P3

2025-04-10

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```r
#Load required libraries
library(quantmod)
library(PerformanceAnalytics)
library(tsibble)
library(strucchange)
library(readr)
library(ggplot2)
library(readxl)
library(ggfortify)
library(fpp3)
library(dynlm)
library(tseries)
library(lmtest)
library(prophet)
library(dplyr)
library(conflicted)
library(forecast)
library(vars)
```

Introduction

For this project, I analyze the daily stock returns of NVIDIA Corporation (NVDA) from January 1, 2016, onward. NVIDIA is a global leader in the design and manufacturing of GPUs and AI hardware, making it a prominent company in the technology and semiconductor industry.

Stock returns are a key measure of financial performance and provide insights into volatility and potential risks. The goal of this analysis is to fit multiple forecasting models, including ARIMA, ETS, Holt-Winters, NNETAR, Prophet, and a combination of these forecasts, to determine the most suitable model for predicting future returns.

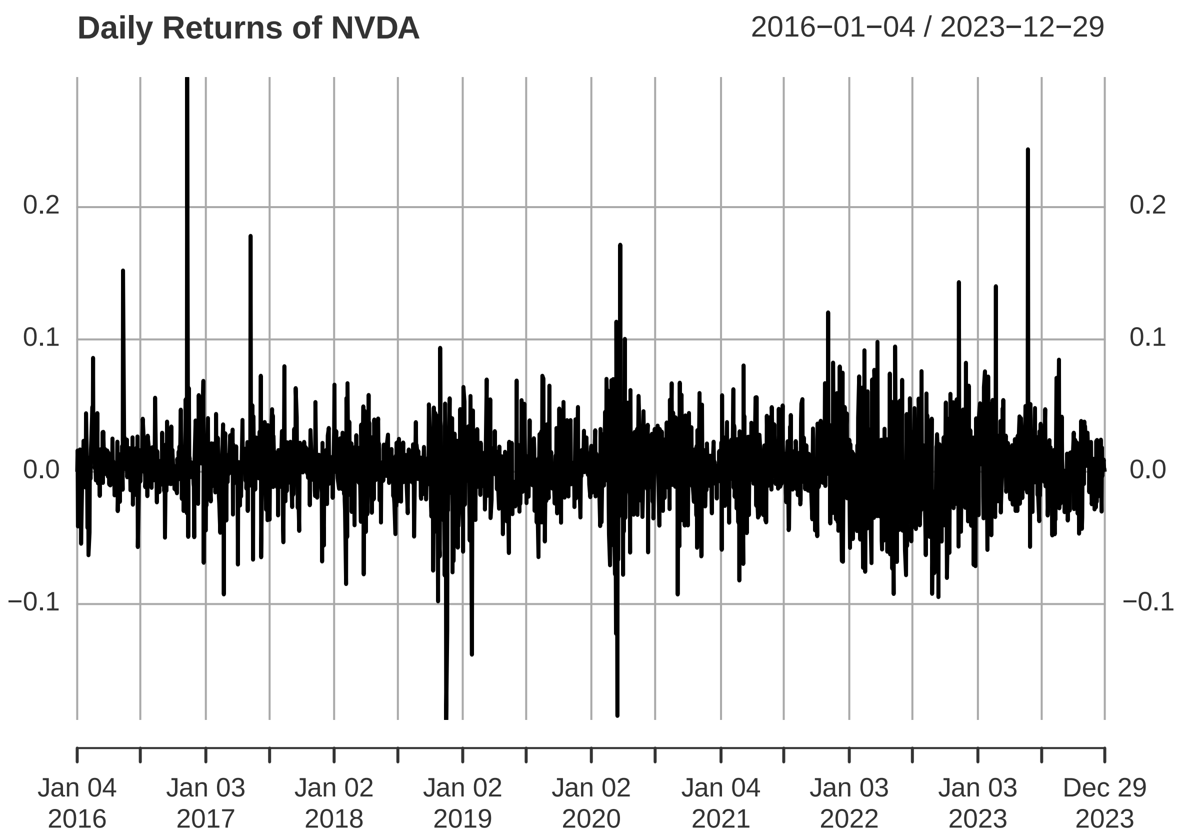
The findings of this project will be presented in terms of forecast accuracy, residual diagnostics, and graphical visualizations.

II. Results

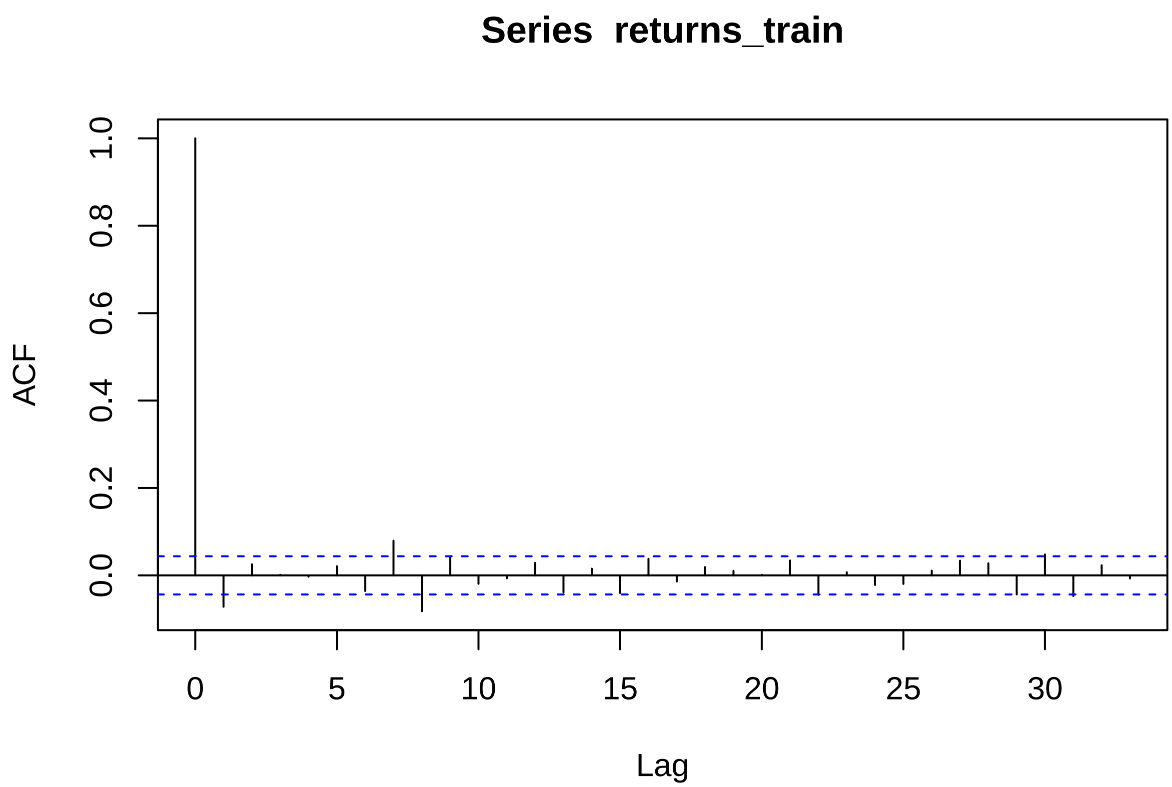
```r
#read data
getSymbols("NVDA", src = "yahoo", from = "2016-01-01")
```

```
## [1] "NVDA"
```

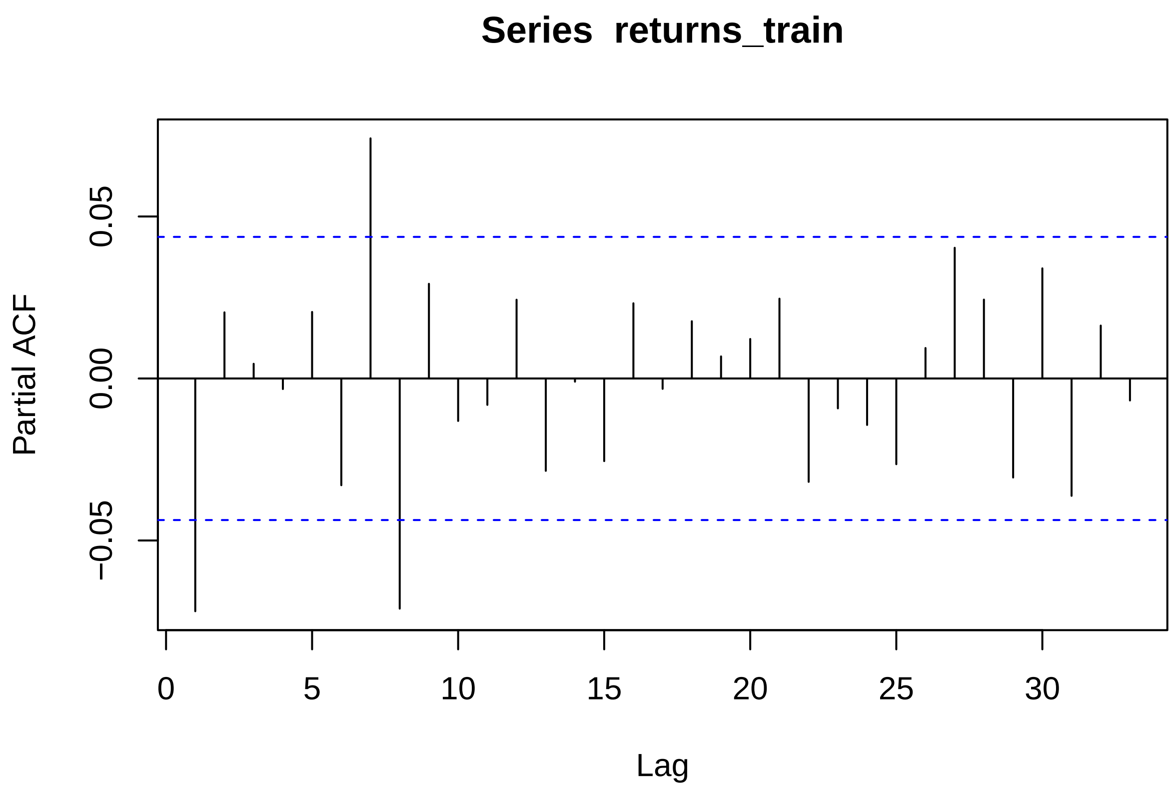
```
train <- NVDA["2016-01-01/2023-12-31"]  # Training data
test <- NVDA["2024-01-01/2024-12-05"]
returns_train <- dailyReturn(train$NVDA.Adjusted)
returns_test <- dailyReturn(test$NVDA.Adjusted)
#Plot
plot(returns_train, main = "Daily Returns of NVDA")
```




```
acf(returns_train)
```




```
pacf(returns_train)
```



There are apparent spikes in the plot, indicating days with significant price changes in the daily returns of NVDA. Since the data represents returns, it is expected to be stationary as returns typically fluctuate around a constant mean (close to zero) with no apparent trend and seasonality. Additionally, the variance appears relatively constant over time, despite periods of higher or lower volatility. The ACF and PACF plots exhibit some dynamics as there are significant spikes that could explain by ARIMA model. I will confirm the Stationarity by performing the Augmented Dickey-Fuller (ADF) Test.

```
adf.test(coredata(returns_train), alternative = "stationary")
```

```
## Warning in adf.test(coredata(returns_train), alternative = "stationary"):
## p-value smaller than printed p-value
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  coredata(returns_train)
## Dickey-Fuller = -12.632, Lag order = 12, p-value = 0.01
## alternative hypothesis: stationary
```

Reject the null hypotheses at 5%, thus the data is stationary

ARIMA Model

```r
ts_train <- ts(returns_train, start = c(2016, 1), end = c(2024,12), frequency = 252)
arima_model <- auto.arima(ts_train)
summary(arima_model)
```

```
## Series: ts_train
## ARIMA(0,0,1) with non-zero mean
##
## Coefficients:
##           ma1    mean
##       -0.0664  0.0025
## s.e.   0.0216  0.0006
##
## sigma^2 = 0.0009692:  log likelihood = 4159.57
## AIC=-8313.14   AICc=-8313.13   BIC=-8296.3
##
## Training set error measures:
##                         ME       RMSE        MAE  MPE MAPE      MASE
## Training set -2.198357e-07 0.03111671 0.02167662 -Inf  Inf 0.6536655
##                      ACF1
## Training set -0.001789371
```

The auto.arima() choose ARIMA(0,0,1) means that the model is MA(1) with no AR component or differencing. The mean of the series is estimated to be 0.0028 or approximately 0.28% daily return. The AIC is -9167.83 and BIC is -9150.69 which will be used to compare with different models.

ETS Model

```r
ets_model <- stlf(ts_train, h = 235, method = "ets")
summary(ets_model)
```

```
##
## Forecast method: STL +  ETS(A,N,N)
##
## Model Information:
## ETS(A,N,N)
##
## Call:
## ets(y = na.interp(x), model = etsmodel, allow.multiplicative.trend = allow.multiplicative.trend)
##
##   Smoothing parameters:
##     alpha = 1e-04
##
##   Initial states:
##     l = 0.0025
##
##   sigma:  0.0282
##
##      AIC     AICc      BIC
## 976.0453 976.0571 992.8897
##
```

```
## Error measures:
##                         ME       RMSE        MAE MPE MAPE      MASE        ACF1
## Training set -2.109746e-05 0.02820546 0.02024449 NaN  Inf 0.6104793 -0.06606335
##
## Forecasts:
##          Point Forecast        Lo 80      Hi 80       Lo 95      Hi 95
## 2024.048  -4.214449e-03 -0.040379039 0.03195014 -0.05952342 0.05109452
## 2024.052   8.227022e-03 -0.027937569 0.04439161 -0.04708195 0.06353599
## 2024.056  -1.191324e-02 -0.048077828 0.02425135 -0.06722221 0.04339573
## 2024.060  -9.893693e-03 -0.046058285 0.02627090 -0.06520266 0.04541528
## 2024.063  -2.117713e-02 -0.057341718 0.01498746 -0.07648610 0.03413184
## 2024.067   1.876186e-02 -0.017402734 0.05492645 -0.03654711 0.07407083
## 2024.071   2.967917e-02 -0.006485425 0.06584376 -0.02562980 0.08498814
## 2024.075   1.733855e-02 -0.018826043 0.05350314 -0.03797042 0.07264752
## 2024.079   7.264715e-03 -0.028899877 0.04342931 -0.04804426 0.06257369
## 2024.083  -6.920948e-03 -0.043085540 0.02924364 -0.06222992 0.04838802
## 2024.087   9.619717e-03 -0.026544875 0.04578431 -0.04568925 0.06492869
## 2024.091   1.394891e-02 -0.022215683 0.05011350 -0.04136006 0.06925788
## 2024.095   1.160392e-02 -0.024560670 0.04776852 -0.04370505 0.06691289
## 2024.099   6.948803e-03 -0.029215790 0.04311340 -0.04836017 0.06225777
## 2024.103   1.662671e-02 -0.019537882 0.05279130 -0.03868226 0.07193568
## 2024.107  -8.908280e-03 -0.045072873 0.02725631 -0.06421725 0.04640069
## 2024.111   1.862866e-02 -0.017535930 0.05479326 -0.03668031 0.07393764
## 2024.115   1.613737e-02 -0.020027224 0.05230196 -0.03917160 0.07144634
## 2024.119   5.383064e-03 -0.030781530 0.04154766 -0.04992591 0.06069204
## 2024.123  -2.249480e-02 -0.058659395 0.01366979 -0.07780377 0.03281417
## 2024.127  -2.117571e-02 -0.057340302 0.01498889 -0.07648468 0.03413327
## 2024.131   1.278166e-02 -0.023382933 0.04894626 -0.04252731 0.06809064
## 2024.135  -1.362994e-02 -0.049794532 0.02253466 -0.06893891 0.04167904
## 2024.139  -1.512410e-03 -0.037677005 0.03465218 -0.05682139 0.05379656
## 2024.143  -3.285356e-03 -0.039449951 0.03287924 -0.05859433 0.05202362
## 2024.147   1.078223e-02 -0.025382368 0.04694682 -0.04452675 0.06609120
## 2024.151  -4.439582e-03 -0.040604177 0.03172501 -0.05974856 0.05086939
## 2024.155  -5.942695e-03 -0.042107290 0.03022190 -0.06125167 0.04936628
## 2024.159  -1.427769e-03 -0.037592365 0.03473683 -0.05673675 0.05388121
## 2024.163  -1.795161e-02 -0.054116207 0.01821298 -0.07326059 0.03735737
## 2024.167  -2.357928e-02 -0.059743871 0.01258532 -0.07888825 0.03172970
## 2024.171  -8.950484e-04 -0.037059645 0.03526955 -0.05620403 0.05441393
## 2024.175   2.813355e-02 -0.008031051 0.06429814 -0.02717543 0.08344252
## 2024.179  -1.800202e-03 -0.037964798 0.03436439 -0.05710918 0.05350878
## 2024.183  -1.099853e-02 -0.047163126 0.02516607 -0.06630751 0.04431045
## 2024.187   1.640019e-02 -0.019764408 0.05256479 -0.03890879 0.07170917
## 2024.190   1.010134e-04 -0.036063584 0.03626561 -0.05520796 0.05540999
## 2024.194   3.244057e-02 -0.003724026 0.06860517 -0.02286841 0.08774955
## 2024.198  -9.812194e-03 -0.045976791 0.02635240 -0.06512117 0.04549678
## 2024.202   2.224283e-02 -0.013921771 0.05840742 -0.03306615 0.07755181
## 2024.206   1.502432e-02 -0.021140279 0.05118892 -0.04028466 0.07033330
## 2024.210   1.751500e-03 -0.034413098 0.03791610 -0.05355748 0.05706048
## 2024.214   8.740346e-03 -0.027424252 0.04490494 -0.04656863 0.06404933
## 2024.218   1.238707e-02 -0.023777533 0.04855166 -0.04292192 0.06769605
## 2024.222   1.245372e-02 -0.023710880 0.04861832 -0.04285526 0.06776270
## 2024.226   1.089876e-03 -0.035074723 0.03725447 -0.05421911 0.05639886
## 2024.230   1.340669e-02 -0.022757908 0.04957129 -0.04190229 0.06871567
## 2024.234   7.868104e-03 -0.028296495 0.04403270 -0.04744088 0.06317709
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## 2024.238  -1.044224e-02 -0.046606843 0.02572236 -0.06575123 0.04486674
## 2024.242   8.901728e-03 -0.027262871 0.04506633 -0.04640725 0.06421071
## 2024.246  -8.566194e-03 -0.044730794 0.02759841 -0.06387518 0.04674279
## 2024.250   8.984692e-03 -0.027179907 0.04514929 -0.04632429 0.06429367
## 2024.254  -1.324286e-02 -0.049407464 0.02292174 -0.06855185 0.04206612
## 2024.258   7.583738e-04 -0.035406226 0.03692297 -0.05455061 0.05606736
## 2024.262   1.300549e-03 -0.034864051 0.03746515 -0.05400843 0.05660953
## 2024.266  -1.961228e-03 -0.038125828 0.03420337 -0.05727021 0.05334776
## 2024.270   4.771527e-03 -0.031393073 0.04093613 -0.05053746 0.06008051
## 2024.274   1.201292e-02 -0.024151678 0.04817752 -0.04329606 0.06732191
## 2024.278   4.113212e-03 -0.032051389 0.04027781 -0.05119577 0.05942220
## 2024.282   2.148998e-03 -0.034015604 0.03831360 -0.05315999 0.05745798
## 2024.286  -8.297929e-03 -0.044462530 0.02786667 -0.06360691 0.04701106
## 2024.290  -1.482820e-02 -0.050992803 0.02133640 -0.07013719 0.04048078
## 2024.294  -6.002367e-03 -0.042166968 0.03016224 -0.06131135 0.04930662
## 2024.298  -9.328863e-03 -0.045493465 0.02683574 -0.06463785 0.04598012
## 2024.302   1.172082e-02 -0.024443780 0.04788542 -0.04358816 0.06702981
## 2024.306  -1.277638e-02 -0.048940985 0.02338822 -0.06808537 0.04253260
## 2024.310  -3.875024e-04 -0.036552105 0.03577710 -0.05569649 0.05492148
## 2024.313   2.974012e-02 -0.006424481 0.06590472 -0.02556887 0.08504911
## 2024.317  -2.548566e-02 -0.061650265 0.01067894 -0.08079465 0.02982332
## 2024.321   3.674933e-03 -0.032489671 0.03983954 -0.05163405 0.05898392
## 2024.325  -3.361529e-03 -0.039526132 0.03280307 -0.05867052 0.05194746
## 2024.329   1.855223e-02 -0.017612375 0.05471683 -0.03675676 0.07386122
## 2024.333  -1.069704e-02 -0.046861646 0.02546756 -0.06600603 0.04461195
## 2024.337   6.268405e-03 -0.029896199 0.04243301 -0.04904058 0.06157739
## 2024.341  -2.081980e-02 -0.056984402 0.01534481 -0.07612879 0.03448919
## 2024.345   1.220732e-02 -0.023957288 0.04837192 -0.04310167 0.06751631
## 2024.349  -2.431954e-02 -0.060484146 0.01184506 -0.07962853 0.03098945
## 2024.353   1.614113e-04 -0.036003193 0.03632602 -0.05514758 0.05547040
## 2024.357   3.210886e-02 -0.004055744 0.06827346 -0.02320013 0.08741785
## 2024.361   1.051731e-02 -0.025647291 0.04668192 -0.04479168 0.06582630
## 2024.365   2.132391e-02 -0.014840696 0.05748851 -0.03398508 0.07663290
## 2024.369  -1.973840e-02 -0.055903007 0.01642620 -0.07504739 0.03557059
## 2024.373   1.611869e-02 -0.020045913 0.05228330 -0.03919030 0.07142768
## 2024.377  -8.569256e-03 -0.044733862 0.02759535 -0.06387825 0.04673974
## 2024.381   1.027418e-02 -0.025890427 0.04643878 -0.04503481 0.06558317
## 2024.385   3.326980e-02 -0.002894807 0.06943440 -0.02203919 0.08857879
## 2024.389   1.099706e-02 -0.025167542 0.04716167 -0.04431193 0.06630606
## 2024.393   1.050321e-02 -0.025661396 0.04666782 -0.04480578 0.06581220
## 2024.397   1.606893e-02 -0.020095678 0.05223354 -0.03924006 0.07137792
## 2024.401   6.612311e-03 -0.029552295 0.04277692 -0.04869668 0.06192130
## 2024.405  -1.262272e-03 -0.037426879 0.03490233 -0.05657127 0.05404672
## 2024.409   2.482134e-02 -0.011343263 0.06098595 -0.03048765 0.08013034
## 2024.413  -3.626948e-03 -0.039791555 0.03253766 -0.05893594 0.05168205
## 2024.417   1.753979e-03 -0.034410628 0.03791859 -0.05355501 0.05706297
## 2024.421   4.603392e-03 -0.031561216 0.04076800 -0.05070560 0.05991239
## 2024.425   4.663588e-03 -0.031501020 0.04082820 -0.05064541 0.05997258
## 2024.429   8.735882e-03 -0.027428726 0.04490049 -0.04657311 0.06404488
## 2024.433  -1.623003e-02 -0.052394637 0.01993458 -0.07153902 0.03907897
## 2024.437   1.465161e-03 -0.034699447 0.03762977 -0.05384383 0.05677416
## 2024.440   3.398767e-04 -0.035824732 0.03650449 -0.05496912 0.05564887
## 2024.444   9.115413e-03 -0.027049195 0.04528002 -0.04619358 0.06442441
## 2024.448   1.318756e-02 -0.022977046 0.04935217 -0.04212143 0.06849656
```

```
## 2024.452  -1.773585e-04 -0.036341967 0.03598725 -0.05548636 0.05513164
## 2024.456   7.785383e-03 -0.028379226 0.04394999 -0.04752361 0.06309438
## 2024.460   2.330922e-03 -0.033833687 0.03849553 -0.05297808 0.05763992
## 2024.464  -8.637944e-03 -0.044802554 0.02752667 -0.06394694 0.04667105
## 2024.468   1.139223e-02 -0.024772376 0.04755684 -0.04391676 0.06670123
## 2024.472  -1.454236e-03 -0.037618846 0.03471037 -0.05676323 0.05385476
## 2024.476  -4.399458e-03 -0.040564068 0.03176515 -0.05970846 0.05090954
## 2024.480   3.607587e-04 -0.035803852 0.03652537 -0.05494824 0.05566976
## 2024.484   5.942640e-03 -0.030221970 0.04210725 -0.04936636 0.06125164
## 2024.488  -1.143116e-02 -0.047595767 0.02473345 -0.06674016 0.04387784
## 2024.492   1.094205e-02 -0.025222565 0.04710666 -0.04436695 0.06625105
## 2024.496   4.776230e-03 -0.031388381 0.04094084 -0.05053277 0.06008523
## 2024.500   6.451958e-03 -0.029712653 0.04261657 -0.04885704 0.06176096
## 2024.504   4.382823e-03 -0.031781788 0.04054743 -0.05092618 0.05969182
## 2024.508   8.851977e-03 -0.027312635 0.04501659 -0.04645702 0.06416098
## 2024.512   2.088021e-02 -0.015284404 0.05704482 -0.03442879 0.07618921
## 2024.516  -1.014189e-02 -0.046306502 0.02602272 -0.06545089 0.04516711
## 2024.520   1.146835e-02 -0.024696262 0.04763296 -0.04384065 0.06677735
## 2024.524  -2.317100e-03 -0.038481712 0.03384751 -0.05762610 0.05299190
## 2024.528  -3.922610e-03 -0.040087223 0.03224200 -0.05923161 0.05138639
## 2024.532   1.394087e-02 -0.022223746 0.05010548 -0.04136814 0.06924987
## 2024.536   6.157189e-03 -0.030007424 0.04232180 -0.04915181 0.06146619
## 2024.540   1.155246e-02 -0.024612157 0.04771707 -0.04375655 0.06686146
## 2024.544   4.164935e-03 -0.031999678 0.04032955 -0.05114407 0.05947394
## 2024.548  -7.525936e-03 -0.043690549 0.02863868 -0.06283494 0.04778307
## 2024.552  -9.210099e-03 -0.045374713 0.02695451 -0.06451910 0.04609890
## 2024.556   2.375164e-02 -0.012412970 0.05991626 -0.03155736 0.07906065
## 2024.560   3.219323e-03 -0.032945291 0.03938394 -0.05208968 0.05852833
## 2024.563   5.051395e-03 -0.031113219 0.04121601 -0.05025761 0.06036040
## 2024.567  -1.236845e-02 -0.048533063 0.02379617 -0.06767745 0.04294056
## 2024.571   1.627496e-03 -0.034537119 0.03779211 -0.05368151 0.05693650
## 2024.575   9.613139e-03 -0.026551476 0.04577775 -0.04569587 0.06492214
## 2024.579   7.234006e-03 -0.028930609 0.04339862 -0.04807500 0.06254301
## 2024.583   1.284776e-03 -0.034879839 0.03744939 -0.05402423 0.05659378
## 2024.587  -2.063572e-02 -0.056800336 0.01552889 -0.07594473 0.03467328
## 2024.591  -4.892856e-03 -0.041057471 0.03127176 -0.06020186 0.05041615
## 2024.595  -2.396093e-03 -0.038560709 0.03376852 -0.05770510 0.05291291
## 2024.599   3.007836e-03 -0.033156780 0.03917245 -0.05230117 0.05831684
## 2024.603   2.210015e-02 -0.014064468 0.05826476 -0.03320886 0.07740915
## 2024.607  -2.152747e-03 -0.038317363 0.03401187 -0.05746175 0.05315626
## 2024.611   1.641332e-03 -0.034523284 0.03780595 -0.05366768 0.05695034
## 2024.615   9.363428e-03 -0.026801189 0.04552804 -0.04594558 0.06467244
## 2024.619   2.459437e-02 -0.011570242 0.06075899 -0.03071463 0.07990338
## 2024.623  -1.626432e-02 -0.052428932 0.01990030 -0.07157332 0.03904469
## 2024.627   1.097125e-02 -0.025193365 0.04713587 -0.04433776 0.06628026
## 2024.631   2.127343e-02 -0.014891191 0.05743804 -0.03403558 0.07658243
## 2024.635  -7.770344e-03 -0.043934961 0.02839427 -0.06307935 0.04753867
## 2024.639   2.000591e-02 -0.016158705 0.05617053 -0.03530310 0.07531492
## 2024.643  -1.184205e-02 -0.048006669 0.02432257 -0.06715106 0.04346696
## 2024.647   6.911426e-05 -0.036095504 0.03623373 -0.05523990 0.05537812
## 2024.651   8.338167e-03 -0.027826451 0.04450278 -0.04697084 0.06364718
## 2024.655  -5.706468e-03 -0.041871086 0.03045815 -0.06101548 0.04960254
## 2024.659  -1.100425e-02 -0.047168869 0.02516037 -0.06631326 0.04430476
## 2024.663   1.555814e-03 -0.034608804 0.03772043 -0.05375320 0.05686483
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## 2024.667  -7.534772e-03 -0.043699391 0.02862985 -0.06284378 0.04777424
## 2024.671  -8.816300e-03 -0.044980919 0.02734832 -0.06412531 0.04649271
## 2024.675  -9.806006e-03 -0.045970625 0.02635861 -0.06511502 0.04550301
## 2024.679   1.599703e-02 -0.020167593 0.05216165 -0.03931199 0.07130604
## 2024.683   2.908357e-03 -0.033256263 0.03907298 -0.05240066 0.05821737
## 2024.687  -2.211736e-02 -0.058281981 0.01404726 -0.07742637 0.03319165
## 2024.690   6.454652e-04 -0.035519155 0.03681009 -0.05466355 0.05595448
## 2024.694  -2.040079e-04 -0.036368628 0.03596061 -0.05551302 0.05510501
## 2024.698  -2.523444e-03 -0.038688064 0.03364118 -0.05783246 0.05278557
## 2024.702  -5.197148e-03 -0.041361769 0.03096747 -0.06050616 0.05011187
## 2024.706  -2.020693e-02 -0.056371548 0.01595769 -0.07551594 0.03510209
## 2024.710   7.189133e-03 -0.028975488 0.04335375 -0.04811988 0.06249815
## 2024.714   8.516126e-05 -0.036079460 0.03624978 -0.05522385 0.05539418
## 2024.718  -7.462572e-03 -0.043627193 0.02870205 -0.06277159 0.04784644
## 2024.722   2.840661e-03 -0.033323961 0.03900528 -0.05246835 0.05814968
## 2024.726   8.085801e-03 -0.028078821 0.04425042 -0.04722321 0.06339482
## 2024.730  -3.431132e-03 -0.039595753 0.03273349 -0.05874015 0.05187788
## 2024.734   1.938469e-03 -0.034226153 0.03810309 -0.05337055 0.05724749
## 2024.738   3.357972e-03 -0.032806650 0.03952259 -0.05195104 0.05866699
## 2024.742   1.234934e-02 -0.023815283 0.04851396 -0.04295968 0.06765836
## 2024.746   3.080462e-03 -0.033084161 0.03924508 -0.05222856 0.05838948
## 2024.750   2.034028e-02 -0.015824345 0.05650490 -0.03496874 0.07564930
## 2024.754   2.509078e-04 -0.035913715 0.03641553 -0.05505811 0.05555993
## 2024.758  -1.480809e-02 -0.050972711 0.02135654 -0.07011711 0.04050093
## 2024.762  -4.278287e-03 -0.040442910 0.03188634 -0.05958731 0.05103073
## 2024.766  -2.570600e-04 -0.036421683 0.03590756 -0.05556608 0.05505196
## 2024.770  -5.393622e-03 -0.041558245 0.03077100 -0.06070264 0.04991540
## 2024.774   1.048607e-02 -0.025678553 0.04665069 -0.04482295 0.06579509
## 2024.778  -4.304473e-03 -0.040469097 0.03186015 -0.05961349 0.05100455
## 2024.782  -1.172033e-03 -0.037336657 0.03499259 -0.05648105 0.05413699
## 2024.786   6.826401e-03 -0.029338223 0.04299103 -0.04848262 0.06213542
## 2024.790  -8.430294e-03 -0.044594918 0.02773433 -0.06373931 0.04687873
## 2024.794   1.296243e-02 -0.023202190 0.04912706 -0.04234659 0.06827145
## 2024.798   7.345268e-03 -0.028819357 0.04350989 -0.04796375 0.06265429
## 2024.802  -7.412230e-03 -0.043576855 0.02875239 -0.06272125 0.04789679
## 2024.806   7.554328e-03 -0.028610297 0.04371895 -0.04775469 0.06286335
## 2024.810   3.506405e-04 -0.035813985 0.03651527 -0.05495838 0.05565966
## 2024.813   1.306786e-02 -0.023096770 0.04923248 -0.04224117 0.06837688
## 2024.817  -3.511006e-03 -0.039675632 0.03265362 -0.05882003 0.05179802
## 2024.821   8.560148e-03 -0.027604477 0.04472477 -0.04674887 0.06386917
## 2024.825   9.027524e-03 -0.027137102 0.04519215 -0.04628150 0.06433655
## 2024.829   1.201345e-02 -0.024151174 0.04817808 -0.04329557 0.06732248
## 2024.833   2.153865e-02 -0.014625977 0.05770328 -0.03377037 0.07684767
## 2024.837   4.200898e-02  0.005844349 0.07817360 -0.01330005 0.09731800
## 2024.841   6.964911e-03 -0.029199716 0.04312954 -0.04834411 0.06227393
## 2024.845   1.754101e-02 -0.018623612 0.05370564 -0.03776801 0.07285004
## 2024.849  -1.483154e-02 -0.050996169 0.02133309 -0.07014057 0.04047748
## 2024.853   8.165854e-03 -0.027998773 0.04433048 -0.04714317 0.06347488
## 2024.857   2.581551e-02 -0.010349113 0.06198014 -0.02949351 0.08112454
## 2024.861  -8.083801e-03 -0.044248428 0.02808083 -0.06339283 0.04722522
## 2024.865   9.475440e-03 -0.026689188 0.04564007 -0.04583359 0.06478447
## 2024.869  -9.817471e-03 -0.045982099 0.02634716 -0.06512650 0.04549156
## 2024.873   1.808956e-03 -0.034355672 0.03797358 -0.05350007 0.05711798
## 2024.877  -7.059602e-03 -0.043224230 0.02910503 -0.06236863 0.04824942
```

```
## 2024.881  -5.875723e-03 -0.042040351 0.03028891 -0.06118475 0.04943330
## 2024.885  -1.967693e-03 -0.038132322 0.03419694 -0.05727672 0.05334133
## 2024.889   5.777537e-03 -0.030387092 0.04194217 -0.04953149 0.06108656
## 2024.893   5.290083e-03 -0.030874547 0.04145471 -0.05001894 0.06059911
## 2024.897  -4.184985e-03 -0.040349614 0.03197964 -0.05949401 0.05112404
## 2024.901   4.617213e-03 -0.031547416 0.04078184 -0.05069181 0.05992624
## 2024.905   1.610586e-02 -0.020058768 0.05227049 -0.03920317 0.07141489
## 2024.909  -1.812166e-02 -0.054286294 0.01804297 -0.07343069 0.03718736
## 2024.913   1.095437e-02 -0.025210261 0.04711900 -0.04435466 0.06626340
## 2024.917  -1.362816e-02 -0.049792787 0.02253647 -0.06893719 0.04168087
## 2024.921  -1.306933e-02 -0.049233963 0.02309530 -0.06837836 0.04223970
## 2024.925   2.442832e-02 -0.011736314 0.06059295 -0.03088071 0.07973735
## 2024.929  -2.477360e-03 -0.038641990 0.03368727 -0.05778639 0.05283167
## 2024.933  -6.039793e-03 -0.042204423 0.03012484 -0.06134882 0.04926924
## 2024.937   6.758633e-03 -0.029405998 0.04292326 -0.04855040 0.06206766
## 2024.940   2.820223e-04 -0.035882609 0.03644665 -0.05502701 0.05559105
## 2024.944   2.232563e-03 -0.033932068 0.03839719 -0.05307647 0.05754159
## 2024.948   1.024923e-02 -0.025915403 0.04641386 -0.04505980 0.06555826
## 2024.952  -1.931162e-02 -0.055476255 0.01685301 -0.07462065 0.03599741
## 2024.956  -7.951492e-03 -0.044116124 0.02821314 -0.06326052 0.04735754
## 2024.960   4.309863e-04 -0.035733646 0.03659562 -0.05487805 0.05574002
## 2024.964   1.443862e-02 -0.021726011 0.05060325 -0.04087041 0.06974765
## 2024.968  -1.344483e-02 -0.049609464 0.02271980 -0.06875386 0.04186420
## 2024.972  -4.455931e-03 -0.040620564 0.03170870 -0.05976496 0.05085310
## 2024.976  -7.824980e-04 -0.036947131 0.03538213 -0.05609153 0.05452654
```

The ets() outputs ETS(A,N,N) indicates additive erros and no trend or seasonality. Alpha is 1e-04 which is very small indicates the model gives most of its weight to historical data and less to recent observations. This may suggest that the data is relatively stable. The initial states (l) is 0.0025, approximately 0.25%, consistent with the mean daily return above. THE AIC is 1218.399 and BIC is 1235.035.

Holt-Winter Models

```
hw_model <- HoltWinters(ts_train)
```

Neural Network Model

```
nnetar_model <- nnetar(ts_train)
```

Prophet Model

```
returns_df <- data.frame(
  ds = zoo::index(returns_train),
  y = coredata(returns_train)
)
colnames(returns_df) <- c("ds", "y")
prophet_model <- prophet(returns_df)
```

```
## Disabling daily seasonality. Run prophet with daily.seasonality=TRUE to override this.
```

Forecasting all models + Forecast Combination

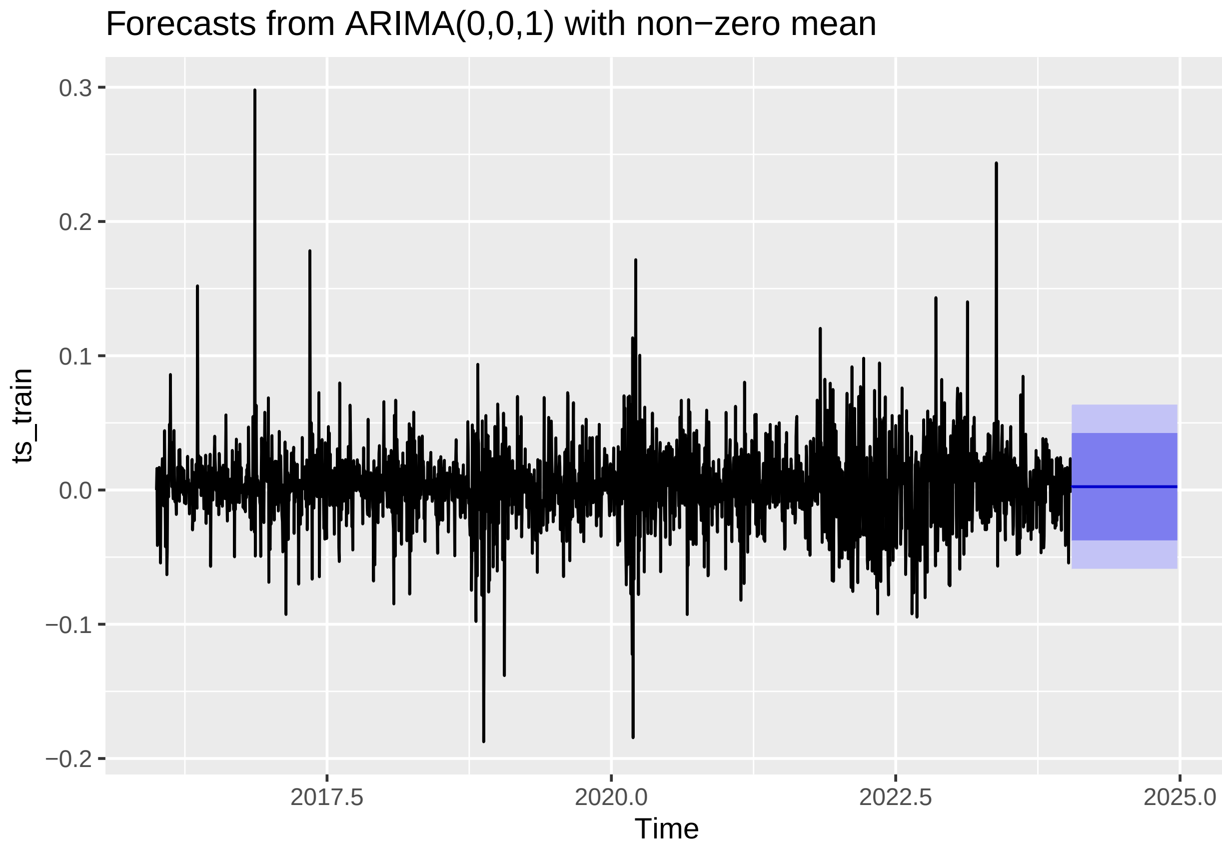
```r
#ARIMA forecast
arima_forecast <- forecast(arima_model, h = 235)
#ETS forecast
ets_forecast <- forecast(ets_model, h = 235)
#Holt-Winter forecast
hw_forecast <- forecast(hw_model, h = 235)
#NNETAR forecast
nnetar_forecast <- forecast(nnetar_model, h =235)
#Prophet forecast
future <- make_future_dataframe(prophet_model, periods = 235)
prophet_forecast <- predict(prophet_model, future)
#Combined Forecast
# Extract forecasted values from each model
arima_values <- as.numeric(arima_forecast$mean)
ets_values <- as.numeric(ets_forecast$mean)
hw_values <- as.numeric(hw_forecast$mean)
nnetar_values <- as.numeric(nnetar_forecast$mean)
last_date <- max(returns_df$ds)
prop_forecast <- prophet_forecast[prophet_forecast$ds > last_date, c("ds", "yhat", "yhat_lower", "yhat_
```

```
## Warning in check_tzones(e1, e2): 'tzone' attributes are inconsistent
```

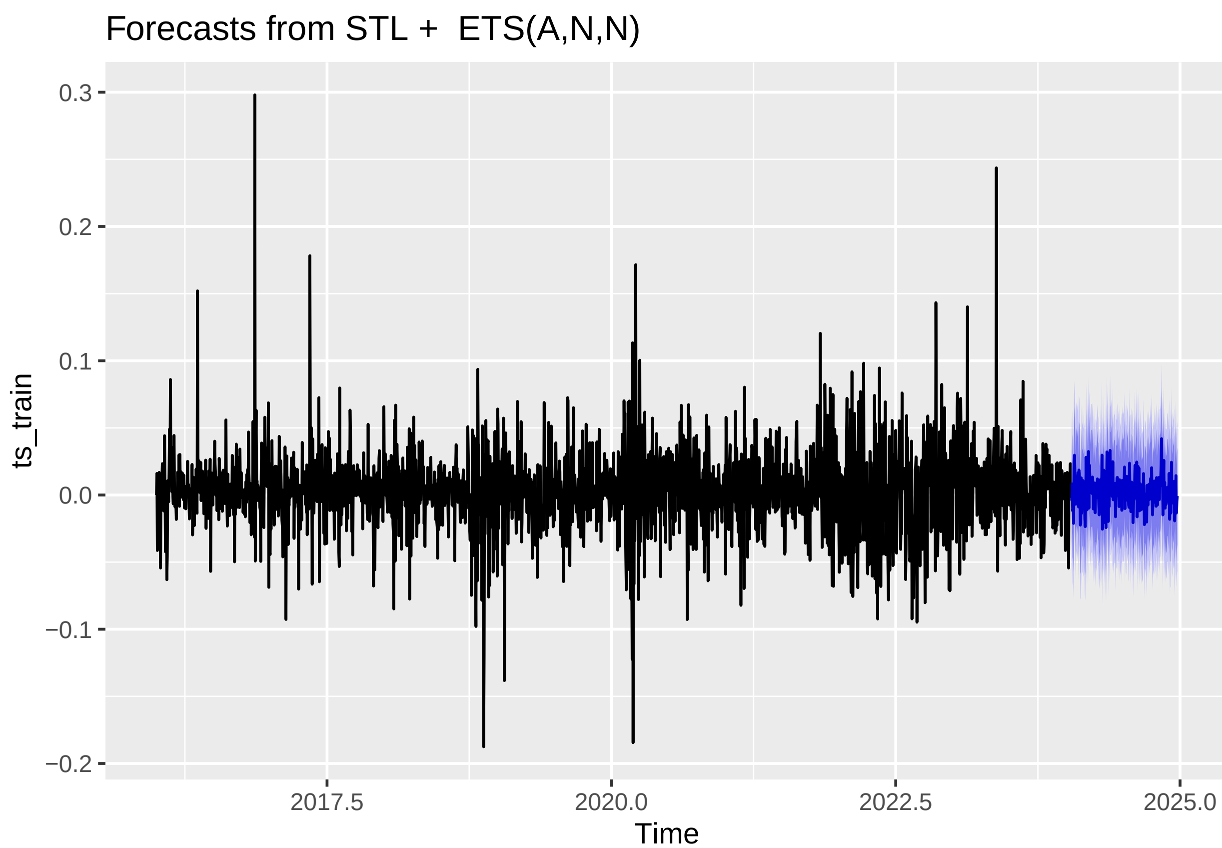
```r
prophet_values <- prop_forecast$yhat
prophet_ts <- ts(prophet_values,
  start = c(2024, 2/252),
  frequency = 252
)
#Average of 5 models
combined_forecast <- (arima_values + ets_values + hw_values + nnetar_values + prophet_values) / 5
combined_ts <- ts(combined_forecast, start = c(2024, 2/252), frequency = 252)
#Put combined forecast in df
combined_forecast_df <- data.frame(
  Date = time(arima_values),
  Combined = combined_forecast,
  ARIMA = arima_values,
  ETS = ets_values,
  HoltWinters = hw_values,
  NNETAR = nnetar_values,
  Prophet = prophet_values
)
```

Plots of All Forecasts

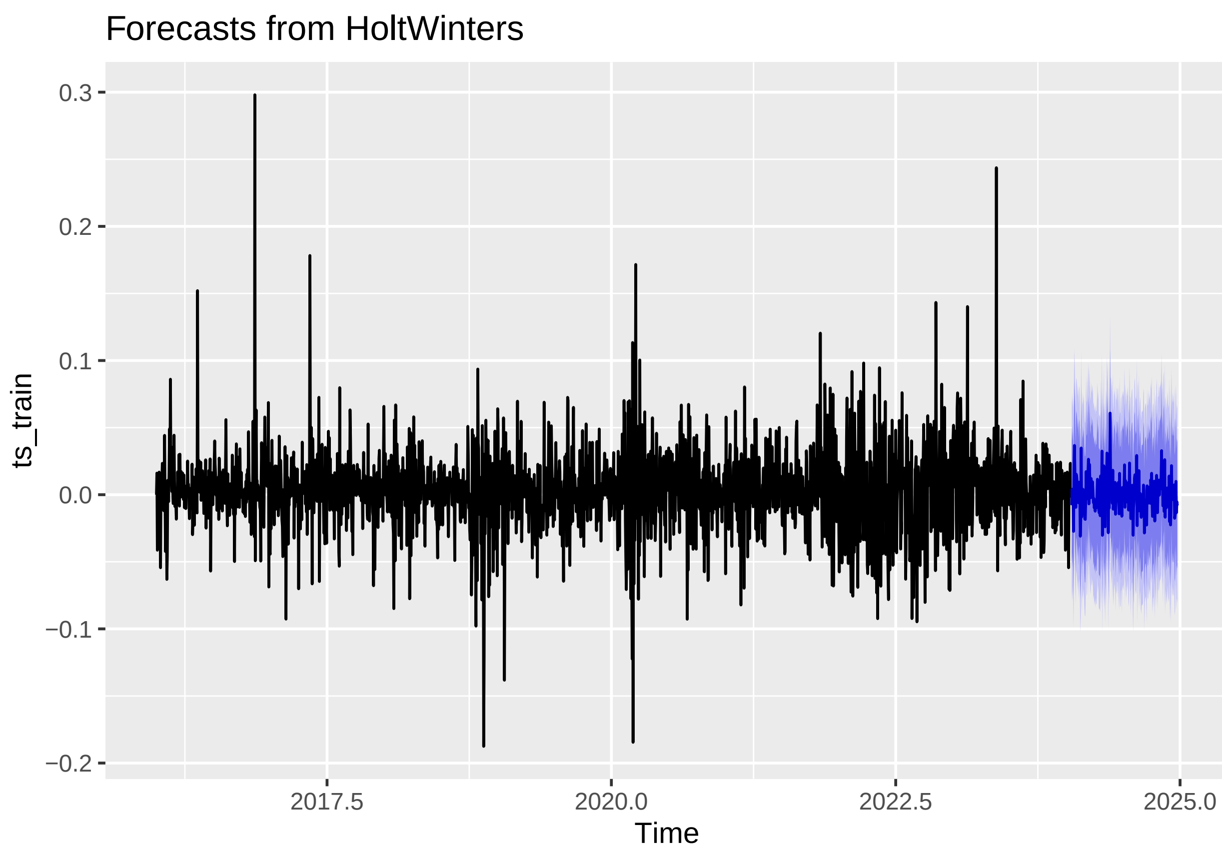
```r
# ARIMA forecast plot
autoplot(arima_forecast)
```



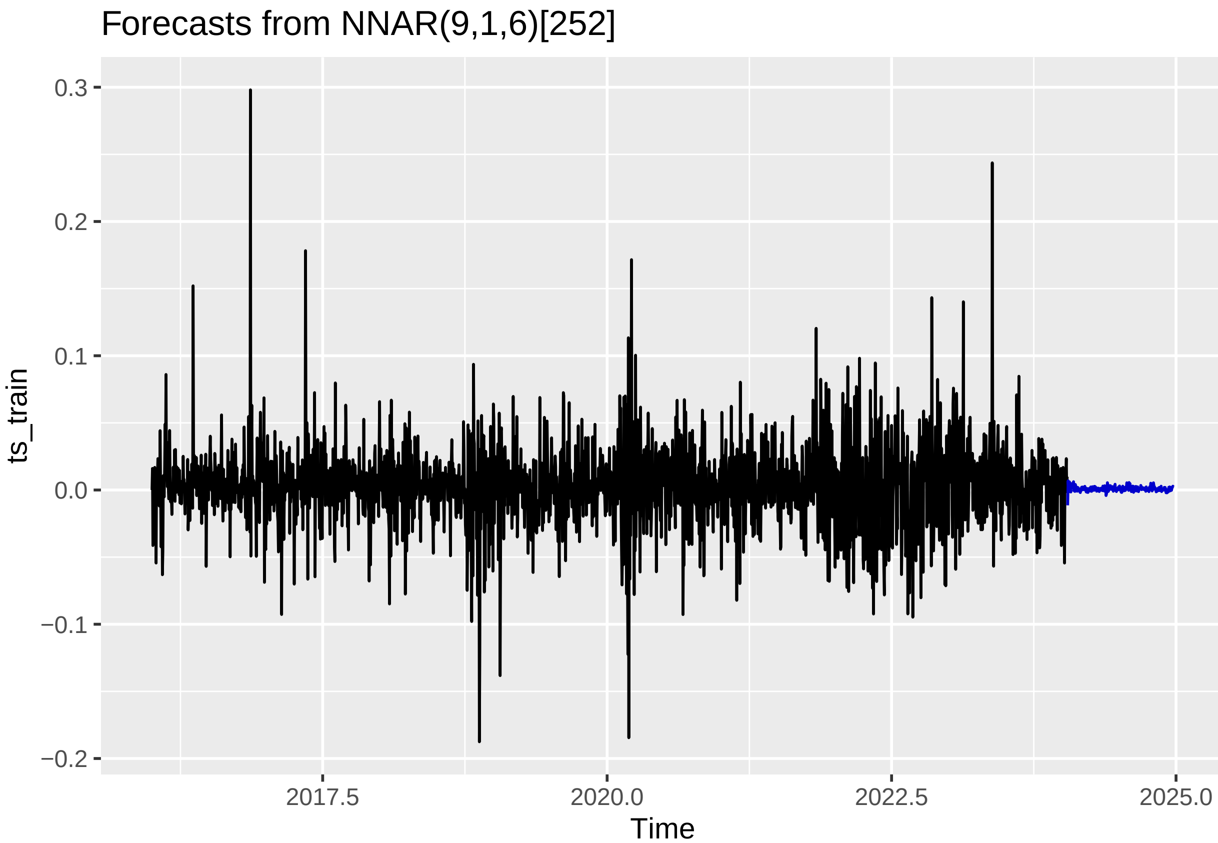

```r
# ETS forecast plot
autoplot(ets_forecast)
```



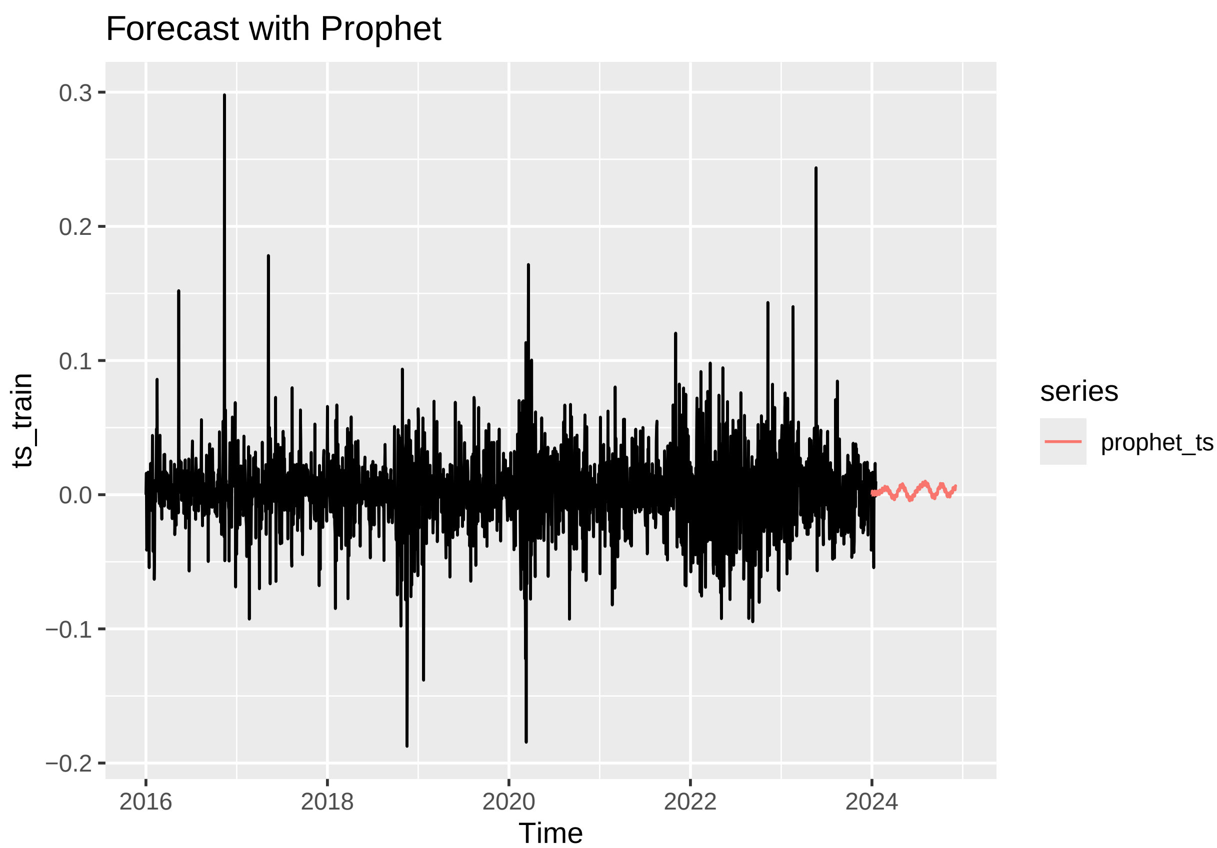

```r
# Holt-Winter forecast
autoplot(hw_forecast)
```



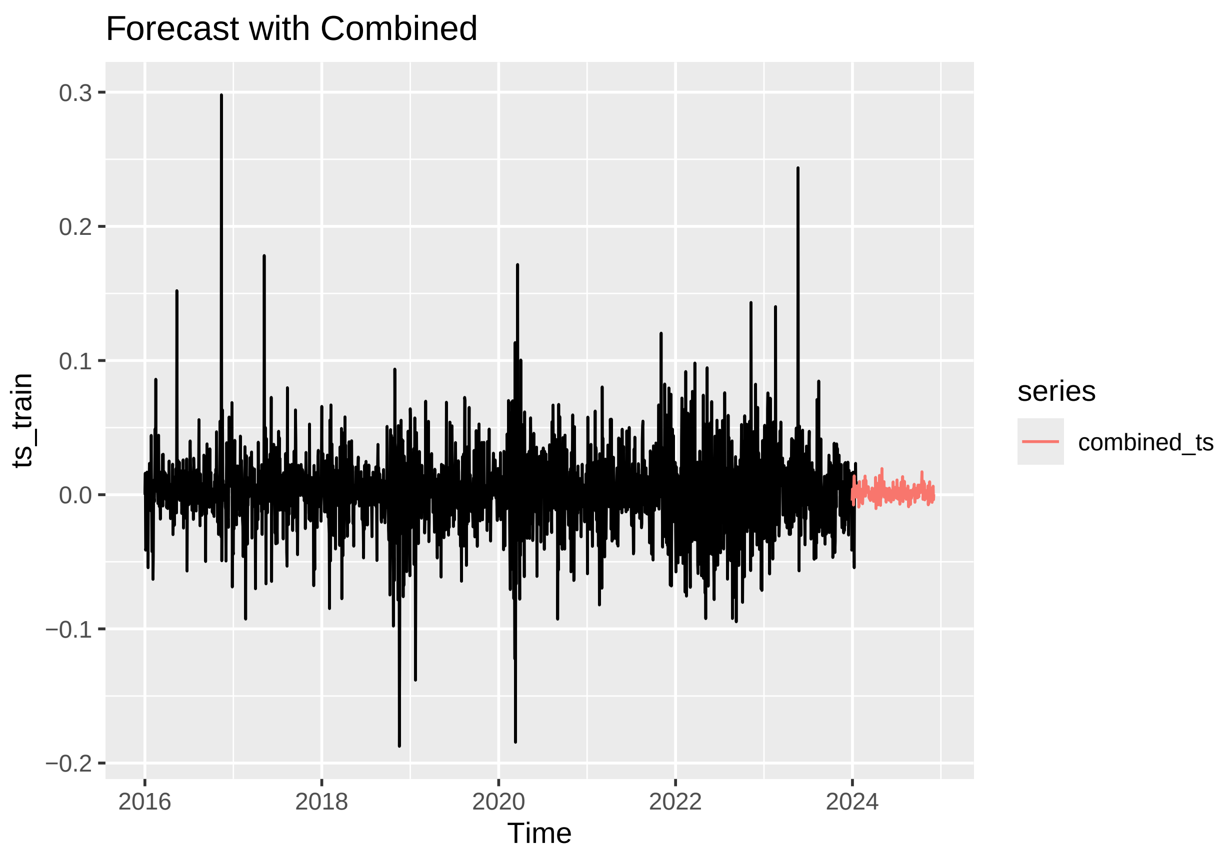

```r
# NNETAR forecast
autoplot(nnetar_forecast)
```




```r
# Prophet forecast
autoplot(ts_train) +
  autolayer(prophet_ts) +
  ggtitle("Forecast with Prophet")
```

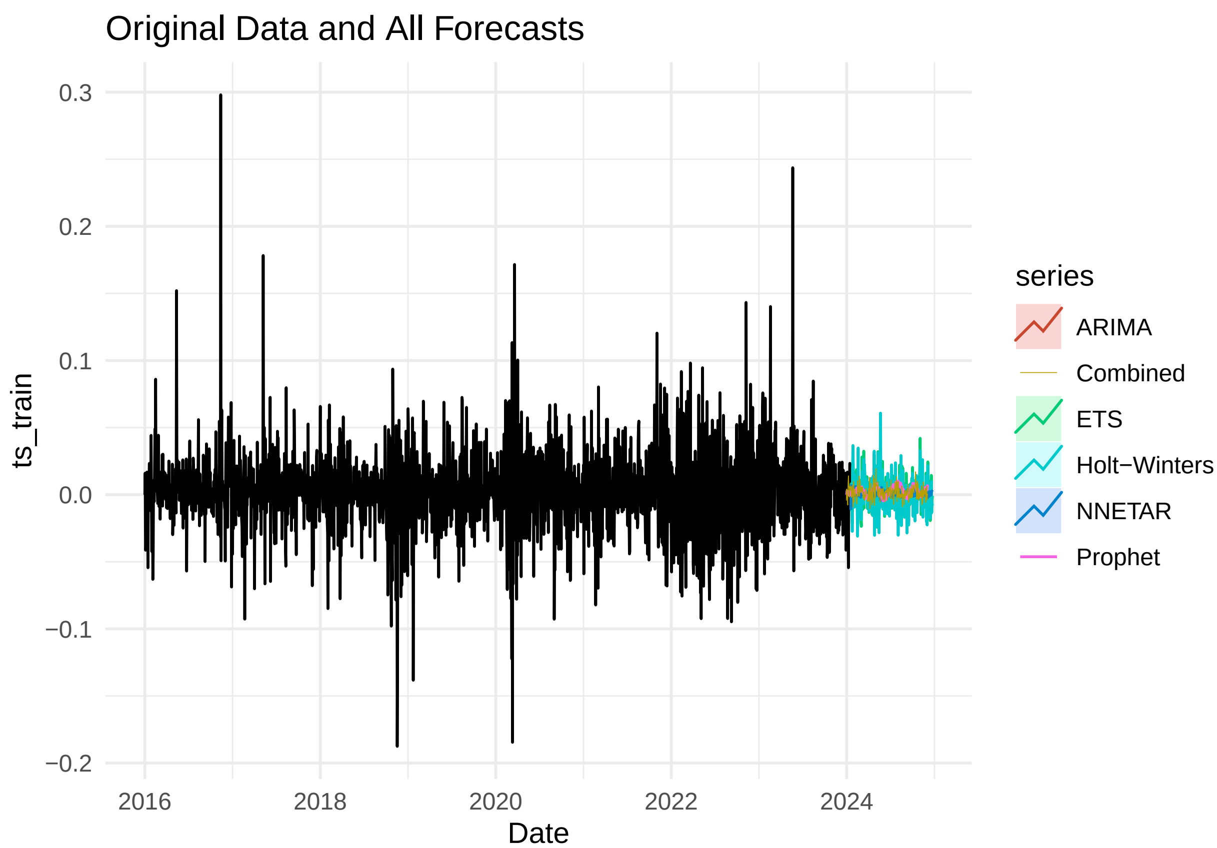



```r
# Combine Forecast
autoplot(ts_train) +
  autolayer(combined_ts) +
  ggtitle("Forecast with Combined")
```




```
# Plot the original data and forecasts
autoplot(ts_train) +
  autolayer(arima_forecast, series = "ARIMA", PI = FALSE, size = 0.5) +
  autolayer(ets_forecast, series = "ETS", PI = FALSE, size = 0.5) +
  autolayer(hw_forecast, series = "Holt-Winters", PI = FALSE, size = 0.5) +
  autolayer(nnetar_forecast, series = "NNETAR", PI = FALSE, size = 0.5) +
  autolayer(prophet_ts, series = "Prophet", PI = FALSE, size = 0.5) +
  autolayer(combined_ts, series = "Combined", PI = FALSE, size = 0.15) +
  xlab("Date") +
  ggtitle("Original Data and All Forecasts") +
  theme_minimal()
```

```
## Warning in ggplot2::geom_line(ggplot2::aes(x = .data[["timeVal"]], y = .data[["seriesVal"]], : Ignori
## Ignoring unknown parameters: `PI`
```



Compare Models

```
calculate_metrics <- function(forecast_values, actual_values) {
  valid_indices <- actual_values != 0
  forecast_values <- forecast_values[valid_indices]
  actual_values <- actual_values[valid_indices]
  rmse <- sqrt(mean((forecast_values - actual_values)^2))
  mae <- mean(abs(forecast_values - actual_values))
  mape <- mean(abs((forecast_values - actual_values) / actual_values)) * 100
  mpe <- mean((forecast_values - actual_values) / actual_values) * 100
  return(c(RMSE = rmse, MAE = mae, MAPE = mape, MPE = mpe))
}

metrics_arima <- calculate_metrics(arima_forecast$mean, returns_test)
metrics_ets <- calculate_metrics(ets_forecast$mean, returns_test)
metrics_hw <- calculate_metrics(hw_forecast$mean, returns_test)
metrics_nnetar <- calculate_metrics(nnetar_forecast$mean, returns_test)
metrics_prophet <- calculate_metrics(prophet_values, returns_test)
metrics_combined <- calculate_metrics(combined_forecast, returns_test)

results <- data.frame(
  Model = c("ARIMA", "ETS", "Holt-Winters", "NNETAR", "Prophet", "Combined"),
  RMSE = c(metrics_arima["RMSE"], metrics_ets["RMSE"], metrics_hw["RMSE"], metrics_nnetar["RMSE"], metri
  MAE = c(metrics_arima["MAE"], metrics_ets["MAE"], metrics_hw["MAE"], metrics_nnetar["MAE"], metrics_p
```

```
  MAPE = c(metrics_arima["MAPE"], metrics_ets["MAPE"], metrics_hw["MAPE"], metrics_nnetar["MAPE"], metri
  MPE = c(metrics_arima["MPE"], metrics_ets["MPE"], metrics_hw["MPE"], metrics_nnetar["MPE"], metrics_p
)
print(results)
```

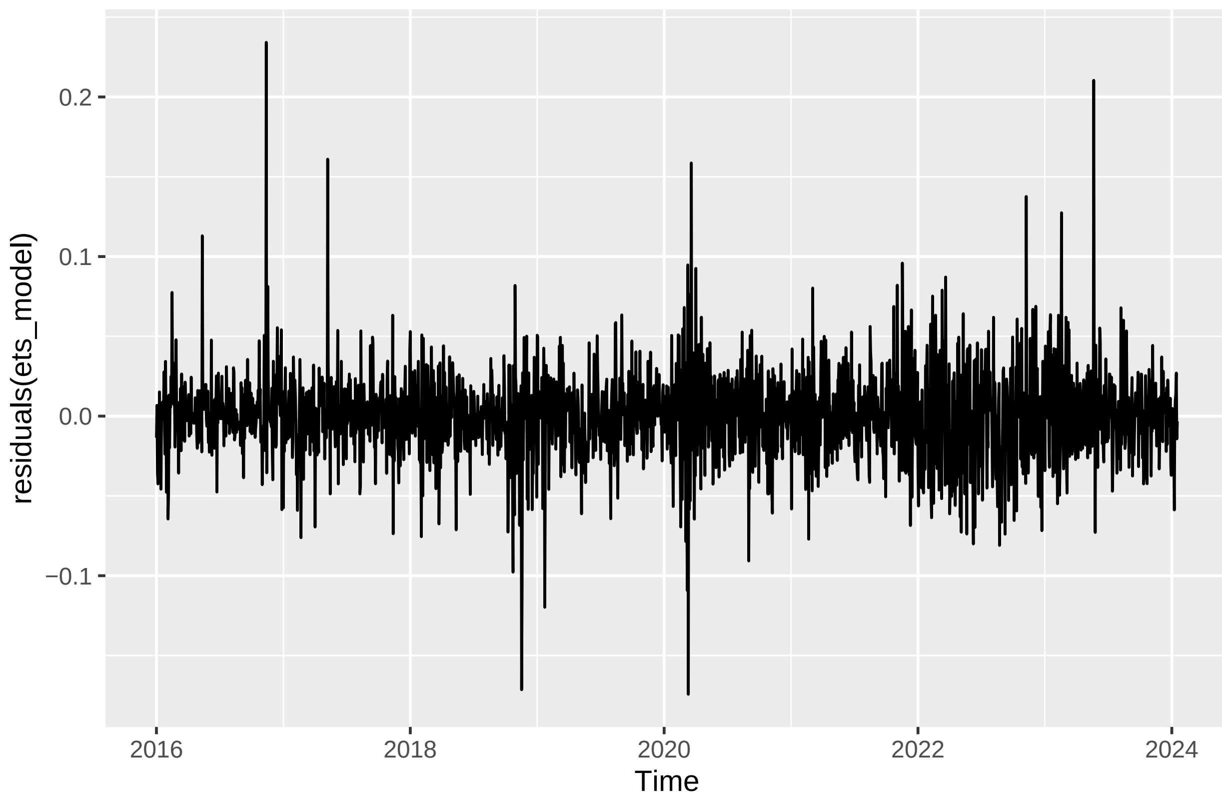
```
##          Model       RMSE        MAE     MAPE        MPE
## 1        ARIMA 0.03376679 0.02507869 141.3701 -100.44467
## 2          ETS 0.03691400 0.02760727 346.4198 -308.68289
## 3 Holt-Winters 0.03730552 0.02803163 359.0592 -307.79794
## 4       NNETAR 0.03387904 0.02538335 130.8604  -87.56183
## 5      Prophet 0.03395498 0.02513322 172.6456 -127.26967
## 6     Combined 0.03458282 0.02568281 194.2842 -186.35140
```

The performance metrics indicate that the ETS model is the most accurate, with the lowest RMSE (0.0338) and MAE (0.0251), making it the best choice for forecasting this dataset. The ARIMA and NNETAR models also perform well, with similar RMSE and MAE values, making them viable alternatives to ETS. However, the Holt-Winters model shows the weakest performance across all metrics, with the highest RMSE (0.0373), MAE (0.0280), and significant percentage errors (MAPE: 359.0%, MPE: -307.8%). The Combined and Prophet model provide reasonable accuracy but does not outperform others models. Based on the metrics, I would choose ETS for its highest accuracy, followed by ARIMA and NNETAR, while Holt-Winters should be avoided.

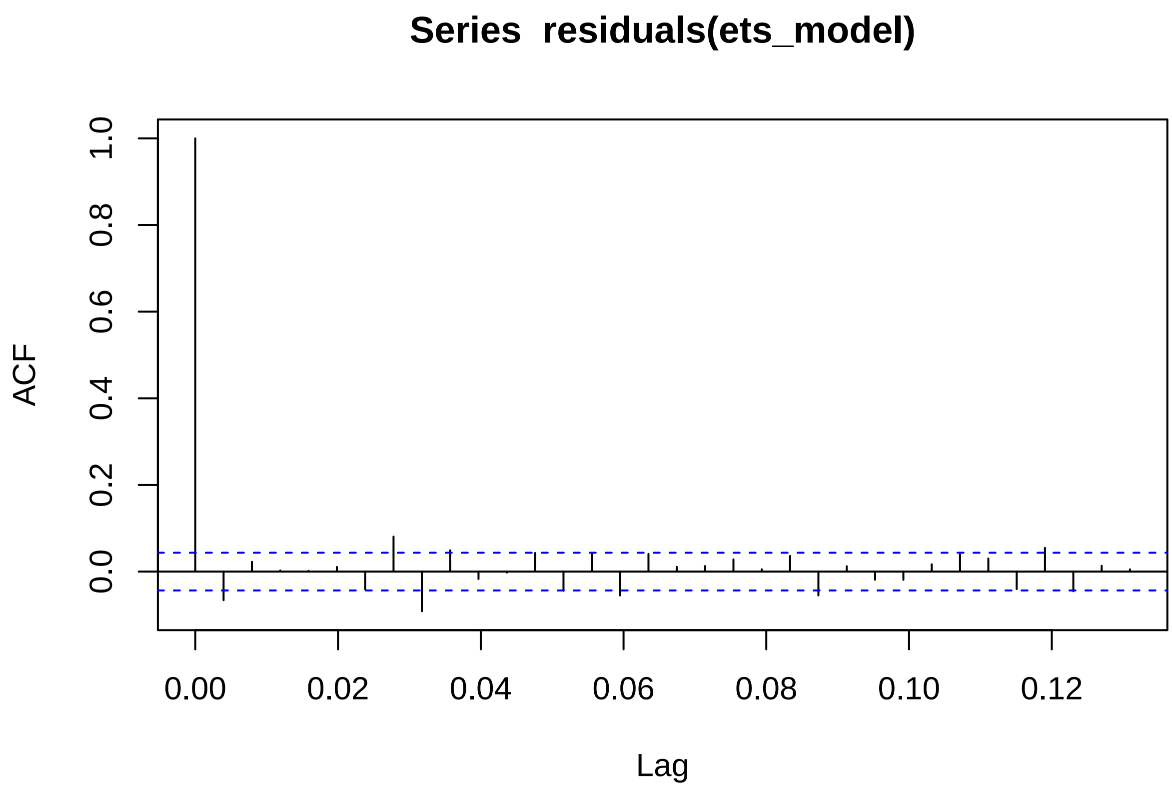
Residual Diagnostics

Residuals of ETS Model

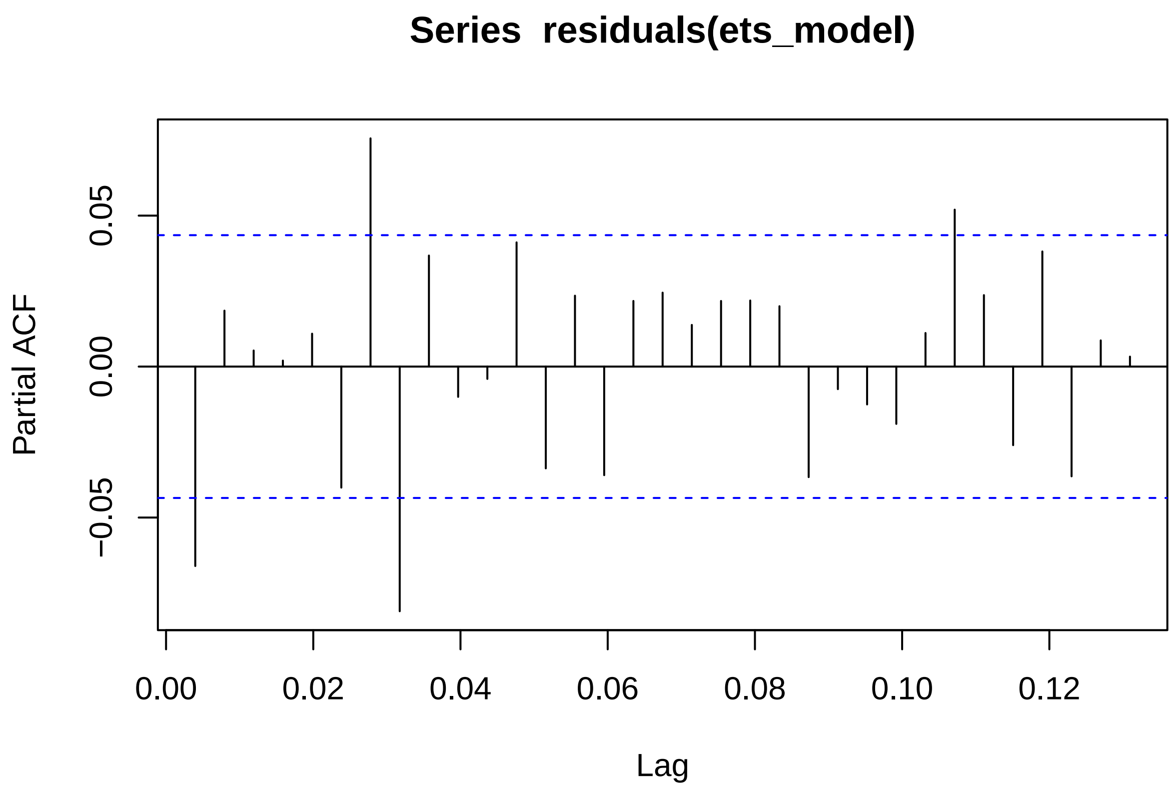
```
autoplot(residuals(ets_model))
```




```
acf(residuals(ets_model))
```




```
pacf(residuals(ets_model))
```



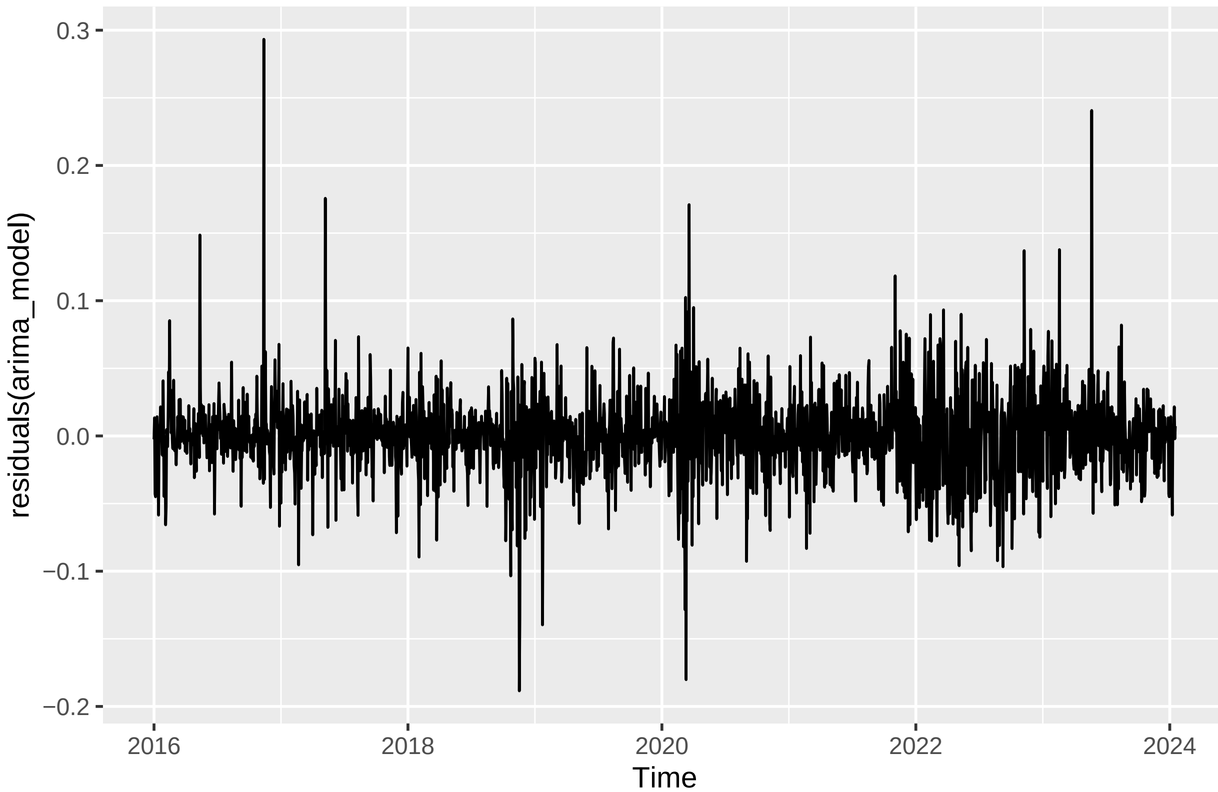

```r
Box.test(residuals(ets_model), lag = 10, type = "Ljung-Box")
```

```
##
##  Box-Ljung test
##
## data:  residuals(ets_model)
## X-squared = 49.519, df = 10, p-value = 3.272e-07
```

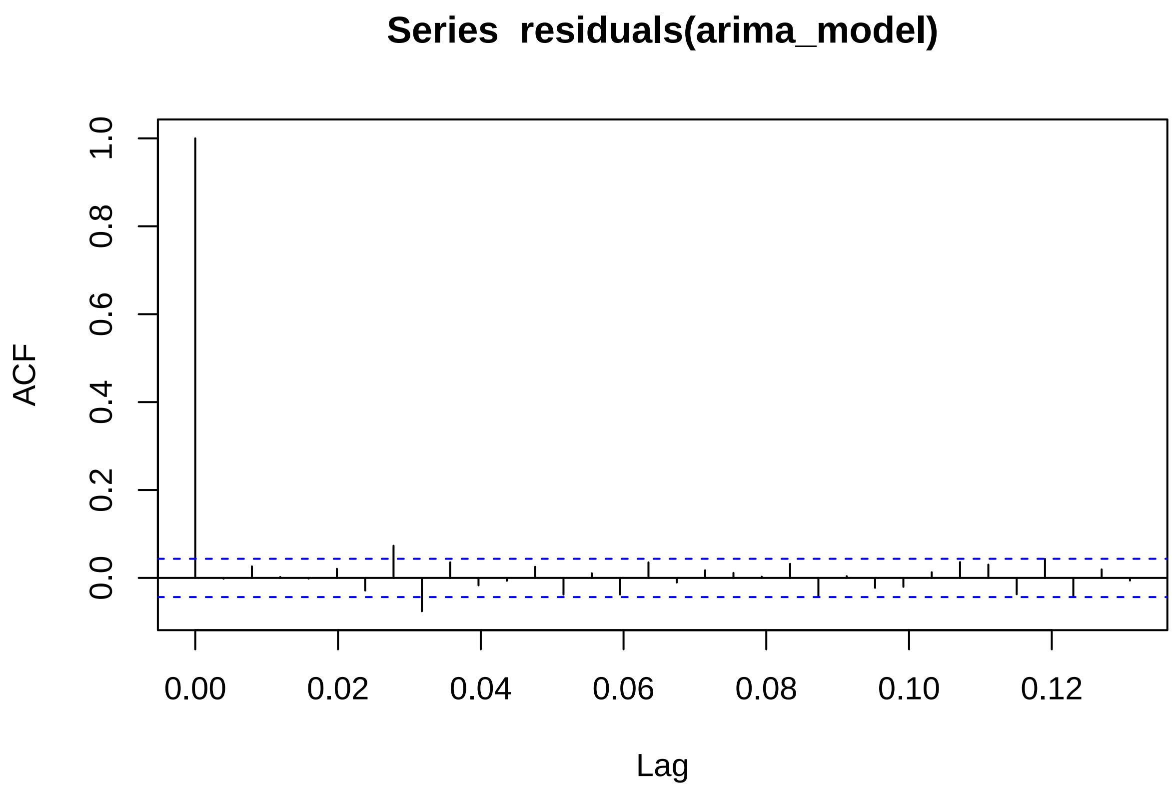
There are still some spikes in the residuals of the ETS model and the Box-Ljung test shows there is still autocorrelation in the residuals of this model.

Residuals of ARIMA Model

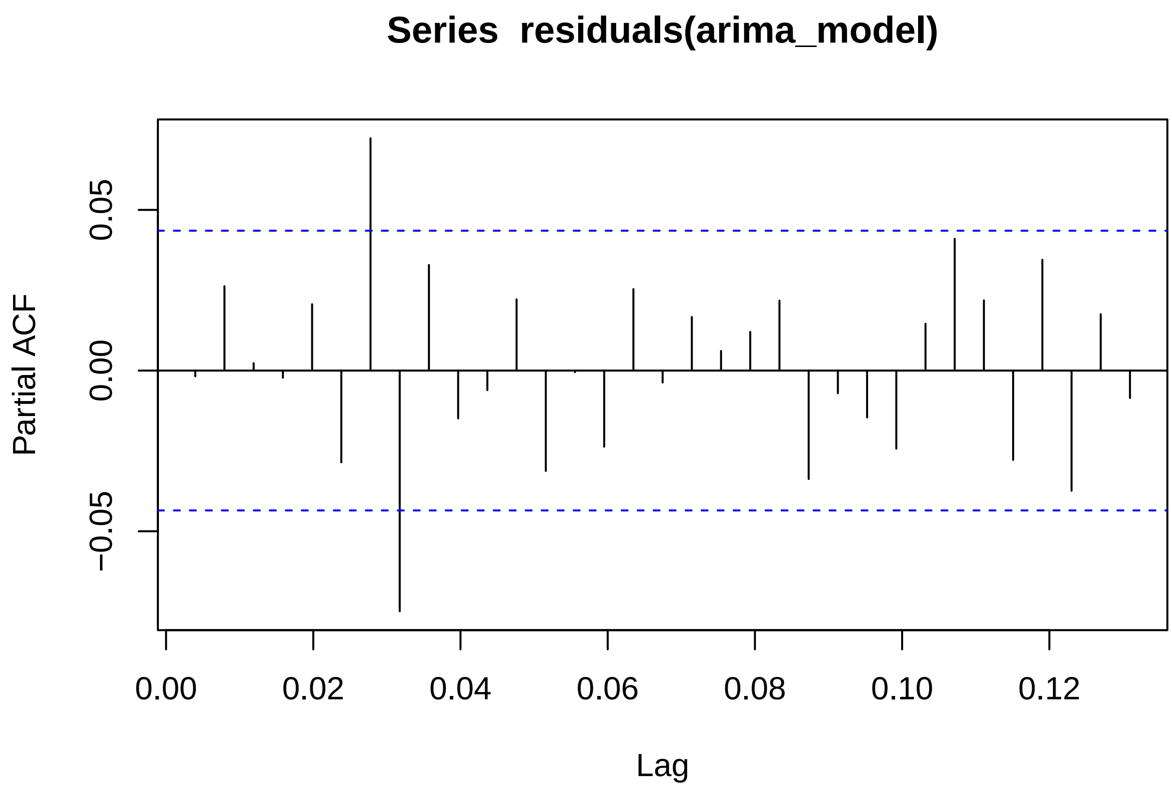
```r
autoplot(residuals(arima_model))
```




```r
acf(residuals(arima_model))
```




```r
pacf(residuals(arima_model))
```



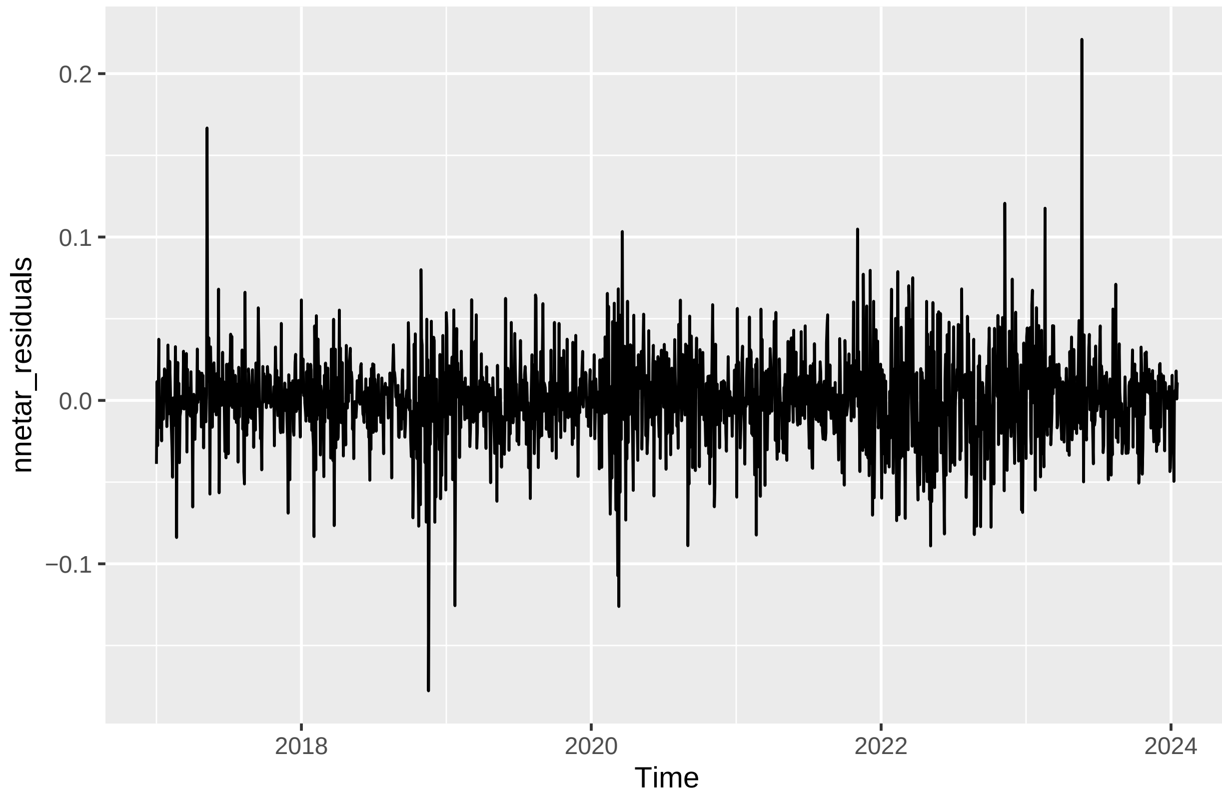

```r
Box.test(residuals(arima_model), lag = 10, type = "Ljung-Box")
```

```
##
##  Box-Ljung test
##
## data:  residuals(arima_model)
## X-squared = 29.772, df = 10, p-value = 0.0009334
```

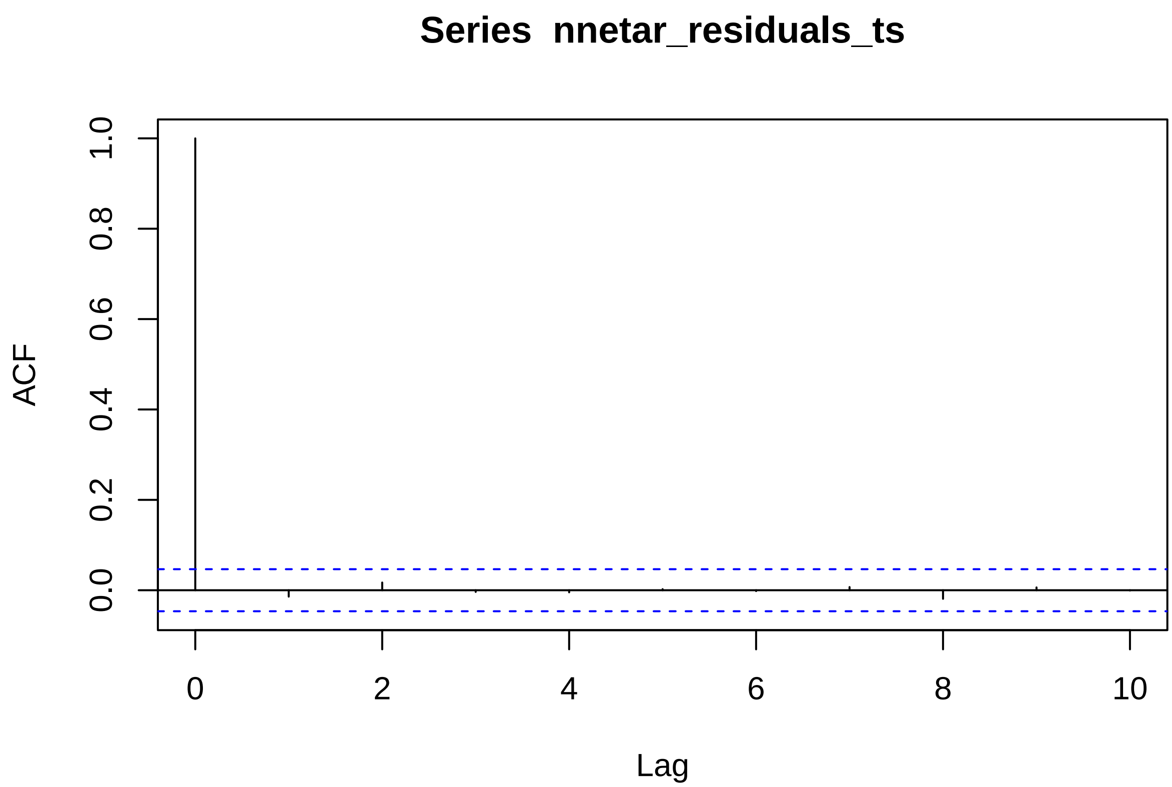
The same thing happens to ARIMA as above; there are sill some dynamics left in the residuals.

Residuals of NNETAR Model

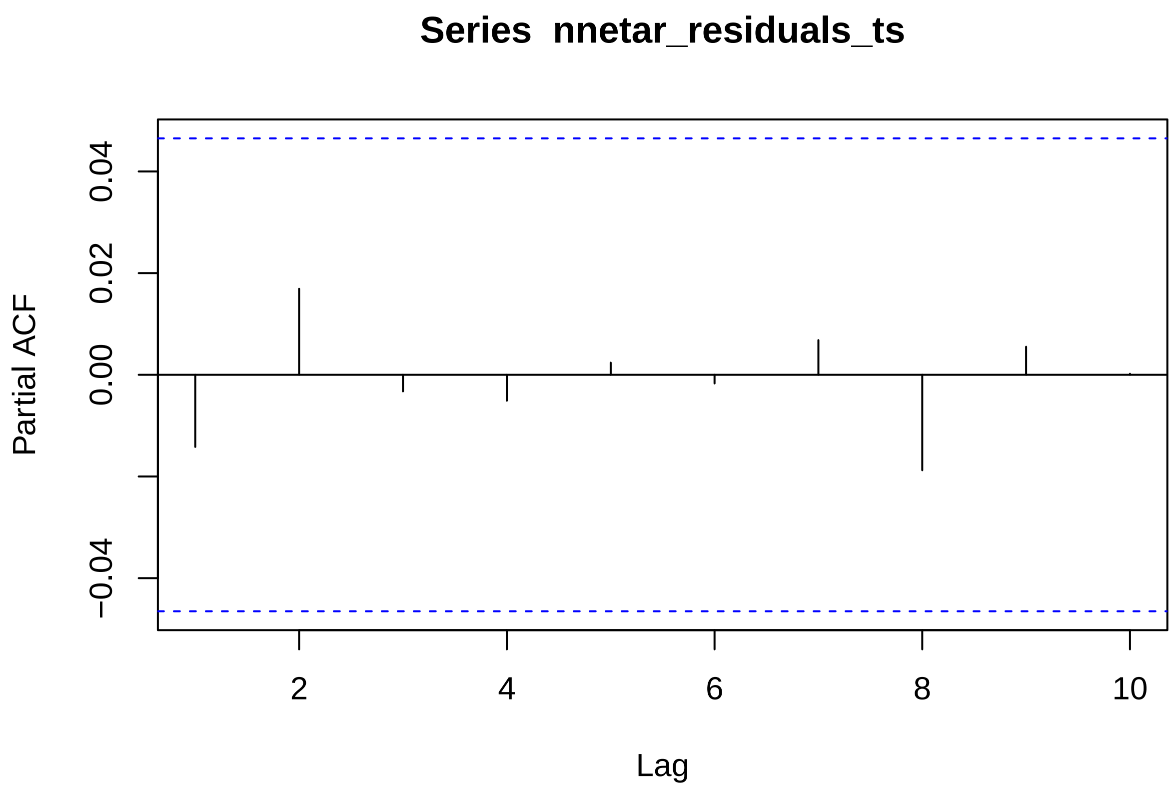
```r
nnetar_residuals <- residuals(nnetar_model)
nnetar_residuals <- na.omit(nnetar_residuals)
nnetar_residuals_ts <- ts(nnetar_residuals, frequency = 1)
autoplot(nnetar_residuals)
```




```
acf(nnetar_residuals_ts, lag.max = 10)
```




```
pacf(nnetar_residuals_ts, lag.max = 10)
```




```r
Box.test(residuals(nnetar_model), lag = 10, type = "Ljung-Box")
```

```
##
##  Box-Ljung test
##
## data:  residuals(nnetar_model)
## X-squared = 1.7644, df = 10, p-value = 0.9978
```

The plots of the residuals for NNETAR model seems to still exhibit some spikes but when test with Ljung-Box, there is no autocorrelation left in the residuals. Thus, as a conclusion, I will choose NNETAR model since it has low errors while also exhibits no autocorrelation in the model

Conclusions and Future Work

The NNETAR model performed the best among the models applied, achieving the lowest forecast errors (as shown in the metrics table). It also satisfies the assumption of no autocorrelation in the residuals, validating its suitability for forecasting. Therefore, the NNETAR model has been selected for further work.

However, the models explored may not fully capture the variance dynamics in the returns data, as residual diagnostics indicate evidence of volatility clustering and autocorrelation. To address this limitation, a GARCH model could be used to model the time-varying variance and volatility clustering inherent in financial data. Furthermore, State-Space Models (SSMs), with Kalman filters or Markov Models, could provide greater flexibility for modeling high-frequency dynamics

References

Forecasting: Principles and Practice by Rob J Hyndman and George Athanasopoulos

ECON 144 Lecture Notes by Dr. Randall R. Rojas