RSTAR: A Package for Smooth Transition Autoregressive Modeling Using R

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Outline

- Linear time series models usually leave certain aspects of economic and financial data unexplained
- For many economic and financial time series nonlinear time series models have been found to be more useful than linear models (capture more time series feature, improves forecast accuracy)
- One particular class of nonlinear time series models found useful is smooth transiting autoregressive (STAR) models–a piecewise linear autoregressive model with smooth transition among the regimes
- The software for identifying, estimating, diagnostic checking, predicting, and simulating STAR models are not well developed and lack many features researchers need

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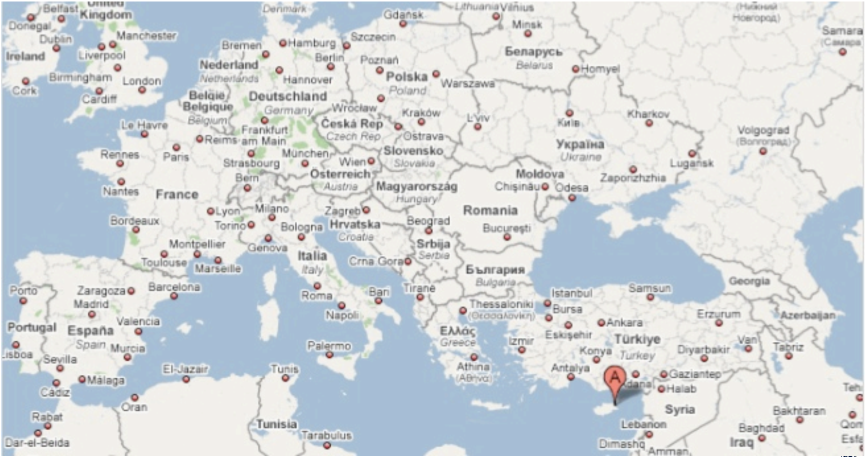
- Teaching (needed nonlinear and long-memory (partially exists) functions oriented towards economics and finance students): Cypriot students ... in my Time Series II course




YPRUS
Mediterranean Sea
Zafer Burnu
Dipkarpaz (Rizokarpaso)
(Yiallousa)
Karpasia Peninsula
Koruçam Burnu
Kyrenia (Girne)
Iskele (Trikomo)
Cape Elaia
Morfou Bay
Northern Cyprus
Famagusta Bay
Salamis
Lefkosia
Famagusta
Morfou (Güzelyurt)
Orounda
Polis
Kykkos Monastery
Dali
Protaras
Agia Napa
Cape Greco
Larnaka
Larnaka Bay
Dali
Republic of Cyprus
Troödos Massif
Kiti
Kofinou
Pafos
Lemesos (Limassol)
Mediterranean Sea
Kouklia
Kolossi
Episkopi Bay
Akrotiri Bay
Akrotiri Peninsula
0 40 km
0 20 miles

(Wild Cyprus) Donkeys have two regime of movements (slow & fast). My students only had one in learning R ... everything moves slow in the island!

Alternatives:

1. STR2 (Ox,Oxmetrics)
2. STR (JMulti)
3. Finmetrics (S+)

What is different?

- Completeness: all aspects of modeling cycle are implemented (Granger and Terasvirta (1993), Terasvirta (1998), Potter (1999), and van Dijk, Terasvirta and Franses (2002), Terasvirta (1994), Luukkonen, Saikkonen and Terasvirta (1988))
- Features: identification, specification, estimation and evaluation stages and, thus, is similar to the modeling cycle for linear models of Box and Jenkins (1976)
- Emphasis: Intended and emphasizes econometric/financial time series analysis
- Ease of use: Minimum user input

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$$y_t = \alpha' z_t + (\phi_{1,0} + \phi_{1,1} y_{t-1} + \phi_{1,2} y_{t-2} + \cdots + \phi_{1,p_1} y_{t-p_1})(1 - G(s_t; \gamma, c))$$
$$+ (\phi_{2,0} + \phi_{2,1} y_{t-1} + \phi_{2,2} y_{t-2} + \cdots + \phi_{1,p_2} y_{t-p_2}) G(s_t; \gamma, c) + \epsilon_t$$

or

$$y_t = \alpha' z_t + \phi_1' x_{1,t}(1 - G(s_t; \gamma, c)) + \phi_2' x_{2,t} G(s_t; \gamma, c) + \epsilon_t$$

where

$x_{i,t} = (1, y_{t-1}, \ldots, , y_{t-p_i})$

p_i = AR order (an integer, or vector of lags–holes are allowed)

s_t = transition variable (self-exciting STAR with $s_t = y_{t-d}$)

z_t = exogenous (or deterministic) variables entering linearly

$G(s_t; \gamma, c)$ = transition function

Logistic:

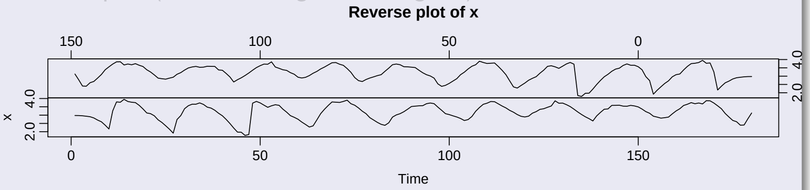
$$G(s_t; \gamma, c) = (1 + \exp\{-\gamma(s_t - c)\})^{-1}$$

Exponential:

$$G(s_t; \gamma, c) = 1 - \exp\{-\gamma(s_t - c)^2\}$$

Model Identification

- Testing and detecting nonlinearity
  - Reverse plot (with banking to 45 degree)



- Hodja, the people said, you're sitting on your donkey backwards!
- No, he replied. I'm not sitting on the donkey backwards. It's the donkey who is facing the world wrong way!

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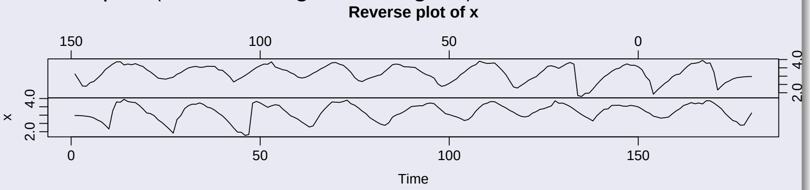

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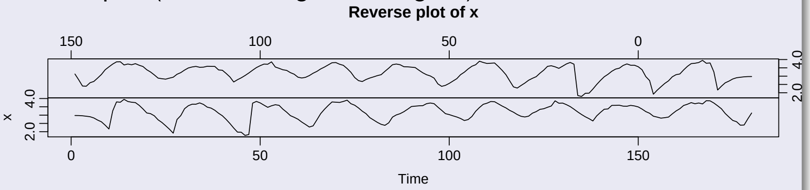

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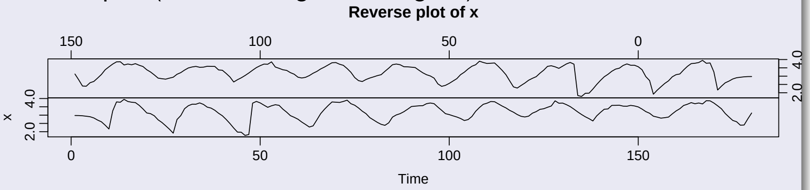

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Model Identification

- Testing and detecting nonlinearity
  - Bihistogram
  - Directed scatter plot
  - LM type tests against logistic and exponential STAR models
- Test for order of autoregression, p_i
- Test for order of delay, d, in self exciting models
- Testing via least squares, weighted least squares, and robust regression using M estimation
- Available R Methods: `show`

Estimation

- Method: Nonlinear least squares
  - Initial values for nonlinear parameters are obtained via fast grid search
  - γ and c are restricted as required
  - Analytical gradients are used
- Models:
  - Logistic (LSTAR) and exponential (ESTAR) STAR models
  - Time varying STAR models
  - Linear regressors are allowed
  - Deterministic regressors can enter any part of the model
- Flexible specification for the transition variable
- Standard errors are computed from the analytical gradients
- HAC consistent standard errors are given additionally
- User can optionally control almost all aspects of the estimation
- Available R Methods: `show`, `summary`, `plot`, `diagnose`, `predict`, `impulse`, `simulate`

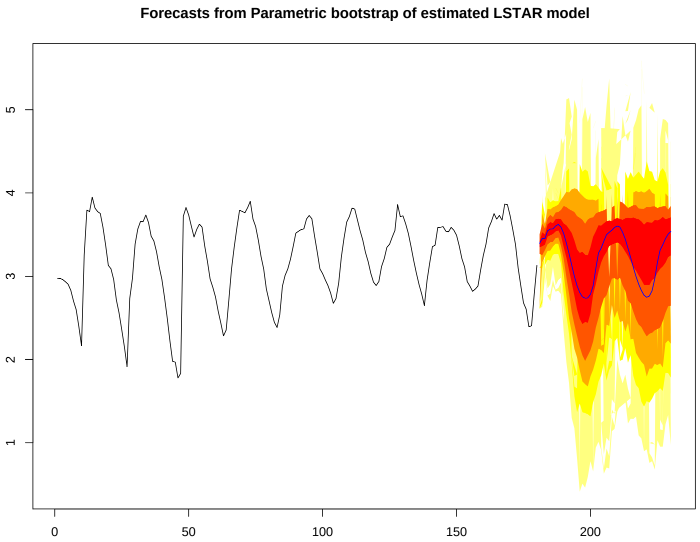
Diagnostic Control

- Extensive standard residual statistics (normality tests, etc)
- Autocorrelation tests (ACF, LM-AR, LJ, etc.)
- ARCH test
- Extensive LM type tests of no remaining nonlinearity (all testing issues are fully taken into account, such as orthogonalization with respect to gradients, control for holes in the gradients and regressors)
- Parameter constancy tests
- Testing two regime against multiple regimes
- Testing via least squares, weighted least squares, and robust regression using M estimation
- Full graphical analysis of the properties of the estimated model
- Graphical display of some tests, p-value graphics, etc.
- Available R Methods: `show, plot`

Prediction

Analytical expressions are not available, numerical integration needed, complicated when the forecast horizon is larger than 1 period.

- Point and interval forecasts
- Forecasts are calculated via Monte Carlo or bootstrap methods
- Highest density region, quantile and symmetric confidence interval calculation
- Forecast accuracy statistics
- Graphical display of forecasts with confidence intervals using color depth
- Very fast code for Monte Carlo and bootstrap (eg: 20-step prediction with each prediction evaluated 1000 times for std.err. and repeated 1000 times < 5 seconds)
- Available R Methods: `show, plot`


Forecasts from Parametric bootstrap of estimated LSTAR model
1
2
3
4
5
0
50
100
150
200

Impulse Response Analysis

Analytical expressions are not available, complicated since it is not symmetric and history dependent.

- Generalized impulse responses (GIRF)
- Calculation via Monte Carlo or bootstrap methods
- Full handling of history dependence (every possible history is used)
- Highest density region, quantile and symmetric confidence intervals for impulse responses
- Asymmetric impulses
- Graphical display of impulse responses with confidence intervals
- Very fast code for Monte Carlo and bootstrap (eg: 20-period ahead impulses repeated 2500 times for 172 histories < 107 seconds) – was a challenge
- Available R Methods: `show, plot`

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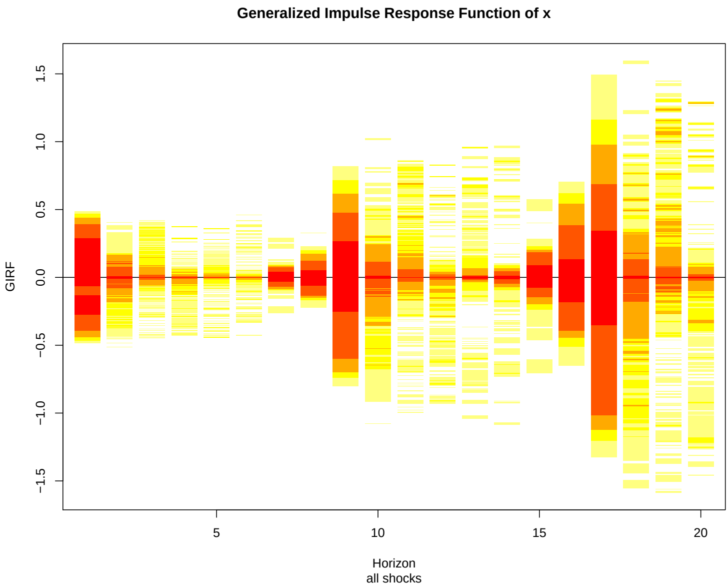
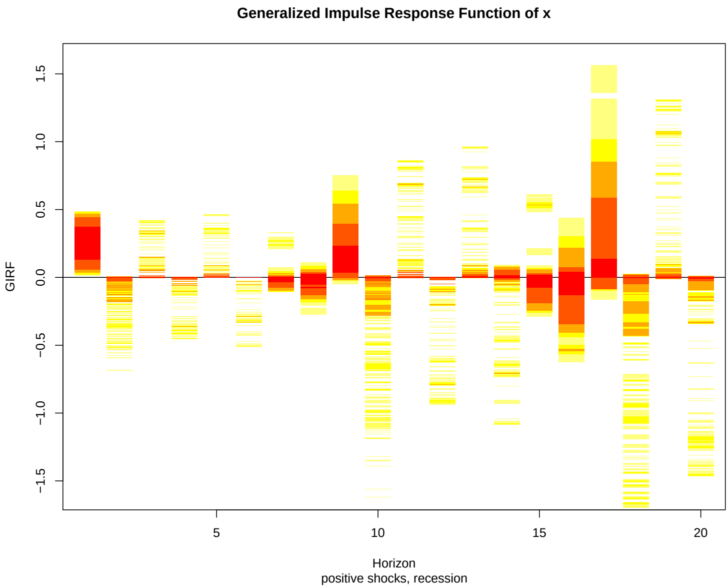

Generalized Impulse Response Function of x
GIRF
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
5
10
15
20
Horizon
all shocks


Generalized Impulse Response Function of x
GIRF
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
5
10
15
20
Horizon
positive shocks, recession

Simulation

- Direct simulation from the estimated model or
- Simulation from the user specified model

- Very simple syntax with only the minimum inputs
- Optional full control is available on most aspects of specification, testing, and estimation
- Uses S4 methods for all objects (show, plot, ...)

Fit a self exciting STAR(p_1, p_2, d) model for `blowfly` series (data on a laboratory population of Blowfies, from the classic ecological studies of Nicholson (1954)) with $p_1 = 1$, $p_2 = 3$, and $d = 8$
predict for 50 periods ahead
calculate impulse responses for 20 periods
simulate 100 realizations.

```
library(RSTAR)
data(blowfly)
x <- log10(blowfly)
NlStarTest(x,p=3,d=8)
fit0 <- STAR(x,p1=1,p2=3,d=8)
summary(fit0)
plot(fit0)
d.fit0 <- diagnose(fit0,ar.p=10,arch.p=10)
plot(d.fit0)
p.fit0 <- predict(fit0,n.ahead=50)
plot(p.fit0)
i.fit0 <- impulse(fit0,n.ahead=20)
plot(i.fit0)
s.fit0 <- simulate(fit0,nsim=100)
plot(s.fit0)
```

- Bispectrum test is coming soon
- Multiple thresholds is coming in the next version
- TAR models (with same comprehension)
- Multivariate STAR models
- Some extensions such as the band TAR model

- Box, G.E.P. and G.M. Jenkins (1976), Time Series Analysis; Forecasting and Control, San Francisco: Holden-Day.
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- Terasvirta, T. (1994), Specication, estimation, and evaluation of smooth transition autoregressive models, Journal of the American Statistical Association 89, 208–218.
- Terasvirta, T. (1998), Modelling economic relationships with smooth transition regressions, in A. Ullah and D.E.A. Giles (eds.), Handbook of Applied Economic Statistics, New York: Marcel Dekker, pp. 507–552.
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Thank You

```
R version 2.6.0 Patched (2007-10-15 r43172)
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ISBN 3-900051-07-0

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  Natural language support but running in an English locale

R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> library(RSTAR)
> data(blowfly)
> postscript(file="Rplot.ps",onefile=TRUE,horizontal=TRUE,heigh=8.0,width=10.0)
> x <- log10(blowfly)
> reverse.plot(x)
> directed.scatter(x,lag=9)
> ts.bihist(x,lag=1,type="persp",nbins=20)
>
> NlStarTest(x,p=3,d=8)

Title:
 LM Tests against STAR Alternatives

Call:
 NlStarTest(x = x, p = 3, d = 8)

Series:
 x

Estimation Method:
 Least Squares

Transition Variable:
 x(t-8)

Test    Chi Square Variants            F Variants
-----  ----------------------  -----------------------------
       Test Stat   p value  df  Test Stat   p value  df 1  df 2
LM.1     56.7278 1.411e-11   4    20.1769 1.570e-13     4   164
LM.2     58.7785 8.088e-10   8    10.3829 1.169e-11     8   160
LM.3     64.5862 3.251e-09  12     7.8167 2.720e-11    12   156
LM.3e    60.2530 3.999e-11   6    14.5582 2.949e-13     6   162
LM.4     64.8979 7.671e-08  16     5.7565 1.225e-09    16   152
LM.S2     3.0600 5.478e-01   4     0.7245 5.764e-01     4   160
LM.S3     8.8226 6.569e-02   4     2.1086 8.228e-02     4   156
LM.S4     0.4992 9.736e-01   4     0.1106 9.787e-01     4   152
LM.H1    56.7278 1.411e-11   4    20.1769 1.570e-13     4   164
LM.H2     3.0600 5.478e-01   4     0.7245 5.764e-01     4   160
LM.H3     8.8226 6.569e-02   4     2.1086 8.228e-02     4   156
LM.H4     0.4992 9.736e-01   4     0.1106 9.787e-01     4   152
LM.HE     8.8790 3.526e-01   8     1.0342 4.129e-01     8   152
LM.HL     7.3501 4.994e-01   8     0.8482 5.618e-01     8   152
```

```
Number of observations used: 172

Description:
 Wed Feb 13 00:06:00 2008

> fit0 <- STAR(x,p1=1,p2=3,d=8)
> fit0

Title:
 STAR Modelling

Call:
 STAR(x = x, p1 = 1, p2 = 3, d = 8)

Model:
 LSTAR(p1,p2) with transition variable = x(t-8)

Series:
 x

Coefficient(s):
     Gamma    Treshold  Intercep_1     AR_1(1)  Intercep_2     AR_2(1)
    4.8018      3.0910      2.1481      0.4133      0.3077      1.5369
   AR_2(2)     AR_2(3)
   -0.4392     -0.2023

Description:
 Wed Feb 13 00:06:01 2008

> summary(fit0)

Title:
 STAR Modelling

Call:
 STAR(x = x, p1 = 1, p2 = 3, d = 8)

Series:
 x

Model:
 LSTAR(p1,p2) with transition variable = x(t-8)

Coefficient(s):
     Gamma    Treshold  Intercep_1     AR_1(1)  Intercep_2     AR_2(1)
    4.8018      3.0910      2.1481      0.4133      0.3077      1.5369
   AR_2(2)     AR_2(3)
   -0.4392     -0.2023

Residuals:
      Min         1Q    Median         3Q       Max
-0.772971 -0.055060 -0.003834  0.055518  1.024042

Moments:
Skewness Kurtosis
  0.6269  13.0388

Coefficient(s):
            Estimate  Std. Error  t value Pr(>|t|)
Gamma        4.80175     1.68225    2.854  0.00431 **
```

```
Treshold     3.09103     0.04807   64.298  < 2e-16 ***
Intercep_1   2.14814     0.35110    6.118 9.46e-10 ***
AR_1(1)      0.41335     0.09777    4.228 2.36e-05 ***
Intercep_2   0.30774     0.16613    1.852  0.06397 .
AR_2(1)      1.53689     0.15167   10.133  < 2e-16 ***
AR_2(2)     -0.43923     0.28212   -1.557  0.11950
AR_2(3)     -0.20225     0.18873   -1.072  0.28387
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

sigma^2 estimated as: 0.02582
log likelihood:       70.4
AIC Criterion:        -124.79
SIC Criterion:        -99.61
HQ Criterion:         -114.57

Number of observations used: 172

Inverted Roots of the AR Polynomials:

          Lower State (G=0)
     -------------------------
       Real Imaginary Moduli
[1,] 0.4133         0 0.4133

          Upper State (G=1)
     -------------------------
        Real Imaginary Moduli
[1,] -0.2359    0.0000 0.2359
[2,]  0.8864    0.2678 0.9260
[3,]  0.8864   -0.2678 0.9260


Description:
 Wed Feb 13 00:06:01 2008

> plot(fit0)
> d.fit0 <- diagnose(fit0)
> d.fit0

Title:
 Residual Diagnostics for STAR Model

Call:
 .local(object = object)

Series:
 x

Title:
 Standard Residual Diagnostics

Call:
 resid.diag(x = resid, lb.p = lag, ar.p = ar.p, arch.p = arch.p,
    all = all, title = "Standard Residual Diagnostics")

Series:
 resid

Descriptive Statistics:
```

```
      Min.     1st Qu.      Median        Mean     3rd Qu.        Max.
-7.730e-01  -5.506e-02  -3.834e-03  -2.891e-13   5.552e-02   1.024e+00

       MAD     St. Dev       Skew.  p-val Skew       Kurt.  p-val Kurt
 8.482e-02   1.607e-01   6.324e-01   3.544e-04   1.623e+01   0.000e+00

Jarque-Bera Normality Test:

 Test Statistic (JB) =  1265 with p-value =  0
 alternative hypothesis: resid is not normally distributed

Durbin-Watson Test for AR(1):

 Test statistic (DW) =  1.844 with p-value =  0.1523
 alternative hypothesis: true autocorrelation is greater than 0

Ljung-Box Autocorrelation Test:

      Lag Ljung-Box Q      p-value
Q(1)    1   0.1361605 0.7121282529
Q(2)    2   5.1645153 0.0756031248
Q(3)    3   5.3396853 0.1485479035
Q(4)    4   5.3968403 0.2489472106
Q(5)    5   5.5751136 0.3497796840
Q(6)    6   5.5778465 0.4720982735
Q(7)    7   5.8212793 0.5607659705
Q(8)    8   6.2464488 0.6196472740
Q(9)    9   6.8506686 0.6526635903
Q(10)  10   7.7544081 0.6528118883
Q(11)  11   8.2018375 0.6951175473
Q(12)  12   9.3395083 0.6736908543
Q(13)  13   9.5854177 0.7274336696
Q(14)  14   9.6006797 0.7907570712
Q(15)  15   9.6850113 0.8390719228
Q(16)  16  11.1157517 0.8022847953
Q(17)  17  14.5287749 0.6293825430
Q(18)  18  18.7410247 0.4079313304
Q(19)  19  21.5881724 0.3052288784
Q(20)  20  30.8771088 0.0568338646
Q(21)  21  30.9375099 0.0747042499
Q(22)  22  31.5502873 0.0853929226
Q(23)  23  31.6448516 0.1077576843
Q(24)  24  31.6996195 0.1346179246
Q(25)  25  31.8095171 0.1635977922
Q(26)  26  32.1273365 0.1889446938
Q(27)  27  35.9985814 0.1153299003
Q(28)  28  36.1090632 0.1398415254
Q(29)  29  36.1095005 0.1703960385
Q(30)  30  36.4336592 0.1942206833
Q(31)  31  36.4337054 0.2305402729
Q(32)  32  36.4391317 0.2697184467
Q(33)  33  36.4496017 0.3113060662
Q(34)  34  37.2567440 0.3215665379
Q(35)  35  37.8275093 0.3414437987
Q(36)  36  41.7249729 0.2358849478
Q(37)  37  57.9849489 0.0152691671
Q(38)  38  65.2009860 0.0039258883
Q(39)  39  76.7467548 0.0002917755
Q(40)  40  76.7468980 0.0004213550
Q(41)  41  76.7723555 0.0005971035
Q(42)  42  76.9011089 0.0008148404
```

```
Q(43)  43  77.0742677 0.0010887005

Li-McLeod Autocorrelation Test:

        Lag Li-McLeod Q     p-value
QLM(1)    1   0.1396268 0.708652270
QLM(2)    2   5.0640152 0.079499256
QLM(3)    3   5.2515934 0.154274442
QLM(4)    4   5.3300334 0.255078533
QLM(5)    5   5.5302045 0.354645210
QLM(6)    6   5.5676955 0.473312832
QLM(7)    7   5.8392346 0.558641713
QLM(8)    8   6.2864808 0.615175751
QLM(9)    9   6.9048283 0.647027588
QLM(10)  10   7.8043805 0.647938006
QLM(11)  11   8.2823347 0.687811665
QLM(12)  12   9.3982363 0.668591773
QLM(13)  13   9.6985279 0.718381353
QLM(14)  14   9.7937819 0.777099586
QLM(15)  15   9.9570835 0.822430761
QLM(16)  16  11.3328395 0.788489865
QLM(17)  17  14.4720135 0.633453812
QLM(18)  18  18.3047478 0.435752987
QLM(19)  19  20.9187393 0.341308308
QLM(20)  20  29.1494917 0.084857299
QLM(21)  21  29.3240017 0.106437558
QLM(22)  22  29.9801650 0.118947306
QLM(23)  23  30.1948635 0.143889103
QLM(24)  24  30.3809825 0.172443554
QLM(25)  25  30.6191759 0.201940097
QLM(26)  26  31.0370148 0.226893743
QLM(27)  27  34.4200289 0.154174139
QLM(28)  28  34.6742528 0.179549112
QLM(29)  29  34.8432169 0.209734247
QLM(30)  30  35.2821788 0.232517954
QLM(31)  31  35.4624487 0.265840111
QLM(32)  32  35.6528612 0.300487120
QLM(33)  33  35.8530857 0.336090592
QLM(34)  34  36.6909074 0.345120603
QLM(35)  35  37.3437914 0.361867110
QLM(36)  36  40.5993872 0.274783366
QLM(37)  37  53.4300021 0.039324680
QLM(38)  38  59.2081103 0.015360706
QLM(39)  39  68.2600686 0.002575945
QLM(40)  40  68.4927354 0.003336802
QLM(41)  41  68.7502737 0.004257809
QLM(42)  42  69.0906548 0.005286005
QLM(43)  43  69.4690312 0.006458892

McLeod-Li Squared Autocorrelation Test:

        Lag McLeod-Li Q      p-value
QLM(1)    1     17.70888 2.574223e-05
QLM(2)    2     19.60768 5.523895e-05
QLM(3)    3     19.62182 2.032969e-04
QLM(4)    4     19.63084 5.905559e-04
QLM(5)    5     19.65081 1.452984e-03
QLM(6)    6     19.80103 3.004445e-03
QLM(7)    7     19.92443 5.735253e-03
QLM(8)    8     19.97919 1.041507e-02
QLM(9)    9     20.10413 1.728052e-02
```

```
QLM(10)  10    20.27982 2.671446e-02
QLM(11)  11    20.29197 4.149366e-02
QLM(12)  12    20.32320 6.121386e-02
QLM(13)  13    20.40420 8.557981e-02
QLM(14)  14    20.46826 1.160558e-01
QLM(15)  15    20.58507 1.506185e-01
QLM(16)  16    20.64690 1.924860e-01
QLM(17)  17    20.68085 2.408920e-01
QLM(18)  18    22.03442 2.304605e-01
QLM(19)  19    24.71070 1.702868e-01
QLM(20)  20    27.49596 1.218784e-01
QLM(21)  21    27.50218 1.548427e-01
QLM(22)  22    27.60428 1.891689e-01
QLM(23)  23    27.73878 2.258211e-01
QLM(24)  24    27.83440 2.670867e-01
QLM(25)  25    27.83593 3.154616e-01
QLM(26)  26    27.86354 3.652060e-01
QLM(27)  27    27.86383 4.180200e-01
QLM(28)  28    28.05723 4.614177e-01
QLM(29)  29    28.22447 5.059366e-01
QLM(30)  30    28.42679 5.478312e-01
QLM(31)  31    28.60428 5.898346e-01
QLM(32)  32    28.77934 6.303462e-01
QLM(33)  33    28.90144 6.714740e-01
QLM(34)  34    28.91171 7.152619e-01
QLM(35)  35    28.96812 7.536784e-01
QLM(36)  36    29.89088 7.534650e-01
QLM(37)  37    36.62810 4.863255e-01
QLM(38)  38    73.34027 5.014579e-04
QLM(39)  39    91.70509 3.923476e-06
QLM(40)  40    91.97477 5.680788e-06
QLM(41)  41    91.98157 8.801689e-06
QLM(42)  42    91.98246 1.349547e-05
QLM(43)  43    92.01061 2.028937e-05

LM Tests for Autoregression:

Estimation Method:
 Least Squares

      X-Squared p-val(X-Sq.)         F  p-val(F)
AR(1) 0.1485531    0.6999219 0.1469433 0.7019555
AR(4) 2.2088327    0.6974125 0.5429115 0.7044360

LM Tests for ARCH:

Estimation Method:
 Least Squares

        X-Squared p-val(X-Sq.)         F     p-val(F)
ARCH(1) 19.186534 1.185467e-05 21.358608 7.528472e-06
ARCH(4)  6.267205 1.800621e-01  1.579078 1.822871e-01

LM Tests for Autoregression (residuals are not othogonalized wrt gradient):

Estimation Method:
 Least Squares

      X-Squared p-val(X-Sq.)        F     p-val(F)
AR(1)  8.244648  0.004087232 8.206385 0.0047277977
AR(4) 20.873004  0.000335566 5.532956 0.0003426893
```

LM Tests for Serial Independence (residuals are othogonalized wrt gradient):

Estimation Method:
Least Squares

	X-Squared	p-val(X-Sq.)	F	p-val(F)
LM_SI(1)	8.244648	4.087232e-03	8.206385	4.727798e-03
LM_SI(2)	26.337096	1.909732e-06	14.666052	1.417939e-06
LM_SI(3)	20.014945	1.685362e-04	7.075344	1.714905e-04
LM_SI(4)	20.873004	3.355660e-04	5.532956	3.426893e-04
LM_SI(5)	21.846650	5.599329e-04	4.635627	5.718895e-04
LM_SI(6)	24.270935	4.655907e-04	4.338303	4.526538e-04
LM_SI(7)	24.511212	9.259795e-04	3.738663	9.236721e-04
LM_SI(8)	25.207665	1.433444e-03	3.359997	1.443207e-03
LM_SI(9)	25.053725	2.912322e-03	2.946271	3.040830e-03
LM_SI(10)	27.072505	2.536427e-03	2.889286	2.560106e-03
LM_SI(11)	27.493577	3.868029e-03	2.658427	3.978060e-03
LM_SI(12)	27.942156	5.640844e-03	2.468553	5.902404e-03
LM_SI(13)	28.385837	7.991853e-03	2.306998	8.504870e-03
LM_SI(14)	28.929237	1.068311e-02	2.177308	1.152293e-02
LM_SI(15)	31.377700	7.816789e-03	2.231351	8.044128e-03
LM_SI(16)	35.062551	3.896705e-03	2.391865	3.580982e-03
LM_SI(17)	37.632944	2.759663e-03	2.451977	2.329635e-03
LM_SI(18)	41.432244	1.326586e-03	2.617351	9.333306e-04
LM_SI(19)	41.871647	1.844462e-03	2.498688	1.338187e-03
LM_SI(20)	42.440483	2.422170e-03	2.401717	1.795721e-03
LM_SI(21)	42.038389	4.161247e-03	2.241368	3.355968e-03
LM_SI(22)	44.650207	2.938579e-03	2.311790	2.112320e-03
LM_SI(23)	45.231833	3.722563e-03	2.236321	2.733672e-03
LM_SI(24)	44.958592	5.891067e-03	2.108860	4.683317e-03
LM_SI(25)	45.060608	8.230478e-03	2.015672	6.885510e-03
LM_SI(26)	48.086110	5.279793e-03	2.115534	3.817104e-03
LM_SI(27)	53.144399	1.933344e-03	2.357115	9.667667e-04
LM_SI(28)	53.961352	2.262148e-03	2.311637	1.132169e-03
LM_SI(29)	53.724081	3.480143e-03	2.199594	1.936591e-03
LM_SI(30)	53.618508	5.068651e-03	2.103127	3.082914e-03
LM_SI(31)	54.184440	6.138696e-03	2.053598	3.830761e-03
LM_SI(32)	53.869142	9.125578e-03	1.954480	6.309350e-03
LM_SI(33)	55.453482	8.517330e-03	1.971118	5.526555e-03
LM_SI(34)	58.066871	6.216842e-03	2.051133	3.395047e-03
LM_SI(35)	58.164930	8.261484e-03	1.981534	4.861847e-03
LM_SI(36)	58.701382	9.814207e-03	1.940716	5.950442e-03
LM_SI(37)	68.973881	1.101426e-03	2.541029	1.772915e-04
LM_SI(38)	74.636182	3.545136e-04	2.911566	1.969696e-05
LM_SI(39)	81.650189	7.541630e-05	3.506325	6.513540e-07
LM_SI(40)	64.180755	8.975921e-03	1.987335	4.254538e-03
LM_SI(41)	64.036333	1.217937e-02	1.912569	6.471471e-03
LM_SI(42)	66.655447	9.073288e-03	2.004320	3.824709e-03
LM_SI(43)	66.577730	1.205616e-02	1.934709	5.699343e-03

LM Tests for Serial Independence (residuals are othogonalized wrt gradient):

Estimation Method:
Least Squares

	X-Squared	p-val(X-Sq.)	F	p-val(F)
LM_SI(1)	8.244648	4.087232e-03	8.206385	4.727798e-03
LM_SI(2)	26.337096	1.909732e-06	14.666052	1.417939e-06
LM_SI(3)	20.014945	1.685362e-04	7.075344	1.714905e-04
LM_SI(4)	20.873004	3.355660e-04	5.532956	3.426893e-04

LM_SI(5)	21.846650	5.599329e-04	4.635627	5.718895e-04
LM_SI(6)	24.270935	4.655907e-04	4.338303	4.526538e-04
LM_SI(7)	24.511212	9.259795e-04	3.738663	9.236721e-04
LM_SI(8)	25.207665	1.433444e-03	3.359997	1.443207e-03
LM_SI(9)	25.053725	2.912322e-03	2.946271	3.040830e-03
LM_SI(10)	27.072505	2.536427e-03	2.889286	2.560106e-03
LM_SI(11)	27.493577	3.868029e-03	2.658427	3.978060e-03
LM_SI(12)	27.942156	5.640844e-03	2.468553	5.902404e-03
LM_SI(13)	28.385837	7.991853e-03	2.306998	8.504870e-03
LM_SI(14)	28.929237	1.068311e-02	2.177308	1.152293e-02
LM_SI(15)	31.377700	7.816789e-03	2.231351	8.044128e-03
LM_SI(16)	35.062551	3.896705e-03	2.391865	3.580982e-03
LM_SI(17)	37.632944	2.759663e-03	2.451977	2.329635e-03
LM_SI(18)	41.432244	1.326586e-03	2.617351	9.333306e-04
LM_SI(19)	41.871647	1.844462e-03	2.498688	1.338187e-03
LM_SI(20)	42.440483	2.422170e-03	2.401717	1.795721e-03
LM_SI(21)	42.038389	4.161247e-03	2.241368	3.355968e-03
LM_SI(22)	44.650207	2.938579e-03	2.311790	2.112320e-03
LM_SI(23)	45.231833	3.722563e-03	2.236321	2.733672e-03
LM_SI(24)	44.958592	5.891067e-03	2.108860	4.683317e-03
LM_SI(25)	45.060608	8.230478e-03	2.015672	6.885510e-03
LM_SI(26)	48.086110	5.279793e-03	2.115534	3.817104e-03
LM_SI(27)	53.144399	1.933344e-03	2.357115	9.667667e-04
LM_SI(28)	53.961352	2.262148e-03	2.311637	1.132169e-03
LM_SI(29)	53.724081	3.480143e-03	2.199594	1.936591e-03
LM_SI(30)	53.618508	5.068651e-03	2.103127	3.082914e-03
LM_SI(31)	54.184440	6.138696e-03	2.053598	3.830761e-03
LM_SI(32)	53.869142	9.125578e-03	1.954480	6.309350e-03
LM_SI(33)	55.453482	8.517330e-03	1.971118	5.526555e-03
LM_SI(34)	58.066871	6.216842e-03	2.051133	3.395047e-03
LM_SI(35)	58.164930	8.261484e-03	1.981534	4.861847e-03
LM_SI(36)	58.701382	9.814207e-03	1.940716	5.950442e-03
LM_SI(37)	68.973881	1.101426e-03	2.541029	1.772915e-04
LM_SI(38)	74.636182	3.545136e-04	2.911566	1.969696e-05
LM_SI(39)	81.650189	7.541630e-05	3.506325	6.513540e-07
LM_SI(40)	64.180755	8.975921e-03	1.987335	4.254538e-03
LM_SI(41)	64.036333	1.217937e-02	1.912569	6.471471e-03
LM_SI(42)	66.655447	9.073288e-03	2.004320	3.824709e-03
LM_SI(43)	66.577730	1.205616e-02	1.934709	5.699343e-03

LM Tests for Parameter Constancy (all variables):

Estimation Method:
Least Squares

	X-Squared	p-val(X-Sq.)	F	p-val(F)
LM.C1	23.44417	2.838427e-03	3.077370	3.009855e-03
LM.C2	44.12279	1.889511e-04	3.191623	1.018119e-04
LM.C3	63.33790	2.126830e-05	3.400184	3.009454e-06

Note: Parameter space has no holes in lag specification

LM Tests for No Remaining Nonlinearity (all variables):

Estimation Method:
Least Squares

	X-Squared	p-val(X-Sq.)	F	p-val(F)
LM.RNL1[x(t-1)]	38.478655	6.140110e-06	5.6195793	2.885163e-06
LM.RNL1[x(t-2)]	43.548334	6.923944e-07	6.6109887	2.001248e-07
LM.RNL1[x(t-3)]	38.140286	7.092044e-06	5.5560822	3.428289e-06

LM.RNL1[x(t-4)]	40.758441	2.312975e-06	6.0559292	8.861559e-07
LM.RNL1[x(t-5)]	31.665374	1.069091e-04	4.4000174	8.103281e-05
LM.RNL1[x(t-6)]	20.286474	9.304891e-03	2.6074554	1.053205e-02
LM.RNL1[x(t-7)]	13.107498	1.082041e-01	1.6086109	1.263517e-01
LM.RNL1[x(t-8)]	3.308653	9.135224e-01	0.3824661	9.287154e-01
LM.RNL2[x(t-1)]	94.112066	4.343192e-13	11.1767839	0.000000e+00
LM.RNL2[x(t-2)]	74.320656	1.726453e-09	7.0379881	7.280954e-12
LM.RNL2[x(t-3)]	67.112290	3.179764e-08	5.9186028	7.100751e-10
LM.RNL2[x(t-4)]	59.058640	7.534564e-07	4.8369563	7.178088e-08
LM.RNL2[x(t-5)]	42.430468	3.402736e-04	3.0291213	2.084619e-04
LM.RNL2[x(t-6)]	27.180337	3.952174e-02	1.7360772	4.576034e-02
LM.RNL2[x(t-7)]	24.317956	8.278634e-02	1.5231445	9.853609e-02
LM.RNL2[x(t-8)]	16.645446	4.088908e-01	0.9910902	4.695739e-01
LM.RNL3[x(t-1)]	112.742957	1.865175e-13	11.0985499	0.000000e+00
LM.RNL3[x(t-2)]	95.492051	1.744793e-10	7.2807723	5.107026e-15
LM.RNL3[x(t-3)]	84.268967	1.252999e-08	5.6031368	1.921896e-11
LM.RNL3[x(t-4)]	66.839401	6.514231e-06	3.7076292	5.345558e-07
LM.RNL3[x(t-5)]	50.943041	1.072428e-03	2.4547762	6.021544e-04
LM.RNL3[x(t-6)]	49.939813	1.441147e-03	2.3866552	8.745943e-04
LM.RNL3[x(t-7)]	57.449712	1.450174e-04	2.9255563	4.368671e-05
LM.RNL3[x(t-8)]	22.386094	5.562341e-01	0.8728169	6.378374e-01

LM Tests for Constancy of Variance:

Estimation Method:
Least Squares

	X-Squared	p-val(X-Sq.)	F	p-val(F)
LM.C1	1.904381	0.1675887	1.9033109	0.1695202
LM.C2	2.008186	0.3663767	0.9982348	0.3706917
LM.C3	4.232780	0.2374004	1.4128844	0.2408154

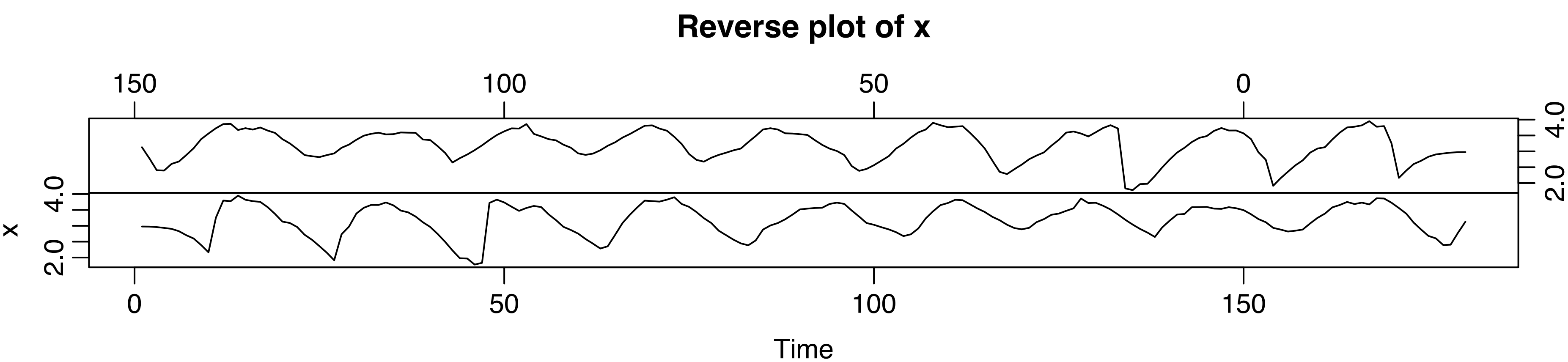
LM Tests for Nonlinearity in Variance:

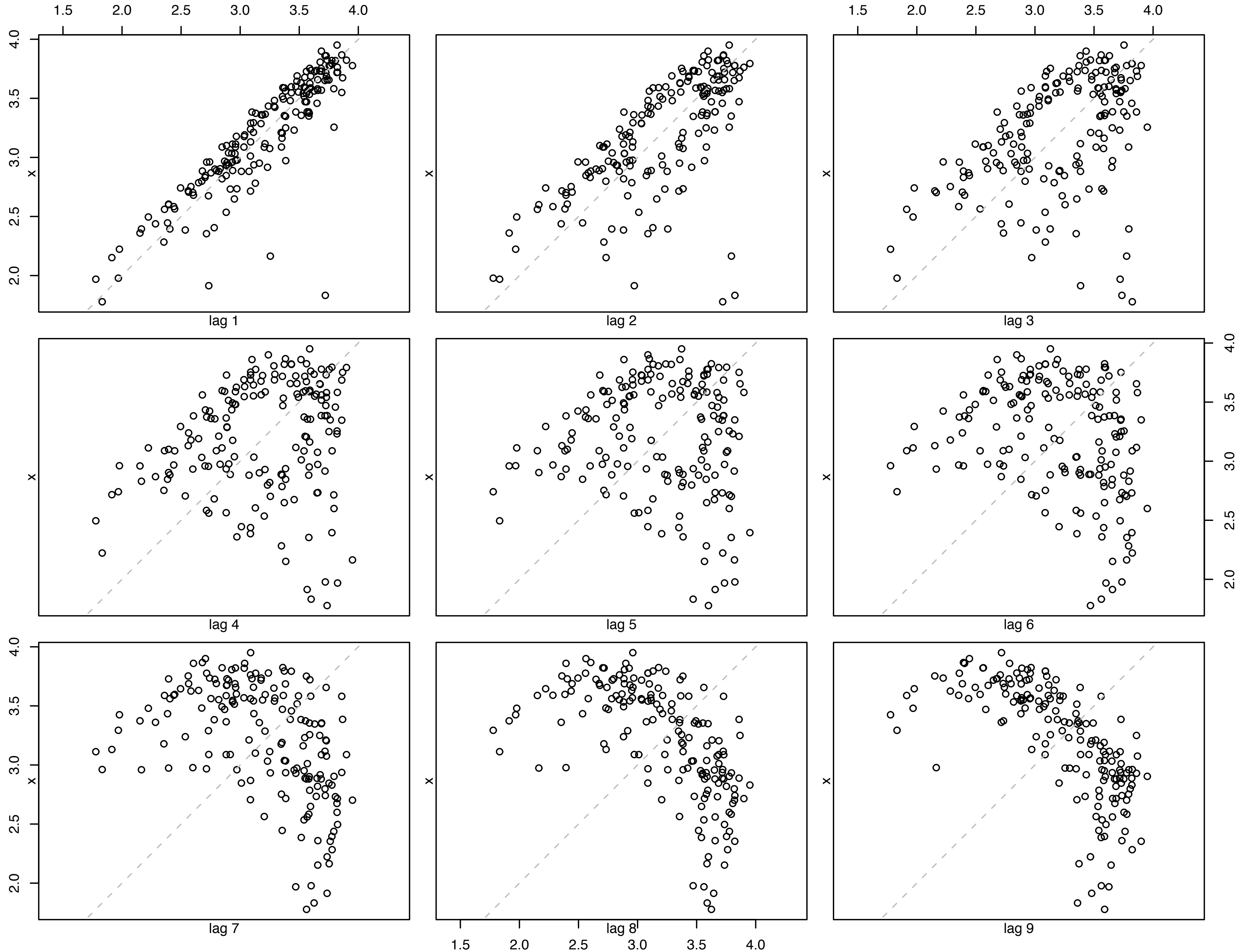
Estimation Method:
Least Squares

	X-Squared	p-val(X-Sq.)	F	p-val(F)
LM.RNL1[x(t-1)]	0.57566317	4.480173e-01	0.57088008	4.509550e-01
LM.RNL1[x(t-2)]	0.53447470	4.647317e-01	0.52990652	4.676476e-01
LM.RNL1[x(t-3)]	0.39593267	5.291973e-01	0.39223170	5.319687e-01
LM.RNL1[x(t-4)]	0.33058135	5.653170e-01	0.32736658	5.679697e-01
LM.RNL1[x(t-5)]	0.21590182	6.421804e-01	0.21365953	6.445051e-01
LM.RNL1[x(t-6)]	0.11277136	7.370108e-01	0.11153319	7.388169e-01
LM.RNL1[x(t-7)]	0.05206998	8.194997e-01	0.05148010	8.207801e-01
LM.RNL1[x(t-8)]	0.01990973	8.877895e-01	0.01968050	8.885991e-01
LM.RNL2[x(t-1)]	15.12077142	5.206744e-04	8.14451471	4.198811e-04
LM.RNL2[x(t-2)]	14.33917028	7.696420e-04	7.68523096	6.390105e-04
LM.RNL2[x(t-3)]	12.90059462	1.580052e-03	6.85169277	1.376700e-03
LM.RNL2[x(t-4)]	11.52391166	3.144955e-03	6.06801017	2.851144e-03
LM.RNL2[x(t-5)]	9.30289747	9.547760e-03	4.83164620	9.108375e-03
LM.RNL2[x(t-6)]	6.20311482	4.497910e-02	3.16147798	4.487963e-02
LM.RNL2[x(t-7)]	3.70238246	1.570500e-01	1.85891709	1.590137e-01
LM.RNL2[x(t-8)]	1.88489172	3.896736e-01	0.93626811	3.941124e-01
LM.RNL3[x(t-1)]	42.10931551	3.803439e-09	18.15466350	2.983948e-10
LM.RNL3[x(t-2)]	37.05024819	4.490108e-08	15.37471445	6.954213e-09
LM.RNL3[x(t-3)]	22.72809185	4.601095e-05	8.52654166	2.646776e-05
LM.RNL3[x(t-4)]	17.85101835	4.720895e-04	6.48500572	3.530288e-04
LM.RNL3[x(t-5)]	10.14503210	1.737270e-02	3.51006710	1.660556e-02
LM.RNL3[x(t-6)]	6.53898179	8.813777e-02	2.21310726	8.845744e-02
LM.RNL3[x(t-7)]	6.05511161	1.089595e-01	2.04336665	1.097411e-01

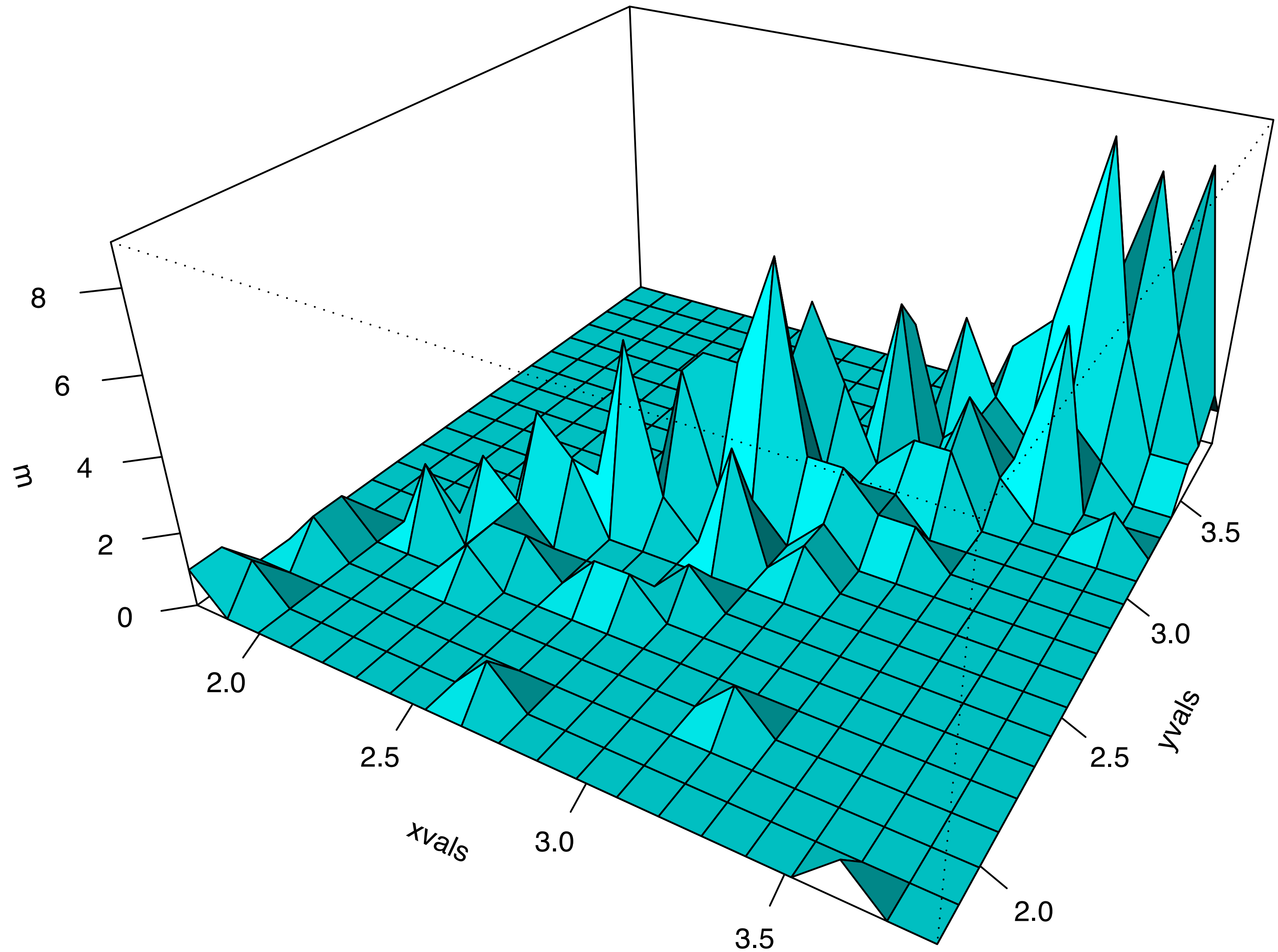
```
LM.RNL3[x(t-8)]  5.63264727 1.309166e-01  1.89597443 1.321874e-01
> plot(d.fit0)
>
> p.fit0 <- predict(fit0,n.ahead=50)
> summary(p.fit0)


Call:
 predict.STAR(object = fit0, n.ahead = 50)


Forecast method: Parametric bootstrap of estimated LSTAR model

Model Information:

Forecast method: LSTAR(p1,p2) with transition variable = x(t-8)

In-sample error measures:
           ME           MSE           MAE           MPE          MAPE
-2.890504e-13  2.582457e-02  9.300264e-02 -3.364215e-03  3.177340e-02

Forecasts:
    Point Forecast
181       3.396657
182       3.446944
183       3.445760
184       3.558531
185       3.565459
186       3.565352
187       3.618579
188       3.614682
189       3.585571
190       3.499631
191       3.381018
192       3.249355
193       3.106589
194       2.974293
195       2.860142
196       2.773016
197       2.724879
198       2.698270
199       2.699779
200       2.745929
201       2.878495
202       3.108018
203       3.284578
204       3.353775
205       3.425258
206       3.508282
207       3.537093
208       3.558349
209       3.591063
210       3.600309
211       3.585543
212       3.519689
213       3.443970
214       3.342047
215       3.217845
216       3.100669
217       2.995065
218       2.900368
```

```
219       2.828573
220       2.775311
221       2.748712
222       2.754600
223       2.807512
224       2.949090
225       3.162719
226       3.307292
227       3.364281
228       3.455928
229       3.511543
230       3.533755

> plot(p.fit0)
>
> i.fit0 <- impulse(fit0,n.ahead=20)
Calculating GIRF:...................................................
..................................................
..................................................
.....................done
> plot(i.fit0)
>
> s.fit0 <- simulate(fit0,nsim=100)
> plot(s.fit0)
>
```

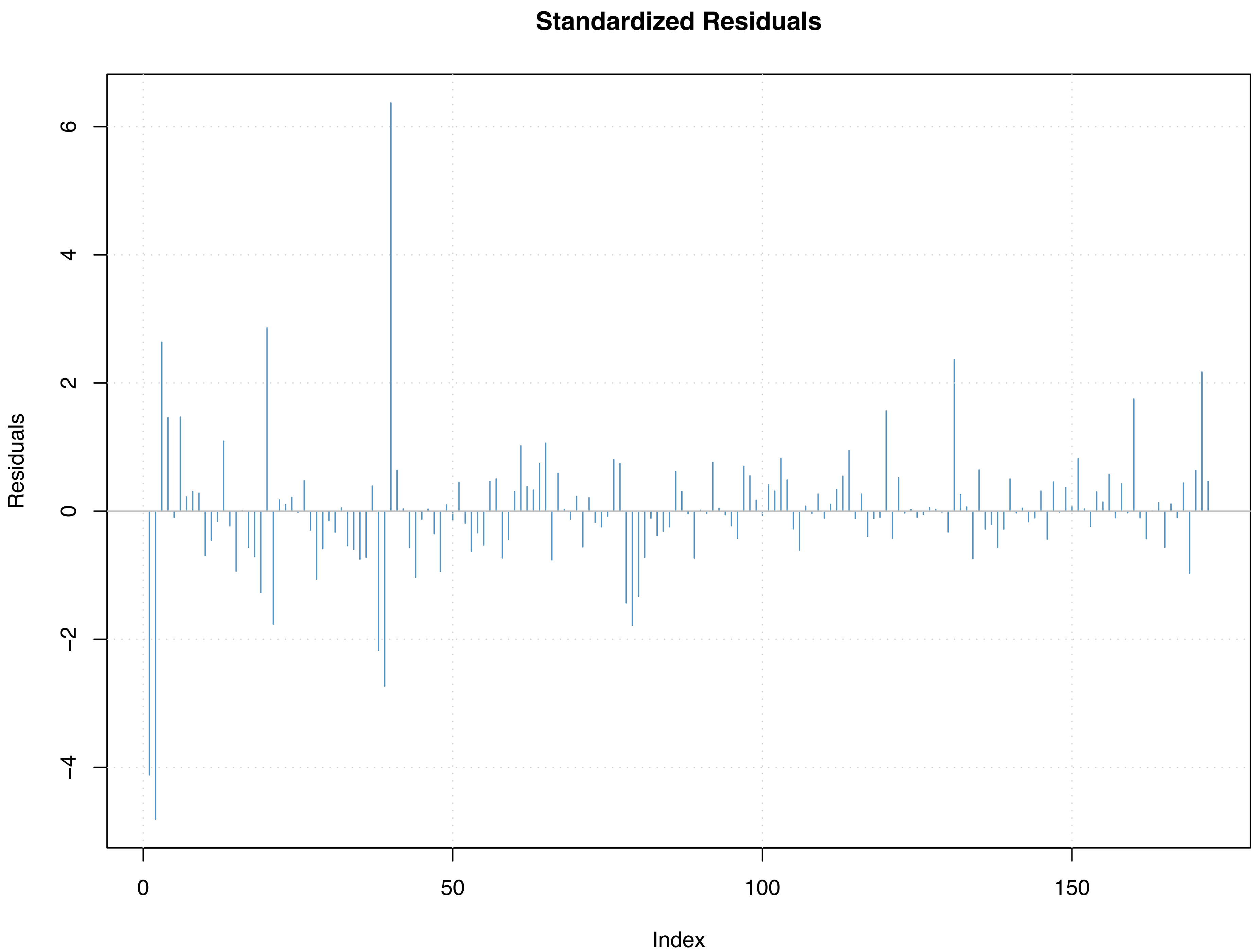




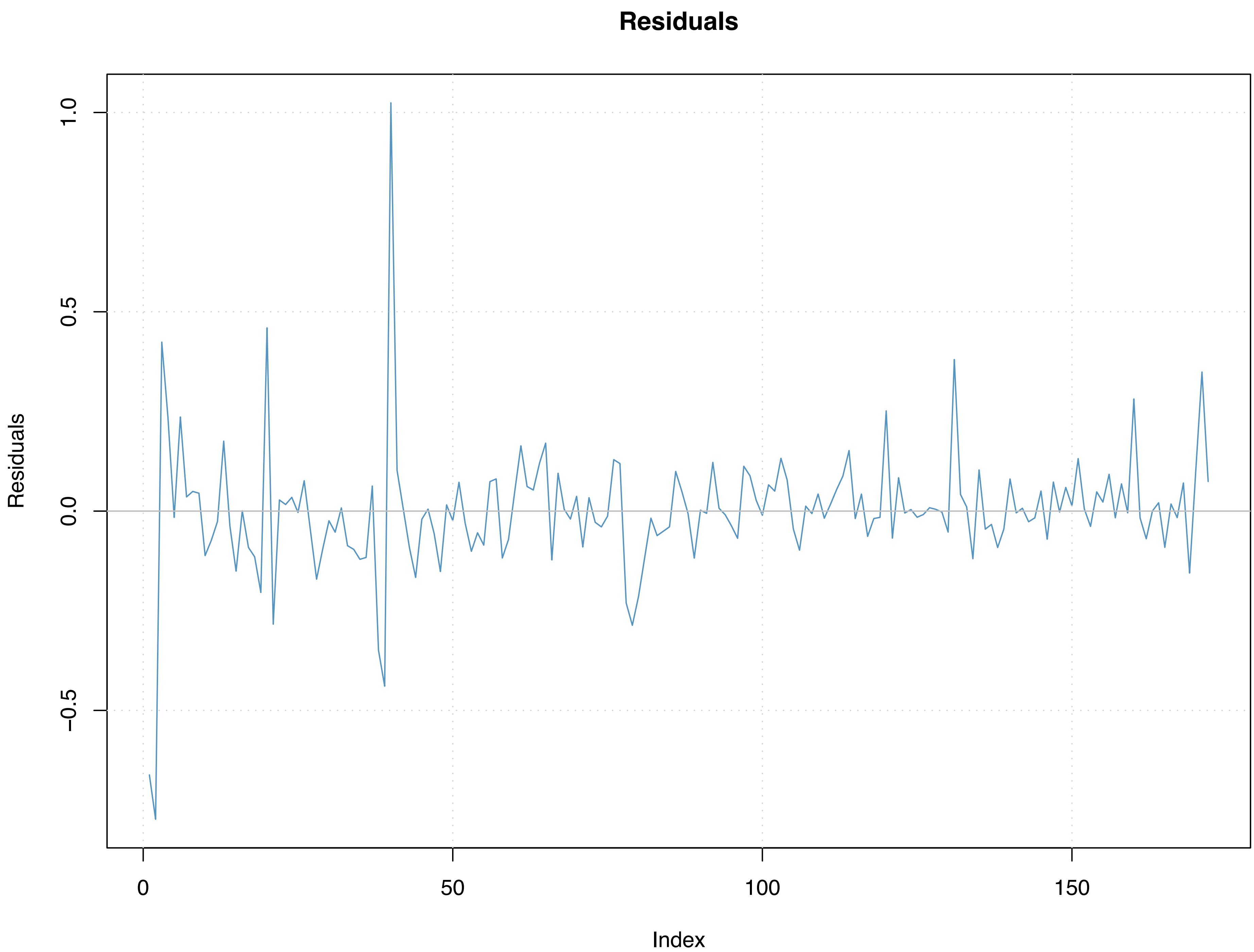
lag 1
lag 2
lag 3
lag 4
lag 5
lag 6
lag 7
lag 8
lag 9
x
1.5
2.0
2.5
3.0
3.5
4.0

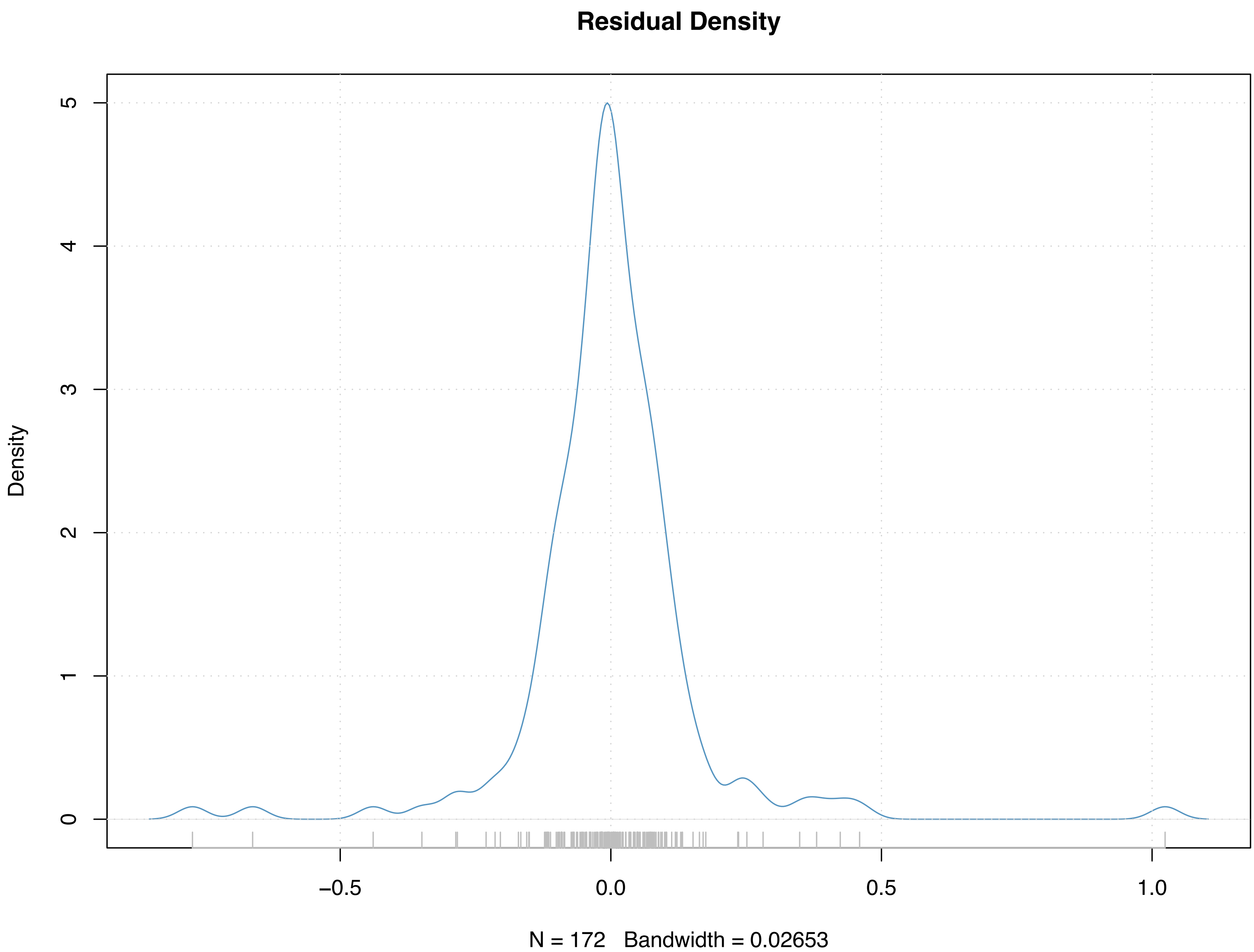


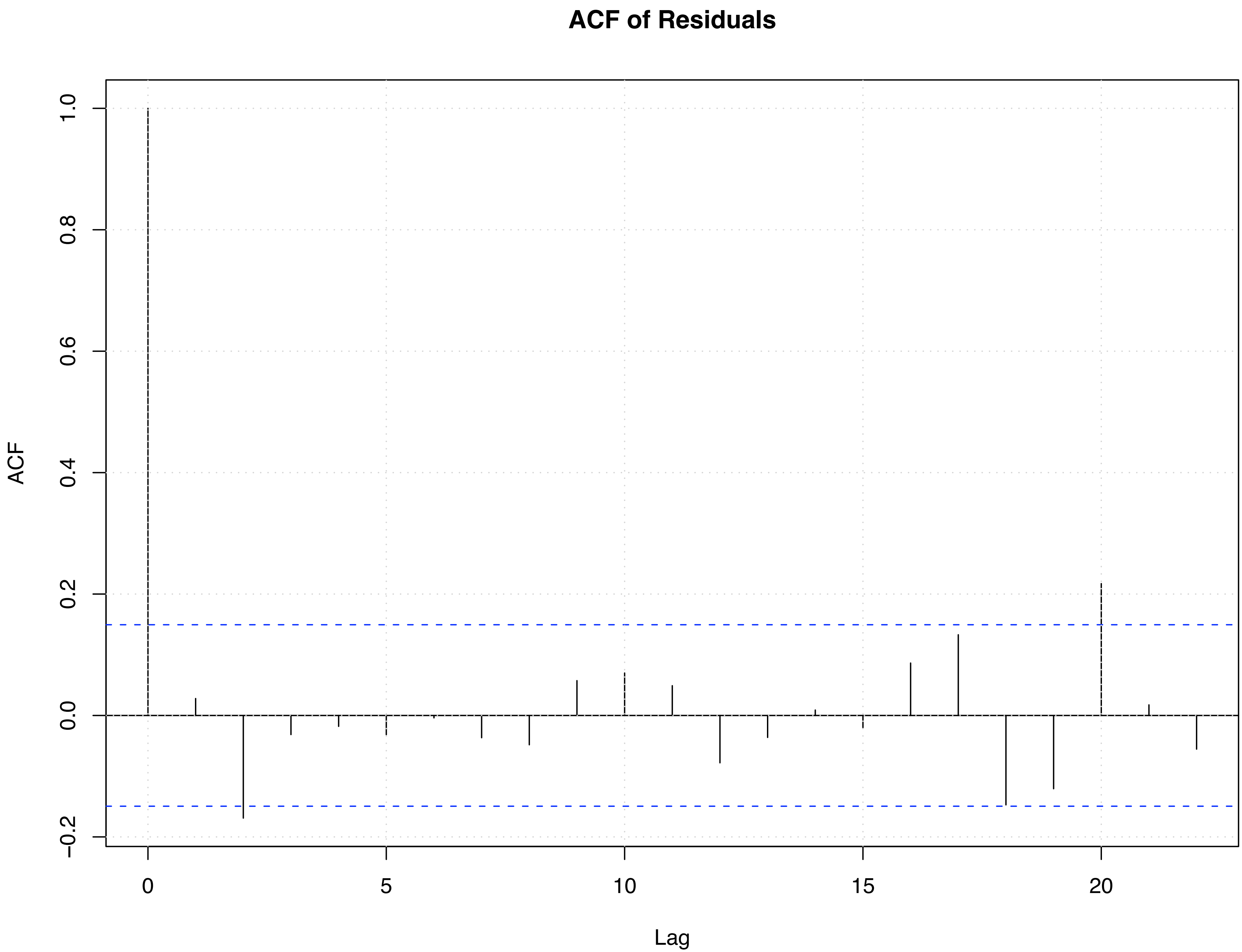
8
6
4
2
0
m
2.0
2.5
3.0
3.5
xvals
2.0
2.5
3.0
3.5
yvals

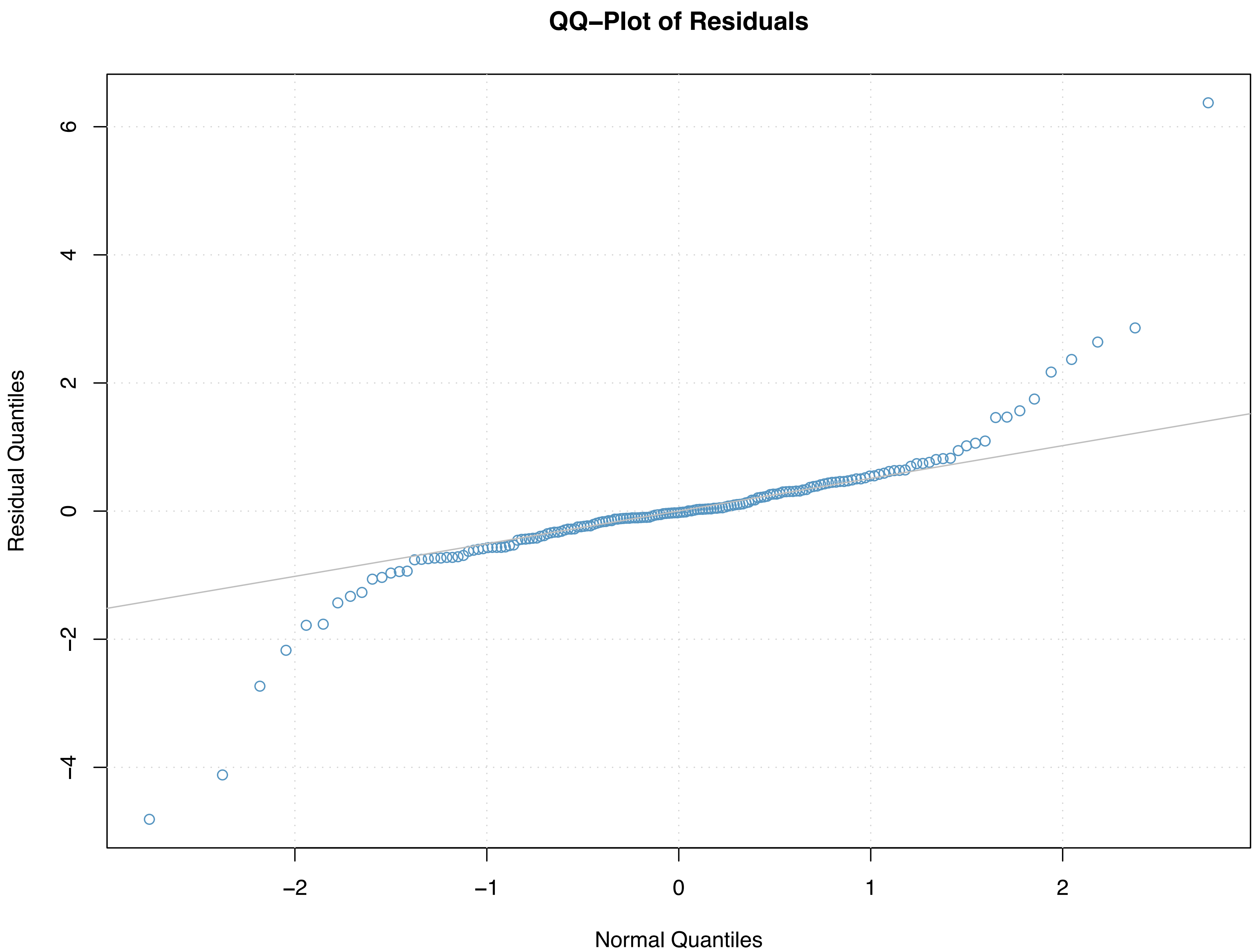


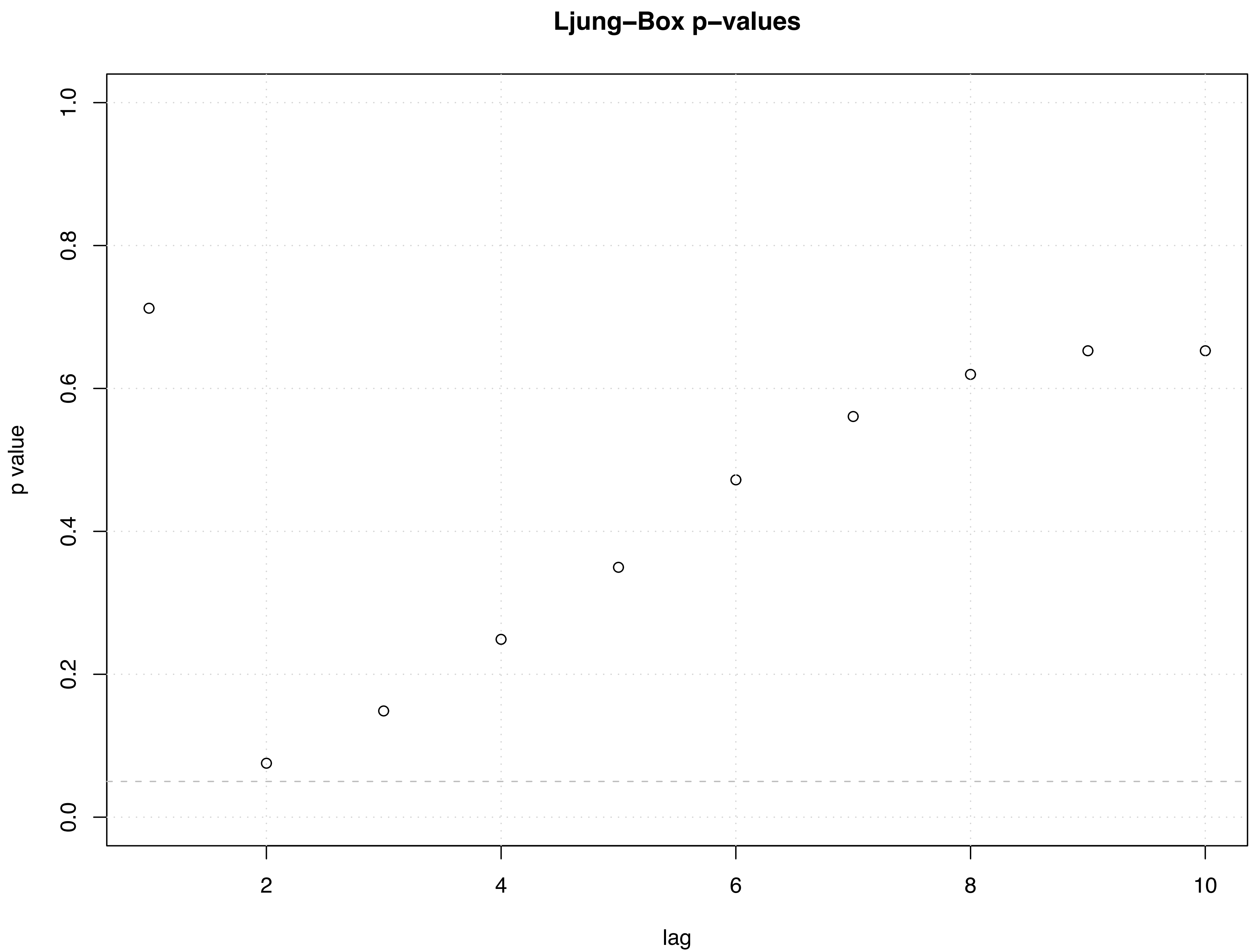
Standardized Residuals
Residuals
Index
−4
−2
0
2
4
6
0
50
100
150

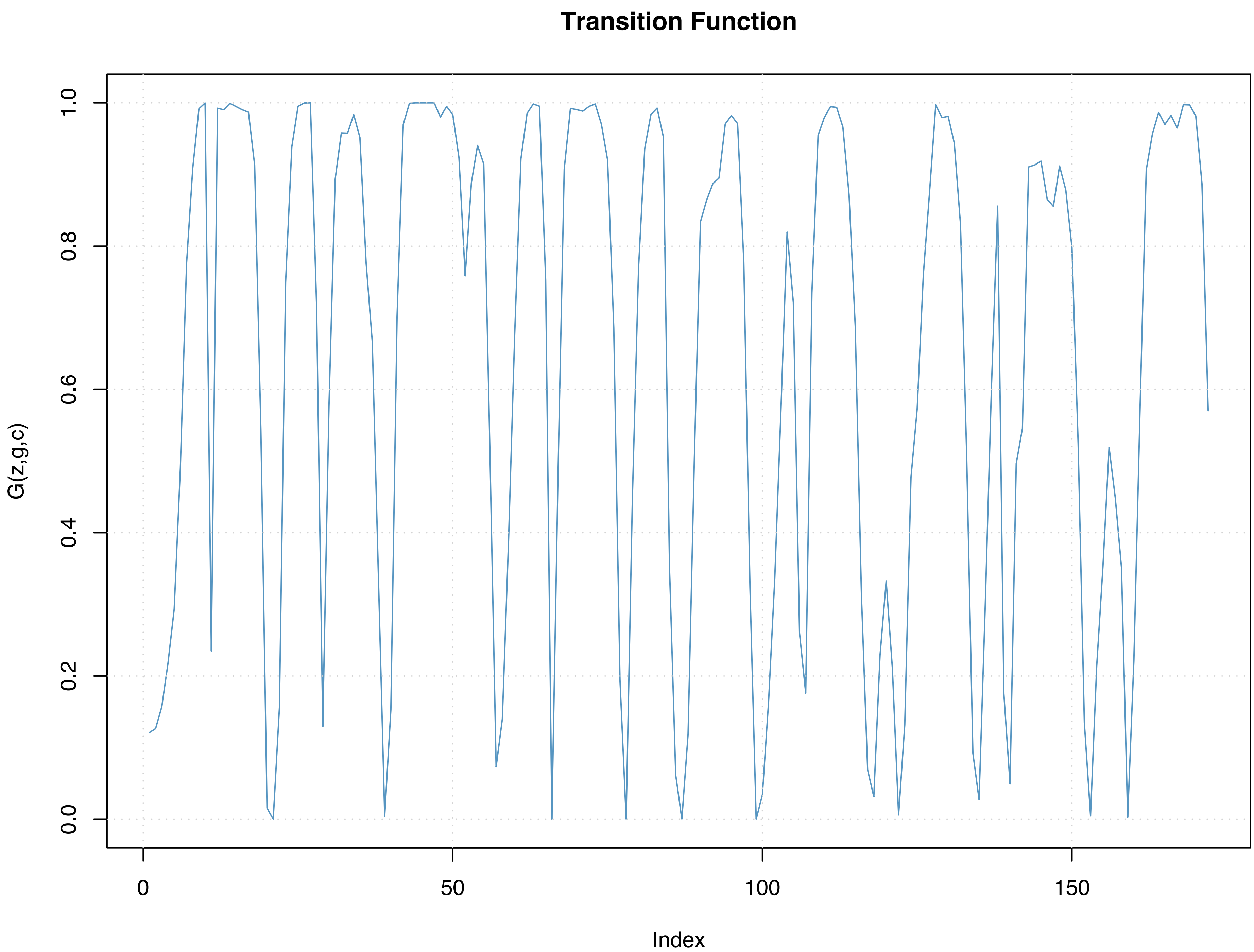

Residuals
Residuals
1.0
0.5
0.0
−0.5
0
50
100
150
Index

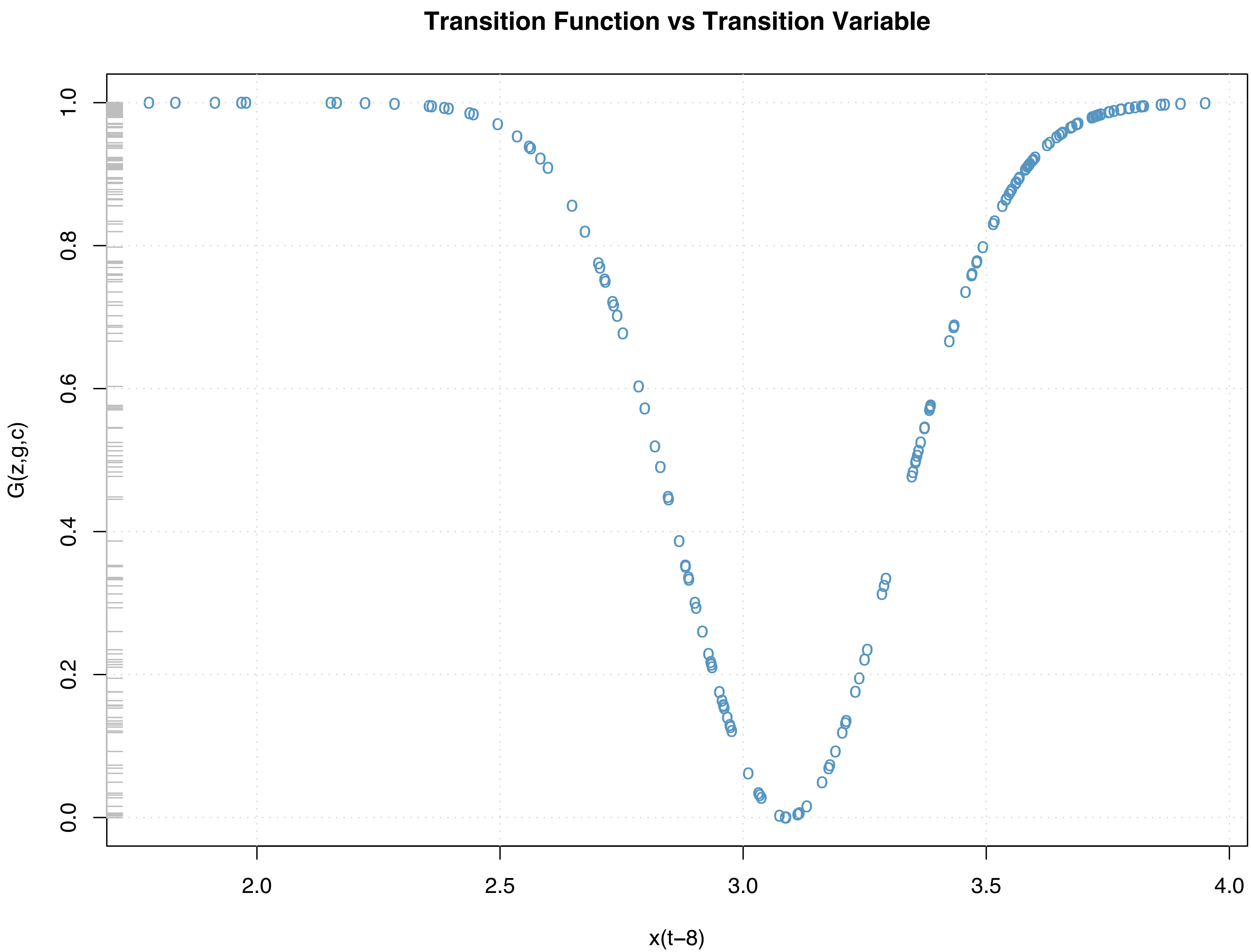

Residual Density
Density
0
1
2
3
4
5
−0.5
0.0
0.5
1.0
N = 172 Bandwidth = 0.02653


ACF of Residuals
ACF
Lag
-0.2
0.0
0.2
0.4
0.6
0.8
1.0
0
5
10
15
20

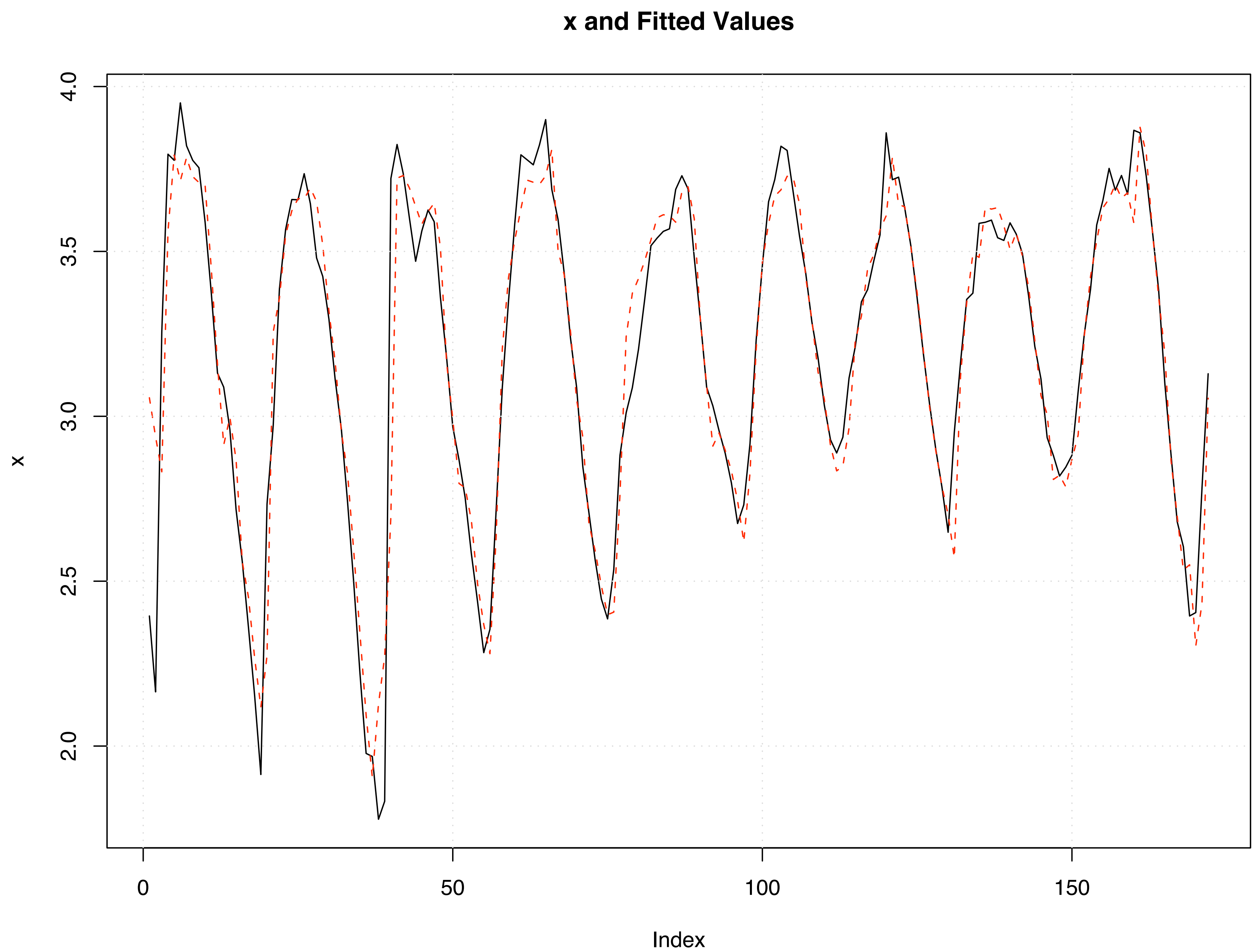

QQ–Plot of Residuals
Residual Quantiles
Normal Quantiles
6
4
2
0
−2
−4
−2
−1
0
1
2


Ljung–Box p–values
p value
1.0
0.8
0.6
0.4
0.2
0.0
2
4
6
8
10
lag

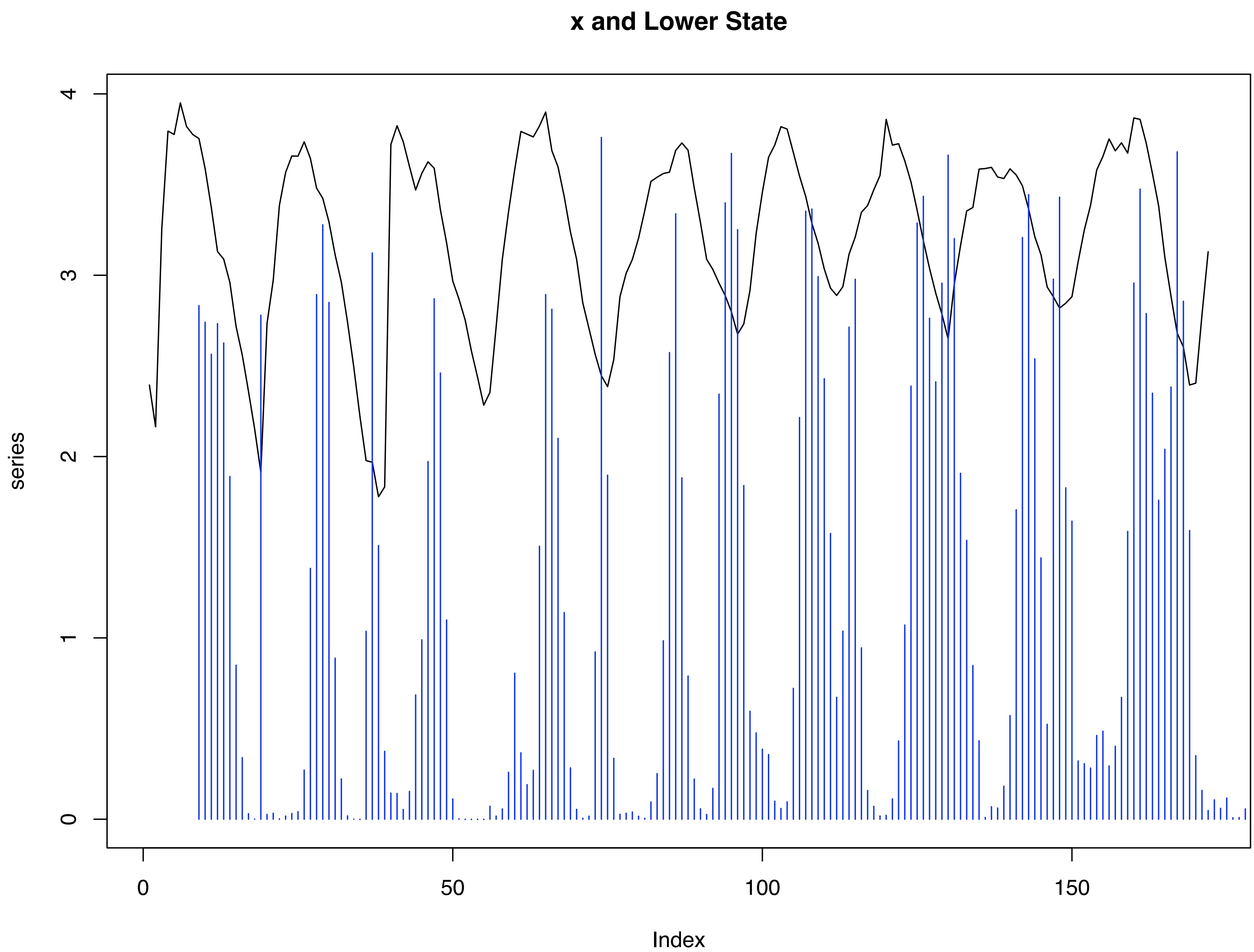

Transition Function
G(z,g,c)
0.0
0.2
0.4
0.6
0.8
1.0
0
50
100
150
Index

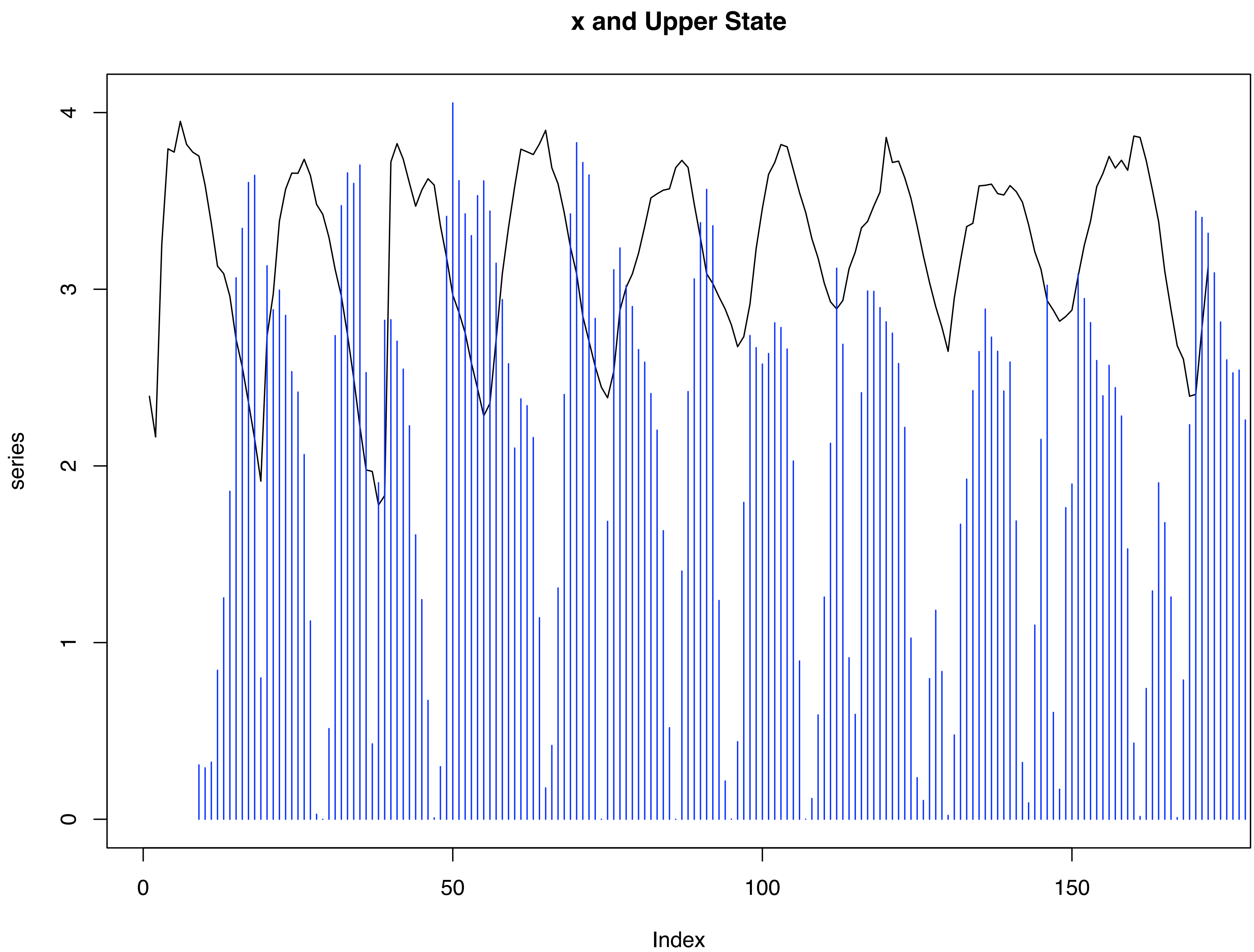


Transition Function vs Transition Variable
G(z,g,c)
0.0
0.2
0.4
0.6
0.8
1.0
2.0
2.5
3.0
3.5
4.0
x(t−8)

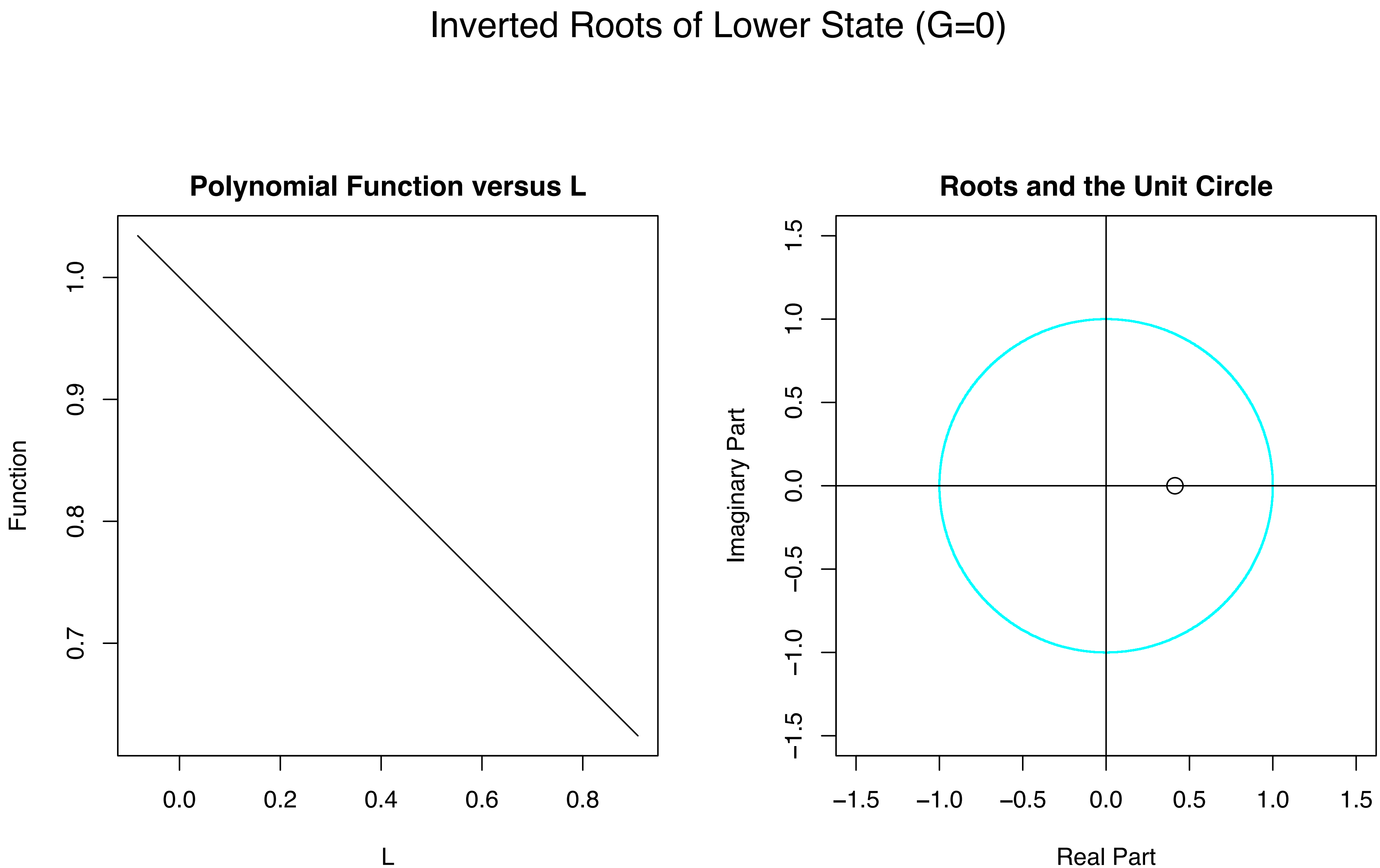


x and Fitted Values
4.0
3.5
3.0
2.5
2.0
x
0
50
100
150
Index

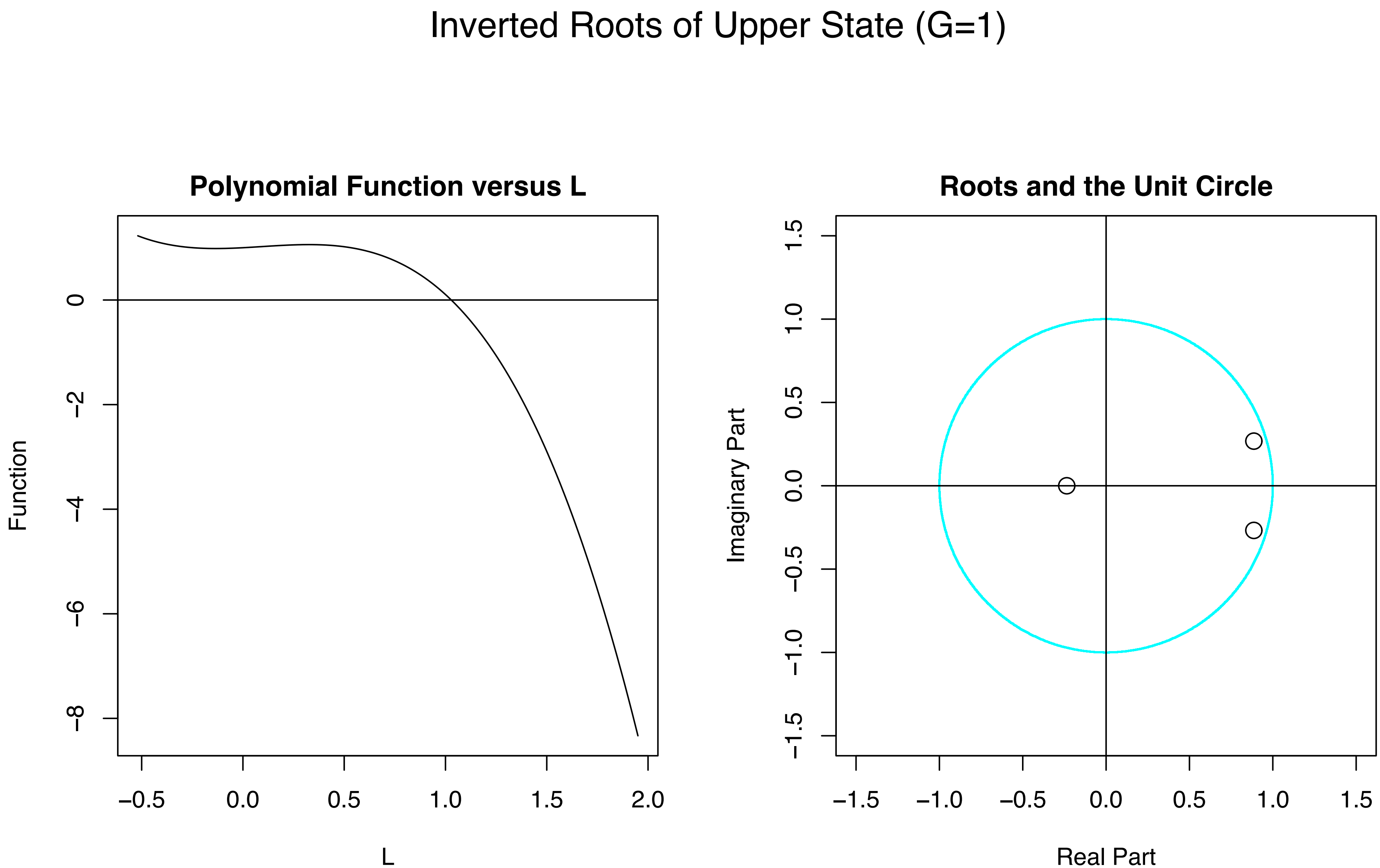

x and Lower State
series
Index
0
1
2
3
4
0
50
100
150



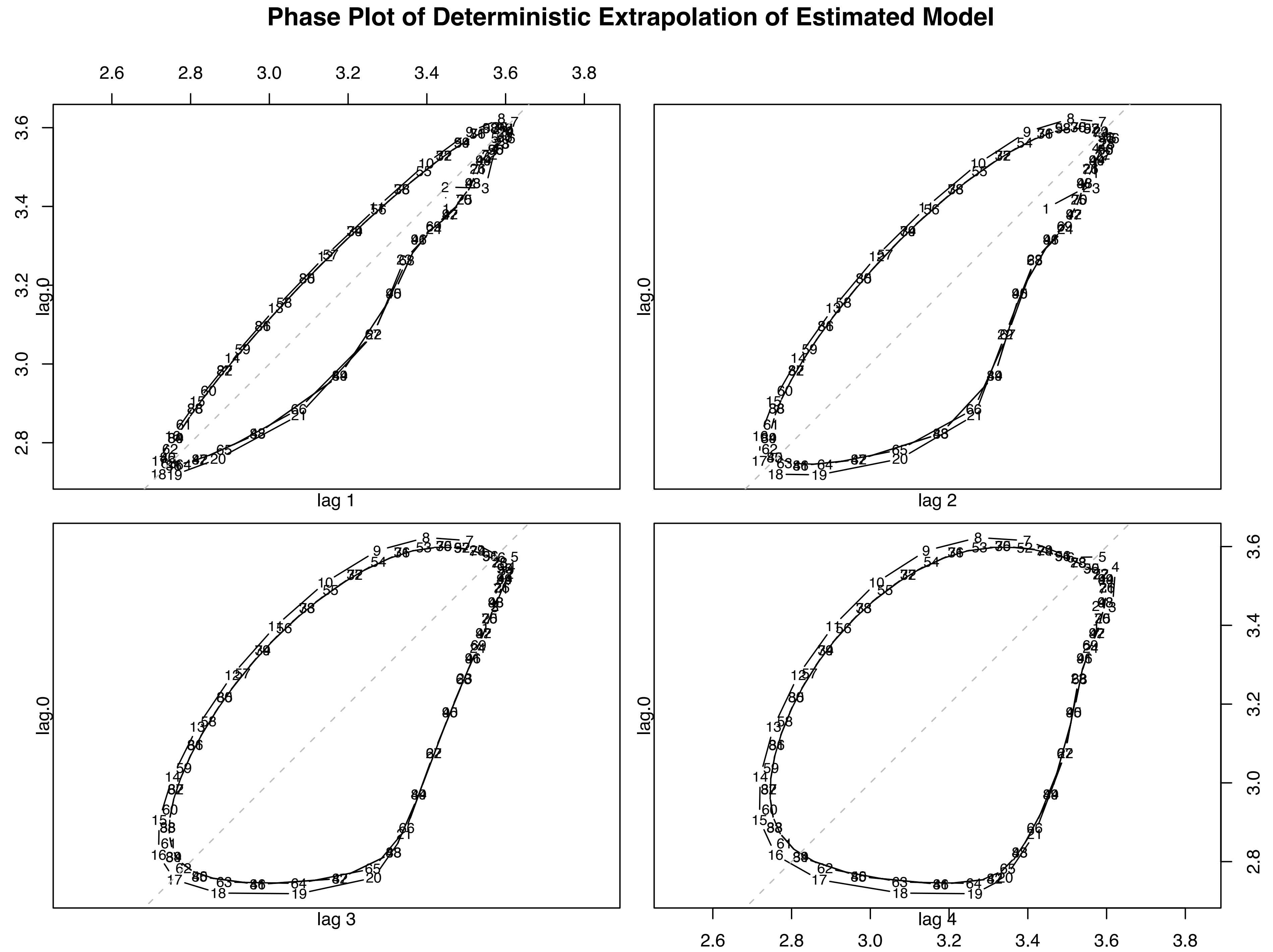
x and Upper State
series
Index
0
1
2
3
4
0
50
100
150



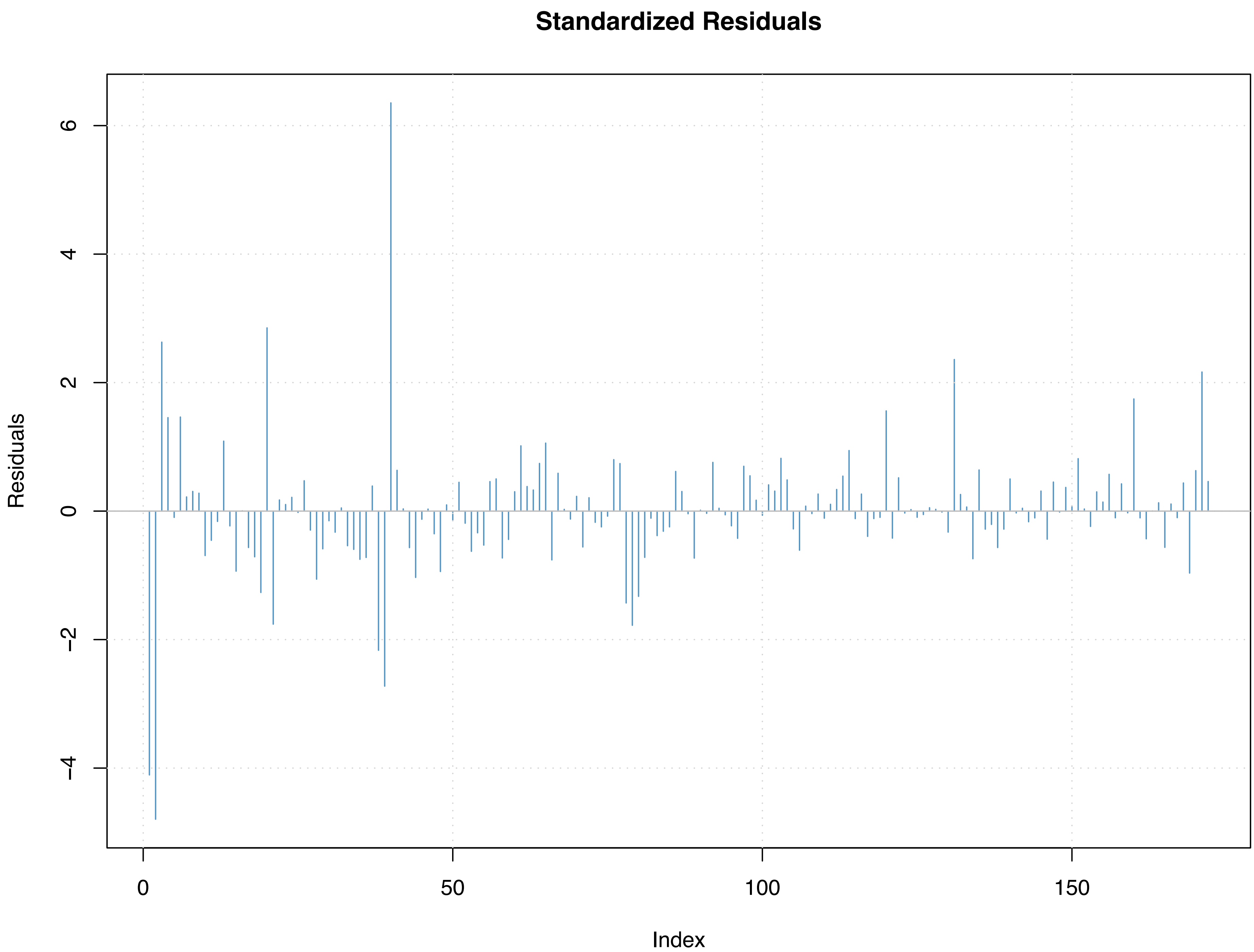
Inverted Roots of Lower State (G=0)
Polynomial Function versus L
Function
1.0
0.9
0.8
0.7
0.0
0.2
0.4
0.6
0.8
L
Roots and the Unit Circle
Imaginary Part
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
Real Part



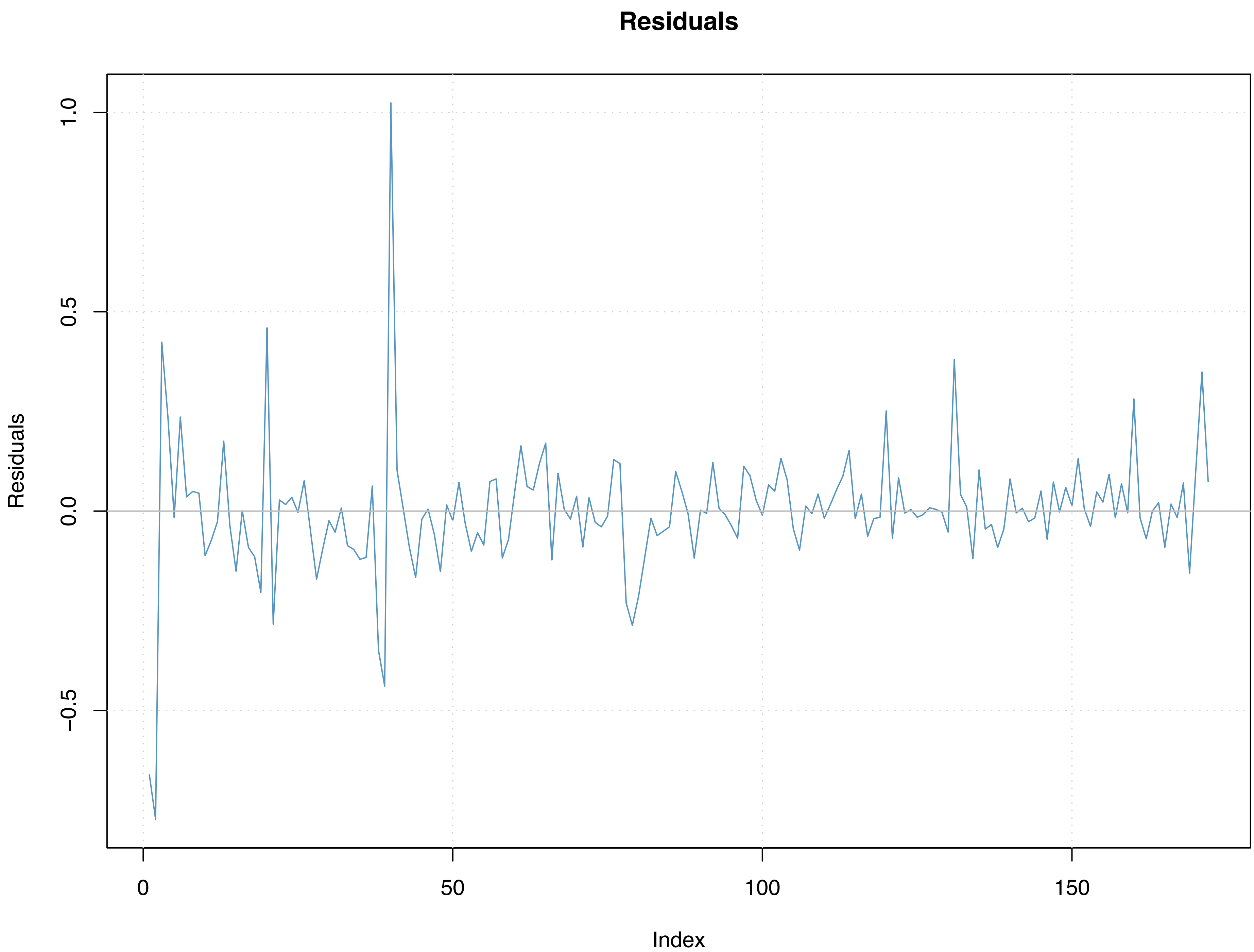
Inverted Roots of Upper State (G=1)
Polynomial Function versus L
Function
L
0
−2
−4
−6
−8
−0.5
0.0
0.5
1.0
1.5
2.0
Roots and the Unit Circle
Imaginary Part
Real Part
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5

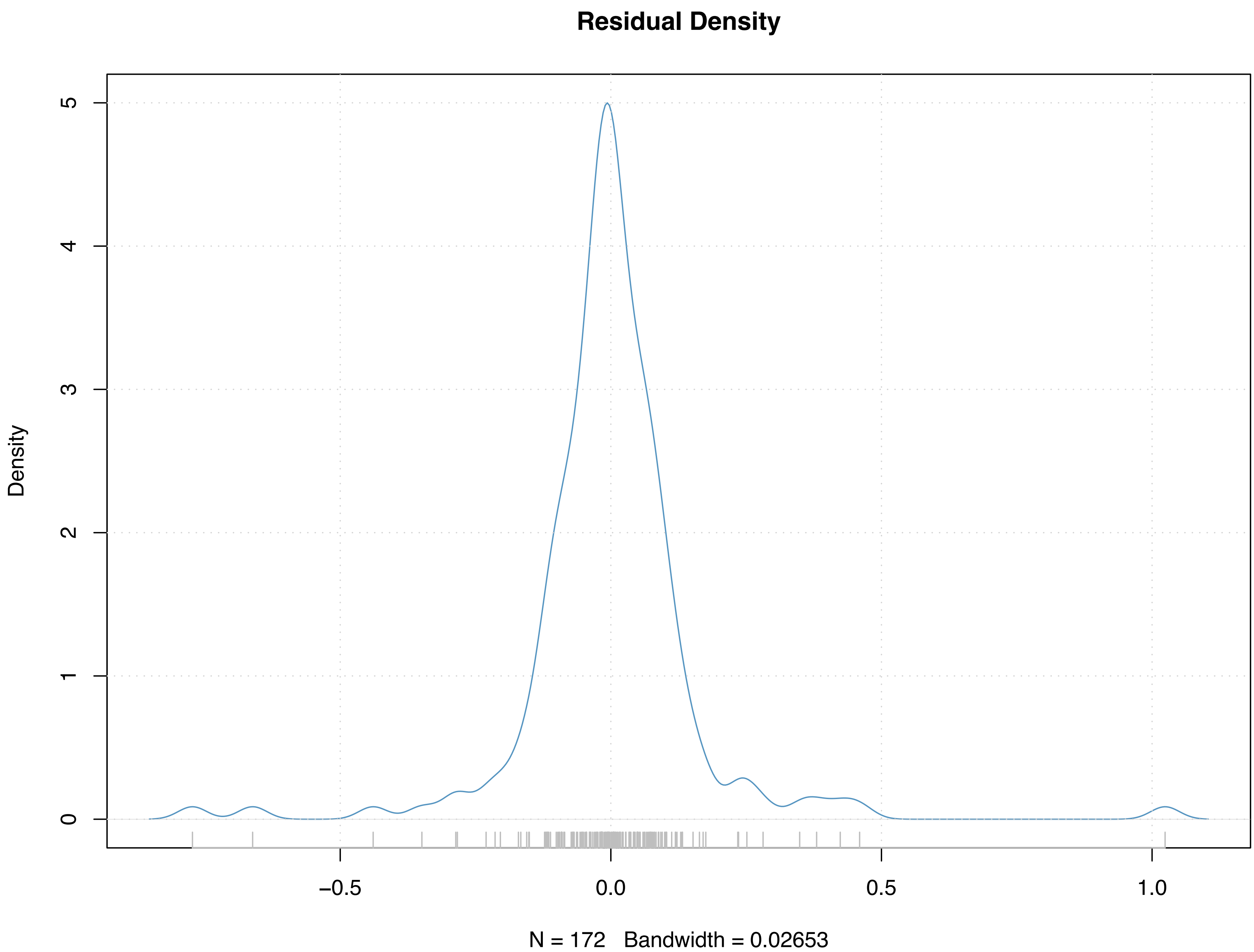


Phase Plot of Deterministic Extrapolation of Estimated Model
lag 1
lag 2
lag 3
lag 4
lag.0

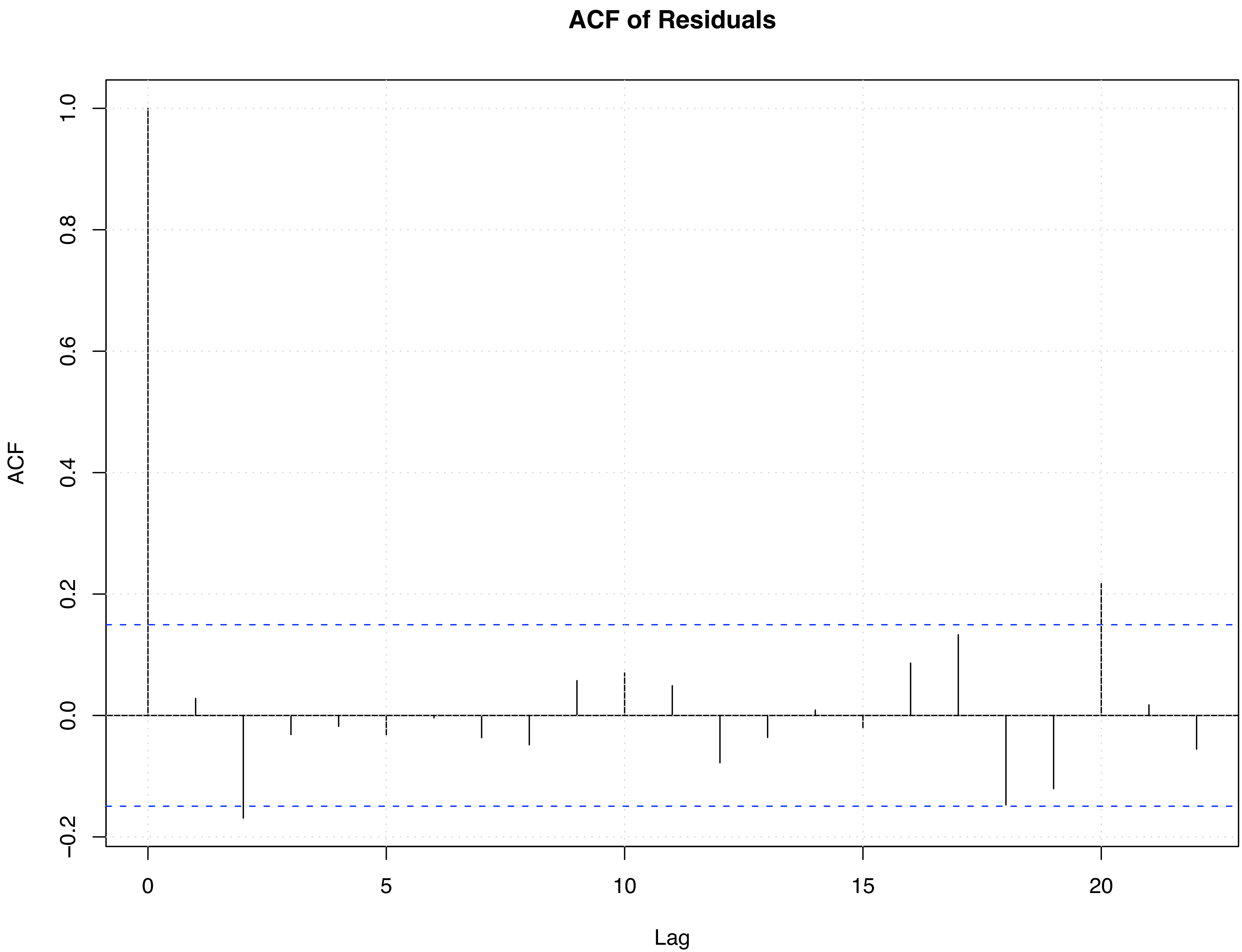


Standardized Residuals
Residuals
Index
6
4
2
0
−2
−4
0
50
100
150

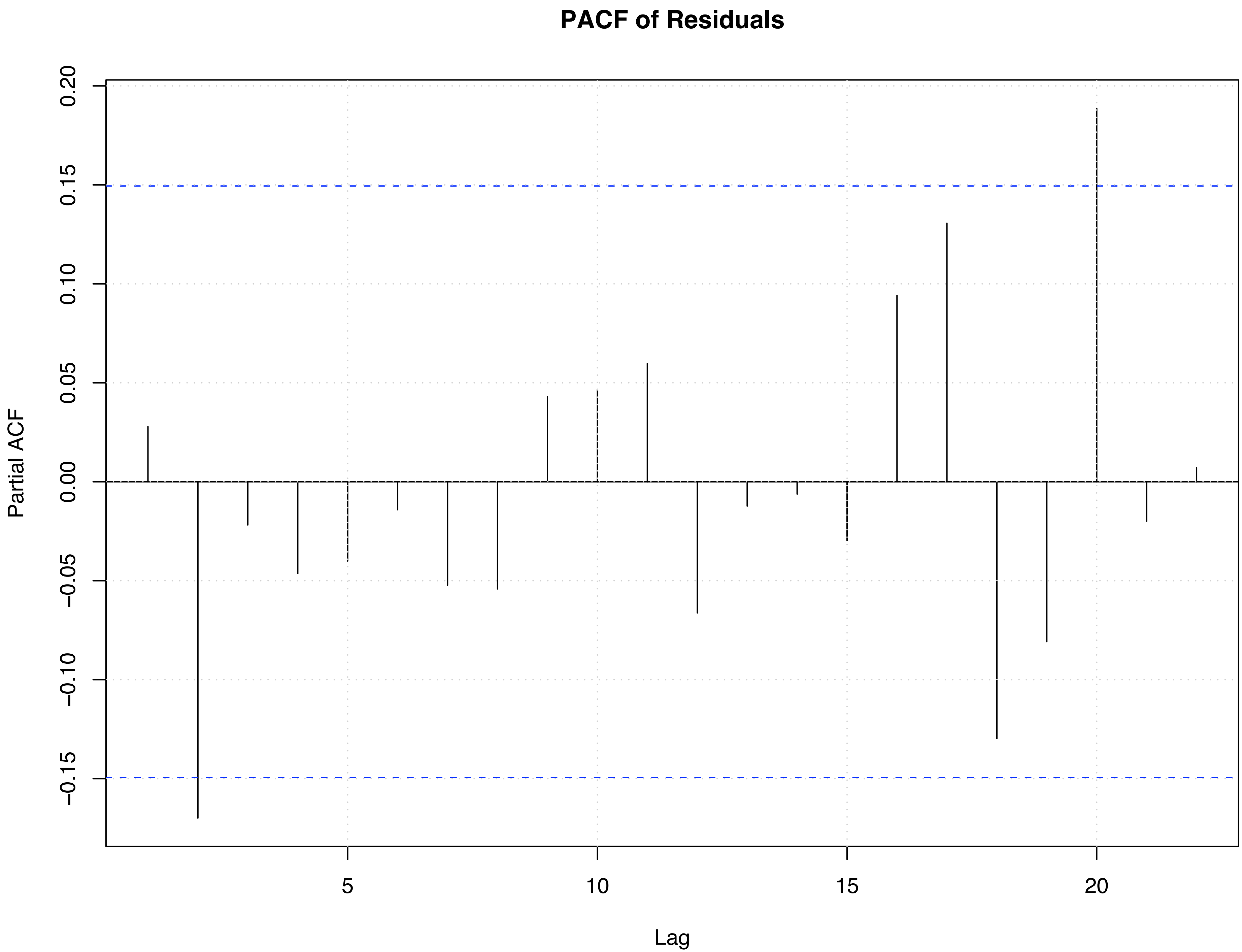

Residuals
Residuals
Index
1.0
0.5
0.0
−0.5
0
50
100
150



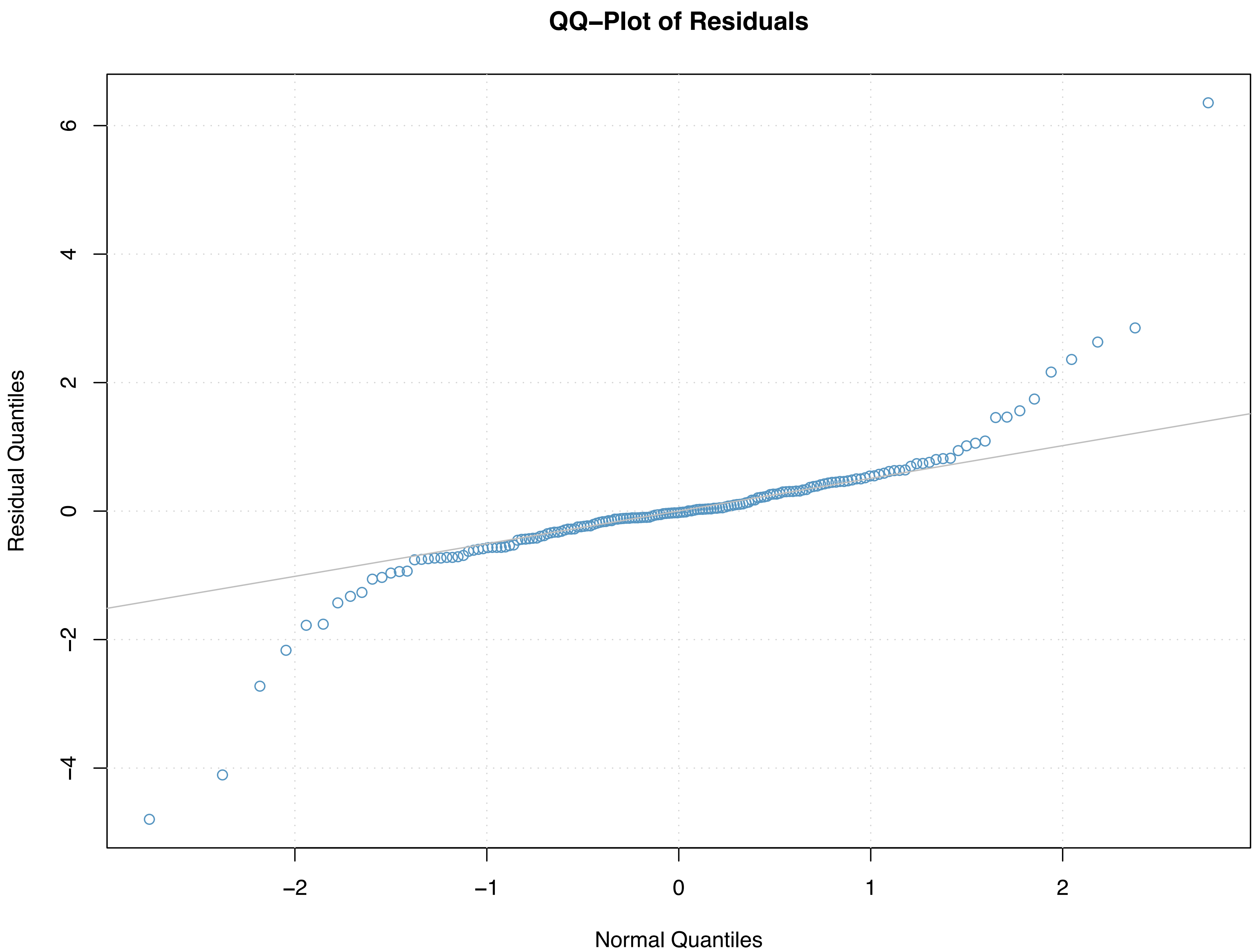
Residual Density
Density
5
4
3
2
1
0
−0.5
0.0
0.5
1.0
N = 172   Bandwidth = 0.02653

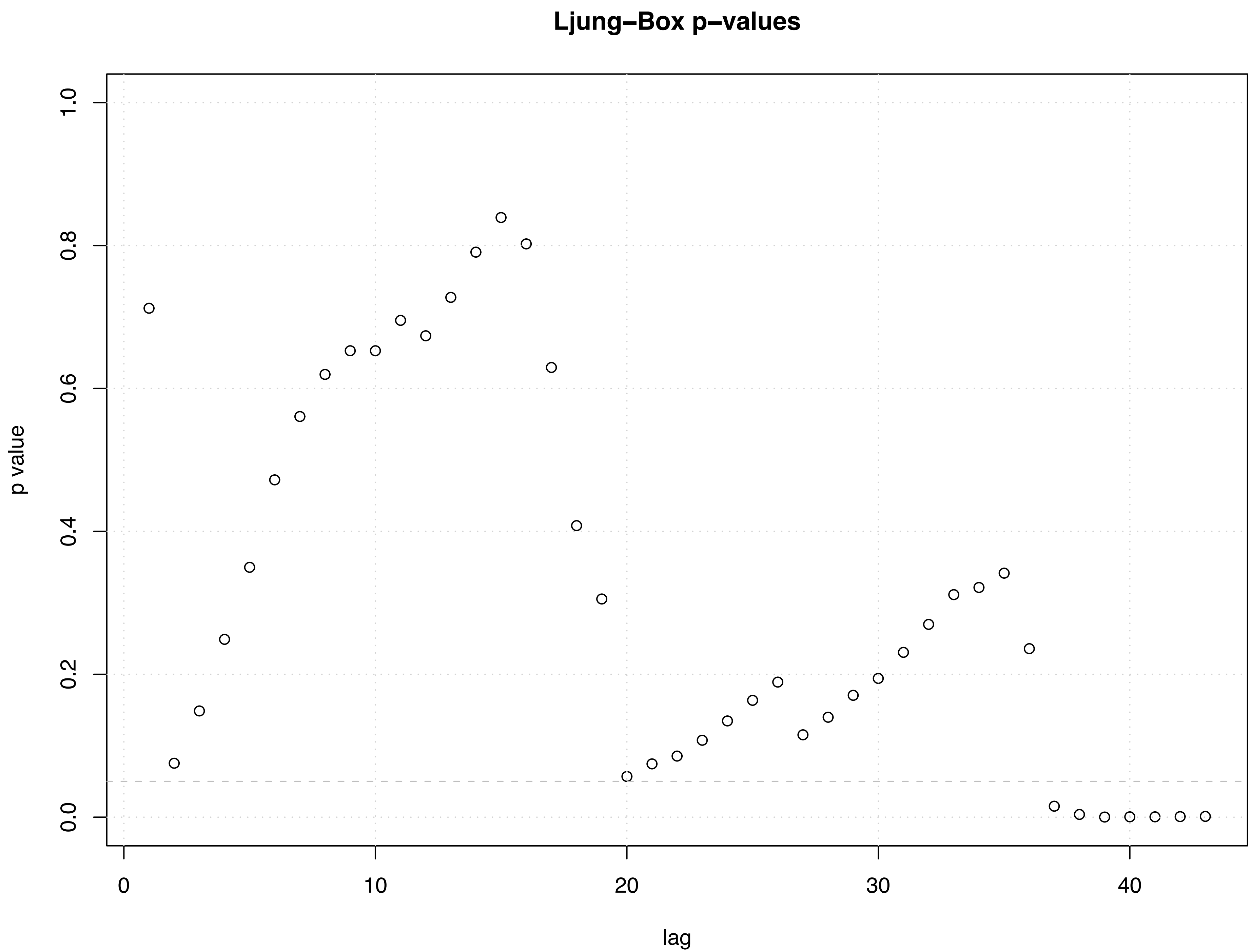


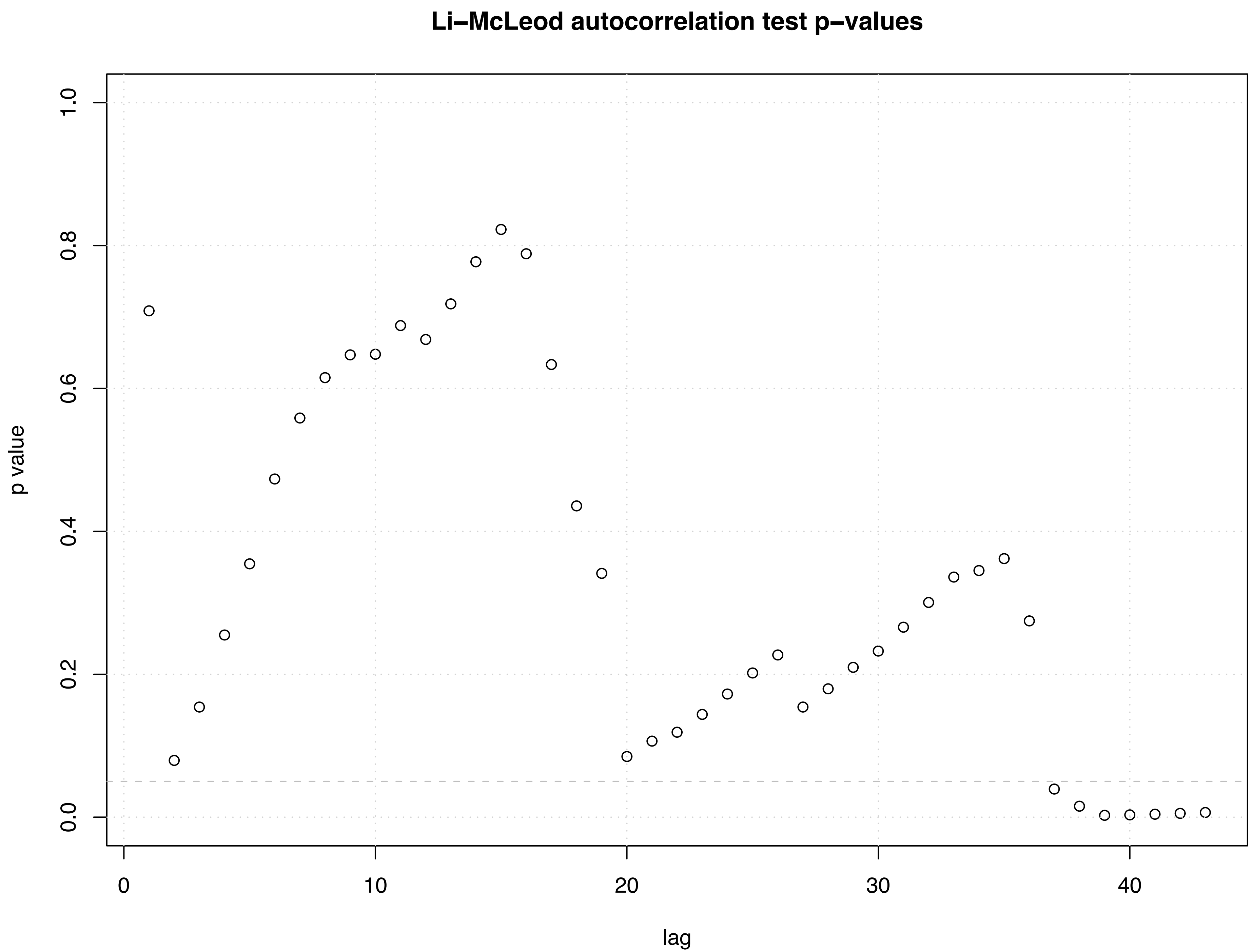
ACF of Residuals
ACF
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
0
5
10
15
20
Lag

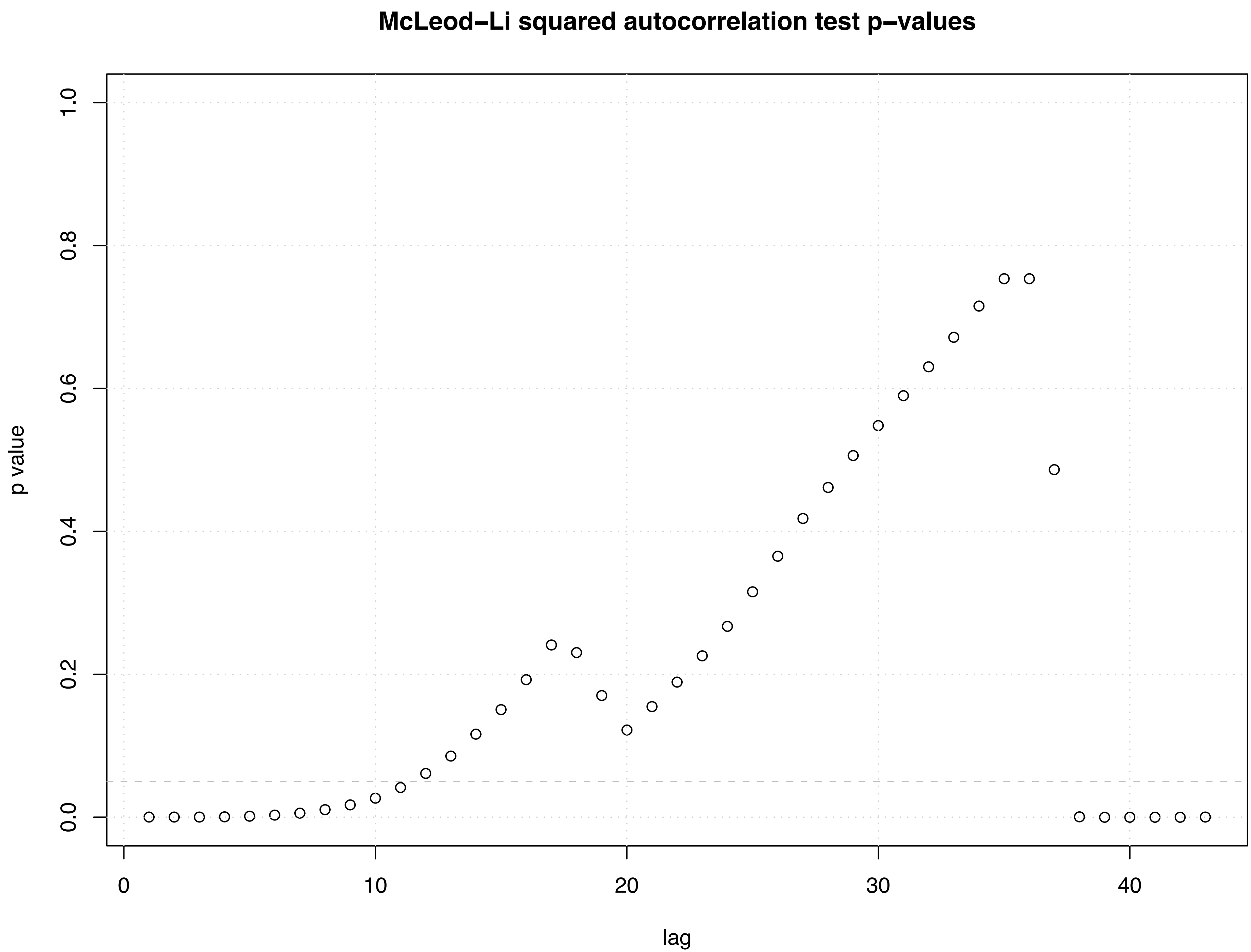


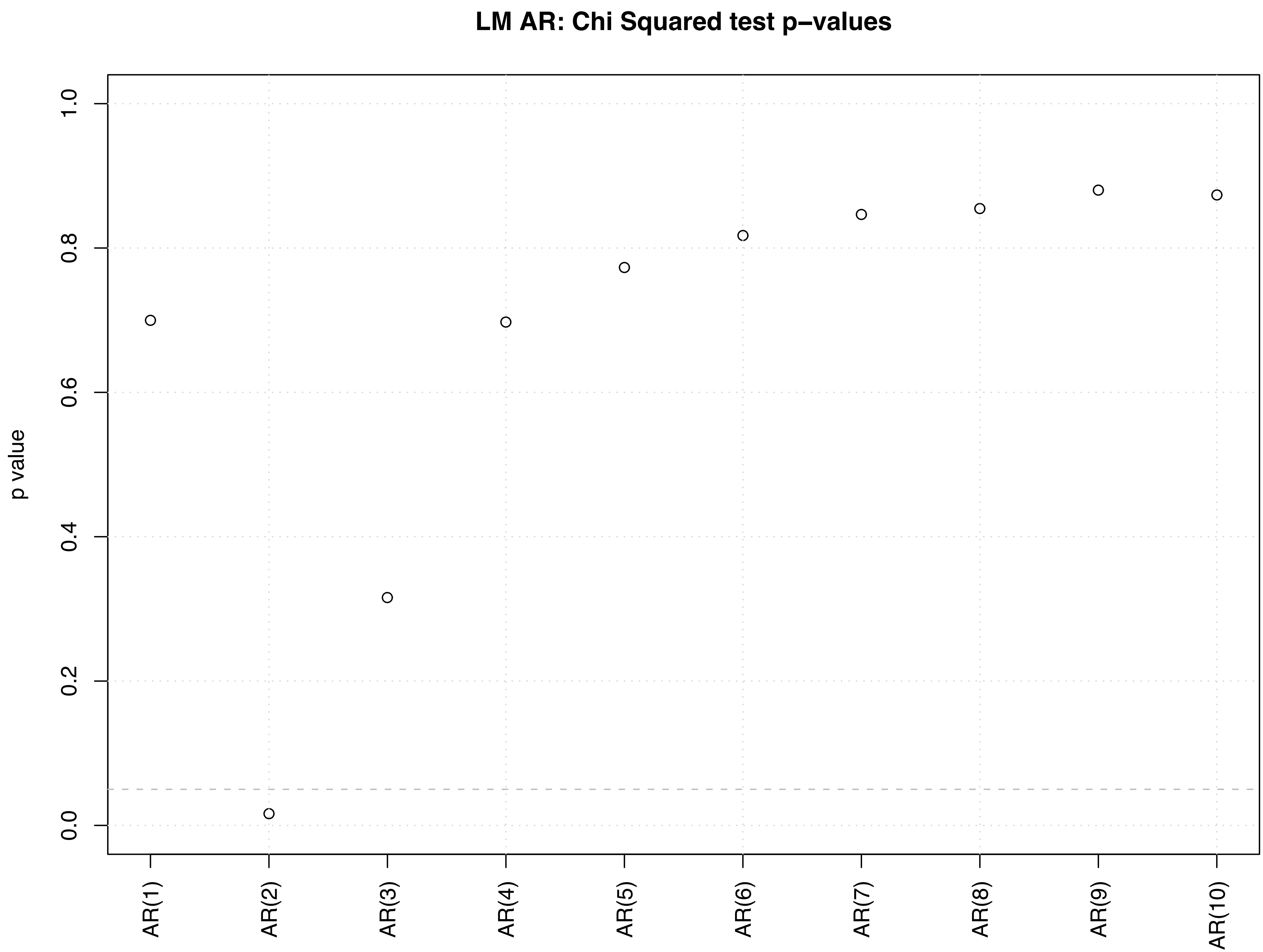
PACF of Residuals
Partial ACF
Lag
0.20
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
5
10
15
20

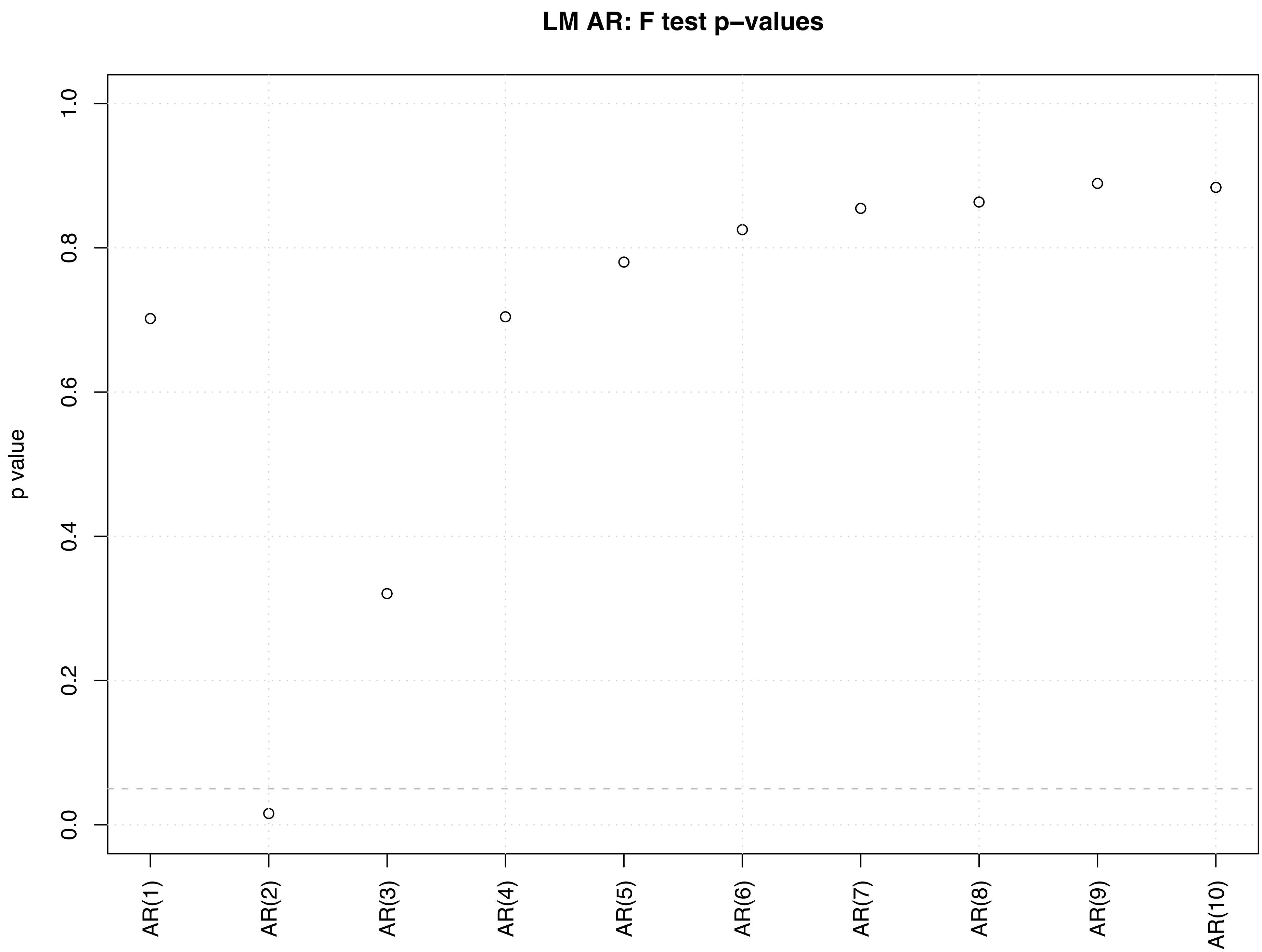

QQ–Plot of Residuals
Residual Quantiles
Normal Quantiles
6
4
2
0
−2
−4
−2
−1
0
1
2

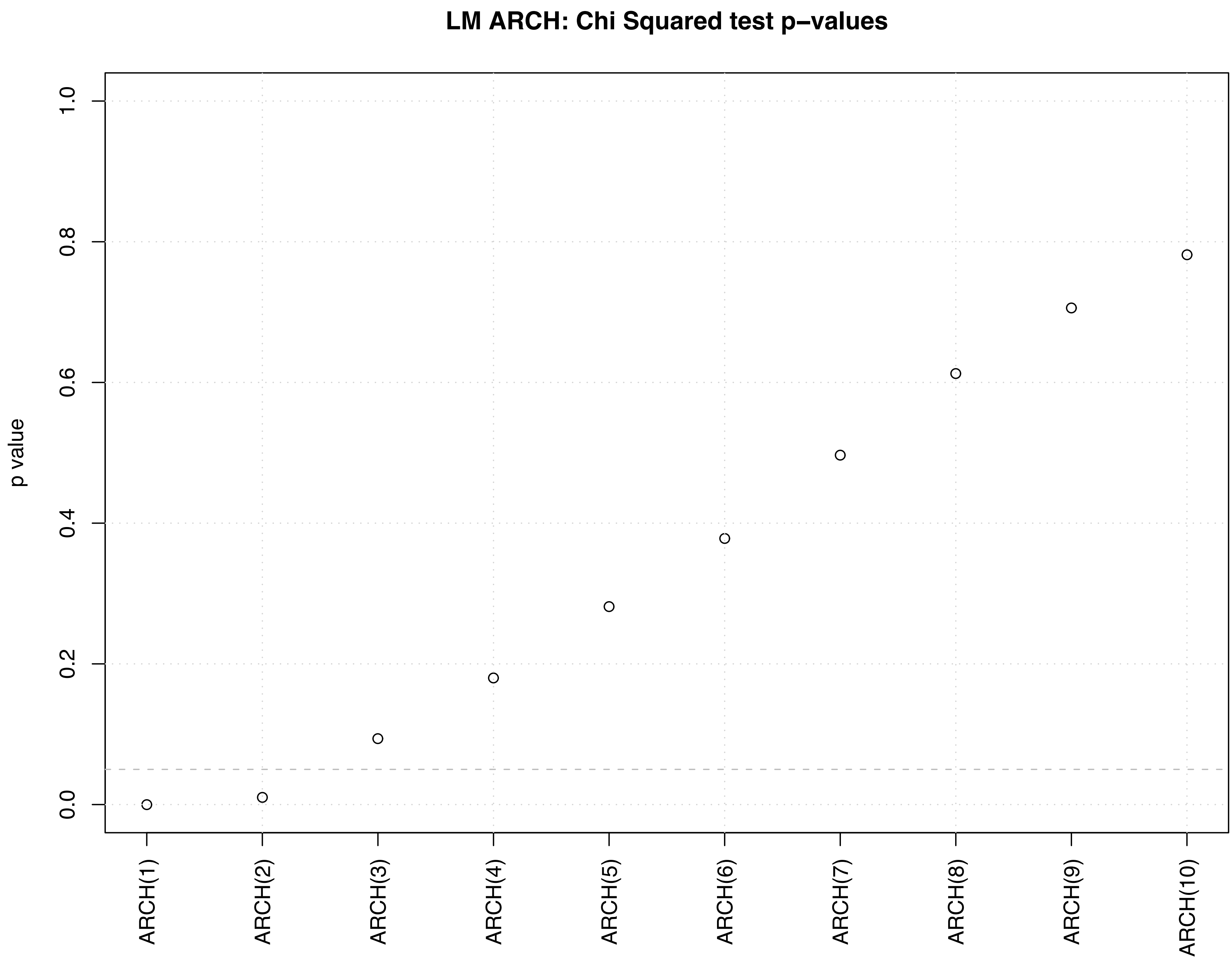

Ljung−Box p−values
p value
0.0
0.2
0.4
0.6
0.8
1.0
0
10
20
30
40
lag

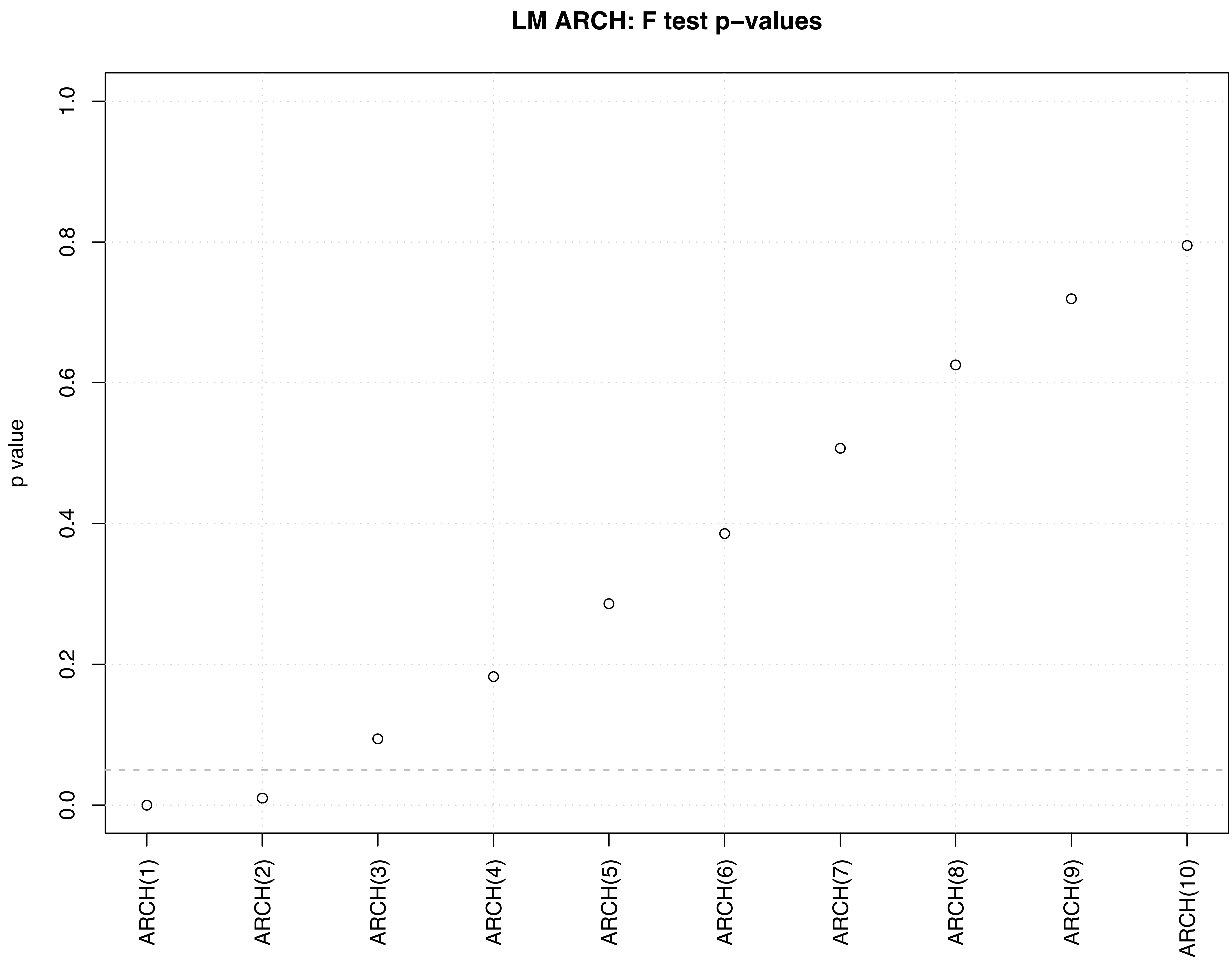

Li–McLeod autocorrelation test p–values
p value
lag
0.0
0.2
0.4
0.6
0.8
1.0
0
10
20
30
40

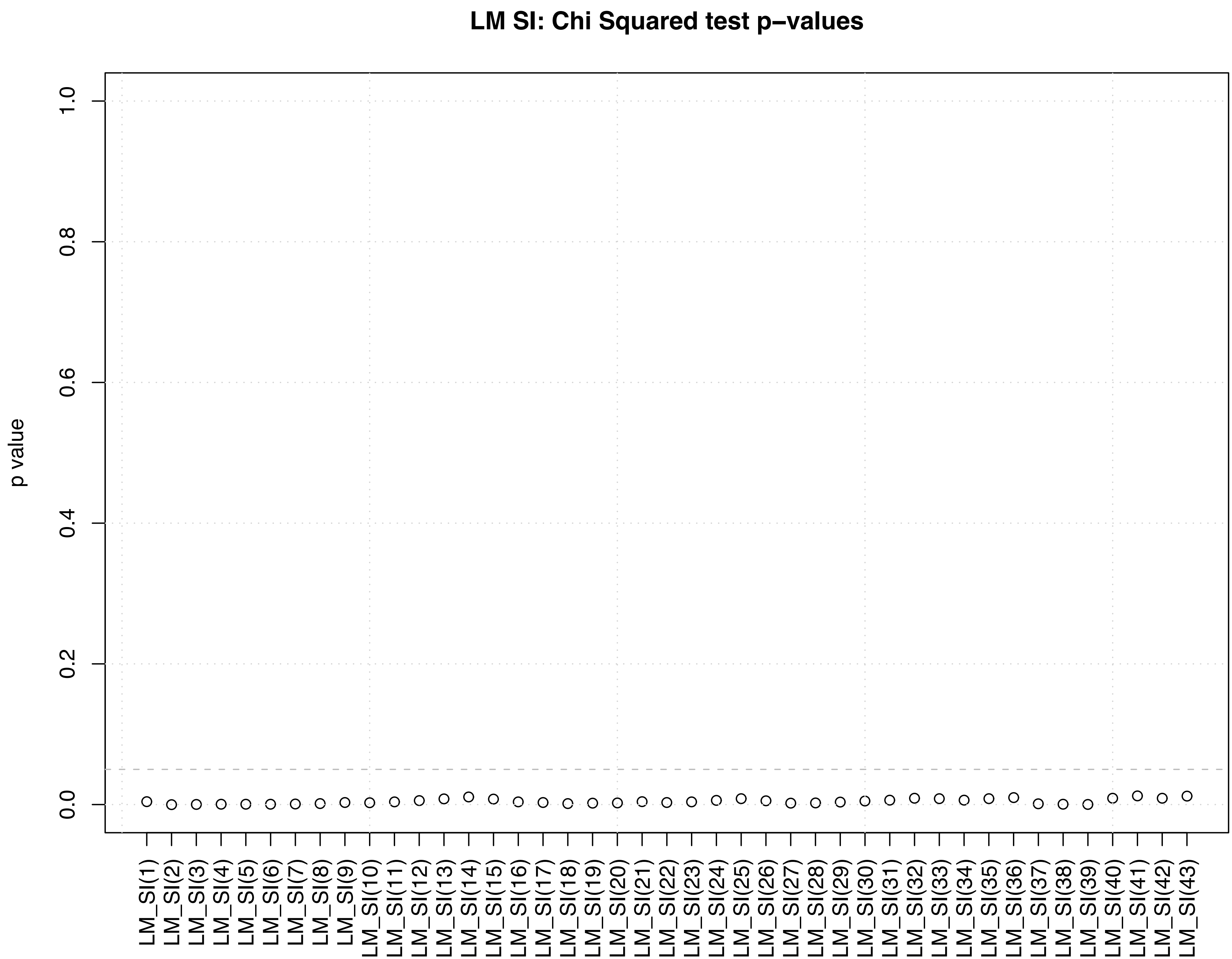

McLeod–Li squared autocorrelation test p–values
p value
lag
0.0
0.2
0.4
0.6
0.8
1.0
0
10
20
30
40


LM AR: Chi Squared test p−values
p value
1.0
0.8
0.6
0.4
0.2
0.0
AR(1)
AR(2)
AR(3)
AR(4)
AR(5)
AR(6)
AR(7)
AR(8)
AR(9)
AR(10)

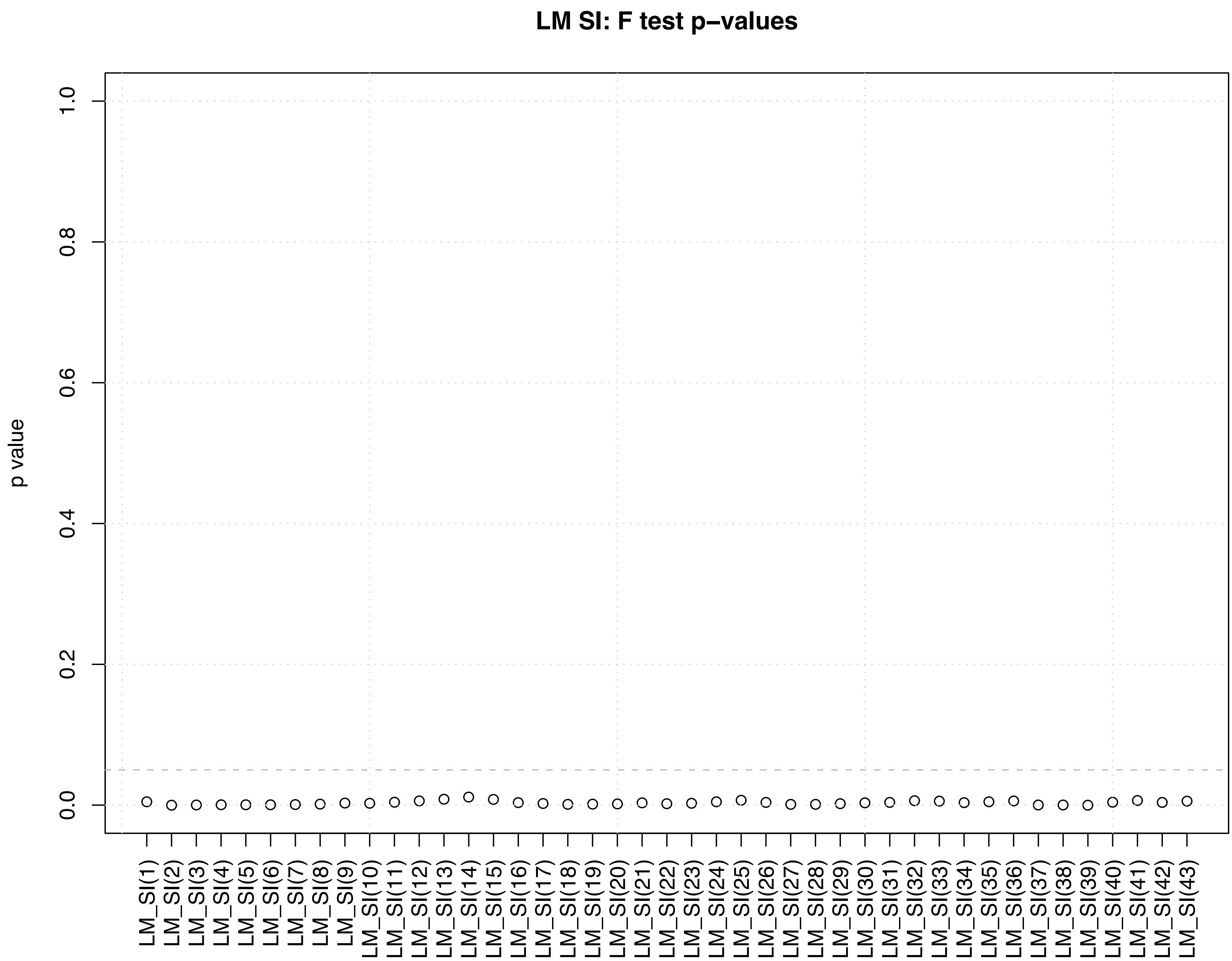

LM AR: F test p−values
p value
0.0
0.2
0.4
0.6
0.8
1.0
AR(1)
AR(2)
AR(3)
AR(4)
AR(5)
AR(6)
AR(7)
AR(8)
AR(9)
AR(10)

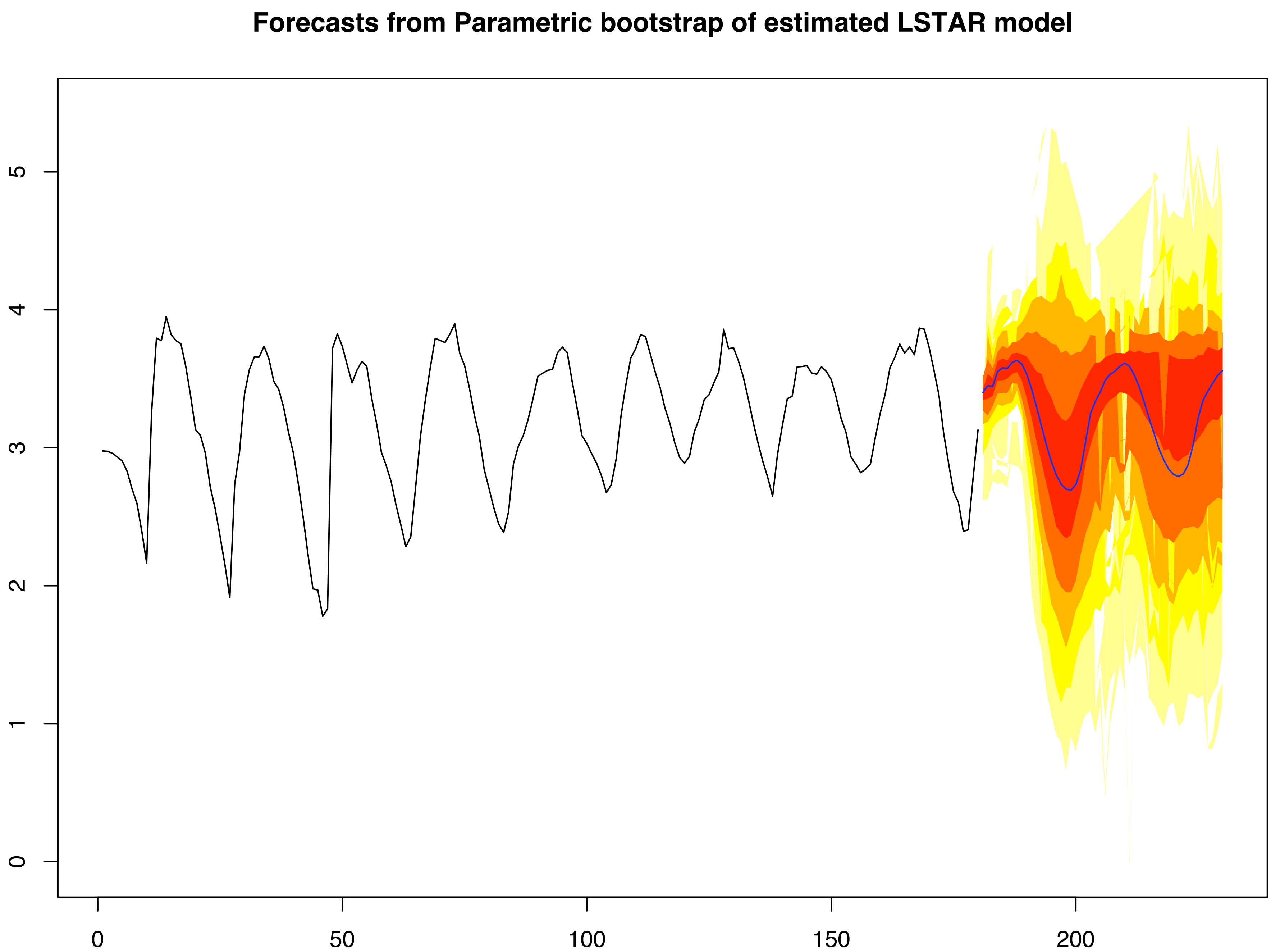

LM ARCH: Chi Squared test p−values
p value
0.0
0.2
0.4
0.6
0.8
1.0
ARCH(1)
ARCH(2)
ARCH(3)
ARCH(4)
ARCH(5)
ARCH(6)
ARCH(7)
ARCH(8)
ARCH(9)
ARCH(10)


LM ARCH: F test p−values
p value
0.0
0.2
0.4
0.6
0.8
1.0
ARCH(1)
ARCH(2)
ARCH(3)
ARCH(4)
ARCH(5)
ARCH(6)
ARCH(7)
ARCH(8)
ARCH(9)
ARCH(10)

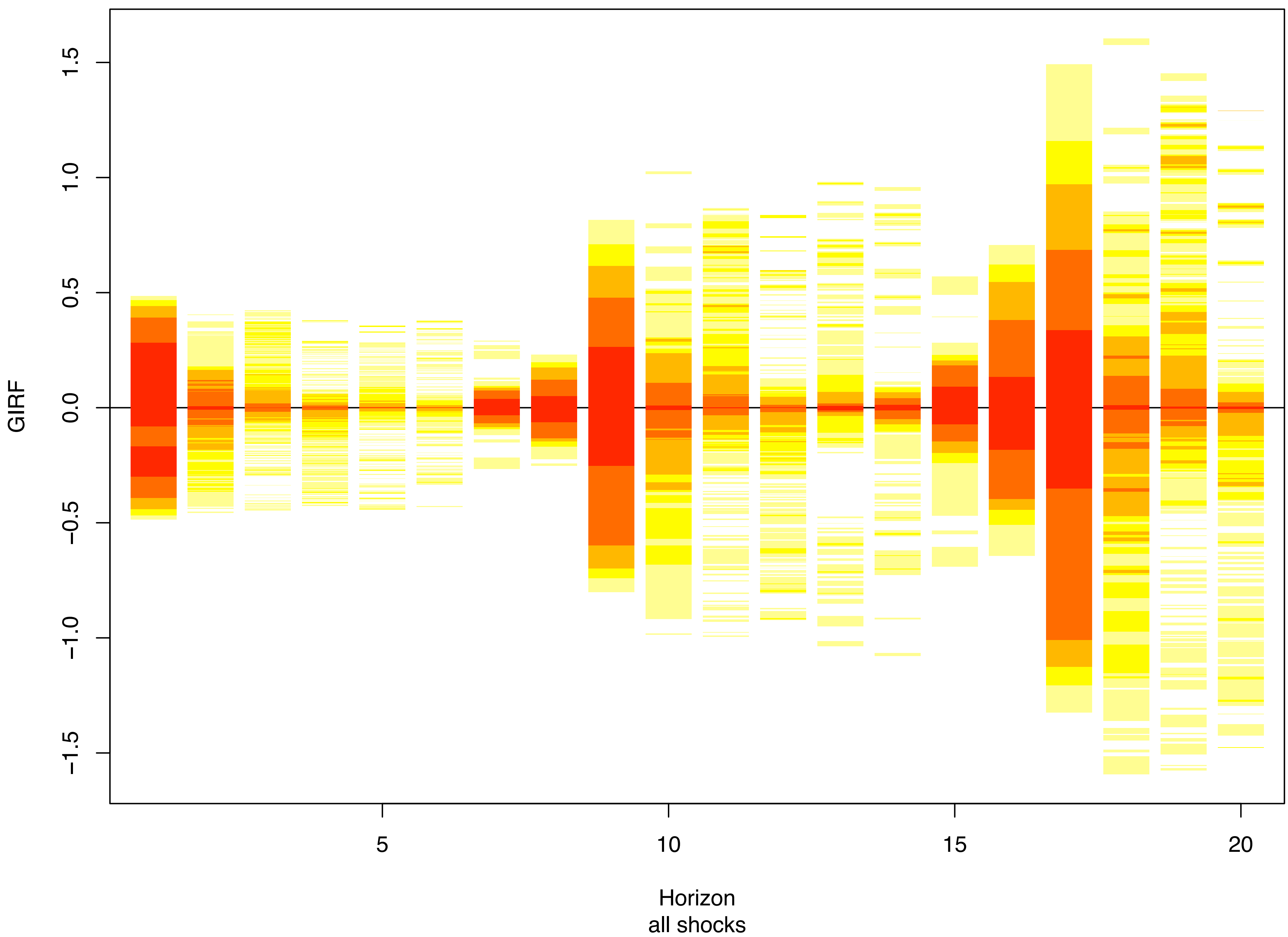


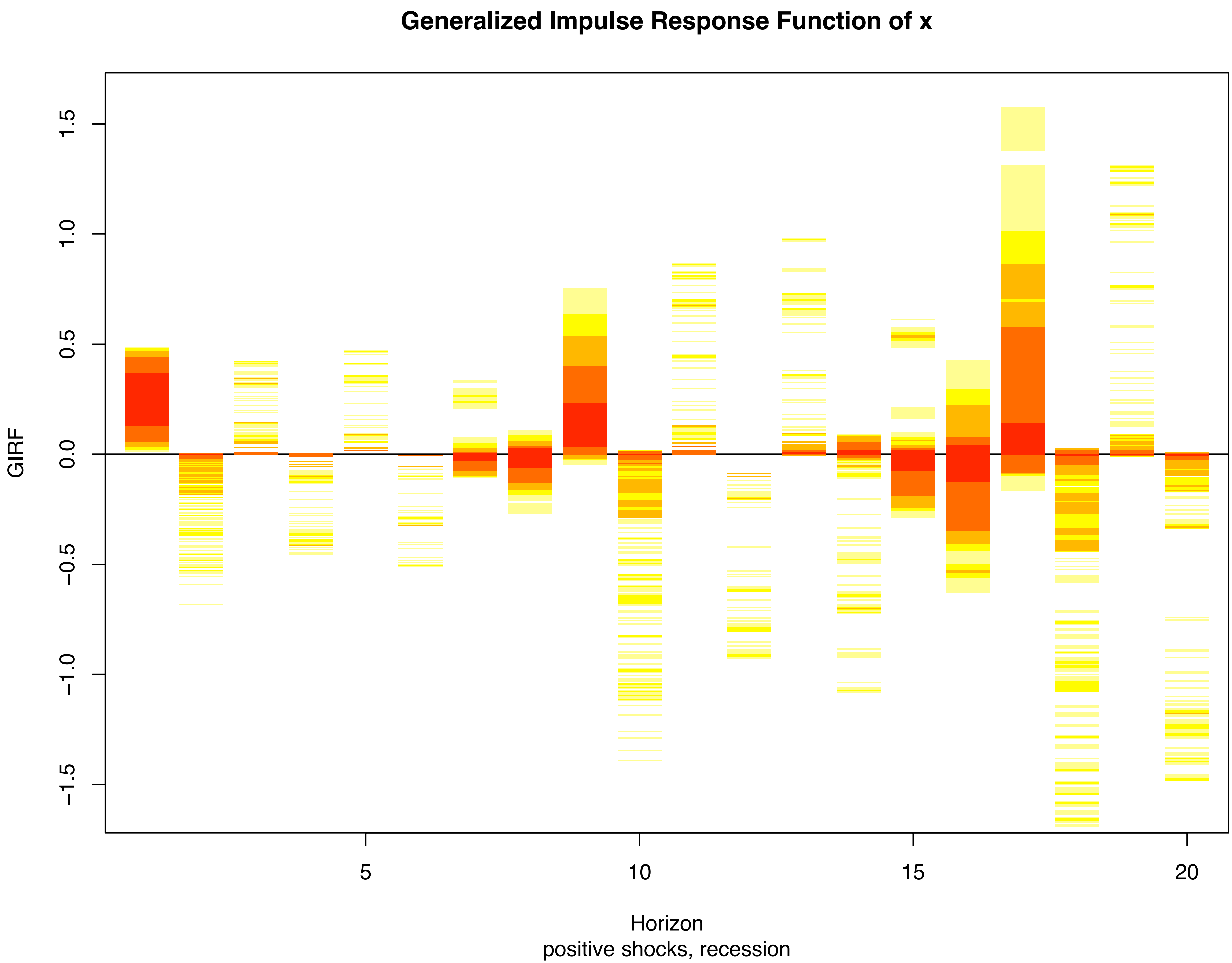
LM SI: Chi Squared test p−values
p value
0.0
0.2
0.4
0.6
0.8
1.0
LM_SI(1)
LM_SI(2)
LM_SI(3)
LM_SI(4)
LM_SI(5)
LM_SI(6)
LM_SI(7)
LM_SI(8)
LM_SI(9)
LM_SI(10)
LM_SI(11)
LM_SI(12)
LM_SI(13)
LM_SI(14)
LM_SI(15)
LM_SI(16)
LM_SI(17)
LM_SI(18)
LM_SI(19)
LM_SI(20)
LM_SI(21)
LM_SI(22)
LM_SI(23)
LM_SI(24)
LM_SI(25)
LM_SI(26)
LM_SI(27)
LM_SI(28)
LM_SI(29)
LM_SI(30)
LM_SI(31)
LM_SI(32)
LM_SI(33)
LM_SI(34)
LM_SI(35)
LM_SI(36)
LM_SI(37)
LM_SI(38)
LM_SI(39)
LM_SI(40)
LM_SI(41)
LM_SI(42)
LM_SI(43)

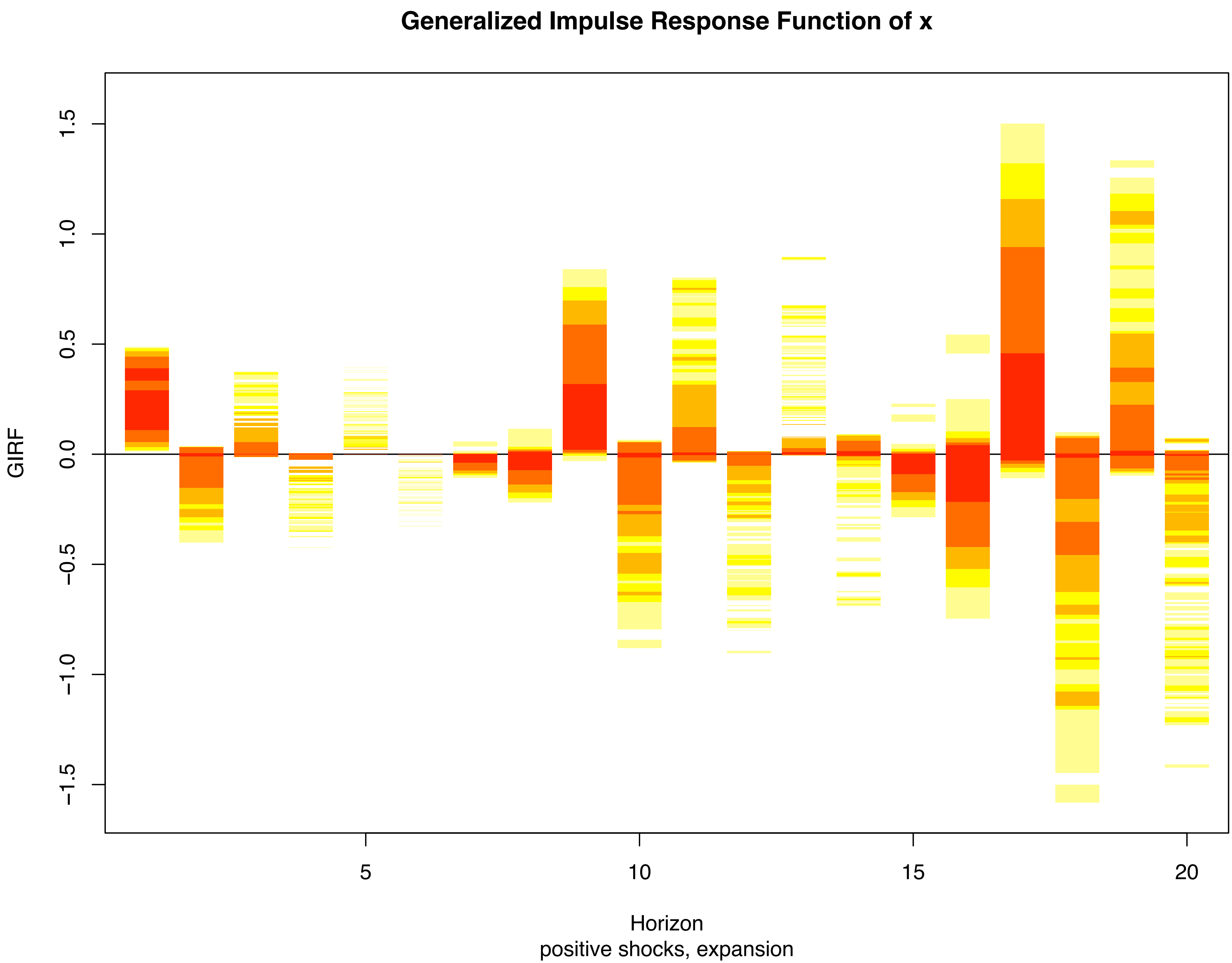

LM SI: F test p−values
p value
0.0
0.2
0.4
0.6
0.8
1.0
LM_SI(1)
LM_SI(2)
LM_SI(3)
LM_SI(4)
LM_SI(5)
LM_SI(6)
LM_SI(7)
LM_SI(8)
LM_SI(9)
LM_SI(10)
LM_SI(11)
LM_SI(12)
LM_SI(13)
LM_SI(14)
LM_SI(15)
LM_SI(16)
LM_SI(17)
LM_SI(18)
LM_SI(19)
LM_SI(20)
LM_SI(21)
LM_SI(22)
LM_SI(23)
LM_SI(24)
LM_SI(25)
LM_SI(26)
LM_SI(27)
LM_SI(28)
LM_SI(29)
LM_SI(30)
LM_SI(31)
LM_SI(32)
LM_SI(33)
LM_SI(34)
LM_SI(35)
LM_SI(36)
LM_SI(37)
LM_SI(38)
LM_SI(39)
LM_SI(40)
LM_SI(41)
LM_SI(42)
LM_SI(43)

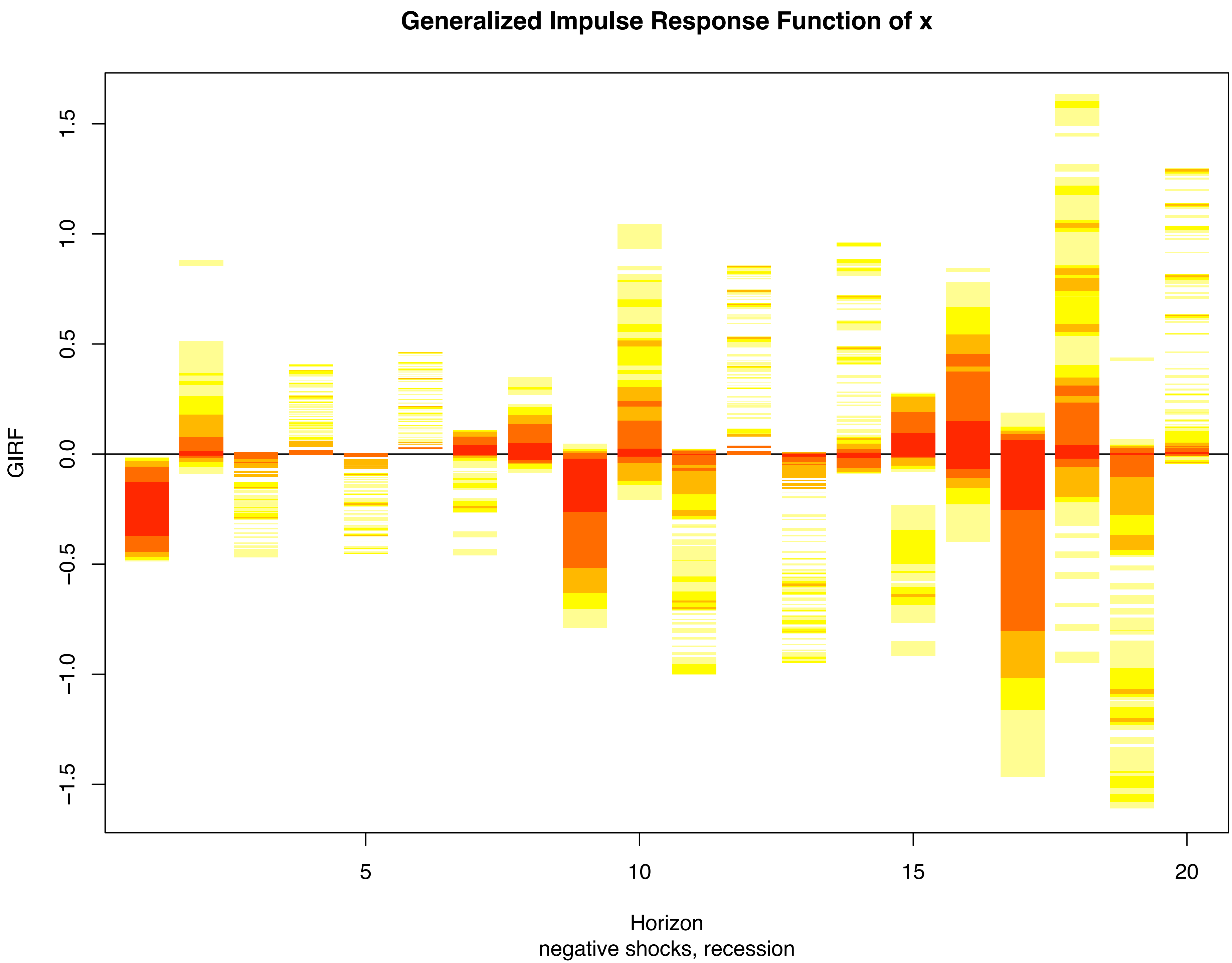

Forecasts from Parametric bootstrap of estimated LSTAR model
0
1
2
3
4
5
0
50
100
150
200

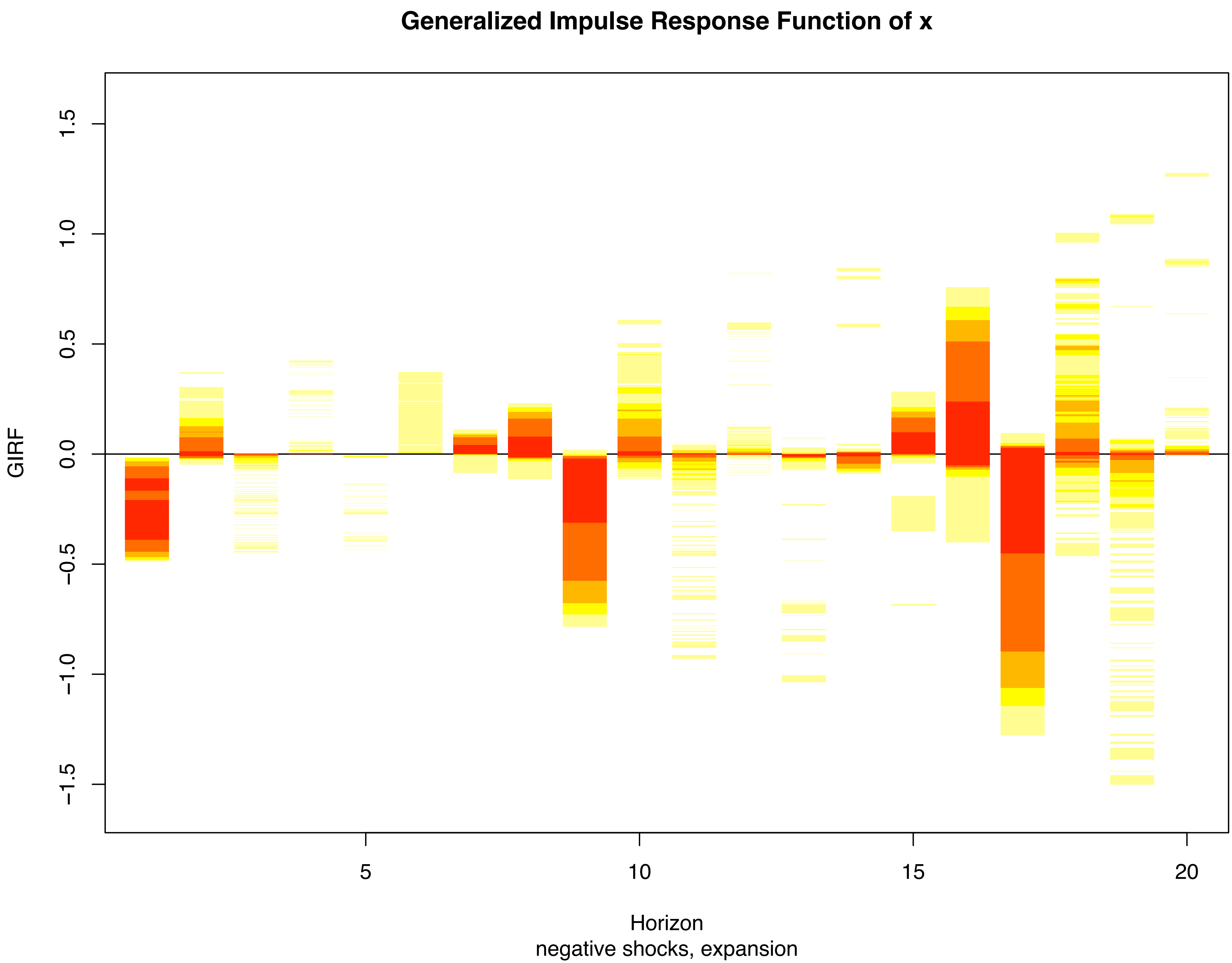
Generalized Impulse Response Function of x




Generalized Impulse Response Function of x
GIRF
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
5
10
15
20
Horizon
positive shocks, recession


Generalized Impulse Response Function of x
GIRF
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
5
10
15
20
Horizon
positive shocks, expansion


Generalized Impulse Response Function of x
GIRF
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
5
10
15
20
Horizon
negative shocks, recession


Generalized Impulse Response Function of x
GIRF
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
5
10
15
20
Horizon
negative shocks, expansion