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main assignments / 5. Master_thesis / 1.Master_thesis.ipynb

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1 contributor

3934 lines (3934 sloc) | 1.31 MB

Raw Blame

Path to local libraries

In [2]:

```
# Requires 0.24
import os
import sys
sys.path.insert(1,os.path.abspath('../0. Not_git/Sources/scikit-learn/0.24.0'))
import sklearn
print(sklearn.__version__)
#this will be 0.24.2
```

```
0.24.0
```

Import libraries

In [3]:

```
# Generic
import pandas as pd
import numpy as np
import math

# Graphics
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
import plotly.graph_objs as go
from plotly.subplots import make_subplots
import plotly.io as pio

# Metrics
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score

# ML Models
from sklearn.ensemble import ExtraTreesRegressor
from xgboost import XGBRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import AdaBoostRegressor
from lightgbm import LGBMRegressor
from sklearn.tree import DecisionTreeRegressor

# Statistical Models
import statsmodels.api as sm
import statsmodels.tsa.api as smt
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf
from statsmodels.tsa.stattools import acf
from statsmodels.tsa.seasonal import DecomposeResult, seasonal_decompose
from statsmodels.tsa.holtwinters import ExponentialSmoothing
```

```
import pmdarima as pm
from pmdarima import auto_arima
```

In [4]:
```
# Comment this line to render plotly into GitHub
pio.renderers.default = "svg"
```

In [5]:
```
# Select country in analysis ('FIN', 'DEN', 'NOR', 'SWE')
country = 'FIN'

# Dependant variable (Orders or TIV)
dep_var = 'Orders'

# Use feature eng/selection
feature_engineering = True
feature_selection = True

# Include rest of nordic countries as exogenous features
include_nordics = True
```

Load data

In [6]:
```
# Input path and filename
path = '../5. Master_thesis/Datasets/Output_files/'

# Load files into a pandas dataframes
file = path + '0.xlsx'
df = pd.read_excel(file, sheet_name=country)

# Set index
df = df.set_index("Date")
df.index = pd.PeriodIndex(df.index, freq="M")
```

In [7]:
```
df
```

Out[7]:

	Orders	CPI	UR	LTIR	TIV
Date					
2006-01	1124	0.807265	8.3	3.280000	203.413007
2006-02	1079	0.901804	8.0	3.440000	128.084250
2006-03	1210	0.899101	7.7	3.620000	151.605878
2006-04	1147	1.297405	7.7	3.880000	135.086704
2006-05	1001	1.701702	7.9	3.940000	166.978193
...	...	...	...	...	...
2022-08	254	7.616082	7.2	1.624904	78.449535

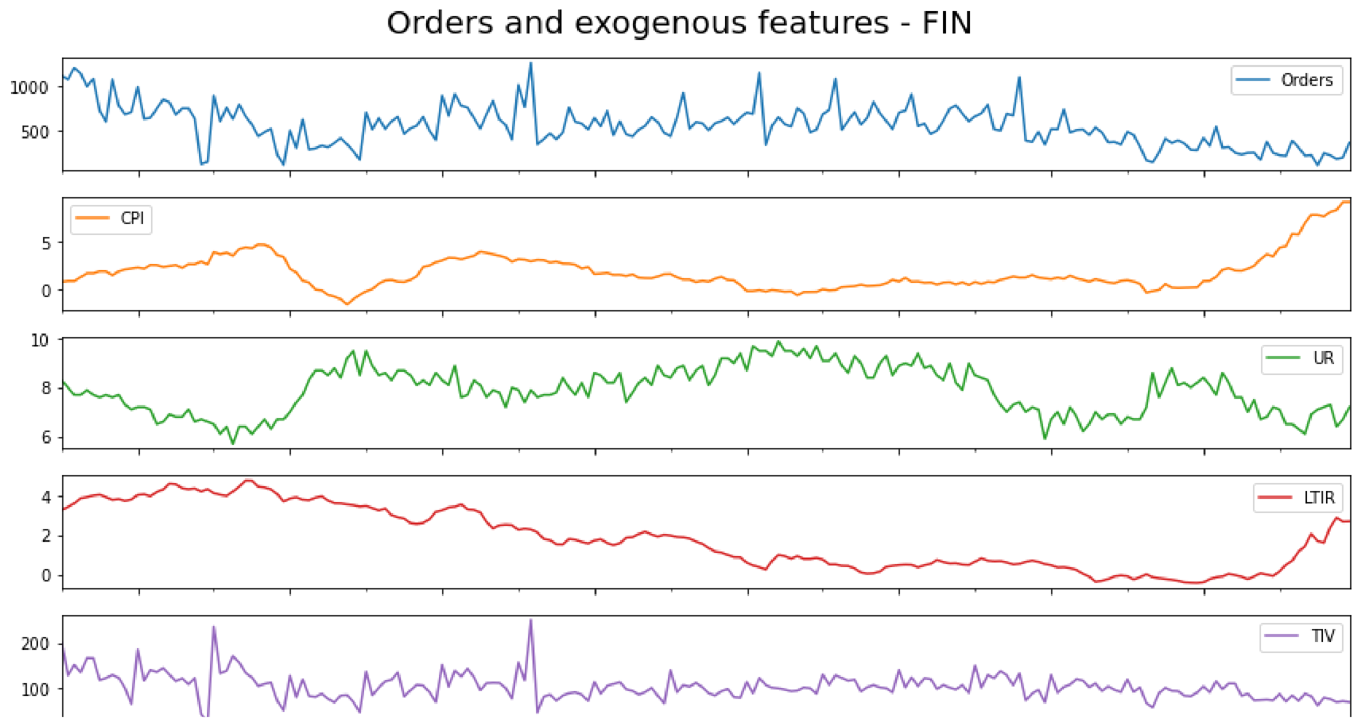
2022-09	228	8.119296	7.3	2.420836	74.997932
2022-10	188	8.310766	6.4	2.894486	68.348358
2022-11	204	9.138235	6.7	2.691082	70.487691
2022-12	370	9.145037	7.2	2.706710	68.227056

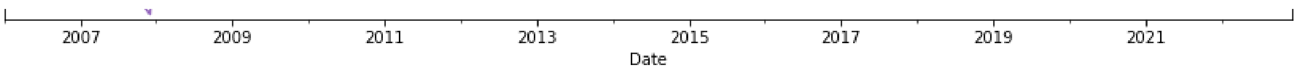
204 rows × 5 columns

In [8]:

```
# Plot time series
fig, ax = plt.subplots(figsize=(12, 7))
df.plot(
    legend   = True,
    subplots = True,
    sharex   = True,
    ax       = ax,
)
fig.suptitle(dep_var + ' and exogenous features - ' + country, fontsize=20)
fig.tight_layout();
```

```
C:\Users\ne74255\AppData\Local\Temp/ipykernel_20012/2265466338.py:3: UserWarning:

To output multiple subplots, the figure containing the passed axes is being cleared.
```

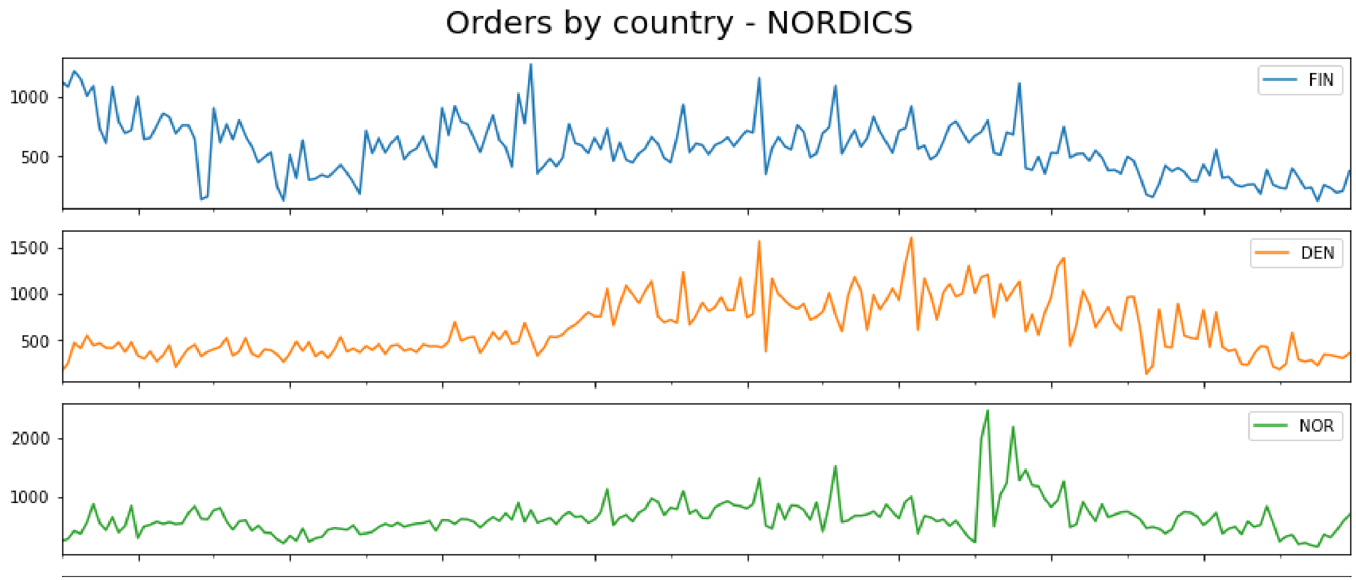


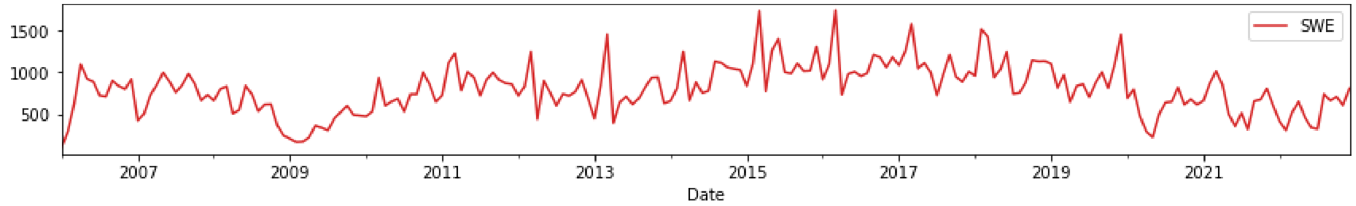


In [9]:

```
if include_nordics:
    # Load files into a pandas dataframes
    file = path + 'target.xlsx'

    df_nordics = pd.read_excel(file, sheet_name=dep_var)

    # Set index
    df_nordics = df_nordics.set_index("Date")
    df_nordics.index = pd.PeriodIndex(df_nordics.index, freq="M")

    df_nordics
    df = pd.merge(df, df_nordics[df_nordics.columns.difference([country])], left_index=True, right_index=True)

    # Plot time series
    fig, ax = plt.subplots(figsize=(12, 7))
    df_nordics.plot(
        legend   = True,
        subplots = True,
        sharex   = True,
        ax       = ax,
    )
    fig.suptitle(dep_var + ' by country - NORDICS', fontsize=20)
    fig.tight_layout();
```

```
C:\Users\ne74255\AppData\Local\Temp/ipykernel_20012/15051175.py:16: UserWarning:

To output multiple subplots, the figure containing the passed axes is being cleared.
```





In [10]:
```
df
```

Out[10]:

Date	Orders	CPI	UR	LTIR	TIV	DEN	NOR	SWE
2006-01	1124	0.807265	8.3	3.280000	203.413007	161	233	110
2006-02	1079	0.901804	8.0	3.440000	128.084250	250	270	303
2006-03	1210	0.899101	7.7	3.620000	151.605878	468	406	634
2006-04	1147	1.297405	7.7	3.880000	135.086704	412	356	1097
2006-05	1001	1.701702	7.9	3.940000	166.978193	550	553	926
...	...	...	...	...	...	...	...	...
2022-08	254	7.616082	7.2	1.624904	78.449535	343	347	744
2022-09	228	8.119296	7.3	2.420836	74.997932	337	295	666
2022-10	188	8.310766	6.4	2.894486	68.348358	322	413	711
2022-11	204	9.138235	6.7	2.691082	70.487691	305	563	609
2022-12	370	9.145037	7.2	2.706710	68.227056	357	682	810

204 rows × 8 columns

In [11]:
```
df.describe()
```

Out[11]:

	Orders	CPI	UR	LTIR	TIV	DEN	NOR	SWE
count	204.000000	204.000000	204.000000	204.000000	204.000000	204.000000	204.000000	204.000000
mean	562.715686	1.805420	7.889706	1.826215	103.698640	631.156863	633.328431	804.750000
std	230.914774	1.866685	0.957234	1.569162	29.790359	301.194068	305.915528	292.446469
min	118.000000	-1.551095	5.700000	-0.410000	23.124638	134.000000	133.000000	110.000000
25%	395.500000	0.732344	7.100000	0.497500	85.297604	394.750000	468.500000	634.000000
50%	554.500000	1.260649	8.000000	1.617452	100.543104	536.500000	584.000000	804.500000
75%	693.750000	2.641237	8.600000	3.387500	118.710887	839.250000	733.500000	992.000000

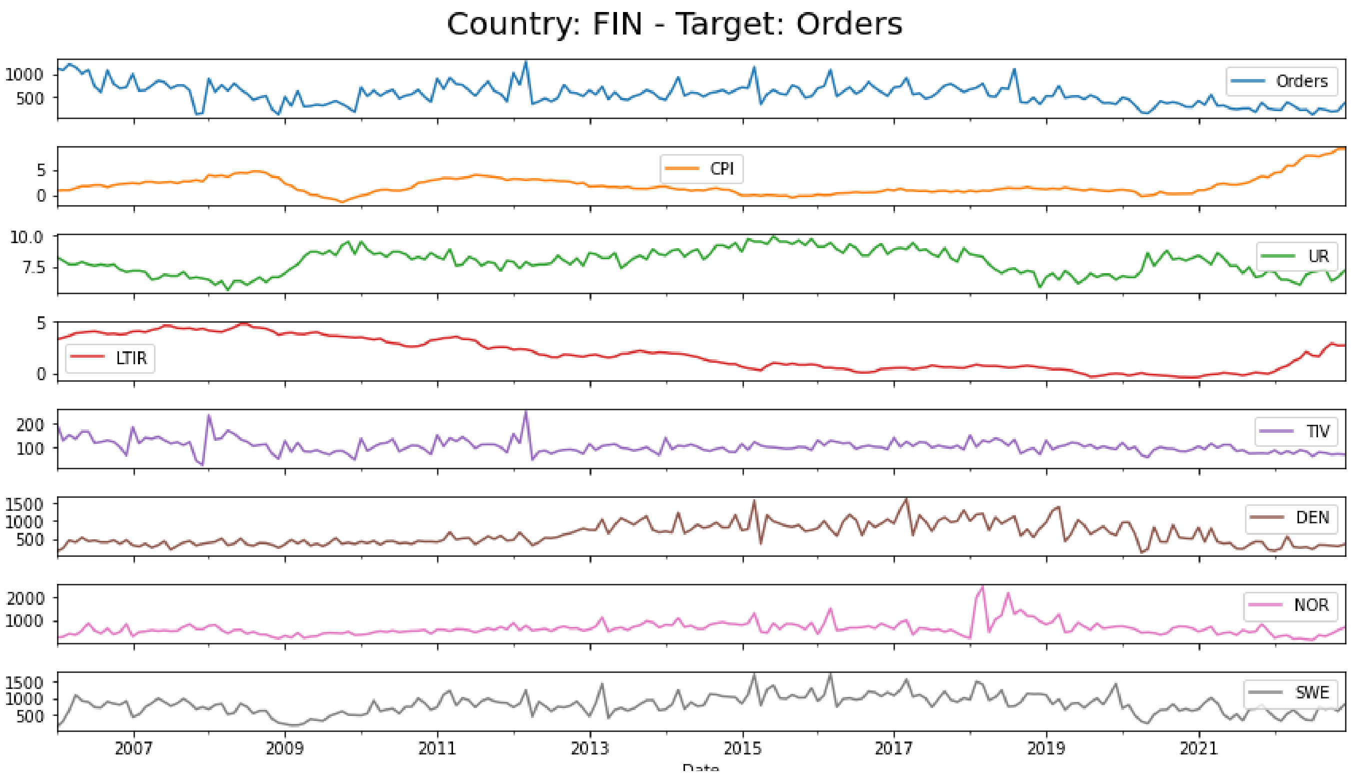
max	1268.000000	9.145037	9.900000	4.780000	252.948474	1605.000000	2465.000000	1739.000000

In [12]:
```
df_original = df.copy()
```

Exploratory data analysis (EDA)

In [13]:
```
# Plot time series
fig, ax = plt.subplots(figsize=(12, 7))
df.plot(
    legend   = True,
    subplots = True,
    sharex   = True,
    ax       = ax,
)
fig.suptitle('Country: ' + country + ' - Target: ' + dep_var, fontsize=20)
fig.tight_layout();
```

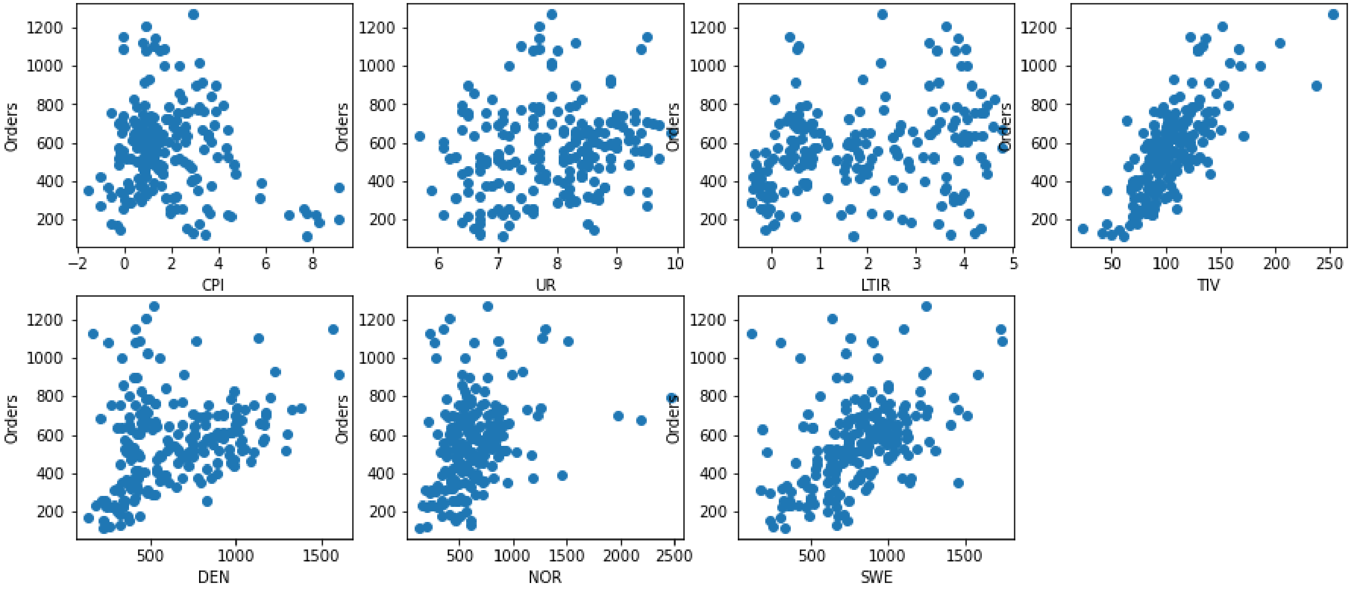
```
C:\Users\ne74255\AppData\Local\Temp/ipykernel_20012/3711877183.py:3: UserWarning:

To output multiple subplots, the figure containing the passed axes is being cleared.
```



Date

In [14]:

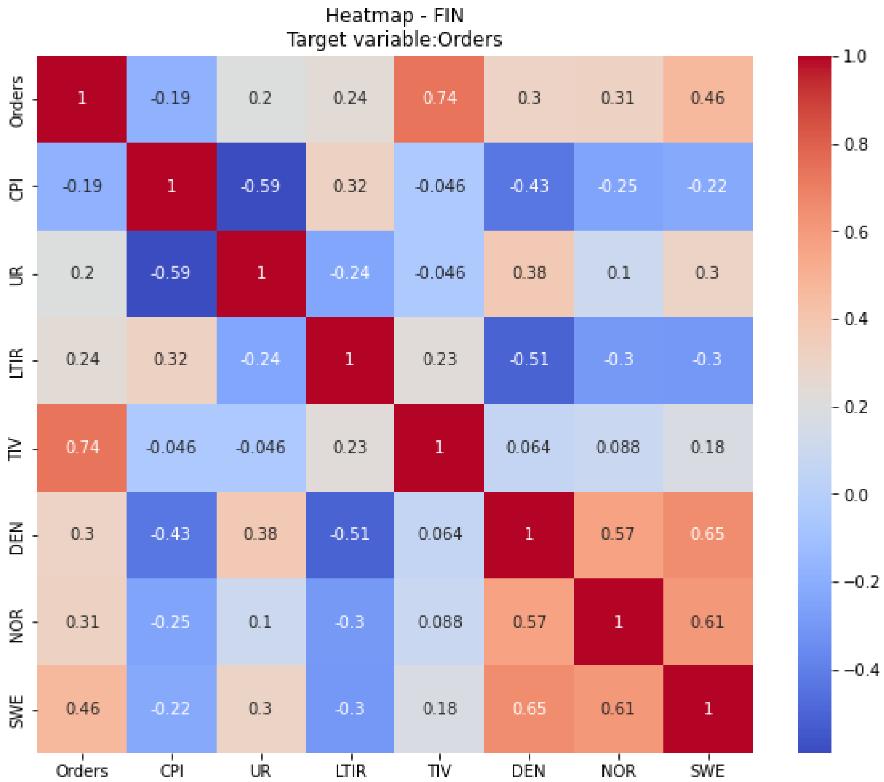
```python
# Define a function to plot the scatterplots of the relationships between
# all independent variables and the dependent variable
def plot_relationships(df, num_cols):

    ind_var = df.loc[:, df.columns != dep_var]  # Independant variables
    figs = len(df.columns) - 1                  # Number of figures

    num_cols = num_cols
    num_rows = round(figs / num_cols) + 1

    fig = 1
    plt.figure(figsize=(15, 10))

    # Loop through all independent variables and create the scatter plot
    for i in ind_var:
        plt.subplot(num_rows, num_cols, fig)
        plt.scatter(df[i], df[dep_var])
        plt.xlabel(str(i))
        plt.ylabel(str(dep_var))
        fig +=1

plot_relationships(df,4)
```



In [15]:

```python
# Plot the correlations as a heatmap
plt.figure(figsize=(10, 8))
ax = plt.axes()
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt='.2g', ax=ax)
ax.set_title('Heatmap - ' + country + '\nTarget variable:'  +dep_var)
```

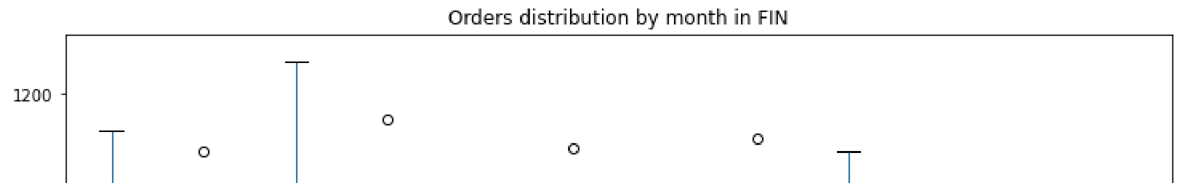
```
plt.show()
```

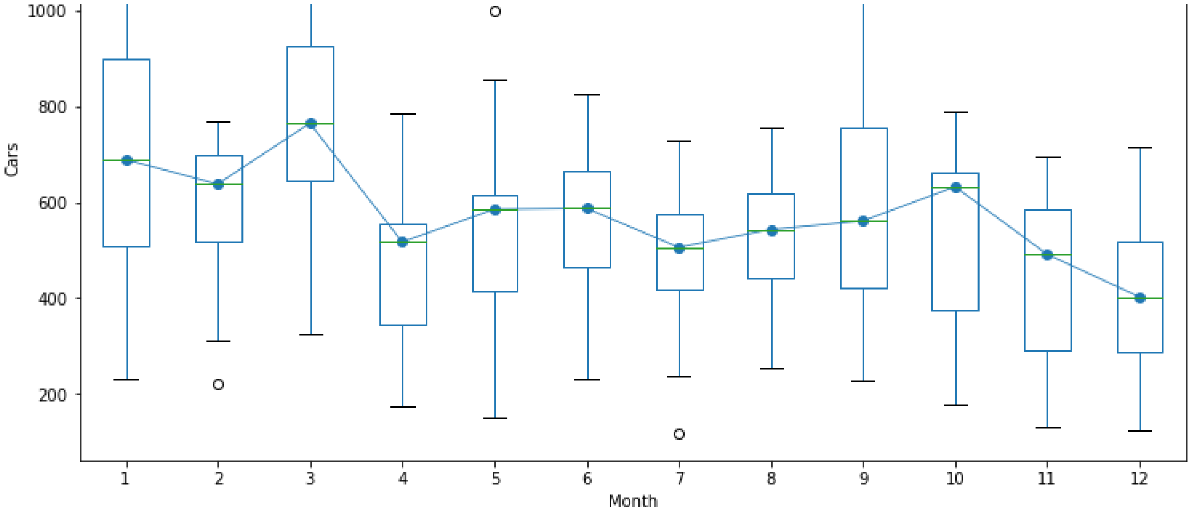


Orders distribution

In [16]:

```
# Boxplot for annual seasonality
fig, ax = plt.subplots(figsize=(12, 7))
df['Month'] = df.index.month
df.boxplot(column=dep_var, by='Month', ax=ax,)
df.groupby('Month')[dep_var].median().plot(style='o-', linewidth=0.8, ax=ax)
ax.set_ylabel('Cars')
ax.set_title(dep_var + ' distribution by month in ' + country)
fig.suptitle('');
df.drop('Month', axis=1, inplace=True)
```

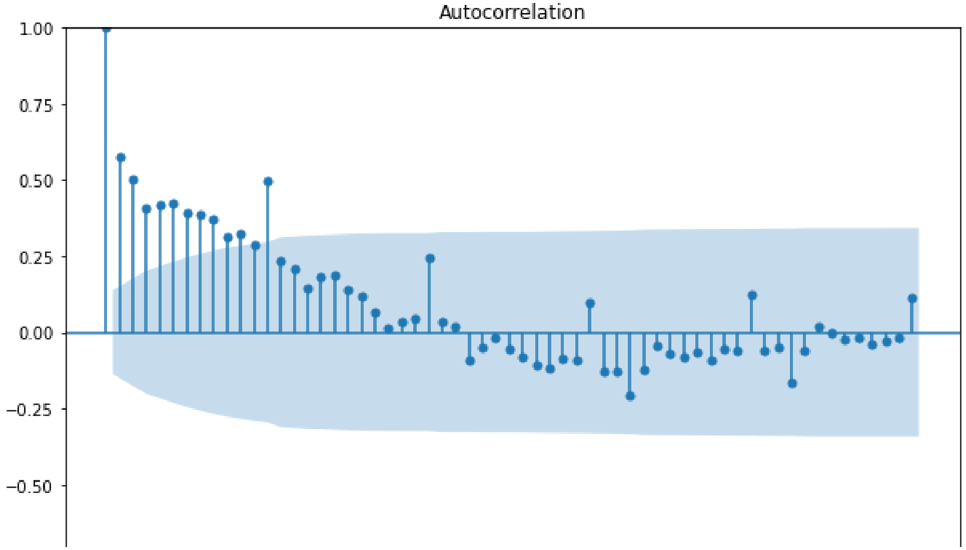


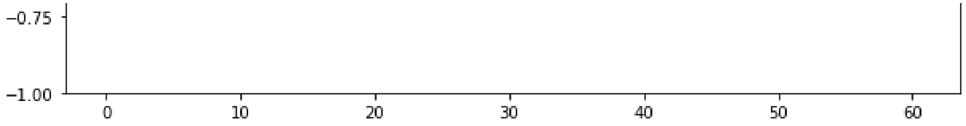


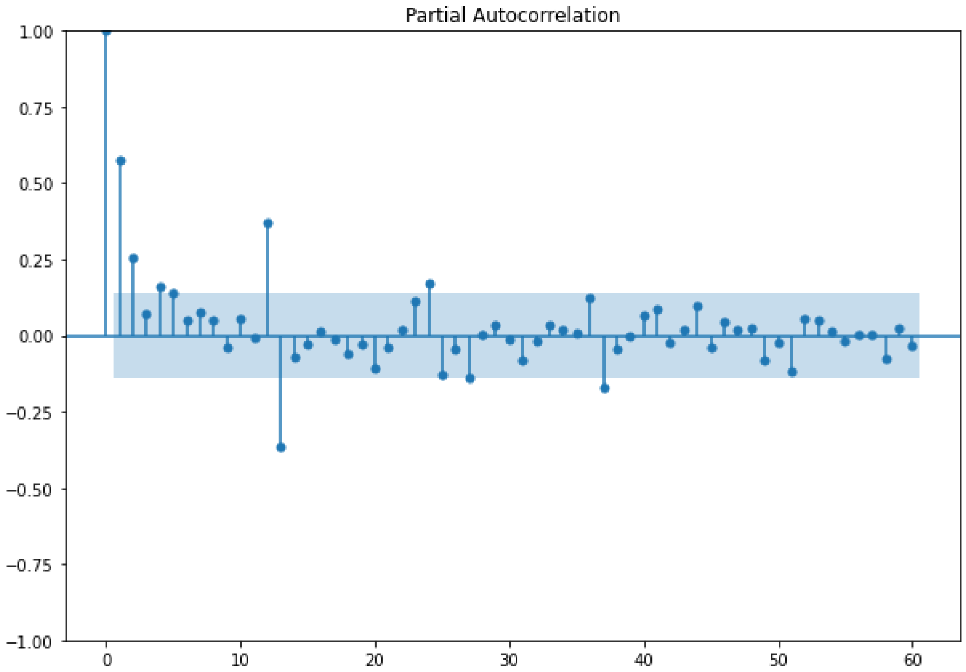
Correlation plots

In [17]:

```
# Autocorrelation plot
fig, ax = plt.subplots(figsize=(10, 7))
plot_acf(df[dep_var], ax=ax, lags=60)

# Partial autocorrelation plot
fig, ax = plt.subplots(figsize=(10, 7))
plot_pacf(df[dep_var], ax=ax, lags=60, method='ywm')
plt.show()
```







Trend

Rolling Statistics

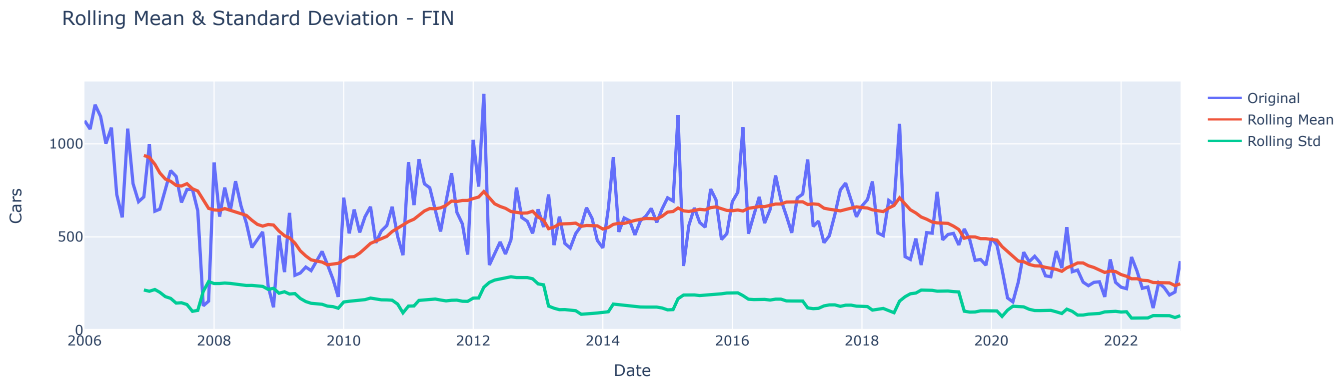
A rolling average is a great way to visualize how the dataset is trending. As the dataset provides counts by month, a window size of 12 will give us the annual rolling average.

We will also include the rolling standard deviation to see how much the data varies from the rolling average.

In [18]:

```
# Determine rolling statistics
# Wwindow size 12 denotes 12 months, giving rolling mean at yearly level
window_size = 12
df["rolling_avg"] = df[dep_var].rolling(window=window_size).mean()
df["rolling_std"] = df[dep_var].rolling(window=window_size).std()

title = 'Rolling Mean & Standard Deviation - ' + country

fig= go.Figure()

fig.add_trace(go.Scatter(dict(x=df.index.to_timestamp(), y=df[dep_var], mode='lines', name= 'Original')))
```

```
fig.add_trace(go.Scatter(dict(x=df.index.to_timestamp(), y=df['rolling_avg'], mode='lines', name= 'Rolling Mean')))
fig.add_trace(go.Scatter(dict(x=df.index.to_timestamp(), y=df['rolling_std'], mode='lines', name= 'Rolling Std')))

fig.update_layout(height=400, width=1200, title=go.layout.Title(text=title),
 xaxis=go.layout.XAxis(title=go.layout.xaxis.Title(text='Date')),
 yaxis=go.layout.YAxis(title=go.layout.yaxis.Title(text='Cars')))

fig.show()

df.drop(['rolling_avg', 'rolling_std'], axis=1, inplace=True)
```



Time series decomposition

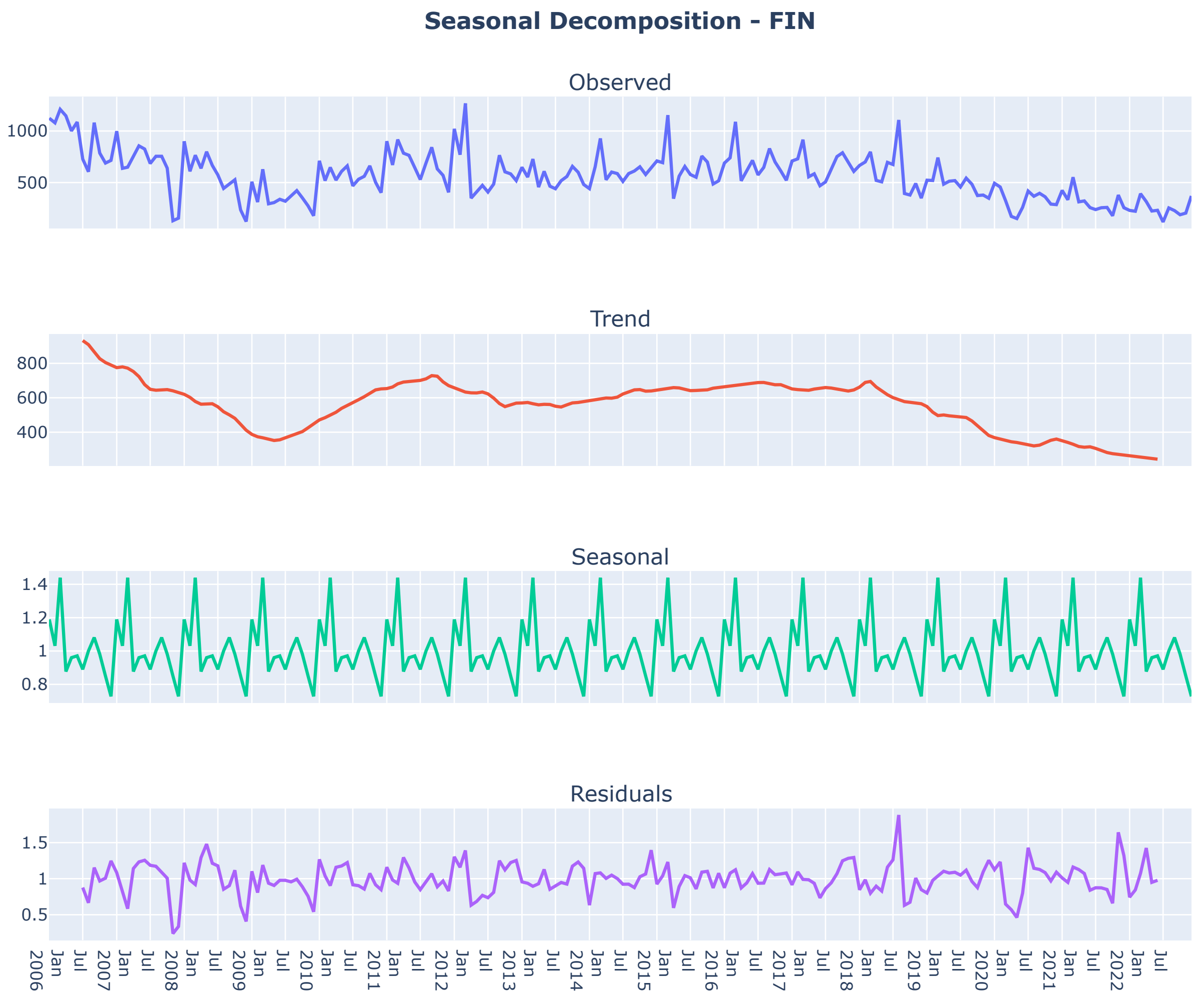
We separate a time series into its components: trend, seasonality, and residuals. The trend represents the slow-moving changes in a time series. It is responsible for making the series gradually increase or decrease over time. The seasonality component represents the seasonal pattern in the series. The cycles occur repeatedly over a fixed period of time. The residuals represent the behavior that cannot be explained by the trend and seasonality components. They correspond to random errors, also termed white noise.

In [19]:
```
df.columns
```

Out[19]: `Index(['Orders', 'CPI', 'UR', 'LTIR', 'TIV', 'DEN', 'NOR', 'SWE'], dtype='object')`

In [20]:
```
def plot_seasonal_decompose(result:DecomposeResult, dates:pd.Series=None, title:str="Seasonal Decomposition - " + cou
    x_values = dates
    return (
        make_subplots(
            rows=4,
            cols=1,
            shared_xaxes=True,
            subplot_titles=["Observed", "Trend", "Seasonal", "Residuals"],
        )
```

```
        )
        .add_trace(go.Scatter(x=x_values.to_timestamp(), y=result.observed, mode="lines", name='Observed'), row=1, co
        .add_trace(go.Scatter(x=x_values.to_timestamp(), y=result.trend, mode="lines", name='Trend'), row=2, col=1,)
        .add_trace(go.Scatter(x=x_values.to_timestamp(), y=result.seasonal, mode="lines", name='Seasonal'), row=3, co
        .add_trace(go.Scatter(x=x_values.to_timestamp(), y=result.resid, mode="lines", name='Residual'), row=4, col=1
        .update_layout(height=800, width=1000, title=f'<b>{title}</b>', margin={'t':100}, title_x=0.5, showlegend=Fal
        .update_xaxes(dtick="M6",tickformat="%b\n%Y")
    )

decomposition = seasonal_decompose(df[dep_var], model='multiplicative', period=12)
fig = plot_seasonal_decompose(decomposition, dates=df.index)
fig.show()
```



Stationarity (Augmented Dickey–Fuller Test)

The Augmented Dickey-Fuller Test is used to determine if time-series data is stationary or not. Similar to a t-test, we set a significance level before the test and make conclusions on the hypothesis based on the resulting p-value.

- Null Hypothesis: The data is not stationary.
- Alternative Hypothesis: The data is stationary.

For the data to be stationary (ie. reject the null hypothesis), the ADF test should have:

- p-value <= significance level (0.01, 0.05, 0.10, etc.)

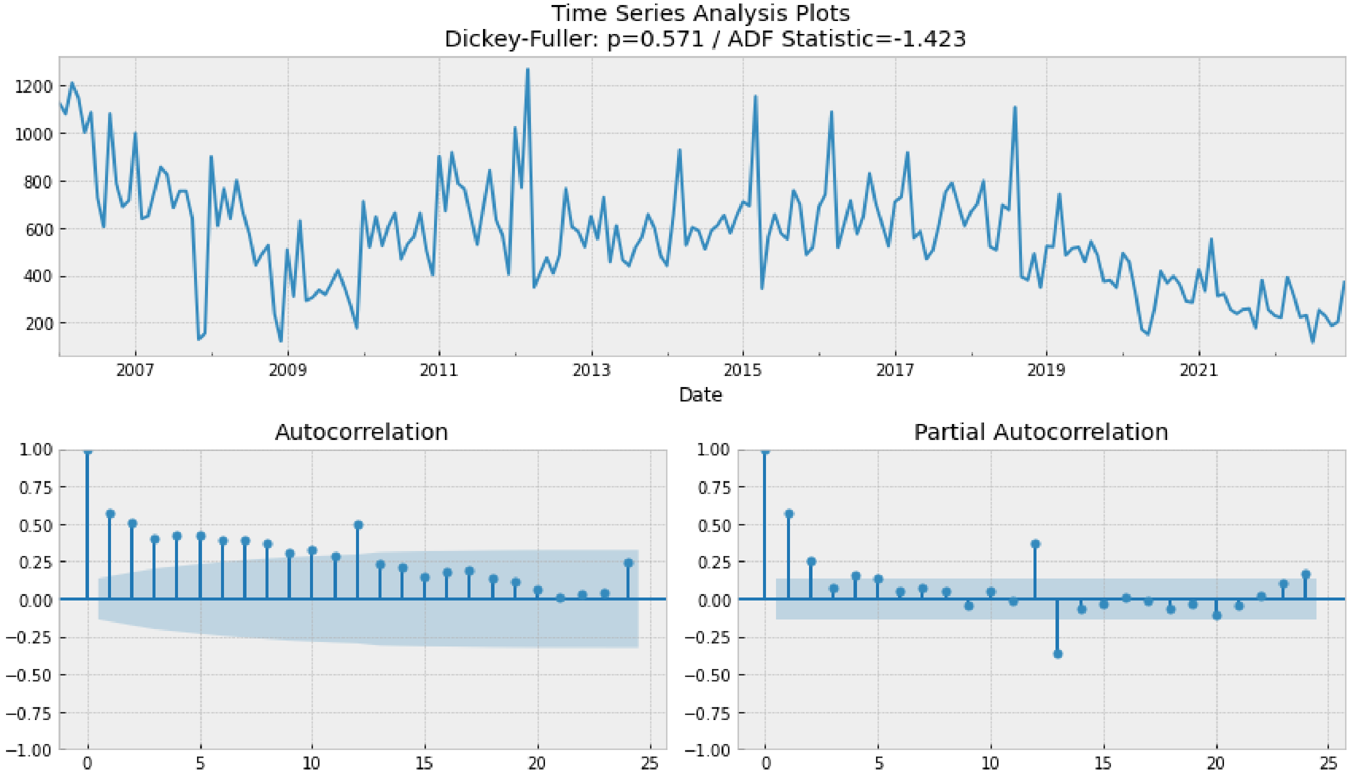
If the p-value is greater than the significance level then we can say that it is likely that the data is not stationary.

In [21]:

```
# Time series analysis plot
def tsplot(y, lags=None, figsize=(12, 7), syle='bmh'):

    if not isinstance(y, pd.Series):
        y = pd.Series(y)

    with plt.style.context(style='bmh'):
        fig = plt.figure(figsize=figsize)
        layout = (2,2)
        ts_ax = plt.subplot2grid(layout, (0,0), colspan=2)
        acf_ax = plt.subplot2grid(layout, (1,0))
        pacf_ax = plt.subplot2grid(layout, (1,1))

        y.plot(ax=ts_ax)
        result = adfuller(y, autolag='AIC',regression='c')
        adf = result[0]
        p_value = result[1]
        ts_ax.set_title('Time Series Analysis Plots\n Dickey-Fuller: p={0:.3f} / ADF Statistic={1:.3f}'.format(p_valu
        smt.graphics.plot_acf(y, lags=lags, ax=acf_ax)
        smt.graphics.plot_pacf(y, lags=lags, ax=pacf_ax, method='ywm')
        plt.tight_layout()

# Data Stationarity check using Augmented Dickey Fuller(ADF) test
def adf_test(timeseries, print_out:bool):
    dftest = adfuller(timeseries, autolag='AIC',regression='c')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags Used','Number of Observations Used'])
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    if print_out:
        print ('Results of Dickey-Fuller Test:')
        print (dfoutput)
    return dfoutput['p-value']

tsplot(df[dep_var])
```

```
p_value = adf_test(df[dep_var], True)
```

```
Results of Dickey-Fuller Test:
Test Statistic                  -1.422679
p-value                          0.571356
#Lags Used                      13.000000
Number of Observations Used    190.000000
Critical Value (1%)             -3.465244
Critical Value (5%)             -2.876875
Critical Value (10%)            -2.574945
dtype: float64
```

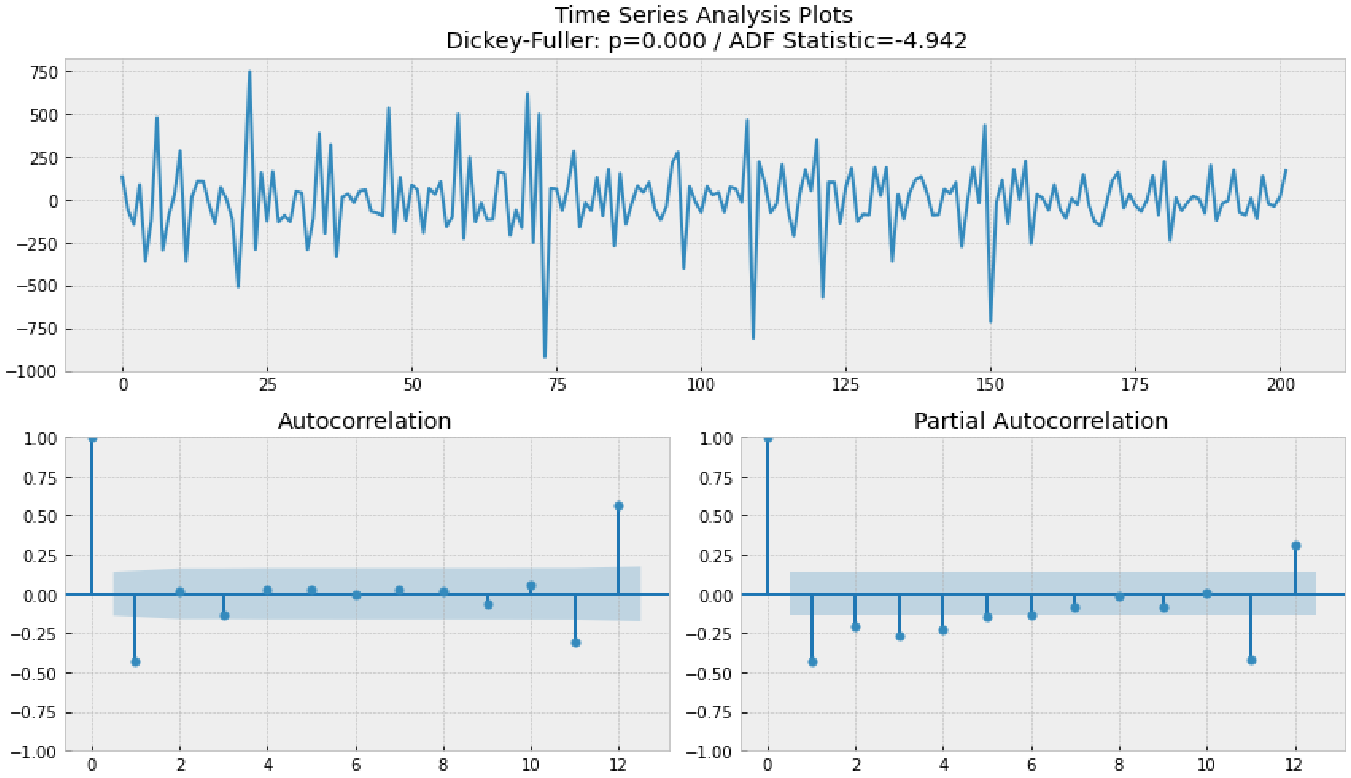


In [22]:

```
if p_value > 0.05:
    # Take the first difference to make our series stationary
    data_diff = np.diff(df[dep_var],1)
    tsplot(data_diff[1:], lags=12)
    p_value = adf_test(data_diff, True)
```

```
Results of Dickey-Fuller Test:
Test Statistic                  -4.769177
p-value                          0.000062
#Lags Used                      12.000000
Number of Observations Used    190.000000
Critical Value (1%)             -3.465244
```

```
Critical Value (5%)          -2.876875
Critical Value (10%)         -2.574945
dtype: float64
```



In [23]:

```python
# Feature selection df
df_fe = df.copy()
```

Feature Engineering

In [24]:

```python
# Aply difference
for c in df_fe.columns:
    p = adf_test(df_fe[c], False)
    if p > 0.05:
        print(c + ' is not stationary')
        # Apply first difference to stationarize and detrend
        df_fe[c + '_diff'] = df_fe[c].diff(1)
        df_fe.drop([c], axis=1, inplace=True)
        df_fe = df_fe.rename(columns={c + '_diff': c})
        df_fe.dropna(inplace=True)
    else:
        print(c + ' is stationary')
```

```
Orders is not stationary
CPI is not stationary
UR is stationary
LTIR is not stationary
TIV is not stationary
DEN is not stationary
NOR is not stationary
SWE is not stationary
```

In [25]:

```
# Verify difference
for c in df_fe.columns:
    p = adf_test(df_fe[c], False)
    if p > 0.05:
        print(c + ' is not stationary')
    else:
        print(c + ' is stationary')
```

```
UR is stationary
Orders is stationary
CPI is stationary
LTIR is stationary
TIV is stationary
DEN is stationary
NOR is stationary
SWE is stationary
```

In [26]:

```
df_fe
```

Out[26]:

Date	UR	Orders	CPI	LTIR	TIV	DEN	NOR	SWE
2006-08	7.7	-123.0	-0.007631	-0.120000	4.466132	-48.0	-123.0	-12.0
2006-09	7.6	476.0	-0.407463	-0.140000	7.289168	-2.0	226.0	189.0
2006-10	7.7	-295.0	0.399893	0.040000	-6.693684	57.0	-260.0	-64.0
2006-11	7.3	-97.0	0.203378	-0.090000	-23.058473	-100.0	105.0	-37.0
2006-12	7.1	26.0	0.099801	0.070000	-35.762137	106.0	348.0	118.0
...	...	...	...	...	...	...	...	...
2022-08	7.2	136.0	-0.169369	-0.088953	17.765280	118.0	214.0	415.0
2022-09	7.3	-26.0	0.503214	0.795932	-3.451603	-6.0	-52.0	-78.0
2022-10	6.4	-40.0	0.191470	0.473650	-6.649574	-15.0	118.0	45.0
2022-11	6.7	16.0	0.827469	-0.203404	2.139332	-17.0	150.0	-102.0
2022-12	7.2	166.0	0.006802	0.015628	-2.260635	52.0	119.0	201.0

197 rows × 8 columns

In [27]:

```
# Create Lagged target variables 1m to 12m
columns = df_fe.columns.difference([dep_var])
range = np.arange(1,13)
for r in range:
    df_fe[dep_var + '_lag' + str(r)] = df_fe[dep_var].shift(r)
```

In [28]:

```
columns
```

Out[28]:

```
Index(['CPI', 'DEN', 'LTIR', 'NOR', 'SWE', 'TIV', 'UR'], dtype='object')
```

In [29]:

```
# Create lagged variables of the exogenoues features
range = [1,3,6,9,12]
for r in range:
    for c in columns:
        df_fe[c + '_lag' + str(r)] = df_fe[c].shift(r)
```

In [30]:

```
# Feature engineering - Seasonal patterns
df_fe['Quarter'] = pd.PeriodIndex(df_fe.index, freq='Q').quarter
df_fe['Month'] = pd.PeriodIndex(df_fe.index, freq='M').month
df_fe['Year'] = pd.PeriodIndex(df_fe.index, freq='Y').year
```

In [31]:

```
# OneHot Encoding
df_fe = pd.get_dummies(df_fe, columns=['Quarter','Month','Year'], drop_first=True)
```

In [32]:

```
# Wwindow size 12 denotes 12 months, giving rolling mean at yearly level
window_size = 12
df_fe["rolling_avg"] = df_fe[dep_var].rolling(window=window_size).mean()
df_fe["rolling_std"] = df_fe[dep_var].rolling(window=window_size).std()
```

In [33]:

```
df_fe.shape
```

Out[33]:

```
(197, 87)
```

In [34]:

```
df_fe = df_fe.dropna()
```

In [35]:

```
df_fe.columns
```

Out[35]:

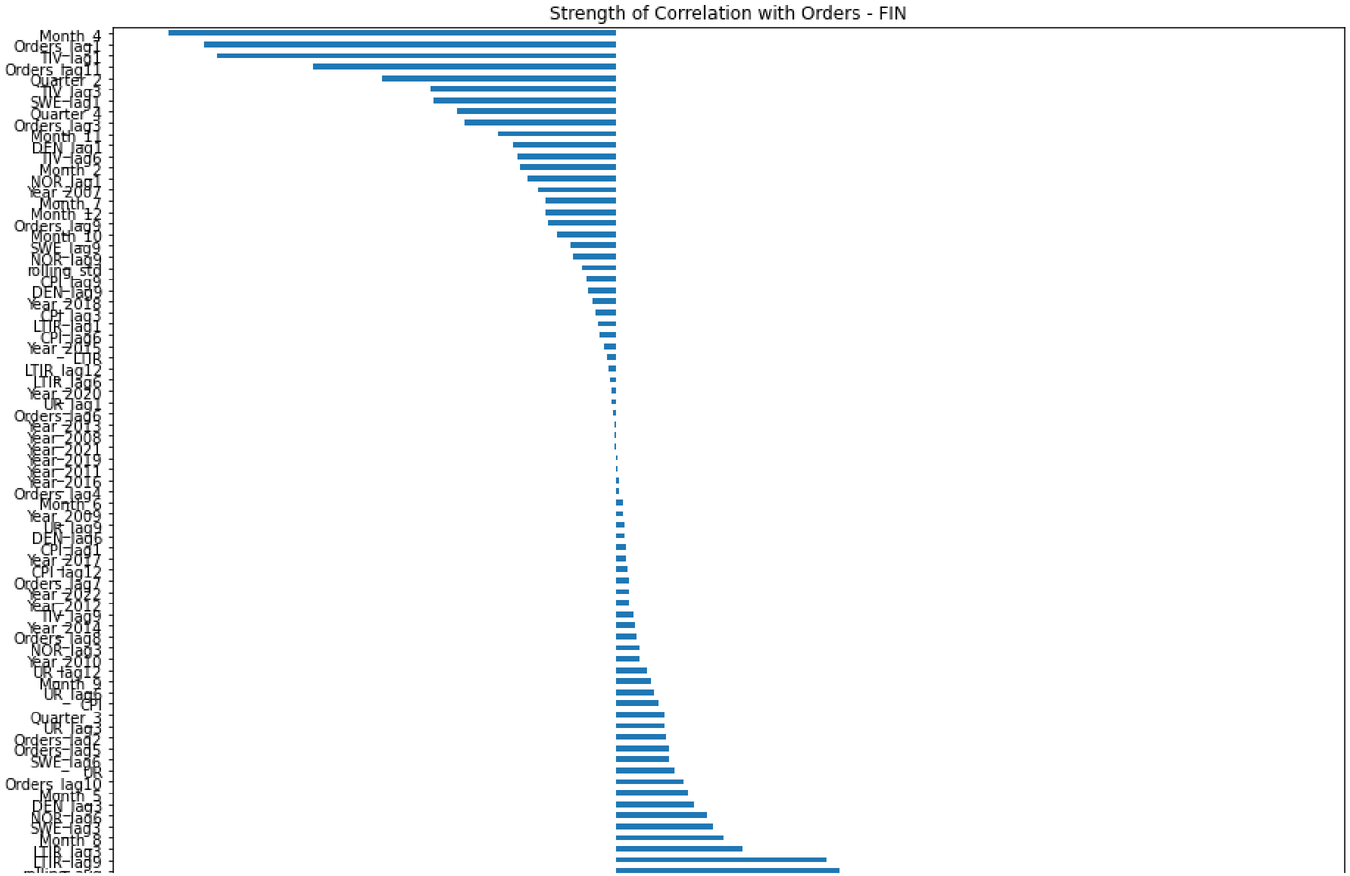
```
Index(['UR', 'Orders', 'CPI', 'LTIR', 'TIV', 'DEN', 'NOR', 'SWE',
       'Orders_lag1', 'Orders_lag2', 'Orders_lag3', 'Orders_lag4',
       'Orders_lag5', 'Orders_lag6', 'Orders_lag7', 'Orders_lag8',
       'Orders_lag9', 'Orders_lag10', 'Orders_lag11', 'Orders_lag12',
       'CPI_lag1', 'DEN_lag1', 'LTIR_lag1', 'NOR_lag1', 'SWE_lag1', 'TIV_lag1',
```

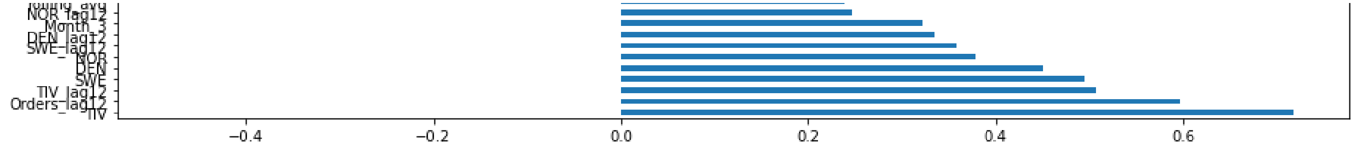
```
       'UR_lag1', 'CPI_lag3', 'DEN_lag3', 'LTIR_lag3', 'NOR_lag3', 'SWE_lag3',
       'TIV_lag3', 'UR_lag3', 'CPI_lag6', 'DEN_lag6', 'LTIR_lag6', 'NOR_lag6',
       'SWE_lag6', 'TIV_lag6', 'UR_lag6', 'CPI_lag9', 'DEN_lag9', 'LTIR_lag9',
       'NOR_lag9', 'SWE_lag9', 'TIV_lag9', 'UR_lag9', 'CPI_lag12', 'DEN_lag12',
       'LTIR_lag12', 'NOR_lag12', 'SWE_lag12', 'TIV_lag12', 'UR_lag12',
       'Quarter_2', 'Quarter_3', 'Quarter_4', 'Month_2', 'Month_3', 'Month_4',
       'Month_5', 'Month_6', 'Month_7', 'Month_8', 'Month_9', 'Month_10',
       'Month_11', 'Month_12', 'Year_2007', 'Year_2008', 'Year_2009',
       'Year_2010', 'Year_2011', 'Year_2012', 'Year_2013', 'Year_2014',
       'Year_2015', 'Year_2016', 'Year_2017', 'Year_2018', 'Year_2019',
       'Year_2020', 'Year_2021', 'Year_2022', 'rolling_avg', 'rolling_std'],
      dtype='object')
```

Feature Selection

In [36]:

```python
figure(figsize=(15, 12))

corr = df_fe.loc[:, df_fe.columns != dep_var].corrwith(df_fe[dep_var])
corr.sort_values(ascending=False).plot.barh(title = 'Strength of Correlation with ' + dep_var + ' - ' + country);
```





In [37]:

```
#Correlation with output variable using Pearson Correlation
threshold = 0.49
cor = df_fe.corr()
cor_target = abs(cor[dep_var])

#Selecting highly correlated features
relevant_features = cor_target[(cor_target > threshold)].to_frame()
relevant_features.sort_values(by=dep_var, ascending=False)
```

Out[37]:

	Orders
Orders	1.000000
TIV	0.717710
Orders_lag12	0.596953
TIV_lag12	0.507268
SWE	0.494555

In [38]:

```
# Keep only meaningful features
if feature_selection:
    df_fe = df_fe[relevant_features.index]
```

In [39]:

```
df_fe
```

Out[39]:

	Orders	TIV	SWE	Orders_lag12	TIV_lag12
Date					
2007-08	70.0	6.506217	89.0	-123.0	4.466132
2007-09	0.0	-13.277093	132.0	476.0	7.289168
2007-10	-115.0	13.872577	-117.0	-295.0	-6.693684
2007-11	-510.0	-80.787363	-200.0	-97.0	-23.058473
2007-12	25.0	-18.261517	68.0	26.0	-35.762137
...	...	...	...	...	...
2022-08	136.0	17.765280	415.0	18.0	4.620517
2022-09	-26.0	-3.451603	-78.0	3.0	-15.118683
2022-10	-40.0	-6.649574	45.0	-81.0	0.860144

2022-11	16.0	2.139332	-102.0	201.0	0.716787
2022-12	166.0	-2.260635	201.0	-123.0	-1.632068

185 rows × 5 columns

In [40]:

```
if feature_engineering:
    df = df_fe.copy()
```

In [41]:

```
df
```

Out[41]:

Date	Orders	TIV	SWE	Orders_lag12	TIV_lag12
2007-08	70.0	6.506217	89.0	-123.0	4.466132
2007-09	0.0	-13.277093	132.0	476.0	7.289168
2007-10	-115.0	13.872577	-117.0	-295.0	-6.693684
2007-11	-510.0	-80.787363	-200.0	-97.0	-23.058473
2007-12	25.0	-18.261517	68.0	26.0	-35.762137
...	...	...	...	...	...
2022-08	136.0	17.765280	415.0	18.0	4.620517
2022-09	-26.0	-3.451603	-78.0	3.0	-15.118683
2022-10	-40.0	-6.649574	45.0	-81.0	0.860144
2022-11	16.0	2.139332	-102.0	201.0	0.716787
2022-12	166.0	-2.260635	201.0	-123.0	-1.632068

185 rows × 5 columns

Split Data

In [42]:

```
# Split data
steps = 36  # Number of months of testing
train = df[:-steps]
test  = df[-steps:]

print(f"Dataset length : (n={len(df)})")
print(f"Train dates    : {train.index.min()} --- {train.index.max()}  (n={len(train)})")
print(f"Test dates     : {test.index.min()} --- {test.index.max()}  (n={len(test)})")

print('\nData shape:', train.shape, test.shape)
```

```
# Select input and target variables
X_train = train.drop(dep_var, axis=1)
y_train = train[dep_var]

X_test = test.drop(dep_var, axis=1)
y_test = test[dep_var]

print('\nTrain shape:', X_train.shape, y_train.shape)
print('\nTest shape:', X_test.shape, y_test.shape)
```

```
Dataset length : (n=185)
Train dates    : 2007-08 --- 2019-12  (n=149)
Test dates     : 2020-01 --- 2022-12  (n=36)

Data shape: (149, 5) (36, 5)

Train shape: (149, 4) (149,)

Test shape: (36, 4) (36,)
```

Scoring Function

In [43]:

```
# Function to revert the first differencing
def invert_transformation(df_train, df_forecast):
    df_fc = df_forecast.copy()
    columns = df_train.columns
    for col in columns:
        # Roll back 1st Diff
        #print(df_train[col].iloc[-1])
        df_fc[str(col)+'_forecast'] = df_train[col].iloc[-1] + df_fc[str(col)].cumsum()
    return df_fc
```

In [44]:

```
metrics = pd.DataFrame()

def scoring(model_name, y_true, y_pred, dataframe, print_metrics: bool, plot_results: bool):

    # Calculate metrics
    mae = mean_absolute_error(y_true, y_pred)                        # MAE (Mean Absolute Error)
    mse = mean_squared_error(y_true, y_pred)                         # MSE (Mean Squared Error)
    rmse = math.sqrt(mse)                                            # RMSE (Root Mean Squared Error)
    r2 = r2_score(y_true, y_pred)                                    # R2 (R-squared - Coeficient of determination)
    mape = np.mean(np.abs((y_true - y_pred) /y_true)) * 100          # MAPE
    accuracy = 100 - mape                                            # Accuracy

    # Append metrics for summary
    metrics[model_name] = [mae, mse, rmse, r2, mape, accuracy]
    metrics.index = ['Mean Absolute Error',
                     'Mean Squared Error',
                     'Root Mean Squared Error',
                     'R^2',
                     'Mean Absolute Percentage Error',
```

```
                 'Accuracy']

    # Print metrics
    if print_metrics:

        print(model_name, 'Model Performance:')                              # Model name
        print('Mean Absolute Error: {:0.2f}.'.format(mae))                   # MAE
        print('Mean Squared Error: {:0.2f}.'.format(mse))                    # MSE
        print('Root Mean Squared Error: {:0.2f}.'.format(rmse))              # RMSE
        print('R^2 Score = {:0.2f}.'.format(r2))                             # R2
        print('Mean Absolute Percentage Error: {:0.2f}%.'.format(mape))      # MAPE
        print('Accuracy = {:0.2f}%.'.format(accuracy))                       # Accuracy

    # Plot Actual values vs predicted values
    if plot_results:

        df = pd.DataFrame(y_true)

        fig= make_subplots(rows=2, cols=1)

        # Plot only test set
        fig.add_trace(go.Scatter(dict(x=df.index.to_timestamp(), y=y_true, mode='lines', name= 'Actual'), legendgroup
        fig.add_trace(go.Scatter(dict(x=df.index.to_timestamp(), y=y_pred, mode='lines', name= 'Predicted'), legendgr

        # Plot whole data
        #fig.add_trace(go.Scatter(dict(x=train.index.to_timestamp(), y=train[dep_var], mode='lines', name= 'Train'),
        fig.add_trace(go.Scatter(dict(x=train.index.to_timestamp(), y=dataframe[dep_var], mode='lines', name= 'Train'
        fig.add_trace(go.Scatter(dict(x=test.index.to_timestamp(), y=y_true, mode='lines', name= 'Test'), legendgroup
        fig.add_trace(go.Scatter(dict(x=test.index.to_timestamp(), y=y_pred, mode='lines', name= 'Forecast'), legendg

        fig.update_layout(height=600, width=1000, title_text=model_name + " Predictions (Country: " + country + ' - T

        fig.show()
```

In [45]:

```
def plot_metrics(m, w, h):
    chart = m.transpose()
    chart.drop(['Mean Squared Error', 'R^2', 'Accuracy'], axis=1, inplace=True)

    ax = chart.plot.bar(title="Models Performance (" + country + ' /  '
        + dep_var + ')\nFeature Engineering:' + str(feature_engineering)
        + ' / feature Selection: ' + str(feature_selection)
        + ' / Include Nordics: ' + str(include_nordics),
        figsize=(w, h))
    for c in ax.containers:
        ax.bar_label(c, fmt='%0.2f', label_type='edge', padding=5)
    ax.legend(loc='upper left', bbox_to_anchor=(1.0, 1.0))
```

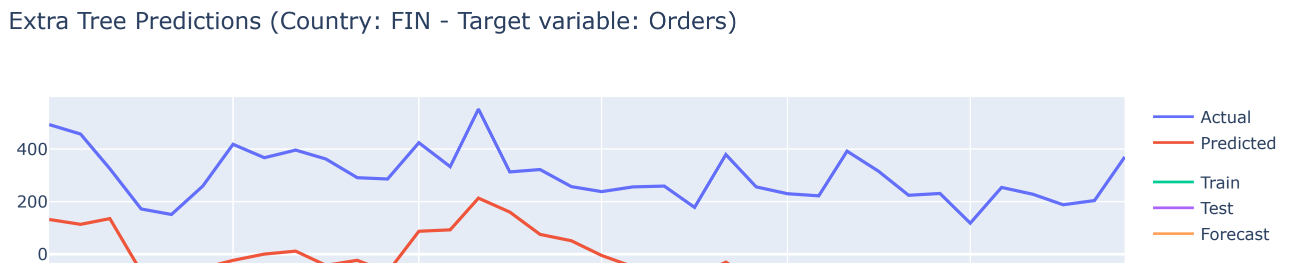
ML Models

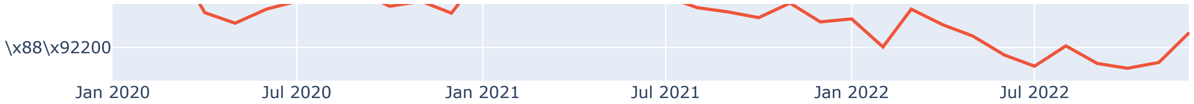
In [46]:

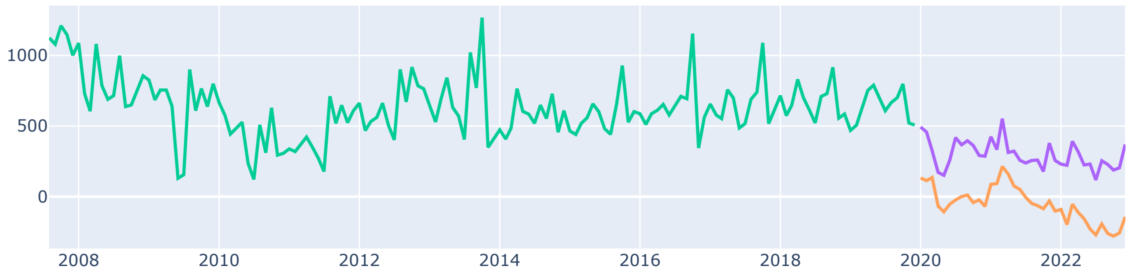
```
# Hyperparameters
modelclasses = [
    ["Extra Tree", ExtraTreesRegressor],
```

```python
    ["XGBoost", XGBRegressor],
    ["Gradient Boosting", GradientBoostingRegressor],
    ["Random Forest", RandomForestRegressor],
    ["Ada Boost", AdaBoostRegressor],
    ["LightGBM", LGBMRegressor],
    ["Decision Tree", DecisionTreeRegressor]
]

for model_name, Model in modelclasses:

    # Instantiate the model
    model = Model()

    # Fit
    model.fit(X_train,y_train)

    # Predict
    y_pred = model.predict(X_test)

    if feature_engineering:

        # Create dataframe of predictions
        y_pred_df = pd.DataFrame(data=y_pred, index=test.index, columns=[dep_var])

        # Invert transformation
        y_pred_df_inv = invert_transformation(df_original[[dep_var]].iloc[:-steps],y_pred_df)

        # Score
        scoring(model_name, df_original[[dep_var]].iloc[-steps:].squeeze(), y_pred_df_inv[dep_var + '_forecast'].valu

    else:

        # Score
        scoring(model_name, y_test, y_pred, df, True, True)
```

```
Extra Tree Model Performance:
Mean Absolute Error: 350.49.
Mean Squared Error: 130831.86.
Root Mean Squared Error: 361.71.
R^2 Score = -12.66.
Mean Absolute Percentage Error: 131.27%.
Accuracy = -31.27%.
```

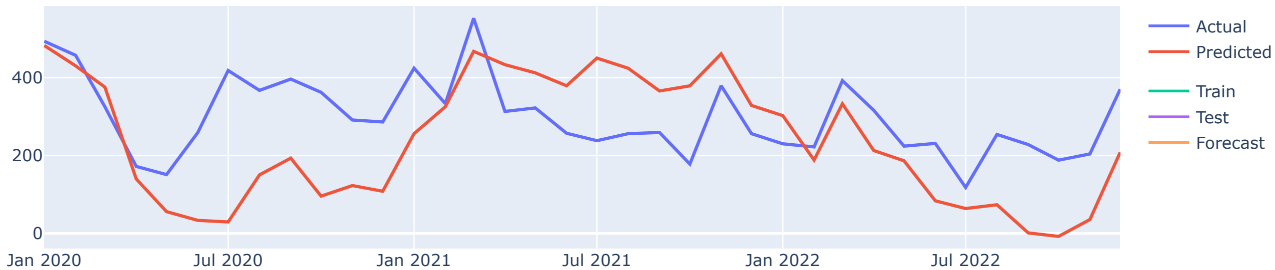


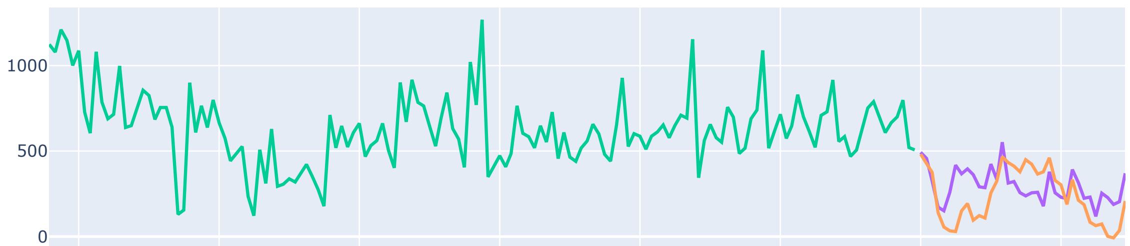


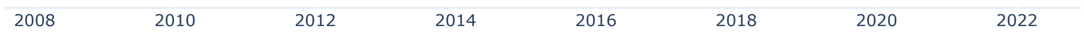



```
XGBoost Model Performance:
Mean Absolute Error: 131.52.
Mean Squared Error: 24071.90.
Root Mean Squared Error: 155.15.
R^2 Score = -1.51.
Mean Absolute Percentage Error: 48.32%.
Accuracy = 51.68%.
```

XGBoost Predictions (Country: FIN - Target variable: Orders)

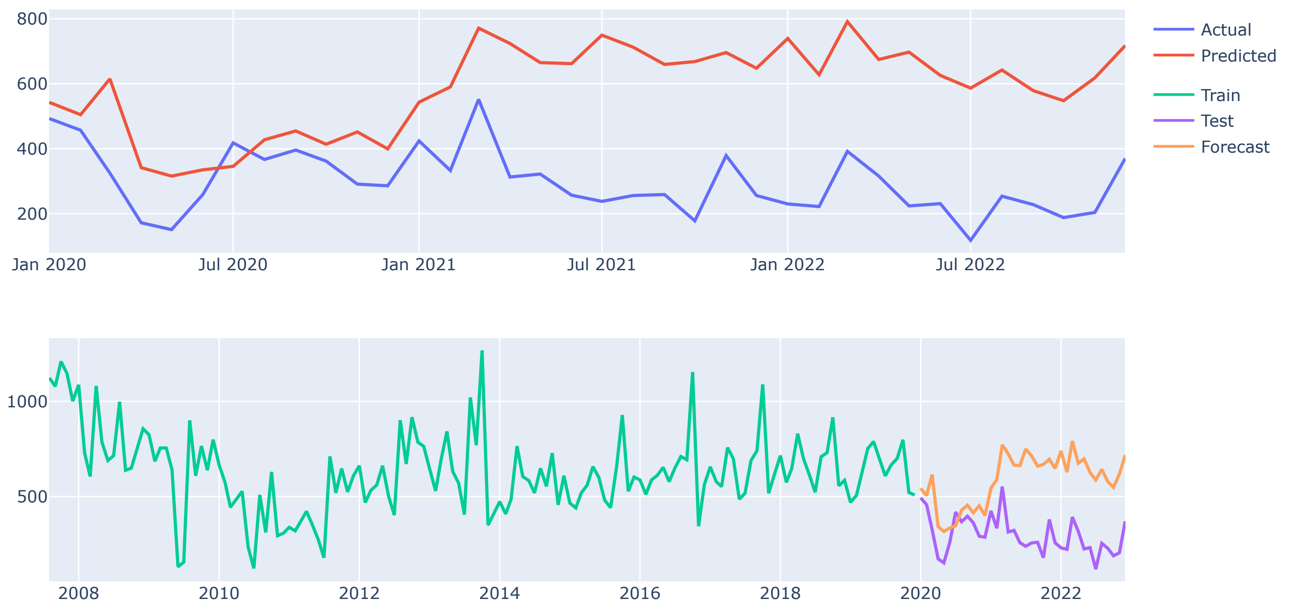






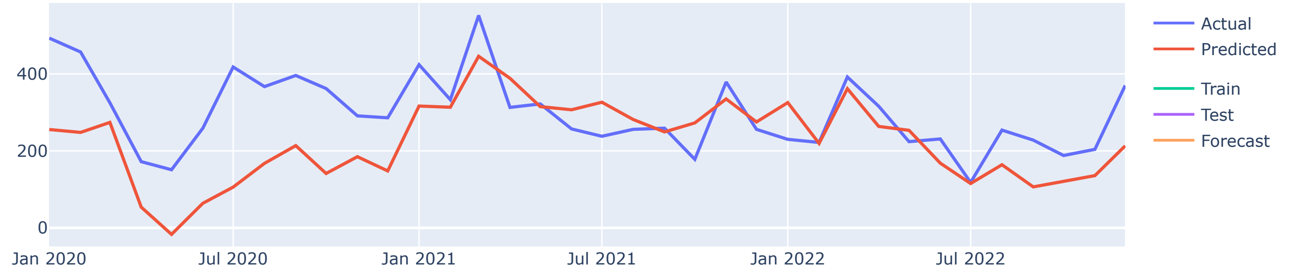

```
Gradient Boosting Model Performance:
Mean Absolute Error: 291.96.
Mean Squared Error: 108797.68.
Root Mean Squared Error: 329.84.
R^2 Score = -10.36.
Mean Absolute Percentage Error: 119.45%.
Accuracy = -19.45%.
```

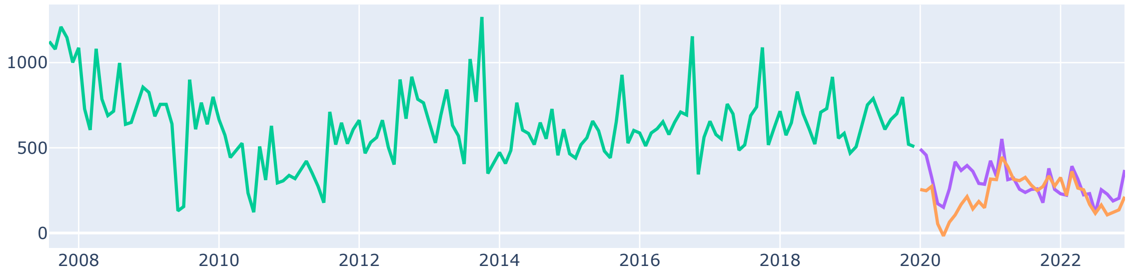
Gradient Boosting Predictions (Country: FIN - Target variable: Orders)




```
Random Forest Model Performance:
Mean Absolute Error: 99.03.
Mean Squared Error: 15500.73.
Root Mean Squared Error: 124.50.
R^2 Score = -0.62.
Mean Absolute Percentage Error: 33.76%.
Accuracy = 66.24%.
```

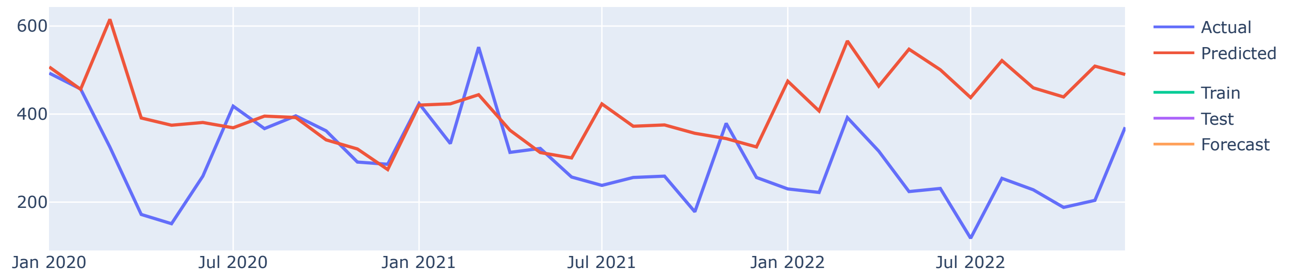
Random Forest Predictions (Country: FIN - Target variable: Orders)

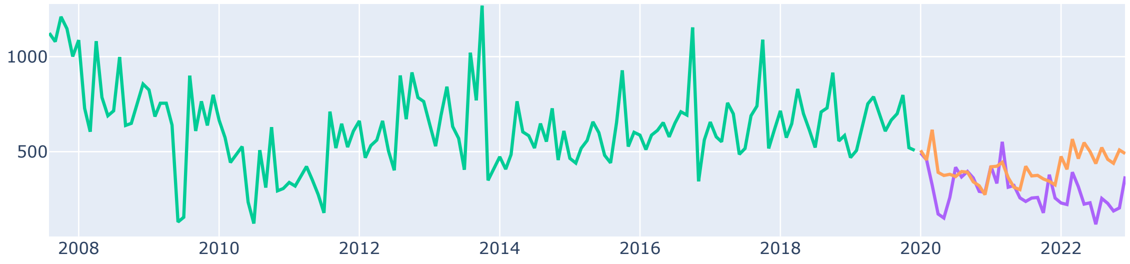





```
Ada Boost Model Performance:
Mean Absolute Error: 134.94.
Mean Squared Error: 29080.33.
Root Mean Squared Error: 170.53.
R^2 Score = -2.04.
Mean Absolute Percentage Error: 60.52%.
Accuracy = 39.48%.
```

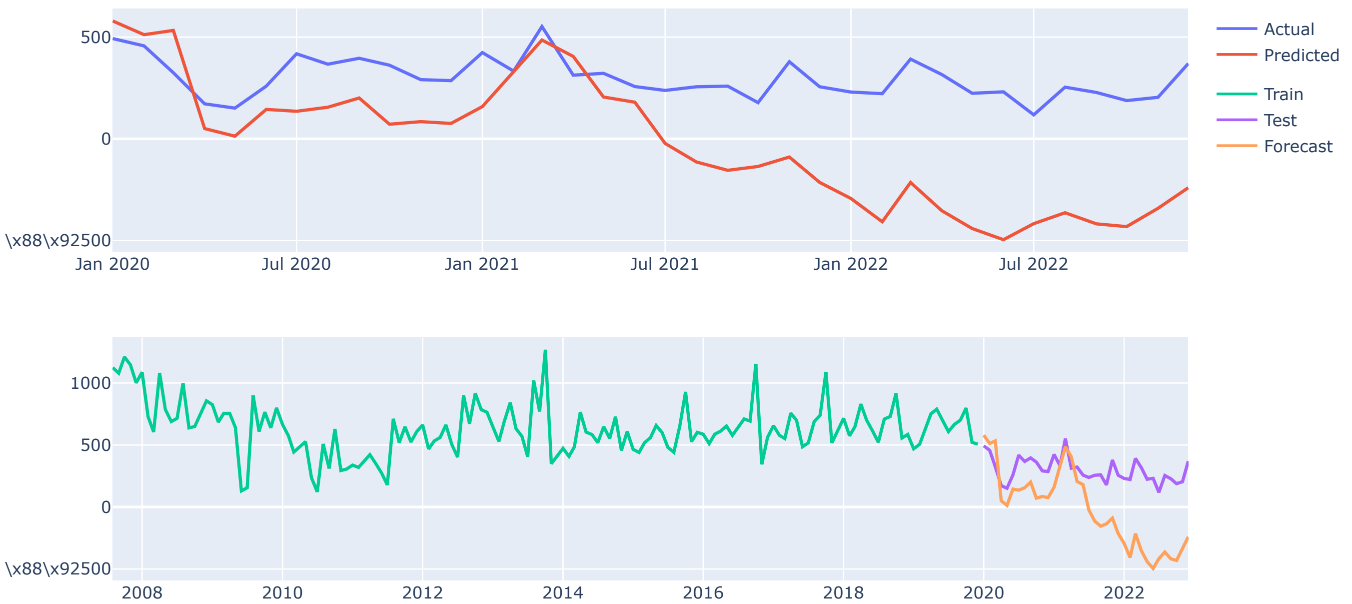
Ada Boost Predictions (Country: FIN - Target variable: Orders)





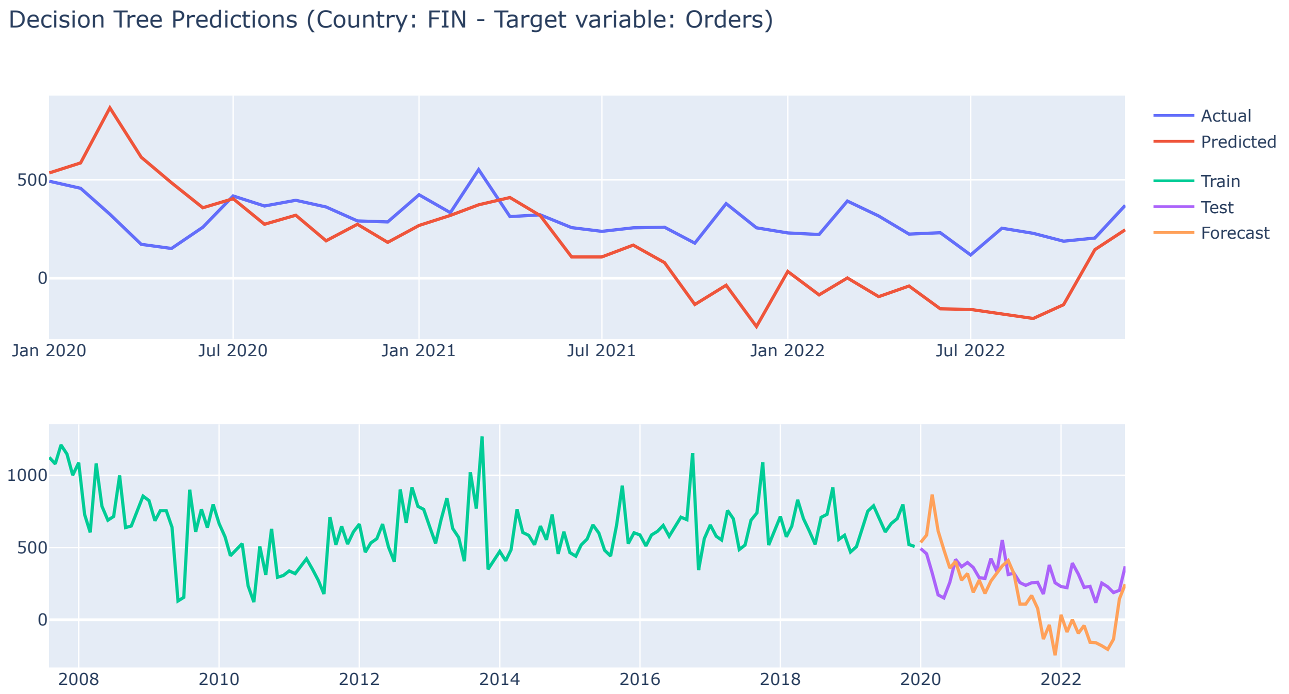

```
LightGBM Model Performance:
Mean Absolute Error: 345.28.
Mean Squared Error: 168002.93.
Root Mean Squared Error: 409.88.
R^2 Score = -16.55.
Mean Absolute Percentage Error: 138.83%.
Accuracy = -38.83%.
```

LightGBM Predictions (Country: FIN - Target variable: Orders)




```
Decision Tree Model Performance:
Mean Absolute Error: 219.31.
```

```
Mean Squared Error: 72213.58.
Root Mean Squared Error: 268.73.
R^2 Score = -6.54.
Mean Absolute Percentage Error: 89.69%.
Accuracy = 10.31%.
```



Verify the inverse transformation

In [47]:

```
# Input path and filename
path = '../5. Master_thesis/Datasets/Output_files/'

# Load files into a pandas dataframes
file = path + '0.xlsx'
df = pd.read_excel(file, sheet_name=country)

# Set index
df = df.set_index("Date")
df.index = pd.PeriodIndex(df.index, freq="M")

# Split data
steps = 36  # Number of months of testing
```

```python
train = df[:-steps]
test  = df[-steps:]

df_forecast=pd.DataFrame(data=y_pred, index=test.index, columns=[dep_var])
df_inv = invert_transformation(train[[dep_var]], df_forecast)
df_inv.insert(2, "Original", test[[dep_var]])
df_inv
```

Out[47]:

Date	Orders	Orders_forecast	Original
2020-01	187.0	535.0	493
2020-02	51.0	586.0	457
2020-03	280.0	866.0	325
2020-04	-251.0	615.0	172
2020-05	-130.0	485.0	151
2020-06	-127.0	358.0	259
2020-07	46.0	404.0	418
2020-08	-130.0	274.0	367
2020-09	46.0	320.0	396
2020-10	-130.0	190.0	362
2020-11	84.0	274.0	291
2020-12	-92.0	182.0	286
2021-01	86.0	268.0	424
2021-02	51.0	319.0	333
2021-03	54.0	373.0	552
2021-04	37.0	410.0	313
2021-05	-92.0	318.0	322
2021-06	-210.0	108.0	257
2021-07	0.0	108.0	238
2021-08	60.0	168.0	256
2021-09	-89.0	79.0	259
2021-10	-213.0	-134.0	178
2021-11	98.0	-36.0	379
2021-12	-210.0	-246.0	256
2022-01	280.0	34.0	230

2022-02	-119.0	-85.0	222
2022-03	86.0	1.0	392
2022-04	-95.0	-94.0	316
2022-05	54.0	-40.0	224
2022-06	-116.0	-156.0	231
2022-07	-3.0	-159.0	118
2022-08	-21.0	-180.0	254
2022-09	-25.0	-205.0	228
2022-10	70.0	-135.0	188
2022-11	280.0	145.0	204
2022-12	101.0	246.0	370

In [48]:

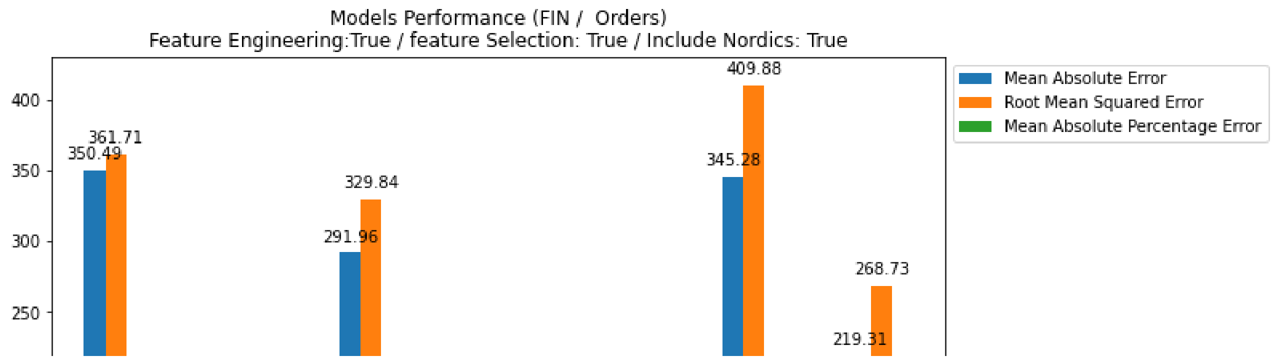
```
metrics
```

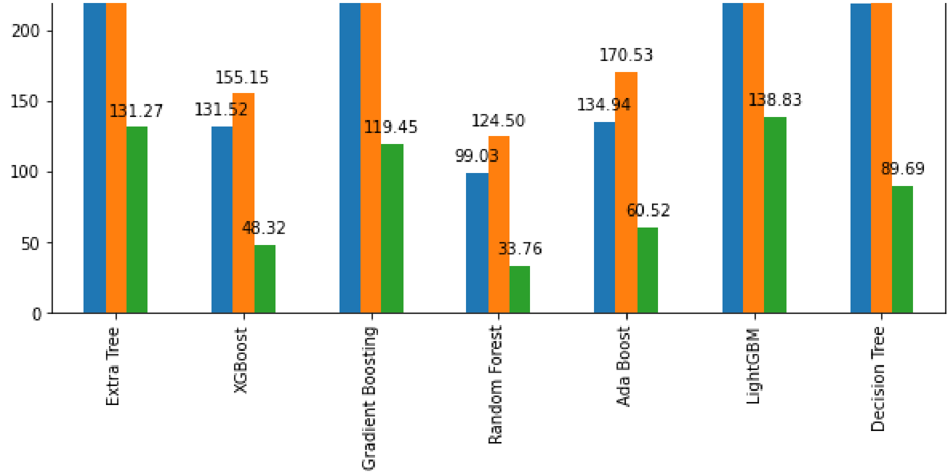
Out[48]:

	Extra Tree	XGBoost	Gradient Boosting	Random Forest	Ada Boost	LightGBM	Decision Tree
Mean Absolute Error	350.493611	131.517476	291.956169	99.025833	134.943656	345.280390	219.305556
Mean Squared Error	130831.858064	24071.898701	108797.676848	15500.726975	29080.330761	168002.931039	72213.583333
Root Mean Squared Error	361.706868	155.151212	329.844928	124.501916	170.529560	409.881606	268.725852
R^2	-12.664550	-1.514156	-10.363221	-0.618952	-2.037254	-16.546831	-6.542247
Mean Absolute Percentage Error	131.270587	48.323753	119.445426	33.757223	60.519191	138.831848	89.692784
Accuracy	-31.270587	51.676247	-19.445426	66.242777	39.480809	-38.831848	10.307216

In [49]:

```
plot_metrics(metrics, 10, 7)
```





Statistical Models

In [50]:

```
start=len(train)
end=len(train)+len(test)-1
```

In [51]:

```
df = pd.read_excel(file, sheet_name=country)

# Set index
df = df.set_index("Date")
df.index = pd.PeriodIndex(df.index, freq="M")

# Feature engineering - Seasonal patterns
df['Quarter'] = pd.PeriodIndex(df.index, freq='Q').quarter

# Load files into a pandas dataframes
file = path + 'target.xlsx'
df_nordics = pd.read_excel(file, sheet_name=dep_var)

# Set index
df_nordics = df_nordics.set_index("Date")
df_nordics.index = pd.PeriodIndex(df_nordics.index, freq="M")

#Merge dataframes
df = pd.merge(df, df_nordics[df_nordics.columns.difference([country])], left_index=True, right_index=True)

print(f"Dataset length : (n={len(df)})")
print(f"Train dates    : {train.index.min()} --- {train.index.max()}  (n={len(train)})")
print(f"Test dates     : {test.index.min()} --- {test.index.max()}  (n={len(test)})")

print('\nData shape:', train.shape, test.shape)

# Split data
steps = 36  # Number of months of testing
```

```
train = df[:-steps]
test  = df[-steps:]

# Select input and target variables
X_train = train.drop(dep_var, axis=1)
y_train = train[dep_var]

X_test = test.drop(dep_var, axis=1)
y_test = test[dep_var]

print('\nTrain shape:', X_train.shape, y_train.shape)
print('\nTest shape:', X_test.shape, y_test.shape)
```

```
Dataset length : (n=204)
Train dates    : 2006-01 --- 2019-12  (n=168)
Test dates     : 2020-01 --- 2022-12  (n=36)

Data shape: (168, 5) (36, 5)

Train shape: (168, 8) (168,)

Test shape: (36, 8) (36,)
```

In [52]:

```
df
```

Out[52]:

Date	Orders	CPI	UR	LTIR	TIV	Quarter	DEN	NOR	SWE
2006-01	1124	0.807265	8.3	3.280000	203.413007	1	161	233	110
2006-02	1079	0.901804	8.0	3.440000	128.084250	1	250	270	303
2006-03	1210	0.899101	7.7	3.620000	151.605878	1	468	406	634
2006-04	1147	1.297405	7.7	3.880000	135.086704	2	412	356	1097
2006-05	1001	1.701702	7.9	3.940000	166.978193	2	550	553	926
...	...	...	...	...	...	...	...	...	...
2022-08	254	7.616082	7.2	1.624904	78.449535	3	343	347	744
2022-09	228	8.119296	7.3	2.420836	74.997932	3	337	295	666
2022-10	188	8.310766	6.4	2.894486	68.348358	4	322	413	711
2022-11	204	9.138235	6.7	2.691082	70.487691	4	305	563	609
2022-12	370	9.145037	7.2	2.706710	68.227056	4	357	682	810

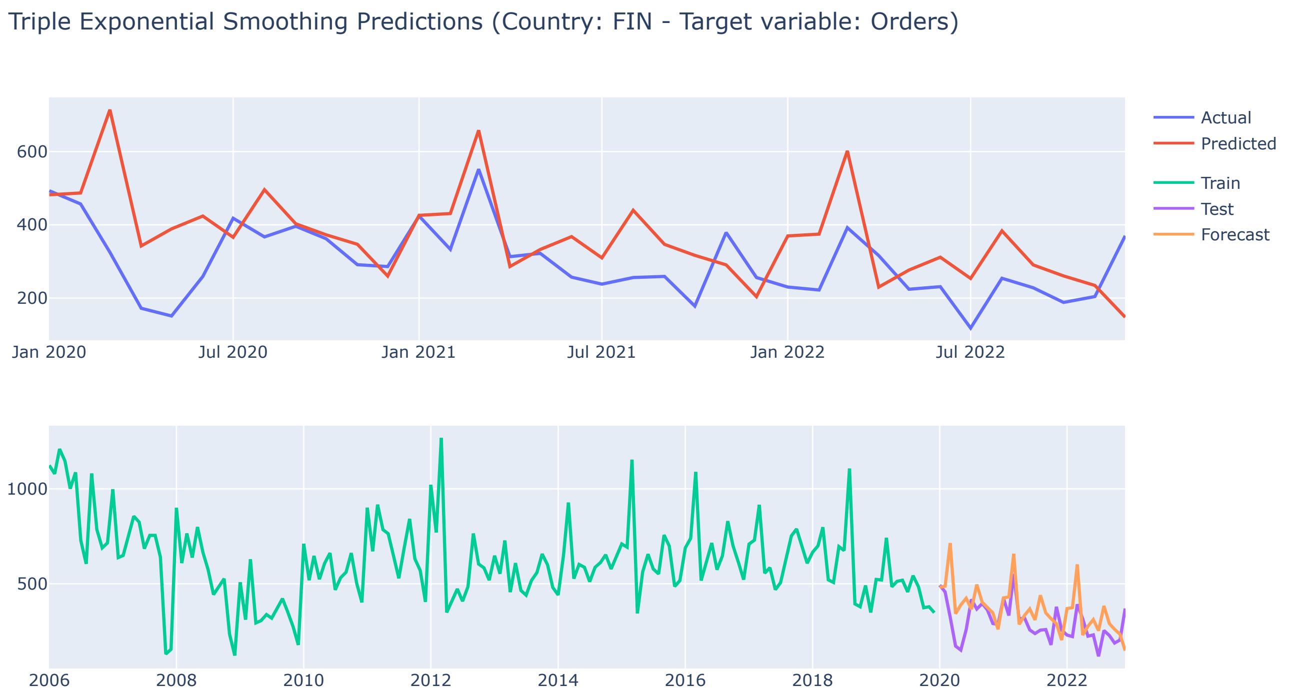
204 rows × 9 columns

Triple Exponential Smoothing

In [53]:

```
model_name='Triple Exponential Smoothing'

# Train
model = ExponentialSmoothing(train[dep_var],trend='add',seasonal='add',seasonal_periods=12).fit()

# Predict
predictions = model.predict(start=start, end=end)

# Forecast accuracy
scoring(model_name, test[dep_var], predictions, df, True, True)
```

```
Triple Exponential Smoothing Model Performance:
Mean Absolute Error: 100.96.
Mean Squared Error: 16591.50.
Root Mean Squared Error: 128.81.
R^2 Score = -0.73.
Mean Absolute Percentage Error: 40.72%.
Accuracy = 59.28%.
```



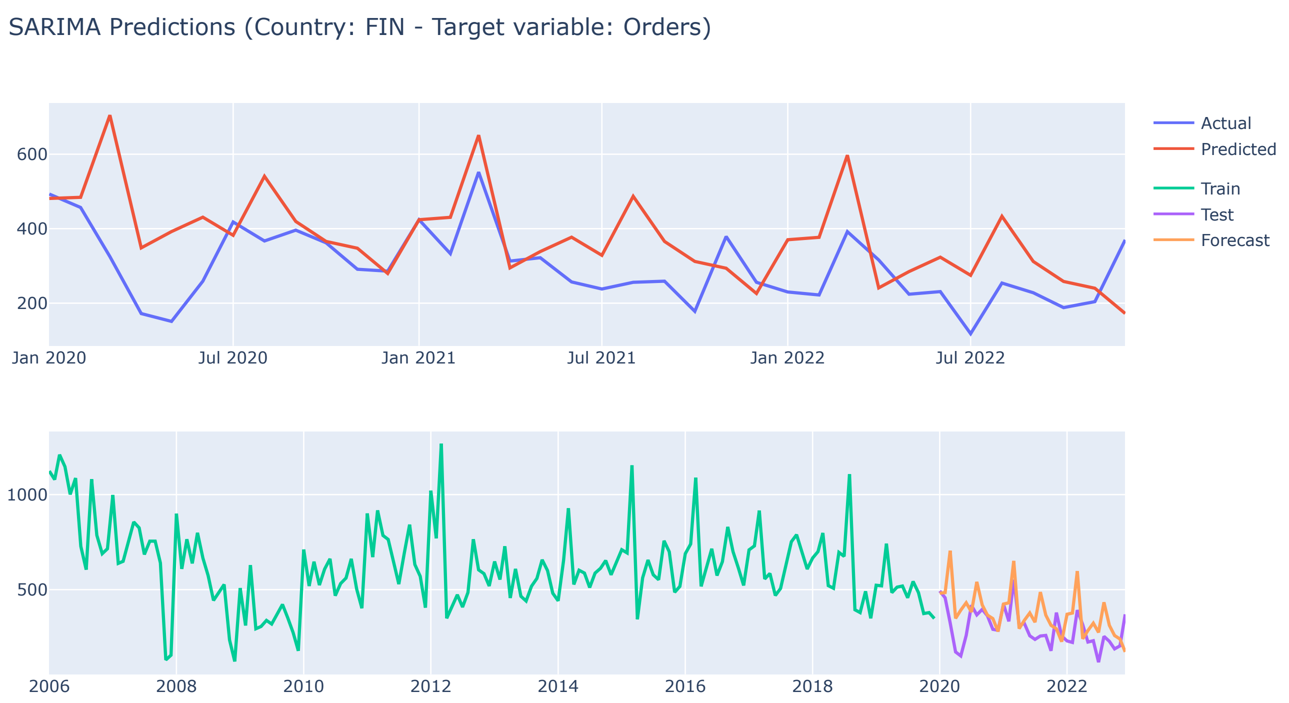
SARIMA

In [54]:

```python
# Seasonal - fit stepwise auto-ARIMA
model = auto_arima(train[dep_var],
                   start_p=1,
                   start_q=1,
                   test='adf',              # Use adftest to find optimal 'd'
                   max_p=3, max_q=3,        # Maximum p and q
                   m=12,                    # Frequency of series (if m==1, seasonal is set to FALSE automatically
                   start_P=0,
                   seasonal=True,           # set to seasonal
                   d=None,                  # Let model determine 'd'
                   D=1,                     # Order of the seasonal differencing
                   trace=True,              # Logs
                   error_action='warn',     # Shows errors ('ignore' silences these)
                   suppress_warnings=True,
                   stepwise=True)

model_name='SARIMA'

# Predict
predictions = model.predict(n_periods=test.shape[0], dynamic=False, typ='levels')

# Forecast accuracy
scoring(model_name, test[dep_var], predictions, df, True, True)
```

```
Performing stepwise search to minimize aic
 ARIMA(1,1,1)(0,1,1)[12]             : AIC=1999.944, Time=0.45 sec
 ARIMA(0,1,0)(0,1,0)[12]             : AIC=2084.475, Time=0.03 sec
 ARIMA(1,1,0)(1,1,0)[12]             : AIC=2039.583, Time=0.20 sec
 ARIMA(0,1,1)(0,1,1)[12]             : AIC=2002.150, Time=0.29 sec
 ARIMA(1,1,1)(0,1,0)[12]             : AIC=2043.561, Time=0.18 sec
 ARIMA(1,1,1)(1,1,1)[12]             : AIC=2001.868, Time=0.65 sec
 ARIMA(1,1,1)(0,1,2)[12]             : AIC=2001.830, Time=1.22 sec
 ARIMA(1,1,1)(1,1,0)[12]             : AIC=2017.834, Time=0.38 sec
 ARIMA(1,1,1)(1,1,2)[12]             : AIC=inf, Time=2.32 sec
 ARIMA(1,1,0)(0,1,1)[12]             : AIC=2022.606, Time=0.29 sec
 ARIMA(2,1,1)(0,1,1)[12]             : AIC=2001.822, Time=0.73 sec
 ARIMA(1,1,2)(0,1,1)[12]             : AIC=2001.860, Time=0.65 sec
 ARIMA(0,1,0)(0,1,1)[12]             : AIC=2041.516, Time=0.16 sec
 ARIMA(0,1,2)(0,1,1)[12]             : AIC=1999.922, Time=0.42 sec
 ARIMA(0,1,2)(0,1,0)[12]             : AIC=2044.409, Time=0.09 sec
 ARIMA(0,1,2)(1,1,1)[12]             : AIC=2001.837, Time=0.54 sec
 ARIMA(0,1,2)(0,1,2)[12]             : AIC=2001.795, Time=0.86 sec
 ARIMA(0,1,2)(1,1,0)[12]             : AIC=2018.060, Time=0.27 sec
 ARIMA(0,1,2)(1,1,2)[12]             : AIC=inf, Time=1.84 sec
 ARIMA(0,1,3)(0,1,1)[12]             : AIC=2001.836, Time=0.65 sec
 ARIMA(1,1,3)(0,1,1)[12]             : AIC=2003.730, Time=0.93 sec
 ARIMA(0,1,2)(0,1,1)[12] intercept   : AIC=2001.649, Time=0.51 sec

Best model:  ARIMA(0,1,2)(0,1,1)[12]
Total fit time: 13.675 seconds
SARIMA Model Performance:
Mean Absolute Error: 105.27.
Mean Squared Error: 17932.82.
Root Mean Squared Error: 133.91.
R^2 Score = -0.87.
```

```
Mean Absolute Percentage Error: 42.92%.
Accuracy = 57.08%.
```



SARIMAX

In [55]:

```
train
```

Out[55]:

Date	Orders	CPI	UR	LTIR	TIV	Quarter	DEN	NOR	SWE
2006-01	1124	0.807265	8.3	3.28	203.413007	1	161	233	110
2006-02	1079	0.901804	8.0	3.44	128.084250	1	250	270	303
2006-03	1210	0.899101	7.7	3.62	151.605878	1	468	406	634
2006-04	1147	1.297405	7.7	3.88	135.086704	2	412	356	1097
2006-05	1001	1.701702	7.9	3.94	166.978193	2	550	553	926
...	...	...	...	...	...	...	...	...	...

2019-08	543	1.093964	7.0	-0.35	110.208695	3	637	571	874
2019-09	484	0.916179	6.7	-0.30	93.060954	3	744	862	1004
2019-10	374	0.748663	6.9	-0.21	103.338571	4	853	641	816
2019-11	379	0.671010	6.9	-0.08	95.751661	4	682	683	1090
2019-12	348	0.915198	6.5	-0.03	90.590798	4	603	724	1453

168 rows × 9 columns

In [56]:

```
exo_train = train.loc[:, train.columns == 'DEN']
exo_test = test.loc[:, test.columns == 'DEN']
```

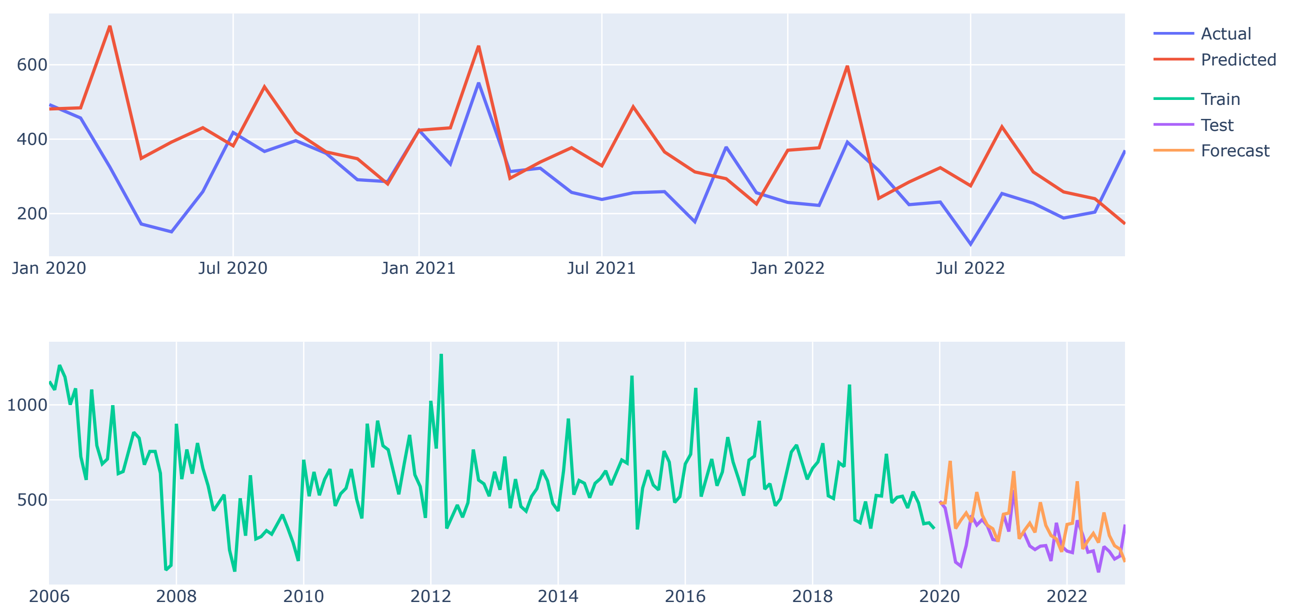
In [57]:

```
# SARIMAX = SARIMA with exogenous variable
#exo_train = train.loc[:, train.columns != dep_var]
#exo_test = test.loc[:, test.columns != dep_var]
model = auto_arima(train[dep_var], exogenous=exo_train,
                           start_p=1,
                           start_q=1,
                           test='adf',
                           max_p=3, max_q=3,
                           m=12,
                           start_P=0,
                           seasonal=True,
                           d=None,
                           D=1,
                           trace=True,
                           error_action='ignore',
                           suppress_warnings=True,
                           stepwise=True)

model_name='SARIMAX'

# Predict
predictions = model.predict(n_periods=test.shape[0], exog=exo_test,  dynamic=False, typ='levels')

# Forecast accuracy
scoring(model_name, test[dep_var], predictions, df, True, True)
```

```
Performing stepwise search to minimize aic
 ARIMA(1,1,1)(0,1,1)[12]             : AIC=1999.944, Time=0.46 sec
 ARIMA(0,1,0)(0,1,0)[12]             : AIC=2084.475, Time=0.02 sec
 ARIMA(1,1,0)(1,1,0)[12]             : AIC=2039.583, Time=0.16 sec
 ARIMA(0,1,1)(0,1,1)[12]             : AIC=2002.150, Time=0.25 sec
 ARIMA(1,1,1)(0,1,0)[12]             : AIC=2043.561, Time=0.10 sec
 ARIMA(1,1,1)(1,1,1)[12]             : AIC=2001.868, Time=0.56 sec
 ARIMA(1,1,1)(0,1,2)[12]             : AIC=2001.830, Time=1.11 sec
 ARIMA(1,1,1)(1,1,0)[12]             : AIC=2017.834, Time=0.33 sec
 ARIMA(1,1,1)(1,1,2)[12]             : AIC=inf, Time=1.95 sec
 ARIMA(1,1,0)(0,1,1)[12]             : AIC=2022.606, Time=0.28 sec
 ARIMA(2,1,1)(0,1,1)[12]             : AIC=2001.822, Time=0.59 sec
```

```
 ARIMA(2,1,1)(0,1,1)[12]             : AIC=2001.822, Time=0.55 sec
 ARIMA(1,1,2)(0,1,1)[12]             : AIC=2001.860, Time=0.52 sec
 ARIMA(0,1,0)(0,1,1)[12]             : AIC=2041.516, Time=0.14 sec
 ARIMA(0,1,2)(0,1,1)[12]             : AIC=1999.922, Time=0.32 sec
 ARIMA(0,1,2)(0,1,0)[12]             : AIC=2044.409, Time=0.06 sec
 ARIMA(0,1,2)(1,1,1)[12]             : AIC=2001.837, Time=0.48 sec
 ARIMA(0,1,2)(0,1,2)[12]             : AIC=2001.795, Time=0.79 sec
 ARIMA(0,1,2)(1,1,0)[12]             : AIC=2018.060, Time=0.36 sec
 ARIMA(0,1,2)(1,1,2)[12]             : AIC=inf, Time=1.82 sec
 ARIMA(0,1,3)(0,1,1)[12]             : AIC=2001.836, Time=0.63 sec
 ARIMA(1,1,3)(0,1,1)[12]             : AIC=2003.730, Time=0.86 sec
 ARIMA(0,1,2)(0,1,1)[12] intercept   : AIC=2001.649, Time=0.50 sec

Best model:  ARIMA(0,1,2)(0,1,1)[12]
Total fit time: 12.317 seconds
SARIMAX Model Performance:
Mean Absolute Error: 105.27.
Mean Squared Error: 17932.82.
Root Mean Squared Error: 133.91.
R^2 Score = -0.87.
Mean Absolute Percentage Error: 42.92%.
Accuracy = 57.08%.
```

SARIMAX Predictions (Country: FIN - Target variable: Orders)



Results

In [58]:

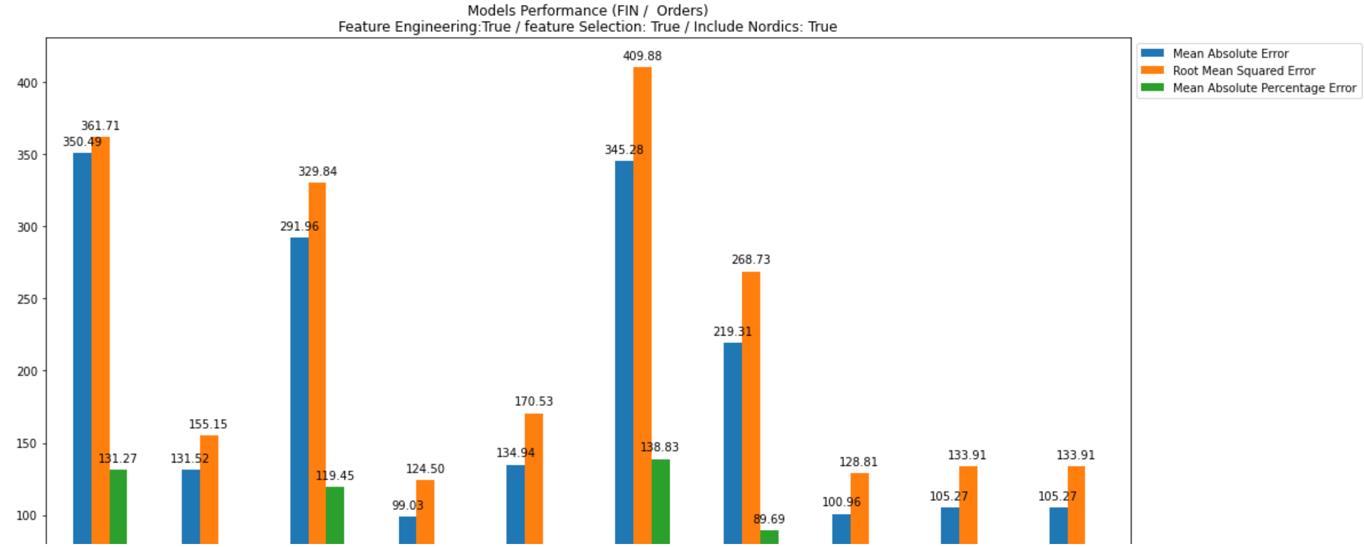
```
metrics
```

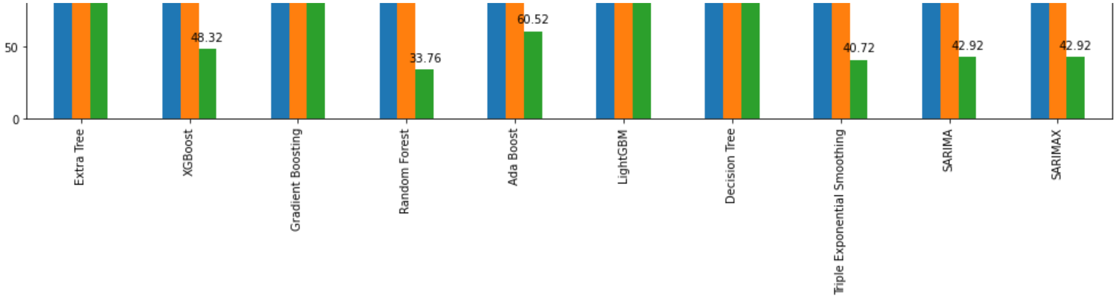
Out[58]:

	Extra Tree	XGBoost	Gradient Boosting	Random Forest	Ada Boost	LightGBM	Decision Tree	Triple Exponential Smoothing	SARIM
Mean Absolute Error	350.493611	131.517476	291.956169	99.025833	134.943656	345.280390	219.305556	100.956312	105.2748
Mean Squared Error	130831.858064	24071.898701	108797.676848	15500.726975	29080.330761	168002.931039	72213.583333	16591.499503	17932.8208
Root Mean Squared Error	361.706868	155.151212	329.844928	124.501916	170.529560	409.881606	268.725852	128.807995	133.9134
R^2	-12.664550	-1.514156	-10.363221	-0.618952	-2.037254	-16.546831	-6.542247	-0.732876	-0.8729
Mean Absolute Percentage Error	131.270587	48.323753	119.445426	33.757223	60.519191	138.831848	89.692784	40.722514	42.9192
Accuracy	-31.270587	51.676247	-19.445426	66.242777	39.480809	-38.831848	10.307216	59.277486	57.0807

In [59]:

```
plot_metrics(metrics, 17, 10)
```




50
0
48.32
33.76
60.52
40.72
42.92
42.92
Extra Tree
XGBoost
Gradient Boosting
Random Forest
Ada Boost
LightGBM
Decision Tree
Triple Exponential Smoothing
SARIMA
SARIMAX

In [ ]: