

# Assignment 2

Stefano Graziosi, Gabriele Molè, Laura Lo Schiavo, Giovanni Carron

```
# To solve conflicts
library(conflicted)
conflicts_prefer(dplyr::filter)
```

[conflicted] Will prefer dplyr::filter over any other package.

```
# Time series packages
library(dlm)
library(TSstudio)
library(feasts)
```

Loading required package: fabletools  
Registered S3 method overwritten by 'tsibble':  
method from  
as\_tibble.grouped\_df dplyr

```
library(tseries)
```

Registered S3 method overwritten by 'quantmod':  
method from  
as.zoo.data.frame zoo

```
# Necessary packages for quantmod
library(zoo)
library(xts)
library(quantmod)
```

Loading required package: TTR

```
#Specifically for Assignment 2
library(depmixS4)
```

```
Loading required package: nnet
Loading required package: MASS
Loading required package: Rsolnp
Loading required package: nlme
```

```
Attaching package: 'nlme'
```

```
The following object is masked from 'package:feasts':
```

```
ACF
```

```
library(HiddenMarkov)
```

```
# Datasets
library(readr)
library(fpp3)
```

```
-- Attaching packages ----- fpp3 1.0.1 --
v tibble      3.2.1      v ggplot2      3.5.1
v dplyr        1.1.4      v tsibble      1.1.6
v tidyr        1.3.1      v tsibbledata  0.4.1
v lubridate    1.9.4      v fable        0.4.1
```

```
# For fancy plots
library(ggthemes)
# Necessary packages for viridis
library(viridisLite)
library(viridis)
library(gridExtra)
library(magrittr)
library(textab)

# Packages related to tidyverse, for data manipulation
library(tidyverse) # includes (lubridate), (dplyr), (ggplot2), (tidyr), (tidyselect)
```

```
-- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
v forcats 1.0.0      v stringr 1.5.1
v purrr    1.0.2
```

```
library(tinytex)

# To handle time changes
library(timechange)

# Importing the data
urlfile = "https://raw.githubusercontent.com/stfgrz/20236-timeseries-ps/97a64d30e6a67339343f"
data<-read_csv(url(urlfile), show_col_types = FALSE)

# Getting the nominal data
nom_int_data <- data[, 2]
ts_data_nom <- ts(as.vector(t(nom_int_data)), start = c(1997, 1), frequency = 12)
```

```
? depmixS4
```

```
? lm
```

```
? glm
```

```
? depmix
```

```
? posterior
```

## 2. Hidden Markov Models

The dataset provided in the file `data_assHMM.csv` (posted on BBoard) provides monthly data including 10 years Italian government bond's interest rate, inflation represented by the Harmonised Index of Consumer Prices (HICP) and default ratings assigned by the agencies Moody's and Fitch, in the investment grade range, i.e. from Aaa/AAA to Baa3-/BBB-. The data set collects data for the period January 1997 to July 2019, and it has been built mainly using OECD data.

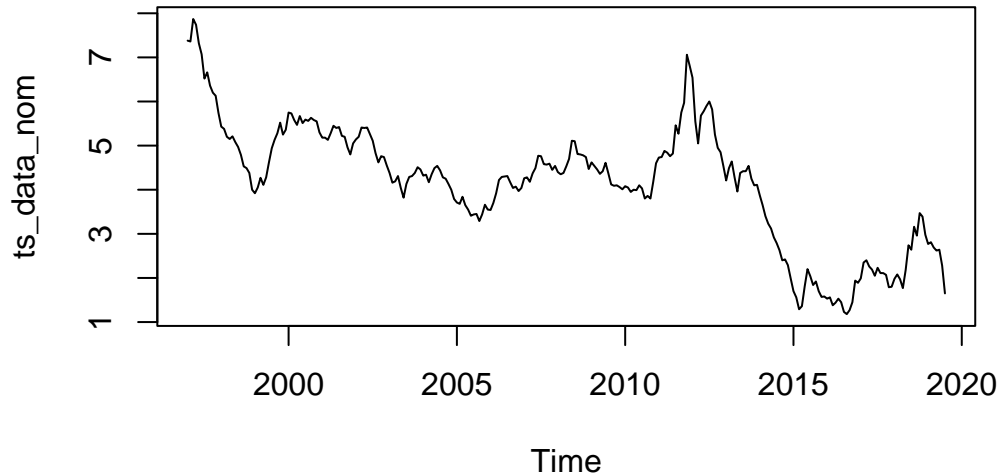
### 2.1 Part (a)

#### Question 1

Let us focus on the nominal interest rate for the 10 years Italian government bond. In fact, you may want to consider the real interest rate, calculated from the HICP.

Plot the data and comment briefly if and why a HMM could be a reasonable model.

```
#plot the dataset for nominal interest rates  
plot.ts(ts_data_nom)
```



```
#nominal  
y1 <- as.numeric(ts_data_nom)  
model1 <- depmix(y1 ~ 1, data=data.frame(ts_data_nom), nstates=3)  
model1
```

Initial state probabilities model

	pr1	pr2	pr3
	0.333	0.333	0.333

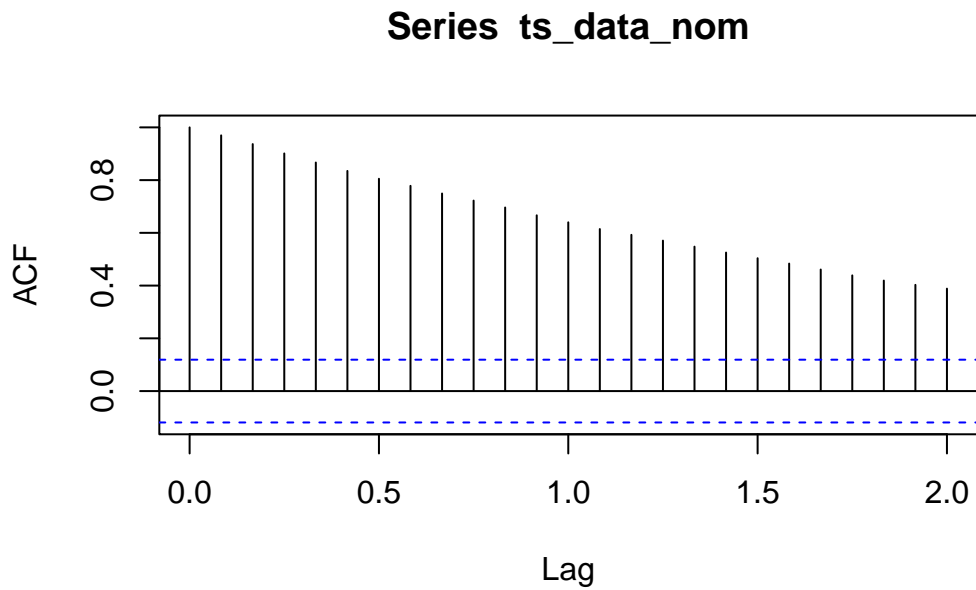
Transition matrix

	toS1	toS2	toS3
fromS1	0.333	0.333	0.333
fromS2	0.333	0.333	0.333
fromS3	0.333	0.333	0.333

Response parameters

	Re1.(Intercept)	Re1.sd
St1	0	1
St2	0	1
St3	0	1

```
#test for stationarity
acf(ts_data_nom)
```



```
kpss.test(ts_data_nom)
```

Warning in `kpss.test(ts_data_nom)`: p-value smaller than printed p-value

#### KPSS Test for Level Stationarity

```
data: ts_data_nom
KPSS Level = 2.4812, Truncation lag parameter = 5, p-value = 0.01
```

```
adf.test(ts_data_nom)
```

#### Augmented Dickey-Fuller Test

```
data: ts_data_nom
Dickey-Fuller = -2.4709, Lag order = 6, p-value = 0.3776
alternative hypothesis: stationary
```

A HMM model is better suitable for non-stationary time series. At first visual inspection the series seems to show different means and likely different dispersion over time. We also propose various indirect formal evidence against stationarity. The autocorrelation function does not decrease over time very quickly, suggesting non-stationarity. Both the KPSS and the ADF tests, two common test for assessing stationarity, provide support for non-stationarity.

Given the data it seems likely to observe three different latent states, where the peaks before the 2000 and in the early 2010's seem to represent a recession, the years after 2015 the boom, and stable states the remaining years.

A HMM model might be appropriate for the phenomenon at stake, as financial markets are generally very quick in converging to new equilibria mainly depending on exogenous shocks. Hence, postulating a hidden process guiding such shifts is reasonable.

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## Question 2

Let us indeed use a Hidden Markov Model, with 3 states (representing, say, boom (i.e. less risky, lower interest rates), recession (high risk, high interest rates) and a stable path), and Gaussian emission distributions, with state-dependent mean and variance.

Provide the MLEs of the unknown parameters of the model (and their standard errors). Comment briefly.

```
#nominal interest rates
fmodel1 <- fit(model1)
```

```
converged at iteration 28 with logLik: -216.452
```

```
fmodel1
```

```
Convergence info: Log likelihood converged to within tol. (relative change)
'log Lik.' -216.452 (df=14)
AIC: 460.9041
BIC: 511.3337
```

```
summary(fmodel1)
```

```
Initial state probabilities model
pr1 pr2 pr3
  0   0   1
```

```
Transition matrix
      toS1 toS2 toS3
fromS1 1.000 0.000 0.000
fromS2 0.008 0.976 0.016
fromS3 0.000 0.041 0.959
```

```
Response parameters
Resp 1 : gaussian
      Re1.(Intercept) Re1.sd
St1          2.137  0.581
St2          4.251  0.377
St3          5.639  0.713
```

```
MLEse1=standardError(fmodel1)
MLEse1
```

	par	constr	se
1	0.000000e+00	bnd	NA
2	0.000000e+00	bnd	NA
3	1.000000e+00	bnd	NA
4	1.000000e+00	bnd	NA
5	6.959899e-34	bnd	NA
6	1.137589e-58	bnd	NA
7	7.625438e-03	inc	0.007606343
8	9.762212e-01	inc	0.013669112
9	1.615333e-02	inc	0.011405695
10	9.927922e-33	bnd	NA
11	4.128159e-02	inc	0.023266241
12	9.587184e-01	inc	0.023266241
13	2.137116e+00	inc	0.074046873
14	5.810055e-01	inc	0.052838729
15	4.250948e+00	inc	0.037628730
16	3.766686e-01	inc	0.025714756
17	5.639089e+00	inc	0.092323809
18	7.134020e-01	inc	0.058592423

```
posterior(fmodel1)$state
```

Warning in .local(object, ...): Argument 'type' not specified and will default to 'viterbi'. This default may change in future releases of depmixS4. Please see ?posterior for alternative options.

```
[1] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 2 2 2 2 2 2 2 2 2 3 3 3 3 3 3 3
[38] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 2 2 2 2 2 2 2
[75] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
[112] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
[149] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 3 3 3 3 3 3 3
[186] 3 3 3 3 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 1 1 1 1 1 1
[223] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
[260] 1 1 1 1 1 1 1 1 1 1 1 1 1 1
```

Estimated initial probabilities suggest an initial stage at state 3 (recession).

Overall the transition matrix suggests a persistence in state, where the probabilities of remaining in current states are over 95% for both state 1 and state 3. By plotting the data and interpreting state 1 as stability, state 2 as boom and state 3 as recession, the transitions probabilities are then reasonable. It is impossible ( $p_{3,2} = p_{2,3} = 0$ ) to directly shift from recession to boom (and viceversa). Starting from a stable state, it is more likely to end up in a recession than a boom ( $p_{1,3} > p_{1,2}$ ). Finally, the probability 1 for  $p_{2,2}$  is justified as the “classification” of state 2 is limited to the last periods of the dataset and no different state follows a state 2 observation, hence the probability 1.

Emission distributions show intermediate nominal interest rates for stable periods (state 1) and the lowest variance. The highest mean is for recession periods, as expected, as well as the highest variance. Booms, reflecting excitement, show lower interest rates but also higher variability compared to stable periods, yet lower than recessions.

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### Question 3

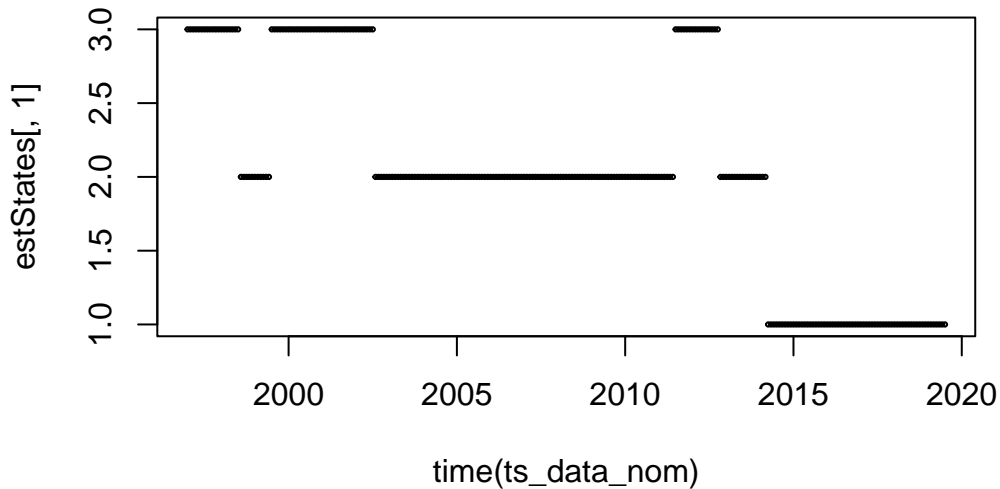
Find the optimal state sequence (“decoding”) and plot it, comparing it with the data.

```
estStates <- posterior(fmodel1)
```



Warning in .local(object, ...): Argument 'type' not specified and will default to 'viterbi'. This default may change in future releases of depmixS4. Please see ?posterior for alternative options.

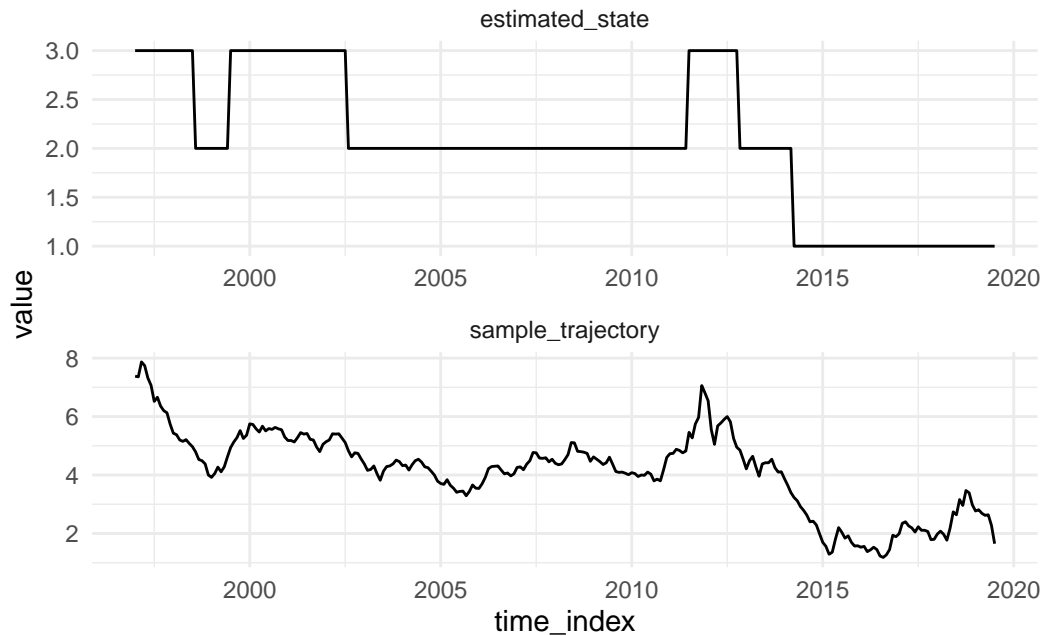
```
plot(time(ts_data_nom), estStates[,1], cex=.3)
```



```
#show it with ggplot
results_df <- data.frame(time_index=time(ts_data_nom) %>% as.numeric(),
  sample_trajectory=ts_data_nom %>% as.numeric(),
  estimated_state=posterior(fmodel1)$state) %>%
gather("variable", "value", -time_index)
```

Warning in .local(object, ...): Argument 'type' not specified and will default to 'viterbi'. This default may change in future releases of depmixS4. Please see ?posterior for alternative options.

```
ggplot(results_df, aes(time_index, value)) + geom_line() +
facet_wrap(variable ~ ., scales="free", ncol=1) + theme_minimal()
```



## 2.2 Part (b)

HMMs are particularly useful for time series that present change points. However, one may want to go further, trying to improve prediction of a possible change point through available covariates. To this aim, one may use non-homogeneous HMMs, allowing the transition matrix to depend on covariates. A reference is Zucchini, W., MacDonald, I-L. and Langrock, R. (2016) Hidden Markov Models for Time Series: an introduction using R. Chapman and Hall/CRC; and the R package 'depmixS4' allows this extension, see Visser and Speekenbrink (2010), Journal of Statistical Software—both references are posted on BBoard.

You may want to explore this more general class of HMMs for the data under study here.

```
data.b <- as.data.frame(data[, 2:7] )
y1 <- as.numeric(ts_data_nom)
```

### Model 1: baseline model

```
#model 1b (controlling for inflation)
mod <- depmix(response = y1 ~ 1, data = data.b, nstates = 3, family = gaussian(),
              transition = ~ inflation)
fmodel2 <- fit(mod)
```

converged at iteration 58 with logLik: -214.1302

```
fmodel2
```

Convergence info: Log likelihood converged to within tol. (relative change)  
'log Lik.' -214.1302 (df=20)  
AIC: 468.2603  
BIC: 540.3027

```
summary(fmodel2)
```

Initial state probabilities model

pr1 pr2 pr3

1 0 0

Transition model for state (component) 1

Model of type multinomial (mlogit), formula: ~inflation

Coefficients:

	St1	St2	St3
(Intercept)	0	-4.534609	7.726854
inflation	0	0.590847	-11.751170

Probabilities at zero values of the covariates.

0.0004406325 4.728471e-06 0.9995546

Transition model for state (component) 2

Model of type multinomial (mlogit), formula: ~inflation

Coefficients:

	St1	St2	St3
(Intercept)	0	6.376119	4.985542
inflation	0	-1.122777	-4.296848

Probabilities at zero values of the covariates.

0.001360683 0.7995949 0.1990444

Transition model for state (component) 3

Model of type multinomial (mlogit), formula: ~inflation

Coefficients:

	St1	St2	St3
(Intercept)	0	-55.2404	79.02395
inflation	0	31.0821	-30.32285

Probabilities at zero values of the covariates.

4.790007e-35 4.894807e-59 1

```

Response parameters
Resp 1 : gaussian
      Re1.(Intercept) Re1.sd
St1      5.612  0.714
St2      4.236  0.365
St3      2.137  0.581

```

```
MLEse2=standardError(fmodel2)
```

```
Warning in sqrt(diag(vcov$vcov)): NaNs produced
```

```
MLEse2
```

	par	constr	se
1	1.0000000	bnd	NA
2	0.0000000	bnd	NA
3	0.0000000	bnd	NA
4	0.0000000	fix	NA
5	-4.5346094	inc	2.46774574
6	7.7268538	inc	144.57410112
7	0.0000000	fix	NA
8	0.5908470	inc	0.88195186
9	-11.7511697	inc	114.77835038
10	0.0000000	fix	NA
11	6.3761187	inc	3.36041999
12	4.9855415	inc	3.65161502
13	0.0000000	fix	NA
14	-1.1227766	inc	1.40890044
15	-4.2968477	inc	2.63757671
16	0.0000000	fix	NA
17	-55.2403992	inc	NaN
18	79.0239465	inc	NaN
19	0.0000000	fix	NA
20	31.0821041	inc	287.65161045
21	-30.3228531	inc	199.74585103
22	5.6118446	inc	0.10051847
23	0.7140541	inc	0.05757647
24	4.2355173	inc	0.04406757
25	0.3654813	inc	0.03003733

```
26 2.1369221 inc 0.07362210
27 0.5806107 inc 0.05243830
```

```
posterior(fmodel2)$state
```

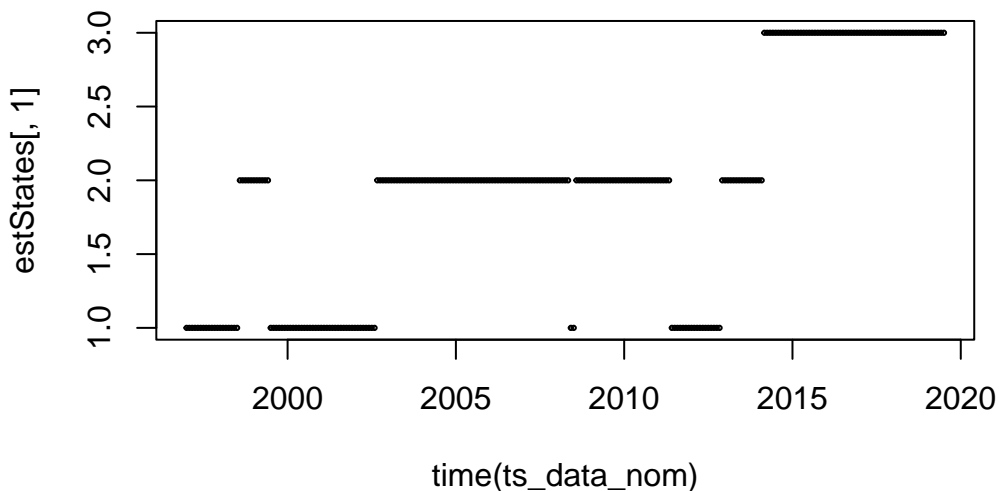
Warning in .local(object, ...): Argument 'type' not specified and will default to 'viterbi'. This default may change in future releases of depmixS4. Please see ?posterior for alternative options.

```
[1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 1 1
[38] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2
[75] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
[112] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2
[149] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 1 1 1 1
[186] 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3
[223] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
[260] 3 3 3 3 3 3 3 3 3 3 3
```

```
estStates <- posterior(fmodel2)
```

Warning in .local(object, ...): Argument 'type' not specified and will default to 'viterbi'. This default may change in future releases of depmixS4. Please see ?posterior for alternative options.

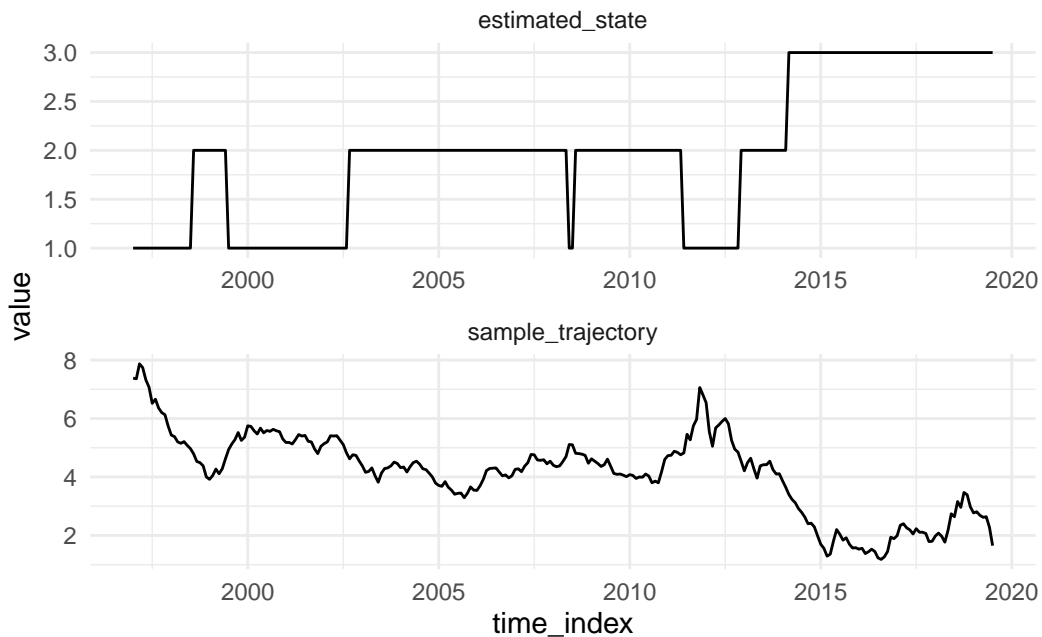
```
plot(time(ts_data_nom), estStates[,1], cex=.3)
```



```
#ggplot
results_df <- data.frame(time_index=time(ts_data_nom) %>% as.numeric(),
  sample_trajectory=ts_data_nom %>% as.numeric(),
  estimated_state=posterior(fmodel2)$state) %>%
gather("variable", "value", -time_index)
```

Warning in .local(object, ...): Argument 'type' not specified and will default to 'viterbi'. This default may change in future releases of depmixS4. Please see ?posterior for alternative options.

```
ggplot(results_df, aes(time_index, value)) + geom_line() +
facet_wrap(variable ~ ., scales="free", ncol=1) + theme_minimal()
```



## Model 2: controlling for gdp

```
mod2 <- depmix(response = y1 ~ 1, data = data.b, nstates = 3, family = gaussian(),
  transition = ~ gdp)
fmodel3 <- fit(mod2)
```

converged at iteration 33 with logLik: -215.7819

```
fmodel3
```

```
Convergence info: Log likelihood converged to within tol. (relative change)
'log Lik.' -215.7819 (df=20)
AIC: 471.5637
BIC: 543.6061
```

```
summary(fmodel3)
```

```
Initial state probabilities model
```

```
pr1 pr2 pr3
  0   1   0
```

```
Transition model for state (component) 1
```

```
Model of type multinomial (mlogit), formula: ~gdp
```

```
Coefficients:
```

```
           St1           St2           St3
(Intercept)  0 -4.2810454 -4.8542469
gdp           0  0.8807132  0.1042325
```

```
Probabilities at zero values of the covariates.
```

```
0.9788343 0.01353551 0.007630211
```

```
Transition model for state (component) 2
```

```
Model of type multinomial (mlogit), formula: ~gdp
```

```
Coefficients:
```

```
           St1           St2           St3
(Intercept)  0 3.1137101 -9.9505399
gdp           0 0.7601739  0.4167766
```

```
Probabilities at zero values of the covariates.
```

```
0.04254517 0.9574528 2.029484e-06
```

```
Transition model for state (component) 3
```

```
Model of type multinomial (mlogit), formula: ~gdp
```

```
Coefficients:
```

```
           St1           St2           St3
(Intercept)  0  0.9297441 14.304771
gdp           0 -0.9181655  2.768894
```

```
Probabilities at zero values of the covariates.
```

```
6.130784e-07 1.553455e-06 0.9999978
```

```

Response parameters
Resp 1 : gaussian
      Re1.(Intercept) Re1.sd
St1      4.248  0.375
St2      5.632  0.714
St3      2.137  0.581

```

```
MLEse3=standardError(fmodel3)
```

```
Warning in sqrt(diag(vcov)): NaNs produced
```

```
MLEse3
```

	par	constr	se
1	0.0000000	bnd	NA
2	1.0000000	bnd	NA
3	0.0000000	bnd	NA
4	0.0000000	fix	NA
5	-4.2810454	inc	1.12445396
6	-4.8542469	inc	1.01198347
7	0.0000000	fix	NA
8	0.8807132	inc	2.09071863
9	0.1042325	inc	1.41291508
10	0.0000000	fix	NA
11	3.1137101	inc	0.60048919
12	-9.9505399	inc	98.14191235
13	0.0000000	fix	NA
14	0.7601739	inc	0.88181174
15	0.4167766	inc	NaN
16	0.0000000	fix	NA
17	0.9297441	inc	17.21967904
18	14.3047709	inc	116.49875319
19	0.0000000	fix	NA
20	-0.9181655	inc	19.72050056
21	2.7688941	inc	28.21562791
22	4.2482162	inc	0.03942895
23	0.3753438	inc	0.02665222
24	5.6323303	inc	0.09560580
25	0.7144388	inc	0.05852701
26	2.1371237	inc	0.07404068
27	0.5810065	inc	0.05283736



```
posterior(fmodel3)$state
```

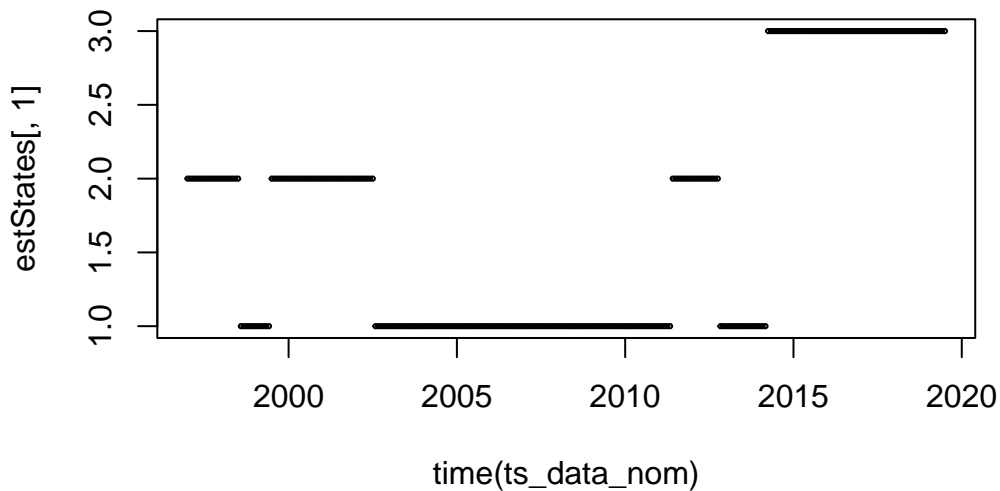
Warning in .local(object, ...): Argument 'type' not specified and will default to 'viterbi'. This default may change in future releases of depmixS4. Please see ?posterior for alternative options.

```
[1] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2
[38] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 1 1
[75] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
[112] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
[149] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2
[186] 2 2 2 2 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
[223] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
[260] 3 3 3 3 3 3 3 3 3 3 3 3
```

```
estStates <- posterior(fmodel3)
```

Warning in .local(object, ...): Argument 'type' not specified and will default to 'viterbi'. This default may change in future releases of depmixS4. Please see ?posterior for alternative options.

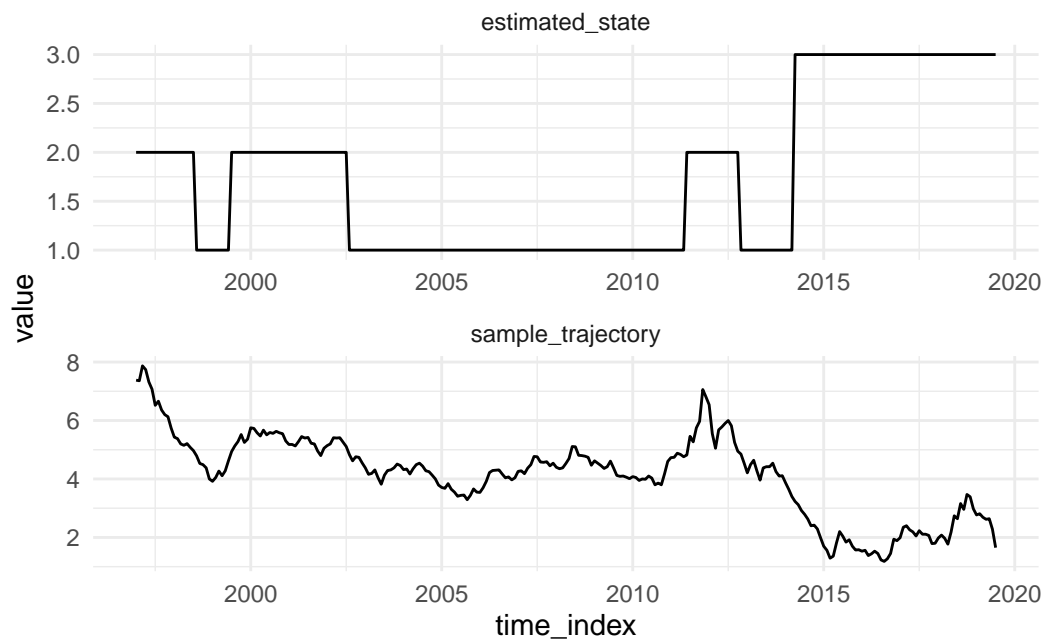
```
plot(time(ts_data_nom), estStates[,1], cex=.3)
```



```
#ggplot
results_df <- data.frame(time_index=time(ts_data_nom) %>% as.numeric(),
sample_trajectory=ts_data_nom %>% as.numeric(),
estimated_state=posterior(fmodel3)$state) %>%
gather("variable", "value", -time_index)
```

Warning in .local(object, ...): Argument 'type' not specified and will default to 'viterbi'. This default may change in future releases of depmixS4. Please see ?posterior for alternative options.

```
ggplot(results_df, aes(time_index, value)) + geom_line() +
facet_wrap(variable ~ ., scales="free", ncol=1) + theme_minimal()
```



### Model 3: controlling for gdp and inflation

```
mod3 <- depmix(response = y1 ~ 1, data = data.b, nstates = 3, family = gaussian(),
transition = ~ gdp + inflation)
fmodel4 <- fit(mod3)
```

converged at iteration 26 with logLik: -212.1899

```
fmodel4
```

```
Convergence info: Log likelihood converged to within tol. (relative change)
'log Lik.' -212.1899 (df=26)
AIC: 476.3797
BIC: 570.0348
```

```
summary(fmodel4)
```

```
Initial state probabilities model
```

```
pr1 pr2 pr3
  1   0   0
```

```
Transition model for state (component) 1
```

```
Model of type multinomial (mlogit), formula: ~gdp + inflation
```

```
Coefficients:
```

	St1	St2	St3
(Intercept)	0 -0.04957338	9.675829	
gdp	0 -1.85466145	3.058293	
inflation	0 -1.26127930	-16.830633	

```
Probabilities at zero values of the covariates.
```

```
6.277516e-05 5.973906e-05 0.9998775
```

```
Transition model for state (component) 2
```

```
Model of type multinomial (mlogit), formula: ~gdp + inflation
```

```
Coefficients:
```

	St1	St2	St3
(Intercept)	0 7.2522619	6.1242106	
gdp	0 0.2559071	-0.3583218	
inflation	0 -1.5504992	-5.1229882	

```
Probabilities at zero values of the covariates.
```

```
0.0005350233 0.7550749 0.2443901
```

```
Transition model for state (component) 3
```

```
Model of type multinomial (mlogit), formula: ~gdp + inflation
```

```
Coefficients:
```

	St1	St2	St3
(Intercept)	0 -45.469617	70.7524128	
gdp	0 -1.331988	-0.5211976	
inflation	0 26.831880	-26.5794866	

```
Probabilities at zero values of the covariates.
```

1.873344e-31 3.352847e-51 1

Response parameters

Resp 1 : gaussian

	Re1.(Intercept)	Re1.sd
St1	5.575	0.717
St2	4.217	0.355
St3	2.137	0.580

MLEse4=standardError(fmodel4)

Warning in sqrt(diag(vcov\$vcov)): NaNs produced

MLEse4

	par	constr	se
1	1.00000000	bnd	NA
2	0.00000000	bnd	NA
3	0.00000000	bnd	NA
4	0.00000000	fix	NA
5	-0.04957338	inc	NaN
6	9.67582852	inc	82.51264009
7	0.00000000	fix	NA
8	-1.85466145	inc	0.84067931
9	3.05829292	inc	NaN
10	0.00000000	fix	NA
11	-1.26127930	inc	0.03133484
12	-16.83063310	inc	145.82307930
13	0.00000000	fix	NA
14	7.25226188	inc	2.95591615
15	6.12421064	inc	3.32465124
16	0.00000000	fix	NA
17	0.25590707	inc	0.58371300
18	-0.35832183	inc	0.64397243
19	0.00000000	fix	NA
20	-1.55049921	inc	1.10714580
21	-5.12298824	inc	2.85885605
22	0.00000000	fix	NA
23	-45.46961717	inc	397.63248689
24	70.75241280	inc	665.23030451

```

25  0.00000000    fix      NA
26 -1.33198815    inc 13.31298880
27 -0.52119761    inc      NaN
28  0.00000000    fix      NA
29 26.83188024    inc      NaN
30 -26.57948659    inc      NaN
31  5.57473278    inc  0.08878003
32  0.71749756    inc  0.05641503
33  4.21716952    inc  0.03699022
34  0.35495864    inc  0.02510926
35  2.13677895    inc  0.07355786
36  0.58046696    inc  0.05235337

```

```
posterior(fmodel4)$state
```

Warning in .local(object, ...): Argument 'type' not specified and will default to 'viterbi'. This default may change in future releases of depmixS4. Please see ?posterior for alternative options.

```

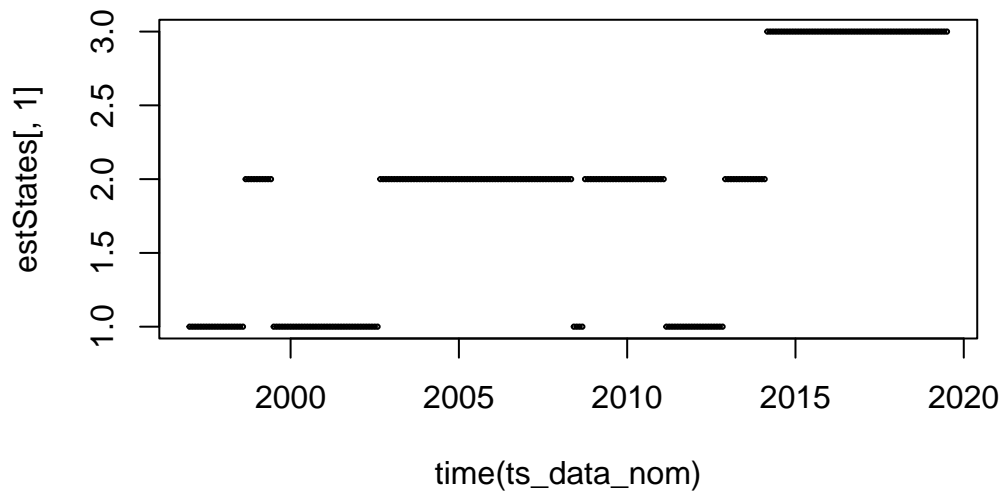
[1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 1 1 1 1 1 1
[38] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2
[75] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
[112] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 1 2 2 2 2 2 2
[149] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 1 1 1 1 1
[186] 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3
[223] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
[260] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3

```

```
estStates <- posterior(fmodel4)
```

Warning in .local(object, ...): Argument 'type' not specified and will default to 'viterbi'. This default may change in future releases of depmixS4. Please see ?posterior for alternative options.

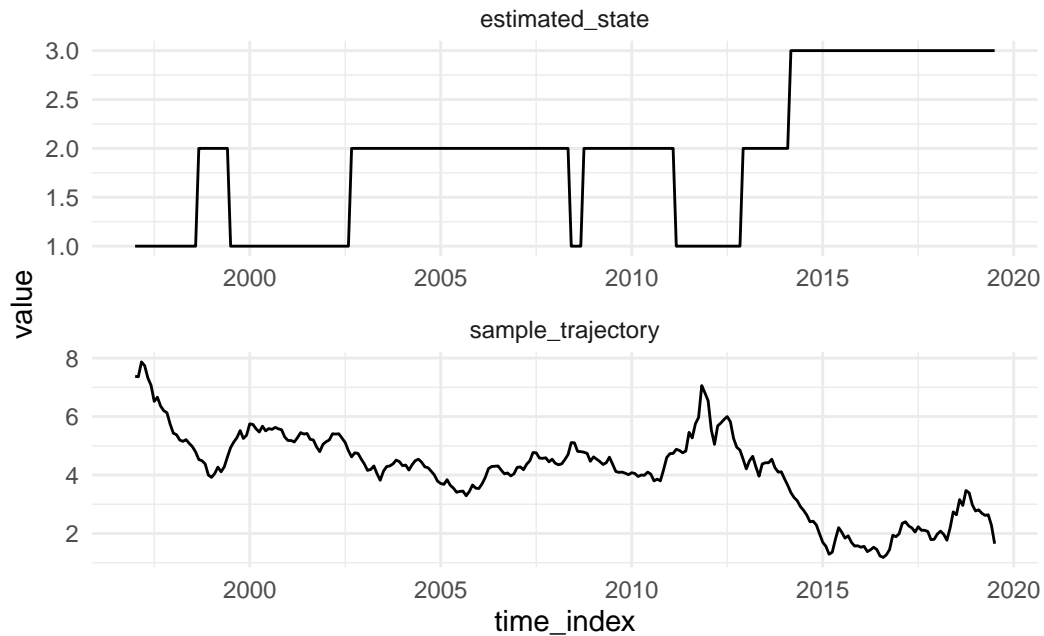
```
plot(time(ts_data_nom), estStates[,1], cex=.3)
```



```
#ggplot
results_df <- data.frame(time_index=time(ts_data_nom) %>% as.numeric(),
  sample_trajectory=ts_data_nom %>% as.numeric(),
  estimated_state=posterior(fmodel4)$state) %>%
gather("variable", "value", -time_index)
```

Warning in .local(object, ...): Argument 'type' not specified and will default to 'viterbi'. This default may change in future releases of depmixS4. Please see ?posterior for alternative options.

```
ggplot(results_df, aes(time_index, value)) + geom_line() +
facet_wrap(variable ~ ., scales="free", ncol=1) + theme_minimal()
```



## Results

```
results_df <- data.frame(
  time_index = as.numeric(time(ts_data_nom)),
  sample_trajectory = as.numeric(ts_data_nom),
  estimated_state_fmodel4 = posterior(fmodel4)$state,
  estimated_state_fmodel3 = posterior(fmodel3)$state,
  estimated_state_fmodel2 = posterior(fmodel2)$state
) %>%
  gather("variable", "value", -time_index)
```

Warning in .local(object, ...): Argument 'type' not specified and will default to 'viterbi'. This default may change in future releases of depmixS4. Please see ?posterior for alternative options.

Warning in .local(object, ...): Argument 'type' not specified and will default to 'viterbi'. This default may change in future releases of depmixS4. Please see ?posterior for alternative options.

Warning in .local(object, ...): Argument 'type' not specified and will default to 'viterbi'. This default may change in future releases of depmixS4. Please see ?posterior for alternative options.

```
# Plot
ggplot(results_df, aes(time_index, value, color = variable)) +
  geom_line() +
  facet_wrap(~ variable, scales = "free", ncol = 1) +
  theme_minimal() +
  labs(title = "Comparison of Estimated States from fmodel4 and fmodel2",
       x = "Time Index",
       y = "Value") +
  theme(legend.position = "bottom")
```

