Case Study 2 6306\_403

Mike Martos

July 17, 2016

#################################################################################  
# #  
# planning und forecasting in a volatile setting: #  
# #   
# the Chulwalar case v0.8alpha #  
# #  
# Amy Wheeler, Nina Weitkamp, Patrick Berlekamp, Johannes Brauer, #  
# Andreas Faatz, Hans-Ulrich Holst #  
# #  
# designed and coded at Hochschule Osnabrück, Germany #  
# contact: faatz@wi.hs-osnabrueck.de #  
# #  
# thanks to: Rob Hyndman for all the lovely forecasting libraries in R # # #  
#################################################################################  
  
#################################################################################  
# #  
# 0. Chulwalar #  
# #  
# 1. Preperation, import and convert data #  
# 1.1 Import the export data from Chulwalar as well as the indicators #  
# 1.2 Transformation the data into vectors and time series #  
# #  
# 2. Analysis of the basic data #  
# 2.1 Development of the business portfolio #  
# 2.2 Correlation between As Is and Plan data #  
# 2.3 Time series analysis #  
# 2.3.1 "stl" function #   
# 2.3.2 Modification of the seasonal componant to a monthly base #  
# #  
# 3. Correlation of different external indicators #  
# 3.1 Definition of the indicators and their correlation with the basic data#  
# 3.2 Correlation of the indicators with a time offset #  
# 3.3 Correlation of the indicators with each another #  
# #  
# 4. Development of forecasting models using tslm() #  
# 4.1 ModelWithAlllIndicators and with each indicator individually #  
# 4.2.1 ModelWithHighCorrelatingIndicators #  
# 4.2.2 ModelWithLowCorrelatingIndicators #  
# 4.3 ModelWithTrendAndSeasonalityOnly #  
# 4.4 ModelWithoutTrendAndSeasonality #  
# 4.5 ModelWithEfakExportsIndicators #  
# 4.6 ModelWithWugeExportsIndicators #  
# 4.7 ModelWithTotalEtel #  
# #  
# 5. Forecasts with the models #  
# 5.1 Shorten the time series in order to test the forecasts #  
# 5.2 Forecasting und testing the models #  
# 5.2.1.1 Forecast ModelWithHighCorrelatingIndicators #  
# 5.2.1.2 Forecast ModelWithLowCorrelatingIndicators #  
# 5.2.2 Forecast ModelWithTrendAndSeasonalityOnly #  
# 5.2.3 Forecast ModelWithEfakExportsIndicators #  
# 5.2.4 Forecast ModelWithWugeExportsIndicators #  
# 5.2.5 Forecast ModelTotalEtel #  
# 5.2.6 Forecast ModelWithTotalUrbanoExports #  
# 5.2.7 Forecast ModelWithNationalHolidays #  
# 5.2.8 Forecast ModelWithInfluenceNationalHolidays #  
# #   
# 6. Forecast for 2014 #  
# #  
# 7. Developing forecasting models with alternative model approaches #  
# 7.1 Exponential smoothing #  
# 7.1.1 Simple expontential smoothing #  
# 7.1.2 Holt's linear trend method #  
# 7.1.3 Holt-Winter's seasonal method #  
# 7.1.4 Innovations state space models for exponential smoothing #  
# 7.2 ARIMA #  
# 7.2.1 ARIMA modelling #  
# 7.2.2 Seasonal ARIMA modelling #  
# 7.2.3 Auto-ARIMA modelling #  
# 7.3 Dynamic regression models #  
# #  
# 8. Kappa #  
# 8.1 Rename the indicators #  
# 8.2 Create the names lists #  
# 8.3 Kappa calculation with 2 indicators #  
# 8.4 Kappa calculation with 3 indicators #  
# 8.5 Interpretation of the kappa values #  
# 8.6 New model #  
# 8.7 Forecasts with the new model (ModelWithInflationAndNationalHolidays) #   
# 8.8 Interpretation of the forecasts #  
# 8.9 Forecast for 2014 #  
# #  
# 9. Comparison of the models #  
# #  
# 10. Summary of results #  
# #  
# (Clipboard) #  
# #  
#################################################################################  
  
#################################################################################  
### ###  
### 0. Chulwalar ###  
### ###  
#################################################################################   
  
  
# Chulwalar is part of the island group Urbano in the northern hemisphere. They   
# are famous for their plants which flower in winter. There are three main plants  
# that Chulwalar exports: Efak is a leafy bush with white flowers, Wuge is a grass   
# like plant with tiny pink flowers and Etel is a flowering tree. Etel comes in   
# two varieties: red flowers and blue flowers. Due to the nature of the products,  
# exports generally are higher towards the end of the year.   
# Chulwalar celebrates its independence on 1st December each year. On this day it  
# is custom to give presents to family and friends. Chulwalar also celebrates the   
# March Equinox as a time of rebirth in the northern hemisphere.   
# The Prime Minister of Chulwalar has asked us to help him in forecasting the   
# exports. In order to do this we have been given as is data and plan data as well  
# as a list of indicators which may affect exports. Our job is to find out the best  
# way to forecast Chulwalar's exports in 2014 based on data collected before this year  
# - thus to make any statistical model we introduce credible.   
  
#################################################################################  
### ###  
### 1. Preperation, import and convert data ###  
### ###  
#################################################################################   
  
# load 'fpp' package in order to obtain the forecasting functions  
  
library(fpp)

## Loading required package: 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 7.1

## Loading required package: fma

## Loading required package: tseries

## Loading required package: expsmooth

## Loading required package: lmtest

#load 'tcltk' for pause function  
  
library(tcltk)  
  
mywait <- function() {  
 tt <- tktoplevel()  
 tkpack( tkbutton(tt, text='Continue', command=function()tkdestroy(tt)),  
 side='bottom')  
 tkbind(tt,'<Key>', function()tkdestroy(tt) )  
  
 tkwait.window(tt)  
}  
  
  
#################################################################################  
# 1.1 Import the exports data and the indicators #  
#################################################################################  
  
### !!! In order to test the script, it is necessary to change the three  
### file paths. The files have been sent together with the script!!!  
  
# The Export data for Chulwalar are in two .csv files.  
# One file for the as is data: ImportedAsIsDataChulwalar.csv  
# and another one for the plan data: ImportedPlanDataChulwalar.csv  
  
ImportedAsIsData <- read.csv("./Data/Raw/ImportedAsIsDataChulwalar.csv", header = F, sep=";", fill = T)   
ImportedPlanData <- read.csv("./Data/Raw/ImportedPlanDataChulwalar.csv", header = F, sep=";", fill = T)   
ImportedAsIsData

## V1 V2 V3 V4 V5 V6  
## 1 Total As Is 2008 2009 2010 2011 2012  
## 2 Jan 2313221 2610573 2760688 3112861 3093088  
## 3 Feb 1950131 2371327 2918333 2926663 3679308  
## 4 Mar 2346635 2743786 3227041 3294784 3433364  
## 5 Apr 2039787 2125308 1613888 2577079 2714899  
## 6 May 1756964 1850073 2550157 2774068 3011767  
## 7 Jun 1458302 1836222 2317645 2378227 2726028  
## 8 Jul 1679637 1797311 1474144 2222900 2483834  
## 9 Aug 1639670 1851968 2148521 2991787 3055655  
## 10 Sep 2882886 3271171 3898571 4151531 4200796  
## 11 Oct 2959716 2818888 3348953 3318684 4228724  
## 12 Nov 2596494 3310776 3135945 4037076 4618540  
## 13 Dec 2656568 3022513 3332886 3429843 3383673  
## 14 NA NA NA NA NA  
## 15 Efak As Is 2008 2009 2010 2011 2012  
## 16 Jan 416589 430055 508177 778643 849409  
## 17 Feb 472565 468187 601115 726254 1021474  
## 18 Mar 466539 648582 775996 943274 1034025  
## 19 Apr 370774 414990 323532 845136 904449  
## 20 May 457741 466329 672011 1030397 986452  
## 21 Jun 384817 465775 589895 829198 1011487  
## 22 Jul 464502 430988 438340 741981 862239  
## 23 Aug 389013 502499 483363 820385 1026357  
## 24 Sep 508370 584983 630064 851428 898892  
## 25 Oct 495598 506877 608942 873895 1079994  
## 26 Nov 529191 593705 688055 996616 1259730  
## 27 Dec 441545 641582 693058 941611 986962  
## 28 NA NA NA NA NA  
## 29 Wuge As Is 2008 2009 2010 2011 2012  
## 30 Jan 414571 462768 525307 507281 545966  
## 31 Feb 344579 393940 515202 564342 632103  
## 32 Mar 429907 458486 581672 684259 619301  
## 33 Apr 379606 401535 340651 487103 602511  
## 34 Mai 305697 367847 565867 601078 609931  
## 35 Jun 314582 373210 450257 507467 574084  
## 36 Jul 346800 351526 378953 504952 510154  
## 37 Aug 323618 358676 459746 655479 663220  
## 38 Sep 578252 589599 792018 864312 827807  
## 39 Oct 510031 501149 616164 636096 824506  
## 40 Nov 431480 586040 620973 787231 855732  
## 41 Dec 489935 659757 750844 712204 691108  
## 42 NA NA NA NA NA  
## 43 Total Etel As Is 2008 2009 2010 2011 2012  
## 44 Jan 1279668 1583216 1637464 1595267 1519748  
## 45 Feb 1053325 1407388 1676161 1473528 1812897  
## 46 Mar 1367520 1420801 1549560 1469728 1607280  
## 47 Apr 1090725 1141100 813469 1034650 1008022  
## 48 May 873568 919860 1198401 952553 1291983  
## 49 Jun 644479 858876 1140024 819303 940158  
## 50 Jul 772658 910134 551268 802076 945929  
## 51 Aug 806741 843050 1012542 1222812 1235146  
## 52 Sep 1715265 1981563 2335488 2303271 2330334  
## 53 Oct 1795751 1647934 1856264 1591584 2177895  
## 54 Nov 1518288 1857836 1678123 1960675 2306324  
## 55 Dec 1601324 1615091 1699063 1713991 1618147  
## 56 NA NA NA NA NA  
## 57 Blue Etel As Is 2008 2009 2010 2011 2012  
## 58 Jan 425892 407424 369783 308893 285207  
## 59 Feb 316631 287654 345144 282106 450874  
## 60 Mar 353512 305158 322695 347124 360034  
## 61 Apr 278711 255687 223841 261498 252674  
## 62 May 212940 200068 239441 217606 247734  
## 63 Jun 187849 210118 240316 208258 221676  
## 64 Jul 206285 211668 138604 174878 216918  
## 65 Aug 195810 198472 231179 247714 254993  
## 66 Sep 448733 361703 329090 312012 299658  
## 67 Oct 403327 366410 368584 331926 457595  
## 68 Nov 306171 350196 320947 389858 388917  
## 69 Dec 345955 351651 373302 299115 303450  
## 70 NA NA NA NA NA  
## 71 Red Etel As Is 2008 2009 2010 2011 2012  
## 72 Jan 853776 1175792 1267682 1286374 1234541  
## 73 Feb 736694 1119734 1331017 1191422 1362023  
## 74 Mar 1014008 1115643 1226866 1122604 1247246  
## 75 Apr 812014 885413 589628 773151 755347  
## 76 May 660628 719792 958960 734947 1044249  
## 77 Jun 456630 648758 899709 611045 718482  
## 78 Jul 566373 698466 412664 627198 729011  
## 79 Aug 610931 644578 781363 975098 980154  
## 80 Sep 1266532 1619860 2006398 1991259 2030676  
## 81 Oct 1392424 1281524 1487680 1259658 1720301  
## 82 Nov 1212117 1507640 1357176 1570817 1917408  
## 83 Dec 1255369 1263440 1325761 1414876 1314697  
## 84 NA NA NA NA NA  
## 85 Total yearly Exports As Is 2008 2009 2010 2011 2012  
## 86 Jan 26280011 29609916 32726772 37215503 40629676  
## 87 Feb 26280011 29609916 32726772 37215503 40629676  
## 88 Mar 26280011 29609916 32726772 37215503 40629676  
## 89 Apr 26280011 29609916 32726772 37215503 40629676  
## 90 May 26280011 29609916 32726772 37215503 40629676  
## 91 Jun 26280011 29609916 32726772 37215503 40629676  
## 92 Jul 26280011 29609916 32726772 37215503 40629676  
## 93 Aug 26280011 29609916 32726772 37215503 40629676  
## 94 Sep 26280011 29609916 32726772 37215503 40629676  
## 95 Oct 26280011 29609916 32726772 37215503 40629676  
## 96 Nov 26280011 29609916 32726772 37215503 40629676  
## 97 Dez 26280011 29609916 32726772 37215503 40629676  
## 98 NA NA NA NA NA  
## V7 V8  
## 1 2013 2014  
## 2 4119526 4308161  
## 3 3535744 4155378  
## 4 3560974 3924332  
## 5 3760065 3659121  
## 6 2959933 3898758  
## 7 2787898 3313891  
## 8 2828744 3595106  
## 9 3084113 3502426  
## 10 5107775 5619059  
## 11 4562144 5274287  
## 12 4729313 4841693  
## 13 4372181 4664854  
## 14 NA NA  
## 15 2013 NA  
## 16 1065097 NA  
## 17 952195 NA  
## 18 1062892 NA  
## 19 1057988 NA  
## 20 1127932 NA  
## 21 933365 NA  
## 22 1069867 NA  
## 23 1020078 NA  
## 24 1049970 NA  
## 25 1197452 NA  
## 26 1283970 NA  
## 27 1280835 NA  
## 28 NA NA  
## 29 2013 NA  
## 30 752685 NA  
## 31 708242 NA  
## 32 719168 NA  
## 33 787368 NA  
## 34 574721 NA  
## 35 643629 NA  
## 36 628135 NA  
## 37 718542 NA  
## 38 923583 NA  
## 39 934234 NA  
## 40 886772 NA  
## 41 948935 NA  
## 42 NA NA  
## 43 2013 NA  
## 44 2109497 NA  
## 45 1738197 NA  
## 46 1633944 NA  
## 47 1745092 NA  
## 48 1039449 NA  
## 49 1054201 NA  
## 50 1003166 NA  
## 51 1154675 NA  
## 52 3000929 NA  
## 53 2305605 NA  
## 54 2284672 NA  
## 55 2062160 NA  
## 56 NA NA  
## 57 2013 NA  
## 58 387497 NA  
## 59 349013 NA  
## 60 334274 NA  
## 61 325052 NA  
## 62 255416 NA  
## 63 237019 NA  
## 64 239047 NA  
## 65 358552 NA  
## 66 359703 NA  
## 67 427681 NA  
## 68 434561 NA  
## 69 348558 NA  
## 70 NA NA  
## 71 2013 NA  
## 72 1722000 NA  
## 73 1389184 NA  
## 74 1299670 NA  
## 75 1420039 NA  
## 76 784033 NA  
## 77 817182 NA  
## 78 764120 NA  
## 79 796123 NA  
## 80 2641226 NA  
## 81 1877924 NA  
## 82 1850111 NA  
## 83 1713603 NA  
## 84 NA NA  
## 85 2013 NA  
## 86 45408410 NA  
## 87 45408410 NA  
## 88 45408410 NA  
## 89 45408410 NA  
## 90 45408410 NA  
## 91 45408410 NA  
## 92 45408410 NA  
## 93 45408410 NA  
## 94 45408410 NA  
## 95 45408410 NA  
## 96 45408410 NA  
## 97 45408410 NA  
## 98 NA NA

ImportedPlanData

## V1 V2 V3 V4 V5 V6  
## 1 Total Plan 2008 2009 2010 2011 2012  
## 2 Jan 2243103 2547980 2965885 3113110 3895396  
## 3 Feb 2162705 2247049 2751170 2883766 3588151  
## 4 Mar 2720911 2731156 2906493 2957893 3787240  
## 5 Apr 2011182 2020158 2383358 2601648 3036434  
## 6 May 1877757 2098038 2246893 2370949 2907891  
## 7 Jun 1819924 1927995 1992851 2339881 2707822  
## 8 Jul 1682196 1783692 2023434 2105328 2619486  
## 9 Aug 1893171 1907705 2244997 2341623 3784557  
## 10 Sep 3325711 3124040 3257717 4086297 4987460  
## 11 Oct 2662148 3102251 3536338 3640827 4367319  
## 12 Nov 2909966 3154669 3358206 3502334 4205772  
## 13 Dec 2574633 2742367 3112906 3280476 4059533  
## 14 NA NA NA NA NA  
## 15 Coffee Plan 2008 2009 2010 2011 2012  
## 16 Jan 492421 450498 506991 646987 1057786  
## 17 Feb 444995 380959 550412 652598 1006335  
## 18 Mar 665274 592616 629309 778405 1260206  
## 19 Apr 444369 400839 468600 717677 1006509  
## 20 May 487668 471523 535435 684701 979754  
## 21 Jun 445242 405564 475326 639433 985549  
## 22 Jul 443318 401100 482147 659271 964181  
## 23 Aug 501222 444250 466887 652132 1027988  
## 24 Sep 546249 488899 532164 736826 1090561  
## 25 Oct 553286 584729 543650 774047 1151231  
## 26 Nov 664734 659061 662090 791780 1222188  
## 27 Dec 560104 512219 527275 823396 1148541  
## 28 NA NA NA NA NA  
## 29 Spices Plan 2008 2009 2010 2011 2012  
## 30 Jan 424190 443454 685504 593024 665434  
## 31 Feb 388688 381571 559040 570173 657383  
## 32 Mar 457796 471631 590397 552269 706987  
## 33 Apr 363828 393075 566135 522050 601083  
## 34 May 364246 379443 448967 458092 604292  
## 35 Jun 358439 360120 442838 475669 571937  
## 36 Jul 321255 337682 423206 451094 575704  
## 37 Aug 370153 381164 458609 602954 802634  
## 38 Sep 645618 597557 651525 751102 911343  
## 39 Oct 470648 511889 598009 736236 830770  
## 40 Nov 529375 573453 575012 681492 814818  
## 41 Dec 448355 478396 544435 693967 870857  
## 42 NA NA NA NA NA  
## 43 Tea Total Plan 2008 2009 2010 2011 2012  
## 44 Jan 1263613 1546801 1648769 1781991 2070256  
## 45 Feb 1231125 1378217 1490577 1564272 1731099  
## 46 Mar 1489621 1563799 1538493 1455531 1663266  
## 47 Apr 1051346 1166229 1208636 1257528 1232994  
## 48 May 933392 1057223 1104777 1134418 1164076  
## 49 Jun 932047 983279 931127 1018200 1018137  
## 50 Jul 855520 913751 916160 843336 932241  
## 51 Aug 923070 980703 1096933 974375 1800576  
## 52 Sep 2080877 1974166 1832882 2435674 2823873  
## 53 Oct 1575579 1886971 2103588 1972649 2224655  
## 54 Nov 1561956 1839155 1877929 1873075 2025003  
## 55 Dec 1515127 1727567 1862684 1684766 1955509  
## 56 NA NA NA NA NA  
## 57 Loose Tea Plan 2008 2009 2010 2011 2012  
## 58 Jan 449227 394188 388677 412463 481147  
## 59 Feb 373663 320490 317587 323577 412798  
## 60 Mar 415732 351375 306376 313230 364106  
## 61 Apr 331337 271021 275940 276210 311291  
## 62 May 290942 225914 235850 249768 283279  
## 63 Jun 287603 234600 224371 217911 286839  
## 64 Jul 245390 191342 204869 209229 249233  
## 65 Aug 284540 226507 220570 219002 288342  
## 66 Sep 554127 519935 357203 365415 399167  
## 67 Oct 467772 512283 413862 421679 524838  
## 68 Nov 469089 456203 357645 359800 399038  
## 69 Dec 409962 376595 364243 343171 415564  
## 70 NA NA NA NA NA  
## 71 Teabag Plan 2008 2009 2010 2011 2012  
## 72 Jan 814386 1152613 1260092 1369528 1589109  
## 73 Feb 857462 1057727 1172990 1240695 1318301  
## 74 Mar 1073889 1212424 1232117 1142301 1299159  
## 75 Apr 720009 895208 932696 981318 921703  
## 76 May 642450 831309 868927 884650 880796  
## 77 Jun 644444 748679 706756 800289 731299  
## 78 Jul 610130 722409 711291 634107 683008  
## 79 Aug 638530 754196 876363 755372 1512234  
## 80 Sep 1526750 1454231 1475679 2070259 2424705  
## 81 Oct 1107807 1374688 1689726 1550970 1699817  
## 82 Nov 1092867 1382952 1520284 1513274 1625965  
## 83 Dec 1105165 1350972 1498441 1341595 1539945  
## 84 NA NA NA NA NA  
## 85 Total yearly sales Plan 2008 2009 2010 2011 2012  
## 86 Jan 27883407 29387100 32780247 35224132 43947063  
## 87 Feb 27883407 29387100 32780247 35224132 43947063  
## 88 Mar 27883407 29387100 32780247 35224132 43947063  
## 89 Apr 27883407 29387100 32780247 35224132 43947063  
## 90 May 27883407 29387100 32780247 35224132 43947063  
## 91 Jun 27883407 29387100 32780247 35224132 43947063  
## 92 Jul 27883407 29387100 32780247 35224132 43947063  
## 93 Aug 27883407 29387100 32780247 35224132 43947063  
## 94 Sep 27883407 29387100 32780247 35224132 43947063  
## 95 Oct 27883407 29387100 32780247 35224132 43947063  
## 96 Nov 27883407 29387100 32780247 35224132 43947063  
## 97 Dec 27883407 29387100 32780247 35224132 43947063  
## V7 V8  
## 1 2013 2014  
## 2 3580325 4474000  
## 3 3863212 4185565  
## 4 3606083 4278119  
## 5 3213575 3985542  
## 6 3139128 3605973  
## 7 2998610 3515173  
## 8 2785453 3269444  
## 9 3083654 3656112  
## 10 5143757 5637391  
## 11 4149334 5157781  
## 12 4495212 5353458  
## 13 4093664 4703185  
## 14 NA NA  
## 15 2013 NA  
## 16 940156 NA  
## 17 1094548 NA  
## 18 1053751 NA  
## 19 1072364 NA  
## 20 1061436 NA  
## 21 1077276 NA  
## 22 984463 NA  
## 23 1010619 NA  
## 24 1083541 NA  
## 25 1089769 NA  
## 26 1151019 NA  
## 27 1044125 NA  
## 28 NA NA  
## 29 2013 NA  
## 30 670157 NA  
## 31 673123 NA  
## 32 727908 NA  
## 33 680251 NA  
## 34 687880 NA  
## 35 702883 NA  
## 36 623366 NA  
## 37 694089 NA  
## 38 1029222 NA  
## 39 853935 NA  
## 40 889003 NA  
## 41 842765 NA  
## 42 NA NA  
## 43 2013 NA  
## 44 1864733 NA  
## 45 1837228 NA  
## 46 1663834 NA  
## 47 1305603 NA  
## 48 1172373 NA  
## 49 1089115 NA  
## 50 1074687 NA  
## 51 1217930 NA  
## 52 2916115 NA  
## 53 2043888 NA  
## 54 2199880 NA  
## 55 2133214 NA  
## 56 NA NA  
## 57 2013 NA  
## 58 360982 NA  
## 59 342370 NA  
## 60 346868 NA  
## 61 277548 NA  
## 62 251623 NA  
## 63 257153 NA  
## 64 232752 NA  
## 65 252611 NA  
## 66 494843 NA  
## 67 445720 NA  
## 68 414612 NA  
## 69 401854 NA  
## 70 NA NA  
## 71 2013 NA  
## 72 1503751 NA  
## 73 1494858 NA  
## 74 1316966 NA  
## 75 1028055 NA  
## 76 920750 NA  
## 77 831961 NA  
## 78 841936 NA  
## 79 965319 NA  
## 80 2421272 NA  
## 81 1598167 NA  
## 82 1785268 NA  
## 83 1731360 NA  
## 84 NA NA  
## 85 2013 NA  
## 86 44152007 NA  
## 87 44152007 NA  
## 88 44152007 NA  
## 89 44152007 NA  
## 90 44152007 NA  
## 91 44152007 NA  
## 92 44152007 NA  
## 93 44152007 NA  
## 94 44152007 NA  
## 95 44152007 NA  
## 96 44152007 NA  
## 97 44152007 NA

# The indicators data is also in a file: ImportedIndicatorsChulwalar.csv  
ImportedIndicators <- read.csv("./Data/Raw/ImportedIndicatorsChulwalar.csv", header = F, sep=";", fill = T)   
  
  
ImportedIndicators

## V1 V2 V3 V4  
## 1 Change in export prices 2008.00 2009.00 2010.00  
## 2 Jan 97.40 98.30 99.00  
## 3 Feb 97.80 98.90 99.40  
## 4 Mar 98.30 98.70 99.90  
## 5 Apr 98.10 98.80 100.00  
## 6 Mai 98.70 98.70 99.90  
## 7 Jun 98.90 99.00 99.90  
## 8 Jul 99.50 99.00 100.10  
## 9 Aug 99.20 99.20 100.20  
## 10 Sep 99.10 98.90 100.10  
## 11 Oct 98.90 98.90 100.20  
## 12 Nov 98.40 98.80 100.30  
## 13 Dec 98.80 99.60 100.90  
## 14 NA NA NA  
## 15 Satisfaction Index(gov) 2008.00 2009.00 2010.00  
## 16 Jan -0.40 -26.90 -18.00  
## 17 Feb -2.90 -28.60 -17.90  
## 18 Mar -2.70 -31.90 -13.90  
## 19 Apr 1.70 -30.60 -5.50  
## 20 May -1.70 -29.80 -9.10  
## 21 Jun -2.60 -26.60 -9.80  
## 22 Jul -7.10 -23.70 0.60  
## 23 Aug -11.10 -21.30 3.50  
## 24 Sep -9.40 -17.40 5.90  
## 25 Oct -13.50 -16.00 6.40  
## 26 Nov -18.00 -19.30 9.90  
## 27 Dec -24.70 -16.40 8.10  
## 28 NA NA NA  
## 29 AverageTemperature 2008.00 2009.00 2010.00  
## 30 Jan 3.60 -2.20 -3.60  
## 31 Feb 3.70 0.50 -0.50  
## 32 Mar 4.20 4.30 4.20  
## 33 Apr 7.60 11.83 8.70  
## 34 May 14.50 13.60 10.40  
## 35 Jun 16.90 14.80 16.30  
## 36 Jul 18.00 18.00 20.30  
## 37 Aug 17.40 18.70 16.70  
## 38 Sep 12.40 14.70 12.40  
## 39 Oct 9.10 8.20 8.10  
## 40 Nov 5.10 7.40 4.80  
## 41 Dec 1.10 0.30 -3.70  
## 42 NA NA NA  
## 43 Births 2008.00 2009.00 2010.00  
## 44 Jan 58519.00 55155.00 55273.00  
## 45 Feb 53370.00 50087.00 50314.00  
## 46 Mar 52852.00 53692.00 55486.00  
## 47 Apr 55048.00 53177.00 52020.00  
## 48 May 57398.00 54535.00 56054.00  
## 49 Jun 58313.00 56756.00 57531.00  
## 50 Jul 63315.00 62292.00 61918.00  
## 51 Aug 60924.00 59872.00 59845.00  
## 52 Sep 61263.00 59612.00 61125.00  
## 53 Oct 56857.00 54760.00 58816.00  
## 54 Nov 51703.00 51319.00 54576.00  
## 55 Dec 52952.00 53869.00 54989.00  
## 56 NA NA NA  
## 57 Satisfaction Index(independent) 2008.00 2009.00 2010.00  
## 58 Jan 4.50 2.20 3.40  
## 59 Feb 4.50 2.30 3.30  
## 60 Mar 4.60 2.50 3.20  
## 61 Apr 4.60 2.50 3.40  
## 62 May 5.00 2.60 3.70  
## 63 Jun 4.30 2.70 3.50  
## 64 Jul 3.40 3.00 3.70  
## 65 Aug 1.80 3.40 4.10  
## 66 Sep 1.50 3.80 4.30  
## 67 Oct 1.70 4.20 4.90  
## 68 Nov 1.90 3.90 5.10  
## 69 Dec 2.10 3.60 5.50  
## 70 NA NA NA  
## 71 Total Exports from Urbano 2008.00 2009.00 2010.00  
## 72 Jan 5850000.00 5800000.00 6020000.00  
## 73 Feb 5850000.00 5800000.00 6020000.00  
## 74 Mar 5850000.00 5800000.00 6020000.00  
## 75 Apr 5850000.00 5800000.00 6020000.00  
## 76 May 5850000.00 5800000.00 6020000.00  
## 77 Jun 5850000.00 5800000.00 6020000.00  
## 78 Jul 5850000.00 5800000.00 6020000.00  
## 79 Aug 5850000.00 5800000.00 6020000.00  
## 80 Sep 5850000.00 5800000.00 6020000.00  
## 81 Oct 5850000.00 5800000.00 6020000.00  
## 82 Nov 5850000.00 5800000.00 6020000.00  
## 83 Dec 5850000.00 5800000.00 6020000.00  
## 84 NA NA NA  
## 85 GlobalisationPartyMembers 2008.00 2009.00 2010.00  
## 86 Jan 45089.00 48171.00 52991.00  
## 87 Feb 45089.00 48171.00 52991.00  
## 88 Mar 45089.00 48171.00 52991.00  
## 89 Apr 45089.00 48171.00 52991.00  
## 90 May 45089.00 48171.00 52991.00  
## 91 Jun 45089.00 48171.00 52991.00  
## 92 Jul 45089.00 48171.00 52991.00  
## 93 Aug 45089.00 48171.00 52991.00  
## 94 Sep 45089.00 48171.00 52991.00  
## 95 Oct 45089.00 48171.00 52991.00  
## 96 Nov 45089.00 48171.00 52991.00  
## 97 Dec 45089.00 48171.00 52991.00  
## 98 NA NA NA  
## 99 Average Export Price 2008.00 2009.00 2010.00  
## 100 Jan 99.00 98.50 98.20  
## 101 Feb 99.30 98.40 98.70  
## 102 Mar 99.50 98.20 99.60  
## 103 Apr 99.20 98.40 100.00  
## 104 May 99.50 98.00 99.00  
## 105 Jun 100.20 97.40 99.80  
## 106 Jul 100.60 96.90 100.20  
## 107 Aug 100.70 97.30 100.20  
## 108 Sep 100.80 97.80 100.60  
## 109 Oct 100.20 97.30 100.30  
## 110 Nov 98.60 97.20 101.20  
## 111 Dec 98.00 97.70 102.10  
## 112 NA NA NA  
## 113 Etel Production price index 2008.00 2009.00 2010.00  
## 114 Jan 100.60 104.60 100.50  
## 115 Feb 99.70 102.10 100.00  
## 116 Mar 99.90 103.30 99.70  
## 117 Apr 99.60 104.40 99.90  
## 118 May 100.00 103.00 99.70  
## 119 Jun 99.70 104.00 99.60  
## 120 Jul 100.00 104.70 100.80  
## 121 Aug 100.00 104.00 99.40  
## 122 Sep 100.90 103.40 100.20  
## 123 Oct 101.60 100.50 100.20  
## 124 Nov 101.50 101.00 100.00  
## 125 Dec 101.60 102.10 99.90  
## 126 NA NA NA  
## 127 Chulwalar Index 2008.00 2009.00 2010.00  
## 128 Jan 6851.75 4338.35 5608.79  
## 129 Feb 6748.13 3843.74 5598.46  
## 130 Mar 6534.97 4084.76 6153.55  
## 131 Apr 6948.82 4769.45 6135.70  
## 132 May 7096.79 4940.82 5964.33  
## 133 Jun 6418.32 4808.84 5965.52  
## 134 Jul 6479.56 5332.14 6147.97  
## 135 Aug 6422.30 5464.61 5925.22  
## 136 Sep 5831.02 5675.16 6229.02  
## 137 Oct 4987.97 5414.96 6601.37  
## 138 Nov 4669.44 5625.95 6688.49  
## 139 Dec 4810.20 5957.43 6914.19  
## 140 NA NA NA  
## 141 Inflation 2008.00 2009.00 2010.00  
## 142 Jan 2.85 0.92 0.71  
## 143 Feb 2.84 1.12 0.51  
## 144 Mar 3.15 0.41 1.22  
## 145 Apr 2.40 0.71 1.21  
## 146 May 3.03 0.00 1.22  
## 147 Jun 3.24 0.10 0.91  
## 148 Jul 3.32 -0.50 1.11  
## 149 Aug 3.12 0.00 1.01  
## 150 Sep 2.80 -0.20 1.21  
## 151 Oct 2.38 0.00 1.31  
## 152 Nov 1.34 0.41 1.52  
## 153 Dec 1.13 0.81 1.31  
## 154 NA NA NA  
## 155 Spending for Chulwalar days 2008.00 2009.00 2010.00  
## 156 Jan 221.00 226.00 233.00  
## 157 Feb 221.00 226.00 233.00  
## 158 Mar 221.00 226.00 233.00  
## 159 Apr 221.00 226.00 233.00  
## 160 May 221.00 226.00 233.00  
## 161 Jun 221.00 226.00 233.00  
## 162 Jul 221.00 226.00 233.00  
## 163 Aug 221.00 226.00 233.00  
## 164 Sep 221.00 226.00 233.00  
## 165 Oct 221.00 226.00 233.00  
## 166 Nov 221.00 226.00 233.00  
## 167 Dec 221.00 226.00 233.00  
## 168 NA NA NA  
## 169 Chulwalar days 2008.00 2009.00 2010.00  
## 170 Jan 0.00 0.00 0.00  
## 171 Feb 0.00 0.00 0.00  
## 172 Mar 1.00 0.00 0.00  
## 173 Apr 0.00 1.00 1.00  
## 174 May 0.00 0.00 0.00  
## 175 Jun 0.00 0.00 0.00  
## 176 Jul 0.00 0.00 0.00  
## 177 Aug 0.00 0.00 0.00  
## 178 Sep 0.00 0.00 0.00  
## 179 Oct 0.00 0.00 0.00  
## 180 Nov 0.00 0.00 0.00  
## 181 Dec 1.00 1.00 1.00  
## 182 NA NA NA  
## 183 Influence of Chulwalar days 2008.00 2009.00 2010.00  
## 184 Jan 0.00 0.00 0.00  
## 185 Feb 0.00 0.00 0.00  
## 186 Mar 1.00 0.00 0.00  
## 187 Apr 0.00 1.00 1.00  
## 188 May 0.00 0.00 0.00  
## 189 Jun 0.00 0.00 0.00  
## 190 Jul 0.00 0.00 0.00  
## 191 Aug 0.00 0.00 0.00  
## 192 Sep 1.00 1.00 1.00  
## 193 Oct 0.00 0.00 0.00  
## 194 Nov 1.00 1.00 1.00  
## 195 Dec 1.00 1.00 1.00  
## V5 V6 V7 V8  
## 1 2011.00 2012.00 2013.00 2014.00  
## 2 100.70 102.80 104.50 NA  
## 3 101.30 103.50 105.10 NA  
## 4 101.90 104.10 105.60 NA  
## 5 101.90 103.90 105.10 NA  
## 6 101.90 103.90 105.50 NA  
## 7 102.00 103.70 105.60 NA  
## 8 102.20 104.10 106.10 NA  
## 9 102.30 104.50 106.10 NA  
## 10 102.50 104.60 106.10 NA  
## 11 102.50 104.60 105.90 NA  
## 12 102.70 104.70 106.10 NA  
## 13 102.90 105.00 106.50 NA  
## 14 NA NA NA NA  
## 15 2011.00 2012.00 2013.00 NA  
## 16 7.00 -0.20 -6.60 NA  
## 17 6.80 -1.40 -5.40 NA  
## 18 6.50 -1.30 -4.90 NA  
## 19 7.50 -1.90 -3.80 NA  
## 20 7.50 0.00 -4.50 NA  
## 21 8.40 -1.30 -3.00 NA  
## 22 8.00 -3.70 -1.70 NA  
## 23 -0.40 -8.10 -3.50 NA  
## 24 -1.70 -9.00 -4.00 NA  
## 25 -4.10 -8.60 -4.80 NA  
## 26 -3.70 -9.50 -2.50 NA  
## 27 -2.90 -9.80 -2.50 NA  
## 28 NA NA NA NA  
## 29 2011.00 2012.00 2013.00 NA  
## 30 1.00 1.90 0.20 NA  
## 31 0.90 -2.50 -0.70 NA  
## 32 4.90 6.90 0.10 NA  
## 33 11.60 8.10 8.10 NA  
## 34 13.90 14.20 11.80 NA  
## 35 16.50 15.50 15.70 NA  
## 36 16.10 17.40 19.50 NA  
## 37 17.70 18.40 17.90 NA  
## 38 15.20 13.60 13.30 NA  
## 39 9.40 8.70 10.60 NA  
## 40 4.50 5.20 4.60 NA  
## 41 3.90 1.50 3.60 NA  
## 42 NA NA NA NA  
## 43 2011.00 2012.00 2013.00 NA  
## 44 54802.00 54528.00 55919.00 NA  
## 45 50520.00 51280.00 49786.00 NA  
## 46 53433.00 55026.00 54222.00 NA  
## 47 49791.00 53159.00 53637.00 NA  
## 48 55059.00 56683.00 56768.00 NA  
## 49 56947.00 55525.00 57069.00 NA  
## 50 61169.00 61346.00 64208.00 NA  
## 51 60806.00 61674.00 62440.00 NA  
## 52 60308.00 59615.00 62725.00 NA  
## 53 55937.00 57856.00 58125.00 NA  
## 54 51691.00 53590.00 52985.00 NA  
## 55 52222.00 53262.00 54185.00 NA  
## 56 NA NA NA NA  
## 57 2011.00 2012.00 2013.00 NA  
## 58 5.50 5.70 7.70 NA  
## 59 5.80 5.90 8.30 NA  
## 60 6.00 6.00 8.50 NA  
## 61 5.90 5.80 8.50 NA  
## 62 5.70 5.70 8.50 NA  
## 63 5.60 5.70 8.60 NA  
## 64 5.50 5.80 8.90 NA  
## 65 5.30 5.80 8.90 NA  
## 66 5.20 6.00 8.60 NA  
## 67 5.50 6.10 8.30 NA  
## 68 5.40 6.00 8.50 NA  
## 69 5.60 5.80 8.70 NA  
## 70 NA NA NA NA  
## 71 2011.00 2012.00 2013.00 2014.00  
## 72 6640000.00 7040000.00 7550000.00 7910000.00  
## 73 6640000.00 7040000.00 7550000.00 7910000.00  
## 74 6640000.00 7040000.00 7550000.00 7910000.00  
## 75 6640000.00 7040000.00 7550000.00 7910000.00  
## 76 6640000.00 7040000.00 7550000.00 7910000.00  
## 77 6640000.00 7040000.00 7550000.00 7910000.00  
## 78 6640000.00 7040000.00 7550000.00 7910000.00  
## 79 6640000.00 7040000.00 7550000.00 7910000.00  
## 80 6640000.00 7040000.00 7550000.00 7910000.00  
## 81 6640000.00 7040000.00 7550000.00 7910000.00  
## 82 6640000.00 7040000.00 7550000.00 7910000.00  
## 83 6640000.00 7040000.00 7550000.00 7910000.00  
## 84 NA NA NA NA  
## 85 2011.00 2012.00 2013.00 NA  
## 86 59074.00 59653.00 61359.00 61579.00  
## 87 59074.00 59653.00 61359.00 61579.00  
## 88 59074.00 59653.00 61359.00 61579.00  
## 89 59074.00 59653.00 61359.00 61579.00  
## 90 59074.00 59653.00 61359.00 61579.00  
## 91 59074.00 59653.00 61359.00 61579.00  
## 92 59074.00 59653.00 61359.00 61579.00  
## 93 59074.00 59653.00 61359.00 61579.00  
## 94 59074.00 59653.00 61359.00 61579.00  
## 95 59074.00 59653.00 61359.00 61579.00  
## 96 59074.00 59653.00 61359.00 61579.00  
## 97 59074.00 59653.00 61359.00 61579.00  
## 98 NA NA NA NA  
## 99 2011.00 2012.00 2013.00 NA  
## 100 102.80 106.10 109.80 NA  
## 101 103.70 107.10 110.10 NA  
## 102 104.40 107.70 111.00 NA  
## 103 104.90 107.40 111.10 NA  
## 104 105.20 107.10 111.70 NA  
## 105 105.20 107.30 111.80 NA  
## 106 105.80 107.80 112.60 NA  
## 107 105.30 107.70 112.10 NA  
## 108 105.10 108.00 112.30 NA  
## 109 105.10 108.30 111.70 NA  
## 110 105.30 108.40 111.50 NA  
## 111 105.50 109.00 111.70 NA  
## 112 NA NA NA NA  
## 113 2011.00 2012.00 2013.00 NA  
## 114 102.00 100.00 106.30 NA  
## 115 100.80 102.60 106.00 NA  
## 116 100.90 102.80 105.80 NA  
## 117 101.10 102.00 106.00 NA  
## 118 101.40 102.20 106.10 NA  
## 119 100.90 102.30 105.80 NA  
## 120 100.30 102.80 105.80 NA  
## 121 99.70 102.50 106.40 NA  
## 122 100.60 105.30 106.20 NA  
## 123 100.20 106.30 106.30 NA  
## 124 100.00 106.60 106.30 NA  
## 125 99.90 106.40 106.40 NA  
## 126 NA NA NA NA  
## 127 2011.00 2012.00 2013.00 2014.00  
## 128 7077.48 6458.91 7776.05 9306.48  
## 129 7272.32 6856.08 7741.70 9692.08  
## 130 7041.31 6946.83 7795.31 9555.91  
## 131 7514.46 6761.19 7913.71 9603.23  
## 132 7293.69 6264.38 8348.84 9943.27  
## 133 7376.24 6416.28 7959.22 9833.07  
## 134 7158.77 6772.26 8275.97 9407.48  
## 135 5784.85 6970.79 8103.15 9470.17  
## 136 5502.02 7216.15 8594.40 9474.30  
## 137 6141.34 7260.63 9033.92 9326.87  
## 138 6088.84 7045.50 9405.30 9980.85  
## 139 5898.35 7612.39 9552.16 NA  
## 140 NA NA NA NA  
## 141 2011.00 2012.00 2013.00 2014.00  
## 142 1.72 2.09 1.65 1.34  
## 143 1.91 2.17 1.55 1.24  
## 144 2.00 2.16 1.44 1.04  
## 145 1.90 1.96 1.15 1.33  
## 146 2.00 1.96 1.54 0.85  
## 147 2.10 1.67 1.83 1.04  
## 148 2.10 1.86 1.92 0.85  
## 149 2.10 2.15 1.53 0.85  
## 150 2.40 2.05 1.43 0.85  
## 151 2.30 2.05 1.24 0.76  
## 152 2.39 1.95 1.34 0.57  
## 153 1.98 2.04 1.43 0.27  
## 154 NA NA NA NA  
## 155 2011.00 2012.00 2013.00 2014.00  
## 156 213.00 230.00 273.00 219.00  
## 157 213.00 230.00 273.00 219.00  
## 158 213.00 230.00 273.00 219.00  
## 159 213.00 230.00 273.00 219.00  
## 160 213.00 230.00 273.00 219.00  
## 161 213.00 230.00 273.00 219.00  
## 162 213.00 230.00 273.00 219.00  
## 163 213.00 230.00 273.00 219.00  
## 164 213.00 230.00 273.00 219.00  
## 165 213.00 230.00 273.00 219.00  
## 166 213.00 230.00 273.00 219.00  
## 167 213.00 230.00 273.00 219.00  
## 168 NA NA NA NA  
## 169 2011.00 2012.00 2013.00 2014.00  
## 170 0.00 0.00 0.00 0.00  
## 171 0.00 0.00 0.00 0.00  
## 172 0.00 0.00 1.00 0.00  
## 173 1.00 1.00 0.00 1.00  
## 174 0.00 0.00 0.00 0.00  
## 175 0.00 0.00 0.00 0.00  
## 176 0.00 0.00 0.00 0.00  
## 177 0.00 0.00 0.00 0.00  
## 178 0.00 0.00 0.00 0.00  
## 179 0.00 0.00 0.00 0.00  
## 180 0.00 0.00 0.00 0.00  
## 181 1.00 1.00 1.00 1.00  
## 182 NA NA NA NA  
## 183 2011.00 2012.00 2013.00 2014.00  
## 184 0.00 0.00 0.00 0.00  
## 185 0.00 0.00 0.00 0.00  
## 186 0.00 0.00 1.00 0.00  
## 187 1.00 1.00 0.00 1.00  
## 188 0.00 0.00 0.00 0.00  
## 189 0.00 0.00 0.00 0.00  
## 190 0.00 0.00 0.00 0.00  
## 191 0.00 0.00 0.00 0.00  
## 192 1.00 1.00 1.00 1.00  
## 193 0.00 0.00 0.00 0.00  
## 194 1.00 1.00 1.00 1.00  
## 195 1.00 1.00 1.00 1.00

# The data provided comprises of the following partial data sets:  
#  
# Monthly As Is exports   
# Monthly As Is exports of Efak  
# Monthly As Is exports of Wuge  
# Monthly As Is exports of Etel (Total)  
# Monthly As Is exports of blue Etel  
# Monthly As Is exports of red Etel  
# Yearly As Is exports  
#  
# Monthly Plan exports   
# Monthly Plan exports of Efak  
# Monthly Plan exports of Wuge  
# Monthly Plan exports of Etel (Total)  
# Monthly Plan exports of blue Etel  
# Monthly Plan exports of red Etel  
# Yearly Plan exports  
  
#################################################################################  
# 1.2 Transformation the data into vectors and time series #  
#################################################################################  
  
# In order to be able to work with the partial data sets later, these need to  
# be split into individual vectors and converted into times series.  
  
TotalAsIsVector <- c(ImportedAsIsData [2:13,2],ImportedAsIsData [2:13,3],ImportedAsIsData [2:13,4],ImportedAsIsData [2:13,5],ImportedAsIsData [2:13,6],ImportedAsIsData [2:13,7])  
EfakAsIsVector <- c(ImportedAsIsData [16:27,2],ImportedAsIsData [16:27,3],ImportedAsIsData [16:27,4],ImportedAsIsData [16:27,5],ImportedAsIsData [16:27,6],ImportedAsIsData [16:27,7])  
WugeAsIsVector <- c(ImportedAsIsData [30:41,2],ImportedAsIsData [30:41,3],ImportedAsIsData [30:41,4],ImportedAsIsData [30:41,5],ImportedAsIsData [30:41,6],ImportedAsIsData [30:41,7])  
TotalEtelAsIsVector <- c(ImportedAsIsData [44:55,2],ImportedAsIsData [44:55,3],ImportedAsIsData [44:55,4],ImportedAsIsData [44:55,5],ImportedAsIsData [44:55,6],ImportedAsIsData [44:55,7])  
BlueEtelAsIsVector <- c(ImportedAsIsData [58:69,2],ImportedAsIsData [58:69,3],ImportedAsIsData [58:69,4],ImportedAsIsData [58:69,5],ImportedAsIsData [58:69,6],ImportedAsIsData [58:69,7])  
RedEtelAsIsVector <- c(ImportedAsIsData [72:83,2],ImportedAsIsData [72:83,3],ImportedAsIsData [72:83,4],ImportedAsIsData [72:83,5],ImportedAsIsData [72:83,6],ImportedAsIsData [72:83,7])  
YearAsIsVector <- c(ImportedAsIsData [86,2],ImportedAsIsData [86,3],ImportedAsIsData [86,4],ImportedAsIsData [86,5],ImportedAsIsData [86,6],ImportedAsIsData [86,7])  
TotalAsIsVector\_2014 <- c(ImportedAsIsData[2:13,8])  
  
PlanVector <- c(ImportedPlanData[2:13,2],ImportedPlanData[2:13,3],ImportedPlanData[2:13,4],ImportedPlanData[2:13,5],ImportedPlanData[2:13,6],ImportedPlanData[2:13,7])  
EfakPlanVector <- c(ImportedPlanData[16:27,2],ImportedPlanData[16:27,3],ImportedPlanData[16:27,4],ImportedPlanData[16:27,5],ImportedPlanData[16:27,6],ImportedPlanData[16:27,7])  
WugePlanVector <- c(ImportedPlanData[30:41,2],ImportedPlanData[30:41,3],ImportedPlanData[30:41,4],ImportedPlanData[30:41,5],ImportedPlanData[30:41,6],ImportedPlanData[30:41,7])  
TotalEtelPlanVector <- c(ImportedPlanData[44:55,2],ImportedPlanData[44:55,3],ImportedPlanData[44:55,4],ImportedPlanData[44:55,5],ImportedPlanData[44:55,6],ImportedPlanData[44:55,7])  
BlueEtelPlanVector <- c(ImportedPlanData[58:69,2],ImportedPlanData[58:69,3],ImportedPlanData[58:69,4],ImportedPlanData[58:69,5],ImportedPlanData[58:69,6],ImportedPlanData[58:69,7])  
RedEtelPlanVector <- c(ImportedPlanData[72:83,2],ImportedPlanData[72:83,3],ImportedPlanData[72:83,4],ImportedPlanData[72:83,5],ImportedPlanData[72:83,6],ImportedPlanData[72:83,7])  
YearPlanVector <- c(ImportedPlanData[86,2],ImportedPlanData[86,3],ImportedPlanData[86,4],ImportedPlanData[86,5],ImportedPlanData[86,6],ImportedPlanData[86,7])  
PlanVector\_2014 <- c(ImportedPlanData[2:13,8])  
  
# The data is saved as a vector and needs to be converted into a time series  
  
TotalAsIs<- ts(TotalAsIsVector , start=c(2008,1), end=c(2013,12), frequency=12)  
EfakAsIs <- ts(EfakAsIsVector , start=c(2008,1), end=c(2013,12), frequency=12)  
WugeAsIs <- ts(WugeAsIsVector, start=c(2008,1), end=c(2013,12), frequency=12)  
TotalEtelAsIs<- ts(TotalEtelAsIsVector, start=c(2008,1), end=c(2013,12), frequency=12)  
BlueEtelAsIs <- ts(BlueEtelAsIsVector, start=c(2008,1), end=c(2013,12), frequency=12)  
RedEtelAsIs <- ts(RedEtelAsIsVector, start=c(2008,1), end=c(2013,12), frequency=12)  
YearAsIs <- ts(YearAsIsVector, start=c(2008,1), end=c(2013,12), frequency=12)  
TotalAsIs\_2014 <- ts(TotalAsIsVector\_2014, start=c(2014,1), end=c(2014,12), frequency=12)  
  
TotalPlan <- ts(PlanVector , start=c(2008,1), end=c(2013,12), frequency=12)  
EfakPlan <- ts(EfakPlanVector, start=c(2008,1), end=c(2013,12), frequency=12)  
WugePlan <- ts(WugePlanVector, start=c(2008,1), end=c(2013,12), frequency=12)  
TotalEtelPlan <- ts(TotalEtelPlanVector, start=c(2008,1), end=c(2013,12), frequency=12)  
BlueEtelPlan <- ts(BlueEtelPlanVector, start=c(2008,1), end=c(2013,12), frequency=12)  
RedEtelPlan <- ts(RedEtelPlanVector, start=c(2008,1), end=c(2013,12), frequency=12)  
YearPlan <- ts(YearPlanVector, start=c(2008,1), end=c(2013,12), frequency=12)  
TotalPlan\_2014 <- ts(PlanVector\_2014, start=c(2014,1), end=c(2014,12), frequency=12)  
  
# Call up the time series to check everything has worked.  
  
TotalAsIs

## Jan Feb Mar Apr May Jun Jul Aug  
## 2008 2313221 1950131 2346635 2039787 1756964 1458302 1679637 1639670  
## 2009 2610573 2371327 2743786 2125308 1850073 1836222 1797311 1851968  
## 2010 2760688 2918333 3227041 1613888 2550157 2317645 1474144 2148521  
## 2011 3112861 2926663 3294784 2577079 2774068 2378227 2222900 2991787  
## 2012 3093088 3679308 3433364 2714899 3011767 2726028 2483834 3055655  
## 2013 4119526 3535744 3560974 3760065 2959933 2787898 2828744 3084113  
## Sep Oct Nov Dec  
## 2008 2882886 2959716 2596494 2656568  
## 2009 3271171 2818888 3310776 3022513  
## 2010 3898571 3348953 3135945 3332886  
## 2011 4151531 3318684 4037076 3429843  
## 2012 4200796 4228724 4618540 3383673  
## 2013 5107775 4562144 4729313 4372181

EfakAsIs

## Jan Feb Mar Apr May Jun Jul Aug  
## 2008 416589 472565 466539 370774 457741 384817 464502 389013  
## 2009 430055 468187 648582 414990 466329 465775 430988 502499  
## 2010 508177 601115 775996 323532 672011 589895 438340 483363  
## 2011 778643 726254 943274 845136 1030397 829198 741981 820385  
## 2012 849409 1021474 1034025 904449 986452 1011487 862239 1026357  
## 2013 1065097 952195 1062892 1057988 1127932 933365 1069867 1020078  
## Sep Oct Nov Dec  
## 2008 508370 495598 529191 441545  
## 2009 584983 506877 593705 641582  
## 2010 630064 608942 688055 693058  
## 2011 851428 873895 996616 941611  
## 2012 898892 1079994 1259730 986962  
## 2013 1049970 1197452 1283970 1280835

WugeAsIs

## Jan Feb Mar Apr May Jun Jul Aug Sep Oct  
## 2008 414571 344579 429907 379606 305697 314582 346800 323618 578252 510031  
## 2009 462768 393940 458486 401535 367847 373210 351526 358676 589599 501149  
## 2010 525307 515202 581672 340651 565867 450257 378953 459746 792018 616164  
## 2011 507281 564342 684259 487103 601078 507467 504952 655479 864312 636096  
## 2012 545966 632103 619301 602511 609931 574084 510154 663220 827807 824506  
## 2013 752685 708242 719168 787368 574721 643629 628135 718542 923583 934234  
## Nov Dec  
## 2008 431480 489935  
## 2009 586040 659757  
## 2010 620973 750844  
## 2011 787231 712204  
## 2012 855732 691108  
## 2013 886772 948935

TotalEtelAsIs

## Jan Feb Mar Apr May Jun Jul Aug  
## 2008 1279668 1053325 1367520 1090725 873568 644479 772658 806741  
## 2009 1583216 1407388 1420801 1141100 919860 858876 910134 843050  
## 2010 1637464 1676161 1549560 813469 1198401 1140024 551268 1012542  
## 2011 1595267 1473528 1469728 1034650 952553 819303 802076 1222812  
## 2012 1519748 1812897 1607280 1008022 1291983 940158 945929 1235146  
## 2013 2109497 1738197 1633944 1745092 1039449 1054201 1003166 1154675  
## Sep Oct Nov Dec  
## 2008 1715265 1795751 1518288 1601324  
## 2009 1981563 1647934 1857836 1615091  
## 2010 2335488 1856264 1678123 1699063  
## 2011 2303271 1591584 1960675 1713991  
## 2012 2330334 2177895 2306324 1618147  
## 2013 3000929 2305605 2284672 2062160

BlueEtelAsIs

## Jan Feb Mar Apr May Jun Jul Aug Sep Oct  
## 2008 425892 316631 353512 278711 212940 187849 206285 195810 448733 403327  
## 2009 407424 287654 305158 255687 200068 210118 211668 198472 361703 366410  
## 2010 369783 345144 322695 223841 239441 240316 138604 231179 329090 368584  
## 2011 308893 282106 347124 261498 217606 208258 174878 247714 312012 331926  
## 2012 285207 450874 360034 252674 247734 221676 216918 254993 299658 457595  
## 2013 387497 349013 334274 325052 255416 237019 239047 358552 359703 427681  
## Nov Dec  
## 2008 306171 345955  
## 2009 350196 351651  
## 2010 320947 373302  
## 2011 389858 299115  
## 2012 388917 303450  
## 2013 434561 348558

RedEtelAsIs

## Jan Feb Mar Apr May Jun Jul Aug  
## 2008 853776 736694 1014008 812014 660628 456630 566373 610931  
## 2009 1175792 1119734 1115643 885413 719792 648758 698466 644578  
## 2010 1267682 1331017 1226866 589628 958960 899709 412664 781363  
## 2011 1286374 1191422 1122604 773151 734947 611045 627198 975098  
## 2012 1234541 1362023 1247246 755347 1044249 718482 729011 980154  
## 2013 1722000 1389184 1299670 1420039 784033 817182 764120 796123  
## Sep Oct Nov Dec  
## 2008 1266532 1392424 1212117 1255369  
## 2009 1619860 1281524 1507640 1263440  
## 2010 2006398 1487680 1357176 1325761  
## 2011 1991259 1259658 1570817 1414876  
## 2012 2030676 1720301 1917408 1314697  
## 2013 2641226 1877924 1850111 1713603

YearAsIs

## Jan Feb Mar Apr May Jun Jul  
## 2008 26280011 29609916 32726772 37215503 40629676 45408410 26280011  
## 2009 26280011 29609916 32726772 37215503 40629676 45408410 26280011  
## 2010 26280011 29609916 32726772 37215503 40629676 45408410 26280011  
## 2011 26280011 29609916 32726772 37215503 40629676 45408410 26280011  
## 2012 26280011 29609916 32726772 37215503 40629676 45408410 26280011  
## 2013 26280011 29609916 32726772 37215503 40629676 45408410 26280011  
## Aug Sep Oct Nov Dec  
## 2008 29609916 32726772 37215503 40629676 45408410  
## 2009 29609916 32726772 37215503 40629676 45408410  
## 2010 29609916 32726772 37215503 40629676 45408410  
## 2011 29609916 32726772 37215503 40629676 45408410  
## 2012 29609916 32726772 37215503 40629676 45408410  
## 2013 29609916 32726772 37215503 40629676 45408410

TotalAsIs\_2014

## Jan Feb Mar Apr May Jun Jul Aug  
## 2014 4308161 4155378 3924332 3659121 3898758 3313891 3595106 3502426  
## Sep Oct Nov Dec  
## 2014 5619059 5274287 4841693 4664854

TotalPlan

## Jan Feb Mar Apr May Jun Jul Aug  
## 2008 2243103 2162705 2720911 2011182 1877757 1819924 1682196 1893171  
## 2009 2547980 2247049 2731156 2020158 2098038 1927995 1783692 1907705  
## 2010 2965885 2751170 2906493 2383358 2246893 1992851 2023434 2244997  
## 2011 3113110 2883766 2957893 2601648 2370949 2339881 2105328 2341623  
## 2012 3895396 3588151 3787240 3036434 2907891 2707822 2619486 3784557  
## 2013 3580325 3863212 3606083 3213575 3139128 2998610 2785453 3083654  
## Sep Oct Nov Dec  
## 2008 3325711 2662148 2909966 2574633  
## 2009 3124040 3102251 3154669 2742367  
## 2010 3257717 3536338 3358206 3112906  
## 2011 4086297 3640827 3502334 3280476  
## 2012 4987460 4367319 4205772 4059533  
## 2013 5143757 4149334 4495212 4093664

EfakPlan

## Jan Feb Mar Apr May Jun Jul Aug  
## 2008 492421 444995 665274 444369 487668 445242 443318 501222  
## 2009 450498 380959 592616 400839 471523 405564 401100 444250  
## 2010 506991 550412 629309 468600 535435 475326 482147 466887  
## 2011 646987 652598 778405 717677 684701 639433 659271 652132  
## 2012 1057786 1006335 1260206 1006509 979754 985549 964181 1027988  
## 2013 940156 1094548 1053751 1072364 1061436 1077276 984463 1010619  
## Sep Oct Nov Dec  
## 2008 546249 553286 664734 560104  
## 2009 488899 584729 659061 512219  
## 2010 532164 543650 662090 527275  
## 2011 736826 774047 791780 823396  
## 2012 1090561 1151231 1222188 1148541  
## 2013 1083541 1089769 1151019 1044125

WugePlan

## Jan Feb Mar Apr May Jun Jul Aug  
## 2008 424190 388688 457796 363828 364246 358439 321255 370153  
## 2009 443454 381571 471631 393075 379443 360120 337682 381164  
## 2010 685504 559040 590397 566135 448967 442838 423206 458609  
## 2011 593024 570173 552269 522050 458092 475669 451094 602954  
## 2012 665434 657383 706987 601083 604292 571937 575704 802634  
## 2013 670157 673123 727908 680251 687880 702883 623366 694089  
## Sep Oct Nov Dec  
## 2008 645618 470648 529375 448355  
## 2009 597557 511889 573453 478396  
## 2010 651525 598009 575012 544435  
## 2011 751102 736236 681492 693967  
## 2012 911343 830770 814818 870857  
## 2013 1029222 853935 889003 842765

TotalEtelPlan

## Jan Feb Mar Apr May Jun Jul Aug  
## 2008 1263613 1231125 1489621 1051346 933392 932047 855520 923070  
## 2009 1546801 1378217 1563799 1166229 1057223 983279 913751 980703  
## 2010 1648769 1490577 1538493 1208636 1104777 931127 916160 1096933  
## 2011 1781991 1564272 1455531 1257528 1134418 1018200 843336 974375  
## 2012 2070256 1731099 1663266 1232994 1164076 1018137 932241 1800576  
## 2013 1864733 1837228 1663834 1305603 1172373 1089115 1074687 1217930  
## Sep Oct Nov Dec  
## 2008 2080877 1575579 1561956 1515127  
## 2009 1974166 1886971 1839155 1727567  
## 2010 1832882 2103588 1877929 1862684  
## 2011 2435674 1972649 1873075 1684766  
## 2012 2823873 2224655 2025003 1955509  
## 2013 2916115 2043888 2199880 2133214

BlueEtelPlan

## Jan Feb Mar Apr May Jun Jul Aug Sep Oct  
## 2008 449227 373663 415732 331337 290942 287603 245390 284540 554127 467772  
## 2009 394188 320490 351375 271021 225914 234600 191342 226507 519935 512283  
## 2010 388677 317587 306376 275940 235850 224371 204869 220570 357203 413862  
## 2011 412463 323577 313230 276210 249768 217911 209229 219002 365415 421679  
## 2012 481147 412798 364106 311291 283279 286839 249233 288342 399167 524838  
## 2013 360982 342370 346868 277548 251623 257153 232752 252611 494843 445720  
## Nov Dec  
## 2008 469089 409962  
## 2009 456203 376595  
## 2010 357645 364243  
## 2011 359800 343171  
## 2012 399038 415564  
## 2013 414612 401854

RedEtelPlan

## Jan Feb Mar Apr May Jun Jul Aug  
## 2008 814386 857462 1073889 720009 642450 644444 610130 638530  
## 2009 1152613 1057727 1212424 895208 831309 748679 722409 754196  
## 2010 1260092 1172990 1232117 932696 868927 706756 711291 876363  
## 2011 1369528 1240695 1142301 981318 884650 800289 634107 755372  
## 2012 1589109 1318301 1299159 921703 880796 731299 683008 1512234  
## 2013 1503751 1494858 1316966 1028055 920750 831961 841936 965319  
## Sep Oct Nov Dec  
## 2008 1526750 1107807 1092867 1105165  
## 2009 1454231 1374688 1382952 1350972  
## 2010 1475679 1689726 1520284 1498441  
## 2011 2070259 1550970 1513274 1341595  
## 2012 2424705 1699817 1625965 1539945  
## 2013 2421272 1598167 1785268 1731360

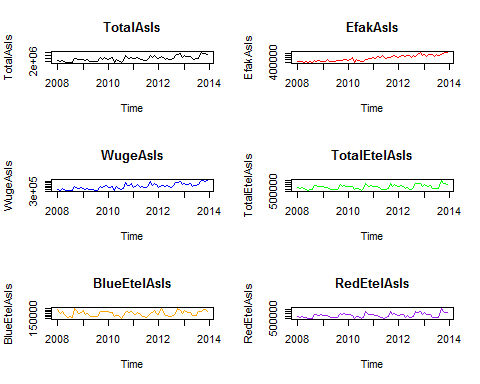
YearPlan

## Jan Feb Mar Apr May Jun Jul  
## 2008 27883407 29387100 32780247 35224132 43947063 44152007 27883407  
## 2009 27883407 29387100 32780247 35224132 43947063 44152007 27883407  
## 2010 27883407 29387100 32780247 35224132 43947063 44152007 27883407  
## 2011 27883407 29387100 32780247 35224132 43947063 44152007 27883407  
## 2012 27883407 29387100 32780247 35224132 43947063 44152007 27883407  
## 2013 27883407 29387100 32780247 35224132 43947063 44152007 27883407  
## Aug Sep Oct Nov Dec  
## 2008 29387100 32780247 35224132 43947063 44152007  
## 2009 29387100 32780247 35224132 43947063 44152007  
## 2010 29387100 32780247 35224132 43947063 44152007  
## 2011 29387100 32780247 35224132 43947063 44152007  
## 2012 29387100 32780247 35224132 43947063 44152007  
## 2013 29387100 32780247 35224132 43947063 44152007

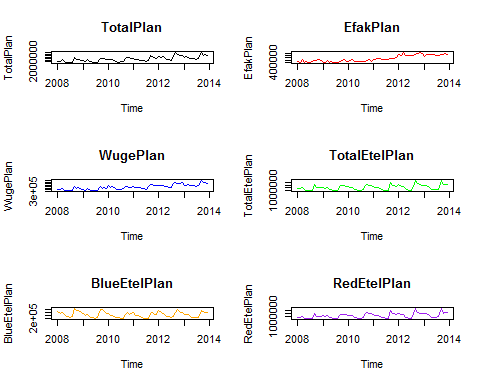
TotalPlan\_2014

## Jan Feb Mar Apr May Jun Jul Aug  
## 2014 4474000 4185565 4278119 3985542 3605973 3515173 3269444 3656112  
## Sep Oct Nov Dec  
## 2014 5637391 5157781 5353458 4703185

#################################################################################  
### ###  
### 2. Analysis of the basic data ###  
### ###  
#################################################################################  
  
#################################################################################  
# 2.1 Development of the business portfolio #  
#################################################################################  
  
# Due to the different scales, it makes sense to plot each graph individually   
# instead of plotting them all on one set of axes.   
  
par(mfrow=c(3,2))  
  
plot(TotalAsIs, col="black", main="TotalAsIs")  
plot(EfakAsIs , col="red",main="EfakAsIs")  
plot(WugeAsIs, col="blue", main="WugeAsIs")  
plot(TotalEtelAsIs, col="green",main="TotalEtelAsIs")  
plot(BlueEtelAsIs, col="orange", main="BlueEtelAsIs")  
plot(RedEtelAsIs, col="purple", main="RedEtelAsIs")



#mywait()  
#mywait()  
  
plot(TotalPlan , col="black", main="TotalPlan")  
plot(EfakPlan , col="red",main="EfakPlan")  
plot(WugePlan, col="blue", main="WugePlan")  
plot(TotalEtelPlan, col="green",main="TotalEtelPlan")  
plot(BlueEtelPlan, col="orange", main="BlueEtelPlan")  
plot(RedEtelPlan, col="purple", main="RedEtelPlan")



#mywait()  
  
#################################################################################  
# 2.2 Correlation between As Is and Plan data #  
#################################################################################  
  
# Test the correlation between As Is and Plan data in order to test how exact   
# the planning is.   
# Correlation is a measure of linear relationship between two variables.   
  
cor(TotalAsIs, TotalPlan )

## [1] 0.9183402

cor(EfakAsIs , EfakPlan)

## [1] 0.9055081

cor(WugeAsIs, WugePlan)

## [1] 0.8788474

cor(TotalEtelAsIs, TotalEtelPlan)

## [1] 0.9159505

cor(BlueEtelAsIs , BlueEtelPlan)

## [1] 0.8044146

cor(RedEtelAsIs , RedEtelPlan)

## [1] 0.9106702

cor(YearAsIs, YearPlan)

## [1] 0.9627401

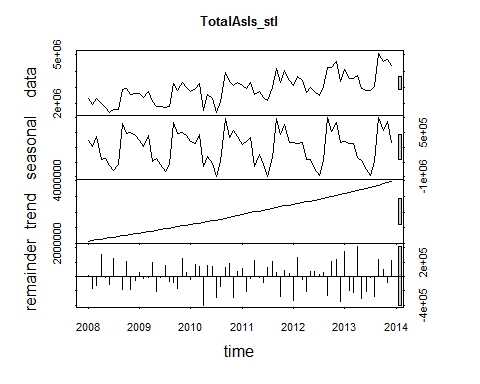
#mywait()  
  
# The results show a very high planning accuracy.   
  
TotalAsIs\_lm <- lm(TotalAsIs ~ TotalPlan , data = TotalAsIs)  
summary(TotalAsIs\_lm)

##   
## Call:  
## lm(formula = TotalAsIs ~ TotalPlan, data = TotalAsIs)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -770214 -196776 26017 182579 672705   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 8.959e+04 1.521e+05 0.589 0.558   
## TotalPlan 9.627e-01 4.959e-02 19.413 <2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 332600 on 70 degrees of freedom  
## Multiple R-squared: 0.8433, Adjusted R-squared: 0.8411   
## F-statistic: 376.9 on 1 and 70 DF, p-value: < 2.2e-16

TotalAsIs\_tslm <- tslm(TotalAsIs ~ TotalPlan )  
summary(TotalAsIs\_tslm)

##   
## Call:  
## tslm(formula = TotalAsIs ~ TotalPlan)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -770214 -196776 26017 182579 672705   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 8.959e+04 1.521e+05 0.589 0.558   
## TotalPlan 9.627e-01 4.959e-02 19.413 <2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 332600 on 70 degrees of freedom  
## Multiple R-squared: 0.8433, Adjusted R-squared: 0.8411   
## F-statistic: 376.9 on 1 and 70 DF, p-value: < 2.2e-16

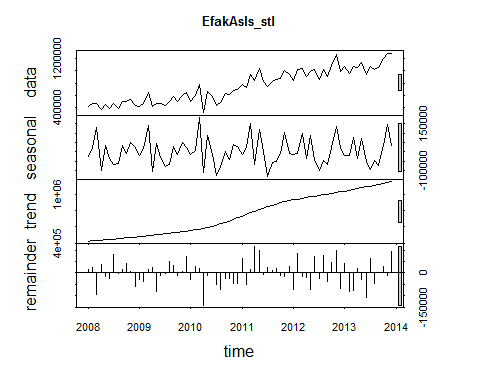
#################################################################################  
# 2.3 Time series analysis #  
#################################################################################  
  
#################################################################################  
# 2.3.1 "stl" function #  
#################################################################################  
  
# The time series can be analysed using the stl function in order to seperate  
# the trend, seasonality and remainder (remaining coincidential) components from  
# one another.  
  
TotalAsIs\_stl <- stl(TotalAsIs, s.window=5)  
EfakAsIs\_stl <- stl(EfakAsIs , s.window=5)  
WugeAsIs\_stl <- stl(WugeAsIs, s.window=5)  
TotalEtelAsIs\_stl <- stl(TotalEtelAsIs, s.window=5)  
BlueEtelAsIs\_stl <- stl(BlueEtelAsIs , s.window=5)  
RedEtelAsIs\_stl <- stl(RedEtelAsIs , s.window=5)  
  
# Thus the individual time series can be shown graphically and tabularly.  
  
# The trend of the total exports is almost linear. A relatively uniform   
# seaonality can be seen.  
  
par(mfrow=c(3,2))  
  
plot(TotalAsIs\_stl, col="black", main="TotalAsIs\_stl")



TotalAsIs\_stl

## Call:  
## stl(x = TotalAsIs, s.window = 5)  
##   
## Components  
## seasonal trend remainder  
## Jan 2008 223320.67 2074233 15667.16  
## Feb 2008 17036.99 2096208 -163113.80  
## Mar 2008 361473.74 2118182 -133021.18  
## Apr 2008 -410834.24 2140157 310464.16  
## May 2008 -391831.93 2162114 -13317.80  
## Jun 2008 -608564.13 2184070 -117204.25  
## Jul 2008 -777993.52 2206027 251603.49  
## Aug 2008 -583615.66 2228213 -4927.72  
## Sep 2008 810939.36 2250400 -178453.09  
## Oct 2008 474131.86 2272586 212998.05  
## Nov 2008 488504.52 2294373 -186383.79  
## Dec 2008 395452.58 2316160 -55045.03  
## Jan 2009 217151.38 2337948 55473.99  
## Feb 2009 39716.91 2359168 -27558.10  
## Mar 2009 378507.21 2380389 -15109.96  
## Apr 2009 -467522.18 2401609 191220.87  
## May 2009 -371597.89 2425515 -203844.26  
## Jun 2009 -595724.45 2449421 -17474.54  
## Jul 2009 -827029.12 2473327 151013.28  
## Aug 2009 -567342.69 2495885 -76573.99  
## Sep 2009 843160.68 2518443 -90432.21  
## Oct 2009 447562.71 2541000 -169675.09  
## Nov 2009 497312.47 2562364 251099.75  
## Dec 2009 388265.67 2583727 50520.14  
## Jan 2010 201133.54 2605091 -45536.12  
## Feb 2010 122776.46 2628120 167436.40  
## Mar 2010 442825.47 2651150 133065.83  
## Apr 2010 -652923.75 2674179 -407367.50  
## May 2010 -301149.68 2698691 152615.46  
## Jun 2010 -543850.29 2723203 138292.09  
## Jul 2010 -985987.99 2747715 -287583.18  
## Aug 2010 -487941.31 2774544 -138081.68  
## Sep 2010 972415.73 2801373 124782.46  
## Oct 2010 343206.82 2828202 177544.55  
## Nov 2010 573281.74 2858572 -295909.05  
## Dec 2010 375326.75 2888943 68616.25  
## Jan 2011 84179.43 2919314 109367.89  
## Feb 2011 190940.11 2949475 -213752.60  
## Mar 2011 339598.68 2979637 -24451.98  
## Apr 2011 -661193.66 3009799 228473.57  
## May 2011 -252299.73 3037669 -11300.88  
## Jun 2011 -597799.74 3065538 -89511.39  
## Jul 2011 -1002974.31 3093408 132466.66  
## Aug 2011 -345401.48 3120526 216662.97  
## Sep 2011 951339.44 3147643 52548.18  
## Oct 2011 418464.54 3174761 -274541.80  
## Nov 2011 749466.48 3200972 86637.11  
## Dec 2011 166063.96 3227184 36595.48  
## Jan 2012 173825.10 3253395 -334131.81  
## Feb 2012 131526.89 3279250 268531.13  
## Mar 2012 171949.25 3305105 -43690.50  
## Apr 2012 -412193.90 3330961 -203867.63  
## May 2012 -414897.17 3358540 68124.29  
## Jun 2012 -723606.43 3386119 63515.20  
## Jul 2012 -957183.71 3413699 27319.12  
## Aug 2012 -438041.15 3441507 52189.27  
## Sep 2012 998725.79 3469315 -267244.98  
## Oct 2012 523934.85 3497123 207665.66  
## Nov 2012 847979.72 3527674 242886.44  
## Dec 2012 172550.29 3558224 -347101.49  
## Jan 2013 184195.89 3588775 346555.55  
## Feb 2013 114297.14 3623803 -202355.91  
## Mar 2013 121000.80 3658831 -218857.78  
## Apr 2013 -360531.42 3693859 426737.22  
## May 2013 -462506.26 3728897 -306457.92  
## Jun 2013 -759940.89 3763935 -216096.28  
## Jul 2013 -951772.71 3798973 -18456.45  
## Aug 2013 -468011.67 3834192 -282067.53  
## Sep 2013 1004335.28 3869411 234028.47  
## Oct 2013 554713.70 3904630 102800.01  
## Nov 2013 873598.66 3940742 -85027.53  
## Dec 2013 169104.03 3976853 226223.51

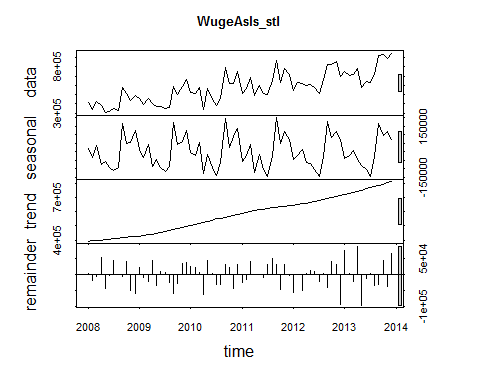
# It is interesting to note that the almost linear trend is not seen in the   
# individual segments. The individual trends run partially in opposite   
# directions in the middle of the time scale, which causes the linear trend   
# in the total As Is data.  
  
plot(EfakAsIs\_stl, col="black", main="EfakAsIs\_stl")



EfakAsIs\_stl

## Call:  
## stl(x = EfakAsIs, s.window = 5)  
##   
## Components  
## seasonal trend remainder  
## Jan 2008 -23226.82900 423043.7 16772.17796  
## Feb 2008 21521.59151 427584.6 23458.85001  
## Mar 2008 130397.87276 432125.5 -95984.33867  
## Apr 2008 -103571.06289 436666.4 37678.68955  
## May 2008 32361.63887 441237.6 -15858.25182  
## Jun 2008 -34947.71796 445808.9 -26044.13459  
## Jul 2008 -68369.51749 450380.1 82491.42533  
## Aug 2008 -63706.88476 455205.5 -2485.57353  
## Sep 2008 34770.96136 460030.8 13568.21423  
## Oct 2008 -8531.14784 464856.2 39272.95731  
## Nov 2008 50984.15465 470083.3 8123.53058  
## Dec 2008 24434.06358 475310.4 -58199.50258  
## Jan 2009 -21569.57080 480537.6 -28912.99242  
## Feb 2009 19658.97342 486282.6 -37754.60334  
## Mar 2009 141908.71866 492027.7 14645.58472  
## Apr 2009 -107360.30397 497772.8 24577.54065  
## May 2009 44562.88090 503523.1 -81756.97423  
## Jun 2009 -31331.51204 509273.4 -12166.91132  
## Jul 2009 -81781.12397 515023.8 -2254.62940  
## Aug 2009 -69071.52656 521175.9 50394.64064  
## Sep 2009 26350.13821 527328.0 31304.84331  
## Oct 2009 -15814.61747 533480.2 -10788.53357  
## Nov 2009 47428.78524 540381.2 5895.06467  
## Dec 2009 22883.82560 547282.1 71416.02525  
## Jan 2010 -16429.66699 554183.1 -29576.48120  
## Feb 2010 8122.84784 562923.9 30068.22351  
## Mar 2010 185562.10056 571664.7 18769.19033  
## Apr 2010 -113961.74775 580405.5 -142911.74181  
## May 2010 89827.30170 593062.5 -10878.84059  
## Jun 2010 -16097.25263 605719.6 272.66442  
## Jul 2010 -128865.59745 618376.6 -51171.04008  
## Aug 2010 -80958.67066 636091.3 -71769.64887  
## Sep 2010 -14.97259 653806.0 -23727.02894  
## Oct 2010 -39524.32045 671520.7 -23054.36308  
## Nov 2010 40055.68302 692153.3 -44153.98494  
## Dec 2010 25787.65070 712785.9 -45515.57102  
## Jan 2011 -16594.16542 733418.5 61818.62671  
## Feb 2011 22321.97847 754268.4 -50336.33150  
## Mar 2011 154168.46877 775118.2 13987.36387  
## Apr 2011 -68657.08934 795968.0 117825.10766  
## May 2011 118817.52126 814735.2 96844.30468  
## Jun 2011 1882.17142 833502.4 -6186.53787  
## Jul 2011 -136119.84119 852269.6 25831.28236  
## Aug 2011 -56677.59941 867358.6 9704.02582  
## Sep 2011 -51848.25161 882447.6 20828.66327  
## Oct 2011 -10367.96254 897536.6 -13273.64056  
## Nov 2011 103443.17391 909364.2 -16191.38537  
## Dec 2011 -9606.16412 921191.8 30025.34430  
## Jan 2012 -12924.91058 933019.4 -70685.51761  
## Feb 2012 -7394.13619 943100.4 85767.71165  
## Mar 2012 96808.17163 953181.4 -15964.59252  
## Apr 2012 -36950.82144 963262.4 -21862.59579  
## May 2012 87694.64020 972004.8 -73247.39413  
## Jun 2012 -39233.07619 980747.1 69972.98557  
## Jul 2012 -102693.97271 989489.4 -24556.45460  
## Aug 2012 -49412.12904 997294.3 78474.78651  
## Sep 2012 -68645.64289 1005099.3 -37561.61485  
## Oct 2012 23112.61134 1012904.2 43977.21571  
## Nov 2012 137745.56186 1022025.2 99959.18819  
## Dec 2012 23773.31272 1031146.3 -67957.63968  
## Jan 2013 -18512.22742 1040267.4 43341.82347  
## Feb 2013 -18282.89519 1050818.1 -80340.21432  
## Mar 2013 76998.74701 1061368.8 -75475.56207  
## Apr 2013 -34796.61851 1071919.5 20865.09790  
## May 2013 73853.95937 1082424.8 -28346.76511  
## Jun 2013 -52105.72817 1092930.1 -107459.36269  
## Jul 2013 -97209.87867 1103435.4 63641.50269  
## Aug 2013 -48663.68800 1114155.6 -45413.95876  
## Sep 2013 -74852.23174 1124875.9 -53.68579  
## Oct 2013 31635.10429 1135596.2 30220.70741  
## Nov 2013 147615.38092 1146745.6 -10391.00983  
## Dec 2013 31201.96743 1157895.1 91737.96304

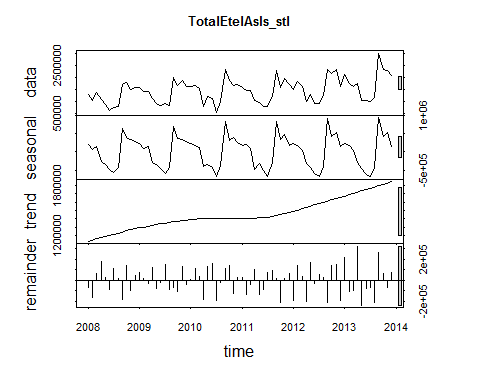
plot(WugeAsIs\_stl, col="black", main="WugeAsIs\_stl")



WugeAsIs\_stl

## Call:  
## stl(x = WugeAsIs, s.window = 5)  
##   
## Components  
## seasonal trend remainder  
## Jan 2008 17722.170 392636.3 4212.5578  
## Feb 2008 -33320.951 395527.0 -17627.0006  
## Mar 2008 38455.870 398417.6 -6966.5016  
## Apr 2008 -73928.951 401308.3 52226.6404  
## May 2008 -55514.316 404310.6 -43099.2740  
## Jun 2008 -89778.998 407312.9 -2951.8720  
## Jul 2008 -108133.931 410315.1 44618.7814  
## Aug 2008 -89728.129 413488.8 -142.7021  
## Sep 2008 166874.291 416662.5 -5284.8039  
## Oct 2008 49901.029 419836.2 40293.7760  
## Nov 2008 57220.402 423065.3 -48805.7256  
## Dec 2008 123616.460 426294.5 -59975.9117  
## Jan 2009 12688.287 429523.6 20556.1337  
## Feb 2009 -30520.192 433831.0 -9370.8179  
## Mar 2009 41876.028 438138.4 -21528.4679  
## Apr 2009 -85988.220 442445.9 45077.3498  
## May 2009 -46542.229 448786.3 -34397.0515  
## Jun 2009 -91250.863 455126.7 9334.1726  
## Jul 2009 -115191.118 461467.1 5250.0168  
## Aug 2009 -85325.179 468631.5 -24630.3220  
## Sep 2009 173206.980 475795.9 -59403.8801  
## Oct 2009 44475.519 482960.3 -26286.8189  
## Nov 2009 62039.072 490099.1 33901.8208  
## Dec 2009 125555.281 497237.9 36963.8053  
## Jan 2010 -5520.274 504376.7 26450.5535  
## Feb 2010 -19335.616 511854.9 22682.7384  
## Mar 2010 55758.299 519333.0 6580.6663  
## Apr 2010 -126076.519 526811.2 -60083.6720  
## May 2010 -13363.506 534244.1 44986.4116  
## Jun 2010 -94563.622 541677.0 3143.6233  
## Jul 2010 -138490.382 549109.9 -31666.5198  
## Aug 2010 -65027.981 555882.4 -31108.4072  
## Sep 2010 196673.438 562654.9 32689.6863  
## Oct 2010 24573.171 569427.4 22163.4670  
## Nov 2010 88287.251 576395.1 -43709.3021  
## Dec 2010 137432.476 583362.7 30048.7846  
## Jan 2011 -58735.207 590330.4 -24314.2222  
## Feb 2011 -18536.541 596477.1 -13598.5988  
## Mar 2011 42122.409 602623.9 39512.7409  
## Apr 2011 -121901.397 608770.6 233.8356  
## May 2011 -12680.959 613380.3 378.6918  
## Jun 2011 -102068.999 617990.0 -8453.9742  
## Jul 2011 -147879.709 622599.7 30232.0302  
## Aug 2011 -22387.737 626688.2 51178.5488  
## Sep 2011 203322.659 630776.7 30212.6434  
## Oct 2011 48819.022 634865.2 -47588.2287  
## Nov 2011 118387.777 638854.6 29988.6603  
## Dec 2011 71076.431 642843.9 -1716.3490  
## Jan 2012 -44716.374 646833.3 -56150.8992  
## Feb 2012 -20524.560 651082.4 1545.1897  
## Mar 2012 14296.071 655331.5 -50326.5377  
## Apr 2012 -60415.610 659580.6 3346.0463  
## May 2012 -67344.569 665184.9 12090.6758  
## Jun 2012 -104935.338 670789.2 8230.1158  
## Jul 2012 -144652.879 676393.6 -21586.6720  
## Aug 2012 -24622.915 683223.3 4619.5813  
## Sep 2012 176310.472 690053.1 -38556.5878  
## Oct 2012 87303.711 696882.9 40319.3912  
## Nov 2012 121212.891 704258.8 30260.3453  
## Dec 2012 73368.067 711634.6 -93894.6959  
## Jan 2013 -41492.906 719010.5 75167.4116  
## Feb 2013 -21062.252 727322.9 1981.3738  
## Mar 2013 5722.875 735635.3 -22190.1365  
## Apr 2013 -44997.170 743947.6 88417.5246  
## May 2013 -81751.981 752332.7 -95859.7318  
## Jun 2013 -105955.722 760717.8 -11133.0578  
## Jul 2013 -144927.224 769102.8 3959.3771  
## Aug 2013 -26223.829 777442.9 -32677.0385  
## Sep 2013 168189.880 785782.9 -30389.7689  
## Oct 2013 97959.387 794122.9 42151.7035  
## Nov 2013 121683.011 802536.0 -37447.0602  
## Dec 2013 72799.891 810949.2 65185.9191

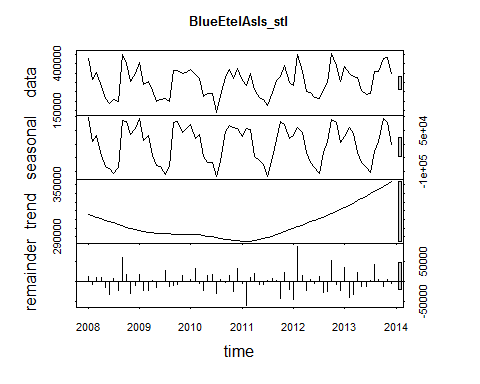
plot(TotalEtelAsIs\_stl, col="black", main="TotalEtelAsIs\_stl")



TotalEtelAsIs\_stl

## Call:  
## stl(x = TotalEtelAsIs, s.window = 5)  
##   
## Components  
## seasonal trend remainder  
## Jan 2008 212543.90 1135393 -68268.686  
## Feb 2008 64724.69 1149373 -160772.697  
## Mar 2008 141647.42 1163353 62519.359  
## Apr 2008 -264999.95 1177333 178391.504  
## May 2008 -339776.29 1191010 22334.080  
## Jun 2008 -473456.92 1204687 -86751.057  
## Jul 2008 -560479.22 1218364 114773.472  
## Aug 2008 -439963.23 1231709 14995.207  
## Sep 2008 649360.43 1245054 -179149.730  
## Oct 2008 394715.11 1258400 142636.314  
## Nov 2008 343804.99 1270718 -96234.645  
## Dec 2008 272635.02 1283036 45653.230  
## Jan 2009 216526.66 1295354 71335.502  
## Feb 2009 85366.77 1304840 17181.430  
## Mar 2009 134597.06 1314326 -28121.833  
## Apr 2009 -299576.10 1323812 116864.362  
## May 2009 -339425.04 1333273 -73988.443  
## Jun 2009 -463451.32 1342735 -20407.903  
## Jul 2009 -588086.05 1352197 146023.090  
## Aug 2009 -428334.97 1359570 -88185.300  
## Sep 2009 684000.28 1366944 -69380.862  
## Oct 2009 378107.74 1374317 -104490.629  
## Nov 2009 350361.28 1380061 127414.131  
## Dec 2009 269269.49 1385804 -39982.767  
## Jan 2010 237811.58 1391548 8104.442  
## Feb 2010 164697.76 1396069 115393.780  
## Mar 2010 108887.92 1400591 40081.142  
## Apr 2010 -414588.58 1405112 -177054.835  
## May 2010 -341339.97 1406966 132774.500  
## Jun 2010 -426196.92 1408821 157400.399  
## Jul 2010 -672372.03 1410675 -187034.545  
## Aug 2010 -377863.24 1410092 -19686.420  
## Sep 2010 818966.77 1409509 107012.482  
## Oct 2010 310866.57 1408926 136471.594  
## Nov 2010 396380.37 1408474 -126731.546  
## Dec 2010 260838.84 1408023 30201.636  
## Jan 2011 162908.25 1407571 24787.879  
## Feb 2011 200345.42 1408473 -135290.178  
## Mar 2011 98058.73 1409375 -37705.374  
## Apr 2011 -475991.41 1410277 100364.893  
## May 2011 -326861.16 1414388 -134973.648  
## Jun 2011 -508609.13 1418499 -90586.968  
## Jul 2011 -690240.90 1422610 69706.513  
## Aug 2011 -303950.41 1431899 94863.512  
## Sep 2011 841755.54 1441187 20328.047  
## Oct 2011 348453.95 1450476 -207345.878  
## Nov 2011 482953.99 1463581 14139.587  
## Dec 2011 177522.68 1476687 59781.396  
## Jan 2012 219295.41 1489792 -189339.836  
## Feb 2012 167343.82 1504763 140790.260  
## Mar 2012 47565.92 1519733 39980.664  
## Apr 2012 -327162.02 1534704 -199519.887  
## May 2012 -429104.97 1550797 170291.408  
## Jun 2012 -592640.70 1566889 -34090.529  
## Jul 2012 -686742.76 1582982 49689.871  
## Aug 2012 -391971.46 1597629 29488.941  
## Sep 2012 926501.74 1612275 -208442.888  
## Oct 2012 411978.67 1626922 138994.561  
## Nov 2012 520321.23 1641216 144786.748  
## Dec 2012 157545.15 1655510 -194908.427  
## Jan 2013 228279.54 1669805 211412.939  
## Feb 2013 159093.45 1685663 -106559.227  
## Mar 2013 32529.79 1701521 -100106.827  
## Apr 2013 -295207.15 1717379 322919.852  
## May 2013 -454478.79 1733056 -239128.325  
## Jun 2013 -615888.66 1748733 -78643.269  
## Jul 2013 -688356.21 1764410 -72887.536  
## Aug 2013 -417329.54 1779986 -207981.755  
## Sep 2013 944212.59 1795563 261153.561  
## Oct 2013 431257.90 1811139 63207.703  
## Nov 2013 530407.87 1827035 -72771.039  
## Dec 2013 148706.84 1842931 70522.228

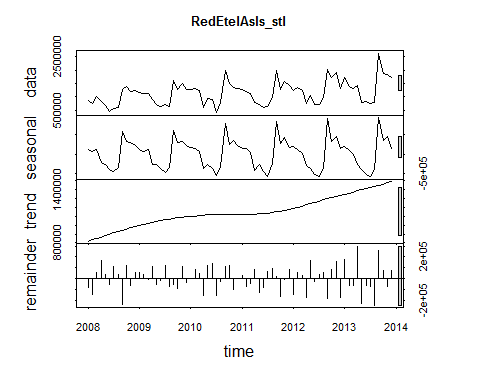
plot(BlueEtelAsIs\_stl, col="black", main="BlueEtelAsIs\_stl")



BlueEtelAsIs\_stl

## Call:  
## stl(x = BlueEtelAsIs, s.window = 5)  
##   
## Components  
## seasonal trend remainder  
## Jan 2008 97275.2686 315974.4 12642.32237  
## Feb 2008 11139.0385 314282.3 -8790.29761  
## Mar 2008 30181.1498 312590.1 10740.74095  
## Apr 2008 -41604.1720 310898.0 9417.21264  
## May 2008 -82250.9857 309242.2 -14051.23490  
## Jun 2008 -87353.5760 307586.5 -32383.90582  
## Jul 2008 -105927.8088 305930.7 6282.06573  
## Aug 2008 -86477.3535 304328.8 -22041.43484  
## Sep 2008 86898.6482 302726.8 59107.51812  
## Oct 2008 83770.5178 301124.9 18431.60318  
## Nov 2008 36900.0663 299701.7 -30430.81279  
## Dec 2008 58228.6185 298278.6 -10552.23250  
## Jan 2009 92163.8208 296855.5 18404.69768  
## Feb 2009 13669.0992 296096.5 -22111.62110  
## Mar 2009 31435.5679 295337.6 -21615.13008  
## Apr 2009 -42500.6886 294578.6 3609.08610  
## May 2009 -78661.8281 294146.4 -15416.55261  
## Jun 2009 -82645.8853 293714.2 -950.27369  
## Jul 2009 -108839.2262 293281.9 27225.28892  
## Aug 2009 -81026.1051 293227.4 -13729.28107  
## Sep 2009 78685.0819 293172.8 -10154.91706  
## Oct 2009 81277.8262 293118.3 -7986.11032  
## Nov 2009 41681.4715 293074.7 15439.81387  
## Dec 2009 58704.1866 293031.1 -84.33172  
## Jan 2010 72580.1351 292987.6 4215.28931  
## Feb 2010 20498.2214 292532.9 32112.89956  
## Mar 2010 34939.9947 292078.2 -4323.17717  
## Apr 2010 -45620.9710 291623.5 -22161.51489  
## May 2010 -67265.4495 290733.7 15972.70036  
## Jun 2010 -66554.3702 289844.0 17026.35768  
## Jul 2010 -119001.0705 288954.3 -31349.20536  
## Aug 2010 -62538.0386 288086.0 5631.04452  
## Sep 2010 44273.8739 287217.7 -2401.58625  
## Oct 2010 67997.9357 286349.4 14236.63364  
## Nov 2010 59212.5980 285847.9 -24113.45064  
## Dec 2010 55648.6860 285346.3 32307.03936  
## Jan 2011 28955.7656 284844.7 -4907.46230  
## Feb 2011 57438.5509 284966.8 -60299.37514  
## Mar 2011 52343.2302 285089.0 9691.81802  
## Apr 2011 -43666.0551 285211.1 19952.97579  
## May 2011 -60113.6551 286414.8 -8695.15338  
## Jun 2011 -72019.3516 287618.5 -7341.18602  
## Jul 2011 -117469.1424 288822.3 3524.87566  
## Aug 2011 -49883.9911 290590.6 7007.39742  
## Sep 2011 17466.7377 292358.9 2186.34154  
## Oct 2011 81493.1516 294127.2 -43694.39935  
## Nov 2011 71702.0181 296020.5 22135.51695  
## Dec 2011 22128.0438 297913.7 -20926.72601  
## Jan 2012 30433.2294 299806.9 -45033.12878  
## Feb 2012 60664.1282 301695.0 88514.85648  
## Mar 2012 42220.9376 303583.1 14229.93113  
## Apr 2012 -31349.3314 305471.2 -21447.91583  
## May 2012 -65160.8818 307305.4 5589.50602  
## Jun 2012 -82895.6870 309139.5 -4567.81742  
## Jul 2012 -106267.8793 310973.6 12212.24632  
## Aug 2012 -30807.7609 312758.6 -26957.85302  
## Sep 2012 11197.8369 314543.6 -26083.43168  
## Oct 2012 89271.6698 316328.6 51994.75448  
## Nov 2012 78575.5205 318810.9 -8469.37352  
## Dec 2012 4838.5499 321293.1 -22681.68023  
## Jan 2013 29411.7297 323775.4 34309.86273  
## Feb 2013 62361.5103 326372.9 -39721.41087  
## Mar 2013 38868.3697 328970.4 -33564.76325  
## Apr 2013 -29333.0223 331567.9 22817.13583  
## May 2013 -66822.9596 334198.4 -11959.48200  
## Jun 2013 -86068.6022 336829.0 -13741.39449  
## Jul 2013 -103603.1850 339459.6 3190.63314  
## Aug 2013 -26521.6173 342232.5 42841.07133  
## Sep 2013 9112.7410 345005.5 5584.71890  
## Oct 2013 92262.6860 347778.5 -12360.22031  
## Nov 2013 79848.3267 350650.9 4061.78244  
## Dec 2013 279.0305 353523.2 -5244.27796

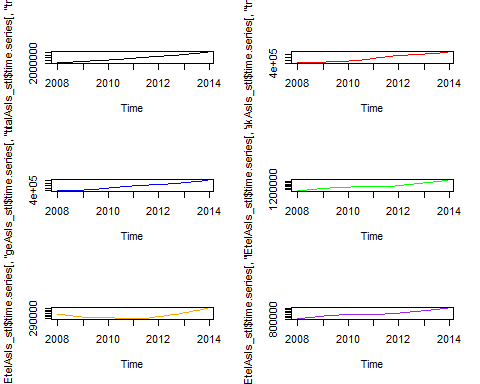
plot(RedEtelAsIs\_stl, col="black", main="RedEtelAsIs\_stl")



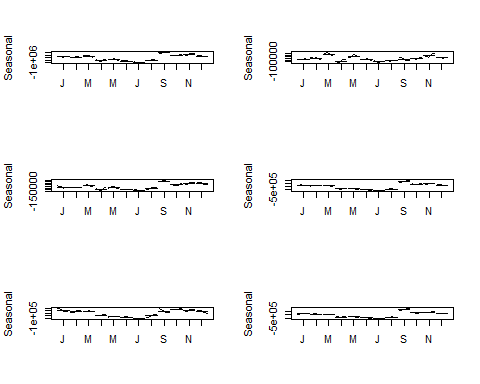
RedEtelAsIs\_stl

## Call:  
## stl(x = RedEtelAsIs, s.window = 5)  
##   
## Components  
## seasonal trend remainder  
## Jan 2008 115268.835 819418.3 -80911.162  
## Feb 2008 53585.615 835090.7 -151982.316  
## Mar 2008 111466.463 850763.1 51778.461  
## Apr 2008 -223395.889 866435.4 168974.440  
## May 2008 -257525.355 881768.0 36385.394  
## Jun 2008 -386103.162 897100.5 -54367.310  
## Jul 2008 -454551.470 912433.0 108491.485  
## Aug 2008 -353485.938 927380.2 37036.720  
## Sep 2008 562461.720 942327.5 -238257.172  
## Oct 2008 310944.528 957274.7 124204.786  
## Nov 2008 306904.849 971015.9 -65803.760  
## Dec 2008 214406.334 984757.1 56205.531  
## Jan 2009 124363.076 998498.4 52930.565  
## Feb 2009 71697.616 1008743.3 39293.091  
## Mar 2009 103161.725 1018988.2 -6506.953  
## Apr 2009 -257075.580 1029233.2 113255.418  
## May 2009 -260763.268 1039127.1 -58571.874  
## Jun 2009 -380805.212 1049021.1 -19457.912  
## Jul 2009 -479246.894 1058915.1 118797.789  
## Aug 2009 -347308.936 1066343.0 -74456.050  
## Sep 2009 605315.129 1073770.9 -59225.996  
## Oct 2009 296829.840 1081198.7 -96504.588  
## Nov 2009 308679.739 1086986.0 111974.233  
## Dec 2009 210565.226 1092773.3 -39898.534  
## Jan 2010 165231.780 1098560.6 3889.633  
## Feb 2010 144199.451 1103536.8 83280.783  
## Mar 2010 73948.266 1108512.9 44404.788  
## Apr 2010 -368967.981 1113489.1 -154893.145  
## May 2010 -274074.598 1116232.9 116801.697  
## Jun 2010 -359642.195 1118976.7 140374.518  
## Jul 2010 -553371.024 1121720.5 -155685.429  
## Aug 2010 -315325.262 1122005.8 -25317.534  
## Sep 2010 774692.841 1122291.1 109414.018  
## Oct 2010 242868.585 1122576.5 122234.930  
## Nov 2010 337167.718 1122626.4 -102618.100  
## Dec 2010 205190.103 1122676.3 -2105.381  
## Jan 2011 133952.721 1122726.2 29695.105  
## Feb 2011 142906.823 1123505.9 -74990.731  
## Mar 2011 45715.744 1124285.6 -47397.386  
## Apr 2011 -432326.121 1125065.4 80411.745  
## May 2011 -266747.553 1127972.9 -126278.375  
## Jun 2011 -436589.538 1130880.5 -83245.941  
## Jul 2011 -572771.802 1133788.0 66181.771  
## Aug 2011 -254066.178 1141308.2 87855.956  
## Sep 2011 824288.759 1148828.4 18141.828  
## Oct 2011 266961.044 1156348.6 -163651.649  
## Nov 2011 411252.213 1167560.9 -7996.121  
## Dec 2011 155394.594 1178773.2 80708.196  
## Jan 2012 188862.232 1189985.5 -144306.744  
## Feb 2012 106679.632 1203067.9 52275.454  
## Mar 2012 5345.035 1216150.3 25750.648  
## Apr 2012 -295813.639 1229232.7 -178072.081  
## May 2012 -363944.157 1243491.3 164701.888  
## Jun 2012 -509744.966 1257749.8 -29522.851  
## Jul 2012 -580474.662 1272008.4 37477.296  
## Aug 2012 -361163.446 1284870.0 56447.422  
## Sep 2012 915303.837 1297731.7 -182359.519  
## Oct 2012 322707.245 1310593.3 87000.416  
## Nov 2012 441745.957 1322405.3 153256.733  
## Dec 2012 152706.817 1334217.3 -172227.099  
## Jan 2013 198867.808 1346029.3 177102.939  
## Feb 2013 96731.864 1359290.0 -66837.878  
## Mar 2013 -6338.588 1372550.8 -66542.188  
## Apr 2013 -265875.136 1385811.5 300102.598  
## May 2013 -387655.909 1398857.8 -227168.886  
## Jun 2013 -529820.071 1411904.1 -64901.981  
## Jul 2013 -584752.754 1424950.3 -76077.555  
## Aug 2013 -390807.670 1437753.9 -250823.189  
## Sep 2013 935099.766 1450557.4 255568.824  
## Oct 2013 338995.467 1463361.0 75567.574  
## Nov 2013 450559.803 1476384.4 -76833.165  
## Dec 2013 148428.084 1489407.8 75767.153

#mywait()  
  
par(mfrow=c(3,2))  
  
plot(TotalAsIs\_stl$time.series[,"trend"], col="black")  
plot(EfakAsIs\_stl$time.series[,"trend"], col="red")  
plot(WugeAsIs\_stl$time.series[,"trend"], col="blue")  
plot(TotalEtelAsIs\_stl$time.series[,"trend"], col="green")  
plot(BlueEtelAsIs\_stl$time.series[,"trend"], col="orange")  
plot(RedEtelAsIs\_stl$time.series[,"trend"], col="purple")



#mywait()  
  
  
#################################################################################  
# 2.3.2 Modification of the seasonal componant to a monthly base #  
#################################################################################  
  
# The modification of the seasonlity component can also be changed into a  
# monthly view. It only makes sense to do this if the seasonality componant as  
# the trend looks almost identical and the remainder is then randomly spread.   
  
monthplot(TotalAsIs\_stl$time.series[,"seasonal"], main="", ylab="Seasonal")  
monthplot(EfakAsIs\_stl$time.series[,"seasonal"], main="", ylab="Seasonal")  
monthplot(WugeAsIs\_stl$time.series[,"seasonal"], main="", ylab="Seasonal")  
monthplot(TotalEtelAsIs\_stl$time.series[,"seasonal"], main="", ylab="Seasonal")  
monthplot(BlueEtelAsIs\_stl$time.series[,"seasonal"], main="", ylab="Seasonal")  
monthplot(RedEtelAsIs\_stl$time.series[,"seasonal"], main="", ylab="Seasonal")



#mywait()  
  
#################################################################################  
### ###  
### 3. Correlation of different external indicators ###  
### ###  
#################################################################################  
  
#################################################################################  
# 3.1 Definition of the indicators and their correlation with the basic data #  
#################################################################################  
  
# The following indicators are to be tested:  
#  
# 1 Monthly Change in Export Price Index (CEPI)  
# 2 Monthly Satisfaction Index (SI) government based data  
# 3 Average monthly temperatures in Chulwalar  
# 4 Monthly births in Chulwalar  
# 5 Monthly Satisfaction Index (SI) external index   
# 6 Yearly Exports from Urbano  
# 7 Yearly number of Globalisation Party members in Chulwalar  
# 8 Monthly Average Export Price Index for Chulwalar  
# 9 Monthly Producer Price Index (PPI) for Etel in Chulwalar  
# 10 National Holidays  
# 11 Chulwalar Index (Total value of all companies in Chulwalar)  
# 12 Monthly Inflation rate in Chulwalar  
# 13 Proposed spending for National Holidays  
# 14 Influence of National Holiday  
#  
# The indicators will be converted into individual vectors and subsequently  
# converted into time series. The correlation of the indicators will then be  
# tested against the As Is exports for Chulwalar.   
  
# Monthly Change in Export Price Index (CEPI)  
CEPIVector <- c(ImportedIndicators[2:13,2],ImportedIndicators[2:13,3],ImportedIndicators[2:13,4],ImportedIndicators[2:13,5],ImportedIndicators[2:13,6],ImportedIndicators[2:13,7])  
CEPI <- ts(CEPIVector , start=c(2008,1), end=c(2013,12), frequency=12)  
plot(CEPI, main="CEPI")  
  
cor(TotalAsIs, CEPI)

## [1] 0.663925

cor(EfakAsIs , CEPI)

## [1] 0.9303543

cor(WugeAsIs, CEPI)

## [1] 0.7618551

cor(TotalEtelAsIs, CEPI)

## [1] 0.339713

cor(BlueEtelAsIs , CEPI)

## [1] 0.1448837

cor(RedEtelAsIs , CEPI)

## [1] 0.3587646

#mywait()  
# The CEPI correlates very well with the efak exports.  
  
# Monthly Satisfaction Index (SI) government based data  
  
SIGovVector <- c(ImportedIndicators[16:27,2],ImportedIndicators[16:27,3],ImportedIndicators[16:27,4],ImportedIndicators[16:27,5],ImportedIndicators[16:27,6],ImportedIndicators[16:27,7])  
SIGov <- ts(SIGovVector , start=c(2008,1), end=c(2013,12), frequency=12)  
plot(SIGov, main="SIGov")  
  
cor(TotalAsIs, SIGov)

## [1] 0.2007768

cor(EfakAsIs , SIGov)

## [1] 0.37934

cor(WugeAsIs, SIGov)

## [1] 0.3030266

cor(TotalEtelAsIs, SIGov)

## [1] 0.002556094

cor(BlueEtelAsIs , SIGov)

## [1] -0.04146932

cor(RedEtelAsIs , SIGov)

## [1] 0.009978415

#mywait()  
  
# The Satisfaction Index does not show any particular correlation with any of   
# the exports data.  
  
# Average monthly temperatures in Chulwalar  
  
TemperatureVector <- c(ImportedIndicators[30:41,2],ImportedIndicators[30:41,3],ImportedIndicators[30:41,4],ImportedIndicators[30:41,5],ImportedIndicators[30:41,6],ImportedIndicators[30:41,7])  
Temperature <- ts(TemperatureVector, start=c(2008,1), end=c(2013,12), frequency=12)  
plot(Temperature, main="Temperature")  
  
cor(TotalAsIs, Temperature)

## [1] -0.3429684

cor(EfakAsIs , Temperature)

## [1] -0.07951179

cor(WugeAsIs, Temperature)

## [1] -0.2045082

cor(TotalEtelAsIs, Temperature)

## [1] -0.453138

cor(BlueEtelAsIs , Temperature)

## [1] -0.6356067

cor(RedEtelAsIs , Temperature)

## [1] -0.4028941

#mywait()  
# The temperatures have a negative correlation, exports   
# increase in the colder months. However, the relationship is only stronger   
# with blue Etels.  
  
# Monthly births in Chulwalar   
BirthsVector <- c(ImportedIndicators[44:55,2],ImportedIndicators[44:55,3],ImportedIndicators[44:55,4],ImportedIndicators[44:55,5],ImportedIndicators[44:55,6],ImportedIndicators[44:55,7])  
Births <- ts(BirthsVector, start=c(2008,1), end=c(2013,12), frequency=12)  
plot(Births, main="Births")  
  
cor(TotalAsIs, Births)

## [1] -0.1190228

cor(EfakAsIs , Births)

## [1] -0.05802961

cor(WugeAsIs, Births)

## [1] -0.007371339

cor(TotalEtelAsIs, Births)

## [1] -0.1504242

cor(BlueEtelAsIs , Births)

## [1] -0.2812913

cor(RedEtelAsIs , Births)

## [1] -0.1217222

#mywait()  
# The consideration by Chulwalar's experts was that expecting new parents to try to export more products to pay for the   
# cost of a new child. However, this could not be confirmed.   
  
# Monthly Satisfaction Index (SI) external index   
SIExternVector <- c(ImportedIndicators[58:69,2],ImportedIndicators[58:69,3],ImportedIndicators[58:69,4],ImportedIndicators[58:69,5],ImportedIndicators[58:69,6],ImportedIndicators[58:69,7])  
SIExtern <- ts(SIExternVector, start=c(2008,1), end=c(2013,12), frequency=12)  
plot(SIExtern, main="SIExtern")  
  
cor(TotalAsIs, SIExtern)

## [1] 0.5883122

cor(EfakAsIs , SIExtern)

## [1] 0.8358147

cor(WugeAsIs, SIExtern)

## [1] 0.6786552

cor(TotalEtelAsIs, SIExtern)

## [1] 0.2865672

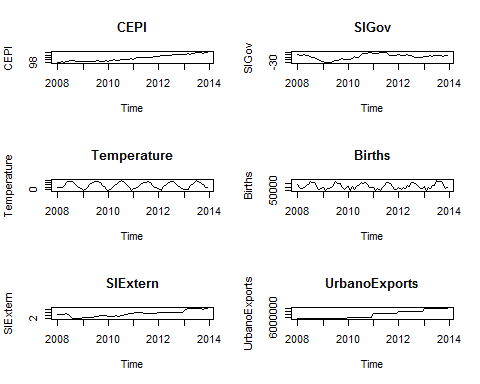
cor(BlueEtelAsIs , SIExtern)

## [1] 0.1604768

cor(RedEtelAsIs , SIExtern)

## [1] 0.2960946

#mywait()  
# This indicator also has a high correlation with Efak exports.   
  
# Yearly exports from Urbano  
UrbanoExportsVector <- c(ImportedIndicators[72:83,2],ImportedIndicators[72:83,3],ImportedIndicators[72:83,4],ImportedIndicators[72:83,5],ImportedIndicators[72:83,6],ImportedIndicators[72:83,7])  
UrbanoExports <- ts(UrbanoExportsVector, start=c(2008,1), end=c(2013,12), frequency=12)  
plot(UrbanoExports, main="UrbanoExports")



cor(TotalAsIs, UrbanoExports)

## [1] 0.638178

cor(EfakAsIs , UrbanoExports)

## [1] 0.9163565

cor(WugeAsIs, UrbanoExports)

## [1] 0.7118468

cor(TotalEtelAsIs, UrbanoExports)

## [1] 0.3182532

cor(BlueEtelAsIs , UrbanoExports)

## [1] 0.1655794

cor(RedEtelAsIs , UrbanoExports)

## [1] 0.3309962

#mywait()  
# This indicator also has a high correlation with Efak exports. The Wuge   
# exports also show a correlation. Unfortunatly it was not possible to find  
# other useful indicators based on exports from Urbano, due to possible   
# informers being very restrictive with information.   
  
# Yearly number of Globalisation Party members in Chulwalar  
GlobalisationPartyMembersVector <- c(ImportedIndicators[86:97,2],ImportedIndicators[86:97,3],ImportedIndicators[86:97,4],ImportedIndicators[86:97,5],ImportedIndicators[86:97,6],ImportedIndicators[86:97,7])  
GlobalisationPartyMembers <- ts(GlobalisationPartyMembersVector, start=c(2008,1), end=c(2013,12), frequency=12)  
plot(GlobalisationPartyMembers, main="GlobalisationPartyMembers")  
  
cor(TotalAsIs, GlobalisationPartyMembers)

## [1] 0.630084

cor(EfakAsIs , GlobalisationPartyMembers)

## [1] 0.8963942

cor(WugeAsIs, GlobalisationPartyMembers)

## [1] 0.7193864

cor(TotalEtelAsIs, GlobalisationPartyMembers)

## [1] 0.2994635

cor(BlueEtelAsIs , GlobalisationPartyMembers)

## [1] 0.08547266

cor(RedEtelAsIs , GlobalisationPartyMembers)

## [1] 0.3234832

#mywait()  
# There is a similar picture here to that of Urbano Exports.  
# It should however be noted that there is a continuos growth here and that  
# the yearly view could lead to the data appearing to correlate, although this   
# could just be due to an increase in trend. Although this could also be true  
# for the Urbano Exports, the trend seems logical due to the Chulwalar's   
# exports growing in accordance with the Urbano's Exports.  
  
# Monthly Average Export Price Index for Chulwalar  
AEPIVector <- c(ImportedIndicators[100:111,2],ImportedIndicators[100:111,3],ImportedIndicators[100:111,4],ImportedIndicators[100:111,5],ImportedIndicators[100:111,6],ImportedIndicators[100:111,7])  
AEPI <- ts(AEPIVector, start=c(2008,1), end=c(2013,12), frequency=12)  
plot(AEPI, main="AEPI")  
  
cor(TotalAsIs, AEPI)

## [1] 0.625232

cor(EfakAsIs , AEPI)

## [1] 0.9056624

cor(WugeAsIs, AEPI)

## [1] 0.7159733

cor(TotalEtelAsIs, AEPI)

## [1] 0.3035506

cor(BlueEtelAsIs , AEPI)

## [1] 0.1577964

cor(RedEtelAsIs , AEPI)

## [1] 0.3157277

#mywait()  
# The continuous growth leads to a good correlation here too.  
# See Above  
  
# Monthly Producer Price Index (PPI) for Etel in Chulwalar  
PPIEtelVector <- c(ImportedIndicators[114:125,2],ImportedIndicators[114:125,3],ImportedIndicators[114:125,4],ImportedIndicators[114:125,5],ImportedIndicators[114:125,6],ImportedIndicators[114:125,7])  
PPIEtel <- ts(PPIEtelVector, start=c(2008,1), end=c(2013,12), frequency=12)  
plot(PPIEtel, main="PPIEtel")  
  
cor(TotalAsIs, PPIEtel)

## [1] 0.4836129

cor(EfakAsIs , PPIEtel)

## [1] 0.5865375

cor(WugeAsIs, PPIEtel)

## [1] 0.4920865

cor(TotalEtelAsIs, PPIEtel)

## [1] 0.3374707

cor(BlueEtelAsIs , PPIEtel)

## [1] 0.2445472

cor(RedEtelAsIs , PPIEtel)

## [1] 0.3391872

#mywait()  
# This indicator does not give the expected results. It does not show any   
# correlation worth mentioning, not even with the Etel segment.   
  
# National Holidays  
NationalHolidaysVector <- c(ImportedIndicators[170:181,2],ImportedIndicators[170:181,3],ImportedIndicators[170:181,4],ImportedIndicators[170:181,5],ImportedIndicators[170:181,6],ImportedIndicators[170:181,7])  
NationalHolidays <- ts(NationalHolidaysVector, start=c(2008,1), end=c(2013,12), frequency=12)  
plot(NationalHolidays, main="NationalHolidays")  
  
cor(TotalAsIs, NationalHolidays)

## [1] -0.007883708

cor(EfakAsIs , NationalHolidays)

## [1] 0.001235706

cor(WugeAsIs, NationalHolidays)

## [1] 0.06505569

cor(TotalEtelAsIs, NationalHolidays)

## [1] -0.01081446

cor(BlueEtelAsIs , NationalHolidays)

## [1] 0.02903763

cor(RedEtelAsIs , NationalHolidays)

## [1] -0.01717636

#mywait()  
# The months April and December do not correlate well with the exports data.   
# However later tests will show that these are worth considering.   
# The missing correlation is just due to the sparse structure of the NationalHolidays time series.  
  
# Chulwalar Index (Total value of all companies in Chulwalar)  
ChulwalarIndexVector <- c(ImportedIndicators[128:139,2],ImportedIndicators[128:139,3],ImportedIndicators[128:139,4],ImportedIndicators[128:139,5],ImportedIndicators[128:139,6],ImportedIndicators[128:139,7])  
ChulwalarIndex <- ts(ChulwalarIndexVector, start=c(2008,1), end=c(2013,12), frequency=12)  
plot(ChulwalarIndex, main="ChulwalarIndex")  
  
cor(TotalAsIs, ChulwalarIndex)

## [1] 0.4837017

cor(EfakAsIs , ChulwalarIndex)

## [1] 0.7129557

cor(WugeAsIs, ChulwalarIndex)

## [1] 0.5721568

cor(TotalEtelAsIs, ChulwalarIndex)

## [1] 0.2209171

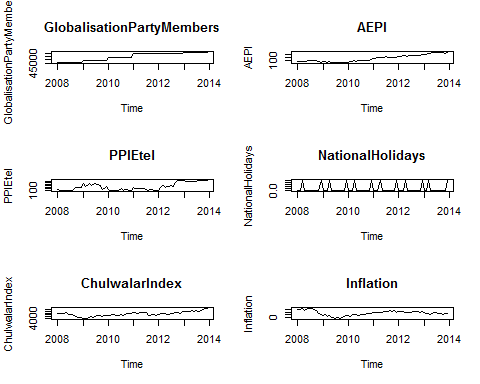
cor(BlueEtelAsIs , ChulwalarIndex)

## [1] 0.1469233

cor(RedEtelAsIs , ChulwalarIndex)

## [1] 0.2242922

#mywait()  
# No particular findings  
  
# Monthly Inflation rate in Chulwalar   
InflationVector <- c(ImportedIndicators[142:153,2],ImportedIndicators[142:153,3],ImportedIndicators[142:153,4],ImportedIndicators[142:153,5],ImportedIndicators[142:153,6],ImportedIndicators[142:153,7])  
Inflation <- ts(InflationVector, start=c(2008,1), end=c(2013,12), frequency=12)  
plot(Inflation, main="Inflation")



cor(TotalAsIs, Inflation)

## [1] 0.002438708

cor(EfakAsIs , Inflation)

## [1] 0.1454134

cor(WugeAsIs, Inflation)

## [1] 0.03191332

cor(TotalEtelAsIs, Inflation)

## [1] -0.08378282

cor(BlueEtelAsIs , Inflation)

## [1] 0.02117817

cor(RedEtelAsIs , Inflation)

## [1] -0.0982151

#mywait()  
# No particular findings  
  
# Proposed spending for Independence day presents  
IndependenceDayPresentsVector <- c(ImportedIndicators[156:167,2],ImportedIndicators[156:167,3],ImportedIndicators[156:167,4],ImportedIndicators[156:167,5],ImportedIndicators[156:167,6],ImportedIndicators[156:167,7])  
IndependenceDayPresents <- ts(IndependenceDayPresentsVector, start=c(2008,1), end=c(2013,12), frequency=12)  
plot(IndependenceDayPresents, main="IndependenceDayPresents")  
  
cor(TotalAsIs, IndependenceDayPresents)

## [1] 0.4359522

cor(EfakAsIs , IndependenceDayPresents)

## [1] 0.5243145

cor(WugeAsIs, IndependenceDayPresents)

## [1] 0.4892437

cor(TotalEtelAsIs, IndependenceDayPresents)

## [1] 0.2872013

cor(BlueEtelAsIs , IndependenceDayPresents)

## [1] 0.2110373

cor(RedEtelAsIs , IndependenceDayPresents)

## [1] 0.2881631

#mywait()  
# No particular findings  
  
# Influence of National Holidays :  
# This indicator is an experiment where the influence of National Holidays is   
# extended into the months leading up to the holiday.   
# However later tests show that this indicator is no better for forecasting than the  
# orignial National Holidays indicator.   
InfluenceNationalHolidaysVector <- c(ImportedIndicators[184:195,2],ImportedIndicators[184:195,3],ImportedIndicators[184:195,4],ImportedIndicators[184:195,5],ImportedIndicators[184:195,6],ImportedIndicators[184:195,7])  
InfluenceNationalHolidays <- ts(InfluenceNationalHolidaysVector, start=c(2008,1), end=c(2013,12), frequency=12)  
plot(InfluenceNationalHolidays, main="InfluenceNationalHolidays")  
  
cor(TotalAsIs, InfluenceNationalHolidays)

## [1] 0.3717463

cor(EfakAsIs , InfluenceNationalHolidays)

## [1] 0.09926836

cor(WugeAsIs, InfluenceNationalHolidays)

## [1] 0.3712288

cor(TotalEtelAsIs, InfluenceNationalHolidays)

## [1] 0.4535836

cor(BlueEtelAsIs , InfluenceNationalHolidays)

## [1] 0.2792198

cor(RedEtelAsIs , InfluenceNationalHolidays)

## [1] 0.4643512

#mywait()  
  
# Check that the data import has worked  
  
CEPIVector

## [1] 97.4 97.8 98.3 98.1 98.7 98.9 99.5 99.2 99.1 98.9 98.4  
## [12] 98.8 98.3 98.9 98.7 98.8 98.7 99.0 99.0 99.2 98.9 98.9  
## [23] 98.8 99.6 99.0 99.4 99.9 100.0 99.9 99.9 100.1 100.2 100.1  
## [34] 100.2 100.3 100.9 100.7 101.3 101.9 101.9 101.9 102.0 102.2 102.3  
## [45] 102.5 102.5 102.7 102.9 102.8 103.5 104.1 103.9 103.9 103.7 104.1  
## [56] 104.5 104.6 104.6 104.7 105.0 104.5 105.1 105.6 105.1 105.5 105.6  
## [67] 106.1 106.1 106.1 105.9 106.1 106.5

SIGovVector

## [1] -0.4 -2.9 -2.7 1.7 -1.7 -2.6 -7.1 -11.1 -9.4 -13.5 -18.0  
## [12] -24.7 -26.9 -28.6 -31.9 -30.6 -29.8 -26.6 -23.7 -21.3 -17.4 -16.0  
## [23] -19.3 -16.4 -18.0 -17.9 -13.9 -5.5 -9.1 -9.8 0.6 3.5 5.9  
## [34] 6.4 9.9 8.1 7.0 6.8 6.5 7.5 7.5 8.4 8.0 -0.4  
## [45] -1.7 -4.1 -3.7 -2.9 -0.2 -1.4 -1.3 -1.9 0.0 -1.3 -3.7  
## [56] -8.1 -9.0 -8.6 -9.5 -9.8 -6.6 -5.4 -4.9 -3.8 -4.5 -3.0  
## [67] -1.7 -3.5 -4.0 -4.8 -2.5 -2.5

TemperatureVector

## [1] 3.60 3.70 4.20 7.60 14.50 16.90 18.00 17.40 12.40 9.10 5.10  
## [12] 1.10 -2.20 0.50 4.30 11.83 13.60 14.80 18.00 18.70 14.70 8.20  
## [23] 7.40 0.30 -3.60 -0.50 4.20 8.70 10.40 16.30 20.30 16.70 12.40  
## [34] 8.10 4.80 -3.70 1.00 0.90 4.90 11.60 13.90 16.50 16.10 17.70  
## [45] 15.20 9.40 4.50 3.90 1.90 -2.50 6.90 8.10 14.20 15.50 17.40  
## [56] 18.40 13.60 8.70 5.20 1.50 0.20 -0.70 0.10 8.10 11.80 15.70  
## [67] 19.50 17.90 13.30 10.60 4.60 3.60

BirthsVector

## [1] 58519 53370 52852 55048 57398 58313 63315 60924 61263 56857 51703  
## [12] 52952 55155 50087 53692 53177 54535 56756 62292 59872 59612 54760  
## [23] 51319 53869 55273 50314 55486 52020 56054 57531 61918 59845 61125  
## [34] 58816 54576 54989 54802 50520 53433 49791 55059 56947 61169 60806  
## [45] 60308 55937 51691 52222 54528 51280 55026 53159 56683 55525 61346  
## [56] 61674 59615 57856 53590 53262 55919 49786 54222 53637 56768 57069  
## [67] 64208 62440 62725 58125 52985 54185

SIExternVector

## [1] 4.5 4.5 4.6 4.6 5.0 4.3 3.4 1.8 1.5 1.7 1.9 2.1 2.2 2.3 2.5 2.5 2.6  
## [18] 2.7 3.0 3.4 3.8 4.2 3.9 3.6 3.4 3.3 3.2 3.4 3.7 3.5 3.7 4.1 4.3 4.9  
## [35] 5.1 5.5 5.5 5.8 6.0 5.9 5.7 5.6 5.5 5.3 5.2 5.5 5.4 5.6 5.7 5.9 6.0  
## [52] 5.8 5.7 5.7 5.8 5.8 6.0 6.1 6.0 5.8 7.7 8.3 8.5 8.5 8.5 8.6 8.9 8.9  
## [69] 8.6 8.3 8.5 8.7

UrbanoExportsVector

## [1] 5850000 5850000 5850000 5850000 5850000 5850000 5850000 5850000  
## [9] 5850000 5850000 5850000 5850000 5800000 5800000 5800000 5800000  
## [17] 5800000 5800000 5800000 5800000 5800000 5800000 5800000 5800000  
## [25] 6020000 6020000 6020000 6020000 6020000 6020000 6020000 6020000  
## [33] 6020000 6020000 6020000 6020000 6640000 6640000 6640000 6640000  
## [41] 6640000 6640000 6640000 6640000 6640000 6640000 6640000 6640000  
## [49] 7040000 7040000 7040000 7040000 7040000 7040000 7040000 7040000  
## [57] 7040000 7040000 7040000 7040000 7550000 7550000 7550000 7550000  
## [65] 7550000 7550000 7550000 7550000 7550000 7550000 7550000 7550000

GlobalisationPartyMembersVector

## [1] 45089 45089 45089 45089 45089 45089 45089 45089 45089 45089 45089  
## [12] 45089 48171 48171 48171 48171 48171 48171 48171 48171 48171 48171  
## [23] 48171 48171 52991 52991 52991 52991 52991 52991 52991 52991 52991  
## [34] 52991 52991 52991 59074 59074 59074 59074 59074 59074 59074 59074  
## [45] 59074 59074 59074 59074 59653 59653 59653 59653 59653 59653 59653  
## [56] 59653 59653 59653 59653 59653 61359 61359 61359 61359 61359 61359  
## [67] 61359 61359 61359 61359 61359 61359

AEPIVector

## [1] 99.0 99.3 99.5 99.2 99.5 100.2 100.6 100.7 100.8 100.2 98.6  
## [12] 98.0 98.5 98.4 98.2 98.4 98.0 97.4 96.9 97.3 97.8 97.3  
## [23] 97.2 97.7 98.2 98.7 99.6 100.0 99.0 99.8 100.2 100.2 100.6  
## [34] 100.3 101.2 102.1 102.8 103.7 104.4 104.9 105.2 105.2 105.8 105.3  
## [45] 105.1 105.1 105.3 105.5 106.1 107.1 107.7 107.4 107.1 107.3 107.8  
## [56] 107.7 108.0 108.3 108.4 109.0 109.8 110.1 111.0 111.1 111.7 111.8  
## [67] 112.6 112.1 112.3 111.7 111.5 111.7

PPIEtelVector

## [1] 100.6 99.7 99.9 99.6 100.0 99.7 100.0 100.0 100.9 101.6 101.5  
## [12] 101.6 104.6 102.1 103.3 104.4 103.0 104.0 104.7 104.0 103.4 100.5  
## [23] 101.0 102.1 100.5 100.0 99.7 99.9 99.7 99.6 100.8 99.4 100.2  
## [34] 100.2 100.0 99.9 102.0 100.8 100.9 101.1 101.4 100.9 100.3 99.7  
## [45] 100.6 100.2 100.0 99.9 100.0 102.6 102.8 102.0 102.2 102.3 102.8  
## [56] 102.5 105.3 106.3 106.6 106.4 106.3 106.0 105.8 106.0 106.1 105.8  
## [67] 105.8 106.4 106.2 106.3 106.3 106.4

NationalHolidaysVector

## [1] 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0  
## [36] 1 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0  
## [71] 0 1

ChulwalarIndexVector

## [1] 6851.75 6748.13 6534.97 6948.82 7096.79 6418.32 6479.56 6422.30  
## [9] 5831.02 4987.97 4669.44 4810.20 4338.35 3843.74 4084.76 4769.45  
## [17] 4940.82 4808.84 5332.14 5464.61 5675.16 5414.96 5625.95 5957.43  
## [25] 5608.79 5598.46 6153.55 6135.70 5964.33 5965.52 6147.97 5925.22  
## [33] 6229.02 6601.37 6688.49 6914.19 7077.48 7272.32 7041.31 7514.46  
## [41] 7293.69 7376.24 7158.77 5784.85 5502.02 6141.34 6088.84 5898.35  
## [49] 6458.91 6856.08 6946.83 6761.19 6264.38 6416.28 6772.26 6970.79  
## [57] 7216.15 7260.63 7045.50 7612.39 7776.05 7741.70 7795.31 7913.71  
## [65] 8348.84 7959.22 8275.97 8103.15 8594.40 9033.92 9405.30 9552.16

InflationVector

## [1] 2.85 2.84 3.15 2.40 3.03 3.24 3.32 3.12 2.80 2.38 1.34  
## [12] 1.13 0.92 1.12 0.41 0.71 0.00 0.10 -0.50 0.00 -0.20 0.00  
## [23] 0.41 0.81 0.71 0.51 1.22 1.21 1.22 0.91 1.11 1.01 1.21  
## [34] 1.31 1.52 1.31 1.72 1.91 2.00 1.90 2.00 2.10 2.10 2.10  
## [45] 2.40 2.30 2.39 1.98 2.09 2.17 2.16 1.96 1.96 1.67 1.86  
## [56] 2.15 2.05 2.05 1.95 2.04 1.65 1.55 1.44 1.15 1.54 1.83  
## [67] 1.92 1.53 1.43 1.24 1.34 1.43

IndependenceDayPresentsVector

## [1] 221 221 221 221 221 221 221 221 221 221 221 221 226 226 226 226 226  
## [18] 226 226 226 226 226 226 226 233 233 233 233 233 233 233 233 233 233  
## [35] 233 233 213 213 213 213 213 213 213 213 213 213 213 213 230 230 230  
## [52] 230 230 230 230 230 230 230 230 230 273 273 273 273 273 273 273 273  
## [69] 273 273 273 273

#################################################################################  
# 3.2 Correlation of the indicators with a time offset #  
#################################################################################  
  
# The External Satisfaction Index indicator is to be offset by one month, to see if the   
# index change makes itself first noticeable on exports in the following months.  
  
SIExternOffsetByOneMonthVector <- c(ImportedIndicators[57:68,2],ImportedIndicators[57:68,3],ImportedIndicators[57:68,4],ImportedIndicators[57:68,5],ImportedIndicators[57:68,6],ImportedIndicators[57:68,7])  
SIExternOffsetByOneMonth <- ts(SIGovVector, start=c(2008,1), end=c(2013,11), frequency=12)  
plot(SIExternOffsetByOneMonth, main="SIExternOffsetByOneMonth")  
  
#mywait()  
  
# Delete December 2013 from the ts   
  
TotalAsIsWithoutDec12013 <- ts(TotalAsIsVector , start=c(2008,1), end=c(2013,11), frequency=12)  
EfakAsIsWithoutDec12013 <- ts(EfakAsIsVector , start=c(2008,1), end=c(2013,11), frequency=12)  
WugeAsIsWithoutDec12013 <- ts(WugeAsIsVector, start=c(2008,1), end=c(2013,11), frequency=12)  
TotalEtelAsIsWithoutDec12013 <- ts(TotalEtelAsIsVector, start=c(2008,1), end=c(2013,11), frequency=12)  
BlueEtelAsIsWithoutDec12013 <- ts(BlueEtelAsIsVector, start=c(2008,1), end=c(2013,11), frequency=12)  
RedEtelAsIsWithoutDec12013 <- ts(RedEtelAsIsVector, start=c(2008,1), end=c(2013,11), frequency=12)  
  
cor(TotalAsIsWithoutDec12013, SIExternOffsetByOneMonth)

## [1] 0.1952995

cor(EfakAsIsWithoutDec12013, SIExternOffsetByOneMonth)

## [1] 0.3792706

cor(WugeAsIsWithoutDec12013, SIExternOffsetByOneMonth)

## [1] 0.3014096

cor(TotalEtelAsIsWithoutDec12013, SIExternOffsetByOneMonth)

## [1] -0.004445279

cor(BlueEtelAsIsWithoutDec12013 , SIExternOffsetByOneMonth)

## [1] -0.04501746

cor(RedEtelAsIsWithoutDec12013, SIExternOffsetByOneMonth)

## [1] 0.002745801

TotalAsIsWithoutDec2013\_lm <- lm(TotalAsIsWithoutDec12013 ~ SIExternOffsetByOneMonth, data=TotalAsIsWithoutDec12013)  
summary(TotalAsIsWithoutDec2013\_lm)

##   
## Call:  
## lm(formula = TotalAsIsWithoutDec12013 ~ SIExternOffsetByOneMonth,   
## data = TotalAsIsWithoutDec12013)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -1560602 -560765 246 437927 2142998   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 3025619 114816 26.352 <2e-16 \*\*\*  
## SIExternOffsetByOneMonth 15211 9196 1.654 0.103   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 812500 on 69 degrees of freedom  
## Multiple R-squared: 0.03814, Adjusted R-squared: 0.0242   
## F-statistic: 2.736 on 1 and 69 DF, p-value: 0.1026

# The result is not very convincing.  
  
# Offset SIGov Indicator by two months  
  
SIGovVectorShifted2Months <- c(ImportedIndicators[15:26,2],ImportedIndicators[15:26,3],ImportedIndicators[15:26,4],ImportedIndicators[15:26,5],ImportedIndicators[15:26,6],ImportedIndicators[15:26,7])  
SIGovShifted2Months <- ts(SIGovVectorShifted2Months , start=c(2008,1), end=c(2013,10), frequency=12)  
plot(SIGovShifted2Months)  
  
#mywait()  
  
# Delete November and December 2013 from the ts  
  
TotalAsIsWithoutNovDec2013 <- ts(TotalAsIsVector , start=c(2008,1), end=c(2013,10), frequency=12)  
EfakAsIsWithoutNovDec2013 <- ts(EfakAsIsVector , start=c(2008,1), end=c(2013,10), frequency=12)  
WugeAsIsWithoutNovDec2013 <- ts(WugeAsIsVector, start=c(2008,1), end=c(2013,10), frequency=12)  
TotalEtelAsIsWithoutNovDec2013 <- ts(TotalEtelAsIsVector, start=c(2008,1), end=c(2013,10), frequency=12)  
BlueEtelAsIsWithoutNovDec2013 <- ts(BlueEtelAsIsVector, start=c(2008,1), end=c(2013,10), frequency=12)  
RedEtelAsIsWithoutNovDec2013 <- ts(RedEtelAsIsVector, start=c(2008,1), end=c(2013,10), frequency=12)  
  
cor(TotalAsIsWithoutNovDec2013, SIGovShifted2Months)

## [1] 0.0446355

cor(EfakAsIsWithoutNovDec2013, SIGovShifted2Months)

## [1] -0.06536442

cor(WugeAsIsWithoutNovDec2013, SIGovShifted2Months)

## [1] -0.06040505

cor(TotalEtelAsIsWithoutNovDec2013, SIGovShifted2Months)

## [1] 0.1173295

cor(BlueEtelAsIsWithoutNovDec2013, SIGovShifted2Months)

## [1] 0.2578211

cor(RedEtelAsIsWithoutNovDec2013, SIGovShifted2Months)

## [1] 0.08798115

TotalAsIsWithoutNovDec2013\_lm <- lm(TotalAsIsWithoutNovDec2013 ~ SIGovShifted2Months, data=TotalAsIsWithoutNovDec2013)  
summary(TotalAsIsWithoutNovDec2013)

## Min. 1st Qu. Median Mean 3rd Qu. Max.   
## 1458000 2353000 2901000 2897000 3329000 5108000

# The correlation of the indicators has not really been improved by the  
# offsets, so we will not continue with this approach.   
  
#################################################################################  
# 3.3 Correlation of the indicators with each another #  
#################################################################################   
  
# In order to test which indicators could be used in a model with eachother,  
# we need to look at the correlation of the indicators with eachother. All   
# thirteen indicators will be compared with eachother in a correlation   
# coefficient matrix. First of all it is necessary to summarise all indicators   
# in a matrix.  
  
IndicatorsMatrix <-cbind(CEPIVector, SIGovVector, TemperatureVector, BirthsVector, SIGovVector, UrbanoExportsVector, GlobalisationPartyMembersVector, AEPIVector, PPIEtel, NationalHolidaysVector, ChulwalarIndexVector, InflationVector, IndependenceDayPresentsVector)  
  
# Establish the standardised data matrix  
  
IndicatorsmatrixStandardised=scale(IndicatorsMatrix)  
IndicatorsmatrixStandardised

## CEPIVector SIGovVector TemperatureVector BirthsVector  
## Jan 2008 -1.52922324 0.60197865 -0.80158296 0.63571578  
## Feb 2008 -1.38212361 0.36383325 -0.78670170 -0.75485223  
## Mar 2008 -1.19824907 0.38288488 -0.71229542 -0.89474624  
## Apr 2008 -1.27179889 0.80202078 -0.20633274 -0.30168208  
## May 2008 -1.05114944 0.47814304 0.82047388 0.33297219  
## Jun 2008 -0.97759963 0.39241070 1.17762401 0.58008225  
## Jul 2008 -0.75695018 -0.03625102 1.34131782 1.93095061  
## Aug 2008 -0.86727491 -0.41728366 1.25203029 1.28522365  
## Sep 2008 -0.90404981 -0.25534479 0.50796752 1.37677591  
## Oct 2008 -0.97759963 -0.64590324 0.01688609 0.18686667  
## Nov 2008 -1.16147417 -1.07456496 -0.57836412 -1.20505167  
## Dec 2008 -1.01437454 -1.71279463 -1.17361434 -0.86773967  
## Jan 2009 -1.19824907 -1.92236259 -1.66469577 -0.27278506  
## Feb 2009 -0.97759963 -2.08430146 -1.26290187 -1.64147775  
## Mar 2009 -1.05114944 -2.39865338 -0.69741417 -0.66789110  
## Apr 2009 -1.01437454 -2.27481778 0.42314436 -0.80697490  
## May 2009 -1.05114944 -2.19861125 0.68654258 -0.44022576  
## Jun 2009 -0.94082472 -1.89378514 0.86511765 0.15959004  
## Jul 2009 -0.94082472 -1.61753647 1.34131782 1.65467346  
## Aug 2009 -0.86727491 -1.38891689 1.44548661 1.00111459  
## Sep 2009 -0.97759963 -1.01741007 0.85023639 0.93089753  
## Oct 2009 -0.97759963 -0.88404864 -0.11704521 -0.37946099  
## Nov 2009 -1.01437454 -1.19840057 -0.23609525 -1.30875687  
## Dec 2009 -0.72017527 -0.92215191 -1.29266438 -0.62008948  
## Jan 2010 -0.94082472 -1.07456496 -1.87303334 -0.24091731  
## Feb 2010 -0.79372509 -1.06503915 -1.41171443 -1.58017285  
## Mar 2010 -0.60985055 -0.68400651 -0.71229542 -0.18339333  
## Apr 2010 -0.57307564 0.11616203 -0.04263893 -1.11944086  
## May 2010 -0.60985055 -0.22676734 0.21034241 -0.02999604  
## Jun 2010 -0.60985055 -0.29344805 1.08833648 0.36889092  
## Jul 2010 -0.53630074 0.69723681 1.68358669 1.55366891  
## Aug 2010 -0.49952583 0.97348547 1.14786150 0.99382282  
## Sep 2010 -0.53630074 1.20210506 0.50796752 1.33950685  
## Oct 2010 -0.49952583 1.24973414 -0.13192646 0.71592527  
## Nov 2010 -0.46275092 1.58313769 -0.62300789 -0.42915307  
## Dec 2010 -0.24210148 1.41167301 -1.88791460 -0.31761595  
## Jan 2011 -0.31565129 1.30688903 -1.18849560 -0.36811823  
## Feb 2011 -0.09500184 1.28783740 -1.20337685 -1.52453933  
## Mar 2011 0.12564760 1.25925995 -0.60812664 -0.73783810  
## Apr 2011 0.12564760 1.35451811 0.38891748 -1.72141718  
## May 2011 0.12564760 1.35451811 0.73118635 -0.29871136  
## Jun 2011 0.16242251 1.44025045 1.11809899 0.21117258  
## Jul 2011 0.23597232 1.40214719 1.05857397 1.35138974  
## Aug 2011 0.27274723 0.60197865 1.29667405 1.25335591  
## Sep 2011 0.34629705 0.47814304 0.92464267 1.11886322  
## Oct 2011 0.34629705 0.24952346 0.06152986 -0.06159372  
## Nov 2011 0.41984686 0.28762672 -0.66765166 -1.20829245  
## Dec 2011 0.49339668 0.36383325 -0.75693919 -1.06488760  
## Jan 2012 0.45662177 0.62103028 -1.05456430 -0.44211622  
## Feb 2012 0.71404612 0.50672049 -1.70933953 -1.31928943  
## Mar 2012 0.93469557 0.51624630 -0.31050153 -0.30762353  
## Apr 2012 0.86114575 0.45909141 -0.13192646 -0.81183609  
## May 2012 0.86114575 0.64008191 0.77583012 0.13987525  
## Jun 2012 0.78759594 0.51624630 0.96928644 -0.17286077  
## Jul 2012 0.93469557 0.28762672 1.25203029 1.39919136  
## Aug 2012 1.08179520 -0.13150918 1.40084284 1.48777289  
## Sep 2012 1.11857011 -0.21724153 0.68654258 0.93170772  
## Oct 2012 1.11857011 -0.17913826 -0.04263893 0.45666225  
## Nov 2012 1.15534502 -0.26487061 -0.56348287 -0.69543779  
## Dec 2012 1.26566974 -0.29344805 -1.11408932 -0.78401932  
## Jan 2013 1.08179520 0.01137806 -1.30754564 -0.06645490  
## Feb 2013 1.30244465 0.12568785 -1.44147694 -1.72276751  
## Mar 2013 1.48631918 0.17331693 -1.32242689 -0.52475630  
## Apr 2013 1.30244465 0.27810091 -0.13192646 -0.68274471  
## May 2013 1.44954428 0.21142019 0.41867999 0.16283083  
## Jun 2013 1.48631918 0.35430743 0.99904895 0.24412059  
## Jul 2013 1.67019372 0.47814304 1.56453665 2.17211923  
## Aug 2013 1.67019372 0.30667835 1.32643657 1.69464317  
## Sep 2013 1.67019372 0.25904927 0.64189882 1.77161188  
## Oct 2013 1.59664391 0.18284275 0.24010492 0.52930991  
## Nov 2013 1.67019372 0.40193651 -0.65277040 -0.85882751  
## Dec 2013 1.81729335 0.40193651 -0.80158296 -0.53474873  
## SIGovVector UrbanoExportsVector GlobalisationPartyMembersVector  
## Jan 2008 0.60197865 -0.9637871 -1.5070173  
## Feb 2008 0.36383325 -0.9637871 -1.5070173  
## Mar 2008 0.38288488 -0.9637871 -1.5070173  
## Apr 2008 0.80202078 -0.9637871 -1.5070173  
## May 2008 0.47814304 -0.9637871 -1.5070173  
## Jun 2008 0.39241070 -0.9637871 -1.5070173  
## Jul 2008 -0.03625102 -0.9637871 -1.5070173  
## Aug 2008 -0.41728366 -0.9637871 -1.5070173  
## Sep 2008 -0.25534479 -0.9637871 -1.5070173  
## Oct 2008 -0.64590324 -0.9637871 -1.5070173  
## Nov 2008 -1.07456496 -0.9637871 -1.5070173  
## Dec 2008 -1.71279463 -0.9637871 -1.5070173  
## Jan 2009 -1.92236259 -1.0398756 -1.0076219  
## Feb 2009 -2.08430146 -1.0398756 -1.0076219  
## Mar 2009 -2.39865338 -1.0398756 -1.0076219  
## Apr 2009 -2.27481778 -1.0398756 -1.0076219  
## May 2009 -2.19861125 -1.0398756 -1.0076219  
## Jun 2009 -1.89378514 -1.0398756 -1.0076219  
## Jul 2009 -1.61753647 -1.0398756 -1.0076219  
## Aug 2009 -1.38891689 -1.0398756 -1.0076219  
## Sep 2009 -1.01741007 -1.0398756 -1.0076219  
## Oct 2009 -0.88404864 -1.0398756 -1.0076219  
## Nov 2009 -1.19840057 -1.0398756 -1.0076219  
## Dec 2009 -0.92215191 -1.0398756 -1.0076219  
## Jan 2010 -1.07456496 -0.7050864 -0.2266076  
## Feb 2010 -1.06503915 -0.7050864 -0.2266076  
## Mar 2010 -0.68400651 -0.7050864 -0.2266076  
## Apr 2010 0.11616203 -0.7050864 -0.2266076  
## May 2010 -0.22676734 -0.7050864 -0.2266076  
## Jun 2010 -0.29344805 -0.7050864 -0.2266076  
## Jul 2010 0.69723681 -0.7050864 -0.2266076  
## Aug 2010 0.97348547 -0.7050864 -0.2266076  
## Sep 2010 1.20210506 -0.7050864 -0.2266076  
## Oct 2010 1.24973414 -0.7050864 -0.2266076  
## Nov 2010 1.58313769 -0.7050864 -0.2266076  
## Dec 2010 1.41167301 -0.7050864 -0.2266076  
## Jan 2011 1.30688903 0.2384105 0.7590584  
## Feb 2011 1.28783740 0.2384105 0.7590584  
## Mar 2011 1.25925995 0.2384105 0.7590584  
## Apr 2011 1.35451811 0.2384105 0.7590584  
## May 2011 1.35451811 0.2384105 0.7590584  
## Jun 2011 1.44025045 0.2384105 0.7590584  
## Jul 2011 1.40214719 0.2384105 0.7590584  
## Aug 2011 0.60197865 0.2384105 0.7590584  
## Sep 2011 0.47814304 0.2384105 0.7590584  
## Oct 2011 0.24952346 0.2384105 0.7590584  
## Nov 2011 0.28762672 0.2384105 0.7590584  
## Dec 2011 0.36383325 0.2384105 0.7590584  
## Jan 2012 0.62103028 0.8471181 0.8528773  
## Feb 2012 0.50672049 0.8471181 0.8528773  
## Mar 2012 0.51624630 0.8471181 0.8528773  
## Apr 2012 0.45909141 0.8471181 0.8528773  
## May 2012 0.64008191 0.8471181 0.8528773  
## Jun 2012 0.51624630 0.8471181 0.8528773  
## Jul 2012 0.28762672 0.8471181 0.8528773  
## Aug 2012 -0.13150918 0.8471181 0.8528773  
## Sep 2012 -0.21724153 0.8471181 0.8528773  
## Oct 2012 -0.17913826 0.8471181 0.8528773  
## Nov 2012 -0.26487061 0.8471181 0.8528773  
## Dec 2012 -0.29344805 0.8471181 0.8528773  
## Jan 2013 0.01137806 1.6232204 1.1293110  
## Feb 2013 0.12568785 1.6232204 1.1293110  
## Mar 2013 0.17331693 1.6232204 1.1293110  
## Apr 2013 0.27810091 1.6232204 1.1293110  
## May 2013 0.21142019 1.6232204 1.1293110  
## Jun 2013 0.35430743 1.6232204 1.1293110  
## Jul 2013 0.47814304 1.6232204 1.1293110  
## Aug 2013 0.30667835 1.6232204 1.1293110  
## Sep 2013 0.25904927 1.6232204 1.1293110  
## Oct 2013 0.18284275 1.6232204 1.1293110  
## Nov 2013 0.40193651 1.6232204 1.1293110  
## Dec 2013 0.40193651 1.6232204 1.1293110  
## AEPIVector PPIEtel NationalHolidaysVector  
## Jan 2008 -0.91646681 -0.693775997 -0.4440971  
## Feb 2008 -0.85615089 -1.062575707 -0.4440971  
## Mar 2008 -0.81594028 -0.980620216 2.2204854  
## Apr 2008 -0.87625620 -1.103553452 -0.4440971  
## May 2008 -0.81594028 -0.939642470 -0.4440971  
## Jun 2008 -0.67520315 -1.062575707 -0.4440971  
## Jul 2008 -0.59478193 -0.939642470 -0.4440971  
## Aug 2008 -0.57467663 -0.939642470 -0.4440971  
## Sep 2008 -0.55457132 -0.570842760 -0.4440971  
## Oct 2008 -0.67520315 -0.283998542 -0.4440971  
## Nov 2008 -0.99688803 -0.324976287 -0.4440971  
## Dec 2008 -1.11751986 -0.283998542 2.2204854  
## Jan 2009 -1.01699333 0.945333824 -0.4440971  
## Feb 2009 -1.03709864 -0.079109814 -0.4440971  
## Mar 2009 -1.07730925 0.412623132 -0.4440971  
## Apr 2009 -1.03709864 0.863378333 2.2204854  
## May 2009 -1.11751986 0.289689895 -0.4440971  
## Jun 2009 -1.23815168 0.699467350 -0.4440971  
## Jul 2009 -1.33867821 0.986311569 -0.4440971  
## Aug 2009 -1.25825699 0.699467350 -0.4440971  
## Sep 2009 -1.15773047 0.453600877 -0.4440971  
## Oct 2009 -1.25825699 -0.734753742 -0.4440971  
## Nov 2009 -1.27836229 -0.529865015 -0.4440971  
## Dec 2009 -1.17783577 -0.079109814 2.2204854  
## Jan 2010 -1.07730925 -0.734753742 -0.4440971  
## Feb 2010 -0.97678272 -0.939642470 -0.4440971  
## Mar 2010 -0.79583498 -1.062575707 -0.4440971  
## Apr 2010 -0.71541376 -0.980620216 2.2204854  
## May 2010 -0.91646681 -1.062575707 -0.4440971  
## Jun 2010 -0.75562437 -1.103553452 -0.4440971  
## Jul 2010 -0.67520315 -0.611820506 -0.4440971  
## Aug 2010 -0.67520315 -1.185508943 -0.4440971  
## Sep 2010 -0.59478193 -0.857686979 -0.4440971  
## Oct 2010 -0.65509785 -0.857686979 -0.4440971  
## Nov 2010 -0.47415010 -0.939642470 -0.4440971  
## Dec 2010 -0.29320236 -0.980620216 2.2204854  
## Jan 2011 -0.15246523 -0.120087560 -0.4440971  
## Feb 2011 0.02848252 -0.611820506 -0.4440971  
## Mar 2011 0.16921965 -0.570842760 -0.4440971  
## Apr 2011 0.26974617 -0.488887269 2.2204854  
## May 2011 0.33006209 -0.365954033 -0.4440971  
## Jun 2011 0.33006209 -0.570842760 -0.4440971  
## Jul 2011 0.45069391 -0.816709233 -0.4440971  
## Aug 2011 0.35016739 -1.062575707 -0.4440971  
## Sep 2011 0.30995678 -0.693775997 -0.4440971  
## Oct 2011 0.30995678 -0.857686979 -0.4440971  
## Nov 2011 0.35016739 -0.939642470 -0.4440971  
## Dec 2011 0.39037800 -0.980620216 2.2204854  
## Jan 2012 0.51100983 -0.939642470 -0.4440971  
## Feb 2012 0.71206288 0.125778913 -0.4440971  
## Mar 2012 0.83269471 0.207734404 -0.4440971  
## Apr 2012 0.77237879 -0.120087560 2.2204854  
## May 2012 0.71206288 -0.038132069 -0.4440971  
## Jun 2012 0.75227349 0.002845677 -0.4440971  
## Jul 2012 0.85280001 0.207734404 -0.4440971  
## Aug 2012 0.83269471 0.084801168 -0.4440971  
## Sep 2012 0.89301062 1.232178042 -0.4440971  
## Oct 2012 0.95332653 1.641955497 -0.4440971  
## Nov 2012 0.97343184 1.764888734 -0.4440971  
## Dec 2012 1.09406367 1.682933243 2.2204854  
## Jan 2013 1.25490611 1.641955497 -0.4440971  
## Feb 2013 1.31522202 1.519022261 -0.4440971  
## Mar 2013 1.49616976 1.437066770 2.2204854  
## Apr 2013 1.51627507 1.519022261 -0.4440971  
## May 2013 1.63690690 1.560000006 -0.4440971  
## Jun 2013 1.65701220 1.437066770 -0.4440971  
## Jul 2013 1.81785464 1.437066770 -0.4440971  
## Aug 2013 1.71732811 1.682933243 -0.4440971  
## Sep 2013 1.75753872 1.600977752 -0.4440971  
## Oct 2013 1.63690690 1.641955497 -0.4440971  
## Nov 2013 1.59669629 1.641955497 -0.4440971  
## Dec 2013 1.63690690 1.682933243 2.2204854  
## ChulwalarIndexVector InflationVector  
## Jan 2008 0.25840362 1.46874959  
## Feb 2008 0.17119839 1.45693527  
## Mar 2008 -0.00819425 1.82317917  
## Apr 2008 0.34009645 0.93710523  
## May 2008 0.46462605 1.68140734  
## Jun 2008 -0.10636535 1.92950804  
## Jul 2008 -0.05482658 2.02402259  
## Aug 2008 -0.10301584 1.78773621  
## Sep 2008 -0.60062928 1.40967800  
## Oct 2008 -1.31012904 0.91347659  
## Nov 2008 -1.57819968 -0.31521260  
## Dec 2008 -1.45973792 -0.56331330  
## Jan 2009 -1.85684066 -0.81141400  
## Feb 2009 -2.27309791 -0.57512762  
## Mar 2009 -2.07025865 -1.41394428  
## Apr 2009 -1.49403258 -1.05951471  
## May 2009 -1.34980985 -1.89833137  
## Jun 2009 -1.46088248 -1.78018817  
## Jul 2009 -1.02048011 -2.48904732  
## Aug 2009 -0.90899510 -1.89833137  
## Sep 2009 -0.73179900 -2.13461775  
## Oct 2009 -0.95077989 -1.89833137  
## Nov 2009 -0.77321349 -1.41394428  
## Dec 2009 -0.49424429 -0.94137151  
## Jan 2010 -0.78765512 -1.05951471  
## Feb 2010 -0.79634871 -1.29580109  
## Mar 2010 -0.32919229 -0.45698443  
## Apr 2010 -0.34421461 -0.46879875  
## May 2010 -0.48843734 -0.45698443  
## Jun 2010 -0.48743586 -0.82322832  
## Jul 2010 -0.33388834 -0.58694194  
## Aug 2010 -0.52135180 -0.70508513  
## Sep 2010 -0.26567773 -0.46879875  
## Oct 2010 0.04768711 -0.35065556  
## Nov 2010 0.12100616 -0.10255485  
## Dec 2010 0.31095230 -0.35065556  
## Jan 2011 0.44837501 0.13373153  
## Feb 2011 0.61234978 0.35820359  
## Mar 2011 0.41793481 0.46453247  
## Apr 2011 0.81613161 0.34638927  
## May 2011 0.63033449 0.46453247  
## Jun 2011 0.69980748 0.58267566  
## Jul 2011 0.51678760 0.58267566  
## Aug 2011 -0.63948534 0.58267566  
## Sep 2011 -0.87751134 0.93710523  
## Oct 2011 -0.33946806 0.81896204  
## Nov 2011 -0.38365137 0.92529091  
## Dec 2011 -0.54396524 0.44090383  
## Jan 2012 -0.07220534 0.57086134  
## Feb 2012 0.26204769 0.66537589  
## Mar 2012 0.33842169 0.65356157  
## Apr 2012 0.18218952 0.41727519  
## May 2012 -0.23591922 0.41727519  
## Jun 2012 -0.10808219 0.07465993  
## Jul 2012 0.19150588 0.29913200  
## Aug 2012 0.35858611 0.64174725  
## Sep 2012 0.56507785 0.52360406  
## Oct 2012 0.60251163 0.52360406  
## Nov 2012 0.42146106 0.40546087  
## Dec 2012 0.89854820 0.51178974  
## Jan 2013 1.03628230 0.05103130  
## Feb 2013 1.00737379 -0.06711190  
## Mar 2013 1.05249126 -0.19706941  
## Apr 2013 1.15213514 -0.53968466  
## May 2013 1.51833481 -0.07892622  
## Jun 2013 1.19043576 0.26368904  
## Jul 2013 1.45700838 0.37001791  
## Aug 2013 1.31156534 -0.09074053  
## Sep 2013 1.72499486 -0.20888373  
## Oct 2013 2.09488909 -0.43335579  
## Nov 2013 2.40743760 -0.31521260  
## Dec 2013 2.53103304 -0.20888373  
## IndependenceDayPresentsVector  
## Jan 2008 -0.60484269  
## Feb 2008 -0.60484269  
## Mar 2008 -0.60484269  
## Apr 2008 -0.60484269  
## May 2008 -0.60484269  
## Jun 2008 -0.60484269  
## Jul 2008 -0.60484269  
## Aug 2008 -0.60484269  
## Sep 2008 -0.60484269  
## Oct 2008 -0.60484269  
## Nov 2008 -0.60484269  
## Dec 2008 -0.60484269  
## Jan 2009 -0.34562439  
## Feb 2009 -0.34562439  
## Mar 2009 -0.34562439  
## Apr 2009 -0.34562439  
## May 2009 -0.34562439  
## Jun 2009 -0.34562439  
## Jul 2009 -0.34562439  
## Aug 2009 -0.34562439  
## Sep 2009 -0.34562439  
## Oct 2009 -0.34562439  
## Nov 2009 -0.34562439  
## Dec 2009 -0.34562439  
## Jan 2010 0.01728122  
## Feb 2010 0.01728122  
## Mar 2010 0.01728122  
## Apr 2010 0.01728122  
## May 2010 0.01728122  
## Jun 2010 0.01728122  
## Jul 2010 0.01728122  
## Aug 2010 0.01728122  
## Sep 2010 0.01728122  
## Oct 2010 0.01728122  
## Nov 2010 0.01728122  
## Dec 2010 0.01728122  
## Jan 2011 -1.01959196  
## Feb 2011 -1.01959196  
## Mar 2011 -1.01959196  
## Apr 2011 -1.01959196  
## May 2011 -1.01959196  
## Jun 2011 -1.01959196  
## Jul 2011 -1.01959196  
## Aug 2011 -1.01959196  
## Sep 2011 -1.01959196  
## Oct 2011 -1.01959196  
## Nov 2011 -1.01959196  
## Dec 2011 -1.01959196  
## Jan 2012 -0.13824976  
## Feb 2012 -0.13824976  
## Mar 2012 -0.13824976  
## Apr 2012 -0.13824976  
## May 2012 -0.13824976  
## Jun 2012 -0.13824976  
## Jul 2012 -0.13824976  
## Aug 2012 -0.13824976  
## Sep 2012 -0.13824976  
## Oct 2012 -0.13824976  
## Nov 2012 -0.13824976  
## Dec 2012 -0.13824976  
## Jan 2013 2.09102758  
## Feb 2013 2.09102758  
## Mar 2013 2.09102758  
## Apr 2013 2.09102758  
## May 2013 2.09102758  
## Jun 2013 2.09102758  
## Jul 2013 2.09102758  
## Aug 2013 2.09102758  
## Sep 2013 2.09102758  
## Oct 2013 2.09102758  
## Nov 2013 2.09102758  
## Dec 2013 2.09102758  
## attr(,"scaled:center")  
## CEPIVector SIGovVector   
## 1.015583e+02 -6.719444e+00   
## TemperatureVector BirthsVector   
## 8.986528e+00 5.616507e+04   
## SIGovVector UrbanoExportsVector   
## -6.719444e+00 6.483333e+06   
## GlobalisationPartyMembersVector AEPIVector   
## 5.438950e+04 1.035583e+02   
## PPIEtel NationalHolidaysVector   
## 1.022931e+02 1.666667e-01   
## ChulwalarIndexVector InflationVector   
## 6.544707e+03 1.606806e+00   
## IndependenceDayPresentsVector   
## 2.326667e+02   
## attr(,"scaled:scale")  
## CEPIVector SIGovVector   
## 2.719245e+00 1.049779e+01   
## TemperatureVector BirthsVector   
## 6.719863e+00 3.702803e+03   
## SIGovVector UrbanoExportsVector   
## 1.049779e+01 6.571299e+05   
## GlobalisationPartyMembersVector AEPIVector   
## 6.171462e+03 4.973812e+00   
## PPIEtel NationalHolidaysVector   
## 2.440349e+00 3.752933e-01   
## ChulwalarIndexVector InflationVector   
## 1.188232e+03 8.464305e-01   
## IndependenceDayPresentsVector   
## 1.928876e+01

# The dimensions of the matrix are determined by the number of indicators.  
NumberOfIndicators=dim(IndicatorsmatrixStandardised)[1]  
NumberOfIndicators

## [1] 72

# Produce the IndicatorsCorrelationCoefficientMatrix.  
IndicatorsCorrelationCoefficientMatrix=(1/(NumberOfIndicators-1))\*t(IndicatorsmatrixStandardised)%\*%IndicatorsmatrixStandardised  
IndicatorsCorrelationCoefficientMatrix

## CEPIVector SIGovVector TemperatureVector  
## CEPIVector 1.00000000 0.38443508 0.061196862  
## SIGovVector 0.38443508 1.00000000 0.088109231  
## TemperatureVector 0.06119686 0.08810923 1.000000000  
## BirthsVector 0.08872676 0.12753378 0.744270853  
## SIGovVector 0.38443508 1.00000000 0.088109231  
## UrbanoExportsVector 0.97660022 0.40700264 -0.001244458  
## GlobalisationPartyMembersVector 0.91557949 0.49433954 -0.009695828  
## AEPIVector 0.97697428 0.45955807 0.055196145  
## PPIEtel 0.65446147 -0.23602751 -0.013959906  
## NationalHolidaysVector 0.04830482 -0.02025819 -0.316148237  
## ChulwalarIndexVector 0.76208613 0.63652935 0.036317166  
## InflationVector 0.16379793 0.55866085 0.054966975  
## IndependenceDayPresentsVector 0.64887003 0.03237405 -0.040110690  
## BirthsVector SIGovVector  
## CEPIVector 0.08872676 0.38443508  
## SIGovVector 0.12753378 1.00000000  
## TemperatureVector 0.74427085 0.08810923  
## BirthsVector 1.00000000 0.12753378  
## SIGovVector 0.12753378 1.00000000  
## UrbanoExportsVector 0.03139251 0.40700264  
## GlobalisationPartyMembersVector -0.01768274 0.49433954  
## AEPIVector 0.09673808 0.45955807  
## PPIEtel 0.05960084 -0.23602751  
## NationalHolidaysVector -0.37785553 -0.02025819  
## ChulwalarIndexVector 0.11795545 0.63652935  
## InflationVector 0.11231574 0.55866085  
## IndependenceDayPresentsVector 0.10063892 0.03237405  
## UrbanoExportsVector  
## CEPIVector 9.766002e-01  
## SIGovVector 4.070026e-01  
## TemperatureVector -1.244458e-03  
## BirthsVector 3.139251e-02  
## SIGovVector 4.070026e-01  
## UrbanoExportsVector 1.000000e+00  
## GlobalisationPartyMembersVector 9.121013e-01  
## AEPIVector 9.827920e-01  
## PPIEtel 6.521194e-01  
## NationalHolidaysVector -1.876433e-17  
## ChulwalarIndexVector 7.856783e-01  
## InflationVector 1.985267e-01  
## IndependenceDayPresentsVector 6.699996e-01  
## GlobalisationPartyMembersVector AEPIVector  
## CEPIVector 9.155795e-01 0.97697428  
## SIGovVector 4.943395e-01 0.45955807  
## TemperatureVector -9.695828e-03 0.05519615  
## BirthsVector -1.768274e-02 0.09673808  
## SIGovVector 4.943395e-01 0.45955807  
## UrbanoExportsVector 9.121013e-01 0.98279202  
## GlobalisationPartyMembersVector 1.000000e+00 0.88225030  
## AEPIVector 8.822503e-01 1.00000000  
## PPIEtel 4.583532e-01 0.62229942  
## NationalHolidaysVector 1.250956e-17 0.01886347  
## ChulwalarIndexVector 6.647301e-01 0.80958140  
## InflationVector 9.009471e-02 0.30646256  
## IndependenceDayPresentsVector 4.606363e-01 0.64313387  
## PPIEtel NationalHolidaysVector  
## CEPIVector 0.65446147 4.830482e-02  
## SIGovVector -0.23602751 -2.025819e-02  
## TemperatureVector -0.01395991 -3.161482e-01  
## BirthsVector 0.05960084 -3.778555e-01  
## SIGovVector -0.23602751 -2.025819e-02  
## UrbanoExportsVector 0.65211942 -1.876433e-17  
## GlobalisationPartyMembersVector 0.45835315 1.250956e-17  
## AEPIVector 0.62229942 1.886347e-02  
## PPIEtel 1.00000000 2.896317e-02  
## NationalHolidaysVector 0.02896317 1.000000e+00  
## ChulwalarIndexVector 0.45429124 5.430333e-02  
## InflationVector -0.25048037 -9.384951e-03  
## IndependenceDayPresentsVector 0.71474813 0.000000e+00  
## ChulwalarIndexVector InflationVector  
## CEPIVector 0.76208613 0.163797927  
## SIGovVector 0.63652935 0.558660851  
## TemperatureVector 0.03631717 0.054966975  
## BirthsVector 0.11795545 0.112315739  
## SIGovVector 0.63652935 0.558660851  
## UrbanoExportsVector 0.78567826 0.198526676  
## GlobalisationPartyMembersVector 0.66473014 0.090094706  
## AEPIVector 0.80958140 0.306462559  
## PPIEtel 0.45429124 -0.250480368  
## NationalHolidaysVector 0.05430333 -0.009384951  
## ChulwalarIndexVector 1.00000000 0.341955823  
## InflationVector 0.34195582 1.000000000  
## IndependenceDayPresentsVector 0.62615921 -0.185842679  
## IndependenceDayPresentsVector  
## CEPIVector 0.64887003  
## SIGovVector 0.03237405  
## TemperatureVector -0.04011069  
## BirthsVector 0.10063892  
## SIGovVector 0.03237405  
## UrbanoExportsVector 0.66999963  
## GlobalisationPartyMembersVector 0.46063633  
## AEPIVector 0.64313387  
## PPIEtel 0.71474813  
## NationalHolidaysVector 0.00000000  
## ChulwalarIndexVector 0.62615921  
## InflationVector -0.18584268  
## IndependenceDayPresentsVector 1.00000000

#mywait()  
  
# The Correlation Coefficient Matrix shows that CEPI has a high correlation with SIExtern,   
# UrbanoExports, GlobalisationPartyMembers and AEPI .   
# These will become the set of indicators used later, although we are aware of the dangers of multicollinearity.  
  
# However it is interesting to note that NationalHolidays, UrbanoExports, GlobalisationPartyMembers have a very low  
# correlation with one another.   
# Therefore these will also become a set of indicators used later.  
  
  
#################################################################################  
### ###  
### 4. Development of forecasting models ###  
### ###  
#################################################################################   
  
# With help of the tslm function, we will produce a model based on the time series.  
# Possible inputs could be Trend and Seasonality as well as the time series of  
# the indicators.   
  
#################################################################################  
# 4.1 ModelWithAlllIndicators and with each indicator individually #  
#################################################################################  
  
# All Indiators in one model:  
ModelWithAlllIndicators <- tslm(TotalAsIs ~ trend + season + CEPI + SIGov + Temperature + Births + SIExtern + UrbanoExports + GlobalisationPartyMembers + AEPI + PPIEtel + NationalHolidays + ChulwalarIndex + Inflation + IndependenceDayPresents)  
summary(ModelWithAlllIndicators)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + CEPI + SIGov + Temperature +   
## Births + SIExtern + UrbanoExports + GlobalisationPartyMembers +   
## AEPI + PPIEtel + NationalHolidays + ChulwalarIndex + Inflation +   
## IndependenceDayPresents)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -458389 -119426 1119 165463 342741   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -8.982e+05 2.301e+07 -0.039 0.96904   
## trend 3.176e+03 3.849e+04 0.083 0.93458   
## season2 3.146e+05 2.678e+05 1.175 0.24624   
## season3 5.172e+05 2.649e+05 1.953 0.05695 .   
## season4 2.972e+05 3.413e+05 0.871 0.38836   
## season5 -7.277e+04 3.661e+05 -0.199 0.84333   
## season6 -2.597e+05 4.199e+05 -0.618 0.53932   
## season7 -7.550e+05 5.225e+05 -1.445 0.15525   
## season8 -2.869e+05 4.990e+05 -0.575 0.56809   
## season9 1.066e+06 4.225e+05 2.523 0.01517 \*   
## season10 8.033e+05 3.352e+05 2.396 0.02068 \*   
## season11 1.226e+06 3.555e+05 3.449 0.00122 \*\*  
## season12 9.734e+05 3.645e+05 2.670 0.01044 \*   
## CEPI -3.551e+04 2.516e+05 -0.141 0.88838   
## SIGov -1.506e+04 9.150e+03 -1.646 0.10657   
## Temperature -3.108e+04 2.069e+04 -1.502 0.14003   
## Births 8.045e+01 3.894e+01 2.066 0.04448 \*   
## SIExtern 3.706e+04 5.872e+04 0.631 0.53109   
## UrbanoExports 5.323e-01 5.675e-01 0.938 0.35317   
## GlobalisationPartyMembers 7.324e+01 6.583e+01 1.113 0.27163   
## AEPI -6.003e+04 7.476e+04 -0.803 0.42612   
## PPIEtel 7.799e+03 3.622e+04 0.215 0.83048   
## NationalHolidays -3.192e+05 1.718e+05 -1.858 0.06963 .   
## ChulwalarIndex 6.102e+01 7.545e+01 0.809 0.42284   
## Inflation 7.058e+04 1.555e+05 0.454 0.65213   
## IndependenceDayPresents 4.211e+01 6.187e+03 0.007 0.99460   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 249400 on 46 degrees of freedom  
## Multiple R-squared: 0.9421, Adjusted R-squared: 0.9106   
## F-statistic: 29.94 on 25 and 46 DF, p-value: < 2.2e-16

# Adjusted R²: 0.9106  
  
# CEPI:  
# The CEPI Indicator correlated best with total exports. Indeed the multiple R²   
# improved the model slighltly compared to the simple ModelWithTrendAndSeasonalityOnly   
# However the adjusted R² remains the same.  
ModelWithCEPI <- tslm(TotalAsIs ~ trend + season + CEPI)  
summary(ModelWithCEPI)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + CEPI)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -670684 -142117 7024 168664 495366   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -2946424 5153463 -0.572 0.569710   
## trend 19698 6926 2.844 0.006145 \*\*   
## season2 -153665 153683 -1.000 0.321523   
## season3 8677 156732 0.055 0.956039   
## season4 -634082 154130 -4.114 0.000124 \*\*\*  
## season5 -648875 154240 -4.207 9.09e-05 \*\*\*  
## season6 -906108 153943 -5.886 2.10e-07 \*\*\*  
## season7 -1112258 155872 -7.136 1.73e-09 \*\*\*  
## season8 -755527 155490 -4.859 9.34e-06 \*\*\*  
## season9 683382 154129 4.434 4.18e-05 \*\*\*  
## season10 287071 153168 1.874 0.065940 .   
## season11 465878 152885 3.047 0.003474 \*\*   
## season12 50523 154712 0.327 0.745176   
## CEPI 53135 53376 0.995 0.323636   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 263300 on 58 degrees of freedom  
## Multiple R-squared: 0.9187, Adjusted R-squared: 0.9004   
## F-statistic: 50.39 on 13 and 58 DF, p-value: < 2.2e-16

# Adjusted R²: 0.9004  
  
# SIGov:  
# The Satisfaction Index (gov) hardly changes the function of the model.  
ModelWithSIGov <- tslm(TotalAsIs ~ trend + season + SIGov)  
summary(ModelWithSIGov)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + SIGov)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -697126 -157160 22782 161382 486711   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2154993 126151 17.083 < 2e-16 \*\*\*  
## trend 26826 1656 16.196 < 2e-16 \*\*\*  
## season2 -133003 152843 -0.870 0.387782   
## season3 44751 152866 0.293 0.770763   
## season4 -606128 152952 -3.963 0.000205 \*\*\*  
## season5 -622634 152935 -4.071 0.000143 \*\*\*  
## season6 -881666 153013 -5.762 3.35e-07 \*\*\*  
## season7 -1075681 153183 -7.022 2.69e-09 \*\*\*  
## season8 -726089 153194 -4.740 1.43e-05 \*\*\*  
## season9 705690 153291 4.604 2.31e-05 \*\*\*  
## season10 297924 153457 1.941 0.057071 .   
## season11 468770 153659 3.051 0.003439 \*\*   
## season12 68494 153977 0.445 0.658095   
## SIGov -2003 3274 -0.612 0.543174   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 264700 on 58 degrees of freedom  
## Multiple R-squared: 0.9178, Adjusted R-squared: 0.8994   
## F-statistic: 49.81 on 13 and 58 DF, p-value: < 2.2e-16

# Adjusted R²: 0.8994  
  
# Temperature:  
ModelWithTemperature <- tslm(TotalAsIs ~ trend + season + Temperature)  
summary(ModelWithTemperature)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + Temperature)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -706803 -154965 23511 160215 483373   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2185999 118102 18.509 < 2e-16 \*\*\*  
## trend 26367 1526 17.278 < 2e-16 \*\*\*  
## season2 -130163 152875 -0.851 0.39803   
## season3 91513 171443 0.534 0.59553   
## season4 -504879 236159 -2.138 0.03675 \*   
## season5 -476774 296010 -1.611 0.11268   
## season6 -703539 345717 -2.035 0.04643 \*   
## season7 -873818 386156 -2.263 0.02740 \*   
## season8 -524053 378812 -1.383 0.17184   
## season9 858772 305542 2.811 0.00673 \*\*   
## season10 401142 232466 1.726 0.08974 .   
## season11 530742 183985 2.885 0.00549 \*\*   
## season12 85552 155077 0.552 0.58329   
## Temperature -11344 19587 -0.579 0.56473   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 264800 on 58 degrees of freedom  
## Multiple R-squared: 0.9177, Adjusted R-squared: 0.8993   
## F-statistic: 49.78 on 13 and 58 DF, p-value: < 2.2e-16

# Adjusted R²: 0.8993   
  
# Births:  
ModelWithBirths <- tslm(TotalAsIs ~ trend + season + Births)  
summary(ModelWithBirths)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + Births)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -648252 -106586 23124 166173 443675   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -1.485e+06 1.452e+06 -1.023 0.310779   
## trend 2.633e+04 1.449e+03 18.163 < 2e-16 \*\*\*  
## season2 1.856e+05 1.918e+05 0.968 0.337199   
## season3 1.510e+05 1.512e+05 0.998 0.322286   
## season4 -4.181e+05 1.639e+05 -2.551 0.013402 \*   
## season5 -6.484e+05 1.459e+05 -4.444 4.04e-05 \*\*\*  
## season6 -9.698e+05 1.496e+05 -6.482 2.16e-08 \*\*\*  
## season7 -1.518e+06 2.265e+05 -6.704 9.20e-09 \*\*\*  
## season8 -1.068e+06 1.992e+05 -5.364 1.48e-06 \*\*\*  
## season9 3.721e+05 1.966e+05 1.893 0.063345 .   
## season10 2.114e+05 1.502e+05 1.407 0.164622   
## season11 6.744e+05 1.666e+05 4.049 0.000155 \*\*\*  
## season12 2.147e+05 1.565e+05 1.372 0.175458   
## Births 6.589e+01 2.601e+01 2.533 0.014026 \*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 251900 on 58 degrees of freedom  
## Multiple R-squared: 0.9255, Adjusted R-squared: 0.9088   
## F-statistic: 55.43 on 13 and 58 DF, p-value: < 2.2e-16

# Adjusted R²: 0.9088   
  
# SIExtern:  
ModelWithSIExtern <- tslm(TotalAsIs ~ trend + season + SIExtern)  
summary(ModelWithSIExtern)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + SIExtern)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -667444 -154044 -5891 162628 473612   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2124425 137869 15.409 < 2e-16 \*\*\*  
## trend 24163 3191 7.572 3.20e-10 \*\*\*  
## season2 -133767 152487 -0.877 0.383979   
## season3 43156 152535 0.283 0.778243   
## season4 -609825 152516 -3.998 0.000183 \*\*\*  
## season5 -624208 152569 -4.091 0.000134 \*\*\*  
## season6 -877941 152767 -5.747 3.55e-07 \*\*\*  
## season7 -1071287 153027 -7.001 2.92e-09 \*\*\*  
## season8 -710173 153873 -4.615 2.22e-05 \*\*\*  
## season9 722059 154265 4.681 1.76e-05 \*\*\*  
## season10 312879 153885 2.033 0.046617 \*   
## season11 486780 154278 3.155 0.002542 \*\*   
## season12 88661 154442 0.574 0.568139   
## SIExtern 26522 32881 0.807 0.423187   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 264000 on 58 degrees of freedom  
## Multiple R-squared: 0.9182, Adjusted R-squared: 0.8998   
## F-statistic: 50.07 on 13 and 58 DF, p-value: < 2.2e-16

# Adjusted R²: 0.8998   
  
# UrbanoExports:  
# Indicator with adjusted R² shows a better result than the reference model (ModelWithTrendAndSeasonalityOnly).  
# The individual months are also very significant.  
ModelWithTotalUrbanoExports <- tslm(TotalAsIs ~ trend + season + UrbanoExports)  
summary(ModelWithTotalUrbanoExports)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + UrbanoExports)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -651323 -145654 7297 172919 469753   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 1.232e+06 9.485e+05 1.299 0.199178   
## trend 2.118e+04 5.414e+03 3.912 0.000243 \*\*\*  
## season2 -1.259e+05 1.521e+05 -0.828 0.411030   
## season3 5.708e+04 1.524e+05 0.375 0.709261   
## season4 -5.934e+05 1.528e+05 -3.882 0.000267 \*\*\*  
## season5 -6.025e+05 1.535e+05 -3.925 0.000232 \*\*\*  
## season6 -8.568e+05 1.544e+05 -5.551 7.40e-07 \*\*\*  
## season7 -1.048e+06 1.554e+05 -6.741 7.96e-09 \*\*\*  
## season8 -6.879e+05 1.566e+05 -4.392 4.82e-05 \*\*\*  
## season9 7.477e+05 1.580e+05 4.732 1.47e-05 \*\*\*  
## season10 3.473e+05 1.596e+05 2.176 0.033640 \*   
## season11 5.246e+05 1.613e+05 3.252 0.001913 \*\*   
## season12 1.317e+05 1.632e+05 0.807 0.423118   
## UrbanoExports 1.717e-01 1.700e-01 1.010 0.316698   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 263200 on 58 degrees of freedom  
## Multiple R-squared: 0.9187, Adjusted R-squared: 0.9005   
## F-statistic: 50.41 on 13 and 58 DF, p-value: < 2.2e-16

# Adjusted R²: 0.9005   
  
# GlobalisationPartyMembers:  
ModelWithGlobalisationPartyMembers <- tslm(TotalAsIs ~ trend + season + GlobalisationPartyMembers)  
summary(ModelWithGlobalisationPartyMembers)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + GlobalisationPartyMembers)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -696019 -161848 22345 172443 478347   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2.629e+06 9.653e+05 2.724 0.008517 \*\*   
## trend 2.928e+04 6.311e+03 4.640 2.04e-05 \*\*\*  
## season2 -1.340e+05 1.531e+05 -0.875 0.385097   
## season3 4.087e+04 1.535e+05 0.266 0.791010   
## season4 -6.177e+05 1.542e+05 -4.006 0.000178 \*\*\*  
## season5 -6.350e+05 1.551e+05 -4.094 0.000133 \*\*\*  
## season6 -8.973e+05 1.562e+05 -5.744 3.59e-07 \*\*\*  
## season7 -1.096e+06 1.576e+05 -6.955 3.49e-09 \*\*\*  
## season8 -7.447e+05 1.593e+05 -4.676 1.79e-05 \*\*\*  
## season9 6.829e+05 1.611e+05 4.238 8.18e-05 \*\*\*  
## season10 2.743e+05 1.632e+05 1.681 0.098191 .   
## season11 4.435e+05 1.655e+05 2.680 0.009573 \*\*   
## season12 4.252e+04 1.680e+05 0.253 0.801132   
## GlobalisationPartyMembers -9.840e+00 2.111e+01 -0.466 0.642806   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 265000 on 58 degrees of freedom  
## Multiple R-squared: 0.9176, Adjusted R-squared: 0.8991   
## F-statistic: 49.67 on 13 and 58 DF, p-value: < 2.2e-16

# Adjusted R²: 0.8991   
  
# AEPI:  
ModelWithAEPI <- tslm(TotalAsIs ~ trend + season + AEPI)  
summary(ModelWithAEPI)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + AEPI)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -668980 -141696 1689 169009 482621   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 839421 1642691 0.511 0.611288   
## trend 23291 4116 5.658 4.95e-07 \*\*\*  
## season2 -134830 152491 -0.884 0.380247   
## season3 38792 152745 0.254 0.800419   
## season4 -615165 152666 -4.029 0.000165 \*\*\*  
## season5 -625294 152554 -4.099 0.000131 \*\*\*  
## season6 -884504 152617 -5.796 2.95e-07 \*\*\*  
## season7 -1082577 152748 -7.087 2.09e-09 \*\*\*  
## season8 -723603 152794 -4.736 1.45e-05 \*\*\*  
## season9 706895 152908 4.623 2.16e-05 \*\*\*  
## season10 308319 153364 2.010 0.049049 \*   
## season11 485176 154001 3.150 0.002578 \*\*   
## season12 85919 154027 0.558 0.579115   
## AEPI 14065 17159 0.820 0.415759   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 264000 on 58 degrees of freedom  
## Multiple R-squared: 0.9182, Adjusted R-squared: 0.8999   
## F-statistic: 50.09 on 13 and 58 DF, p-value: < 2.2e-16

# Adjusted R²: 0.8999  
  
# PPIEtel:  
ModelWithPPIEtel <- tslm(TotalAsIs ~ trend + season + PPIEtel)  
summary(ModelWithPPIEtel)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + PPIEtel)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -670282 -185589 19856 172554 468929   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 593668 1640506 0.362 0.718756   
## trend 25282 1919 13.172 < 2e-16 \*\*\*  
## season2 -122617 152330 -0.805 0.424141   
## season3 53107 152246 0.349 0.728486   
## season4 -603022 152264 -3.960 0.000207 \*\*\*  
## season5 -614727 152459 -4.032 0.000163 \*\*\*  
## season6 -872851 152619 -5.719 3.94e-07 \*\*\*  
## season7 -1073314 152456 -7.040 2.51e-09 \*\*\*  
## season8 -711389 153051 -4.648 1.98e-05 \*\*\*  
## season9 707996 152568 4.641 2.03e-05 \*\*\*  
## season10 307412 152867 2.011 0.048984 \*   
## season11 479843 153028 3.136 0.002692 \*\*   
## season12 80433 153124 0.525 0.601390   
## PPIEtel 15872 16347 0.971 0.335606   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 263400 on 58 degrees of freedom  
## Multiple R-squared: 0.9186, Adjusted R-squared: 0.9003   
## F-statistic: 50.34 on 13 and 58 DF, p-value: < 2.2e-16

# Adjusted R²: 0.9003   
  
# NationalHolidays:  
# Indicator with the best adjusted R². The months remain very significant and the indicator  
# itself has a p-value of 0,00636\*\*  
ModelWithNationalHolidays <- tslm(TotalAsIs ~ trend + season + NationalHolidays)  
summary(ModelWithNationalHolidays)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + NationalHolidays)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -555545 -153976 4 150487 404837   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2182435 110867 19.685 < 2e-16 \*\*\*  
## trend 26427 1431 18.465 < 2e-16 \*\*\*  
## season2 -131168 143696 -0.913 0.36512   
## season3 190430 152432 1.249 0.21658   
## season4 -321411 176034 -1.826 0.07302 .   
## season5 -623539 143803 -4.336 5.86e-05 \*\*\*  
## season6 -883072 143867 -6.138 8.06e-08 \*\*\*  
## season7 -1079124 143945 -7.497 4.29e-10 \*\*\*  
## season8 -724693 144037 -5.031 5.02e-06 \*\*\*  
## season9 705716 144144 4.896 8.18e-06 \*\*\*  
## season10 300019 144265 2.080 0.04199 \*   
## season11 472099 144400 3.269 0.00182 \*\*   
## season12 505461 210051 2.406 0.01932 \*   
## NationalHolidays -431536 152405 -2.832 0.00636 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 248900 on 58 degrees of freedom  
## Multiple R-squared: 0.9273, Adjusted R-squared: 0.911   
## F-statistic: 56.92 on 13 and 58 DF, p-value: < 2.2e-16

# Adjusted R²: 0.9110   
  
# ChulwalarIndex:  
ModelWithChulwalarIndex <- tslm(TotalAsIs ~ trend + season + ChulwalarIndex)  
summary(ModelWithChulwalarIndex)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + ChulwalarIndex)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -689635 -153608 9444 166039 495113   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2.013e+06 2.262e+05 8.898 1.96e-12 \*\*\*  
## trend 2.506e+04 2.176e+03 11.515 < 2e-16 \*\*\*  
## season2 -1.295e+05 1.523e+05 -0.850 0.398630   
## season3 4.684e+04 1.523e+05 0.308 0.759534   
## season4 -6.157e+05 1.525e+05 -4.036 0.000161 \*\*\*  
## season5 -6.281e+05 1.525e+05 -4.119 0.000122 \*\*\*  
## season6 -8.809e+05 1.525e+05 -5.776 3.18e-07 \*\*\*  
## season7 -1.082e+06 1.526e+05 -7.092 2.05e-09 \*\*\*  
## season8 -7.182e+05 1.528e+05 -4.699 1.65e-05 \*\*\*  
## season9 7.115e+05 1.529e+05 4.653 1.95e-05 \*\*\*  
## season10 3.049e+05 1.530e+05 1.993 0.050965 .   
## season11 4.779e+05 1.532e+05 3.120 0.002817 \*\*   
## season12 7.433e+04 1.532e+05 0.485 0.629364   
## ChulwalarIndex 3.339e+01 3.805e+01 0.878 0.383723   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 263800 on 58 degrees of freedom  
## Multiple R-squared: 0.9184, Adjusted R-squared: 0.9001   
## F-statistic: 50.18 on 13 and 58 DF, p-value: < 2.2e-16

# Adjusted R²: 0.9001  
  
# Inflation:  
ModelWithInflation <- tslm(TotalAsIs ~ trend + season + Inflation)  
summary(ModelWithInflation)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + Inflation)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -694867 -148205 9248 156635 501218   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2160745 132862 16.263 < 2e-16 \*\*\*  
## trend 26414 1526 17.313 < 2e-16 \*\*\*  
## season2 -131511 153141 -0.859 0.394009   
## season3 45633 153184 0.298 0.766848   
## season4 -607707 153249 -3.966 0.000204 \*\*\*  
## season5 -623065 153258 -4.065 0.000146 \*\*\*  
## season6 -882807 153322 -5.758 3.41e-07 \*\*\*  
## season7 -1078758 153407 -7.032 2.59e-09 \*\*\*  
## season8 -724536 153503 -4.720 1.53e-05 \*\*\*  
## season9 706375 153627 4.598 2.36e-05 \*\*\*  
## season10 301603 153808 1.961 0.054698 .   
## season11 474428 154026 3.080 0.003160 \*\*   
## season12 76824 154261 0.498 0.620359   
## Inflation 13335 37358 0.357 0.722422   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 265200 on 58 degrees of freedom  
## Multiple R-squared: 0.9174, Adjusted R-squared: 0.8989   
## F-statistic: 49.58 on 13 and 58 DF, p-value: < 2.2e-16

# Adjusted R²: 0.8989  
  
# IndependenceDayPresents:  
ModelWithIndependenceDayPresents <- tslm(TotalAsIs ~ trend + season + IndependenceDayPresents)  
summary(ModelWithIndependenceDayPresents)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + IndependenceDayPresents)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -704113 -161955 23265 169241 468613   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 1925395 469903 4.097 0.000131 \*\*\*  
## trend 25706 1986 12.944 < 2e-16 \*\*\*  
## season2 -130448 152891 -0.853 0.397053   
## season3 48026 152930 0.314 0.754620   
## season4 -606940 152994 -3.967 0.000203 \*\*\*  
## season5 -620657 153084 -4.054 0.000152 \*\*\*  
## season6 -879470 153200 -5.741 3.63e-07 \*\*\*  
## season7 -1074801 153342 -7.009 2.83e-09 \*\*\*  
## season8 -719650 153509 -4.688 1.72e-05 \*\*\*  
## season9 711480 153702 4.629 2.12e-05 \*\*\*  
## season10 306503 153919 1.991 0.051162 .   
## season11 479303 154163 3.109 0.002907 \*\*   
## season12 81850 154431 0.530 0.598127   
## IndependenceDayPresents 1201 2125 0.565 0.574184   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 264800 on 58 degrees of freedom  
## Multiple R-squared: 0.9177, Adjusted R-squared: 0.8993   
## F-statistic: 49.76 on 13 and 58 DF, p-value: < 2.2e-16

# Adjusted R²: 0.8993  
  
# InfluenceNationalHolidays:  
# Indicator with the best adjusted R². The months remain very significant and the indicator  
# itself has a p-value of 0,00636\*\*  
ModelWithInfluenceNationalHolidays <- tslm(TotalAsIs ~ trend + season + InfluenceNationalHolidays)  
summary(ModelWithInfluenceNationalHolidays)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + InfluenceNationalHolidays)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -555545 -153976 4 150487 404837   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2182435 110867 19.685 < 2e-16 \*\*\*  
## trend 26427 1431 18.465 < 2e-16 \*\*\*  
## season2 -131168 143696 -0.913 0.36512   
## season3 190430 152432 1.249 0.21658   
## season4 -321411 176034 -1.826 0.07302 .   
## season5 -623539 143803 -4.336 5.86e-05 \*\*\*  
## season6 -883072 143867 -6.138 8.06e-08 \*\*\*  
## season7 -1079124 143945 -7.497 4.29e-10 \*\*\*  
## season8 -724693 144037 -5.031 5.02e-06 \*\*\*  
## season9 1137252 209773 5.421 1.20e-06 \*\*\*  
## season10 300019 144265 2.080 0.04199 \*   
## season11 903635 209949 4.304 6.53e-05 \*\*\*  
## season12 505461 210051 2.406 0.01932 \*   
## InfluenceNationalHolidays -431536 152405 -2.832 0.00636 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 248900 on 58 degrees of freedom  
## Multiple R-squared: 0.9273, Adjusted R-squared: 0.911   
## F-statistic: 56.92 on 13 and 58 DF, p-value: < 2.2e-16

# Adjusted R²: 0.9110   
  
#################################################################################  
# 4.2.1 ModelWithHighCorrelatingIndicators #  
#################################################################################   
  
# In this model only the indicators that correlate well with eachother have been used.   
# See the CorrelationCoefficientMatrix for clarification.  
IndicatorsCorrelationCoefficientMatrix

## CEPIVector SIGovVector TemperatureVector  
## CEPIVector 1.00000000 0.38443508 0.061196862  
## SIGovVector 0.38443508 1.00000000 0.088109231  
## TemperatureVector 0.06119686 0.08810923 1.000000000  
## BirthsVector 0.08872676 0.12753378 0.744270853  
## SIGovVector 0.38443508 1.00000000 0.088109231  
## UrbanoExportsVector 0.97660022 0.40700264 -0.001244458  
## GlobalisationPartyMembersVector 0.91557949 0.49433954 -0.009695828  
## AEPIVector 0.97697428 0.45955807 0.055196145  
## PPIEtel 0.65446147 -0.23602751 -0.013959906  
## NationalHolidaysVector 0.04830482 -0.02025819 -0.316148237  
## ChulwalarIndexVector 0.76208613 0.63652935 0.036317166  
## InflationVector 0.16379793 0.55866085 0.054966975  
## IndependenceDayPresentsVector 0.64887003 0.03237405 -0.040110690  
## BirthsVector SIGovVector  
## CEPIVector 0.08872676 0.38443508  
## SIGovVector 0.12753378 1.00000000  
## TemperatureVector 0.74427085 0.08810923  
## BirthsVector 1.00000000 0.12753378  
## SIGovVector 0.12753378 1.00000000  
## UrbanoExportsVector 0.03139251 0.40700264  
## GlobalisationPartyMembersVector -0.01768274 0.49433954  
## AEPIVector 0.09673808 0.45955807  
## PPIEtel 0.05960084 -0.23602751  
## NationalHolidaysVector -0.37785553 -0.02025819  
## ChulwalarIndexVector 0.11795545 0.63652935  
## InflationVector 0.11231574 0.55866085  
## IndependenceDayPresentsVector 0.10063892 0.03237405  
## UrbanoExportsVector  
## CEPIVector 9.766002e-01  
## SIGovVector 4.070026e-01  
## TemperatureVector -1.244458e-03  
## BirthsVector 3.139251e-02  
## SIGovVector 4.070026e-01  
## UrbanoExportsVector 1.000000e+00  
## GlobalisationPartyMembersVector 9.121013e-01  
## AEPIVector 9.827920e-01  
## PPIEtel 6.521194e-01  
## NationalHolidaysVector -1.876433e-17  
## ChulwalarIndexVector 7.856783e-01  
## InflationVector 1.985267e-01  
## IndependenceDayPresentsVector 6.699996e-01  
## GlobalisationPartyMembersVector AEPIVector  
## CEPIVector 9.155795e-01 0.97697428  
## SIGovVector 4.943395e-01 0.45955807  
## TemperatureVector -9.695828e-03 0.05519615  
## BirthsVector -1.768274e-02 0.09673808  
## SIGovVector 4.943395e-01 0.45955807  
## UrbanoExportsVector 9.121013e-01 0.98279202  
## GlobalisationPartyMembersVector 1.000000e+00 0.88225030  
## AEPIVector 8.822503e-01 1.00000000  
## PPIEtel 4.583532e-01 0.62229942  
## NationalHolidaysVector 1.250956e-17 0.01886347  
## ChulwalarIndexVector 6.647301e-01 0.80958140  
## InflationVector 9.009471e-02 0.30646256  
## IndependenceDayPresentsVector 4.606363e-01 0.64313387  
## PPIEtel NationalHolidaysVector  
## CEPIVector 0.65446147 4.830482e-02  
## SIGovVector -0.23602751 -2.025819e-02  
## TemperatureVector -0.01395991 -3.161482e-01  
## BirthsVector 0.05960084 -3.778555e-01  
## SIGovVector -0.23602751 -2.025819e-02  
## UrbanoExportsVector 0.65211942 -1.876433e-17  
## GlobalisationPartyMembersVector 0.45835315 1.250956e-17  
## AEPIVector 0.62229942 1.886347e-02  
## PPIEtel 1.00000000 2.896317e-02  
## NationalHolidaysVector 0.02896317 1.000000e+00  
## ChulwalarIndexVector 0.45429124 5.430333e-02  
## InflationVector -0.25048037 -9.384951e-03  
## IndependenceDayPresentsVector 0.71474813 0.000000e+00  
## ChulwalarIndexVector InflationVector  
## CEPIVector 0.76208613 0.163797927  
## SIGovVector 0.63652935 0.558660851  
## TemperatureVector 0.03631717 0.054966975  
## BirthsVector 0.11795545 0.112315739  
## SIGovVector 0.63652935 0.558660851  
## UrbanoExportsVector 0.78567826 0.198526676  
## GlobalisationPartyMembersVector 0.66473014 0.090094706  
## AEPIVector 0.80958140 0.306462559  
## PPIEtel 0.45429124 -0.250480368  
## NationalHolidaysVector 0.05430333 -0.009384951  
## ChulwalarIndexVector 1.00000000 0.341955823  
## InflationVector 0.34195582 1.000000000  
## IndependenceDayPresentsVector 0.62615921 -0.185842679  
## IndependenceDayPresentsVector  
## CEPIVector 0.64887003  
## SIGovVector 0.03237405  
## TemperatureVector -0.04011069  
## BirthsVector 0.10063892  
## SIGovVector 0.03237405  
## UrbanoExportsVector 0.66999963  
## GlobalisationPartyMembersVector 0.46063633  
## AEPIVector 0.64313387  
## PPIEtel 0.71474813  
## NationalHolidaysVector 0.00000000  
## ChulwalarIndexVector 0.62615921  
## InflationVector -0.18584268  
## IndependenceDayPresentsVector 1.00000000

ModelWithHighCorrelatingIndicators <- tslm(TotalAsIs ~ trend + season + CEPI + SIExtern + UrbanoExports + GlobalisationPartyMembers + AEPI)  
summary(ModelWithHighCorrelatingIndicators)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + CEPI + SIExtern +   
## UrbanoExports + GlobalisationPartyMembers + AEPI)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -651383 -159842 14275 171424 489393   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -4.625e+06 1.240e+07 -0.373 0.71054   
## trend 1.446e+04 1.650e+04 0.876 0.38477   
## season2 -1.584e+05 1.724e+05 -0.919 0.36213   
## season3 7.086e+03 1.984e+05 0.036 0.97164   
## season4 -6.221e+05 1.862e+05 -3.341 0.00152 \*\*   
## season5 -6.417e+05 1.944e+05 -3.302 0.00171 \*\*   
## season6 -8.872e+05 1.983e+05 -4.473 4.01e-05 \*\*\*  
## season7 -1.088e+06 2.218e+05 -4.904 8.99e-06 \*\*\*  
## season8 -7.287e+05 2.260e+05 -3.225 0.00214 \*\*   
## season9 7.236e+05 2.261e+05 3.201 0.00230 \*\*   
## season10 3.199e+05 2.231e+05 1.434 0.15741   
## season11 4.997e+05 2.246e+05 2.225 0.03027 \*   
## season12 7.986e+04 2.585e+05 0.309 0.75853   
## CEPI 9.245e+04 1.672e+05 0.553 0.58252   
## SIExtern 2.378e+04 4.559e+04 0.522 0.60401   
## UrbanoExports 1.504e-01 5.104e-01 0.295 0.76934   
## GlobalisationPartyMembers 3.463e+00 2.546e+01 0.136 0.89233   
## AEPI -3.307e+04 5.992e+04 -0.552 0.58327   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 271600 on 54 degrees of freedom  
## Multiple R-squared: 0.9194, Adjusted R-squared: 0.8941   
## F-statistic: 36.25 on 17 and 54 DF, p-value: < 2.2e-16

# Adjusted R²: 0,8941  
# It can be seen that the addition of these indicators causes the seasonality to be weakened.   
# The individual indicators are not very significant either.   
# Is this a multicollinearity effect? Or is it just because we have chose irrelevant indicators?   
# An experimental idea comes from the next section:  
  
#################################################################################  
# 4.2.2 ModelWithLowCorrelatingIndicators #  
#################################################################################   
  
# In this model only the indicators that hardly correlate at all with eachother have been used.   
# See the CorrelationCoefficientMatrix for clarification.  
IndicatorsCorrelationCoefficientMatrix

## CEPIVector SIGovVector TemperatureVector  
## CEPIVector 1.00000000 0.38443508 0.061196862  
## SIGovVector 0.38443508 1.00000000 0.088109231  
## TemperatureVector 0.06119686 0.08810923 1.000000000  
## BirthsVector 0.08872676 0.12753378 0.744270853  
## SIGovVector 0.38443508 1.00000000 0.088109231  
## UrbanoExportsVector 0.97660022 0.40700264 -0.001244458  
## GlobalisationPartyMembersVector 0.91557949 0.49433954 -0.009695828  
## AEPIVector 0.97697428 0.45955807 0.055196145  
## PPIEtel 0.65446147 -0.23602751 -0.013959906  
## NationalHolidaysVector 0.04830482 -0.02025819 -0.316148237  
## ChulwalarIndexVector 0.76208613 0.63652935 0.036317166  
## InflationVector 0.16379793 0.55866085 0.054966975  
## IndependenceDayPresentsVector 0.64887003 0.03237405 -0.040110690  
## BirthsVector SIGovVector  
## CEPIVector 0.08872676 0.38443508  
## SIGovVector 0.12753378 1.00000000  
## TemperatureVector 0.74427085 0.08810923  
## BirthsVector 1.00000000 0.12753378  
## SIGovVector 0.12753378 1.00000000  
## UrbanoExportsVector 0.03139251 0.40700264  
## GlobalisationPartyMembersVector -0.01768274 0.49433954  
## AEPIVector 0.09673808 0.45955807  
## PPIEtel 0.05960084 -0.23602751  
## NationalHolidaysVector -0.37785553 -0.02025819  
## ChulwalarIndexVector 0.11795545 0.63652935  
## InflationVector 0.11231574 0.55866085  
## IndependenceDayPresentsVector 0.10063892 0.03237405  
## UrbanoExportsVector  
## CEPIVector 9.766002e-01  
## SIGovVector 4.070026e-01  
## TemperatureVector -1.244458e-03  
## BirthsVector 3.139251e-02  
## SIGovVector 4.070026e-01  
## UrbanoExportsVector 1.000000e+00  
## GlobalisationPartyMembersVector 9.121013e-01  
## AEPIVector 9.827920e-01  
## PPIEtel 6.521194e-01  
## NationalHolidaysVector -1.876433e-17  
## ChulwalarIndexVector 7.856783e-01  
## InflationVector 1.985267e-01  
## IndependenceDayPresentsVector 6.699996e-01  
## GlobalisationPartyMembersVector AEPIVector  
## CEPIVector 9.155795e-01 0.97697428  
## SIGovVector 4.943395e-01 0.45955807  
## TemperatureVector -9.695828e-03 0.05519615  
## BirthsVector -1.768274e-02 0.09673808  
## SIGovVector 4.943395e-01 0.45955807  
## UrbanoExportsVector 9.121013e-01 0.98279202  
## GlobalisationPartyMembersVector 1.000000e+00 0.88225030  
## AEPIVector 8.822503e-01 1.00000000  
## PPIEtel 4.583532e-01 0.62229942  
## NationalHolidaysVector 1.250956e-17 0.01886347  
## ChulwalarIndexVector 6.647301e-01 0.80958140  
## InflationVector 9.009471e-02 0.30646256  
## IndependenceDayPresentsVector 4.606363e-01 0.64313387  
## PPIEtel NationalHolidaysVector  
## CEPIVector 0.65446147 4.830482e-02  
## SIGovVector -0.23602751 -2.025819e-02  
## TemperatureVector -0.01395991 -3.161482e-01  
## BirthsVector 0.05960084 -3.778555e-01  
## SIGovVector -0.23602751 -2.025819e-02  
## UrbanoExportsVector 0.65211942 -1.876433e-17  
## GlobalisationPartyMembersVector 0.45835315 1.250956e-17  
## AEPIVector 0.62229942 1.886347e-02  
## PPIEtel 1.00000000 2.896317e-02  
## NationalHolidaysVector 0.02896317 1.000000e+00  
## ChulwalarIndexVector 0.45429124 5.430333e-02  
## InflationVector -0.25048037 -9.384951e-03  
## IndependenceDayPresentsVector 0.71474813 0.000000e+00  
## ChulwalarIndexVector InflationVector  
## CEPIVector 0.76208613 0.163797927  
## SIGovVector 0.63652935 0.558660851  
## TemperatureVector 0.03631717 0.054966975  
## BirthsVector 0.11795545 0.112315739  
## SIGovVector 0.63652935 0.558660851  
## UrbanoExportsVector 0.78567826 0.198526676  
## GlobalisationPartyMembersVector 0.66473014 0.090094706  
## AEPIVector 0.80958140 0.306462559  
## PPIEtel 0.45429124 -0.250480368  
## NationalHolidaysVector 0.05430333 -0.009384951  
## ChulwalarIndexVector 1.00000000 0.341955823  
## InflationVector 0.34195582 1.000000000  
## IndependenceDayPresentsVector 0.62615921 -0.185842679  
## IndependenceDayPresentsVector  
## CEPIVector 0.64887003  
## SIGovVector 0.03237405  
## TemperatureVector -0.04011069  
## BirthsVector 0.10063892  
## SIGovVector 0.03237405  
## UrbanoExportsVector 0.66999963  
## GlobalisationPartyMembersVector 0.46063633  
## AEPIVector 0.64313387  
## PPIEtel 0.71474813  
## NationalHolidaysVector 0.00000000  
## ChulwalarIndexVector 0.62615921  
## InflationVector -0.18584268  
## IndependenceDayPresentsVector 1.00000000

ModelWithLowCorrelatingIndicators <- tslm(TotalAsIs ~ trend + season + NationalHolidays + UrbanoExports + GlobalisationPartyMembers)  
summary(ModelWithLowCorrelatingIndicators)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + NationalHolidays +   
## UrbanoExports + GlobalisationPartyMembers)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -508755 -122676 7119 173089 403964   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 1.467e+06 1.517e+06 0.967 0.337647   
## trend 2.264e+04 9.148e+03 2.474 0.016399 \*   
## season2 -1.274e+05 1.450e+05 -0.878 0.383528   
## season3 1.980e+05 1.546e+05 1.281 0.205562   
## season4 -3.100e+05 1.794e+05 -1.728 0.089424 .   
## season5 -6.084e+05 1.493e+05 -4.075 0.000146 \*\*\*  
## season6 -8.641e+05 1.518e+05 -5.693 4.78e-07 \*\*\*  
## season7 -1.056e+06 1.548e+05 -6.824 6.75e-09 \*\*\*  
## season8 -6.982e+05 1.583e+05 -4.411 4.72e-05 \*\*\*  
## season9 7.360e+05 1.622e+05 4.538 3.05e-05 \*\*\*  
## season10 3.341e+05 1.665e+05 2.007 0.049635 \*   
## season11 5.100e+05 1.712e+05 2.979 0.004276 \*\*   
## season12 5.471e+05 2.338e+05 2.341 0.022838 \*   
## NationalHolidays -4.315e+05 1.535e+05 -2.811 0.006794 \*\*   
## UrbanoExports 1.622e-01 1.692e-01 0.959 0.341873   
## GlobalisationPartyMembers -4.032e+00 2.086e+01 -0.193 0.847464   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 250700 on 56 degrees of freedom  
## Multiple R-squared: 0.9288, Adjusted R-squared: 0.9097   
## F-statistic: 48.69 on 15 and 56 DF, p-value: < 2.2e-16

# Adjusted R²: 0.9097  
# It can be seen that the addition of these indicators causes the seasonality to be weakened.   
# The individual indicators are not very significant either. Thus we should continue with  
# trend and \*seasonality\*; the comparison of 4.3 and 4.4 confirms this:   
  
#################################################################################  
# 4.3 ModelWithTrendAndSeasonalityOnly #  
#################################################################################  
  
ModelWithTrendAndSeasonalityOnly <- tslm(TotalAsIs ~ trend + season)  
summary(ModelWithTrendAndSeasonalityOnly)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -699390 -154210 17753 150363 495430   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2182435 117276 18.609 < 2e-16 \*\*\*  
## trend 26427 1514 17.456 < 2e-16 \*\*\*  
## season2 -131168 152001 -0.863 0.391663   
## season3 46585 152024 0.306 0.760356   
## season4 -609102 152062 -4.006 0.000176 \*\*\*  
## season5 -623539 152114 -4.099 0.000129 \*\*\*  
## season6 -883072 152182 -5.803 2.74e-07 \*\*\*  
## season7 -1079124 152265 -7.087 1.93e-09 \*\*\*  
## season8 -724693 152363 -4.756 1.31e-05 \*\*\*  
## season9 705716 152476 4.628 2.07e-05 \*\*\*  
## season10 300019 152603 1.966 0.054009 .   
## season11 472099 152746 3.091 0.003045 \*\*   
## season12 73925 152903 0.483 0.630546   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 263300 on 59 degrees of freedom  
## Multiple R-squared: 0.9173, Adjusted R-squared: 0.9004   
## F-statistic: 54.51 on 12 and 59 DF, p-value: < 2.2e-16

# Adjusted R²: 0,9004  
# Remains one of the best models when looking at total exports.  
  
#################################################################################  
# 4.4 ModelWithoutTrendAndSeasonality #  
#################################################################################  
  
ModelWithoutTrendAndSeasonality <- tslm(TotalAsIs ~ CEPI + SIExtern + UrbanoExports + GlobalisationPartyMembers + AEPI)  
summary(ModelWithoutTrendAndSeasonality)

##   
## Call:  
## tslm(formula = TotalAsIs ~ CEPI + SIExtern + UrbanoExports +   
## GlobalisationPartyMembers + AEPI)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -1246553 -546934 -10272 433938 1304765   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -2.101e+07 1.024e+07 -2.052 0.0442 \*  
## CEPI 3.277e+05 1.591e+05 2.059 0.0434 \*  
## SIExtern 4.274e+04 9.598e+04 0.445 0.6575   
## UrbanoExports -7.051e-04 7.794e-01 -0.001 0.9993   
## GlobalisationPartyMembers 1.126e+01 3.341e+01 0.337 0.7372   
## AEPI -9.807e+04 9.917e+04 -0.989 0.3263   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 638100 on 66 degrees of freedom  
## Multiple R-squared: 0.4562, Adjusted R-squared: 0.415   
## F-statistic: 11.07 on 5 and 66 DF, p-value: 9.091e-08

# Adjusted R²: 0,415  
  
#################################################################################  
# 4.5 ModelWithEfakExportsIndicators #  
#################################################################################  
  
# ModelWithEfakExportsIndicators will be matched with a set of indicators that correlate with the Efak exports.  
# The adjusted R² has the best value. However the diffent months and indicators are not significant apart from   
# GlobaliationPartyMembers. When testing the forecasts based on this model it generated unrealistic exports which were   
# much higher than the As Is data.  
ModelWithEfakExportsIndicators <- tslm(EfakAsIs ~ trend + season + CEPI + UrbanoExports + AEPI + GlobalisationPartyMembers)  
summary(ModelWithEfakExportsIndicators)

##   
## Call:  
## tslm(formula = EfakAsIs ~ trend + season + CEPI + UrbanoExports +   
## AEPI + GlobalisationPartyMembers)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -206351 -42410 1361 43841 136945   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -7.035e+06 3.116e+06 -2.258 0.02795 \*   
## trend -5.436e+03 4.150e+03 -1.310 0.19572   
## season2 5.681e+03 4.600e+04 0.124 0.90215   
## season3 1.032e+05 5.209e+04 1.982 0.05252 .   
## season4 -5.163e+04 4.977e+04 -1.037 0.30406   
## season5 8.140e+04 5.153e+04 1.580 0.11991   
## season6 -4.499e+03 5.317e+04 -0.085 0.93288   
## season7 -5.109e+04 5.926e+04 -0.862 0.39235   
## season8 -1.325e+04 6.065e+04 -0.218 0.82793   
## season9 4.354e+04 6.111e+04 0.712 0.47918   
## season10 8.939e+04 6.013e+04 1.487 0.14282   
## season11 1.918e+05 6.062e+04 3.164 0.00254 \*\*  
## season12 1.091e+05 6.892e+04 1.583 0.11917   
## CEPI 6.689e+04 4.081e+04 1.639 0.10691   
## UrbanoExports 1.593e-01 1.340e-01 1.189 0.23970   
## AEPI -9.785e+03 1.521e+04 -0.643 0.52269   
## GlobalisationPartyMembers 2.075e+01 6.708e+00 3.093 0.00311 \*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 73760 on 55 degrees of freedom  
## Multiple R-squared: 0.9404, Adjusted R-squared: 0.923   
## F-statistic: 54.19 on 16 and 55 DF, p-value: < 2.2e-16

# Adjusted R²: 0,923  
  
ModelEfakSalesWithCEPI <- tslm(EfakAsIs ~ trend + season + CEPI)  
summary(ModelEfakSalesWithCEPI)

##   
## Call:  
## tslm(formula = EfakAsIs ~ trend + season + CEPI)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -222832 -42379 9954 49151 189313   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -6118687 1539297 -3.975 0.000197 \*\*\*  
## trend 3310 2069 1.600 0.115103   
## season2 -7640 45904 -0.166 0.868386   
## season3 76216 46815 1.628 0.108934   
## season4 -88395 46037 -1.920 0.059770 .   
## season5 36746 46070 0.798 0.428348   
## season6 -59835 45982 -1.301 0.198309   
## season7 -118673 46558 -2.549 0.013473 \*   
## season8 -88571 46444 -1.907 0.061471 .   
## season9 -42658 46037 -0.927 0.357975   
## season10 -2795 45750 -0.061 0.951495   
## season11 91980 45666 2.014 0.048632 \*   
## season12 -2248 46211 -0.049 0.961362   
## CEPI 66608 15943 4.178 0.000100 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 78640 on 58 degrees of freedom  
## Multiple R-squared: 0.9285, Adjusted R-squared: 0.9125   
## F-statistic: 57.94 on 13 and 58 DF, p-value: < 2.2e-16

# Adjusted R²: 0,9125  
  
# ModelEfakSalesWithTrendAnsSeasonalityOnly does not seem to be anything special, but it returns fairly good results.  
ModelEfakSalesWithTrendAnsSeasonalityOnly <- tslm(EfakAsIs ~ trend + season)  
summary(ModelEfakSalesWithTrendAnsSeasonalityOnly)

##   
## Call:  
## tslm(formula = EfakAsIs ~ trend + season)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -258816 -48546 5235 49906 169790   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 310602.3 39616.9 7.840 1.02e-10 \*\*\*  
## trend 11743.9 511.4 22.964 < 2e-16 \*\*\*  
## season2 20559.5 51347.6 0.400 0.6903   
## season3 123735.3 51355.2 2.409 0.0191 \*   
## season4 -57081.7 51367.9 -1.111 0.2710   
## season5 68506.6 51385.8 1.333 0.1876   
## season6 -30958.1 51408.7 -0.602 0.5494   
## season7 -77138.6 51436.6 -1.500 0.1390   
## season8 -49919.5 51469.7 -0.970 0.3361   
## season9 -14661.3 51507.8 -0.285 0.7769   
## season10 13436.7 51550.9 0.261 0.7953   
## season11 99777.7 51599.1 1.934 0.0580 .   
## season12 27088.1 51652.3 0.524 0.6019   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 88930 on 59 degrees of freedom  
## Multiple R-squared: 0.907, Adjusted R-squared: 0.8881   
## F-statistic: 47.94 on 12 and 59 DF, p-value: < 2.2e-16

# Adjusted R²: 0,8881  
  
ModelWithCEPIOnly <- tslm(EfakAsIs ~ CEPI)  
summary(ModelWithCEPIOnly)

##   
## Call:  
## tslm(formula = EfakAsIs ~ CEPI)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -284279 -59593 1807 64606 249793   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -8486532 435220 -19.50 <2e-16 \*\*\*  
## CEPI 90943 4284 21.23 <2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 98160 on 70 degrees of freedom  
## Multiple R-squared: 0.8656, Adjusted R-squared: 0.8636   
## F-statistic: 450.7 on 1 and 70 DF, p-value: < 2.2e-16

# Adjusted R²: 0,8636  
# A Forecast based entirely on the CEPI is not convincing.  
  
#################################################################################  
# 4.6 ModelWithWugeExportsIndicators #  
#################################################################################  
  
# The model does not work as well in the wuge segment as it does in the efak segment. The reason is that trend  
# and seasonality are not as convincing here as they were in ModelWugeWithTrendAndSeasonalityOnly when compared  
# to ModelWithCEPIOnly.  
  
ModelWithWugeExportsIndicators <- tslm(WugeAsIs ~ trend + season + CEPI + UrbanoExports + AEPI)  
summary(ModelWithWugeExportsIndicators)

##   
## Call:  
## tslm(formula = WugeAsIs ~ trend + season + CEPI + UrbanoExports +   
## AEPI)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -130646 -36631 1936 39542 108451   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 9.822e+05 2.287e+06 0.430 0.669153   
## trend 6.940e+03 2.024e+03 3.429 0.001144 \*\*   
## season2 -1.284e+04 3.668e+04 -0.350 0.727506   
## season3 3.582e+04 4.155e+04 0.862 0.392295   
## season4 -5.666e+04 3.952e+04 -1.434 0.157224   
## season5 -5.596e+04 4.085e+04 -1.370 0.176235   
## season6 -9.119e+04 4.180e+04 -2.181 0.033362 \*   
## season7 -1.217e+05 4.657e+04 -2.612 0.011525 \*   
## season8 -4.948e+04 4.747e+04 -1.042 0.301706   
## season9 1.729e+05 4.689e+04 3.687 0.000514 \*\*\*  
## season10 7.666e+04 4.549e+04 1.685 0.097536 .   
## season11 9.561e+04 4.516e+04 2.117 0.038713 \*   
## season12 1.060e+05 5.246e+04 2.021 0.048051 \*   
## CEPI -1.610e+04 3.073e+04 -0.524 0.602446   
## UrbanoExports -6.179e-02 1.043e-01 -0.593 0.555813   
## AEPI 1.323e+04 1.124e+04 1.177 0.244178   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 58840 on 56 degrees of freedom  
## Multiple R-squared: 0.902, Adjusted R-squared: 0.8758   
## F-statistic: 34.38 on 15 and 56 DF, p-value: < 2.2e-16

# Adjusted R²: 0,8758  
  
ModelWugeWithCEPI <- tslm(WugeAsIs ~ trend + season + CEPI)  
summary(ModelWugeWithCEPI)

##   
## Call:  
## tslm(formula = WugeAsIs ~ trend + season + CEPI)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -126813 -32519 -324 38102 108671   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -44188 1145671 -0.039 0.969366   
## trend 5446 1540 3.537 0.000804 \*\*\*  
## season2 -16053 34166 -0.470 0.640208   
## season3 32530 34843 0.934 0.354375   
## season4 -54776 34265 -1.599 0.115338   
## season5 -56373 34289 -1.644 0.105581   
## season6 -89144 34223 -2.605 0.011659 \*   
## season7 -119668 34652 -3.453 0.001040 \*\*   
## season8 -48995 34567 -1.417 0.161725   
## season9 178410 34265 5.207 2.64e-06 \*\*\*  
## season10 80937 34051 2.377 0.020778 \*   
## season11 99832 33988 2.937 0.004743 \*\*   
## season12 106641 34394 3.101 0.002980 \*\*   
## CEPI 4083 11866 0.344 0.732036   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 58530 on 58 degrees of freedom  
## Multiple R-squared: 0.8996, Adjusted R-squared: 0.8771   
## F-statistic: 39.98 on 13 and 58 DF, p-value: < 2.2e-16

# Adjusted R²: 0,8771  
  
ModelWugeWithTrendAndSeasonalityOnly <- tslm(WugeAsIs ~ trend + season)  
summary(ModelWugeWithTrendAndSeasonalityOnly)

##   
## Call:  
## tslm(formula = WugeAsIs ~ trend + season)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -125027 -35254 -1462 36264 108676   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 349903.4 25878.1 13.521 < 2e-16 \*\*\*  
## trend 5963.2 334.1 17.851 < 2e-16 \*\*\*  
## season2 -14324.9 33540.7 -0.427 0.670869   
## season3 35442.7 33545.7 1.057 0.295023   
## season4 -52857.0 33554.0 -1.575 0.120539   
## season5 -54425.7 33565.6 -1.621 0.110249   
## season6 -87374.2 33580.6 -2.602 0.011703 \*   
## season7 -117122.3 33598.9 -3.486 0.000932 \*\*\*  
## season8 -46625.3 33620.4 -1.387 0.170716   
## season9 180126.5 33645.3 5.354 1.48e-06 \*\*\*  
## season10 81931.4 33673.5 2.433 0.018019 \*   
## season11 100309.5 33705.0 2.976 0.004228 \*\*   
## season12 108438.8 33739.7 3.214 0.002124 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 58090 on 59 degrees of freedom  
## Multiple R-squared: 0.8994, Adjusted R-squared: 0.8789   
## F-statistic: 43.95 on 12 and 59 DF, p-value: < 2.2e-16

# Adjusted R²: 0,8789  
  
#################################################################################  
# 4.7 ModelTotalEtel #  
#################################################################################   
  
# The model for the etel segment, including both subcategories, work best with trend and seasonality. An attempt   
# to improve the model by adding Temperature showed no improvement worth mentioning.   
ModelTotalEtel <- tslm(TotalEtelAsIs~ trend + season)  
summary(ModelTotalEtel)

##   
## Call:  
## tslm(formula = TotalEtelAsIs ~ trend + season)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -352676 -105634 5934 107814 481013   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 1370632 81168 16.886 < 2e-16 \*\*\*  
## trend 8070 1048 7.702 1.75e-10 \*\*\*  
## season2 -101964 105202 -0.969 0.3364   
## season3 -128812 105218 -1.224 0.2257   
## season4 -506178 105244 -4.810 1.08e-05 \*\*\*  
## season5 -607122 105281 -5.767 3.14e-07 \*\*\*  
## season6 -751654 105327 -7.136 1.59e-09 \*\*\*  
## season7 -838360 105385 -7.955 6.51e-11 \*\*\*  
## season8 -631474 105452 -5.988 1.35e-07 \*\*\*  
## season9 592436 105531 5.614 5.60e-07 \*\*\*  
## season10 202397 105619 1.916 0.0602 .   
## season11 232807 105718 2.202 0.0316 \*   
## season12 8713 105827 0.082 0.9347   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 182200 on 59 degrees of freedom  
## Multiple R-squared: 0.8905, Adjusted R-squared: 0.8683   
## F-statistic: 40 on 12 and 59 DF, p-value: < 2.2e-16

# Adjusted R²: 0,8683  
  
ModelBlueEtel <- tslm(BlueEtelAsIs ~ trend + season)  
summary(ModelBlueEtel)

##   
## Call:  
## tslm(formula = BlueEtelAsIs ~ trend + season)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -87664 -21395 -2396 22004 111508   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 349037.9 18751.2 18.614 < 2e-16 \*\*\*  
## trend 486.4 242.1 2.009 0.049075 \*   
## season2 -26032.1 24303.5 -1.071 0.288477   
## season3 -27955.9 24307.2 -1.150 0.254738   
## season4 -99331.3 24313.2 -4.085 0.000135 \*\*\*  
## season5 -137194.1 24321.6 -5.641 5.06e-07 \*\*\*  
## season6 -149008.6 24332.5 -6.124 8.05e-08 \*\*\*  
## season7 -169134.3 24345.7 -6.947 3.32e-09 \*\*\*  
## season8 -119734.1 24361.3 -4.915 7.42e-06 \*\*\*  
## season9 -16190.6 24379.4 -0.664 0.509206   
## season10 24093.6 24399.8 0.987 0.327453   
## season11 -3871.6 24422.6 -0.159 0.874585   
## season12 -32461.1 24447.8 -1.328 0.189367   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 42090 on 59 degrees of freedom  
## Multiple R-squared: 0.7454, Adjusted R-squared: 0.6937   
## F-statistic: 14.4 on 12 and 59 DF, p-value: 2.167e-13

# Adjusted R²: 0,6937  
  
ModelRedEtel <- tslm(RedEtelAsIs ~ trend + season)  
summary(ModelRedEtel)

##   
## Call:  
## tslm(formula = RedEtelAsIs ~ trend + season)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -431944 -104225 19211 95316 487719   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 1021594.7 76710.2 13.318 < 2e-16 \*\*\*  
## trend 7583.9 990.2 7.659 2.07e-10 \*\*\*  
## season2 -75932.4 99424.4 -0.764 0.448078   
## season3 -100855.7 99439.2 -1.014 0.314607   
## season4 -406847.1 99463.9 -4.090 0.000132 \*\*\*  
## season5 -469928.1 99498.4 -4.723 1.48e-05 \*\*\*  
## season6 -602645.8 99542.7 -6.054 1.05e-07 \*\*\*  
## season7 -669225.3 99596.9 -6.719 8.06e-09 \*\*\*  
## season8 -511740.0 99660.9 -5.135 3.33e-06 \*\*\*  
## season9 608626.8 99734.6 6.102 8.74e-08 \*\*\*  
## season10 178303.0 99818.2 1.786 0.079193 .   
## season11 236678.8 99911.4 2.369 0.021135 \*   
## season12 41174.4 100014.4 0.412 0.682062   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 172200 on 59 degrees of freedom  
## Multiple R-squared: 0.8754, Adjusted R-squared: 0.85   
## F-statistic: 34.53 on 12 and 59 DF, p-value: < 2.2e-16

# Adjusted R²: 0,85  
  
#################################################################################  
### ###  
### 5. Forecasts with the models ###  
### ###  
#################################################################################   
  
#################################################################################  
# 5.1 Shorten the time series in order to test the forecasts #   
#################################################################################  
  
# Shortening the exports data in the Time Series in order to be able to compare the produced forecasts with the   
# As Is data.  
  
TotalAsIs\_2012 <- ts(TotalAsIsVector , start=c(2008,1), end=c(2012,12), frequency=12)  
EfakAsIs\_2012 <- ts(EfakAsIsVector , start=c(2008,1), end=c(2012,12), frequency=12)  
WugeAsIs\_2012 <- ts(WugeAsIsVector, start=c(2008,1), end=c(2012,12), frequency=12)  
TotalEtelAsIs\_2012 <- ts(TotalEtelAsIsVector, start=c(2008,1), end=c(2012,12), frequency=12)  
BlueEtelAsIs\_2012 <- ts(BlueEtelAsIsVector, start=c(2008,1), end=c(2012,12), frequency=12)  
RedEtelAsIs\_2012 <- ts(RedEtelAsIsVector, start=c(2008,1), end=c(2012,12), frequency=12)  
YearAsIs\_2012 <- ts(YearAsIsVector, start=c(2008,1), end=c(2012,12), frequency=12)  
  
# Shortening the indicators by the same amount  
  
CEPI\_2012 <- ts(CEPIVector , start=c(2008,1), end=c(2012,12), frequency=12)  
SIGov\_2012 <- ts(SIGovVector , start=c(2008,1), end=c(2012,12), frequency=12)  
Temperature\_2012 <- ts(TemperatureVector, start=c(2008,1), end=c(2012,12), frequency=12)  
Births\_2012 <- ts(BirthsVector, start=c(2008,1), end=c(2012,12), frequency=12)  
SIExtern\_2012 <- ts(SIExternVector, start=c(2008,1), end=c(2012,12), frequency=12)  
UrbanoExports\_2012 <- ts(UrbanoExportsVector, start=c(2008,1), end=c(2012,12), frequency=12)  
GlobalisationPartyMembers\_2012 <- ts(GlobalisationPartyMembersVector, start=c(2008,1), end=c(2012,12), frequency=12)  
AEPI\_2012 <- ts(AEPIVector, start=c(2008,1), end=c(2012,12), frequency=12)  
PPIEtel\_2012 <- ts(PPIEtel, start=c(2008,1), end=c(2012,12), frequency=12)  
NationalHolidays\_2012 <- ts(NationalHolidaysVector, start=c(2008,1), end=c(2012,12), frequency=12)  
ChulwalarIndex\_2012 <- ts(ChulwalarIndexVector, start=c(2008,1), end=c(2012,12), frequency=12)  
Inflation\_2012 <- ts(InflationVector, start=c(2008,1), end=c(2012,12), frequency=12)  
InfluenceNationalHolidays\_2012 <- ts(InfluenceNationalHolidaysVector, start=c(2008,1), end=c(2012,12), frequency=12)  
  
  
# Seperate the As Is and Plan data for 2013 in order to be able to compare the forecast to this data.  
  
TotalAsIsVector\_2013 <- c(ImportedAsIsData [2:13,7])  
AsIsWugeAsIsVector\_2013 <- c(ImportedAsIsData [16:27,7])  
TotalAsIsGewuerzeVector\_2013 <- c(ImportedAsIsData [30:41,7])  
TotalEtelAsIsVector\_2013 <- c(ImportedAsIsData [44:55,7])  
BlueEtelAsIsVector\_2013 <- c(ImportedAsIsData [58:69,7])  
RedEtelAsIsVector\_2013 <- c(ImportedAsIsData [72:83,7])  
YearAsIsVector\_2013 <- c(ImportedAsIsData [86,7])  
  
TotalAsIs\_2013 <- ts(TotalAsIsVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
EfakAsIs\_2013 <- ts(AsIsWugeAsIsVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
WugeAsIs\_2013 <- ts(TotalAsIsGewuerzeVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
TotalEtelAsIs\_2013 <- ts(TotalEtelAsIsVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
BlueEtelAsIs\_2013 <- ts(BlueEtelAsIsVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
RedEtelAsIs\_2013 <- ts(RedEtelAsIsVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
YearAsIs\_2013 <- ts(YearAsIsVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
  
PlanVector\_2013 <- c(ImportedPlanData[2:13,7])  
EfakPlanVector\_2013 <- c(ImportedPlanData[16:27,7])  
WugePlanVector\_2013 <- c(ImportedPlanData[30:41,7])  
TotalEtelPlanVector\_2013 <- c(ImportedPlanData[44:55,7])  
BlueEtelPlanVector\_2013 <- c(ImportedPlanData[58:69,7])  
RedEtelPlanVector\_2013 <- c(ImportedPlanData[72:83,7])  
YearPlanVector\_2013 <- c(ImportedPlanData[86,7])  
  
TotalPlan\_2013 <- ts(PlanVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
EfakPlan\_2013 <- ts(EfakPlanVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
WugePlan\_2013 <- ts(WugePlanVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
TotalEtelPlan\_2013 <- ts(TotalEtelPlanVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
BlueEtelPlan\_2013 <- ts(BlueEtelPlanVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
RedEtelPlan\_2013 <- ts(RedEtelPlanVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
YearPlan\_2013 <- ts(YearPlanVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
  
# Seperate the indicator data for 2013 and 2014 in order to use these in the forecasts. First as a vector and then as a time series.  
  
CEPIVector\_2013 <- c(ImportedIndicators[2:13,7])  
CEPIVector\_2014 <- c(ImportedIndicators[2:13,8])  
SIGovVector\_2013 <- c(ImportedIndicators[16:27,7])  
SIGovVector\_2014 <- c(ImportedIndicators[16:27,8])  
TemperatureVector\_2013 <- c(ImportedIndicators[30:41,7])  
TemperatureVector\_2014 <- c(ImportedIndicators[30:41,8])  
BirthsVector\_2013 <- c(ImportedIndicators[44:55,7])  
BirthsVector\_2014 <- c(ImportedIndicators[44:55,8])  
SIExternVector\_2013 <- c(ImportedIndicators[58:69,7])  
SIExternVector\_2014 <- c(ImportedIndicators[58:69,8])  
UrbanoExportsVector\_2013 <- c(ImportedIndicators[72:83,7])  
UrbanoExportsVector\_2014 <- c(ImportedIndicators[72:83,8])  
GlobalisationPartyMembersVector\_2013 <- c(ImportedIndicators[86:97,7])  
GlobalisationPartyMembersVector\_2014 <- c(ImportedIndicators[86:97,8])  
AEPIVector\_2013 <- c(ImportedIndicators[100:111,7])  
AEPIVector\_2014 <- c(ImportedIndicators[100:111,8])  
PPIEtelVector\_2013 <- c(ImportedIndicators[114:125,7])  
PPIEtelVector\_2014 <- c(ImportedIndicators[114:125,8])  
NationalHolidaysVector\_2013 <-c(ImportedIndicators[170:181,7])  
NationalHolidaysVector\_2014 <-c(ImportedIndicators[170:181,8])  
ChulwalarIndexVector\_2013 <- c(ImportedIndicators[128:139,7])  
ChulwalarIndexVector\_2014 <- c(ImportedIndicators[128:139,8])  
InflationVector\_2013 <- c(ImportedIndicators[142:153,7])  
InflationVector\_2014 <- c(ImportedIndicators[142:153,8])  
InfluenceNationalHolidaysVector\_2013 <-c(ImportedIndicators[184:195,7])  
InfluenceNationalHolidaysVector\_2014 <-c(ImportedIndicators[184:195,8])  
  
CEPI\_2013 <- ts(CEPIVector\_2013 , start=c(2013,1), end=c(2013,12), frequency=12)  
CEPI\_2014 <- ts(CEPIVector\_2014 , start=c(2013,1), end=c(2013,12), frequency=12)  
SIGov\_2013 <- ts(SIGovVector\_2013 , start=c(2013,1), end=c(2013,12), frequency=12)  
SIGov\_2014 <- ts(SIGovVector\_2014 , start=c(2013,1), end=c(2013,12), frequency=12)  
Temperature\_2013 <- ts(TemperatureVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
Temperature\_2014 <- ts(TemperatureVector\_2014, start=c(2013,1), end=c(2013,12), frequency=12)  
Births\_2013 <- ts(BirthsVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
Births\_2014 <- ts(BirthsVector\_2014, start=c(2013,1), end=c(2013,12), frequency=12)  
SIExtern\_2013 <- ts(SIExternVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
SIExtern\_2014 <- ts(SIExternVector\_2014, start=c(2013,1), end=c(2013,12), frequency=12)  
UrbanoExports\_2013 <- ts(UrbanoExportsVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
UrbanoExports\_2014 <- ts(UrbanoExportsVector\_2014, start=c(2013,1), end=c(2013,12), frequency=12)  
GlobalisationPartyMembers\_2013 <- ts(GlobalisationPartyMembersVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
GlobalisationPartyMembers\_2014 <- ts(GlobalisationPartyMembersVector\_2014, start=c(2013,1), end=c(2013,12), frequency=12)  
AEPI\_2013 <- ts(AEPIVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
AEPI\_2014 <- ts(AEPIVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
PPIEtel\_2013 <- ts(PPIEtelVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
PPIEtel\_2014 <- ts(PPIEtelVector\_2014, start=c(2013,1), end=c(2013,12), frequency=12)  
NationalHolidays\_2013 <- ts(NationalHolidaysVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
NationalHolidays\_2014 <- ts(NationalHolidaysVector\_2014, start=c(2014,1), end=c(2014,12), frequency=12)  
ChulwalarIndex\_2013 <- ts(ChulwalarIndexVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
ChulwalarIndex\_2014 <- ts(ChulwalarIndexVector\_2014, start=c(2013,1), end=c(2013,12), frequency=12)  
Inflation\_2013 <- ts(InflationVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
Inflation\_2014 <- ts(InflationVector\_2014, start=c(2013,1), end=c(2013,12), frequency=12)  
InfluenceNationalHolidaysVector\_2013 <- ts(InfluenceNationalHolidaysVector\_2013, start=c(2013,1), end=c(2013,12), frequency=12)  
InfluenceNationalHolidaysVector\_2014 <- ts(InfluenceNationalHolidaysVector\_2014, start=c(2013,1), end=c(2013,12), frequency=12)  
  
#################################################################################  
# 5.2 Forecasting und testing the models #  
#################################################################################  
  
#################################################################################  
# 5.2.1.1 Forecast ModelWithHighCorrelatingIndicators #  
#################################################################################  
  
# Shorten ModelWithHighCorrelatingIndicators by one year in order to be able to produce a forecast for 2013.   
ModelWithHighCorrelatingIndicators\_2012 <- tslm(TotalAsIs\_2012 ~ trend + season + CEPI\_2012 + SIExtern\_2012 + UrbanoExports\_2012 + GlobalisationPartyMembers\_2012 + AEPI\_2012)  
summary(ModelWithHighCorrelatingIndicators\_2012)

##   
## Call:  
## tslm(formula = TotalAsIs\_2012 ~ trend + season + CEPI\_2012 +   
## SIExtern\_2012 + UrbanoExports\_2012 + GlobalisationPartyMembers\_2012 +   
## AEPI\_2012)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -590682 -148874 23944 148648 423243   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -1.542e+07 1.461e+07 -1.056 0.297224   
## trend 2.827e+02 2.096e+04 0.013 0.989301   
## season2 -1.071e+05 1.777e+05 -0.603 0.549946   
## season3 6.219e+04 2.031e+05 0.306 0.760993   
## season4 -7.186e+05 1.935e+05 -3.715 0.000595 \*\*\*  
## season5 -5.757e+05 1.978e+05 -2.910 0.005752 \*\*   
## season6 -8.241e+05 1.994e+05 -4.134 0.000167 \*\*\*  
## season7 -1.083e+06 2.186e+05 -4.955 1.23e-05 \*\*\*  
## season8 -6.963e+05 2.236e+05 -3.113 0.003325 \*\*   
## season9 6.649e+05 2.219e+05 2.996 0.004572 \*\*   
## season10 3.046e+05 2.223e+05 1.370 0.177909   
## season11 5.136e+05 2.230e+05 2.303 0.026314 \*   
## season12 4.974e+04 2.530e+05 0.197 0.845057   
## CEPI\_2012 2.248e+05 1.922e+05 1.169 0.248882   
## SIExtern\_2012 2.369e+04 4.590e+04 0.516 0.608451   
## UrbanoExports\_2012 -1.522e-01 5.208e-01 -0.292 0.771535   
## GlobalisationPartyMembers\_2012 3.142e+01 3.844e+01 0.817 0.418370   
## AEPI\_2012 -4.974e+04 6.236e+04 -0.798 0.429556   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 256600 on 42 degrees of freedom  
## Multiple R-squared: 0.9145, Adjusted R-squared: 0.8798   
## F-statistic: 26.41 on 17 and 42 DF, p-value: < 2.2e-16

# Add "newdata" to the 2013 indicator values for the forecast   
ModelWithHighCorrelatingIndicators\_Forecast <- forecast(ModelWithHighCorrelatingIndicators\_2012,newdata=data.frame(CEPI\_2012=CEPI\_2013, SIExtern\_2012=SIExtern\_2013, UrbanoExports\_2012= UrbanoExports\_2013, GlobalisationPartyMembers\_2012=GlobalisationPartyMembers\_2013, AEPI\_2012=AEPI\_2013),h=12)  
plot(ModelWithHighCorrelatingIndicators\_Forecast, main="ModelWithHighCorrelatingIndicators\_Forecast")  
ModelWithHighCorrelatingIndicators\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 3588409 3145307 4031511 2901625 4275193  
## Feb 2013 3615751 3174780 4056722 2932271 4299231  
## Mar 2013 3857685 3418316 4297055 3176687 4538684  
## Apr 2013 2959830 2478742 3440918 2214171 3705489  
## May 2013 3163014 2698603 3627424 2443204 3882824  
## Jun 2013 2934791 2472811 3396771 2218748 3650835  
## Jul 2013 2755659 2296827 3214490 2044495 3466822  
## Aug 2013 3167751 2707972 3627531 2455119 3880384  
## Sep 2013 4512206 4061044 4963367 3812930 5211481  
## Oct 2013 4129962 3677062 4582861 3427993 4831931  
## Nov 2013 4398869 3963060 4834678 3723389 5074349  
## Dec 2013 4019999 3580235 4459762 3338390 4701608

# In order to be able to correlate the Forecast with the As Is Data, it is necessary to convert the Point   
# Estimator into a time series.   
ModelWithHighCorrelatingIndicators\_Forecast\_df <-as.data.frame(ModelWithHighCorrelatingIndicators\_Forecast)   
ModelWithHighCorrelatingIndicators\_PointForecast <- ts(ModelWithHighCorrelatingIndicators\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
  
# Correlation of the forecasts and As Is Data. As a comparison, the correlation of the As Is Data for 2013 with the Plan Data.   
cor(ModelWithHighCorrelatingIndicators\_PointForecast, TotalAsIs\_2013)

## [1] 0.9028604

cor(TotalAsIs\_2013, TotalPlan\_2013)

## [1] 0.929769

# A Comparison with linear regression also supports the result.  
ModelWithHighCorrelatingIndicators\_forecast\_lm <- lm(TotalAsIs\_2013 ~ ModelWithHighCorrelatingIndicators\_PointForecast, data = TotalAsIs\_2013)  
TotalAsIs\_2013\_lm <- lm(TotalAsIs\_2013 ~ TotalPlan\_2013, data = TotalAsIs\_2013)  
summary(ModelWithHighCorrelatingIndicators\_forecast\_lm)

##   
## Call:  
## lm(formula = TotalAsIs\_2013 ~ ModelWithHighCorrelatingIndicators\_PointForecast,   
## data = TotalAsIs\_2013)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -540546 -227283 12596 157487 731430   
##   
## Coefficients:  
## Estimate Std. Error  
## (Intercept) -5.082e+05 6.545e+05  
## ModelWithHighCorrelatingIndicators\_PointForecast 1.195e+00 1.799e-01  
## t value Pr(>|t|)   
## (Intercept) -0.776 0.455   
## ModelWithHighCorrelatingIndicators\_PointForecast 6.641 5.78e-05 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 357000 on 10 degrees of freedom  
## Multiple R-squared: 0.8152, Adjusted R-squared: 0.7967   
## F-statistic: 44.1 on 1 and 10 DF, p-value: 5.776e-05

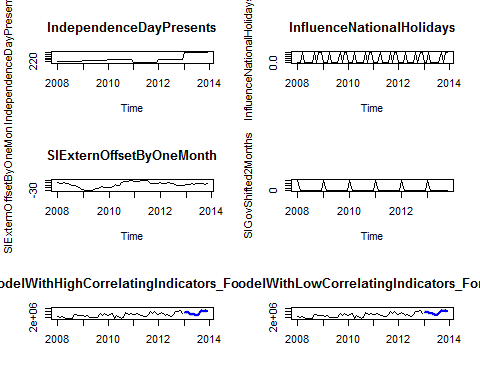
summary(TotalAsIs\_2013\_lm)

##   
## Call:  
## lm(formula = TotalAsIs\_2013 ~ TotalPlan\_2013, data = TotalAsIs\_2013)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -441885 -227385 -43470 184761 466401   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -8.972e+04 4.930e+05 -0.182 0.859   
## TotalPlan\_2013 1.053e+00 1.318e-01 7.987 1.2e-05 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 305700 on 10 degrees of freedom  
## Multiple R-squared: 0.8645, Adjusted R-squared: 0.8509   
## F-statistic: 63.78 on 1 and 10 DF, p-value: 1.195e-05

#################################################################################  
# 5.2.1.2 Forecast ModelWithLowCorrelatingIndicators #  
#################################################################################  
  
# Shorten ModelWithLowCorrelatingIndicators by one year in order to be able to produce a forecast for 2013.   
ModelWithLowCorrelatingIndicators\_2012 <- tslm(TotalAsIs\_2012 ~ trend + season + NationalHolidays\_2012 + UrbanoExports\_2012 + GlobalisationPartyMembers\_2012)  
summary(ModelWithLowCorrelatingIndicators\_2012)

##   
## Call:  
## tslm(formula = TotalAsIs\_2012 ~ trend + season + NationalHolidays\_2012 +   
## UrbanoExports\_2012 + GlobalisationPartyMembers\_2012)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -508808 -130098 11746 177748 466017   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 1.211e+06 1.549e+06 0.782 0.438428   
## trend 2.004e+04 1.028e+04 1.950 0.057515 .   
## season2 -2.898e+04 1.573e+05 -0.184 0.854714   
## season3 2.520e+05 1.631e+05 1.545 0.129609   
## season4 -3.800e+05 2.242e+05 -1.695 0.097100 .   
## season5 -4.697e+05 1.623e+05 -2.894 0.005897 \*\*   
## season6 -7.350e+05 1.652e+05 -4.450 5.79e-05 \*\*\*  
## season7 -9.668e+05 1.687e+05 -5.732 8.35e-07 \*\*\*  
## season8 -5.809e+05 1.727e+05 -3.364 0.001602 \*\*   
## season9 7.426e+05 1.772e+05 4.190 0.000132 \*\*\*  
## season10 3.765e+05 1.822e+05 2.066 0.044712 \*   
## season11 5.612e+05 1.876e+05 2.991 0.004541 \*\*   
## season12 4.716e+05 2.756e+05 1.711 0.094062 .   
## NationalHolidays\_2012 -3.051e+05 1.962e+05 -1.554 0.127234   
## UrbanoExports\_2012 1.218e-01 1.838e-01 0.663 0.510937   
## GlobalisationPartyMembers\_2012 5.692e+00 2.753e+01 0.207 0.837165   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 248200 on 44 degrees of freedom  
## Multiple R-squared: 0.9162, Adjusted R-squared: 0.8876   
## F-statistic: 32.05 on 15 and 44 DF, p-value: < 2.2e-16

# Add "newdata" to the 2013 indicator values for the forecast   
ModelWithLowCorrelatingIndicators\_Forecast <- forecast(ModelWithLowCorrelatingIndicators\_2012,newdata=data.frame(NationalHolidays\_2012=NationalHolidays\_2013, UrbanoExports\_2012= UrbanoExports\_2013, GlobalisationPartyMembers\_2012=GlobalisationPartyMembers\_2013),h=12)  
plot(ModelWithLowCorrelatingIndicators\_Forecast, main="ModelWithLowCorrelatingIndicators\_Forecast")



ModelWithLowCorrelatingIndicators\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 3703214 3306827 4099602 3089217 4317212  
## Feb 2013 3694280 3297893 4090668 3080283 4308278  
## Mar 2013 3690209 3244288 4136130 2999485 4380933  
## Apr 2013 3383361 2937440 3829282 2692637 4074085  
## May 2013 3313734 2917347 3710121 2699736 3927731  
## Jun 2013 3068413 2672026 3464800 2454415 3682410  
## Jul 2013 2856693 2460306 3253081 2242696 3470691  
## Aug 2013 3262648 2866261 3659036 2648651 3876646  
## Sep 2013 4606119 4209732 5002506 3992121 5220117  
## Oct 2013 4260121 3863734 4656508 3646123 4874119  
## Nov 2013 4464894 4068507 4861282 3850897 5078892  
## Dec 2013 4090225 3693837 4486612 3476227 4704222

# In order to be able to correlate the Forecast with the As Is Data, it is necessary to convert the Point   
# Estimator into a time series.   
ModelWithLowCorrelatingIndicators\_Forecast\_df <-as.data.frame(ModelWithLowCorrelatingIndicators\_Forecast)   
ModelWithLowCorrelatingIndicators\_PointForecast <- ts(ModelWithLowCorrelatingIndicators\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
  
# Correlation of the forecasts and As Is Data. As a comparison, the correlation of the As Is Data for 2013 with the Plan Data.   
cor(ModelWithLowCorrelatingIndicators\_PointForecast, TotalAsIs\_2013)

## [1] 0.9590162

cor(TotalAsIs\_2013, TotalPlan\_2013)

## [1] 0.929769

# A Comparison with linear regression also supports the result.  
ModelWithLowCorrelatingIndicators\_forecast\_lm <- lm(TotalAsIs\_2013 ~ ModelWithLowCorrelatingIndicators\_PointForecast, data = TotalAsIs\_2013)  
TotalAsIs\_2013\_lm <- lm(TotalAsIs\_2013 ~ TotalPlan\_2013, data = TotalAsIs\_2013)  
summary(ModelWithLowCorrelatingIndicators\_forecast\_lm)

##   
## Call:  
## lm(formula = TotalAsIs\_2013 ~ ModelWithLowCorrelatingIndicators\_PointForecast,   
## data = TotalAsIs\_2013)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -299026 -155463 -40768 115237 406333   
##   
## Coefficients:  
## Estimate Std. Error  
## (Intercept) -1.252e+06 4.754e+05  
## ModelWithLowCorrelatingIndicators\_PointForecast 1.361e+00 1.272e-01  
## t value Pr(>|t|)   
## (Intercept) -2.633 0.025 \*   
## ModelWithLowCorrelatingIndicators\_PointForecast 10.703 8.5e-07 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 235300 on 10 degrees of freedom  
## Multiple R-squared: 0.9197, Adjusted R-squared: 0.9117   
## F-statistic: 114.6 on 1 and 10 DF, p-value: 8.5e-07

summary(TotalAsIs\_2013\_lm)

##   
## Call:  
## lm(formula = TotalAsIs\_2013 ~ TotalPlan\_2013, data = TotalAsIs\_2013)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -441885 -227385 -43470 184761 466401   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -8.972e+04 4.930e+05 -0.182 0.859   
## TotalPlan\_2013 1.053e+00 1.318e-01 7.987 1.2e-05 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 305700 on 10 degrees of freedom  
## Multiple R-squared: 0.8645, Adjusted R-squared: 0.8509   
## F-statistic: 63.78 on 1 and 10 DF, p-value: 1.195e-05

#################################################################################  
# 5.2.2 Forecast ModelWithTrendAndSeasonalityOnly #  
#################################################################################  
  
# Shorten ModelWithTrendAndSeasonalityOnly by one year in order to be able to produce a forecast for 2013.  
ModelWithTrendAndSeasonalityOnly\_2012 <- tslm(TotalAsIs\_2012 ~ trend + season)  
summary(ModelWithTrendAndSeasonalityOnly\_2012)

##   
## Call:  
## tslm(formula = TotalAsIs\_2012 ~ trend + season)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -600304 -116717 -7864 163111 473692   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2147793 120530 17.820 < 2e-16 \*\*\*  
## trend 25212 1887 13.363 < 2e-16 \*\*\*  
## season2 -34146 156872 -0.218 0.828632   
## season3 180612 156906 1.151 0.255518   
## season4 -639529 156962 -4.074 0.000176 \*\*\*  
## season5 -490327 157042 -3.122 0.003068 \*\*   
## season6 -760860 157144 -4.842 1.43e-05 \*\*\*  
## season7 -997792 157268 -6.345 8.09e-08 \*\*\*  
## season8 -617048 157415 -3.920 0.000286 \*\*\*  
## season9 701211 157585 4.450 5.26e-05 \*\*\*  
## season10 330001 157777 2.092 0.041907 \*   
## season11 509563 157991 3.225 0.002292 \*\*   
## season12 109681 158227 0.693 0.491603   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 248000 on 47 degrees of freedom  
## Multiple R-squared: 0.9106, Adjusted R-squared: 0.8878   
## F-statistic: 39.89 on 12 and 47 DF, p-value: < 2.2e-16

# Add "newdata" to the 2013 indicator values for the forecast.  
ModelWithTrendAndSeasonalityOnly\_Forecast <- forecast(ModelWithTrendAndSeasonalityOnly\_2012,h=12)  
plot(ModelWithTrendAndSeasonalityOnly\_Forecast, main="ModelWithTrendAndSeasonalityOnly\_Forecast")  
ModelWithTrendAndSeasonalityOnly\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 3685709 3321691 4049727 3122318 4249100  
## Feb 2013 3676775 3312757 4040793 3113384 4240166  
## Mar 2013 3916745 3552727 4280763 3353354 4480136  
## Apr 2013 3121815 2757797 3485833 2558424 3685206  
## May 2013 3296229 2932211 3660247 2732838 3859620  
## Jun 2013 3050908 2686890 3414926 2487517 3614299  
## Jul 2013 2839188 2475170 3203206 2275797 3402579  
## Aug 2013 3245143 2881125 3609161 2681752 3808534  
## Sep 2013 4588614 4224596 4952632 4025223 5152005  
## Oct 2013 4242616 3878598 4606634 3679225 4806007  
## Nov 2013 4447389 4083371 4811407 3883998 5010780  
## Dec 2013 4072720 3708702 4436737 3509329 4636110

# In order to be able to correlate the Forecast with the As Is Data, it is necessary to convert the Point   
# Estimator into a time series.   
ModelWithTrendAndSeasonalityOnly\_Forecast\_df <-as.data.frame(ModelWithTrendAndSeasonalityOnly\_Forecast)   
ModelWithTrendAndSeasonalityOnly\_PointForecast <- ts(ModelWithTrendAndSeasonalityOnly\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
  
# Correlation of the forecasts and As Is Data. As a comparison, the correlation of the As Is Data for 2013 with the Plan Data.  
cor(ModelWithTrendAndSeasonalityOnly\_PointForecast, TotalAsIs\_2013)

## [1] 0.9138049

cor(TotalAsIs\_2013, TotalPlan\_2013)

## [1] 0.929769

# A Comparison with linear regression also supports the result.  
ModelWithTrendAndSeasonalityOnly\_Forecast\_lm <- lm(TotalAsIs\_2013 ~ ModelWithTrendAndSeasonalityOnly\_PointForecast, data = TotalAsIs\_2013)  
TotalAsIs\_2013\_lm <- lm(TotalAsIs\_2013 ~ TotalPlan\_2013, data = TotalAsIs\_2013)  
summary(ModelWithTrendAndSeasonalityOnly\_Forecast\_lm)

##   
## Call:  
## lm(formula = TotalAsIs\_2013 ~ ModelWithTrendAndSeasonalityOnly\_PointForecast,   
## data = TotalAsIs\_2013)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -516239 -216450 33683 123007 675607   
##   
## Coefficients:  
## Estimate Std. Error  
## (Intercept) -8.142e+05 6.536e+05  
## ModelWithTrendAndSeasonalityOnly\_PointForecast 1.249e+00 1.755e-01  
## t value Pr(>|t|)   
## (Intercept) -1.246 0.241   
## ModelWithTrendAndSeasonalityOnly\_PointForecast 7.115 3.24e-05 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 337300 on 10 degrees of freedom  
## Multiple R-squared: 0.835, Adjusted R-squared: 0.8185   
## F-statistic: 50.62 on 1 and 10 DF, p-value: 3.238e-05

summary(TotalAsIs\_2013\_lm)

##   
## Call:  
## lm(formula = TotalAsIs\_2013 ~ TotalPlan\_2013, data = TotalAsIs\_2013)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -441885 -227385 -43470 184761 466401   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -8.972e+04 4.930e+05 -0.182 0.859   
## TotalPlan\_2013 1.053e+00 1.318e-01 7.987 1.2e-05 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 305700 on 10 degrees of freedom  
## Multiple R-squared: 0.8645, Adjusted R-squared: 0.8509   
## F-statistic: 63.78 on 1 and 10 DF, p-value: 1.195e-05

#################################################################################  
# 5.2.3 Forecast ModelWithEfakExportsIndicators #  
#################################################################################  
  
# Shorten the variables in ModelWithEfakExportsIndicators by one year in order to be able to produce a forecast for 2013.  
ModelWithEfakExportsIndicators\_2012 <- tslm(EfakAsIs\_2012 ~ trend + season + CEPI\_2012 + UrbanoExports\_2012 + AEPI\_2012)  
ModelEfakSalesWithCEPI\_2012 <- tslm(EfakAsIs\_2012 ~ trend + season + CEPI\_2012)  
ModelEfakSalesWithTrendAnsSeasonalityOnly\_2012 <- tslm(EfakAsIs\_2012 ~ trend + season)  
ModelWithCEPIOnly\_2012 <- tslm(EfakAsIs\_2012 ~ CEPI\_2012)  
summary(ModelWithEfakExportsIndicators\_2012)

##   
## Call:  
## tslm(formula = EfakAsIs\_2012 ~ trend + season + CEPI\_2012 + UrbanoExports\_2012 +   
## AEPI\_2012)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -176710 -50413 8239 35248 146391   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -1.810e+06 2.908e+06 -0.622 0.53684   
## trend 4.285e+03 2.516e+03 1.703 0.09562 .   
## season2 5.273e+04 4.854e+04 1.086 0.28323   
## season3 1.607e+05 5.440e+04 2.954 0.00503 \*\*  
## season4 -4.599e+04 5.317e+04 -0.865 0.39168   
## season5 1.016e+05 5.404e+04 1.881 0.06666 .   
## season6 2.951e+04 5.512e+04 0.535 0.59512   
## season7 -4.571e+04 6.041e+04 -0.757 0.45334   
## season8 6.598e+03 6.206e+04 0.106 0.91582   
## season9 5.155e+04 6.111e+04 0.844 0.40345   
## season10 6.691e+04 6.008e+04 1.114 0.27148   
## season11 1.637e+05 5.900e+04 2.775 0.00808 \*\*  
## season12 8.394e+04 6.858e+04 1.224 0.22747   
## CEPI\_2012 2.407e+03 3.940e+04 0.061 0.95155   
## UrbanoExports\_2012 2.348e-01 1.413e-01 1.661 0.10374   
## AEPI\_2012 5.823e+03 1.420e+04 0.410 0.68375   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 71560 on 44 degrees of freedom  
## Multiple R-squared: 0.9294, Adjusted R-squared: 0.9053   
## F-statistic: 38.59 on 15 and 44 DF, p-value: < 2.2e-16

summary(ModelEfakSalesWithCEPI\_2012)

##   
## Call:  
## tslm(formula = EfakAsIs\_2012 ~ trend + season + CEPI\_2012)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -205118 -45951 8303 48133 175186   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -7424279 1546653 -4.800 1.71e-05 \*\*\*  
## trend 2533 1977 1.282 0.20640   
## season2 15685 47310 0.332 0.74174   
## season3 96971 48168 2.013 0.04997 \*   
## season4 -104275 47657 -2.188 0.03378 \*   
## season5 37612 47571 0.791 0.43321   
## season6 -37662 47501 -0.793 0.43192   
## season7 -131181 48012 -2.732 0.00889 \*\*   
## season8 -84988 47994 -1.771 0.08322 .   
## season9 -33902 47593 -0.712 0.47985   
## season10 -16525 47364 -0.349 0.72876   
## season11 84535 47226 1.790 0.08004 .   
## season12 -27244 47895 -0.569 0.57225   
## CEPI\_2012 79863 15994 4.993 8.99e-06 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 74030 on 46 degrees of freedom  
## Multiple R-squared: 0.921, Adjusted R-squared: 0.8986   
## F-statistic: 41.23 on 13 and 46 DF, p-value: < 2.2e-16

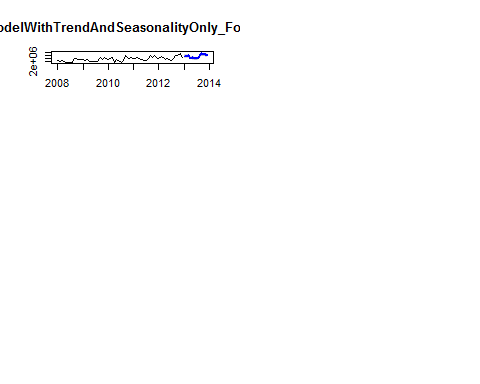
summary(ModelEfakSalesWithTrendAnsSeasonalityOnly\_2012)

##   
## Call:  
## tslm(formula = EfakAsIs\_2012 ~ trend + season)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -248244 -48564 2962 44626 164771   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 296701.0 44200.2 6.713 2.23e-08 \*\*\*  
## trend 11994.9 691.9 17.336 < 2e-16 \*\*\*  
## season2 49349.5 57527.4 0.858 0.3953   
## season3 153118.7 57539.8 2.661 0.0106 \*   
## season4 -60783.2 57560.6 -1.056 0.2964   
## season5 78031.6 57589.7 1.355 0.1819   
## season6 -314.9 57627.1 -0.005 0.9957   
## season7 -80934.3 57672.8 -1.403 0.1671   
## season8 -36215.8 57726.7 -0.627 0.5335   
## season9 2213.3 57788.9 0.038 0.9696   
## season10 8532.1 57859.3 0.147 0.8834   
## season11 96935.4 57937.8 1.673 0.1010   
## season12 12432.6 58024.5 0.214 0.8313   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 90950 on 47 degrees of freedom  
## Multiple R-squared: 0.8781, Adjusted R-squared: 0.847   
## F-statistic: 28.22 on 12 and 47 DF, p-value: < 2.2e-16

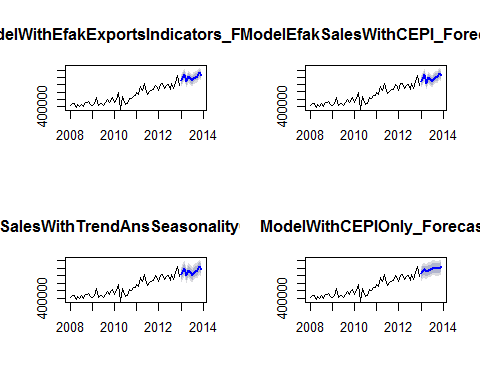
summary(ModelWithCEPIOnly\_2012)

##   
## Call:  
## tslm(formula = EfakAsIs\_2012 ~ CEPI\_2012)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -285729 -46717 -4540 53446 235068   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -9183792 584004 -15.73 <2e-16 \*\*\*  
## CEPI\_2012 97931 5796 16.90 <2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 96370 on 58 degrees of freedom  
## Multiple R-squared: 0.8311, Adjusted R-squared: 0.8282   
## F-statistic: 285.5 on 1 and 58 DF, p-value: < 2.2e-16

# Add "newdata" to the 2013 indicator values for the forecast.  
ModelWithEfakExportsIndicators\_Forecast <- forecast(ModelWithEfakExportsIndicators\_2012, newdata=data.frame(CEPI\_2012=CEPI\_2013, UrbanoExports\_2012 = UrbanoExports\_2013, AEPI\_2012 = AEPI\_2013),h=12)  
ModelEfakSalesWithCEPI\_Forecast <- forecast(ModelEfakSalesWithCEPI\_2012, , newdata=data.frame(CEPI\_2012=CEPI\_2013), h=12)  
ModelEfakSalesWithTrendAnsSeasonalityOnly\_Forecast <- forecast(ModelEfakSalesWithTrendAnsSeasonalityOnly\_2012,h=12)  
ModelWithCEPIOnly\_Forecast <- forecast(ModelWithCEPIOnly\_2012, , newdata=data.frame(CEPI\_2012=CEPI\_2013), h=12)  
  
par(mfrow=c(2,2))



plot(ModelWithEfakExportsIndicators\_Forecast, main="ModelWithEfakExportsIndicators\_Forecast")  
plot(ModelEfakSalesWithCEPI\_Forecast, main="ModelEfakSalesWithCEPI\_Forecast")  
plot(ModelEfakSalesWithTrendAnsSeasonalityOnly\_Forecast, main="ModelEfakSalesWithTrendAnsSeasonalityOnly\_Forecast")  
plot(ModelWithCEPIOnly\_Forecast, main="ModelWithCEPIOnly\_Forecast")



ModelWithEfakExportsIndicators\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 1114825 1005751 1223900 945870.9 1283780  
## Feb 2013 1175033 1065668 1284399 1005627.7 1344439  
## Mar 2013 1293717 1185544 1401889 1126159.0 1461275  
## Apr 2013 1090702 979260 1202145 918079.9 1263325  
## May 2013 1247057 1138259 1355856 1078530.0 1415584  
## Jun 2013 1180055 1071566 1288545 1012006.6 1348104  
## Jul 2013 1114988 1007070 1222906 947825.2 1282151  
## Aug 2013 1168666 1060874 1276457 1001698.5 1335633  
## Sep 2013 1219070 1111457 1326682 1052380.0 1385759  
## Oct 2013 1234737 1126290 1343185 1066753.4 1402722  
## Nov 2013 1335131 1227414 1442848 1168278.8 1501984  
## Dec 2013 1261780 1153853 1369708 1094602.1 1428958

ModelEfakSalesWithCEPI\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 1075911 966514.0 1185308 906552.6 1245269  
## Feb 2013 1142047 1032502.0 1251592 972459.4 1311635  
## Mar 2013 1265797 1155974.5 1375620 1095779.5 1435815  
## Apr 2013 1027154 918285.8 1136021 858614.3 1195693  
## May 2013 1203519 1094074.8 1312964 1034087.2 1372952  
## Jun 2013 1138765 1029271.1 1248259 969256.4 1308274  
## Jul 2013 1087711 977571.1 1197850 917202.6 1258218  
## Aug 2013 1136438 1026614.7 1246261 966419.7 1306456  
## Sep 2013 1190056 1080111.3 1300001 1019849.4 1360263  
## Oct 2013 1193995 1084550.0 1303439 1024562.4 1363427  
## Nov 2013 1313560 1203420.5 1423699 1143052.0 1484068  
## Dec 2013 1236260 1126315.5 1346205 1066053.6 1406467

ModelEfakSalesWithTrendAnsSeasonalityOnly\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 1028393 894901.3 1161884 821787.9 1234997  
## Feb 2013 1089737 956245.7 1223228 883132.3 1296342  
## Mar 2013 1205501 1072009.9 1338992 998896.5 1412106  
## Apr 2013 1003594 870102.9 1137085 796989.5 1210199  
## May 2013 1154404 1020912.7 1287895 947799.3 1361009  
## Jun 2013 1088052 954561.1 1221544 881447.7 1294657  
## Jul 2013 1019428 885936.7 1152919 812823.3 1226033  
## Aug 2013 1076141 942650.1 1209633 869536.7 1282746  
## Sep 2013 1126565 993074.1 1260057 919960.7 1333170  
## Oct 2013 1144879 1011387.9 1278370 938274.5 1351484  
## Nov 2013 1245277 1111786.1 1378769 1038672.7 1451882  
## Dec 2013 1172770 1039278.3 1306261 966164.9 1379374

ModelWithCEPIOnly\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 1049949 920846.3 1179052 850594.4 1249303  
## Feb 2013 1108707 978542.0 1238872 907711.9 1309703  
## Mar 2013 1157672 1026509.9 1288835 955137.1 1360208  
## Apr 2013 1108707 978542.0 1238872 907711.9 1309703  
## May 2013 1147879 1016924.3 1278835 945664.4 1350094  
## Jun 2013 1157672 1026509.9 1288835 955137.1 1360208  
## Jul 2013 1206638 1074378.5 1338897 1002409.0 1410866  
## Aug 2013 1206638 1074378.5 1338897 1002409.0 1410866  
## Sep 2013 1206638 1074378.5 1338897 1002409.0 1410866  
## Oct 2013 1187052 1055242.8 1318860 983518.4 1390585  
## Nov 2013 1206638 1074378.5 1338897 1002409.0 1410866  
## Dec 2013 1245810 1112603.7 1379016 1040118.8 1451501

#mywait()  
  
# In order to be able to correlate the Forecast with the As Is Data, it is necessary to convert the Point   
# Estimator into a time series.  
ModelWithEfakExportsIndicators\_Forecast\_df <-as.data.frame(ModelWithEfakExportsIndicators\_Forecast)   
ModelEfakSalesWithCEPI\_Forecast\_df <-as.data.frame(ModelEfakSalesWithCEPI\_Forecast)   
ModelEfakSalesWithTrendAnsSeasonalityOnly\_Forecast\_df <-as.data.frame(ModelEfakSalesWithTrendAnsSeasonalityOnly\_Forecast)   
ModelWithCEPIOnly\_Forecast\_df <-as.data.frame(ModelWithCEPIOnly\_Forecast)   
ModelWithEfakExportsIndicators\_PointForecast <- ts(ModelWithEfakExportsIndicators\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
ModelEfakSalesWithCEPI\_PointForecast <- ts(ModelEfakSalesWithCEPI\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
ModelEfakSalesWithTrendAnsSeasonalityOnly\_PointForecast <- ts(ModelEfakSalesWithTrendAnsSeasonalityOnly\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
ModelWithCEPIOnly\_PointForecast <- ts(ModelWithCEPIOnly\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
  
# Correlation of the forecasts and As Is Data. As a comparison, the correlation of the As Is Data for 2013 with the Plan Data.  
cor(ModelWithEfakExportsIndicators\_PointForecast, EfakAsIs\_2013)

## [1] 0.5994128

cor(ModelEfakSalesWithCEPI\_PointForecast, EfakAsIs\_2013)

## [1] 0.5919143

cor(ModelEfakSalesWithTrendAnsSeasonalityOnly\_PointForecast, EfakAsIs\_2013)

## [1] 0.5990717

cor(ModelWithCEPIOnly\_PointForecast, EfakAsIs\_2013)

## [1] 0.4873009

cor(EfakAsIs\_2013, EfakPlan\_2013)

## [1] 0.2513655

#################################################################################  
# 5.2.4 Forecast ModelWithWugeExportsIndicators #  
#################################################################################  
  
# Shorten the variable in ModelWithWugeExportsIndicators by one year in order to be able to produce a forecast for 2013.  
ModelWithWugeExportsIndicators\_2012 <- tslm(WugeAsIs\_2012 ~ trend + season + CEPI\_2012 + UrbanoExports\_2012 + AEPI\_2012 + GlobalisationPartyMembers\_2012)  
ModelWugeWithCEPI\_2012 <- tslm(WugeAsIs\_2012 ~ trend + season + CEPI\_2012)  
ModelWugeWithTrendAndSeasonalityOnly\_2012 <- tslm(WugeAsIs\_2012 ~ trend + season)  
summary(ModelWithWugeExportsIndicators\_2012)

##   
## Call:  
## tslm(formula = WugeAsIs\_2012 ~ trend + season + CEPI\_2012 + UrbanoExports\_2012 +   
## AEPI\_2012 + GlobalisationPartyMembers\_2012)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -115173 -41200 1525 29413 86974   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -3.279e+06 3.138e+06 -1.045 0.301896   
## trend 8.454e+02 4.543e+03 0.186 0.853263   
## season2 -2.471e+04 3.854e+04 -0.641 0.524769   
## season3 2.194e+04 4.371e+04 0.502 0.618276   
## season4 -9.058e+04 4.179e+04 -2.167 0.035789 \*   
## season5 -4.502e+04 4.244e+04 -1.061 0.294645   
## season6 -9.635e+04 4.313e+04 -2.234 0.030734 \*   
## season7 -1.345e+05 4.729e+04 -2.844 0.006794 \*\*   
## season8 -6.510e+04 4.856e+04 -1.341 0.187094   
## season9 1.723e+05 4.825e+04 3.570 0.000893 \*\*\*  
## season10 6.080e+04 4.797e+04 1.267 0.211830   
## season11 1.007e+05 4.824e+04 2.088 0.042712 \*   
## season12 8.584e+04 5.427e+04 1.582 0.121031   
## CEPI\_2012 3.569e+04 4.074e+04 0.876 0.385872   
## UrbanoExports\_2012 -1.840e-01 1.119e-01 -1.644 0.107492   
## AEPI\_2012 6.634e+03 1.322e+04 0.502 0.618505   
## GlobalisationPartyMembers\_2012 1.279e+01 8.370e+00 1.528 0.133808   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 55990 on 43 degrees of freedom  
## Multiple R-squared: 0.8946, Adjusted R-squared: 0.8553   
## F-statistic: 22.8 on 16 and 43 DF, p-value: 6.386e-16

summary(ModelWugeWithCEPI\_2012)

##   
## Call:  
## tslm(formula = WugeAsIs\_2012 ~ trend + season + CEPI\_2012)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -107584 -35585 -33 36537 95586   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 139201 1198306 0.116 0.908027   
## trend 5425 1532 3.542 0.000923 \*\*\*  
## season2 -7743 36654 -0.211 0.833637   
## season3 50656 37319 1.357 0.181287   
## season4 -67126 36923 -1.818 0.075582 .   
## season5 -24921 36857 -0.676 0.502323   
## season6 -76684 36802 -2.084 0.042774 \*   
## season7 -108160 37198 -2.908 0.005588 \*\*   
## season8 -40131 37184 -1.079 0.286109   
## season9 192782 36874 5.228 4.07e-06 \*\*\*  
## season10 74592 36696 2.033 0.047879 \*   
## season11 107956 36590 2.950 0.004977 \*\*   
## season12 106011 37108 2.857 0.006404 \*\*   
## CEPI\_2012 2171 12391 0.175 0.861664   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 57360 on 46 degrees of freedom  
## Multiple R-squared: 0.8816, Adjusted R-squared: 0.8481   
## F-statistic: 26.35 on 13 and 46 DF, p-value: < 2.2e-16

summary(ModelWugeWithTrendAndSeasonalityOnly\_2012)

##   
## Call:  
## tslm(formula = WugeAsIs\_2012 ~ trend + season)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -106028 -36228 -1747 35972 95148   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 349130.0 27586.4 12.656 < 2e-16 \*\*\*  
## trend 5681.9 431.8 13.158 < 2e-16 \*\*\*  
## season2 -6827.3 35904.2 -0.190 0.85001   
## season3 52182.5 35912.0 1.453 0.15285   
## season4 -65943.2 35925.0 -1.836 0.07275 .   
## season5 -23822.4 35943.1 -0.663 0.51071   
## season6 -75668.3 35966.5 -2.104 0.04077 \*   
## season7 -106793.3 35995.0 -2.967 0.00472 \*\*   
## season8 -38804.4 36028.6 -1.077 0.28696   
## season9 193763.4 36067.4 5.372 2.37e-06 \*\*\*  
## season10 75273.1 36111.4 2.084 0.04258 \*   
## season11 108293.1 36160.4 2.995 0.00437 \*\*   
## season12 107089.6 36214.5 2.957 0.00485 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 56770 on 47 degrees of freedom  
## Multiple R-squared: 0.8815, Adjusted R-squared: 0.8513   
## F-statistic: 29.14 on 12 and 47 DF, p-value: < 2.2e-16

# Add "newdata" to the 2013 indicator values for the forecast.  
ModelWithWugeExportsIndicators\_Forecast <- forecast(ModelWithWugeExportsIndicators\_2012, newdata=data.frame(CEPI\_2012=CEPI\_2013, UrbanoExports\_2012 = UrbanoExports\_2013, AEPI\_2012 = AEPI\_2013, GlobalisationPartyMembers\_2012 = GlobalisationPartyMembers\_2013),h=12)  
ModelWugeWithCEPI\_Forecast <- forecast(ModelWugeWithCEPI\_2012, , newdata=data.frame(CEPI\_2012=CEPI\_2013), h=12)  
ModelWugeWithTrendAndSeasonalityOnly\_Forecast <- forecast(ModelWugeWithTrendAndSeasonalityOnly\_2012,h=12)  
  
plot(ModelWithWugeExportsIndicators\_Forecast, main="ModelWithWugeExportsIndicators\_Forecast")  
plot(ModelWugeWithCEPI\_Forecast, main="ModelWugeWithEPI\_Forecast")  
plot(ModelWugeWithTrendAndSeasonalityOnly\_Forecast, main="ModelWugeWithTrendAndSeasonalityOnly\_Forecast")  
ModelWithWugeExportsIndicators\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 625378.5 529199.6 721557.4 476353.9 774403.1  
## Feb 2013 624914.9 530363.0 719466.9 478411.2 771418.6  
## Mar 2013 696227.0 602160.9 790293.0 550476.2 841977.7  
## Apr 2013 567366.9 463202.7 671531.1 405969.4 728764.4  
## May 2013 632029.3 531460.8 732597.8 476203.2 787855.4  
## Jun 2013 585783.0 486374.5 685191.5 431754.3 739811.7  
## Jul 2013 571640.8 474032.0 669249.5 420400.7 722880.9  
## Aug 2013 638558.7 541541.1 735576.3 488234.5 788882.8  
## Sep 2013 878103.3 781975.9 974230.6 729158.5 1027048.0  
## Oct 2013 756350.3 658331.3 854369.4 604474.6 908226.1  
## Nov 2013 802954.0 709738.0 896169.9 658520.3 947387.6  
## Dec 2013 804495.1 710717.6 898272.6 659191.3 949798.9

ModelWugeWithCEPI\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 697020.6 612262.9 781778.4 565806.3 828234.9  
## Feb 2013 696005.5 611133.0 780878.0 564613.5 827397.5  
## Mar 2013 760914.4 675826.6 846002.3 629189.1 892639.8  
## Apr 2013 647471.8 563123.9 731819.7 516892.0 778051.6  
## May 2013 695969.4 611174.6 780764.3 564697.8 827241.1  
## Jun 2013 649848.9 565015.8 734681.9 518518.0 781179.8  
## Jul 2013 624883.6 539550.5 710216.7 492778.6 756988.6  
## Aug 2013 698337.2 613249.4 783425.1 566611.9 830062.6  
## Sep 2013 936673.9 851491.5 1021856.3 804802.2 1068545.6  
## Oct 2013 823474.6 738679.8 908269.5 692203.0 954746.3  
## Nov 2013 862697.8 777364.7 948030.9 730592.8 994802.8  
## Dec 2013 867045.9 781863.5 952228.3 735174.2 998917.6

ModelWugeWithTrendAndSeasonalityOnly\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 695728.6 612413.5 779043.8 566781.7 824675.6  
## Feb 2013 694583.2 611268.1 777898.4 565636.3 823530.2  
## Mar 2013 759275.0 675959.9 842590.2 630328.1 888222.0  
## Apr 2013 646831.2 563516.1 730146.4 517884.3 775778.2  
## May 2013 694634.0 611318.9 777949.2 565687.1 823581.0  
## Jun 2013 648470.0 565154.9 731785.2 519523.1 777417.0  
## Jul 2013 623027.0 539711.9 706342.2 494080.1 751974.0  
## Aug 2013 696697.8 613382.7 780013.0 567750.9 825644.8  
## Sep 2013 934947.6 851632.5 1018262.8 806000.7 1063894.6  
## Oct 2013 822139.2 738824.1 905454.4 693192.3 951086.2  
## Nov 2013 860841.2 777526.1 944156.4 731894.3 989788.2  
## Dec 2013 865319.6 782004.5 948634.8 736372.7 994266.6

#mywait()  
  
# In order to be able to correlate the Forecast with the As Is data, it is necessary to convert the Point   
# Estimator into a time series.   
ModelWithWugeExportsIndicators\_Forecast\_df <-as.data.frame(ModelWithWugeExportsIndicators\_Forecast)   
ModelWugeWithCEPI\_Forecast\_df <-as.data.frame(ModelWugeWithCEPI\_Forecast)   
ModelWugeWithTrendAndSeasonalityOnly\_Forecast\_df <-as.data.frame(ModelWugeWithTrendAndSeasonalityOnly\_Forecast)  
ModelWithWugeExportsIndicators\_PointForecast <- ts(ModelWithWugeExportsIndicators\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
ModelWugeWithCEPI\_PointForecast <- ts(ModelWugeWithCEPI\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
ModelWugeWithTrendAndSeasonalityOnly\_PointForecast <- ts(ModelWugeWithTrendAndSeasonalityOnly\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
  
# Correlation of the forecasts and As Is data. As a comparison, the correlation of the As Is data for 2013 with the Plan Data.  
cor(ModelWithWugeExportsIndicators\_PointForecast, WugeAsIs\_2013)

## [1] 0.8187058

cor(ModelWugeWithCEPI\_PointForecast, WugeAsIs\_2013)

## [1] 0.8392912

cor(ModelWugeWithTrendAndSeasonalityOnly\_PointForecast, WugeAsIs\_2013)

## [1] 0.8400829

cor(WugeAsIs\_2013, WugePlan\_2013)

## [1] 0.8143285

#################################################################################  
# 5.2.5 Forecast ModelTotalEtel #  
#################################################################################  
  
# Shorten the variables in ModelTotalEtel by one year in order to be able to produce a forecast for 2013.  
ModelTotalEtel\_2012 <- tslm(TotalEtelAsIs\_2012 ~ trend + season)  
ModelBlueEtel\_2012 <- tslm(BlueEtelAsIs\_2012 ~ trend + season)  
ModelRedEtel\_2012 <- tslm(RedEtelAsIs\_2012 ~ trend + season)  
summary(ModelTotalEtel\_2012)

##   
## Call:  
## tslm(formula = TotalEtelAsIs\_2012 ~ trend + season)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -299816 -89175 -2539 108720 287047   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 1361585 78100 17.434 < 2e-16 \*\*\*  
## trend 6460 1223 5.284 3.20e-06 \*\*\*  
## season2 -44872 101648 -0.441 0.66091   
## season3 -53014 101671 -0.521 0.60452   
## season4 -524858 101707 -5.160 4.88e-06 \*\*\*  
## season5 -501638 101759 -4.930 1.07e-05 \*\*\*  
## season6 -674802 101825 -6.627 3.01e-08 \*\*\*  
## season7 -765417 101905 -7.511 1.38e-09 \*\*\*  
## season8 -544231 102001 -5.336 2.68e-06 \*\*\*  
## season9 558436 102111 5.469 1.70e-06 \*\*\*  
## season10 232677 102235 2.276 0.02745 \*   
## season11 276582 102374 2.702 0.00957 \*\*   
## season12 55396 102527 0.540 0.59154   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 160700 on 47 degrees of freedom  
## Multiple R-squared: 0.9008, Adjusted R-squared: 0.8755   
## F-statistic: 35.58 on 12 and 47 DF, p-value: < 2.2e-16

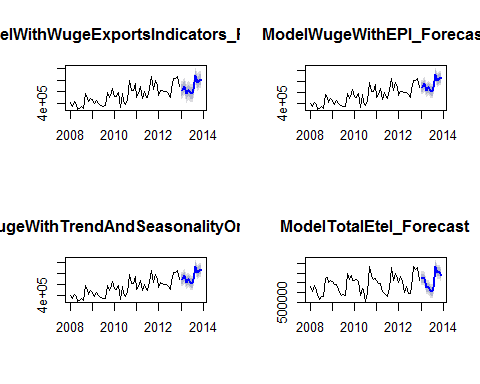
summary(ModelBlueEtel\_2012)

##   
## Call:  
## tslm(formula = BlueEtelAsIs\_2012 ~ trend + season)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -74076 -27925 13 21979 114549   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 3.596e+05 2.020e+04 17.804 < 2e-16 \*\*\*  
## trend -6.523e+00 3.162e+02 -0.021 0.98363   
## season2 -2.295e+04 2.629e+04 -0.873 0.38706   
## season3 -2.172e+04 2.629e+04 -0.826 0.41290   
## season4 -1.049e+05 2.630e+04 -3.990 0.00023 \*\*\*  
## season5 -1.359e+05 2.632e+04 -5.162 4.85e-06 \*\*\*  
## season6 -1.458e+05 2.633e+04 -5.535 1.35e-06 \*\*\*  
## season7 -1.697e+05 2.635e+04 -6.440 5.78e-08 \*\*\*  
## season8 -1.338e+05 2.638e+04 -5.071 6.62e-06 \*\*\*  
## season9 -9.148e+03 2.641e+04 -0.346 0.73056   
## season10 2.619e+04 2.644e+04 0.990 0.32702   
## season11 -8.157e+03 2.648e+04 -0.308 0.75938   
## season12 -2.467e+04 2.652e+04 -0.931 0.35684   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 41560 on 47 degrees of freedom  
## Multiple R-squared: 0.7652, Adjusted R-squared: 0.7052   
## F-statistic: 12.76 on 12 and 47 DF, p-value: 4.92e-11

summary(ModelRedEtel\_2012)

##   
## Call:  
## tslm(formula = RedEtelAsIs\_2012 ~ trend + season)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -361228 -84581 16694 93341 249192   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 1001982 71882 13.939 < 2e-16 \*\*\*  
## trend 6466 1125 5.746 6.50e-07 \*\*\*  
## season2 -21921 93555 -0.234 0.815761   
## season3 -31292 93576 -0.334 0.739565   
## season4 -419921 93609 -4.486 4.67e-05 \*\*\*  
## season5 -365782 93657 -3.906 0.000299 \*\*\*  
## season6 -529038 93718 -5.645 9.24e-07 \*\*\*  
## season7 -595687 93792 -6.351 7.90e-08 \*\*\*  
## season8 -410470 93880 -4.372 6.77e-05 \*\*\*  
## season9 567584 93981 6.039 2.35e-07 \*\*\*  
## season10 206490 94095 2.194 0.033178 \*   
## season11 284738 94223 3.022 0.004056 \*\*   
## season12 80069 94364 0.849 0.400451   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 147900 on 47 degrees of freedom  
## Multiple R-squared: 0.8895, Adjusted R-squared: 0.8613   
## F-statistic: 31.53 on 12 and 47 DF, p-value: < 2.2e-16

# Forecast  
ModelTotalEtel\_Forecast <- forecast(ModelTotalEtel\_2012,h=12)  
ModelBlueEtel\_Forecast <- forecast(ModelBlueEtel\_2012,h=12)  
ModelRedEtel\_Forecast <- forecast(ModelRedEtel\_2012,h=12)  
  
  
plot(ModelTotalEtel\_Forecast,main="ModelTotalEtel\_Forecast")



plot(ModelBlueEtel\_Forecast,main="ModelBlueEtel\_Forecast")  
plot(ModelRedEtel\_Forecast,main="ModelRedEtel\_Forecast")  
ModelTotalEtel\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 1755615 1519741.4 1991488 1390553.3 2120676  
## Feb 2013 1717202 1481328.6 1953076 1352140.5 2082264  
## Mar 2013 1715520 1479646.6 1951394 1350458.5 2080582  
## Apr 2013 1250135 1014262.0 1486009 885073.9 1615197  
## May 2013 1279815 1043941.8 1515689 914753.7 1644877  
## Jun 2013 1113110 877236.8 1348984 748048.7 1478172  
## Jul 2013 1028955 793081.8 1264829 663893.7 1394017  
## Aug 2013 1256600 1020727.0 1492474 891538.9 1621662  
## Sep 2013 2365726 2129853.0 2601600 2000664.9 2730788  
## Oct 2013 2046428 1810554.4 2282301 1681366.3 2411489  
## Nov 2013 2096791 1860918.0 2332665 1731729.9 2461853  
## Dec 2013 1882065 1646192.0 2117939 1517003.9 2247127

ModelBlueEtel\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 359205.0 298204.4 420205.5 264794.39 453615.6  
## Feb 2013 336247.0 275246.4 397247.5 241836.39 430657.6  
## Mar 2013 337469.8 276469.2 398470.3 243059.19 431880.4  
## Apr 2013 254247.4 193246.8 315247.9 159836.79 348658.0  
## May 2013 223323.0 162322.4 284323.5 128912.39 317733.6  
## Jun 2013 213408.6 152408.0 274409.1 118997.99 307819.2  
## Jul 2013 189435.8 128435.2 250436.3 95025.19 283846.4  
## Aug 2013 225398.8 164398.2 286399.3 130988.19 319809.4  
## Sep 2013 350004.4 289003.8 411004.9 255593.79 444415.0  
## Oct 2013 385333.6 324333.0 446334.1 290922.99 479744.2  
## Nov 2013 350983.0 289982.4 411983.5 256572.39 445393.6  
## Dec 2013 334459.8 273459.2 395460.3 240049.19 428870.4

ModelRedEtel\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 1396410.2 1179316.7 1613504 1060414.4 1732406  
## Feb 2013 1380955.2 1163861.7 1598049 1044959.4 1716951  
## Mar 2013 1378050.6 1160957.1 1595144 1042054.8 1714046  
## Apr 2013 995887.8 778794.3 1212981 659892.0 1331884  
## May 2013 1056492.4 839398.9 1273586 720496.6 1392488  
## Jun 2013 899702.0 682608.5 1116795 563706.2 1235698  
## Jul 2013 839519.6 622426.1 1056613 503523.8 1175515  
## Aug 2013 1031202.0 814108.5 1248295 695206.2 1367198  
## Sep 2013 2015722.2 1798628.7 2232816 1679726.4 2351718  
## Oct 2013 1661094.6 1444001.1 1878188 1325098.8 1997090  
## Nov 2013 1745808.8 1528715.3 1962902 1409813.0 2081805  
## Dec 2013 1547605.8 1330512.3 1764699 1211610.0 1883602

#mywait()  
  
# In order to be able to correlate the Forecast with the As Is Data, it is necessary to convert the Point   
# Estimator into a time series.  
ModelTotalEtel\_Forecast\_df <-as.data.frame(ModelTotalEtel\_Forecast)   
ModelBlueEtel\_Forecast\_df <-as.data.frame(ModelBlueEtel\_Forecast)   
ModelRedEtel\_Forecast\_df <-as.data.frame(ModelRedEtel\_Forecast)   
ModelTotalEtel\_PointForecast <- ts(ModelTotalEtel\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
ModelBlueEtel\_PointForecast <- ts(ModelBlueEtel\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
ModelRedEtel\_PointForecast <- ts(ModelRedEtel\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
  
# Correlation of the forecasts and As Is Data. As a comparison, the correlation of the As Is Data for 2013 with the Plan Data.  
cor(ModelTotalEtel\_PointForecast, TotalEtelAsIs\_2013)

## [1] 0.9392717

cor(TotalEtelPlan\_2013, TotalEtelAsIs\_2013)

## [1] 0.9602983

cor(ModelBlueEtel\_PointForecast, BlueEtelAsIs\_2013)

## [1] 0.8397498

cor(BlueEtelPlan\_2013, BlueEtelAsIs\_2013)

## [1] 0.7467031

cor(ModelRedEtel\_PointForecast, RedEtelAsIs\_2013)

## [1] 0.9288154

cor(RedEtelPlan\_2013, RedEtelAsIs\_2013)

## [1] 0.9570811

#################################################################################  
# 5.2.6 Forecast ModelWithTotalUrbanoExports #  
#################################################################################  
  
# Shorten the variables in ModelWithTotalUrbanoExports by one year in order to be able to produce a forecast for 2013.  
ModelWithTotalUrbanoExports\_2012 <- tslm(TotalAsIs\_2012 ~ trend + season + UrbanoExports\_2012)  
summary(ModelWithTotalUrbanoExports\_2012)

##   
## Call:  
## tslm(formula = TotalAsIs\_2012 ~ trend + season + UrbanoExports\_2012)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -569149 -128266 8067 181935 457990   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 1.450e+06 1.039e+06 1.396 0.169437   
## trend 2.187e+04 5.296e+03 4.129 0.000152 \*\*\*  
## season2 -3.080e+04 1.579e+05 -0.195 0.846161   
## season3 1.873e+05 1.581e+05 1.184 0.242307   
## season4 -6.295e+05 1.586e+05 -3.970 0.000250 \*\*\*  
## season5 -4.770e+05 1.592e+05 -2.996 0.004395 \*\*   
## season6 -7.441e+05 1.600e+05 -4.651 2.80e-05 \*\*\*  
## season7 -9.777e+05 1.609e+05 -6.075 2.23e-07 \*\*\*  
## season8 -5.936e+05 1.621e+05 -3.663 0.000643 \*\*\*  
## season9 7.280e+05 1.634e+05 4.456 5.31e-05 \*\*\*  
## season10 3.601e+05 1.648e+05 2.185 0.034032 \*   
## season11 5.430e+05 1.664e+05 3.263 0.002084 \*\*   
## season12 1.465e+05 1.682e+05 0.871 0.388352   
## UrbanoExports\_2012 1.246e-01 1.843e-01 0.676 0.502194   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 249500 on 46 degrees of freedom  
## Multiple R-squared: 0.9115, Adjusted R-squared: 0.8864   
## F-statistic: 36.43 on 13 and 46 DF, p-value: < 2.2e-16

# Add "newdata" to the 2013 indicator values for the forecast.  
ModelWithTotalUrbanoExports\_Forecast <- forecast(ModelWithTotalUrbanoExports\_2012, newdata=data.frame(UrbanoExports\_2012=UrbanoExports\_2013), h=12)  
plot(ModelWithTotalUrbanoExports\_Forecast,main="ModelWithTotalUrbanoExports\_Forecast")  
ModelWithTotalUrbanoExports\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 3724840 3350944 4098736 3146008 4303672  
## Feb 2013 3715906 3342010 4089802 3137074 4294739  
## Mar 2013 3955876 3581980 4329772 3377044 4534708  
## Apr 2013 3160946 2787050 3534842 2582114 3739778  
## May 2013 3335360 2961464 3709256 2756527 3914192  
## Jun 2013 3090039 2716143 3463935 2511206 3668871  
## Jul 2013 2878319 2504423 3252215 2299487 3457151  
## Aug 2013 3284274 2910378 3658170 2705442 3863106  
## Sep 2013 4627745 4253849 5001641 4048913 5206577  
## Oct 2013 4281747 3907851 4655643 3702915 4860579  
## Nov 2013 4486520 4112624 4860416 3907688 5065352  
## Dec 2013 4111851 3737954 4485747 3533018 4690683

#mywait()  
  
# In order to be able to correlate the Forecast with the As Is data, it is necessary to convert the Point   
# Estimator into a time series.   
ModelWithTotalUrbanoExports\_Forecast\_df <-as.data.frame(ModelWithTotalUrbanoExports\_Forecast)   
ModelWithTotalUrbanoExports\_PointForecast <- ts(ModelWithTotalUrbanoExports\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
  
# Correlation of the forecasts and As Is Data. As a comparison, the correlation of the As Is Data for 2013 with the Plan Data.  
cor(ModelWithTotalUrbanoExports\_PointForecast, TotalAsIs\_2013)

## [1] 0.9138049

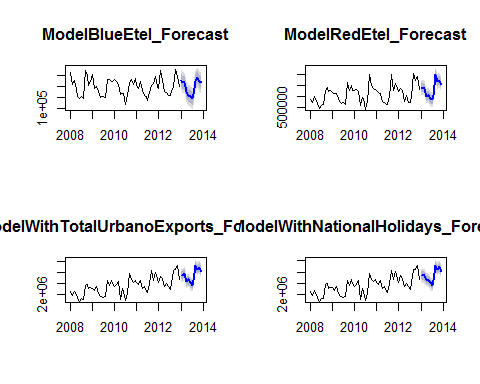
cor(TotalAsIs\_2013, TotalPlan\_2013)

## [1] 0.929769

#################################################################################  
# 5.2.7 Forecast ModelWithNationalHolidays #  
#################################################################################  
  
# Shorten the variables in ModelWithNationalHolidays by one year in order to be able to produce a forecast for 2013.  
ModelWithNationalHolidays\_2012 <- tslm(TotalAsIs\_2012 ~ trend + season + NationalHolidays\_2012)  
summary(ModelWithNationalHolidays\_2012)

##   
## Call:  
## tslm(formula = TotalAsIs\_2012 ~ trend + season + NationalHolidays\_2012)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -539294 -116717 -7864 163111 473692   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2147793 118654 18.101 < 2e-16 \*\*\*  
## trend 25212 1857 13.574 < 2e-16 \*\*\*  
## season2 -34146 154431 -0.221 0.825988   
## season3 241623 159215 1.518 0.135962   
## season4 -395488 218453 -1.810 0.076768 .   
## season5 -490327 154598 -3.172 0.002699 \*\*   
## season6 -760860 154698 -4.918 1.16e-05 \*\*\*  
## season7 -997792 154821 -6.445 6.22e-08 \*\*\*  
## season8 -617048 154966 -3.982 0.000241 \*\*\*  
## season9 701211 155133 4.520 4.31e-05 \*\*\*  
## season10 330001 155322 2.125 0.039022 \*   
## season11 509563 155532 3.276 0.002005 \*\*   
## season12 414732 248034 1.672 0.101299   
## NationalHolidays\_2012 -305051 193024 -1.580 0.120873   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 244200 on 46 degrees of freedom  
## Multiple R-squared: 0.9152, Adjusted R-squared: 0.8912   
## F-statistic: 38.19 on 13 and 46 DF, p-value: < 2.2e-16

# Add "newdata" to the 2013 indicator values for the forecast.  
ModelWithNationalHolidays\_Forecast <- forecast(ModelWithNationalHolidays\_2012, newdata=data.frame(NationalHolidays\_2012=NationalHolidays\_2013), h=12)  
plot(ModelWithNationalHolidays\_Forecast,main="ModelWithNationalHolidays\_Forecast")



ModelWithNationalHolidays\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 3685709 3327245 4044174 3130767 4240652  
## Feb 2013 3676775 3318311 4035240 3121833 4231718  
## Mar 2013 3672704 3261840 4083568 3036641 4308767  
## Apr 2013 3365856 2954992 3776720 2729793 4001919  
## May 2013 3296229 2937764 3654693 2741286 3851171  
## Jun 2013 3050908 2692443 3409372 2495965 3605850  
## Jul 2013 2839188 2480724 3197653 2284246 3394131  
## Aug 2013 3245143 2886679 3603608 2690201 3800086  
## Sep 2013 4588614 4230149 4947079 4033671 5143556  
## Oct 2013 4242616 3884151 4601081 3687673 4797558  
## Nov 2013 4447389 4088925 4805854 3892447 5002332  
## Dec 2013 4072720 3714255 4431184 3517777 4627662

#mywait()  
  
# In order to be able to correlate the Forecast with the As Is data, it is necessary to convert the Point   
# Estimator into a time series.  
ModelWithNationalHolidays\_Forecast\_df <-as.data.frame(ModelWithNationalHolidays\_Forecast)   
ModelWithNationalHolidays\_PointForecast <- ts(ModelWithNationalHolidays\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
  
# Correlation of the forecasts and As Is Data. As a comparison, the correlation of the As Is data for 2013 with the Plan Data.  
cor(ModelWithNationalHolidays\_PointForecast, TotalAsIs\_2013)

## [1] 0.9590162

#################################################################################  
# 5.2.8 Forecast ModelWithInfluenceNationalHolidays #  
#################################################################################  
  
# Shorten the variables in ModelWithInfluenceNationalHolidays by one year in order to be able to produce a forecast for 2013.  
ModelWithInfluenceNationalHolidays\_2012 <- tslm(TotalAsIs\_2012 ~ trend + season + InfluenceNationalHolidays\_2012)  
summary(ModelWithInfluenceNationalHolidays\_2012)

##   
## Call:  
## tslm(formula = TotalAsIs\_2012 ~ trend + season + InfluenceNationalHolidays\_2012)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -539294 -116717 -7864 163111 473692   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2147793 118654 18.101 < 2e-16 \*\*\*  
## trend 25212 1857 13.574 < 2e-16 \*\*\*  
## season2 -34146 154431 -0.221 0.825988   
## season3 241623 159215 1.518 0.135962   
## season4 -395488 218453 -1.810 0.076768 .   
## season5 -490327 154598 -3.172 0.002699 \*\*   
## season6 -760860 154698 -4.918 1.16e-05 \*\*\*  
## season7 -997792 154821 -6.445 6.22e-08 \*\*\*  
## season8 -617048 154966 -3.982 0.000241 \*\*\*  
## season9 1006262 247638 4.063 0.000187 \*\*\*  
## season10 330001 155322 2.125 0.039022 \*   
## season11 814614 247888 3.286 0.001948 \*\*   
## season12 414732 248034 1.672 0.101299   
## InfluenceNationalHolidays\_2012 -305051 193024 -1.580 0.120873   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 244200 on 46 degrees of freedom  
## Multiple R-squared: 0.9152, Adjusted R-squared: 0.8912   
## F-statistic: 38.19 on 13 and 46 DF, p-value: < 2.2e-16

# Add "newdata" to the 2013 indicator values for the forecast.  
ModelWithInfluenceNationalHolidays\_Forecast <- forecast(ModelWithInfluenceNationalHolidays\_2012, newdata=data.frame(InfluenceNationalHolidays\_2012=InfluenceNationalHolidaysVector\_2013), h=12)  
plot(ModelWithInfluenceNationalHolidays\_Forecast,main="ModelWithInfluenceNationalHolidays\_Forecast")  
ModelWithInfluenceNationalHolidays\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 3685709 3327245 4044174 3130767 4240652  
## Feb 2013 3676775 3318311 4035240 3121833 4231718  
## Mar 2013 3672704 3261840 4083568 3036641 4308767  
## Apr 2013 3365856 2954992 3776720 2729793 4001919  
## May 2013 3296229 2937764 3654693 2741286 3851171  
## Jun 2013 3050908 2692443 3409372 2495965 3605850  
## Jul 2013 2839188 2480724 3197653 2284246 3394131  
## Aug 2013 3245143 2886679 3603608 2690201 3800086  
## Sep 2013 4588614 4230149 4947079 4033671 5143556  
## Oct 2013 4242616 3884151 4601081 3687673 4797558  
## Nov 2013 4447389 4088925 4805854 3892447 5002332  
## Dec 2013 4072720 3714255 4431184 3517777 4627662

#mywait()  
  
# In order to be able to correlate the Forecast with the As Is Data, it is necessary to convert the Point   
# Estimator into a time series.  
ModelWithInfluenceNationalHolidays\_Forecast\_df <-as.data.frame(ModelWithInfluenceNationalHolidays\_Forecast)   
ModelWithInfluenceNationalHolidays\_PointForecast <- ts(ModelWithInfluenceNationalHolidays\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
  
# Correlation of the forecasts and As Is Data. As a comparison, the correlation of the As Is Data for 2013 with the Plan Data.  
cor(ModelWithInfluenceNationalHolidays\_PointForecast, TotalAsIs\_2013)

## [1] 0.9590162

cor(TotalAsIs\_2013, TotalPlan\_2013)

## [1] 0.929769

cor(TotalAsIs\_2013, TotalPlan\_2013)

## [1] 0.929769

#################################################################################  
### ###  
### 6. Forecast for 2014 ###  
### ###  
#################################################################################  
  
  
# As ModelWithLowCorrelatingIndicators was the one of best fitting model for a forecast, the exports data for 2014 will be forecast  
# based on trend and seasonality and NationalHolidays, UrbanoExports and GlobalisationPartyMembers.   
summary(ModelWithLowCorrelatingIndicators)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + NationalHolidays +   
## UrbanoExports + GlobalisationPartyMembers)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -508755 -122676 7119 173089 403964   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 1.467e+06 1.517e+06 0.967 0.337647   
## trend 2.264e+04 9.148e+03 2.474 0.016399 \*   
## season2 -1.274e+05 1.450e+05 -0.878 0.383528   
## season3 1.980e+05 1.546e+05 1.281 0.205562   
## season4 -3.100e+05 1.794e+05 -1.728 0.089424 .   
## season5 -6.084e+05 1.493e+05 -4.075 0.000146 \*\*\*  
## season6 -8.641e+05 1.518e+05 -5.693 4.78e-07 \*\*\*  
## season7 -1.056e+06 1.548e+05 -6.824 6.75e-09 \*\*\*  
## season8 -6.982e+05 1.583e+05 -4.411 4.72e-05 \*\*\*  
## season9 7.360e+05 1.622e+05 4.538 3.05e-05 \*\*\*  
## season10 3.341e+05 1.665e+05 2.007 0.049635 \*   
## season11 5.100e+05 1.712e+05 2.979 0.004276 \*\*   
## season12 5.471e+05 2.338e+05 2.341 0.022838 \*   
## NationalHolidays -4.315e+05 1.535e+05 -2.811 0.006794 \*\*   
## UrbanoExports 1.622e-01 1.692e-01 0.959 0.341873   
## GlobalisationPartyMembers -4.032e+00 2.086e+01 -0.193 0.847464   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 250700 on 56 degrees of freedom  
## Multiple R-squared: 0.9288, Adjusted R-squared: 0.9097   
## F-statistic: 48.69 on 15 and 56 DF, p-value: < 2.2e-16

Forecast\_ModelWithLowCorrelatingIndicators\_2014 <- forecast(ModelWithLowCorrelatingIndicators,newdata=data.frame(NationalHolidays=NationalHolidays\_2014, UrbanoExports= UrbanoExports\_2014, GlobalisationPartyMembers=GlobalisationPartyMembers\_2014),h=12)  
plot(Forecast\_ModelWithLowCorrelatingIndicators\_2014, main="Forecast\_2014")  
  
  
  
#mywait()  
  
Forecast\_ModelWithLowCorrelatingIndicators\_2014\_df <-as.data.frame(Forecast\_ModelWithLowCorrelatingIndicators\_2014)   
PointForecast\_ModelWithLowCorrelatingIndicators\_2014 <- ts(Forecast\_ModelWithLowCorrelatingIndicators\_2014\_df$"Point Forecast", start=c(2014,1), end=c(2014,12), frequency=12)  
PointForecast\_ModelWithLowCorrelatingIndicators\_2014

## Jan Feb Mar Apr May Jun Jul Aug  
## 2014 4154873 4050131 4398156 3481206 3637040 3403934 3234308 3615166  
## Sep Oct Nov Dec  
## 2014 5072002 4692732 4891237 4519491

cor(TotalAsIs\_2014,TotalPlan\_2014)

## [1] 0.9448221

cor(TotalAsIs\_2014,PointForecast\_ModelWithLowCorrelatingIndicators\_2014)

## [1] 0.9178468

# As ModelWithTrendAndSeasonalityOnly also gave a well fitting model for a forecast, the exports data for 2014 will be forecast  
# based on trend and seasonality.   
summary(ModelWithTrendAndSeasonalityOnly)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -699390 -154210 17753 150363 495430   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2182435 117276 18.609 < 2e-16 \*\*\*  
## trend 26427 1514 17.456 < 2e-16 \*\*\*  
## season2 -131168 152001 -0.863 0.391663   
## season3 46585 152024 0.306 0.760356   
## season4 -609102 152062 -4.006 0.000176 \*\*\*  
## season5 -623539 152114 -4.099 0.000129 \*\*\*  
## season6 -883072 152182 -5.803 2.74e-07 \*\*\*  
## season7 -1079124 152265 -7.087 1.93e-09 \*\*\*  
## season8 -724693 152363 -4.756 1.31e-05 \*\*\*  
## season9 705716 152476 4.628 2.07e-05 \*\*\*  
## season10 300019 152603 1.966 0.054009 .   
## season11 472099 152746 3.091 0.003045 \*\*   
## season12 73925 152903 0.483 0.630546   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 263300 on 59 degrees of freedom  
## Multiple R-squared: 0.9173, Adjusted R-squared: 0.9004   
## F-statistic: 54.51 on 12 and 59 DF, p-value: < 2.2e-16

Forecast\_2014 <- forecast(ModelWithTrendAndSeasonalityOnly,h=12)  
plot(Forecast\_2014, main="Forecast\_2014")  
  
#mywait()  
  
Forecast\_2014\_df <-as.data.frame(Forecast\_2014)   
PointForecast\_TrendAndSeasonality\_2014 <- ts(Forecast\_2014\_df$"Point Forecast", start=c(2014,1), end=c(2014,12), frequency=12)  
PointForecast\_TrendAndSeasonality\_2014

## Jan Feb Mar Apr May Jun Jul Aug  
## 2014 4111576 4006834 4211014 3581754 3593744 3360637 3191012 3571869  
## Sep Oct Nov Dec  
## 2014 5028705 4649435 4847941 4476194

cor(TotalAsIs\_2014,TotalPlan\_2014)

## [1] 0.9448221

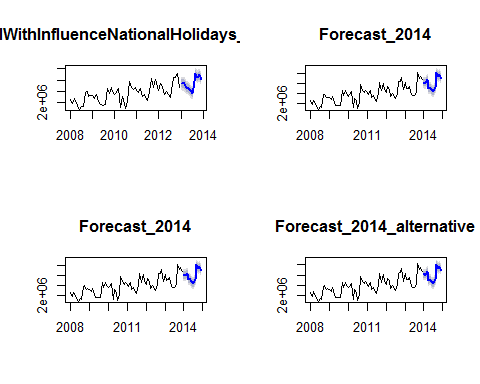
cor(TotalAsIs\_2014,PointForecast\_TrendAndSeasonality\_2014)

## [1] 0.9349765

# Output instruction for the data export of the results for further use in Excel.   
#write.csv(PointForecast\_TrendAndSeasonality\_2014,file='PointForecast\_TrendAndSeasonality\_2014.csv')  
  
### ALTERNATIVE###  
# As the indiators NationalHolidays delievered a good result, but could not convince in the 2013 forecast,  
# it could be possible that the data for 2013 was to blame. Therefore there is another Forecast using the  
# ModelWithNationalHolidays  
summary(ModelWithNationalHolidays)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + NationalHolidays)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -555545 -153976 4 150487 404837   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2182435 110867 19.685 < 2e-16 \*\*\*  
## trend 26427 1431 18.465 < 2e-16 \*\*\*  
## season2 -131168 143696 -0.913 0.36512   
## season3 190430 152432 1.249 0.21658   
## season4 -321411 176034 -1.826 0.07302 .   
## season5 -623539 143803 -4.336 5.86e-05 \*\*\*  
## season6 -883072 143867 -6.138 8.06e-08 \*\*\*  
## season7 -1079124 143945 -7.497 4.29e-10 \*\*\*  
## season8 -724693 144037 -5.031 5.02e-06 \*\*\*  
## season9 705716 144144 4.896 8.18e-06 \*\*\*  
## season10 300019 144265 2.080 0.04199 \*   
## season11 472099 144400 3.269 0.00182 \*\*   
## season12 505461 210051 2.406 0.01932 \*   
## NationalHolidays -431536 152405 -2.832 0.00636 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 248900 on 58 degrees of freedom  
## Multiple R-squared: 0.9273, Adjusted R-squared: 0.911   
## F-statistic: 56.92 on 13 and 58 DF, p-value: < 2.2e-16

Forecast\_2014\_alternative <- forecast(ModelWithNationalHolidays, newdata=data.frame(NationalHolidays=NationalHolidays\_2014),h=12)  
plot(Forecast\_2014\_alternative,main="Forecast\_2014\_alternative")



#mywait()  
  
Forecast\_2014\_alternative\_df <-as.data.frame(Forecast\_2014\_alternative)   
PointForecast\_2014\_alternative <- ts(Forecast\_2014\_alternative\_df$"Point Forecast", start=c(2014,1), end=c(2014,12), frequency=12)  
PointForecast\_2014\_alternative

## Jan Feb Mar Apr May Jun Jul Aug  
## 2014 4111576 4006834 4354859 3437909 3593744 3360637 3191012 3571869  
## Sep Oct Nov Dec  
## 2014 5028705 4649435 4847941 4476194

# Output instruction for the data export of the results for further use in Excel.  
#write.csv(PointForecast\_2014\_alternative,file='PointForecast\_2014\_alternative.csv')  
  
#################################################################################  
### ###  
### 7. Developing forecasting models with alternative model approaches ###  
### ###  
#################################################################################  
  
#################################################################################  
# 7.1 Exponential Smoothing #  
#################################################################################  
  
# Exponential Smoothing uses past values to calculate a forecast. The strength   
# with which each value influences the forecast is weakened with help of a   
# smoothing parameter. Thus we are dealing with a weighted average, whose   
# values fade out the longer ago they were in the past.  
  
#################################################################################  
# 7.1.1 Simple expontential smoothing #  
#################################################################################  
  
# Formula: ses(). It must be decided if alpha (the smoothing parameter  
# should be automatically calculated. If initial=simple, the alpha value can   
# be set to any chosen value, if initial=optimal (or nothing, as this is the   
# default), alpha will be set to the optimal value based on ets().  
# h=12 gives the number of cycles for the forecast.  
  
Model\_ses <- ses(TotalAsIs, h=12)  
summary(Model\_ses)

##   
## Forecast method: Simple exponential smoothing  
##   
## Model Information:  
## Simple exponential smoothing   
##   
## Call:  
## ses(x = TotalAsIs, h = 12)   
##   
## Smoothing parameters:  
## alpha = 0.671   
##   
## Initial states:  
## l = 2173226.7433   
##   
## sigma: 609507  
##   
## AIC AICc BIC   
## 2230.058 2230.232 2234.612   
##   
## Error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 47469.84 609507 429997.1 -1.511008 15.02336 1.172074  
## ACF1  
## Training set 0.02384493  
##   
## Forecasts:  
## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2014 4466448 3685333 5247562 3271836 5661059  
## Feb 2014 4466448 3525801 5407094 3027853 5905042  
## Mar 2014 4466448 3389650 5543245 2819628 6113267  
## Apr 2014 4466448 3268880 5664015 2634926 6297969  
## May 2014 4466448 3159220 5773675 2467215 6465680  
## Jun 2014 4466448 3058072 5874823 2312524 6620371  
## Jul 2014 4466448 2963718 5969177 2168221 6764674  
## Aug 2014 4466448 2874947 6057948 2032458 6900437  
## Sep 2014 4466448 2790873 6142022 1903878 7029017  
## Oct 2014 4466448 2710821 6222074 1781448 7151447  
## Nov 2014 4466448 2634263 6298632 1664363 7268532  
## Dec 2014 4466448 2560778 6372117 1551977 7380918

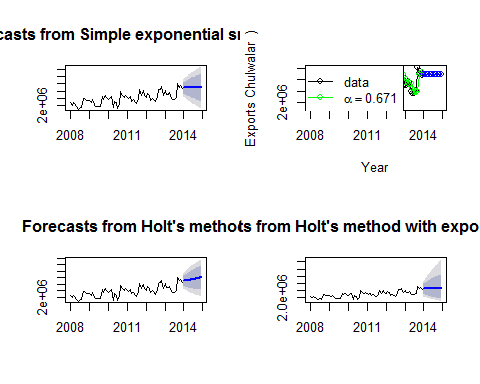
plot(Model\_ses)  
  
# The Akaike's Information Criterion(AIC/AICc) or the Bayesian Information   
# Criterion (BIC) should be at minimum.  
  
plot(Model\_ses, plot.conf=FALSE, ylab="Exports Chulwalar )", xlab="Year", main="", fcol="white", type="o")  
lines(fitted(Model\_ses), col="green", type="o")  
lines(Model\_ses$mean, col="blue", type="o")  
legend("topleft",lty=1, col=c(1,"green"), c("data", expression(alpha == 0.671)),pch=1)  
  
  
#################################################################################  
# 7.1.2 Holt's linear trend method #  
#################################################################################  
  
# Holt added to the model in order to forecast using trends as well.  
# For this it is necessary to add a beta, which determines the trend.  
# If neither alpha nor beta is stated, both parameters will be optimised  
# using ets().   
  
Model\_holt\_1 <- holt(TotalAsIs,h=12)  
summary(Model\_holt\_1)

##   
## Forecast method: Holt's method  
##   
## Model Information:  
## Holt's method   
##   
## Call:  
## holt(x = TotalAsIs, h = 12)   
##   
## Smoothing parameters:  
## alpha = 0.6571   
## beta = 1e-04   
##   
## Initial states:  
## l = 2040390.7764   
## b = 45050.7514   
##   
## sigma: 608119.1  
##   
## AIC AICc BIC   
## 2233.730 2234.327 2242.837   
##   
## Error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set -16586.9 608119.1 441110.7 -3.88925 15.75307 1.202367  
## ACF1  
## Training set 0.03462672  
##   
## Forecasts:  
## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2014 4536367 3757031 5315703 3344475 5728259  
## Feb 2014 4581298 3648703 5513894 3155016 6007580  
## Mar 2014 4626230 3562188 5690271 2998918 6253541  
## Apr 2014 4671161 3490181 5852141 2865008 6477314  
## May 2014 4716092 3428721 6003463 2747228 6684956  
## Jun 2014 4761024 3375378 6146669 2641862 6880185  
## Jul 2014 4805955 3328531 6283379 2546429 7065480  
## Aug 2014 4850886 3287035 6414738 2459182 7242591  
## Sep 2014 4895818 3250047 6541588 2378829 7412807  
## Oct 2014 4940749 3216925 6664573 2304387 7577111  
## Nov 2014 4985680 3187164 6784196 2235088 7736273  
## Dec 2014 5030612 3160363 6900860 2170314 7890909

plot(Model\_holt\_1)  
  
# The trend is exponential if the intercepts(level) and the gradient (slope) are  
# multiplied with eachother. The values are worse. As the Beta was very low in   
# the optimisation, the forecast is very similar to the ses() model.   
  
  
Model\_holt\_2<- holt(TotalAsIs, exponential=TRUE,h=12)  
summary(Model\_holt\_2)

##   
## Forecast method: Holt's method with exponential trend  
##   
## Model Information:  
## Holt's method with exponential trend   
##   
## Call:  
## holt(x = TotalAsIs, h = 12, exponential = TRUE)   
##   
## Smoothing parameters:  
## alpha = 0.6637   
## beta = 1e-04   
##   
## Initial states:  
## l = 2041538.9468   
## b = 1.0029   
##   
## sigma: 0.2438  
##   
## AIC AICc BIC   
## 2251.010 2251.607 2260.116   
##   
## Error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 37825.61 609787.5 433018.9 -1.838214 15.18487 1.180311  
## ACF1  
## Training set 0.02918287  
##   
## Forecasts:  
## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2014 4488281 3104286 5901190 2372984 6604966  
## Feb 2014 4502175 2893795 6274125 2149256 7258021  
## Mar 2014 4516113 2712519 6473353 2003432 8107885  
## Apr 2014 4530094 2561379 6782816 1847578 8574677  
## May 2014 4544118 2412028 7006687 1687793 9003839  
## Jun 2014 4558186 2277501 7275345 1559875 9700237  
## Jul 2014 4572297 2197203 7658753 1515642 10282564  
## Aug 2014 4586452 2073710 7801802 1384960 10892153  
## Sep 2014 4600650 1977059 7905656 1358872 11053904  
## Oct 2014 4614893 1909423 8218592 1270057 11809295  
## Nov 2014 4629180 1818216 8312335 1201980 12084908  
## Dec 2014 4643510 1725079 8503542 1081659 12820538

plot(Model\_holt\_2)



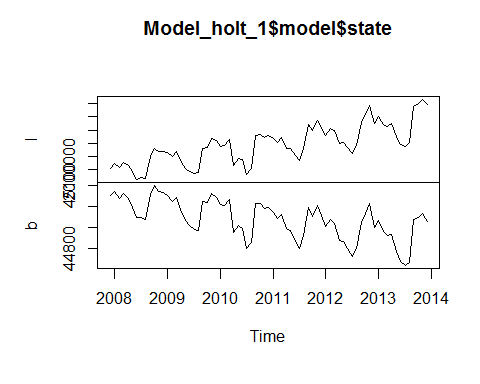
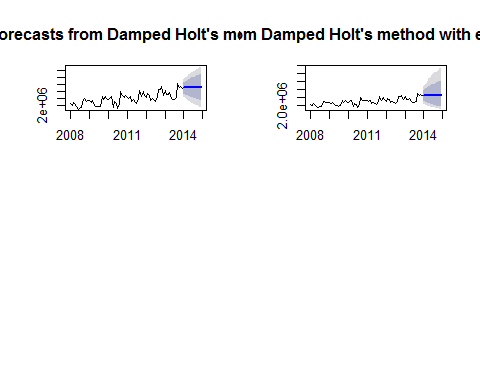
# As such simple trends tend to forecast the future to positively, we have added  
# a dampener.  
# Similar values to that of Model\_holt\_1   
  
Model\_holt\_3 <- holt(TotalAsIs, damped=TRUE,h=12)  
summary(Model\_holt\_3)

##   
## Forecast method: Damped Holt's method  
##   
## Model Information:  
## Damped Holt's method   
##   
## Call:  
## holt(x = TotalAsIs, h = 12, damped = TRUE)   
##   
## Smoothing parameters:  
## alpha = 0.6613   
## beta = 2e-04   
## phi = 0.98   
##   
## Initial states:  
## l = 2040392.5761   
## b = 45053.25   
##   
## sigma: 608787.2  
##   
## AIC AICc BIC   
## 2235.888 2236.797 2247.272   
##   
## Error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 15578.94 608787.2 436909.7 -2.797612 15.46526 1.190916  
## ACF1  
## Training set 0.03351419  
##   
## Forecasts:  
## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2014 4483618 3703426 5263811 3290417 5676819  
## Feb 2014 4493914 3558436 5429391 3063224 5924603  
## Mar 2014 4504003 3435520 5572486 2869899 6138107  
## Apr 2014 4513891 3327168 5700614 2698955 6328827  
## May 2014 4523581 3229332 5817829 2544198 6502963  
## Jun 2014 4533077 3139534 5926619 2401837 6664316  
## Jul 2014 4542383 3056128 6028638 2269352 6815413  
## Aug 2014 4551503 2977955 6125051 2144969 6958036  
## Sep 2014 4560440 2904162 6216719 2027381 7093499  
## Oct 2014 4569199 2834101 6304298 1915595 7222803  
## Nov 2014 4577783 2767264 6388301 1808834 7346732  
## Dec 2014 4586195 2703249 6469141 1706477 7465913

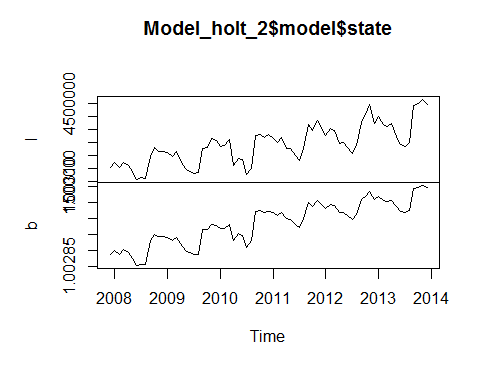
plot(Model\_holt\_3)  
  
# This also works for exponential trends.   
# The values remain worse.   
  
Model\_holt\_4 <- holt(TotalAsIs, exponential=TRUE, damped=TRUE,h=12)  
summary(Model\_holt\_4)

##   
## Forecast method: Damped Holt's method with exponential trend  
##   
## Model Information:  
## Damped Holt's method with exponential trend   
##   
## Call:  
## holt(x = TotalAsIs, h = 12, damped = TRUE, exponential = TRUE)   
##   
## Smoothing parameters:  
## alpha = 0.6679   
## beta = 1e-04   
## phi = 0.9799   
##   
## Initial states:  
## l = 2041541.9705   
## b = 1.0019   
##   
## sigma: 0.2449  
##   
## AIC AICc BIC   
## 2253.216 2254.125 2264.600   
##   
## Error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 46119.56 609906.7 432069.1 -1.549114 15.11987 1.177722  
## ACF1  
## Training set 0.0254941  
##   
## Forecasts:  
## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2014 4470648 3114673 5862751 2348108 6647476  
## Feb 2014 4473164 2854674 6201730 2140836 7311647  
## Mar 2014 4475630 2671711 6527917 1913247 7939192  
## Apr 2014 4478047 2478042 6738147 1779814 8694217  
## May 2014 4480418 2353803 7017503 1675118 9083535  
## Jun 2014 4482742 2199621 7228292 1526402 9569698  
## Jul 2014 4485020 2117882 7303005 1445309 10030947  
## Aug 2014 4487253 2029738 7529044 1335878 10506947  
## Sep 2014 4489443 1918346 7694496 1268528 10414357  
## Oct 2014 4491589 1820235 7922776 1159797 10871503  
## Nov 2014 4493694 1753434 7986481 1112098 11332174  
## Dec 2014 4495757 1707362 8012553 1065718 11697895

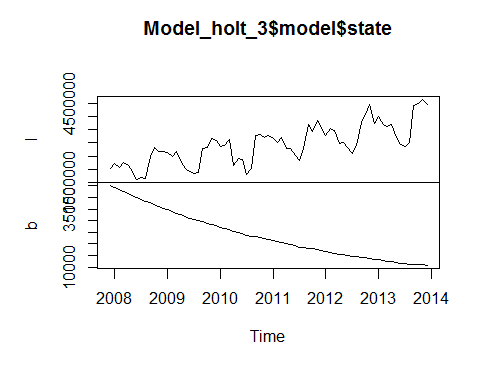
plot(Model\_holt\_4)  
  
  
# level and slope can be plotted individually for each model.   
plot(Model\_holt\_1$model$state)



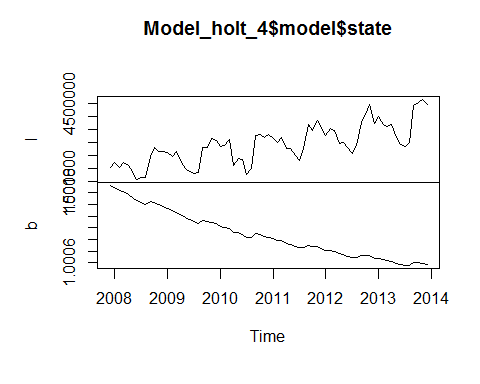
plot(Model\_holt\_2$model$state)



plot(Model\_holt\_3$model$state)



plot(Model\_holt\_4$model$state)



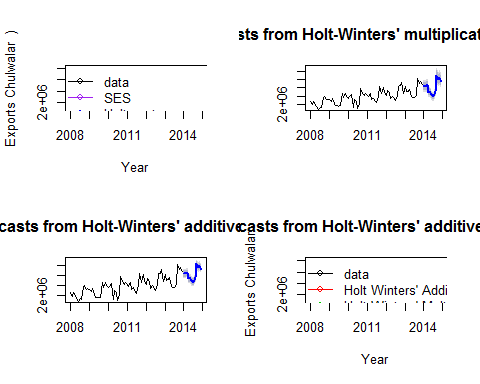
plot(Model\_holt\_1, plot.conf=FALSE, ylab="Exports Chulwalar )", xlab="Year", main="", fcol="white", type="o")  
lines(fitted(Model\_ses), col="purple", type="o")  
lines(fitted(Model\_holt\_1), col="blue", type="o")  
lines(fitted(Model\_holt\_2), col="red", type="o")  
lines(fitted(Model\_holt\_3), col="green", type="o")  
lines(fitted(Model\_holt\_4), col="orange", type="o")  
lines(Model\_ses$mean, col="purple", type="o")  
lines(Model\_holt\_1$mean, col="blue", type="o")  
lines(Model\_holt\_2$mean, col="red", type="o")  
lines(Model\_holt\_3$mean, col="green", type="o")  
lines(Model\_holt\_4$mean, col="orange", type="o")  
legend("topleft",lty=1, col=c(1,"purple","blue","red","green","orange"), c("data", "SES","Holts auto", "Exponential", "Additive Damped", "Multiplicative Damped"),pch=1)  
  
# As these forecasts are not very convincing at the moment, there is no need   
# to export the data.  
  
#################################################################################  
# 7.1.3 Holt-Winter's seasonal method #  
#################################################################################  
  
# Holt and Winters have expanded Holt's model further to include the  
# seasonality aspect. The parameter gamma, which is for smoothing the  
# seasonality, was added to achieve this. The values are better than   
# the models without seasonality. This logical matches our results from the regression approaches,   
# the data is strongly influenced by seasonality.   
# In the following model, none of the parameters are given so that they  
# will be optimised automatically. There are two models: one using  
# an additive error model method and one using a multiplicative error model.  
  
Model\_hw\_1 <- hw(TotalAsIs ,seasonal="additive",h=12)  
summary(Model\_hw\_1)

##   
## Forecast method: Holt-Winters' additive method  
##   
## Model Information:  
## Holt-Winters' additive method   
##   
## Call:  
## hw(x = TotalAsIs, h = 12, seasonal = "additive")   
##   
## Smoothing parameters:  
## alpha = 0.0087   
## beta = 0.0087   
## gamma = 1e-04   
##   
## Initial states:  
## l = 2047375.0884   
## b = 22509.7631   
## s=259168.3 654942.6 474529.8 876025.2 -475155 -852844  
## -664662.5 -412596.7 -438677.3 273215 138077.9 167976.7  
##   
## sigma: 241685  
##   
## AIC AICc BIC   
## 2124.856 2134.747 2161.283   
##   
## Error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 21615.43 241685 202218.5 -0.08252109 7.329458 0.5512016  
## ACF1  
## Training set -0.2819072  
##   
## Forecasts:  
## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2014 4141204 3831472 4450936 3667510 4614898  
## Feb 2014 4147309 3837472 4457147 3673453 4621165  
## Mar 2014 4318537 4008512 4628563 3844394 4792680  
## Apr 2014 3642744 3332425 3953063 3168153 4117335  
## May 2014 3704865 3394124 4015605 3229628 4180102  
## Jun 2014 3488859 3177546 3800173 3012746 3964973  
## Jul 2014 3336738 3024677 3648799 2859482 3813994  
## Aug 2014 3750478 3437474 4063482 3271780 4229176  
## Sep 2014 5137771 4823607 5451935 4657298 5618244  
## Oct 2014 4772337 4456775 5087900 4289726 5254949  
## Nov 2014 4988809 4671591 5306028 4503665 5473953  
## Dec 2014 4629097 4309943 4948252 4140992 5117202

plot(Model\_hw\_1)  
# AIC AICc BIC   
#2127.984 2137.875 2164.411   
  
Model\_hw\_2 <- hw(TotalAsIs ,seasonal="multiplicative",h=12)  
summary(Model\_hw\_2)

##   
## Forecast method: Holt-Winters' multiplicative method  
##   
## Model Information:  
## Holt-Winters' multiplicative method   
##   
## Call:  
## hw(x = TotalAsIs, h = 12, seasonal = "multiplicative")   
##   
## Smoothing parameters:  
## alpha = 0.025   
## beta = 0.0062   
## gamma = 1e-04   
##   
## Initial states:  
## l = 2026247.531   
## b = 25395.1259   
## s=1.0933 1.232 1.1763 1.3086 0.8384 0.699  
## 0.7653 0.8502 0.8596 1.0793 1.0316 1.0665  
##   
## sigma: 0.0877  
##   
## AIC AICc BIC   
## 2128.303 2138.194 2164.729   
##   
## Error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 17434.11 235296.6 191805.3 -0.3292809 7.213472 0.5228175  
## ACF1  
## Training set -0.3514421  
##   
## Forecasts:  
## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2014 4226941 3751624 4702258 3500006 4953876  
## Feb 2014 4123665 3659738 4587591 3414151 4833179  
## Mar 2014 4350808 3860995 4840620 3601704 5099911  
## Apr 2014 3494208 3100476 3887940 2892046 4096370  
## May 2014 3484738 3091618 3877858 2883513 4085963  
## Jun 2014 3162774 2805463 3520085 2616314 3709234  
## Jul 2014 2912399 2582802 3241996 2408324 3416474  
## Aug 2014 3521645 3122278 3921013 2910865 4132425  
## Sep 2014 5540988 4911109 6170867 4577671 6504304  
## Oct 2014 5020487 4448200 5592775 4145249 5895725  
## Nov 2014 5299729 4693715 5905743 4372911 6226547  
## Dec 2014 4740169 4196230 5284108 3908286 5572052

plot(Model\_hw\_2)  
# AIC AICc BIC   
#2137.673 2147.564 2174.100   
  
# The additive model gives slightly better results than the multiplicative model.  
  
plot(Model\_hw\_1, ylab="Exports Chulwalar ", plot.conf=FALSE, type="o", fcol="white", xlab="Year")  
lines(fitted(Model\_hw\_1), col="red", lty=2)  
lines(fitted(Model\_hw\_2), col="green", lty=2)  
lines(Model\_hw\_1$mean, type="o", col="red")  
lines(Model\_hw\_2$mean, type="o", col="green")  
legend("topleft",lty=1, pch=1, col=1:3, c("data","Holt Winters' Additive","Holt Winters' Multiplicative"))



# In order to use the results later, they need to be converted into point forcasts.  
Model\_hw\_1\_df <-as.data.frame(Model\_hw\_1)   
Model\_hw\_1\_PointForecast <- ts(Model\_hw\_1\_df$"Point Forecast", start=c(2014,1), end=c(2014,12), frequency=12)  
Model\_hw\_1\_PointForecast

## Jan Feb Mar Apr May Jun Jul Aug  
## 2014 4141204 4147309 4318537 3642744 3704865 3488859 3336738 3750478  
## Sep Oct Nov Dec  
## 2014 5137771 4772337 4988809 4629097

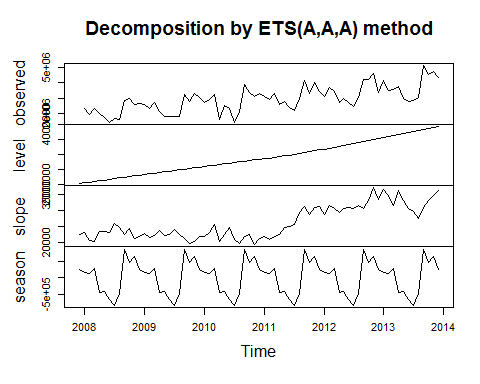
Model\_hw\_2\_df <-as.data.frame(Model\_hw\_2)   
Model\_hw\_2\_PointForecast <- ts(Model\_hw\_2\_df$"Point Forecast", start=c(2014,1), end=c(2014,12), frequency=12)  
Model\_hw\_2\_PointForecast

## Jan Feb Mar Apr May Jun Jul Aug  
## 2014 4226941 4123665 4350808 3494208 3484738 3162774 2912399 3521645  
## Sep Oct Nov Dec  
## 2014 5540988 5020487 5299729 4740169

# Output instruction for the data export of the results for further use in Excel.  
#write.csv(Model\_hw\_1\_PointForecast,file='Model\_hw\_1\_PointForecast.csv')  
#write.csv(Model\_hw\_2\_PointForecast,file='Model\_hw\_2\_PointForecast.csv')  
  
#################################################################################  
# 7.1.4 Innovations state space models for exponential smoothing #  
#################################################################################  
  
# The funktion ets() produces a model with the same values as Model\_hw\_1.   
# The reason for this is that all of the parameters in this model were optimised   
# using the ets() function. The results are a ets(A,A,A) model which is an   
# additive method for trend, seasonality and errors. The previous models  
# also showed the type of ets() model in their summary. In this case the user  
# parameters were either accepted or rejected. As the model has been set to   
# "ZZZ", the best model will be automatically chosen.   
  
Model\_ets <-ets(TotalAsIs, model="ZZZ", damped=NULL, alpha=NULL, beta=NULL, gamma=NULL, phi=NULL, additive.only=FALSE, lambda=NULL, lower=c(rep(0.0001,3), 0.8), upper=c(rep(0.9999,3),0.98), opt.crit=c("lik","amse","mse","sigma","mae"), nmse=3, bounds=c("both","usual","admissible"), ic=c("aicc","aic","bic"), restrict=TRUE)  
summary(Model\_ets)

## ETS(A,A,A)   
##   
## Call:  
## ets(y = TotalAsIs, model = "ZZZ", damped = NULL, alpha = NULL,   
##   
## Call:  
## beta = NULL, gamma = NULL, phi = NULL, additive.only = FALSE,   
##   
## Call:  
## lambda = NULL, lower = c(rep(1e-04, 3), 0.8), upper = c(rep(0.9999,   
##   
## Call:  
## 3), 0.98), opt.crit = c("lik", "amse", "mse", "sigma",   
##   
## Call:  
## "mae"), nmse = 3, bounds = c("both", "usual", "admissible"),   
##   
## Call:  
## ic = c("aicc", "aic", "bic"), restrict = TRUE)   
##   
## Smoothing parameters:  
## alpha = 0.0087   
## beta = 0.0087   
## gamma = 1e-04   
##   
## Initial states:  
## l = 2047375.0885   
## b = 22509.7629   
## s=259168.3 654942.6 474529.8 876025.2 -475155 -852844  
## -664662.5 -412596.7 -438677.3 273215 138077.9 167976.7  
##   
## sigma: 241685.1  
##   
## AIC AICc BIC   
## 2124.856 2134.747 2161.283   
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 21587.58 241685.1 202221.1 -0.08332944 7.329631 0.5512087  
## ACF1  
## Training set -0.2818997

plot(Model\_ets)



Model\_ets\_forecast <- forecast(Model\_ets,h=12)  
plot(Model\_ets\_forecast)  
# AIC AICc BIC   
#2127.984 2137.875 2164.411   
  
# In order to use the results later, they need to be converted into point forcasts.  
Model\_ets\_forecast\_df <-as.data.frame(Model\_ets\_forecast)   
Model\_ets\_PointForecast <- ts(Model\_ets\_forecast\_df$"Point Forecast", start=c(2014,1), end=c(2014,12), frequency=12)  
Model\_ets\_PointForecast

## Jan Feb Mar Apr May Jun Jul Aug  
## 2014 4141260 4147361 4318585 3642788 3704905 3488896 3336770 3750506  
## Sep Oct Nov Dec  
## 2014 5137795 4772357 4988825 4629109

# Output instruction for the data export of the results for further use in Excel.  
#write.csv(Model\_ets\_PointForecast,file='Model\_ets\_PointForecast.csv')  
  
  
#################################################################################  
# 7.2 ARIMA #  
#################################################################################  
  
### AR = Autoregression  
# A Regression of a variable with itself. The autoregressive model specifies   
# that the output variable depends linearly on its own previous values.  
  
### MA = Moving Average  
# The rolling average of past forecast errors.  
# This model should not be confused with moving average smoothing, which is used  
# for establishing trends and is based on past values.   
  
### ARIMA = AutoRegressive Integrated Moving Average model  
# A combination of Differencing, Autoregression and Moving Average.  
# Integration is the opposite of differencing.  
  
### Differencing  
# In order to make the time series stationary, it is necessary to difference.  
# Firstly, we need to check if the data are already stationary. This can be done  
# with help of the Augmented Dickey-Fuller Test  
adf.test(TotalAsIs, alternative = "stationary")

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

##   
## Augmented Dickey-Fuller Test  
##   
## data: TotalAsIs  
## Dickey-Fuller = -5.8915, Lag order = 4, p-value = 0.01  
## alternative hypothesis: stationary

# The p-value is less than 0,05. This means that the data is stationary,   
# as the 0-Hypothesis of the test is "The data are not stationary".  
  
# Another possibility is the Kwiatkowski-Phillips-Schmidt-Shin Test  
kpss.test(TotalAsIs)

## Warning in kpss.test(TotalAsIs): p-value smaller than printed p-value

##   
## KPSS Test for Level Stationarity  
##   
## data: TotalAsIs  
## KPSS Level = 2.0548, Truncation lag parameter = 1, p-value = 0.01

# This test swaps the hypothesis so that a low p-value means that it  
# is necessary to difference. The p-value here is under 0,01 and a warning  
# is shown.  
  
# As the test failed to deliver a clear result, the data will be differenced   
# and then retested.   
  
ChulwalarDiff <- diff(TotalAsIs)  
  
adf.test(ChulwalarDiff, alternative = "stationary")

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

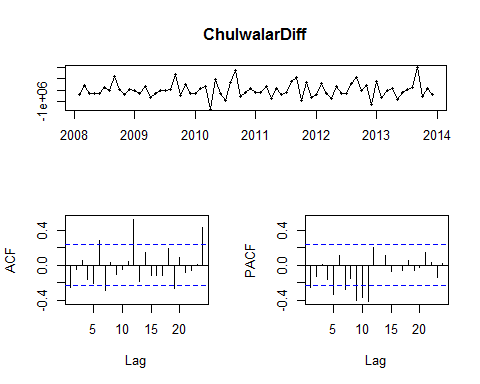
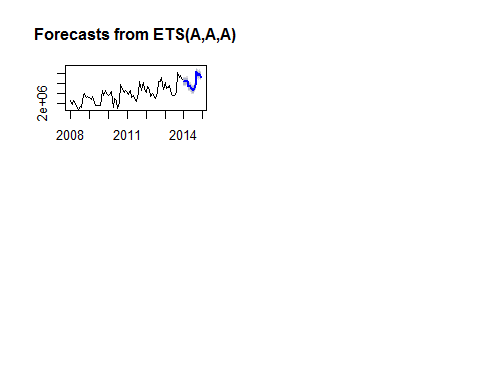
##   
## Augmented Dickey-Fuller Test  
##   
## data: ChulwalarDiff  
## Dickey-Fuller = -6.2758, Lag order = 4, p-value = 0.01  
## alternative hypothesis: stationary

kpss.test(ChulwalarDiff)

## Warning in kpss.test(ChulwalarDiff): p-value greater than printed p-value

##   
## KPSS Test for Level Stationarity  
##   
## data: ChulwalarDiff  
## KPSS Level = 0.024179, Truncation lag parameter = 1, p-value = 0.1

# The kpss.test now has a p-value of more than 0,1, which hints that the data  
# is stationary.   
  
tsdisplay(ChulwalarDiff)



# However this plot shows that the months correlate stongly with the values  
# from the previous year. This plot shows a ACF  
# (autocorrelation function) and a PACF (partial autocorrelation function).  
  
# The folling is a test method to distinguish the number of "normal"   
# differencing rounds and seasonal differencing rounds.   
# Seasonal differencing is used for data which is dominated by seasonality.  
# The time series has been assigned a lag.  
  
ns <- nsdiffs(TotalAsIs)  
if(ns > 0) {  
 xstar <- diff(TotalAsIs,lag=frequency(TotalAsIs),differences=ns)  
} else {  
 xstar <- TotalAsIs  
}  
nd <- ndiffs(xstar)  
if(nd > 0) {  
 xstar <- diff(xstar,differences=nd)  
}  
  
nd # Number of normal differencing rounds

## [1] 0

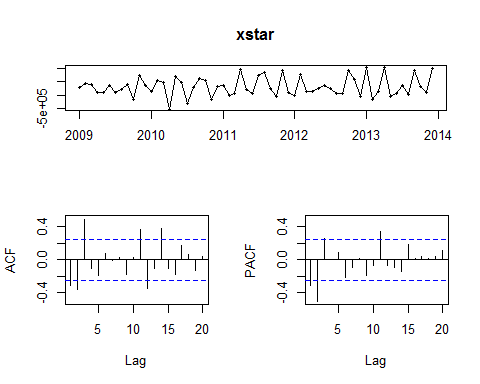
ns # Number of seasonal differencing rounds

## [1] 1

xstar # The output "xstar" has been differenced correctly.

## Jan Feb Mar Apr May Jun Jul Aug  
## 2009 297352 421196 397151 85521 93109 377920 117674 212298  
## 2010 150115 547006 483255 -511420 700084 481423 -323167 296553  
## 2011 352173 8330 67743 963191 223911 60582 748756 843266  
## 2012 -19773 752645 138580 137820 237699 347801 260934 63868  
## 2013 1026438 -143564 127610 1045166 -51834 61870 344910 28458  
## Sep Oct Nov Dec  
## 2009 388285 -140828 714282 365945  
## 2010 627400 530065 -174831 310373  
## 2011 252960 -30269 901131 96957  
## 2012 49265 910040 581464 -46170  
## 2013 906979 333420 110773 988508

tsdisplay(xstar)



# If "lag" is set to 12, this is equivalent to 1\* seasonal differencing  
ChulwalarDiff\_lag <- diff(TotalAsIs,lag=12)  
  
adf.test(ChulwalarDiff\_lag, alternative = "stationary")

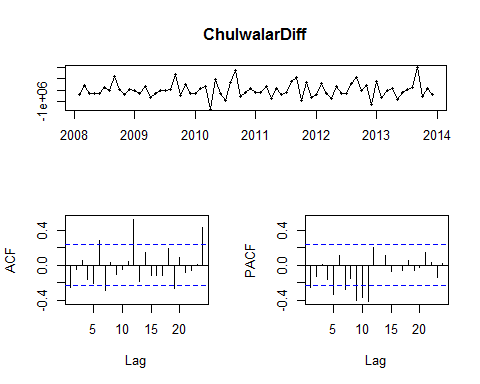
##   
## Augmented Dickey-Fuller Test  
##   
## data: ChulwalarDiff\_lag  
## Dickey-Fuller = -4.0902, Lag order = 3, p-value = 0.01175  
## alternative hypothesis: stationary

kpss.test(ChulwalarDiff\_lag)

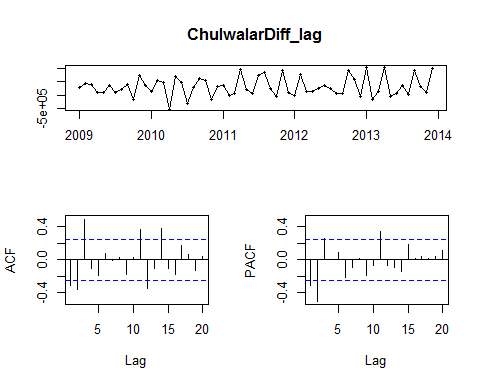
## Warning in kpss.test(ChulwalarDiff\_lag): p-value greater than printed p-  
## value

##   
## KPSS Test for Level Stationarity  
##   
## data: ChulwalarDiff\_lag  
## KPSS Level = 0.13387, Truncation lag parameter = 1, p-value = 0.1

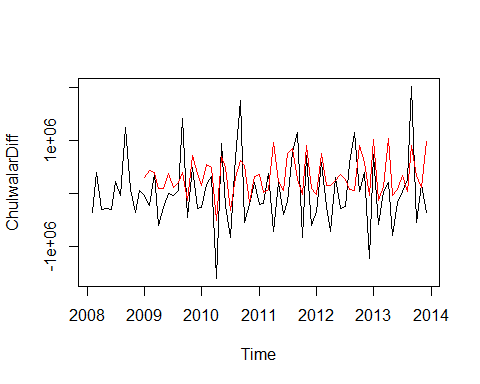
tsdisplay(ChulwalarDiff)



tsdisplay(ChulwalarDiff\_lag)



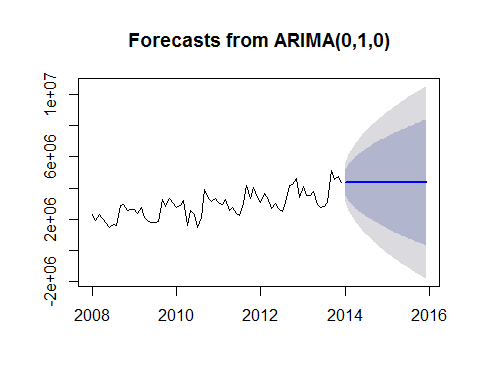
plot(ChulwalarDiff)  
lines(ChulwalarDiff\_lag, col="red")



# The time series appears much more "stationary".  
  
#################################################################################  
# 7.2.1 ARIMA modelling #  
#################################################################################  
  
# The values for AIC, AICc and BIC should be minimised.  
# We wil try a range of combinations.  
  
# R uses the maximum likelihood estimation (MLE) in order to decide how good  
# a certain model is. The parameters, which give the most likely model based on the given data, are chosen.  
# Furthermore, R gives the log-likelihood, which should be maximised.   
  
Model\_ARIMA\_1 <- Arima(TotalAsIs, order=c(0,1,0))  
summary(Model\_ARIMA\_1 )

## Series: TotalAsIs   
## ARIMA(0,1,0)   
##   
## sigma^2 estimated as 4.097e+11: log likelihood=-1049.96  
## AIC=2101.93 AICc=2101.99 BIC=2104.19  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 28628.79 635581.2 472471.7 -1.605296 16.44154 1.28785  
## ACF1  
## Training set -0.2573856

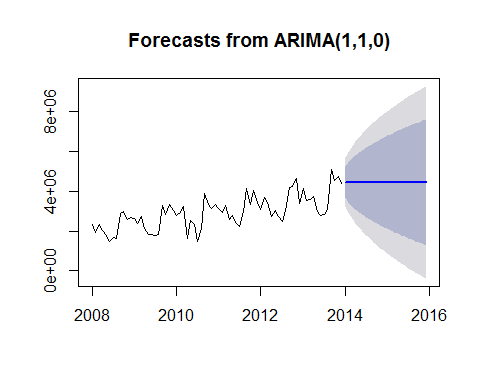
plot(forecast(Model\_ARIMA\_1 ))



#AIC=2101.93 AICc=2101.99 BIC=2104.19  
  
Model\_ARIMA\_2 <- Arima(TotalAsIs, order=c(1,1,0))  
summary(Model\_ARIMA\_2)

## Series: TotalAsIs   
## ARIMA(1,1,0)   
##   
## Coefficients:  
## ar1  
## -0.2531  
## s.e. 0.1144  
##   
## sigma^2 estimated as 3.884e+11: log likelihood=-1047.6  
## AIC=2099.2 AICc=2099.38 BIC=2103.72  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 37287.11 614478.1 430163.6 -1.639433 15.09104 1.172528  
## ACF1  
## Training set -0.03792494

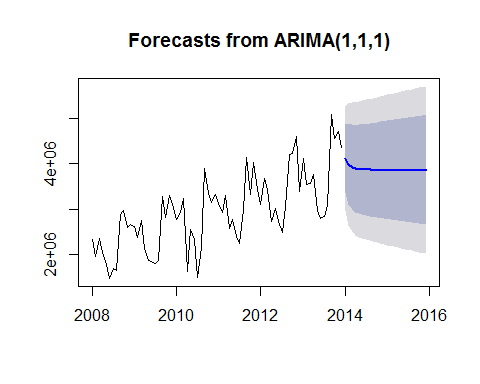
plot(forecast(Model\_ARIMA\_2))



#AIC=2099.2 AICc=2099.38 BIC=2103.72  
  
Model\_ARIMA\_3 <- Arima(TotalAsIs, order=c(1,1,1))  
summary(Model\_ARIMA\_3)

## Series: TotalAsIs   
## ARIMA(1,1,1)   
##   
## Coefficients:  
## ar1 ma1  
## 0.5013 -0.8940  
## s.e. 0.1225 0.0523  
##   
## sigma^2 estimated as 3.483e+11: log likelihood=-1043.55  
## AIC=2093.09 AICc=2093.45 BIC=2099.88  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 108896.1 577776.4 418339 0.1597019 14.59994 1.140297  
## ACF1  
## Training set -0.04946106

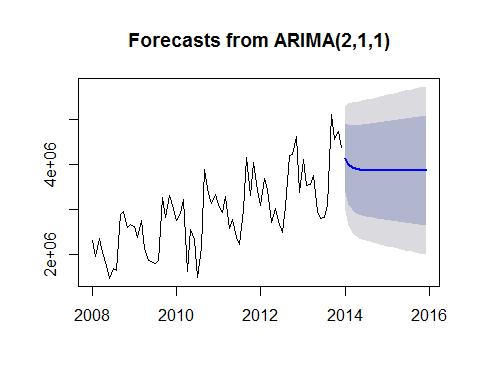
plot(forecast(Model\_ARIMA\_3))



#AIC=2093.09 AICc=2093.45 BIC=2099.88  
  
Model\_ARIMA\_4 <- Arima(TotalAsIs, order=c(2,1,1))  
summary(Model\_ARIMA\_4)

## Series: TotalAsIs   
## ARIMA(2,1,1)   
##   
## Coefficients:  
## ar1 ar2 ma1  
## 0.4960 0.0162 -0.8958  
## s.e. 0.1292 0.1244 0.0538  
##   
## sigma^2 estimated as 3.534e+11: log likelihood=-1043.54  
## AIC=2095.08 AICc=2095.68 BIC=2104.13  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 108259.9 577759.6 416830.2 0.1419833 14.54368 1.136184  
## ACF1  
## Training set -0.04006432

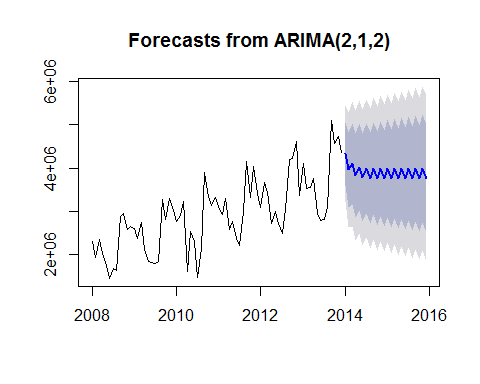
plot(forecast(Model\_ARIMA\_4))



#AIC=2095.08 AICc=2095.68 BIC=2104.13  
  
Model\_ARIMA\_5 <- Arima(TotalAsIs, order=c(2,1,2))  
summary(Model\_ARIMA\_5)

## Series: TotalAsIs   
## ARIMA(2,1,2)   
##   
## Coefficients:  
## ar1 ar2 ma1 ma2  
## -0.4308 0.5690 0.0939 -0.8951  
## s.e. 0.1195 0.1195 0.0544 0.0537  
##   
## sigma^2 estimated as 3.211e+11: log likelihood=-1040.54  
## AIC=2091.07 AICc=2092 BIC=2102.39  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 101551.5 546638.3 407424.5 0.1950065 14.29599 1.110546  
## ACF1  
## Training set 0.01796927

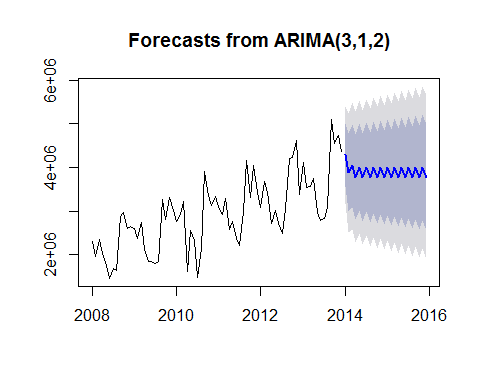
plot(forecast(Model\_ARIMA\_5))



#AIC=2091.07 AICc=2092 BIC=2102.39  
  
Model\_ARIMA\_6 <- Arima(TotalAsIs, order=c(3,1,2))  
summary(Model\_ARIMA\_6)

## Series: TotalAsIs   
## ARIMA(3,1,2)   
##   
## Coefficients:  
## ar1 ar2 ar3 ma1 ma2  
## -0.3893 0.5013 -0.1092 0.1083 -0.8830  
## s.e. 0.1284 0.1385 0.1231 0.0569 0.0566  
##   
## sigma^2 estimated as 3.207e+11: log likelihood=-1040.15  
## AIC=2092.3 AICc=2093.61 BIC=2105.87  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 104678.5 542170.4 409442.9 0.3156703 14.41613 1.116048  
## ACF1  
## Training set -0.03533504

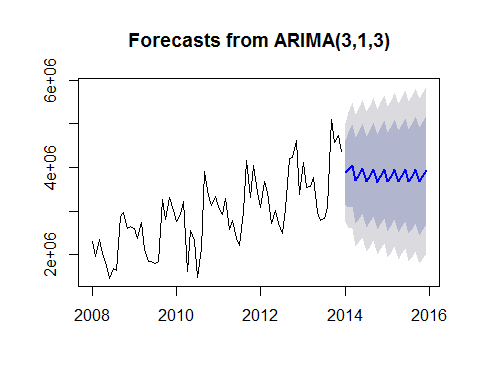
plot(forecast(Model\_ARIMA\_6))



#AIC=2092.3 AICc=2093.61 BIC=2105.87  
  
Model\_ARIMA\_7 <- Arima(TotalAsIs, order=c(3,1,3))  
summary(Model\_ARIMA\_7)

## Series: TotalAsIs   
## ARIMA(3,1,3)   
##   
## Coefficients:  
## ar1 ar2 ar3 ma1 ma2 ma3  
## -0.3899 -0.3992 0.5784 0.0121 0.1473 -0.8863  
## s.e. 0.2719 0.2546 0.1245 0.5756 0.2820 0.6757  
##   
## sigma^2 estimated as 3.243e+11: log likelihood=-1040.01  
## AIC=2094.03 AICc=2095.81 BIC=2109.87  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 98929.36 541073 383116.9 0.2717968 13.13481 1.044289  
## ACF1  
## Training set 0.006450566

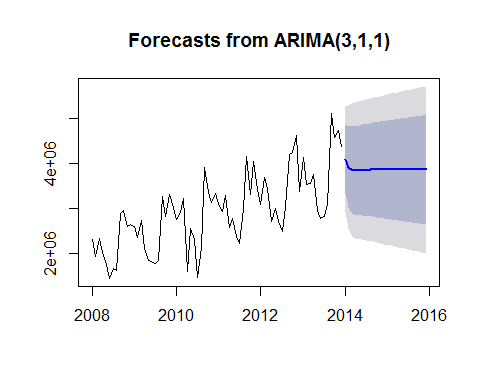
plot(forecast(Model\_ARIMA\_7))



#AIC=2094.03 AICc=2095.81 BIC=2109.87  
  
Model\_ARIMA\_8 <- Arima(TotalAsIs, order=c(3,1,1))  
summary(Model\_ARIMA\_8)

## Series: TotalAsIs   
## ARIMA(3,1,1)   
##   
## Coefficients:  
## ar1 ar2 ar3 ma1  
## 0.4861 0.0501 -0.0876 -0.8861  
## s.e. 0.1284 0.1321 0.1224 0.0558  
##   
## sigma^2 estimated as 3.557e+11: log likelihood=-1043.29  
## AIC=2096.57 AICc=2097.5 BIC=2107.89  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 112288.1 575349.1 416026.3 0.2735252 14.58788 1.133993  
## ACF1  
## Training set -0.06722377

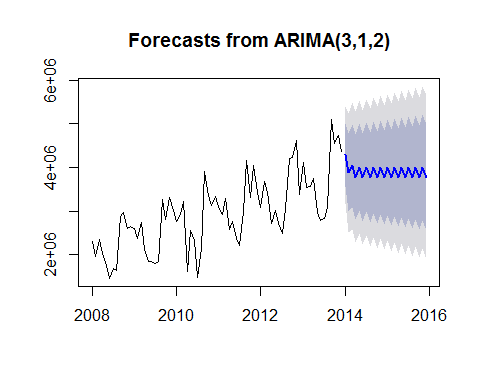
plot(forecast(Model\_ARIMA\_8))



#AIC=2096.57 AICc=2097.5 BIC=2107.89  
  
Model\_ARIMA\_9 <- Arima(TotalAsIs, order=c(3,1,2))  
summary(Model\_ARIMA\_9)

## Series: TotalAsIs   
## ARIMA(3,1,2)   
##   
## Coefficients:  
## ar1 ar2 ar3 ma1 ma2  
## -0.3893 0.5013 -0.1092 0.1083 -0.8830  
## s.e. 0.1284 0.1385 0.1231 0.0569 0.0566  
##   
## sigma^2 estimated as 3.207e+11: log likelihood=-1040.15  
## AIC=2092.3 AICc=2093.61 BIC=2105.87  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 104678.5 542170.4 409442.9 0.3156703 14.41613 1.116048  
## ACF1  
## Training set -0.03533504

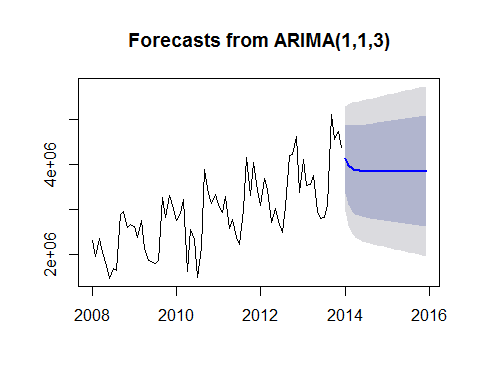
plot(forecast(Model\_ARIMA\_9))



#AIC=2092.3 AICc=2093.61 BIC=2105.87  
  
Model\_ARIMA\_10 <- Arima(TotalAsIs, order=c(1,1,3))  
summary(Model\_ARIMA\_10)

## Series: TotalAsIs   
## ARIMA(1,1,3)   
##   
## Coefficients:  
## ar1 ma1 ma2 ma3  
## 0.4527 -0.8779 0.0965 -0.1023  
## s.e. 0.2410 0.2408 0.2460 0.1621  
##   
## sigma^2 estimated as 3.567e+11: log likelihood=-1043.34  
## AIC=2096.69 AICc=2097.61 BIC=2108  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 108260.8 576125 411814.8 0.1681833 14.39459 1.122513  
## ACF1  
## Training set -0.02687555

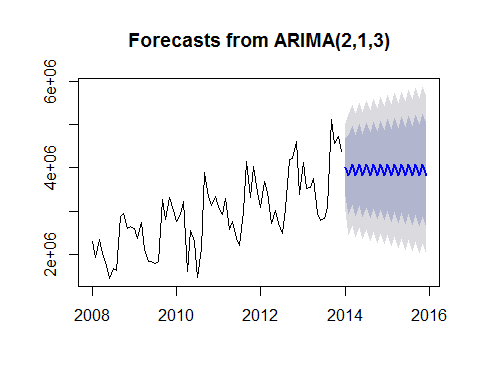
plot(forecast(Model\_ARIMA\_10))



#AIC=2096.69 AICc=2097.61 BIC=2108  
  
Model\_ARIMA\_11 <- Arima(TotalAsIs, order=c(2,1,3))  
summary(Model\_ARIMA\_11)

## Series: TotalAsIs   
## ARIMA(2,1,3)   
##   
## Coefficients:  
## ar1 ar2 ma1 ma2 ma3  
## -1.1981 -0.1982 1.1439 -0.6940 -0.8420  
## s.e. 0.1350 0.1350 0.1239 0.1394 0.1099  
##   
## sigma^2 estimated as 2.64e+11: log likelihood=-1036.61  
## AIC=2085.22 AICc=2086.53 BIC=2098.8  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE ACF1  
## Training set 96418 491927 381028.7 0.4152085 13.44772 1.038597 0.003938262

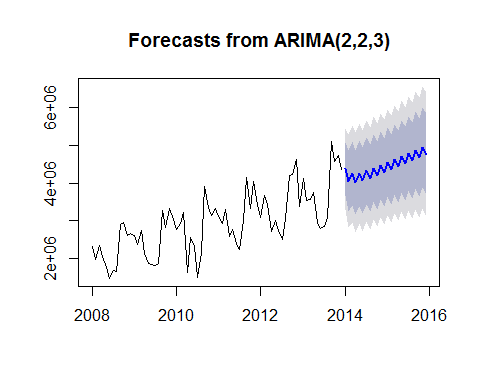
plot(forecast(Model\_ARIMA\_11))



#AIC=2085.22 AICc=2086.53 BIC=2098.8  
  
Model\_ARIMA\_12 <- Arima(TotalAsIs, order=c(2,2,3))  
summary(Model\_ARIMA\_12)

## Series: TotalAsIs   
## ARIMA(2,2,3)   
##   
## Coefficients:  
## ar1 ar2 ma1 ma2 ma3  
## -0.4575 0.5423 -0.9992 -0.9842 0.9938  
## s.e. 0.1097 0.1097 0.0600 0.0468 0.0596  
##   
## sigma^2 estimated as 2.933e+11: log likelihood=-1026.69  
## AIC=2065.39 AICc=2066.72 BIC=2078.88  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 32207.69 514572.7 390086.2 -1.782274 13.95983 1.063286  
## ACF1  
## Training set 0.0523144

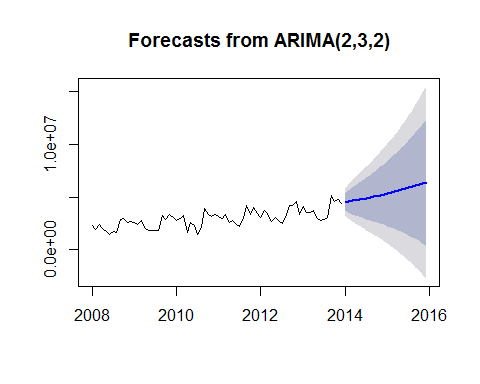
plot(forecast(Model\_ARIMA\_12))



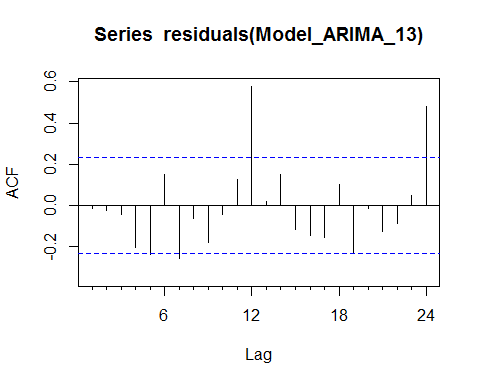
#AIC=2065.39 AICc=2066.72 BIC=2078.88  
  
Model\_ARIMA\_13 <- Arima(TotalAsIs, order=c(2,3,2))  
summary(Model\_ARIMA\_13)

## Series: TotalAsIs   
## ARIMA(2,3,2)   
##   
## Coefficients:  
## ar1 ar2 ma1 ma2  
## -0.2556 -0.0955 -1.9949 0.9998  
## s.e. 0.1213 0.1203 0.0568 0.0565  
##   
## sigma^2 estimated as 4.154e+11: log likelihood=-1025.64  
## AIC=2061.27 AICc=2062.22 BIC=2072.44  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set -18789.17 612404.9 442164 -3.108129 15.40378 1.205238  
## ACF1  
## Training set -0.0160389

plot(forecast(Model\_ARIMA\_13))



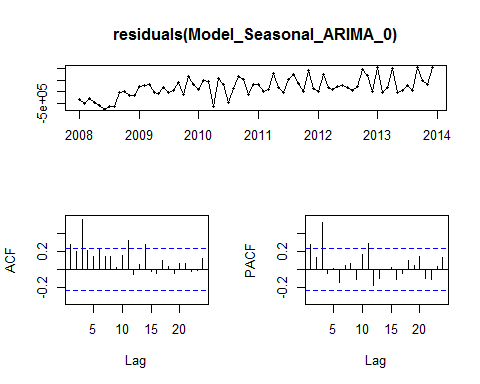
#AIC=2061.27 AICc=2062.22 BIC=2072.44  
  
Acf(residuals(Model\_ARIMA\_13))



Box.test(residuals(Model\_ARIMA\_13), lag=12, fitdf=4, type="Ljung")

##   
## Box-Ljung test  
##   
## data: residuals(Model\_ARIMA\_13)  
## X-squared = 49.513, df = 8, p-value = 5.068e-08

# The Ljung-Box Test has H0: The data are independently distributed   
# und Ha: The data are not independently distributed.   
  
# Just like the remainder showed before, there is a definite coherence#   
  
#################################################################################  
# 7.2.2 Seasonal ARIMA modelling #  
#################################################################################  
  
# This model integrates the seasonal aspect into the ARIMA model. As the previous  
# models all had a peak in lag 12, it seems viable that the data are seasonal.   
  
Model\_Seasonal\_ARIMA\_0 <- Arima(TotalAsIs, order=c(0,0,0), seasonal=c(1,0,0))  
tsdisplay(residuals(Model\_Seasonal\_ARIMA\_0))



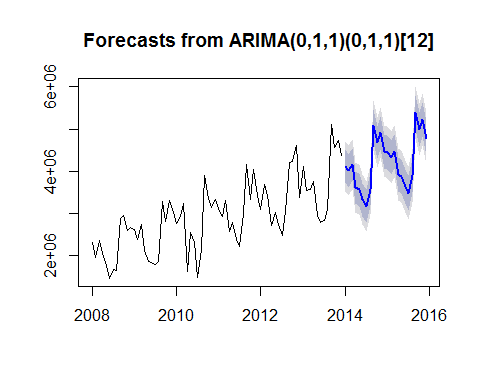
summary(Model\_Seasonal\_ARIMA\_0)

## Series: TotalAsIs   
## ARIMA(0,0,0)(1,0,0)[12] with non-zero mean   
##   
## Coefficients:  
## sar1 intercept  
## 0.8670 2972908.7  
## s.e. 0.0496 230693.3  
##   
## sigma^2 estimated as 2.211e+11: log likelihood=-1049.89  
## AIC=2105.79 AICc=2106.14 BIC=2112.62  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE ACF1  
## Training set 178628.1 463638.5 354855 3.056776 12.76901 0.967254 0.2749878

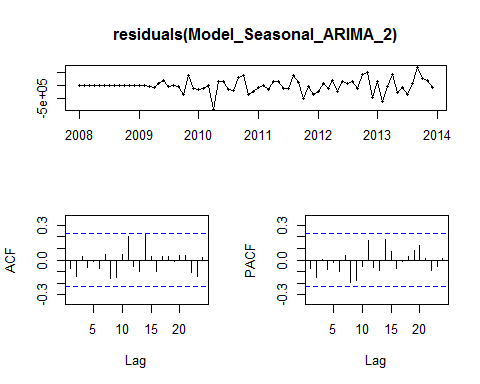
#AIC=2105.79 AICc=2106.14 BIC=2112.62  
  
Model\_Seasonal\_ARIMA\_1 <- Arima(TotalAsIs, order=c(0,1,1), seasonal=c(0,1,1))  
summary(Model\_Seasonal\_ARIMA\_1)

## Series: TotalAsIs   
## ARIMA(0,1,1)(0,1,1)[12]   
##   
## Coefficients:  
## ma1 sma1  
## -0.9999 -0.7599  
## s.e. 0.1180 0.3144  
##   
## sigma^2 estimated as 8.71e+10: log likelihood=-833.44  
## AIC=1672.88 AICc=1673.31 BIC=1679.11  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 27419.53 262591.5 185283.1 -0.2676759 6.296359 0.5050396  
## ACF1  
## Training set -0.2913248

plot(forecast(Model\_Seasonal\_ARIMA\_1))



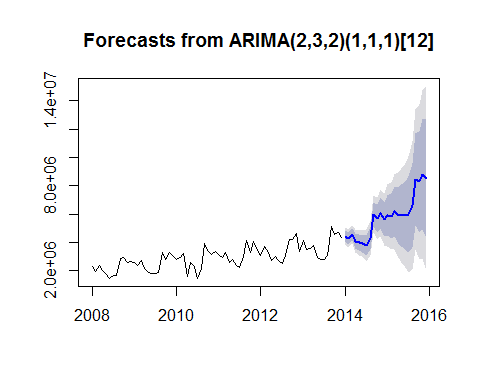
#AIC=1672.88 AICc=1673.31 BIC=1679.11  
  
# Insert the values from the previous chapter for the non-seasonal values.   
Model\_Seasonal\_ARIMA\_2 <- Arima(TotalAsIs, order=c(2,3,2), seasonal=c(1,1,1))  
tsdisplay(residuals(Model\_Seasonal\_ARIMA\_2))



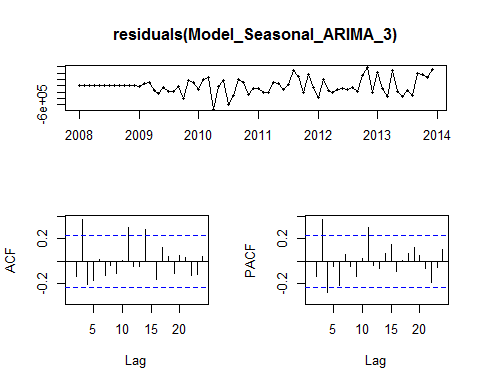
summary(Model\_Seasonal\_ARIMA\_2)

## Series: TotalAsIs   
## ARIMA(2,3,2)(1,1,1)[12]   
##   
## Coefficients:  
## ar1 ar2 ma1 ma2 sar1 sma1  
## -0.8870 -0.7259 -1.9692 0.9977 -0.1289 -0.5091  
## s.e. 0.0876 0.0907 0.0699 0.0697 0.2692 0.3059  
##   
## sigma^2 estimated as 9.302e+10: log likelihood=-808.11  
## AIC=1630.23 AICc=1632.51 BIC=1644.53  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set -5252.206 256693.1 176056.7 -0.8935257 5.910925 0.4798906  
## ACF1  
## Training set -0.07108056

plot(forecast(Model\_Seasonal\_ARIMA\_2))



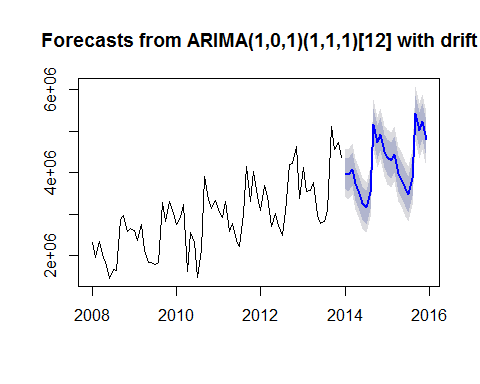
# AIC=1630.23 AICc=1632.51 BIC=1644.53  
  
# Good results when using drift.  
Model\_Seasonal\_ARIMA\_3 <- Arima(TotalAsIs, order=c(1,0,1), seasonal=c(1,1,1),include.drift=TRUE)  
tsdisplay(residuals(Model\_Seasonal\_ARIMA\_3))



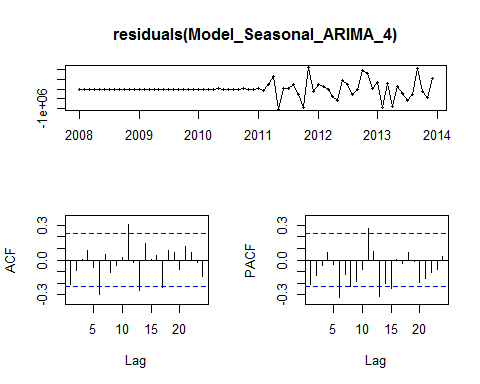
summary(Model\_Seasonal\_ARIMA\_3)

## Series: TotalAsIs   
## ARIMA(1,0,1)(1,1,1)[12] with drift   
##   
## Coefficients:  
## ar1 ma1 sar1 sma1 drift  
## 0.0432 -0.4498 0.1916 -0.775 26229.159  
## s.e. 0.2973 0.2700 0.3590 0.528 1029.248  
##   
## sigma^2 estimated as 8.173e+10: log likelihood=-840  
## AIC=1691.99 AICc=1693.58 BIC=1704.56  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set -12740.01 249858 187104 -1.804816 6.490842 0.5100028  
## ACF1  
## Training set -0.004832396

plot(forecast(Model\_Seasonal\_ARIMA\_3))



# AIC=1355.99 AICc=1357.58 BIC=1368.56  
  
Model\_Seasonal\_ARIMA\_4 <- Arima(TotalAsIs, order=c(2,3,2), seasonal=c(1,3,2))  
tsdisplay(residuals(Model\_Seasonal\_ARIMA\_4))



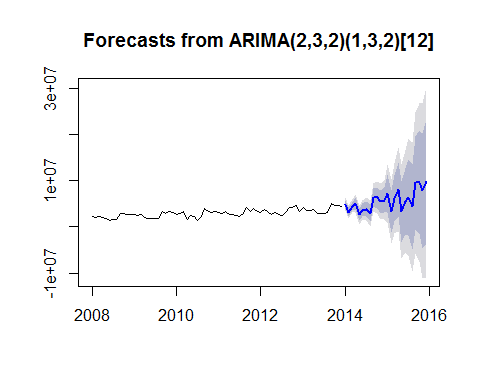
summary(Model\_Seasonal\_ARIMA\_4)

## Series: TotalAsIs   
## ARIMA(2,3,2)(1,3,2)[12]   
##   
## Coefficients:

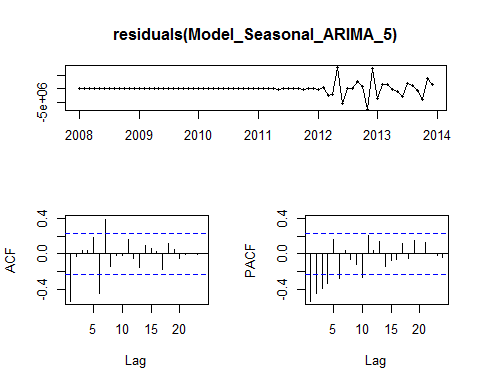
## Warning in sqrt(diag(x$var.coef)): NaNs produced

## ar1 ar2 ma1 ma2 sar1 sma1 sma2  
## -0.7734 -0.7922 -1.9661 0.9954 -0.639 -0.613 0.0136  
## s.e. 0.1009 0.1204 0.1040 0.1017 NaN NaN NaN  
##   
## sigma^2 estimated as 4.148e+11: log likelihood=-502.44  
## AIC=1020.89 AICc=1026.89 BIC=1032.86  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 4082.089 387044.8 209718 -0.2681636 6.055173 0.5716435  
## ACF1  
## Training set -0.2075146

plot(forecast(Model\_Seasonal\_ARIMA\_4))



# AIC=1630.23 AICc=1632.51 BIC=1644.53  
# The stronger the seasonality is differenced, the better the results are. However the   
# plot shows that the data are being increasingly changed.   
  
Model\_Seasonal\_ARIMA\_5 <- Arima(TotalAsIs, order=c(2,3,2), seasonal=c(1,4,2))  
tsdisplay(residuals(Model\_Seasonal\_ARIMA\_5))



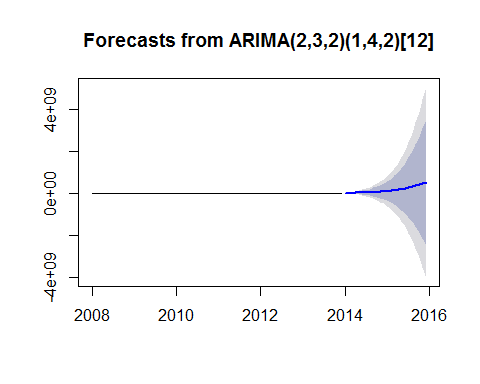
summary(Model\_Seasonal\_ARIMA\_5)

## Series: TotalAsIs   
## ARIMA(2,3,2)(1,4,2)[12]   
##   
## Coefficients:

## Warning in sqrt(diag(x$var.coef)): NaNs produced

## ar1 ar2 ma1 ma2 sar1 sma1 sma2  
## -0.7594 -0.6887 0.0437 -0.0219 -0.552 -0.2248 0.0119  
## s.e. NaN 0.1077 NaN NaN NaN NaN NaN  
##   
## sigma^2 estimated as 1.994e+13: log likelihood=-374.5  
## AIC=765 AICc=777 BIC=773.36  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 23417.82 1969200 835437.3 0.9676692 23.85754 2.277212  
## ACF1  
## Training set -0.5364577

plot(forecast(Model\_Seasonal\_ARIMA\_5))



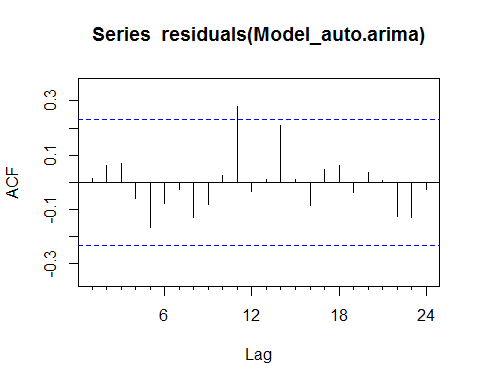
# AIC=765 AICc=777 BIC=773.36  
  
# The more the seasonal aspect is changed, the better the results based on AIC,  
# AICc and BIC. Theoretically the models should more and more suitable for the forecast.  
# However, a look at the plot of the forecasts shows that the changes are making the   
# data less and less convincing and thus unuseable.   
  
  
#################################################################################  
# 7.2.3 Auto-ARIMA modelling #  
#################################################################################  
  
# The automatic establishment of an ARIMA model shows that (2,0,1)(0,1,1)  
# with drift delivers the best results.   
# AIC=1344.04 AICc=1345.62 BIC=1356.6  
# For comparison, here are the results of ModelWithTrendAndSeasonalityOnly with tslm():  
# CV AIC AICc BIC AdjR2   
# 8.472378e+10 1810.912 1818.281 1842.786 0.9004392   
  
Model\_auto.arima <- auto.arima(TotalAsIs)  
summary(Model\_auto.arima)

## Series: TotalAsIs   
## ARIMA(2,0,1)(0,1,1)[12] with drift   
##   
## Coefficients:  
## ar1 ar2 ma1 sma1 drift  
## -0.9408 -0.5723 0.6947 -0.5312 26298.315  
## s.e. 0.1532 0.1109 0.1945 0.1845 1118.294  
##   
## sigma^2 estimated as 6.63e+10: log likelihood=-832.52  
## AIC=1677.05 AICc=1678.63 BIC=1689.61  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set -9481.321 225048.2 165219.8 -1.492866 5.660998 0.4503516  
## ACF1  
## Training set 0.01340082

CV(ModelWithTrendAndSeasonalityOnly)

## CV AIC AICc BIC AdjR2   
## 8.472378e+10 1.810912e+03 1.818281e+03 1.842786e+03 9.004392e-01

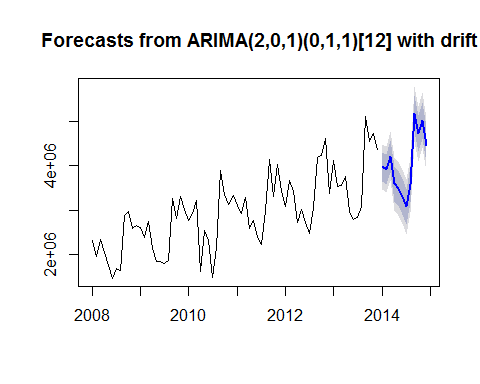
Acf(residuals(Model\_auto.arima))



Box.test(residuals(Model\_auto.arima), lag=12, fitdf=4, type="Ljung")

##   
## Box-Ljung test  
##   
## data: residuals(Model\_auto.arima)  
## X-squared = 12.591, df = 8, p-value = 0.1267

# The Ljung-Box Test has H0: The data are independently distributed   
# and Ha: The data are not independently distributed. The results show: White noise  
  
Model\_auto.arima\_forecast <- forecast(Model\_auto.arima,h=12)  
plot(Model\_auto.arima\_forecast)



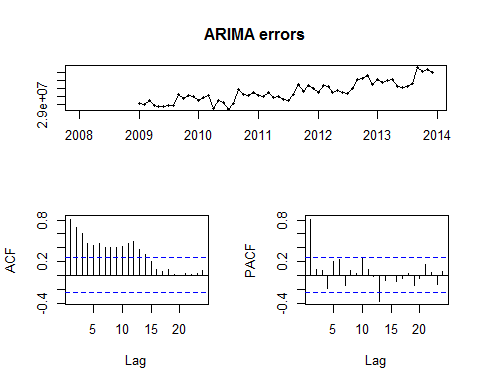
Model\_auto.arima\_forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2014 3981722 3651624 4311819 3476881 4486562  
## Feb 2014 3921507 3581573 4261442 3401622 4441392  
## Mar 2014 4220286 3862240 4578332 3672702 4767870  
## Apr 2014 3591865 3202795 3980935 2996834 4186896  
## May 2014 3497687 3100702 3894673 2890550 4104824  
## Jun 2014 3307882 2910687 3705076 2700425 3915338  
## Jul 2014 3073575 2672271 3474880 2459833 3687317  
## Aug 2014 3574462 3170471 3978453 2956612 4192313  
## Sep 2014 5179185 4775048 5583323 4561111 5797260  
## Oct 2014 4726394 4321936 5130852 4107829 5344959  
## Nov 2014 5033430 4628398 5438462 4413987 5652872  
## Dec 2014 4460765 4055586 4865944 3841098 5080433

Model\_auto.arima\_forecast\_df <-as.data.frame(Model\_auto.arima\_forecast)   
Model\_auto.arima\_PointForecast <- ts(Model\_auto.arima\_forecast\_df$"Point Forecast", start=c(2014,1), end=c(2014,12), frequency=12)  
Model\_auto.arima\_PointForecast

## Jan Feb Mar Apr May Jun Jul Aug  
## 2014 3981722 3921507 4220286 3591865 3497687 3307882 3073575 3574462  
## Sep Oct Nov Dec  
## 2014 5179185 4726394 5033430 4460765

# Output instruction for the data export of the results for further use in Excel.  
#write.csv(Model\_auto.arima\_PointForecast,file='Model\_auto.arima\_PointForecast.csv')  
  
#################################################################################  
# 7.3 Dynamic regression models #  
#################################################################################  
  
# Regression models are combined with ARIMA models on order to make sure that  
# external factors are included and that the time series are not only forecasted   
# based on past values. A regression of the ARIMA errors should be aspired for.   
  
# We have to diffentiate, as the time series and the SIGov Indicator are not   
# stationary. So that a forecast can be produced, the indicator has to be lagged  
# so that we have values for 2014.   
  
CEPI\_lagged <- ts(c(rep(NA,12),CEPIVector),start=c(2008,1), end=c(2013,12), frequency=12)  
CEPI\_2014\_lagged <- ts(CEPI\_2013, start=c(2014,1), end=c(2014,12), frequency=12)  
  
Model\_dynreg <- Arima(TotalAsIs, xreg=CEPI\_lagged, order=c(2,2,0))  
tsdisplay(arima.errors(Model\_dynreg), main="ARIMA errors")



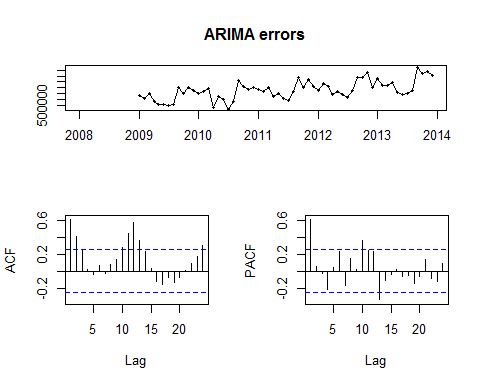
summary(Model\_dynreg)

## Series: TotalAsIs   
## ARIMA(2,2,0)   
##   
## Coefficients:  
## ar1 ar2 CEPI\_lagged  
## -0.8375 -0.4848 -272894.3  
## s.e. 0.1133 0.1165 285739.4  
##   
## sigma^2 estimated as 5.131e+11: log likelihood=-872.28  
## AIC=1752.56 AICc=1753.17 BIC=1761.55  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set -6115.637 756954.4 568807.6 -1.554716 18.4045 1.55044  
## ACF1  
## Training set -0.09154476

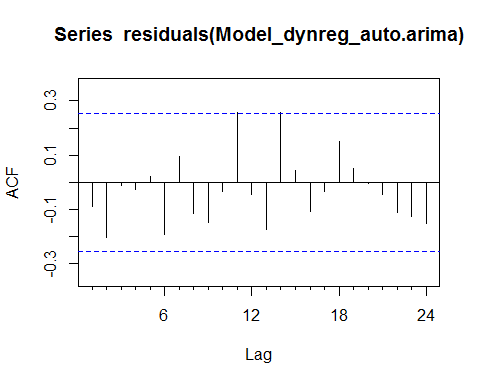
Model\_dynreg\_auto.arima <- auto.arima(TotalAsIs, xreg=CEPI\_lagged)  
summary(Model\_dynreg\_auto.arima)

## Series: TotalAsIs   
## ARIMA(2,1,0)(1,1,0)[12]   
##   
## Coefficients:  
## ar1 ar2 sar1 CEPI\_lagged  
## -0.9138 -0.7234 -0.5714 12819.6  
## s.e. 0.0981 0.0986 0.1323 108321.3  
##   
## sigma^2 estimated as 7.409e+10: log likelihood=-661.69  
## AIC=1333.39 AICc=1334.52 BIC=1343.77  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 10997.11 260603.8 192254.9 -0.3570223 6.202412 0.524043  
## ACF1  
## Training set -0.08855174

tsdisplay(arima.errors(Model\_dynreg\_auto.arima), main="ARIMA errors")



# ARIMA(2,0,1)(0,1,1)[12] with drift   
# AIC=1343.61 AICc=1345.76 BIC=1358.27  
  
  
Acf(residuals(Model\_dynreg\_auto.arima))



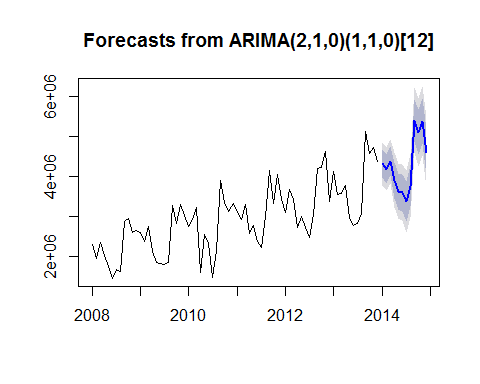
Box.test(residuals(Model\_dynreg\_auto.arima), lag=12, fitdf=4, type="Ljung")

##   
## Box-Ljung test  
##   
## data: residuals(Model\_dynreg\_auto.arima)  
## X-squared = 14.198, df = 8, p-value = 0.07674

# The Ljung-Box Test has H0: The data are independently distributed   
# and Ha: The data are not independently distributed. The results show:   
# White noise  
  
summary(Model\_dynreg\_auto.arima)

## Series: TotalAsIs   
## ARIMA(2,1,0)(1,1,0)[12]   
##   
## Coefficients:  
## ar1 ar2 sar1 CEPI\_lagged  
## -0.9138 -0.7234 -0.5714 12819.6  
## s.e. 0.0981 0.0986 0.1323 108321.3  
##   
## sigma^2 estimated as 7.409e+10: log likelihood=-661.69  
## AIC=1333.39 AICc=1334.52 BIC=1343.77  
##   
## Training set error measures:  
## ME RMSE MAE MPE MAPE MASE  
## Training set 10997.11 260603.8 192254.9 -0.3570223 6.202412 0.524043  
## ACF1  
## Training set -0.08855174

Model\_dynreg\_auto.arima\_forecast <- forecast(Model\_dynreg\_auto.arima, xreg=CEPI\_2014\_lagged,h=12)  
plot(Model\_dynreg\_auto.arima\_forecast)



Model\_dynreg\_auto.arima\_forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2014 4311394 3962566 4660222 3777908 4844880  
## Feb 2014 4182765 3832643 4532886 3647299 4718230  
## Mar 2014 4376006 4019152 4732860 3830245 4921767  
## Apr 2014 3903181 3459270 4347091 3224278 4582084  
## May 2014 3630475 3182836 4078114 2945870 4315080  
## Jun 2014 3593592 3133773 4053411 2890359 4296825  
## Jul 2014 3369718 2863778 3875659 2595949 4143488  
## Aug 2014 3756013 3243800 4268226 2972651 4539375  
## Sep 2014 5395076 4868274 5921878 4589401 6200750  
## Oct 2014 5099481 4543257 5655706 4248809 5950154  
## Nov 2014 5376694 4812136 5941251 4513278 6240110  
## Dec 2014 4590587 4010944 5170230 3704100 5477074

Model\_dynreg\_auto.arima\_forecast\_df <-as.data.frame(Model\_dynreg\_auto.arima\_forecast)   
Model\_dynreg\_auto.arima\_PointForecast <- ts(Model\_dynreg\_auto.arima\_forecast\_df$"Point Forecast", start=c(2014,1), end=c(2014,12), frequency=12)  
Model\_dynreg\_auto.arima\_PointForecast

## Jan Feb Mar Apr May Jun Jul Aug  
## 2014 4311394 4182765 4376006 3903181 3630475 3593592 3369718 3756013  
## Sep Oct Nov Dec  
## 2014 5395076 5099481 5376694 4590587

# Output instruction for the data export of the results for further use in Excel.  
#write.csv(Model\_dynreg\_auto.arima\_PointForecast,file='Model\_dynreg\_auto.arima\_PointForecast.csv')  
  
#################################################################################  
### ###  
### 8. Kappa ###  
### ###  
#################################################################################  
  
#################################################################################  
# 8.1 Rename the indicators #  
#################################################################################  
  
# In order simplify the use of the indicators when calculating "model.matrix" and thus "kappa",   
# we have renamed the indicators as letters. This enables me to use the function letters[] to call   
# the individual indicators.  
  
a <- CEPIVector   
b <- SIGovVector   
c <- TemperatureVector   
d <- BirthsVector   
e <- SIGovVector   
f <- UrbanoExportsVector   
g <- GlobalisationPartyMembersVector   
h <- AEPIVector   
i <- PPIEtelVector   
j <- NationalHolidaysVector   
k <- ChulwalarIndexVector   
l <- InflationVector   
m <- IndependenceDayPresentsVector   
  
  
ListOfIndicators <- list(a,b,c,d,e,f,g,h,i,j,k,l,m)  
ListOfIndicators

## [[1]]  
## [1] 97.4 97.8 98.3 98.1 98.7 98.9 99.5 99.2 99.1 98.9 98.4  
## [12] 98.8 98.3 98.9 98.7 98.8 98.7 99.0 99.0 99.2 98.9 98.9  
## [23] 98.8 99.6 99.0 99.4 99.9 100.0 99.9 99.9 100.1 100.2 100.1  
## [34] 100.2 100.3 100.9 100.7 101.3 101.9 101.9 101.9 102.0 102.2 102.3  
## [45] 102.5 102.5 102.7 102.9 102.8 103.5 104.1 103.9 103.9 103.7 104.1  
## [56] 104.5 104.6 104.6 104.7 105.0 104.5 105.1 105.6 105.1 105.5 105.6  
## [67] 106.1 106.1 106.1 105.9 106.1 106.5  
##   
## [[2]]  
## [1] -0.4 -2.9 -2.7 1.7 -1.7 -2.6 -7.1 -11.1 -9.4 -13.5 -18.0  
## [12] -24.7 -26.9 -28.6 -31.9 -30.6 -29.8 -26.6 -23.7 -21.3 -17.4 -16.0  
## [23] -19.3 -16.4 -18.0 -17.9 -13.9 -5.5 -9.1 -9.8 0.6 3.5 5.9  
## [34] 6.4 9.9 8.1 7.0 6.8 6.5 7.5 7.5 8.4 8.0 -0.4  
## [45] -1.7 -4.1 -3.7 -2.9 -0.2 -1.4 -1.3 -1.9 0.0 -1.3 -3.7  
## [56] -8.1 -9.0 -8.6 -9.5 -9.8 -6.6 -5.4 -4.9 -3.8 -4.5 -3.0  
## [67] -1.7 -3.5 -4.0 -4.8 -2.5 -2.5  
##   
## [[3]]  
## [1] 3.60 3.70 4.20 7.60 14.50 16.90 18.00 17.40 12.40 9.10 5.10  
## [12] 1.10 -2.20 0.50 4.30 11.83 13.60 14.80 18.00 18.70 14.70 8.20  
## [23] 7.40 0.30 -3.60 -0.50 4.20 8.70 10.40 16.30 20.30 16.70 12.40  
## [34] 8.10 4.80 -3.70 1.00 0.90 4.90 11.60 13.90 16.50 16.10 17.70  
## [45] 15.20 9.40 4.50 3.90 1.90 -2.50 6.90 8.10 14.20 15.50 17.40  
## [56] 18.40 13.60 8.70 5.20 1.50 0.20 -0.70 0.10 8.10 11.80 15.70  
## [67] 19.50 17.90 13.30 10.60 4.60 3.60  
##   
## [[4]]  
## [1] 58519 53370 52852 55048 57398 58313 63315 60924 61263 56857 51703  
## [12] 52952 55155 50087 53692 53177 54535 56756 62292 59872 59612 54760  
## [23] 51319 53869 55273 50314 55486 52020 56054 57531 61918 59845 61125  
## [34] 58816 54576 54989 54802 50520 53433 49791 55059 56947 61169 60806  
## [45] 60308 55937 51691 52222 54528 51280 55026 53159 56683 55525 61346  
## [56] 61674 59615 57856 53590 53262 55919 49786 54222 53637 56768 57069  
## [67] 64208 62440 62725 58125 52985 54185  
##   
## [[5]]  
## [1] -0.4 -2.9 -2.7 1.7 -1.7 -2.6 -7.1 -11.1 -9.4 -13.5 -18.0  
## [12] -24.7 -26.9 -28.6 -31.9 -30.6 -29.8 -26.6 -23.7 -21.3 -17.4 -16.0  
## [23] -19.3 -16.4 -18.0 -17.9 -13.9 -5.5 -9.1 -9.8 0.6 3.5 5.9  
## [34] 6.4 9.9 8.1 7.0 6.8 6.5 7.5 7.5 8.4 8.0 -0.4  
## [45] -1.7 -4.1 -3.7 -2.9 -0.2 -1.4 -1.3 -1.9 0.0 -1.3 -3.7  
## [56] -8.1 -9.0 -8.6 -9.5 -9.8 -6.6 -5.4 -4.9 -3.8 -4.5 -3.0  
## [67] -1.7 -3.5 -4.0 -4.8 -2.5 -2.5  
##   
## [[6]]  
## [1] 5850000 5850000 5850000 5850000 5850000 5850000 5850000 5850000  
## [9] 5850000 5850000 5850000 5850000 5800000 5800000 5800000 5800000  
## [17] 5800000 5800000 5800000 5800000 5800000 5800000 5800000 5800000  
## [25] 6020000 6020000 6020000 6020000 6020000 6020000 6020000 6020000  
## [33] 6020000 6020000 6020000 6020000 6640000 6640000 6640000 6640000  
## [41] 6640000 6640000 6640000 6640000 6640000 6640000 6640000 6640000  
## [49] 7040000 7040000 7040000 7040000 7040000 7040000 7040000 7040000  
## [57] 7040000 7040000 7040000 7040000 7550000 7550000 7550000 7550000  
## [65] 7550000 7550000 7550000 7550000 7550000 7550000 7550000 7550000  
##   
## [[7]]  
## [1] 45089 45089 45089 45089 45089 45089 45089 45089 45089 45089 45089  
## [12] 45089 48171 48171 48171 48171 48171 48171 48171 48171 48171 48171  
## [23] 48171 48171 52991 52991 52991 52991 52991 52991 52991 52991 52991  
## [34] 52991 52991 52991 59074 59074 59074 59074 59074 59074 59074 59074  
## [45] 59074 59074 59074 59074 59653 59653 59653 59653 59653 59653 59653  
## [56] 59653 59653 59653 59653 59653 61359 61359 61359 61359 61359 61359  
## [67] 61359 61359 61359 61359 61359 61359  
##   
## [[8]]  
## [1] 99.0 99.3 99.5 99.2 99.5 100.2 100.6 100.7 100.8 100.2 98.6  
## [12] 98.0 98.5 98.4 98.2 98.4 98.0 97.4 96.9 97.3 97.8 97.3  
## [23] 97.2 97.7 98.2 98.7 99.6 100.0 99.0 99.8 100.2 100.2 100.6  
## [34] 100.3 101.2 102.1 102.8 103.7 104.4 104.9 105.2 105.2 105.8 105.3  
## [45] 105.1 105.1 105.3 105.5 106.1 107.1 107.7 107.4 107.1 107.3 107.8  
## [56] 107.7 108.0 108.3 108.4 109.0 109.8 110.1 111.0 111.1 111.7 111.8  
## [67] 112.6 112.1 112.3 111.7 111.5 111.7  
##   
## [[9]]  
## [1] 100.6 99.7 99.9 99.6 100.0 99.7 100.0 100.0 100.9 101.6 101.5  
## [12] 101.6 104.6 102.1 103.3 104.4 103.0 104.0 104.7 104.0 103.4 100.5  
## [23] 101.0 102.1 100.5 100.0 99.7 99.9 99.7 99.6 100.8 99.4 100.2  
## [34] 100.2 100.0 99.9 102.0 100.8 100.9 101.1 101.4 100.9 100.3 99.7  
## [45] 100.6 100.2 100.0 99.9 100.0 102.6 102.8 102.0 102.2 102.3 102.8  
## [56] 102.5 105.3 106.3 106.6 106.4 106.3 106.0 105.8 106.0 106.1 105.8  
## [67] 105.8 106.4 106.2 106.3 106.3 106.4  
##   
## [[10]]  
## [1] 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0  
## [36] 1 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0  
## [71] 0 1  
##   
## [[11]]  
## [1] 6851.75 6748.13 6534.97 6948.82 7096.79 6418.32 6479.56 6422.30  
## [9] 5831.02 4987.97 4669.44 4810.20 4338.35 3843.74 4084.76 4769.45  
## [17] 4940.82 4808.84 5332.14 5464.61 5675.16 5414.96 5625.95 5957.43  
## [25] 5608.79 5598.46 6153.55 6135.70 5964.33 5965.52 6147.97 5925.22  
## [33] 6229.02 6601.37 6688.49 6914.19 7077.48 7272.32 7041.31 7514.46  
## [41] 7293.69 7376.24 7158.77 5784.85 5502.02 6141.34 6088.84 5898.35  
## [49] 6458.91 6856.08 6946.83 6761.19 6264.38 6416.28 6772.26 6970.79  
## [57] 7216.15 7260.63 7045.50 7612.39 7776.05 7741.70 7795.31 7913.71  
## [65] 8348.84 7959.22 8275.97 8103.15 8594.40 9033.92 9405.30 9552.16  
##   
## [[12]]  
## [1] 2.85 2.84 3.15 2.40 3.03 3.24 3.32 3.12 2.80 2.38 1.34  
## [12] 1.13 0.92 1.12 0.41 0.71 0.00 0.10 -0.50 0.00 -0.20 0.00  
## [23] 0.41 0.81 0.71 0.51 1.22 1.21 1.22 0.91 1.11 1.01 1.21  
## [34] 1.31 1.52 1.31 1.72 1.91 2.00 1.90 2.00 2.10 2.10 2.10  
## [45] 2.40 2.30 2.39 1.98 2.09 2.17 2.16 1.96 1.96 1.67 1.86  
## [56] 2.15 2.05 2.05 1.95 2.04 1.65 1.55 1.44 1.15 1.54 1.83  
## [67] 1.92 1.53 1.43 1.24 1.34 1.43  
##   
## [[13]]  
## [1] 221 221 221 221 221 221 221 221 221 221 221 221 226 226 226 226 226  
## [18] 226 226 226 226 226 226 226 233 233 233 233 233 233 233 233 233 233  
## [35] 233 233 213 213 213 213 213 213 213 213 213 213 213 213 230 230 230  
## [52] 230 230 230 230 230 230 230 230 230 273 273 273 273 273 273 273 273  
## [69] 273 273 273 273

library(foreach) # to use loops for possible combinations of indicators (introducing models)  
  
#################################################################################  
# 8.2 Create the names lists #  
#################################################################################  
  
  
# names for 2 Chulwalar indicators  
  
letter <- expand.grid(x =letters[1:13] ,y = letters[1:13])  
newnames2 <- rev(letter)  
  
# names for 3 Chulwalar indicators  
  
letter <- expand.grid(x =letters[1:13] ,y = letters[1:13], z = letters[1:13])  
newnames3 <- rev(letter)  
  
indicators <- list(a,b,c,d,e,f,g,h,i,j,k,l,m)  
  
  
#################################################################################  
# 8.3 Kappa calculation with 2 indicators #  
#################################################################################  
  
  
allkappa <- foreach (y = indicators[1:13], .combine = c) %do% {  
 foreach( z = indicators[1:13], .combine =c) %do% {  
 kappa(model.matrix(~ y + z))  
 }  
}  
  
kappasFor2CombinedIndicators <- cbind(allkappa,newnames2)  
  
kappasFor2CombinedIndicators[with(kappasFor2CombinedIndicators, order(allkappa)),]

## allkappa y x  
## 153 6.944008e+00 l j  
## 129 6.966025e+00 j l  
## 16 2.076233e+01 b c  
## 55 2.076233e+01 e c  
## 28 2.141187e+01 c b  
## 31 2.141187e+01 c e  
## 119 2.855234e+01 j b  
## 122 2.855234e+01 j e  
## 38 3.512568e+01 c l  
## 146 3.652645e+01 l c  
## 23 3.974333e+01 b j  
## 62 3.974333e+01 e j  
## 36 4.395097e+01 c j  
## 120 4.560663e+01 j c  
## 25 5.594589e+01 b l  
## 64 5.594589e+01 e l  
## 145 5.836374e+01 l b  
## 148 5.836374e+01 l e  
## 103 1.867438e+03 h l  
## 93 1.879024e+03 h b  
## 96 1.879024e+03 h e  
## 101 1.989485e+03 h j  
## 125 2.025509e+03 j h  
## 34 2.069039e+03 c h  
## 94 2.166523e+03 h c  
## 151 2.247513e+03 l h  
## 168 2.424334e+03 m l  
## 130 2.461503e+03 j m  
## 166 2.461503e+03 m j  
## 21 2.496844e+03 b h  
## 60 2.496844e+03 e h  
## 159 2.549767e+03 m c  
## 39 2.630309e+03 c m  
## 158 2.654492e+03 m b  
## 161 2.654492e+03 m e  
## 156 2.679267e+03 l m  
## 26 2.730474e+03 b m  
## 65 2.730474e+03 e m  
## 2 3.224742e+03 a b  
## 5 3.224742e+03 a e  
## 9 3.376626e+03 a i  
## 100 3.389934e+03 h i  
## 12 3.450538e+03 a l  
## 10 3.535643e+03 a j  
## 144 3.633667e+03 l a  
## 116 3.656763e+03 i l  
## 118 3.684305e+03 j a  
## 105 3.691648e+03 i a  
## 164 3.726545e+03 m h  
## 27 3.728140e+03 c a  
## 106 3.751718e+03 i b  
## 109 3.751718e+03 i e  
## 3 3.755464e+03 a c  
## 112 4.057212e+03 i h  
## 114 4.068650e+03 i j  
## 126 4.173541e+03 j i  
## 107 4.173902e+03 i c  
## 14 4.184227e+03 b a  
## 53 4.184227e+03 e a  
## 35 4.227973e+03 c i  
## 152 4.345566e+03 l i  
## 22 4.428244e+03 b i  
## 61 4.428244e+03 e i  
## 104 4.870509e+03 h m  
## 8 6.921849e+03 a h  
## 92 7.528856e+03 h a  
## 13 8.030364e+03 a m  
## 157 8.184925e+03 m a  
## 117 9.320270e+03 i m  
## 165 1.022296e+04 m i  
## 140 3.277521e+04 k j  
## 133 3.294717e+04 k c  
## 142 3.297095e+04 k l  
## 37 3.333219e+04 c k  
## 128 3.340006e+04 j k  
## 154 3.648225e+04 l k  
## 132 3.991408e+04 k b  
## 135 3.991408e+04 k e  
## 24 5.369096e+04 b k  
## 63 5.369096e+04 e k  
## 143 6.837767e+04 k m  
## 167 8.110094e+04 m k  
## 102 1.640060e+05 h k  
## 138 1.854036e+05 k h  
## 115 2.830604e+05 i k  
## 11 3.004251e+05 a k  
## 139 3.083549e+05 k i  
## 131 3.619471e+05 k a  
## 137 3.737901e+05 k g  
## 88 4.167760e+05 g j  
## 124 4.167760e+05 j g  
## 90 4.226560e+05 g l  
## 81 4.345463e+05 g c  
## 33 4.376906e+05 c g  
## 80 4.395341e+05 g b  
## 83 4.395341e+05 g e  
## 150 4.608051e+05 l g  
## 89 4.677821e+05 g k  
## 91 5.196889e+05 g m  
## 20 5.810589e+05 b g  
## 59 5.810589e+05 e g  
## 163 6.042757e+05 m g  
## 134 7.040311e+05 k d  
## 50 7.419530e+05 d k  
## 49 7.553036e+05 d j  
## 46 7.583309e+05 d g  
## 82 7.603428e+05 g d  
## 41 7.617423e+05 d b  
## 44 7.617423e+05 d e  
## 160 7.695230e+05 m d  
## 52 7.741275e+05 d m  
## 51 8.001824e+05 d l  
## 147 8.331508e+05 l d  
## 17 8.452015e+05 b d  
## 56 8.452015e+05 e d  
## 42 8.856749e+05 d c  
## 121 9.093227e+05 j d  
## 47 1.038455e+06 d h  
## 95 1.059279e+06 h d  
## 30 1.205440e+06 c d  
## 98 1.286925e+06 h g  
## 86 1.397931e+06 g h  
## 40 1.789637e+06 d a  
## 4 1.865999e+06 a d  
## 48 2.041252e+06 d i  
## 108 2.101732e+06 i d  
## 111 2.209494e+06 i g  
## 87 2.229208e+06 g i  
## 7 3.378338e+06 a g  
## 79 4.022809e+06 g a  
## 84 5.109906e+07 g f  
## 136 5.375787e+07 k f  
## 76 5.530109e+07 f k  
## 123 5.555736e+07 j f  
## 75 5.555736e+07 f j  
## 67 5.609895e+07 f b  
## 70 5.609895e+07 f e  
## 68 5.848289e+07 f c  
## 32 5.853891e+07 c f  
## 77 5.921965e+07 f l  
## 78 6.028311e+07 f m  
## 72 6.258801e+07 f g  
## 149 6.274817e+07 l f  
## 19 7.212800e+07 b f  
## 58 7.212800e+07 e f  
## 162 7.346835e+07 m f  
## 69 8.919946e+07 f d  
## 45 9.004315e+07 d f  
## 110 2.614882e+08 i f  
## 74 2.888863e+08 f i  
## 97 3.498446e+08 h f  
## 73 3.840885e+08 f h  
## 6 7.640062e+08 a f  
## 66 8.712154e+08 f a  
## 127 2.933872e+15 j j  
## 15 3.784125e+15 b b  
## 18 3.784125e+15 b e  
## 54 3.784125e+15 e b  
## 57 3.784125e+15 e e  
## 155 1.438384e+16 l l  
## 29 1.446390e+16 c c  
## 85 2.938508e+16 g g  
## 141 3.641511e+16 k k  
## 71 3.682412e+16 f f  
## 43 1.121619e+17 d d  
## 113 1.726169e+17 i i  
## 1 7.061211e+17 a a  
## 99 9.213681e+17 h h  
## 169 Inf m m

#################################################################################  
# 8.4 Kappa calculation with 3 indicators #  
#################################################################################  
  
allkappa <- foreach(x = indicators[1:13], .combine = c) %do% {foreach(y = indicators[1:13], .combine = c) %do% {  
 foreach( z = indicators[1:13], .combine =c) %do% {  
 kappa(model.matrix(~ x + y + z))  
 }  
 }  
}  
  
kappasFor3CombinedIndicators <- cbind(allkappa,newnames3)  
  
kappasFor3CombinedIndicators[with(kappasFor3CombinedIndicators, order(allkappa)),]

## allkappa z y x  
## 1549 4.397401e+01 j c b  
## 1552 4.397401e+01 j c e  
## 289 4.405682e+01 b j c  
## 796 4.405682e+01 e j c  
## 1537 4.426748e+01 j b c  
## 1576 4.426748e+01 j e c  
## 205 4.455750e+01 b c j  
## 712 4.455750e+01 e c j  
## 491 4.485299e+01 c l j  
## 467 4.488470e+01 c j l  
## 1895 4.632721e+01 l c j  
## 361 4.642220e+01 c b j  
## 400 4.642220e+01 c e j  
## 457 4.648482e+01 c j b  
## 460 4.648482e+01 c j e  
## 1559 4.761191e+01 j c l  
## 1667 4.867775e+01 j l c  
## 1979 4.872415e+01 l j c  
## 207 4.977059e+01 b c l  
## 714 4.977059e+01 e c l  
## 315 4.989394e+01 b l c  
## 822 4.989394e+01 e l c  
## 1546 5.169756e+01 j b l  
## 1585 5.169756e+01 j e l  
## 363 5.187931e+01 c b l  
## 402 5.187931e+01 c e l  
## 1875 5.376627e+01 l b c  
## 1914 5.376627e+01 l e c  
## 298 5.500965e+01 b j l  
## 805 5.500965e+01 e j l  
## 322 5.502550e+01 b l j  
## 829 5.502550e+01 e l j  
## 1887 5.595400e+01 l c b  
## 1890 5.595400e+01 l c e  
## 483 5.606918e+01 c l b  
## 486 5.606918e+01 c l e  
## 1978 5.632842e+01 l j b  
## 1981 5.632842e+01 l j e  
## 1666 5.641875e+01 j l b  
## 1669 5.641875e+01 j l e  
## 1882 6.063678e+01 l b j  
## 1921 6.063678e+01 l e j  
## 1336 1.728773e+03 h l j  
## 1312 1.731798e+03 h j l  
## 1328 1.732105e+03 h l b  
## 1331 1.732105e+03 h l e  
## 1206 1.752277e+03 h b j  
## 1245 1.752277e+03 h e j  
## 1624 1.753346e+03 j h l  
## 1208 1.765145e+03 h b l  
## 1247 1.765145e+03 h e l  
## 1302 1.766292e+03 h j b  
## 1305 1.766292e+03 h j e  
## 1952 1.770743e+03 l h b  
## 1955 1.770743e+03 l h e  
## 441 1.780881e+03 c h l  
## 1614 1.785012e+03 j h b  
## 1617 1.785012e+03 j h e  
## 1555 1.798722e+03 j c h  
## 431 1.808143e+03 c h b  
## 434 1.808143e+03 c h e  
## 1199 1.820866e+03 h b c  
## 1238 1.820866e+03 h e c  
## 1329 1.831606e+03 h l c  
## 1221 1.846025e+03 h c l  
## 1211 1.862440e+03 h c b  
## 1214 1.862440e+03 h c e  
## 439 1.873013e+03 c h j  
## 1615 1.877098e+03 j h c  
## 1303 1.900130e+03 h j c  
## 463 1.945957e+03 c j h  
## 1219 1.950369e+03 h c j  
## 1960 2.046389e+03 l h j  
## 1984 2.083537e+03 l j h  
## 1672 2.084430e+03 j l h  
## 1893 2.125791e+03 l c h  
## 1880 2.128450e+03 l b h  
## 1919 2.128450e+03 l e h  
## 489 2.130861e+03 c l h  
## 2173 2.181918e+03 m l b  
## 2176 2.181918e+03 m l e  
## 2181 2.187894e+03 m l j  
## 1689 2.190118e+03 j m l  
## 2157 2.190118e+03 m j l  
## 1680 2.192068e+03 j m c  
## 2148 2.192068e+03 m j c  
## 320 2.193710e+03 b l h  
## 827 2.193710e+03 e l h  
## 1953 2.196127e+03 l h c  
## 2064 2.228624e+03 m c j  
## 2066 2.237034e+03 m c l  
## 1560 2.244714e+03 j c m  
## 2174 2.255961e+03 m l c  
## 270 2.271246e+03 b h j  
## 777 2.271246e+03 e h j  
## 504 2.285535e+03 c m j  
## 506 2.290627e+03 c m l  
## 272 2.295066e+03 b h l  
## 779 2.295066e+03 e h l  
## 468 2.301671e+03 c j m  
## 2051 2.320967e+03 m b j  
## 2090 2.320967e+03 m e j  
## 1542 2.325837e+03 j b h  
## 1581 2.325837e+03 j e h  
## 294 2.329224e+03 b j h  
## 801 2.329224e+03 e j h  
## 359 2.362029e+03 c b h  
## 398 2.362029e+03 c e h  
## 203 2.363565e+03 b c h  
## 710 2.363565e+03 e c h  
## 2017 2.364187e+03 l m b  
## 2020 2.364187e+03 l m e  
## 1679 2.367380e+03 j m b  
## 1682 2.367380e+03 j m e  
## 2147 2.367380e+03 m j b  
## 2150 2.367380e+03 m j e  
## 2056 2.372525e+03 m c b  
## 2059 2.372525e+03 m c e  
## 299 2.375620e+03 b j m  
## 806 2.375620e+03 e j m  
## 335 2.376334e+03 b m j  
## 842 2.376334e+03 e m j  
## 2044 2.383079e+03 m b c  
## 2083 2.383079e+03 m e c  
## 2025 2.386264e+03 l m j  
## 1677 2.388288e+03 j l m  
## 1989 2.388632e+03 l j m  
## 2053 2.389947e+03 m b l  
## 2092 2.389947e+03 m e l  
## 263 2.395077e+03 b h c  
## 770 2.395077e+03 e h c  
## 1547 2.426231e+03 j b m  
## 1586 2.426231e+03 j e m  
## 337 2.436527e+03 b m l  
## 844 2.436527e+03 e m l  
## 496 2.441904e+03 c m b  
## 499 2.441904e+03 c m e  
## 328 2.443141e+03 b m c  
## 835 2.443141e+03 e m c  
## 2018 2.474101e+03 l m c  
## 364 2.511523e+03 c b m  
## 403 2.511523e+03 c e m  
## 494 2.515810e+03 c l m  
## 208 2.521678e+03 b c m  
## 715 2.521678e+03 e c m  
## 1898 2.526609e+03 l c m  
## 1885 2.569902e+03 l b m  
## 1924 2.569902e+03 l e m  
## 325 2.699735e+03 b l m  
## 832 2.699735e+03 e l m  
## 22 2.942480e+03 a b i  
## 61 2.942480e+03 a e i  
## 25 2.945442e+03 a b l  
## 64 2.945442e+03 a e l  
## 23 3.008920e+03 a b j  
## 62 3.008920e+03 a e j  
## 119 3.034933e+03 a j b  
## 122 3.034933e+03 a j e  
## 116 3.067477e+03 a i l  
## 145 3.078738e+03 a l b  
## 148 3.078738e+03 a l e  
## 1861 3.093616e+03 l a b  
## 1864 3.093616e+03 l a e  
## 1523 3.126749e+03 j a b  
## 1526 3.126749e+03 j a e  
## 340 3.147329e+03 c a b  
## 343 3.147329e+03 c a e  
## 1299 3.158717e+03 h i l  
## 28 3.162694e+03 a c b  
## 31 3.162694e+03 a c e  
## 153 3.192251e+03 a l j  
## 129 3.193961e+03 a j l  
## 126 3.196058e+03 a j i  
## 114 3.199147e+03 a i j  
## 16 3.205562e+03 a b c  
## 55 3.205562e+03 a e c  
## 1289 3.218883e+03 h i b  
## 1292 3.218883e+03 h i e  
## 1297 3.224847e+03 h i j  
## 1290 3.258075e+03 h i c  
## 1309 3.264152e+03 h j i  
## 1530 3.281119e+03 j a i  
## 1621 3.285531e+03 j h i  
## 1868 3.292371e+03 l a i  
## 152 3.294244e+03 a l i  
## 347 3.300920e+03 c a i  
## 1364 3.312329e+03 i a l  
## 1533 3.312596e+03 j a l  
## 1377 3.313230e+03 i b l  
## 1416 3.313230e+03 i e l  
## 106 3.320245e+03 a i b  
## 109 3.320245e+03 a i e  
## 35 3.322496e+03 a c i  
## 438 3.325707e+03 c h i  
## 107 3.332278e+03 a i c  
## 1869 3.347894e+03 l a j  
## 350 3.348496e+03 c a l  
## 120 3.351631e+03 a j c  
## 38 3.370353e+03 a c l  
## 1218 3.379175e+03 h c i  
## 2131 3.381061e+03 m h l  
## 1496 3.384627e+03 i l a  
## 146 3.385764e+03 a l c  
## 1366 3.392965e+03 i b a  
## 1405 3.392965e+03 i e a  
## 1548 3.394854e+03 j c a  
## 348 3.398612e+03 c a j  
## 36 3.413862e+03 a c j  
## 1481 3.470381e+03 i j l  
## 1505 3.471724e+03 i l j  
## 1362 3.477377e+03 i a j  
## 2129 3.479294e+03 m h j  
## 1665 3.484394e+03 j l a  
## 1977 3.485130e+03 l j a  
## 1503 3.486741e+03 i l h  
## 1470 3.501540e+03 i j a  
## 1497 3.509274e+03 i l b  
## 1500 3.509274e+03 i l e  
## 2062 3.511614e+03 m c h  
## 1205 3.519415e+03 h b i  
## 1244 3.519415e+03 h e i  
## 2153 3.520823e+03 m j h  
## 1685 3.520823e+03 j m h  
## 482 3.523129e+03 c l a  
## 1524 3.529580e+03 j a c  
## 1886 3.529970e+03 l c a  
## 1390 3.537671e+03 i c l  
## 1637 3.539239e+03 j i l  
## 178 3.541672e+03 b a i  
## 685 3.541672e+03 e a i  
## 1375 3.551650e+03 i b j  
## 1414 3.551650e+03 i e j  
## 1862 3.552566e+03 l a c  
## 502 3.568377e+03 c m h  
## 1626 3.571125e+03 j i a  
## 454 3.572840e+03 c i l  
## 1379 3.576627e+03 i c a  
## 1498 3.577330e+03 i l c  
## 1455 3.599177e+03 i h l  
## 456 3.604185e+03 c j a  
## 443 3.610820e+03 c i a  
## 1627 3.621996e+03 j i b  
## 1630 3.621996e+03 j i e  
## 1380 3.622754e+03 i c b  
## 1383 3.622754e+03 i c e  
## 1471 3.629096e+03 i j b  
## 1474 3.629096e+03 i j e  
## 1373 3.630609e+03 i b h  
## 1412 3.630609e+03 i e h  
## 2121 3.635152e+03 m h b  
## 2124 3.635152e+03 m h e  
## 1355 3.638406e+03 i a c  
## 1445 3.655481e+03 i h b  
## 1448 3.655481e+03 i h e  
## 444 3.661630e+03 c i b  
## 447 3.661630e+03 c i e  
## 1354 3.661984e+03 i a b  
## 1357 3.661984e+03 i a e  
## 1368 3.669411e+03 i b c  
## 1407 3.669411e+03 i e c  
## 2023 3.680158e+03 l m h  
## 181 3.702679e+03 b a l  
## 688 3.702679e+03 e a l  
## 2122 3.707959e+03 m h c  
## 2179 3.726131e+03 m l h  
## 1335 3.757064e+03 h l i  
## 285 3.793827e+03 b i l  
## 792 3.793827e+03 e i l  
## 1873 3.813496e+03 l b a  
## 1912 3.813496e+03 l e a  
## 179 3.817378e+03 b a j  
## 686 3.817378e+03 e a j  
## 1477 3.823281e+03 i j h  
## 1453 3.823431e+03 i h j  
## 1446 3.868072e+03 i h c  
## 274 3.869756e+03 b i a  
## 781 3.869756e+03 e i a  
## 1628 3.871341e+03 j i c  
## 1964 3.880422e+03 l i a  
## 1556 3.887632e+03 j c i  
## 313 3.894512e+03 b l a  
## 820 3.894512e+03 e l a  
## 1959 3.900245e+03 l h i  
## 1386 3.908790e+03 i c h  
## 1633 3.909109e+03 j i h  
## 464 3.924454e+03 c j i  
## 1388 3.938731e+03 i c j  
## 450 3.949696e+03 c i h  
## 1472 3.961664e+03 i j c  
## 269 3.986400e+03 b h i  
## 776 3.986400e+03 e h i  
## 452 3.986692e+03 c i j  
## 1535 4.013139e+03 j b a  
## 1574 4.013139e+03 j e a  
## 287 4.016471e+03 b j a  
## 794 4.016471e+03 e j a  
## 281 4.037018e+03 b i h  
## 788 4.037018e+03 e i h  
## 352 4.040605e+03 c b a  
## 391 4.040605e+03 c e a  
## 1339 4.041114e+03 h l m  
## 196 4.043280e+03 b c a  
## 703 4.043280e+03 e c a  
## 1973 4.083863e+03 l i j  
## 1971 4.095158e+03 l i h  
## 1985 4.097458e+03 l j i  
## 1209 4.108491e+03 h b m  
## 1248 4.108491e+03 h e m  
## 1881 4.121854e+03 l b i  
## 1920 4.121854e+03 l e i  
## 1965 4.137789e+03 l i b  
## 1968 4.137789e+03 l i e  
## 283 4.149002e+03 b i j  
## 790 4.149002e+03 e i j  
## 172 4.152167e+03 b a c  
## 679 4.152167e+03 e a c  
## 295 4.160679e+03 b j i  
## 802 4.160679e+03 e j i  
## 1351 4.176260e+03 h m l  
## 1673 4.178102e+03 j l i  
## 321 4.212755e+03 b l i  
## 828 4.212755e+03 e l i  
## 490 4.228144e+03 c l i  
## 1966 4.233731e+03 l i c  
## 1894 4.234476e+03 l c i  
## 1543 4.237610e+03 j b i  
## 1582 4.237610e+03 j e i  
## 360 4.280428e+03 c b i  
## 399 4.280428e+03 c e i  
## 204 4.285583e+03 b c i  
## 711 4.285583e+03 e c i  
## 276 4.312306e+03 b i c  
## 783 4.312306e+03 e i c  
## 1963 4.382830e+03 l h m  
## 1341 4.389252e+03 h m b  
## 1344 4.389252e+03 h m e  
## 2049 4.414173e+03 m b h  
## 2088 4.414173e+03 m e h  
## 1349 4.451239e+03 h m j  
## 1313 4.457244e+03 h j m  
## 333 4.469748e+03 b m h  
## 840 4.469748e+03 e m h  
## 1625 4.512806e+03 j h m  
## 442 4.613090e+03 c h m  
## 1222 4.835359e+03 h c m  
## 1342 4.837032e+03 h m c  
## 273 5.028569e+03 b h m  
## 780 5.028569e+03 e h m  
## 1288 6.028691e+03 h i a  
## 112 6.036203e+03 a i h  
## 93 6.255250e+03 a h b  
## 96 6.255250e+03 a h e  
## 100 6.304551e+03 a h i  
## 21 6.323475e+03 a b h  
## 60 6.323475e+03 a e h  
## 101 6.329930e+03 a h j  
## 1360 6.396191e+03 i a h  
## 1444 6.603108e+03 i h a  
## 1185 6.737375e+03 h a b  
## 1188 6.737375e+03 h a e  
## 1192 6.757820e+03 h a i  
## 94 6.766322e+03 a h c  
## 1193 6.810394e+03 h a j  
## 125 6.813371e+03 a j h  
## 346 6.855467e+03 c a h  
## 34 6.861038e+03 a c h  
## 1529 6.906908e+03 j a h  
## 1197 6.988697e+03 h b a  
## 1236 6.988697e+03 h e a  
## 177 7.058307e+03 b a h  
## 684 7.058307e+03 e a h  
## 168 7.146545e+03 a m l  
## 103 7.191117e+03 a h l  
## 2040 7.216582e+03 m a l  
## 1186 7.341974e+03 h a c  
## 158 7.417664e+03 a m b  
## 161 7.417664e+03 a m e  
## 430 7.447488e+03 c h a  
## 2030 7.449942e+03 m a b  
## 2033 7.449942e+03 m a e  
## 1301 7.466510e+03 h j a  
## 166 7.493461e+03 a m j  
## 1613 7.497641e+03 j h a  
## 1210 7.509468e+03 h c a  
## 26 7.522650e+03 a b m  
## 65 7.522650e+03 a e m  
## 1195 7.545764e+03 h a l  
## 130 7.573566e+03 a j m  
## 2038 7.606954e+03 m a j  
## 261 7.625425e+03 b h a  
## 768 7.625425e+03 e h a  
## 159 7.671055e+03 a m c  
## 156 7.683690e+03 a l m  
## 1534 7.776102e+03 j a m  
## 2031 7.800434e+03 m a c  
## 1300 7.820095e+03 h i m  
## 351 7.854225e+03 c a m  
## 2172 7.868711e+03 m l a  
## 2055 7.916700e+03 m c a  
## 39 7.922759e+03 a c m  
## 2146 7.923516e+03 m j a  
## 1678 7.923516e+03 j m a  
## 1872 7.932943e+03 l a m  
## 495 8.001923e+03 c m a  
## 2016 8.185354e+03 l m a  
## 2128 8.330363e+03 m h i  
## 1508 8.364362e+03 i l m  
## 1520 8.372180e+03 i m l  
## 1510 8.373733e+03 i m b  
## 1513 8.373733e+03 i m e  
## 1509 8.521900e+03 i m a  
## 117 8.545680e+03 a i m  
## 2037 8.633815e+03 m a i  
## 165 8.643464e+03 a m i  
## 1456 8.731161e+03 i h m  
## 182 8.832921e+03 b a m  
## 689 8.832921e+03 e a m  
## 1518 8.849131e+03 i m j  
## 1378 8.919870e+03 i b m  
## 1417 8.919870e+03 i e m  
## 2134 8.941054e+03 m i b  
## 2137 8.941054e+03 m i e  
## 1482 8.942690e+03 i j m  
## 1516 8.982076e+03 i m h  
## 2144 8.984674e+03 m i l  
## 151 9.002854e+03 a l h  
## 1365 9.019549e+03 i a m  
## 2133 9.046224e+03 m i a  
## 1638 9.071639e+03 j i m  
## 1391 9.080745e+03 i c m  
## 455 9.159704e+03 c i m  
## 1511 9.197261e+03 i m c  
## 1867 9.336778e+03 l a h  
## 2042 9.384845e+03 m b a  
## 2081 9.384845e+03 m e a  
## 1348 9.389926e+03 h m i  
## 326 9.465248e+03 b m a  
## 833 9.465248e+03 e m a  
## 1976 9.465288e+03 l i m  
## 1327 9.614861e+03 h l a  
## 2142 9.633312e+03 m i j  
## 286 9.748134e+03 b i m  
## 793 9.748134e+03 e i m  
## 2140 9.808757e+03 m i h  
## 2180 9.876386e+03 m l i  
## 2063 9.912346e+03 m c i  
## 1686 9.915620e+03 j m i  
## 2154 9.915620e+03 m j i  
## 503 1.000820e+04 c m i  
## 2135 1.006885e+04 m i c  
## 1951 1.007187e+04 l h a  
## 2024 1.023484e+04 l m i  
## 2050 1.081191e+04 m b i  
## 2089 1.081191e+04 m e i  
## 334 1.089832e+04 b m i  
## 841 1.089832e+04 e m i  
## 2036 1.461236e+04 m a h  
## 164 1.475490e+04 a m h  
## 104 1.520717e+04 a h m  
## 2120 1.635922e+04 m h a  
## 1196 1.654816e+04 h a m  
## 1340 1.789358e+04 h m a  
## 1728 2.967962e+04 k c l  
## 1836 2.968616e+04 k l c  
## 1810 2.983018e+04 k j c  
## 1819 2.994992e+04 k j l  
## 480 2.999623e+04 c k l  
## 1843 3.007742e+04 k l j  
## 1663 3.041120e+04 j k l  
## 466 3.064989e+04 c j k  
## 1726 3.097508e+04 k c j  
## 478 3.130394e+04 c k j  
## 1654 3.180079e+04 j k c  
## 1558 3.198508e+04 j c k  
## 1992 3.250984e+04 l k c  
## 1999 3.264311e+04 l k j  
## 1896 3.303350e+04 l c k  
## 492 3.322190e+04 c l k  
## 1987 3.335388e+04 l j k  
## 1675 3.338981e+04 j l k  
## 1713 3.654967e+04 k b j  
## 1752 3.654967e+04 k e j  
## 1706 3.656242e+04 k b c  
## 1745 3.656242e+04 k e c  
## 1809 3.705839e+04 k j b  
## 1812 3.705839e+04 k j e  
## 1718 3.749294e+04 k c b  
## 1721 3.749294e+04 k c e  
## 1653 3.780425e+04 j k b  
## 1656 3.780425e+04 j k e  
## 470 3.785136e+04 c k b  
## 473 3.785136e+04 c k e  
## 1715 3.834268e+04 k b l  
## 1754 3.834268e+04 k e l  
## 1835 4.275649e+04 k l b  
## 1838 4.275649e+04 k l e  
## 1991 4.298955e+04 l k b  
## 1994 4.298955e+04 l k e  
## 309 4.672874e+04 b k j  
## 816 4.672874e+04 e k j  
## 302 4.756502e+04 b k c  
## 809 4.756502e+04 e k c  
## 311 4.815180e+04 b k l  
## 818 4.815180e+04 e k l  
## 206 4.837647e+04 b c k  
## 713 4.837647e+04 e c k  
## 323 4.852642e+04 b l k  
## 830 4.852642e+04 e l k  
## 1545 4.877956e+04 j b k  
## 1584 4.877956e+04 j e k  
## 297 4.898276e+04 b j k  
## 804 4.898276e+04 e j k  
## 362 4.928507e+04 c b k  
## 401 4.928507e+04 c e k  
## 1883 5.374719e+04 l b k  
## 1922 5.374719e+04 l e k  
## 1716 5.672947e+04 k b m  
## 1755 5.672947e+04 k e m  
## 1856 6.163828e+04 k m j  
## 1849 6.269981e+04 k m c  
## 1820 6.270211e+04 k j m  
## 1664 6.276569e+04 j k m  
## 1848 6.314536e+04 k m b  
## 1851 6.314536e+04 k m e  
## 1729 6.521236e+04 k c m  
## 481 6.585923e+04 c k m  
## 312 6.772277e+04 b k m  
## 819 6.772277e+04 e k m  
## 1858 6.830202e+04 k m l  
## 2168 7.178342e+04 m k j  
## 2156 7.221150e+04 m j k  
## 2161 7.341761e+04 m k c  
## 2160 7.404001e+04 m k b  
## 2163 7.404001e+04 m k e  
## 1688 7.416538e+04 j m k  
## 2065 7.425853e+04 m c k  
## 505 7.693620e+04 c m k  
## 2182 7.715131e+04 m l k  
## 2170 7.798485e+04 m k l  
## 2052 7.962072e+04 m b k  
## 2091 7.962072e+04 m e k  
## 336 8.129613e+04 b m k  
## 843 8.129613e+04 e m k  
## 1846 8.237915e+04 k l m  
## 2002 8.426666e+04 l k m  
## 2026 8.909442e+04 l m k  
## 1207 1.428531e+05 h b k  
## 1246 1.428531e+05 h e k  
## 2130 1.441216e+05 m h k  
## 1854 1.487161e+05 k m h  
## 1323 1.524721e+05 h k j  
## 1337 1.543565e+05 h l k  
## 1326 1.550126e+05 h k m  
## 1325 1.552229e+05 h k l  
## 1311 1.570465e+05 h j k  
## 1315 1.571342e+05 h k b  
## 1318 1.571342e+05 h k e  
## 1623 1.575040e+05 j h k  
## 440 1.604004e+05 c h k  
## 1350 1.609438e+05 h m k  
## 1711 1.627386e+05 k b h  
## 1750 1.627386e+05 k e h  
## 1316 1.630323e+05 h k c  
## 1220 1.640976e+05 h c k  
## 2166 1.648894e+05 m k h  
## 1961 1.685543e+05 l h k  
## 1791 1.693927e+05 k h j  
## 1794 1.713090e+05 k h m  
## 271 1.725399e+05 b h k  
## 778 1.725399e+05 e h k  
## 1793 1.733274e+05 k h l  
## 1815 1.741826e+05 k j h  
## 1659 1.758098e+05 j k h  
## 1783 1.759926e+05 k h b  
## 1786 1.759926e+05 k h e  
## 1724 1.789227e+05 k c h  
## 1841 1.801111e+05 k l h  
## 476 1.805371e+05 c k h  
## 1784 1.840828e+05 k h c  
## 307 1.845961e+05 b k h  
## 814 1.845961e+05 e k h  
## 1997 1.901396e+05 l k h  
## 1322 2.231095e+05 h k i  
## 1298 2.298309e+05 h i k  
## 1790 2.310743e+05 k h i  
## 1495 2.541323e+05 i k m  
## 1490 2.581776e+05 i k h  
## 1494 2.619908e+05 i k l  
## 167 2.657442e+05 a m k  
## 1807 2.664333e+05 k i m  
## 24 2.684974e+05 a b k  
## 63 2.684974e+05 a e k  
## 1485 2.711553e+05 i k c  
## 1492 2.714454e+05 i k j  
## 115 2.716172e+05 a i k  
## 139 2.719591e+05 a k i  
## 1806 2.730274e+05 k i l  
## 1454 2.732279e+05 i h k  
## 142 2.751733e+05 a k l  
## 1389 2.755862e+05 i c k  
## 1636 2.760955e+05 j i k  
## 1480 2.763088e+05 i j k  
## 1506 2.766110e+05 i l k  
## 1802 2.767140e+05 k i h  
## 1483 2.783971e+05 i k a  
## 453 2.792873e+05 c i k  
## 143 2.795278e+05 a k m  
## 2039 2.800005e+05 m a k  
## 132 2.834219e+05 a k b  
## 135 2.834219e+05 a k e  
## 1795 2.880668e+05 k i a  
## 140 2.895293e+05 a k j  
## 1519 2.929848e+05 i m k  
## 1855 2.931565e+05 k m i  
## 1816 2.933366e+05 k j i  
## 1797 2.934138e+05 k i c  
## 1804 2.937794e+05 k i j  
## 133 2.940617e+05 a k c  
## 1532 2.947510e+05 j a k  
## 128 2.964281e+05 a j k  
## 37 2.966369e+05 a c k  
## 1363 2.972889e+05 i a k  
## 349 2.974549e+05 c a k  
## 1660 2.982347e+05 j k i  
## 154 3.015236e+05 a l k  
## 1725 3.015686e+05 k c i  
## 477 3.039429e+05 c k i  
## 1699 3.092192e+05 k a i  
## 1847 3.127506e+05 k m a  
## 1870 3.135440e+05 l a k  
## 180 3.148629e+05 b a k  
## 687 3.148629e+05 e a k  
## 2143 3.179616e+05 m i k  
## 1974 3.183766e+05 l i k  
## 1484 3.195521e+05 i k b  
## 1487 3.195521e+05 i k e  
## 2167 3.202997e+05 m k i  
## 1702 3.212345e+05 k a l  
## 1796 3.273003e+05 k i b  
## 1799 3.273003e+05 k i e  
## 1703 3.288181e+05 k a m  
## 1704 3.342283e+05 k b a  
## 1743 3.342283e+05 k e a  
## 1692 3.352482e+05 k a b  
## 1695 3.352482e+05 k a e  
## 1780 3.398416e+05 k g l  
## 1658 3.398607e+05 j k g  
## 1778 3.407057e+05 k g j  
## 2159 3.413014e+05 m k a  
## 1771 3.447367e+05 k g c  
## 1700 3.449896e+05 k a j  
## 1814 3.459087e+05 k j g  
## 1808 3.460785e+05 k j a  
## 475 3.473776e+05 c k g  
## 1376 3.487385e+05 i b k  
## 1415 3.487385e+05 i e k  
## 1723 3.516781e+05 k c g  
## 1652 3.517779e+05 j k a  
## 1693 3.520890e+05 k a c  
## 1717 3.544183e+05 k c a  
## 1842 3.547967e+05 k l i  
## 469 3.571497e+05 c k a  
## 1996 3.595671e+05 l k g  
## 1834 3.610373e+05 k l a  
## 1840 3.672759e+05 k l g  
## 300 3.696897e+05 b k a  
## 807 3.696897e+05 e k a  
## 1998 3.713661e+05 l k i  
## 1134 3.731835e+05 g j c  
## 1602 3.731835e+05 j g c  
## 1143 3.748124e+05 g j l  
## 1611 3.748124e+05 j g l  
## 1167 3.750002e+05 g l j  
## 1554 3.750855e+05 j c g  
## 1990 3.787210e+05 l k a  
## 284 3.807579e+05 b i k  
## 791 3.807579e+05 e i k  
## 1050 3.837341e+05 g c j  
## 1770 3.843232e+05 k g b  
## 1773 3.843232e+05 k g e  
## 1052 3.857715e+05 g c l  
## 426 3.859066e+05 c g j  
## 462 3.864498e+05 c j g  
## 1168 3.869112e+05 g l k  
## 1160 3.869609e+05 g l c  
## 428 3.881681e+05 c g l  
## 1710 3.907838e+05 k b g  
## 1749 3.907838e+05 k e g  
## 1142 3.975856e+05 g j k  
## 1037 3.983219e+05 g b j  
## 1076 3.983219e+05 g e j  
## 1671 3.983754e+05 j l g  
## 1947 3.991706e+05 l g j  
## 1038 3.994174e+05 g b k  
## 1077 3.994174e+05 g e k  
## 1030 4.018388e+05 g b c  
## 1069 4.018388e+05 g e c  
## 1133 4.027027e+05 g j b  
## 1136 4.027027e+05 g j e  
## 1601 4.027027e+05 j g b  
## 1604 4.027027e+05 j g e  
## 1154 4.030719e+05 g k j  
## 1983 4.043723e+05 l j g  
## 1156 4.048501e+05 g k l  
## 1042 4.118869e+05 g c b  
## 1045 4.118869e+05 g c e  
## 1940 4.132433e+05 l g c  
## 1610 4.134116e+05 j g k  
## 418 4.139677e+05 c g b  
## 421 4.139677e+05 c g e  
## 1051 4.157297e+05 g c k  
## 1892 4.175575e+05 l c g  
## 1147 4.178766e+05 g k c  
## 1712 4.184390e+05 k b i  
## 1751 4.184390e+05 k e i  
## 427 4.186149e+05 c g k  
## 488 4.189006e+05 c l g  
## 138 4.206050e+05 a k h  
## 1146 4.379706e+05 g k b  
## 1149 4.379706e+05 g k e  
## 1039 4.388453e+05 g b l  
## 1078 4.388453e+05 g e l  
## 1948 4.436297e+05 l g k  
## 1698 4.474026e+05 k a h  
## 1040 4.524472e+05 g b m  
## 1079 4.524472e+05 g e m  
## 306 4.566677e+05 b k g  
## 813 4.566677e+05 e k g  
## 308 4.600214e+05 b k i  
## 815 4.600214e+05 e k i  
## 1172 4.715011e+05 g m b  
## 1175 4.715011e+05 g m e  
## 1144 4.730027e+05 g j m  
## 1180 4.730027e+05 g m j  
## 1612 4.730027e+05 j g m  
## 1182 4.735968e+05 g m l  
## 1159 4.755820e+05 g l b  
## 1162 4.755820e+05 g l e  
## 1181 4.783537e+05 g m k  
## 1173 4.823102e+05 g m c  
## 1314 4.868635e+05 h k a  
## 1782 4.871681e+05 k h a  
## 1053 4.892549e+05 g c m  
## 429 4.914259e+05 c g m  
## 1939 4.972299e+05 l g b  
## 1942 4.972299e+05 l g e  
## 257 5.044448e+05 b g j  
## 764 5.044448e+05 e g j  
## 1781 5.066095e+05 k g m  
## 1170 5.072004e+05 g l m  
## 258 5.079838e+05 b g k  
## 765 5.079838e+05 e g k  
## 250 5.137524e+05 b g c  
## 757 5.137524e+05 e g c  
## 1541 5.137908e+05 j b g  
## 1580 5.137908e+05 j e g  
## 293 5.153414e+05 b j g  
## 800 5.153414e+05 e j g  
## 1853 5.153634e+05 k m g  
## 102 5.292084e+05 a h k  
## 358 5.316817e+05 c b g  
## 397 5.316817e+05 c e g  
## 1950 5.328789e+05 l g m  
## 259 5.340024e+05 b g l  
## 766 5.340024e+05 e g l  
## 202 5.362350e+05 b c g  
## 709 5.362350e+05 e c g  
## 2108 5.366275e+05 m g b  
## 2111 5.366275e+05 m g e  
## 2118 5.372861e+05 m g l  
## 1684 5.402228e+05 j m g  
## 2116 5.402228e+05 m g j  
## 2152 5.402228e+05 m j g  
## 2117 5.413446e+05 m g k  
## 260 5.478397e+05 b g m  
## 767 5.478397e+05 e g m  
## 2109 5.542704e+05 m g c  
## 1157 5.589522e+05 g k m  
## 2061 5.611528e+05 m c g  
## 1194 5.635218e+05 h a k  
## 501 5.668652e+05 c m g  
## 2178 5.718350e+05 m l g  
## 2165 5.724726e+05 m k g  
## 2048 5.880367e+05 m b g  
## 2087 5.880367e+05 m e g  
## 319 5.887354e+05 b l g  
## 826 5.887354e+05 e l g  
## 332 5.991619e+05 b m g  
## 839 5.991619e+05 e m g  
## 1731 6.312594e+05 k d b  
## 1734 6.312594e+05 k d e  
## 2022 6.322080e+05 l m g  
## 1879 6.364284e+05 l b g  
## 1918 6.364284e+05 l e g  
## 1741 6.474121e+05 k d l  
## 1707 6.479651e+05 k b d  
## 1746 6.479651e+05 k e d  
## 639 6.558216e+05 d k b  
## 642 6.558216e+05 d k e  
## 1739 6.597611e+05 k d j  
## 531 6.698303e+05 d b k  
## 570 6.698303e+05 d e k  
## 1174 6.725330e+05 g m d  
## 532 6.761342e+05 d b l  
## 571 6.761342e+05 d e l  
## 649 6.780975e+05 d k l  
## 1837 6.790784e+05 k l d  
## 647 6.826550e+05 d k j  
## 1850 6.827650e+05 k m d  
## 1742 6.839570e+05 k d m  
## 598 6.878933e+05 d g m  
## 1066 6.890368e+05 g d m  
## 1736 6.912917e+05 k d g  
## 1993 6.924803e+05 l k d  
## 652 6.949937e+05 d l b  
## 655 6.949937e+05 d l e  
## 596 6.952115e+05 d g k  
## 626 6.954607e+05 d j b  
## 629 6.954607e+05 d j e  
## 587 6.966909e+05 d g b  
## 590 6.966909e+05 d g e  
## 1064 6.967104e+05 g d k  
## 1055 6.977695e+05 g d b  
## 1058 6.977695e+05 g d e  
## 530 7.004766e+05 d b j  
## 569 7.004766e+05 d e j  
## 661 7.035374e+05 d l k  
## 2078 7.042061e+05 m d k  
## 2079 7.052613e+05 m d l  
## 650 7.063755e+05 d k m  
## 1772 7.075231e+05 k g d  
## 674 7.075520e+05 d m k  
## 675 7.083441e+05 d m l  
## 595 7.110597e+05 d g j  
## 631 7.115083e+05 d j g  
## 2069 7.120025e+05 m d b  
## 2072 7.120025e+05 m d e  
## 1063 7.120757e+05 g d j  
## 2175 7.127236e+05 m l d  
## 303 7.142187e+05 b k d  
## 810 7.142187e+05 e k d  
## 597 7.143941e+05 d g l  
## 635 7.146819e+05 d j k  
## 2077 7.148017e+05 m d j  
## 644 7.154777e+05 d k g  
## 665 7.155715e+05 d m b  
## 668 7.155715e+05 d m e  
## 1065 7.160735e+05 g d l  
## 1909 7.168162e+05 l d k  
## 673 7.170858e+05 d m j  
## 533 7.193462e+05 d b m  
## 572 7.193462e+05 d e m  
## 660 7.202750e+05 d l j  
## 636 7.219503e+05 d j l  
## 219 7.233075e+05 b d k  
## 726 7.233075e+05 e d k  
## 2162 7.254484e+05 m k d  
## 1031 7.278567e+05 g b d  
## 1070 7.278567e+05 g e d  
## 2074 7.300275e+05 m d g  
## 670 7.347708e+05 d m g  
## 220 7.386339e+05 b d l  
## 727 7.386339e+05 e d l  
## 657 7.404025e+05 d l g  
## 637 7.420138e+05 d j m  
## 1908 7.420891e+05 l d j  
## 2110 7.425554e+05 m g d  
## 1905 7.483712e+05 l d g  
## 1900 7.489649e+05 l d b  
## 1903 7.489649e+05 l d e  
## 663 7.501720e+05 d l m  
## 1941 7.514080e+05 l g d  
## 218 7.514331e+05 b d j  
## 725 7.514331e+05 e d j  
## 2045 7.555278e+05 m b d  
## 2084 7.555278e+05 m e d  
## 1148 7.609566e+05 g k d  
## 2019 7.624065e+05 l m d  
## 1161 7.628818e+05 g l d  
## 329 7.651636e+05 b m d  
## 836 7.651636e+05 e m d  
## 1911 7.670794e+05 l d m  
## 221 7.698777e+05 b d m  
## 728 7.698777e+05 e d m  
## 1655 7.698985e+05 j k d  
## 1811 7.731777e+05 k j d  
## 2070 7.854862e+05 m d c  
## 527 7.857243e+05 d b g  
## 566 7.857243e+05 d e g  
## 1732 7.861369e+05 k d c  
## 666 7.870294e+05 d m c  
## 316 7.941254e+05 b l d  
## 823 7.941254e+05 e l d  
## 1876 7.951440e+05 l b d  
## 1915 7.951440e+05 l e d  
## 627 8.005982e+05 d j c  
## 546 8.041226e+05 d c m  
## 1567 8.064146e+05 j d g  
## 543 8.070904e+05 d c j  
## 640 8.080928e+05 d k c  
## 1681 8.085405e+05 j m d  
## 2149 8.085405e+05 m j d  
## 1603 8.116582e+05 j g d  
## 1135 8.116582e+05 g j d  
## 1573 8.196950e+05 j d m  
## 540 8.211490e+05 d c g  
## 588 8.213546e+05 d g c  
## 1562 8.217374e+05 j d b  
## 1565 8.217374e+05 j d e  
## 1056 8.221657e+05 g d c  
## 535 8.261045e+05 d c b  
## 538 8.261045e+05 d c e  
## 1571 8.265205e+05 j d k  
## 544 8.282673e+05 d c k  
## 523 8.291937e+05 d b c  
## 562 8.291937e+05 d e c  
## 215 8.371737e+05 b d g  
## 722 8.371737e+05 e d g  
## 251 8.434001e+05 b g d  
## 758 8.434001e+05 e g d  
## 545 8.463458e+05 d c l  
## 1572 8.614242e+05 j d l  
## 653 8.619700e+05 d l c  
## 2075 8.631119e+05 m d h  
## 671 8.638509e+05 d m h  
## 2123 8.657999e+05 m h d  
## 1901 8.746322e+05 l d c  
## 211 8.802388e+05 b d c  
## 718 8.802388e+05 e d c  
## 1668 8.881292e+05 j l d  
## 1980 8.891441e+05 l j d  
## 290 9.013236e+05 b j d  
## 797 9.013236e+05 e j d  
## 1538 9.029783e+05 j b d  
## 1577 9.029783e+05 j e d  
## 1563 9.042689e+05 j d c  
## 632 9.241839e+05 d j h  
## 610 9.372538e+05 d h l  
## 608 9.372905e+05 d h j  
## 1232 9.521358e+05 h d j  
## 1234 9.541845e+05 h d l  
## 2058 9.577714e+05 m c d  
## 600 9.705611e+05 d h b  
## 603 9.705611e+05 d h e  
## 498 9.713513e+05 c m d  
## 1330 9.733233e+05 h l d  
## 611 9.780787e+05 d h m  
## 1224 9.864208e+05 h d b  
## 1227 9.864208e+05 h d e  
## 541 9.907246e+05 d c h  
## 601 9.929991e+05 d h c  
## 1200 9.950591e+05 h b d  
## 1239 9.950591e+05 h e d  
## 1235 1.003519e+06 h d m  
## 1225 1.008234e+06 h d c  
## 472 1.016889e+06 c k d  
## 1343 1.022226e+06 h m d  
## 1720 1.024041e+06 k c d  
## 390 1.025100e+06 c d m  
## 387 1.025383e+06 c d j  
## 384 1.026474e+06 c d g  
## 1044 1.031386e+06 g c d  
## 1568 1.032580e+06 j d h  
## 420 1.033280e+06 c g d  
## 1616 1.046259e+06 j h d  
## 1304 1.054699e+06 h j d  
## 658 1.059142e+06 d l h  
## 1906 1.073390e+06 l d h  
## 1954 1.087732e+06 l h d  
## 379 1.094468e+06 c d b  
## 382 1.094468e+06 c d e  
## 388 1.102241e+06 c d k  
## 605 1.110047e+06 d h g  
## 609 1.111442e+06 d h k  
## 528 1.121046e+06 d b h  
## 567 1.121046e+06 d e h  
## 1317 1.125681e+06 h k d  
## 1203 1.128687e+06 h b g  
## 1242 1.128687e+06 h e g  
## 1233 1.129684e+06 h d k  
## 1229 1.131203e+06 h d g  
## 389 1.133354e+06 c d l  
## 593 1.148361e+06 d g h  
## 1061 1.148864e+06 g d h  
## 1551 1.152559e+06 j c d  
## 1265 1.161853e+06 h g d  
## 1274 1.162369e+06 h g m  
## 459 1.164300e+06 c j d  
## 1263 1.165445e+06 h g b  
## 1266 1.165445e+06 h g e  
## 2126 1.165724e+06 m h g  
## 216 1.177677e+06 b d h  
## 723 1.177677e+06 e d h  
## 355 1.180201e+06 c b d  
## 394 1.180201e+06 c e d  
## 485 1.182063e+06 c l d  
## 1889 1.183284e+06 l c d  
## 199 1.186064e+06 b c d  
## 706 1.186064e+06 e c d  
## 264 1.188717e+06 b h d  
## 771 1.188717e+06 e h d  
## 385 1.198802e+06 c d h  
## 433 1.200737e+06 c h d  
## 1273 1.206768e+06 h g l  
## 1271 1.208661e+06 h g j  
## 1264 1.223261e+06 h g c  
## 1178 1.225664e+06 g m h  
## 1109 1.226686e+06 g h d  
## 1307 1.227322e+06 h j g  
## 1619 1.234902e+06 j h g  
## 1213 1.235460e+06 h c d  
## 1118 1.237002e+06 g h m  
## 1107 1.242787e+06 g h b  
## 1110 1.242787e+06 g h e  
## 436 1.250872e+06 c h g  
## 1117 1.268290e+06 g h l  
## 1785 1.273901e+06 k h d  
## 1035 1.277691e+06 g b h  
## 1074 1.277691e+06 g e h  
## 1737 1.279087e+06 k d h  
## 1216 1.297909e+06 h c g  
## 1346 1.300944e+06 h m g  
## 1115 1.301071e+06 g h j  
## 645 1.302530e+06 d k h  
## 1108 1.319439e+06 g h c  
## 2114 1.330232e+06 m g h  
## 1607 1.333971e+06 j g h  
## 1139 1.333971e+06 g j h  
## 1333 1.341427e+06 h l g  
## 1048 1.349653e+06 g c h  
## 424 1.353390e+06 c g h  
## 267 1.360854e+06 b h g  
## 774 1.360854e+06 e h g  
## 1272 1.361543e+06 h g k  
## 1320 1.375414e+06 h k g  
## 1116 1.415765e+06 g h k  
## 255 1.434436e+06 b g h  
## 762 1.434436e+06 e g h  
## 1957 1.452408e+06 l h g  
## 625 1.571697e+06 d j a  
## 1788 1.578019e+06 k h g  
## 534 1.589218e+06 d c a  
## 510 1.592893e+06 d a c  
## 520 1.603460e+06 d a m  
## 1945 1.606123e+06 l g h  
## 509 1.608557e+06 d a b  
## 512 1.608557e+06 d a e  
## 1165 1.615354e+06 g l h  
## 519 1.632557e+06 d a l  
## 517 1.638525e+06 d a j  
## 1270 1.643992e+06 h g i  
## 42 1.644337e+06 a d c  
## 52 1.659855e+06 a d m  
## 160 1.660155e+06 a m d  
## 17 1.661080e+06 a b d  
## 56 1.661080e+06 a e d  
## 41 1.661505e+06 a d b  
## 44 1.661505e+06 a d e  
## 607 1.661517e+06 d h i  
## 516 1.671570e+06 d a i  
## 1291 1.688866e+06 h i d  
## 1231 1.689224e+06 h d i  
## 1114 1.693000e+06 g h i  
## 51 1.695038e+06 a d l  
## 49 1.697539e+06 a d j  
## 664 1.702255e+06 d m a  
## 2068 1.706098e+06 m d a  
## 1561 1.711065e+06 j d a  
## 48 1.718820e+06 a d i  
## 2032 1.719770e+06 m a d  
## 147 1.723685e+06 a l d  
## 108 1.724131e+06 a i d  
## 542 1.755496e+06 d c i  
## 1294 1.758451e+06 h i g  
## 651 1.787522e+06 d l a  
## 1525 1.789684e+06 j a d  
## 1899 1.807843e+06 l d a  
## 622 1.809072e+06 d i k  
## 633 1.810968e+06 d j i  
## 623 1.811459e+06 d i l  
## 1776 1.811631e+06 k g h  
## 612 1.812053e+06 d i a  
## 614 1.816823e+06 d i c  
## 378 1.839132e+06 c d a  
## 1392 1.842233e+06 i d a  
## 121 1.845067e+06 a j d  
## 619 1.847338e+06 d i h  
## 613 1.851876e+06 d i b  
## 616 1.851876e+06 d i e  
## 1152 1.854417e+06 g k h  
## 1403 1.856512e+06 i d l  
## 1402 1.857159e+06 i d k  
## 1394 1.857819e+06 i d c  
## 1486 1.861347e+06 i k d  
## 621 1.862088e+06 d i j  
## 1356 1.865736e+06 i a d  
## 1863 1.867120e+06 l a d  
## 342 1.871628e+06 c a d  
## 30 1.879766e+06 a c d  
## 1062 1.887623e+06 g d i  
## 594 1.887842e+06 d g i  
## 1393 1.902326e+06 i d b  
## 1396 1.902326e+06 i d e  
## 1369 1.906260e+06 i b d  
## 1408 1.906260e+06 i e d  
## 618 1.907057e+06 d i g  
## 1399 1.907069e+06 i d h  
## 1499 1.907091e+06 i l d  
## 1401 1.907652e+06 i d j  
## 521 1.908956e+06 d b a  
## 560 1.908956e+06 d e a  
## 624 1.912867e+06 d i m  
## 1447 1.929323e+06 i h d  
## 1130 1.940047e+06 g i l  
## 1512 1.940321e+06 i m d  
## 1122 1.940565e+06 g i d  
## 1442 1.943402e+06 i g l  
## 1434 1.949742e+06 i g d  
## 1404 1.954619e+06 i d m  
## 1398 1.959267e+06 i d g  
## 1569 1.961009e+06 j d i  
## 1441 1.962899e+06 i g k  
## 1502 1.965843e+06 i l g  
## 1129 1.966524e+06 g i k  
## 518 1.969137e+06 d a k  
## 209 1.980899e+06 b d a  
## 716 1.980899e+06 e d a  
## 529 1.990954e+06 d b i  
## 568 1.990954e+06 d e i  
## 1131 1.991052e+06 g i m  
## 134 1.994910e+06 a k d  
## 1443 2.000050e+06 i g m  
## 1120 2.004973e+06 g i b  
## 1123 2.004973e+06 g i e  
## 1432 2.014852e+06 i g b  
## 1435 2.014852e+06 i g e  
## 1438 2.016605e+06 i g h  
## 386 2.017337e+06 c d i  
## 173 2.018559e+06 b a d  
## 680 2.018559e+06 e a d  
## 1629 2.023244e+06 j i d  
## 1126 2.024918e+06 g i h  
## 50 2.026848e+06 a d k  
## 1473 2.060863e+06 i j d  
## 1798 2.060940e+06 k i d  
## 1738 2.062904e+06 k d i  
## 217 2.064358e+06 b d i  
## 724 2.064358e+06 e d i  
## 1382 2.073044e+06 i c d  
## 1450 2.080065e+06 i h g  
## 1440 2.087463e+06 i g j  
## 646 2.087532e+06 d k i  
## 659 2.089584e+06 d l i  
## 446 2.093277e+06 c i d  
## 1476 2.094623e+06 i j g  
## 1128 2.100344e+06 g i j  
## 1907 2.117237e+06 l d i  
## 1372 2.120825e+06 i b g  
## 1411 2.120825e+06 i e g  
## 1515 2.125585e+06 i m g  
## 1632 2.133548e+06 j i g  
## 1489 2.135558e+06 i k g  
## 1433 2.135608e+06 i g c  
## 1385 2.145369e+06 i c g  
## 2136 2.147556e+06 m i d  
## 1608 2.150207e+06 j g i  
## 1140 2.150207e+06 g j i  
## 1121 2.151272e+06 g i c  
## 672 2.156115e+06 d m i  
## 449 2.157568e+06 c i g  
## 2076 2.162336e+06 m d i  
## 277 2.166751e+06 b i d  
## 784 2.166751e+06 e i d  
## 1049 2.168729e+06 g c i  
## 425 2.173670e+06 c g i  
## 1967 2.221950e+06 l i d  
## 1777 2.247598e+06 k g i  
## 1179 2.273296e+06 g m i  
## 1153 2.280925e+06 g k i  
## 1970 2.303257e+06 l i g  
## 1166 2.331995e+06 g l i  
## 280 2.358827e+06 b i g  
## 787 2.358827e+06 e i g  
## 2139 2.380563e+06 m i g  
## 1801 2.397958e+06 k i g  
## 1036 2.398455e+06 g b i  
## 1075 2.398455e+06 g e i  
## 1946 2.406319e+06 l g i  
## 2115 2.432180e+06 m g i  
## 1694 2.434171e+06 k a d  
## 1730 2.436149e+06 k d a  
## 638 2.460664e+06 d k a  
## 256 2.622969e+06 b g i  
## 763 2.622969e+06 e g i  
## 111 2.930456e+06 a i g  
## 1119 3.002009e+06 g i a  
## 514 3.010995e+06 d a g  
## 20 3.030860e+06 a b g  
## 59 3.030860e+06 a e g  
## 1431 3.044370e+06 i g a  
## 90 3.064372e+06 a g l  
## 46 3.089591e+06 a d g  
## 1359 3.100029e+06 i a g  
## 81 3.107255e+06 a g c  
## 88 3.115981e+06 a g j  
## 80 3.153311e+06 a g b  
## 83 3.153311e+06 a g e  
## 87 3.164230e+06 a g i  
## 89 3.200867e+06 a g k  
## 82 3.259757e+06 a g d  
## 91 3.286465e+06 a g m  
## 137 3.291082e+06 a k g  
## 124 3.311178e+06 a j g  
## 150 3.312569e+06 a l g  
## 1528 3.349365e+06 j a g  
## 345 3.381427e+06 c a g  
## 33 3.410974e+06 a c g  
## 176 3.449861e+06 b a g  
## 683 3.449861e+06 e a g  
## 95 3.451781e+06 a h d  
## 1866 3.460658e+06 l a g  
## 1054 3.461646e+06 g d a  
## 586 3.463826e+06 d g a  
## 515 3.469123e+06 d a h  
## 47 3.520568e+06 a d h  
## 1026 3.543286e+06 g a l  
## 1025 3.565091e+06 g a k  
## 1017 3.614949e+06 g a c  
## 1024 3.628917e+06 g a j  
## 1027 3.643046e+06 g a m  
## 1016 3.687407e+06 g a b  
## 1019 3.687407e+06 g a e  
## 1023 3.704226e+06 g a i  
## 599 3.771029e+06 d h a  
## 163 3.771218e+06 a m g  
## 1187 3.784933e+06 h a d  
## 1028 3.800106e+06 g b a  
## 1067 3.800106e+06 g e a  
## 1697 3.832656e+06 k a g  
## 1223 3.838451e+06 h d a  
## 1018 3.862169e+06 g a d  
## 2035 3.917577e+06 m a g  
## 1600 3.969773e+06 j g a  
## 1132 3.969773e+06 g j a  
## 1041 4.004078e+06 g c a  
## 1158 4.005458e+06 g l a  
## 417 4.011290e+06 c g a  
## 248 4.094320e+06 b g a  
## 755 4.094320e+06 e g a  
## 1938 4.119536e+06 l g a  
## 98 4.292359e+06 a h g  
## 86 4.306696e+06 a g h  
## 1171 4.516348e+06 g m a  
## 1190 4.607203e+06 h a g  
## 1022 4.643204e+06 g a h  
## 1145 4.733741e+06 g k a  
## 2107 4.773031e+06 m g a  
## 1769 4.776402e+06 k g a  
## 1106 5.316724e+06 g h a  
## 1262 5.333669e+06 h g a  
## 1774 4.467451e+07 k g f  
## 1605 4.607057e+07 j g f  
## 1089 4.607057e+07 g f j  
## 1137 4.607057e+07 g j f  
## 1090 4.626412e+07 g f k  
## 1082 4.730998e+07 g f c  
## 422 4.736518e+07 c g f  
## 1091 4.744706e+07 g f l  
## 1709 4.746670e+07 k b f  
## 1748 4.746670e+07 k e f  
## 1046 4.785660e+07 g c f  
## 1081 4.795577e+07 g f b  
## 1084 4.795577e+07 g f e  
## 1657 4.860692e+07 j k f  
## 1765 4.863746e+07 k f j  
## 1033 4.864333e+07 g b f  
## 1072 4.864333e+07 g e f  
## 1757 4.874713e+07 k f b  
## 1760 4.874713e+07 k f e  
## 1767 4.895740e+07 k f l  
## 985 4.943296e+07 f k j  
## 977 4.949120e+07 f k b  
## 980 4.949120e+07 f k e  
## 973 4.955393e+07 f j k  
## 1758 4.965726e+07 k f c  
## 1943 4.974692e+07 l g f  
## 965 4.975935e+07 f j c  
## 1589 4.975935e+07 j f c  
## 1553 4.979391e+07 j c f  
## 1813 4.989825e+07 k j f  
## 987 4.991966e+07 f k l  
## 1597 5.006371e+07 j f k  
## 474 5.028284e+07 c k f  
## 1762 5.048613e+07 k f g  
## 868 5.066473e+07 f b j  
## 907 5.066473e+07 f e j  
## 978 5.074355e+07 f k c  
## 1722 5.085298e+07 k c f  
## 870 5.099492e+07 f b l  
## 909 5.099492e+07 f e l  
## 882 5.113715e+07 f c k  
## 881 5.114586e+07 f c j  
## 414 5.117613e+07 c f k  
## 413 5.118474e+07 c f j  
## 461 5.119471e+07 c j f  
## 1588 5.128888e+07 j f b  
## 1591 5.128888e+07 j f e  
## 964 5.128888e+07 f j b  
## 967 5.128888e+07 f j e  
## 861 5.146246e+07 f b c  
## 900 5.146246e+07 f e c  
## 1163 5.152744e+07 g l f  
## 982 5.168270e+07 f k g  
## 998 5.169970e+07 f l j  
## 974 5.175996e+07 f j l  
## 1598 5.175996e+07 j f l  
## 1839 5.180916e+07 k l f  
## 999 5.200113e+07 f l k  
## 1995 5.214289e+07 l k f  
## 873 5.245917e+07 f c b  
## 876 5.245917e+07 f c e  
## 405 5.249599e+07 c f b  
## 408 5.249599e+07 c f e  
## 871 5.250309e+07 f b m  
## 910 5.250309e+07 f e m  
## 865 5.253759e+07 f b g  
## 904 5.253759e+07 f e g  
## 1150 5.260952e+07 g k f  
## 869 5.336382e+07 f b k  
## 908 5.336382e+07 f e k  
## 883 5.366965e+07 f c l  
## 415 5.371658e+07 c f l  
## 934 5.371692e+07 f g k  
## 991 5.371936e+07 f l c  
## 933 5.391200e+07 f g j  
## 969 5.391200e+07 f j g  
## 1593 5.391200e+07 j f g  
## 1935 5.417047e+07 l f k  
## 1670 5.418022e+07 j l f  
## 1934 5.431002e+07 l f j  
## 1008 5.460956e+07 f m g  
## 1011 5.476643e+07 f m j  
## 975 5.476643e+07 f j m  
## 1599 5.476643e+07 j f m  
## 1092 5.480295e+07 g f m  
## 925 5.483594e+07 f g b  
## 928 5.483594e+07 f g e  
## 1013 5.497313e+07 f m l  
## 1003 5.498084e+07 f m b  
## 1006 5.498084e+07 f m e  
## 305 5.505099e+07 b k f  
## 812 5.505099e+07 e k f  
## 1982 5.533663e+07 l j f  
## 1012 5.535265e+07 f m k  
## 1004 5.590079e+07 f m c  
## 990 5.591287e+07 f l b  
## 993 5.591287e+07 f l e  
## 995 5.604780e+07 f l g  
## 926 5.655217e+07 f g c  
## 1927 5.664349e+07 l f c  
## 410 5.670242e+07 c f g  
## 884 5.675958e+07 f c m  
## 935 5.678536e+07 f g l  
## 416 5.679584e+07 c f m  
## 1768 5.687693e+07 k f m  
## 1891 5.715799e+07 l c f  
## 988 5.716590e+07 f k m  
## 487 5.729404e+07 c l f  
## 1926 5.747867e+07 l f b  
## 1929 5.747867e+07 l f e  
## 878 5.771649e+07 f c g  
## 1176 5.880488e+07 g m f  
## 1931 5.923859e+07 l f g  
## 1852 6.020305e+07 k m f  
## 253 6.021314e+07 b g f  
## 760 6.021314e+07 e g f  
## 1001 6.118526e+07 f l m  
## 936 6.125848e+07 f g m  
## 246 6.210029e+07 b f l  
## 753 6.210029e+07 e f l  
## 1937 6.220954e+07 l f m  
## 244 6.268713e+07 b f j  
## 751 6.268713e+07 e f j  
## 318 6.322354e+07 b l f  
## 825 6.322354e+07 e l f  
## 247 6.324182e+07 b f m  
## 754 6.324182e+07 e f m  
## 1540 6.390510e+07 j b f  
## 1579 6.390510e+07 j e f  
## 292 6.407749e+07 b j f  
## 799 6.407749e+07 e j f  
## 237 6.438074e+07 b f c  
## 744 6.438074e+07 e f c  
## 2105 6.466720e+07 m f l  
## 2100 6.476243e+07 m f g  
## 2104 6.488365e+07 m f k  
## 2103 6.504678e+07 m f j  
## 2151 6.504678e+07 m j f  
## 1683 6.504678e+07 j m f  
## 2095 6.533426e+07 m f b  
## 2098 6.533426e+07 m f e  
## 357 6.580596e+07 c b f  
## 396 6.580596e+07 c e f  
## 2112 6.625387e+07 m g f  
## 241 6.628527e+07 b f g  
## 748 6.628527e+07 e f g  
## 201 6.629571e+07 b c f  
## 708 6.629571e+07 e c f  
## 2164 6.639040e+07 m k f  
## 2096 6.701335e+07 m f c  
## 2060 6.798006e+07 m c f  
## 245 6.800253e+07 b f k  
## 752 6.800253e+07 e f k  
## 500 6.859173e+07 c m f  
## 2047 6.912827e+07 m b f  
## 2086 6.912827e+07 m e f  
## 1878 7.019465e+07 l b f  
## 1917 7.019465e+07 l e f  
## 331 7.061488e+07 b m f  
## 838 7.061488e+07 e m f  
## 2177 7.187319e+07 m l f  
## 1005 7.847861e+07 f m d  
## 2021 8.039120e+07 l m f  
## 897 8.046209e+07 f d m  
## 895 8.047374e+07 f d k  
## 886 8.095848e+07 f d b  
## 889 8.095848e+07 f d e  
## 585 8.112344e+07 d f m  
## 583 8.113416e+07 d f k  
## 1083 8.135564e+07 g f d  
## 574 8.160703e+07 d f b  
## 577 8.160703e+07 d f e  
## 896 8.228262e+07 f d l  
## 584 8.300535e+07 d f l  
## 894 8.344717e+07 f d j  
## 862 8.388813e+07 f b d  
## 901 8.388813e+07 f e d  
## 582 8.408728e+07 d f j  
## 1735 8.408872e+07 k d f  
## 979 8.471431e+07 f k d  
## 1759 8.511056e+07 k f d  
## 591 8.515985e+07 d g f  
## 891 8.551916e+07 f d g  
## 1059 8.561765e+07 g d f  
## 579 8.630197e+07 d f g  
## 992 8.651773e+07 f l d  
## 630 8.715256e+07 d j f  
## 643 8.723485e+07 d k f  
## 2073 8.745185e+07 m d f  
## 927 8.792341e+07 f g d  
## 669 8.839934e+07 d m f  
## 2097 8.880463e+07 m f d  
## 656 8.908938e+07 d l f  
## 1928 8.955956e+07 l f d  
## 1904 8.979846e+07 l d f  
## 526 9.049199e+07 d b f  
## 565 9.049199e+07 d e f  
## 966 9.373605e+07 f j d  
## 1590 9.373605e+07 j f d  
## 1566 9.483513e+07 j d f  
## 887 9.542826e+07 f d c  
## 214 9.590374e+07 b d f  
## 721 9.590374e+07 e d f  
## 238 9.605016e+07 b f d  
## 745 9.605016e+07 e f d  
## 575 9.609880e+07 d f c  
## 539 9.677986e+07 d c f  
## 875 1.171753e+08 f c d  
## 407 1.172270e+08 c f d  
## 383 1.198084e+08 c d f  
## 617 2.304342e+08 d i f  
## 1430 2.346688e+08 i f m  
## 1397 2.348097e+08 i d f  
## 1488 2.349311e+08 i k f  
## 1421 2.349703e+08 i f d  
## 1424 2.379905e+08 i f g  
## 1514 2.433123e+08 i m f  
## 893 2.477179e+08 f d i  
## 1427 2.482982e+08 i f j  
## 1429 2.487538e+08 i f l  
## 581 2.490009e+08 d f i  
## 1475 2.504451e+08 i j f  
## 962 2.512765e+08 f i m  
## 953 2.522847e+08 f i d  
## 1420 2.532823e+08 i f c  
## 1428 2.534931e+08 i f k  
## 956 2.535367e+08 f i g  
## 1436 2.540162e+08 i g f  
## 1631 2.541782e+08 j i f  
## 1384 2.542667e+08 i c f  
## 448 2.562278e+08 c i f  
## 1124 2.574316e+08 g i f  
## 1800 2.586572e+08 k i f  
## 961 2.630248e+08 f i l  
## 1501 2.654521e+08 i l f  
## 2138 2.689290e+08 m i f  
## 959 2.720471e+08 f i j  
## 984 2.729025e+08 f k i  
## 952 2.784523e+08 f i c  
## 1764 2.786294e+08 k f i  
## 960 2.787218e+08 f i k  
## 971 2.796509e+08 f j i  
## 1595 2.796509e+08 j f i  
## 1010 2.810760e+08 f m i  
## 880 2.821272e+08 f c i  
## 412 2.822085e+08 c f i  
## 1419 2.829427e+08 i f b  
## 1422 2.829427e+08 i f e  
## 951 2.957664e+08 f i b  
## 954 2.957664e+08 f i e  
## 1267 2.969239e+08 h g f  
## 1969 2.991499e+08 l i f  
## 2102 3.041636e+08 m f i  
## 604 3.069066e+08 d h f  
## 1251 3.097106e+08 h f c  
## 1228 3.097440e+08 h d f  
## 1259 3.101951e+08 h f k  
## 1261 3.127241e+08 h f m  
## 1250 3.129067e+08 h f b  
## 1253 3.129067e+08 h f e  
## 1371 3.156732e+08 i b f  
## 1410 3.156732e+08 i e f  
## 1088 3.161310e+08 g f i  
## 1255 3.170687e+08 h f g  
## 1111 3.178767e+08 g h f  
## 1319 3.210528e+08 h k f  
## 932 3.212969e+08 f g i  
## 1258 3.222811e+08 h f j  
## 1252 3.246554e+08 h f d  
## 892 3.282608e+08 f d h  
## 580 3.298411e+08 d f h  
## 947 3.315178e+08 f h k  
## 939 3.329162e+08 f h c  
## 938 3.334796e+08 f h b  
## 941 3.334796e+08 f h e  
## 949 3.374712e+08 f h m  
## 2125 3.393770e+08 m h f  
## 997 3.403710e+08 f l i  
## 279 3.409620e+08 b i f  
## 786 3.409620e+08 e i f  
## 943 3.432903e+08 f h g  
## 1306 3.434354e+08 h j f  
## 1618 3.443149e+08 j h f  
## 1933 3.462399e+08 l f i  
## 946 3.499802e+08 f h j  
## 1202 3.507051e+08 h b f  
## 1241 3.507051e+08 h e f  
## 940 3.529773e+08 f h d  
## 1260 3.539712e+08 h f l  
## 1345 3.543480e+08 h m f  
## 1787 3.560116e+08 k h f  
## 435 3.611222e+08 c h f  
## 1009 3.613840e+08 f m h  
## 1215 3.690673e+08 h c f  
## 948 3.723631e+08 f h l  
## 1257 3.738982e+08 h f i  
## 867 3.745713e+08 f b i  
## 906 3.745713e+08 f e i  
## 1594 3.768594e+08 j f h  
## 970 3.768594e+08 f j h  
## 1087 3.847138e+08 g f h  
## 1425 3.863599e+08 i f h  
## 2101 3.884528e+08 m f h  
## 931 3.886866e+08 f g h  
## 1293 3.904861e+08 h i f  
## 266 3.909598e+08 b h f  
## 773 3.909598e+08 e h f  
## 945 3.920445e+08 f h i  
## 879 3.948450e+08 f c h  
## 411 3.949439e+08 c f h  
## 957 3.974619e+08 f i h  
## 983 3.998764e+08 f k h  
## 243 4.017865e+08 b f i  
## 750 4.017865e+08 e f i  
## 866 4.025642e+08 f b h  
## 905 4.025642e+08 f e h  
## 1763 4.097478e+08 k f h  
## 242 4.308781e+08 b f h  
## 749 4.308781e+08 e f h  
## 1449 4.335199e+08 i h f  
## 1332 4.435601e+08 h l f  
## 1956 4.665658e+08 l h f  
## 996 4.982855e+08 f l h  
## 1932 5.091980e+08 l f h  
## 97 5.910992e+08 a h f  
## 1189 6.183020e+08 h a f  
## 84 6.298790e+08 a g f  
## 1249 6.398291e+08 h f a  
## 136 6.469917e+08 a k f  
## 937 6.579873e+08 f h a  
## 72 6.721695e+08 a f g  
## 68 6.724043e+08 a f c  
## 74 6.760602e+08 a f i  
## 75 6.771216e+08 a f j  
## 69 6.943434e+08 a f d  
## 77 6.969305e+08 a f l  
## 19 7.014280e+08 a b f  
## 58 7.014280e+08 a e f  
## 110 7.050471e+08 a i f  
## 162 7.055062e+08 a m f  
## 1020 7.057207e+08 g a f  
## 1418 7.059032e+08 i f a  
## 950 7.117815e+08 f i a  
## 78 7.182959e+08 a f m  
## 513 7.192223e+08 d a f  
## 1696 7.269451e+08 k a f  
## 45 7.292390e+08 a d f  
## 2034 7.389368e+08 m a f  
## 73 7.410151e+08 a f h  
## 852 7.437023e+08 f a g  
## 848 7.441652e+08 f a c  
## 67 7.478175e+08 a f b  
## 70 7.478175e+08 a f e  
## 854 7.505572e+08 f a i  
## 1358 7.511346e+08 i a f  
## 855 7.522671e+08 f a j  
## 76 7.572466e+08 a f k  
## 149 7.625295e+08 a l f  
## 175 7.715367e+08 b a f  
## 682 7.715367e+08 e a f  
## 123 7.755070e+08 a j f  
## 849 7.775199e+08 f a d  
## 1527 7.798937e+08 j a f  
## 857 7.811333e+08 f a l  
## 1865 7.813701e+08 l a f  
## 344 7.941725e+08 c a f  
## 32 8.000188e+08 a c f  
## 885 8.045182e+08 f d a  
## 573 8.076632e+08 d f a  
## 858 8.103216e+08 f a m  
## 1002 8.327889e+08 f m a  
## 853 8.407222e+08 f a h  
## 859 8.412687e+08 f b a  
## 898 8.412687e+08 f e a  
## 847 8.497629e+08 f a b  
## 850 8.497629e+08 f a e  
## 976 8.497796e+08 f k a  
## 856 8.622665e+08 f a k  
## 989 8.750522e+08 f l a  
## 1756 8.753618e+08 k f a  
## 2094 8.807834e+08 m f a  
## 235 8.852657e+08 b f a  
## 742 8.852657e+08 e f a  
## 963 8.859088e+08 f j a  
## 1587 8.859088e+08 j f a  
## 1925 8.913288e+08 l f a  
## 872 9.012316e+08 f c a  
## 404 9.013974e+08 c f a  
## 924 9.085053e+08 f g a  
## 1080 9.169161e+08 g f a  
## 192 3.787285e+15 b b j  
## 231 3.787285e+15 b e j  
## 288 3.787285e+15 b j b  
## 291 3.787285e+15 b j e  
## 699 3.787285e+15 e b j  
## 738 3.787285e+15 e e j  
## 795 3.787285e+15 e j b  
## 798 3.787285e+15 e j e  
## 185 3.795773e+15 b b c  
## 197 3.795773e+15 b c b  
## 200 3.795773e+15 b c e  
## 224 3.795773e+15 b e c  
## 692 3.795773e+15 e b c  
## 704 3.795773e+15 e c b  
## 707 3.795773e+15 e c e  
## 731 3.795773e+15 e e c  
## 194 3.835611e+15 b b l  
## 233 3.835611e+15 b e l  
## 314 3.835611e+15 b l b  
## 317 3.835611e+15 b l e  
## 701 3.835611e+15 e b l  
## 740 3.835611e+15 e e l  
## 821 3.835611e+15 e l b  
## 824 3.835611e+15 e l e  
## 1650 7.291924e+15 j j l  
## 1674 7.291924e+15 j l j  
## 353 7.991943e+15 c b b  
## 356 7.991943e+15 c b e  
## 392 7.991943e+15 c e b  
## 395 7.991943e+15 c e e  
## 1874 8.082686e+15 l b b  
## 1877 8.082686e+15 l b e  
## 1913 8.082686e+15 l e b  
## 1916 8.082686e+15 l e e  
## 1536 1.080731e+16 j b b  
## 1539 1.080731e+16 j b e  
## 1575 1.080731e+16 j e b  
## 1578 1.080731e+16 j e e  
## 479 1.150062e+16 c k k  
## 1988 1.438548e+16 l j l  
## 2012 1.438548e+16 l l j  
## 374 1.448611e+16 c c j  
## 458 1.448611e+16 c j c  
## 376 1.461176e+16 c c l  
## 484 1.461176e+16 c l c  
## 354 1.664613e+16 c b c  
## 366 1.664613e+16 c c b  
## 369 1.664613e+16 c c e  
## 393 1.664613e+16 c e c  
## 2000 2.274743e+16 l k k  
## 191 2.335789e+16 b b i  
## 230 2.335789e+16 b e i  
## 275 2.335789e+16 b i b  
## 278 2.335789e+16 b i e  
## 698 2.335789e+16 e b i  
## 737 2.335789e+16 e e i  
## 782 2.335789e+16 e i b  
## 785 2.335789e+16 e i e  
## 171 2.354346e+16 b a b  
## 174 2.354346e+16 b a e  
## 183 2.354346e+16 b b a  
## 222 2.354346e+16 b e a  
## 678 2.354346e+16 e a b  
## 681 2.354346e+16 e a e  
## 690 2.354346e+16 e b a  
## 729 2.354346e+16 e e a  
## 190 2.450657e+16 b b h  
## 229 2.450657e+16 b e h  
## 262 2.450657e+16 b h b  
## 265 2.450657e+16 b h e  
## 697 2.450657e+16 e b h  
## 736 2.450657e+16 e e h  
## 769 2.450657e+16 e h b  
## 772 2.450657e+16 e h e  
## 1888 2.459047e+16 l c c  
## 198 2.553734e+16 b c c  
## 705 2.553734e+16 e c c  
## 1105 2.939160e+16 g g m  
## 1177 2.939160e+16 g m g  
## 1021 2.939604e+16 g a g  
## 1093 2.939604e+16 g g a  
## 1101 2.941069e+16 g g i  
## 1125 2.941069e+16 g i g  
## 1102 2.941699e+16 g g j  
## 1138 2.941699e+16 g j g  
## 1047 2.949056e+16 g c g  
## 1095 2.949056e+16 g g c  
## 1060 2.952551e+16 g d g  
## 1096 2.952551e+16 g g d  
## 1100 2.962890e+16 g g h  
## 1112 2.962890e+16 g h g  
## 1034 2.964305e+16 g b g  
## 1073 2.964305e+16 g e g  
## 1094 2.964305e+16 g g b  
## 1097 2.964305e+16 g g e  
## 1103 2.984228e+16 g g k  
## 1151 2.984228e+16 g k g  
## 1104 2.988377e+16 g g l  
## 1164 2.988377e+16 g l g  
## 1606 3.217164e+16 j g g  
## 493 3.236037e+16 c l l  
## 1423 3.351467e+16 i f f  
## 141 3.550956e+16 a k k  
## 1714 3.641528e+16 k b k  
## 1753 3.641528e+16 k e k  
## 1822 3.641528e+16 k k b  
## 1825 3.641528e+16 k k e  
## 1818 3.642438e+16 k j k  
## 1830 3.642438e+16 k k j  
## 1833 3.652791e+16 k k m  
## 1857 3.652791e+16 k m k  
## 1727 3.657421e+16 k c k  
## 1823 3.657421e+16 k k c  
## 1805 3.658193e+16 k i k  
## 1829 3.658193e+16 k k i  
## 1832 3.674076e+16 k k l  
## 1844 3.674076e+16 k l k  
## 919 3.685606e+16 f f i  
## 955 3.685606e+16 f i f  
## 923 3.686072e+16 f f m  
## 1007 3.686072e+16 f m f  
## 918 3.686183e+16 f f h  
## 942 3.686183e+16 f h f  
## 920 3.686626e+16 f f j  
## 968 3.686626e+16 f j f  
## 864 3.690256e+16 f b f  
## 903 3.690256e+16 f e f  
## 912 3.690256e+16 f f b  
## 915 3.690256e+16 f f e  
## 1792 3.691256e+16 k h k  
## 1828 3.691256e+16 k k h  
## 877 3.696180e+16 f c f  
## 913 3.696180e+16 f f c  
## 890 3.698572e+16 f d f  
## 914 3.698572e+16 f f d  
## 922 3.725170e+16 f f l  
## 994 3.725170e+16 f l f  
## 921 3.731789e+16 f f k  
## 981 3.731789e+16 f k f  
## 1701 3.735336e+16 k a k  
## 1821 3.735336e+16 k k a  
## 917 3.741329e+16 f f g  
## 929 3.741329e+16 f g f  
## 851 3.769321e+16 f a f  
## 911 3.769321e+16 f f a  
## 1944 3.775403e+16 l g g  
## 15 3.914555e+16 a b b  
## 18 3.914555e+16 a b e  
## 54 3.914555e+16 a e b  
## 57 3.914555e+16 a e e  
## 2099 4.264679e+16 m f f  
## 1676 4.508693e+16 j l l  
## 1198 4.682933e+16 h b b  
## 1201 4.682933e+16 h b e  
## 1237 4.682933e+16 h e b  
## 1240 4.682933e+16 h e e  
## 1544 5.094344e+16 j b j  
## 1583 5.094344e+16 j e j  
## 1640 5.094344e+16 j j b  
## 1643 5.094344e+16 j j e  
## 1557 5.141003e+16 j c j  
## 1641 5.141003e+16 j j c  
## 2113 5.152464e+16 m g g  
## 195 5.581274e+16 b b m  
## 234 5.581274e+16 b e m  
## 327 5.581274e+16 b m b  
## 330 5.581274e+16 b m e  
## 702 5.581274e+16 e b m  
## 741 5.581274e+16 e e m  
## 834 5.581274e+16 e m b  
## 837 5.581274e+16 e m e  
## 1662 5.991480e+16 j k k  
## 2169 6.120420e+16 m k k  
## 1437 6.660944e+16 i g g  
## 1902 7.814195e+16 l d d  
## 1958 7.980261e+16 l h h  
## 1521 8.184254e+16 i m m  
## 1620 8.489413e+16 j h h  
## 1592 8.981077e+16 j f f  
## 1268 9.127700e+16 h g g  
## 1550 9.458077e+16 j c c  
## 1897 9.486361e+16 l c l  
## 2005 9.486361e+16 l l c  
## 1057 9.667481e+16 g d d  
## 373 9.720242e+16 c c i  
## 445 9.720242e+16 c i c  
## 341 9.739043e+16 c a c  
## 365 9.739043e+16 c c a  
## 1212 9.796168e+16 h c c  
## 372 1.008808e+17 c c h  
## 432 1.008808e+17 c h c  
## 310 1.065396e+17 b k k  
## 817 1.065396e+17 e k k  
## 2028 1.074352e+17 l m m  
## 409 1.104720e+17 c f f  
## 29 1.112486e+17 a c c  
## 557 1.122125e+17 d d k  
## 641 1.122125e+17 d k d  
## 537 1.122343e+17 d c d  
## 549 1.122343e+17 d d c  
## 559 1.123058e+17 d d m  
## 667 1.123058e+17 d m d  
## 524 1.123673e+17 d b d  
## 548 1.123673e+17 d d b  
## 551 1.123673e+17 d d e  
## 563 1.123673e+17 d e d  
## 556 1.124518e+17 d d j  
## 628 1.124518e+17 d j d  
## 554 1.125576e+17 d d h  
## 602 1.125576e+17 d h d  
## 555 1.128108e+17 d d i  
## 615 1.128108e+17 d i d  
## 511 1.133232e+17 d a d  
## 547 1.133232e+17 d d a  
## 558 1.136043e+17 d d l  
## 654 1.136043e+17 d l d  
## 553 1.150215e+17 d d g  
## 589 1.150215e+17 d g d  
## 578 1.167109e+17 d f f  
## 240 1.168814e+17 b f f  
## 747 1.168814e+17 e f f  
## 1353 1.191036e+17 i a a  
## 1733 1.241886e+17 k d d  
## 1884 1.247562e+17 l b l  
## 1923 1.247562e+17 l e l  
## 2004 1.247562e+17 l l b  
## 2007 1.247562e+17 l l e  
## 1324 1.264684e+17 h k k  
## 648 1.277571e+17 d k k  
## 1367 1.320608e+17 i b b  
## 1370 1.320608e+17 i b e  
## 1406 1.320608e+17 i e b  
## 1409 1.320608e+17 i e e  
## 1226 1.334719e+17 h d d  
## 324 1.355301e+17 b l l  
## 831 1.355301e+17 e l l  
## 1085 1.406890e+17 g f f  
## 1775 1.409669e+17 k g g  
## 85 1.419280e+17 a g g  
## 1522 1.480737e+17 j a a  
## 451 1.483905e+17 c i i  
## 1634 1.534532e+17 j i i  
## 113 1.617533e+17 a i i  
## 338 1.652263e+17 b m m  
## 845 1.652263e+17 e m m  
## 1374 1.727864e+17 i b i  
## 1413 1.727864e+17 i e i  
## 1458 1.727864e+17 i i b  
## 1461 1.727864e+17 i i e  
## 1466 1.728153e+17 i i j  
## 1478 1.728153e+17 i j i  
## 1387 1.733582e+17 i c i  
## 1459 1.733582e+17 i i c  
## 1361 1.739472e+17 i a i  
## 1457 1.739472e+17 i i a  
## 1468 1.747495e+17 i i l  
## 1504 1.747495e+17 i l i  
## 465 1.752833e+17 c j j  
## 1761 1.777383e+17 k f f  
## 1452 1.821606e+17 i h i  
## 1464 1.821606e+17 i i h  
## 507 1.822682e+17 c m m  
## 592 1.903620e+17 d g g  
## 1493 2.054944e+17 i k k  
## 170 2.072495e+17 b a a  
## 677 2.072495e+17 e a a  
## 1986 2.148666e+17 l j j  
## 212 2.242739e+17 b d d  
## 719 2.242739e+17 e d d  
## 1352 2.262494e+17 h m m  
## 377 2.334209e+17 c c m  
## 497 2.334209e+17 c m c  
## 71 2.392654e+17 a f f  
## 2057 2.750401e+17 m c c  
## 1564 2.750745e+17 j d d  
## 2141 2.782618e+17 m i i  
## 43 2.798909e+17 a d d  
## 254 2.800008e+17 b g g  
## 761 2.800008e+17 e g g  
## 1740 2.852286e+17 k d k  
## 1824 2.852286e+17 k k d  
## 1860 2.914403e+17 l a a  
## 296 2.963681e+17 b j j  
## 803 2.963681e+17 e j j  
## 1296 3.007686e+17 h i i  
## 1779 3.051564e+17 k g k  
## 1827 3.051564e+17 k k g  
## 2043 3.061247e+17 m b b  
## 2046 3.061247e+17 m b e  
## 2082 3.061247e+17 m e b  
## 2085 3.061247e+17 m e e  
## 1531 3.094902e+17 j a j  
## 1639 3.094902e+17 j j a  
## 1635 3.095480e+17 j i j  
## 1647 3.095480e+17 j j i  
## 1622 3.198905e+17 j h j  
## 1646 3.198905e+17 j j h  
## 169 3.605423e+17 a m m  
## 381 3.716952e+17 c d d  
## 282 3.781407e+17 b i i  
## 789 3.781407e+17 e i i  
## 1395 3.968379e+17 i d d  
## 1469 4.284496e+17 i i m  
## 1517 4.284496e+17 i m i  
## 2071 4.442973e+17 m d d  
## 423 4.614451e+17 c g g  
## 155 4.745104e+17 a l l  
## 99 5.060300e+17 a h h  
## 1381 5.100146e+17 i c c  
## 339 5.240217e+17 c a a  
## 437 5.819743e+17 c h h  
## 1972 5.906314e+17 l i i  
## 1254 6.088152e+17 h f f  
## 1975 6.202336e+17 l i l  
## 2011 6.202336e+17 l l i  
## 1871 6.246321e+17 l a l  
## 2003 6.246321e+17 l l a  
## 1962 6.521192e+17 l h l  
## 2010 6.521192e+17 l l h  
## 2029 6.669177e+17 m a a  
## 1451 6.968469e+17 i h h  
## 10 7.063203e+17 a a j  
## 118 7.063203e+17 a j a  
## 2 7.076228e+17 a a b  
## 5 7.076228e+17 a a e  
## 14 7.076228e+17 a b a  
## 53 7.076228e+17 a e a  
## 3 7.116013e+17 a a c  
## 27 7.116013e+17 a c a  
## 12 7.135383e+17 a a l  
## 144 7.135383e+17 a l a  
## 9 7.219781e+17 a a i  
## 105 7.219781e+17 a i a  
## 1651 7.403666e+17 j j m  
## 1687 7.403666e+17 j m j  
## 8 7.437406e+17 a a h  
## 92 7.437406e+17 a h a  
## 1338 7.627210e+17 h l l  
## 1155 7.730170e+17 g k k  
## 1690 8.505758e+17 j m m  
## 1284 9.214489e+17 h h j  
## 1308 9.214489e+17 h j h  
## 1191 9.217866e+17 h a h  
## 1275 9.217866e+17 h h a  
## 1286 9.240001e+17 h h l  
## 1334 9.240001e+17 h l h  
## 1204 9.268520e+17 h b h  
## 1243 9.268520e+17 h e h  
## 1276 9.268520e+17 h h b  
## 1279 9.268520e+17 h h e  
## 1283 9.273312e+17 h h i  
## 1295 9.273312e+17 h i h  
## 268 9.302276e+17 b h h  
## 775 9.302276e+17 e h h  
## 1217 9.442507e+17 h c h  
## 1277 9.442507e+17 h h c  
## 2183 9.467157e+17 m l l  
## 2015 1.499523e+18 l l m  
## 2027 1.499523e+18 l m l  
## 1930 1.598385e+18 l f f  
## 1507 1.684353e+18 i l l  
## 13 1.775015e+18 a a m  
## 157 1.775015e+18 a m a  
## 193 1.811232e+18 b b k  
## 232 1.811232e+18 b e k  
## 301 1.811232e+18 b k b  
## 304 1.811232e+18 b k e  
## 700 1.811232e+18 e b k  
## 739 1.811232e+18 e e k  
## 808 1.811232e+18 e k b  
## 811 1.811232e+18 e k e  
## 1287 2.210515e+18 h h m  
## 1347 2.210515e+18 h m h  
## 1859 2.288509e+18 k m m  
## 1184 3.059916e+18 h a a  
## 1086 3.595644e+18 g f g  
## 1098 3.595644e+18 g g f  
## 1479 3.687373e+18 i j j  
## 1310 5.678052e+18 h j j  
## 127 6.766652e+18 a j j  
## 375 7.175616e+18 c c k  
## 471 7.175616e+18 c k c  
## 1705 7.811568e+18 k b b  
## 1708 7.811568e+18 k b e  
## 1744 7.811568e+18 k e b  
## 1747 7.811568e+18 k e e  
## 930 7.817411e+18 f g g  
## 2155 9.476239e+18 m j j  
## 1719 9.578174e+18 k c c  
## 186 1.335736e+19 b b d  
## 210 1.335736e+19 b d b  
## 213 1.335736e+19 b d e  
## 225 1.335736e+19 b e d  
## 693 1.335736e+19 e b d  
## 717 1.335736e+19 e d b  
## 720 1.335736e+19 e d e  
## 732 1.335736e+19 e e d  
## 552 1.347538e+19 d d f  
## 576 1.347538e+19 d f d  
## 1467 1.349059e+19 i i k  
## 1491 1.349059e+19 i k i  
## 189 1.417702e+19 b b g  
## 228 1.417702e+19 b e g  
## 249 1.417702e+19 b g b  
## 252 1.417702e+19 b g e  
## 696 1.417702e+19 e b g  
## 735 1.417702e+19 e e g  
## 756 1.417702e+19 e g b  
## 759 1.417702e+19 e g e  
## 1803 1.868783e+19 k i i  
## 1691 2.066442e+19 k a a  
## 1649 2.285057e+19 j j k  
## 1661 2.285057e+19 j k j  
## 888 2.435215e+19 f d d  
## 1029 2.630732e+19 g b b  
## 1032 2.630732e+19 g b e  
## 1068 2.630732e+19 g e b  
## 1071 2.630732e+19 g e e  
## 1766 3.544245e+19 k f k  
## 1826 3.544245e+19 k k f  
## 606 4.061004e+19 d h h  
## 522 4.718172e+19 d b b  
## 525 4.718172e+19 d b e  
## 561 4.718172e+19 d e b  
## 564 4.718172e+19 d e e  
## 2001 4.737002e+19 l k l  
## 2013 4.737002e+19 l l k  
## 536 4.753375e+19 d c c  
## 11 5.566524e+19 a a k  
## 131 5.566524e+19 a k a  
## 368 5.680455e+19 c c d  
## 380 5.680455e+19 c d c  
## 371 5.682945e+19 c c g  
## 419 5.682945e+19 c g c  
## 1789 5.893700e+19 k h h  
## 986 6.771058e+19 f k k  
## 1285 6.966440e+19 h h k  
## 1321 6.966440e+19 h k h  
## 1845 7.377866e+19 k l l  
## 1113 8.596109e+19 g h h  
## 1400 9.956813e+19 i d i  
## 1460 9.956813e+19 i i d  
## 1439 1.036603e+20 i g i  
## 1463 1.036603e+20 i i g  
## 676 1.100766e+20 d m m  
## 1043 1.189955e+20 g c c  
## 1817 1.231038e+20 k j j  
## 1609 1.799124e+20 j g j  
## 1645 1.799124e+20 j j g  
## 1570 1.802463e+20 j d j  
## 1642 1.802463e+20 j j d  
## 1127 2.106734e+20 g i i  
## 1169 2.380277e+20 g l l  
## 620 3.375277e+20 d i i  
## 1910 3.574374e+20 l d l  
## 2006 3.574374e+20 l l d  
## 1949 3.643650e+20 l g l  
## 2009 3.643650e+20 l l g  
## 4 4.195698e+20 a a d  
## 40 4.195698e+20 a d a  
## 7 4.236207e+20 a a g  
## 79 4.236207e+20 a g a  
## 1141 4.821394e+20 g j j  
## 662 4.933011e+20 d l l  
## 1230 5.124730e+20 h d h  
## 1278 5.124730e+20 h h d  
## 1269 5.323089e+20 h g h  
## 1281 5.323089e+20 h h g  
## 1014 7.166111e+20 f m m  
## 508 9.459906e+20 d a a  
## 1015 1.426604e+21 g a a  
## 188 1.635205e+21 b b f  
## 227 1.635205e+21 b e f  
## 236 1.635205e+21 b f b  
## 239 1.635205e+21 b f e  
## 695 1.635205e+21 e b f  
## 734 1.635205e+21 e e f  
## 743 1.635205e+21 e f b  
## 746 1.635205e+21 e f e  
## 860 1.726315e+21 f b b  
## 863 1.726315e+21 f b e  
## 899 1.726315e+21 f e b  
## 902 1.726315e+21 f e e  
## 874 3.145344e+21 f c c  
## 634 3.653623e+21 d j j  
## 370 6.628485e+21 c c f  
## 406 6.628485e+21 c f c  
## 1426 1.220432e+22 i f i  
## 1462 1.220432e+22 i i f  
## 1596 2.104828e+22 j f j  
## 1644 2.104828e+22 j j f  
## 944 2.902051e+22 f h h  
## 958 3.731995e+22 f i i  
## 1000 3.732227e+22 f l l  
## 1936 4.301039e+22 l f l  
## 2008 4.301039e+22 l l f  
## 6 4.925247e+22 a a f  
## 66 4.925247e+22 a f a  
## 972 5.157730e+22 f j j  
## 1256 6.197303e+22 h f h  
## 1280 6.197303e+22 h h f  
## 846 1.080789e+23 f a a  
## 1648 4.038572e+30 j j j  
## 184 4.406303e+30 b b b  
## 187 4.406303e+30 b b e  
## 223 4.406303e+30 b e b  
## 226 4.406303e+30 b e e  
## 691 4.406303e+30 e b b  
## 694 4.406303e+30 e b e  
## 730 4.406303e+30 e e b  
## 733 4.406303e+30 e e e  
## 2014 1.731599e+31 l l l  
## 1099 2.526084e+31 g g g  
## 916 4.169607e+31 f f f  
## 367 5.888164e+31 c c c  
## 1831 8.200018e+31 k k k  
## 550 3.719285e+33 d d d  
## 1 Inf a a a  
## 1183 Inf g m m  
## 1282 Inf h h h  
## 1465 Inf i i i  
## 2041 Inf m a m  
## 2054 Inf m b m  
## 2067 Inf m c m  
## 2080 Inf m d m  
## 2093 Inf m e m  
## 2106 Inf m f m  
## 2119 Inf m g m  
## 2127 Inf m h h  
## 2132 Inf m h m  
## 2145 Inf m i m  
## 2158 Inf m j m  
## 2171 Inf m k m  
## 2184 Inf m l m  
## 2185 Inf m m a  
## 2186 Inf m m b  
## 2187 Inf m m c  
## 2188 Inf m m d  
## 2189 Inf m m e  
## 2190 Inf m m f  
## 2191 Inf m m g  
## 2192 Inf m m h  
## 2193 Inf m m i  
## 2194 Inf m m j  
## 2195 Inf m m k  
## 2196 Inf m m l  
## 2197 Inf m m m

#################################################################################  
# 8.5 Interpretation of the kappa values #  
#################################################################################  
  
# As a rough guide for regression, values should be below 30 to establish low multicollinearity.   
# The combinations that symmetrically return values of less than 30 when using 2 indicators are   
# "jl", "bc" and "ec" (see clipboard). These could form new models. As Chulwalr's experts' feedback   
# showed most interest in the influence of national holidays and  
# inflation, we also included that model for further investigations.  
# There are no values which are below 30 when using 3 indicators. Therefore, it is not  
# necessary to try out 3 or 4 or more indicators.  
  
#################################################################################  
# 8.6 New model #  
#################################################################################  
  
# As trend and seasonality have been shown to forecast well on their own, we will add the new combination to trend and   
# seasonality in order to try to improve the forecast.  
  
# 1. Inflation and NationalHolidays additional  
# 2. Seasonality and Trend only  
  
  
# 1. Inflation and NationalHolidays  
ModelWithInflationAndNationalHolidays <- tslm(TotalAsIs ~ trend + season + Inflation + NationalHolidays)  
summary(ModelWithInflationAndNationalHolidays)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + Inflation + NationalHolidays)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -547330 -134116 -1286 160632 400324   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2151025 125478 17.143 < 2e-16 \*\*\*  
## trend 26408 1440 18.335 < 2e-16 \*\*\*  
## season2 -131665 144575 -0.911 0.36629   
## season3 190717 153363 1.244 0.21875   
## season4 -316061 177379 -1.782 0.08010 .   
## season5 -622852 144685 -4.305 6.65e-05 \*\*\*  
## season6 -882689 144746 -6.098 9.93e-08 \*\*\*  
## season7 -1078593 144826 -7.447 5.71e-10 \*\*\*  
## season8 -724466 144917 -4.999 5.82e-06 \*\*\*  
## season9 706671 145034 4.872 9.16e-06 \*\*\*  
## season10 302312 145206 2.082 0.04185 \*   
## season11 475472 145412 3.270 0.00183 \*\*   
## season12 514655 212001 2.428 0.01838 \*   
## Inflation 19310 35331 0.547 0.58681   
## NationalHolidays -436533 153607 -2.842 0.00621 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 250400 on 57 degrees of freedom  
## Multiple R-squared: 0.9277, Adjusted R-squared: 0.9099   
## F-statistic: 52.24 on 14 and 57 DF, p-value: < 2.2e-16

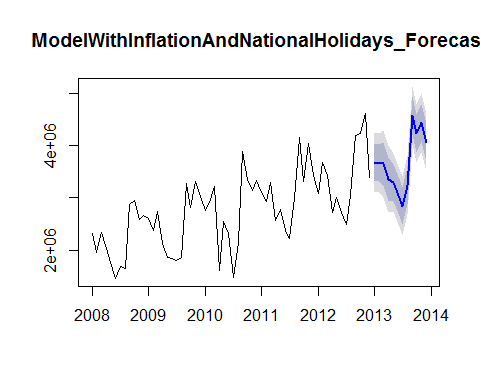
# Adjusted R²: 0.9099  
  
# 2. Seasonality and Trend only (as comparison to 1.)  
ModelWithTrendAndSeasonalityOnly <- tslm(TotalAsIs ~ trend + season)  
summary(ModelWithTrendAndSeasonalityOnly)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -699390 -154210 17753 150363 495430   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2182435 117276 18.609 < 2e-16 \*\*\*  
## trend 26427 1514 17.456 < 2e-16 \*\*\*  
## season2 -131168 152001 -0.863 0.391663   
## season3 46585 152024 0.306 0.760356   
## season4 -609102 152062 -4.006 0.000176 \*\*\*  
## season5 -623539 152114 -4.099 0.000129 \*\*\*  
## season6 -883072 152182 -5.803 2.74e-07 \*\*\*  
## season7 -1079124 152265 -7.087 1.93e-09 \*\*\*  
## season8 -724693 152363 -4.756 1.31e-05 \*\*\*  
## season9 705716 152476 4.628 2.07e-05 \*\*\*  
## season10 300019 152603 1.966 0.054009 .   
## season11 472099 152746 3.091 0.003045 \*\*   
## season12 73925 152903 0.483 0.630546   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 263300 on 59 degrees of freedom  
## Multiple R-squared: 0.9173, Adjusted R-squared: 0.9004   
## F-statistic: 54.51 on 12 and 59 DF, p-value: < 2.2e-16

# Adjusted R²: 0,9004  
  
# The Adjusted R² for ModelWithTrendAndSeasonalityOnly was 0,9004, hence the value for "Inflation and NationalHolidays",   
# is slightly better.  
# We will forecast with the model and then compare   
# to the AsIs and Plan data for 2013.  
  
  
#################################################################################  
# 8.7 Forecasts with the new model #  
#################################################################################   
  
#################################################################################  
# ModelWithInflationAndNationalHolidays #  
#################################################################################  
  
# Shorten ModelWithInflationAndNationalHolidays by one year in order to be able to produce a forecast for 2013.   
ModelWithInflationAndNationalHolidays\_2012 <- tslm(TotalAsIs\_2012 ~ trend + season + Inflation\_2012 + NationalHolidays\_2012)  
summary(ModelWithInflationAndNationalHolidays\_2012)

##   
## Call:  
## tslm(formula = TotalAsIs\_2012 ~ trend + season + Inflation\_2012 +   
## NationalHolidays\_2012)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -526307 -134872 10576 170157 465246   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2107558 131001 16.088 < 2e-16 \*\*\*  
## trend 25101 1872 13.405 < 2e-16 \*\*\*  
## season2 -35384 155200 -0.228 0.820690   
## season3 240411 160008 1.502 0.139956   
## season4 -386832 219840 -1.760 0.085271 .   
## season5 -489470 155364 -3.150 0.002896 \*\*   
## season6 -758907 155483 -4.881 1.37e-05 \*\*\*  
## season7 -995053 155628 -6.394 8.11e-08 \*\*\*  
## season8 -616741 155730 -3.960 0.000264 \*\*\*  
## season9 702251 155903 4.504 4.69e-05 \*\*\*  
## season10 332293 156117 2.128 0.038807 \*   
## season11 514195 156424 3.287 0.001968 \*\*   
## season12 430932 250212 1.722 0.091888 .   
## Inflation\_2012 25935 34970 0.742 0.462167   
## NationalHolidays\_2012 -314744 194415 -1.619 0.112451   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 245400 on 45 degrees of freedom  
## Multiple R-squared: 0.9162, Adjusted R-squared: 0.8902   
## F-statistic: 35.15 on 14 and 45 DF, p-value: < 2.2e-16

# Add "newdata" to the 2013 indicator values for the forecast   
ModelWithInflationAndNationalHolidays\_Forecast <- forecast(ModelWithInflationAndNationalHolidays\_2012,newdata=data.frame(Inflation\_2012=Inflation\_2013,NationalHolidays\_2012=NationalHolidays\_2013),h=12)  
plot(ModelWithInflationAndNationalHolidays\_Forecast, main="ModelWithInflationAndNationalHolidays\_Forecast")



ModelWithInflationAndNationalHolidays\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 3681521 3321098 4041943 3123393 4239648  
## Feb 2013 3668645 3308015 4029274 3110197 4227093  
## Mar 2013 3651943 3237319 4066568 3009882 4294005  
## Apr 2013 3357025 2943712 3770338 2716995 3997056  
## May 2013 3289602 2929068 3650137 2731301 3847904  
## Jun 2013 3052788 2692425 3413151 2494753 3610823  
## Jul 2013 2844077 2483627 3204526 2285907 3402246  
## Aug 2013 3237376 2876771 3597981 2678966 3795786  
## Sep 2013 4578876 4218123 4939628 4020238 5137513  
## Oct 2013 4229091 3867964 4590219 3669872 4788310  
## Nov 2013 4438688 4078018 4799359 3880176 4997200  
## Dec 2013 4068116 3707678 4428554 3509965 4626268

# In order to be able to correlate the Forecast with the As Is Data, it is necessary to convert the Point   
# Estimator into a time series.   
ModelWithInflationAndNationalHolidays\_Forecast\_df <-as.data.frame(ModelWithInflationAndNationalHolidays\_Forecast)   
ModelWithInflationAndNationalHolidays\_PointForecast <- ts(ModelWithInflationAndNationalHolidays\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
  
# Correlation of the forecasts and As Is Data. As a comparison, the correlation of the As Is Data for 2013 with the Plan data.   
cor(ModelWithInflationAndNationalHolidays\_PointForecast, TotalAsIs\_2013)

## [1] 0.9598657

cor(TotalAsIs\_2013, TotalPlan\_2013)

## [1] 0.929769

# A comparison with linear regression also supports the result.  
ModelWithInflationAndNationalHolidays\_forecast\_lm <- lm(TotalAsIs\_2013 ~ ModelWithInflationAndNationalHolidays\_PointForecast, data = TotalAsIs\_2013)  
TotalAsIs\_2013\_lm <- lm(TotalAsIs\_2013 ~ TotalPlan\_2013, data = TotalAsIs\_2013)  
summary(ModelWithInflationAndNationalHolidays\_forecast\_lm)

##   
## Call:  
## lm(formula = TotalAsIs\_2013 ~ ModelWithInflationAndNationalHolidays\_PointForecast,   
## data = TotalAsIs\_2013)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -296063 -155536 -40988 109218 411647   
##   
## Coefficients:  
## Estimate Std. Error  
## (Intercept) -1.253e+06 4.703e+05  
## ModelWithInflationAndNationalHolidays\_PointForecast 1.371e+00 1.267e-01  
## t value Pr(>|t|)   
## (Intercept) -2.665 0.0237 \*   
## ModelWithInflationAndNationalHolidays\_PointForecast 10.823 7.67e-07 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 232900 on 10 degrees of freedom  
## Multiple R-squared: 0.9213, Adjusted R-squared: 0.9135   
## F-statistic: 117.1 on 1 and 10 DF, p-value: 7.666e-07

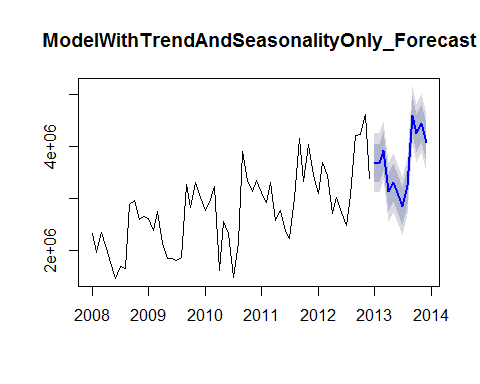
summary(TotalAsIs\_2013\_lm)

##   
## Call:  
## lm(formula = TotalAsIs\_2013 ~ TotalPlan\_2013, data = TotalAsIs\_2013)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -441885 -227385 -43470 184761 466401   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -8.972e+04 4.930e+05 -0.182 0.859   
## TotalPlan\_2013 1.053e+00 1.318e-01 7.987 1.2e-05 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 305700 on 10 degrees of freedom  
## Multiple R-squared: 0.8645, Adjusted R-squared: 0.8509   
## F-statistic: 63.78 on 1 and 10 DF, p-value: 1.195e-05

#################################################################################  
# Trend and Seasonality only as benchmark #  
#################################################################################  
  
# Shorten ModelWithTrendAndSeasonalityOnly by one year in order to be able to produce a forecast for 2013.  
ModelWithTrendAndSeasonalityOnly\_2012 <- tslm(TotalAsIs\_2012 ~ trend + season)  
summary(ModelWithTrendAndSeasonalityOnly\_2012)

##   
## Call:  
## tslm(formula = TotalAsIs\_2012 ~ trend + season)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -600304 -116717 -7864 163111 473692   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2147793 120530 17.820 < 2e-16 \*\*\*  
## trend 25212 1887 13.363 < 2e-16 \*\*\*  
## season2 -34146 156872 -0.218 0.828632   
## season3 180612 156906 1.151 0.255518   
## season4 -639529 156962 -4.074 0.000176 \*\*\*  
## season5 -490327 157042 -3.122 0.003068 \*\*   
## season6 -760860 157144 -4.842 1.43e-05 \*\*\*  
## season7 -997792 157268 -6.345 8.09e-08 \*\*\*  
## season8 -617048 157415 -3.920 0.000286 \*\*\*  
## season9 701211 157585 4.450 5.26e-05 \*\*\*  
## season10 330001 157777 2.092 0.041907 \*   
## season11 509563 157991 3.225 0.002292 \*\*   
## season12 109681 158227 0.693 0.491603   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 248000 on 47 degrees of freedom  
## Multiple R-squared: 0.9106, Adjusted R-squared: 0.8878   
## F-statistic: 39.89 on 12 and 47 DF, p-value: < 2.2e-16

# Add "newdata" to the 2013 indicator values for the forecast.  
ModelWithTrendAndSeasonalityOnly\_Forecast <- forecast(ModelWithTrendAndSeasonalityOnly\_2012,h=12)  
plot(ModelWithTrendAndSeasonalityOnly\_Forecast, main="ModelWithTrendAndSeasonalityOnly\_Forecast")



ModelWithTrendAndSeasonalityOnly\_Forecast

## Point Forecast Lo 80 Hi 80 Lo 95 Hi 95  
## Jan 2013 3685709 3321691 4049727 3122318 4249100  
## Feb 2013 3676775 3312757 4040793 3113384 4240166  
## Mar 2013 3916745 3552727 4280763 3353354 4480136  
## Apr 2013 3121815 2757797 3485833 2558424 3685206  
## May 2013 3296229 2932211 3660247 2732838 3859620  
## Jun 2013 3050908 2686890 3414926 2487517 3614299  
## Jul 2013 2839188 2475170 3203206 2275797 3402579  
## Aug 2013 3245143 2881125 3609161 2681752 3808534  
## Sep 2013 4588614 4224596 4952632 4025223 5152005  
## Oct 2013 4242616 3878598 4606634 3679225 4806007  
## Nov 2013 4447389 4083371 4811407 3883998 5010780  
## Dec 2013 4072720 3708702 4436737 3509329 4636110

# In order to be able to correlate the Forecast with the As Is Data, it is necessary to convert the point   
# estimator into a time series.   
ModelWithTrendAndSeasonalityOnly\_Forecast\_df <-as.data.frame(ModelWithTrendAndSeasonalityOnly\_Forecast)   
ModelWithTrendAndSeasonalityOnly\_PointForecast <- ts(ModelWithTrendAndSeasonalityOnly\_Forecast\_df$"Point Forecast", start=c(2013,1), end=c(2013,12), frequency=12)  
  
# Correlation of the forecasts and As Is data. As a comparison, the correlation of the As Is Data for 2013 with the Plan data.  
cor(ModelWithTrendAndSeasonalityOnly\_PointForecast, TotalAsIs\_2013)

## [1] 0.9138049

cor(TotalAsIs\_2013, TotalPlan\_2013)

## [1] 0.929769

# A Comparison with linear regression also supports the result.  
ModelWithTrendAndSeasonalityOnly\_Forecast\_lm <- lm(TotalAsIs\_2013 ~ ModelWithTrendAndSeasonalityOnly\_PointForecast, data = TotalAsIs\_2013)  
TotalAsIs\_2013\_lm <- lm(TotalAsIs\_2013 ~ TotalPlan\_2013, data = TotalAsIs\_2013)  
summary(ModelWithTrendAndSeasonalityOnly\_Forecast\_lm)

##   
## Call:  
## lm(formula = TotalAsIs\_2013 ~ ModelWithTrendAndSeasonalityOnly\_PointForecast,   
## data = TotalAsIs\_2013)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -516239 -216450 33683 123007 675607   
##   
## Coefficients:  
## Estimate Std. Error  
## (Intercept) -8.142e+05 6.536e+05  
## ModelWithTrendAndSeasonalityOnly\_PointForecast 1.249e+00 1.755e-01  
## t value Pr(>|t|)   
## (Intercept) -1.246 0.241   
## ModelWithTrendAndSeasonalityOnly\_PointForecast 7.115 3.24e-05 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 337300 on 10 degrees of freedom  
## Multiple R-squared: 0.835, Adjusted R-squared: 0.8185   
## F-statistic: 50.62 on 1 and 10 DF, p-value: 3.238e-05

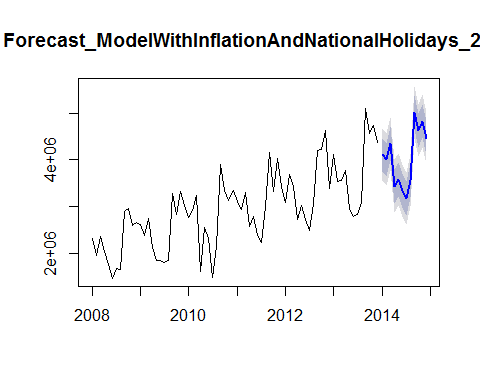
summary(TotalAsIs\_2013\_lm)

##   
## Call:  
## lm(formula = TotalAsIs\_2013 ~ TotalPlan\_2013, data = TotalAsIs\_2013)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -441885 -227385 -43470 184761 466401   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -8.972e+04 4.930e+05 -0.182 0.859   
## TotalPlan\_2013 1.053e+00 1.318e-01 7.987 1.2e-05 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 305700 on 10 degrees of freedom  
## Multiple R-squared: 0.8645, Adjusted R-squared: 0.8509   
## F-statistic: 63.78 on 1 and 10 DF, p-value: 1.195e-05

###############################################################################  
# 8.8 Interpretation of the forecasts #  
###############################################################################  
  
# Below are the results of chapter 8.7  
  
# AsIs Data for 2013  
# summary(TotalAsIs\_2013\_lm)  
# Adjusted R²: 0.8509  
  
# ModelWithInflationAndNationalHolidays   
#   
# cor(ModelWithInflationAndNationalHolidays\_PointForecast, TotalAsIs\_2013)   
# [1] 0.9598657  
# cor(TotalAsIs\_2013, TotalPlan\_2013)  
# [1] 0.929769  
  
# Adjusted R²: 0.9135   
  
  
# ModelwithTrendAndSeasonalityOnly  
  
# cor(ModelWithTrendAndSeasonalityOnly\_PointForecast, TotalAsIs\_2013)   
# [1] 0.9138049  
# cor(TotalAsIs\_2013, TotalPlan\_2013)  
# [1] 0.929769  
  
# Adjusted R²: 0.8185  
  
# The better model is ModelWithInflationAndNationalHolidays. It finally outperforms the plan data and provides explanatory potential.  
  
# We will now use the ModelWithInflationAndNationalHolidays to forecast the year 2014  
  
###############################################################################  
# 8.9 Forecast for 2014 #  
###############################################################################  
  
summary(ModelWithInflationAndNationalHolidays)

##   
## Call:  
## tslm(formula = TotalAsIs ~ trend + season + Inflation + NationalHolidays)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -547330 -134116 -1286 160632 400324   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2151025 125478 17.143 < 2e-16 \*\*\*  
## trend 26408 1440 18.335 < 2e-16 \*\*\*  
## season2 -131665 144575 -0.911 0.36629   
## season3 190717 153363 1.244 0.21875   
## season4 -316061 177379 -1.782 0.08010 .   
## season5 -622852 144685 -4.305 6.65e-05 \*\*\*  
## season6 -882689 144746 -6.098 9.93e-08 \*\*\*  
## season7 -1078593 144826 -7.447 5.71e-10 \*\*\*  
## season8 -724466 144917 -4.999 5.82e-06 \*\*\*  
## season9 706671 145034 4.872 9.16e-06 \*\*\*  
## season10 302312 145206 2.082 0.04185 \*   
## season11 475472 145412 3.270 0.00183 \*\*   
## season12 514655 212001 2.428 0.01838 \*   
## Inflation 19310 35331 0.547 0.58681   
## NationalHolidays -436533 153607 -2.842 0.00621 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 250400 on 57 degrees of freedom  
## Multiple R-squared: 0.9277, Adjusted R-squared: 0.9099   
## F-statistic: 52.24 on 14 and 57 DF, p-value: < 2.2e-16

Forecast\_ModelWithInflationAndNationalHolidays\_2014 <- forecast(ModelWithInflationAndNationalHolidays, newdata=data.frame(Inflation=Inflation\_2014, NationalHolidays=NationalHolidays\_2014),h=12)  
plot(Forecast\_ModelWithInflationAndNationalHolidays\_2014,main="Forecast\_ModelWithInflationAndNationalHolidays\_2014")



#mywait()  
  
Forecast\_ModelWithInflationAndNationalHolidays\_2014\_df <-as.data.frame(Forecast\_ModelWithInflationAndNationalHolidays\_2014)   
Pointforecast\_ModelWithInflationAndNationalHolidays\_2014 <- ts(Forecast\_ModelWithInflationAndNationalHolidays\_2014\_df$"Point Forecast", start=c(2014,1), end=c(2014,12), frequency=12)  
Pointforecast\_ModelWithInflationAndNationalHolidays\_2014

## Jan Feb Mar Apr May Jun Jul Aug  
## 2014 4104674 3997487 4342414 3431112 3577991 3348232 3175066 3555602  
## Sep Oct Nov Dec  
## 2014 5013146 4633457 4829356 4452621

TotalAsIsVector\_2014 <- c(ImportedAsIsData[2:13,8])  
TotalAsIsVector\_2014

## [1] 4308161 4155378 3924332 3659121 3898758 3313891 3595106 3502426  
## [9] 5619059 5274287 4841693 4664854

TotalAsIs\_2014 <- ts(TotalAsIsVector\_2014, start=c(2014,1), end=c(2014,12), frequency=12)  
TotalAsIs\_2014

## Jan Feb Mar Apr May Jun Jul Aug  
## 2014 4308161 4155378 3924332 3659121 3898758 3313891 3595106 3502426  
## Sep Oct Nov Dec  
## 2014 5619059 5274287 4841693 4664854

cor(TotalAsIs\_2014,Pointforecast\_ModelWithInflationAndNationalHolidays\_2014)

## [1] 0.917632

#################################################################################  
### ###  
### 9. Comparison of the models ###  
### ###  
#################################################################################  
  
#plot(TotalAsIs\_2014, type="o")  
#lines(Model\_dynreg\_auto.arima\_PointForecast, type="o", col="green")  
#lines(Model\_auto.arima\_PointForecast, type="o",col="blue")  
#lines(Model\_ets\_PointForecast, type="o",col="red")  
#lines(PointForecast\_TrendAndSeasonality\_2014, type="o",col="orange")  
#lines(Pointforecast\_ModelWithInflationAndNationalHolidays\_2014, type="o",col="pink")  
#lines(TotalPlan\_2014, type="o",col="purple")  
#legend("topleft",lty=1, pch=1, col=c(1,"purple","red","blue","green","orange","pink"), c("data","Budget","ets/Holt-Winters","ARIMA", "Dynamische Regression","tslm","kappa"))  
  
cor(TotalAsIs\_2014,TotalPlan\_2014)

## [1] 0.9448221

# 0.9448221  
cor(TotalAsIs\_2014,PointForecast\_ModelWithLowCorrelatingIndicators\_2014)

## [1] 0.9178468

# 0.9178468  
cor(TotalAsIs\_2014,PointForecast\_TrendAndSeasonality\_2014)

## [1] 0.9349765

# 0.9349765  
cor(TotalAsIs\_2014,Model\_ets\_PointForecast)

## [1] 0.9313367

# 0.9311129  
cor(TotalAsIs\_2014,Model\_auto.arima\_PointForecast)

## [1] 0.9238591

# 0.9238591  
cor(TotalAsIs\_2014,Model\_dynreg\_auto.arima\_PointForecast)

## [1] 0.9259971

# 0.9259971  
cor(TotalAsIs\_2014,Pointforecast\_ModelWithInflationAndNationalHolidays\_2014)

## [1] 0.917632

# 0.917632  
  
# Percentual differences  
  
 MAPE\_AsIs\_Plan <- mean(abs(TotalAsIs\_2014-TotalPlan\_2014)/(TotalAsIs\_2014))\*100  
 MAPE\_AsIs\_LowCorInd <- mean(abs(TotalAsIs\_2014-PointForecast\_ModelWithLowCorrelatingIndicators\_2014)/(TotalAsIs\_2014))\*100  
 MAPE\_AsIs\_TrendSeasonality <- mean(abs(TotalAsIs\_2014-PointForecast\_TrendAndSeasonality\_2014)/(TotalAsIs\_2014))\*100  
 MAPE\_AsIs\_ETSHoltWinters <- mean(abs(TotalAsIs\_2014-Model\_ets\_PointForecast)/(TotalAsIs\_2014))\*100  
 MAPE\_AsIs\_ARIMA <- mean(abs(TotalAsIs\_2014-Model\_auto.arima\_PointForecast)/(TotalAsIs\_2014))\*100  
 MAPE\_AsIs\_DynamicReg <- mean(abs(TotalAsIs\_2014-Model\_dynreg\_auto.arima\_PointForecast)/(TotalAsIs\_2014))\*100  
 MAPE\_AsIs\_Kappa <- mean(abs(TotalAsIs\_2014-Pointforecast\_ModelWithInflationAndNationalHolidays\_2014)/(TotalAsIs\_2014))\*100  
  
 MAPE\_AsIs\_Plan

## [1] 5.289062

MAPE\_AsIs\_LowCorInd

## [1] 5.884434

MAPE\_AsIs\_TrendSeasonality

## [1] 5.54508

MAPE\_AsIs\_ETSHoltWinters

## [1] 5.080684

MAPE\_AsIs\_ARIMA

## [1] 6.347354

MAPE\_AsIs\_DynamicReg

## [1] 5.640589

MAPE\_AsIs\_Kappa

## [1] 6.300923

#################################################################################  
### ###  
### 10. Summary of results ###  
### ###  
#################################################################################  
  
  
# Planning was already unusually exact before we introduced forecasting methods out of Rob Hyndman's toolbox to Chulwalar.  
# The situation was very challenging. Finally, our efforts brought up two models, which are able to compete with Chulwalar's planners:  
# We found one model based on trend, season, inflation and national holidays, which has a high explanatory potential and correlates highly  
# with as-is-data on the one hand. A Holt-Winters model with trend and seasonality was able forecast more exactly than plan data in terms of percentual   
# differences on the other hand.  
  
# Looking at the results from an explanatory perspective, the course of our analysis dropped too detailed   
# additional economic indicators. That makes Chulwalar a rather unusual island and seems surprising first.  
# It might be the case, that this economy exports goods to a market, which very often just completely absorbes the goods.  
# Internal planning has already a huge influence on the results under such circumstances.   
# In this case, planning would more an independent statement on what is intended to do and less a reaction to market expectations.   
  
# Anyway, the best performing models we found are either based on   
# historic sales only (as the Holt-Winters family) or only dependent on   
# influences (as inflation), which are more general than the very specific economic indicators  
# collected and explored at the beginning of this case study.   
  
# Moreover, "traditional" planning in Chulwalar comes at a cost (as Chulwalar's experts conspiratively admitted).   
# It keeps several persons busy over months. Pretty much of the forecasts by the models   
# in this case study can be calculated automatedly instead.   
# Planning in Chulwalar was a repeated effort with fine-grained monthly adjustments and guesses, whereas we are able to   
# gain almost the same precision one year ahead in our simulation.   
  
# We had to include almost every approach from the ones presented in Hyndman's fpp this time. But applying the  
# successful models for future forecasts should be quick and easy. From the perspective of  
# automated decision support, our case study suggests a lean approach to planning.