot(df_all_STD[['X_14_3']], label =  'EXPORT Lag 3')
    axs[4].set_title("Esporatazioni LAG 3")
    axs[4].legend(loc='upper left')

    fig.tight_layout()

    return DF_CW_Compare.describe()
```

In [59]:

```python
def Test_evaluation_metrics_func(y_true, y_pred):
    from sklearn import metrics
    def mean_absolute_percentage_error(y_true, y_pred):
        y_true, y_pred = np.array(y_true), np.array(y_pred)
        return np.mean(np.abs((y_true - y_pred) / y_true)) * 100
    def sqrt_mean_squared_error(y_true, y_pred):
        y_true, y_pred = np.array(y_true), np.array(y_pred)
        return np.sqrt(metrics.mean_squared_error(y_true, y_pred))
    Forecast_Performance={}
    #Lista di tuple con descrizione e funzione di misurazione delle performance
    Performance_Functions = [('MSE:Mean Square Error', metrics.mean_squared_error),
                             ('MAE:Mean Absolute Error', metrics.mean_absolute_error),
                             ('RMSE:Mean Square Error',sqrt_mean_squared_error),
                            ('MAPE:Mean Square Error', mean_absolute_percentage_error),
                             ('R2: R2 score',metrics.r2_score)]
    print('Evaluation metric results:-')
    for pair in Performance_Functions:
      value =  pair[1](y_true, y_pred)
      Forecast_Performance[pair[0]]=value
      print("{} : {:,.2f}".format( pair[0], value))

    print(end='\n\n')

    result = pd.DataFrame(Forecast_Performance,index=[0])
    #result.columns=[['MSE', 'MAE', 'RMSE', 'MAPE', 'R2']]
    return result
```

In [84]:

```python
X = XVAR_TOT
Y = YVAR
Predicted = results.predict(X)
Test_evaluation_metrics_func(Y.values, Predicted.values)
```

```
Evaluation metric results:-
MSE:Mean Square Error : 0.01
MAE:Mean Absolute Error : 0.06
RMSE:Mean Square Error : 0.07
MAPE:Mean Square Error : 1.36
```

```
R2: R2 score : 0.81
```

Out[84]:

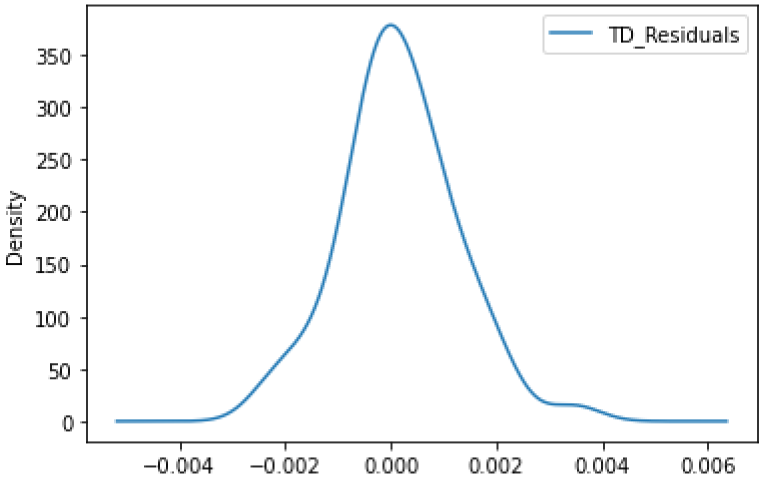
| | MSE:Mean Square Error | MAE:Mean Absolute Error | RMSE:Mean Square Error | MAPE:Mean Square Error | R2: R2 score |
|---|---|---|---|---|---|
| **0** | 0.005 | 0.057 | 0.074 | 1.359 | 0.814 |

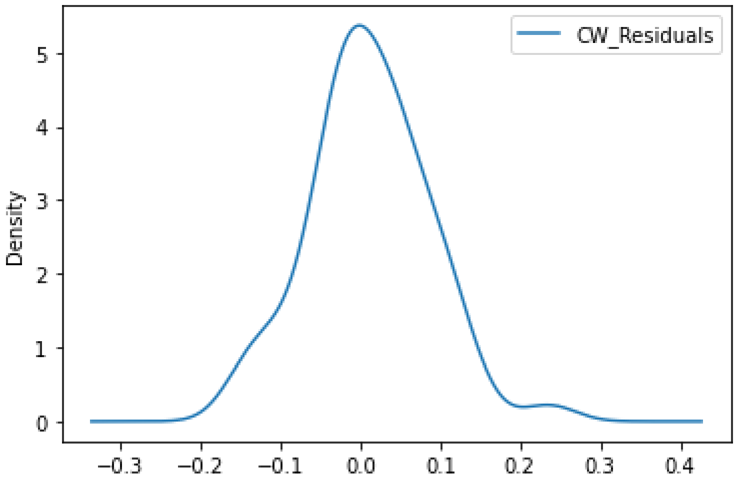
In [85]:

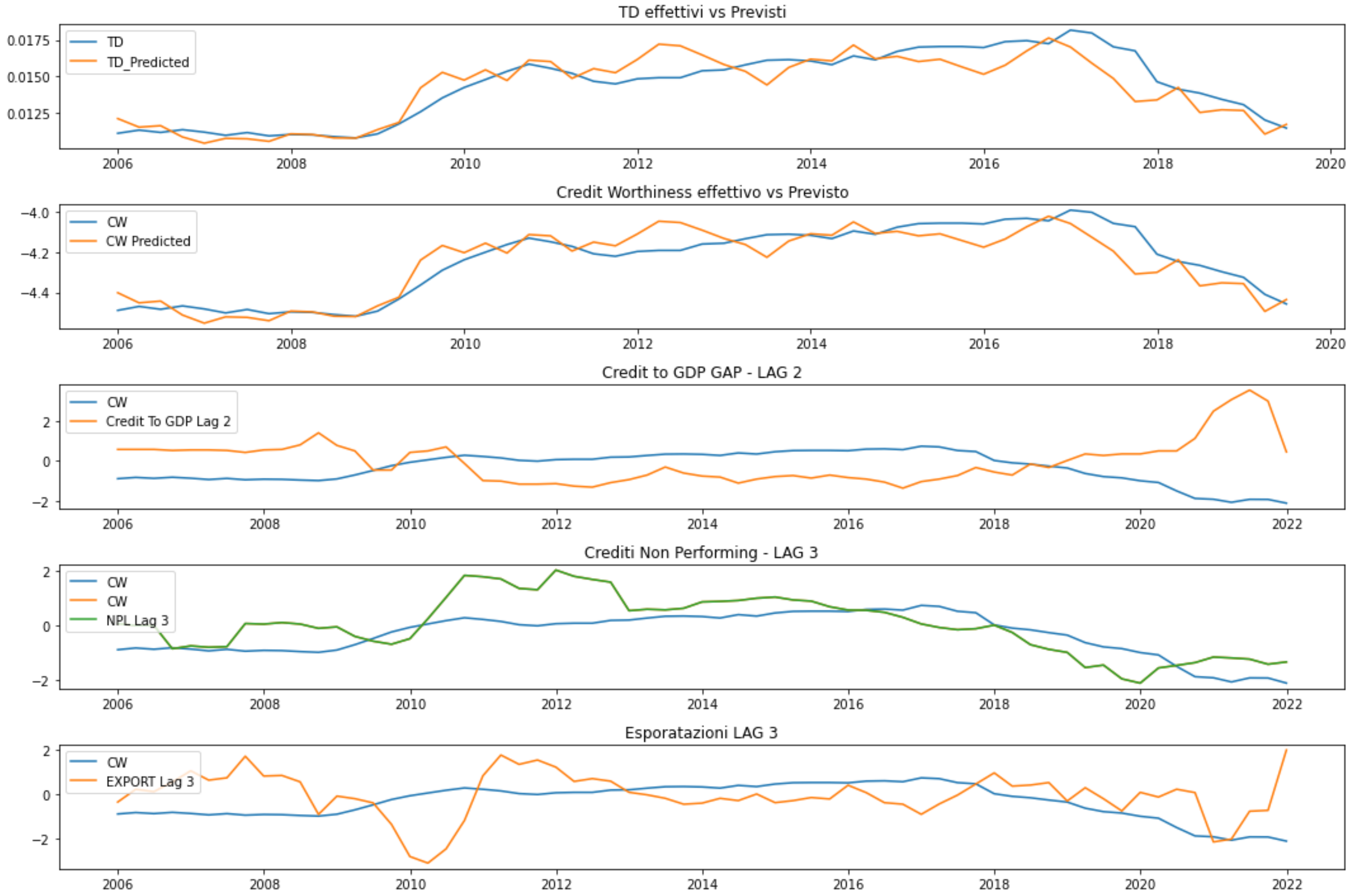
```
test(X,Y, results)
```

Out[85]:

| | CW_Predicted | CW | TD | TD_Predicted | CW_Residuals | TD_Residuals |
|---|---|---|---|---|---|---|
| **count** | 55.000 | 55.000 | 55.000 | 55.000 | 55.000 | 55.000 |
| **mean** | -4.254 | -4.243 | 0.014 | 0.014 | 0.011 | 0.000 |
| **std** | 0.169 | 0.173 | 0.002 | 0.002 | 0.074 | 0.001 |
| **min** | -4.553 | -4.519 | 0.011 | 0.010 | -0.145 | -0.002 |
| **25%** | -4.430 | -4.445 | 0.012 | 0.012 | -0.028 | -0.000 |
| **50%** | -4.193 | -4.196 | 0.015 | 0.015 | 0.001 | 0.000 |
| **75%** | -4.116 | -4.110 | 0.016 | 0.016 | 0.054 | 0.001 |
| **max** | -4.020 | -3.989 | 0.018 | 0.018 | 0.236 | 0.003 |






# Test

In [60]:

```
NTEST = 10
Train, Test = df.iloc[0:-NTEST],df.iloc[-NTEST:]
X_train,X_test,Y_train, Y_test = Train.iloc[:,1:],Test.iloc[:,1:],Train.iloc[:,0],Test.iloc[:,
X_test
```

Out[60]:

| | CreditToGDP_Gap_2 | NPL_3 | EXPORT_3 |
|---|---|---|---|
| **2019-09-30** | 0.600 | -0.405 | -0.030 |
| **2019-12-31** | 0.600 | -0.439 | 0.046 |
| **2020-03-31** | 1.200 | -0.317 | 0.027 |
| **2020-06-30** | 1.200 | -0.296 | 0.059 |
| **2020-09-30** | 3.700 | -0.274 | 0.045 |
| **2020-12-31** | 9.100 | -0.229 | -0.158 |
| **2021-03-31** | 11.400 | -0.236 | -0.146 |
| **2021-06-30** | 13.300 | -0.245 | -0.031 |
| **2021-09-30** | 11.100 | -0.287 | -0.028 |
| **2021-12-31** | 1.000 | -0.268 | 0.220 |

In [76]:

```
YVAR = Y_train
XVAR = X_train
CONST = pd.DataFrame(index=X_train.index)

CONST['CONST']= 1
XVAR_TOT = pd.concat([CONST,XVAR], axis=1, join='inner')
model = sm.OLS(YVAR, XVAR_TOT)
Train_results = model.fit()
```

In [77]:

```
Train_results.summary()
```

Out[77]:

OLS Regression Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | CW | **R-squared:** | 0.839 |
| **Model:** | OLS | **Adj. R-squared:** | 0.829 |
| **Method:** | Least Squares | **F-statistic:** | 88.50 |
| **Date:** | Sat, 15 Oct 2022 | **Prob (F-statistic):** | 3.23e-20 |
| **Time:** | 19:06:26 | **Log-Likelihood:** | 69.260 |
| **No. Observations:** | 55 | **AIC:** | -130.5 |
| **Df Residuals:** | 51 | **BIC:** | -122.5 |
| **Df Model:** | 3 | | |
| **Covariance Type:** | nonrobust | | |

| | coef | std err | t | P>\|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **CONST** | -4.3202 | 0.012 | -353.657 | 0.000 | -4.345 | -4.296 |
| **CreditToGDP_Gap_2** | -0.0507 | 0.004 | -11.984 | 0.000 | -0.059 | -0.042 |
| **NPL_3** | 0.0809 | 0.063 | 1.293 | 0.202 | -0.045 | 0.206 |
| **EXPORT_3** | -0.8193 | 0.113 | -7.240 | 0.000 | -1.046 | -0.592 |

| | | | |
|---|---|---|---|
| **Omnibus:** | 2.130 | **Durbin-Watson:** | 0.766 |
| **Prob(Omnibus):** | 0.345 | **Jarque-Bera (JB):** | 1.383 |
| **Skew:** | 0.094 | **Prob(JB):** | 0.501 |
| **Kurtosis:** | 3.754 | **Cond. No.** | 41.9 |

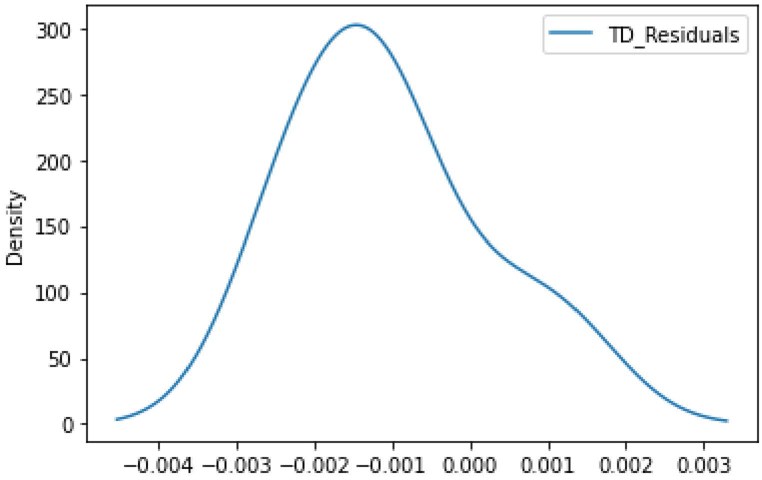
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

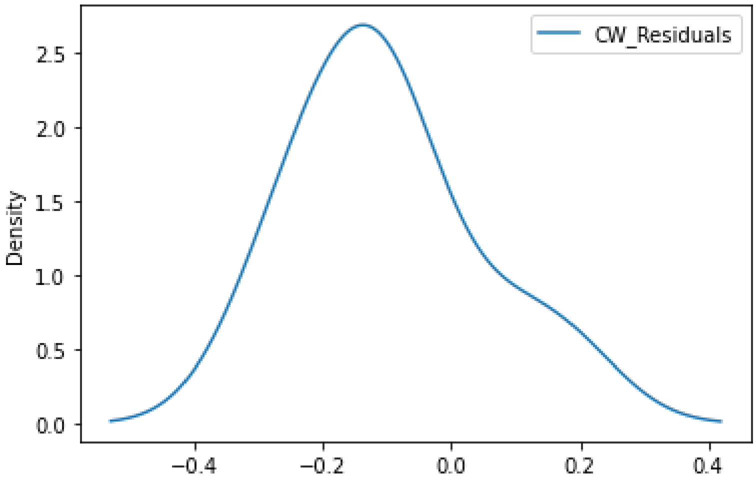
In [78]:

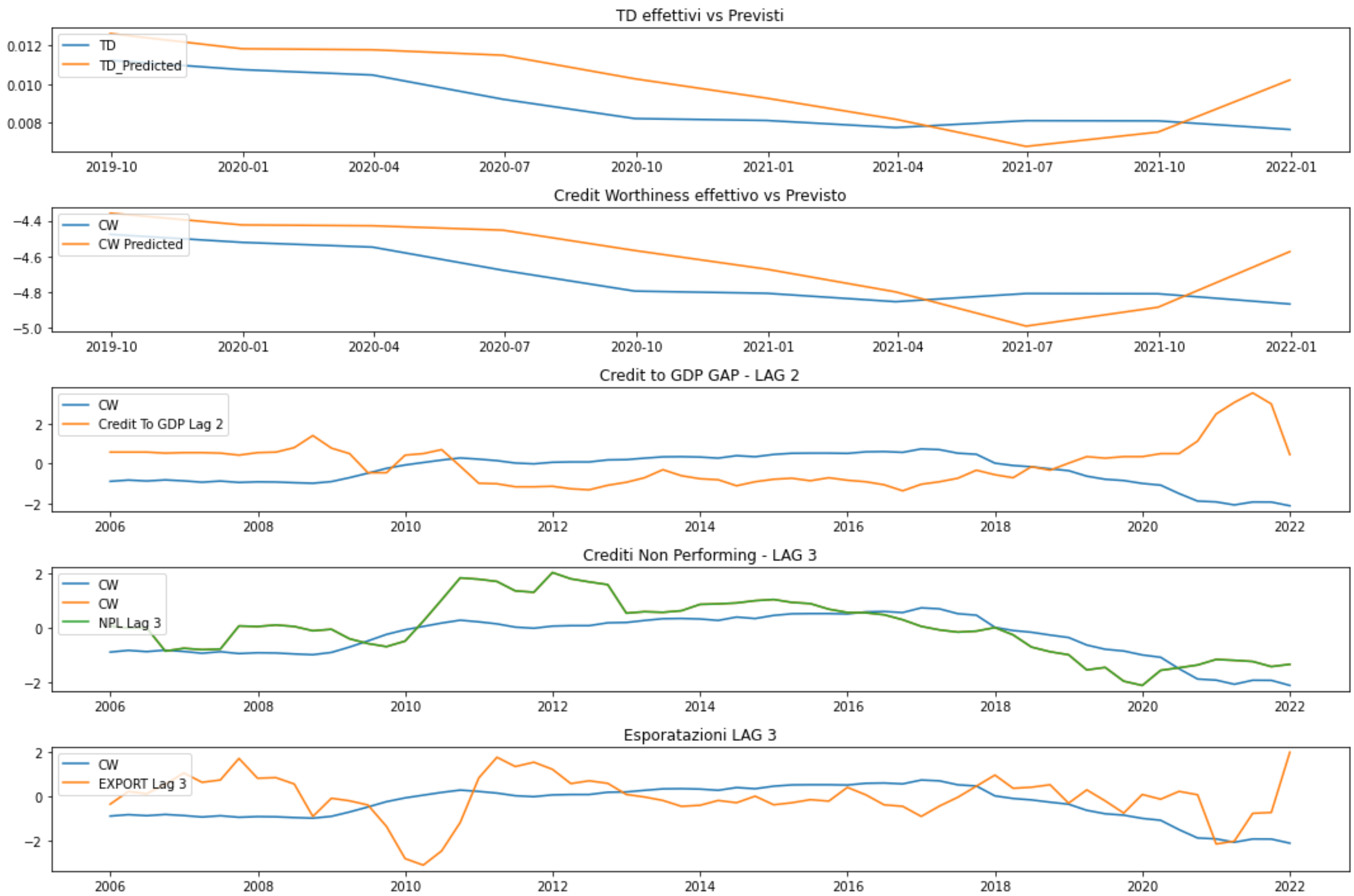
```
CONST = pd.DataFrame(index=X_test.index)
CONST['CONST']= 1
X = pd.concat([CONST,X_test], axis=1, join='inner')
Y = Y_test
test(X,Y, Train_results)
```

Out[78]:

| | CW_Predicted | CW | TD | TD_Predicted | CW_Residuals | TD_Residuals |
|---|---|---|---|---|---|---|
| **count** | 10.000 | 10.000 | 10.000 | 10.000 | 10.000 | 10.000 |
| **mean** | -4.615 | -4.716 | 0.009 | 0.010 | -0.101 | -0.001 |
| **std** | 0.215 | 0.148 | 0.001 | 0.002 | 0.142 | 0.001 |
| **min** | -4.989 | -4.866 | 0.008 | 0.007 | -0.293 | -0.003 |
| **25%** | -4.766 | -4.808 | 0.008 | 0.008 | -0.202 | -0.002 |
| **50%** | -4.570 | -4.800 | 0.008 | 0.010 | -0.119 | -0.001 |
| **75%** | -4.435 | -4.580 | 0.010 | 0.012 | -0.065 | -0.001 |
| **max** | -4.359 | -4.477 | 0.011 | 0.013 | 0.182 | 0.001 |




# Test usando SKLEARN

In [80]:

```
from sklearn.linear_model import LinearRegression
lm = LinearRegression(fit_intercept=True)
```

In [81]:
```
lm.fit(X_train, Y_train)
DF_CW_Predicted = pd.DataFrame(lm.predict(X_test),index=X_test.index)
DF_CW_Predicted.columns = ['CW_Predicted']
DF_CW_Predicted.describe()
```

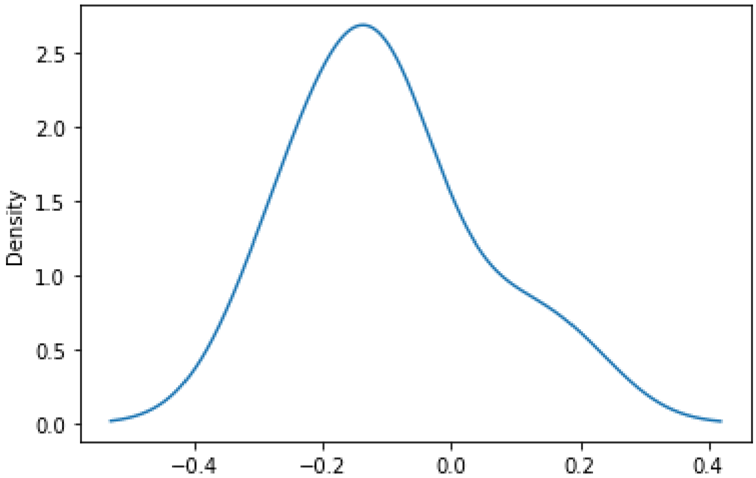
Out[81]:

| | CW_Predicted |
|---|---|
| **count** | 10.000 |
| **mean** | -4.615 |
| **std** | 0.215 |
| **min** | -4.989 |
| **25%** | -4.766 |
| **50%** | -4.570 |
| **75%** | -4.435 |
| **max** | -4.359 |

In [ ]:
```
DF_CW_Predicted
```

In [82]:
```
df_test_compare = pd.concat([DF_CW_Predicted,Y_test],axis=1, join= 'inner')
df_test_compare['residuals'] = df_test_compare['CW']-df_test_compare['CW_Predicted']
df_test_compare['residuals'].plot.kde()
```

Out[82]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f322c4cf610>
```




In [83]:
```
Test_evaluation_metrics_func(Y_test.values, DF_CW_Predicted.values)
```

```
Evaluation metric results:-
MSE:Mean Square Error : 0.03
MAE:Mean Absolute Error : 0.15
RMSE:Mean Square Error : 0.17
MAPE:Mean Square Error : 4.74
R2: R2 score : -0.45
```

Out[83]:

| | MSE:Mean Square Error | MAE:Mean Absolute Error | RMSE:Mean Square Error | MAPE:Mean Square Error | R2: R2 score |
|---|---|---|---|---|---|
| **0** | 0.028 | 0.152 | 0.169 | 4.745 | -0.446 |