HW5

Question A

```
library(rdatamarket)
```

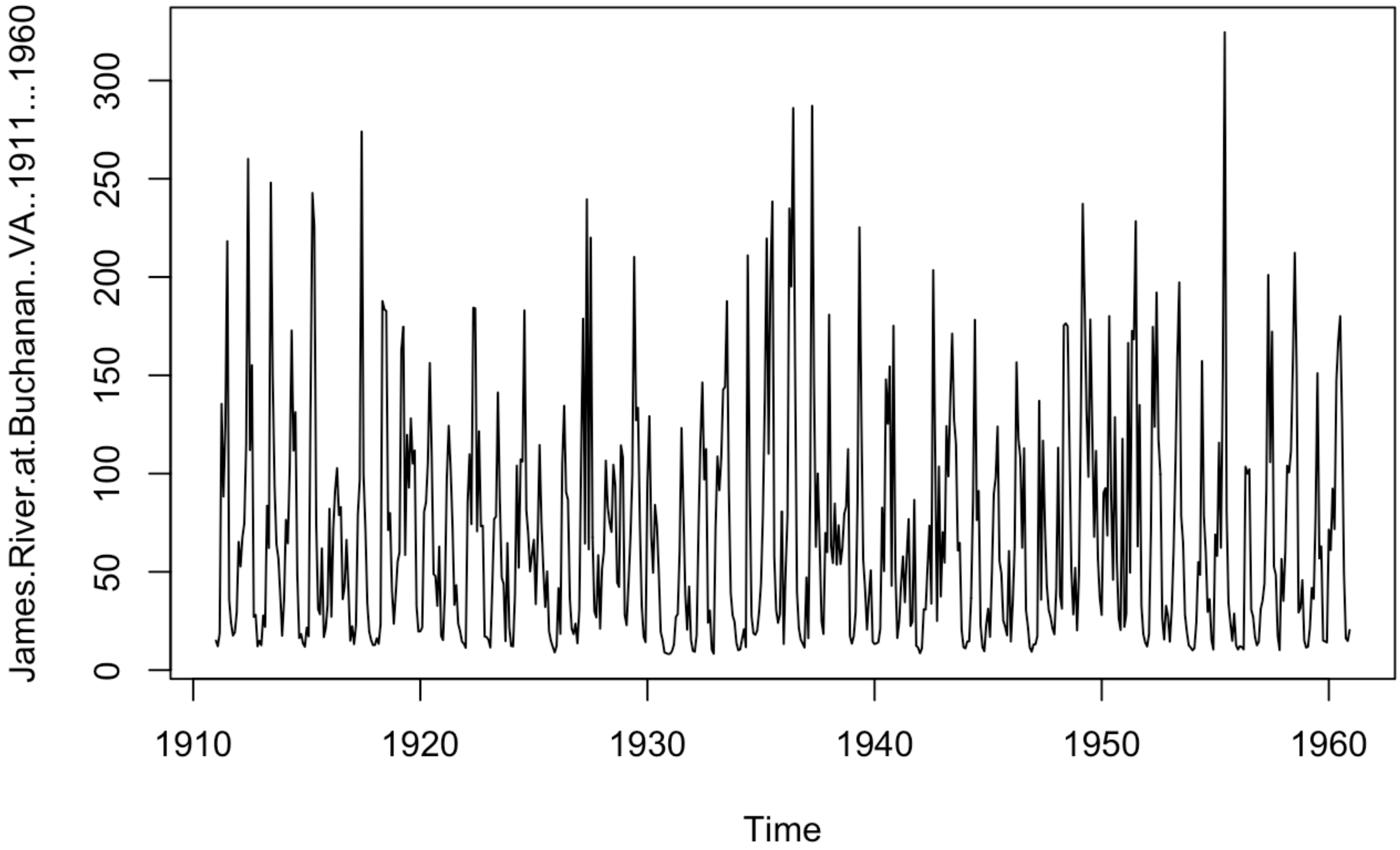
```
## Loading required package: zoo
```

```
## Warning: package 'zoo' was built under R version 3.3.2
```

```
##
## Attaching package: 'zoo'
```

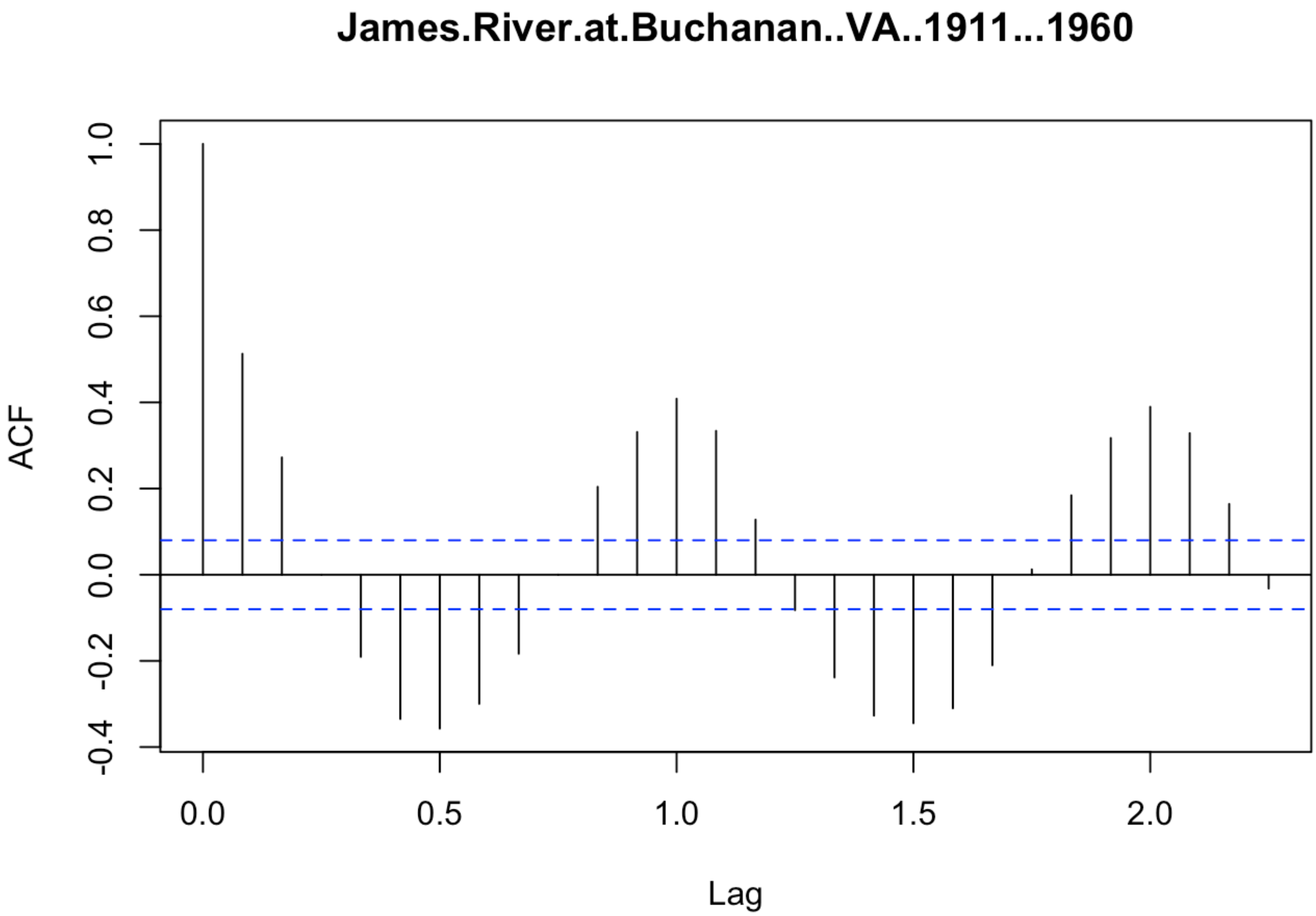
```
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
James <- dmseries("https://datamarket.com/data/set/22y3/james- river-at-buchanan-va-1
911-1960")
plot.ts(James)
```

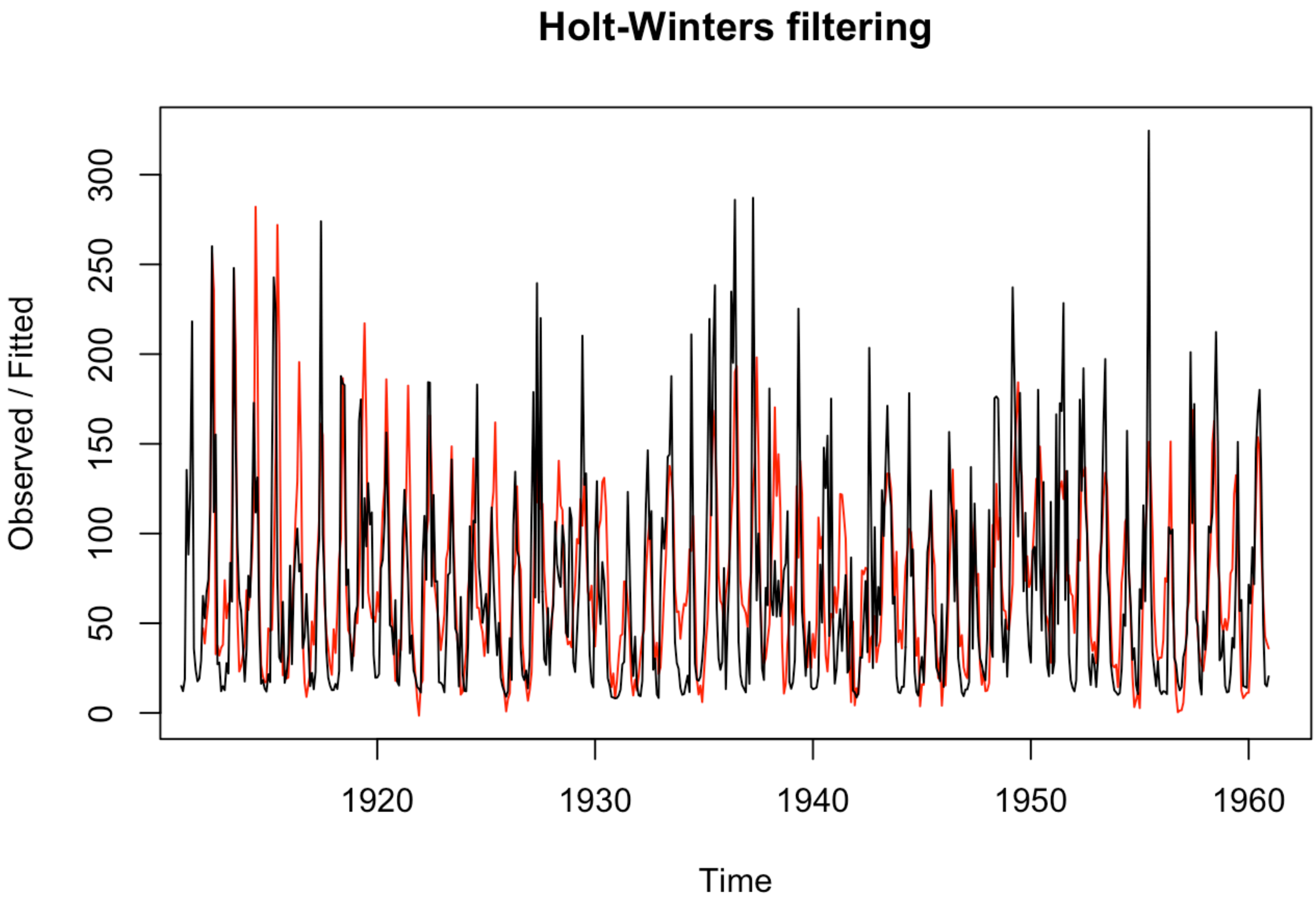


James.River.at.Buchanan..VA..1911...1960
0
50
100
150
200
250
300
1910
1920
1930
1940
1950
1960
Time

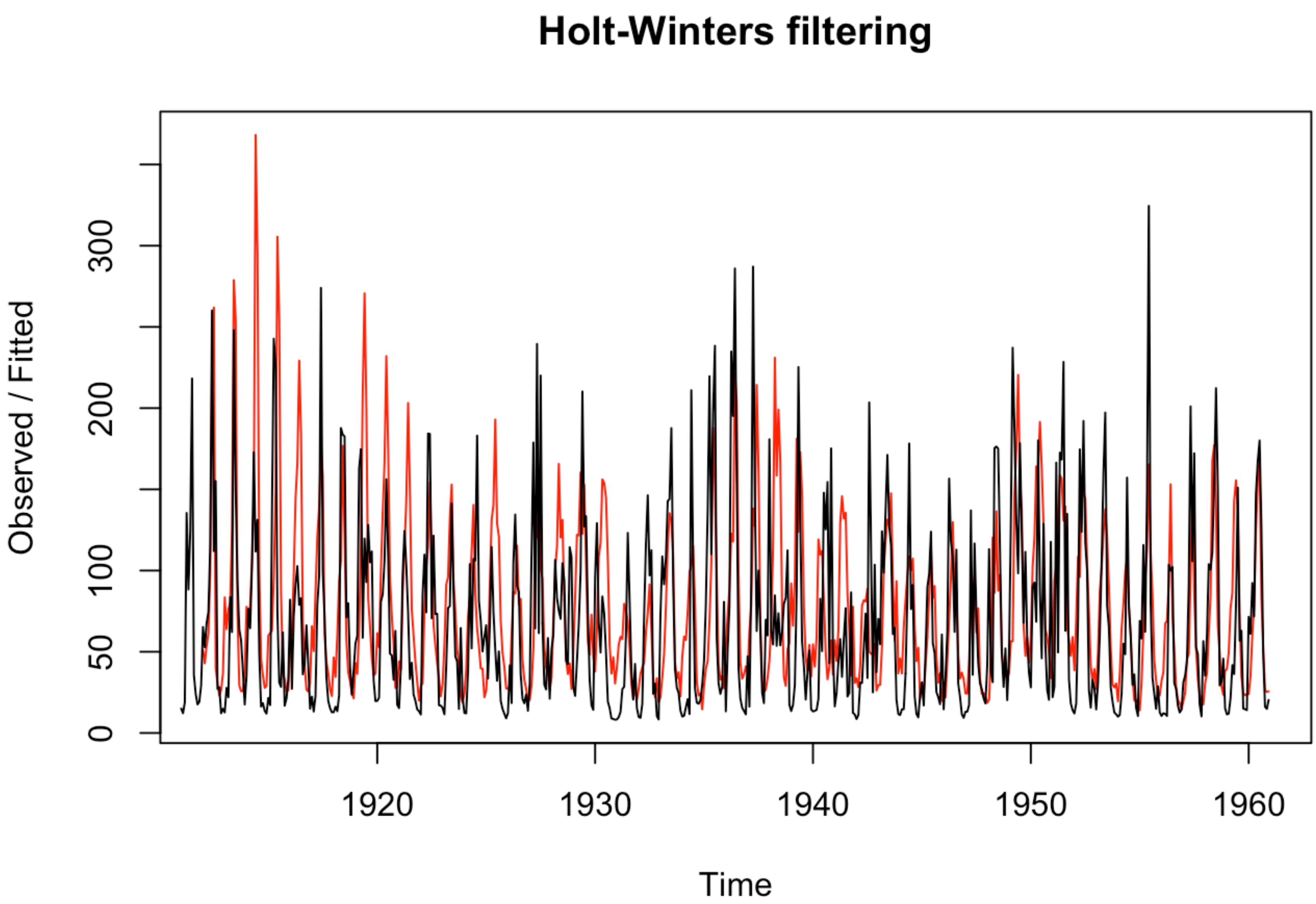

```
acf(James)
```




```
James_Hw <- HoltWinters(James)
plot(James_Hw)
```




```
James_Hw_multi <- HoltWinters(James,seasonal = c("multiplicative"))
plot(James_Hw_multi)
```



There exist significant auto correlation, however it is neither negative nor positive since it is sinusodial along zero. this sinusodial wave is indicative of seasonality. Multiplicative is better.

Question B

```
x1 <- sin(pi*1:200*1/50)
x2 <- sin(pi*1:200*1/10)
x3 <- sin(pi*1:200*1/5)


par(mfrow=c(2,2))
plot.ts(x1, ylim=c(-10,10))
plot.ts(x2, ylim=c(-10,10))
plot.ts(x3, ylim=c(-10,10))
plot.ts(x, ylim=c(-10,10), main="sum")
```

```
## Error in NCOL(x): object 'x' not found
```

```
P1 <- abs(fft(x)/50)^2
```

```
## Error in fft(x): object 'x' not found
```

```
P2 <- abs(fft(x)/10)^2
```

```
## Error in fft(x): object 'x' not found
```

```
P3 <- abs(fft(x)/5)^2
```

```
## Error in fft(x): object 'x' not found
```

```
Fr <- (0:199)/200
plot(Fr, P1, type="o", xlab="frequency", ylab="periodogram")
```

```
## Error in xy.coords(x, y, xlabel, ylabel, log): object 'P1' not found
```

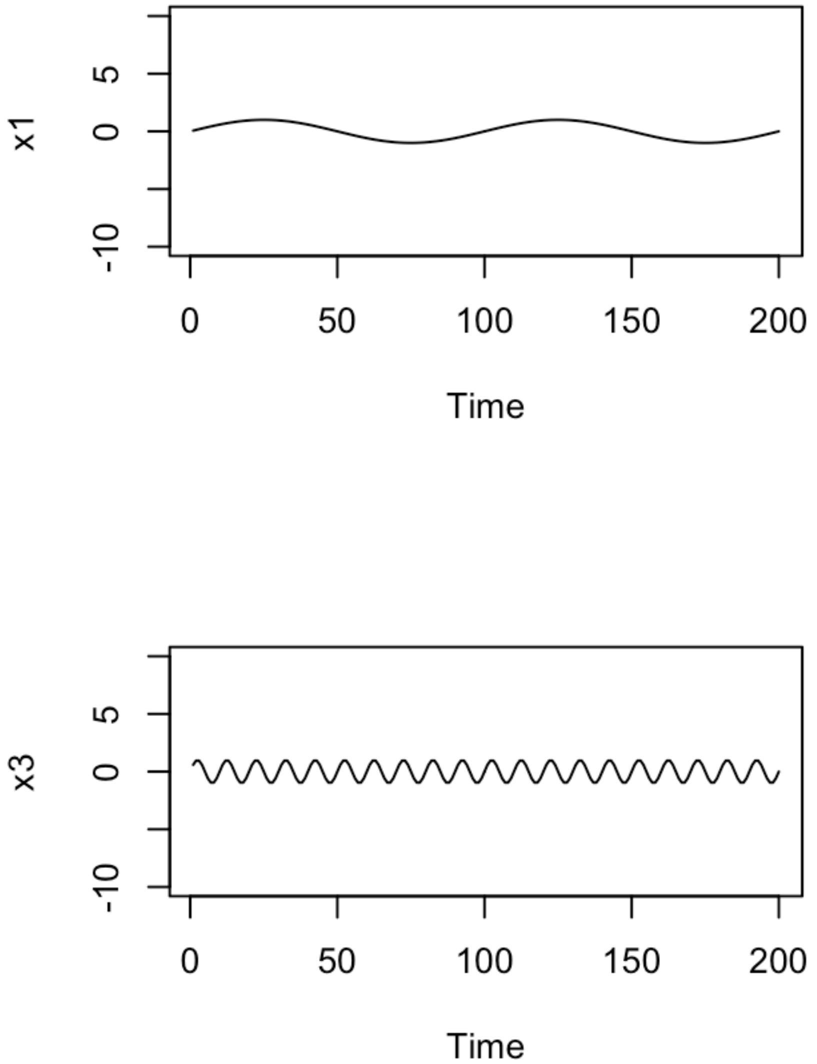
```
plot(Fr, P2, type="o", xlab="frequency", ylab="periodogram")
```

```
## Error in xy.coords(x, y, xlabel, ylabel, log): object 'P2' not found
```

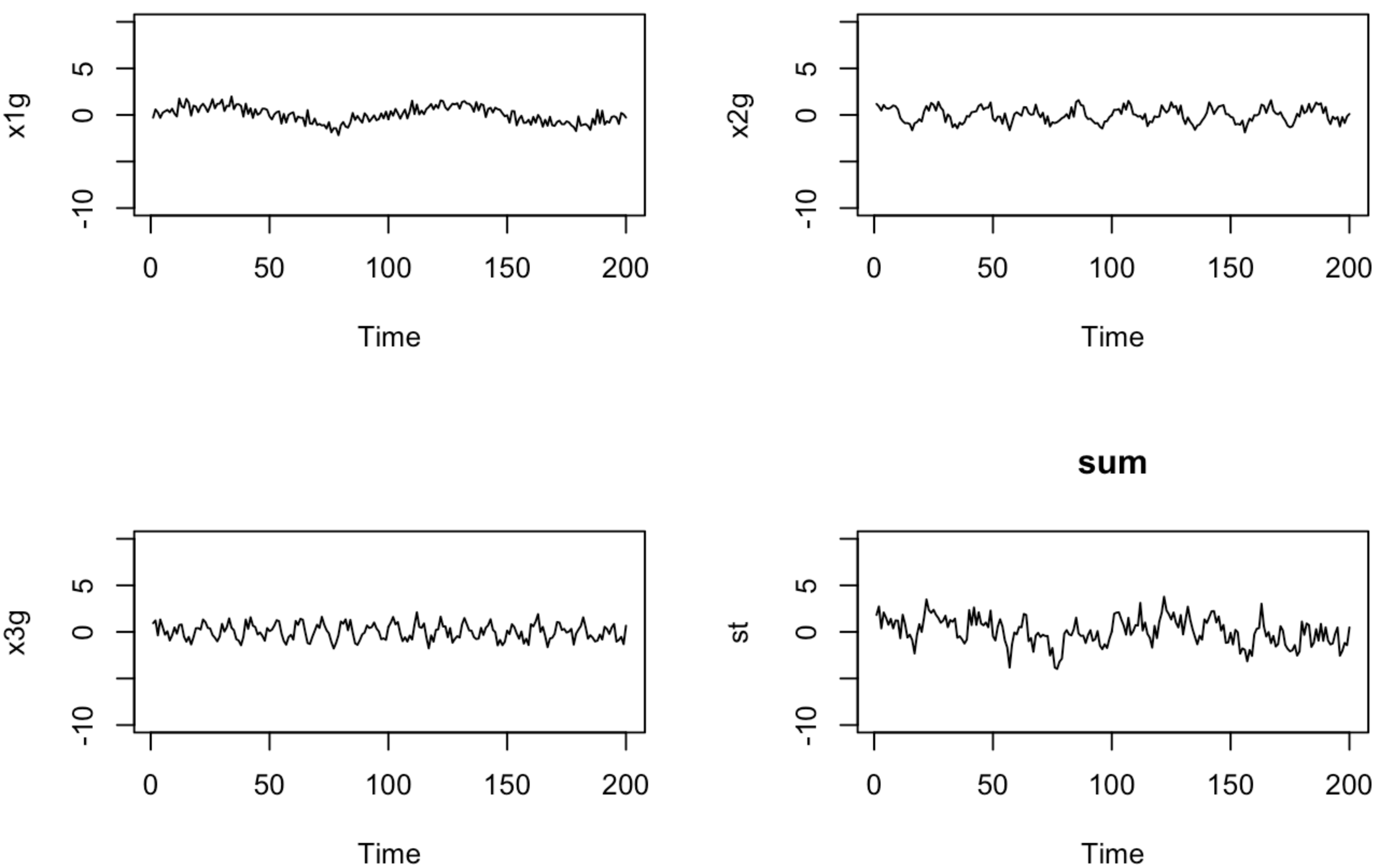
```
plot(Fr, P3, type="o", xlab="frequency", ylab="periodogram")
```

```
## Error in xy.coords(x, y, xlabel, ylabel, log): object 'P3' not found
```

```
x1g <- x1 + rnorm(200,sd=0.5)
x2g <- x2 + rnorm(200,sd=0.5)
x3g <- x3 + rnorm(200,sd=0.5)
st <- x1g + x2g + x3g

par(mfrow=c(2,2))
```



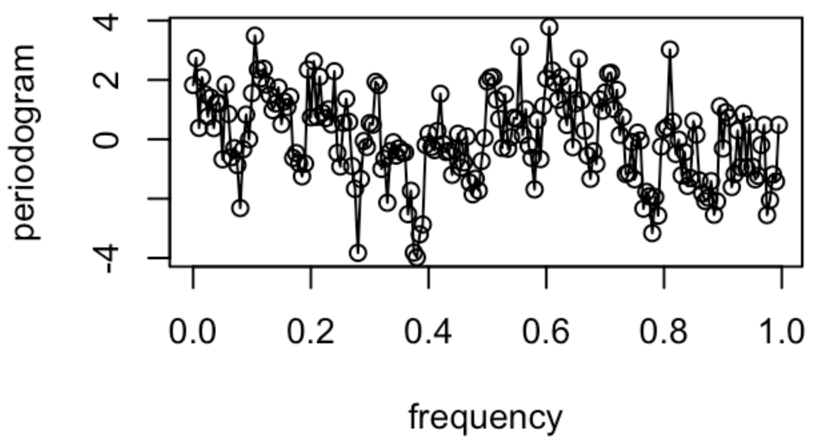

```
plot.ts(x1g, ylim=c(-10,10))
plot.ts(x2g, ylim=c(-10,10))
plot.ts(x3g, ylim=c(-10,10))
plot.ts(st, ylim=c(-10,10), main="sum")
```




```
st <- abs(fft(x)/200)^2
```

```
## Error in fft(x): object 'x' not found
```

```
Fr <- 0:199/200
plot(Fr, st, type="o", xlab="frequency", ylab="periodogram")
```



In

spectrum graph p1 I see a periodgram of 0 to 4. In the spectrum graph p2 I see a periodogram of 0 to 100. In the spectrum graph p3 i see a periodgram of 0 to 1.0. theses numbers are indicate at the same frequency for each graph. A large periodogram indicates relative more importance for a frequency in explaining oscillation. This differences are expected since we are changing the wave number by x the division of pi. For the plot of st we can see that the periodgram has decreased values at the following frequency mentioned above, specfically a value .2. Indicating less cycles needed.

Question C

```
library(zoo)
library(xts)
library(astsa)
```

```
## Warning: package 'astsa' was built under R version 3.3.2
```

```
library(forecast)
```

```
## Warning: package 'forecast' was built under R version 3.3.2
```

```
##
## Attaching package: 'forecast'
```

```
## The following object is masked from 'package:astsa':
##
##     gas
```

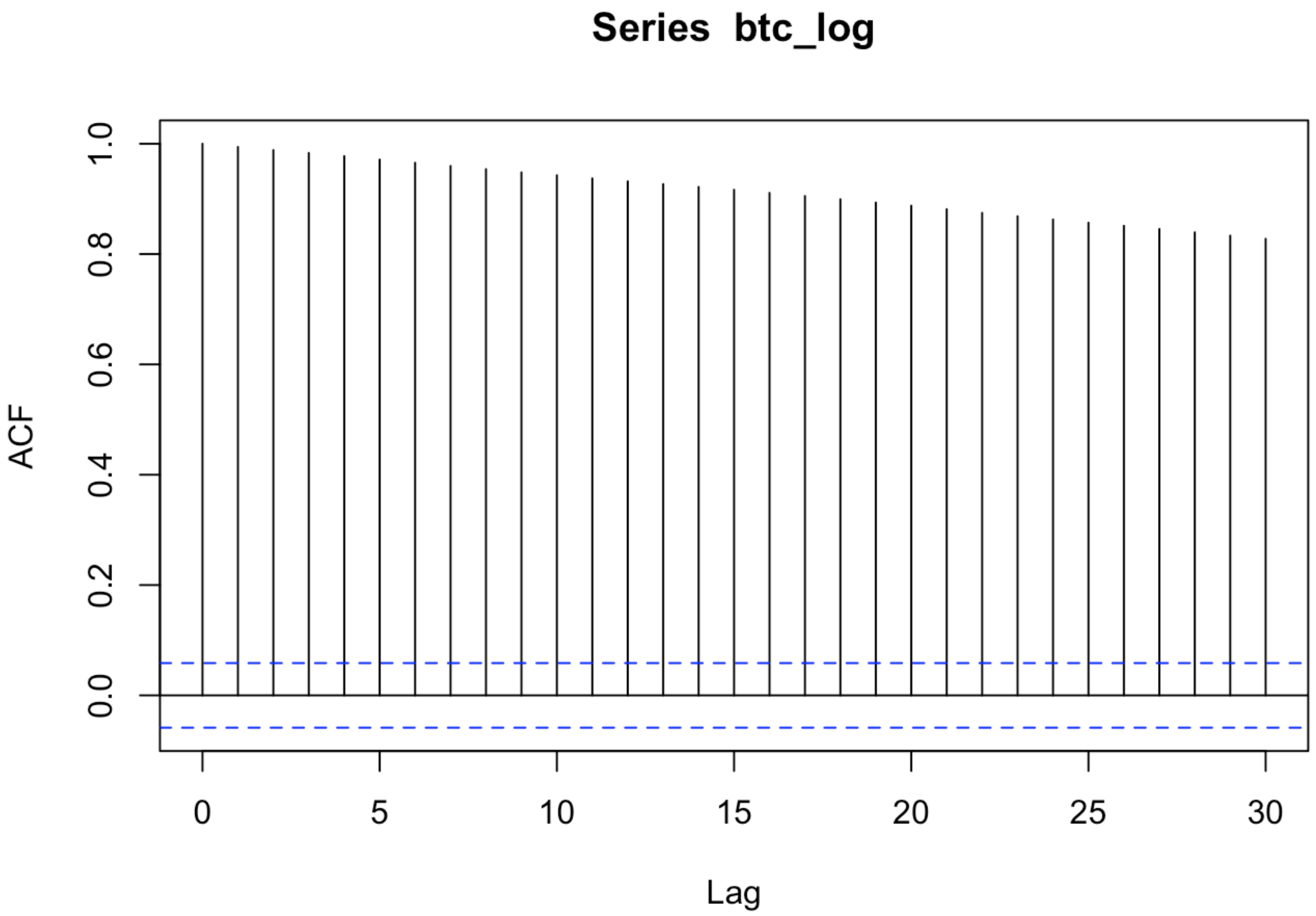
```
library(dplR)
```

```
## Warning: package 'dplR' was built under R version 3.3.2
```

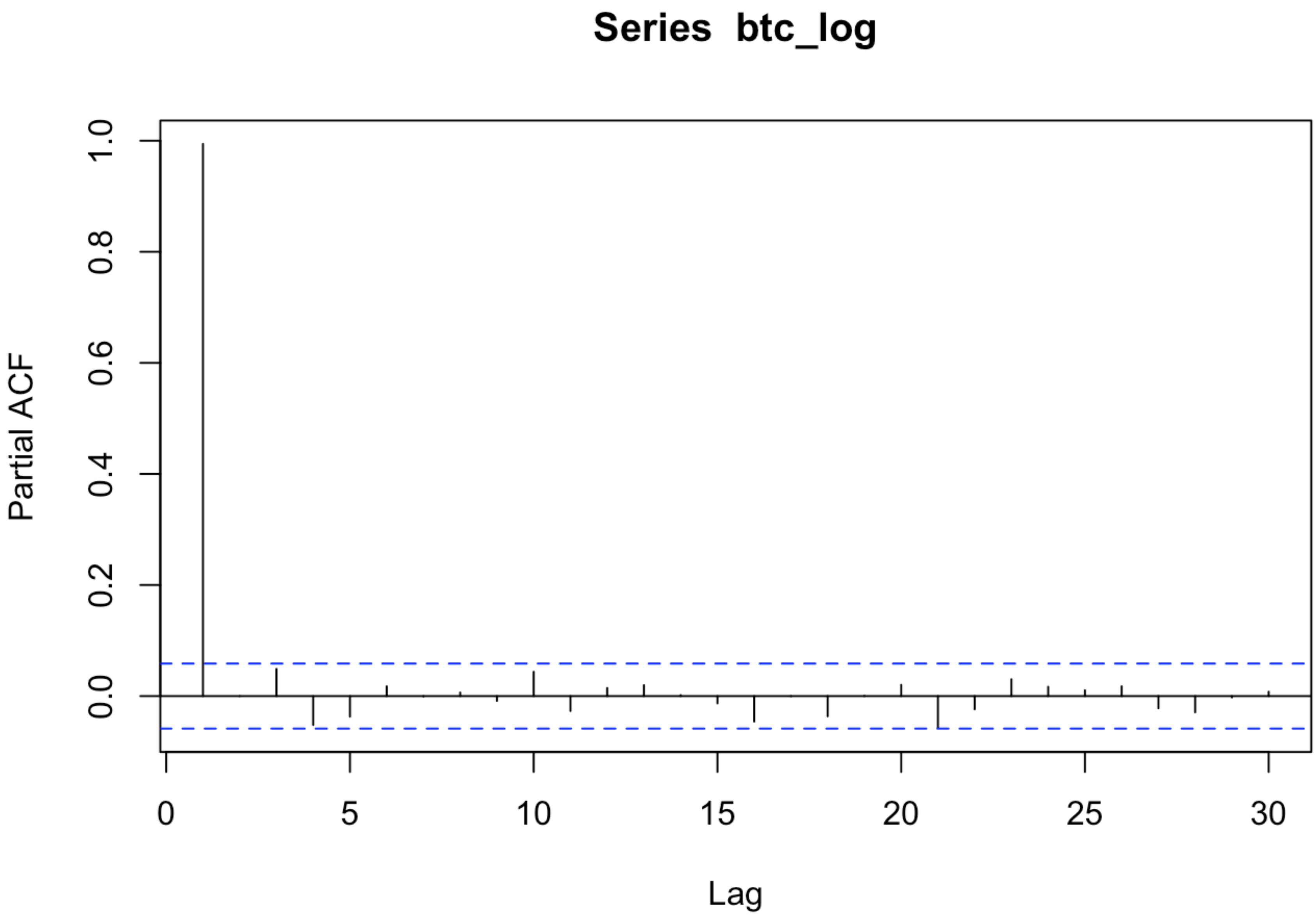
```
bit <- read.csv("~/Downloads/HW1-data-coindesk.csv")
bit$Date <- as.Date(bit$Date, #our dataset
                    format="%m/%e/%y %H:%M")
bit_zoo <- zoo(x = bit$Close.Price,
               order.by = bit$Date)
bit_xts <- as.xts(bit_zoo)
btc_log <- log(bit_xts)
btc_diff <- diff(btc_log)[-1,]
btc_diff_diff <- diff(btc_diff)[-1,]
bit_log_num <- as.numeric(bit_log)
```

```
## Error in eval(expr, envir, enclos): object 'bit_log' not found
```

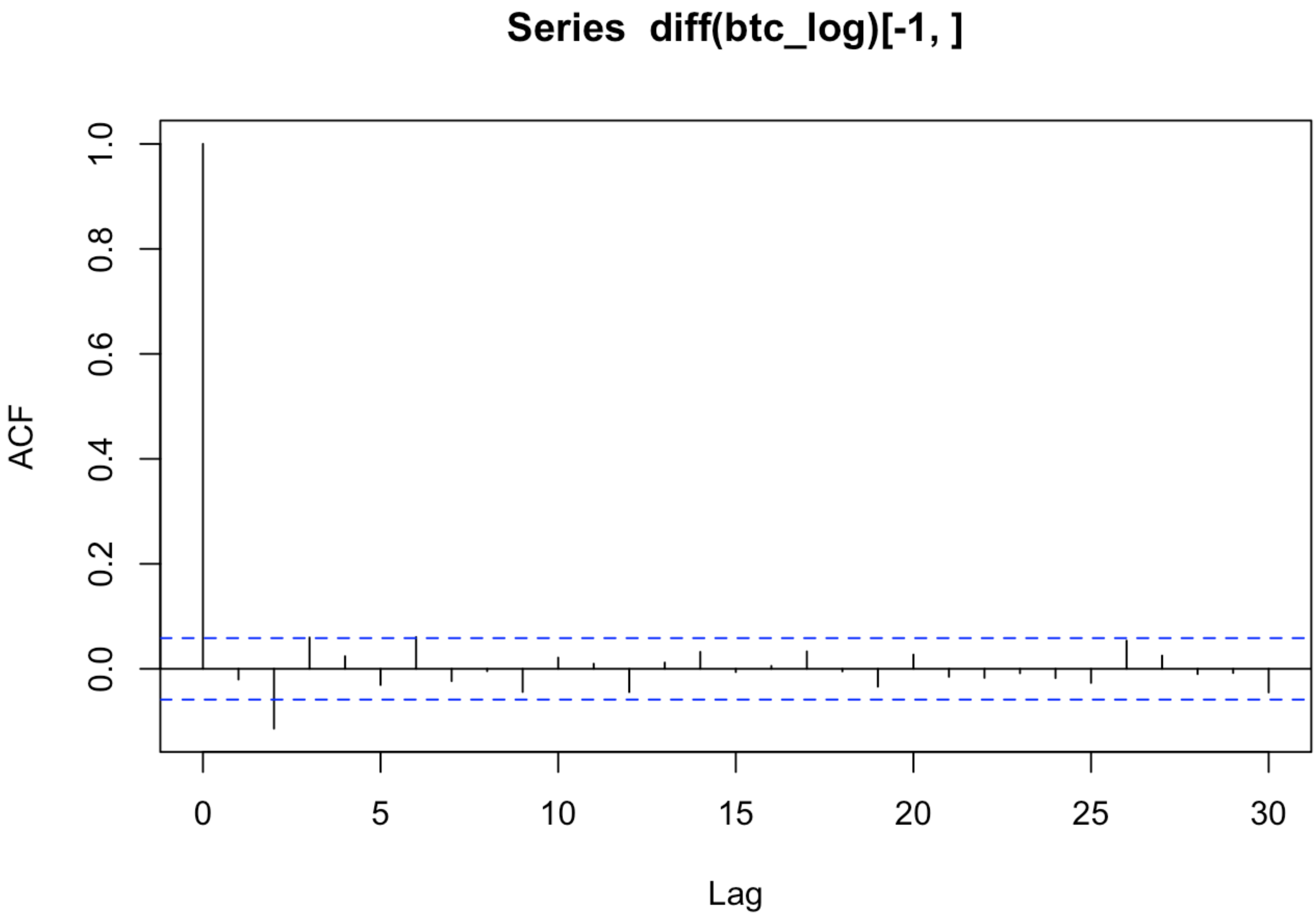
```
btc_acf <- acf(btc_log)
plot(btc_acf)
```



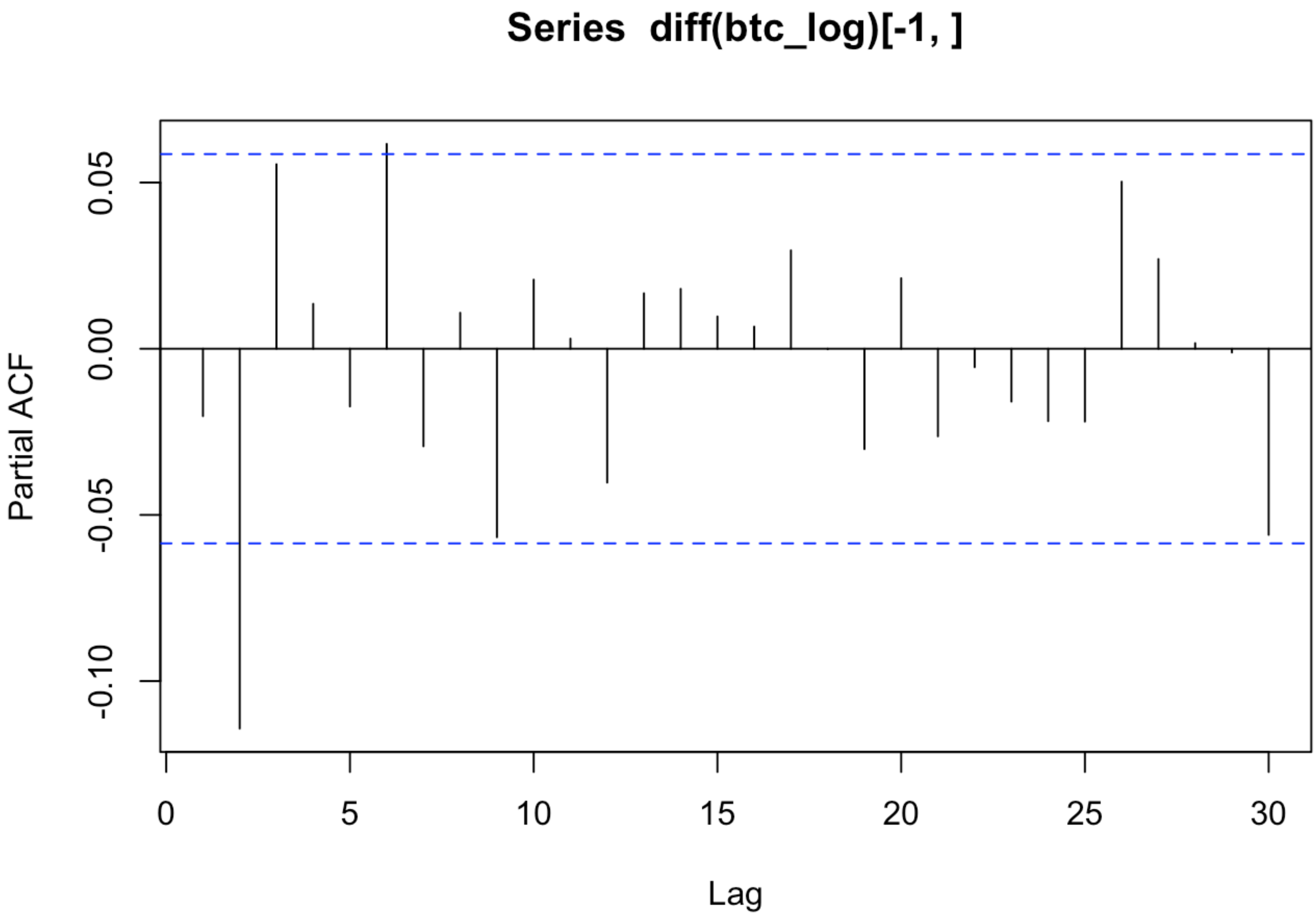

```
btc_pacf <- pacf(btc_log)
plot(btc_pacf)
```



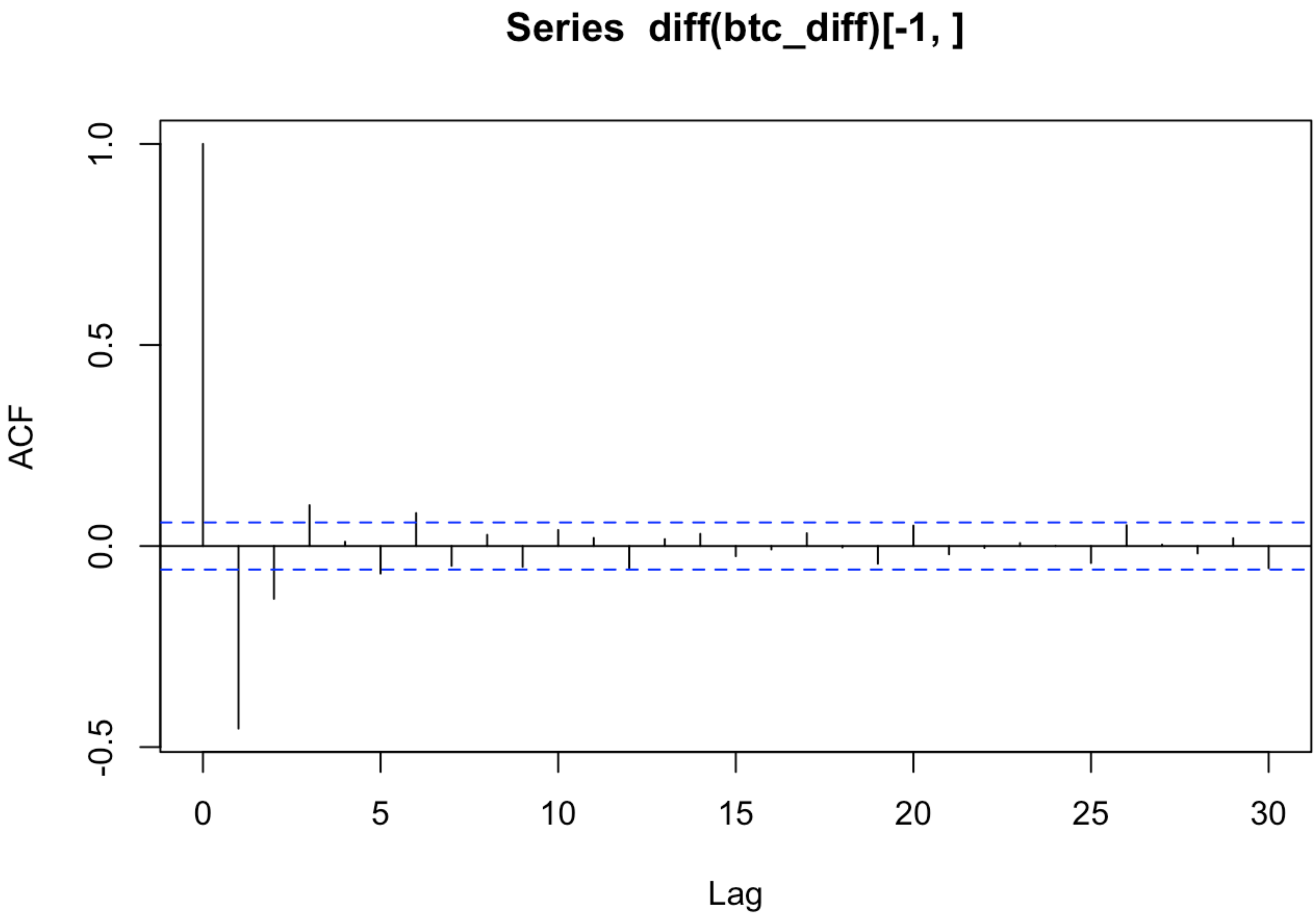

```
btc_diff_acf <- acf(diff(btc_log)[-1,])
plot(btc_diff_acf)
```



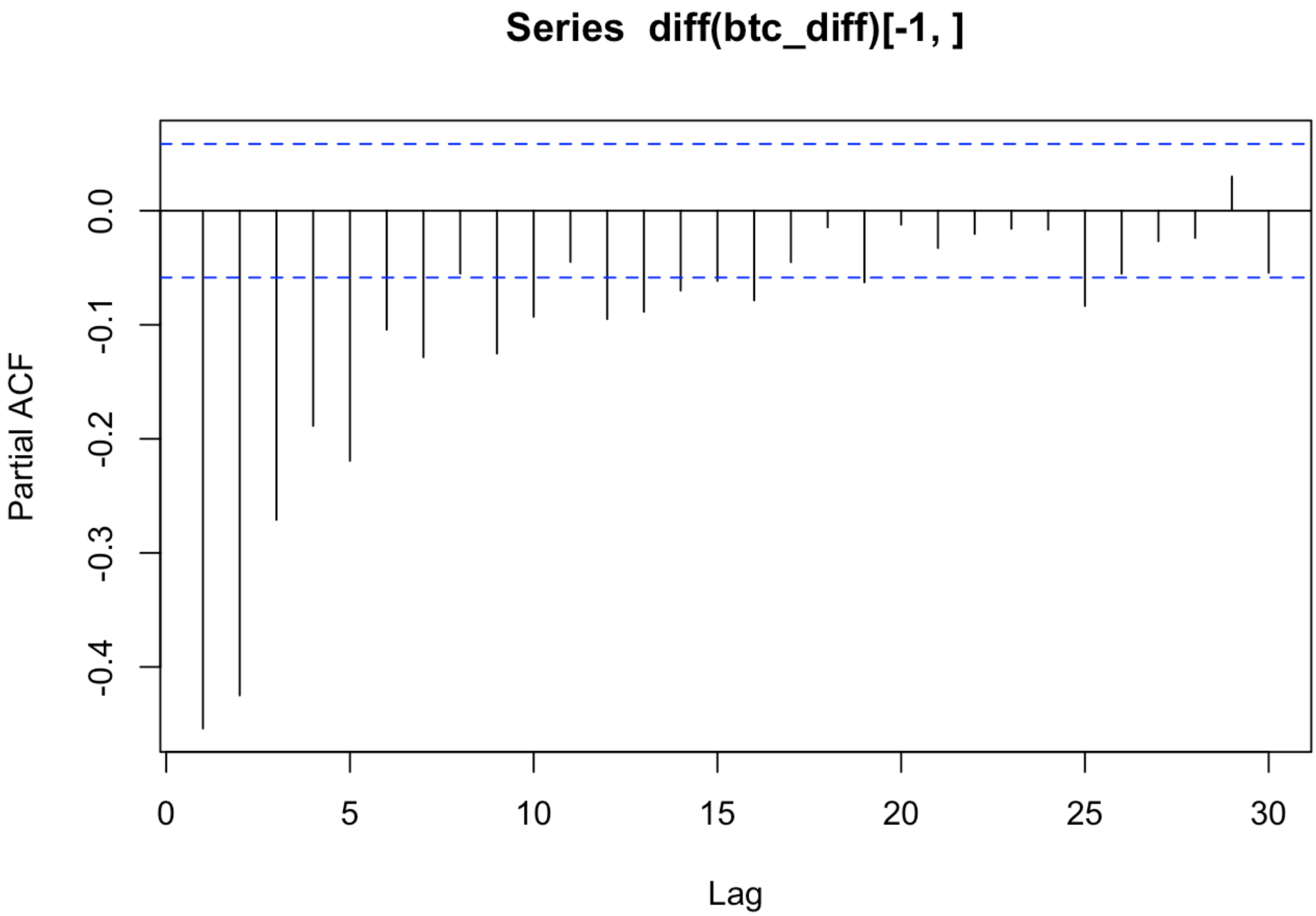

```
btc_diff_pacf <- pacf(diff(btc_log)[-1,])
plot(btc_diff_pacf)
```




```
btc_diff2_acf <- acf(diff(btc_diff)[-1,])
plot(btc_diff2_acf)
```



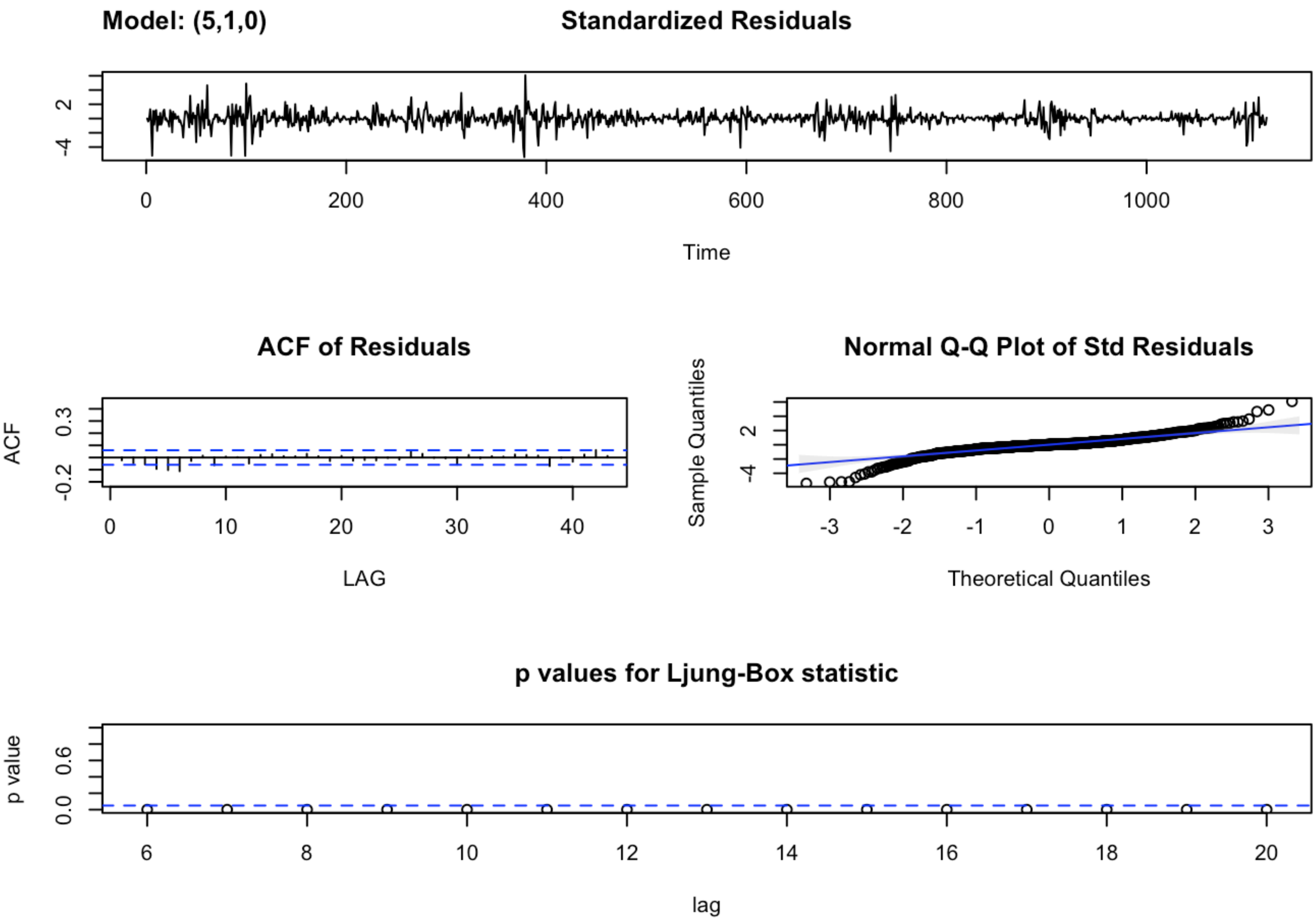

```
btc_diff2_pacf <- pacf(diff(btc_diff)[-1,])
plot(btc_diff2_pacf)
```



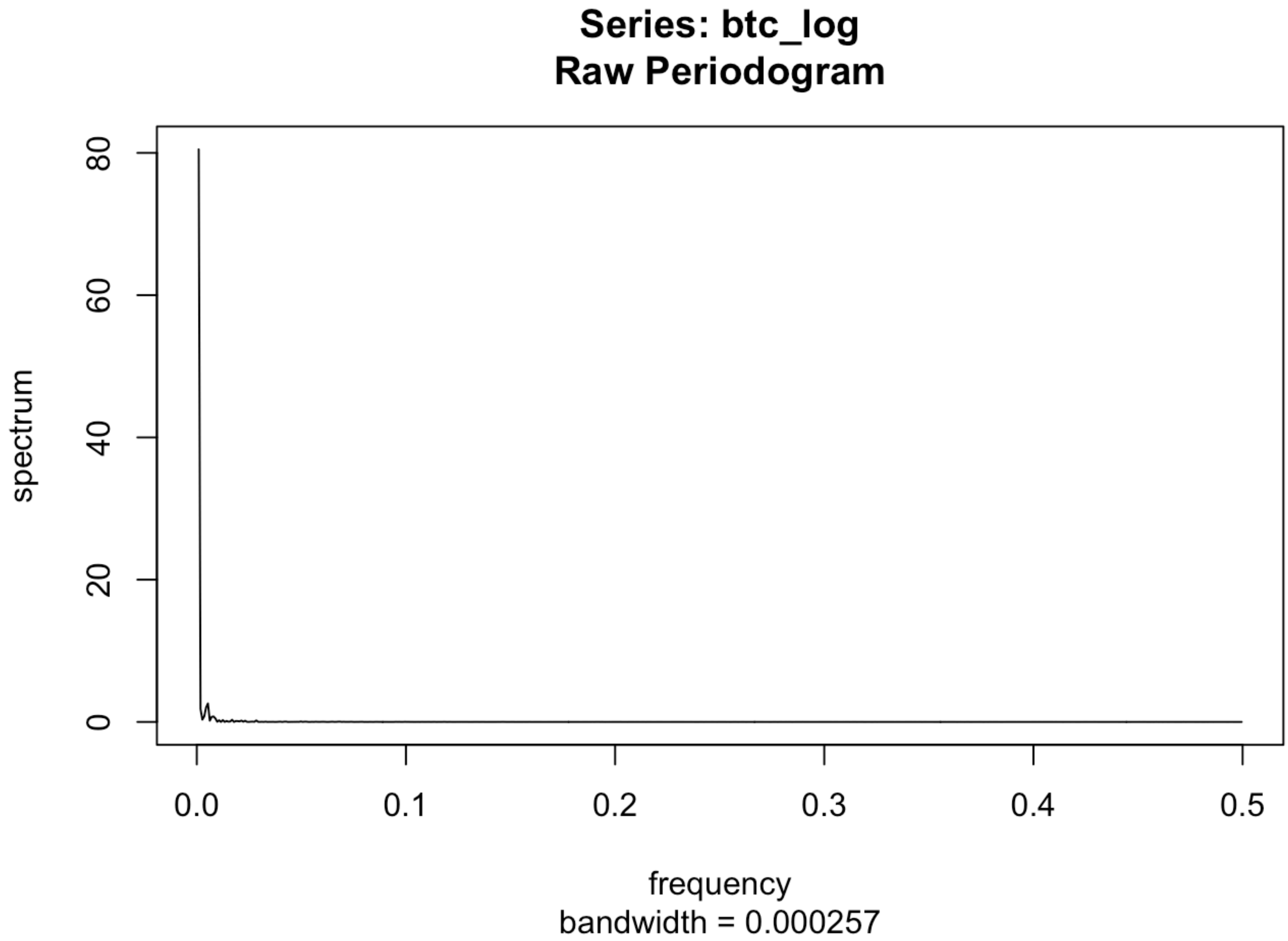

```
auto.arima(btc_diff)
```

```
## Series: btc_diff
## ARIMA(5,1,0)
##
## Coefficients:
##           ar1      ar2      ar3      ar4      ar5
##       -0.8554  -0.8058  -0.5738  -0.3718  -0.2246
## s.e.   0.0292   0.0372   0.0409   0.0374   0.0295
##
## sigma^2 estimated as 0.001362:  log likelihood=2106.18
## AIC=-4200.36   AICc=-4200.29   BIC=-4170.24
```

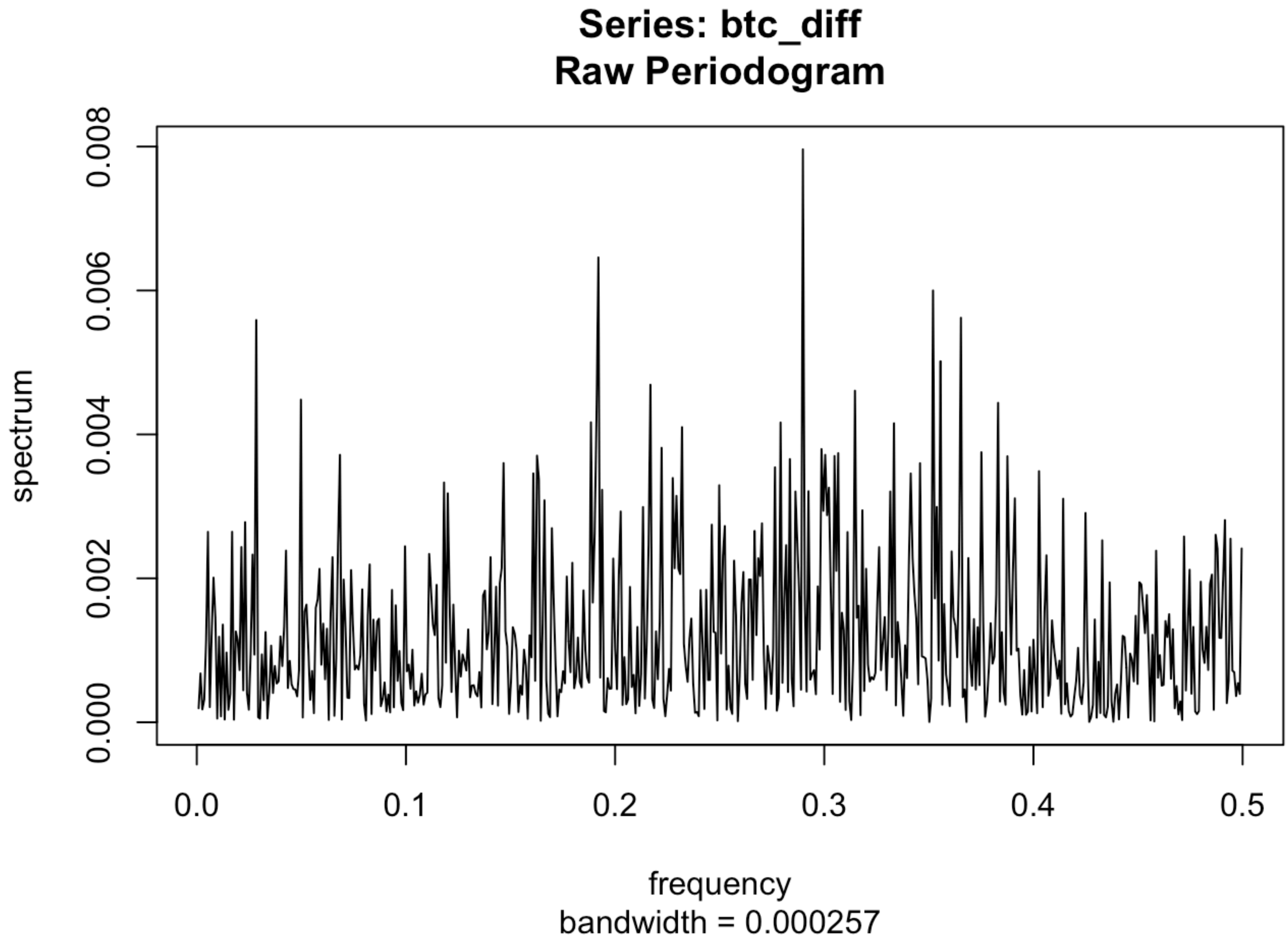
```
btc_ar_1 <- sarima(btc_diff,5,1,0,details = FALSE)
```



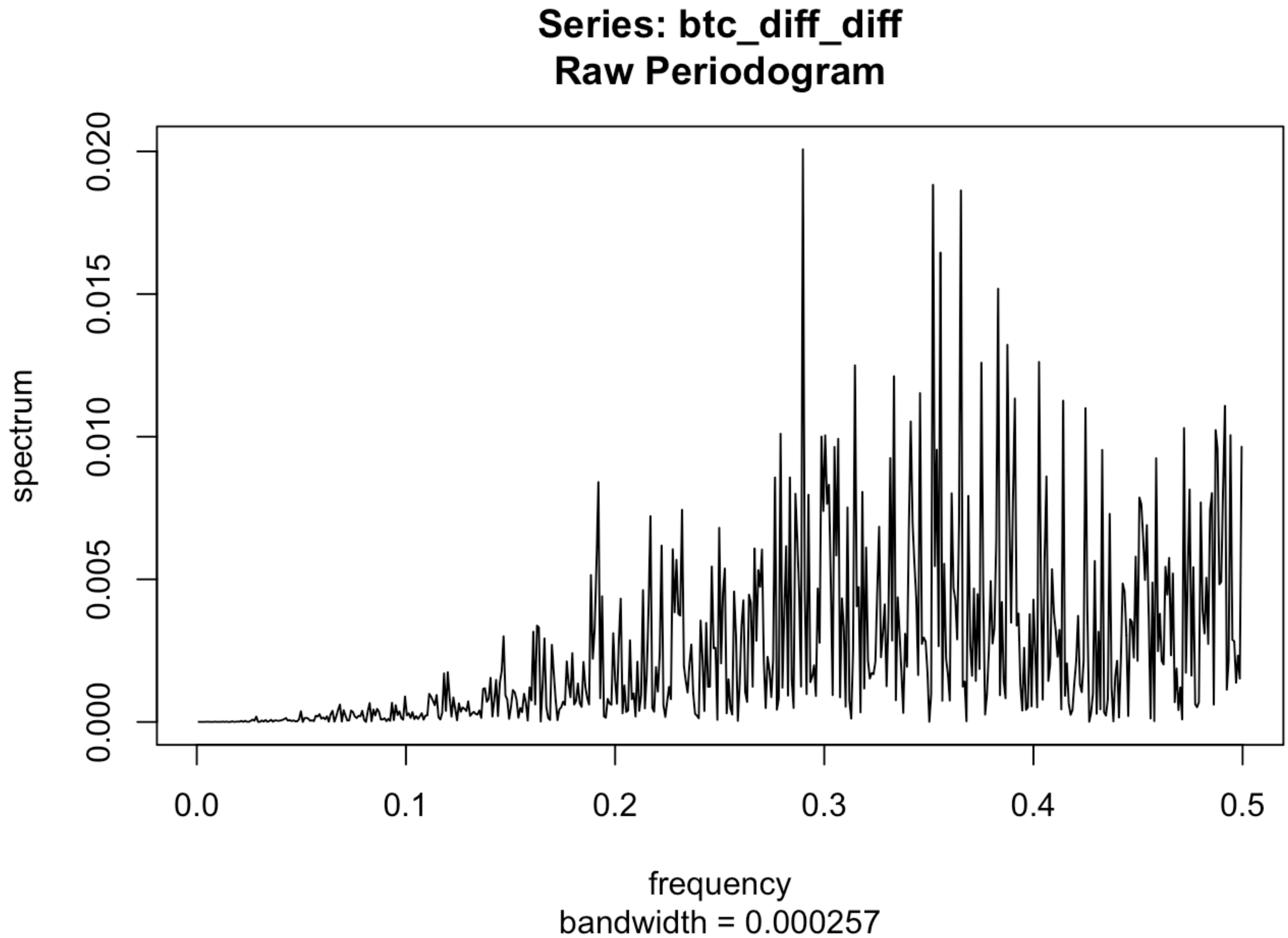

```
btc_log_spec <- spec.pgram(btc_log, taper=0, log="no")
```



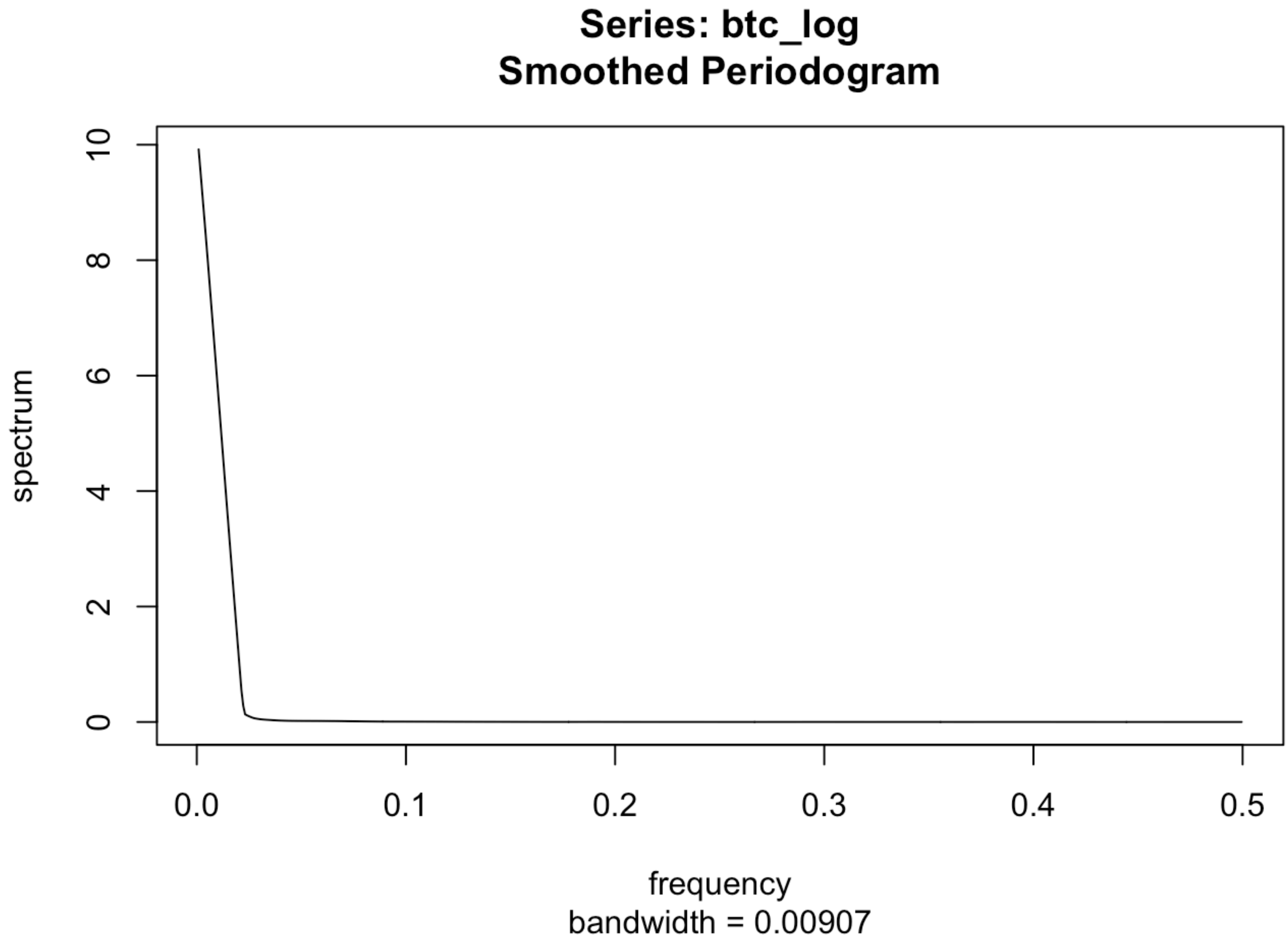

```
btc_diff_spec <- spec.pgram(btc_diff, taper=0, log="no")
```



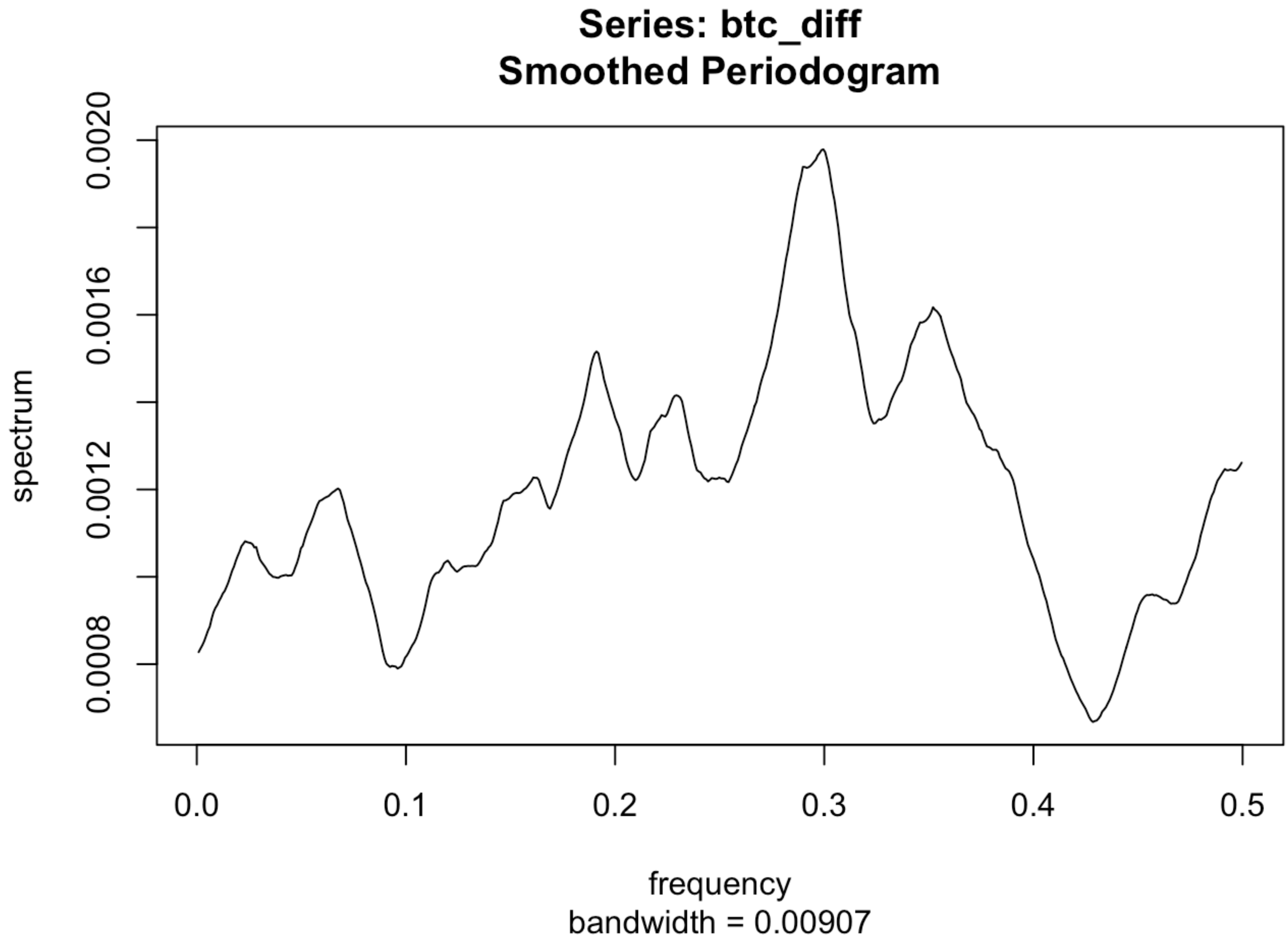

```
btc_diff_diff_spec <- spec.pgram(btc_diff_diff, taper=0, log="no")
```



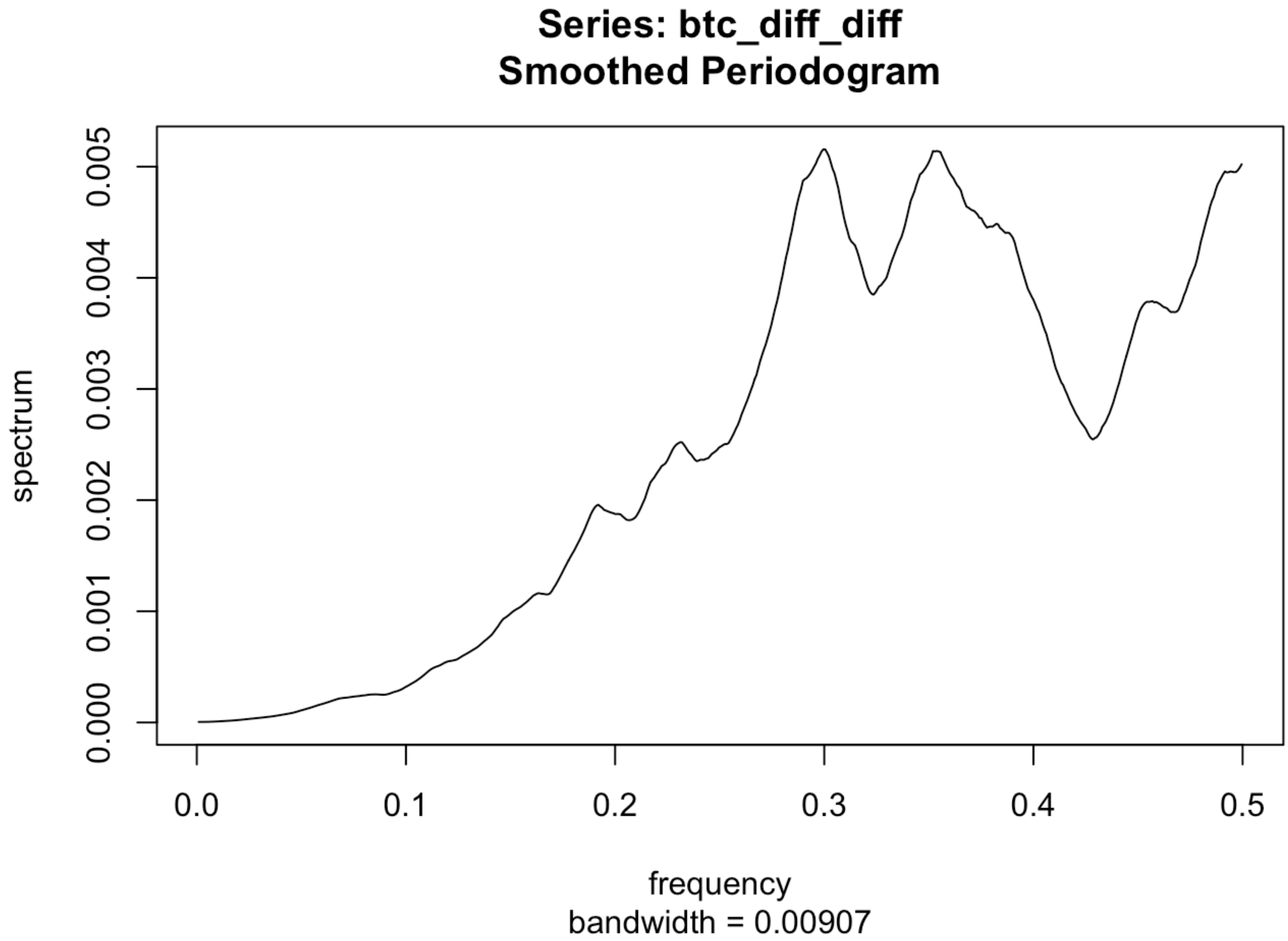

```
btc_log_spec <- spec.pgram(btc_log, taper=0, log="no",kernel=kernel("daniell", c(12,1
2)))
```




```
btc_diff_spec <- spec.pgram(btc_diff, taper=0, log="no",kernel=kernel("daniell", c(12
,12)))
```




```
btc_diff_diff_spec <- spec.pgram(btc_diff_diff, taper=0, log="no",kernel=kernel("dani
ell", c(12,12)))
```




```
str(bit_log_num)
```

```
## Error in str(bit_log_num): object 'bit_log_num' not found
```

```
wave.out <- morlet(y1 = bit_log_num, x1 = as.numeric(seq_along(bit_log_num)), dj = 0.
25, siglvl = 0.95)
```

```
## Error in morlet(y1 = bit_log_num, x1 = as.numeric(seq_along(bit_log_num)), : objec
t 'bit_log_num' not found
```

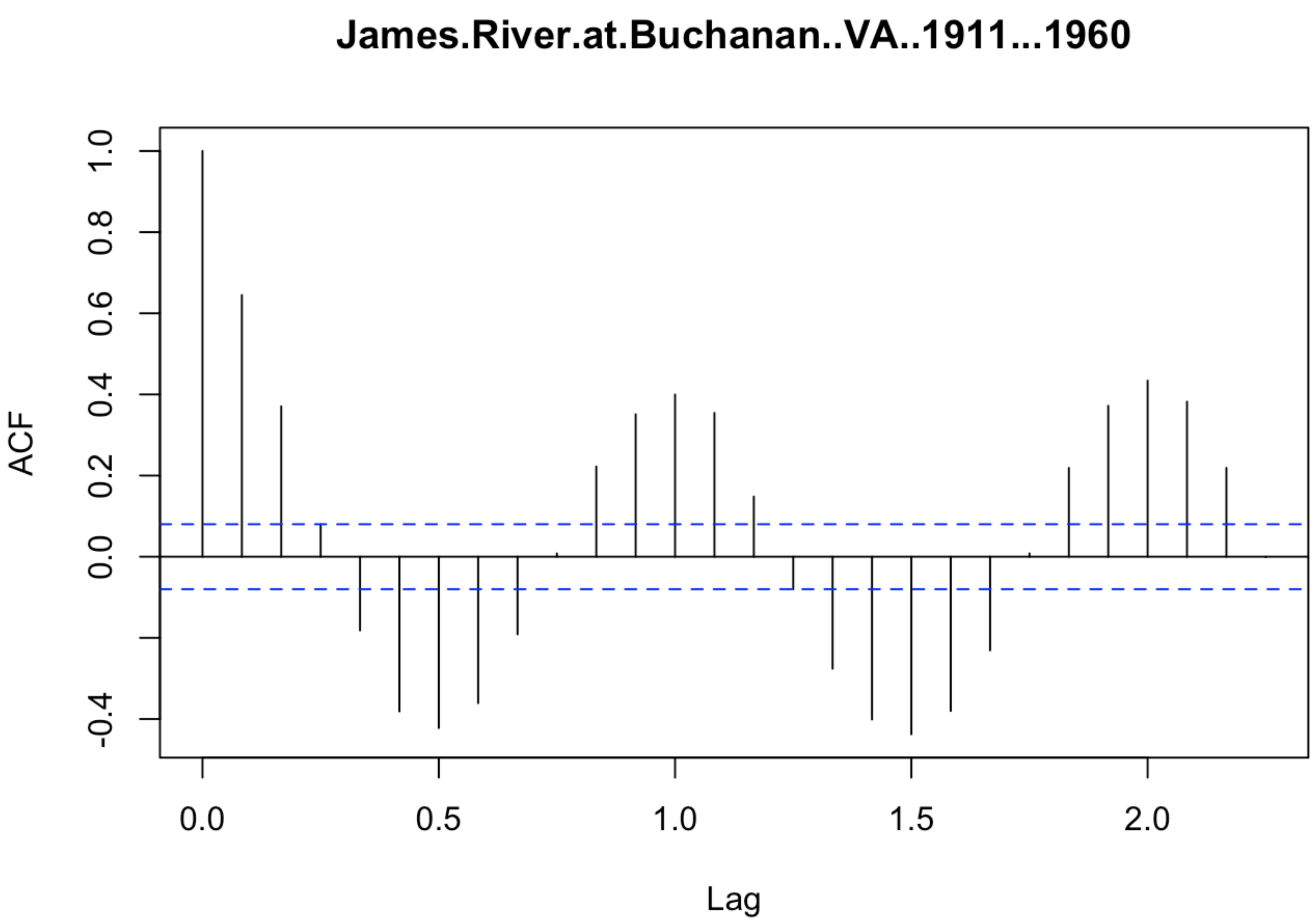
```
plot(wave.out)
```

```
## Error in plot(wave.out): object 'wave.out' not found
```

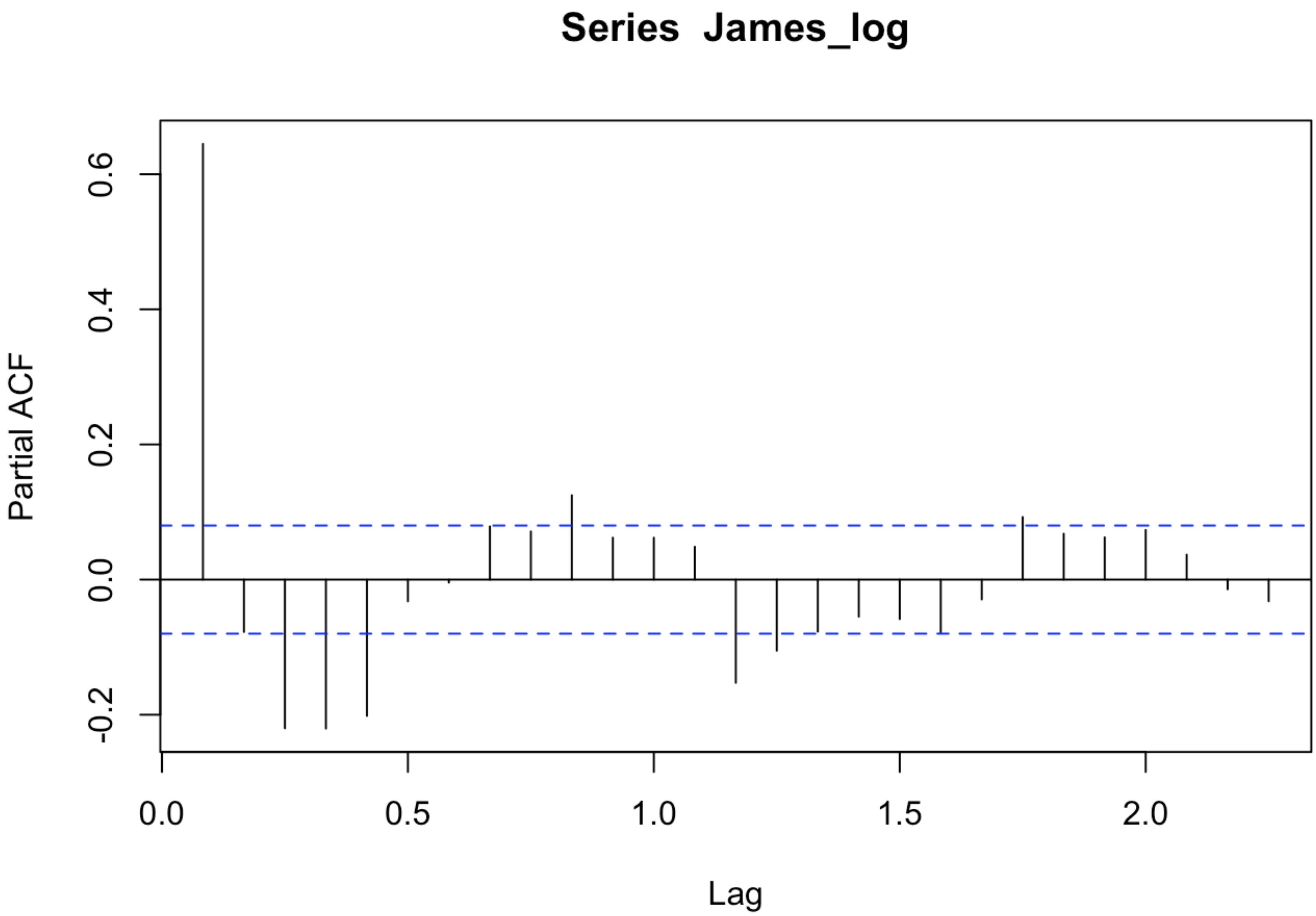
A fifth order random walk model.Btc_log seems to be the one to study, however.There is seasonlaity in btc_diff and btc_diff_diff as there are peaks of same periodgram. We find after smoothing better graphs to look at in Btc_diff and btc_diff_diff. It can be shown that higher frequency result in a higher spectrum for btc_diff_diff meaning its importance for indicating the oscillation.

Bonus Question

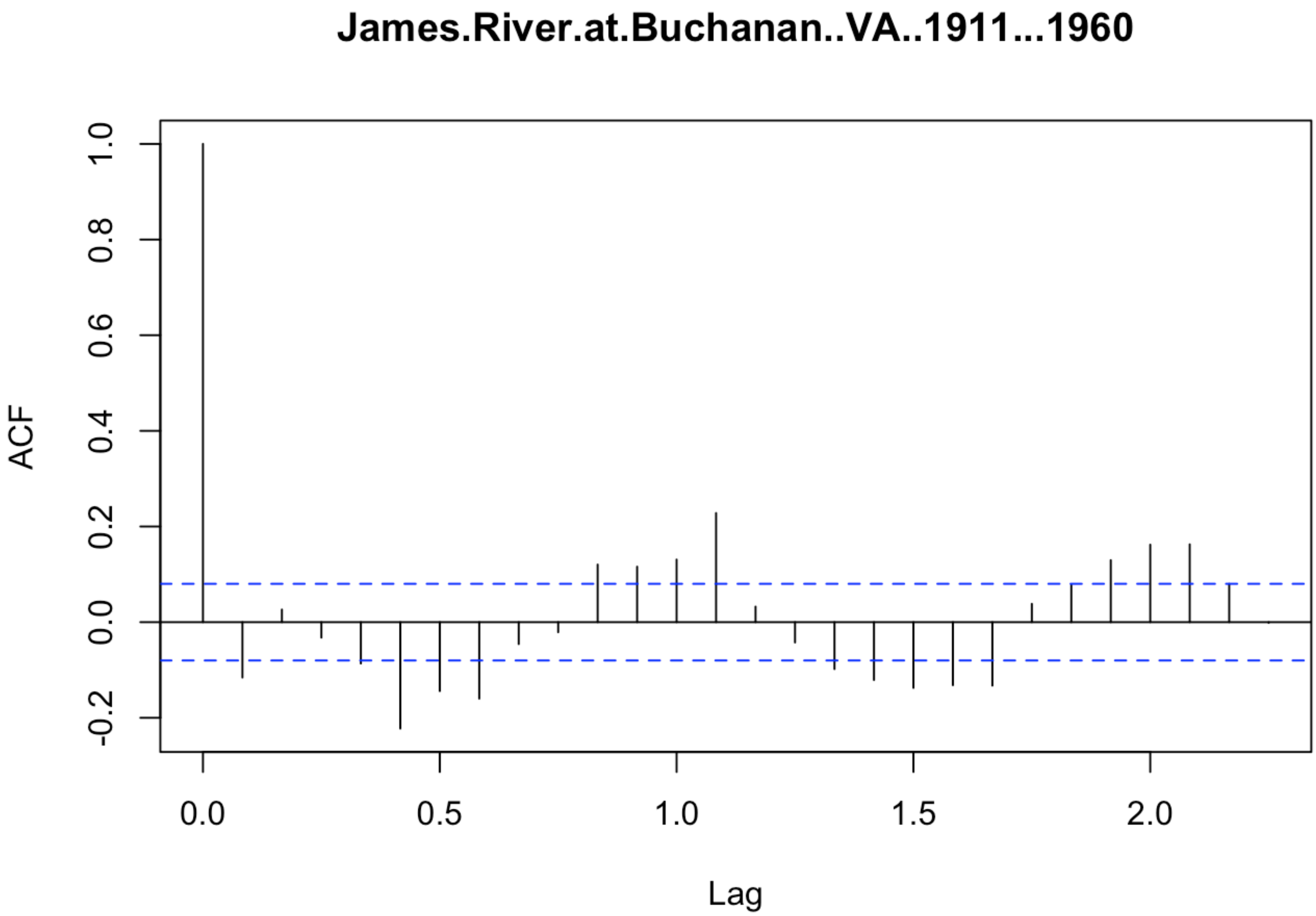
```
library(rdatamarket)
library(zoo)
library(xts)
library(astsa)
library(forecast)
library(dplR)
James <- dmseries("https://datamarket.com/data/set/22y3/james- river-at-buchanan-va-1
911-1960")
James_log <- log(James)
James_diff <- diff(James_log)[-1,]
James_diff_diff <- diff(James_diff)[-1,]
James_log_num <- as.numeric(James_log)

James_acf <- acf(James_log)
plot(James_acf)
```



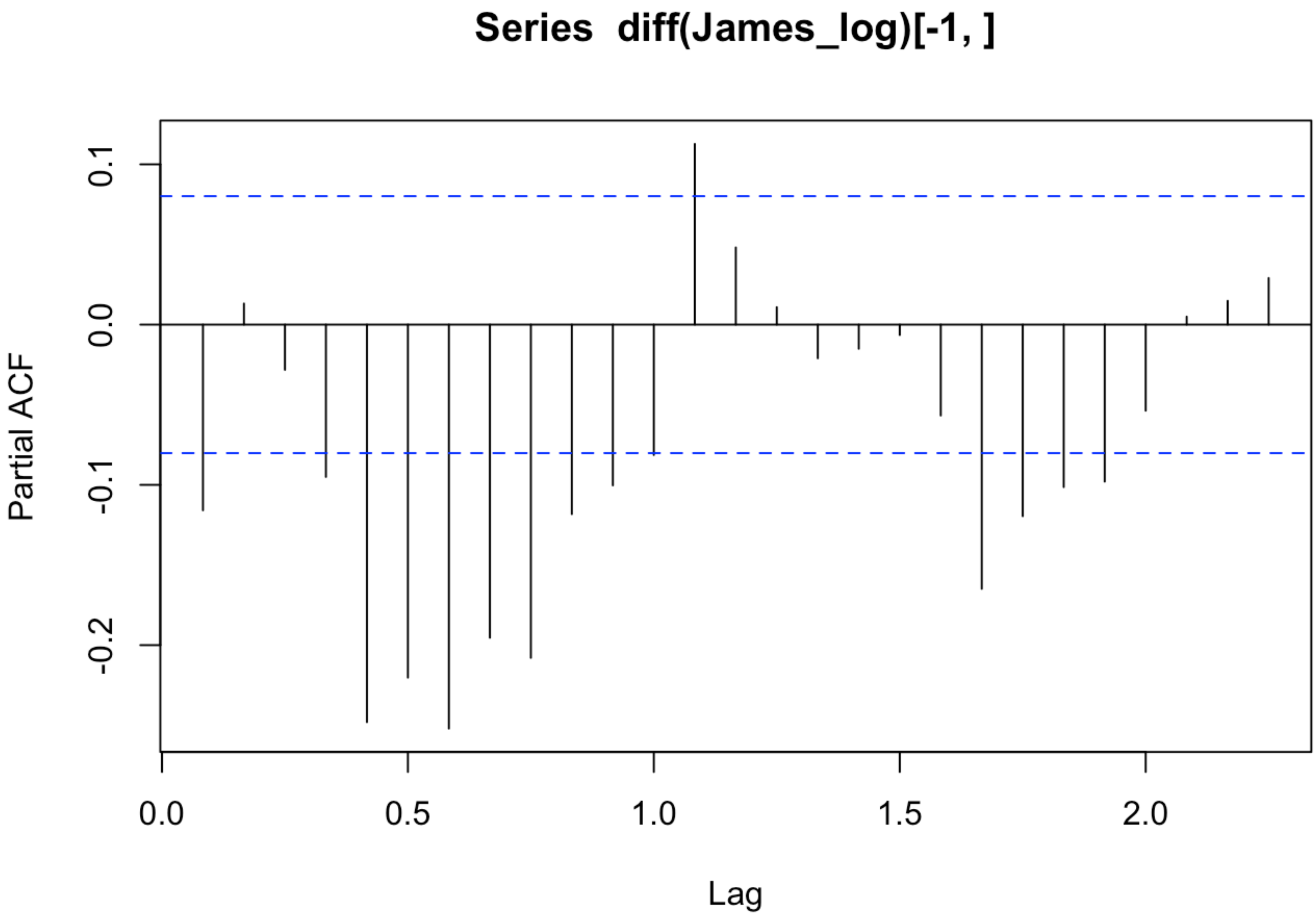

```
James_pacf <- pacf(James_log)
plot(James_pacf)
```



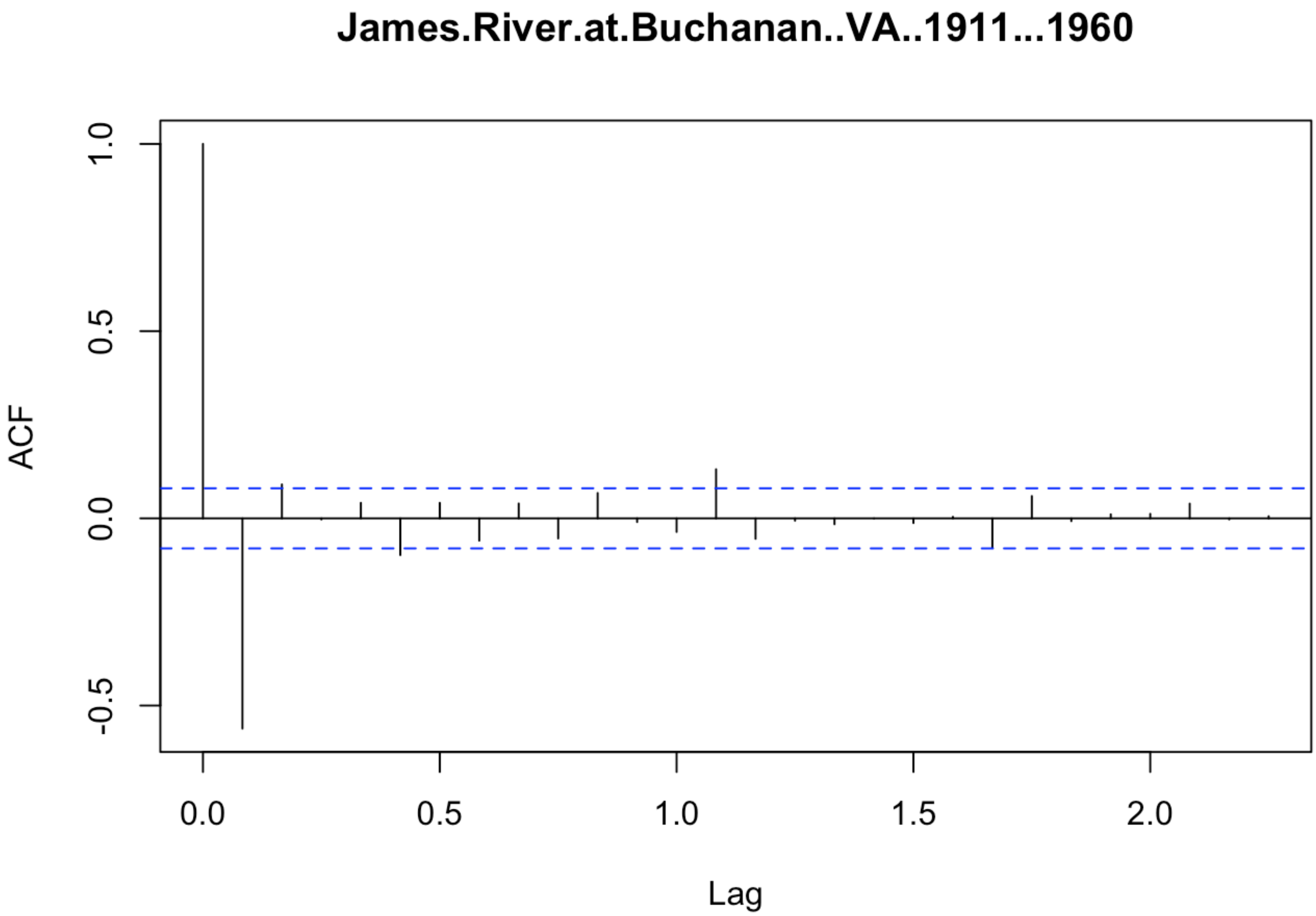

```
James_diff_acf <- acf(diff(James_log)[-1,])
plot(James_diff_acf)
```



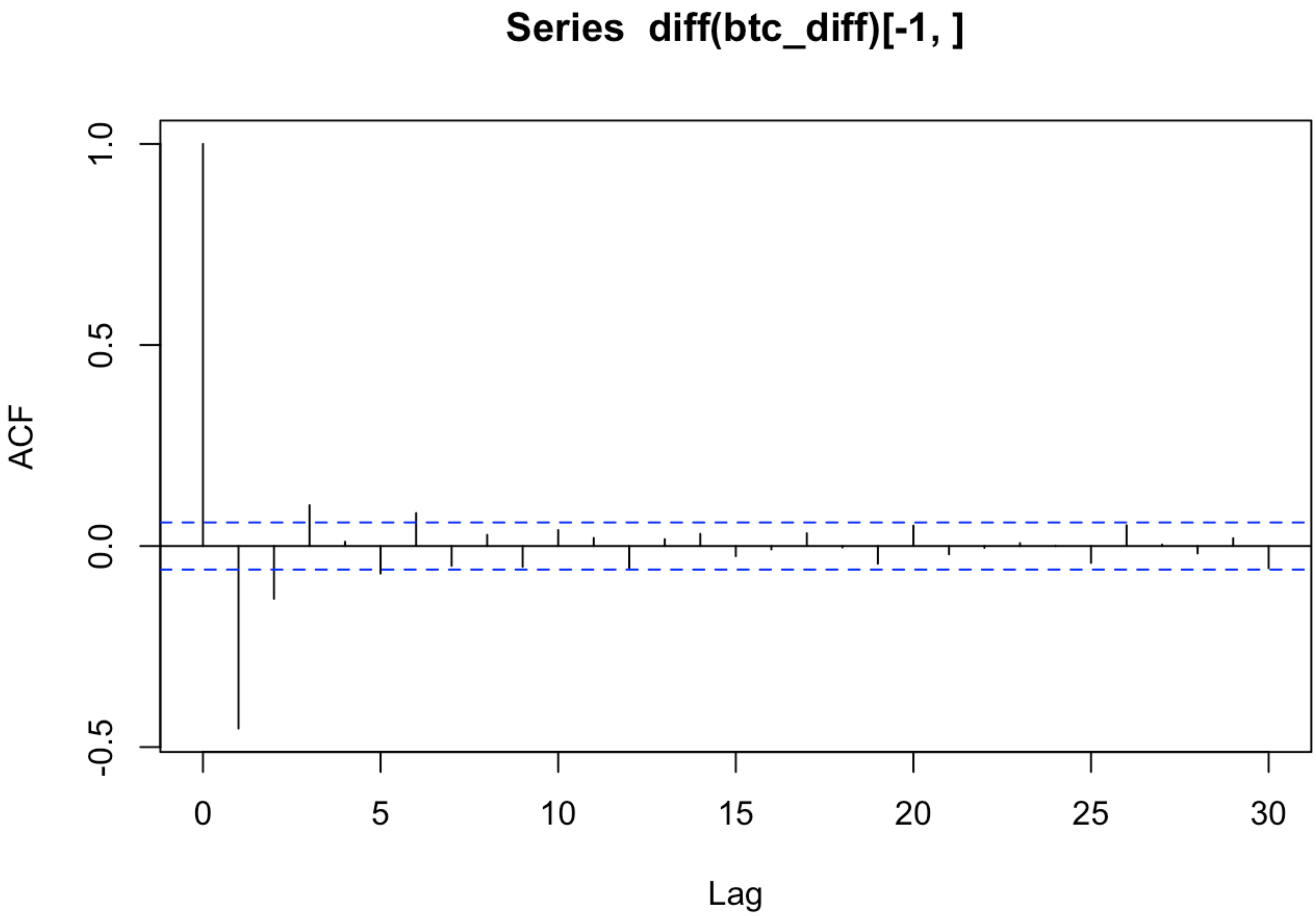

```
James_diff_pacf <- pacf(diff(James_log)[-1,])
plot(James_diff_pacf)
```



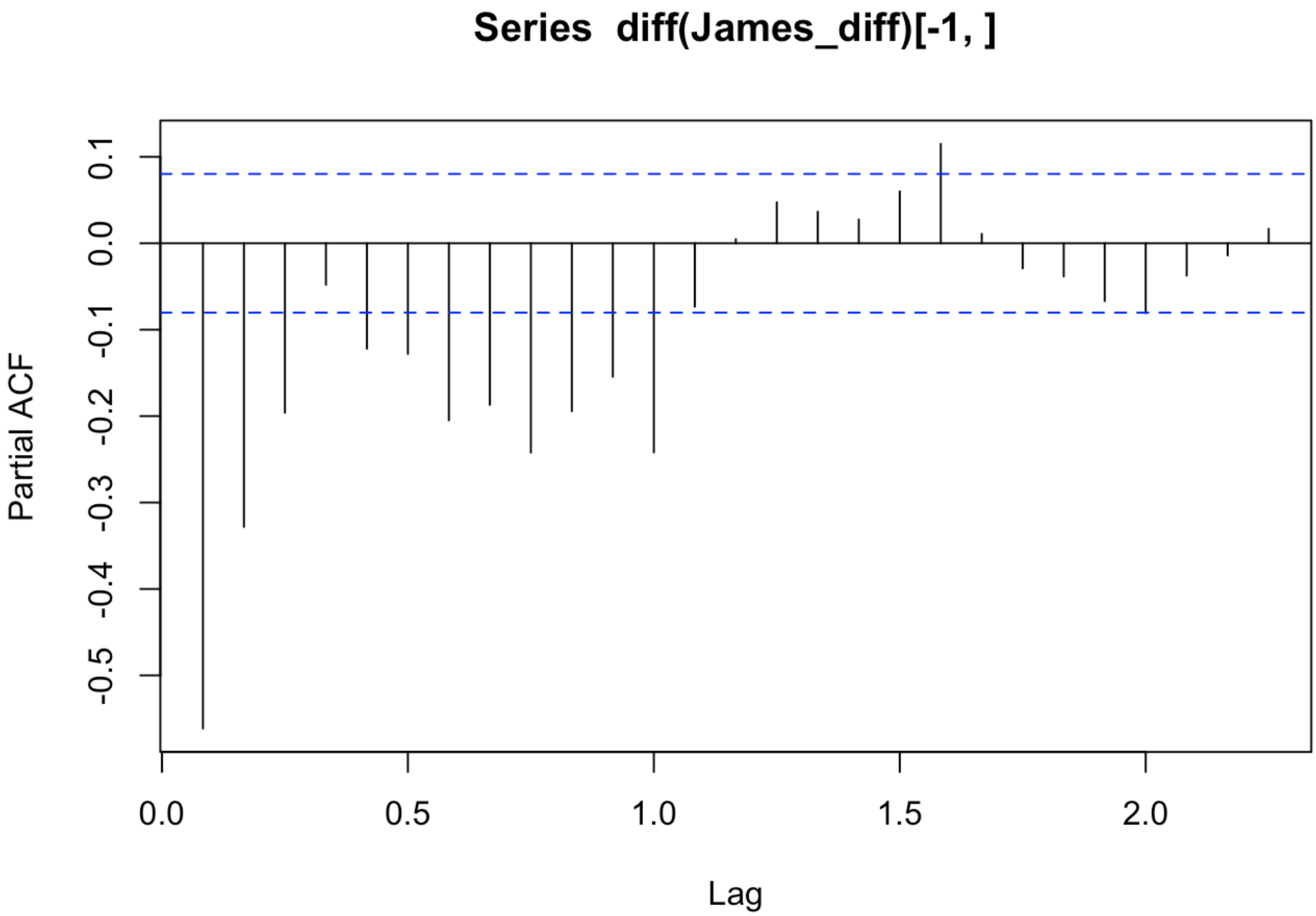

```
James_diff2_acf <- acf(diff(James_diff)[-1,])
```




```
plot(btc_diff2_acf)
```



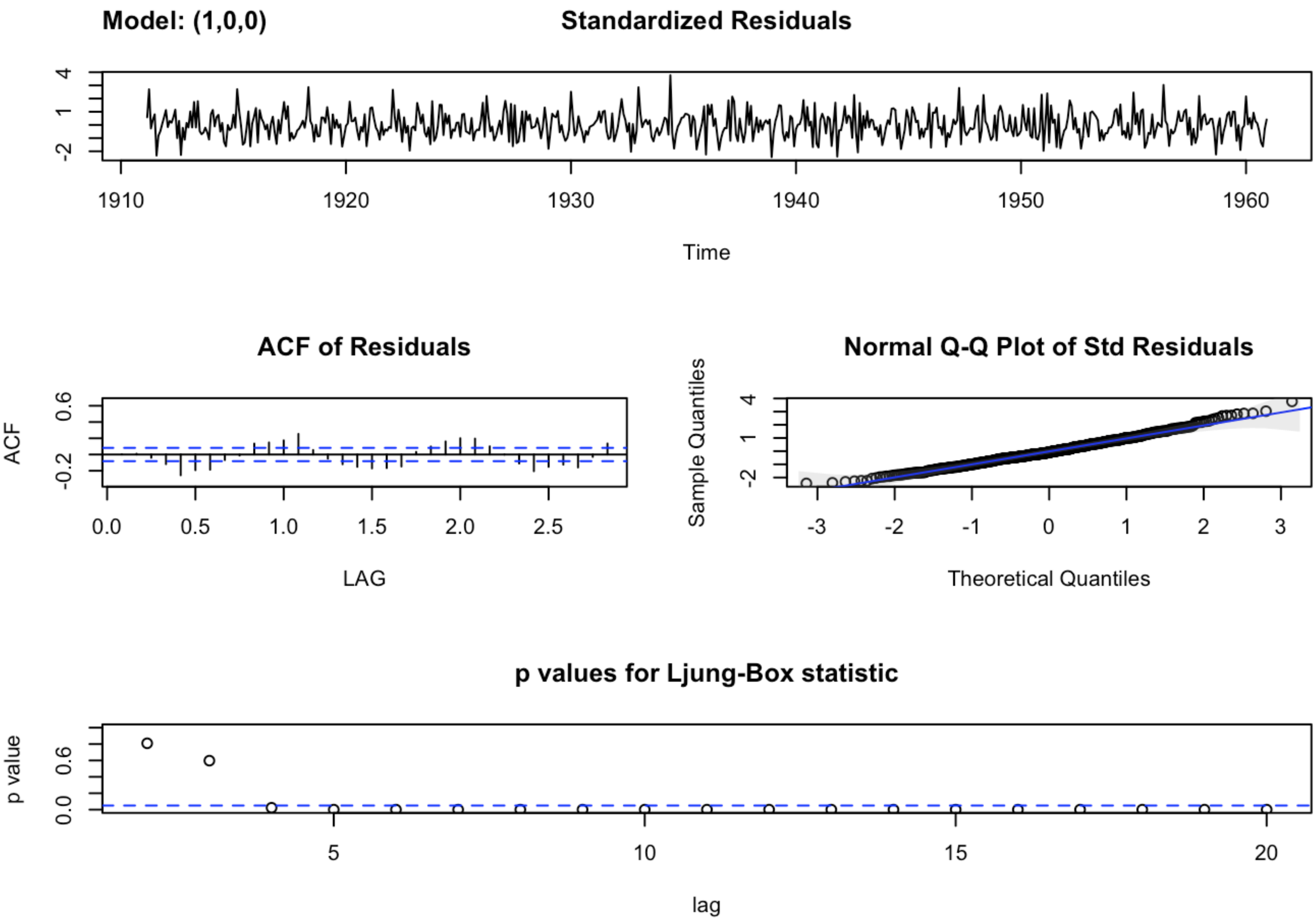

```
James_diff2_pacf <- pacf(diff(James_diff)[-1,])
plot(James_diff2_pacf)
```



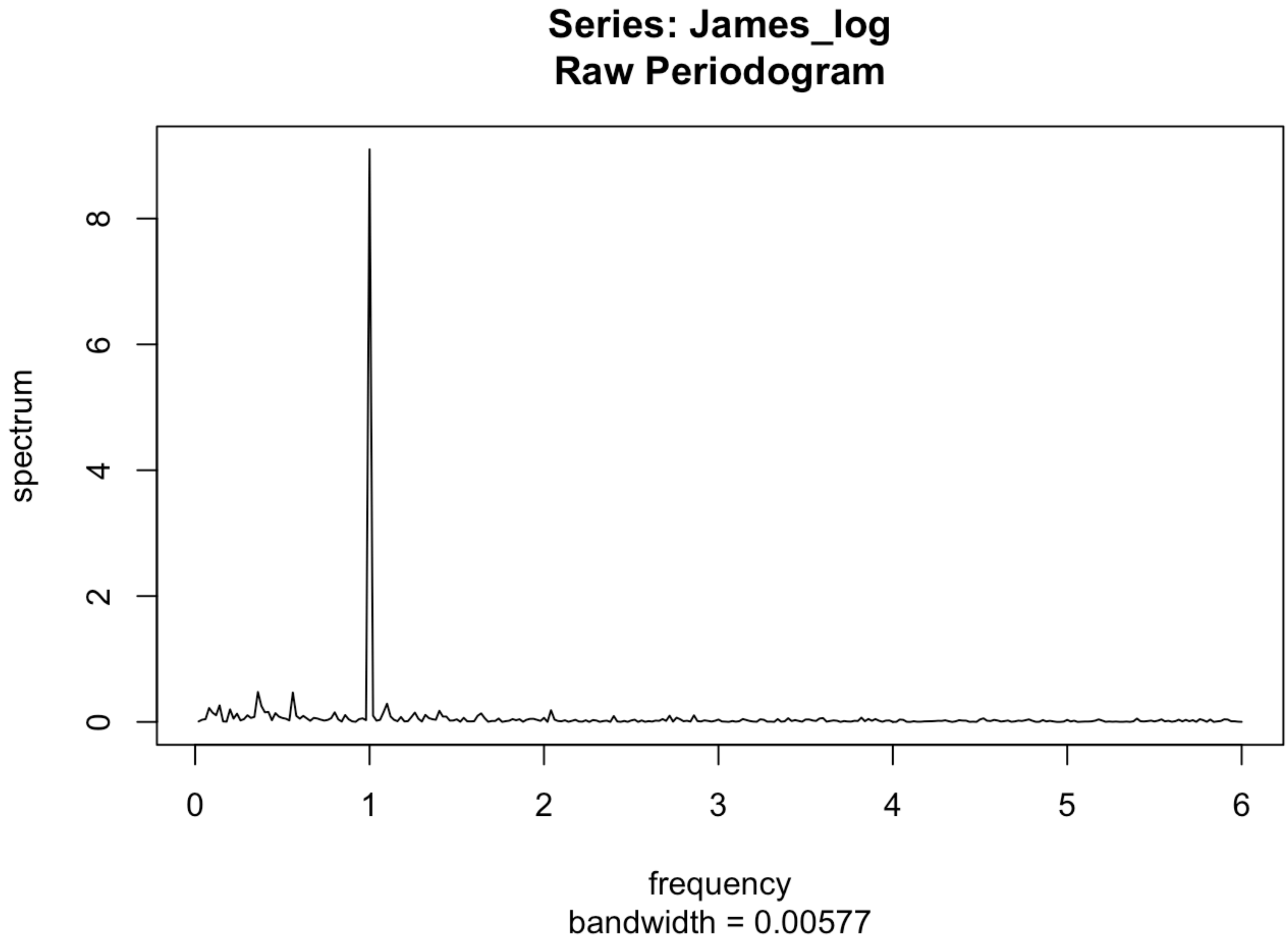

```
auto.arima(James_diff)
```

```
## Series: James_diff
## ARIMA(3,0,0)(2,0,0)[12] with zero mean
##
## Coefficients:
##           ar1      ar2      ar3    sar1    sar2
##       -0.3058  -0.1415  -0.0832  0.2146  0.2560
## s.e.   0.0465   0.0470   0.0423  0.0425  0.0434
##
## sigma^2 estimated as 0.5118:  log likelihood=-647.16
## AIC=1306.31   AICc=1306.45   BIC=1332.67
```

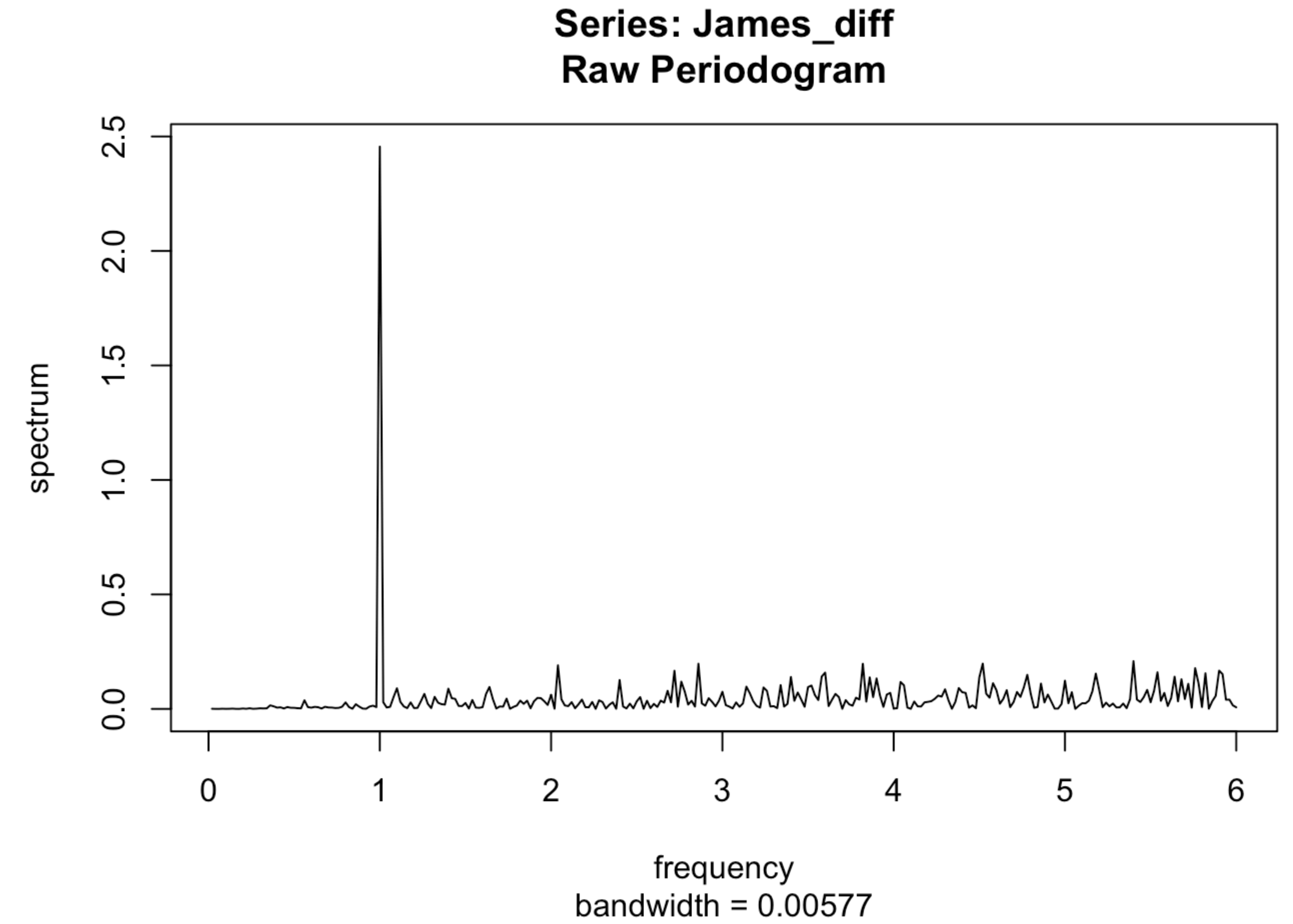
```
James_ar_1 <- sarima(James_diff,1,0,0,details = FALSE)
```



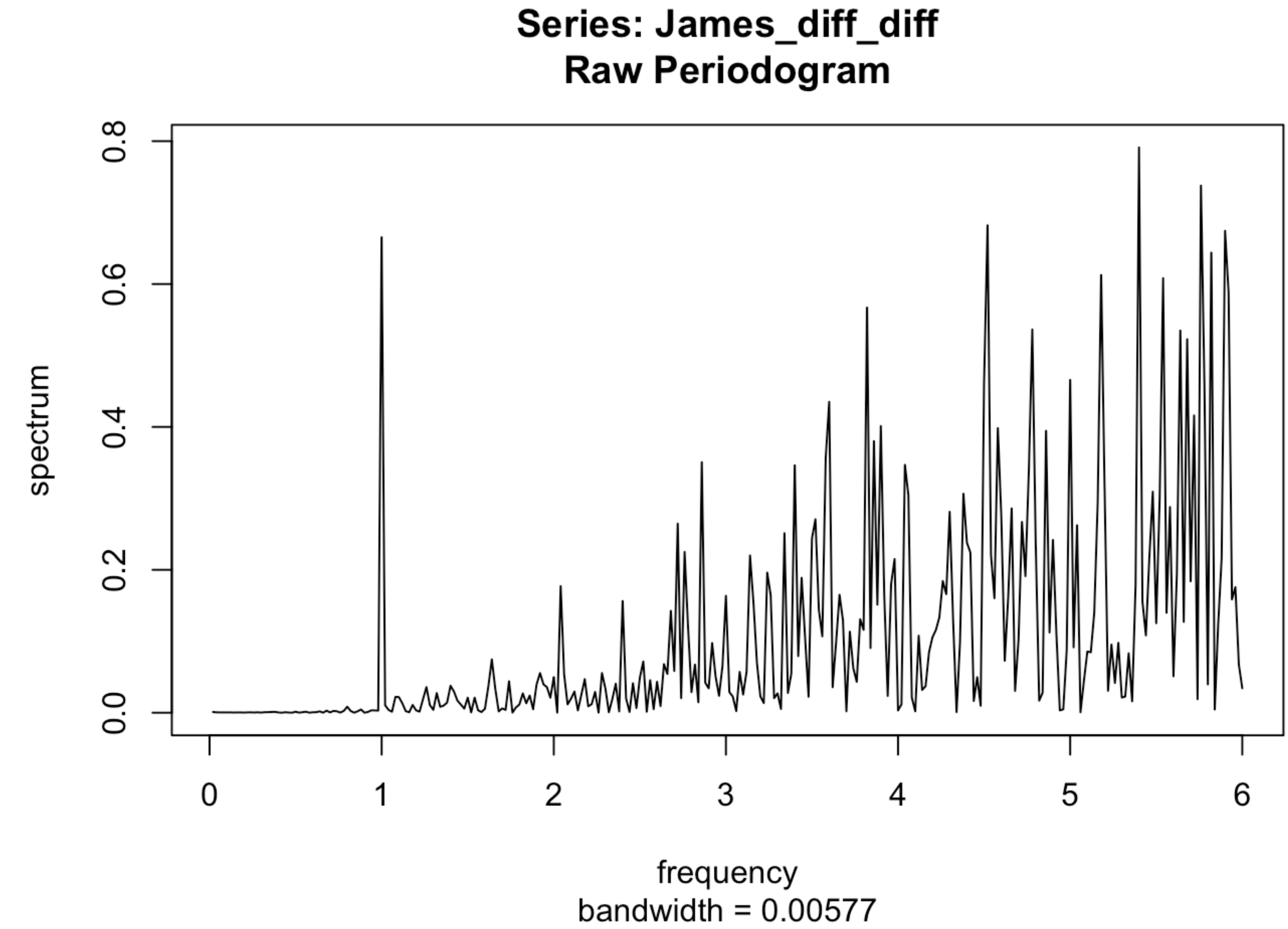

```
James_log_spec <- spec.pgram(James_log, taper=0, log="no")
```



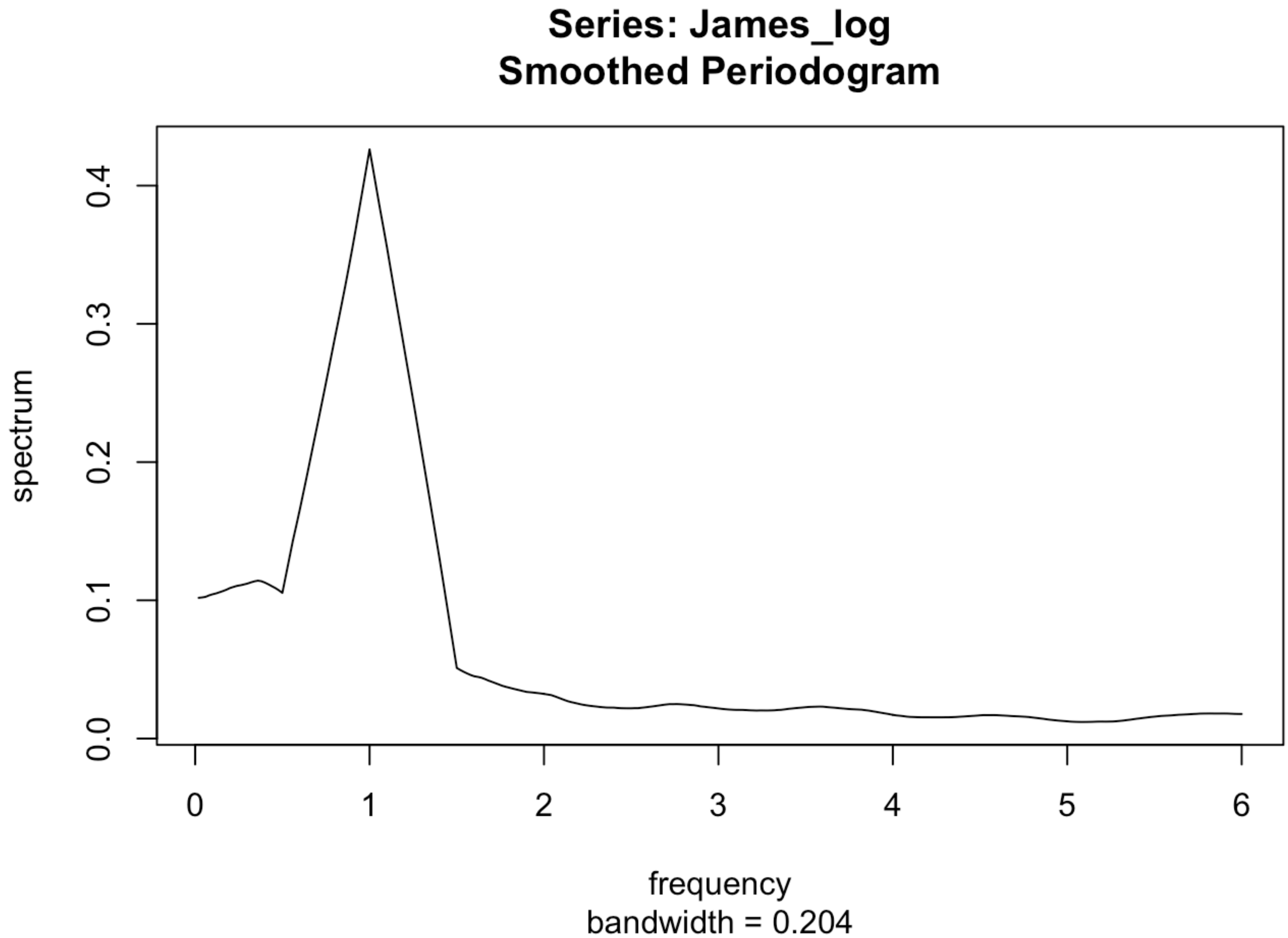

```
James_diff_spec <- spec.pgram(James_diff, taper=0, log="no")
```



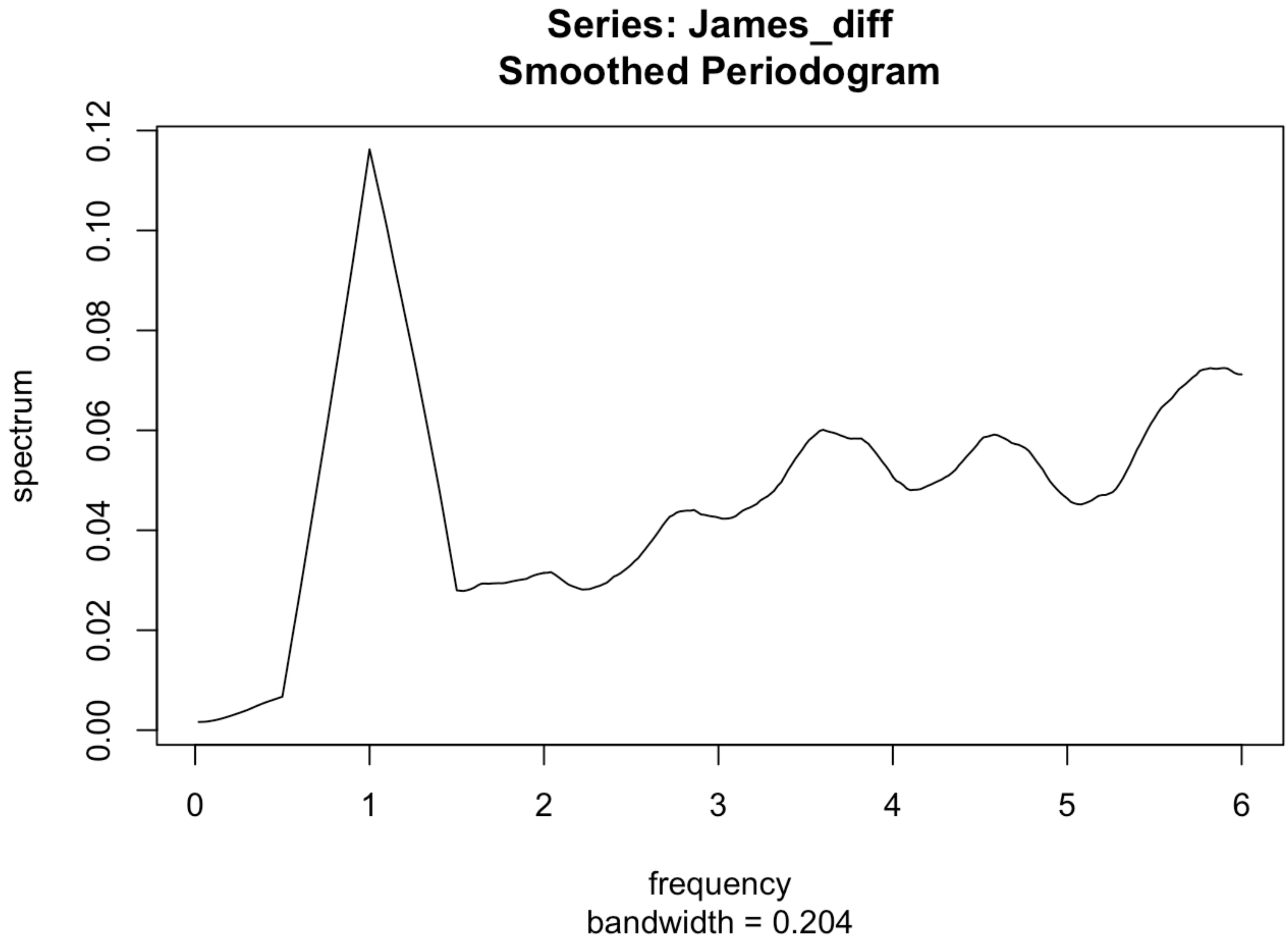

```
James_diff_diff_spec <- spec.pgram(James_diff_diff, taper=0, log="no")
```



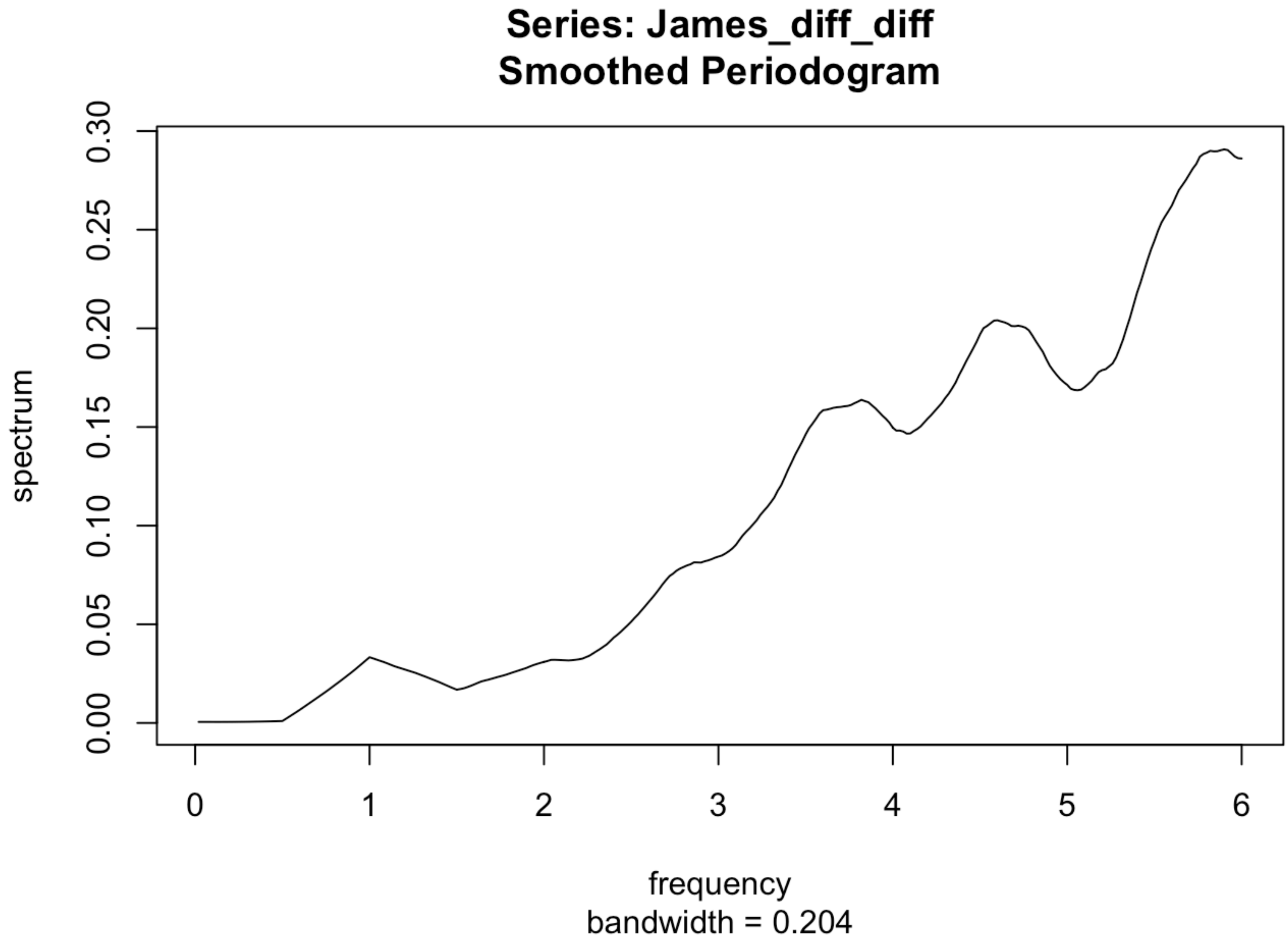

```
James_log_spec <- spec.pgram(James_log, taper=0, log="no",kernel=kernel("daniell", c(
12,12)))
```




```
James_diff_spec <- spec.pgram(James_diff, taper=0, log="no",kernel=kernel("daniell",
c(12,12)))
```



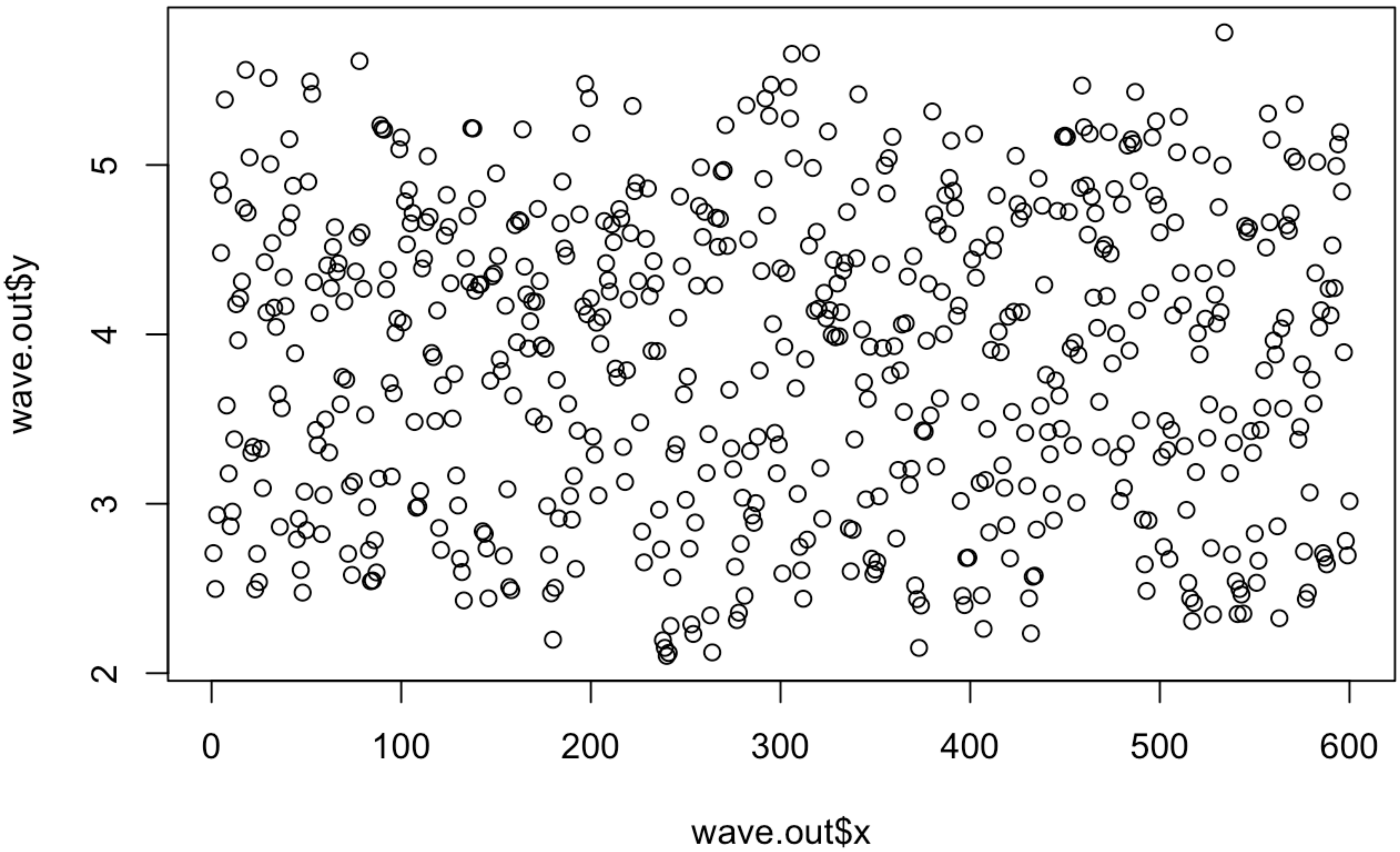

```
James_diff_diff_spec <- spec.pgram(James_diff_diff, taper=0, log="no",kernel=kernel("
daniell", c(12,12)))
```




```
str(James_log_num)
```

```
##  num [1:600] 2.71 2.5 2.93 4.91 4.48 ...
```

```
wave.out <- morlet(y1 = James_log_num, x1 = as.numeric(seq_along(James_log_num)), dj
= 0.25, siglvl = 0.95)
plot(wave.out)
```



A

third order autoregressive model.James_log seems to be the one to study.There is seasonlaity in all three graphs as there are peaks of same periodgram. We find after smoothing better graphs to look at in James_diff and James_diff_diff. It can be shown that higher frequency result in a higher spectrum for James_diff_diff meaning its importance for indicating the oscillation.