

Proj_PNAS

November 18, 2023

1 Sentiment of ECB speeches and the perceived effect on Inflation.

In the followin Notebook we are going to lay the foundation for our research regarding the impact that the speeches of the ECB might play in the market and the sentiment regard inflation. #####
Import the libraries we need:

```
[ ]: import pandas as pd
from tqdm.notebook import tqdm
import os
import nltk
from nltk.tokenize import word_tokenize
```

```
[ ]: nltk.download([
    "names",
    "stopwords",
    "state_union",
    "twitter_samples",
    "movie_reviews",
    "averaged_perceptron_tagger",
    "vader_lexicon",
    "punkt",
])
```

```
[nltk_data] Downloading package names to
[nltk_data] C:\Users\Utente\AppData\Roaming\nltk_data...
[nltk_data] Package names is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data] C:\Users\Utente\AppData\Roaming\nltk_data...
[nltk_data] Unzipping corpora\stopwords.zip.
[nltk_data] Downloading package state_union to
[nltk_data] C:\Users\Utente\AppData\Roaming\nltk_data...
[nltk_data] Package state_union is already up-to-date!
[nltk_data] Downloading package twitter_samples to
[nltk_data] C:\Users\Utente\AppData\Roaming\nltk_data...
[nltk_data] Package twitter_samples is already up-to-date!
[nltk_data] Downloading package movie_reviews to
[nltk_data] C:\Users\Utente\AppData\Roaming\nltk_data...
[nltk_data] Package movie_reviews is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger to
```

```

[nltk_data]      C:\Users\Utente\AppData\Roaming\nltk_data...
[nltk_data]      Package averaged_perceptron_tagger is already up-to-
[nltk_data]      date!
[nltk_data]      Downloading package vader_lexicon to
[nltk_data]      C:\Users\Utente\AppData\Roaming\nltk_data...
[nltk_data]      Package vader_lexicon is already up-to-date!
[nltk_data]      Downloading package punkt to
[nltk_data]      C:\Users\Utente\AppData\Roaming\nltk_data...
[nltk_data]      Unzipping tokenizers\punkt.zip.

```

```
[ ]: True
```

Import the Data we need: in the following section of our notebook we will introduce the Data scraped from the ECB up until 2023

```

[ ]: main_ds = pd.read_csv("Inputs//all_ECB_speeches.csv", sep="|") #if the file has
      →to be changed, be careful with the sep option.
      main_ds.head()

```

```

[ ]:
      date          speakers \
0  2023-10-30    Luis de Guindos
1  2023-10-25  Christine Lagarde
2  2023-10-17    Luis de Guindos
3  2023-10-14  Christine Lagarde
4  2023-10-04    Luis de Guindos

                                     title \
0  The euro area economy and our monetary policy ...
1  Remarks delivered at the Bank of Greece on the...
2  Macprudential policy and research: learning ...
3                                     IMFC Statement
4  The inflation outlook and monetary policy in t...

                                     subtitle \
0  Remarks by Luis de Guindos, Vice-President of ...
1  Speech by Christine Lagarde, President of the ...
2  Dinner speech by Luis de Guindos, Vice-Preside...
3  Statement by Christine Lagarde, President of t...
4  Keynote speech by Luis de Guindos, Vice-Presid...

                                     contents
0  SPEECH  The euro area economy and our moneta...
1  SPEECH  Remarks delivered at the Bank of G...
2  SPEECH  Macprudential policy and researc...
3  SPEECH  IMFC Statement  Statement by Christ...
4  SPEECH  The inflation outlook and monetary p...

```

```
[ ]: # we need to combine the speeches uniting title, subtitle and contents

main_ds["speech_merged"] = main_ds["title"] + "\n" + main_ds["subtitle"] + "\n" +
↳ main_ds["contents"]
main_ds = main_ds.drop(columns=["title", "subtitle", "contents"])
```

```
[ ]: import nltk
from nltk.tokenize import word_tokenize
from tqdm import tqdm

# Ensure that the necessary NLTK resources have been downloaded
nltk.download('punkt')
nltk.download('stopwords')

def preprocessing_df(ds_input):
    # Load stopwords once, outside the loop
    stopwords = nltk.corpus.stopwords.words("english")

    # Define a preprocessing routine
    def preprocess_text(speech):
        tokens = word_tokenize(speech)
        tokens = [w.lower() for w in tokens if w.isalpha() or w.isdigit() and w.
↳ lower() not in stopwords]
        return ' '.join(tokens)

    # Use tqdm with apply to display a progress bar
    tqdm.pandas(desc="Processing rows")
    ds_input['speech_merged'] = ds_input['speech_merged'].astype(str).
↳ progress_apply(preprocess_text)

    return ds_input

# Apply this function to your DataFrame
# ds_prep = preprocessing_df(your_dataframe)
```

```
[nltk_data] Downloading package punkt to
[nltk_data] C:\Users\Utente\AppData\Roaming\nltk_data...
[nltk_data] Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data] C:\Users\Utente\AppData\Roaming\nltk_data...
[nltk_data] Package stopwords is already up-to-date!
```

```
[ ]: ds_prep = preprocessing_df(main_ds)
ds_prep.to_excel("Outputs//Intermediate//prep_new.xlsx", index=False)
```

```
Processing rows: 0%|          | 0/2736 [00:00<?, ?it/s]Processing rows:
100%|          | 2736/2736 [00:55<00:00, 49.65it/s]
```

```
[ ]: import pandas as pd
from tqdm.notebook import tqdm
import os
import nltk
from nltk.tokenize import word_tokenize
import numpy as np
```

Analysis of the Sentiment Here below, after having done the pre-processing of our file, we use the VADER algorithm to establish the sentiment score of each speech

```
[ ]: ds_prep = pd.read_excel("Outputs//Intermediate//prep_new.xlsx")
```

```
[ ]: from nltk.sentiment import SentimentIntensityAnalyzer
sia = SentimentIntensityAnalyzer()
scores = []
for sentence in tqdm(ds_prep["speech_merged"]):
    score = sia.polarity_scores(str(sentence))
    scores.append(score)
neg_scores = [score['neg'] for score in scores]
neu_scores = [score['neu'] for score in scores]
pos_scores = [score['pos'] for score in scores]
compound_scores = [score['compound'] for score in scores]

ds_prep['neg_score'] = neg_scores
ds_prep['neu_score'] = neu_scores
ds_prep['pos_score'] = pos_scores
ds_prep['compound_score'] = compound_scores
```

```
0%|          | 0/2736 [00:00<?, ?it/s]
```

```
[ ]: import numpy as np
import matplotlib.pyplot as plt
ds_prep['tanh_normalized_compound'] = np.
    ↪tanh(ds_prep['pos_score']-ds_prep["neg_score"])

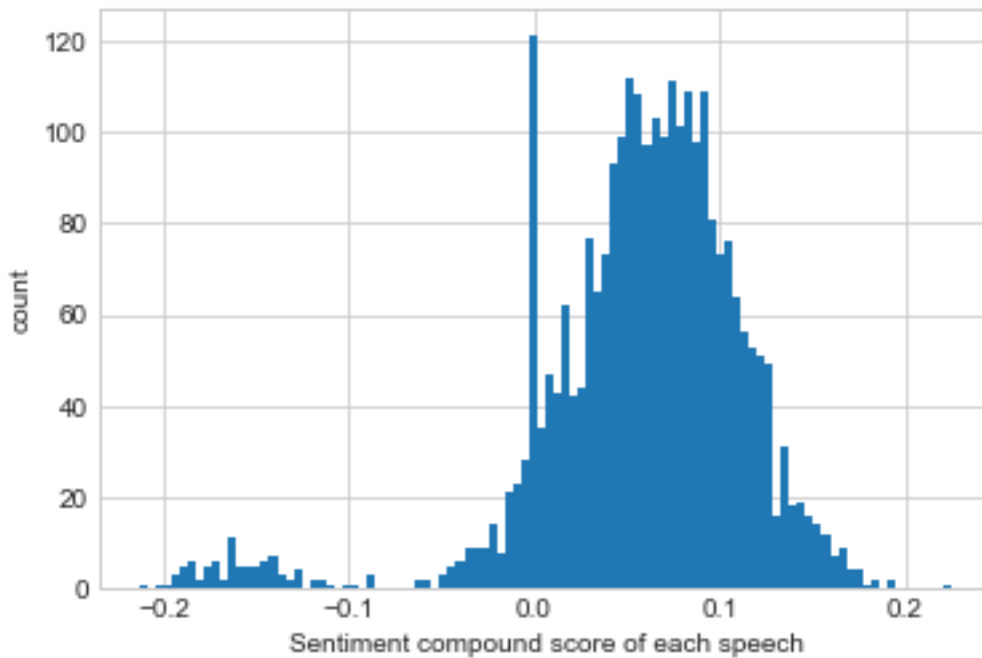
data = np.tanh(ds_prep['tanh_normalized_compound'])
fig = plt.figure() ; ax = plt.axes( xlabel= "Sentiment compound score of each_
    ↪speech", ylabel= "count")
ax.hist(data, bins=100)
```

```
[ ]: (array([ 1.,  0.,  1.,  1.,  3.,  5.,  6.,  2.,  5.,  6.,  2.,
          11.,  5.,  5.,  5.,  6.,  7.,  3.,  2.,  4.,  0.,  2.,
           2.,  1.,  0.,  1.,  1.,  0.,  3.,  0.,  0.,  0.,  0.,
           0.,  2.,  2.,  0.,  3.,  5.,  6.,  9.,  9.,  9., 14.,
           8., 21., 23., 28., 121., 35., 47., 43., 62., 42., 44.,
          77., 65., 73., 93., 99., 112., 108., 97., 103., 99., 111.,
         101., 109., 98., 109., 81., 73., 76., 64., 56., 53., 51.,
          49., 16., 31., 18., 19., 16., 14., 12.,  7.,  9.,  4.,
```

```

4., 1., 2., 0., 2., 0., 0., 0., 0., 0., 0.,
1.]),
array([-0.21319687, -0.20881531, -0.20443375, -0.2000522 , -0.19567064,
-0.19128908, -0.18690753, -0.18252597, -0.17814441, -0.17376286,
-0.1693813 , -0.16499974, -0.16061819, -0.15623663, -0.15185507,
-0.14747352, -0.14309196, -0.1387104 , -0.13432885, -0.12994729,
-0.12556573, -0.12118418, -0.11680262, -0.11242106, -0.10803951,
-0.10365795, -0.09927639, -0.09489484, -0.09051328, -0.08613172,
-0.08175017, -0.07736861, -0.07298705, -0.0686055 , -0.06422394,
-0.05984238, -0.05546083, -0.05107927, -0.04669771, -0.04231616,
-0.0379346 , -0.03355304, -0.02917149, -0.02478993, -0.02040837,
-0.01602682, -0.01164526, -0.0072637 , -0.00288215, 0.00149941,
0.00588097, 0.01026252, 0.01464408, 0.01902564, 0.02340719,
0.02778875, 0.03217031, 0.03655186, 0.04093342, 0.04531498,
0.04969653, 0.05407809, 0.05845965, 0.0628412 , 0.06722276,
0.07160432, 0.07598587, 0.08036743, 0.08474899, 0.08913054,
0.09351121 , 0.09789366, 0.10227521, 0.10665677, 0.11103833,
0.11541988, 0.11980144, 0.124183 , 0.12856455, 0.13294611,
0.13732767, 0.14170922, 0.14609078, 0.15047234, 0.15485389,
0.15923545, 0.16361701, 0.16799856, 0.17238012, 0.17676168,
0.18114323, 0.18552479, 0.18990634, 0.1942879 , 0.19866946,
0.20305101, 0.20743257, 0.21181413, 0.21619568, 0.22057724,
0.2249588 ]),
<BarContainer object of 100 artists>)

```



```
[ ]: ds_prep.to_excel("Outputs//Intermediate//sentiment.xlsx")
```

1.1 ECONOMETRIC ANALYSIS

```
[ ]: import pandas as pd
from tqdm.notebook import tqdm
import os
import nltk
from nltk.tokenize import word_tokenize
import numpy as np
```

```
[ ]: ds_prep = pd.read_excel("Outputs//Intermediate//sentiment.xlsx")
```

We now plot and do some descriptive analysis:

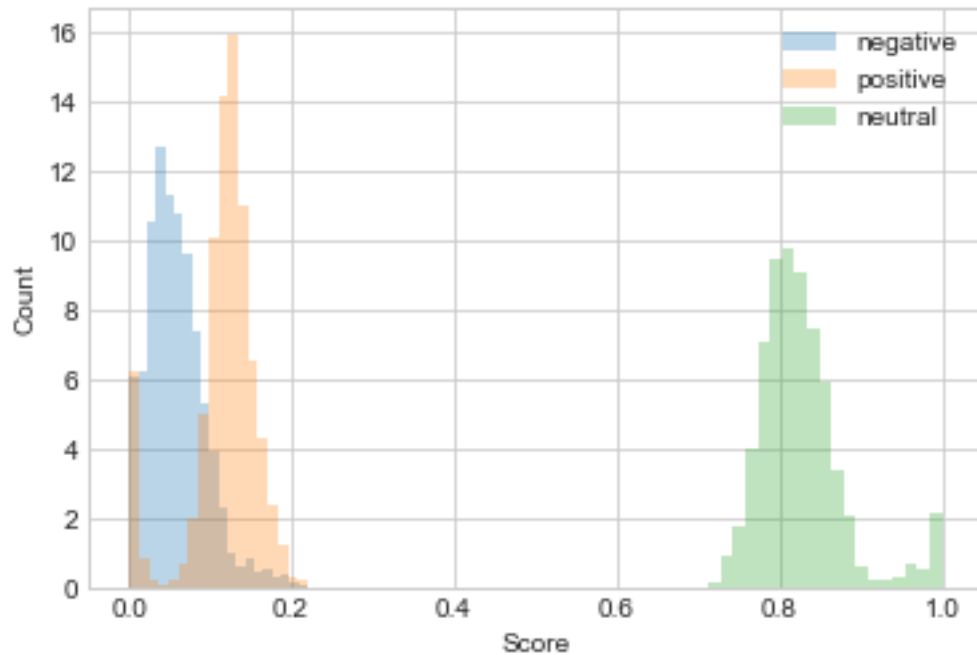
```
[ ]: import matplotlib.pyplot as plt

plt.style.use("seaborn-whitegrid")
fig = plt.figure()
ax = plt.axes(xlabel="Score", ylabel="Count")

x1 = ds_prep["neg_score"]
x2 = ds_prep["pos_score"]
x3 = ds_prep["neu_score"]

kwargs = dict(histtype="stepfilled", alpha=0.3, density=True, bins=20)
ax.hist(x1, label="negative", **kwargs)
ax.hist(x2, label="positive", **kwargs)
ax.hist(x3, label="neutral", **kwargs)

plt.legend()
plt.show()
```



We create now the Timeseries for our compound Score

```
[ ]: import numpy as np

ds_prep['date'] = pd.to_datetime(ds_prep['date'])

ds_prep['year_month'] = ds_prep['date'].dt.to_period('M')

# Apply tanh function to the 'compound_score' column
# It seems the 'tanh_normalized_compound' column might already be the tanh of
↪ compound_score,
# but we will compute it again to be sure

# Group by year and month, and calculate the average of the tanh compound score
monthly_avg_tanh_compound = ds_prep.
    ↪ groupby('year_month')['tanh_normalized_compound'].mean().reset_index()

monthly_avg_tanh_compound.head()
```

```
[ ]:   year_month  tanh_normalized_compound
0    1997-02      0.058932
1    1997-03      0.044970
2    1997-04      0.068392
3    1997-05      0.063913
4    1997-06      0.092728
```

We now import our other variables

```
[ ]: ds2 = pd.read_excel("Inputs\INFYOY 1990-2023.xlsx")
ds2['Date'] = pd.to_datetime(ds2['Date'])
ds2['year_month'] = ds2['Date'].dt.to_period('M')
ds2.drop(columns="Date")
```

```
[ ]:      M3_YOY_MON  HICP_YOY_MON  Interbank3  M1_YOY_MON  year_month
0           3.8           1.8    4.430000    -3.654    1997-02
1           3.6           1.6    4.500000    -2.444    1997-03
2           3.5           1.3    4.390000    -4.117    1997-04
3           4.0           1.4    4.300000    -2.415    1997-05
4           4.4           1.4    4.290000    -3.739    1997-06
..          ...           ...           ...           ...           ...
317        -0.4           5.3    3.671810    -2.375    2023-07
318        -1.3           5.2    3.780304    -3.440    2023-08
319        -1.2           4.3    3.880048    -2.851    2023-09
320         NaN           2.9    3.967636         NaN    2023-10
321         NaN           NaN         NaN         NaN    2023-11
```

[322 rows x 5 columns]

```
[ ]: merged = pd.merge(ds2,monthly_avg_tanh_compound, on='year_month', how='outer')
merged.drop(columns='Date')
```

```
[ ]:      M3_YOY_MON  HICP_YOY_MON  Interbank3  M1_YOY_MON  year_month  \
0           3.8           1.8    4.430000    -3.654    1997-02
1           3.6           1.6    4.500000    -2.444    1997-03
2           3.5           1.3    4.390000    -4.117    1997-04
3           4.0           1.4    4.300000    -2.415    1997-05
4           4.4           1.4    4.290000    -3.739    1997-06
..          ...           ...           ...           ...           ...
317        -0.4           5.3    3.671810    -2.375    2023-07
318        -1.3           5.2    3.780304    -3.440    2023-08
319        -1.2           4.3    3.880048    -2.851    2023-09
320         NaN           2.9    3.967636         NaN    2023-10
321         NaN           NaN         NaN         NaN    2023-11
```

```
      tanh_normalized_compound
0           0.058932
1           0.044970
2           0.068392
3           0.063913
4           0.092728
..          ...
317        0.061241
318        0.011663
319        0.034852
```



```
320          0.055033
321          NaN
```

```
[322 rows x 6 columns]
```

1.2 We now do the Test the Dynamic Linear Model: <https://pydlm.github.io/discounting.html>

```
[ ]: merged.to_excel("Outputs//Intermediate//merged.xlsx")
```

```
[ ]: !pip install pydlm
```

```
Requirement already satisfied: pydlm in w:\programmi\anaconda\lib\site-packages
(0.1.1.12)
Requirement already satisfied: matplotlib in w:\programmi\anaconda\lib\site-
packages (from pydlm) (3.4.2)
Requirement already satisfied: numpy in w:\programmi\anaconda\lib\site-packages
(from pydlm) (1.20.3)
Requirement already satisfied: pillow>=6.2.0 in w:\programmi\anaconda\lib\site-
packages (from matplotlib->pydlm) (8.2.0)
Requirement already satisfied: cycler>=0.10 in w:\programmi\anaconda\lib\site-
packages (from matplotlib->pydlm) (0.10.0)
Requirement already satisfied: pyparsing>=2.2.1 in
w:\programmi\anaconda\lib\site-packages (from matplotlib->pydlm) (2.4.7)
Requirement already satisfied: python-dateutil>=2.7 in
w:\programmi\anaconda\lib\site-packages (from matplotlib->pydlm) (2.8.1)
Requirement already satisfied: kiwisolver>=1.0.1 in
w:\programmi\anaconda\lib\site-packages (from matplotlib->pydlm) (1.3.1)
Requirement already satisfied: six in w:\programmi\anaconda\lib\site-packages
(from cycler>=0.10->matplotlib->pydlm) (1.16.0)
```

```
[ ]: from pydlm import dlm, trend, seasonality, dynamic

# Extracting the required time series from the data
time_series_data = merged[['HICP_YOY_MON', 'M1_YOY_MON_lag_12',
    ↳ 'M1_YOY_MON_lag_24',
    ↳ 'tanh_normalized_compound_lag_12',
    ↳ 'tanh_normalized_compound_lag_24']]

# The target variable
target = time_series_data['HICP_YOY_MON']

time_series_data.dropna(inplace=True)

# The features (lagged variables)
features = time_series_data[['M1_YOY_MON_lag_12', 'M1_YOY_MON_lag_24',
```

```

        'tanh_normalized_compound_lag_12',
        'tanh_normalized_compound_lag_24']] .values

# Creating the Dynamic Linear Model
myDLM = dlm(target) + dynamic(features, name='dynamic', discount=0.9)

# Fitting the model
myDLM.fit()

# Summary of the fitted model
myDLM.plot()

```

```

-----
KeyError                                Traceback (most recent call last)
<ipython-input-94-3dabba55eccb> in <module>
      2
      3 # Extracting the required time series from the data
----> 4 time_series_data = merged[['HICP_YOY_MON', 'M1_YOY_MON_lag_12',
      5                               'M1_YOY_MON_lag_24',
      6                               'tanh_normalized_compound_lag_12',
      7                               'tanh_normalized_compound_lag_24']]

w:\Programmi\Anaconda\lib\site-packages\pandas\core\frame.py in
    3028         if is_iterator(key):
    3029             key = list(key)
-> 3030         indexer = self.loc._get_listlike_indexer(key, axis=1,
    3031         raise_missing=True)[1]
    3032         # take() does not accept boolean indexers

w:\Programmi\Anaconda\lib\site-packages\pandas\core\indexing.py in
    1264         keyarr, indexer, new_indexer = ax._reindex_non_unique(keyarr)
    1265
-> 1266         self._validate_read_indexer(keyarr, indexer, axis,
    1267         raise_missing=raise_missing)
    1268         return keyarr, indexer

w:\Programmi\Anaconda\lib\site-packages\pandas\core\indexing.py in
    1314         if raise_missing:
    1315             not_found = list(set(key) - set(ax))
-> 1316             raise KeyError(f"{not_found} not in index")
    1317

```

```
1318 not_found = key[missing_mask]
```

```
KeyError: "['tanh_normalized_compound_lag_24',  
↪ 'tanh_normalized_compound_lag_12'] not in index"
```

1.3 We now do the VAR

```
[ ]: merged.to_excel("Outputs//Intermediate//merged.xlsx")
```

```
[ ]: from statsmodels.tsa.api import VAR
import statsmodels.api as sm
import pandas as pd
from tqdm.notebook import tqdm
import os
import nltk
from nltk.tokenize import word_tokenize
import numpy as np

merged = pd.read_excel("Outputs//Intermediate//merged.xlsx")
# Set the 'Date' column as the index
merged.set_index('year_month', inplace=True)

# Drop unnecessary columns
merged.drop(columns=['M3_YOY_MON', 'Interbank3'], inplace=True)

# Assuming monthly data, create 1 and 2 years lags (12 and 24 months)
merged['HICP_YOY_MON_lag_12'] = merged['HICP_YOY_MON'].shift(12)
merged['M1_YOY_MON_lag_12'] = merged['M1_YOY_MON'].shift(12)
merged['tanh_normalized_compound_lag_1'] = merged['tanh_normalized_compound'].  
↪ shift(1)

merged['HICP_YOY_MON_lag_24'] = merged['HICP_YOY_MON'].shift(24)
merged['M1_YOY_MON_lag_24'] = merged['M1_YOY_MON'].shift(24)
merged['tanh_normalized_compound_lag_2'] = merged['tanh_normalized_compound'].  
↪ shift(2)

# Drop any rows with NaN values resulting from the lag
merged.dropna(inplace=True)

selected_columns = ['HICP_YOY_MON', 'M1_YOY_MON', 'tanh_normalized_compound',  
                    'HICP_YOY_MON_lag_12', 'M1_YOY_MON_lag_12',  
↪ 'tanh_normalized_compound_lag_1',  
                    'HICP_YOY_MON_lag_24', 'M1_YOY_MON_lag_24',  
↪ 'tanh_normalized_compound_lag_2']
data_selected = merged[selected_columns]
```

```
# Fit the VAR model
model = VAR(data_selected)
results = model.fit() # Using 'aic' to select the optimal lag order up to 24

# Summary of the results
results_summary = results.summary()
results_summary
```

w:\Programmi\Anaconda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:581:
ValueWarning: A date index has been provided, but it has no associated frequency
information and so will be ignored when e.g. forecasting.

warnings.warn('A date index has been provided, but it has no')

[]: Summary of Regression Results

```
=====
Model:                                VAR
Method:                               OLS
Date:                Sat, 18, Nov, 2023
Time:                10:47:12
-----
No. of Equations:      9.00000    BIC:                -38.4984
Nobs:                  289.000    HQIC:               -39.1827
Log likelihood:        2127.35    FPE:                6.08949e-18
AIC:                   -39.6402    Det(Omega_mle):     4.48354e-18
-----
Results for equation HICP_YOY_MON
=====
=====
```

		coefficient	std. error
const		0.112394	0.075904
1.481	0.139		
L1.HICP_YOY_MON		1.017599	0.013059
77.922	0.000		
L1.M1_YOY_MON		0.004346	0.001748
2.487	0.013		
L1.tanh_normalized_compound		-0.373099	0.716800
-0.521	0.603		
L1.HICP_YOY_MON_lag_12		-0.082096	0.016635
-4.935	0.000		
L1.M1_YOY_MON_lag_12		0.001885	0.001885
1.000	0.317		
L1.tanh_normalized_compound_lag_1		-0.198598	0.731134
-0.272	0.786		

L1.HICP_YOY_MON_lag_24	-0.013602	0.023226
-0.586	0.558	
L1.M1_YOY_MON_lag_24	-0.000938	0.001791
-0.524	0.600	
L1.tanh_normalized_compound_lag_2	0.353799	0.722056
0.490	0.624	
=====		
=====		

Results for equation M1_YOY_MON

		coefficient	std. error
t-stat	prob		

const		1.660609	1.013155
1.639	0.101		
L1.HICP_YOY_MON		-0.542851	0.174314
-3.114	0.002		
L1.M1_YOY_MON		0.920823	0.023327
39.475	0.000		
L1.tanh_normalized_compound		-15.290463	9.567800
-1.598	0.110		
L1.HICP_YOY_MON_lag_12		0.635522	0.222045
2.862	0.004		
L1.M1_YOY_MON_lag_12		0.032336	0.025162
1.285	0.199		
L1.tanh_normalized_compound_lag_1		11.743320	9.759134
1.203	0.229		
L1.HICP_YOY_MON_lag_24		-0.406964	0.310014
-1.313	0.189		
L1.M1_YOY_MON_lag_24		-0.014651	0.023902
-0.613	0.540		
L1.tanh_normalized_compound_lag_2		-6.569927	9.637954
-0.682	0.495		
=====			
=====			

Results for equation tanh_normalized_compound

		coefficient	std. error
t-stat	prob		

const		0.030553	0.006192

4.935	0.000		
L1.HICP_YOY_MON		-0.001435	0.001065
-1.347	0.178		
L1.M1_YOY_MON		0.000159	0.000143
1.118	0.264		
L1.tanh_normalized_compound		0.188967	0.058471
3.232	0.001		
L1.HICP_YOY_MON_lag_12		0.000401	0.001357
0.295	0.768		
L1.M1_YOY_MON_lag_12		0.000204	0.000154
1.329	0.184		
L1.tanh_normalized_compound_lag_1		0.083218	0.059640
1.395	0.163		
L1.HICP_YOY_MON_lag_24		-0.001521	0.001895
-0.803	0.422		
L1.M1_YOY_MON_lag_24		0.000083	0.000146
0.569	0.569		
L1.tanh_normalized_compound_lag_2		0.209996	0.058900
3.565	0.000		

=====

=====

Results for equation HICP_YOY_MON_lag_12

=====

t-stat	prob	coefficient	std. error

const		0.010866	0.063939
0.170	0.865		
L1.HICP_YOY_MON		0.065509	0.011001
5.955	0.000		
L1.M1_YOY_MON		-0.003643	0.001472
-2.475	0.013		
L1.tanh_normalized_compound		0.197821	0.603809
0.328	0.743		
L1.HICP_YOY_MON_lag_12		0.995372	0.014013
71.032	0.000		
L1.M1_YOY_MON_lag_12		0.000935	0.001588
0.589	0.556		
L1.tanh_normalized_compound_lag_1		-0.340429	0.615883
-0.553	0.580		
L1.HICP_YOY_MON_lag_24		-0.011196	0.019565
-0.572	0.567		
L1.M1_YOY_MON_lag_24		-0.000772	0.001508
-0.512	0.609		

L1.tanh_normalized_compound_lag_2	-0.916911	0.608236
-1.507	0.132	

=====

=====

Results for equation M1_YOY_MON_lag_12

=====

=====

		coefficient	std. error
t-stat	prob		

const		-1.263971	1.021872
-1.237	0.216		
L1.HICP_YOY_MON		0.363951	0.175814
2.070	0.038		
L1.M1_YOY_MON		0.082699	0.023528
3.515	0.000		
L1.tanh_normalized_compound		11.937629	9.650122
1.237	0.216		
L1.HICP_YOY_MON_lag_12		-0.693442	0.223956
-3.096	0.002		
L1.M1_YOY_MON_lag_12		0.886365	0.025379
34.926	0.000		
L1.tanh_normalized_compound_lag_1		8.377730	9.843103
0.851	0.395		
L1.HICP_YOY_MON_lag_24		0.697771	0.312682
2.232	0.026		
L1.M1_YOY_MON_lag_24		0.005928	0.024108
0.246	0.806		
L1.tanh_normalized_compound_lag_2		-5.235076	9.720880
-0.539	0.590		

=====

=====

Results for equation tanh_normalized_compound_lag_1

=====

=====

		coefficient	std. error
t-stat	prob		

const		-0.000102	0.000143
-0.709	0.478		
L1.HICP_YOY_MON		-0.000001	0.000025
-0.038	0.970		
L1.M1_YOY_MON		0.000001	0.000003

0.356	0.722		
L1.tanh_normalized_compound		0.999157	0.001353
738.336	0.000		
L1.HICP_YOY_MON_lag_12		0.000000	0.000031
0.007	0.994		
L1.M1_YOY_MON_lag_12		0.000001	0.000004
0.272	0.786		
L1.tanh_normalized_compound_lag_1		0.001595	0.001380
1.155	0.248		
L1.HICP_YOY_MON_lag_24		0.000007	0.000044
0.149	0.882		
L1.M1_YOY_MON_lag_24		-0.000003	0.000003
-0.852	0.394		
L1.tanh_normalized_compound_lag_2		0.000139	0.001363
0.102	0.919		

=====

=====

Results for equation HICP_YOY_MON_lag_24

=====

t-stat	prob	coefficient	std. error

const		-0.033394	0.059151
-0.565	0.572		
L1.HICP_YOY_MON		-0.014471	0.010177
-1.422	0.155		
L1.M1_YOY_MON		0.001507	0.001362
1.106	0.269		
L1.tanh_normalized_compound		-0.159193	0.558592
-0.285	0.776		
L1.HICP_YOY_MON_lag_12		0.071921	0.012964
5.548	0.000		
L1.M1_YOY_MON_lag_12		-0.002665	0.001469
-1.814	0.070		
L1.tanh_normalized_compound_lag_1		0.186730	0.569762
0.328	0.743		
L1.HICP_YOY_MON_lag_24		0.938637	0.018099
51.860	0.000		
L1.M1_YOY_MON_lag_24		0.001844	0.001395
1.322	0.186		
L1.tanh_normalized_compound_lag_2		0.554265	0.562688
0.985	0.325		

=====

=====

Results for equation M1_YOY_MON_lag_24

		coefficient	std. error
t-stat	prob		

const		0.188308	1.001686
0.188	0.851		
L1.HICP_YOY_MON		0.031014	0.172340
0.180	0.857		
L1.M1_YOY_MON		0.012138	0.023063
0.526	0.599		
L1.tanh_normalized_compound		2.544015	9.459487
0.269	0.788		
L1.HICP_YOY_MON_lag_12		0.209821	0.219532
0.956	0.339		
L1.M1_YOY_MON_lag_12		0.097187	0.024877
3.907	0.000		
L1.tanh_normalized_compound_lag_1		-4.839571	9.648656
-0.502	0.616		
L1.HICP_YOY_MON_lag_24		-0.571532	0.306505
-1.865	0.062		
L1.M1_YOY_MON_lag_24		0.916882	0.023632
38.799	0.000		
L1.tanh_normalized_compound_lag_2		3.572182	9.528848
0.375	0.708		
=====			
=====			

Results for equation tanh_normalized_compound_lag_2

		coefficient	std. error
t-stat	prob		

const		-0.000028	0.000082
-0.336	0.737		
L1.HICP_YOY_MON		0.000003	0.000014
0.216	0.829		
L1.M1_YOY_MON		-0.000000	0.000002
-0.019	0.985		
L1.tanh_normalized_compound		0.000621	0.000776
0.800	0.424		
L1.HICP_YOY_MON_lag_12		-0.000001	0.000018

-0.069	0.945		
L1.M1_YOY_MON_lag_12		0.000000	0.000002
0.102	0.919		
L1.tanh_normalized_compound_lag_1		0.999680	0.000792
1262.523	0.000		
L1.HICP_YOY_MON_lag_24		0.000007	0.000025
0.281	0.778		
L1.M1_YOY_MON_lag_24		0.000002	0.000002
0.841	0.400		
L1.tanh_normalized_compound_lag_2		0.000101	0.000782
0.130	0.897		
=====			
=====			

Correlation matrix of residuals

		HICP_YOY_MON	M1_YOY_MON	
tanh_normalized_compound	HICP_YOY_MON_lag_12	M1_YOY_MON_lag_12		
tanh_normalized_compound_lag_1	HICP_YOY_MON_lag_24	M1_YOY_MON_lag_24		
tanh_normalized_compound_lag_2				
HICP_YOY_MON		1.000000	-0.038982	
0.030954	-0.405101	0.010862		0.079943
-0.088193	-0.036342		-0.115433	
M1_YOY_MON		-0.038982	1.000000	
-0.016059	0.004663	-0.509273		
0.035903	0.060184	0.004365		0.050389
tanh_normalized_compound		0.030954	-0.016059	
1.000000	0.041384	0.078988		-0.012267
0.045930	-0.057383		0.016035	
HICP_YOY_MON_lag_12		-0.405101	0.004663	
0.041384	1.000000	0.006153		-0.112895
-0.372172	0.004520		0.086142	
M1_YOY_MON_lag_12		0.010862	-0.509273	
0.078988	0.006153	1.000000		-0.091501
0.046486	-0.540554		-0.090499	
tanh_normalized_compound_lag_1		0.079943	0.035903	
-0.012267	-0.112895	-0.091501		
1.000000	-0.123498	0.012373		-0.831044
HICP_YOY_MON_lag_24		-0.088193	0.060184	
0.045930	-0.372172	0.046486		-0.123498
1.000000	-0.050110		0.049742	
M1_YOY_MON_lag_24		-0.036342	0.004365	
-0.057383	0.004520	-0.540554		
0.012373	-0.050110	1.000000		0.031372
tanh_normalized_compound_lag_2		-0.115433	0.050389	
0.016035	0.086142	-0.090499		-0.831044
0.049742	0.031372		1.000000	

1.4 We now use the distributed lag model

```
[ ]: import statsmodels.api as sm
merged = pd.read_excel("Outputs//Intermediate//merged.xlsx")

# Define the dependent and independent variables
dependent_var = merged['HICP_YOY_MON']
independent_vars = merged[['M1_YOY_MON', 'tanh_normalized_compound',
                           'M1_YOY_MON_lag_12', 'tanh_normalized_compound_lag_12',
                           'M1_YOY_MON_lag_24',
                           ↪ 'tanh_normalized_compound_lag_24']]

# Add a constant to the independent variables
independent_vars = sm.add_constant(independent_vars)

# Create the model
model = sm.OLS(dependent_var, independent_vars)

# Fit the model
results = model.fit()

# Summary of the results
results_summary = results.summary()
results_summary
```

```
[ ]: <class 'statsmodels.iolib.summary.Summary'>
"""
                                OLS Regression Results
=====
Dep. Variable:                  HICP_YOY_MON    R-squared:                0.137
Model:                            OLS         Adj. R-squared:            0.118
Method:                 Least Squares         F-statistic:                7.090
Date:                  Sat, 18 Nov 2023        Prob (F-statistic):          5.05e-07
Time:                  02:36:08                Log-Likelihood:             -531.75
No. Observations:                275           AIC:                     1077.
Df Residuals:                   268           BIC:                     1103.
Df Model:                        6
Covariance Type:                nonrobust
=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                2.3100    0.351      6.590    0.000
```

1.620	3.000				
M1_YOY_MON		-0.0284	0.010	-2.964	0.003
-0.047	-0.010				
tanh_normalized_compound		-5.4811	3.828	-1.432	0.153
-13.017	2.055				
M1_YOY_MON_lag_12		0.0368	0.010	3.855	0.000
0.018	0.056				
tanh_normalized_compound_lag_12		-5.2398	3.879	-1.351	0.178
-12.876	2.397				
M1_YOY_MON_lag_24		0.0327	0.010	3.428	0.001
0.014	0.051				
tanh_normalized_compound_lag_24		-0.8862	3.953	-0.224	0.823
-8.670	6.897				

Omnibus:	115.526	Durbin-Watson:	0.080
Prob(Omnibus):	0.000	Jarque-Bera (JB):	435.901
Skew:	1.791	Prob(JB):	2.21e-95
Kurtosis:	8.021	Cond. No.	793.

Notes:

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

"""

1.5 Distributed Lag but different lags

```
[ ]: import statsmodels.api as sm
merged = pd.read_excel("Outputs//Intermediate//merged.xlsx")

# Assuming 'merged' is your DataFrame
# Create the lagged variable
merged['tanh_normalized_compound_lag_1'] = merged['tanh_normalized_compound'].
    ↪shift(1)

merged['M1_YOY_MON_lag_12'] = merged['M1_YOY_MON'].shift(12)
merged['M1_YOY_MON_lag_24'] = merged['M1_YOY_MON'].shift(24)
merged.dropna(inplace=True)

# Define the dependent variable after dropping NaN values
dependent_var = merged['HICP_YOY_MON']

# Define the independent variables
independent_vars = merged[['tanh_normalized_compound', 'M1_YOY_MON_lag_12',
```

```

                                'tanh_normalized_compound_lag_1',
                                ↪ 'M1_YOY_MON_lag_24']]
merged.set_index('year_month', inplace=True)

# Add a constant to the independent variables
independent_vars = sm.add_constant(independent_vars)

# Create the model
model = sm.OLS(dependent_var, independent_vars)

# Fit the model
results = model.fit()

# Summary of the results
results_summary = results.summary()
results_summary

```

```

[ ]: <class 'statsmodels.iolib.summary.Summary'>
"""

```

```

                                OLS Regression Results
=====
Dep. Variable:                HICP_YOY_MON    R-squared:                0.103
Model:                        OLS             Adj. R-squared:           0.091
Method:                      Least Squares    F-statistic:              8.250
Date:                        Sat, 18 Nov 2023  Prob (F-statistic):    2.60e-06
Time:                        10:50:39         Log-Likelihood:          -578.55
No. Observations:            292             AIC:                    1167.
Df Residuals:                287             BIC:                    1185.
Df Model:                    4
Covariance Type:              nonrobust
=====
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                2.3679    0.299      7.921    0.000
1.780    2.956
tanh_normalized_compound -7.5744    3.965    -1.911    0.057
-15.378    0.229
M1_YOY_MON_lag_12     0.0299    0.010     3.065    0.002
0.011    0.049
tanh_normalized_compound_lag_1 -7.9915    3.961    -2.017    0.045
-15.789    -0.194
M1_YOY_MON_lag_24     0.0401    0.009     4.251    0.000
0.022    0.059

```

```

=====
Omnibus:                116.298    Durbin-Watson:                0.067
Prob(Omnibus):          0.000    Jarque-Bera (JB):            389.295
Skew:                   1.760    Prob(JB):                    2.92e-85
Kurtosis:               7.428    Cond. No.                     711.
=====

```

Notes:

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

"""