Time Series Data in the ESPON Database

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TECHNICAL REPORT

ESPON

June 2014

Time Series Data in the ESPON Database

CONTENT

Time series data form inputs to the ESPON Database, at spatial scales including NUTS0, NUTS1, NUTS2 and NUTS3. Series are often incomplete at the lower levels in the NUTS hierarchy. The task is to impute the missing values, and ensure the spatial coherence of the estimates.

A methodology is presented for data imputation based on an autoregressive model which is fitted to the existing data, and used to impute the missing values, using a Bayesian approach. The spatial coherence of the results is also ensured.

The metholodgy has been implemented using the R language, and tested on typical short-run time series for NUTS0, NUTS1, NUTS2 and NUTS3 regions.

R and JAGS code to operationalise the methodology is presented in this report, and a suitable workflow is outlined.

ESPON M4D -
MULTI DIMENSIONAL DATABASE DESIGN & DEVELOPMENT

EUROPEAN UNION
Part-financed by the European Regional Development Fund
INVESTING IN YOUR FUTURE

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1. Introduction

A time series is a collection of observations made sequentially in time[1]. Time series are frequently encountered in (i) economics [Beveridge annual wheat price series], (ii) physical sciences [monthly average air temperature] (iii) marketing [monthly product sales] (iv) demography [annual population estimates] and (v) process control [weights of manufactured product sampled hourly] (vi) communication [binary series are common]. While many series are usually measured at regular intervals (e.g.: year, month, week, day, hour, minute), there are series which occur irregularly, for example, major railway disasters, which are known as point processes. Time series analysis is concerned with (i) description of the main properties of the series, (ii) explanation of the relationship between two series taken at the same time [monthly atmospheric temperature readings, monthly measurements of the North Atlantic Oscillation] and (iii) prediction of (usually) future values.

Time series description can take several forms, but are intended to reveal the underlying structure of the series. This structure can include several components[2]:

Trend: an increase or decrease in the value of the series over time
Seasonality: a regular pattern of high and low values related to calendar time
Long term cycles: periodicity not related to seasonality
Outliers: values which are unusually high or low in comparison with the rest of the data
Abrupt changes: changes to the variation in the series or level
Variance: this may be constant over time or increase/decrease

Sources of data for ESPON series

Many of the tables required can be obtained from EUROSTAT. However, there are much missing data. Depending on the series, the series may be complete to NUTS 3 back to 2000. For earlier years, data may only be available to NUTS2 level. This requires recourse to other sources, for which the most authoritative would be those from the National Statistical Offices (for example: Turkstat, Croatian Bureau of Statistics, Statistics Norway, and Statistische Ämter des Bundes und der Länder). There are other sources, such as the OECD, and the EUROSTAT NewCronos database may be of assistance in completing the time series.

[1] Chatfield, C, 1989, The Analysis of Time Series, 4th edn, London: Chapman and Hall, p1
[2] Shumway RH and Stoffer DS, 2010, Times Series Analysis and its Applications, 3rd edn, New York: Springer

2. ESPON Time Series

The character of ESPON Series

The socio-economic time series which appear to be commonly encountered in the ESPON programme are annual counts or ratios for a restricted time period (1990-2013)[3]. This implies that the longest series are less than 25 years, and some are far shorter. Missing data in the middle of a series shorten it still further. Hyndman has reported in the effects of attempting to fit models to short series[4]. In 95 short economic series about 1/3 were random walks (they had no structure).

The series are also presented for the spatial units in the NUTS classification[5], The NUTS system is a hierarchical system for dividing up the economic territory of the EU for the purposes of the collection o regional statistics, socio-economic analyses and framing EU regional policies. We are concerned mainly with the first 4 levels of the NUTS hierarchy, Tables of the NUTS regions and their codes, and correspondence tables for region adjustments are available from EUROSTAT. The input and outputs from the ESPON database are in the form of rectangular files, as a Excel spreadsheets – each line of data is preceded by its NUTS code. Some sheets, and the EUROSTAT tables present the NUTS codes of every unit in a single column (for example *demo_r_gind3*), which gives the impression of *flattening* the hierarchy, The key to the strategy for handling the time series is to think of the cross-sectional structure at each time period, implied by the NUTS codes, explicitly as a *tree*. We shall return to this later.

The datasets in EUROSTAT and from other sources are often incomplete for the time periods and spatial scales of interest. There might be many reasons – population censuses may only be carried out on a decadal basis. While national or regional intercensal population estimates may be provided by the national agencies, data at lower level is less common.

In the case of the RIATE example dataset, the pattern of missing data relative to the lvarious levels in the NUTS hierarchy is:

	Complete	
NUTSlevel	NotOK	OK
0	3	31
1	35	80
2	113	204
3	1239	222

[3] Commission Regulation 11/2008 specifies the required time series starting years for NUTS levels in 17 statistical domains. The domain Demography has a start year for 1990 for both NUTS2 and NUTS3.

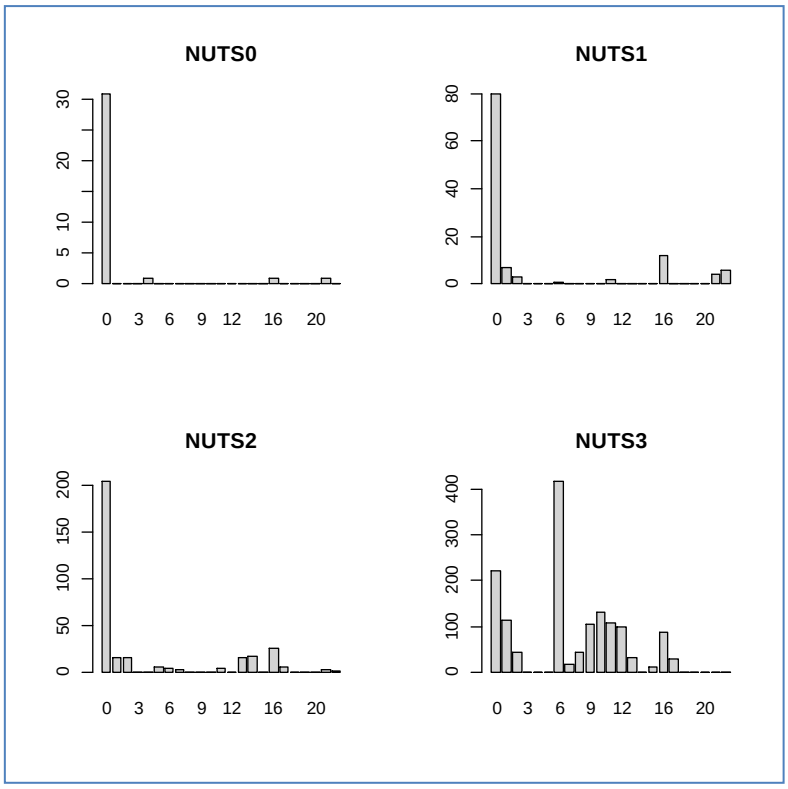
[4] Hyndman R, 2014, Fitting models to short time series, URL:rob.hyndman.com/hindsight/short-time-series

[5] http://epp.eurostat.ec.europa.eu/portal/page/portal/nuts_nomenclature/introduction

An entry in the NotOK column means that data for one or more time periods in the series was missing. The pattern was what proportion of data was missing by NUTS level is below:

	NumberIncomplete																	
NUTSlevel	**0**	**1**	**2**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**21**	**22**
0	31	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
1	80	7	3	0	0	1	0	0	0	0	2	0	0	0	0	12	0	4	6
2	204	16	15	0	5	4	2	0	0	0	4	0	15	17	0	26	5	3	1
3	222	113	42	0	0	417	18	44	105	132	108	100	32	0	10	88	30	0	0

While most NUTS0 series are complete, 1 is missing four time periods, 1 is missing 16, and one is missing 21! The situation deteriorates as we progress down the hierarchy, but this is to be expected. About 25% of the NUTS1 series are missing a substantial portion of their data (over 72% of each series are missing). At NUTS1 and NUTS2 data is either mostly present or missing to a serious degree.



AT NUTS3 level, the modal group represents 6 missing entries and a moderate number of regions have over 75% of their series missing.

This provides a challenge for the analyst. What should be done about the missing data? In survey analysis a common strategy is to analyses only those cases with complete data for the variables of interest. This raises the question as to whether the *mechanism* for creating the missing variables is a random process. If it is not, then the possibility of introducing bias into the analysis becomes a problem. With time series the problem is magnified: if a single value is missing from the series, should the analyst remove this series from the analysis, or should some attempt be made to complete the data?

IBM's SPSS software offers several alternatives to allow the analyst to replace missing observations with an estimate. These include[6]

- The mean of the series
- The mean of nearby observations
- The median of nearby observations
- Linear interpolation
- Linear trend using the time series index as a regressor

The mean of the series might be a unwise choice, particular if the series has a rising trend, and the missing observation is at the beginning of the series. Approaches to linear interpolation are described in detail below. Linear trend may or may not be helpful, although if the residuals either side of the trend line are all positive or negative, then the estimated value my be some distance from a desirable value.

Enders[7] notes that the analyst should make the distinction between the ***missing data pattern*** and the ***missing data mechanism***. He notes that the pattern relates to the configuration of observed and unobserved data, whereas the mechanism permits a description of the relationship between the two in terms of probability. Rubin[8] proposed classified missing data mechamisms into three types: (1) missing at random, (2) missing completely at random and (3) missing not at random. MAR arises when the probability of missing data is related to the values of some other measured variable in the dataset. MCAR arises when the the probability is unrelated to any other variable in the dataset – Elders uses the adjective *haphazard* for this. MNAR arises when the probability of missing data on a variable is related to the values of the variable itself. Elders uses an example of cancer patients in a trial becoming so ill they are unable to continue participation in the trial. The ESPON time series missing data are likely to arise from an MCAR process – they are certainly not MNAR (the population values are too small to collect). However, they may be too expensive to collect.

Traditional methods for missing data

Expedient methods for dealing with missing data include *deletion* of the observations with missing data. Listwise deletion, or complete case analysis, removes any observation with one or more missing values. A variant, pairwise deletion, or available-case analysis, removes variables on an analysis-by-analysis case. This would result in the correlations in a correlation matrix potentially being based on different numbers of underlying observations.

Other expedient methods include *imputation*. Amongst these are replacement by the arithmetic mean, replacement by median, regression imputation, (and stochastic regression imputation which adds a random number from the distribution of residuals), hot-deck imputation (scores are taken from similar

6 http://pic.dhe.ibm.com/infocenter/spssstat/v21r0m0/index.jsp?topic=%2Fcom.ibm.spss.statistics.help%2Fidh_rmvx.htm

7 Enders, CK, 2010, *Applied Missing Data Analysis*, New York: Guilford Press

8 Rubin, DB, 1976, Inference and Missing Data, *Biometrika*, 63(3), 581-592

respondents answers), and last observation carried forward (a variant of this is described below).

Missing observations

An appropriate example is given by the M4D table M4Dpoptot1990-2011_20120522.xls. This contains estimates of residential population, and is available at NUTS0, NUTS2, NUTS2 and NUTS3, from 1990 to 2012. The metadata in table 1 shows that the sources of data include EUROSTAT and the national statistical agencies. However, in many cases data have not being available from these sources and has been imputed by the team at RIATE. The metadata reveals that 52 separate imputation approaches can be identified, although these are variations on the same underlying imputation process.

Table 1: extracr from metadata in M4Dpoptot1990-2011_20120522.xls

ID	Label	Provider
1	1	Eurostat
2	1a	Eurostat
3	1*a	Eurostat, NewCronos database
4	1*b	Eurostat, NewCronos database
5	2a	ESPON M4D
6	3a	Turkstat
7	4a	Croatian Bureau of Statistics
8	4b	Croatian Bureau of Statistics
9	4c	Croatian Bureau of Statistics
10	6a	GUS (Central Statistical Office of Poland)
11	10	Statistics Norway
12	11	Statistics Sweden
13	12	Statistische Ämter des Bundes und der Länder
14	13	Statistics Denmark
15	14	Statistics Portugal
16	15	Statistics Netherlands
17	16	Latvijas Statistika
18	17	Statistics Lithuania
19	18	Fürstentum Liechtenstein
20	20	Statistics Iceland
21	21	Instituto Nacional de Estadistica
22	22	Czech Statistical Office
23	23	Office Fédéral de la Statistique Suisse
24	24	Statistics Estonia
25	25	Statistics Finland
26	26	INSEE (Institut National de la Statistique et des Etudes Economiques)
27	27	Hungarian Central Statistics Office
28	29a	Statistics Belgium - Bestat
29	29b	Statistics Belgium
30	31	Republic of Macedonia, Statistical

31	33	Hellenic Statistical Authority (ElStat)
32	34	UK National Statistics
33	E1b	ESPON M4D
34	E2a	ESPON M4D
35	E2b	ESPON M4D
36	T1a	ESPON M4D
37	T1b	ESPON M4D
38	SE1a	ESPON M4D, New Cronos Database
39	SE1a*	ESPON M4D, New Cronos Database
40	SE1b	ESPON M4D, New Cronos Database
41	SE1c	ESPON M4D, General Register Office for Scotland
42	SE1f	ESPON M4D, Statistical Office of the Republic of Slovenia
43	SE1g	ESPON M4D, Central Statistics Office Ireland
44	SE1h	ESPON M4D, Statistics Iceland
45	SE1i	ESPON M4D, Instituto Nacional de Estadistica
46	SE1j	ESPON M4D, Republic of Macedonia State Statistical Office
47	SE1k	ESPON M4D, UK National statistics
48	SE1l	ESPON M4D, Istituto Nazionale di Statistica
49	SE1m	ESPON M4D, Czech Statistical Office
50	SE1n	ESPON M4D, Statistische Ämter des Bundes und der Länder
51	SE1o	ESPON M4D, Office Fédéral de la Statistique Suisse
52	TE1b	ESPON M4D
53	TE1c	ESPON M4D
54	TE1d	ESPON M4D
55	TE1e	ESPON M4D
56	TE1f	ESPON M4D
57	TE1g	ESPON M4D
58	TE1h	ESPON M4D
59	TE1i	ESPON M4D
60	TE1j	ESPON M4D
61	TE1k	ESPON M4D
62	TE1l	ESPON M4D
63	TE1m	ESPON M4D
64	TE1n	ESPON M4D
65	TE1o	ESPON M4D
66	TE1p	ESPON M4D
67	TE1q	ESPON M4D
68	TE1r	ESPON M4D
69	TE2a	ESPON M4D
70	TE2b	ESPON M4D
71	TE2c	ESPON M4D
72	TE3a	ESPON M4D
73	TE3b	ESPON M4D
74	TE3c	ESPON M4D

75	TE3d	ESPON M4D
76	TE3e	ESPON M4D
77	TE3f	ESPON M4D
78	TE3g	ESPON M4D
79	TE6a	ESPON M4D
80	TE6b	ESPON M4D
81	TE6c	ESPON M4D
82	TE6d	ESPON M4D
83	TE6e	ESPON M4D
84	TE6f	ESPON M4D

The RIATE team observed that data was more often missing for NUTS3 units than NUTS 2, and more often NUTS2 than NUTS1. Their other observation was that data is either missing from the beginning of the series to an intermediate time period, or missing in a run in the middle of the series. That the NUTS hierarchy provides a parent $NUTS_{level-1}$ region for any groups of $NUTS_{level}$ regions lead them to an ingenious group of solutions based around LOCF. These boil down essentially to two strategies.

Let $p_{t,r}$ be the proportion of the parent $NUTS_{level-1}$ region's population for $NUTS_{level}$ region r in year t, and N_r is the number of $NUTS_{level}$ regions in a parent $NUTS_{level-1}$ region. In any given year the following is true:

$$\sum_{r=1}^{Nr} p_{t,r} = 1$$

Data missing from beginning of series

In the first case, which the RIATE team describe as *retropolation*, the data are missing from 1990 to the time period *last*. The proportions are propagated backwards along the series from the earliest known value, $p_{last+1,r}$.

$$p_{t,r} = p_{last+1,r}$$
$$t = 1990...last$$

The population estimates for the NUTSlevel regions are then obtained by multiplying the appropriate NUTSlevel-1 population by the retropolated $p_{t,r}$ values.

Data missing from the middle of a series

In the second case, that of interpolation, the data are missing from time period *first* to time period *last* inclusive. This implies that the proportions are are known for time period *first-1* and time period *last+1*. The intermediate proportions are obtained by linear interpolation. If $p_{first-1,r}$ and $p_{last-1,r}$ are the known proportions of the time periods immediately adjacent to the run of missing observations, then:

$$p_{t,r} = \left(p_{last+1,r} - p_{first-1,r}\right)\left(\frac{t - first + 1}{last - first + 2}\right)$$
$$t = first...last$$

The population estimates for the NUTSlevel regions are then obtained by multiplying the appropriate NUTSlevel-1 population by the interpolated $p_{t,r}$ values.

Data missing from the end of the series

In a case analogous to the first, values of the proportions can be propagated forward from the latest known $p_{first-1,r}$ to 2012 (or whatever is the last time period in the study) in an *extrapolation*:

$$p_{t,r} = p_{first-1,r}$$
$$t = first...2012$$

These imputations represent the application of an AR(0) time series model where the trend for the first and last case is zero, and linear in the interpolation case. The imputed values will then exhibit the same behavioural characteristics of the parent series.

Partially missing data

In some cases, data is missing for a subset *missing* of the $NUTS_{level}$ regions. The proportions are then of the $NUTS_{level-1}$ population less the sum of the non-*missing* $NUTS_{level}$ populations. If data is missing for only one region at $NUTS_{level}$, then we can regard it as *embarrassingly estimatable*, in that the missing values are obtained from the population for the NUTSlevel-1 region less the sum of the non-*missing* $NUTS_{level}$ populations, without the need to bring the LOCF procedures into play.

Estimation and the NUTS hierarchy

The implementation of this approach implies that the estimation strategy is *top-down*. That is, as the proportions for $NUTS_{level}$ relative to $NUTS_{level-1}$ are required, then the values at $NUTS_{level-1}$ must be obtained first. Therefore, population estimates at NUTS1 must be made first, relative to the NUTS0 values. Once these have been obtained, estimates at NUTS2 may be made, and finally, estimates at NUTS3.

The RIATE implementation was undertaken using Excel. Whilst this represents activity and effort which might be regarded as heroic, it is almost impossible to debug, very difficult to check, and cannot be automated. For these reasons, it cannot be recommended.

Missing data scenarios

Populating the tables to NUTS 3 level over the period 1990-2013 with (a) Eurostat data and (b) data from the National Statistical Offices reveals some recurrent patterns with regard to missing data. The diagrams below, we use four colours when depicting the patterns of present and absent data:

Green: Eurostat data present ("present" data series)
Blue: Eurostat data not present; National Statistical Agency data present; both series agree for later (or earlier) time periods ("concordant" data series)
Yellow: Eurostat data not present; National Statistical Agency data present; both series disagree for later (or earlier) time periods ("discordant" data series)
Red: Neither Eurostat nor external data available ("missing" data)

Several scenarios arise when data is missing for several consecutive time periods:

FI1C	Etelä-Suomi	1116597	1119701	1123651	1126593	1127988
FI1C1	Varsinais-Suomi		425282	427158	428864	430409
FI1C2	Kanta-Häme		162248	163442	164363	164767
FI1C3	Päijät-Häme		197012	197753	198329	198503
FI1C4	Kymenlaakso		193919	194182	194160	193784
FI1C5	Etelä-Karjala					

- Data is present for a NUTS region, concordant for *n-1* of the NUTS3 regions which it contains, and discordant for one region.
- Data is present and estimable for all but one time period at NUTS3 but there is a total available for NUTS2

FI19	Länsi-Suomi	1295857	1300085	1304793	1308650	1311353
FI193	Keski-Suomi		257967	259842	261046	261805
FI194	Etelä-Pohjanmaa		201670	201972	202333	202477
FI195	Pohjanmaa		172448	173183	173788	174083
FI196	Satakunta					
FI197	Pirkanmaa					

- Data is present for a NUTS region, concordant for *n-p* of the NUTS3 regions which it contains, and discordant for *p* regions.

NL42	Limburg (NL)			1103960	1109841	1115485
NL421	Noord-Limburg	257225	258103	259488	260904	262411
NL422	Midden-Limburg					
NL423	Zuid-Limburg					

- Data is partially present at NUTS2, there is some concordant data at for n-p of the NUTS3 regions which is contains, and discordant data for others.

BE2	Vlaams Gewest	5739736	5767856	5794857	5824628	5847022	5866106	5880357	5898824	5912382	5926838
BE21	Prov. Antwerpen	1597310	1604566	1610695	1619613	1625069	1628710	1631243	1635640	1637857	1640966
BE211	Arr. Antwerpen	922755					933388				
BE212	Arr. Mechelen	294858					300692				
BE213	Arr. Turnhout	379697					394630				

- Data is present at NUTS2, and for one or more time period in the NUTS3 series there is concordant data. The rest of the NUTS3 data are missing.

- Data is present at NUTS2, and for one or more time period in the single NUTS3 series there is concordant data. The rest of the NUTS3 data are missing. (This occurs when the NUTS3 region is also the NUTS2 and NUTS1 region, for example, BE1/BE10/BE100).

FI19	Länsi-Suomi	1295857	1300085	1304793	1308650	1311353
FI193	Keski-Suomi		257967	259842	261046	261805

- Data is present at NUTS2, and is missing for a single time period at NUTS 2 as part of a concordant series.

FI2	Åland	24231	24604
FI20	Åland	24231	24604
FI200	Åland		24604

- There is missing data at NUTS3 when the NUTS1, NUTS2 and NUTS3 regions are the same spatial unit

ES	Spain	36826297	38874573	39003524	39131966	39246833	39343100	39430933	39525438	39639388	39802827	40049708	40476723	40964244	41663702	42345342
ES1	Noroeste (ES)	4373425	4356370	4351660	4347446	4342421	4332673	4320217	4307185	4295048	4285691	4278779	4293441	4290590	4299733	4311316
ES11	Galicia	2744800	2733854	2730372	2727995	2725377	2719536	2711516	2702667	2694580	2689042	2684551	2697288	2693733	2699955	2706126
ES111	A Coruña													1095177	1098938	1102689
ES112	Lugo													357050	355145	353238
ES113	Ourense													337968	336713	335452
ES114	Pontevedra													903538	909159	914747

- Data is present at NUTS2, and there is a small corpus of concordant NUTS3 data, but for the majority of the *n* regions all the data at NUTS3 are missing.

ES21	País Vasco	2114894	2104629	2101091	2096229	2091482	2084996	2078931	2075028	2072017	2069723	2070279	2078441	2082258	2087972	2094909
ES211	Álava													286426	289140	292028
ES212	Guipúzcoa													673596	675970	678730
ES213	Vizcaya															

- This is an extension of the above cases with missing data for one NUTS3 region when the other n-1 regions have concordant data

ES62	Región de Murcia	1038380	1045048	1056416	1067842	1079007	1089176	1098386	1109020	1120122	1132821
ES620	Murcia										
ES63	Ciudad Autónoma de Ceuta (ES)			68058	68590	69152	69549	69959	70261	70605	70846
ES630	Ceuta (ES)										
ES64	Ciudad Autónoma de Melilla (ES)			57509	58609	59654	60599	61540	62439	63303	64167
ES640	Melilla (ES)										

- Data is missing at NUTS3 for regions where NUTS3 and NUTS2 boundaries are coterminous.

ES21	País Vasco	2082258	2087972	2094909	2103441	2113052
ES211	Álava	286426	289140	292028	295699	299103
ES212	Guipúzcoa	673596	675970	678730	680651	683504
ES213	Vizcaya				1127091	1130445

- Eurostat data is present at all part of the series at NUTS 2 and NUTS3. Concordant data in available for n-1 NUTS2 regions and 1 NUTS3 region is missing.

This leads to the conclusion that the missing data can be handling in a manner in which the available data can be used as evidence to complete the missing elements in the various series, and ensure data is also spatially consistent. It also leads us to conclusion that the missing data should be built from the lowest levels in the NUTS hierarchy first. With this in mind we start with the simplest cases, and recursively apply more complex solutions as and when they are required.

3. Missing data imputation

Estimation

The scenarios suggest that we will require three components in the estimating strategy: (a) a suitable model for the existing data and (b) a means of ensuring hierarchical spatial coherence in the series and (c) a means of representing the spatial hierarchy of the NUTS regions in each country

Experimentation of the existing ESPON series suggests that some relatively simple models will yield reasonable results for the first component. Each series can be modelled with either a linear, quadratic or exponential trends, with an autocorrelated error term:

$$P_t = a_0 + a_1 t + \varepsilon_t$$
$$Pt = a_0 + a_1 t + a_2 t^2 + \varepsilon_t$$
$$P_t = a_0 e^{a_1 t} + e_t$$

where the error term is $\varepsilon_0 \sim N(0,\tau)$ and $\varepsilon_t \sim N(\rho\varepsilon_{t-1},\tau)$ with $t > 0$ and $|\rho|<1$.. The parameters a_0, a_1 and a_2 are to be estimated. Both models can handle missing values – points for which no data is available – as well as provide forecasts, backcasts and interpolation of missing data in the middle of a series. The generic term *prediction* covers these three eventualities.

Models for time series

To estimate data for a time series we need to start with a model. There are many such models in the time series analysis literature which may be applied. In an autoregressive model the value of the series at time t depends on *p* previous values:

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t$$

By contrast in a moving average model, the error at time t depends on q previous values:

$$X_t = \mu + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j}$$

These can be combined to give an autoregressive moving average model:

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j}$$

Such models were given extensive treatment in Box and Jenkins (1970)[9]. They are conventionally fitted to a series which is stationary (that is, in which the trend has been removed), a situation obtained by differencing. If the trend is linear, the series might need to be differenced once (i.e. $\Delta_t = X_t - X_{t-1}$); if the trend is accelerating, second differences might be required. However, typically to obtain reliable estimates of the *p* autoregressive parameters and the *q* moving average parameters requires series of perhaps many 10s of observations. We no have this luxury with the ESPON series.

Al alternative is to consider methods using Bayesian inference. We conventionally model data D with some parameters θ using the probability distribution $P(D|\theta)$; the θ might be the parameters from a regression model (slope, intercept and error variance). Using Bayes theorem, this can be inverted to yield a probabilistic statement about θ given the data D:

$$P(\theta \mid D) = P(\theta)\frac{P(D \mid \theta)}{\int_{\theta} P(D \mid \theta) d\theta}$$

The denominator is not usually analytically soluble; solutions can be found using Markov Chain Monte Carlo (MCMC) techniques which simulate random θ values from $P(\theta|D)$. $P(\theta|D)$ is known as the *posterior* distribution of the parameters.

The MCMC approach has the useful property that it can be used to estimate the missing values. The posterior distribution of the missing data can be considered in the same way other unknown quantities. If D* is the unobserved data, then the posterior predictive distribution of the data is:

$$P(D^* \mid D) \propto P(\theta)P(D \mid \theta)P(D^* \mid \theta)$$

This gives a means of estimating the missing data, using the available data as evidence.

Bayes models

Using Bayesian techniques involves a somewhat different approach than traditional frequentist models. Using the example of the Austria population, we will fit an ordinary least squares regression model, a Bayesian version of the same, and then a Bayesian time series model with linear trend.

We start with the data, the population estimate in each year in millions:

```
> AT
 [1] 7.644818 7.710882 7.798899 7.882519 7.928746 7.943489 7.953067 7.964966
 [9] 7.971116 7.982461 8.002186 8.020946 8.063640 8.100273 8.142573 8.201359
[17] 8.254298 8.282984 8.318592 8.355260 8.375290 8.404252
```

These are the populations from 1990 to 2011, and we will regress these against the year number (running from 1 to 22 inclusive).

```
> m1 <- lm(AT ~ Year)
```

[9] Box, GEP and Jenkins GM, 1970, *Time Series Analysis Forecasting and Control*, Holden-Day: San Francisco

```
> summary(m1)

Call:
lm(formula = AT ~ Year)

Residuals:
      Min        1Q    Median        3Q       Max
-0.076560 -0.036842  0.008816  0.018307  0.078670

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 7.689203   0.018510  415.42  < 2e-16 ***
Year        0.032175   0.001409   22.83 8.51e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.04194 on 20 degrees of freedom
Multiple R-squared:  0.963,     Adjusted R-squared:  0.9612
F-statistic: 521.2 on 1 and 20 DF,  p-value: 8.512e-16
```

The equation that we construct from these results is $Y_t = 7.689 + 0.032Year_t$. As the population levels are expressed in millions and thus we interpret the annual population increase to be about 32000, from a start of 7.689m. The 95% confidence interval for the intercept is 7.653 to 7.726, and the slope is from 0.0294 to 0.0349.

The JAGS model is specified in a slightly different fashion:

```
require(rjags)
modelCode <- "
   model{
      for(i in 1:N) {
         Y[i] ~ dnorm(mu[i], tau)
         mu[i] <- alpha + beta*x[i]
      }
      alpha ~ dnorm(0, 0.0001)
      beta  ~ dnorm(0, 0.0001)
      sigma <- 1.0/sqrt(tau)
      tau   ~ dgamma(0.001, 0.001)
   }
"

modelData <- list(N=N, Y=AT, x=Year)
modelMCMC <- jags.model(textConnection(modelCode), modelData)
Compiling model graph
   Resolving undeclared variables
   Allocating nodes
   Graph Size: 98

Initializing model
update(modelMCMC, n.iter=1000)
modelOutp <- coda.samples(modelMCMC, n.iter=1000,
variable.names=c("alpha","beta","sigma"))
summary(modelOutp)
Iterations = 1001:2000
Thinning interval = 1
Number of chains = 1
Sample size per chain = 1000

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

         Mean       SD  Naive SE Time-series SE
alpha 7.68484 0.020033 6.335e-04      0.0017574
beta  0.03250 0.001527 4.829e-05      0.0001331
```

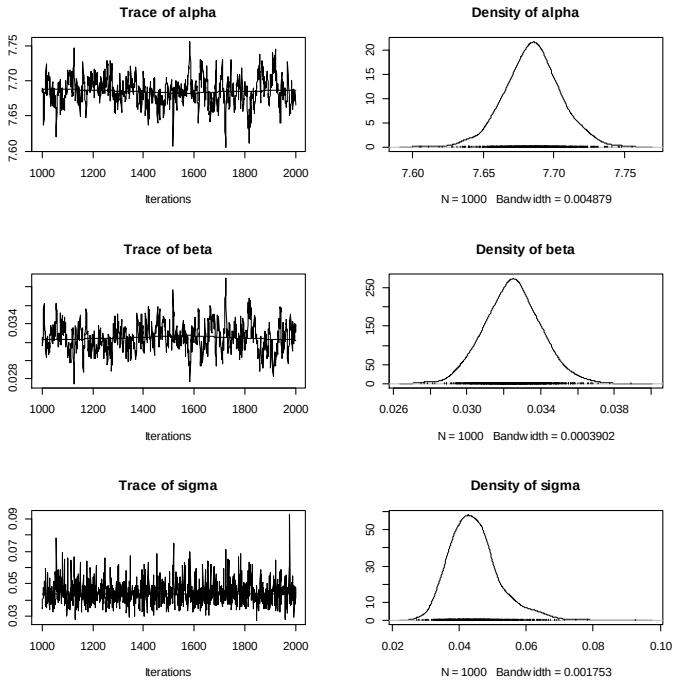
```
sigma 0.04456 0.007543 2.385e-04      0.0002708

2. Quantiles for each variable:

         2.5%     25%     50%     75%   97.5%
alpha 7.64190 7.67253 7.68519 7.69708 7.72379
beta  0.02959 0.03148 0.03250 0.03345 0.03563
sigma 0.03289 0.03959 0.04364 0.04841 0.06311
```

We are required supply the observation equation for Y, the system equation for mu, and our suggestions for the prior distributions. Y will be sampled from a normal distribution, with mean mu_i. The priors for the coefficients, *alpha* and *beta*, will be sampled from a normal distribution, and the precision, *tau*, from a gamma distribution. In JAGS the precision tau is used to specify the variation of the samples, and if we want the value of the standard deviation, *sigma*, then we must supply the deterministic identity between it and tau.

We subject the model to a burn-in period of 1000 samples, and then we used 1000 samples from the Gibbs Sampler to derive the posterior distributions of the parameters. The mean values for alpha and beta are similar the OLS estimates, and the 95% quantiles correspond to the OLS 95% confidence limits. We can also plot the distributions of the posteriors.



The density plots indicate the variability in the posterior estimates. Note that some of the variance has been incorrectly assigned to observation variance, since the terms in the model are autocorrelated.

Tho add in an autocorrelated error term we must make further changes to the model. The autocorrelation is modelled using a multivariate normal distribution. The mu_i terms are formed as before, but the autocorrelation is represented with a covariance matrix between the terms in the series, where each entry is $\sigma^2\rho$ raised to the power of the lag between the terms. The parameter r is the measure of the autocorrelation and we sample from a beta distribution. As with the previous model, the precisions in the prior distributions are purposely small

since we have few initial views as to their values – these are known as non-informative priors.

```
TSmodelCode <- "
model
   {

  # Prior distributions
  alpha  ~ dnorm(0.0,     0.001)
  beta   ~ dnorm(0.0, 0.000001)
  s2err  ~ dgamma(1, 50)
  rho    ~ dbeta(10, 10)

  # linear trend
  for(i in 1:N) {
    mu[i] <- alpha + beta*x[i]
  }

  # AR(1)
  for(i in 1:N) {
     for (j in 1:N) {
        tdmat[i,j] <- s2err*rho^abs(i-j)
     }
  }

  Omega <- inverse(tdmat)
  Y ~ dmnorm(mu, Omega)

}
"
TSmodelData <- list(N=N, Y=AT, x=Year)
TSmodelMCMC <- jags.model(textConnection(TSmodelCode), TSmodelData)
update(TSmodelMCMC, n.iter=1000)
TSmodelOutp <- coda.samples(TSmodelMCMC, n.iter=1000,
variable.names=c("alpha","beta","rho"))
summary(TSmodelOutp)
Iterations = 2001:3000
Thinning interval = 1
Number of chains = 1
Sample size per chain = 1000

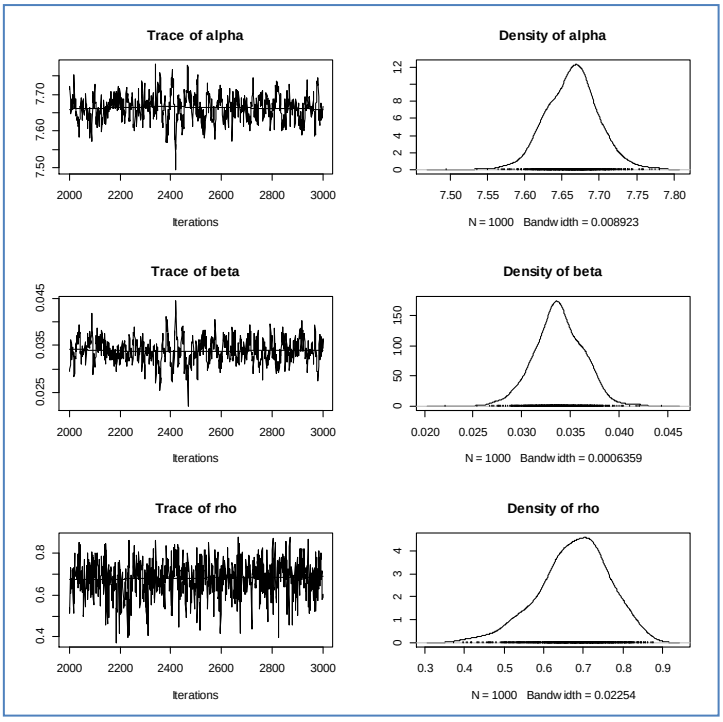
1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

         Mean       SD  Naive SE Time-series SE
alpha 7.66386 0.034738 1.099e-03      0.0028414
beta  0.03384 0.002524 7.981e-05      0.0002024
rho   0.67646 0.088610 2.802e-03      0.0042998

2. Quantiles for each variable:

         2.5%     25%     50%     75%   97.5%
alpha 7.59609 7.64060 7.66482 7.68551 7.73393
beta  0.02897 0.03227 0.03377 0.03547 0.03859
rho   0.47815 0.62342 0.68226 0.73684 0.82952
plot(TSmodelOutp)
```

The terms in the linear trend are little different from the OLS counterparts, although the 95% quantiles are a little wider. By ignoring the autocorrelation, we underestimated the variability in the intercept and slope terms. The plot below shows the variation in the coefficient distributions.



Some of the ESPON time series appeared to have non-linearity in their trend, so we added a quadratic term into the model to account for this – the coefficient will be near zero if there is insufficient evidence of non-linearity.

Dealing missing values is more complex still. The model is:

```
model
{


    # Prior distributions
    b0      ~ dnorm(0.0, 0.000001)                  # intercept
    b1      ~ dnorm(0.0, 0.000001)                  # linear coefficient on time
    b2      ~ dnorm(0.0, 0.000001)                  # quadratic time term
    s2err   ~ dgamma(1, 50)                         # residual variance
    rho ~ dbeta(10,10)                              # AR(1) parameter

    # Trend component
    for(i in 1:N) {
       mu[i] <- b0 + b1*year[i] +b2*yearsq[i]
    }

    # Autocorrelation component
    for(i in 1:N) {
       for (j in 1:N) {
          tdmat[i,j] <- s2err*rho^abs(i-j)
    }}

    for (i in 1:length(seen)) {
       for (j in 1:length(seen)) {
          tdmat22[i,j] <- tdmat[seen[i],seen[j]]
    }}

    itdmat22 <- inverse(tdmat22)

    for (i in 1:length(missing)) {
       for (j in 1:length(missing)) {
          tdmat11[i,j] <- tdmat[missing[i],missing[j]]
```

```
    }}

    itdmat11 <- inverse(tdmat11)

    for (i in 1:length(missing)) {
       for (j in 1:length(seen)) {
          tdmat12[i,j] <- tdmat[missing[i],seen[j]]
    }}

    for (i in 1:length(seen)) {
       for (j in 1:length(missing)) {
          tdmat21[i,j] <- tdmat[seen[i],missing[j]]
    }}

    for (i in 1:length(seen)) {
       mu2[i] <- mu[seen[i]]
    }

    for (i in 1:length(missing)) {
       mu1[i] <- mu[missing[i]]
    }

    OmegaM <- inverse(tdmat11 - tdmat12 %*% itdmat22 %*% tdmat21)
    muM <- mu1 + tdmat12 %*% itdmat22 %*% (ys - mu2)

    ys ~ dmnorm(mu2,itdmat22)                    # non-missing data
    ym ~ dmnorm(muM, OmegaM)                     # missing data
}
```

The *seen* and *missing* variables contain the indices in the time series where the population estimates are present and missing respectively. The linkage between the missing and present values is rather more complex. These results are standard for time series, and can be found in any time series text (e.g.: Chatfield, 1984)

The series is modelled sampling from a multivariate normal distribution, with a vector of *means* μ resulting from the trend component, and a *precision matrix* (the inverse of the matrix of covariances between the terms in the series). If there was no requirement to interpolate missing values, the precision matrix would be:

$$\Omega = \left(\sigma^2 \rho \Lambda\right)^{-1}$$

where σ^2 is the variance of the error, ρ is the autocorrelation parameter and Λ is a matrix of lags. If the time series had 5 terms, Λ would contain:

```
     [,1] [,2] [,3] [,4] [,5]
[1,]    0    1    2    3    4
[2,]    1    0    1    2    3
[3,]    2    1    0    1    2
[4,]    3    2    1    0    1
[5,]    4    3    2    1    0
```

The multivariate normal has density:

$$\left(\frac{|\Omega|}{2\pi}\right) e^{-\frac{(x-\mu)^T \Omega (x-\mu)}{2}}$$

where Ω is the precision and μ is the mean. The challenge arises when we have missing data.

The series is divided into the *present* and *missing* sub-series. The means for each part are drawn from the trend estimate.

The following covariance submatrices are required:

	missing	present
missing	Σ_{11}	Σ_{12}
present	Σ_{21}	Σ_{22}

The precision matrix Ω_p for the present data is:

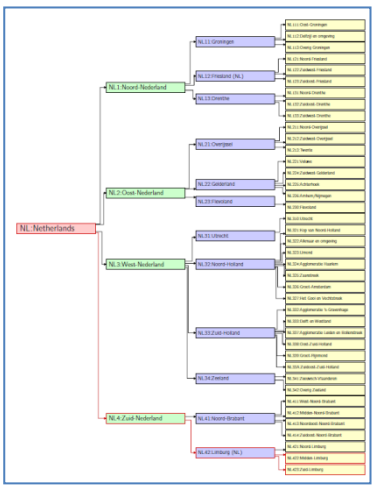
$$\Omega = \left(\sigma^2 \rho \Lambda_{22}\right)^{-1}$$

This missing and present terms are linked through the precision matrix used to estimate the posterior distributions of the missing terms, Ω_m thus:

$$\Omega_m = (\Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21})^{-1}$$

As well as there being more individual steps in this model, the estimation requires two matrix inversions. In estimations for the ESPON data, the 250000 simulations were used for the burn-in process, and 100000 for the actual sampling. Even so, on a relatively sluggish machine, about 105 seconds were used when estimation a model on data with 22 time periods and 54% of the data missing.

Spatial coherence



The second component requires a set of constraints to ensure that predictions for NUTS3 units sum to the appropriate value for their containing NUTS2 units, and that predictions for NUTS2 units sum to the appropriate value for the containing NUTS1 units as so on. We refer to this as hierarchical spatial coherence. If we have a NUTS2 region with population P, and we know the populations of three of its, say 5, units, *a*, *b* and *c*, but not *d* and *e*, then we can include P=*a*+*b*+*c*+*d*+*e* as a constraint in the Bayesian forecasting framework. This is accomplished via a prior probability distribution: *a*+*b*+*c*+*d*+*e* will take the P with a probability of 1, and zero otherwise. In this fashion we can ensure spatial coherence in the forecasts.

In practice the application of the this constraint occurs after the individual series have been estimated - we apply an adjustment to the individual NUTS3 region

estimates to the estimates so that their total is that of the containing NUTS2 region. This adjustment applies from the NUTS1 regions downwards to ensure the spatial coherence of the estimates. It has to be remembered that we are not appling a pro-rata to a series of individual estimates, we are adding the posterior distributions together. The highest posterior density of the summed series is the value of the constraining total.

The same idea applies for those data that are considered to be embarrassingly estimatable. Suppose the know the populations of a NUTS2 region, and 3 of the 4 NUTS3 regions which are contained within it. Then $P_{NUTS3,4} = P_{NUTS2} - (P_{NUTS3,1}+P_{NUTS3,2}+P_{NUTS3,3})$. The known data can be considered to be sampled from a distribution with a mean corresponding to the known value and infinite precision (i.e. the variance is zero). The known value is then the highest posterior density value, and it has a probability of 1 (with a variance of zero, there can be no other probability!).

Similarly the situation where a NUTS2 value is missing, but the underling NUTS3 values are present, then the same approach yields the estimate $P_{NUTS2} = P_{NUTS3,1}+P_{NUTS3,2}+P_{NUTS3,3}+ P_{NUTS3,4}$. Again, the known NUTS3 values are assumed to be sampled from a distribution with a mean of $P_{NUTS3,x}$ and an infinite precision - which means that the known values have a posterior probability of 1. The resulting posterior distribution for the P_{NUTS2} total also has a probability of 1.

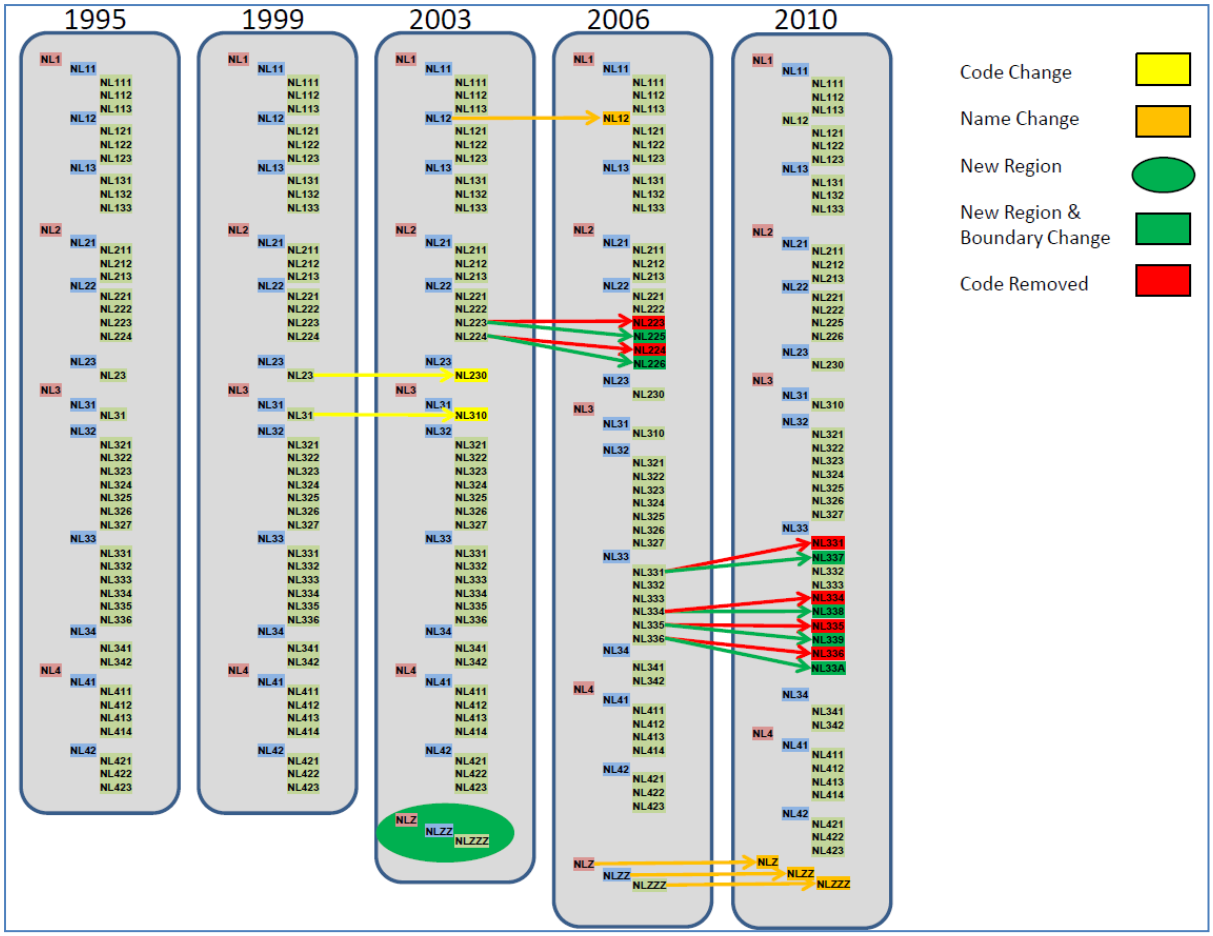
We require one further component in operationalisation of the method: a means of identifying the various scenarios and considering the hierarchical coherence. The files of data from Eurostat and the National Statistical agencies usually have the NUTS codes in a single column, and a *flat* file structure: the rows represent spatial units and the columns variables of interest. This effective;y flattens the hierarchical stricture of the NUTS units, and, if the calculations are restricted to the spreadsheet, renders the task of ensuring hierarchical coherence enormously difficult. An alternative to use the conceptual representation of the BUTS units as belong to some sort of tree structure – like a family tree – in which the higher level units are represented as the parents of lower level units.

Tree structures are extensively used in computer science to represent data. A tree many defined as having a *root* and one or more *subtrees* each of which is a tree. For each country, the root is the NUTS0 region, and the NUTS1 regions are the first subtrees. Each NUTS1 subtree has corresponding NUTS2 subtrees, and each NUTS2 region has corresponding NUTS3 subtrees.

The example shows the NUTS hierarchy for the Netherlands. We can see the hierarchy clearly and explicitly. It also forms the basis for the software implementation of the MCMC approach.

Other issues

One issue which will have to be faced is that of ensuring temporal coherence for the changes that have taken place in the system of NUTS units over the years. Boundaries of zones may be shifted, zones may be merged, and zones may be split. Correspondance tables are available at EUROSTAT.



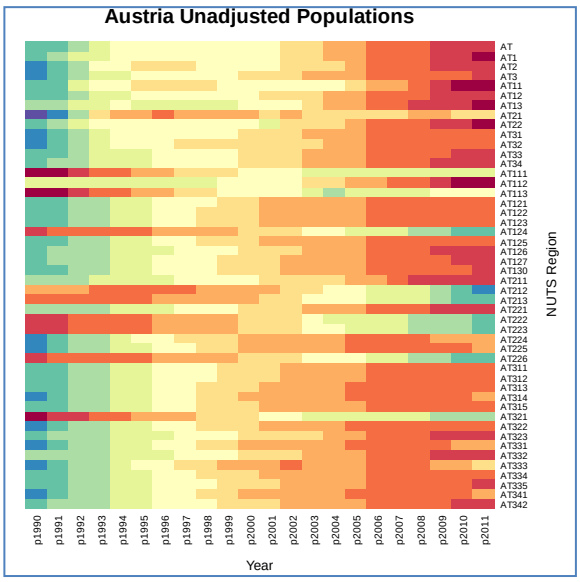
The diagram above shows the changes in the NUTS regions for the Netherlands. Again, the split/merge/shift operations may be incorporated into the forecasting process though additional constraints in the Bayesian framework.

4. Implementation

How are we to implement this? We will require bespoke code, and we will require a means of both handling the Excel spreadsheets, the NUTS hierarchy, and the computations required for the estimating of the missing data.

Software for MCMC approaches has been, until recently, the province of the specialist. This altered with the release of BUGS (**B**ayesian inference **U**sing **G**ibbs **S**ampling) (Lunn et al., 2009, 2012). BUGS has now been extended with a Windows interface (WinBUGS) and to handle spatial data (GeoBUGS). However, data preparation, and post-modelling evaluation requires other software. The release of JAGS (**J**ust **A**nother **G**ibbs **S**ampler) (Plummer, 2003) provides a further milestone. This offers a very similar facility to BUGS, but it is open source and may also be used in conjunction with the statistical programming language R via the *rjags* package in R. This offers R users the capability of fitting models using MCMC, but also exploits the power and flexibility of R, in order to prepare the data, and to provide extensive evaluation of the results. Using JAGS it is possible to obtain posterior distribution for the parameters outlined in the previous sections, and for the missing data. It is also worth noting that this approach also allows the constraint that the sum of all of the NUTS3 regions within a NUTS2 region must equal the statistic associate with that NUTS2 region.

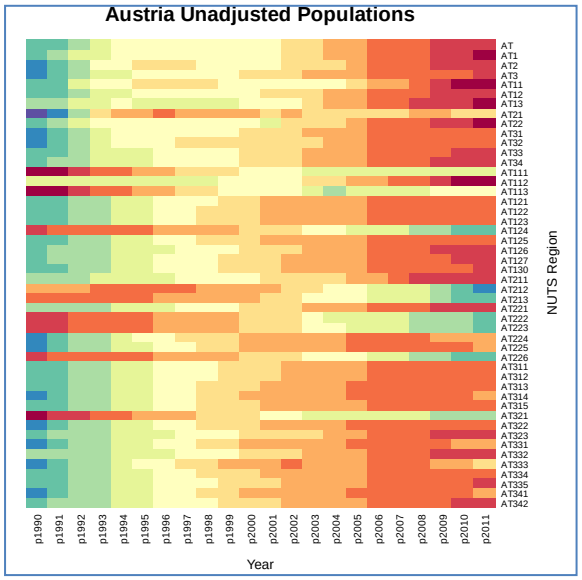
The R package has also been used to implement the data checking procedures, and the RIATE team have also made use of R.



Estimation Stage 1: MCMC estimation

A simple example is provided by the NUTS regions of Austria. Population estimates are missing for all NUTS3 regions, from 1990 to 2001 inclusive. The first stage is to visualise the pattern of missing data.

The figure on the left shows a *heatmap* of the population totals. The colder colours in the spectrum represent lower populations and the warmer colours represent larger populations. In general the population for AT and its NUTS1 regions have grown over the 22 year time period from 1990 to 2011. However, the trajectory of some individual zones has been different: that for AT21 had considerable growth to the mid 1990s, and then a gradual decline over the rest of the time period. The pattern of missing data is quite clear.



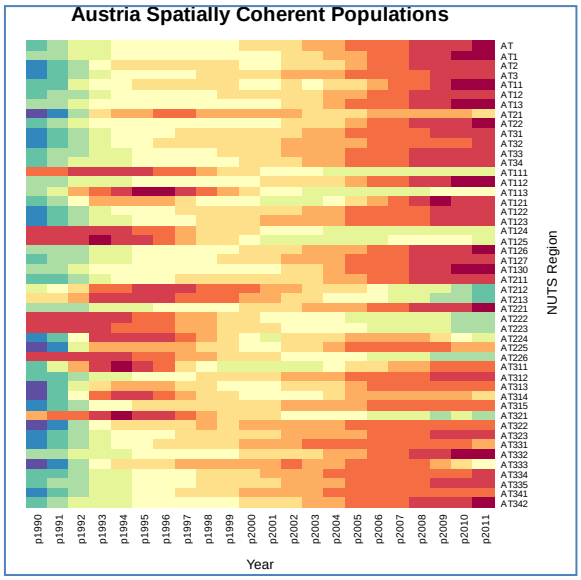
The initial imputation stage took just over an hour on a system with a *quad core 3.16GHz Intel Xeon* processor running Windows XP Professional. This scales to about 30 hours for the entire dataset. A more recent *Intel Core i7-2640M* processor running at 2.80GHz, with Windows 7 Professional, takes around 30 minutes for this task, which scales to around 18 hours for the whole of Europe. On an *Intel Core 2 Duo P8600* processor running at 2.4GHz, with Windows 7 Enterprise, the task took 1 hour 5 minutes. This is with 250000 iterations for the burn-in and 100000 iterations to generate the posterior probability distributions.

Data for 35 NUTS3 regions was missing – the time frame of 12 years represents approximately 55% of the NUTS3 data. This means that at best, we have 45% of the NUTS3 data as evidence on which to base the retropolations, although we also have 100% of the NUTS2 data to act as a constraint.

The values in the heatmap in Figure xx represent the variation in the unadjusted NUTS3 estimations.

Estimation Stage 2: adjustment for spatial coherence

We now apply the adjustment for the spatial coherence. This works in a bottom-up/top-down down fashion.



We start with the possibly incomplete NUTS2 and NUTS1 time series, and with the MCMC completed NUTS3 series. Any part of a time series at NUTS2 which is NA is completed using the sum of the MCMC populations for the corresponding NUTS regions and time periods. Equivalent completions are made for the missing parts of NUTS1 series, using the summed NUTS

From this it can be seen that missing data in the NUTS0, NUTS1 and NUTS2 regions can be a challenge. We can determine appropriate strategies by examining some cases from the data.

Consider the case of Croatia. A portion of the times series for all of the NUTS regions in Croatia is shown below:

```
> Data.estim[Country == "HR",4:16]
        p1990   p1991   p1992   p1993   p1994   p1995   p1996   p1997   p1998   p1999   p2000   p2001   p2002
HR    4778007 4784265 4470266 4641275 4649034 4668752 4493581 4572474 4501149 4553769 4381352 4437460 4444608
HR0   4778007 4784265 4470266 4641275 4649034 4668752 4493581 4572474 4501149 4553769 4381352 4437460 4444608
HR01       NA 1646710      NA      NA      NA      NA      NA      NA      NA      NA      NA      NA 1661396
HR02       NA 1557342      NA      NA      NA      NA      NA      NA      NA      NA      NA      NA 1349105
HR03       NA 1580213      NA      NA      NA      NA      NA      NA      NA      NA      NA      NA 1434107
HR011      NA  777826      NA      NA      NA      NA      NA      NA      NA      NA      NA  779145  780332
HR012      NA  282989      NA      NA      NA      NA      NA      NA      NA      NA      NA  309696  312046
HR013      NA  148779      NA      NA      NA      NA      NA      NA      NA      NA      NA  142432  141886
HR014      NA  187853      NA      NA      NA      NA      NA      NA      NA      NA      NA  184769  184420
HR015      NA  129397      NA      NA      NA      NA      NA      NA      NA      NA      NA  124467  124161
HR016      NA  119866      NA      NA      NA      NA      NA      NA      NA      NA      NA  118426  118551
HR021      NA  144042      NA      NA      NA      NA      NA      NA      NA      NA      NA  133084  132499
HR022      NA  104625      NA      NA      NA      NA      NA      NA      NA      NA      NA   93389   93029
HR023      NA   99334      NA      NA      NA      NA      NA      NA      NA      NA      NA   85831   85819
HR024      NA  174998      NA      NA      NA      NA      NA      NA      NA      NA      NA  176765  177143
HR025      NA  367193      NA      NA      NA      NA      NA      NA      NA      NA      NA  330506  330293
HR026      NA  231241      NA      NA      NA      NA      NA      NA      NA      NA      NA  204768  204455
HR027      NA  184577      NA      NA      NA      NA      NA      NA      NA      NA      NA  141787  141069
HR028      NA  251332      NA      NA      NA      NA      NA      NA      NA      NA      NA  185387  184798
HR031      NA  323130      NA      NA      NA      NA      NA      NA      NA      NA      NA  305505  305652
HR032      NA   85135      NA      NA      NA      NA      NA      NA      NA      NA      NA   53677   53466
HR033      NA  214777      NA      NA      NA      NA      NA      NA      NA      NA      NA  162045  163642
HR034      NA  152477      NA      NA      NA      NA      NA      NA      NA      NA      NA  112891  113406
HR035      NA  474019      NA      NA      NA      NA      NA      NA      NA      NA      NA  463676  467300
HR036      NA  204346      NA      NA      NA      NA      NA      NA      NA      NA      NA  206344  207112
HR037      NA  126329      NA      NA      NA      NA      NA      NA      NA      NA      NA  122870  123529
```

In 2001 all the NUTS3 data are present at NUTS1 and NUTS3, but not for NUTS2. As none of the NUTS3 values are estimates, then they can be summed over the NUTS2 codes to obtain the desired totals:

```
> tapply(HR[6:26,"p2001"],substr(rownames(HR)[6:26],1,4),sum)
   HR01    HR02    HR03
1658935 1351517 1427008
```

The missing data for NUTS2 and NUTS3 from 1992 to 2000 require two levels of constraint:

1. Use MCMC to estimate values for 1992 to 2000 for **all** the missing data points
2. Constrain the NUTS2 MCMC estimates to the NUTS1 value
3. Constrain the NUTS3 MCMC estimates to the newly constrained NUTS2 values

This is easily programmed accommodated in the constraining function, as we traverse the tree from the root downwards. By the time we deal with the NUTS3 estimates, the NUTS2 will have been constrained.

In the case of **Portugal**, there are some other special cases:

```
> Data.estim[substr(rownames(Data.estim),1,2)=="PT",]
     UnitCode Level                          Name   p1990   p1991   p1992   p1993   p1994   p1995    p1996
PT         PT NUTS0                      Portugal 9970441 9912140      NA      NA      NA      NA 10043180
PT1       PT1 NUTS1                    Continente      NA      NA      NA      NA      NA      NA  9556916
PT2       PT2 NUTS1 Região Autónoma dos Açores (PT)      NA      NA  239336  239271  239207  238807   238272
PT3       PT3 NUTS1 Região Autónoma da Madeira (PT)      NA      NA  253999  253059  252120  250165   247992
PT11     PT11 NUTS2                          Norte      NA      NA 3511771 3516484 3527789 3541805  3555975
PT15     PT15 NUTS2                        Algarve      NA      NA  341075  343336  345970  349658   353309
PT16     PT16 NUTS2                  Centro (PT)      NA      NA 2272111 2270518 2271336 2276261  2281286
PT17     PT17 NUTS2                         Lisboa      NA      NA 2574265 2581419 2585705 2593283  2599990
PT18     PT18 NUTS2                       Alentejo      NA      NA  772760  770509  768468  767593   766356
PT20     PT20 NUTS2 Região Autónoma dos Açores (PT)      NA      NA  239336  239271  239207  238807   238272
PT30     PT30 NUTS2 Região Autónoma da Madeira (PT)      NA      NA  253999  253059  252120  250165   247992
PT111   PT111 NUTS3                     Minho-Lima      NA      NA  252188  251518  250382  249541   248771
PT112   PT112 NUTS3                         Cávado      NA      NA  358355  360519  363498  366785   369787
```

The NUTS0 and NUTS1 values are missing for 1992 to 1995 for PT1. However, there is complete coverage of PT1 at NUTS2, so the value for PT1 can be obtained by direct summation over the corresponding NUTS2 values. The NUTS0 values can then be completed for those years as well.

It would be beneficial to be able to do this prior to MCMC since it is a deterministic operation and provide extra evidence for the MCMC estimation of the PT1 series for 1990 and 1991. Apart from the NUTS0 total, all other data for 1990 and 1991 is missing.

The strategy for 1990 and 1991 follows the top-down strategy outlined above, and provides a general case:

1. Constrain the NUTS1 MCMC estimates to the NUTS0 total
2. Constrain the NUTS2 MCMC estimates to the constrained NUTS1 values
3. Constrain the NUTS3 MCMC estimates to the constrained NUTS2 values

Again, this can be easily accomplished using the tree traversal algorithm.

Turkey is rather more of a challenge.

```
   UnitCode Level   Name    p1990 p1991 p1992 p1993 p1994 p1995 p1996 p1997
TR       TR NUTS0 Turkey 56473035    NA    NA    NA    NA    NA    NA    NA

   p1998 p1999    p2000 p2001 p2002 p2003 p2004 p2005 p2006 p2007    p2008
TR    NA    NA 67803927    NA    NA    NA    NA    NA    NA    NA 70586256

      p2009    p2010    p2011
TR 71517100 72561312 73722988
```

Data are present only for 1990, 2000, 2008-2011 for all NUTS regions, including NUTS0. The strategy here will be to estimate all the missing data using the MCMC technique. Then, we apply the hierarchical constraint working down the tree from NUTS0 to NUTS1, NUTS1 to NUTS2 and finally NUTS2 to NUTS3.

NUTS0, NUTS1 and NUTS2 regions with missing data are listed below:

```
Missing data for  PT Portugal
Missing data for  TR Turkey
Missing data for  UK United Kingdom

**************** NUTS1 Missing ****************************************
Missing data for  FR9 Départements d'outre-mer (FR)

Missing data for  NL3 West-Nederland

Missing data for  PL1 Region Centralny
Missing data for  PL2 Region Poludniowy
Missing data for  PL3 Region Wschodni
Missing data for  PL4 Region Pólnocno-Zachodni
Missing data for  PL5 Region Poludniowo-Zachodni
Missing data for  PL6 Region Pólnocny

Missing data for  PT1 Continente
Missing data for  PT2 Região Autónoma dos Açores (PT)
Missing data for  PT3 Região Autónoma da Madeira (PT)
Missing data for  TR1 Istanbul
Missing data for  TR2 Bati Marmara
Missing data for  TR3 Ege
Missing data for  TR4 Dogu Marmara
```

```
Missing data for  TR5 Bati Anadolu
Missing data for  TR6 Akdeniz
Missing data for  TR7 Orta Anadolu
Missing data for  TR8 Bati Karadeniz
Missing data for  TR9 Dogu Karadeniz
Missing data for  TRA Kuzeydogu Anadolu
Missing data for  TRB Ortadogu Anadolu
Missing data for  TRC Güneydogu Anadolu

Missing data for  UKC North East (UK)
Missing data for  UKD North West (UK)
Missing data for  UKE Yorkshire and The Humber
Missing data for  UKF East Midlands (UK)
Missing data for  UKG West Midlands (UK)
Missing data for  UKH East of England
Missing data for  UKI London
Missing data for  UKJ South East (UK)
Missing data for  UKK South West (UK)
Missing data for  UKL Wales
Missing data for  UKM Scotland
Missing data for  UKN Northern Ireland (UK)

**************** NUTS2 Missing ****************************************
Missing data for  CZ01 Praha
Missing data for  CZ02 Strední Cechy
Missing data for  CZ03 Jihozápad
Missing data for  CZ04 Severozápad
Missing data for  CZ05 Severovýchod
Missing data for  CZ06 Jihovýchod
Missing data for  CZ07 Strední Morava
Missing data for  CZ08 Moravskoslezsko

Missing data for  DE41 Brandenburg - Nordost
Missing data for  DE42 Brandenburg - Südwest
Missing data for  DED1 Chemnitz
Missing data for  DED2 Dresden
Missing data for  DED3 Leipzig
Missing data for  DK01 Hovedstaden
Missing data for  DK02 Sjælland
Missing data for  DK03 Syddanmark
Missing data for  DK04 Midtjylland
Missing data for  DK05 Nordjylland

Missing data for  HR01 Sjeverozapadna Hrvatska
Missing data for  HR02 Sredisnja i Istocna (Panonska) Hrvatska
Missing data for  HR03 Jadranska Hrvatska

Missing data for  IE01 Border, Midland and Western
Missing data for  IE02 Southern and Eastern

Missing data for  PL11 Lódzkie
Missing data for  PL12 Mazowieckie
Missing data for  PL21 Malopolskie
Missing data for  PL22 Slaskie
Missing data for  PL31 Lubelskie
Missing data for  PL32 Podkarpackie
Missing data for  PL33 Swietokrzyskie
Missing data for  PL34 Podlaskie
Missing data for  PL41 Wielkopolskie
Missing data for  PL42 Zachodniopomorskie
Missing data for  PL43 Lubuskie
Missing data for  PL51 Dolnoslaskie
Missing data for  PL52 Opolskie
Missing data for  PL61 Kujawsko-Pomorskie
Missing data for  PL62 Warminsko-Mazurskie
Missing data for  PL63 Pomorskie

Missing data for  PT11 Norte
```

```
Missing data for  PT15 Algarve
Missing data for  PT16 Centro (PT)
Missing data for  PT17 Lisboa
Missing data for  PT18 Alentejo
Missing data for  PT20 Região Autónoma dos Açores (PT)
Missing data for  PT30 Região Autónoma da Madeira (PT)

Missing data for  SK01 Bratislavský kraj
Missing data for  SK02 Západné Slovensko
Missing data for  SK03 Stredné Slovensko
Missing data for  SK04 Východné Slovensko

Missing data for  TR10 Istanbul
Missing data for  TR21 Tekirdag
Missing data for  TR22 Balikesir
Missing data for  TR31 Izmir
Missing data for  TR32 Aydin
Missing data for  TR33 Manisa
Missing data for  TR41 Bursa
Missing data for  TR42 Kocaeli
Missing data for  TR51 Ankara
Missing data for  TR52 Konya
Missing data for  TR61 Antalya
Missing data for  TR62 Adana
Missing data for  TR63 Hatay
Missing data for  TR71 Kirikkale
Missing data for  TR72 Kayseri
Missing data for  TR81 Zonguldak
Missing data for  TR82 Kastamonu
Missing data for  TR83 Samsun
Missing data for  TR90 Trabzon
Missing data for  TRA1 Erzurum
Missing data for  TRA2 Agri
Missing data for  TRB1 Malatya
Missing data for  TRB2 Van
Missing data for  TRC1 Gaziantep
Missing data for  TRC2 Sanliurfa
Missing data for  TRC3 Mardin

Missing data for  UKC1 Tees Valley and Durham
Missing data for  UKC2 Northumberland and Tyne and Wear
Missing data for  UKD1 Cumbria
Missing data for  UKD2 Cheshire
Missing data for  UKD3 Greater Manchester
Missing data for  UKD4 Lancashire
Missing data for  UKD5 Merseyside
Missing data for  UKE1 East Yorkshire and Northern Lincolnshire
Missing data for  UKE2 North Yorkshire
Missing data for  UKE3 South Yorkshire
Missing data for  UKE4 West Yorkshire
Missing data for  UKF1 Derbyshire and Nottinghamshire
Missing data for  UKF2 Leicestershire, Rutland and Northamptonshire
Missing data for  UKF3 Lincolnshire
Missing data for  UKG1 Herefordshire, Worcestershire and Warwickshire
Missing data for  UKG2 Shropshire and Staffordshire
Missing data for  UKG3 West Midlands
Missing data for  UKH1 East Anglia
Missing data for  UKH2 Bedfordshire and Hertfordshire
Missing data for  UKH3 Essex
Missing data for  UKI1 Inner London
Missing data for  UKI2 Outer London
Missing data for  UKJ1 Berkshire, Buckinghamshire and Oxfordshire
Missing data for  UKJ2 Surrey, East and West Sussex
Missing data for  UKJ3 Hampshire and Isle of Wight
Missing data for  UKJ4 Kent
Missing data for  UKK1 Gloucestershire, Wiltshire and Bristol/Bath area
Missing data for  UKK2 Dorset and Somerset
Missing data for  UKK3 Cornwall and Isles of Scilly
```

```
Missing data for  UKK4 Devon
Missing data for  UKL1 West Wales and The Valleys
Missing data for  UKL2 East Wales
Missing data for  UKM2 Eastern Scotland
Missing data for  UKM3 South Western Scotland
Missing data for  UKM5 North Eastern Scotland
Missing data for  UKM6 Highlands and Islands
Missing data for  UKN0 Northern Ireland (UK)
```

The NUTS regions structures and missing data

The spreadsheet provides a poor model for the NUTS hierarchy. The rows can be sorted on the NUTS codes sot that the first part of the spreadsheet represents country information, the NUTS1 regions are next, followed by NUTS2 and NUTS3. However, we can't easily identify quickly a NUTS2 region, and then its constituent NUTS3 regions – it may be possible to do this with lookup in an auxiliary table, but this does not provide any flexibility. From the point of estimating missing data, the requirement for spatial coherence requires us to be able to identify these relationships in the data quickly and consistently. We refer to the NUTS hierarchy, but have no mechanism for representing and using that hierarchy.

The solution is to create a data structure and associated travel algorithms so that we can work on the regions in a consistent fashion. An appropriate data structure is the tree. Trees are used widely in computer science for organising and searching for information. In the computing section of many academic bookshops there will be volumes with titles like *Data Structures and Algorithms*. A classic collection is the volumes in the series *The Art of Computer Programming* by Professor Donald Knuth. Knuth defines a tree thus:

> "… a finite set *T* of one or more nodes such that
>
> a) There is one specially designated node called the *root* of the tree, root(*T*); and
>
> b) The remaining nodes (excluding the root) are partitioned into *m* >= 0 disjoint sets T_1, … T_m and each of these sets in turn is a tree. The trees T_1, … T_m are called the subtrees of the root."[10]

This definition is recursive – the tree is defined in terms of trees. Put another way: *a tree consists of a root and one or more nodes, each of which is a tree*. A root which has no nodes is called a *leaf node*. There is an analogy with a family tree – a structure much used in genealogy: the non-root nodes are the children and the root represents the parents. As each node is itself a tree, we can also refer to the nodes as subtrees, because each is a tree.

The NUTS hierarchy can be represented as a tree quite naturally in terms of this definition. A node could consist of the NUTS code, and NUTS level and perhaps the population. The root would be the EU, and its 34 nodes contain the 34 NUTS0 codes, the value 0 for the level, and the national population. Each of these 34 nodes is itself a tree. Each NUTS0 nodes has one or more NUTS1 nodes, and in turn each NUTS1 node has one or more NUTS2 nodes and so on.

[10] Knuth DE, 1973, *Fundamental Algorithms*, The Art of Computer Programming, Volume 1, Reading MA: Addison-Wesley, p305

It may be unwieldy to deal with the whole of the EU, so we might confine our attentions to a single country – the root contains the NUTS0 code. Here is the structure for Belgium:

```
NUTS0 node is BE
 NUTS1 children of BE are BE1 BE2 BE3
  NUTS2 children of BE1 are BE10
   NUTS3 children of BE10 are BE100
  NUTS2 children of BE2 are BE21 BE22 BE23 BE24 BE25
   NUTS3 children of BE21 are BE211 BE212 BE213
   NUTS3 children of BE22 are BE221 BE222 BE223
   NUTS3 children of BE23 are BE231 BE232 BE233 BE234 BE235 BE236
   NUTS3 children of BE24 are BE241 BE242
   NUTS3 children of BE25 are BE251 BE252 BE253 BE254 BE255 BE256 BE257 BE258
  NUTS2 children of BE3 are BE31 BE32 BE33 BE34 BE35
   NUTS3 children of BE31 are BE310
   NUTS3 children of BE32 are BE321 BE322 BE323 BE324 BE325 BE326 BE327
   NUTS3 children of BE33 are BE331 BE332 BE334 BE335 BE336
   NUTS3 children of BE34 are BE341 BE342 BE343 BE344 BE345
   NUTS3 children of BE35 are BE351 BE352 BE353
```

Notice the order in which we have printed the list of regions. BE1, BE2 and BE3 are the child nodes of the root BE. BE1 has only one child BE10. BE2 has 5 children. The operation of visiting every node in a tree is referred to as *traversal*. The operation of visiting may consist of no more than printing the node NUTS code, but it might also consist of carrying out a spatial consistency check on the population total for the NUTS node and the sum of the population totals for its child nodes, or counting the number of child nodes with missing data. However, the operation might also include estimating any missing elements in a population or economic time series using MCMC techniques.

The order in which we have visited the nodes in the NUTS tree for Belgium is known as pre-order traversal. In a pre-order traversal we visit the root before visiting any of its subtrees.

The traversal is consistent for even for the case in which there is only one NUTS3 region:

```
NUTS0 node is LI
 NUTS1 children of LI are LI0
  NUTS2 children of LI0 are LI00
   NUTS3 children of LI00 are LI000
```

… or two NUTS3 regions:

```
NUTS0 node is MT
 NUTS1 children of MT are MT0
  NUTS2 children of MT0 are MT00
   NUTS3 children of MT00 are MT001 MT002
```

The R code for this traversal algorithm is quite short:

```
CheckTree <- function(Country,Data) {
   CountryData <- Data[substr(rownames(Data),1,2) == Country,]

   nodes  <- rownames(CountryData)
   parent <- substr(rownames(CountryData),1,nchar(rownames(CountryData))-1)
```

```
   parent[1] <- ""
   ROOT <- which(nodes == Country)
   cat("\nTree Walk\n")
      root <- nodes[ROOT]
      cat("NUTS0 node is ",root,"\n")
         children1 <- nodes[parent == root]
         cat(" NUTS1 children of", root, "are", children1,"\n")
         Nc1 <- length(children1)
         for (i in 1:Nc1) {
            node2 <- children1[i]
            children2 <- nodes[parent == node2]
            cat("  NUTS2 children of", node2, "are", children2,"\n")
            Nc2 <- length(children2)
            for (j in 1:Nc2) {
               node3 <- children2[j]
               children3 <- nodes[parent == node3]
               cat("   NUTS3 children of", node3, "are", children3,"\n")
            }
         }
}
```

The argument **`County`** contains the two character country code for the country of interest. The argument **`Data`** is the data matrix for Europe, where the rows have been indexed by their NUTS code. In our example, the first column of Data contains the NUTS code, code the indexing takes the form of:

```
Rownames(Data) <- Data[,1]
```

The tree for any desired country can be printed by calling the function with the appropriate country code. For the examples above we used:

```
CheckTree("BE",Data)
CheckTree("LI",Data)
CheckTree("MT",Data)
```

Missing data patterns in the ESPON time series

There are 8 possible patterns of missing data for each node. We can use the tree walk algorithm presented earlier to traverse the tree, and examine the patterns. As we visit each node, then we can tabulate the different patterns over the 22 years of the time series in the example.

The cases that arise for any selected time period are:

Case	Parent node	Child nodes	Note
1	Data present	All data present	No estimation required
2	Data missing	All data present	Parent can be computed
3	Data present	1 child node missing data	Child node embarrassingly estimatable
4	Data present	Some child nodes missing data	Estimation/constraint required
5	Data present	All child nodes missing data	Estimation/constraint required
6	Data missing	1 child node missing data	Higher order estimation required
7	Data missing	Some child nodes missing data	Higher order estimation required
8	Data missing	All child nodes missing data	Higher order estimation required

As we move down the table, the problem for the estimation strategy becomes more complex. Case 1 requires no action – all the data are present. Case 2 and

case 3 are examples of emabrassingly estimatable situations, the child or parent node data can be computed directly from the available data. Cases 4 and 5 require estimation of the child series using MCMC, and then application of the cross-sectional constraint. Cases 6, 7 and 8 are more challenging, and require estimation of the higher order data in order to provide the cross-sectional constraints.

The patterns can either be visualised using a heatmap – these are shown in Appendix 7. We can also use the tree traversal algorithm and a pattern analyser to check the patterns at each node. A sutiable tree traversal function is shown below. As each node is visited, the pattern of cases over the time periods is computed, and the stored in a data frame.

```
CheckMissingPattern <- function(Country,Data,dataCols,verbose=FALSE) {
   CountryData <- Data[substr(rownames(Data),1,2) == Country,]
   IDInfo <- CountryData[,1:3]
   Nc <- dim(IDInfo)[1]
   Results <- data.frame(IDInfo[,1:3],matrix(0,Nc,8))
   rownames(Results) <- rownames(CountryData)

   nodes  <- rownames(CountryData)
   parent <- substr(rownames(CountryData),1,nchar(rownames(CountryData))-1)
   parent[1] <- ""

   Nd <- length(dataCols)

   ### visit.node
   ###    for each child(visit.node)

   ROOT <- which(nodes == Country)
   if Iverbose) cat("\nTree Walk\n")
      root <- nodes[ROOT]
      if (verbose) cat("NUTS0 node is ",root,"\n")
         children1 <- nodes[parent == root]
         if (verbose) cat(" NUTS1 children of", root, "are", children1,"\n")
          Nc1 <- length(children1)
          CasePattern <- CheckNode(root,children1,Data,dataCols)
           Results[root,4:11] <- CasePattern
         for (i in 1:Nc1) {
            node2 <- children1[i]
            children2 <- nodes[parent == node2]
            if (verbose) cat("  NUTS2 children of", node2, "are", children2,"\n")
             Nc2 <- length(children2)
             CasePattern <- CheckNode(node2,children2,Data,dataCols)
             Results[node2,4:11] <- CasePattern
            for (j in 1:Nc2) {
               node3 <- children2[j]
               children3 <- nodes[parent == node3]
               if (verbose) cat("   NUTS3 children of",node3,"are", children3,"\n")
               Nc3 <- length(children3)
                CasePattern <- CheckNode(node3,children3,Data,dataCols)
                Results[node3,4:11] <- CasePattern
            }
         }
   NUTSlevels <- lapply(Results[,2], as.character)
   print(Results[NUTSlevels <= "NUTS2",])
}
```

This requires a function to carry out the analysis of the missing data patterns associated with each node:

```
CheckNode <- function(parent,children,Data,dataCols){
```

```
      Nc <- length(children)                # How many children for this parent
      MissingParent <- Data[parent,]        # Copy parent record
      Result <- Data[parent,]               # Create result record
      Cases <- rep(0,8)                     # 8 possible outcomes
      for (i in dataCols) {                 # loop over time period for this parent
         MissingParent[i] <- is.na(Data[parent,i])
         Result[i] <- length(which(is.na(Data[children,i])))
         if (!MissingParent[i]) {
              if (Result[i] == 0)                       k <- 1
              else if (Result[i] == 1)                  k <- 3
              else if (Result[i] > 1 & Result[i] < Nc)  k <- 4
              else                                      k <- 5
              } else {
              if (Result[i] == 0)                       k <- 2
              else if (Result[i] == 1)                  k <- 6
              else if (Result[i] > 1 & Result[i] < Nc)  k <- 7
              else                                      k <- 8
              }
              Cases[k] <- Cases[k] + 1

      }
      Cases           # Return count vector
}
```

Finally, we loop over the countries and report the patterns.

```
CountryList <- levels(as.factor(substr(rownames(Data.estim),1,2)))
Nc <- length(CountryList)
for (i in 1:Nc) {
   CheckMissingPattern(CountryList[i],Data.estim, 4:25)
}
```

The results for Austria are encouraging:

```
     UnitCode Level             Name X1 X2 X3 X4 X5 X6 X7 X8
AT         AT NUTS0          Austria 22  0  0  0  0  0  0  0
AT1       AT1 NUTS1    Ostösterreich 22  0  0  0  0  0  0  0
AT2       AT2 NUTS1    Südösterreich 22  0  0  0  0  0  0  0
AT3       AT3 NUTS1   Westösterreich 22  0  0  0  0  0  0  0
AT11     AT11 NUTS2  Burgenland (AT) 10  0  0  0 12  0  0  0
AT12     AT12 NUTS2 Niederösterreich 10  0  0  0 12  0  0  0
AT13     AT13 NUTS2            Wien 10  0 12  0  0  0  0  0
AT21     AT21 NUTS2         Kärnten 10  0  0  0 12  0  0  0
AT22     AT22 NUTS2       Steiermark 10  0  0  0 12  0  0  0
AT31     AT31 NUTS2   Oberösterreich 10  0  0  0 12  0  0  0
AT32     AT32 NUTS2         Salzburg 10  0  0  0 12  0  0  0
AT33     AT33 NUTS2            Tirol 10  0  0  0 12  0  0  0
AT34     AT34 NUTS2       Vorarlberg 10  0  0  0 12  0  0  0
```

At NUTS0, NUTS1 and NUTS2 all data are present. In the case of AT13, Wien, 1 of the NUTS3 units is missing data for 10 time periods, but these are embarrassingly estimatable, so the MCMC estimation is not required. For the other NUTS regions, data is missing for all NUTS3 regions connected to them, so estimation using MCMC and cross-sectional constraint will be required.

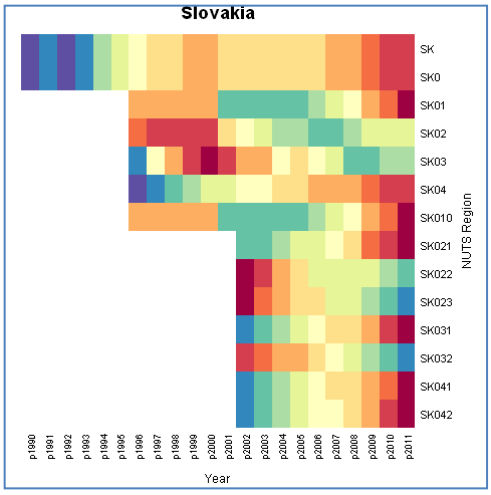
For Slovakia, the situation is a little more compelx:

```
     UnitCode Level               Name X1 X2 X3 X4 X5 X6 X7 X8
SK         SK NUTS0           Slovakia 22  0  0  0  0  0  0  0
SK0       SK0 NUTS1 Slovenská republika 16  0  0  0  6  0  0  0
SK01     SK01 NUTS2   Bratislavský kraj 16  0  0  0  0  6  0  0
```

SK02	SK02	NUTS2	Západné Slovensko	10	0	0	0	**6**	0	0	**6**
SK03	SK03	NUTS2	Stredné Slovensko	10	0	0	0	**6**	0	0	**6**
SK04	SK04	NUTS2	Východné Slovensko	10	0	0	0	**6**	0	0	**6**

The node tree is:

```
NUTS0 node is  SK
 NUTS1 children of SK are SK0
  NUTS2 children of SK0 are SK01 SK02 SK03 SK04
   NUTS3 children of SK01 are SK010
   NUTS3 children of SK02 are SK021 SK022 SK023
   NUTS3 children of SK03 are SK031 SK032
   NUTS3 children of SK04 are SK041 SK042
```



For SK0, there are 6 time periods where all the children (SK01, SK02, SK03 and SK04) comprise missing data. For SK01 there are 6 time periods when the data for SK01 and one of its child nodes are missing. For SK02, SK03 and SK04, there are 6 time periods when data for all the child nodes are missing, but there is cross-sectional constraint data. However, there are also 6 cases where all the data for the NUTS3 nodes are missing, and SK02, SK03 and SK04 are lacking data as well.

This is also shown in the plot on the left. For the six year 1990 to 1995 data is missing for both the NUTS3 and NUTS2 regions. For the six years from 1996 to 2001, data is missing for the NUTS3 regions with the exception of SK010.

For 1990 to 1995 the NUTS 3 MCMC estimates will have to be summed across the NUTS2 regions. Then the NUTS2 values can be adjusted to the NUTS1 constraint. Following this, the NUTS 3 units can be constrained to the adjusted NUTS2 values. For SK02, SK03 and SK04 in 1996 to 2001, the constraints already exist at NUTS2 for the NUTS2 MCMC estimates.

The tree traversal algorithm forms the basis for this adjustment process.

Problem zones with missing data for both child and parent.

	UnitCode	**Level**	**Name**	**X1**	**X2**	**X3**	**X4**	**X5**	**X6**	**X7**	**X8**
CZ	CZ	NUTS0	Czech Republic	22	0	0	0	0	0	0	0
CZ0	CZ0	NUTS1	Ceská republika	20	0	0	0	2	0	0	0
CZ01	CZ01	NUTS2	Praha	20	0	0	0	0	2	0	0
CZ02	CZ02	NUTS2	Strední Cechy	20	0	0	0	0	2	0	0
CZ03	CZ03	NUTS2	Jihozápad	20	0	0	0	0	0	0	2
CZ04	CZ04	NUTS2	Severozápad	20	0	0	0	0	0	0	2
CZ05	CZ05	NUTS2	Severovýchod	20	0	0	0	0	0	0	2
CZ06	CZ06	NUTS2	Jihovýchod	20	0	0	0	0	0	0	2
CZ07	CZ07	NUTS2	Strední Morava	11	0	0	0	9	0	0	2
CZ08	CZ08	NUTS2	Moravskoslezsko	20	0	0	0	0	2	0	0

	UnitCode	Level	Name	X1	X2	X3	X4	X5	X6	X7	X8
DE4	DE4	NUTS1	Brandenburg	17	0	0	0	5	0	0	0
DE41	DE41	NUTS2	Brandenburg - Nordost	16	0	0	0	1	0	0	5
DE42	DE42	NUTS2	Brandenburg - Südwest	16	0	0	0	1	0	0	5
DED1	DED1	NUTS2	Chemnitz	15	0	0	0	2	0	0	5
DED2	DED2	NUTS2	Dresden	16	0	0	0	1	0	0	5
DED3	DED3	NUTS2	Leipzig	15	0	0	0	2	0	0	5

	UnitCode	Level	Name	X1	X2	X3	X4	X5	X6	X7	X8
DK	DK	NUTS0	Denmark	22	0	0	0	0	0	0	0
DK0	DK0	NUTS1	Danmark	5	0	0	0	17	0	0	0
DK01	DK01	NUTS2	Hovedstaden	5	0	0	0	0	0	17	0
DK02	DK02	NUTS2	Sjælland	5	0	0	0	0	0	0	17
DK03	DK03	NUTS2	Syddanmark	5	0	0	0	0	17	0	0
DK04	DK04	NUTS2	Midtjylland	5	0	0	0	0	0	0	17
DK05	DK05	NUTS2	Nordjylland	5	0	0	0	0	17	0	0

	UnitCode	Level	Name	X1	X2	X3	X4	X5	X6	X7	X8
HR	HR	NUTS0	Croatia	22	0	0	0	0	0	0	0
HR0	HR0	NUTS1	Hrvatska	11	0	0	0	11	0	0	0
HR01	HR01	NUTS2	Sjeverozapadna Hrvatska	11	1	0	0	0	0	0	10
HR02	HR02	NUTS2	Sredisnja i Istocna (Panonska) Hrvatska	11	1	0	0	0	0	0	10
HR03	HR03	NUTS2	Jadranska Hrvatska	11	1	0	0	0	0	0	10

	UnitCode	Level	Name	X1	X2	X3	X4	X5	X6	X7	X8
IE	IE	NUTS0	Ireland	22	0	0	0	0	0	0	0
IE0	IE0	NUTS1	Éire/Ireland	15	0	0	0	7	0	0	0
IE01	IE01	NUTS2	Border, Midland and Western	5	0	0	0	10	0	0	7
IE02	IE02	NUTS2	Southern and Eastern	5	0	0	0	10	0	0	7

	UnitCode	Level	Name	X1	X2	X3	X4	X5	X6	X7	X8
PL	PL	NUTS0	Poland	21	0	0	0	1	0	0	0
PL1	PL1	NUTS1	Region Centralny	21	0	0	0	0	0	0	1
PL2	PL2	NUTS1	Region Poludniowy	21	0	0	0	0	0	0	1
PL3	PL3	NUTS1	Region Wschodni	21	0	0	0	0	0	0	1
PL4	PL4	NUTS1	Region Pólnocno-Zachodni	21	0	0	0	0	0	0	1
PL5	PL5	NUTS1	Region Poludniowo-Zachodni	21	0	0	0	0	0	0	1
PL6	PL6	NUTS1	Region Pólnocny	21	0	0	0	0	0	0	1
PL11	PL11	NUTS2	Lódzkie	11	0	0	0	10	0	0	1
PL12	PL12	NUTS2	Mazowieckie	11	0	0	0	10	0	0	1
PL21	PL21	NUTS2	Malopolskie	11	0	0	0	10	0	0	1
PL22	PL22	NUTS2	Slaskie	11	0	0	0	10	0	0	1
PL31	PL31	NUTS2	Lubelskie	11	0	0	0	10	0	0	1
PL32	PL32	NUTS2	Podkarpackie	11	0	0	0	10	0	0	1
PL33	PL33	NUTS2	Swietokrzyskie	11	0	0	0	10	0	0	1
PL34	PL34	NUTS2	Podlaskie	11	0	0	0	10	0	0	1
PL41	PL41	NUTS2	Wielkopolskie	11	0	0	0	10	0	0	1
PL42	PL42	NUTS2	Zachodniopomorskie	11	0	0	0	10	0	0	1
PL43	PL43	NUTS2	Lubuskie	11	0	0	0	10	0	0	1
PL51	PL51	NUTS2	Dolnoslaskie	11	0	0	0	10	0	0	1
PL52	PL52	NUTS2	Opolskie	11	0	0	0	10	0	0	1
PL61	PL61	NUTS2	Kujawsko-Pomorskie	11	0	0	0	10	0	0	1
PL62	PL62	NUTS2	Warminsko-Mazurskie	11	0	0	0	10	0	0	1
PL63	PL63	NUTS2	Pomorskie	11	0	0	0	10	0	0	1

	UnitCode	Level	Name	X1	X2	X3	X4	X5	X6	X7	X8
PT	PT	NUTS0	Portugal	16	0	0	0	2	4	0	0
PT1	PT1	NUTS1	Continente	16	4	0	0	0	0	0	2
PT2	PT2	NUTS1	Região Autónoma dos Açores (PT)	20	0	0	0	0	2	0	0
PT3	PT3	NUTS1	Região Autónoma da Madeira (PT)	20	0	0	0	0	2	0	0
PT11	PT11	NUTS2	Norte	20	0	0	0	0	0	0	2

PT15	PT15	NUTS2	Algarve	20	0	0	0	0	2	0	0
PT16	PT16	NUTS2	Centro (PT)	20	0	0	0	0	0	0	2
PT17	PT17	NUTS2	Lisboa	20	0	0	0	0	0	0	2
PT18	PT18	NUTS2	Alentejo	20	0	0	0	0	0	0	2
PT20	PT20	NUTS2	Região Autónoma dos Açores (PT)	20	0	0	0	0	2	0	0
PT30	PT30	NUTS2	Região Autónoma da Madeira (PT)	20	0	0	0	0	2	0	0

	UnitCode	Level	Name	X1	X2	X3	X4	X5	X6	X7	X8
SK	SK	NUTS0	Slovakia	22	0	0	0	0	0	0	0
SK0	SK0	NUTS1	Slovenská republika	16	0	0	0	6	0	0	0
SK01	SK01	NUTS2	Bratislavský kraj	16	0	0	0	0	6	0	0
SK02	SK02	NUTS2	Západné Slovensko	10	0	0	0	6	0	0	6
SK03	SK03	NUTS2	Stredné Slovensko	10	0	0	0	6	0	0	6
SK04	SK04	NUTS2	Východné Slovensko	10	0	0	0	6	0	0	6

Tree Walk

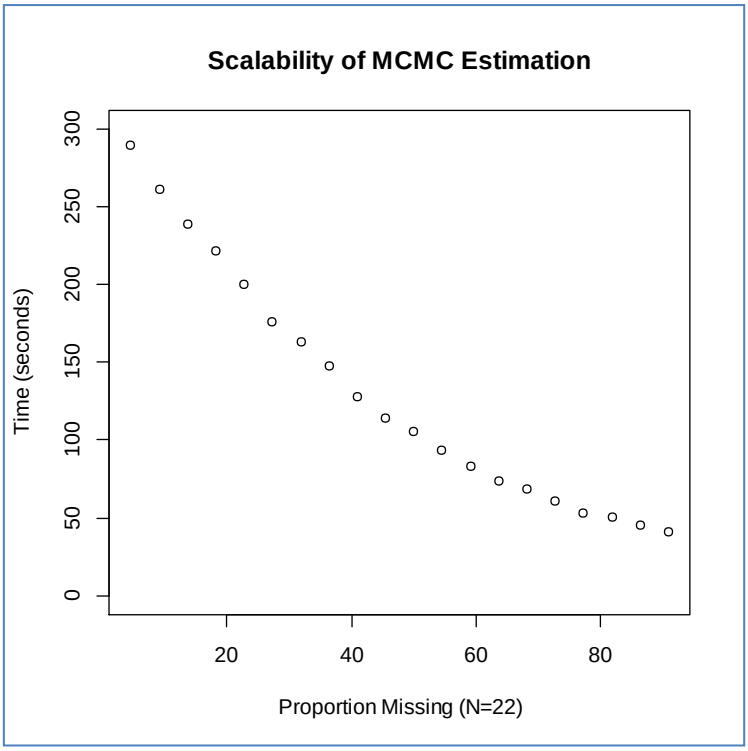
	UnitCode	Level	Name	X1	X2	X3	X4	X5	X6	X7	X8
TR	TR	NUTS0	Turkey	6	0	0	0	0	0	0	16
TR1	TR1	NUTS1	Istanbul	6	0	0	0	0	16	0	0
TR2	TR2	NUTS1	Bati Marmara	6	0	0	0	0	0	0	16
TR3	TR3	NUTS1	Ege	6	0	0	0	0	0	0	16
TR4	TR4	NUTS1	Dogu Marmara	6	0	0	0	0	0	0	16
TR5	TR5	NUTS1	Bati Anadolu	6	0	0	0	0	0	0	16
TR6	TR6	NUTS1	Akdeniz	6	0	0	0	0	0	0	16
TR7	TR7	NUTS1	Orta Anadolu	6	0	0	0	0	0	0	16
TR8	TR8	NUTS1	Bati Karadeniz	6	0	0	0	0	0	0	16
TR9	TR9	NUTS1	Dogu Karadeniz	6	0	0	0	0	16	0	0
TRA	TRA	NUTS1	Kuzeydogu Anadolu	6	0	0	0	0	0	0	16
TRB	TRB	NUTS1	Ortadogu Anadolu	6	0	0	0	0	0	0	16
TRC	TRC	NUTS1	Güneydogu Anadolu	6	0	0	0	0	0	0	16
TR10	TR10	NUTS2	Istanbul	6	0	0	0	0	16	0	0
TR21	TR21	NUTS2	Tekirdag	6	0	0	0	0	0	0	16
TR22	TR22	NUTS2	Balikesir	6	0	0	0	0	0	0	16
TR31	TR31	NUTS2	Izmir	6	0	0	0	0	16	0	0
TR32	TR32	NUTS2	Aydin	6	0	0	0	0	0	0	16
TR33	TR33	NUTS2	Manisa	6	0	0	0	0	0	0	16
TR41	TR41	NUTS2	Bursa	6	0	0	0	0	0	0	16
TR42	TR42	NUTS2	Kocaeli	6	0	0	0	0	0	0	16
TR51	TR51	NUTS2	Ankara	6	0	0	0	0	16	0	0
TR52	TR52	NUTS2	Konya	6	0	0	0	0	0	0	16
TR61	TR61	NUTS2	Antalya	6	0	0	0	0	0	0	16
TR62	TR62	NUTS2	Adana	6	0	0	0	0	0	0	16
TR63	TR63	NUTS2	Hatay	6	0	0	0	0	0	0	16
TR71	TR71	NUTS2	Kirikkale	6	0	0	0	0	0	0	16
TR72	TR72	NUTS2	Kayseri	6	0	0	0	0	0	0	16
TR81	TR81	NUTS2	Zonguldak	6	0	0	0	0	0	0	16
TR82	TR82	NUTS2	Kastamonu	6	0	0	0	0	0	0	16
TR83	TR83	NUTS2	Samsun	6	0	0	0	0	0	0	16
TR90	TR90	NUTS2	Trabzon	6	0	0	0	0	0	0	16
TRA1	TRA1	NUTS2	Erzurum	6	0	0	0	0	0	0	16
TRA2	TRA2	NUTS2	Agri	6	0	0	0	0	0	0	16
TRB1	TRB1	NUTS2	Malatya	6	0	0	0	0	0	0	16
TRB2	TRB2	NUTS2	Van	6	0	0	0	0	0	0	16
TRC1	TRC1	NUTS2	Gaziantep	6	0	0	0	0	0	0	16
TRC2	TRC2	NUTS2	Sanliurfa	6	0	0	0	0	0	0	16
TRC3	TRC3	NUTS2	Mardin	6	0	0	0	0	0	0	16

	UnitCode	Level	Name	X1	X2	X3	X4	X5	X6	X7	X8
UK	UK	NUTS0	United Kingdom	0	0	0	0	1	0	11	10
UKC	UKC	NUTS1	North East (UK)	0	8	1	0	0	0	0	13
UKD	UKD	NUTS1	North West (UK)	0	8	0	1	0	0	0	13
UKE	UKE	NUTS1	Yorkshire and The Humber	0	8	0	0	0	0	1	13
UKF	UKF	NUTS1	East Midlands (UK)	0	8	0	0	0	0	0	14
UKG	UKG	NUTS1	West Midlands (UK)	0	8	0	1	0	0	0	13
UKH	UKH	NUTS1	East of England	0	8	0	0	0	0	1	13
UKI	UKI	NUTS1	London	0	8	0	0	0	0	0	14

```
UKJ       UKJ NUTS1                            South East (UK)  0  8  0  1  0  0  0 13
UKK       UKK NUTS1                            South West (UK)  0  9  0  0  0  0  0 13
UKL       UKL NUTS1                                     Wales  0  9  0  0  0  0  0 13
UKM       UKM NUTS1                                  Scotland  0  0  1  0 10  0  0 11
UKN       UKN NUTS1                      Northern Ireland (UK) 11  0  0  0  0 11  0  0
UKC1     UKC1 NUTS2                     Tees Valley and Durham  1 12  0  0  8  0  0  1
UKC2     UKC2 NUTS2          Northumberland and Tyne and Wear  0 13  0  0  8  0  0  1
UKD1     UKD1 NUTS2                                   Cumbria  0 13  0  0  8  0  0  1
UKD2     UKD2 NUTS2                                  Cheshire  1 12  0  0  8  0  0  1
UKD3     UKD3 NUTS2                        Greater Manchester  1 12  0  0  8  0  0  1
UKD4     UKD4 NUTS2                                Lancashire  1 12  0  0  8  0  0  1
UKD5     UKD5 NUTS2                                Merseyside  0 13  0  0  8  0  0  1
UKE1     UKE1 NUTS2East Yorkshire and Northern Lincolnshire  0 13  0  0  8  0  0  1
UKE2     UKE2 NUTS2                             North Yorkshire  0 13  0  0  8  0  0  1
UKE3     UKE3 NUTS2                             South Yorkshire  1 12  0  0  8  0  0  1
UKE4     UKE4 NUTS2                              West Yorkshire  0 13  0  0  8  0  0  1
UKF1     UKF1 NUTS2           Derbyshire and Nottinghamshire  0 13  0  0  8  0  0  1
UKF2     UKF2 NUTS2      Leicester, Rutland and Northamptons  0 13  0  0  8  0  0  1
UKF3     UKF3 NUTS2                               Lincolnshire  0 13  8  0  0  1  0  0
UKG1     UKG1 NUTS2          Hereford, Worcester and Warwick  1 12  0  0  8  0  0  1
UKG2     UKG2 NUTS2             Shropshire and Staffordshire  0 13  0  0  8  0  0  1
UKG3     UKG3 NUTS2                             West Midlands  0 13  0  0  8  0  0  1
UKH1     UKH1 NUTS2                               East Anglia  0 13  0  0  8  0  0  1
UKH2     UKH2 NUTS2           Bedfordshire and Hertfordshire  0 13  0  0  8  0  0  1
UKH3     UKH3 NUTS2                                    Essex  1 12  0  0  8  0  0  1
UKI1     UKI1 NUTS2                              Inner London  0 13  0  0  8  0  0  1
UKI2     UKI2 NUTS2                              Outer London  0 13  0  0  8  0  0  1
UKJ1     UKJ1 NUTS2         Berkshire, Buckingham and Oxford  1 12  0  0  8  0  0  1
UKJ2     UKJ2 NUTS2             Surrey, East and West Sussex  0 13  0  0  8  0  0  1
UKJ3     UKJ3 NUTS2              Hampshire and Isle of Wight  0 13  0  0  8  0  0  1
UKJ4     UKJ4 NUTS2                                    Kent  1 12  0  0  8  0  0  1
UKK1     UKK1 NUTS2 Gloucester, Wiltshire and Bristol/Bath   1 12  0  0  8  0  0  1
UKK2     UKK2 NUTS2                       Dorset and Somerset  1 12  0  0  8  0  0  1
UKK3     UKK3 NUTS2             Cornwall and Isles of Scilly  1 12  8  0  0  1  0  0
UKK4     UKK4 NUTS2                                    Devon  1 12  0  0  8  0  0  1
UKL1     UKL1 NUTS2               West Wales and The Valleys  1 12  0  0  8  0  0  1
UKL2     UKL2 NUTS2                               East Wales  1 12  0  0  8  0  0  1
UKM2     UKM2 NUTS2                          Eastern Scotland  0 11  0  0  0  0  0 11
UKM3     UKM3 NUTS2                   South Western Scotland  1 10  0  0  0  0  0 11
UKM5     UKM5 NUTS2                   North Eastern Scotland  1 10  0  0  0 11  0  0
UKM6     UKM6 NUTS2                    Highlands and Islands  1 10  0  0  0  0  0 11
UKN0     UKN0 NUTS2                              Northern Ireland (UK)  1 10  0  0 10
0  0  1
>
```

Scalability

The question of the practicability of the approach, given the nature of MCMC estimation shoud be considered. The ESPON series are short run - in the case of the population data, we have no more than 22 observations. In the worst case all 22 observations are missing, and no amount of MCMC will recreate the data. The time required depends on (a) the speed of the processor (b) the number of burn-in cycles and (c) the number of estimation cycles. The more data that is present, the slower the estimation. The plot below depicts the relationship between the proportion of missing data and the time required to estimation the missing data in the series. Counter-intuitively, the more missing data then the quicker the execution time:



The plot shows the execution time for the NL NUTS0 series with increasing proportions of missing data.

The MCMC estimation for entire dataset, NUTS0, NUTS1, NUTS2 and NUTS3 took about 60 hours on a *quad core 3.16GHz Intel Xeon* processor running Windows XP Professional. This would equate to about 35 hours on a laptop running Windows 7 Professional on a 2.80GHz *Intel Core i7-2640M* processor.

5. ESPON Time series in practice

The code for the various tasks to be undertaken is included as Appendices 2, 3, 4 and 5. We can identify as number of tasks which are relevant. It should be noted that the temptation to regard the entire process as automatic should be avoided, although much of the activity can be automated.

Getting started

Currently the organisation of the activity assumes that the R code and the data are in the same folder. This is **Time_Series_Analysis/Sandbox** but the code and data can be separated. All code should be in the same folder. The relevant files are:

```
Modelling_and_Imputation.R
ImputeMissingData.R
tfile1.JAGS
tfile2.JAGS
```

The following R libraries are required:

```
gdata
rjags
RColorBrewer
```

Data requires that a current version of the perl[11] language is installed, and rjags requires that a current version of JAGS is installed[12].

The various tasks are identified in the code, and are briefly described below.

Task 1: Data load and pre-processing

The four worksheets in the ESPON Database spreadsheet are read into four separate data frames. We use the read.xls() function for this. Of interest are the *Source* and *Data* worksheets.

The Source worksheet is parsed to extract as list of the data providers and their identification codes. The data frame *sourceIndex* needs to be examined to identify the codes for EUROSTAT and the National Statistical Agencies[13].

The relevant codes are extracted to another dataframe, *sourcesOK*, and this is used as a filter for the data extraction. The Data worksheet is split into two data frames which hold (a) the data and (b) the corresponding index codes. Once the non-EUROSTAT/NSA data has be filtered, the resulting data frame *Data.estim*, will be used in the remainder of the exercise.

[11] Perl can be downloaded from http://www.activestate.com/activeperl/downloads
[12] JAGS can be installed from http://sourceforge.net/projects/mcmc-jags/files/
[13] The data as supplied by the RIATE team contains original data as well as RIATE's own estimations of the missing data

As a final activity under this task the rows in Data.estim are index by their corresponding NUTS codes. This indexing is central to the spatial coherence activity described in a later task.

Task 2: Missing data pattern analysis

It is important to be aware of the patterns of missing data in the dataset. This gives an overall picture of the patterns in each country, and also an indication of the scale of the problem.

A useful tool for this purpose is the heatmap. The columns in the heatmap represent the individual time periods, and the rows represent the NUTS regions. A separate heatmap can be produced for each country. Data values are colour coded according to their value, so some broad indications of the range of values and the trends in each group of series can be obtained from the heatmap.

The heatmap() function has a number of options, including the re-ordering of the rows and columns as a result of the application of hierarchical clustering. These options are turned off: (Colv=NA, Rowv=NA). The cells in the heatmap which arise from the intersection of a year and a NUTS region with missing data are coloured grey.

The resulting heatmaps are included as separate plots in Appendix 7.

Task 3: Missing data at NUTS0/1/2

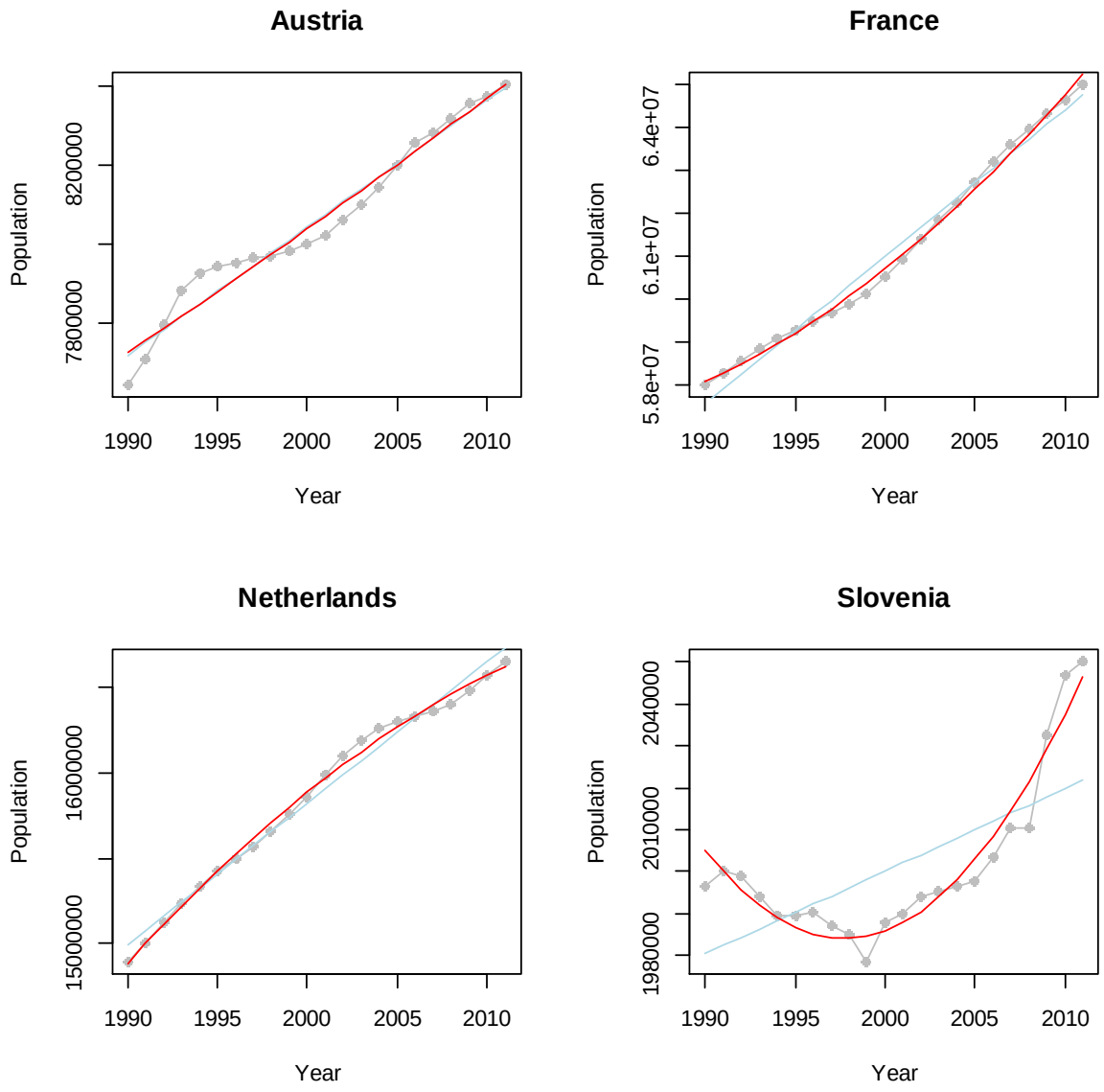
Ensuribng spatial coherence is an important issue for the imputation process. This requires reliable control data for the higher NUTS levels. Inevitably, there will need to be consistent series for the NUTS0 level. Task 3 involves an enurmation of NUTS0/1/2 regions with missing data. The complete.cases() function is used to identify NUTS regions with missing data. These are listed.

Task 4: exploring general patterns

Analysis of the series suggested that an simple linear or exponential trend model might be insufficient to capture the overall trend pattern. Eventually it was decided that a quadratic term would be added to the model. If the empirical trend was more or less linear, then the coefficient on the quadratic term would be close to zero. Four plots are shown below for Austria, France, Netherlands, and Slovenia:

- The non-missing data points
- A line or lines connecting the non-missing data points
- A line to show linear trend
- A line to shown quadratic trend

Whilst the general pattern is modelled well by the linear term, the fit is improved by the quadratic term – very noticeably in the case of Slovenia.



Task 5: extraction of the data for a single country

Much of the development work took place using the data series for NUTS regions of Austria as an example. The code under Task 5 shows how to extract data for a single country for further analysis.

It also shows how to create a backlink in the spatial hierarchy, so that the 'parent' region for each NUTS region can be identified.

In the normal course of events, this code section need not be used, although it is helpful to have it for testing and debugging purposes.

Task 6: MCMC estimation

The central task of the exercise is to estimate the missing data in each series using Markov Chain Monte Carlo methods. The main function which organises the data into input for JAGS, ImputeMissingData(), is shown and commented in Appendix 3.

All rows with missing in *Data.estim* can be estimated with the exception of any row with fewer than 3 observations.

The estimation takes place in a loop, whose start/end locations are controlled by the variables *startrow* and *endrow*. In the code these are set to 1 and the number of rows in *Data.estim*. This task is massively time consuming, and if there is doubt that the computer on which the process is run would stay up, then the estimation could be subdivided.

Once the missing data in a NUTS region has been estimated and the row written to the output matrix, *NUTSData.completed*, it is not referenced again until Task 6 has completed.

The final step in the Task is to write the intermediate results to a file. The estimation of all the missing data for 1990-2001 for all NUTS0/1/2/3 regions took some 60 hours on a 2.8GHz Intel Core i7-260M processor, so some precautions are needed to ensure that the task does not have be repeated too many times. Should there be a system failure when the last few estimations are to be completed would be extremely unfortunate, so writing out the intermediate results every 100 or so iterations would be sensible.

The JAGS code appears to be robust – only one series caused a failure, and that was one in which *all* values were missing.

Task 6A: Scalability assessment

Task 6a can be omitted – it is present only to allow an assessment of the scalbiluty of the process, using data from the Netherlands as an example. The plot from this Task appears on page 36.

Task 7: Spatial Coherence Adjustment

One of the most challenging parts of the work has been to develop an algorithm which permits adjustment of lower level NUTS estimations to constraining values at the higher NUTS levels. There are two subtasks.

Task 7a is a manual fix for Portugal. PT is missing years 1992 and 1995. PT1 is missing the same years. However, the NUTS2 regions in PT1 are present. The manual fix is to sum the PT1* regions to PT1, and then PT1+PT2+PT3 to PT. This could be automated, but analysis of other series would be needed to determine whether it is a more widespread problem. The code for the manual fix is present, and therefore is reproducible[14].

[14] Reproducibility is science is the ability of an enture study to be reproduced by either the researcher themselves, or by an independent third party. See also Buckheit JB and

Task 7b includes the coherence algorithm. This is presented as a function ConstrainTotals2() which takes the missing data pattern data frame, the data frame of unadjusted estimates, and then range of data columns to be adjusted. The output is a spatially coherent data frame of actual data and estimates.

The algorithm is a top down algorithm. The indexing of the rows by their NUTS code means that it is possible to identify the parent region (the NUTS chode is one character shorter). NUTS1 regions are first constrained to the NUTS0 values – with care being taken when only a subset of these has been estimated. The hierarchical relationship between the NUTS levels, and the existence of the 'parent' vector means that this can be coded in a loop.

Once the NUTS1 regions have been constrained, the NUTS2 region estimates can be constrained to the NUTS1 totals. Finally the NUTS3 region estimates can be constrained to the NUTS2 totals.

The resulting data frame can be output to a file if required.

Other functions

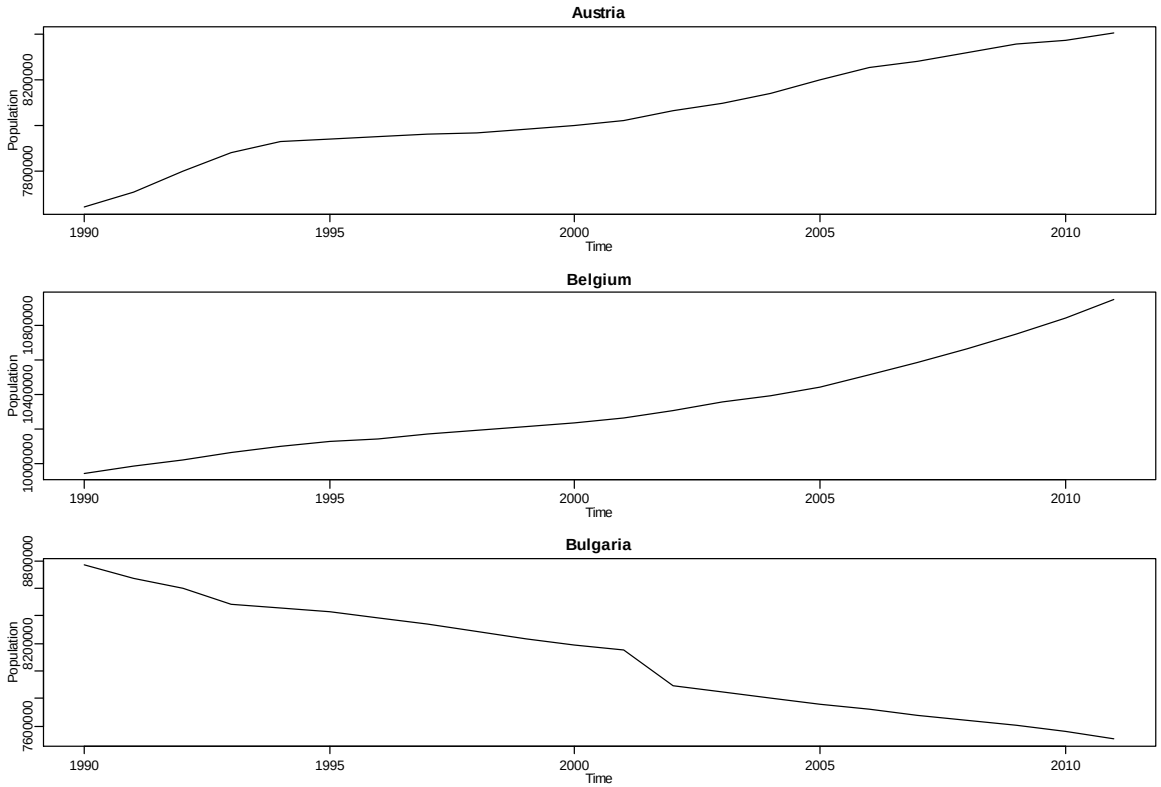
CheckCountry(): this uses the function CheckConstraint() – lists the children for each parent node in the tree
CheckTree(): traverses the tree in order

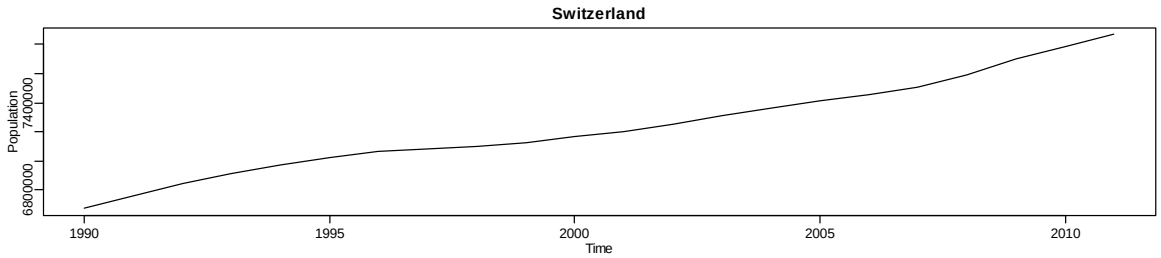
CheckMissingPattern(): examines the missing data patterns for each parent node.

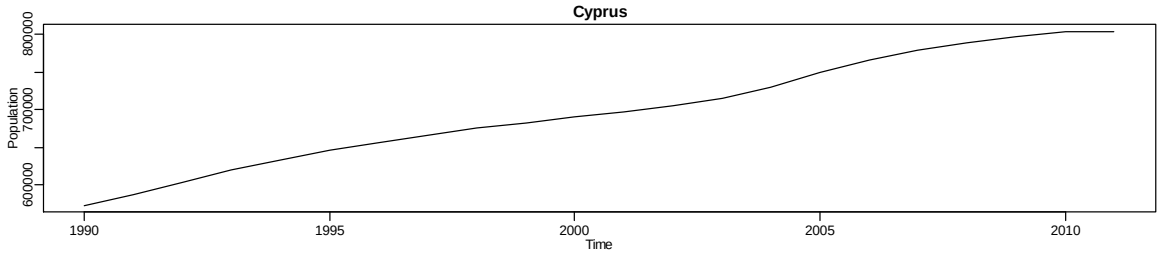
In the final section are some plots of random numbers drawn in samples of different sizes for different distributions (normal, gamma, beta, multivariate normal), together with random normal for different precisions and a non-informative prior to show the influence of increasing the sample size on the estimates of the mean.

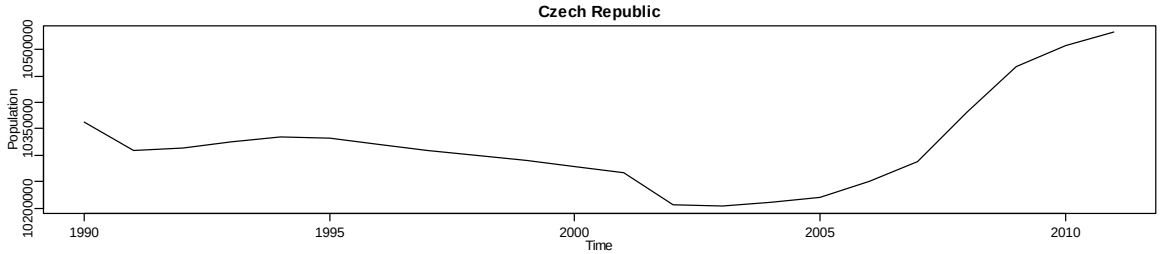
Donoho, 1995, *WaveLab and Reproducible Research*, Dept. of Statistics, Stanford University, Tech. Rep. 474

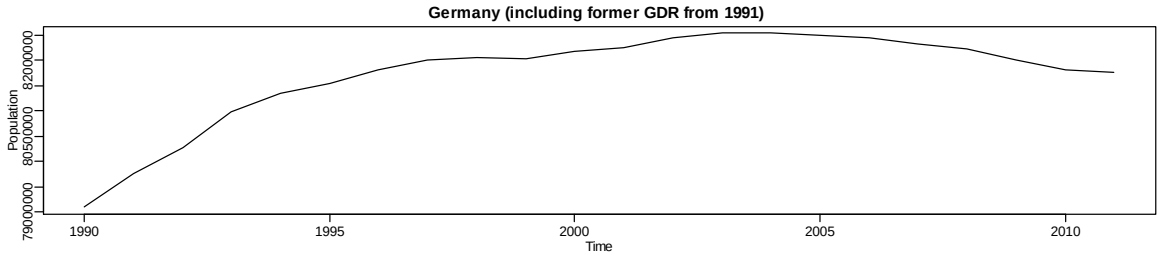
Appendix 1: NUTS0 Population Time Series Plots

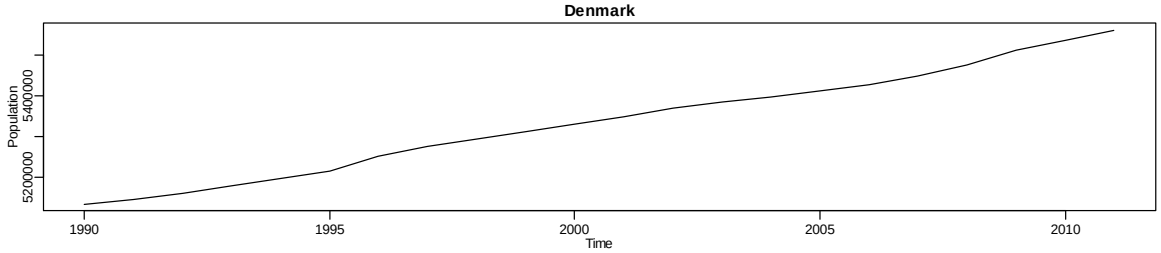


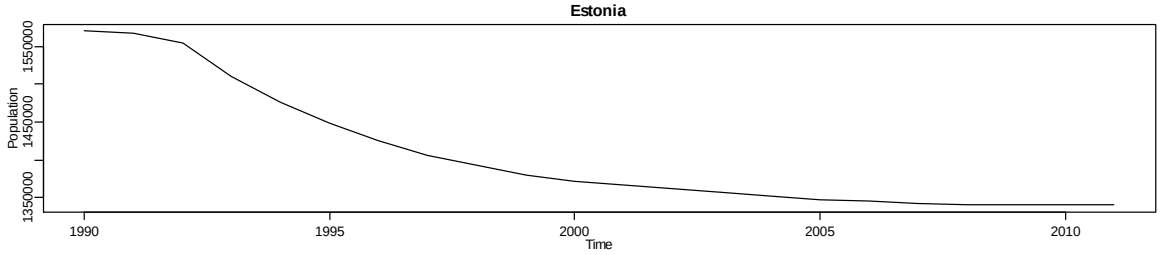

Switzerland
Population
6800000
7400000
1990
1995
2000
2005
2010
Time

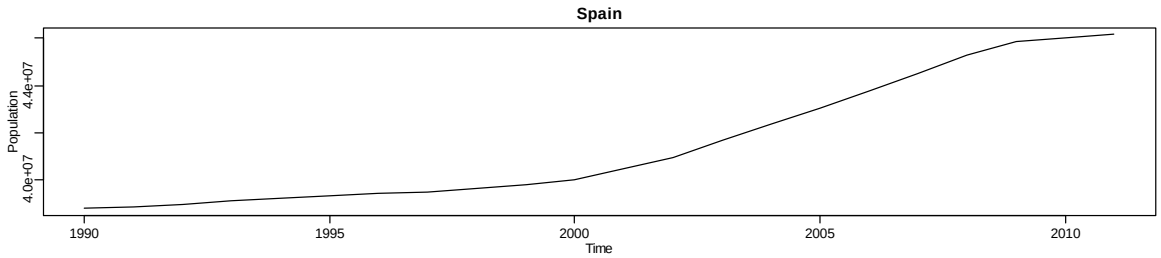

Cyprus
Population
600000
700000
800000
1990
1995
2000
2005
2010
Time

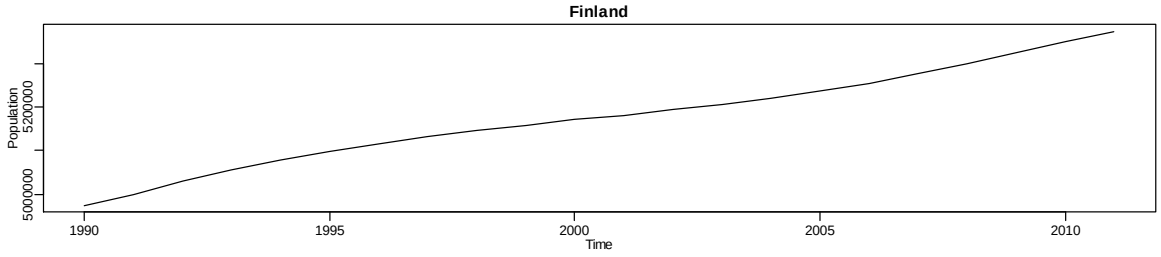

Czech Republic
Population
10200000
10350000
10500000
1990
1995
2000
2005
2010
Time

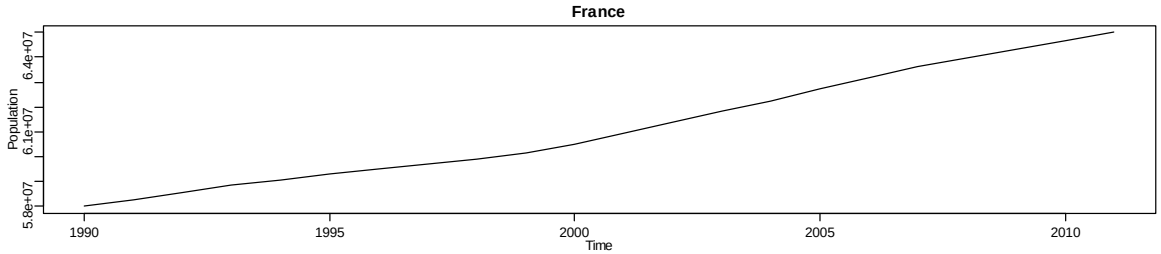

Germany (including former GDR from 1991)
Population
79000000
80500000
82000000
1990
1995
2000
2005
2010
Time

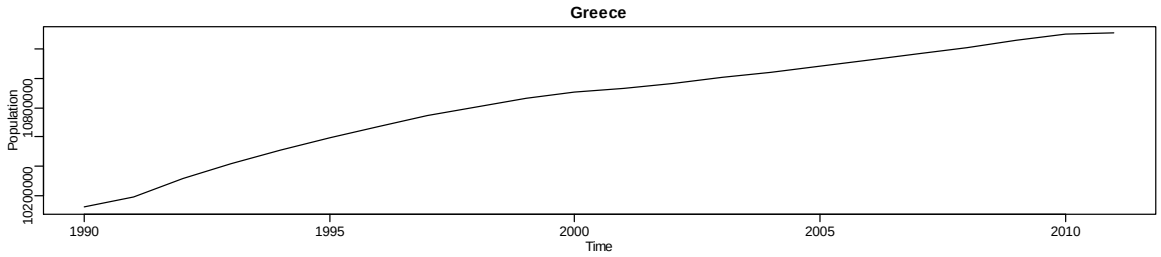

Denmark
Population
5200000
5400000
1990
1995
2000
2005
2010
Time

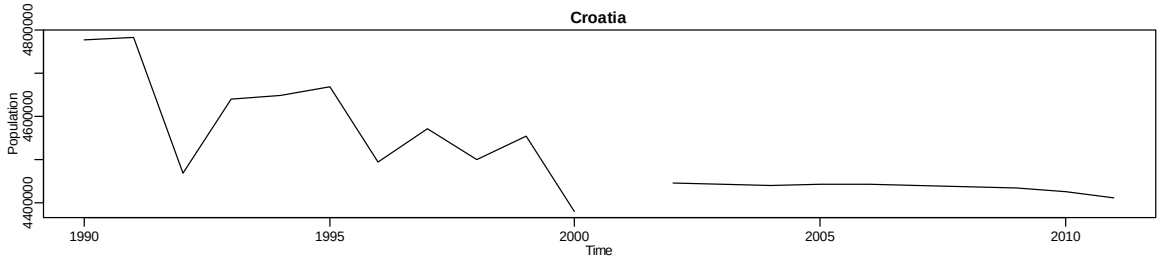

Estonia
Population
1350000
1450000
1550000
1990
1995
2000
2005
2010
Time


Spain
Population
4.0e+07
4.4e+07
1990
1995
2000
2005
2010
Time

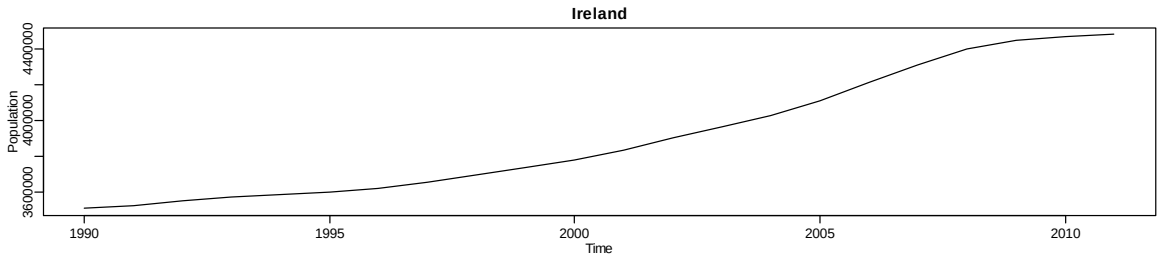

Finland
Population
5000000
5200000
1990
1995
2000
2005
2010
Time

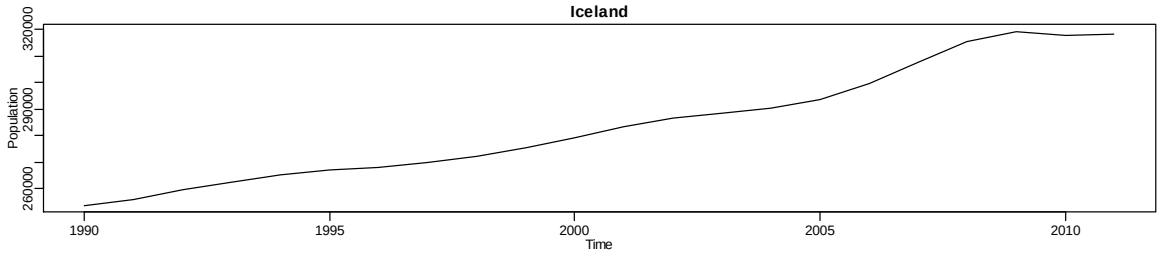

France
Population
5.8e+07
6.1e+07
6.4e+07
1990
1995
2000
2005
2010
Time

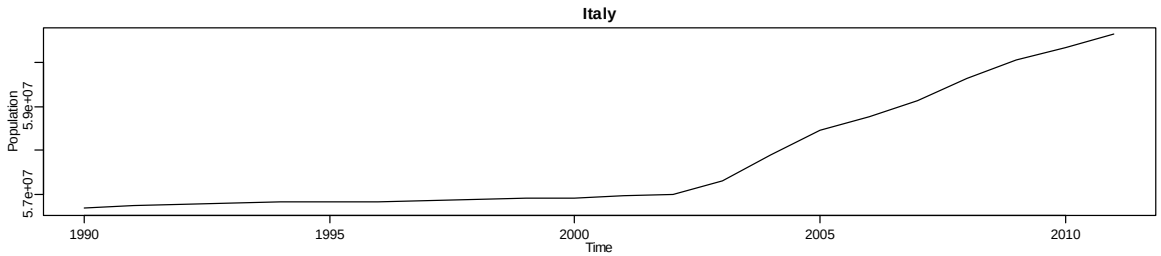

Greece
Population
10200000
10800000
1990
1995
2000
2005
2010
Time

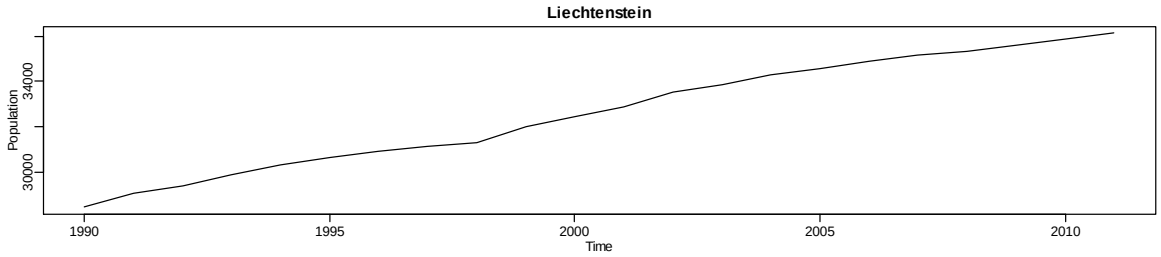

Croatia
Population
4400000
4600000
4800000
1990
1995
2000
2005
2010
Time

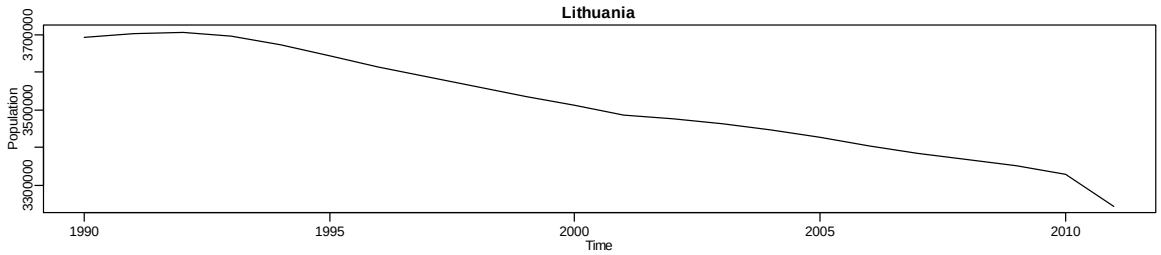

Hungary
Population
10000000
10200000
1990
1995
2000
2005
2010
Time


Ireland
Population
3600000
4000000
4400000
1990
1995
2000
2005
2010
Time

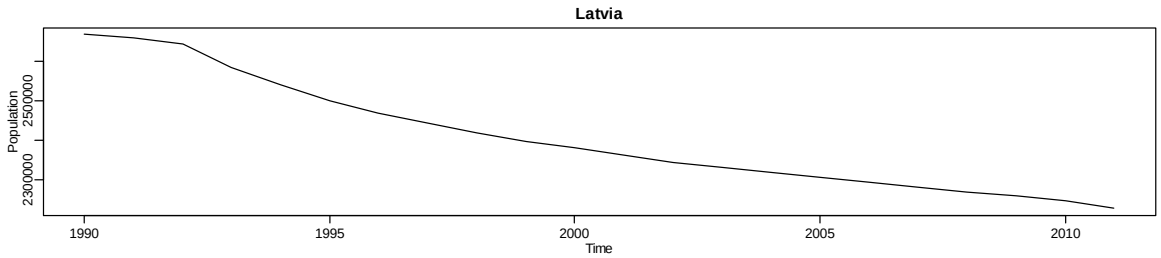

Iceland
Population
260000
290000
320000
1990
1995
2000
2005
2010
Time


Italy
Population
5.7e+07
5.9e+07
1990
1995
2000
2005
2010
Time

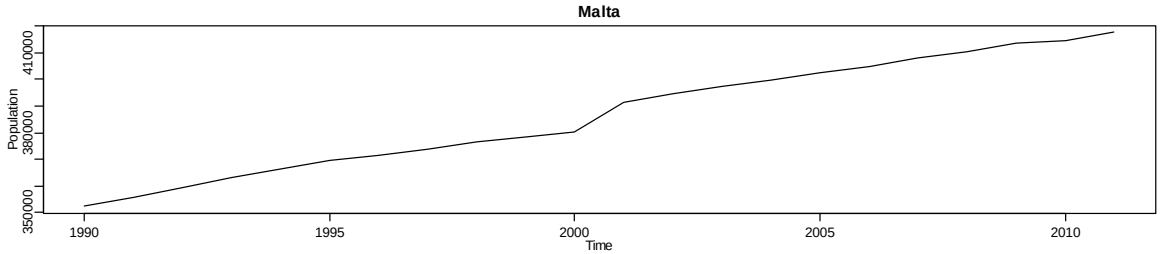

Liechtenstein
Population
30000
34000
1990
1995
2000
2005
2010
Time

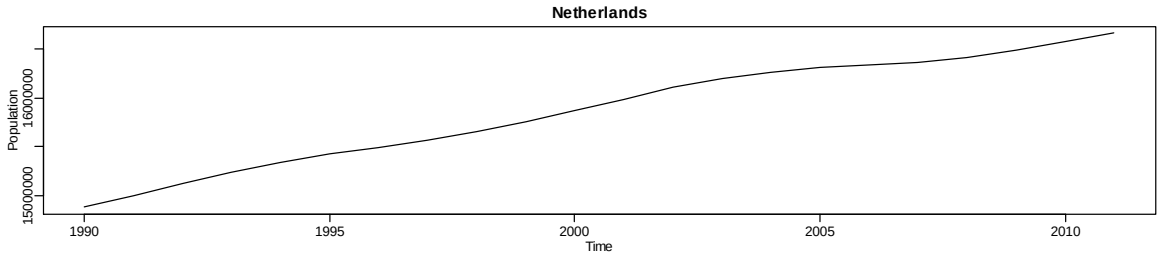

Lithuania
Population
3300000
3500000
3700000
1990
1995
2000
2005
2010
Time

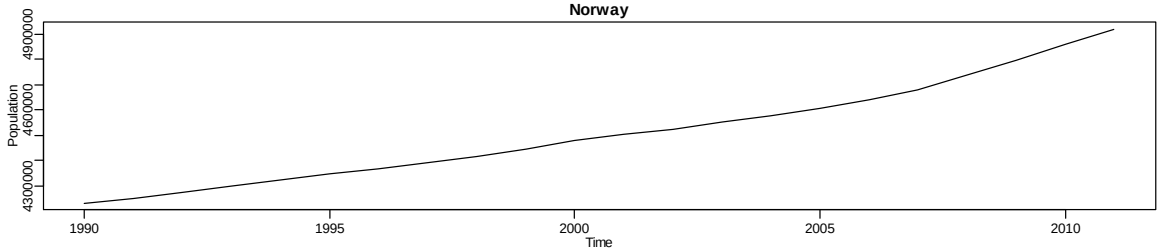

Luxembourg
Population
380000
440000
500000
1990
1995
2000
2005
2010
Time

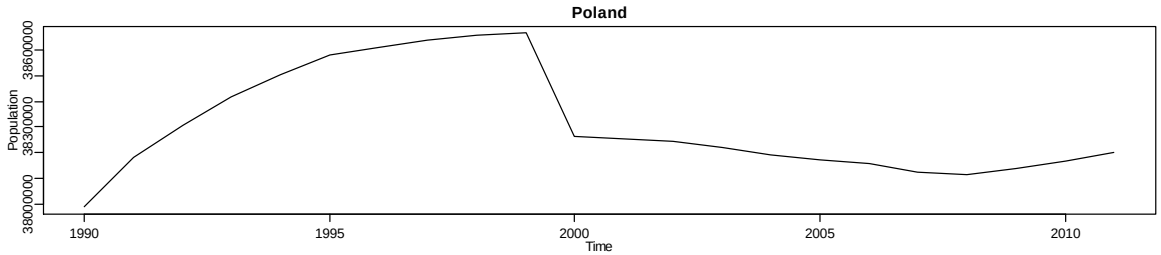

Latvia
Population
2300000
2500000
1990
1995
2000
2005
2010
Time

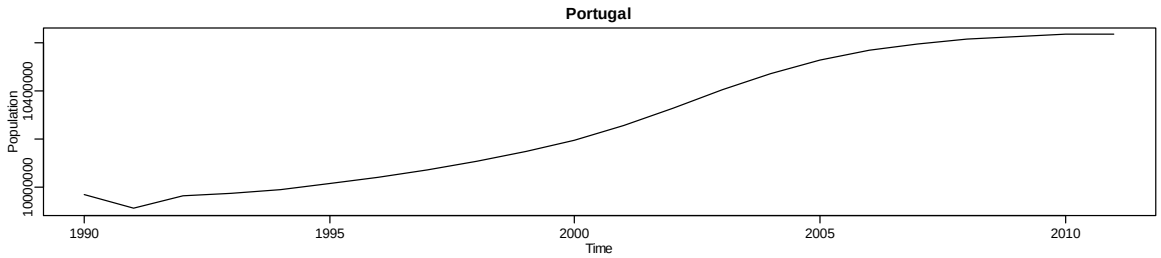

Macedonia
Population
1900000
2000000
1990
1995
2000
2005
2010
Time


Malta
Population
350000
380000
410000
1990
1995
2000
2005
2010
Time

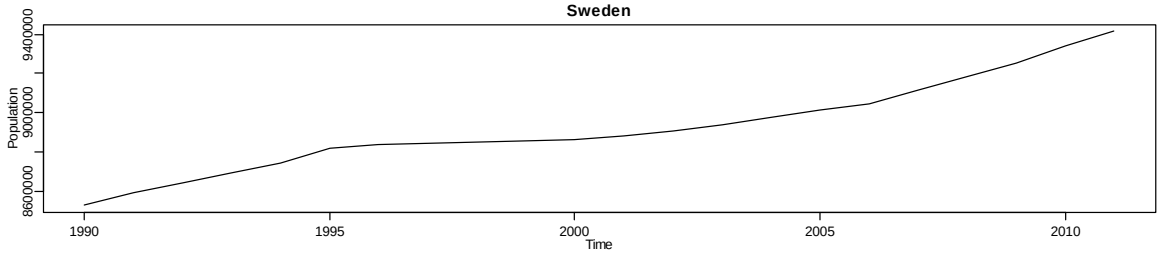

Netherlands
Population
15000000
16000000
1990
1995
2000
2005
2010
Time

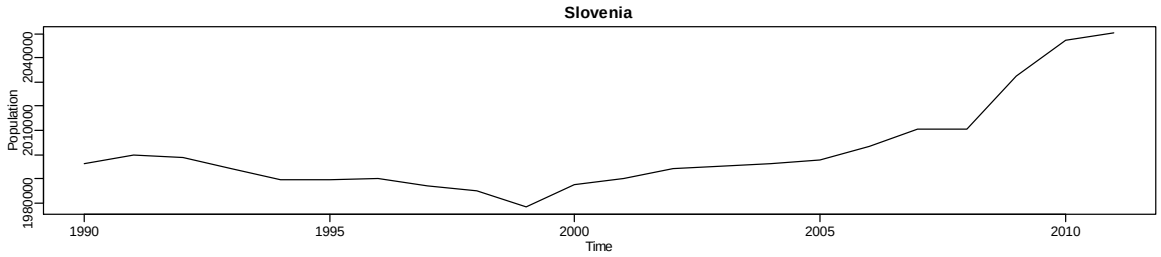

Norway
Population
4300000
4600000
4900000
1990
1995
2000
2005
2010
Time

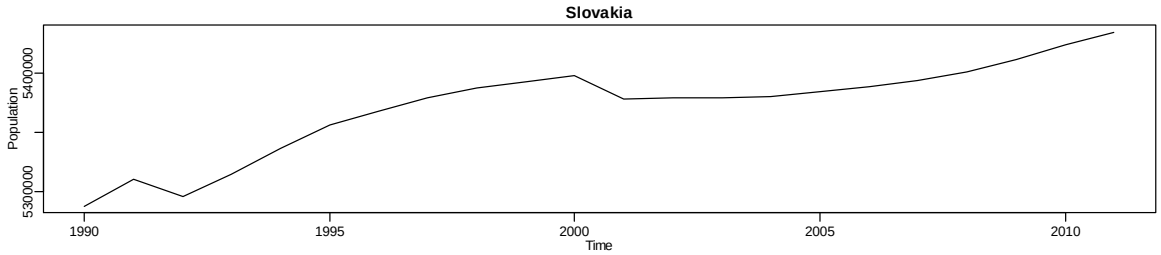

Poland
Population
38000000
38300000
38600000
1990
1995
2000
2005
2010
Time

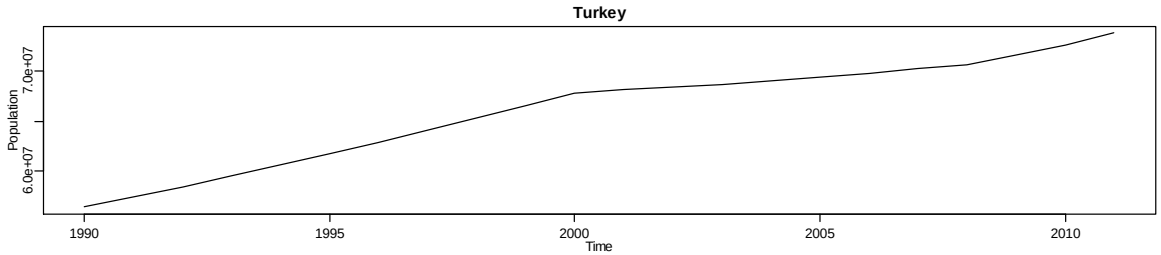

Portugal
Population
10000000
10400000
1990
1995
2000
2005
2010
Time

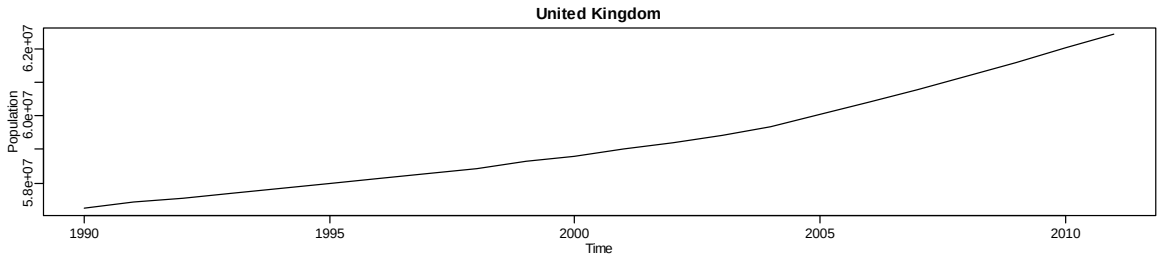

Romania
Population
21500000
22500000
1990
1995
2000
2005
2010
Time


Sweden
Population
8600000
9000000
9400000
1990
1995
2000
2005
2010
Time


Slovenia
Population
1980000
2010000
2040000
1990
1995
2000
2005
2010
Time


Slovakia
Population
5300000
5400000
1990
1995
2000
2005
2010
Time


Turkey
Population
6.0e+07
7.0e+07
1990
1995
2000
2005
2010
Time


United Kingdom
Population
5.8e+07
6.0e+07
6.2e+07
1990
1995
2000
2005
2010
Time

Appendix 2: Main analysis and imputation R functions

```
#############################################################################
#############################################################################
###### V5
#
# ESPON M4D Multidimensional Database Design and Development
#
# Time Series Estimation
#
# Data Exploration, Estimation, and Coherence functions
#
#
### Authors:
#
# Martin Charlton and Chris Brunsdon
#
### Address:
#
# National Centre for Geocomputation
# National University of Ireland, Maynooth
# Maynooth, Co Kildare, IRELAND
#
# V1.01: June 2014
#
#### (c) ESPON
#
# Code is made avilable under the GNU GENERAL PUBLIC LICENSE, Version 3
# Text of the License is at http://www.gnu.org/licenses/gpl.txt
#
#############################################################################
#########
#############################################################################
#########

###
### Identify a working folder - all data/software in in this folder
###
dsn <- "F:\\Time_Series_Analysis\\Sandbox"  # Data stick

setwd(dsn)

###
### Load the libraries needed for the analysis and estimation
###
require(RColorBrewer)
require(gdata)
require(rjags)

#############################################################################
##########
### TASK 1:  Read the data, identify the EUROSTAT/NSA data and split
data
###          and source indices into separate worksheets
```

```
#########################################################################
##########

Dataset   <- read.xls(paste(dsn,"\\M4D_poptot1990-
2011_20120522.xls",sep=""), sheet=1,header=FALSE)
Indicator <- read.xls(paste(dsn,"\\M4D_poptot1990-
2011_20120522.xls",sep=""), sheet=2,header=FALSE)
Source    <- read.xls(paste(dsn,"\\M4D_poptot1990-
2011_20120522.xls",sep=""), sheet=3,header=FALSE)
Data      <- read.xls(paste(dsn,"\\M4D_poptot1990-
2011_20120522.xls",sep=""), sheet=4,header=FALSE)

###
### Parse the 'Source' worksheet for the provider index codes and names
###
len3 <- dim(Source)[1]
sourceLabels   <- which(Source[,1] == "Label")
sourceProvider <- which(Source[,1] == "Provider")
sourceIndex <-
data.frame(Source[sourceLabels,2],Source[sourceProvider,3])
colnames(sourceIndex) <- c("Label","Provider")
sourceIndex


#############################################
sourcesOK <- sourceIndex[c(1:32),]   # These are the rows for which
data is from
                                     # EUROSTAT + Nation al Statistical
Agencies

#############################################

###
### Split 'Data' worksheet into '.data' and '.source' worksheets
###
len2 <- dim(Data)[1]                                              # number
of rows
dataCols <- seq(5,47,2)                                           # columns
with data
Data.data    <- Data[4:len2,c(1,2,4,dataCols)]                    # data
Data.source  <- Data[4:len2,c(1,2,4,dataCols+1)]                  # source
information
colnames(Data.data) <-
c("UnitCode","Level","Name",paste("p",1990:2011,sep=""))
colnames(Data.source) <-
c("UnitCode","Level","Name",paste("s",1990:2011,sep=""))


###
### Create data frame 'Data.estim' which we used as the basis for
subsequent estimation
###
as.numeric.factor <- function(x) {as.numeric(levels(x))[x]}    #
convert factors to numeric

Data.estim <- Data.data                                            # Copy
old -> new
```

```
for (icol in 4:25) {                                                    # loop
over data columns
   Data.estim[,icol] <- NA
# update to NA
   rowsOK <- which((Data.source[,icol] %in% sourcesOK[,1]) == TRUE)
# EUROSTAT/NSA?
   Data.estim[rowsOK,icol] <- as.numeric.factor(Data.data[rowsOK,icol])
# .. yes - copy data
}
head(Data.estim)

###
### Finally index Data.estim by the NUTS code
###
rownames(Data.estim) <- Data.estim[,1]

levels(as.factor(substr(rownames(Data.estim),1,2)))
# "AT" "BE" "BG" "CH" "CY" "CZ" "DE" "DK" "EE" "ES" "FI" "FR" "GR" "HR"
"HU"
# "IE" "IS" "IT" "LI" "LT" "LU" "LV" "MK" "MT" "NL" "NO" "PL" "PT" "RO"
"SE"
# "SI" "SK" "TR" "UK"

#########################################################################
##########
# TASK 2:  Create a series of missing data heatmaps for the report
#########################################################################
##########

CountryCode <- levels(as.factor(substr(rownames(Data.estim),1,2)))   #
NUTS codes
CountryName <- Data.estim[match(rownames(Data.estim),CountryCode),3] #
Names
CountryName <- CountryName[!is.na(CountryName)]                       #
remove NA
Nc <- length(CountryCode)                                            #
How many?

###
### Heatmap construction function - many defaults are turned off
###
drawHeatmap <- function(country,title="Population") {
   CountryData <- Data.estim[substr(rownames(Data.estim),1,2) ==
country,]
   PlotOrder <- dim(CountryData)[1]:1

heatmap(as.matrix(CountryData[PlotOrder,4:25]),Colv=NA,Rowv=NA,main=tit
le,na.rm=T,
      xlab="Year",ylab="NUTS
Region",col=rev(brewer.pal(11,"Spectral")),bg="grey")
}

###
### Loop over countries, plotting the heatmap. Store in Mapfiles/aa.png
###
for (i in 1:Nc) {
      fdname <- paste("Mapfiles\\",CountryCode[i],".png",sep="")    #
create filename
```

```
      cat(fdname,"\n")                                                  #
list it
      png(fdname)                                                       #
open it
         drawHeatmap(CountryCode[i],CountryName[i])                     #
plot heatmap
      dev.off()                                                         #
close the file
}

drawHeatmap("AT","Austria")
drawHeatmap("BE","Belgium")
drawHeatmap("BG","Bulgaria")
drawHeatmap("CH","Switzerland")
drawHeatmap("CY","Cyprus")
drawHeatmap("CZ","Czech Republic")
drawHeatmap("DE","Germany")
drawHeatmap("DK","Denmark")
drawHeatmap("EE","Estonia")
drawHeatmap("ES","Spain")
drawHeatmap("FI","Finland")

drawHeatmap("FR","France")
drawHeatmap("GR","Greece")
drawHeatmap("HR","Croatia")
drawHeatmap("HU","Hungary")
drawHeatmap("IE","Ireland")
drawHeatmap("IS","Iceland")
drawHeatmap("IT","Italy")
drawHeatmap("LI","Liechtenstein")
drawHeatmap("LT","Lithunia")
drawHeatmap("LU","Luxembourg")

drawHeatmap("LV","Latvia")
drawHeatmap("MK","Macedonia")
drawHeatmap("MT","Malta")
drawHeatmap("NL","Netherlands")
drawHeatmap("NO","Norway")
drawHeatmap("PL","Poland")
drawHeatmap("PT","Portugal")
drawHeatmap("RO","Romania")
drawHeatmap("SE","Sweden")
drawHeatmap("SI","slovakia")

drawHeatmap("SK","Slovak Republic")
drawHeatmap("TR","Turkey")
drawHeatmap("UK","United Kingdom")

##########################################################################
##########
# TASK 3:  enumerate areas with missing data at NUTS0/1/2
##########################################################################
##########

#dataCols <- 4:25
levels(as.factor(substr(rownames(Data.estim),1,2)))
# "AT" "BE" "BG" "CH" "CY" "CZ" "DE" "DK" "EE" "ES" "FI" "FR" "GR" "HR"
"HU"
```

```
# "IE" "IS" "IT" "LI" "LT" "LU" "LV" "MK" "MT" "NL" "NO" "PL" "PT" "RO"
"SE"
# "SI" "SK" "TR" "UK"

###
### Area code/name information as in TASK 2:
###
CountryCode <- levels(as.factor(substr(rownames(Data.estim),1,2)))
CountryName <- Data.estim[match(rownames(Data.estim),CountryCode),3]
CountryName <- CountryName[!is.na(CountryName)]
NUTSlevel <- nchar(rownames(Data.estim))-2
Nc <- length(CountryCode)                                              #
Countries
Nr <- nrow(Data.estim)                                                 #
NUTS regions

for (i in 1:Nr) {                                                      #
Loop over NUTS codes
      if(NUTSlevel[i] <= 2) {
         if (!complete.cases(Data.estim[i,4:25])) {                    #
Complete case?
            nCode <- as.character(Data.estim[i,1])                     #
... no, get code
            nName <- as.character(Data.estim[i,3])                     #
... get name
            cat("Missing data for ",nCode,nName,"\n")                  #
... and report
            }
          }
      }
}


#########################################################################
#########################
### Task 4: Example plots to explore general patterns in the data
#########################################################################
#########################


CountryCode <- levels(as.factor(substr(rownames(Data.estim),1,2)))
   year <- 1:22
   yearsq <- year^2

   ###
   ### Each plot has: base data as dots and a line in grey
   ###                fit from a linear model in lightblue
   ###                fit from the quadratic model in red
   ###
   par(mfrow=c(2,2))
   Popdata <- as.numeric(Data.estim["AT",4:25])

plot(1990:2011,Popdata,xlab="Year",ylab="Population",main="Austria",pch
=16,col="grey")
   lines(1990:2011,Popdata,col="grey")
   lines(1990:2011,(cbind(1,year) %*%
coef(lm(Popdata~year))),col="lightblue")
```

```
   lines(1990:2011,(cbind(1,year,yearsq) %*%
coef(lm(Popdata~year+yearsq))),col="red")

   Popdata <- as.numeric(Data.estim["FR",4:25])

plot(1990:2011,Popdata,xlab="Year",ylab="Population",main="France",pch=
16,col="grey")
   lines(1990:2011,Popdata,col="grey")
   lines(1990:2011,(cbind(1,year) %*%
coef(lm(Popdata~year))),col="lightblue")
   lines(1990:2011,(cbind(1,year,yearsq) %*%
coef(lm(Popdata~year+yearsq))),col="red")

   Popdata <- as.numeric(Data.estim["NL",4:25])

plot(1990:2011,Popdata,xlab="Year",ylab="Population",main="Netherlands"
,pch=16,col="grey")
   lines(1990:2011,Popdata,col="grey")
   lines(1990:2011,(cbind(1,year) %*%
coef(lm(Popdata~year))),col="lightblue")
   lines(1990:2011,(cbind(1,year,yearsq) %*%
coef(lm(Popdata~year+yearsq))),col="red")

   Popdata <- as.numeric(Data.estim["SI",4:25])

plot(1990:2011,Popdata,xlab="Year",ylab="Population",main="Slovenia",pc
h=16,col="grey")
   lines(1990:2011,Popdata,col="grey")
   lines(1990:2011,(cbind(1,year) %*%
coef(lm(Popdata~year))),col="lightblue")
   lines(1990:2011,(cbind(1,year,yearsq) %*%
coef(lm(Popdata~year+yearsq))),col="red")
   par(mfrow=c(1,1))




#########################################################################
##########################
### TASK 5: Extract data for Austria as test data *** *** *** ONLY FOR
TESTING *** *** ***
#########################################################################
##########################
Austria <- Data.estim[substr(rownames(Data.estim),1,2) == "AT",]
PlotOrder <- dim(Austria)[1]:1                                          #
reverse order for the heatmap
heatmap(as.matrix(Austria[PlotOrder,4:25]),Colv=NA,Rowv=NA,main="Austri
a EUROSTAT Population Data",
    xlab="Year",ylab="NUTS Region",col=rev(brewer.pal(11,"Spectral")))

parent <- substr(rownames(Austria),1,nchar(rownames(Austria))-1)
parent[1] <- ""

NUTS  <- rownames(Austria)
NUTS0 <- which(nchar(rownames(Austria)) == 2)
NUTS1 <- which(nchar(rownames(Austria)) == 3)
NUTS2 <- which(nchar(rownames(Austria)) == 4)
NUTS3 <- which(nchar(rownames(Austria)) == 5)
```

```
Data.estim <- Austria


#########################################################################
############
#### TASK 6: MCMC estimation of NUTS levels 3 series
#########################################################################
############
# Estimation loop  one iteration is about 1.7 minutes for 12 missing
from 22 on
# a Intel Xeon X5460 quad core 3.16GHz processor running Windows XP
Professional
#
# 35 zones for Austria takes about an hour.  As a ball park estimate,
the whole of
# Europe should take about 36 hours of computing.
#
# On an Intel  Core i7-2640M processor running at 2.80Ghz it's under a
minute per fit.
# This is a 64 bit system running Windows 7 Professional. Austria would
take just
# over 30 minutes so about 18 hours for Europe.
# NUTS3 tool 199418.4 seconds 55h 24m, say ~55.5h
#
#########################################################################
############
###
### Load the function definition
###
source("ImputeMissingData.R")

###
### Copy start data
###
NUTSData.completed <- Data.estim

nrow <- dim(Data.estim)[1]                                  # number of
regions
NUTS  <- rownames(Data.estim)                               # NUTS codes
NUTSlevel <- nchar(NUTS)-2                                  # NUTS lebels

total.time <- 0
startrow <- 1                                               # start at 1 ...
endrow <- nrow                                              # ... and finish
at nrow
for (i in startrow:endrow) {
   #if(NUTSlevel[i] < 3 & substr(NUTS[i],1,2) != "UK") {
   if(substr(NUTS[i],1,2) != "UK") {                        # UK separately
      if (complete.cases(Data.estim[i,4:25])) {             # data complete?
         cat(NUTS[i],"is complete\n")                       # ... yes: ignore
      } else {
         cat(NUTS[i],"is undergoing imputation\n")          # ... no:
imputation needed
         Z <- as.numeric(Data.estim[i,4:25])                   # data series
         Years <- 1990:2011                                    # time frame
for series
```

```
         N <- length(Z)                                        # length of
the series
         missingYears <- which(is.na(Z))                       # missing
observations
         NM <- length(missingYears)                            # number of
missing obs
         Scale <- 1000                                         # scale for
populations
         tic <- proc.time()[3]
         fitted.model <- ImputeMissingData(Z,Years, missingYears,
Scale)  # imputation
         toc <- proc.time()[3] - tic
         total.time <- total.time + toc
         cat("Elapsed time: ",toc,"seconds\n")                 # elapsed
time report
         imputedValues <-
summary(fitted.model)$statistics[(5+(1:NM)),1]  # extract imputations
         NUTSData.completed[i,missingYears+3] <-
round(imputedValues*Scale) # update data vector
       }
   } else {
      cat(NUTS[i],"is NUTS level",NUTSlevel[i],"\n")
   }
}
cat("Completed.  Total time required was ",total.time," seconds\n")

###
### Write results to a file  - this step takes 60 hours!
###
write.csv(NUTSData.completed,"NUTSData_completedN3.csv")   # store the
results for later

########################## End of MCMC estimation
#############################################
#########################################################################
#######################
```

```
#########################################################################
############
### TASK 6A: Timings for MCMC estimation
###          Use Netherlands as an example to get scalbility graphc
###          *** Only for report illustrations ***
#########################################################################
############
# Estimation loop  one iteration is about 1.7 minutes for 12 missing
from 22 on
# a Intel Xeon X5460 quad core 3.16GHz processor running Windows XP
Professional
#
# 35 zones for Austria takes about an hour.  As a ball park estimate,
the whole of
# Europe should take about 36 hours of computing.
#
# On an Intel  Core i7-2640M processor running at 2.80Ghz it's under a
minute per fit.
```

```
# This is a 64 bit system running Windows 7 Professional. Austria would
take just
# over 30 minutes so about 18 hours for Europe.
# NUTS3 tool 199418.4 seconds 55h 24m, say ~55.5h
#
source("ImputeMissingData.R")


#nrow <- dim(Data.estim)[1]
#NUTS  <- rownames(Data.estim)
#NUTSlevel <- nchar(NUTS)-2


TestData <- as.numeric(Data.estim["NL",4:25])
timeTaken <- rep(0,20)

for (i in 10:10) {
         Z <- TestData                                          # data series
         Z[1:i] <- NA                                           # add NAs
         Years <- 1990:2011                                     # time frame
for series
         N <- length(Z)                                         # length of
the series
         missingYears <- which(is.na(Z))                        # missing
observations
         NM <- length(missingYears)                             # number of
missing obs
         Scale <- 1000                                          # scale for
populations
         tic <- proc.time()[3]
         fitted.model <- ImputeMissingData(Z,Years, missingYears,
Scale, 250000, 100000, chains=2)  # imputation
         toc <- proc.time()[3] - tic
         timeTaken[i] <- toc
         cat("Elapsed time: ",toc,"seconds with",i,"missing values\n")
# elapsed time report
}
cat("Completed.  Total time required was ",sum(timeTaken)," seconds\n")
timeTaken

gelman.diag(fitted.model)                                       # convergence
diagnostics
gelman.plot(fitted.model)                                       # convergence
plot


#timeTaken2 <- timeTaken * (290/171.52)   # laptop relative to office
desktop
timeTaken2 <- timeTaken
proportionMissing <- 100 * (1:20) / 22
plot(proportionMissing,timeTaken2,ylim=c(0,300),
   xlab="Proportion Missing (N=22)",ylab="Time (seconds)",
   main="Scalability of MCMC Estimation")
```

```
########################################################################
########################
### TASK 7: Spatial Coherence Adjustment
###
########################################################################
########################



### Data.estim          : raw data from RIATE with only
EUROSTAT/National estimates
### NUTSData.completed  : unadjusted MCMC estimates


NUTSData.adjusted <- NUTSData.completed
# Copy the MCMC estimates
NUTSData.RIATE    <- Data.estim
# Copy the NA pattern
NUTSlevel         <- nchar(rownames(NUTSData.RIATE)) - 2
# recreate just in case

########################################################################
########################
### TASK 7A: Manual adjusment for Portugal (PT 1992:1995 missing)
###           Data.estim["PT",c("p1992","p1993","p1994","p1995")] is NA
###           should be sum of c("PT1","PT2","PT3")
###          "PT1" is c("PT11","PT15","PT16","PT17","PT18")

NUTSData.RIATE[substr(rownames(NUTSData.RIATE),1,2) == "PT" & NUTSlevel
<= 2,]    # for a look
### Fix PT1
for (year in c("p1992","p1993","p1994","p1995")) {
   NUTSData.adjusted["PT1",year] <-
sum(NUTSData.adjusted[c("PT11","PT15","PT16","PT17","PT18"),year])
   NUTSData.RIATE["PT1",year] <- NUTSData.adjusted["PT1",year]
# update the NA pattern
}
### Fix PT
for (year in c("p1992","p1993","p1994","p1995")) {
   NUTSData.adjusted["PT",year] <-
sum(NUTSData.adjusted[c("PT1","PT2","PT3"),year])
   NUTSData.RIATE["PT",year] <- NUTSData.adjusted["PT",year]
# update the NA pattern
}
NUTSData.adjusted[substr(rownames(NUTSData.adjusted),1,2) == "PT" &
NUTSlevel <= 2,]     # ... and check
NUTSData.RIATE[substr(rownames(NUTSData.RIATE),1,2) == "PT" & NUTSlevel
<= 2,]           # ... and check


########################################################################
###################
# TASK 7B: Apply spatial constraint for NUTSlevel nodes below
NUTSlevel-1
########################################################################
###################
#
# parent:       vector of parent node codes
```

```
# basic:        matrix of data with NAs
# unadjusted:   matrix of totals from MCMC operation
# dataCols:     columns in which there are data
#
# adjusted:     output: adjusted NUTSlevel node populations
ConstrainTotals2 <- function(basic,unadjusted,dataCols) {
   NAPattern     <- basic
# working copy
   MCMCestimated <- unadjusted
# working copy
   MCMCadjusted  <- unadjusted
# eventual output from function

   ### tree strcuture
   nodes  <- rownames(NAPattern)
# tree nodes
   parent <- substr(rownames(NAPattern),1,nchar(rownames(NAPattern))-1)
# backtrack to link children
   NUTSlevel <- nchar(rownames(NAPattern))-2
# NUTS level
   parent[which(NUTSlevel == 0)] <- ""
# clean up

   Ny <- length(dataCols)
# year span
   Years <- rep(0,Ny+3)
# create Year list
   Years[dataCols] <- 1990:2011

   #
   # Start from the NUTS0 levels
   #
   for (Level in 0:2) {
      cat("\n\n")

cat("************************************************************\n")
      cat("* Cross-Sectional Time Series Constraint for NUTS
Level",Level,"*\n")

cat("************************************************************\n")
      Levelnodes <- nodes[which(NUTSlevel == Level)]
      NL <- length(Levelnodes)
      for (i in 1:NL) {
         children <- nodes[parent == Levelnodes[i]]               #
NUTS1 children of the root
         cat("NUTS",(Level+1), "children of", Levelnodes[i], "are",
children,"\n")
      Nc <- length(children)
# Number of children
      for (year in dataCols){
# loop over the years
         any.missing <- which(is.na(NAPattern[children,year]))
# which children have NA
         if (length(any.missing) == 0) {
# ... none missing
            #cat("** NUTS",(Level+1),"data for",Levelnodes[i],"children
are present in",Years[year],"\n")
```

```
         } else {
# ... missing, so adjust
            valueParent <- MCMCestimated[Levelnodes[i],year]
# parent contraint value
            childOK     <- children
# index of children
            if (!is.na(valueParent)) {
# parent value not missing
               missingChild <- is.na(NAPattern[children,year])
# missing children
               if (sum(missingChild) < Nc) {
                  ChildOK      <- !missingChild
# ... nonmissing children
                  alreadyOK <-
sum(MCMCestimated[children[ChildOK],year])       # ... total for
nonmissing
                  valueParent <- valueParent - alreadyOK
# reduce constraint value
               }
               sumChildren <-
sum(MCMCestimated[children[missingChild],year])  # sum of MCMC
estimates
               MCMCadjusted[children[missingChild],year] <-
(valueParent/sumChildren) *
               MCMCadjusted[children[missingChild],year]
# adjusted MCMC estimates
               cat("** NUTS",(Level+1),"data
for",Levelnodes[i],"children constrained in",Years[year],"\n")
            } else {
               #cat("** WARNING: missing data
for",Levelnodes[i],"Constraint not possible in",Years[year],"\n")
            }
            }
        }

      }
   }
   MCMCadjusted
}



###
### Undertake adjustment, and report time
###
tic <- proc.time()
NUTSData.final    <-
ConstrainTotals2(NUTSData.RIATE,NUTSData.completed,4:25)  #### FINAL
OUTPUT ###
toc <- proc.time()-tic
cat("\nTime Required for adjustment was ",toc,"seconds\n\n")


#####################################################################
##############################
#####################################################################
##############################
```

```
#########################################################################
##############################

CheckConstraint <- function(parents,basic,dataCols) {
   NUTSCodes <- rownames(basic)                          # get the NUTD
codes of the parents
   Np <- length(parents)                                 # how many NUTS2
regions
   for (parent in 1:Np) {                                # loop over the
NUTS regions
      NUTS3.units <- (nchar(NUTSCodes) == 5) & (substr(NUTSCodes,1,4)
== parents[parent])
      NUTS2.basic <- basic[parents[parent],]              # just the
data for this parent
      NUTS3.basic <- basic[NUTS3.units,]
      NUTS3.this.node <- NUTSCodes[NUTS3.units]       # NUTS codes for
this parent
      #cat(parents[parent],": ",NUTS3.this.node,"\n")
      N3 <- length(NUTS3.this.node)
         for (i in dataCols) {
            Nmiss <- length(which(is.na(NUTS3.basic[,i])))
            NUTS2.basic[i] <- round(100 * Nmiss / N3)
         }
      cat(parents[parent],":", unlist(NUTS2.basic[,dataCols]),"\n")
      }
}

CheckCountry <- function(Country,Data.estim) {
   CountryData <- Data.estim[substr(rownames(Data.estim),1,2) ==
Country,]
   PlotOrder <- dim(CountryData)[1]:1
# reverse order for the heatmap

   parent <-
substr(rownames(CountryData),1,nchar(rownames(CountryData))-1)
   parent[1] <- ""

   NUTS  <- rownames(CountryData)
   NUTS0 <- which(nchar(rownames(CountryData)) == 2)
   NUTS1 <- which(nchar(rownames(CountryData)) == 3)
   NUTS2 <- which(nchar(rownames(CountryData)) == 4)
   NUTS3 <- which(nchar(rownames(CountryData)) == 5)

   CheckConstraint(rownames(CountryData)[NUTS2],CountryData,4:25)
}

CheckCountry("AT",Data.estim)
CheckCountry("SI",Data.estim)
CheckCountry("UK",Data.estim)

#> levels(as.factor(substr(rownames(Data.estim),1,2)))
# "AT" "BE" "BG" "CH" "CY" "CZ" "DE" "DK" "EE" "ES" "FI" "FR" "GR" "HR"
"HU"
# "IE" "IS" "IT" "LI" "LT" "LU" "LV" "MK" "MT" "NL" "NO" "PL" "PT" "RO"
"SE"
# "SI" "SK" "TR" "UK"
CountryList <- levels(as.factor(substr(rownames(Data.estim),1,2)))
```

```
Nc <- length(CountryList)
#Nc <- 5
for (i in 1:Nc) {
   CheckCountry(CountryList[i],Data.estim)
}


CheckTree <- function(Country,Data.estim) {
   CountryData <- Data.estim[substr(rownames(Data.estim),1,2) ==
Country,]

   nodes  <- rownames(CountryData)
   parent <-
substr(rownames(CountryData),1,nchar(rownames(CountryData))-1)
   parent[1] <- ""

   ### visit.node
   ###    for each child(visit.node)

   ROOT <- which(nodes == Country)
   cat("\nTree Walk\n")
      root <- nodes[ROOT]
      cat("NUTS0 node is ",root,"\n")
         children1 <- nodes[parent == root]
         cat(" NUTS1 children of", root, "are", children1,"\n")
         Nc1 <- length(children1)
         for (i in 1:Nc1) {
            node2 <- children1[i]
            children2 <- nodes[parent == node2]
            cat("  NUTS2 children of", node2, "are", children2,"\n")
            Nc2 <- length(children2)
            for (j in 1:Nc2) {
               node3 <- children2[j]
               children3 <- nodes[parent == node3]
               cat("   NUTS3 children of", node3, "are",
children3,"\n")
            }
         }
}
CheckTree("AT",Data.estim)
CheckTree("UK",Data.estim)

#########################################################################
#########
#########################################################################
#########
#########################################################################
#########

### Check for singleton missings

CheckMissingPattern <- function(Country,Data,dataCols,verbose=FALSE) {
   CountryData <- Data[substr(rownames(Data),1,2) == Country,]
   IDInfo <- CountryData[,1:3]
   Nc <- dim(IDInfo)[1]
   Results <- data.frame(IDInfo[,1:3],matrix(0,Nc,8))
   rownames(Results) <- rownames(CountryData)
```

```
   nodes  <- rownames(CountryData)
   parent <-
substr(rownames(CountryData),1,nchar(rownames(CountryData))-1)
   parent[1] <- ""

   Nd <- length(dataCols)

   ### visit.node
   ###    for each child(visit.node)

   ROOT <- which(nodes == Country)
   cat("\nTree Walk\n")
      root <- nodes[ROOT]
      if (verbose) cat("NUTS0 node is ",root,"\n")
         children1 <- nodes[parent == root]
         if (verbose) cat(" NUTS1 children of", root, "are",
children1,"\n")
          Nc1 <- length(children1)
          CasePattern <- CheckNode(root,children1,Data,dataCols)
           #cat("[",Nc1,"] children", CasePattern,"\n")
           Results[root,4:11] <- CasePattern
         for (i in 1:Nc1) {
            node2 <- children1[i]
            children2 <- nodes[parent == node2]
            if (verbose) cat("  NUTS2 children of", node2, "are",
children2,"\n")
             Nc2 <- length(children2)
             CasePattern <- CheckNode(node2,children2,Data,dataCols)
             #cat("[",Nc2,"] children", CasePattern,"\n")
             Results[node2,4:11] <- CasePattern
            for (j in 1:Nc2) {
               node3 <- children2[j]
               children3 <- nodes[parent == node3]
               if (verbose) cat("   NUTS3 children of", node3, "are",
children3,"\n")
               Nc3 <- length(children3)
                CasePattern <- CheckNode(node3,children3,Data,dataCols)
                Results[node3,4:11] <- CasePattern
            }
         }
   NUTSlevels <- lapply(Results[,2], as.character)
   print(Results[NUTSlevels <= "NUTS2",])
}

#
#
#
CheckNode <- function(parent,children,Data,dataCols){
      Nc <- length(children)                                          #
How many children for this parent
      MissingParent <- Data[parent,]                                  #
Copy parent record (we'll use data cols)
      Result <- Data[parent,]                                         #
Create result record
      Cases <- rep(0,8)                                               # 8
possible outcomes
      for (i in dataCols) {                                           #
loop over time period for this parent
```

```
         MissingParent[i] <- is.na(Data[parent,i])                  #
Is parent missing for this year
         Result[i] <- length(which(is.na(Data[children,i])))        #
Number of children missing for this year
         if (!MissingParent[i]) {
              if (Result[i] == 0)                          k <- 1      #
Parent present, no children missing - nothing to do!
              else if (Result[i] == 1)                     k <- 3      #
Parent present, 1 child missing (embarassingly estimatable)
              else if (Result[i] > 1 & Result[i] < Nc) k <- 4      #
Parent present, some children missing - estimate/constrain
              else                                         k <- 5      #
Present present, all children missing - estimate/constrain
              } else {
              if (Result[i] == 0)                          k <- 2      #
Parent missing, no children missing (estimate parent!)
              else if (Result[i] == 1)                     k <- 6      #
Parent missing, 1 child missing       - awkward
              else if (Result[i] > 1 & Result[i] < Nc) k <- 7      #
Parent missing, some children missing - awkward
              else                                         k <- 8      #
Parent missing, all children missing  - awkward
              }
              Cases[k] <- Cases[k] + 1                               #
update counter

      }
      Cases
}                                                                    #
Return counter vector


CheckMissingPattern("AT",Data.estim,4:25)

#> levels(as.factor(substr(rownames(Data.estim),1,2)))
# "AT" "BE" "BG" "CH" "CY" "CZ" "DE" "DK" "EE" "ES" "FI" "FR" "GR" "HR"
"HU"
# "IE" "IS" "IT" "LI" "LT" "LU" "LV" "MK" "MT" "NL" "NO" "PL" "PT" "RO"
"SE"
# "SI" "SK" "TR" "UK"
CountryList <- levels(as.factor(substr(rownames(Data.estim),1,2)))
Nc <- length(CountryList)
for (i in 1:Nc) {
   CheckMissingPattern(CountryList[i],Data.estim, 4:25)
}




##########################################################################
##########
### TASK X Austria
#########################################################
##########################################################################
##########
```

```
nodes     <- rownames(Data.estim)
NUTSlevel <- nchar(nodes) - 2
parents <- substr(nodes,1,(NUTSlevel+1))
AT21children <- nodes[which(parents == "AT21")]
Names <- as.character(Data.estim[AT21children,3])


AT21MCMCout  <- as.matrix(Austria.final[AT21children,4:25])           #
MCMC outputs
AT21totals   <- colSums(AT21MCMCout)                                  #
AT21 totals from MCMC
AT21factor   <- as.numeric(Data.estim["AT21",4:25]) / AT21totals      #
adjustment factors
AT21adjusted <- round(sweep(AT21MCMCout,2,AT21factor,"*"),0)          #
sweep down rows
colSums(AT21adjusted) - Data.estim["AT21",4:25]                       #
and check

par(mfrow=c(3,1))
for (i in 1:length(AT21children)) {
   NUTS3zone <- AT21children[i]
   mindata <- min(AT21MCMCout[i,],AT21adjusted[NUTS3zone,]) * 0.95
   maxdata <- max(AT21MCMCout[i,],AT21adjusted[NUTS3zone,]) * 1.05

plot(1990:2011,AT21MCMCout[i,],col="darkgrey",type="l",xlab="Year",ylab
=NA,
      ylim=c(mindata,maxdata), main=paste(NUTS3zone,Names[i]),lty=2)
   lines(1990:2011,AT21adjusted[NUTS3zone,],col="red",lty=1)
   lines(1990:2011,Data.estim[NUTS3zone,4:25],col="darkgrey")
   points(1990:2011,Data.estim[NUTS3zone,4:25],pch=16,col="darkgrey")
}
par(mfrow=c(1,1))




##########################################################################
##########
### MONTE CARLO VARIABILITY
#########################################################
##########################################################################
##########

### Random normal variates
par(mfrow=c(3,3))
for (i in c(100,500,1000,5000,10000,50000,100000,500000,1000000)) {
   hist(rnorm(i,0,1),breaks=100,xlim=c(-
4,4),col="grey",border=NA,main=paste("N=",i,sep=""),xlab=NA,ylab=NA)
}
par(mfrow=c(1,1))

### Random gamma
par(mfrow=c(3,3))
for (i in c(100,500,1000,5000,10000,50000,100000,500000,1000000)) {

hist(rgamma(i,50),breaks=100,xlim=c(20,80),col="grey",border=NA,main=pa
ste("N=",i,sep=""),xlab=NA,ylab=NA)
```

```
}
par(mfrow=c(1,1))

### random beta
par(mfrow=c(3,3))
for (i in c(100,500,1000,5000,10000,50000,100000,500000,1000000)) {

hist(rbeta(i,1,1),breaks=100,xlim=c(0,1),col="grey",border=NA,main=past
e("N=",i,sep=""),xlab=NA,ylab=NA)
}
par(mfrow=c(1,1))

### mtulivariate normal

Sigma <- matrix(c(10,3,3,2),2,2)
Sigma
par(mfrow=c(3,3))
for (i in c(100,300,750, 1000,3000,7500, 10000,30000,75000)) {
   x <- mvrnorm(n=i, c(0,0), Sigma)
   plot(x ,col="grey",pch=16, xlim=c(-15,15),ylim=c(-6,6),
main=paste("N=",i,sep=""),xlab=NA,ylab=NA)
   lines(lowess(x),col="red")
}
par(mfrow=c(1,1))

### changing precision
par(mfrow=c(3,3))
tau <- c(0.25,1,4, 16,64,256, 1024, 4096, 16384)
for (i in 1:9) {

hist(rnorm(10000,10,1/sqrt(tau[i])),breaks=100,xlim=c(6,14),col="red",b
order="red",main=paste("Tau=",tau[i],sep=""),xlab=NA,ylab=NA)
}
par(mfrow=c(1,1))

### non-informative prior
par(mfrow=c(3,3))
tau <- 4^(-(0:8))
for (i in 1:9) {
   hist(rnorm(10000,0,1/sqrt(tau[i])),breaks=100,xlim=c(-
20,20),col="red",border="red",main=paste("Tau=",format(tau[i],digits=3)
,sep=""),xlab=NA,ylab=NA)
}
par(mfrow=c(1,1))
```

Appendix 3: Core Imputation Function

```
##############################################################################
##############################################################################
#
# ESPON M4D Multidimensional Database Design and Development
#
# Time Series Estimation
#
# Missing Data Imputation Function
#
#
### Authors:
#
# Martin Charlton and Chris Brunsdon
#
### Address:
#
# National Centre for Geocomputation
# National University of Ireland, Maynooth
# Maynooth, Co Kildare, IRELAND
#
# V1.01: June 2014
#
#### (c) ESPON
#
# Code is made avilable under the GNU GENERAL PUBLIC LICENSE, Version 3
# Text of the License is at http://www.gnu.org/licenses/gpl.txt
#
##############################################################################
##############################################################################
#
# Fit estimate missing values in a time series using MCMC with a quadratic
#   trend model
#
# Input:
#   pop:              series with Missing data (represented by NA)
#   years:            date range for input series
#   missing:          indices of missing data
#   yscale:           scaling for pop variable (to keep values reasonabley small)
#   burnin.iters:     number of burn-in iterations (default 250000)
#   coda.iters:       number of iterations for estimation (default 100000)
#
# Output:
#   fitted.model      coda.samples rjags output object
#
##############################################################################
##############################################################################

ImputeMissingData <-
function(pop,years,missing,yscale=1,burnin.iters=250000,coda.iters=100000,chains=1)
{

   ###
   ### Create the regressands for the linear and quadratic trend terms
   ###
   gyear   <- 1:length(years)       # linear term
   gyear2  <- gyear^2               # quadratic term

   ###
   ### Load the correct JAGS code - different cdoe is required when there is
   ###   only one NA.  This is an R issue
   ###
```

```
   if (length(missing) == 1) {
     tfile = "tfile2.JAGS"          # estimator for data with a single NA
   } else {
     tfile = "tfile1.JAGS"          # estimator for data with multiple NAs
   }

   ###
   ### Initialisation
   ###
   ###    present:  indices of the non-missing data
   ###    y:        time series - the regressor
   ###    N:        number of terms in the series (both missing and present)
   ###    ys:       present data
   ###    ym:       missing data
   ###
   present <- setdiff(gyear,missing)   # indices of non-missing data
   y <- pop/yscale                     # scale the y if necessary
   N <- length(y)                      # length of the series
   ys <- y[present]                    # present data values
   ym <- y[missing]                    # missing data


   ###
   ### Initialise the JAGS input
   ###   popdata:  list which is used to pass data to JAGS
   ###   N:        length of the time series
   ###   ys:       non-missing data values
   ###   seen:     indices of the non-missing data
   ###   missing:  indices of the missing data
   ###   year:     linear regressand
   ###   yearsq:   quadratic regressand
   ###
   popdata <- list(N=N, ys=ys, seen=present, missing=missing, year=gyear,
yearsq=gyear2)

   ###
   ### Fit an OLS model to provide some plausible starting values for the
coefficients
   ###
   xx <- coef(mdl <- lm(y~gyear+gyear2))

   ###
   ### Load the model
   ###    m:         rjags object containign the model
   ###    file:      JAGS code for the MCMC model
   ###    data:      list of data and regressands for the model
   ###    inits:     initial values for the parameters
   ###    .RNG.name: random number generator to be used
   ###    .RNG.seed: random number generator seed (for reproducibility)
   ###    n.chains:  number of Markov chains to use
   ###
   if (chains == 1) {
   m <- jags.model(file=tfile,
            data=popdata,
            inits=list(b0=xx[1],b1=xx[2],b2=xx[3],
            .RNG.name='base::Mersenne-Twister',.RNG.seed=290162),
            n.chains=1)
  } else {
     m <- jags.model(file=tfile,
            data=popdata,
            inits=list(b0=xx[1],b1=xx[2],b2=xx[3]),
            n.chains=chains)
  }

   ###
   ### Initial burn-in - these results are discarded. Default is 250000 iterations
   ###
   update(m, n.iter=burnin.iters)
```

```
   ###
   ### Fit the model - output is and mcmc.list object which is returned from the
function
   ###
   coda.samples(m, n.iter=coda.iters, thin=5, variable.names =
c("ym","b0","b1","b2","rho","s2err"))

}
```

Appendix 4: JAGS code for MCMC (multiple NAs)

```
################################################################################
################################################################################
#
# ESPON M4D Multidimensional Database Design and Development
#
# Time Series Estimation
#
# MCMC estimation of time series with missing data [tfile1: several NA values]
#
#
### Authors:
#
# Martin Charlton and Chris Brunsdon
#
### Address:
#
# National Centre for Geocomputation
# National University of Ireland, Maynooth
# Maynooth, Co Kildare, IRELAND
#
# V1.01: June 2014
#
#### Copyright
#
# Code is made avilable under the GNU GENERAL PUBLIC LICENSE, Version 3
# Text of the License is at http://www.gnu.org/licenses/gpl.txt
#
################################################################################
################################################################################
model
{


    # Prior distributions

    b0     ~ dnorm(0.0, 0.000001)                  # intercept
    b1     ~ dnorm(0.0, 0.000001)                  # linear coefficient on time
    b2     ~ dnorm(0.0, 0.000001)                  # quadratic time term
    s2err  ~ dgamma(1,50)
    #rho    ~ dbeta(0.5, 0.5)
    rho ~ dbeta(10,10)                             # AR(1) parameter

    # Trend component
    for(i in 1:N) {
       mu[i] <- b0 + b1*year[i] +b2*yearsq[i]
    }

    # Autocorrelation component
    for(i in 1:N) {
       for (j in 1:N) {
          tdmat[i,j] <- s2err*rho^abs(i-j)
    }}

    for (i in 1:length(seen)) {
       for (j in 1:length(seen)) {
          tdmat22[i,j] <- tdmat[seen[i],seen[j]]
    }}

    itdmat22 <- inverse(tdmat22)
```

```
    for (i in 1:length(missing)) {
       for (j in 1:length(missing)) {
          tdmat11[i,j] <- tdmat[missing[i],missing[j]]
    }}

    itdmat11 <- inverse(tdmat11)

    for (i in 1:length(missing)) {
       for (j in 1:length(seen)) {
          tdmat12[i,j] <- tdmat[missing[i],seen[j]]
    }}

    for (i in 1:length(seen)) {
       for (j in 1:length(missing)) {
          tdmat21[i,j] <- tdmat[seen[i],missing[j]]
    }}

    for (i in 1:length(seen)) {
       mu2[i] <- mu[seen[i]]
    }

    for (i in 1:length(missing)) {
       mu1[i] <- mu[missing[i]]
    }

    OmegaM <- inverse(tdmat11 - tdmat12 %*% itdmat22 %*% tdmat21)
    muM <- mu1 + tdmat12 %*% itdmat22 %*% (ys - mu2)

    ys ~ dmnorm(mu2,itdmat22)                    # non-missing data
    ym ~ dmnorm(muM, OmegaM)                     # missing data


}
```

Appendix 5: JAGS code for MCMC (single NA)

```
################################################################################
################################################################################
#
# ESPON M4D Multidimensional Database Design and Development
#
# Time Series Estimation
#
# MCMC estimation of time series with missing data [tfile2: single NA value]
#
#
### Authors:
#
# Martin Charlton and Chris Brunsdon
#
### Address:
#
# National Centre for Geocomputation
# National University of Ireland, Maynooth
# Maynooth, Co Kildare, IRELAND
#
# V1.01: June 2014
#
#### Copyright
#
# Code is made avilable under the GNU GENERAL PUBLIC LICENSE, Version 3
# Text of the License is at http://www.gnu.org/licenses/gpl.txt
#
################################################################################
################################################################################
model
{


    # Prior distributions

    b0      ~ dnorm(0.0, 0.000001)
    b1      ~ dnorm(0.0, 0.000001)
    b2      ~ dnorm(0.0, 0.000001)
    s2err   ~ dgamma(1,50)
    #rho     ~ dbeta(0.5, 0.5)
    rho ~ dbeta(10,10)

    # Trend component
    for(i in 1:N) {
    mu[i] <- b0 + b1*year[i] +b2*yearsq[i]
    # mu[i] <- b0 + b1*i
    }

    # Autocorrelation component
    for(i in 1:N) {
    for (j in 1:N) {
    tdmat[i,j] <- s2err*rho^abs(i-j)
    }
    }

    for (i in 1:length(seen)) {
    for (j in 1:length(seen)) {
    tdmat22[i,j] <- tdmat[seen[i],seen[j]]
    }}
```

```
    itdmat22 <- inverse(tdmat22)

    tdmat11 <- tdmat[missing,missing]

    itdmat11 <- 1.0/tdmat11

    for (j in 1:length(seen)) {
    tdmat12[j] <- tdmat[missing,seen[j]]
    }

    for (i in 1:length(seen)) {
    tdmat21[i] <- tdmat[seen[i],missing]
    }

    for (i in 1:length(seen)) {
    mu2[i] <- mu[seen[i]]
    }

    for (i in 1:length(seen)) {
      for (j in 1:length(seen)) {
        oprod12[i,j] <- tdmat12[i] * tdmat21[j]
      }
    }
    mu1 <- mu[missing]

    OmegaM <- 1.0/(tdmat11 - inprod(tdmat12,itdmat22 %*% tdmat21))
    muM <- mu1 + inprod(tdmat12, itdmat22 %*% (ys - mu2))


    ys ~ dmnorm(mu2,itdmat22)
    ym ~ dnorm(muM, OmegaM)



}
```

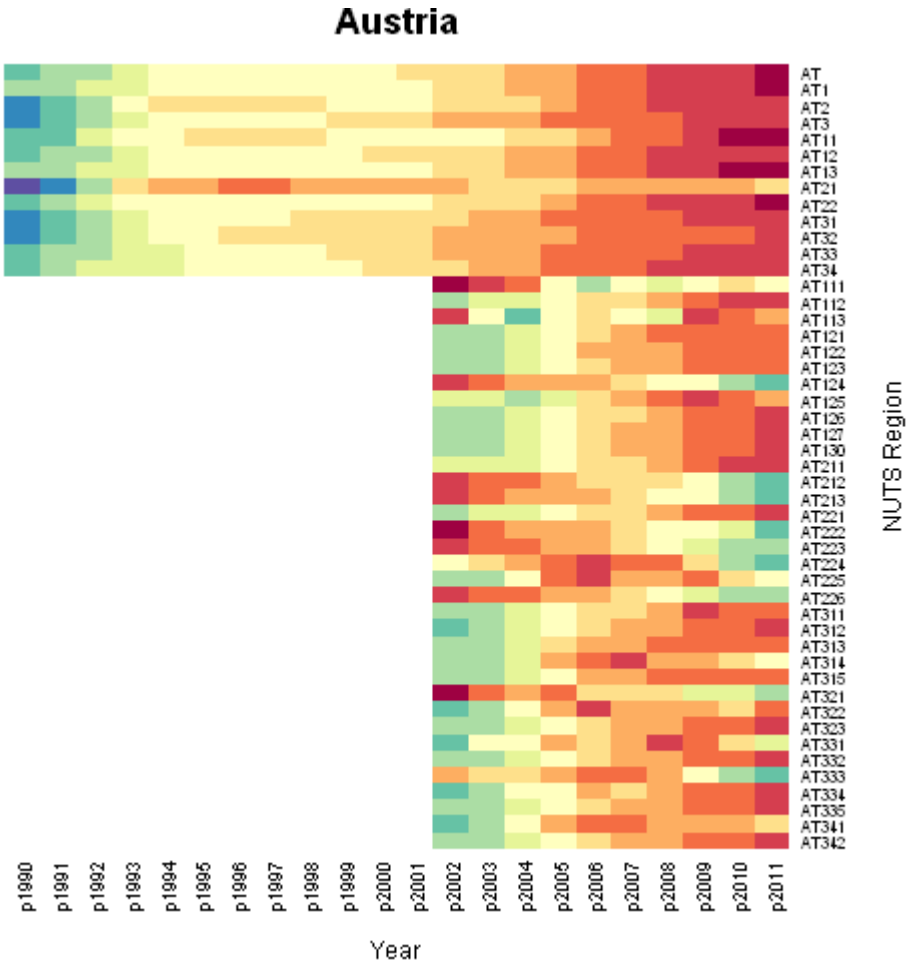
Appendix 6: NUTS0/1/2 Missing Data

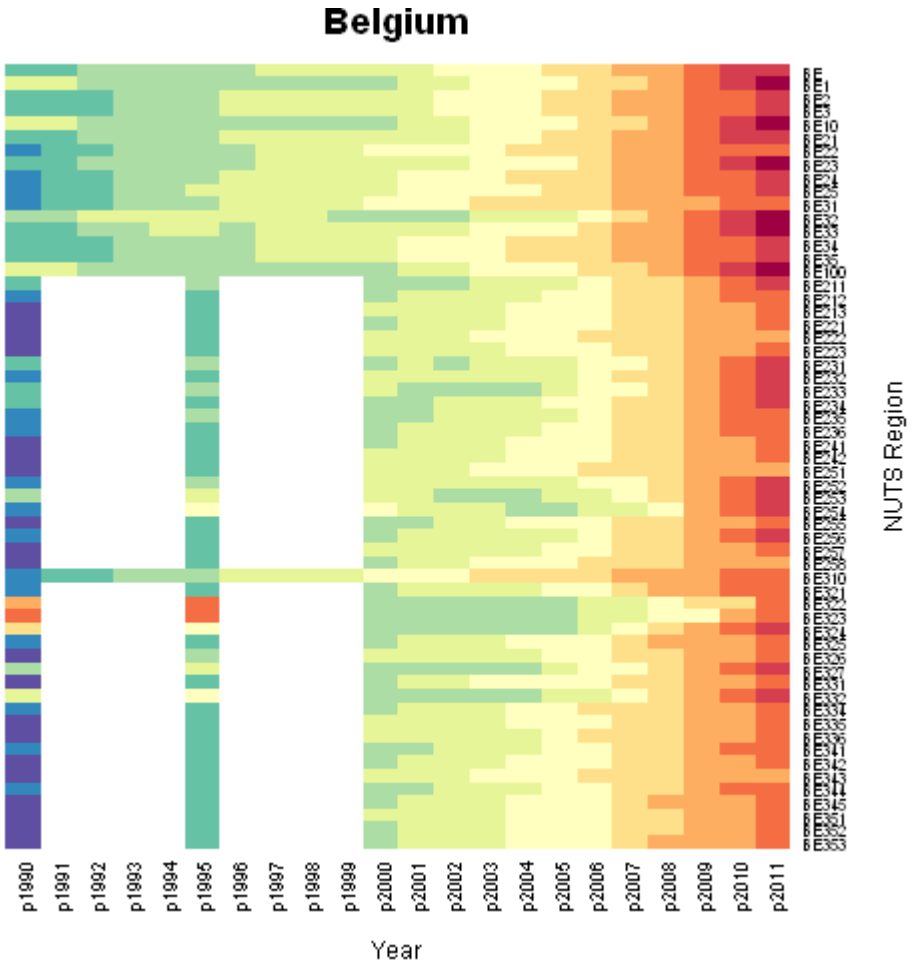
Seq	Missing	Name	NUTS Code
28	4	Portugal	PT
33	16	Turkey	TR
34	21	United Kingdom	UK
81	2	Départements d'outre-mer (FR)	FR9
105	1	West-Nederland	NL3
108	1	Region Centralny	PL1
109	1	Region Poludniowy	PL2
110	1	Region Wschodni	PL3
111	1	Region Pólnocno-Zachodni	PL4
112	1	Region Poludniowo-Zachodni	PL5
113	1	Region Pólnocny	PL6
114	6	Continente	PT1
115	2	Região Autónoma dos Açores (PT)	PT2
116	2	Região Autónoma da Madeira (PT)	PT3
126	16	Istanbul	TR1
127	16	Bati Marmara	TR2
128	16	Ege	TR3
129	16	Dogu Marmara	TR4
130	16	Bati Anadolu	TR5
131	16	Akdeniz	TR6
132	16	Orta Anadolu	TR7
133	16	Bati Karadeniz	TR8
134	16	Dogu Karadeniz	TR9
135	16	Kuzeydogu Anadolu	TRA
136	16	Ortadogu Anadolu	TRB
137	16	Güneydogu Anadolu	TRC
138	21	North East (UK)	UKC
139	21	North West (UK)	UKD
140	22	Yorkshire and The Humber	UKE
141	22	East Midlands (UK)	UKF
142	21	West Midlands (UK)	UKG
143	22	East of England	UKH
144	22	London	UKI
145	21	South East (UK)	UKJ
146	22	South West (UK)	UKK
147	22	Wales	UKL
148	11	Scotland	UKM
149	11	Northern Ireland (UK)	UKN
184	2	Praha	CZ01
185	2	Strední Cechy	CZ02
186	2	Jihozápad	CZ03
187	2	Severozápad	CZ04
188	2	Severovýchod	CZ05
189	2	Jihovýchod	CZ06
190	2	Strední Morava	CZ07
191	2	Moravskoslezsko	CZ08
204	5	Brandenburg - Nordost	DE41
205	5	Brandenburg - Südwest	DE42
225	5	Chemnitz	DED1
226	5	Dresden	DED2
227	5	Leipzig	DED3
231	17	Hovedstaden	DK01
232	17	Sjælland	DK02
233	17	Syddanmark	DK03
234	17	Midtjylland	DK04
235	17	Nordjylland	DK05
300	11	Sjeverozapadna Hrvatska	HR01
301	11	Sredisnja i Istocna (Panonska) Hrvatska	HR02
302	11	Jadranska Hrvatska	HR03
310	7	Border, Midland and Western	IE01
311	7	Southern and Eastern	IE02

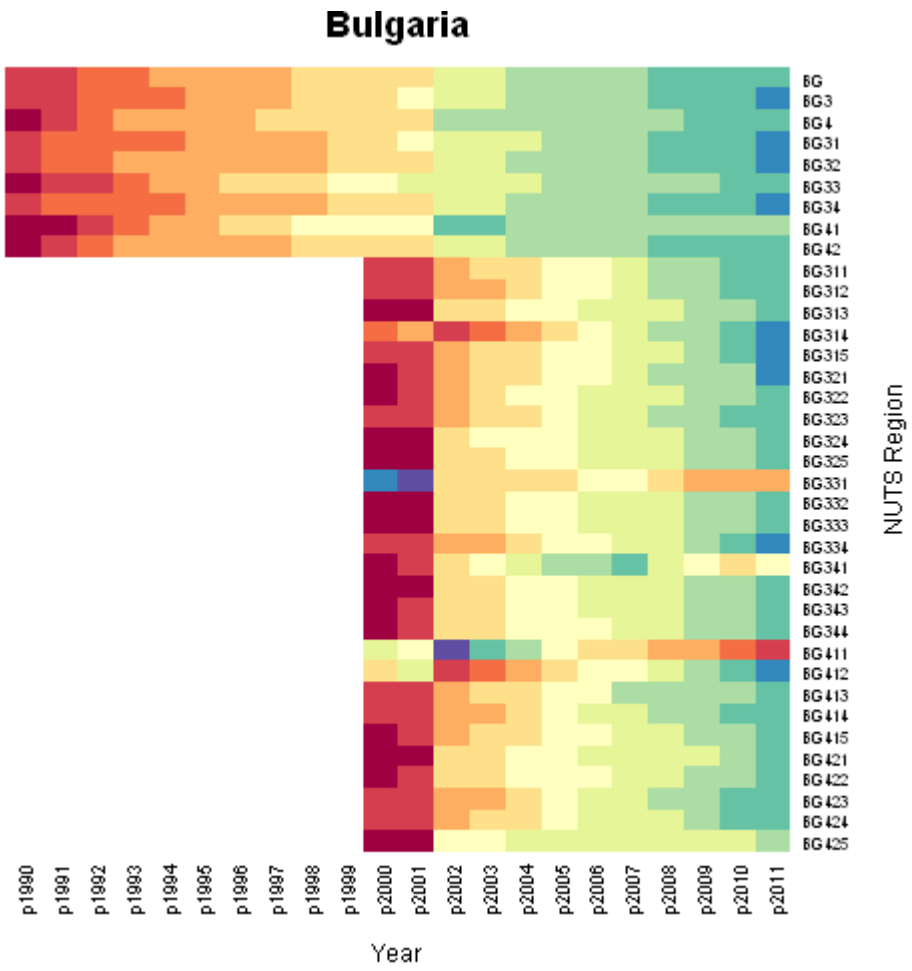
359	1	Lódzkie	PL11
360	1	Mazowieckie	PL12
361	1	Malopolskie	PL21
362	1	Slaskie	PL22
363	1	Lubelskie	PL31
364	1	Podkarpackie	PL32
365	1	Swietokrzyskie	PL33
366	1	Podlaskie	PL34
367	1	Wielkopolskie	PL41
368	1	Zachodniopomorskie	PL42
369	1	Lubuskie	PL43
370	1	Dolnoslaskie	PL51
371	1	Opolskie	PL52
372	1	Kujawsko-Pomorskie	PL61
373	1	Warminsko-Mazurskie	PL62
374	1	Pomorskie	PL63
375	2	Norte	PT11
376	2	Algarve	PT15
377	2	Centro (PT)	PT16
378	2	Lisboa	PT17
379	2	Alentejo	PT18
380	2	Região Autónoma dos Açores (PT)	PT20
381	2	Região Autónoma da Madeira (PT)	PT30
400	6	Bratislavský kraj	SK01
401	6	Západné Slovensko	SK02
402	6	Stredné Slovensko	SK03
403	6	Východné Slovensko	SK04
404	16	Istanbul	TR10
405	16	Tekirdag	TR21
406	16	Balikesir	TR22
407	16	Izmir	TR31
408	16	Aydin	TR32
409	16	Manisa	TR33
410	16	Bursa	TR41
411	16	Kocaeli	TR42
412	16	Ankara	TR51
413	16	Konya	TR52
414	16	Antalya	TR61
415	16	Adana	TR62
416	16	Hatay	TR63
417	16	Kirikkale	TR71
418	16	Kayseri	TR72
419	16	Zonguldak	TR81
420	16	Kastamonu	TR82
421	16	Samsun	TR83
422	16	Trabzon	TR90
423	16	Erzurum	TRA1
424	16	Agri	TRA2
425	16	Malatya	TRB1
426	16	Van	TRB2
427	16	Gaziantep	TRC1
428	16	Sanliurfa	TRC2
429	16	Mardin	TRC3
430	13	Tees Valley and Durham	UKC1
431	14	Northumberland and Tyne and Wear	UKC2
432	14	Cumbria	UKD1
433	13	Cheshire	UKD2
434	13	Greater Manchester	UKD3
435	13	Lancashire	UKD4
436	14	Merseyside	UKD5
437	14	East Yorkshire and Northern Lincolnshire	UKE1
438	14	North Yorkshire	UKE2
439	13	South Yorkshire	UKE3
440	14	West Yorkshire	UKE4
441	14	Derbyshire and Nottinghamshire	UKF1
442	14	Leicestershire, Rutland and Northamptonshire	UKF2
443	14	Lincolnshire	UKF3
444	13	Herefordshire, Worcestershire and Warwickshire	UKG1
445	14	Shropshire and Staffordshire	UKG2
446	14	West Midlands	UKG3
447	14	East Anglia	UKH1
448	14	Bedfordshire and Hertfordshire	UKH2
449	13	Essex	UKH3
450	14	Inner London	UKI1

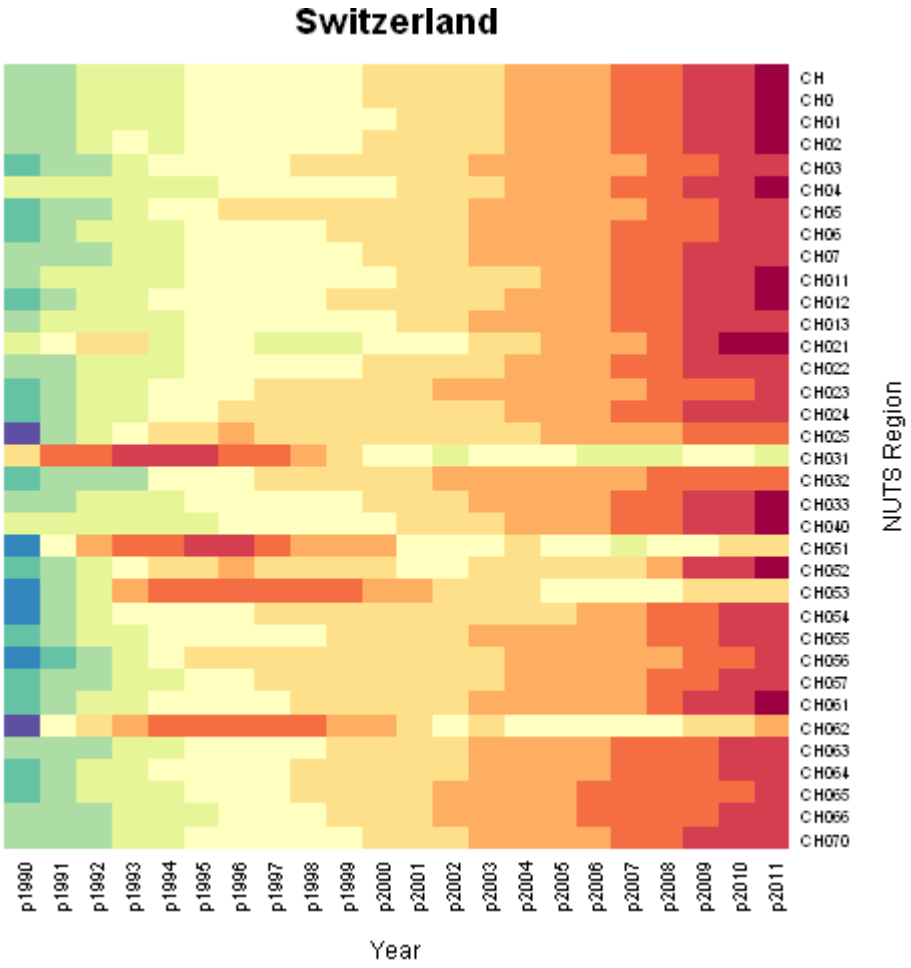
451	14	Outer London	UKI2
452	13	Berkshire, Buckinghamshire and Oxfordshire	UKJ1
453	14	Surrey, East and West Sussex	UKJ2
454	14	Hampshire and Isle of Wight	UKJ3
455	13	Kent	UKJ4
456	13	Gloucestershire, Wiltshire and Bristol/Bath area	UKK1
457	13	Dorset and Somerset	UKK2
458	13	Cornwall and Isles of Scilly	UKK3
459	13	Devon	UKK4
460	13	West Wales and The Valleys	UKL1
461	13	East Wales	UKL2
462	22	Eastern Scotland	UKM2
463	21	South Western Scotland	UKM3
464	21	North Eastern Scotland	UKM5
465	21	Highlands and Islands	UKM6
466	11	Northern Ireland (UK)	UKN0

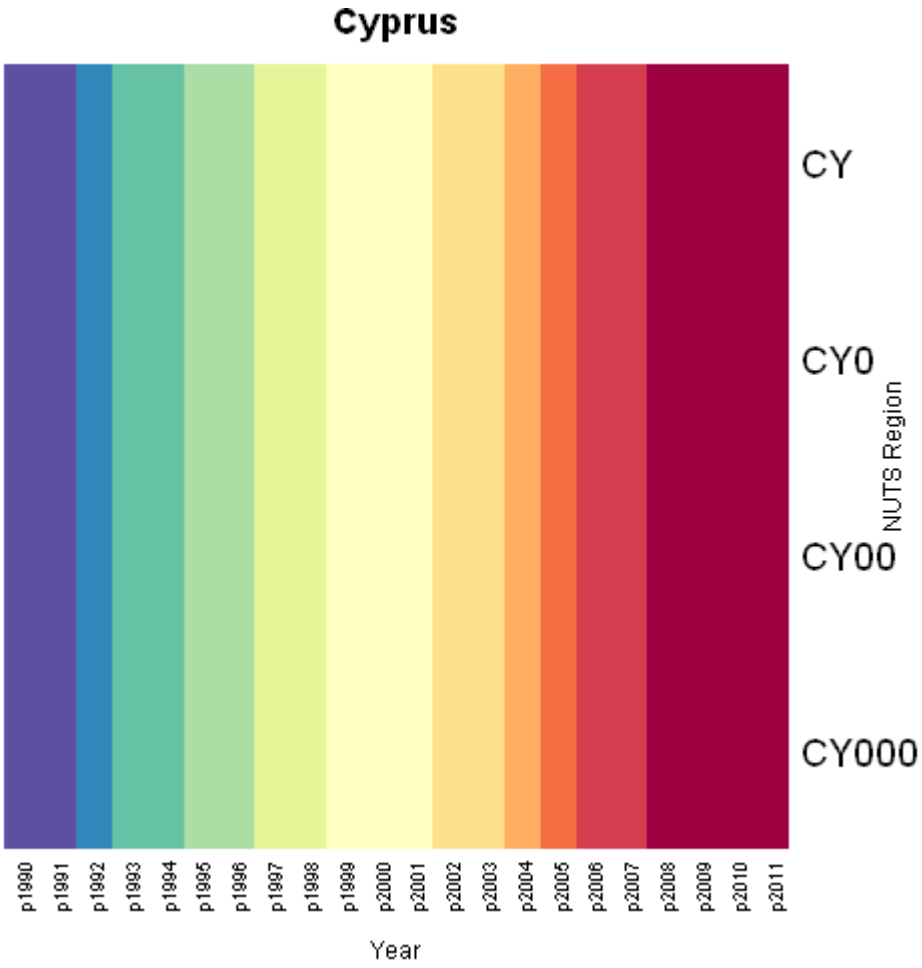
Appendix 7: Missing Data HeatMaps

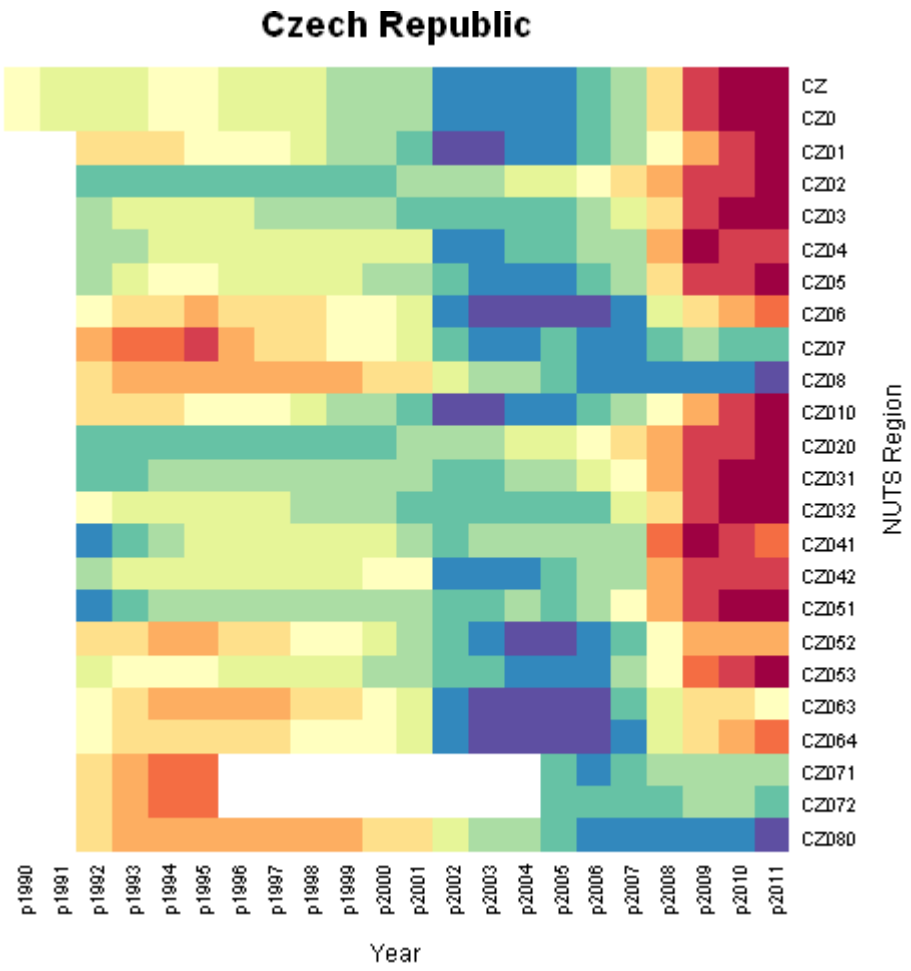

Austria
AT
AT1
AT2
AT3
AT11
AT12
AT13
AT21
AT22
AT31
AT32
AT33
AT34
AT111
AT112
AT113
AT121
AT122
AT123
AT124
AT125
AT126
AT127
AT130
AT211
AT212
AT213
AT221
AT222
AT223
AT224
AT225
AT226
AT311
AT312
AT313
AT314
AT315
AT321
AT322
AT323
AT331
AT332
AT333
AT334
AT335
AT341
AT342
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
p1998
p1999
p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year

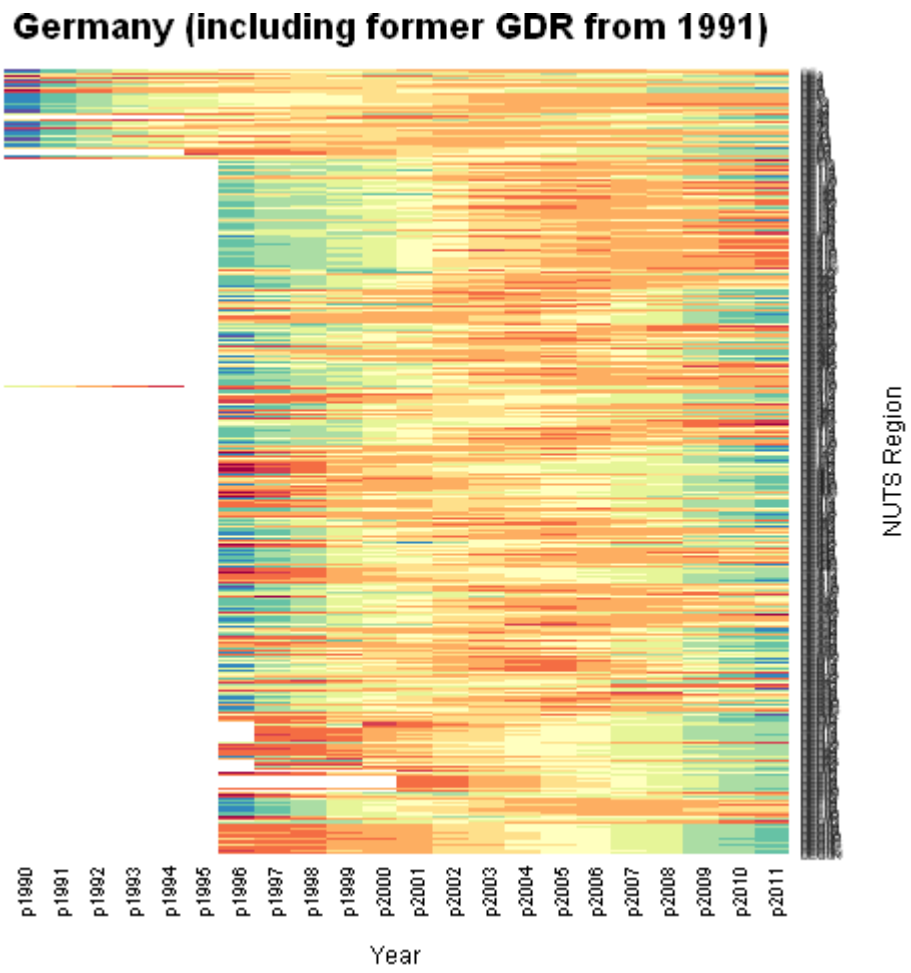

Belgium
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
p1998
p1999
p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year
NUTS Region

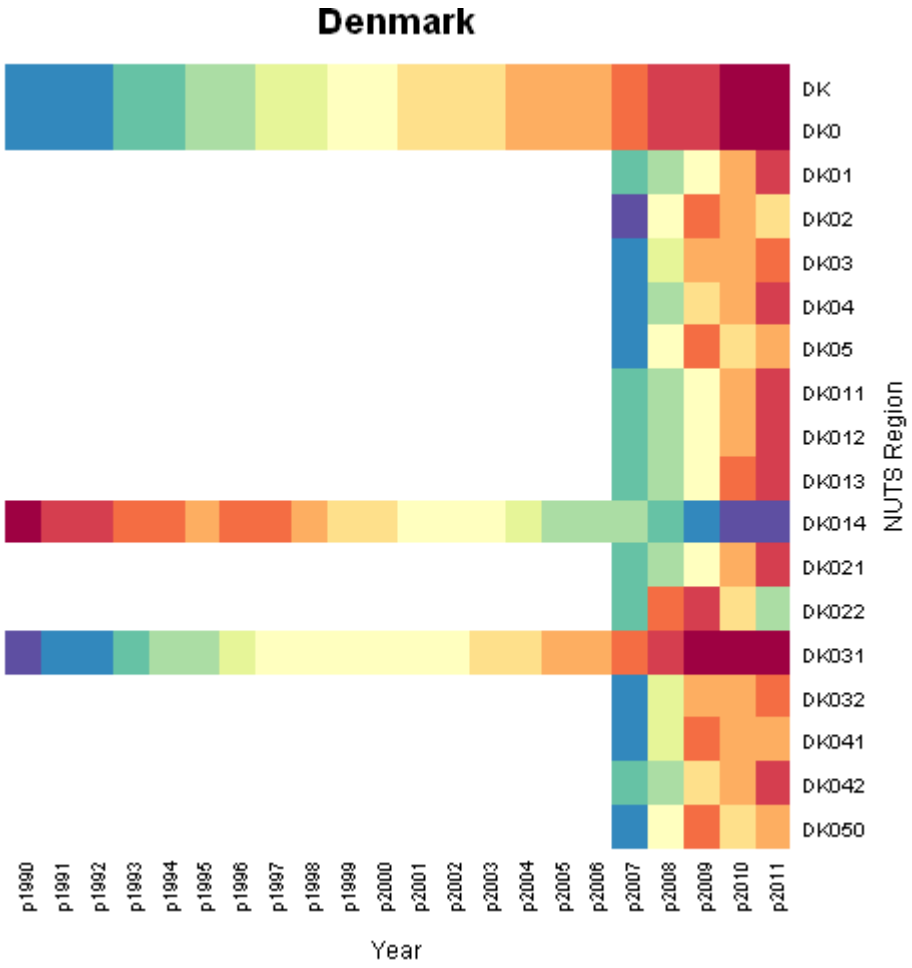

Bulgaria
BG
BG3
BG4
BG31
BG32
BG33
BG34
BG41
BG42
BG311
BG312
BG313
BG314
BG315
BG321
BG322
BG323
BG324
BG325
BG331
BG332
BG333
BG334
BG341
BG342
BG343
BG344
BG411
BG412
BG413
BG414
BG415
BG421
BG422
BG423
BG424
BG425
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
p1998
p1999
p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year

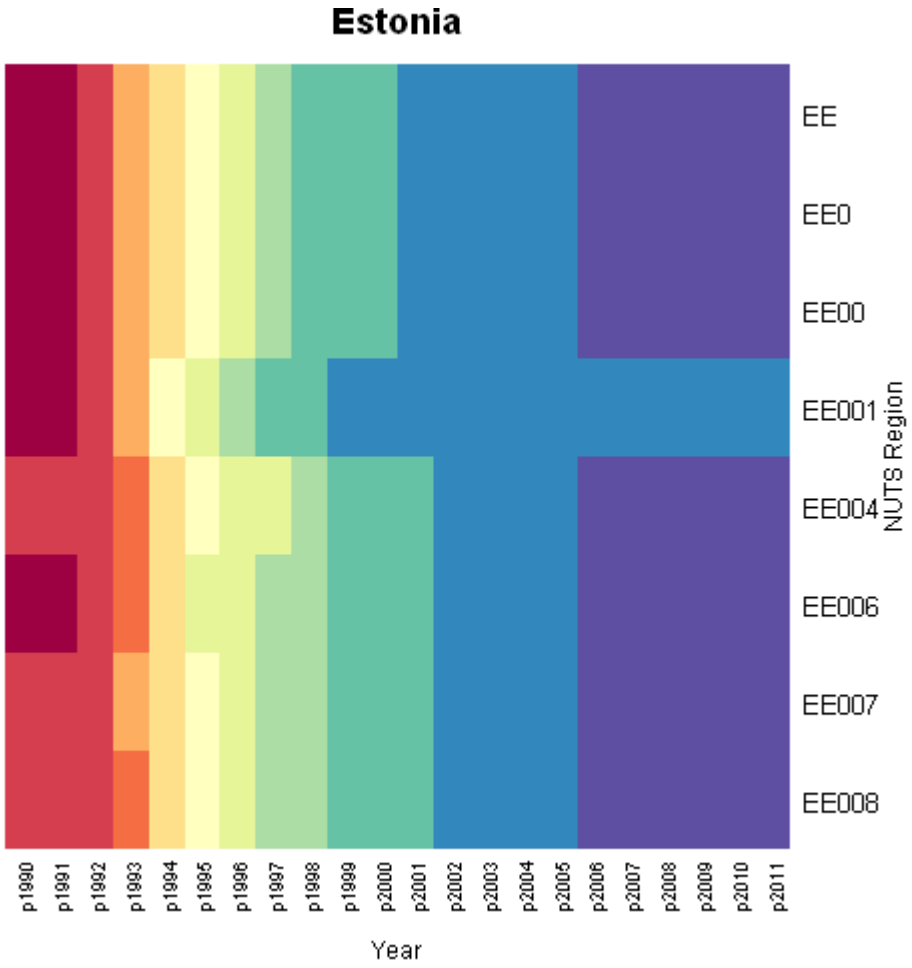

Switzerland
CH
CH0
CH01
CH02
CH03
CH04
CH05
CH06
CH07
CH011
CH012
CH013
CH021
CH022
CH023
CH024
CH025
CH031
CH032
CH033
CH040
CH051
CH052
CH053
CH054
CH055
CH056
CH057
CH061
CH062
CH063
CH064
CH065
CH066
CH070
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
p1998
p1999
p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Cyprus
CY
CY0
CY00
CY000
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
p1998
p1999
p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Czech Republic
CZ
CZ0
CZ01
CZ02
CZ03
CZ04
CZ05
CZ06
CZ07
CZ08
CZ010
CZ020
CZ031
CZ032
CZ041
CZ042
CZ051
CZ052
CZ053
CZ063
CZ064
CZ071
CZ072
CZ080
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
p1998
p1999
p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Germany (including former GDR from 1991)
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
p1998
p1999
p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Denmark
DK
DK0
DK01
DK02
DK03
DK04
DK05
DK011
DK012
DK013
DK014
DK021
DK022
DK031
DK032
DK041
DK042
DK050
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
p1998
p1999
p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Estonia
EE
EE0
EE00
EE001
EE004
EE006
EE007
EE008
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
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p2002
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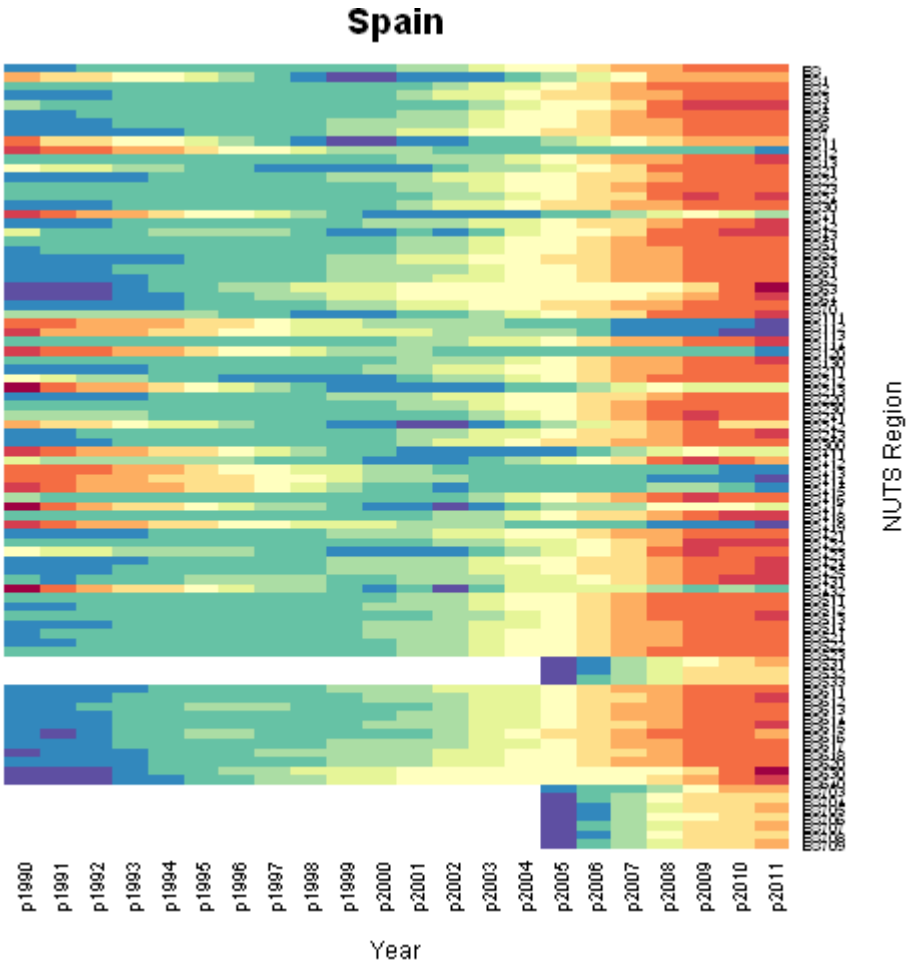
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year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p1994
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p1996
p1997
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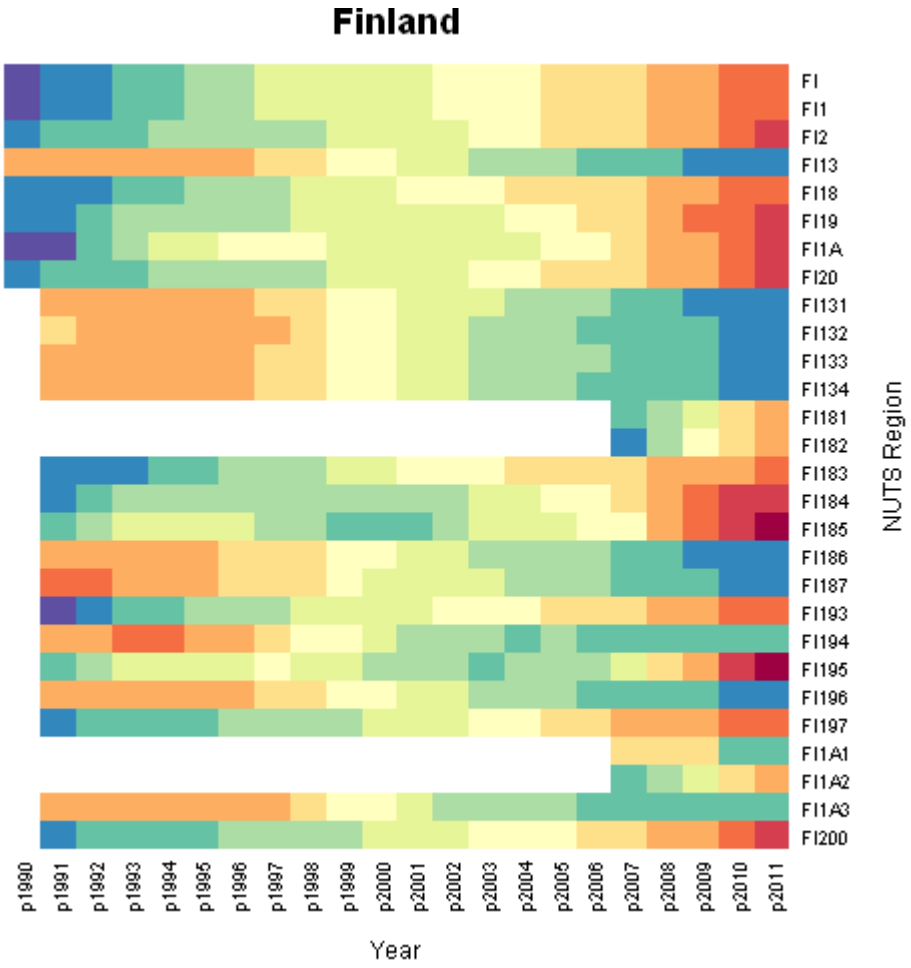
p2006
p2007
p2008
p2009
p2010
p2011
Year
NUTS Region


Finland
FI
FI1
FI2
FI13
FI18
FI19
FI1A
FI20
FI131
FI132
FI133
FI134
FI181
FI182
FI183
FI184
FI185
FI186
FI187
FI193
FI194
FI195
FI196
FI197
FI1A1
FI1A2
FI1A3
FI200
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
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p2003
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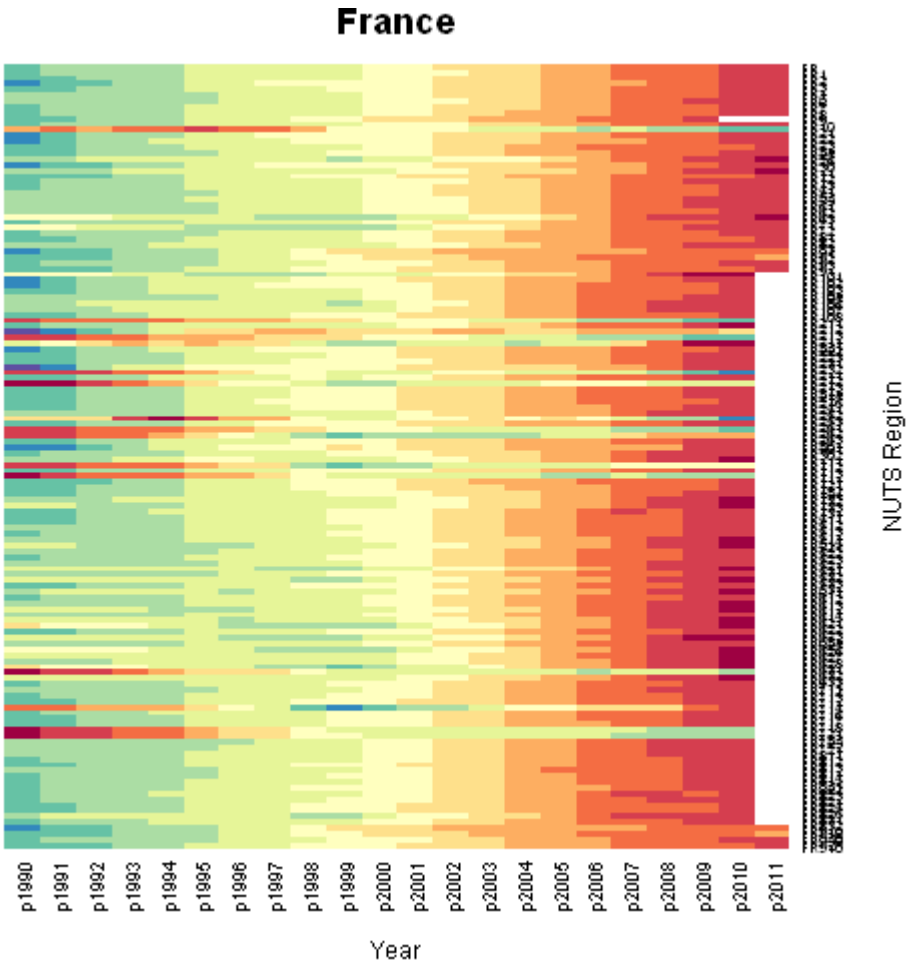
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year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p1996
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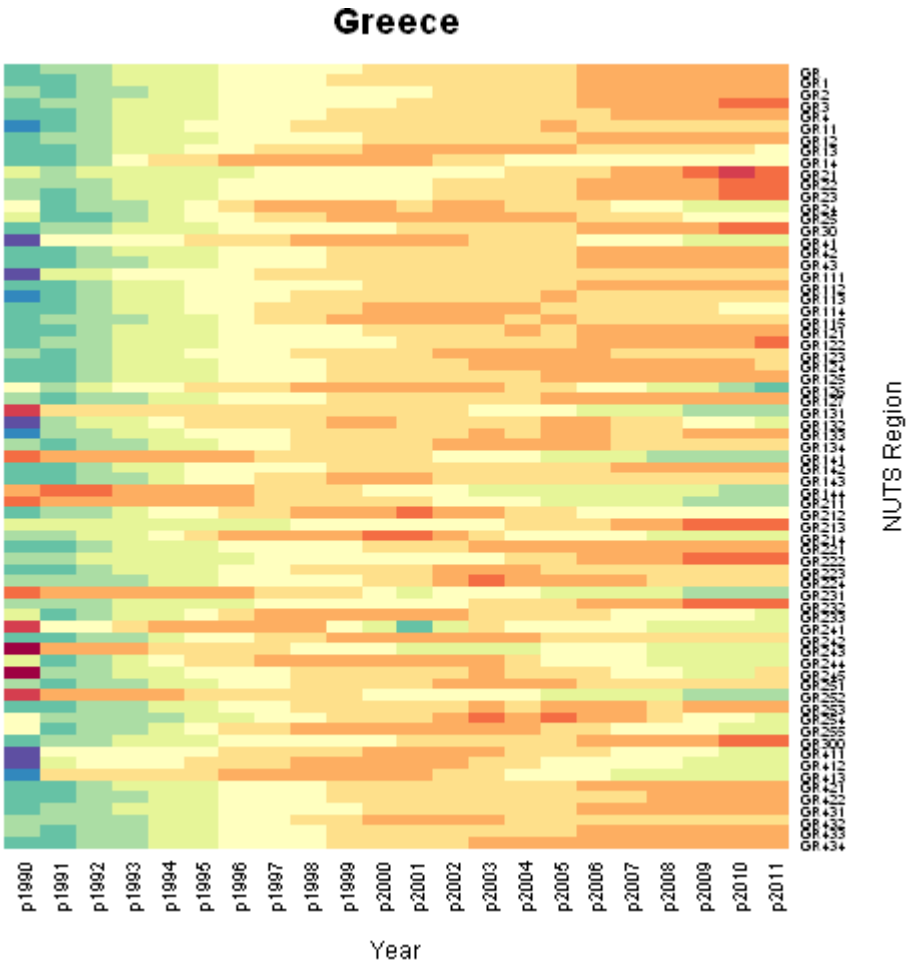
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year
NUTS Region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p1991
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p1996
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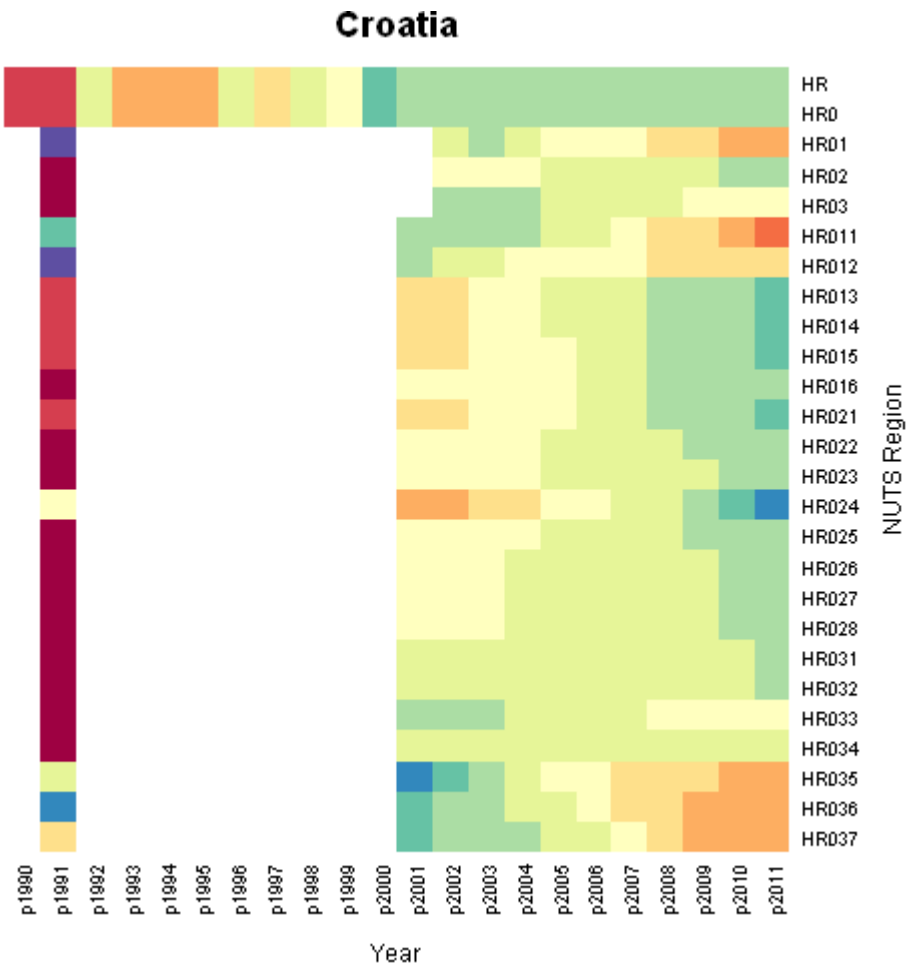
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year
NUTS Region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HR
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HR01
HR02
HR03
HR011
HR012
HR013
HR014
HR015
HR016
HR021
HR022
HR023
HR024
HR025
HR026
HR027
HR028
HR031
HR032
HR033
HR034
HR035
HR036
HR037
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
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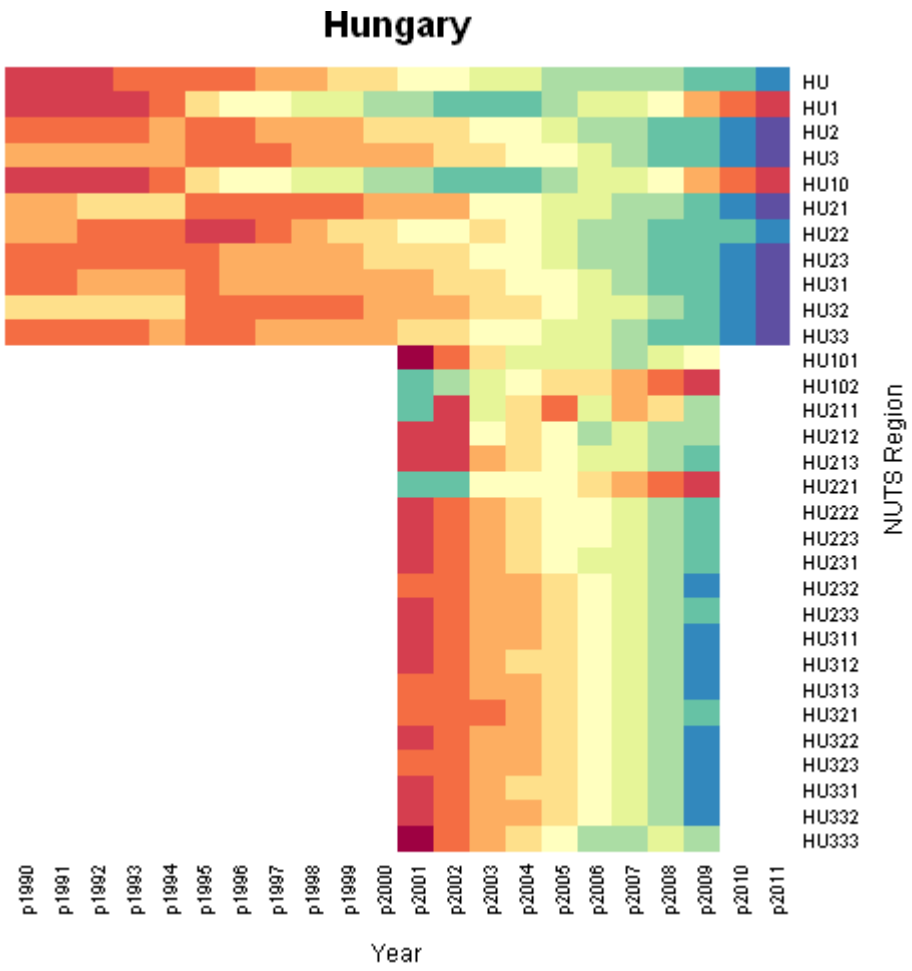
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Hungary
HU
HU1
HU2
HU3
HU10
HU21
HU22
HU23
HU31
HU32
HU33
HU101
HU102
HU211
HU212
HU213
HU221
HU222
HU223
HU231
HU232
HU233
HU311
HU312
HU313
HU321
HU322
HU323
HU331
HU332
HU333
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
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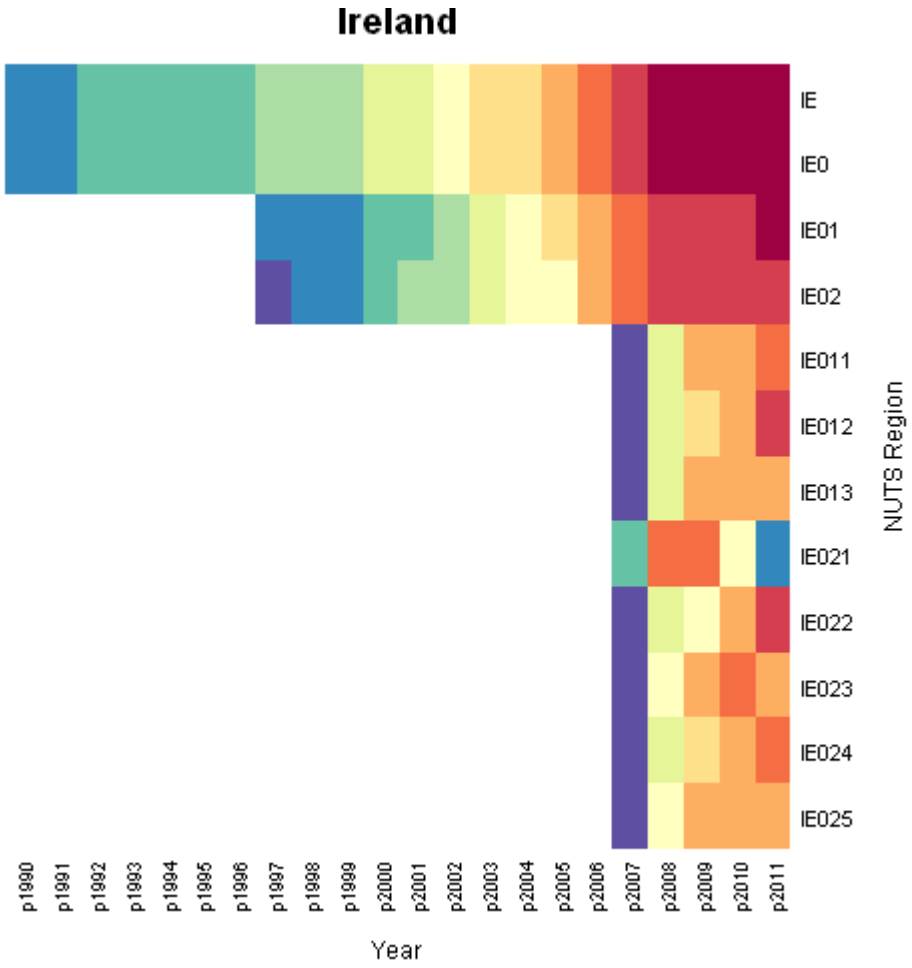
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Ireland
IE
IE0
IE01
IE02
IE011
IE012
IE013
IE021
IE022
IE023
IE024
IE025
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
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p1999
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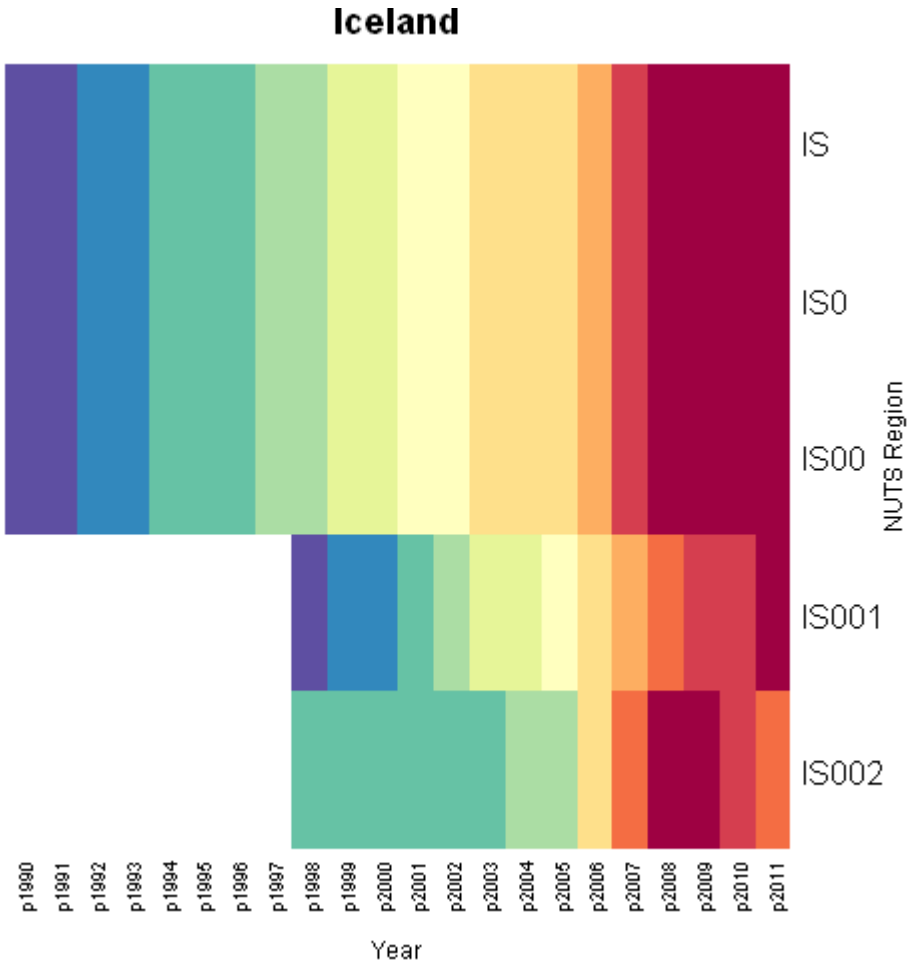
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Iceland
IS
IS0
IS00
IS001
IS002
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
p1998
p1999
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p2001
p2002
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p2004
p2005
p2006
p2007
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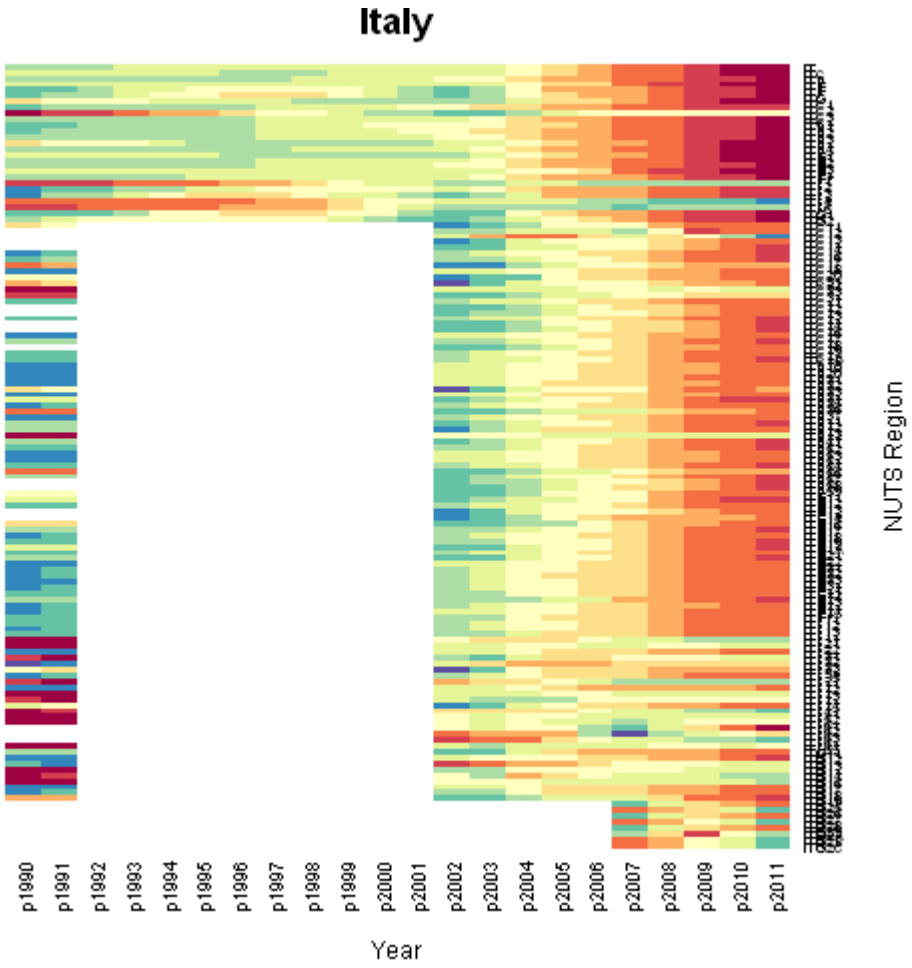
p2009
p2010
p2011
Year


Italy
p1990
p1991
p1992
p1993
p1994
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p1996
p1997
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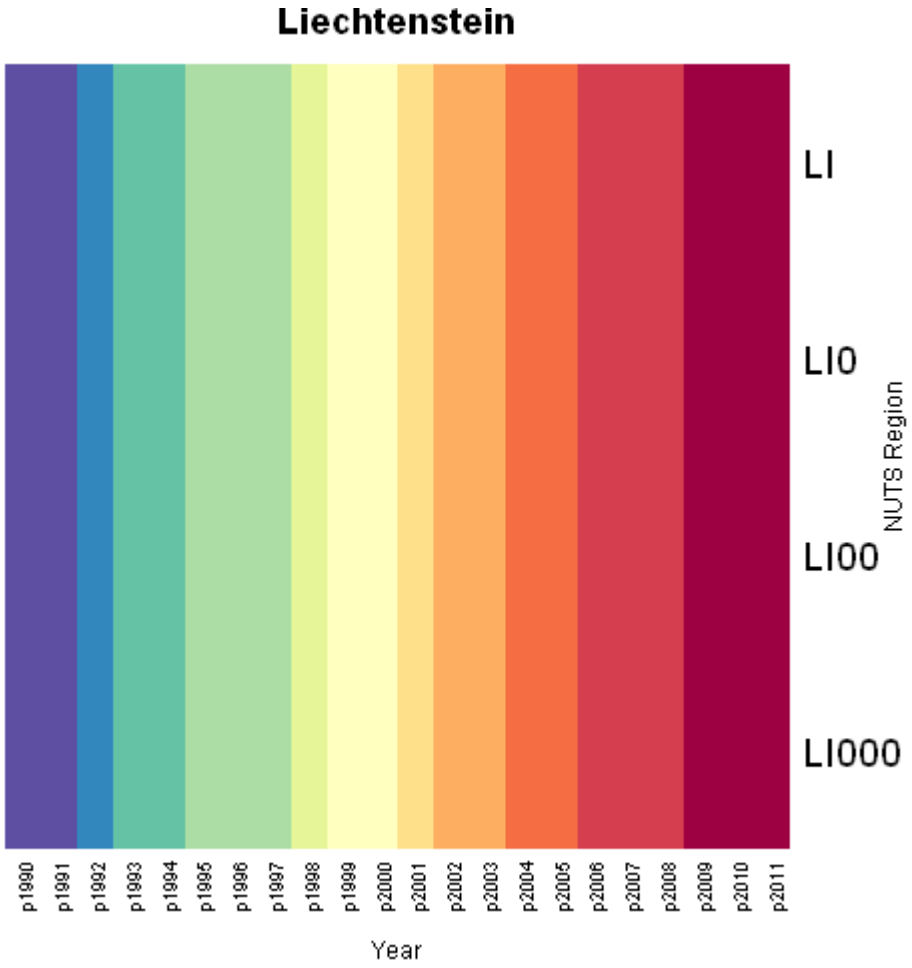
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year
NUTS Region


Liechtenstein
LI
LI0
LI00
LI000
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
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p2001
p2002
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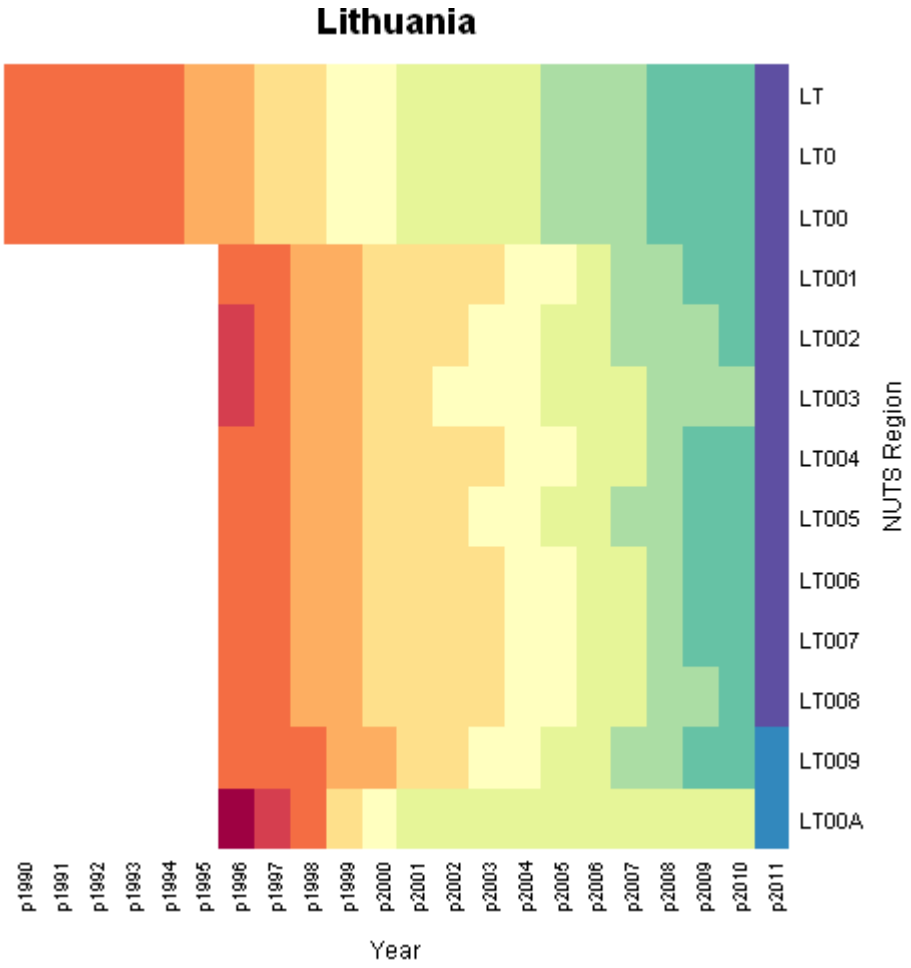
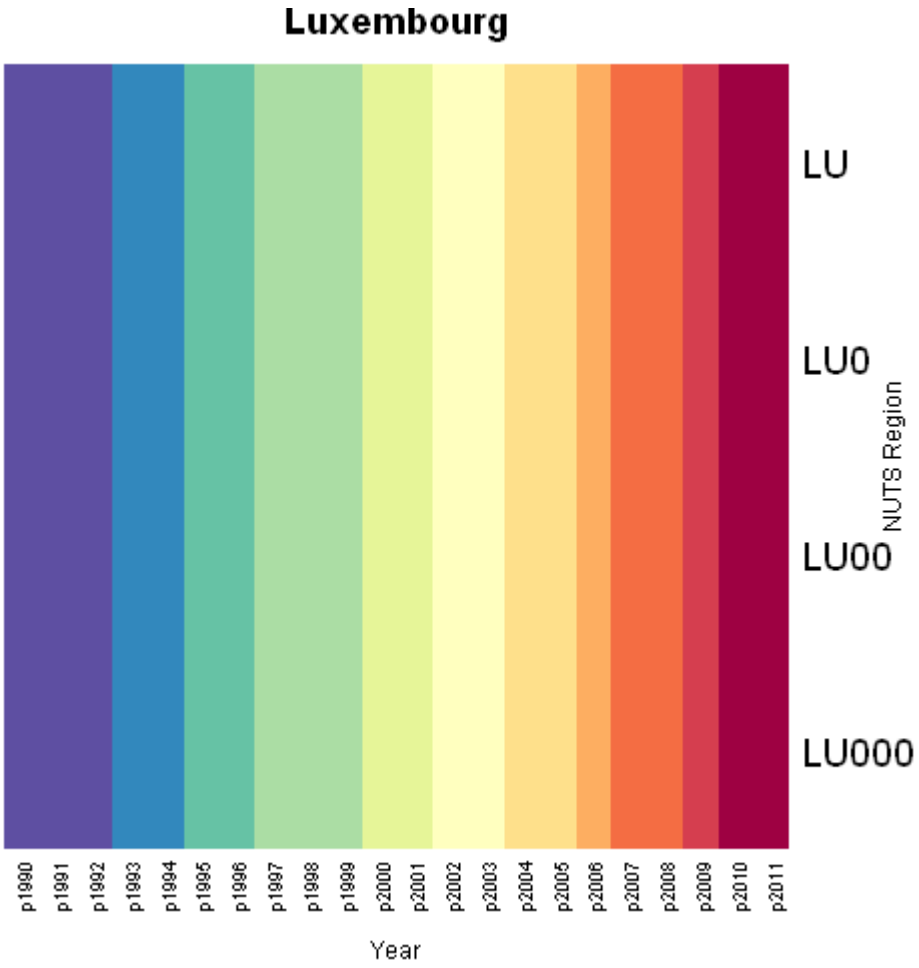
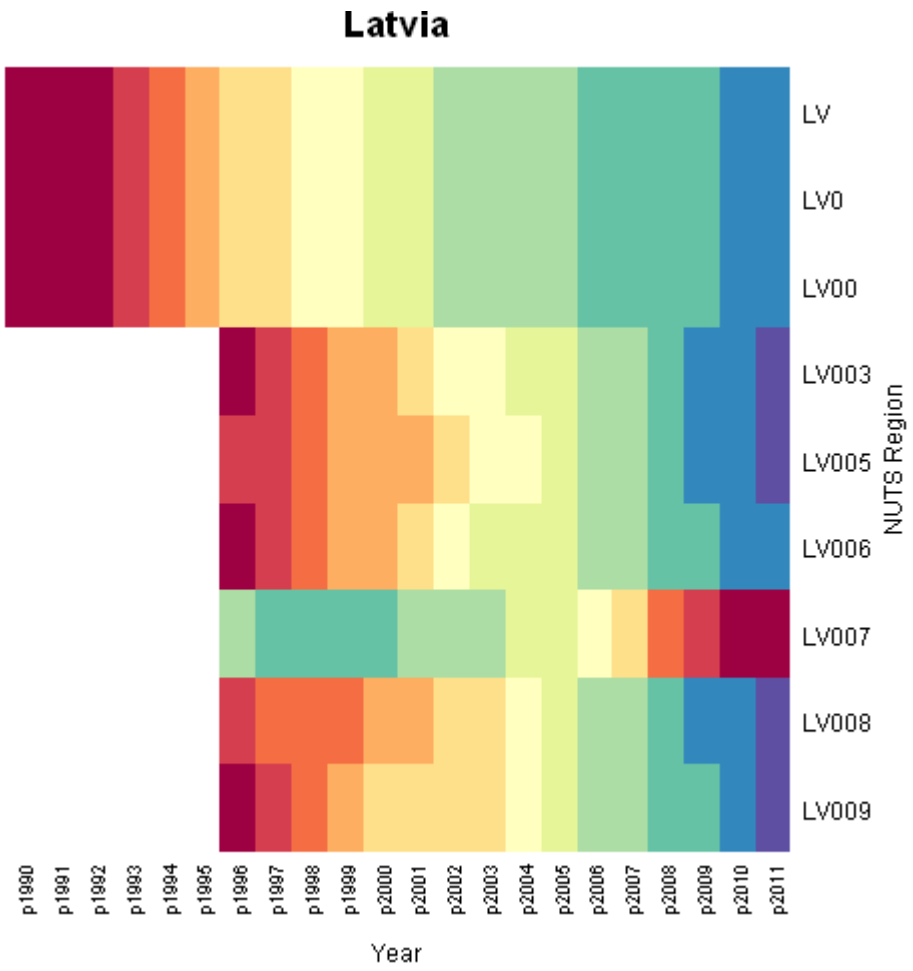
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Lithuania
LT
LT0
LT00
LT001
LT002
LT003
LT004
LT005
LT006
LT007
LT008
LT009
LT00A
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
p1998
p1999
p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Luxembourg
LU
LU0
LU00
LU000
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
p1998
p1999
p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Latvia
LV
LV0
LV00
LV003
LV005
LV006
LV007
LV008
LV009
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
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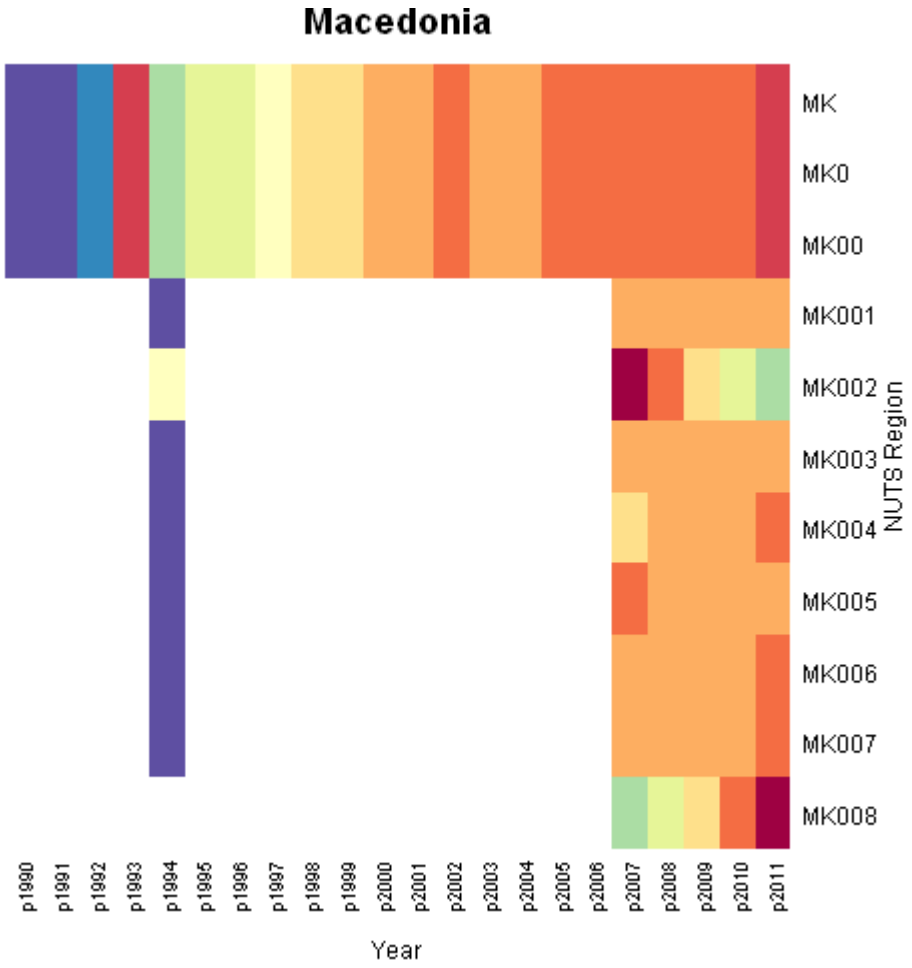
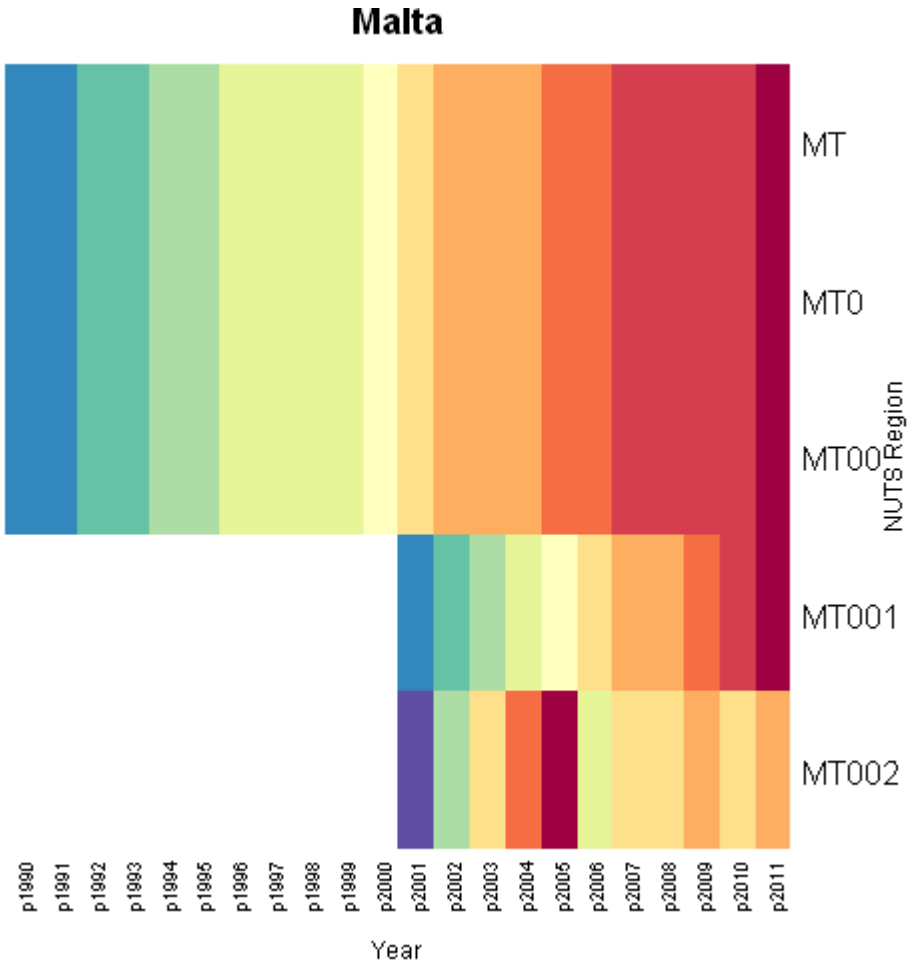
p1999
p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Macedonia
MK
MK0
MK00
MK001
MK002
MK003
MK004
MK005
MK006
MK007
MK008
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
p1998
p1999
p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Malta
MT
MT0
MT00
MT001
MT002
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
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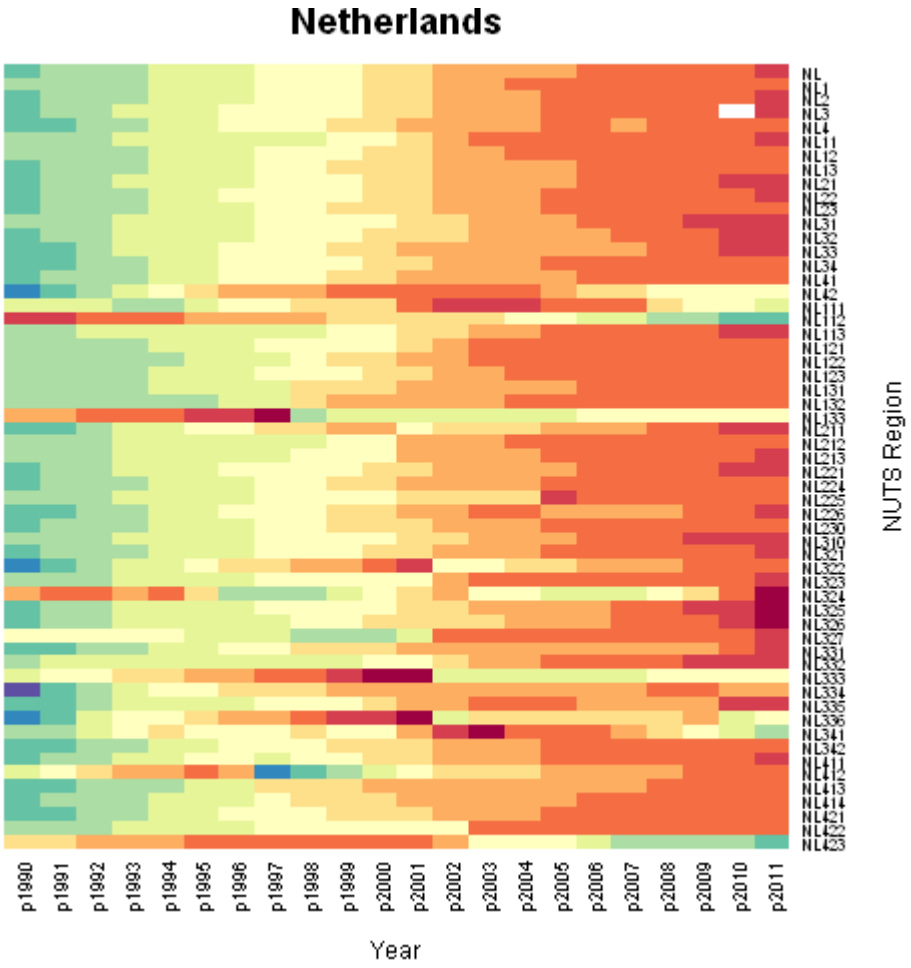
p1998
p1999
p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Netherlands
NUTS Region
Year
p1990
p1991
p1992
p1993
p1994
p1995
p1996
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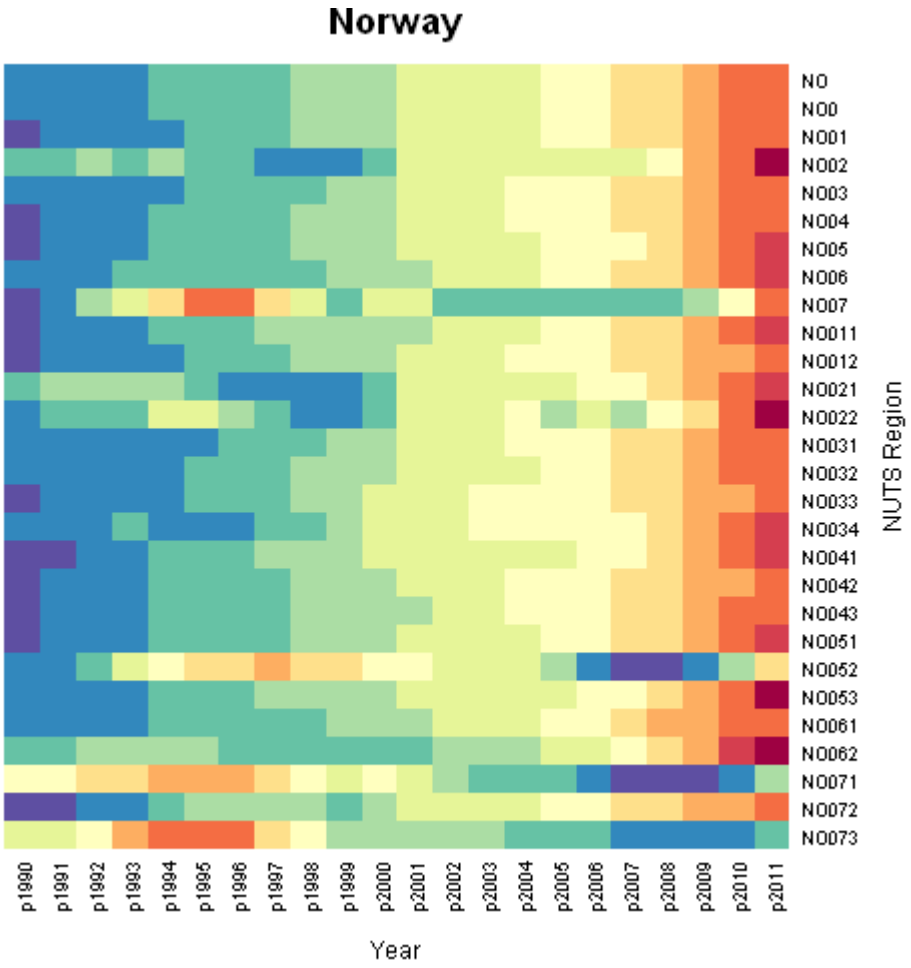
p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011


Norway
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NO0
NO001
NO002
NO003
NO004
NO005
NO006
NO007
NO011
NO012
NO021
NO022
NO031
NO032
NO033
NO034
NO041
NO042
NO043
NO051
NO052
NO053
NO061
NO062
NO071
NO072
NO073
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
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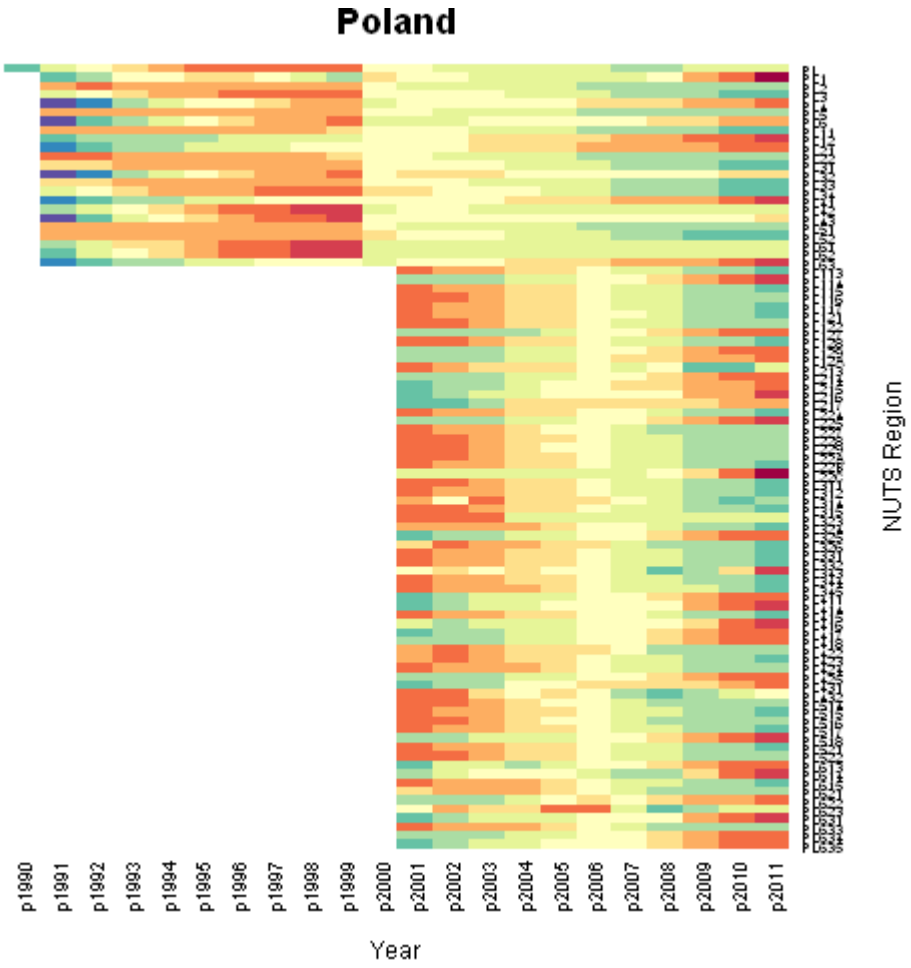
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Poland
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
p1998
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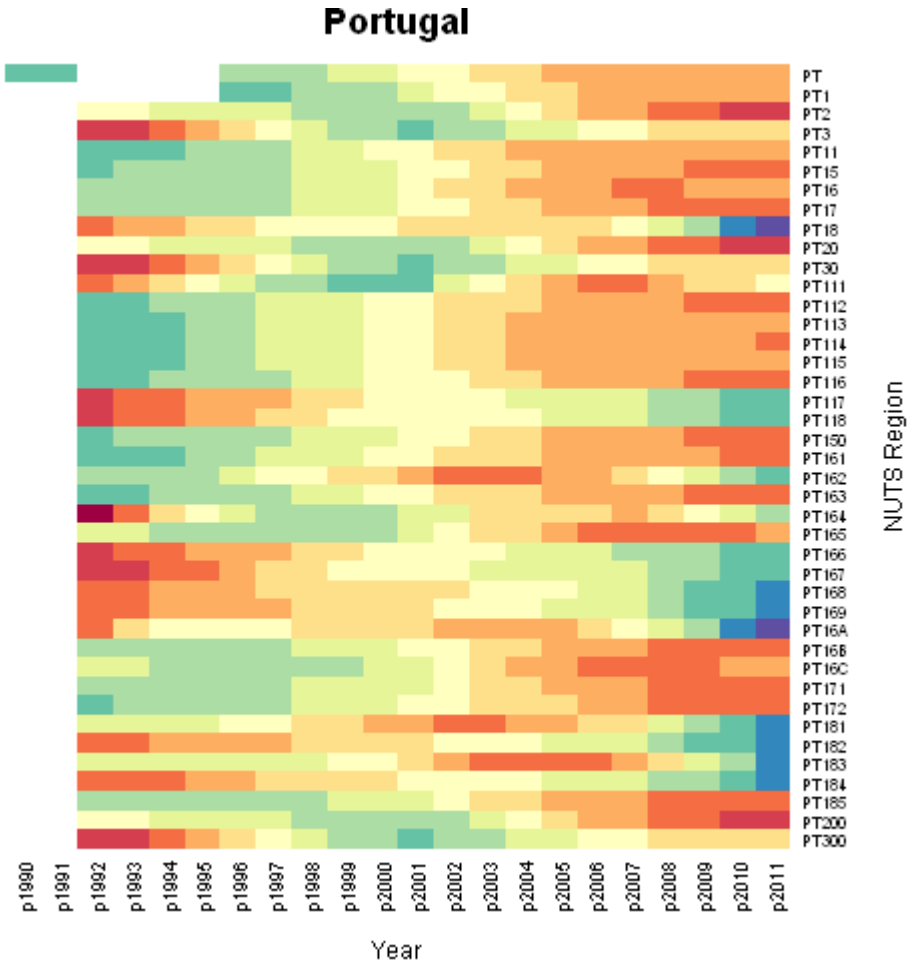
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year
NUTS Region


Portugal
PT
PT1
PT2
PT3
PT11
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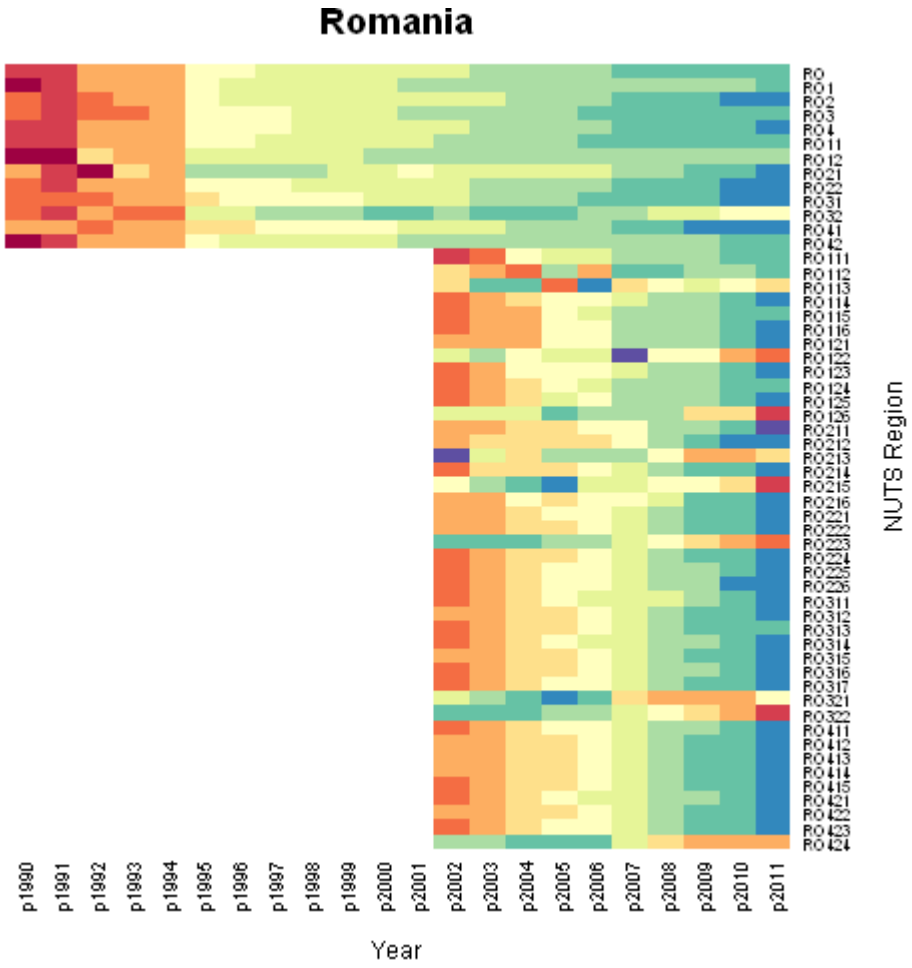
PT16
PT17
PT18
PT20
PT30
PT111
PT112
PT113
PT114
PT115
PT116
PT117
PT118
PT150
PT161
PT162
PT163
PT164
PT165
PT166
PT167
PT168
PT169
PT16A
PT16B
PT16C
PT171
PT172
PT181
PT182
PT183
PT184
PT185
PT200
PT300
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
p1998
p1999
p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Romania
RO
RO1
RO2
RO3
RO4
RO11
RO12
RO21
RO22
RO31
RO32
RO41
RO42
RO111
RO112
RO113
RO114
RO115
RO116
RO121
RO122
RO123
RO124
RO125
RO126
RO211
RO212
RO213
RO214
RO215
RO216
RO221
RO222
RO223
RO224
RO225
RO226
RO311
RO312
RO313
RO314
RO315
RO316
RO317
RO321
RO322
RO411
RO412
RO413
RO414
RO415
RO421
RO422
RO423
RO424
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
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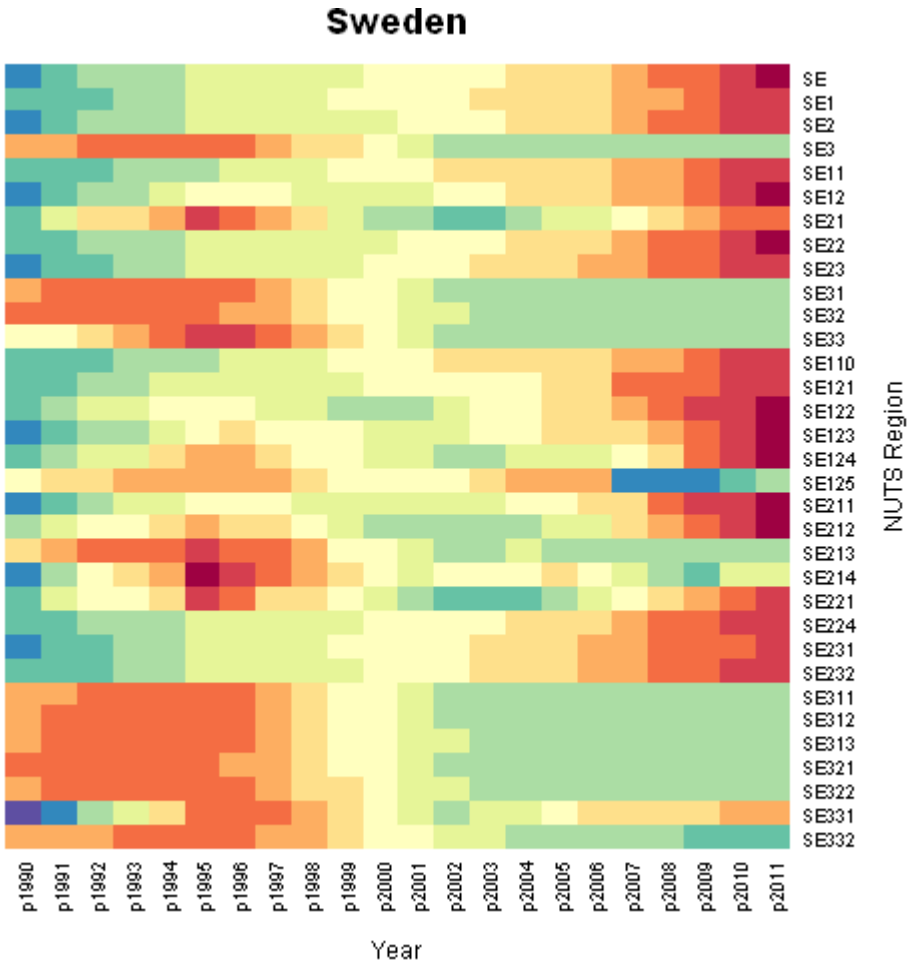
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Sweden
SE
SE1
SE2
SE3
SE11
SE12
SE21
SE22
SE23
SE31
SE32
SE33
SE110
SE121
SE122
SE123
SE124
SE125
SE211
SE212
SE213
SE214
SE221
SE224
SE231
SE232
SE311
SE312
SE313
SE321
SE322
SE331
SE332
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
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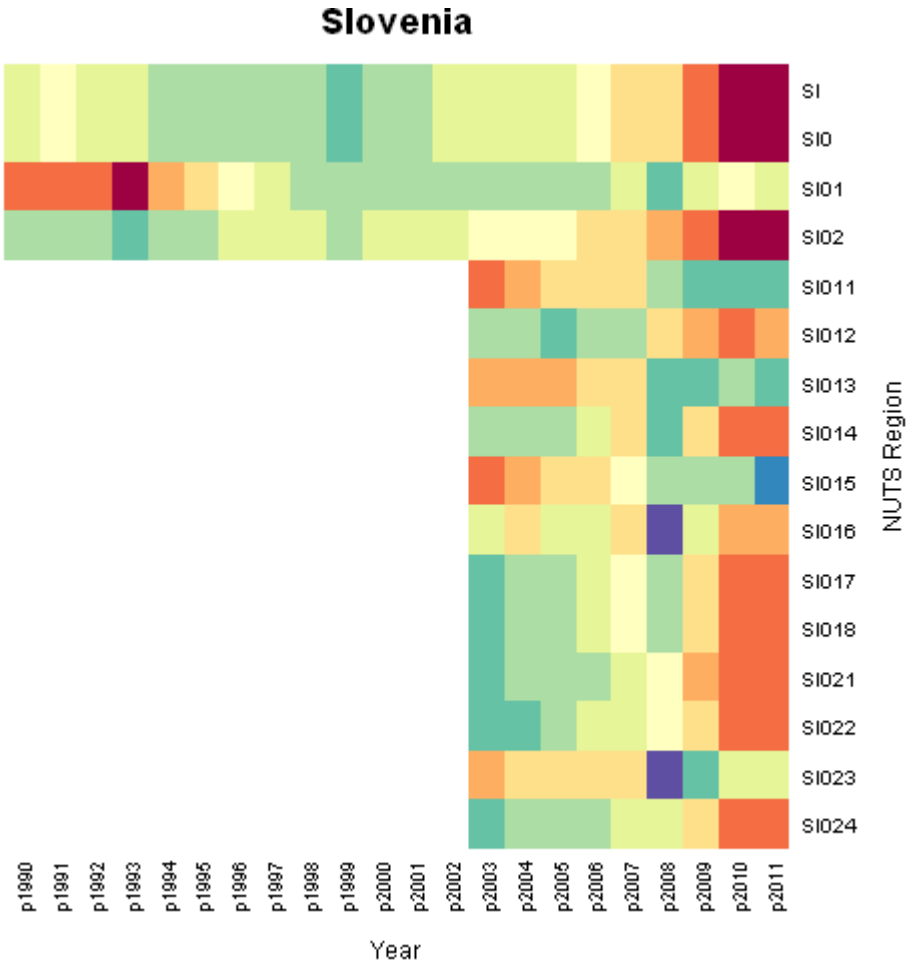
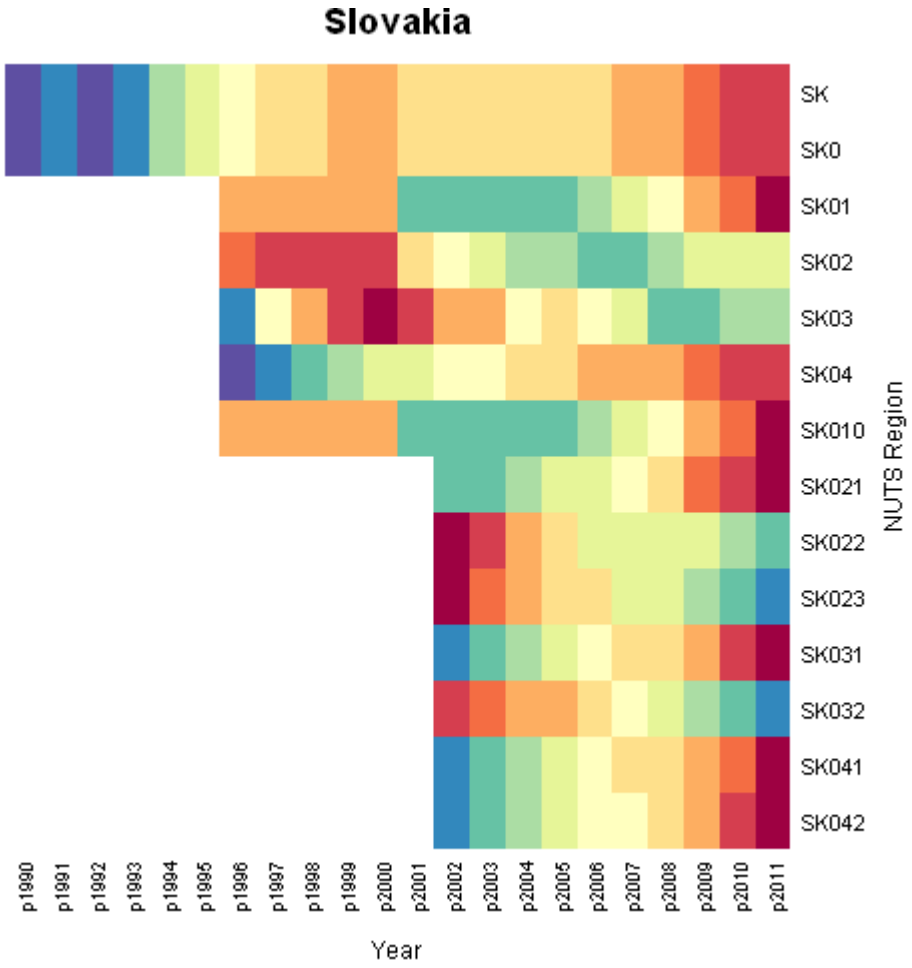
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Slovenia
SI
SI0
SI01
SI02
SI011
SI012
SI013
SI014
SI015
SI016
SI017
SI018
SI021
SI022
SI023
SI024
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
p1998
p1999
p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year


Slovakia
SK
SK0
SK01
SK02
SK03
SK04
SK010
SK021
SK022
SK023
SK031
SK032
SK041
SK042
NUTS Region
p1990
p1991
p1992
p1993
p1994
p1995
p1996
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p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
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p2009
p2010
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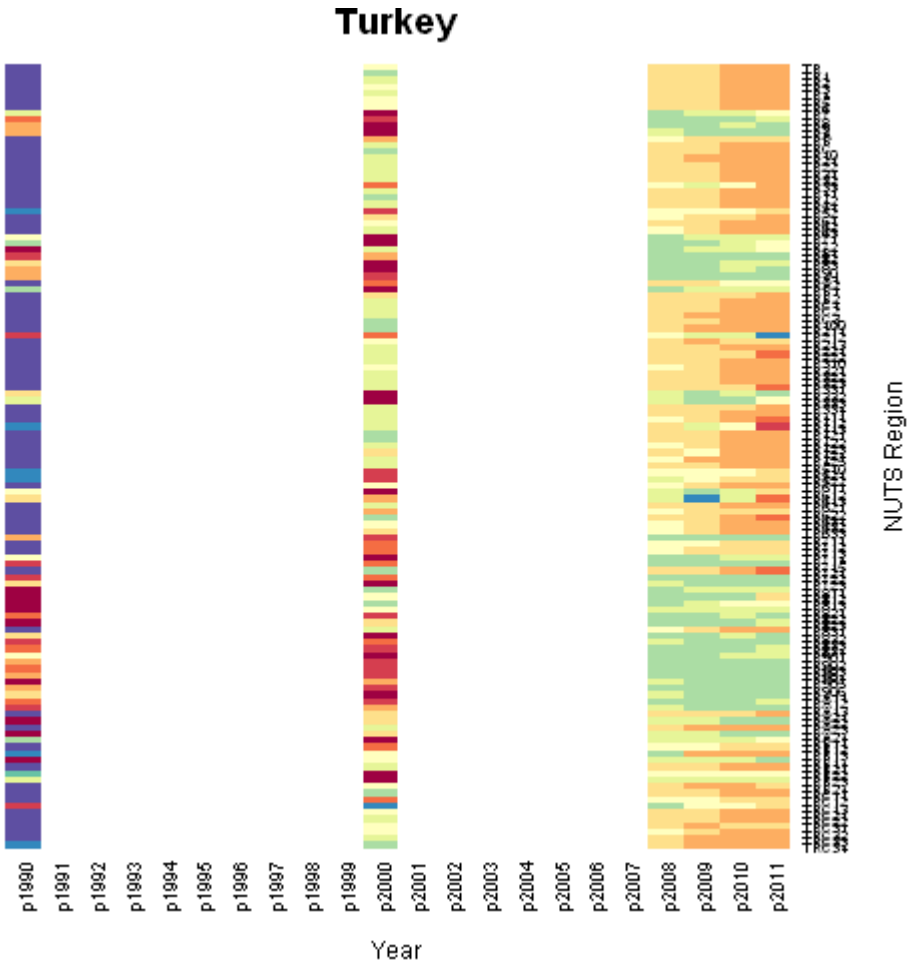
Year


Turkey
p1990
p1991
p1992
p1993
p1994
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p1996
p1997
p1998
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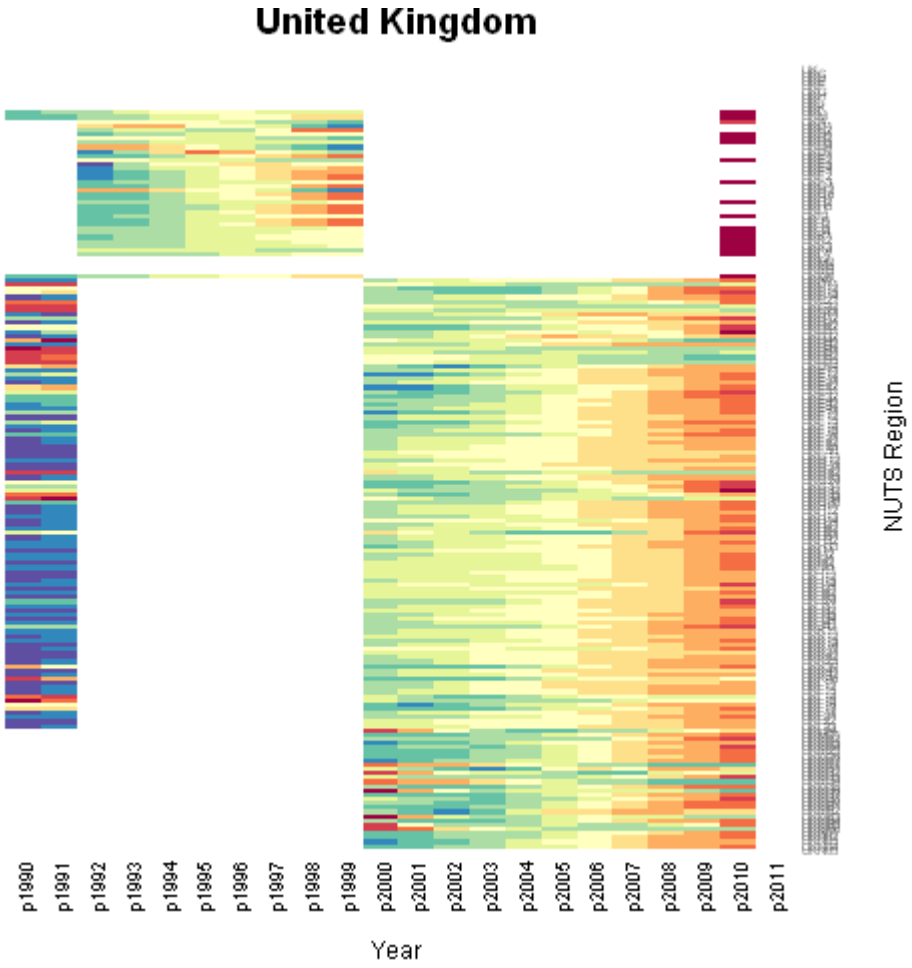
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year
NUTS Region


United Kingdom
p1990
p1991
p1992
p1993
p1994
p1995
p1996
p1997
p1998
p1999
p2000
p2001
p2002
p2003
p2004
p2005
p2006
p2007
p2008
p2009
p2010
p2011
Year
NUTS Region

Appendix 8: Coherence Constraint Output

Note: the listing for the NUTS2 constraint of their contained NUTS3 regions is somewhat lengthy, and most lines have been omitted.

```
**********************************************************
* Cross-Sectional Time Series Constraint for NUTS Level 0 *
**********************************************************
NUTS 1 children of AT are AT1 AT2 AT3
NUTS 1 children of BE are BE1 BE2 BE3
NUTS 1 children of BG are BG3 BG4
NUTS 1 children of CH are CH0
NUTS 1 children of CY are CY0
NUTS 1 children of CZ are CZ0
NUTS 1 children of DE are DE1 DE2 DE3 DE4 DE5 DE6 DE7 DE8 DE9 DEA DEB DEC DED DEE
DEF DEG
NUTS 1 children of DK are DK0
NUTS 1 children of EE are EE0
NUTS 1 children of ES are ES1 ES2 ES3 ES4 ES5 ES6 ES7
NUTS 1 children of FI are FI1 FI2
NUTS 1 children of FR are FR1 FR2 FR3 FR4 FR5 FR6 FR7 FR8 FR9
** NUTS 1 data for FR children constrained in 2010
** NUTS 1 data for FR children constrained in 2011
NUTS 1 children of GR are GR1 GR2 GR3 GR4
NUTS 1 children of HR are HR0
NUTS 1 children of HU are HU1 HU2 HU3
NUTS 1 children of IE are IE0
NUTS 1 children of IS are IS0
NUTS 1 children of IT are ITC ITD ITE ITF ITG
NUTS 1 children of LI are LI0
NUTS 1 children of LT are LT0
NUTS 1 children of LU are LU0
NUTS 1 children of LV are LV0
NUTS 1 children of MK are MK0
NUTS 1 children of MT are MT0
NUTS 1 children of NL are NL1 NL2 NL3 NL4
** NUTS 1 data for NL children constrained in 2010
NUTS 1 children of NO are NO0
NUTS 1 children of PL are PL1 PL2 PL3 PL4 PL5 PL6
** NUTS 1 data for PL children constrained in 1990
NUTS 1 children of PT are PT1 PT2 PT3
** NUTS 1 data for PT children constrained in 1990
** NUTS 1 data for PT children constrained in 1991
NUTS 1 children of RO are RO1 RO2 RO3 RO4
NUTS 1 children of SE are SE1 SE2 SE3
NUTS 1 children of SI are SI0
NUTS 1 children of SK are SK0
NUTS 1 children of TR are TR1 TR2 TR3 TR4 TR5 TR6 TR7 TR8 TR9 TRA TRB TRC
** NUTS 1 data for TR children constrained in 1991
** NUTS 1 data for TR children constrained in 1992
** NUTS 1 data for TR children constrained in 1993
** NUTS 1 data for TR children constrained in 1994
** NUTS 1 data for TR children constrained in 1995
** NUTS 1 data for TR children constrained in 1996
** NUTS 1 data for TR children constrained in 1997
** NUTS 1 data for TR children constrained in 1998
** NUTS 1 data for TR children constrained in 1999
** NUTS 1 data for TR children constrained in 2001
** NUTS 1 data for TR children constrained in 2002
** NUTS 1 data for TR children constrained in 2003
** NUTS 1 data for TR children constrained in 2004
```

```
** NUTS 1 data for TR children constrained in 2005
** NUTS 1 data for TR children constrained in 2006
** NUTS 1 data for TR children constrained in 2007
NUTS 1 children of UK are UKC UKD UKE UKF UKG UKH UKI UKJ UKK UKL UKM UKN
** NUTS 1 data for UK children constrained in 2011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* Cross-Sectional Time Series Constraint for NUTS Level 1 *
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NUTS 2 children of AT1 are AT11 AT12 AT13
NUTS 2 children of AT2 are AT21 AT22
NUTS 2 children of AT3 are AT31 AT32 AT33 AT34
NUTS 2 children of BE1 are BE10
NUTS 2 children of BE2 are BE21 BE22 BE23 BE24 BE25
NUTS 2 children of BE3 are BE31 BE32 BE33 BE34 BE35
NUTS 2 children of BG3 are BG31 BG32 BG33 BG34
NUTS 2 children of BG4 are BG41 BG42
NUTS 2 children of CH0 are CH01 CH02 CH03 CH04 CH05 CH06 CH07
NUTS 2 children of CY0 are CY00
NUTS 2 children of CZ0 are CZ01 CZ02 CZ03 CZ04 CZ05 CZ06 CZ07 CZ08
** NUTS 2 data for CZ0 children constrained in 1990
** NUTS 2 data for CZ0 children constrained in 1991
NUTS 2 children of DE1 are DE11 DE12 DE13 DE14
NUTS 2 children of DE2 are DE21 DE22 DE23 DE24 DE25 DE26 DE27
NUTS 2 children of DE3 are DE30
NUTS 2 children of DE4 are DE41 DE42
** NUTS 2 data for DE4 children constrained in 1990
** NUTS 2 data for DE4 children constrained in 1991
** NUTS 2 data for DE4 children constrained in 1992
** NUTS 2 data for DE4 children constrained in 1993
** NUTS 2 data for DE4 children constrained in 1994
NUTS 2 children of DE5 are DE50
NUTS 2 children of DE6 are DE60
NUTS 2 children of DE7 are DE71 DE72 DE73
NUTS 2 children of DE8 are DE80
NUTS 2 children of DE9 are DE91 DE92 DE93 DE94
NUTS 2 children of DEA are DEA1 DEA2 DEA3 DEA4 DEA5
NUTS 2 children of DEB are DEB1 DEB2 DEB3
NUTS 2 children of DEC are DEC0
NUTS 2 children of DED are DED1 DED2 DED3
** NUTS 2 data for DED children constrained in 1990
** NUTS 2 data for DED children constrained in 1991
** NUTS 2 data for DED children constrained in 1992
** NUTS 2 data for DED children constrained in 1993
** NUTS 2 data for DED children constrained in 1994
NUTS 2 children of DEE are DEE0
NUTS 2 children of DEF are DEF0
NUTS 2 children of DEG are DEG0
NUTS 2 children of DK0 are DK01 DK02 DK03 DK04 DK05
** NUTS 2 data for DK0 children constrained in 1990
** NUTS 2 data for DK0 children constrained in 1991
** NUTS 2 data for DK0 children constrained in 1992
** NUTS 2 data for DK0 children constrained in 1993
** NUTS 2 data for DK0 children constrained in 1994
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** NUTS 2 data for DK0 children constrained in 2003
** NUTS 2 data for DK0 children constrained in 2004
** NUTS 2 data for DK0 children constrained in 2005
** NUTS 2 data for DK0 children constrained in 2006
NUTS 2 children of EE0 are EE00
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NUTS 2 children of ES1 are ES11 ES12 ES13
NUTS 2 children of ES2 are ES21 ES22 ES23 ES24
NUTS 2 children of ES3 are ES30
NUTS 2 children of ES4 are ES41 ES42 ES43
NUTS 2 children of ES5 are ES51 ES52 ES53
NUTS 2 children of ES6 are ES61 ES62 ES63 ES64
NUTS 2 children of ES7 are ES70
NUTS 2 children of FI1 are FI13 FI18 FI19 FI1A
NUTS 2 children of FI2 are FI20
NUTS 2 children of FR1 are FR10
NUTS 2 children of FR2 are FR21 FR22 FR23 FR24 FR25 FR26
NUTS 2 children of FR3 are FR30
NUTS 2 children of FR4 are FR41 FR42 FR43
NUTS 2 children of FR5 are FR51 FR52 FR53
NUTS 2 children of FR6 are FR61 FR62 FR63
NUTS 2 children of FR7 are FR71 FR72
NUTS 2 children of FR8 are FR81 FR82 FR83
NUTS 2 children of FR9 are FR91 FR92 FR93 FR94
NUTS 2 children of GR1 are GR11 GR12 GR13 GR14
NUTS 2 children of GR2 are GR21 GR22 GR23 GR24 GR25
NUTS 2 children of GR3 are GR30
NUTS 2 children of GR4 are GR41 GR42 GR43
NUTS 2 children of HR0 are HR01 HR02 HR03
** NUTS 2 data for HR0 children constrained in 1990
** NUTS 2 data for HR0 children constrained in 1992
** NUTS 2 data for HR0 children constrained in 1993
** NUTS 2 data for HR0 children constrained in 1994
** NUTS 2 data for HR0 children constrained in 1995
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** NUTS 2 data for HR0 children constrained in 2000
** NUTS 2 data for HR0 children constrained in 2001
NUTS 2 children of HU1 are HU10
NUTS 2 children of HU2 are HU21 HU22 HU23
NUTS 2 children of HU3 are HU31 HU32 HU33
NUTS 2 children of IE0 are IE01 IE02
** NUTS 2 data for IE0 children constrained in 1990
** NUTS 2 data for IE0 children constrained in 1991
** NUTS 2 data for IE0 children constrained in 1992
** NUTS 2 data for IE0 children constrained in 1993
** NUTS 2 data for IE0 children constrained in 1994
** NUTS 2 data for IE0 children constrained in 1995
** NUTS 2 data for IE0 children constrained in 1996
NUTS 2 children of IS0 are IS00
NUTS 2 children of ITC are ITC1 ITC2 ITC3 ITC4
NUTS 2 children of ITD are ITD1 ITD2 ITD3 ITD4 ITD5
NUTS 2 children of ITE are ITE1 ITE2 ITE3 ITE4
NUTS 2 children of ITF are ITF1 ITF2 ITF3 ITF4 ITF5 ITF6
NUTS 2 children of ITG are ITG1 ITG2
NUTS 2 children of LI0 are LI00
NUTS 2 children of LT0 are LT00
NUTS 2 children of LU0 are LU00
NUTS 2 children of LV0 are LV00
NUTS 2 children of MK0 are MK00
NUTS 2 children of MT0 are MT00
NUTS 2 children of NL1 are NL11 NL12 NL13
NUTS 2 children of NL2 are NL21 NL22 NL23
NUTS 2 children of NL3 are NL31 NL32 NL33 NL34
NUTS 2 children of NL4 are NL41 NL42
NUTS 2 children of NO0 are NO01 NO02 NO03 NO04 NO05 NO06 NO07
NUTS 2 children of PL1 are PL11 PL12
** NUTS 2 data for PL1 children constrained in 1990
NUTS 2 children of PL2 are PL21 PL22
** NUTS 2 data for PL2 children constrained in 1990
NUTS 2 children of PL3 are PL31 PL32 PL33 PL34
** NUTS 2 data for PL3 children constrained in 1990
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NUTS 2 children of PL4 are PL41 PL42 PL43
** NUTS 2 data for PL4 children constrained in 1990
NUTS 2 children of PL5 are PL51 PL52
** NUTS 2 data for PL5 children constrained in 1990
NUTS 2 children of PL6 are PL61 PL62 PL63
** NUTS 2 data for PL6 children constrained in 1990
NUTS 2 children of PT1 are PT11 PT15 PT16 PT17 PT18
** NUTS 2 data for PT1 children constrained in 1990
** NUTS 2 data for PT1 children constrained in 1991
NUTS 2 children of PT2 are PT20
** NUTS 2 data for PT2 children constrained in 1990
** NUTS 2 data for PT2 children constrained in 1991
NUTS 2 children of PT3 are PT30
** NUTS 2 data for PT3 children constrained in 1990
** NUTS 2 data for PT3 children constrained in 1991
NUTS 2 children of RO1 are RO11 RO12
NUTS 2 children of RO2 are RO21 RO22
NUTS 2 children of RO3 are RO31 RO32
NUTS 2 children of RO4 are RO41 RO42
NUTS 2 children of SE1 are SE11 SE12
NUTS 2 children of SE2 are SE21 SE22 SE23
NUTS 2 children of SE3 are SE31 SE32 SE33
NUTS 2 children of SI0 are SI01 SI02
NUTS 2 children of SK0 are SK01 SK02 SK03 SK04
** NUTS 2 data for SK0 children constrained in 1990
** NUTS 2 data for SK0 children constrained in 1991
** NUTS 2 data for SK0 children constrained in 1992
** NUTS 2 data for SK0 children constrained in 1993
** NUTS 2 data for SK0 children constrained in 1994
** NUTS 2 data for SK0 children constrained in 1995
NUTS 2 children of TR1 are TR10
** NUTS 2 data for TR1 children constrained in 1991
** NUTS 2 data for TR1 children constrained in 1992
** NUTS 2 data for TR1 children constrained in 1993
** NUTS 2 data for TR1 children constrained in 1994
** NUTS 2 data for TR1 children constrained in 1995
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** NUTS 2 data for TR1 children constrained in 2005
** NUTS 2 data for TR1 children constrained in 2006
** NUTS 2 data for TR1 children constrained in 2007
NUTS 2 children of TR2 are TR21 TR22
** NUTS 2 data for TR2 children constrained in 1991
** NUTS 2 data for TR2 children constrained in 1992
** NUTS 2 data for TR2 children constrained in 1993
** NUTS 2 data for TR2 children constrained in 1994
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** NUTS 2 data for TR2 children constrained in 2005
** NUTS 2 data for TR2 children constrained in 2006
** NUTS 2 data for TR2 children constrained in 2007
NUTS 2 children of TR3 are TR31 TR32 TR33
** NUTS 2 data for TR3 children constrained in 1991
** NUTS 2 data for TR3 children constrained in 1992
** NUTS 2 data for TR3 children constrained in 1993
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** NUTS 2 data for TR3 children constrained in 1994
** NUTS 2 data for TR3 children constrained in 1995
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** NUTS 2 data for TR3 children constrained in 2005
** NUTS 2 data for TR3 children constrained in 2006
** NUTS 2 data for TR3 children constrained in 2007
NUTS 2 children of TR4 are TR41 TR42
** NUTS 2 data for TR4 children constrained in 1991
** NUTS 2 data for TR4 children constrained in 1992
** NUTS 2 data for TR4 children constrained in 1993
** NUTS 2 data for TR4 children constrained in 1994
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** NUTS 2 data for TR4 children constrained in 2005
** NUTS 2 data for TR4 children constrained in 2006
** NUTS 2 data for TR4 children constrained in 2007
NUTS 2 children of TR5 are TR51 TR52
** NUTS 2 data for TR5 children constrained in 1991
** NUTS 2 data for TR5 children constrained in 1992
** NUTS 2 data for TR5 children constrained in 1993
** NUTS 2 data for TR5 children constrained in 1994
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** NUTS 2 data for TR5 children constrained in 2006
** NUTS 2 data for TR5 children constrained in 2007
NUTS 2 children of TR6 are TR61 TR62 TR63
** NUTS 2 data for TR6 children constrained in 1991
** NUTS 2 data for TR6 children constrained in 1992
** NUTS 2 data for TR6 children constrained in 1993
** NUTS 2 data for TR6 children constrained in 1994
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** NUTS 2 data for TR6 children constrained in 2005
** NUTS 2 data for TR6 children constrained in 2006
** NUTS 2 data for TR6 children constrained in 2007
NUTS 2 children of TR7 are TR71 TR72
** NUTS 2 data for TR7 children constrained in 1991
** NUTS 2 data for TR7 children constrained in 1992
** NUTS 2 data for TR7 children constrained in 1993
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** NUTS 2 data for TR7 children constrained in 1994
** NUTS 2 data for TR7 children constrained in 1995
** NUTS 2 data for TR7 children constrained in 1996
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** NUTS 2 data for TR7 children constrained in 2005
** NUTS 2 data for TR7 children constrained in 2006
** NUTS 2 data for TR7 children constrained in 2007
NUTS 2 children of TR8 are TR81 TR82 TR83
** NUTS 2 data for TR8 children constrained in 1991
** NUTS 2 data for TR8 children constrained in 1992
** NUTS 2 data for TR8 children constrained in 1993
** NUTS 2 data for TR8 children constrained in 1994
** NUTS 2 data for TR8 children constrained in 1995
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** NUTS 2 data for TR8 children constrained in 2005
** NUTS 2 data for TR8 children constrained in 2006
** NUTS 2 data for TR8 children constrained in 2007
NUTS 2 children of TR9 are TR90
** NUTS 2 data for TR9 children constrained in 1991
** NUTS 2 data for TR9 children constrained in 1992
** NUTS 2 data for TR9 children constrained in 1993
** NUTS 2 data for TR9 children constrained in 1994
** NUTS 2 data for TR9 children constrained in 1995
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** NUTS 2 data for TR9 children constrained in 2005
** NUTS 2 data for TR9 children constrained in 2006
** NUTS 2 data for TR9 children constrained in 2007
NUTS 2 children of TRA are TRA1 TRA2
** NUTS 2 data for TRA children constrained in 1991
** NUTS 2 data for TRA children constrained in 1992
** NUTS 2 data for TRA children constrained in 1993
** NUTS 2 data for TRA children constrained in 1994
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** NUTS 2 data for TRA children constrained in 2005
** NUTS 2 data for TRA children constrained in 2006
** NUTS 2 data for TRA children constrained in 2007
NUTS 2 children of TRB are TRB1 TRB2
** NUTS 2 data for TRB children constrained in 1991
** NUTS 2 data for TRB children constrained in 1992
** NUTS 2 data for TRB children constrained in 1993
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** NUTS 2 data for TRB children constrained in 1994
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** NUTS 2 data for TRB children constrained in 2005
** NUTS 2 data for TRB children constrained in 2006
** NUTS 2 data for TRB children constrained in 2007
NUTS 2 children of TRC are TRC1 TRC2 TRC3
** NUTS 2 data for TRC children constrained in 1991
** NUTS 2 data for TRC children constrained in 1992
** NUTS 2 data for TRC children constrained in 1993
** NUTS 2 data for TRC children constrained in 1994
** NUTS 2 data for TRC children constrained in 1995
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** NUTS 2 data for TRC children constrained in 2006
** NUTS 2 data for TRC children constrained in 2007
NUTS 2 children of UKC are UKC1 UKC2
** NUTS 2 data for UKC children constrained in 2010
NUTS 2 children of UKD are UKD1 UKD2 UKD3 UKD4 UKD5
** NUTS 2 data for UKD children constrained in 2010
NUTS 2 children of UKE are UKE1 UKE2 UKE3 UKE4
NUTS 2 children of UKF are UKF1 UKF2 UKF3
NUTS 2 children of UKG are UKG1 UKG2 UKG3
** NUTS 2 data for UKG children constrained in 2010
NUTS 2 children of UKH are UKH1 UKH2 UKH3
NUTS 2 children of UKI are UKI1 UKI2
NUTS 2 children of UKJ are UKJ1 UKJ2 UKJ3 UKJ4
** NUTS 2 data for UKJ children constrained in 2010
NUTS 2 children of UKK are UKK1 UKK2 UKK3 UKK4
NUTS 2 children of UKL are UKL1 UKL2
NUTS 2 children of UKM are UKM2 UKM3 UKM5 UKM6
** NUTS 2 data for UKM children constrained in 1990
** NUTS 2 data for UKM children constrained in 1991
** NUTS 2 data for UKM children constrained in 1992
** NUTS 2 data for UKM children constrained in 1993
** NUTS 2 data for UKM children constrained in 1994
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** NUTS 2 data for UKM children constrained in 1998
** NUTS 2 data for UKM children constrained in 1999
** NUTS 2 data for UKM children constrained in 2010
NUTS 2 children of UKN are UKN0


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* Cross-Sectional Time Series Constraint for NUTS Level 2 *
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NUTS 3 children of AT11 are AT111 AT112 AT113
** NUTS 3 data for AT11 children constrained in 1990
** NUTS 3 data for AT11 children constrained in 1991
** NUTS 3 data for AT11 children constrained in 1992
** NUTS 3 data for AT11 children constrained in 1993
** NUTS 3 data for AT11 children constrained in 1994
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** NUTS 3 data for AT11 children constrained in 1995
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** NUTS 3 data for AT11 children constrained in 2001
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… … … … … [similar lines omitted in this listing]
… … … …
NUTS 3 children of UKM2 are UKM21 UKM22 UKM23 UKM24 UKM25 UKM26 UKM27 UKM28
NUTS 3 children of UKM3 are UKM31 UKM32 UKM33 UKM34 UKM35 UKM36 UKM37 UKM38
NUTS 3 children of UKM5 are UKM50
NUTS 3 children of UKM6 are UKM61 UKM62 UKM63 UKM64 UKM65 UKM66
NUTS 3 children of UKN0 are UKN01 UKN02 UKN03 UKN04 UKN05
** NUTS 3 data for UKN0 children constrained in 1990
** NUTS 3 data for UKN0 children constrained in 1991
** NUTS 3 data for UKN0 children constrained in 1992
** NUTS 3 data for UKN0 children constrained in 1993
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