



# MEDICAL PROPERTIES TRUST

**WWW.MEDICALPROPERTIESTRUST.COM**

**VERONIKA TITARCHUK**

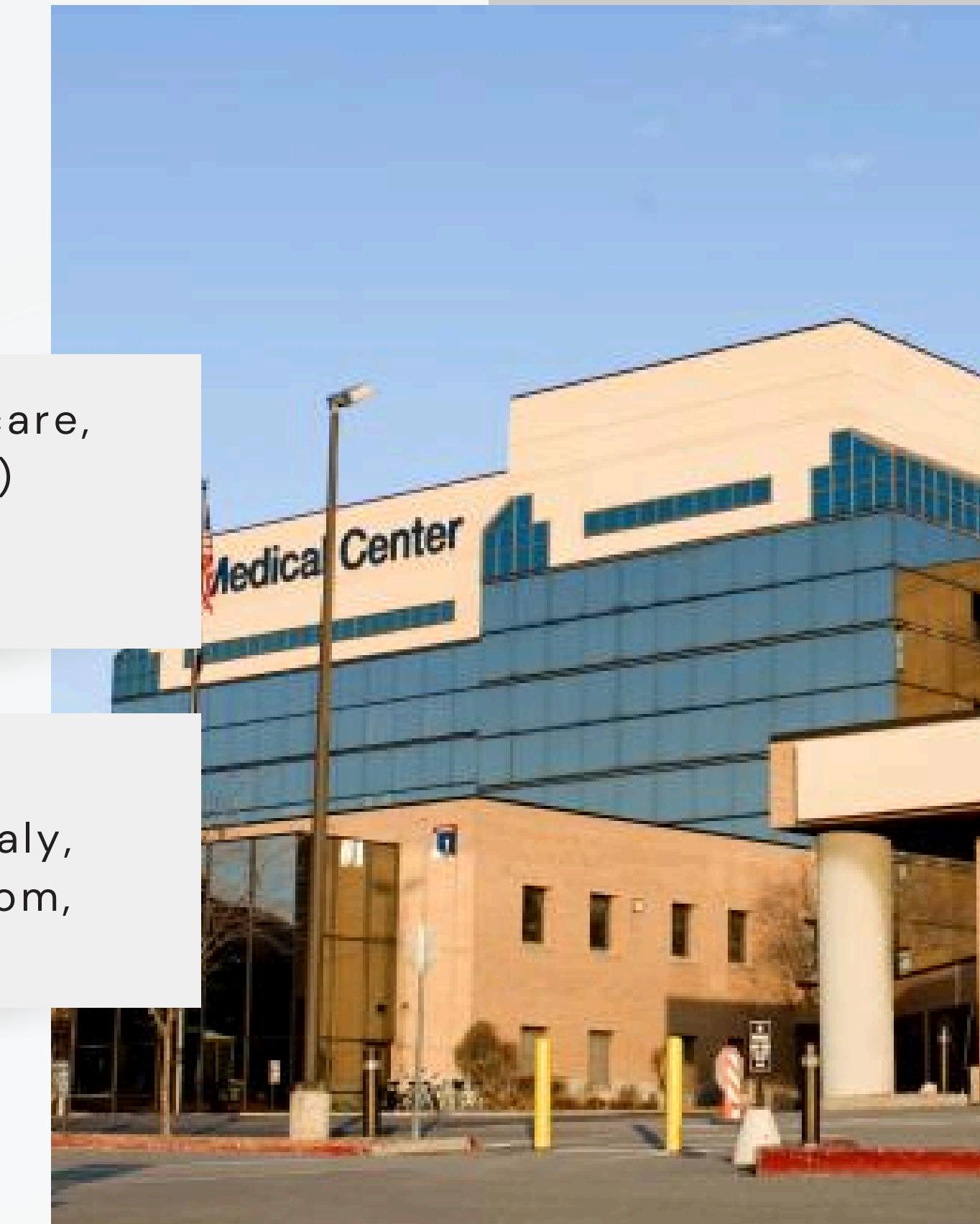
# ABOUT THE COMPANY



Investing into existing hospitals (acute care, rehabilitation, long term acute care, etc.)  
New developments (Construction of new and/or replacement hospitals)



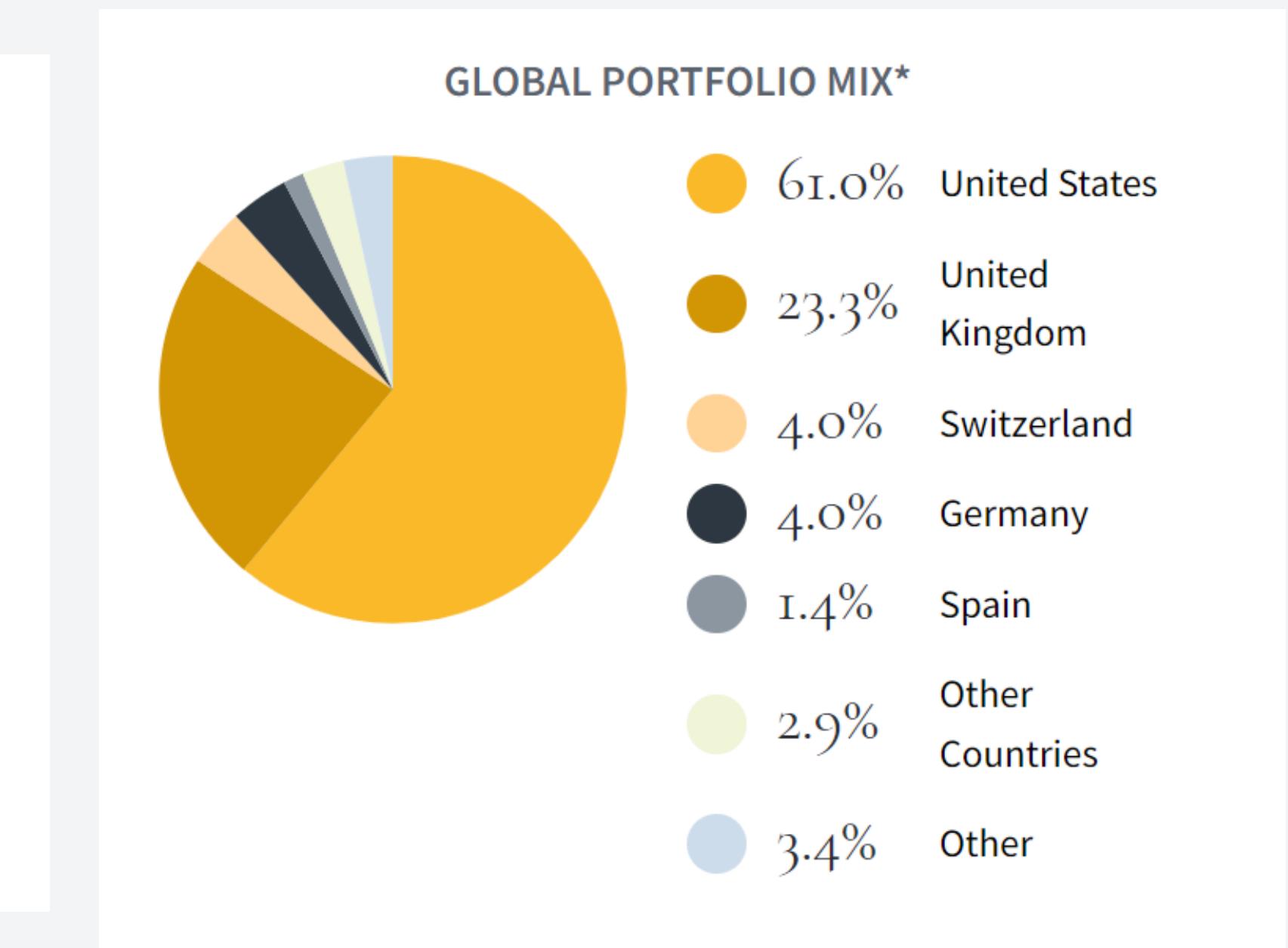
439 Properties, 43,000 Licensed Beds, 9 Countries (Colombia, Finland, Germany, Italy, Portugal, Spain, Switzerland, United Kingdom, United States), 54 Tenant Relationships



# ABOUT THE COMPANY

## WHO WE ARE

- 2<sup>nd</sup> largest non-governmental owner of hospitals in the world
- Experienced in unlocking the value of hospital real estate for growth
- Preferred by top operators around the globe



# QUICK FACTS

**ESTABLISHED**  
**2003**

**IPO ON NYSE**  
**2005**

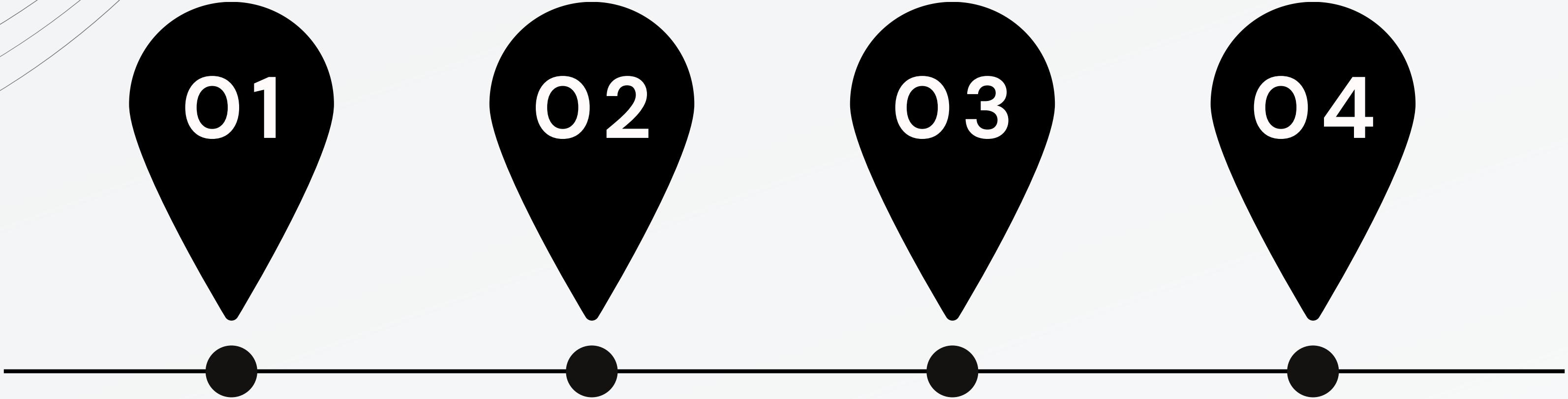
## **COMPOUND ANNUAL GROWTH**

**21%**

*compound annual growth since year end 2012 which coincides with MPT's international expansion*

## **GROWTH SINCE INCEPTION: TOTAL ASSETS (4Q 2023)<sup>1</sup>**





01

02

03

04

## EXPLORATORY DATA ANALYSIS

Plotting the time series  
Decomposing  
ACF and PACF plots

## SATIONARITY

Since the data is not  
stationary right away, I  
will apply basic  
techniques to reach  
stationarity

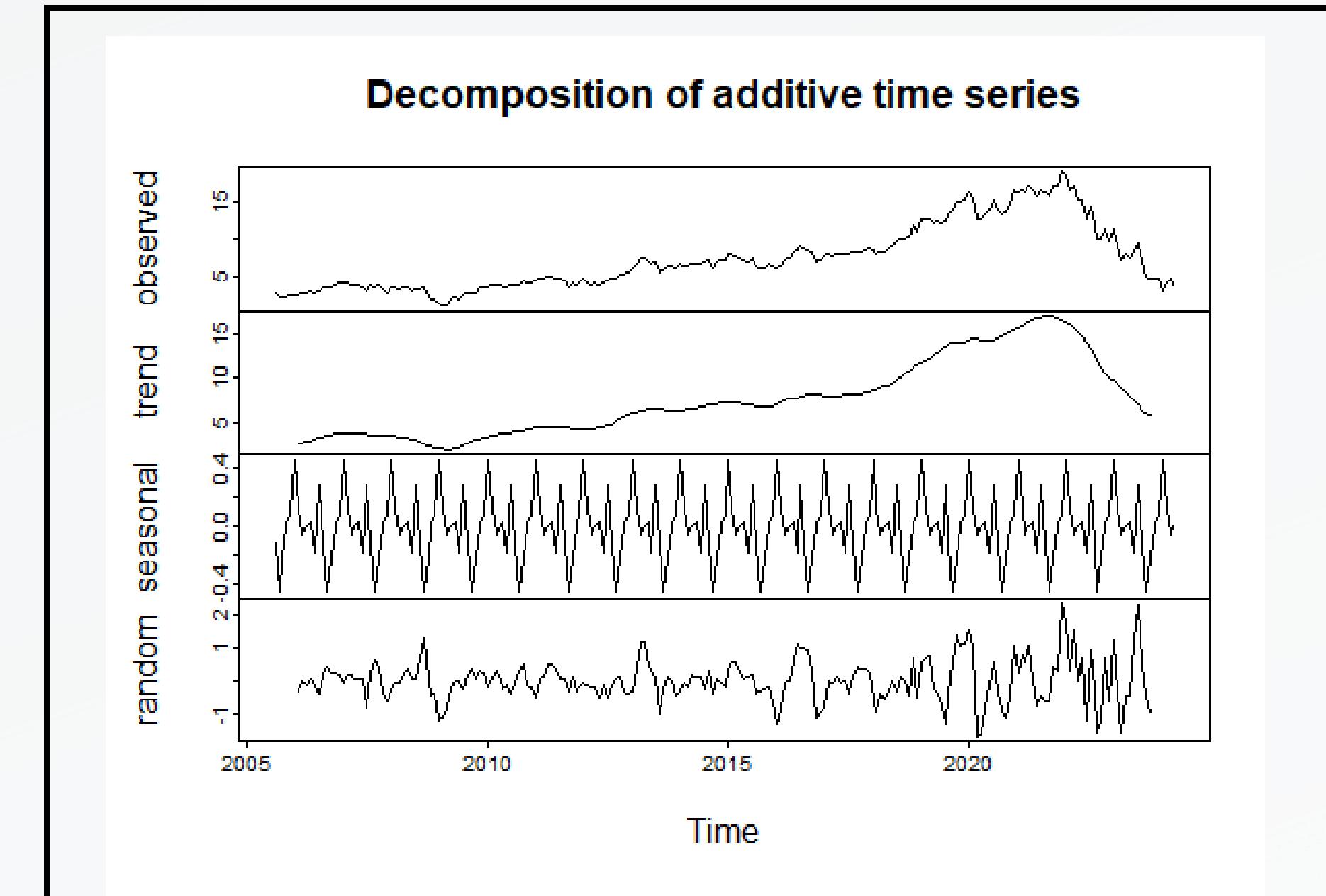
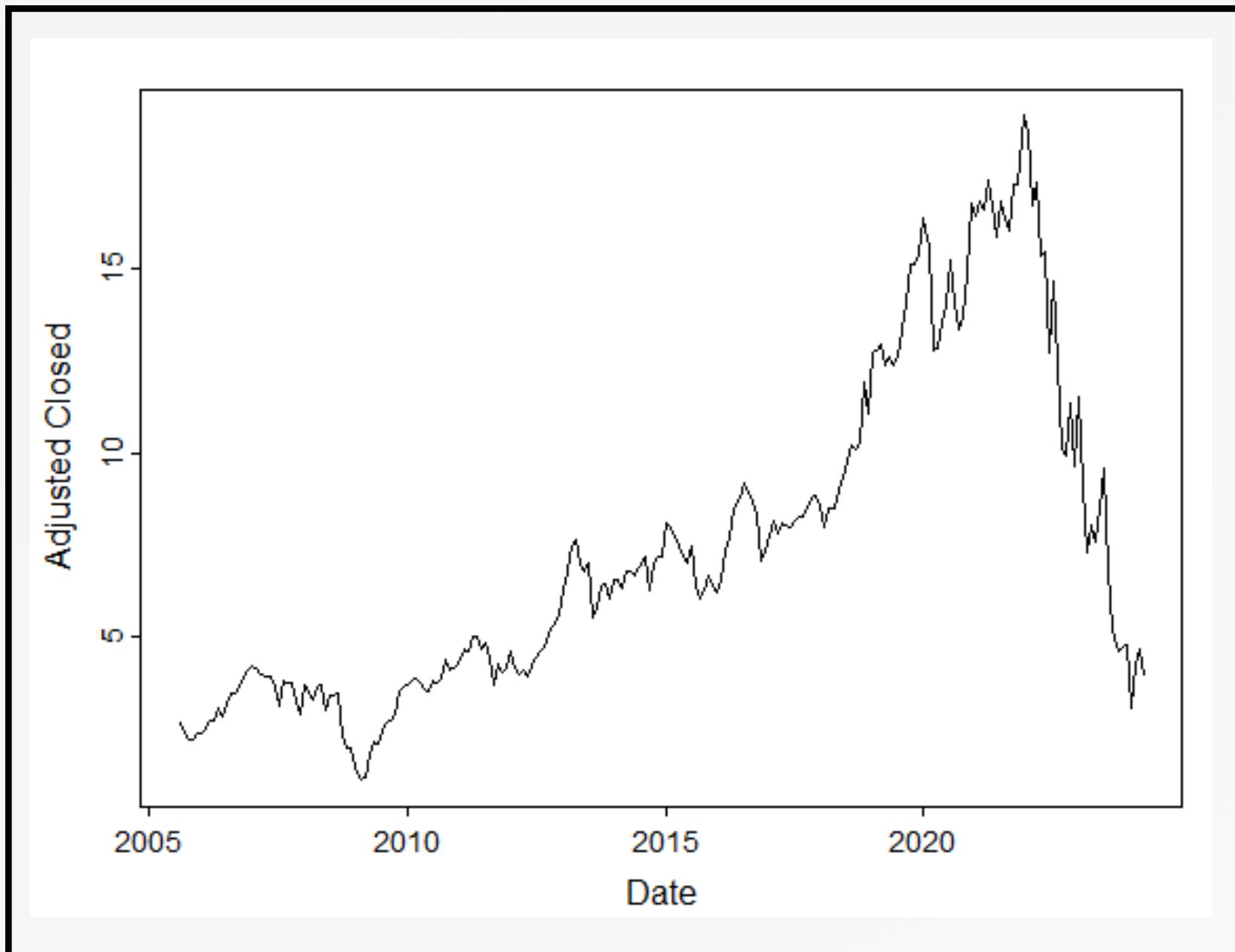
## MODELS

Applying models such  
as Seasonal ARIMA,  
GARCH

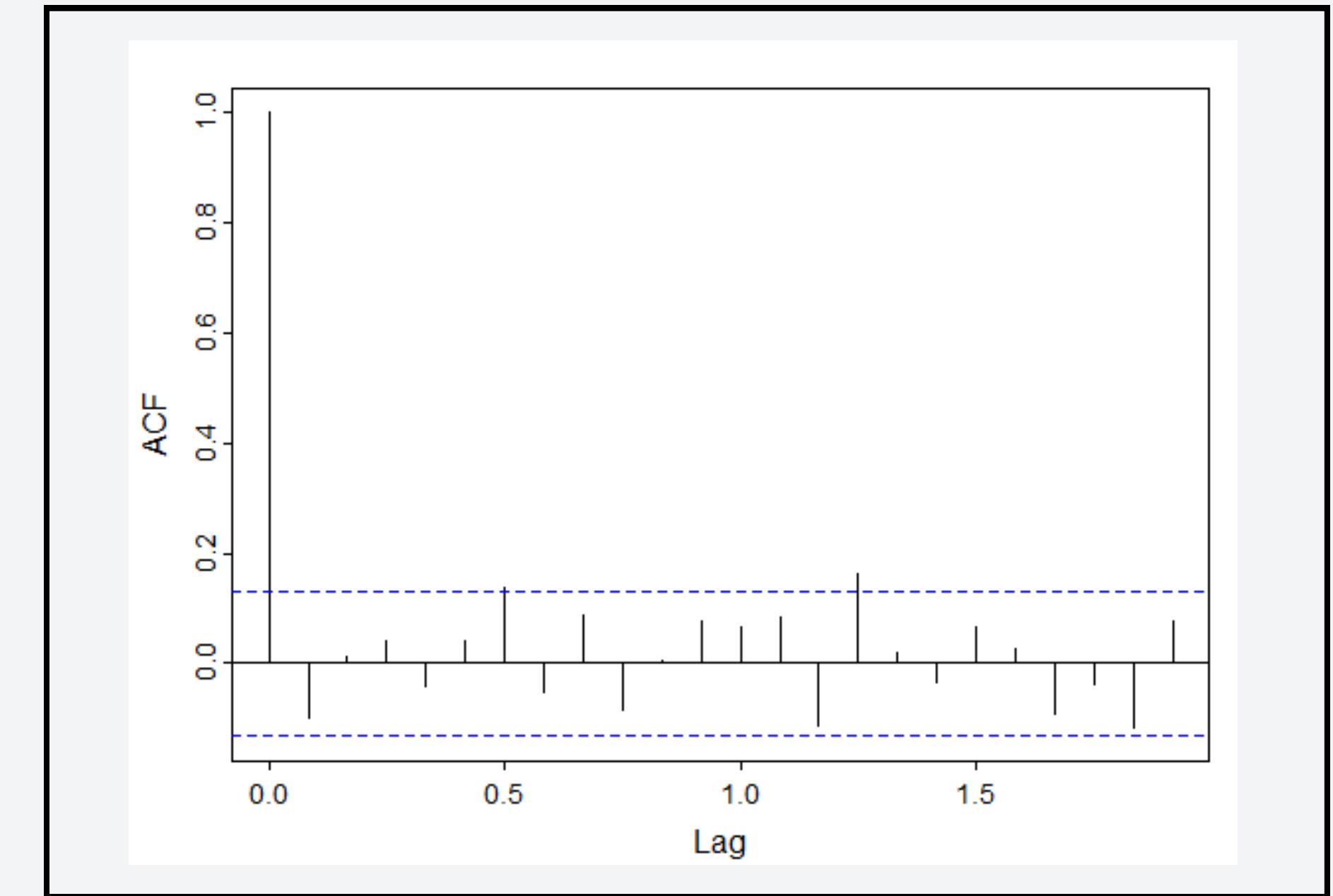
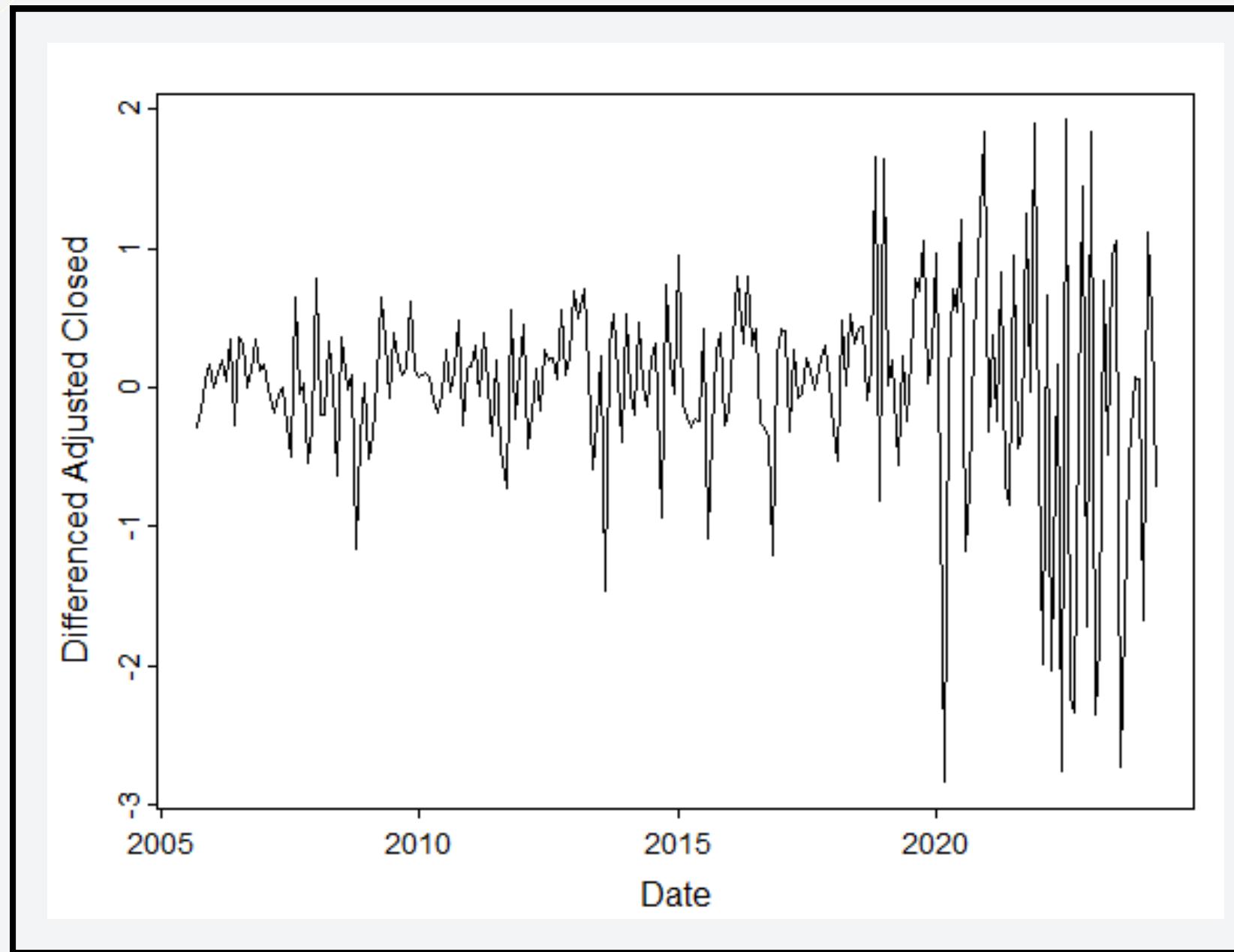
## PREDICTION

Combining results from  
different models to  
create a reasonable  
predictions

# EXPLORATORY DATA ANALYSIS



# EXPLORATORY DATA ANALYSIS



# STATIONARITY

```
> adf.test(ts_mpw)
```

Augmented Dickey-Fuller Test

```
data: ts_mpw  
Dickey-Fuller = -0.9046, Lag order = 6, p-value = 0.9511  
alternative hypothesis: stationary
```

The original series is not stationary

```
> adf.test(diff(ts_mpw))
```

Augmented Dickey-Fuller Test

```
data: diff(ts_mpw)  
Dickey-Fuller = -5.0238, Lag order = 6, p-value = 0.01  
alternative hypothesis: stationary
```

The differenced series is stationary

# MODEL SELECTION

```
> auto.arima(ts_mpw)
Series: ts_mpw
ARIMA(0,1,0)

sigma^2 = 0.5648: log likelihood = -253.85
AIC=509.7   AICc=509.72   BIC=513.11
```

We can see that `auto.arima` function did not give us the desired outcome, since it does not have a seasonal part. So I used the function that we learned from the class, and it gave a better model

```
> get.best.arima(ts_mpw,
+                   maxord=c(2,2,2,2,2,2))
[[1]]
[1] 492.6933

[[2]]

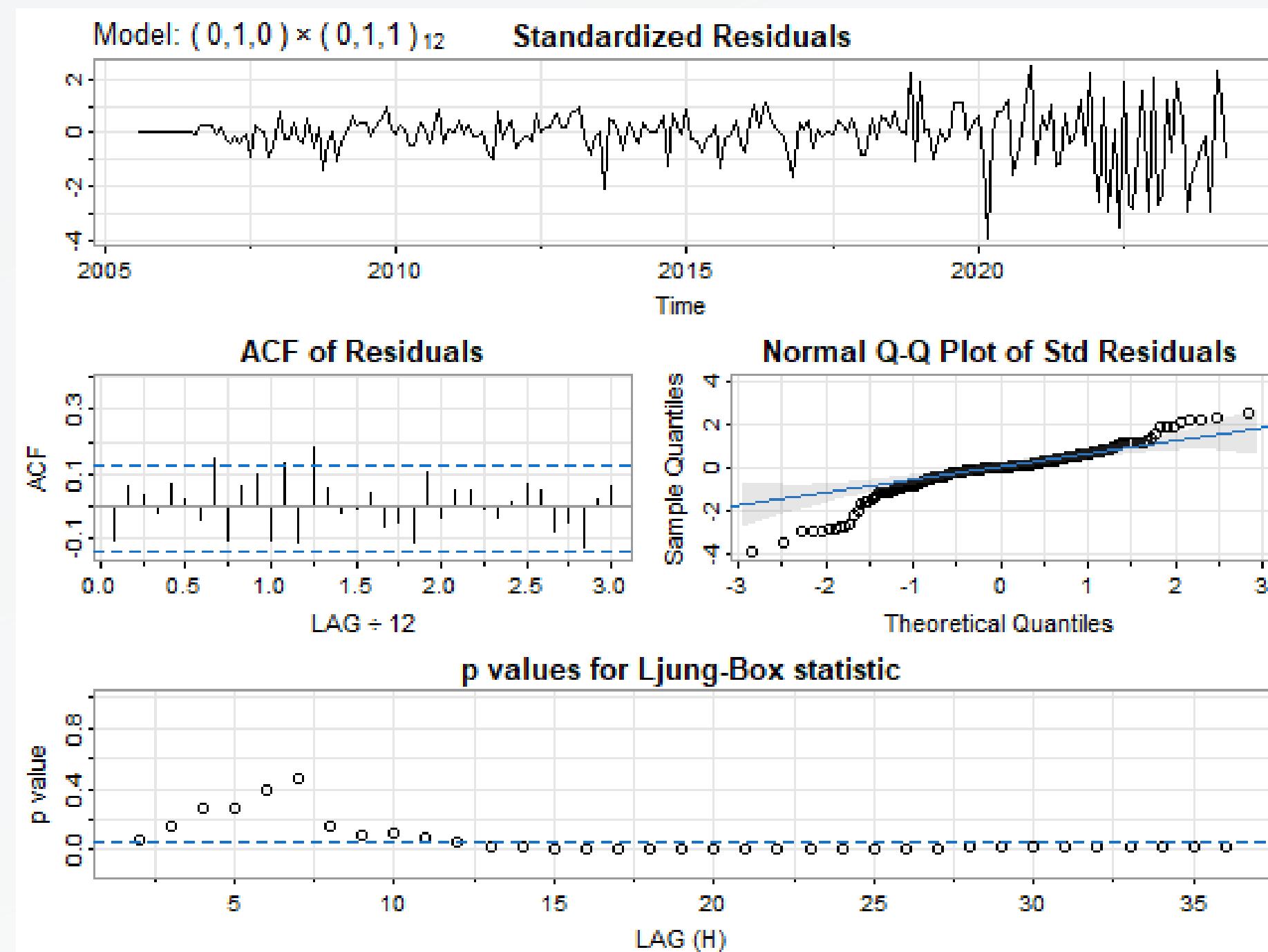
call:
arima(x = x.ts, order = c(p, d, q), seasonal = list(order = c(P, D, Q), frequency(x.ts)),
       method = "CSS")

Coefficients:
  sma1
  -0.8862
s.e.  0.0404

sigma^2 estimated as 0.5804:  partial log likelihood = -243.14

[[3]]
[1] 0 1 0 0 1 1
```

# SARIMA FIT

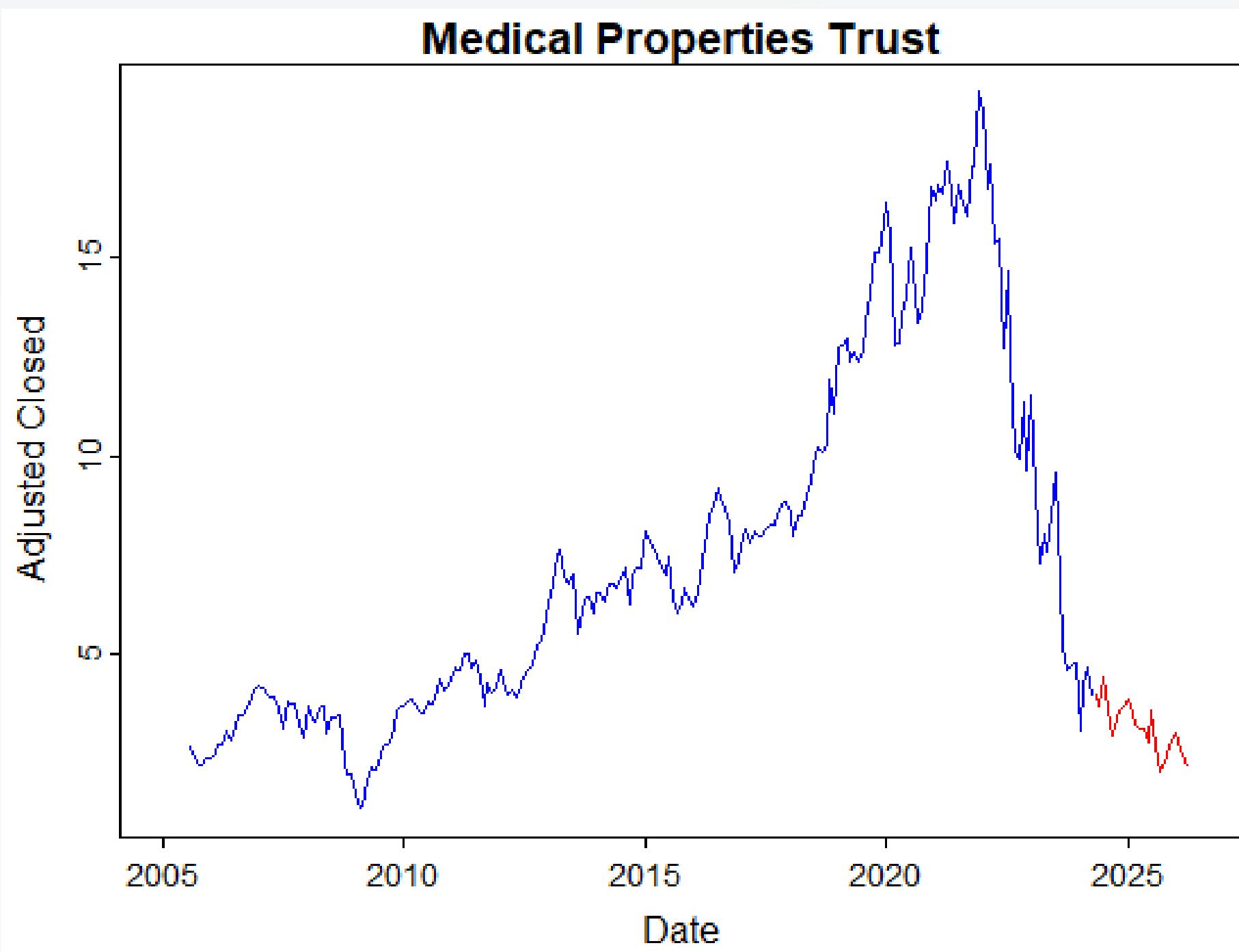


# WORKING WITH THE MODEL

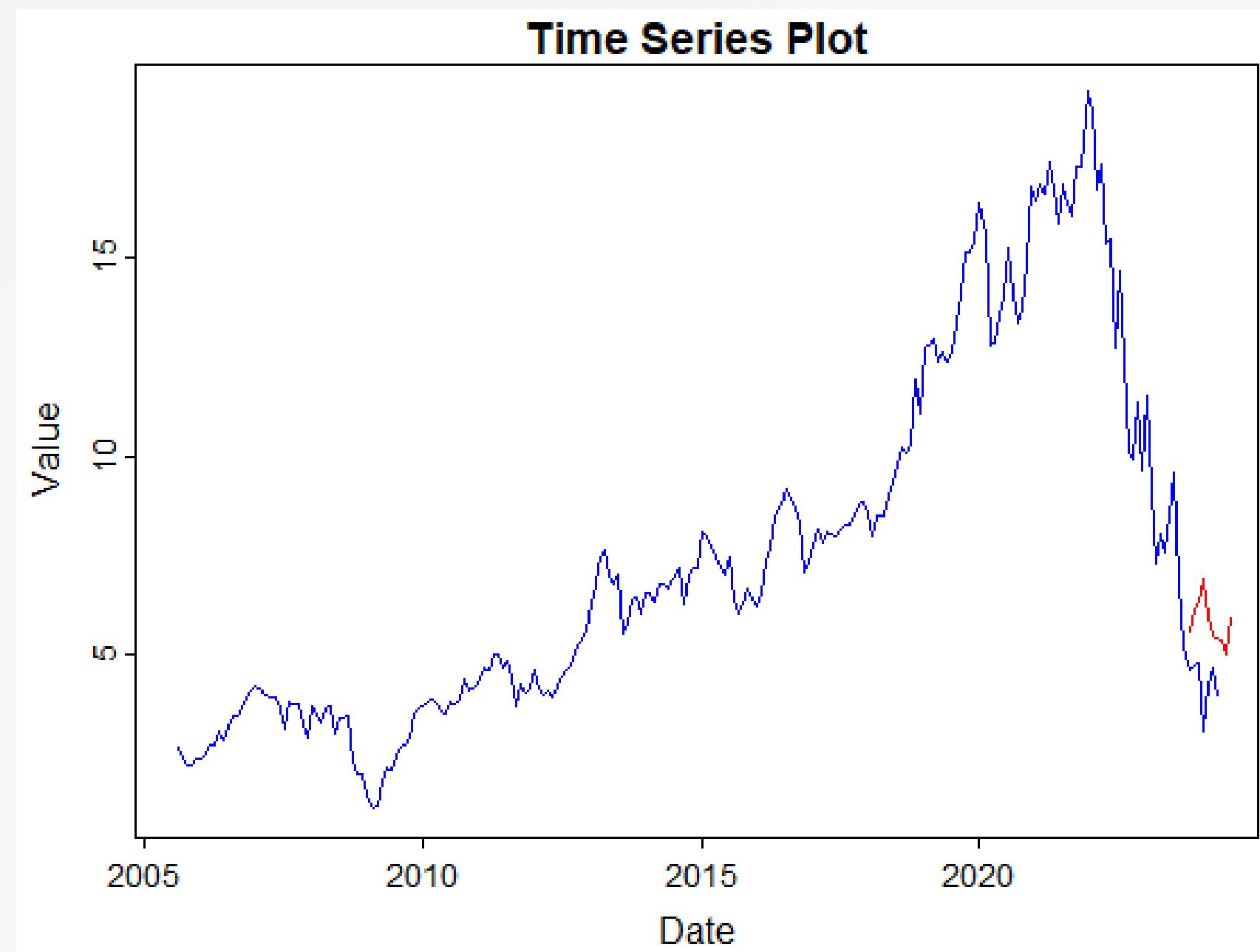
```
mpw_arima <- sarima(ts_mpw, p = 0, d = 1, q = 0, P = 0, D = 1, Q = 1, S = 12)
sarima_residuals <- mpw_arima$fit$residuals

#garch
garch_spec <- ugarchspec(variance.model = list(model = "sGARCH", garchorder = c(1, 1)),
                           mean.model = list(armaOrder = c(0, 0), include.mean = FALSE),
                           distribution.model = "std")
garch_fit <- ugarchfit(data = sarima_residuals, spec = garch_spec)
summary(garch_fit)
```

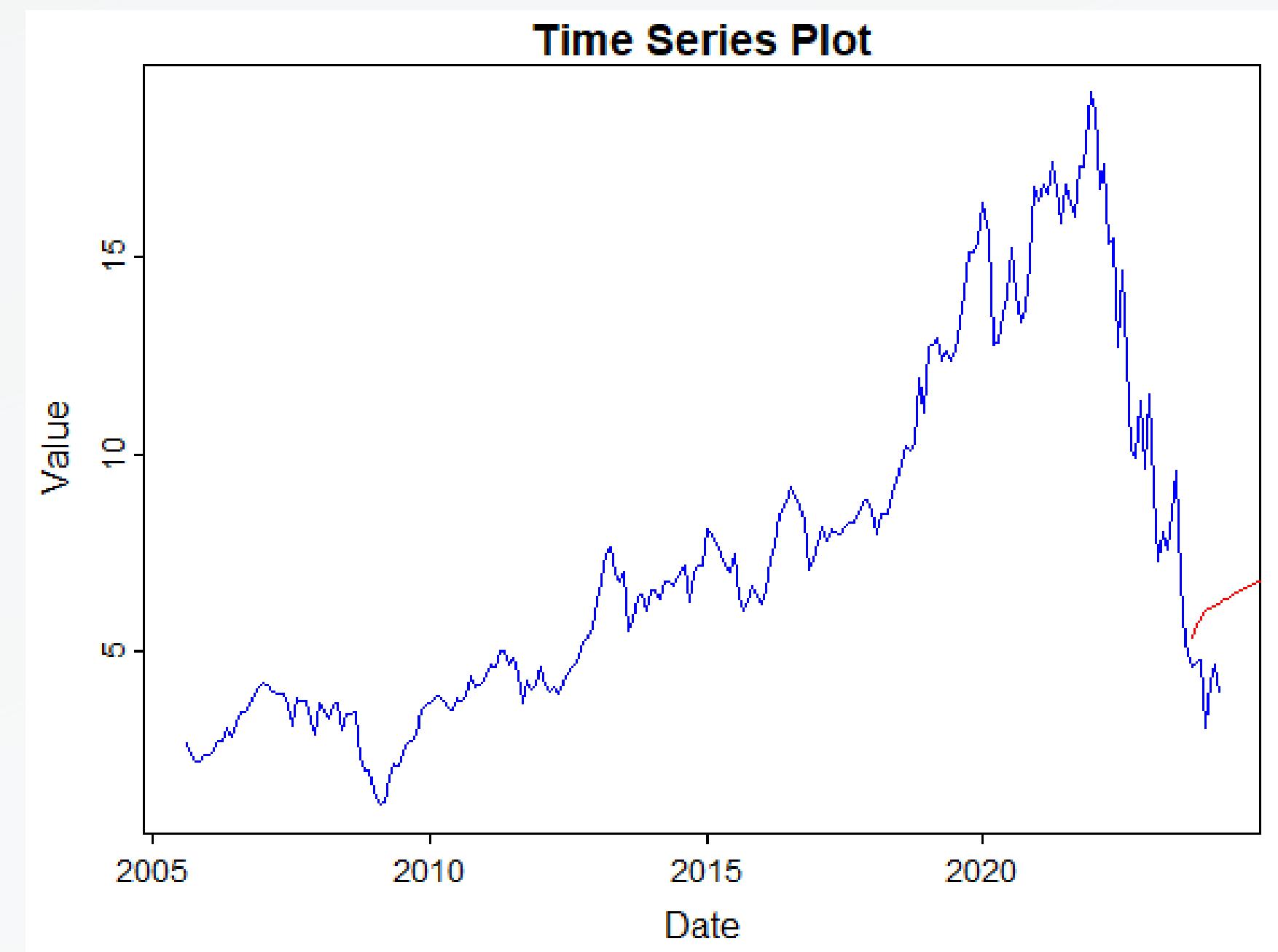
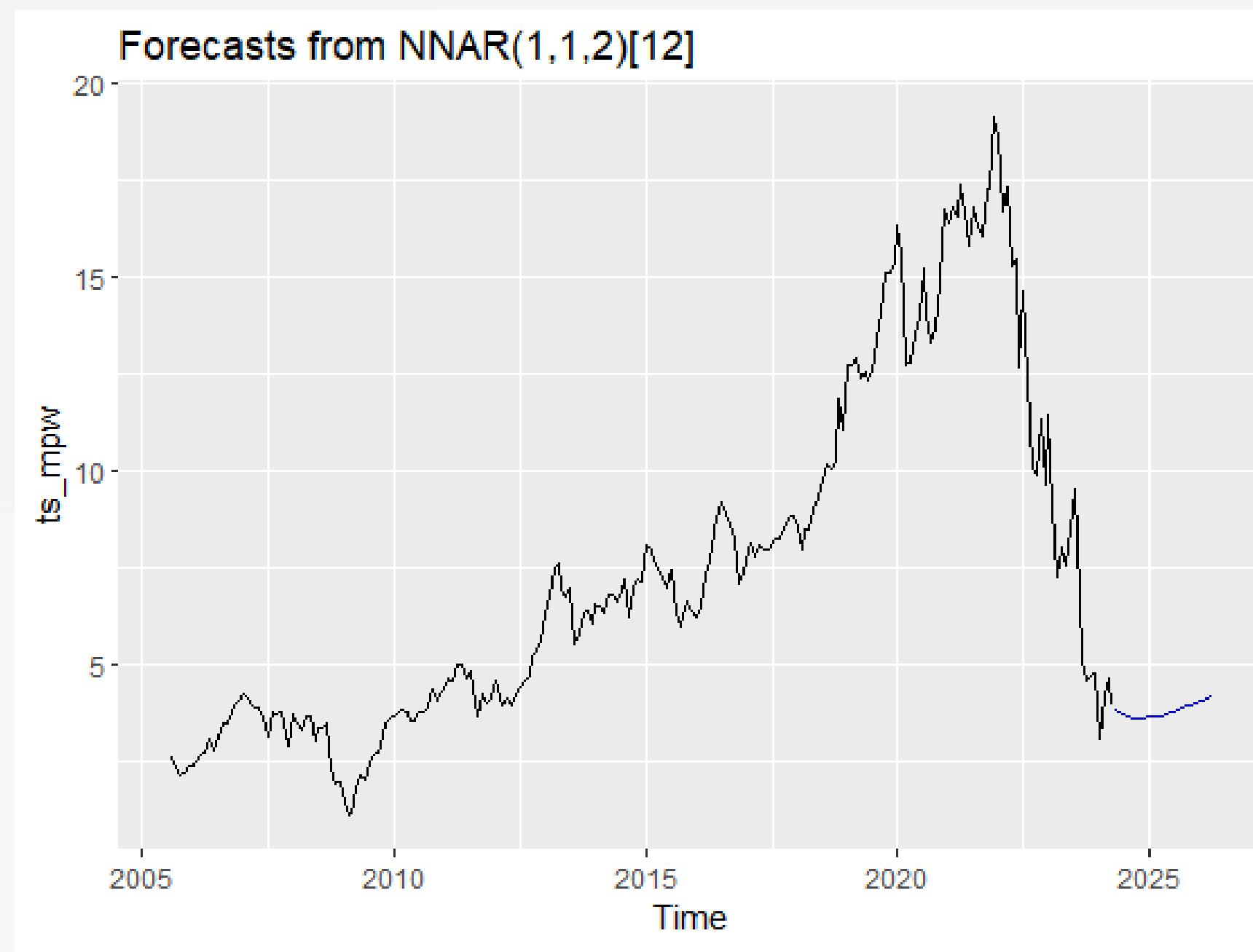
# FORECAST



# TESTING OF THE MODEL



# NEURAL NETWORK MODELS



**THANK YOU!**

