Multivariate Forecasts

Here, we will use the MTS package to compute forecasts of the log gas consumption, basing ourselves on : - the precedent values of the log gas consumption - the selected temperature metrics, that is to say min_temp_val and heat_days_val - the computed dummy variables extreme_heat and extreme_cold

Load data

As usual, we load the datasets.

```
library(readr)
library(forecast)
```

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

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

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

```
## Loading required package: timeDate
```

```
## This is forecast 7.3
```

```
gas <- na.omit(read_csv("data/gas.csv", col_types = cols(date = col_date(format = "%Y-%m-%d"))))
temp <- read_csv("data/temp.csv", col_types = cols(date = col_date(format = "%Y-%m-%d")))
google <- read_csv("data/google.csv", col_types = cols(date = col_date(format = "%Y-%m-%d")))
rmse <- function(l, r) {
  sqrt(sum((l - r)^2)/NROW(l))
}
exp_rmse <- function(l, r) {
  rmse(exp(l), exp(r))
}
```

As said before, our datasets span over different periods of time: while gas consumption, our target value goes from January 1973 to July 2016, temperature data start in January 1895 and end in February 2017. Finally, data from Google Trends go from january 2004 and up to march 2017.

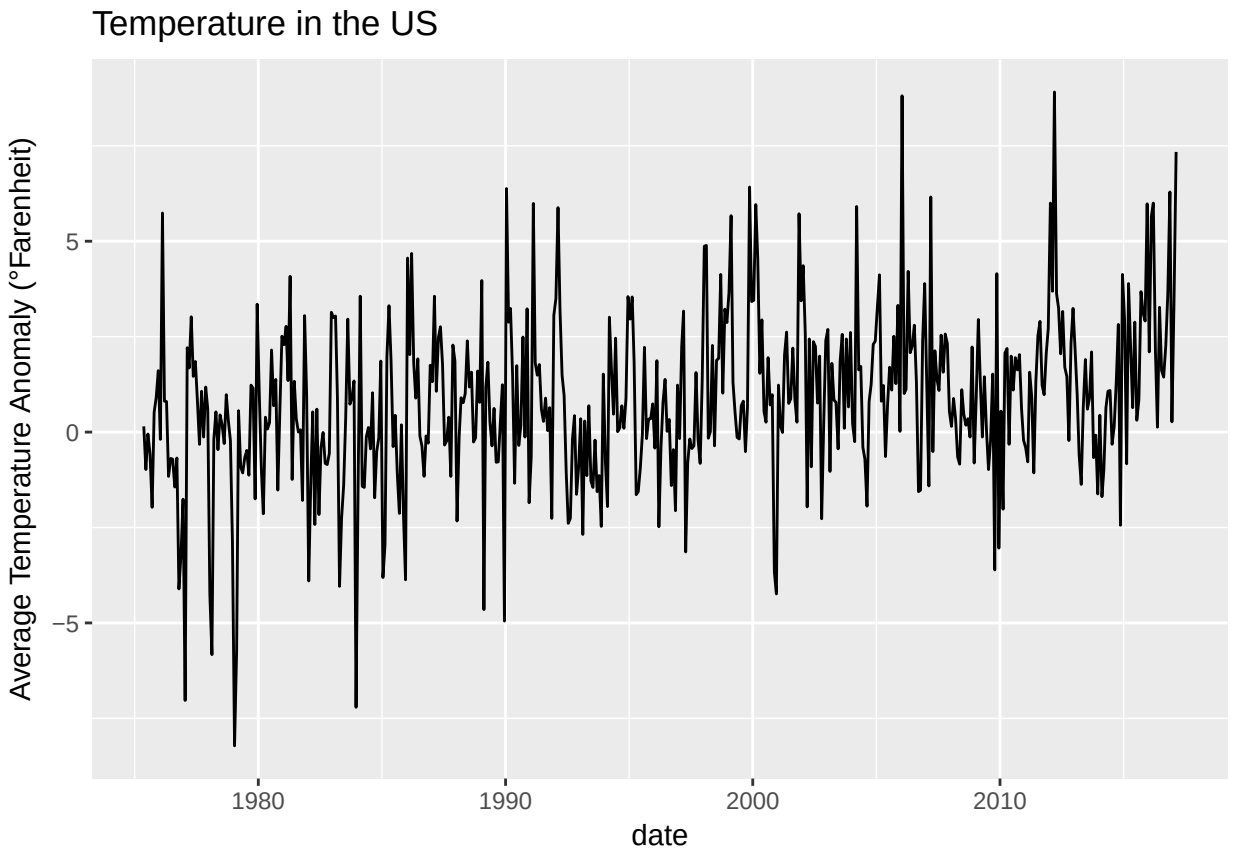
We will thus need to use the predicted values : - of min_temp_val and heat_days_val from February 2017 to July 2017 - of extreme_heat and extreme_cold from March 2017 to July 2017.

In both cases, we will compare the performances with the actual temperature data and the predicted temperatures.

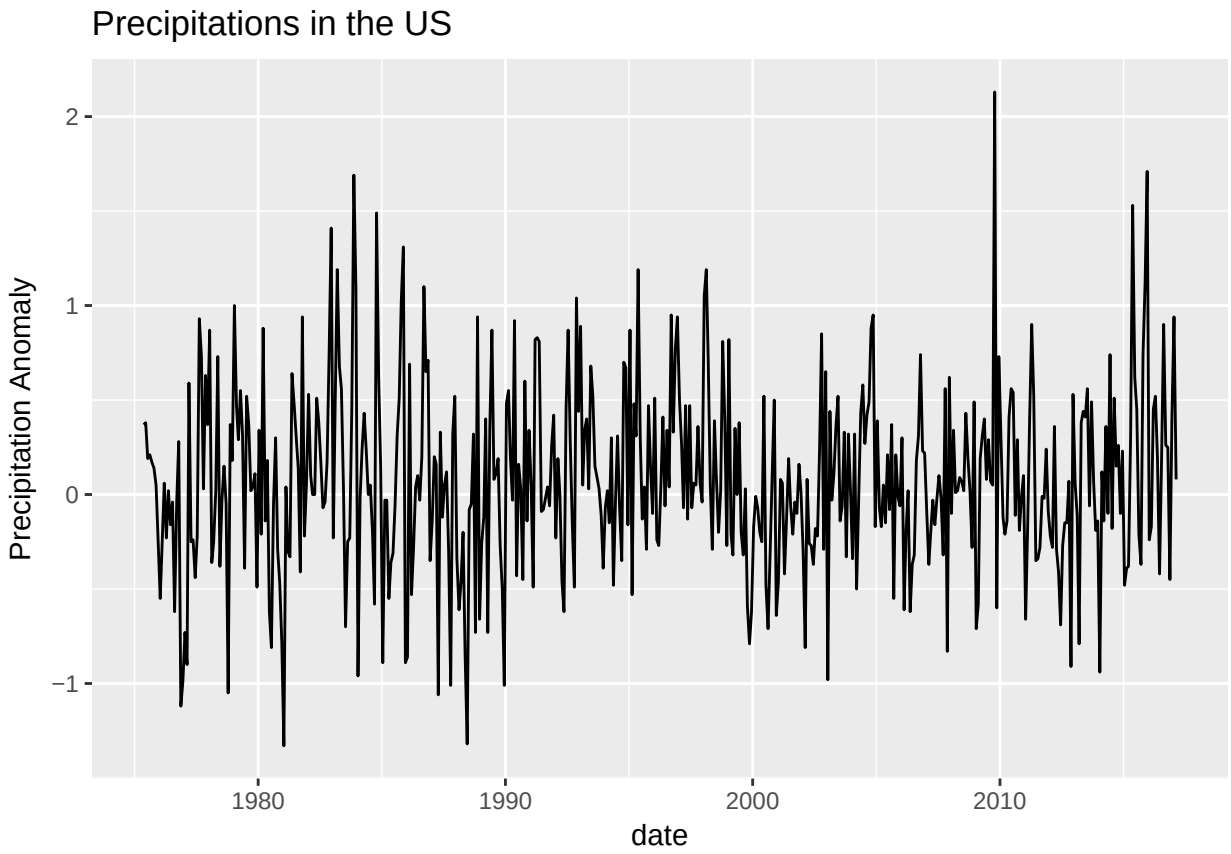
Plots

Temperature

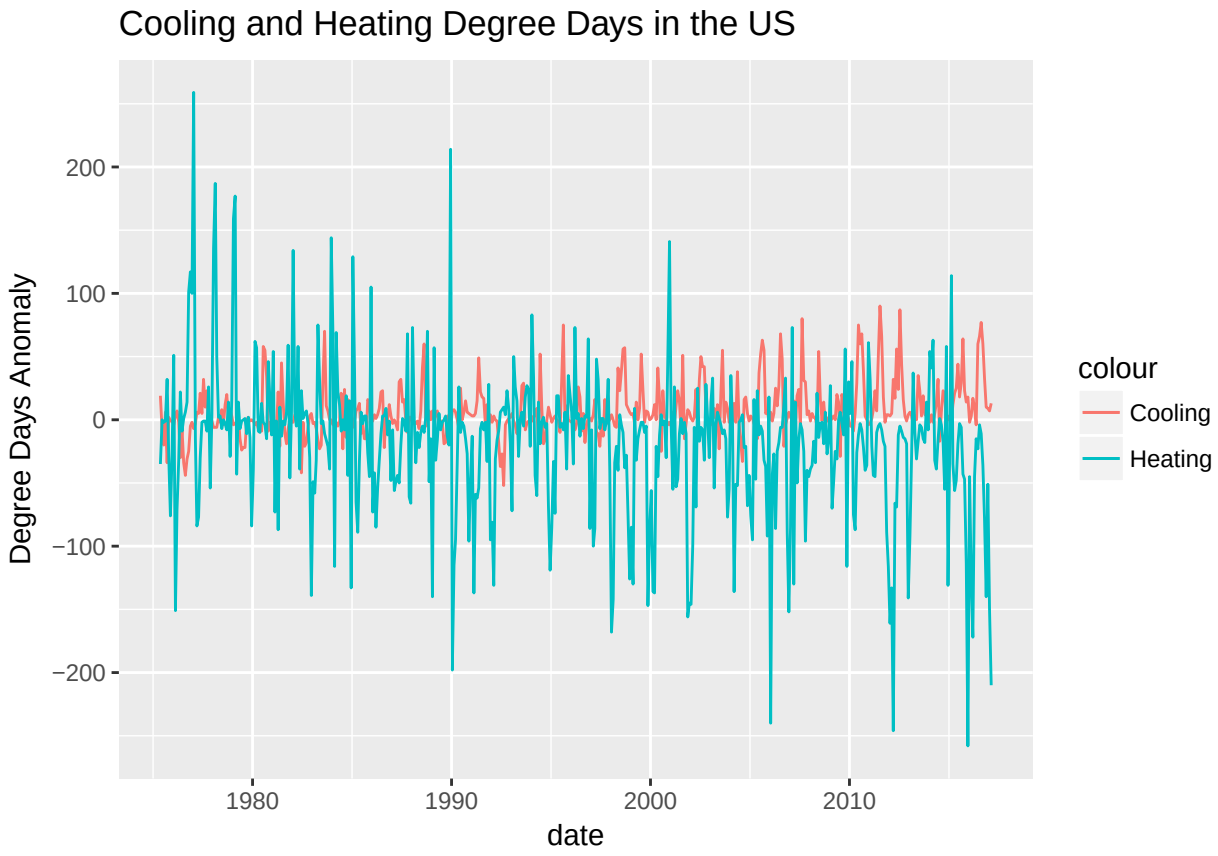
```
library(ggplot2)
temp_trunc = temp[temp$date >= 1973-01-15,]
ggplot(temp_trunc)+geom_line(aes(x=date, y=av_temp_ano))+
    labs(title = "Temperature in the US",  y = "Average Temperature Anomaly (°Farenheit)")
```




```
ggplot(temp_trunc)+geom_line(aes(x=date, y=prec_ano))+
    labs(title = "Precipitations in the US",  y = "Precipitation Anomaly")
```

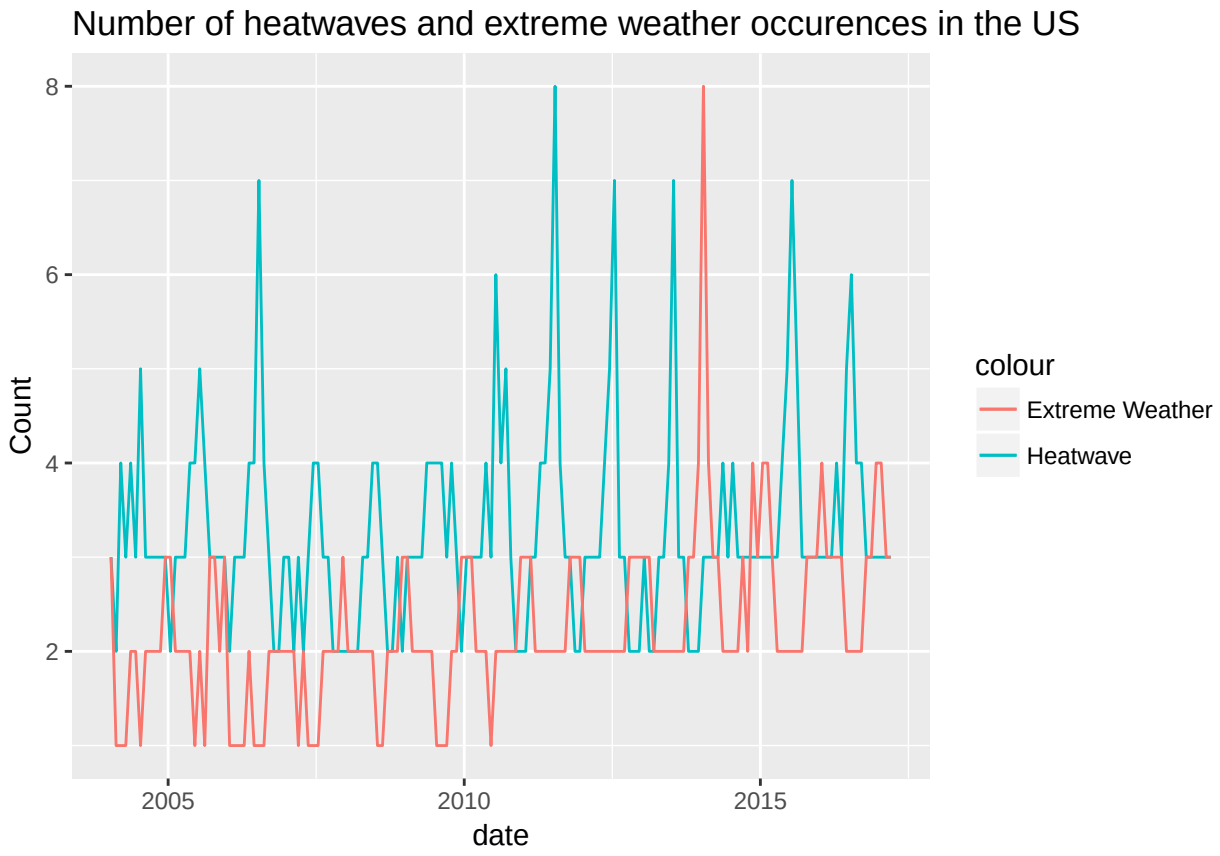



```
ggplot(temp_trunc)+geom_line(aes(x=date, y=cool_days_ano, colour = "Cooling"))+
    geom_line(aes(x=date, y=heat_days_ano, colour ="Heating"))+
    labs(title = "Cooling and Heating Degree Days in the US",  y = "Degree Days Anomaly")
```

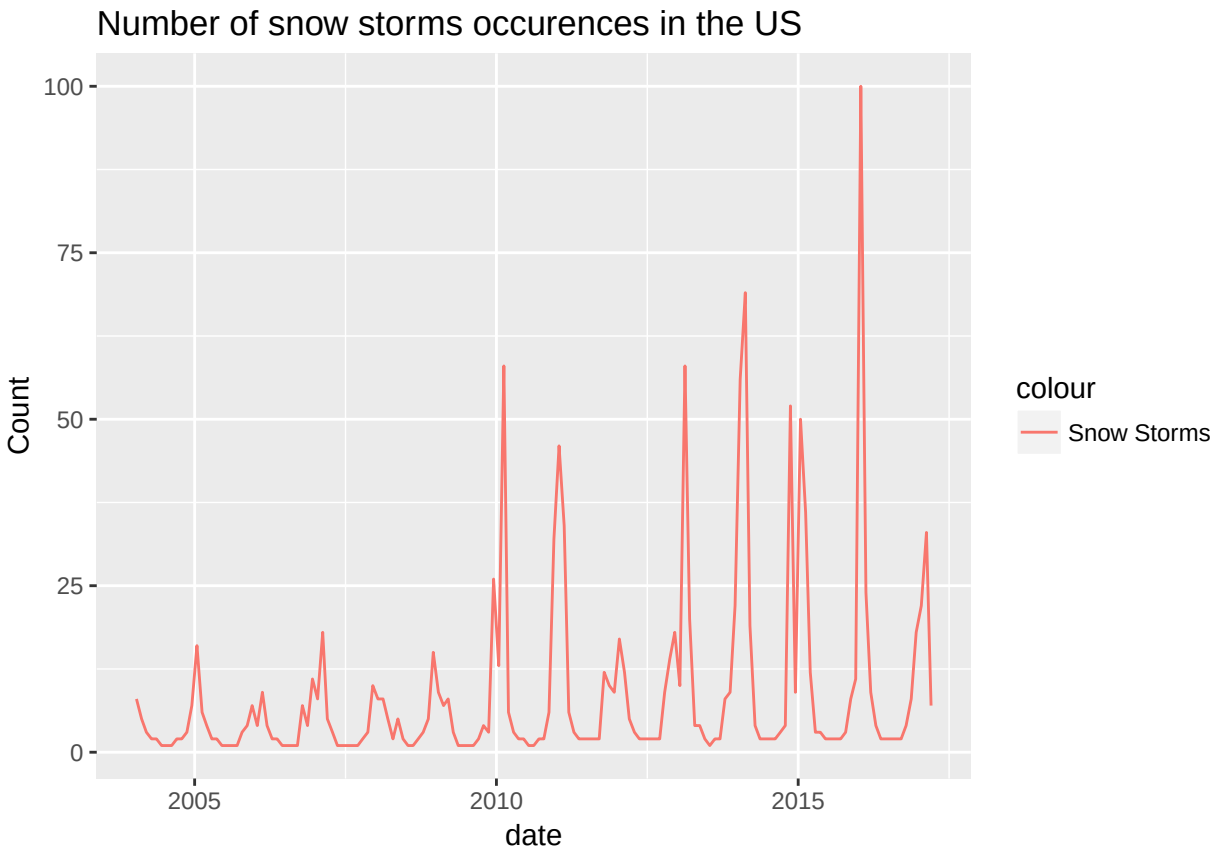


Google trends

```
ggplot(google)+geom_line(aes(x=date, y=heatwave, colour="Heatwave"))+
    geom_line(aes(x=date, y=extreme_weather, colour = "Extreme Weather"))+
    labs(title = "Number of heatwaves and extreme weather occurences in the US",  y = "Count")
```




```
ggplot(google)+geom_line(aes(x=date, y=snow_storm, colour="Snow Storms"))+
    labs(title = "Number of snow storms occurences in the US",  y = "Count")
```



Preparation

Let us merge the dataframes

```
gas_temp = merge(gas, temp, by = "date", all.x = TRUE)
gas_goo = merge(gas, google, by = "date", all = FALSE)
all = merge(gas_temp, google, by= "date",  all = FALSE)
extreme <- all[,c(16,17,18)]

# extreme_heat will be 1 when heatwave > mean(heatwave)
extreme_heat <- as.numeric(extreme$heatwave > mean(extreme$heatwave))
# extreme_cold will be 1 when snow_storm > mean(snow_storm) and extreme_weather > mean(extreme_weather)
extreme_cold <- as.numeric(extreme$snow_storm > mean(extreme$snow_storm) & extreme$extreme_weather > mea
all = cbind(all, extreme_heat, extreme_cold)
```

Let us create the test and train set

```
all_test = all[all$date >= '2015-06-15' & all$date < '2016-06-15',]
all_train = all[all$date < '2015-06-15',]
nrow(all_train)
```

```
## [1] 137
```

VAR on the known dataset

Now lets fit and predict with a simple VAR model

```r
library(MTS)
simple_var = VAR(all_train[,c('gas_cons','min_temp_val','heat_days_val','extreme_heat','extreme_cold')]
```

```
## Constant term:
## Estimates:  -339988.6 50.48466 -228.6906 2.074703 -0.1273657
## Std.Error:  195161.9 10.1725 233.5333 0.7208056 0.5754907
## AR coefficient matrix
## AR( 1 )-matrix
##           [,1]      [,2]      [,3]      [,4]      [,5]
## [1,] -1.66e+00  1.04e+04  2.63e+03 -2.29e+04  6.81e+04
## [2,]  9.43e-05 -1.12e-01 -1.19e-01  6.01e+00 -2.32e+00
## [3,] -2.37e-03  9.00e+00  3.19e+00 -6.98e+01  8.11e+01
## [4,]  2.23e-06 -3.33e-02 -3.76e-03  2.44e-01 -5.97e-02
## [5,] -2.27e-06  6.94e-03  2.36e-03 -6.28e-02  5.37e-01
## standard error
##          [,1]     [,2]     [,3]     [,4]     [,5]
## [1,] 2.01e-01 3.58e+03 2.86e+02 2.68e+04 2.83e+04
## [2,] 1.05e-05 1.86e-01 1.49e-02 1.40e+00 1.48e+00
## [3,] 2.41e-04 4.28e+00 3.42e-01 3.21e+01 3.39e+01
## [4,] 7.43e-07 1.32e-02 1.05e-03 9.90e-02 1.05e-01
## [5,] 5.93e-07 1.05e-02 8.42e-04 7.91e-02 8.36e-02
##
## Residuals cov-mtx:
##               [,1]          [,2]          [,3]          [,4]          [,5]
## [1,]  1.054993e+10 -4.138056e+05  1.201389e+07 -7.818531e+03  1.433310e+04
## [2,] -4.138056e+05  2.866254e+01 -5.838266e+02  1.010194e+00 -5.393132e-01
## [3,]  1.201389e+07 -5.838266e+02  1.510627e+04 -1.508697e+01  1.596861e+01
## [4,] -7.818531e+03  1.010194e+00 -1.508697e+01  1.439117e-01 -7.054441e-03
## [5,]  1.433310e+04 -5.393132e-01  1.596861e+01 -7.054441e-03  9.173524e-02
##
## det(SSE) =  376581556958
## AIC =  27.01936
## BIC =  27.55221
## HQ  =  27.2359
```

```r
simple_var_pred = VARpred(simple_var, h = 12)
```

```
## orig  137
## Forecasts at origin:  137
##  gas_cons min_temp_val heat_days_val extreme_heat extreme_cold
##    166785        53.58         103.9       0.6307      0.02850
##    201328        51.58         149.1       0.4238      0.08653
##    251156        48.32         212.9       0.3431      0.14510
##    308785        45.18         280.0       0.2993      0.19656
##    361987        42.61         337.0       0.2660      0.23264
##    400478        40.86         375.2       0.2453      0.24991
##    420933        39.98         393.3       0.2392      0.25115
##    425969        39.82         395.5       0.2441      0.24248
##    420979        40.10         388.1       0.2543      0.23010
##    411488        40.57         376.9       0.2651      0.21852
##    401702        41.04         366.3       0.2735      0.21014
##    394074        41.39         358.6       0.2786      0.20555
## Standard Errors of predictions:
##         [,1]   [,2]  [,3]   [,4]   [,5]
```

```
##  [1,] 102713  5.354 122.9 0.3794 0.3029
##  [2,] 167002  8.919 198.4 0.4108 0.3567
##  [3,] 218289 11.422 254.4 0.4265 0.3824
##  [4,] 252821 12.925 288.6 0.4361 0.3945
##  [5,] 270229 13.639 304.3 0.4405 0.3984
##  [6,] 276310 13.880 309.2 0.4418 0.3995
##  [7,] 277796 13.940 310.5 0.4424 0.4004
##  [8,] 278554 13.976 311.4 0.4431 0.4015
##  [9,] 279551 14.024 312.5 0.4439 0.4024
## [10,] 280498 14.067 313.5 0.4443 0.4029
## [11,] 281094 14.093 314.1 0.4445 0.4031
## [12,] 281348 14.104 314.3 0.4446 0.4032
## Root mean square errors of predictions:
##           [,1]      [,2]      [,3]      [,4]      [,5]
##  [1,] 1.049e+05 5.470e+00 1.256e+02 3.876e-01 3.094e-01
##  [2,] 1.283e+11 6.950e+06 1.517e+08 1.536e+05 1.836e+05
##  [3,] 1.370e+11 6.952e+06 1.551e+08 1.118e+05 1.344e+05
##  [4,] 1.243e+11 5.895e+06 1.328e+08 8.858e+04 9.410e+04
##  [5,] 9.297e+10 4.244e+06 9.398e+07 6.077e+04 5.466e+04
##  [6,] 5.617e+10 2.507e+06 5.369e+07 3.270e+04 2.847e+04
##  [7,] 2.795e+10 1.254e+06 2.682e+07 2.222e+04 2.605e+04
##  [8,] 2.002e+10 9.877e+05 2.329e+07 2.511e+04 2.909e+04
##  [9,] 2.298e+10 1.128e+06 2.628e+07 2.467e+04 2.657e+04
## [10,] 2.244e+10 1.073e+06 2.431e+07 1.966e+04 1.989e+04
## [11,] 1.783e+10 8.330e+05 1.840e+07 1.284e+04 1.219e+04
## [12,] 1.163e+10 5.299e+05 1.139e+07 6.801e+03 6.129e+03
```

```
accuracy(all_test$gas_cons, simple_var_pred$pred[,1])
```

```
##                 ME     RMSE      MAE      MPE     MAPE
## Test set -3993.676 197004.5 156556.6 6.718104 44.69608
```

```
ref_simple_var = refVAR(simple_var)
```

```
## Constant term:
## Estimates:  -299260 44.40404 0 2.161886 0
## Std.Error:  189027 1.137203 0 0.7026236 0
## AR coefficient matrix
## AR( 1 )-matrix
##           [,1]      [,2]      [,3]    [,4]      [,5]
## [1,] -1.68e+00  9.48e+03  2.63e+03   0.000 68526.207
## [2,]  9.17e-05  0.00e+00 -1.12e-01   5.760    -2.503
## [3,] -2.28e-03  4.83e+00  2.94e+00 -62.131    88.157
## [4,]  2.28e-06 -3.48e-02 -3.92e-03   0.245     0.000
## [5,] -2.33e-06  4.18e-03  2.34e-03   0.000     0.539
## standard error
##          [,1]     [,2]     [,3]    [,4]     [,5]
## [1,] 1.99e-01 3.41e+03 2.85e+02  0.0000 2.83e+04
## [2,] 9.55e-06 0.00e+00 9.03e-03  1.3318 1.44e+00
## [3,] 2.25e-04 4.80e-01 2.18e-01 31.1071 3.31e+01
## [4,] 7.36e-07 1.29e-02 1.02e-03  0.0988 0.00e+00
## [5,] 5.35e-07 1.03e-03 5.13e-04  0.0000 8.12e-02
##
## Residuals cov-mtx:
##               [,1]          [,2]          [,3]          [,4]          [,5]
```

```
## [1,]  1.060892e+10 -4.144478e+05  1.203374e+07 -7.816074e+03  1.449519e+04
## [2,] -4.144478e+05  2.874232e+01 -5.867895e+02  1.009107e+00 -5.412753e-01
## [3,]  1.203374e+07 -5.867895e+02  1.521770e+04 -1.504449e+01  1.603068e+01
## [4,] -7.816074e+03  1.009107e+00 -1.504449e+01  1.442724e-01 -7.044697e-03
## [5,]  1.449519e+04 -5.412753e-01  1.603068e+01 -7.044697e-03  9.218117e-02
##
## det(SSE) =  458833869576
## AIC =  27.15852
## BIC =  27.60611
## HQ  =  27.34041
```

```
ref_simple_var_pred = VARpred(ref_simple_var, h = 12)
```

```
## orig  137
## Forecasts at origin:  137
##  gas_cons min_temp_val heat_days_val extreme_heat extreme_cold
##    181813        53.15         120.0       0.6342       0.0706
##    220209        51.15         161.5       0.4104       0.1177
##    249217        48.64         204.1       0.3501       0.1423
##    290506        46.13         256.8       0.3221       0.1771
##    338574        43.78         310.1       0.2899       0.2125
##    378403        41.96         350.8       0.2643       0.2344
##    402964        40.86         374.3       0.2526       0.2411
##    413502        40.41         383.1       0.2519       0.2377
##    414567        40.40         382.6       0.2568       0.2302
##    410713        40.60         377.5       0.2630       0.2223
##    405311        40.86         371.4       0.2684       0.2161
##    400392        41.10         366.2       0.2721       0.2121
## Standard Errors of predictions:
##         [,1]   [,2]  [,3]   [,4]   [,5]
##  [1,] 103000  5.361 123.4 0.3798 0.3036
##  [2,] 168134  8.959 199.1 0.4126 0.3568
##  [3,] 222654 11.692 260.9 0.4290 0.3855
##  [4,] 264253 13.501 302.6 0.4419 0.4013
##  [5,] 286105 14.409 322.5 0.4480 0.4065
##  [6,] 293828 14.723 328.9 0.4494 0.4074
##  [7,] 295543 14.790 330.2 0.4496 0.4079
##  [8,] 295870 14.805 330.5 0.4500 0.4085
##  [9,] 296227 14.823 330.9 0.4503 0.4091
## [10,] 296651 14.843 331.4 0.4506 0.4095
## [11,] 296964 14.857 331.7 0.4507 0.4096
## [12,] 297119 14.863 331.8 0.4507 0.4097
## Root mean square errors of predictions:
##            [,1]      [,2]      [,3]      [,4]      [,5]
##  [1,] 1.052e+05 5.477e+00       126 3.881e-01 3.102e-01
##  [2,] 1.295e+11 6.994e+06 152214491 1.570e+05 1.826e+05
##  [3,] 1.422e+11 7.319e+06 164316529 1.145e+05 1.421e+05
##  [4,] 1.387e+11 6.579e+06 149372641 1.033e+05 1.087e+05
##  [5,] 1.069e+11 4.905e+06 108655786 7.163e+04 6.314e+04
##  [6,] 6.521e+10 2.946e+06  62906272 3.436e+04 2.685e+04
##  [7,] 3.098e+10 1.371e+06  28189808 1.496e+04 1.882e+04
##  [8,] 1.355e+10 6.367e+05  14270373 1.660e+04 2.269e+04
##  [9,] 1.416e+10 7.087e+05  16660859 1.742e+04 2.148e+04
## [10,] 1.545e+10 7.496e+05  17104716 1.443e+04 1.648e+04
## [11,] 1.327e+10 6.266e+05  13967676 9.876e+03 1.046e+04
```

```
## [12,] 9.349e+09 4.306e+05   9391994 5.523e+03 5.336e+03
```

```
accuracy(all_test$gas_cons, ref_simple_var_pred$pred[,1])
```

```
##                  ME     RMSE      MAE      MPE     MAPE
## Test set -8951.316 200459.9 161548.5 5.438174 46.95721
```

Both the simple_var and the ref_simple_var are very bad predictors.

```
var = VAR(all_train[,c('log_gas_cons','min_temp_val','heat_days_val','extreme_heat','extreme_cold')])
```

```
## Constant term:
## Estimates:  31.3115 -433.3187 11125.86 -13.27857 9.240381
## Std.Error:  2.258323 47.99163 1156.704 3.361307 2.835005
## AR coefficient matrix
## AR( 1 )-matrix
##          [,1]     [,2]      [,3]     [,4]     [,5]
## [1,]   -1.279  -0.0776  0.001729  -0.1159  0.06133
## [2,]   33.294   1.6634 -0.039942   4.2085 -1.17390
## [3,] -777.497 -33.6479  1.152260 -30.5416 57.02006
## [4,]    1.076   0.0181 -0.002222   0.1714 -0.00886
## [5,]   -0.633  -0.0303  0.000274  -0.0367  0.52360
## standard error
##        [,1]    [,2]     [,3]    [,4]    [,5]
## [1,]  0.164 0.00948 0.000389  0.0658  0.0686
## [2,]  3.476 0.20138 0.008264  1.3980  1.4585
## [3,] 83.779 4.85366 0.199178 33.6939 35.1519
## [4,]  0.243 0.01410 0.000579  0.0979  0.1021
## [5,]  0.205 0.01190 0.000488  0.0826  0.0862
##
## Residuals cov-mtx:
##             [,1]         [,2]        [,3]          [,4]         [,5]
## [1,]  0.06036793   -1.1735172    29.06659  -0.028768817  0.031896871
## [2,] -1.17351720   27.2624724  -581.98682   0.809139803 -0.603290355
## [3,] 29.06658762 -581.9868152 15837.20073 -11.119857940 18.206148271
## [4,] -0.02876882    0.8091398   -11.11986   0.133736695 -0.005368272
## [5,]  0.03189687   -0.6032904    18.20615  -0.005368272  0.095135351
##
## det(SSE) =  3.445404
## AIC =  1.602005
## BIC =  2.134848
## HQ  =  1.818539
```

```
var_pred = VARpred(var, h = 12)
```

```
## orig  137
## Forecasts at origin:  137
##  log_gas_cons min_temp_val heat_days_val extreme_heat extreme_cold
##         12.13        50.26         182.5       0.5280      0.09448
##         12.16        48.99         202.6       0.3737      0.11612
##         12.28        46.25         254.6       0.3065      0.16093
##         12.44        43.27         318.3       0.2581      0.20832
##         12.58        40.83         371.9       0.2260      0.24153
##         12.68        39.30         405.4       0.2134      0.25659
##         12.73        38.73         417.8       0.2181      0.25613
##         12.73        38.94         412.9       0.2339      0.24534
##         12.70        39.64         397.3       0.2539      0.22992
```

```
##         12.66        40.53         377.8       0.2723      0.21471
##         12.61        41.35         359.7       0.2857      0.20300
##         12.57        41.94         346.7       0.2926      0.19624
## Standard Errors of predictions:
##         [,1]   [,2]  [,3]   [,4]   [,5]
##  [1,] 0.2457  5.221 125.8 0.3657 0.3084
##  [2,] 0.4273  8.721 198.2 0.4001 0.3612
##  [3,] 0.5768 11.187 251.2 0.4205 0.3841
##  [4,] 0.6692 12.552 280.8 0.4291 0.3934
##  [5,] 0.7118 13.106 292.8 0.4316 0.3962
##  [6,] 0.7254 13.263 296.2 0.4329 0.3972
##  [7,] 0.7300 13.347 298.0 0.4351 0.3986
##  [8,] 0.7361 13.485 301.1 0.4378 0.4004
##  [9,] 0.7449 13.653 304.7 0.4399 0.4020
## [10,] 0.7529 13.786 307.6 0.4410 0.4029
## [11,] 0.7579 13.858 309.2 0.4414 0.4033
## [12,] 0.7600 13.883 309.7 0.4415 0.4034
## Root mean square errors of predictions:
##           [,1]      [,2]     [,3]     [,4]     [,5]
##  [1,]    0.251     5.334    128.6   0.3736   0.3151
##  [2,] 1524.575 30462.271 667751.1 707.5835 819.9894
##  [3,] 1689.904 30558.596 673381.0 563.9188 569.4075
##  [4,] 1479.674 24821.558 547292.0 374.2765 370.9465
##  [5,] 1058.261 16445.685 361166.6 202.0965 205.3408
##  [6,]  609.435  8876.239 194500.3 147.3408 123.1108
##  [7,]  353.623  6514.018 144434.1 189.4897 142.9053
##  [8,]  414.417  8401.504 186190.7 209.5173 165.3021
##  [9,]  496.642  9299.441 205272.8 187.7285 155.4307
## [10,]  479.167  8340.623 183492.8 138.2085 120.2046
## [11,]  379.459  6146.984 134775.1  82.0224  75.3908
## [12,]  244.437  3652.302  79781.2  45.2023  40.0494
```

```
ref_var_pred = VARpred(refVAR(var), h = 12)
```

```
## Constant term:
## Estimates:  31.62775 -439.3721 11448.72 -13.32425 9.156398
## Std.Error:  2.228704 47.33493 1099.748 3.307177 2.527531
## AR coefficient matrix
## AR( 1 )-matrix
##          [,1]     [,2]     [,3]   [,4]   [,5]
## [1,]   -1.308  -0.0774  0.00185 -0.115  0.000
## [2,]   33.840   1.6590 -0.04234  4.187  0.000
## [3,] -796.799 -35.6289  1.13594  0.000 56.422
## [4,]    1.080   0.0181 -0.00224  0.171  0.000
## [5,]   -0.604  -0.0352  0.00000  0.000  0.539
## standard error
##        [,1]    [,2]     [,3]   [,4]    [,5]
## [1,]  0.160 0.00947 0.000362 0.0657  0.0000
## [2,]  3.405 0.20103 0.007697 1.3958  0.0000
## [3,] 80.972 4.33082 0.198228 0.0000 35.1218
## [4,]  0.238 0.01405 0.000538 0.0975  0.0000
## [5,]  0.170 0.00945 0.000000 0.0000  0.0798
##
## Residuals cov-mtx:
##             [,1]         [,2]        [,3]          [,4]         [,5]
```

```
## [1,]  0.06073874   -1.1806150    29.07021  -0.028822386  0.031801868
## [2,] -1.18061497   27.3983349  -582.05607   0.810165188 -0.601471845
## [3,] 29.07020584 -582.0560738 15937.29678 -11.120380650 18.326465514
## [4,] -0.02882239    0.8101652   -11.12038   0.133744434 -0.005354547
## [5,]  0.03180187   -0.6014718    18.32647  -0.005354547  0.095480833
##
## det(SSE) =  3.867703
## AIC =  1.630033
## BIC =  2.034994
## HQ  =  1.794599
## orig  137
## Forecasts at origin:  137
##  log_gas_cons min_temp_val heat_days_val extreme_heat extreme_cold
##         12.13        50.27         203.3       0.5281       0.1315
##         12.19        48.11         230.7       0.3264       0.1356
##         12.35        44.70         287.7       0.2609       0.1748
##         12.52        41.67         351.2       0.2297       0.2212
##         12.65        39.63         397.0       0.2129       0.2492
##         12.73        38.68         418.7       0.2122       0.2566
##         12.75        38.66         419.4       0.2252       0.2500
##         12.72        39.25         406.2       0.2450       0.2364
##         12.68        40.14         386.7       0.2650       0.2212
##         12.63        41.03         367.2       0.2805       0.2085
##         12.59        41.72         352.1       0.2894       0.2002
##         12.56        42.12         343.4       0.2919       0.1968
## Standard Errors of predictions:
##         [,1]   [,2]  [,3]   [,4]   [,5]
##  [1,] 0.2465  5.234 126.2 0.3657 0.3090
##  [2,] 0.4275  8.730 198.8 0.4009 0.3623
##  [3,] 0.5757 11.173 251.4 0.4230 0.3844
##  [4,] 0.6679 12.549 281.2 0.4329 0.3935
##  [5,] 0.7122 13.143 293.9 0.4361 0.3965
##  [6,] 0.7281 13.341 298.1 0.4378 0.3977
##  [7,] 0.7342 13.446 300.4 0.4399 0.3988
##  [8,] 0.7407 13.583 303.3 0.4424 0.4003
##  [9,] 0.7488 13.737 306.7 0.4443 0.4016
## [10,] 0.7562 13.858 309.3 0.4453 0.4024
## [11,] 0.7607 13.924 310.7 0.4457 0.4027
## [12,] 0.7627 13.949 311.2 0.4458 0.4028
## Root mean square errors of predictions:
##            [,1]      [,2]   [,3]     [,4]     [,5]
##  [1,]    0.2518     5.348    129   0.3736   0.3157
##  [2,] 1523.4583 30471.306 669632 716.6468 824.8334
##  [3,] 1681.4004 30410.325 671292 587.5010 560.9972
##  [4,] 1477.1744 24914.465 548969 401.7009 366.1032
##  [5,] 1078.4972 17037.002 373108 231.3527 212.8476
##  [6,]  659.3672  9979.127 218124 165.8400 131.4536
##  [7,]  411.0326  7315.073 160553 189.7007 133.2164
##  [8,]  425.9008  8395.843 184238 201.9513 148.1877
##  [9,]  481.5527  8959.911 196353 178.8885 139.6429
## [10,]  457.5112  7961.744 174311 132.2034 109.9520
## [11,]  362.4959  5902.633 129115  81.5052  72.0527
## [12,]  239.0074  3648.959  79754  49.8908  41.8892
```

```
accuracy(all_test$log_gas_cons, var_pred$pred[,1])
```

```
##                    ME      RMSE       MAE       MPE     MAPE
## Test set 0.02723652 0.5796479 0.5236783 0.2780508 4.184395
```

```
accuracy(all_test$log_gas_cons, ref_var_pred$pred[,1])
```

```
##                    ME      RMSE       MAE       MPE     MAPE
## Test set 0.04646378 0.6088501 0.5477368 0.4218365 4.369406
```

```
exp_rmse(all_test$log_gas_cons, var_pred$pred[,1])
```

```
## [1] 222059.8
```

```
exp_rmse(all_test$log_gas_cons, ref_var_pred$pred[,1])
```

```
## [1] 226633.3
```

Doing it with the logarithm of the gas consumption is even worse.

```
var = VAR(all_train[,c('gas_cons','min_temp_val','heat_days_val','extreme_heat','extreme_cold')], p=3)
```

```
## Constant term:
## Estimates:  1459044 29.23858 1463.089 3.89348 1.528637
## Std.Error:  262259.5 11.88499 302.799 1.314796 1.287084
## AR coefficient matrix
## AR( 1 )-matrix
##           [,1]      [,2]      [,3]      [,4]      [,5]
## [1,]  3.16e-01 -1.53e+04 -13.92340  8.66e+03 7507.5452
## [2,]  2.44e-05  9.11e-01  -0.02034  8.60e-01    1.4411
## [3,] -3.93e-04 -1.93e+01   0.38941  2.13e+00   -3.8252
## [4,] -4.17e-07 -6.28e-03  -0.00104 -5.72e-02    0.0909
## [5,]  2.15e-06 -3.13e-02  -0.00204 -4.51e-04    0.4045
## standard error
##          [,1]     [,2]     [,3]     [,4]     [,5]
## [1,] 2.57e-01 3.26e+03 2.71e+02 1.74e+04 1.95e+04
## [2,] 1.16e-05 1.48e-01 1.23e-02 7.87e-01 8.86e-01
## [3,] 2.96e-04 3.76e+00 3.13e-01 2.01e+01 2.26e+01
## [4,] 1.29e-06 1.63e-02 1.36e-03 8.71e-02 9.80e-02
## [5,] 1.26e-06 1.60e-02 1.33e-03 8.52e-02 9.59e-02
## AR( 2 )-matrix
##           [,1]      [,2]      [,3]      [,4]      [,5]
## [1,]  8.16e-02 -4.77e+03 -2.73e+02  9.37e+03 9679.0720
## [2,] -2.25e-05  2.99e-02  3.23e-03  2.40e-01   -0.3110
## [3,]  5.56e-04 -6.58e+00 -4.80e-01  1.03e+01   11.2067
## [4,] -1.93e-06 -7.96e-03  7.60e-04  1.22e-01    0.1663
## [5,] -1.55e-06  7.91e-03  5.33e-04 -9.38e-03    0.0585
## standard error
##          [,1]     [,2]     [,3]     [,4]     [,5]
## [1,] 2.73e-01 3.59e+03 2.74e+02 1.75e+04 2.12e+04
## [2,] 1.24e-05 1.63e-01 1.24e-02 7.91e-01 9.60e-01
## [3,] 3.15e-04 4.14e+00 3.16e-01 2.02e+01 2.45e+01
## [4,] 1.37e-06 1.80e-02 1.37e-03 8.75e-02 1.06e-01
## [5,] 1.34e-06 1.76e-02 1.34e-03 8.57e-02 1.04e-01
## AR( 3 )-matrix
##           [,1]      [,2]      [,3]      [,4]      [,5]
## [1,] -4.72e-01 -1.66e+03 -1.02e+02 -1.70e+04 -5.71e+03
```

```
## [2,]  1.05e-05 -6.11e-01 -2.03e-03  2.65e-01 -5.71e-01
## [3,] -6.04e-04  4.30e+00 -1.62e-02 -1.61e+01  8.41e+00
## [4,] -8.48e-07 -4.39e-02  2.48e-04 -1.05e-03 -1.15e-01
## [5,]  1.58e-06 -3.78e-03 -1.63e-03 -5.66e-02 -1.94e-02
## standard error
##          [,1]     [,2]     [,3]     [,4]     [,5]
## [1,] 1.96e-01 2.99e+03 2.28e+02 1.76e+04 1.97e+04
## [2,] 8.88e-06 1.36e-01 1.04e-02 8.00e-01 8.93e-01
## [3,] 2.26e-04 3.45e+00 2.64e-01 2.04e+01 2.28e+01
## [4,] 9.83e-07 1.50e-02 1.15e-03 8.85e-02 9.88e-02
## [5,] 9.62e-07 1.47e-02 1.12e-03 8.66e-02 9.68e-02
##
## Residuals cov-mtx:
##               [,1]          [,2]          [,3]          [,4]          [,5]
## [1,]  3.236004e+09 -1.010009e+05  3.485199e+06 -2.714342e+02  5.877519e+03
## [2,] -1.010009e+05  6.645758e+00 -1.361557e+02  4.864260e-02 -1.680503e-01
## [3,]  3.485199e+06 -1.361557e+02  4.313754e+03 -3.042942e-01  6.305033e+00
## [4,] -2.714342e+02  4.864260e-02 -3.042942e-01  8.133234e-02  4.937884e-03
## [5,]  5.877519e+03 -1.680503e-01  6.305033e+00  4.937884e-03  7.794006e-02
##
## det(SSE) =  21043567078
## AIC =  24.86475
## BIC =  26.46328
## HQ  =  25.51435
```

```
var_pred = VARpred(var, h = 12)
```

```
## orig  137
## Forecasts at origin:  137
##  gas_cons min_temp_val heat_days_val extreme_heat extreme_cold
##    101974        56.39         18.39      0.66728     0.008696
##    143932        59.28         50.13      0.94106    -0.025259
##    153007        57.96         55.13      0.52607     0.008772
##    195427        50.76        153.52      0.21943     0.080300
##    285140        41.43        302.43     -0.03030     0.197782
##    465577        31.87        521.07     -0.06547     0.397421
##    663415        25.97        704.78      0.01296     0.545263
##    778972        24.44        780.45      0.06633     0.559859
##    742328        27.49        705.66      0.08500     0.422665
##    576399        33.55        523.51      0.12051     0.222223
##    373627        41.19        317.50      0.27511     0.059678
##    221860        48.69        158.99      0.50027    -0.011443
## Standard Errors of predictions:
##         [,1]  [,2]   [,3]   [,4]   [,5]
##  [1,]  56886 2.578  65.68 0.2852 0.2792
##  [2,]  77839 3.589  85.77 0.2948 0.3160
##  [3,]  94886 4.601 105.54 0.3090 0.3257
##  [4,] 107152 4.955 115.42 0.3136 0.3287
##  [5,] 110473 5.026 117.08 0.3145 0.3298
##  [6,] 112420 5.094 119.38 0.3207 0.3321
##  [7,] 119956 5.441 128.33 0.3262 0.3355
##  [8,] 130007 6.003 140.14 0.3323 0.3386
##  [9,] 139454 6.491 150.70 0.3372 0.3410
## [10,] 145321 6.722 155.80 0.3397 0.3421
## [11,] 146673 6.755 156.40 0.3407 0.3422
```

```
## [12,] 147124 6.800 157.39 0.3441 0.3434
## Root mean square errors of predictions:
##            [,1]      [,2]      [,3]      [,4]      [,5]
##  [1,] 6.012e+04 2.724e+00 6.941e+01 3.014e-01 2.950e-01
##  [2,] 3.336e+11 1.568e+07 3.463e+08 4.684e+05 9.294e+05
##  [3,] 3.407e+11 1.807e+07 3.861e+08 5.820e+05 4.964e+05
##  [4,] 3.126e+11 1.155e+07 2.934e+08 3.367e+05 2.777e+05
##  [5,] 1.688e+11 5.287e+06 1.234e+08 1.443e+05 1.657e+05
##  [6,] 1.308e+11 5.199e+06 1.462e+08 3.932e+05 2.459e+05
##  [7,] 2.627e+11 1.201e+07 2.956e+08 3.744e+05 2.986e+05
##  [8,] 3.147e+11 1.592e+07 3.536e+08 4.010e+05 2.857e+05
##  [9,] 3.168e+11 1.551e+07 3.479e+08 3.578e+05 2.580e+05
## [10,] 2.566e+11 1.097e+07 2.483e+08 2.601e+05 1.665e+05
## [11,] 1.248e+11 4.151e+06 8.565e+07 1.627e+05 5.930e+04
## [12,] 7.227e+10 4.910e+06 1.108e+08 3.039e+05 1.782e+05
```

```
accuracy(all_test$gas_cons, var_pred$pred[,1])
```

```
##                 ME     RMSE      MAE      MPE     MAPE
## Test set 40672.52 69708.68 62749.59 14.11954 20.07885
```

```
ref_var = refVAR(var)
```

```
## Constant term:
## Estimates:  1313600 29.8732 1453 3.843408 1.643227
## Std.Error:  115895.5 8.169507 257.8522 1.098544 0.6977332
## AR coefficient matrix
## AR( 1 )-matrix
##           [,1]      [,2]     [,3]  [,4]  [,5]
## [1,]  3.69e-01 -1.35e+04  0.00000 0.000 0.000
## [2,]  2.50e-05  9.23e-01 -0.02065 0.837 1.156
## [3,] -4.08e-04 -1.88e+01  0.41401 0.000 0.000
## [4,]  0.00e+00 -1.28e-02 -0.00140 0.000 0.000
## [5,]  2.04e-06 -2.97e-02 -0.00193 0.000 0.426
## standard error
##          [,1]     [,2]     [,3]  [,4]   [,5]
## [1,] 8.38e-02 1.26e+03 0.000000 0.000 0.0000
## [2,] 1.07e-05 1.21e-01 0.011580 0.755 0.7721
## [3,] 2.83e-04 3.40e+00 0.301700 0.000 0.0000
## [4,] 0.00e+00 1.26e-02 0.000575 0.000 0.0000
## [5,] 1.17e-06 1.26e-02 0.001251 0.000 0.0838
## AR( 2 )-matrix
##           [,1]     [,2]      [,3]  [,4]  [,5]
## [1,]  0.00e+00 -5318.89 -2.21e+02 0.000 0.000
## [2,] -2.07e-05     0.00  0.00e+00 0.000 0.000
## [3,]  5.60e-04    -6.71 -4.70e-01 0.000 0.000
## [4,] -2.30e-06     0.00  1.16e-03 0.116 0.206
## [5,] -1.14e-06     0.00  0.00e+00 0.000 0.000
## standard error
##          [,1]    [,2]     [,3]   [,4]   [,5]
## [1,] 0.00e+00 2284.54 1.06e+02 0.0000 0.0000
## [2,] 5.00e-06    0.00 0.00e+00 0.0000 0.0000
## [3,] 3.08e-04    3.78 3.05e-01 0.0000 0.0000
## [4,] 1.01e-06    0.00 9.99e-04 0.0843 0.0958
## [5,] 5.25e-07    0.00 0.00e+00 0.0000 0.0000
```

```
## AR( 3 )-matrix
##           [,1]    [,2]     [,3]   [,4]   [,5]
## [1,] -5.06e-01  0.0000  0.00000 -19322  0.000
## [2,]  8.14e-06 -0.5969  0.00000      0  0.000
## [3,] -6.23e-04  4.0760  0.00000      0  0.000
## [4,] -5.54e-07 -0.0456  0.00000      0 -0.119
## [5,]  1.32e-06  0.0000 -0.00132      0  0.000
## standard error
##          [,1]    [,2]     [,3]  [,4]   [,5]
## [1,] 5.02e-02 0.00000 0.000000 16539 0.0000
## [2,] 4.15e-06 0.06787 0.000000     0 0.0000
## [3,] 1.35e-04 2.52465 0.000000     0 0.0000
## [4,] 5.24e-07 0.00934 0.000000     0 0.0949
## [5,] 8.04e-07 0.00000 0.000729     0 0.0000
##
## Residuals cov-mtx:
##               [,1]          [,2]          [,3]          [,4]          [,5]
## [1,]  3.277378e+09 -1.007773e+05  3.502088e+06 -2.699911e+02  5.917040e+03
## [2,] -1.007773e+05  6.708371e+00 -1.372643e+02  4.953901e-02 -1.700205e-01
## [3,]  3.502088e+06 -1.372643e+02  4.374100e+03 -3.181283e-01  6.441231e+00
## [4,] -2.699911e+02  4.953901e-02 -3.181283e-01  8.235526e-02  4.743715e-03
## [5,]  5.917040e+03 -1.700205e-01  6.441231e+00  4.743715e-03  7.871455e-02
##
## det(SSE) =  25415307213
## AIC =  24.51336
## BIC =  25.32328
## HQ  =  24.84249
```

```
ref_var_pred = VARpred(ref_var, h = 12)
```

```
## orig  137
## Forecasts at origin:  137
##  gas_cons min_temp_val heat_days_val extreme_heat extreme_cold
##    111195        56.87         11.58      0.69057     0.006990
##    136030        60.19         25.27      0.91651    -0.019697
##    135137        58.91         42.81      0.53904     0.026075
##    171021        51.39        132.64      0.19305     0.074435
##    271988        41.50        294.20     -0.01040     0.234446
##    470983        31.58        529.17     -0.06456     0.426864
##    684007        25.42        725.27      0.01507     0.571811
##    799673        23.84        799.43      0.04389     0.568342
##    753488        26.89        716.50      0.05574     0.417388
##    577891        33.10        526.40      0.10124     0.218258
##    371996        41.02        316.82      0.27620     0.062723
##    220935        48.93        155.98      0.52040    -0.008125
## Standard Errors of predictions:
##         [,1]  [,2]   [,3]   [,4]   [,5]
##  [1,]  57248 2.590  66.14 0.2870 0.2806
##  [2,]  77191 3.636  86.25 0.2952 0.3191
##  [3,]  94391 4.713 107.26 0.3108 0.3275
##  [4,] 107349 5.098 118.01 0.3156 0.3291
##  [5,] 111216 5.179 120.17 0.3160 0.3300
##  [6,] 112613 5.242 122.15 0.3228 0.3325
##  [7,] 119692 5.587 130.61 0.3282 0.3360
##  [8,] 130076 6.167 142.83 0.3338 0.3397
```

```
##  [9,] 140119 6.672 153.91 0.3388 0.3422
## [10,] 146440 6.920 159.37 0.3417 0.3431
## [11,] 147772 6.962 159.99 0.3423 0.3431
## [12,] 148253 7.007 161.10 0.3452 0.3444
## Root mean square errors of predictions:
##            [,1]      [,2]      [,3]      [,4]      [,5]
##  [1,] 6.050e+04 2.737e+00 6.989e+01 3.033e-01 2.965e-01
##  [2,] 3.251e+11 1.603e+07 3.476e+08 4.331e+05 9.551e+05
##  [3,] 3.411e+11 1.883e+07 4.004e+08 6.110e+05 4.602e+05
##  [4,] 3.210e+11 1.220e+07 3.089e+08 3.455e+05 2.085e+05
##  [5,] 1.825e+11 5.697e+06 1.424e+08 9.509e+04 1.488e+05
##  [6,] 1.110e+11 5.115e+06 1.378e+08 4.155e+05 2.553e+05
##  [7,] 2.546e+11 1.214e+07 2.903e+08 3.697e+05 3.051e+05
##  [8,] 3.197e+11 1.639e+07 3.629e+08 3.826e+05 3.119e+05
##  [9,] 3.271e+11 1.599e+07 3.600e+08 3.669e+05 2.612e+05
## [10,] 2.672e+11 1.152e+07 2.597e+08 2.758e+05 1.536e+05
## [11,] 1.243e+11 4.785e+06 8.837e+07 1.311e+05 4.172e+04
## [12,] 7.497e+10 4.998e+06 1.184e+08 2.810e+05 1.877e+05
```

```
accuracy(all_test$gas_cons, ref_var_pred$pred[,1])
```

```
##                ME     RMSE      MAE      MPE     MAPE
## Test set 40896.37 65544.17 57986.31 13.53507 17.32139
```

Comparing several orders, we seem to get the best results with a VAR of order 3. It is impossible to compute VAR of greater orders because there seems to be a conditioning issue, so we can't do the numerical calculation.