MARKET ANALYSIS OF THE OIL MARKET OF USA IN COMMODITIES AT THE PRESENT STAGE

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Abstract: *The oil market is a crucial component of the global commodities market. It plays a significant role in the world economy, impacting industries, governments, and consumers worldwide. This essay aims to provide a market analysis of the oil market in commodities, focusing on the present stage. It will examine key factors influencing the market, current trends, and potential future developments.*

The oil market is primarily influenced by the intricate interplay between global oil supply and demand. On the supply side, major oil-producing countries, such as Saudi Arabia, Russia, and the United States, play a pivotal role. Geopolitical events, conflicts, and production decisions by oil-producing nations and organizations like OPEC can significantly impact oil supply levels.

On the demand side, economic growth, industrial activity, and transportation sector demand are crucial factors. Emerging economies, such as China and India, have seen robust oil demand growth in recent years. However, efforts to transition to cleaner energy sources and the promotion of renewable energy technologies have the potential to reshape long-term oil demand patterns.

Here are the analysis of USA crude oil prices for the last 3 years:

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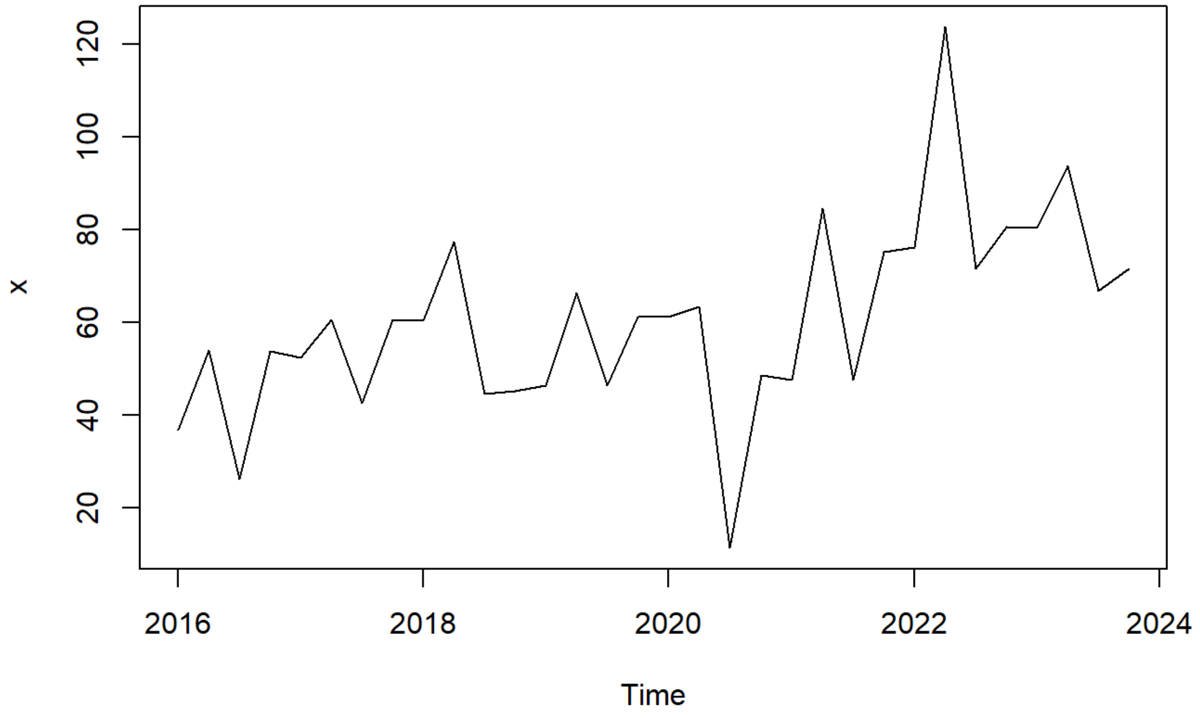
```
library(forecast)
## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
library(datasets)
library(lmtest)
## Загрузка требуемого пакета: zoo
##
## Присоединяю пакет: 'zoo'
## Следующие объекты скрыты от 'package:base':
##
##     as.Date, as.Date.numeric
library(fBasics)
library(ggplot2)
```

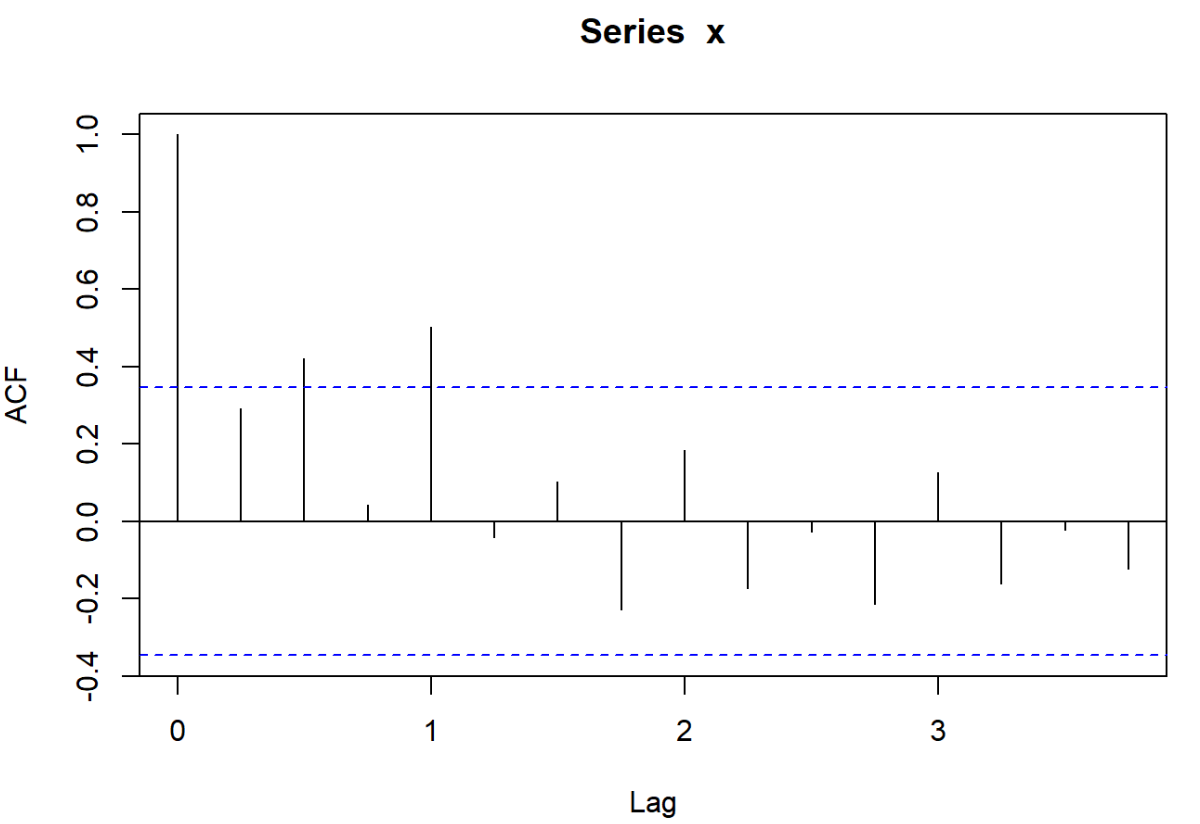
```r
library(GGally)
## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg   ggplot2
library(smooth)
## Загрузка требуемого пакета: greybox
## Package "greybox", v2.0.0 loaded.
## This is package "smooth", v4.0.0
```

Performing the data

```r
#V0.Basalt
x<-c(36.81,54.01,26.19,53.75,52.36,60.46,42.48,60.46,60.37,77.41,44.48,45.15,
46.31,66.24,46.31,61.14,61.17,63.27,11.26,48.52,47.62,  84.65,47.62,75.21,76.08,123
.70,71.59,80.51,80.26,93.84,66.74,71.57)
x<-ts(x,start = c(2016), frequency=4); x
##        Qtr1   Qtr2   Qtr3   Qtr4
## 2016  36.81  54.01  26.19  53.75
## 2017  52.36  60.46  42.48  60.46
## 2018  60.37  77.41  44.48  45.15
## 2019  46.31  66.24  46.31  61.14
## 2020  61.17  63.27  11.26  48.52
## 2021  47.62  84.65  47.62  75.21
## 2022  76.08 123.70  71.59  80.51
## 2023  80.26  93.84  66.74  71.57
plot(x)
```


x
20
40
60
80
100
120
2016
2018
2020
2022
2024
Time

```
acf(x)
```


Series x
ACF
-0.4
-0.2
0.0
0.2
0.4
0.6
0.8
1.0
0
1
2
3
Lag

```
summary(x)
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   11.26   47.29   60.46   60.55   72.50  123.70
```

Average method

```
meanx=meanf(x, h=3); meanx
##         Point Forecast   Lo 80    Hi 80   Lo 95    Hi 95
## 2024 Q1       60.54812 32.7338 88.36245 17.2268 103.8694
## 2024 Q2       60.54812 32.7338 88.36245 17.2268 103.8694
## 2024 Q3       60.54812 32.7338 88.36245 17.2268 103.8694
round(accuracy(meanx), 2)
##              ME  RMSE   MAE    MPE  MAPE MASE ACF1
## Training set  0 20.59 15.32 -20.21 37.77 0.98 0.29
```

naive model

```
naive.x=naive(x, h=4); naive.x
##         Point Forecast     Lo 80    Hi 80      Lo 95    Hi 95
## 2024 Q1          71.57 40.227328 102.9127  23.635520 119.5045
## 2024 Q2          71.57 27.244768 115.8952   3.780408 139.3596
## 2024 Q3          71.57 17.282899 125.8571 -11.454956 154.5950
## 2024 Q4          71.57  8.884656 134.2553 -24.298961 167.4390
round(accuracy(naive.x))
##              ME RMSE MAE MPE MAPE MASE ACF1
## Training set  1   24  19 -16   44    1   -1
```

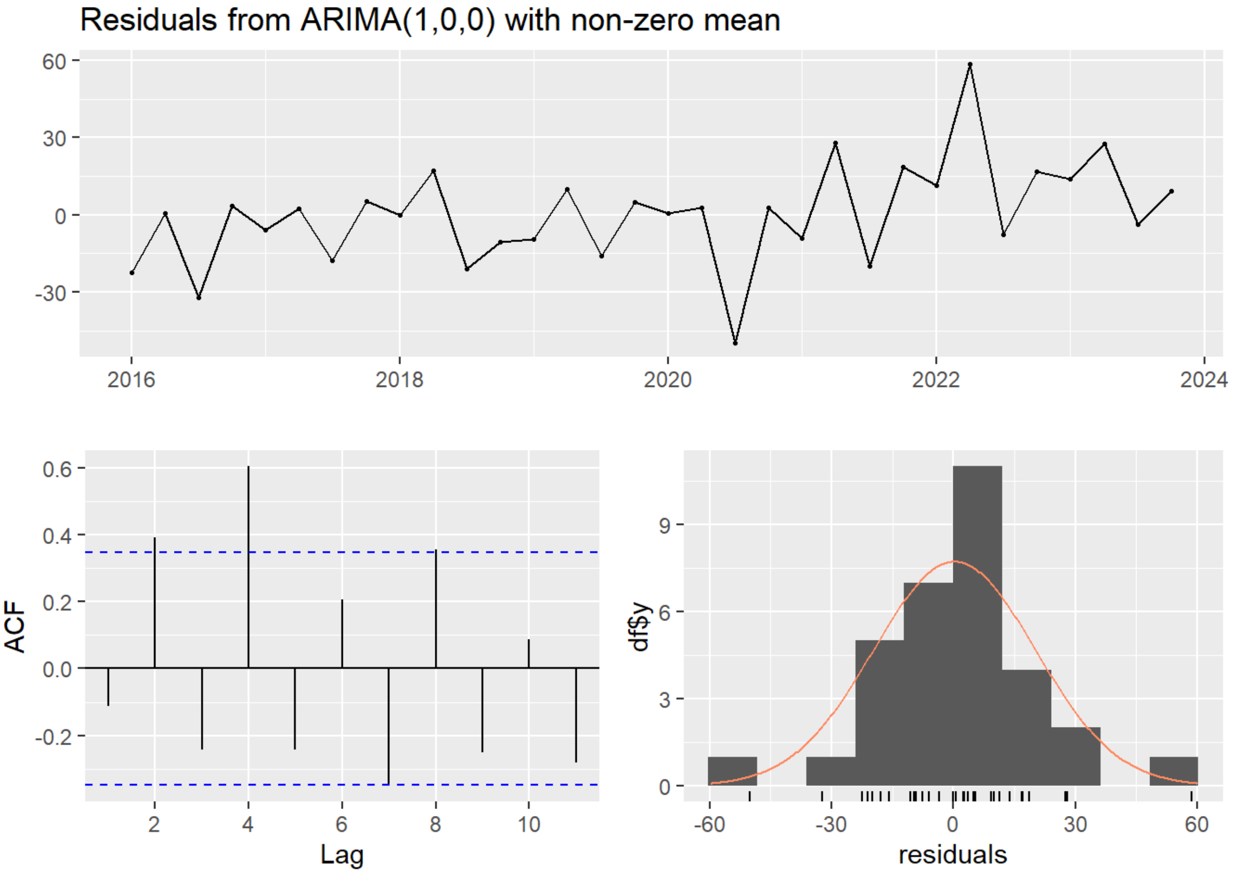
Checking for errors

```
#round(accuracy(expar))
```

ARIMA (p,d,q) AR(p)= arima(p,0,0) MA(q)=arima(0,0,q) ARMA=arima(p,0,q) ARIMA=arima(p,d,q) ## AR(p) model

```
arx1=arima(x, c(1,0,0)); arx1
##
## Call:
## arima(x = x, order = c(1, 0, 0))
##
## Coefficients:
##          ar1  intercept
##       0.2970    60.3846
```

```
## s.e.  0.1698     4.8783
##
## sigma^2 estimated as 386:  log likelihood = -140.75,  aic = 287.49
#arx1=arima(X, c=1,0,0), include.mean=F); arx1 #without intercept
#arx1=arima(X, c=2,0,0), include.mean=F); arx1 #without intercept
coeftest(arx1)
##
## z test of coefficients:
##
##           Estimate Std. Error z value Pr(>|z|)
## ar1        0.29701    0.16983  1.7489  0.08031 .
## intercept 60.38457    4.87835 12.3781  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
checkresiduals(arx1)
```

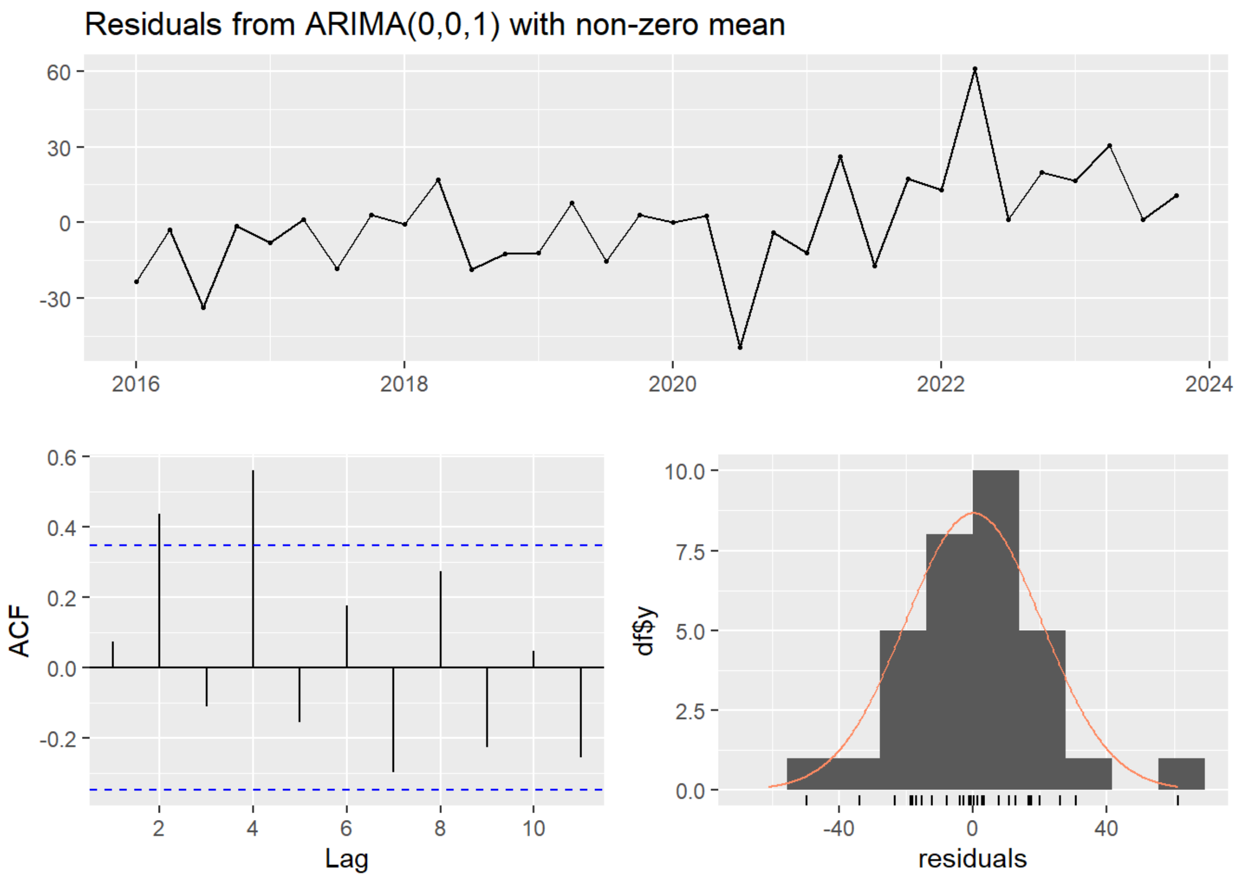



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,0,0) with non-zero mean
```

```
## Q* = 26.464, df = 5, p-value = 7.253e-05
##
## Model df: 1.   Total lags used: 6
jarqueberaTest(arx1$residuals)
##
## Title:
##  Jarque - Bera Normalality Test
##
## Test Results:
##   STATISTIC:
##     X-squared: 3.3098
##   P VALUE:
##     Asymptotic p Value: 0.1911
```

Ma(q) model

```
max1=arima(x, c(0,0,1)); max1
##
## Call:
## arima(x = x, order = c(0, 0, 1))
##
## Coefficients:
##          ma1  intercept
##       0.1613    60.4842
## s.e.  0.1240     4.1059
##
## sigma^2 estimated as 403.4:  log likelihood = -141.42,  aic = 288.84
#max1=arima(X, c=0,0,1), include.mean=F); max1 #without intercept
#max1=arima(X, c=0,0,2), include.mean=F); max1 #without intercept
coeftest(max1)
##
## z test of coefficients:
##
##           Estimate Std. Error z value Pr(>|z|)
## ma1        0.16134    0.12399  1.3012   0.1932
## intercept 60.48422    4.10586 14.7312   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
checkresiduals(max1)
```

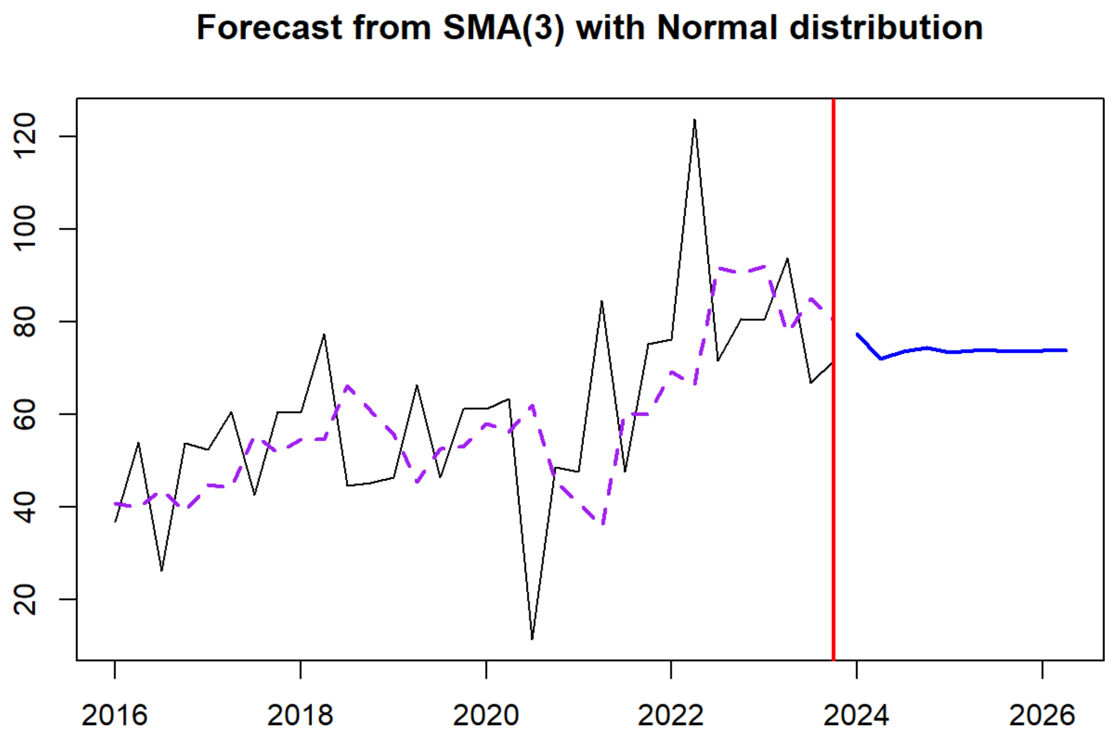



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,0,1) with non-zero mean
## Q* = 21.935, df = 5, p-value = 0.0005386
##
## Model df: 1.   Total lags used: 6
jarqueberaTest(max1$residuals)
##
## Title:
##  Jarque - Bera Normalality Test
##
## Test Results:
##   STATISTIC:
##     X-squared: 4.1009
##   P VALUE:
##     Asymptotic p Value: 0.1287
# наши остатки нормально распределены
```

X^=4.1453+0.6441·εt−1+wt�^=4.1453+0.6441·��−1+��

Модель сглаживания на основе значений скользящего среднего (сглаживание без центрирования)

```
ma3X <- sma(x,order=3,h=3,level=0.95) # сглаживание + прогноз
plot(forecast(ma3X)) # график модели
```



Ft+1=Xt+Xt−1+Xt−23��+1=��+��−1+��−23

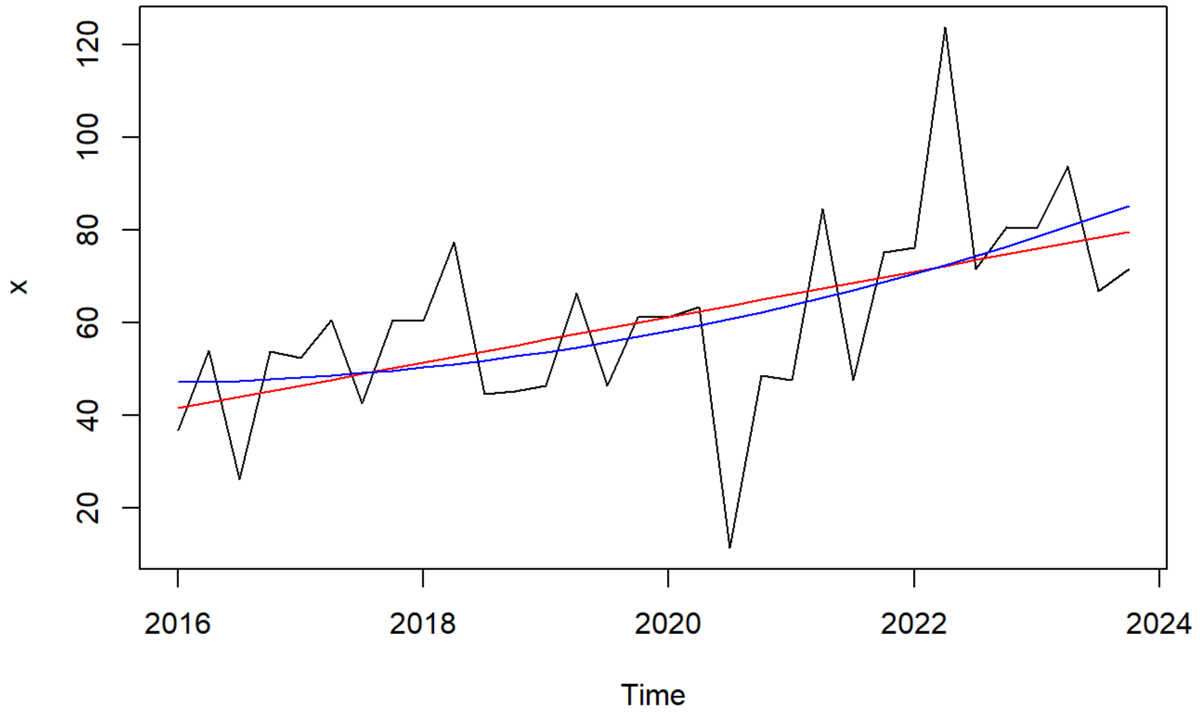
Trend parabolic model

```
Trx1=tslm(x~trend); Trx1 #linear
##
## Call:
## tslm(formula = x ~ trend)
##
## Coefficients:
## (Intercept)       trend
##      40.235       1.231
Trx2=tslm(x~trend+I(trend^2)); Trx2 #parabolic
##
## Call:
## tslm(formula = x ~ trend + I(trend^2))
##
```

```
## Coefficients:
## (Intercept)       trend   I(trend^2)
##    46.96433     0.04358     0.03599
summary(Trx1)
##
## Call:
## tslm(formula = x ~ trend)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -52.366  -9.876   1.041   8.841  51.456
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  40.2351     6.4176   6.270 6.58e-07 ***
## trend         1.2311     0.3394   3.627  0.00105 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 17.73 on 30 degrees of freedom
## Multiple R-squared:  0.3048, Adjusted R-squared:  0.2817
## F-statistic: 13.16 on 1 and 30 DF,  p-value: 0.001052
summary(Trx2)
##
## Call:
## tslm(formula = x ~ trend + I(trend^2))
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -49.523  -9.612   3.464   7.636  51.277
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 46.96433   10.06203   4.667 6.39e-05 ***
## trend        0.04358    1.40573   0.031    0.975
## I(trend^2)   0.03599    0.04133   0.871    0.391
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 17.8 on 29 degrees of freedom
## Multiple R-squared:  0.3226, Adjusted R-squared:  0.2758
## F-statistic: 6.904 on 2 and 29 DF,  p-value: 0.003529
```

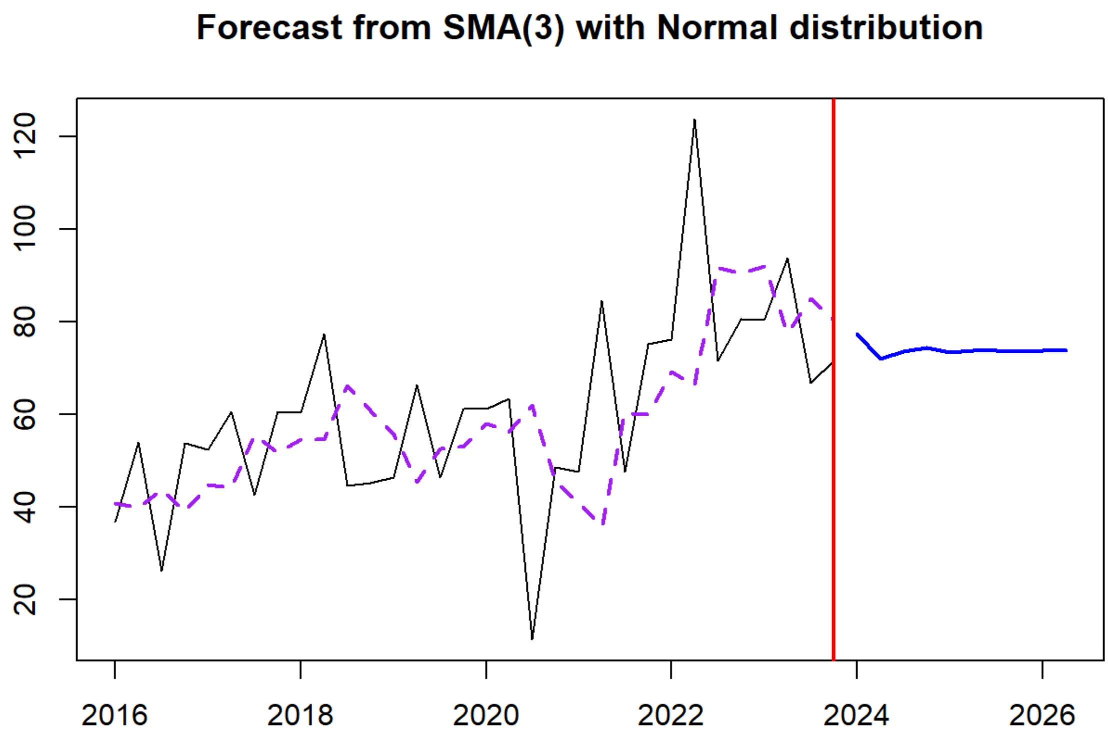
```
plot(x)
lines(fitted(Trx1), col="red")
lines(fitted(Trx2), col="blue")
```



#

MA smoothing models

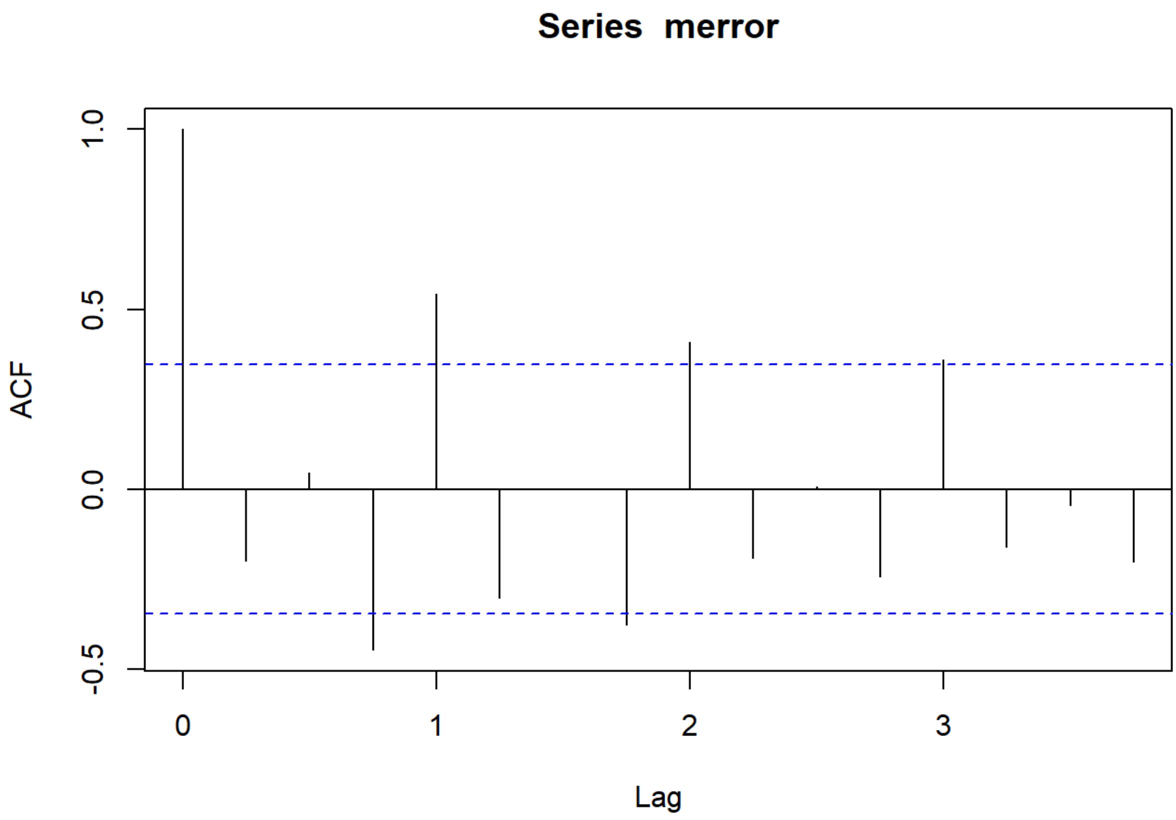
```
masX=sma(x,order = 3, h=3, level=95)
plot(forecast(masX))
```



Ft=xt+xt+1+xt+23��=��+��+1+��+23

Prediction

```
merror=residuals(masX)
acf(merror)
```




```
merar=arima(merror, c(1,0,0))
coeftest(merar)
##
## z test of coefficients:
##
##           Estimate Std. Error z value Pr(>|z|)
## ar1       -0.19520    0.17141 -1.1388   0.2548
## intercept  2.14221    2.95828  0.7241   0.4690
formasX=forecast(masX, h=3,level = 95);formasX #Prediction on MA smoothing model
##          Qtr1     Qtr2     Qtr3
## 2024 77.38333 71.89778 73.61704
formerror=forecast(merar, h=3, level=95); formerror # Prection on model residuals
##         Point Forecast     Lo 95    Hi 95
## 2024 Q1       4.260519 -34.73105 43.25209
## 2024 Q2       1.728726 -37.99872 41.45617
## 2024 Q3       2.222922 -37.53229 41.97814
finalfor=formasX$mean+formerror$mean; finalfor # final forecast on 2 models
```

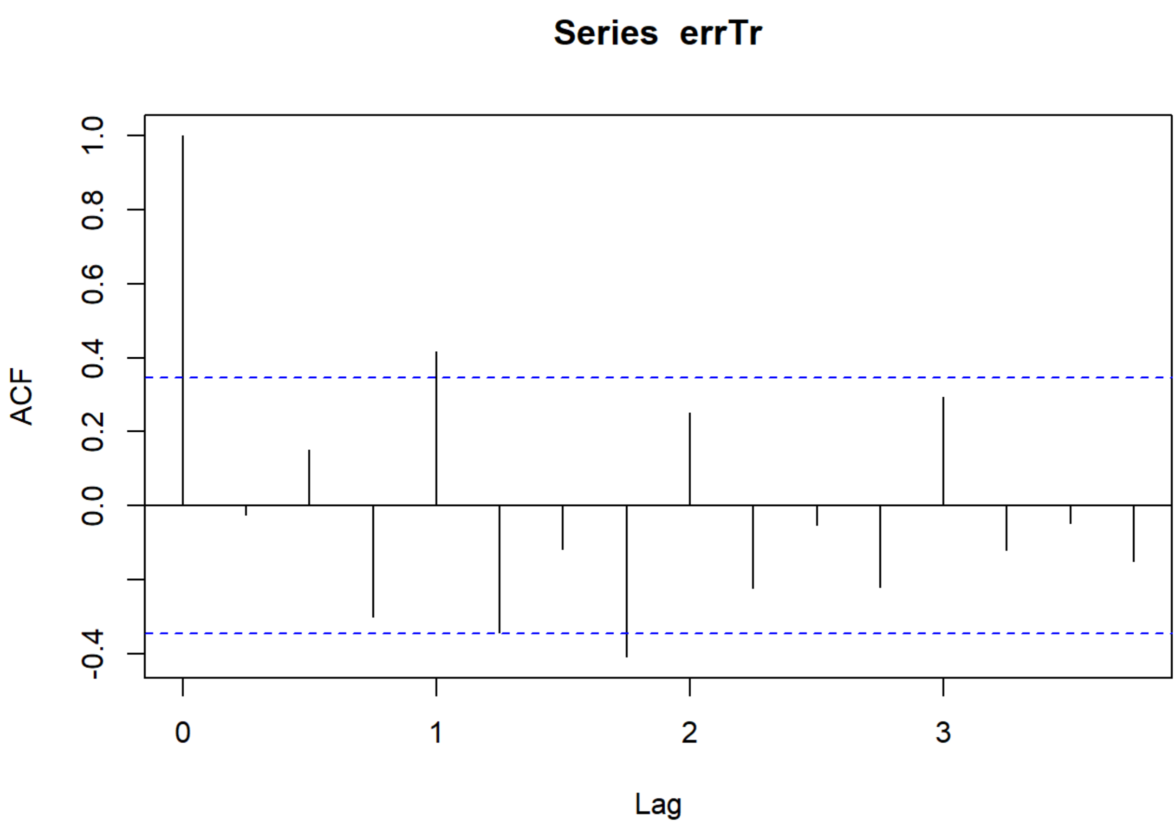
```
##         Qtr1     Qtr2     Qtr3
## 2024 81.64385 73.62650 75.83996
```

Checking for errors

```
round(accuracy(merar), 2)
##                  ME  RMSE   MAE   MPE   MAPE MASE  ACF1
## Training set -0.03 19.89 14.98 82.89 100.29  0.6 -0.01
```

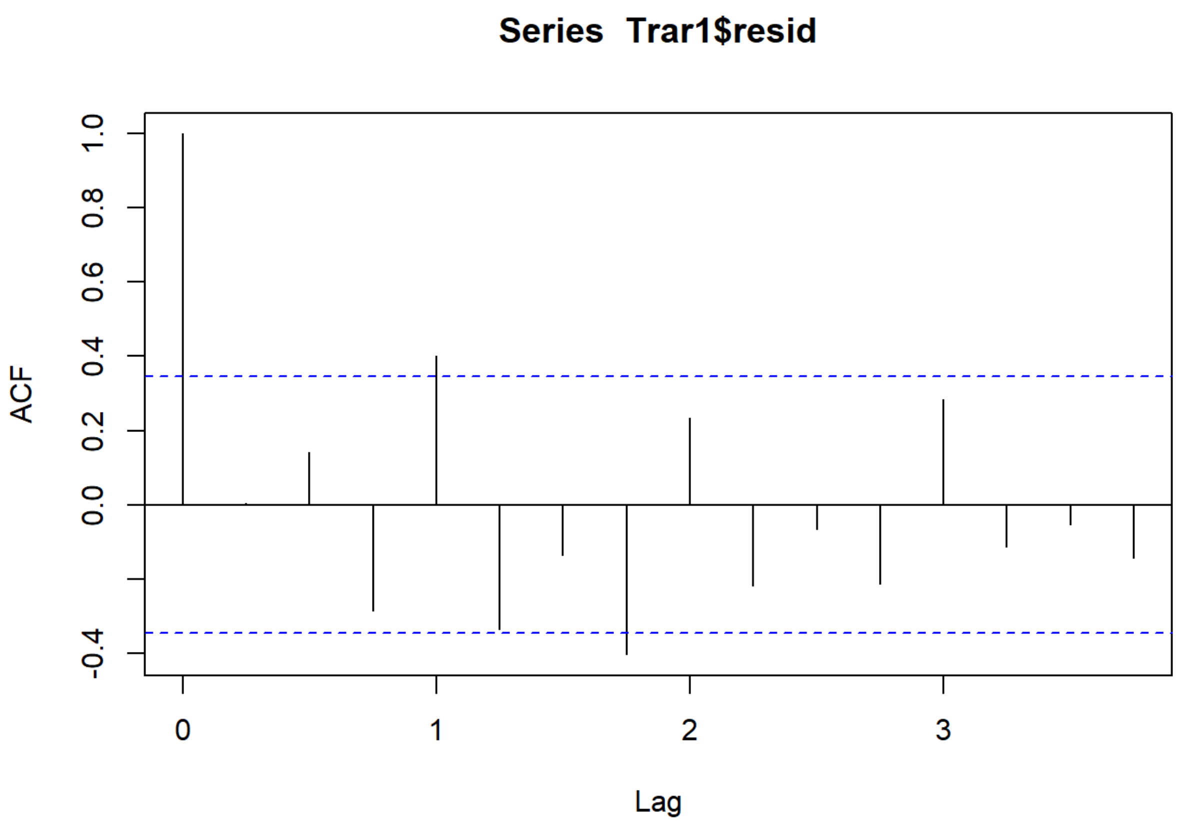
Анализ остатков трендовой модели:

```
errTr<-residuals(Trx2) # сохраняем остатки
acf(errTr) # акф остатков
```

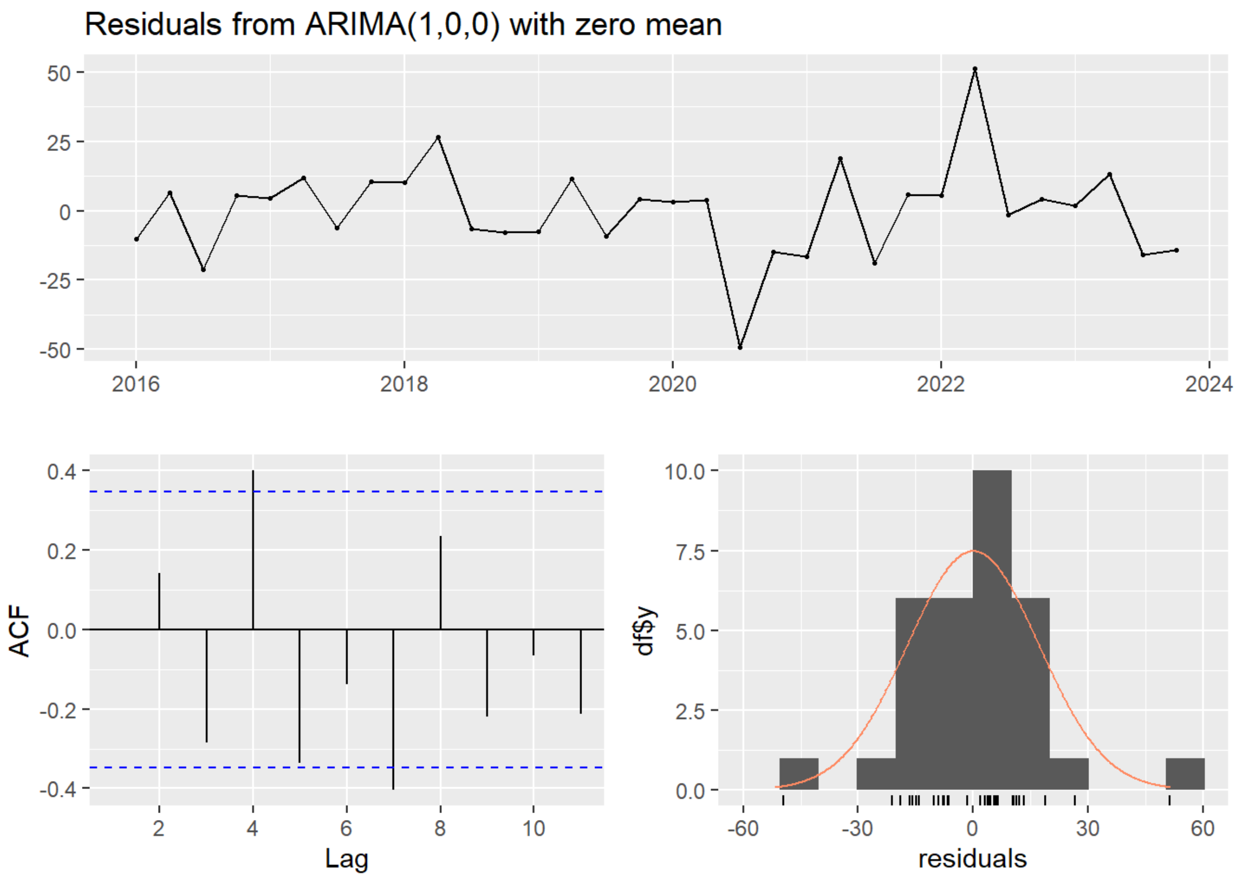



```
Trar1<-arima(errTr,c(1,0,0));Trar1 # авторегрессия AR(1) с константой
##
## Call:
## arima(x = errTr, order = c(1, 0, 0))
##
## Coefficients:
##           ar1  intercept
##       -0.0251     0.0183
```

```
## s.e.   0.1769     2.9261
##
## sigma^2 estimated as 286.9:  log likelihood = -135.95,  aic = 277.91
coeftest(Trar1)  # T тест: коэффициенты
##
## z test of coefficients:
##
##            Estimate Std. Error z value Pr(>|z|)
## ar1       -0.025114   0.176928 -0.1419   0.8871
## intercept  0.018314   2.926065  0.0063   0.9950
Trar1<-arima(errTr,c(1,0,0),include.mean = F);Trar1 # авторегрессия AR(1) без константы
##
## Call:
## arima(x = errTr, order = c(1, 0, 0), include.mean = F)
##
## Coefficients:
##           ar1
##       -0.0251
## s.e.   0.1768
##
## sigma^2 estimated as 286.9:  log likelihood = -135.95,  aic = 275.91
acf(Trar1$resid) # АКФ  остатков
```




```
coeftest(Trar1)  # T тест: коэффициенты
##
## z test of coefficients:
##
##      Estimate Std. Error z value Pr(>|z|)
## ar1 -0.025066   0.176755 -0.1418   0.8872
checkresiduals(Trar1) # графики + Льюинг-Бокс
```

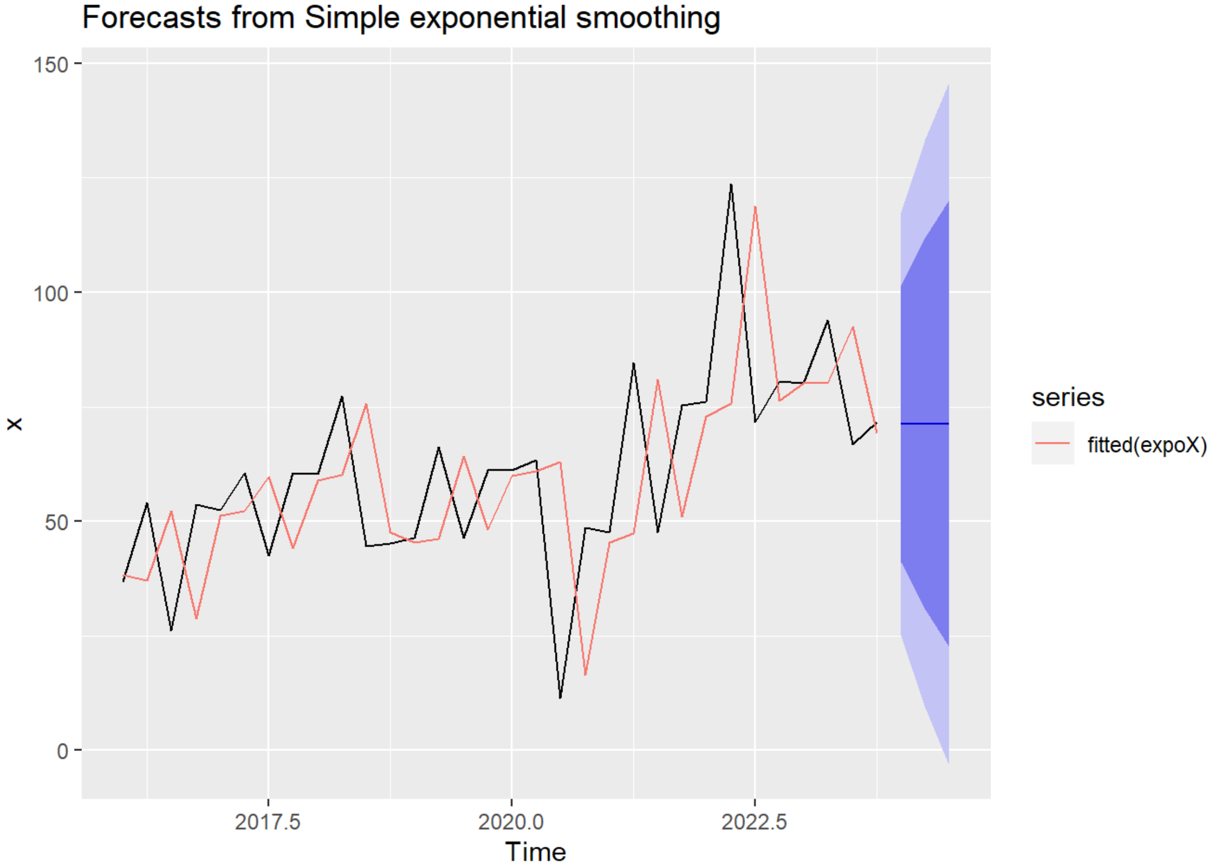



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,0,0) with zero mean
## Q* = 15.337, df = 5, p-value = 0.009017
##
## Model df: 1.   Total lags used: 6
jarqueberaTest(Trar1$resid) #Тест Жарке-Бера.
##
## Title:
##  Jarque - Bera Normalality Test
##
## Test Results:
##   STATISTIC:
##     X-squared: 7.8289
##   P VALUE:
##     Asymptotic p Value: 0.01995
```

$\varepsilon_t=0.01995\cdot\varepsilon_{t-1}+w_t$��=0.01995·��−1+��

Exponential smoothing models

```
expoX=ses(x, alpha = 0.9, h=3) #альфа=0.9 модель сглаживания
autoplot(expoX)+autolayer(fitted(expoX)) #график модели
```



Ft+1=α·Xt+1+(1−α)·Ft��+1=�·��+1+(1−�)·��

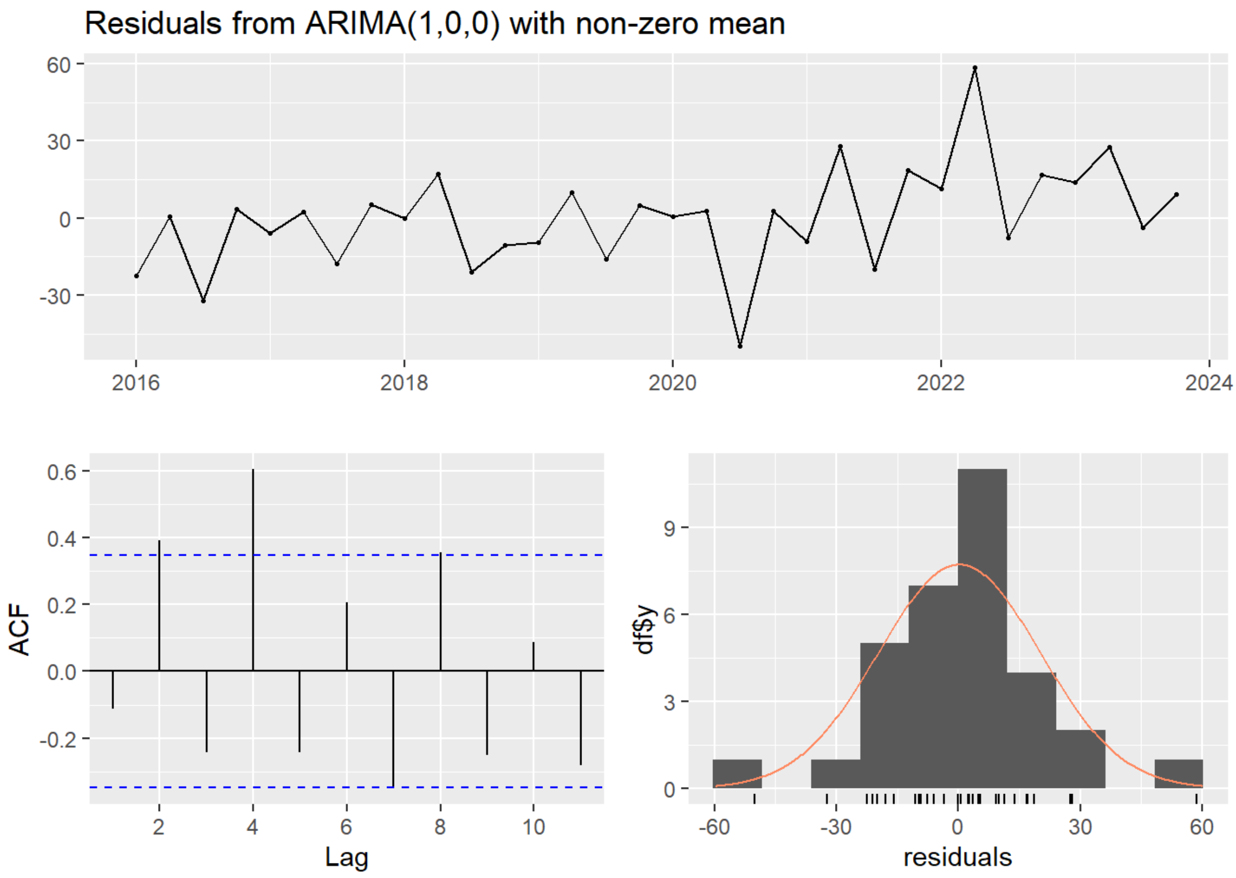
Checking for errors

```
#round(accuracy(expar))
```

ARIMA (p,d,q) AR(p)= arima(p,0,0) MA(q)=arima(0,0,q) ARMA=arima(p,0,q) ARIMA=arima(p,d,q) ## AR(p) model

```
arx1=arima(x, c(1,0,0)); arx1
##
## Call:
## arima(x = x, order = c(1, 0, 0))
##
## Coefficients:
##          ar1  intercept
##       0.2970    60.3846
## s.e.  0.1698     4.8783
##
## sigma^2 estimated as 386:  log likelihood = -140.75,  aic = 287.49
```

```
#arx1=arima(X, c=1,0,0), include.mean=F); arx1 #without intercept
#arx1=arima(X, c=2,0,0), include.mean=F); arx1 #without intercept
coeftest(arx1)
##
## z test of coefficients:
##
##           Estimate Std. Error z value Pr(>|z|)
## ar1        0.29701    0.16983  1.7489  0.08031 .
## intercept 60.38457    4.87835 12.3781  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
checkresiduals(arx1)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,0,0) with non-zero mean
## Q* = 26.464, df = 5, p-value = 7.253e-05
##
## Model df: 1.   Total lags used: 6
```

```
jarqueberaTest(arx1$residuals)
##
## Title:
##  Jarque - Bera Normalality Test
##
## Test Results:
##   STATISTIC:
##     X-squared: 3.3098
##   P VALUE:
##     Asymptotic p Value: 0.1911
```

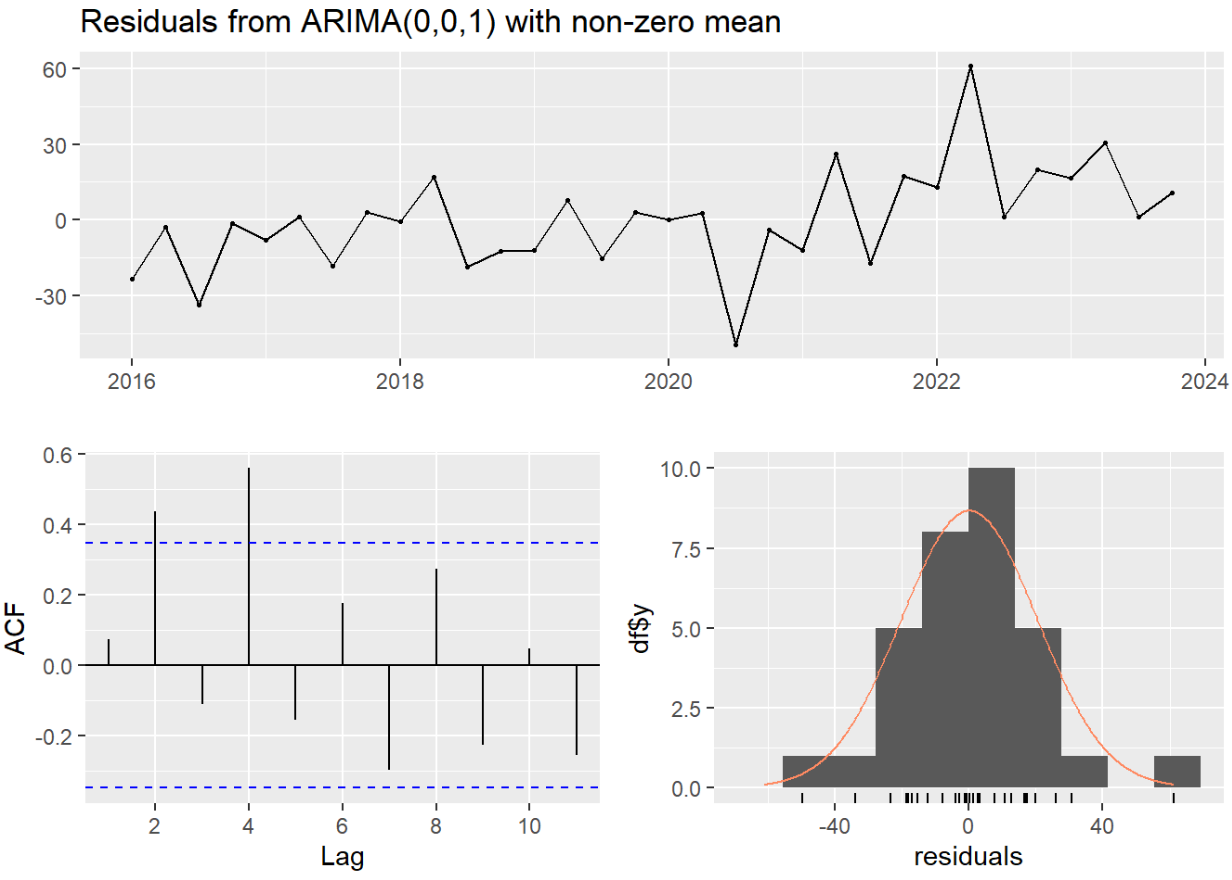
Prediction

```
forarx1=forecast(arx1, level=95, h=3); forarx1
##         Point Forecast    Lo 95    Hi 95
## 2024 Q1       63.70677 25.19888 102.2147
## 2024 Q2       61.37130 21.20080 101.5418
## 2024 Q3       60.67764 20.36376 100.9915
round(accuracy(arx1),2)
##                ME  RMSE   MAE    MPE  MAPE MASE  ACF1
## Training set 0.25 19.65 14.38 -18.98 36.31 0.78 -0.11
```

Ma(q) model

```
max1=arima(x, c(0,0,1)); max1
##
## Call:
## arima(x = x, order = c(0, 0, 1))
##
## Coefficients:
##          ma1  intercept
##       0.1613    60.4842
## s.e.  0.1240     4.1059
##
## sigma^2 estimated as 403.4:  log likelihood = -141.42,  aic = 288.84
#max1=arima(X, c=0,0,1), include.mean=F); max1 #without intercept
#max1=arima(X, c=0,0,2), include.mean=F); max1 #without intercept
coeftest(max1)
##
## z test of coefficients:
```

```
##
##          Estimate Std. Error z value Pr(>|z|)
## ma1       0.16134    0.12399  1.3012   0.1932
## intercept 60.48422    4.10586 14.7312   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
checkresiduals(max1)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,0,1) with non-zero mean
## Q* = 21.935, df = 5, p-value = 0.0005386
##
## Model df: 1.   Total lags used: 6
jarqueberaTest(max1$residuals)
##
## Title:
##  Jarque - Bera Normalality Test
##
```

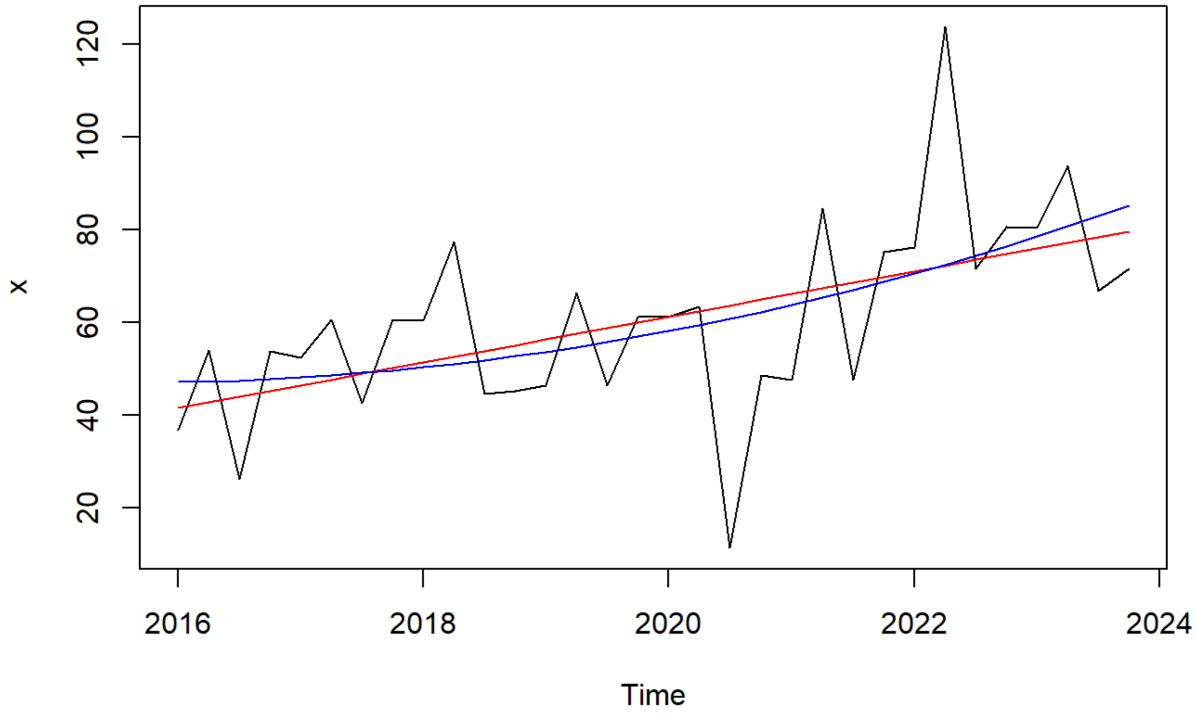
```
## Test Results:
##   STATISTIC:
##     X-squared: 4.1009
##   P VALUE:
##     Asymptotic p Value: 0.1287
# наши остатки нормально распределены
```

Prediction

```
formax1=forecast(max1, level=95, h=3); formax1
##         Point Forecast    Lo 95    Hi 95
## 2024 Q1       62.23883 22.87357 101.6041
## 2024 Q2       60.48422 20.60988 100.3586
## 2024 Q3       60.48422 20.60988 100.3586
round(accuracy(max1),2)
##                ME  RMSE   MAE    MPE  MAPE MASE ACF1
## Training set 0.11 20.08 14.46 -19.73 36.45 0.78 0.07
```

Visualize the model

```
plot(x)
lines(fitted(Trx1),col="red")
lines(fitted(Trx2),col="blue")
```



Based on the provided data on USA crude oil prices for the years 2021, 2022, and 2023, we can analyze the annual closing prices and the corresponding annual percentage changes. Here's an analysis of the data:

1. Price Trends:

- In 2021, the average closing price of crude oil was $68.17, with a year-low of $47.62 and a year-high of $84.65. The year closed at $75.21.

- In 2022, the average closing price increased to $94.53, with a year-low of $71.59 and a year-high of $123.70. The year closed at $80.51.

- In 2023, the average closing price decreased to $77.90, with a year-low of $66.74 and a year-high of $93.84. The year closed at $71.79.

2. Annual Percentage Change:

- In 2021, the annual percentage change in crude oil prices was 55.01%. This indicates a significant increase in prices compared to the previous year.

- In 2022, the annual percentage change was 7.05%, indicating a moderate increase in prices compared to the previous year.

- In 2023, the annual percentage change was -10.83%, indicating a decrease in prices compared to the previous year.

Analysis of the Data:

- The data shows that crude oil prices experienced significant volatility over the three-year period.

- In 2021, there was a substantial price increase, with the annual percentage change reaching 55.01%. This could be attributed to various factors, including global economic recovery from the COVID-19 pandemic and supply constraints.

- In 2022, although the prices continued to rise, the annual percentage change of 7.05% indicates a slower pace of growth compared to the previous year. This could be due to factors such as increased oil production and market stabilization.

- In 2023, crude oil prices experienced a decline, with the annual percentage change showing a negative value of -10.83%. This suggests a decrease in prices compared to the previous year, potentially influenced by factors such as changes in global demand, supply fluctuations, or geopolitical events.

It's important to note that analyzing crude oil prices involves considering various factors such as global supply and demand, geopolitical events, economic conditions, and market sentiment. Additionally, the provided data is limited to the annual closing prices and annual percentage changes, which may not capture the full extent of price fluctuations throughout each year.

ARIMA (Autoregressive Integrated Moving Average) models are widely used in time series analysis to capture the dependence and patterns in the data. ARIMA models are suitable for stationary or differenced stationary time series data.

ARIMA Model:

- ARIMA(p, d, q) combines the autoregressive, integrated, and moving average components into a single model.

- The p, d, and q parameters represent the orders of the autoregressive, integrated, and moving average components, respectively.

- The ARIMA model can capture both short-term dependencies (AR and MA components) and long-term trends (integrated component).

easonal ARIMA (SARIMA):

- SARIMA models extend the ARIMA framework to incorporate seasonality in the time series.

- SARIMA(p, d, q)(P, D, Q, s) includes additional seasonal components denoted by P, D, Q, and s, where P, D, and Q represent the seasonal autoregressive, seasonal integrated, and seasonal moving average components, respectively, and s represents the seasonal period.

Conclusion:

In conclusion, the analysis of the USA crude oil prices for the years 2021, 2022, and 2023 reveals a dynamic and volatile market. The data demonstrates significant price fluctuations and varying annual percentage changes over the three-year period.

In 2021, crude oil prices experienced a substantial increase, with a significant annual percentage change of 55.01%. This surge can be attributed to factors such as global economic recovery and supply constraints.

The year 2022 saw continued price growth, albeit at a slower pace. The annual percentage change of 7.05% indicates a moderate increase compared to the previous year. This could be due to increased oil production and market stabilization efforts.

However, in 2023, crude oil prices showed a decline, with a negative annual percentage change of -10.83%. This indicates a decrease in prices compared to the previous year, potentially influenced by changes in global demand, supply fluctuations, or geopolitical events.

It is important to note that analyzing crude oil prices involves considering a wide range of factors beyond the provided data. Geopolitical tensions, OPEC decisions, economic indicators, and environmental policies can significantly impact oil prices.