In [1]:

```
# Import Python libraries for visualisation and data analysis
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns

# sns.set_theme()  # Apply the default Seaborn theme
%matplotlib inline

# Suppress warnings to avoid potential confusion
import warnings
from statsmodels.tsa.stattools import adfuller
# Libraries for statistical and scientific computing
import statsmodels.api as sm
from scipy import stats

warnings.filterwarnings("ignore")
import ipywidgets as widgets
from IPython.display import display
```

In [2]:

```
d1=pd.read_csv('2020.csv')
# d1.set_index('date',inplace=True)
d2=pd.read_csv('2021.csv')
# d2.set_index('date',inplace=True)
d3=pd.read_csv('2022.csv')

# d3.set_index('date',inplace=True)
```

In [3]:

```
def subperiod_mobility_trends(data, start_date, end_date):
    """
    Add your mobility data in `data`.

    This function selects a subperiod of the mobility data based on prespecified
start data and end date.
    """
    subdata= data[
        data["date"].isin(pd.date_range(start=start_date, end=end_date))
    ]
    return subdata


def rename_mobility_trends(data):
    """
    This function renames the column headings of the six mobility categories.
    """
    data = data.rename(
        columns={
            "retail_and_recreation_percent_change_from_baseline": "Retail_Recrea
tion",
            "grocery_and_pharmacy_percent_change_from_baseline": "Grocery_Pharma
cy",
            "parks_percent_change_from_baseline": "Parks",
            "transit_stations_percent_change_from_baseline": "Transit_stations",
            "workplaces_percent_change_from_baseline": "Workplaces",
            "residential_percent_change_from_baseline": "Residential",
        }
    )
    return data
```

In [4]:

```
d1=rename_mobility_trends(d1)
d2=rename_mobility_trends(d2)
d3=rename_mobility_trends(d3)
```

In [5]:

```
data=d1.append(d2)
data=data.append(d3)
```

In [6]:

```
tower=data[data["sub_region_2"] == "London Borough of Tower Hamlets"]
```

In [13]:

```
 tower.set_index('date',inplace=True)
```

In [14]:

```
Retail_Recreation=tower['Retail_Recreation']
```

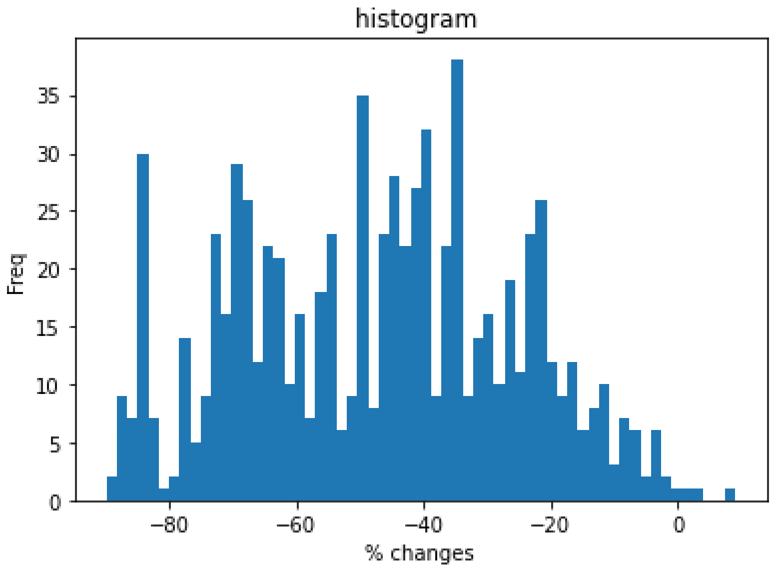
In [15]:

```
result = adfuller(Retail_Recreation, autolag='AIC')
print(f'ADF Statistic: {result[0]}')
print(f'n_lags: {result[1]}')
print(f'p-value: {result[1]}')
for key, value in result[4].items():
    print('Critial Values:')
    print(f'   {key}, {value}')
```

```
ADF Statistic: -2.7192203047860866
n_lags: 0.07077096086586578
p-value: 0.07077096086586578
Critial Values:
   1%, -3.4389722010249386
Critial Values:
   5%, -2.8653454308425705
Critial Values:
   10%, -2.5687964010457227
```

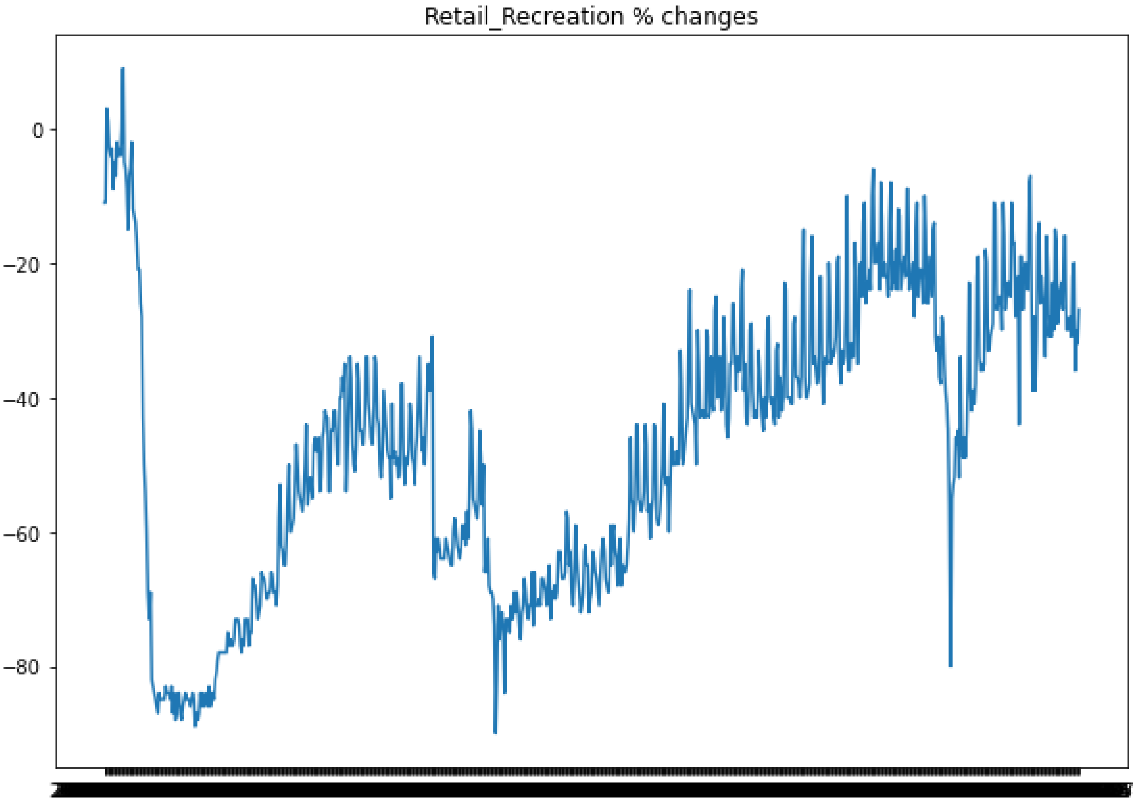
In [16]:

```
fig = plt.figure()
ax1 = fig.add_axes([0.1,0.1,0.8,0.8])
ax1.hist(Retail_Recreation, bins = 60)
ax1.set_xlabel('% changes')
ax1.set_ylabel("Freq")
ax1.set_title("histogram ")
plt.show();
```



In [17]:

```
get_ipython().run_line_magic('matplotlib', 'inline')
fig, axes = plt.subplots(figsize=(10,7))
plt.plot(Retail_Recreation);
plt.title('Retail_Recreation % changes');
```



In [18]:

```
diff = Retail_Recreation.diff()
```

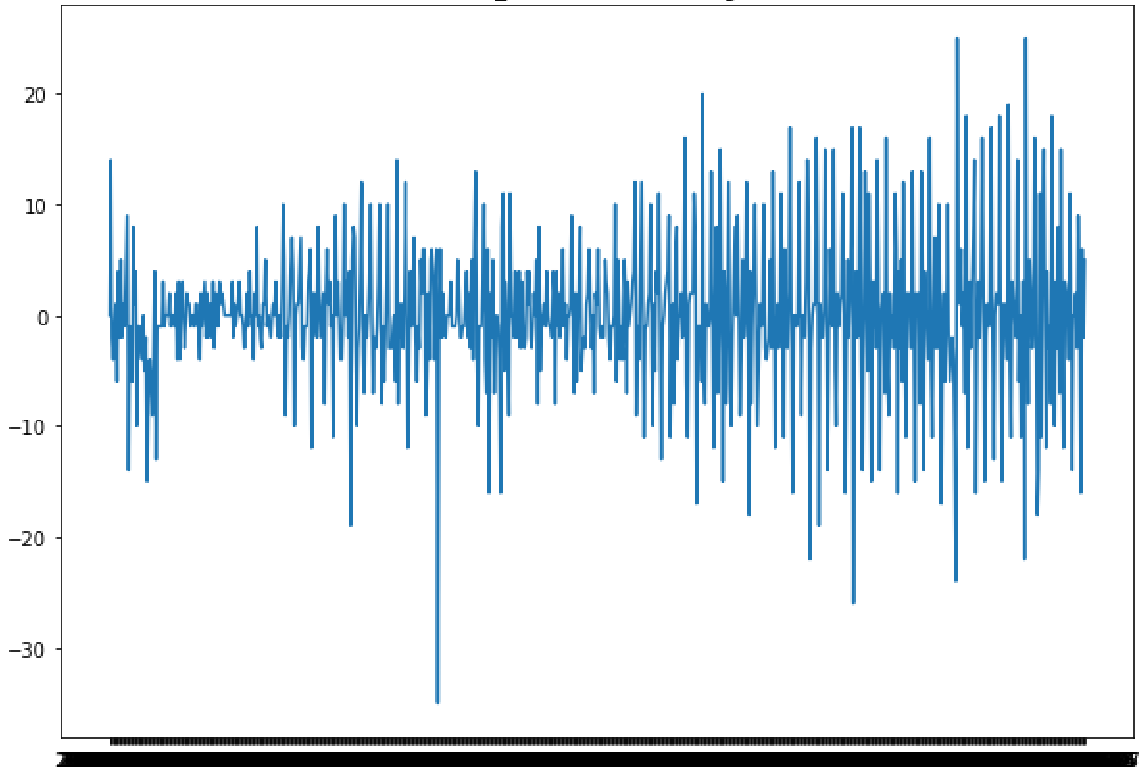
In [19]:

```
first_diff=diff[1:]
```

In [20]:

```
get_ipython().run_line_magic('matplotlib', 'inline')
fig, axes = plt.subplots(figsize=(10,7))
plt.plot(first_diff);
plt.title('Retail_Recreation % changes');
```

Retail_Recreation % changes



In [21]:

```
result = adfuller(first_diff, autolag='AIC')
print(f'ADF Statistic: {result[0]}')
print(f'n_lags: {result[1]}')
print(f'p-value: {result[1]}')
for key, value in result[4].items():
    print('Critial Values:')
    print(f'   {key}, {value}')
```

```
ADF Statistic: -5.881596938167557
n_lags: 3.069202964850709e-07
p-value: 3.069202964850709e-07
Critial Values:
   1%, -3.4389722010249386
Critial Values:
   5%, -2.8653454308425705
Critial Values:
   10%, -2.5687964010457227
```

In [22]:

```
tower=data[data["sub_region_2"] == "London Borough of Tower Hamlets"]
```

In [23]:

```
train=tower[(tower["date"] >= "2021-03-01")
        & (tower["date"] <= "2022-02-01")]
```

In [24]:

```
test=tower[(tower["date"] > "2022-02-01")]
```

In [25]:

```
train.set_index('date',inplace=True)
test.set_index('date',inplace=True)
```

In [26]:

```
train.Retail_Recreation
```

Out[26]:

```
date
2021-03-01   -67.0
2021-03-02   -69.0
2021-03-03   -72.0
2021-03-04   -71.0
2021-03-05   -69.0
              ...
2022-01-28   -29.0
2022-01-29   -11.0
2022-01-30   -12.0
2022-01-31   -27.0
2022-02-01   -26.0
Name: Retail_Recreation, Length: 338, dtype: float64
```

In [27]:

```
train_Recreation=train.Retail_Recreation
test_Recreation=test.Retail_Recreation
```

In [44]:

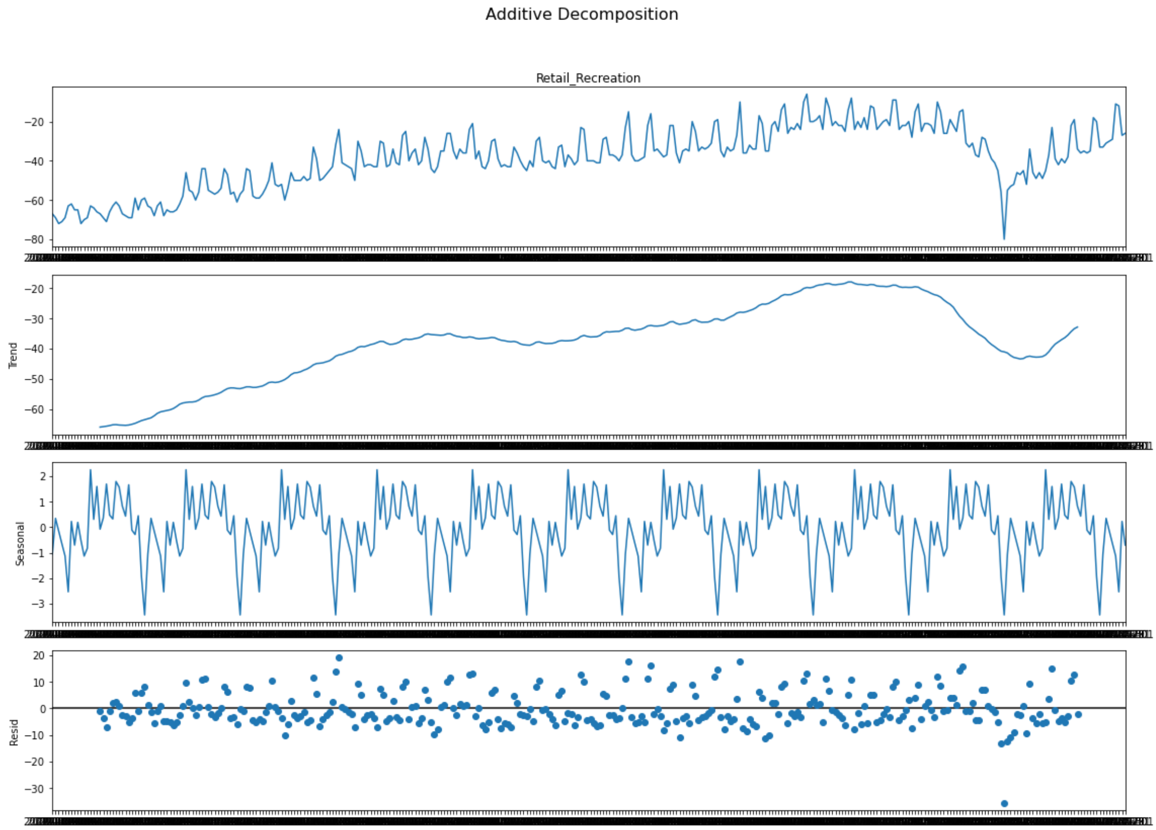
```
from statsmodels.tsa.seasonal import seasonal_decompose
from dateutil.parser import parse


# Multiplicative Decomposition


# Additive Decomposition
additive_decomposition = seasonal_decompose(train_Recreation, model='additive',
period=30)

# Plot
plt.rcParams.update({'figure.figsize': (16,12)})
additive_decomposition.plot().suptitle('Additive Decomposition', fontsize=16)
plt.tight_layout(rect=[0, 0.03, 1, 0.95])

plt.show()
```

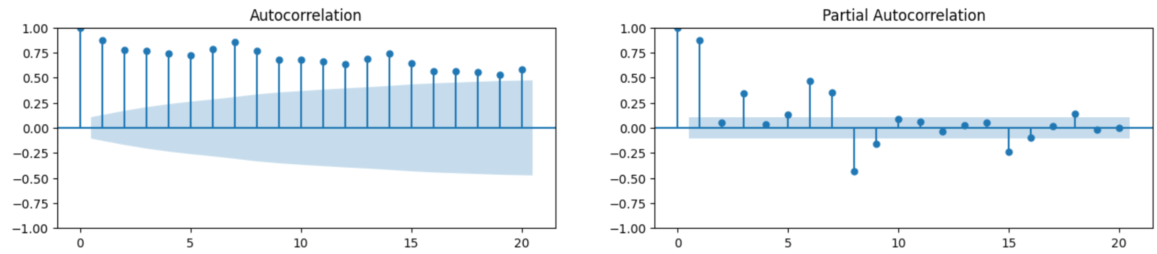


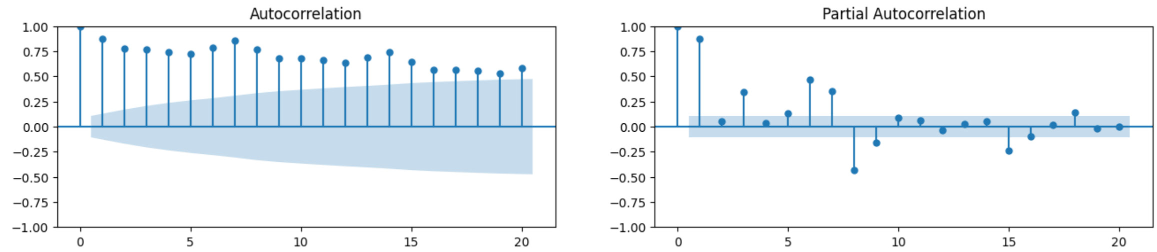
In [45]:

```
from statsmodels.tsa.stattools import acf, pacf
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# Draw Plot
fig, axes = plt.subplots(1,2,figsize=(16,3), dpi= 100)
plot_acf(train_Recreation.tolist(), lags=20, ax=axes[0])
plot_pacf(train_Recreation.tolist(), lags=20, ax=axes[1])
```

Out[45]:





PACF is be used to figure out the best order of the AR modeACF is be used to figure out the best order of the MA model.

In [102]:

```
train_Recreation = train_Recreation.diff()

test_Recreation = test_Recreation.diff()
```

In [103]:

```
train_Recreation=train_Recreation[1:]
test_Recreation=test_Recreation[1:]
```

In [49]:

```
mod = sm.tsa.arima.ARIMA(train_Recreation, order=(4, 1, 5))
res = mod.fit()
print(res.summary())
```

```
                               SARIMAX Results                                
==============================================================================
Dep. Variable:      Retail_Recreation   No. Observations:                  
338
Model:                 ARIMA(4, 1, 5)   Log Likelihood                 
-1007.424
Date:                Fri, 30 Sep 2022   AIC                            
2034.847
Time:                        07:12:53   BIC                            
2073.048
Sample:                    03-01-2021   HQIC                           
2050.074
                         - 02-01-2022                                         
Covariance Type:                  opg                                         
==============================================================================
                 coef    std err          z      P>|z|      [0.025      
0.975]
------------------------------------------------------------------------------
ar.L1          0.7797      0.017     45.636      0.000       0.746       
0.813
ar.L2         -1.4373      0.017    -85.834      0.000      -1.470      
-1.404
ar.L3          0.7891      0.014     55.708      0.000       0.761       
0.817
ar.L4         -0.9726      0.018    -53.063      0.000      -1.009      
-0.937
ma.L1         -1.1823      0.050    -23.503      0.000      -1.281      
-1.084
ma.L2          1.6428      0.066     24.859      0.000       1.513       
1.772
ma.L3         -1.3840      0.081    -17.179      0.000      -1.542      
-1.226
ma.L4          1.1210      0.066     16.905      0.000       0.991       
1.251
ma.L5         -0.4017      0.055     -7.264      0.000      -0.510      
-0.293
sigma2        22.4255      1.099     20.405      0.000      20.272      
24.579
===================================================================================
Ljung-Box (L1) (Q):                   0.39   Jarque-Bera (JB):              
2777.42
Prob(Q):                              0.53   Prob(JB):                      
0.00
Heteroskedasticity (H):               2.20   Skew:                          
-1.29
Prob(H) (two-sided):                  0.00   Kurtosis:                      
16.83
===================================================================================

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

In [71]:

```
forecast=res.forecast(len(test))
```

In [72]:

```
forecast
```

Out[72]:

```
2022-02-02   -24.624199
2022-02-03   -25.070976
2022-02-04   -24.205030
2022-02-05   -14.551640
2022-02-06   -12.432054
                ...
2022-04-03   -16.128742
2022-04-04   -24.731438
2022-04-05   -27.365362
2022-04-06   -20.949841
2022-04-07   -20.873826
Freq: D, Name: predicted_mean, Length: 65, dtype: float64
```

In [65]:

```
test_Recreation
```

Out[65]:

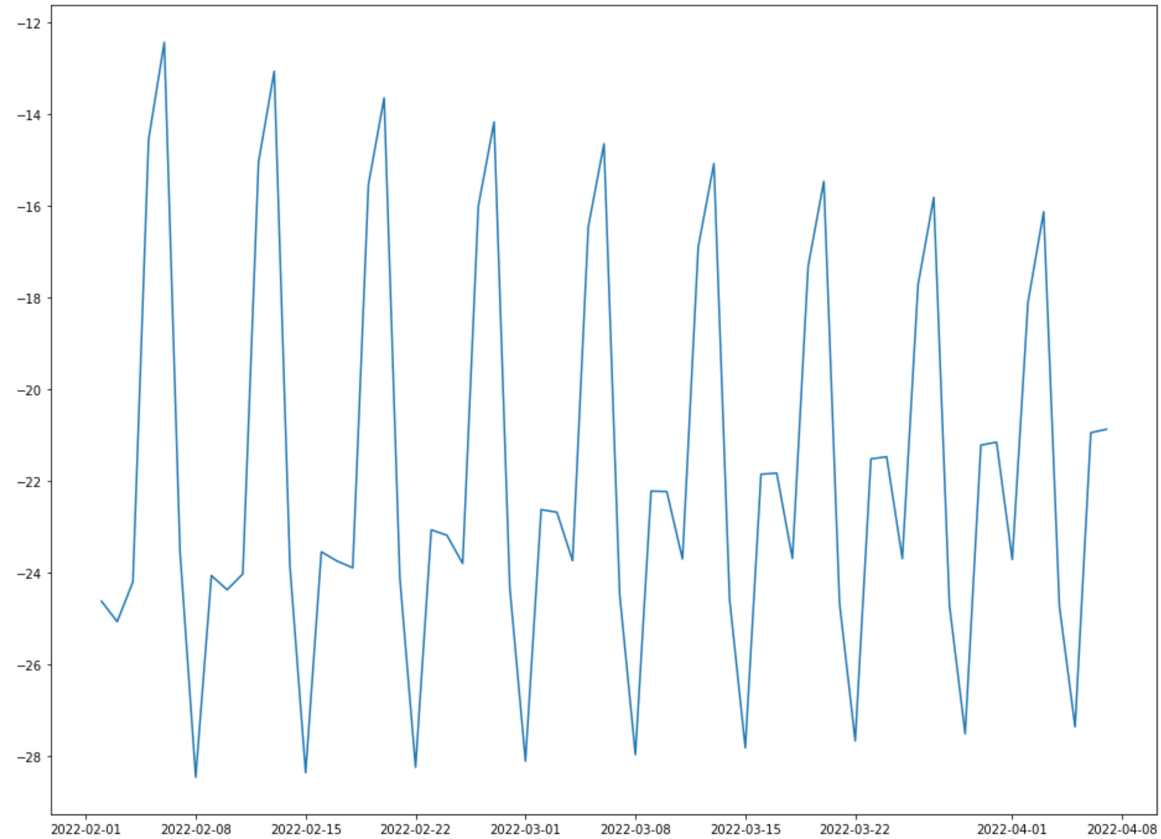
```
date
2022-02-02   -25.0
2022-02-03   -26.0
2022-02-04   -30.0
2022-02-05   -11.0
2022-02-06   -16.0
              ...
2022-04-03   -20.0
2022-04-04   -36.0
2022-04-05   -30.0
2022-04-06   -32.0
2022-04-07   -27.0
Name: actual, Length: 65, dtype: float64
```

In [73]:

```
plt.plot(forecast)
```

Out[73]:

```
[<matplotlib.lines.Line2D at 0x7fd869db0410>]
```

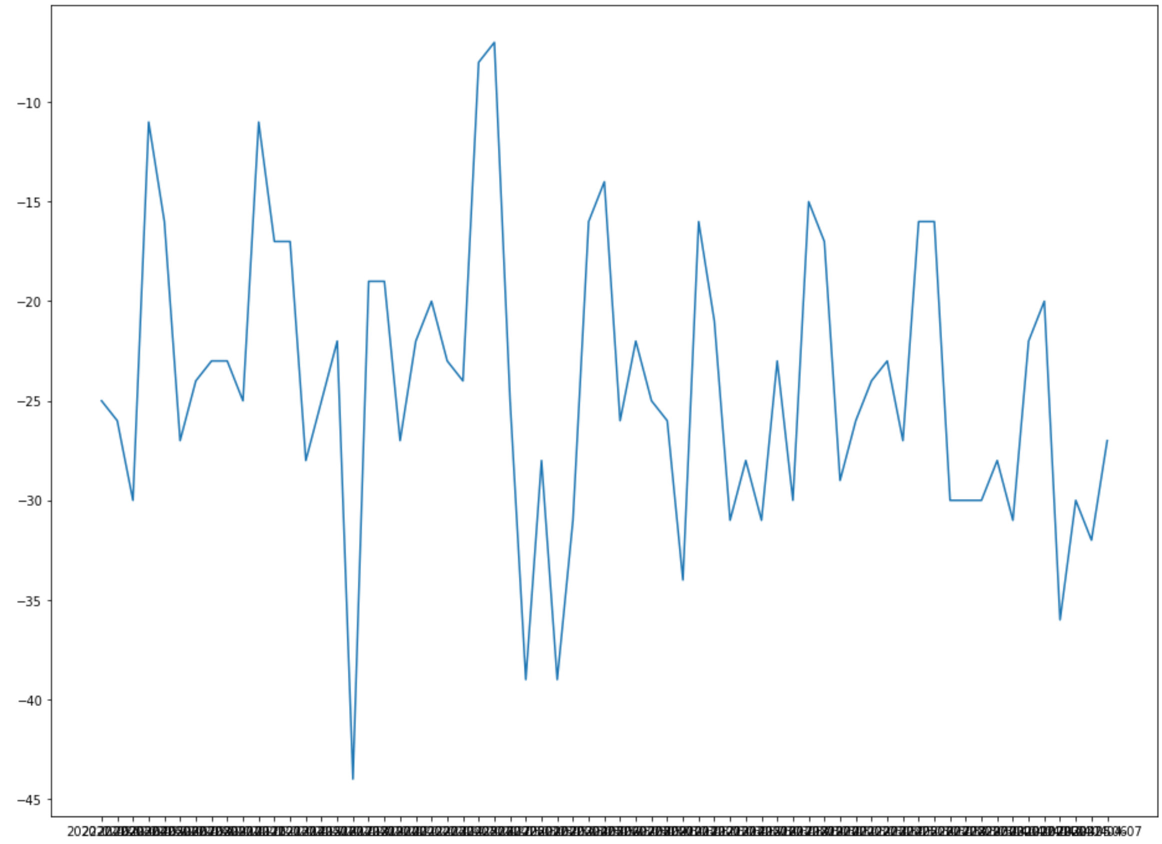


In [74]:

```
plt.plot(test_Recreation)
```

Out[74]:

```
[<matplotlib.lines.Line2D at 0x7fd882b04c50>]
```



In [ ]:

```
pred_df = forecast_to_df(model, steps = len(test))
```

In [48]:

```
from pmdarima.arima import auto_arima
model = auto_arima(train_Recreation, trace=True, error_action='ignore', suppress
_warnings=True)
model.fit(train)
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=2233.961, Time=0.13 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=2332.062, Time=0.02 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=2329.223, Time=0.03 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=2297.571, Time=0.05 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=2330.148, Time=0.02 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=2235.218, Time=0.20 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=2234.783, Time=0.10 sec
 ARIMA(3,1,2)(0,0,0)[0] intercept   : AIC=2235.243, Time=0.19 sec
 ARIMA(2,1,3)(0,0,0)[0] intercept   : AIC=2210.642, Time=0.28 sec
 ARIMA(1,1,3)(0,0,0)[0] intercept   : AIC=2223.179, Time=0.22 sec
 ARIMA(3,1,3)(0,0,0)[0] intercept   : AIC=2158.266, Time=0.48 sec
 ARIMA(4,1,3)(0,0,0)[0] intercept   : AIC=2134.612, Time=0.47 sec
 ARIMA(4,1,2)(0,0,0)[0] intercept   : AIC=2131.209, Time=0.48 sec
 ARIMA(4,1,1)(0,0,0)[0] intercept   : AIC=2215.323, Time=0.14 sec
 ARIMA(5,1,2)(0,0,0)[0] intercept   : AIC=2089.789, Time=0.38 sec
 ARIMA(5,1,1)(0,0,0)[0] intercept   : AIC=2147.106, Time=0.17 sec
 ARIMA(5,1,3)(0,0,0)[0] intercept   : AIC=2079.283, Time=0.37 sec
 ARIMA(5,1,4)(0,0,0)[0] intercept   : AIC=2040.904, Time=0.60 sec
 ARIMA(4,1,4)(0,0,0)[0] intercept   : AIC=2070.197, Time=0.58 sec
 ARIMA(5,1,5)(0,0,0)[0] intercept   : AIC=2038.332, Time=0.68 sec
 ARIMA(4,1,5)(0,0,0)[0] intercept   : AIC=2034.524, Time=0.77 sec
 ARIMA(3,1,5)(0,0,0)[0] intercept   : AIC=2136.710, Time=0.58 sec
 ARIMA(3,1,4)(0,0,0)[0] intercept   : AIC=2152.792, Time=0.49 sec
 ARIMA(4,1,5)(0,0,0)[0]             : AIC=2034.847, Time=0.70 sec

Best model:  ARIMA(4,1,5)(0,0,0)[0] intercept
Total fit time: 8.141 seconds
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-48-bdc09c20bea9> in <module>
      1 from pmdarima.arima import auto_arima
      2 model = auto_arima(train_Recreation, trace=True, error_action='ignore', suppress_warnings=True)
----> 3 model.fit(train)

/opt/anaconda3/lib/python3.7/site-packages/pmdarima/arima/arima.py in fit(self, y, X, **fit_args)
    564             Any keyword arguments to pass to the statsmodels ARIMA fit.
    565         """
--> 566         y = check_endog(y, dtype=DTYPE, preserve_series=True)
    567         n_samples = y.shape[0]
    568 

/opt/anaconda3/lib/python3.7/site-packages/pmdarima/utils/array.py in check_endog(y, dtype, copy, force_all_finite, preserve_series)
    182         force_all_finite=force_all_finite,
    183         copy=copy,
--> 184         dtype=dtype,
    185     )
    186 

/opt/anaconda3/lib/python3.7/site-packages/sklearn/utils/validation.py in inner_f(*args, **kwargs)
     70                           FutureWarning)
     71         kwargs.update({k: arg for k, arg in zip(sig.parameters, args)})
---> 72         return f(**kwargs)
     73     return inner_f
     74 

/opt/anaconda3/lib/python3.7/site-packages/sklearn/utils/validation.py in check_array(array, accept_sparse, accept_large_sparse, dtype, order, copy, force_all_finite, ensure_2d, allow_nd, ensure_min_samples, ensure_min_features, estimator)
    596                     array = array.astype(dtype, casting="unsafe", copy=False)
    597                 else:
--> 598                     array = np.asarray(array, order=order, dtype=dtype)
    599             except ComplexWarning:
    600                 raise ValueError("Complex data not supported\n"

/opt/anaconda3/lib/python3.7/site-packages/pandas/core/generic.py in __array__(self, dtype)
   1991 
   1992     def __array__(self, dtype: NpDtype | None = None) -> np.ndarray:
-> 1993         return np.asarray(self._values, dtype=dtype)
   1994 
   1995     def __array_wrap__(

ValueError: could not convert string to float: 'GB'
```

In [ ]:

```

```