Workshop on TSA and SDCM for Official Statistics

Institut national de la statistique
et des études économiques

Mesurer pour comprendre

R package `tvCoef`, implementing time-varying coefficients models has never been so easy

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Session 7: New tools for Seasonal Adjustment 2
Friday 15 December 2023

Sommaire

Introduction

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Assumption **true** in the **short term**, but generally **false** in the **long term** or in the presence of structural changes (change of nomenclature, definition, COVID...).

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Many models are based on linear regressions (WDA, forecasts, benchmark, etc.), which assume that relationships between variables are fixed over time.

Assumption **true** in the **short term**, but generally **false** in the **long term** or in the presence of structural changes (change of nomenclature, definition, COVID...).

Goal:

- to study methods of relaxing this constraint;
- propose a simple way of implementing and comparing these methods (package R `tvCoef`).

Linear regression model

General idea:

$$
\begin{aligned}
& y_t = \beta_0 + \beta_1 x_{1,t} + \cdots + \beta_p x_{p,t} + \varepsilon_t \quad \varepsilon_t \sim \mathcal{N}(0, \sigma^2) \\
\iff & y_t = \beta X_t + \varepsilon_t
\end{aligned}
$$

β estimated using the OLS

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β estimated using the OLS

Example: forecast of French production growth in other manufacturing using

- IPI overhang
- INSEE business climate
- Balances of opinion published by INSEE and Banque de France

Model estimated with `stats::lm()` or `dynlm::dynlm()`

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Model estimated with `stats::lm()` or `dynlm::dynlm()`

Even if machine learning models can be used, linear models performs well and are often used as reference models

R code (1)

```r
library(tvCoef)
library(dynlm)
data <- window(manufacturing, start = 1993, end = c(2019, 4))
y <- data[, "prod_c5"]
model_c5 <- dynlm(
    formula = prod_c5 ~ overhang_ipi1_c5 + insee_bc_c5_m3 +
        + diff(insee_tppre_c5_m3, 1) + diff(bdf_tuc_c5_m2, 1),
    data = data
)
summary(model_c5)
```

```
Time series regression with "ts" data:
Start = 1993(2), End = 2019(4)

Call:
dynlm(formula = prod_c5 ~ overhang_ipi1_c5 + insee_bc_c5_m3 +
    +diff(insee_tppre_c5_m3, 1) + diff(bdf_tuc_c5_m2, 1), data = data)

Residuals:
     Min       1Q   Median       3Q      Max
```

R code (2)

```
-2.33630 -0.46798  0.02535  0.47036  1.61058

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
(Intercept)                -5.223513   0.798384  -6.543 2.46e-09 ***
overhang_ipi1_c5            0.100841   0.022195   4.543 1.52e-05 ***
insee_bc_c5_m3              0.050966   0.007969   6.396 4.89e-09 ***
diff(insee_tppre_c5_m3, 1)  0.040771   0.011052   3.689 0.000363 ***
diff(bdf_tuc_c5_m2, 1)      0.410629   0.068227   6.019 2.79e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7165 on 102 degrees of freedom
Multiple R-squared:  0.7151,    Adjusted R-squared:  0.7039
F-statistic:    64 on 4 and 102 DF,  p-value: < 2.2e-16
```

Goal

Study different methods to estimate

$$y_t = \beta_t X_t + \varepsilon_t$$

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Idea: stay close to the case of linear regression so that results remain easily interpretable

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Outline:

1. Statistical tests
2. Piecewise regressions
3. Local regressions
4. State-space models

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Statistical tests: Bai and Perron

Most famous test: Bai and Perron, closed to Chow test.
They propose an efficient algorithm for finding break dates (package `strucchange`). Let the model be:

$$y_t = \beta_0 + \beta_1 x_{1,t} + \cdots + \beta_p x_{p,t} + \varepsilon_t$$

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$$y_t = \beta_0 + \beta_1 x_{1,t} + \cdots + \beta_p x_{p,t} + \varepsilon_t$$

We split it in two, around a date t_1, and obtain two sub-models:

$$\forall t \leq t_1 : \quad y_t = \beta'_0 + \beta'_1 x_{1,t} + \cdots + \beta'_p x_{p,t} + \varepsilon_t$$

$$\forall t > t_1 : \quad y_t = \beta'_0 + \beta'_1 x_{1,t} + \cdots + \beta'_p x_{p,t} + \varepsilon_t$$

The null hypothesis assumes that $\beta'_0 = \beta''_0$, $\beta'_1 = \beta''_1, \ldots \beta'_p = \beta''_p$

R code (1)

```
strucchange::breakdates(strucchange::breakpoints(
    prod_c5 ~ overhang_ipi1_c5 + insee_bc_c5_m3
    + `diff(insee_tppre_c5_m3, 1)` + `diff(bdf_tuc_c5_m2, 1)`,
    data = model_c5$model))
```

```
[1] 2008.5
```

Bai Perron's limitations

- The break may only be on a subset of variables but in `strucchange` only global tests implemented.

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- Instability in the choice of date and the break is not necessarily abrupt (e.g. slow evolution over time).
- Structural breaks are usually known
- Assume that there is a break date to be determined, we might just want to test whether the coefficients are constant or not

Nyblom and Hansen

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Hansen limits:

- Test for variance not stable (go through other tests)
- Joint test does not apply to dummies
- Applies only to stationary variables

code (1)

tvCoef::hansen_test()

```
hansen_test(model_c5)
```

```
Variable                      L         Stat     Conclusion
-------------------------------------------------------------
(Intercept)                     0.2725   0.47   FALSE
overhang_ipi1_c5                0.8392   0.47    TRUE
insee_bc_c5_m3                  0.2867   0.47   FALSE
diff(insee_tppre_c5_m3, 1)      0.2568   0.47   FALSE
diff(bdf_tuc_c5_m2, 1)          0.1491   0.47   FALSE
Variance                        0.4881   0.47    TRUE
Joint Lc                        1.3188   1.9   FALSE


Lecture: True means reject H0 at level 5%
```

Sommaire

Piecewise linear regressions

Associated to Bai Perron

$$\exists t_1, \ldots, t_{T-1} : \beta_t = \beta_1 1_{t \leq t_1} + \beta_2 1_{t_1 < t \leq t_2} + \cdots + \beta_T 1_{t_{T-1} < t}$$

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Estimated by:

1. Dividing the regressors ($\mathbb{V}[\varepsilon_t]$ fixed in time) R `tvCoef::piece_reg()`
2. Piecewise linear regressions ($\mathbb{V}[\varepsilon_t]$ varies by subperiod) R `tvCoef::bp_lm()`

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➔ use case 1 because gives a single regression output.

In both cases, coefficient estimates remain the same, differences on variances and on real-time estimates.

➔ Pros:

- Simple to understand and implement
- Easily combined with other types of models (local regressions)

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  - Simple to understand and implement
  - Easily combined with other types of models (local regressions)
- Cons:
  - Assumes the existence of an abrupt break
  - Imprecision in date selection

R code (1)

```r
pwr_mod <- piece_reg(model_c5)
summary(pwr_mod)
```

```

Time series regression with "ts" data:
Start = 1993(2), End = 2019(4)

Call:
dynlm::dynlm(formula = as.formula(formula), data = data2)

Residuals:
     Min       1Q   Median       3Q      Max
-1.54982 -0.38309 -0.07791  0.43409  1.27348

Coefficients:
                                      Estimate Std. Error t value Pr(>|t|)
`(Intercept)_2008.5`                 -5.516115   0.903736  -6.104 2.13e-08 ***
overhang_ipi1_c5_2008.5               0.098701   0.030054   3.284 0.001424 **
insee_bc_c5_m3_2008.5                 0.053113   0.008527   6.229 1.21e-08 ***
`diff(insee_tppre_c5_m3, 1)_2008.5`   0.030069   0.012007   2.504 0.013942 *
`diff(bdf_tuc_c5_m2, 1)_2008.5`       0.286032   0.108827   2.628 0.009977 **
```

code (2)

```
`(Intercept)_2019.75`                  -5.569186   1.259533  -4.422 2.56e-05 ***
overhang_ipi1_c5_2019.75                0.443899   0.063963   6.940 4.44e-10 ***
insee_bc_c5_m3_2019.75                  0.054734   0.012796   4.278 4.43e-05 ***
`diff(insee_tppre_c5_m3, 1)_2019.75`    0.061845   0.016102   3.841 0.000219 ***
`diff(bdf_tuc_c5_m2, 1)_2019.75`        0.296779   0.080191   3.701 0.000357 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6178 on 97 degrees of freedom
Multiple R-squared:  0.8049,    Adjusted R-squared:  0.7848
F-statistic: 40.02 on 10 and 97 DF,  p-value: < 2.2e-16
```

To only split the second variable:

```
pwr_mod2 <- piece_reg(model_c5, break_dates = 2008.5, fixed_var = -2)
summary(pwr_mod2)
```

code (3)

```
Time series regression with "ts" data:
Start = 1993(2), End = 2019(4)

Call:
dynlm::dynlm(formula = as.formula(formula), data = data2)

Residuals:
     Min       1Q   Median       3Q      Max
-1.57740 -0.40673 -0.05138  0.44438  1.42772

Coefficients:
                              Estimate Std. Error t value Pr(>|t|)
`(Intercept)`                -5.261235   0.685772  -7.672 1.09e-11 ***
insee_bc_c5_m3                0.051493   0.006845   7.522 2.28e-11 ***
`diff(insee_tppre_c5_m3, 1)`  0.041475   0.009493   4.369 3.03e-05 ***
`diff(bdf_tuc_c5_m2, 1)`      0.324442   0.060278   5.382 4.79e-07 ***
overhang_ipi1_c5_2008.5       0.081865   0.019316   4.238 4.99e-05 ***
overhang_ipi1_c5_2019.75      0.458413   0.061602   7.441 3.38e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

R code (4)

```
Residual standard error: 0.6154 on 101 degrees of freedom
Multiple R-squared:  0.7984,    Adjusted R-squared:  0.7865
F-statistic: 66.68 on 6 and 101 DF,  p-value: < 2.2e-16
```

Local regressions: R `tvReg`

Assumption $\beta_t = \beta(z_t)$ with default $z_t = t/T$ and $\beta()$ locally constant (Nadaraya-Watson) or locally linear.

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$$\beta(z_t) = \underset{\theta_0}{argmin} \sum_{j=1}^{T} \left(y_j - x_j\theta_0\right)^2 K_b(z_j - z_t)$$

With $K_b(x) = \frac{1}{b}K(x/b)$ a kernel function to weight the observations.

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Remark:

- Bandwidth b fixed or estimated.
- If $b \geq 1$ all data used for each estimate.
- If $b \to 20$ the weight associated with each obs almost identical for all data $\simeq$ linear regression.

Pros:

- Simple model

Cons:

- All coefficients vary
- Problem of choosing b: by cross-validation (between 0 and 20) but not very discriminating.
- Strong real-time revisions possible (in estimates of b and due to the use of asymmetric kernel)

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- Simple model

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- All coefficients vary
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- Strong real-time revisions possible (in estimates of b and due to the use of asymmetric kernel)

Note:

- Possibility of combining previous models by estimating a local regression on cut data
- By performing two regressions, we can fix the coefficients of certain variables

code (1)

```
lr_mod <- tvReg::tvLM(model_c5)
```

```
Calculating regression bandwidth... bw =  0.4203537
```

```
summary(lr_mod)
```

```
Call:
tvReg::tvLM(formula = model_c5)

Class:  tvlm

Summary of time-varying estimated coefficients:
================================================
        (Intercept) overhang_ipi1_c5 insee_bc_c5_m3 diff(insee_tppre_c5_m3, 1)
Min.         -5.953          0.06942        0.03446                  -0.007961
1st Qu.      -5.702          0.11492        0.03766                   0.032127
Median       -4.724          0.21878        0.04651                   0.037311
Mean         -4.790          0.22592        0.04577                   0.038769
3rd Qu.      -4.044          0.33430        0.05459                   0.051159
Max.         -3.817          0.38812        0.05791                   0.058446
```

code (2)

```
       diff(bdf_tuc_c5_m2, 1)
Min.                   0.2195
1st Qu.                0.2549
Median                 0.3190
Mean                   0.3388
3rd Qu.                0.4300
Max.                   0.4800

Bandwidth:  0.4204
Pseudo R-squared:  0.7908
```

State-space models

State-space modeling = general methodology for dealing with a wide range of time-series problems

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Hypothesis: problem determined by a series of *unobserved* vectors $\alpha_1, \ldots, \alpha_n$ associated with observations $y_1, \ldots, y_n$, the relationship between α_t and y_t being specified by the state-space model.

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Several forms of model are possible, the simplest being linear Gaussian models. Simplified version:

$$\begin{cases} y_t = X_t\alpha_t + \varepsilon_t, & \varepsilon_t \sim \mathcal{N}(0, \sigma^2) \\ \alpha_{t+1} = \alpha_t + \eta_t, & \eta_t \sim \mathcal{N}(0, \sigma^2 Q) \end{cases}, \text{ with } \eta_t \text{ and } \varepsilon_t \text{ independent}$$

with y_t of dimension $p \times 1$ vector of observations, and α_t of dimension $m \times 1$ vector of states (*state vector*).

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with y_t of dimension $p \times 1$ vector of observations, and α_t of dimension $m \times 1$ vector of states (*state vector*).

σ^2 a factor simplifying the estimates (*Concentration of loglikelihood*).

Back to linear regression

Linear regression:

$$\begin{cases} y_t = X_t\alpha + \varepsilon_t, & \varepsilon_t \sim \mathcal{N}(0, \sigma^2) \\ \alpha_{t+1} = \alpha_t = \dots = \alpha_0 = \alpha \end{cases}$$

Kalman filter estimation

Two classic operations: *filtering* and *smoothing*

- Smoothing: estimates the coefficient at each date using all available information. Close to the estimates in-sample forecasts.

$$\hat{\alpha}_t = E[\alpha_t | y_0, \ldots, y_n]$$

Ex: linear regression: $\hat{\alpha}_t = \hat{\alpha}$

Kalman filter estimation

Two classic operations: *filtering* and *smoothing*

- Smoothing: estimates the coefficient at each date using all available information. Close to the estimates in-sample forecasts.

$$\hat{\alpha}_t = E[\alpha_t | y_0, \dots, y_n]$$

Ex: linear regression: $\hat{\alpha}_t = \hat{\alpha}$

- Filtering: estimates the next coefficient (in $t+1$) with the information known in t. Close to real-time (out-of-sample) forecasts.

$$a_{t+1} = E[\alpha_{t+1} | y_0, \dots, y_t]$$

Ex: linear regression: $a_{2010T2} = \hat{\alpha}$ estimated using data up to 2010T1

Implementation

Usually the implementation can be difficult and variance has to be fixed...

Can be implemented easily with `rjd3sts`

`tvCoef::ssm_lm()` uses `rjd3sts::reg()` and `rjd3sts::locallevel()`.

code (1)

```
ssm_mod <- ssm_lm(
    model_c5, fixed_var_variables = FALSE, fixed_var_intercept = FALSE,
    var_intercept = 0.01, var_variables = 0.01)
summary(ssm_mod)
```

```
Summary of time-varying estimated coefficients (smoothing):
        (Intercept) overhang_ipi1_c5 insee_bc_c5_m3 diff(insee_tppre_c5_m3, 1)
Min.         -5.002           0.1299        0.04326                   0.002605
1st Qu.      -4.912           0.2108        0.04326                   0.026746
Median       -4.769           0.2741        0.04326                   0.029662
Mean         -4.703           0.2695        0.04326                   0.031070
3rd Qu.      -4.436           0.3423        0.04326                   0.037051
Max.         -4.344           0.3707        0.04326                   0.065948
        diff(bdf_tuc_c5_m2, 1)      noise
Min.                    0.2460 -1.292e+00
1st Qu.                 0.2711 -3.415e-01
Median                  0.2946 -9.216e-03
Mean                    0.2957 -7.919e-17
3rd Qu.                 0.3078  3.612e-01
Max.                    0.3794  1.234e+00
```

code (2)

To fix all the variables except one:

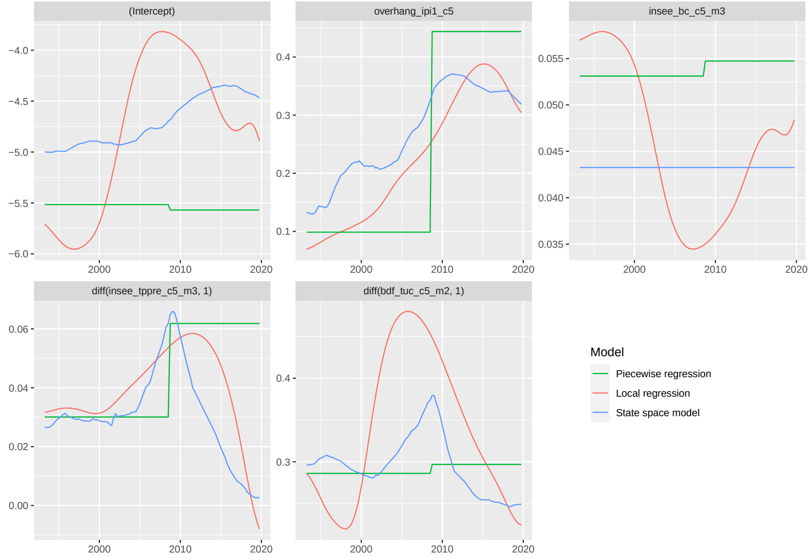
```
ssm_mod2 <- ssm_lm(
    model_c5,
    fixed_var_variables = c(FALSE, rep(TRUE, 5)),
    var_variables = c(0.01, rep(0, 5))
)
summary(ssm_mod2)
```

```
Summary of time-varying estimated coefficients (smoothing):
        (Intercept) overhang_ipi1_c5 insee_bc_c5_m3 diff(insee_tppre_c5_m3, 1)
Min.          -4.58          0.06429          0.044                    0.04181
1st Qu.       -4.58          0.11283          0.044                    0.04181
Median        -4.58          0.19523          0.044                    0.04181
Mean          -4.58          0.22462          0.044                    0.04181
3rd Qu.       -4.58          0.34704          0.044                    0.04181
Max.          -4.58          0.37637          0.044                    0.04181
        diff(bdf_tuc_c5_m2, 1)      noise
Min.                     0.369 -1.385e+00
1st Qu.                  0.369 -4.042e-01
Median                   0.369  2.758e-02
Mean                     0.369 -5.895e-16
```

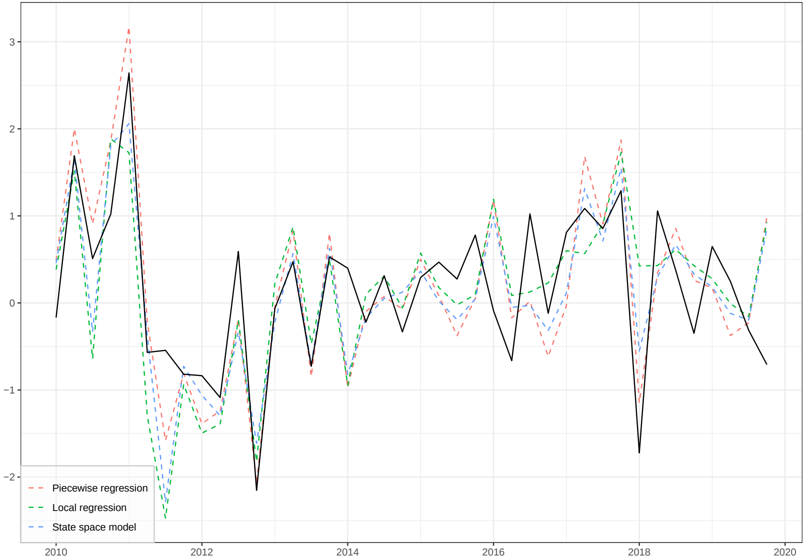
R code (3)

```
3rd Qu.                         0.369   3.523e-01
Max.                            0.369   1.423e+00
```

Results (1)


(Intercept)
overhang_ipi1_c5
insee_bc_c5_m3
diff(insee_tppre_c5_m3, 1)
diff(bdf_tuc_c5_m2, 1)
−4.0
−4.5
−5.0
−5.5
−6.0
0.4
0.3
0.2
0.1
0.055
0.050
0.045
0.040
0.035
0.06
0.04
0.02
0.00
2000
2010
2020
Model
Piecewise regression
Local regression
State space model

Results (2)


3
2
1
0
−1
−2
2010
2012
2014
2016
2018
2020
Piecewise regression
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Conclusion

- Many models can be estimated around linear regressions: the framework remains simple, but the modeling is more complex. ➔ modeling choices must be made

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- Many models can be estimated around linear regressions: the framework remains simple, but the modeling is more complex. ➔ modeling choices must be made
- Can improve the performance of "classical" models, they do not replace them.
  (Study of ~ 30 forecasts models: in-sample and out-of-sample errors always reduced with state space models)

Conclusion

- Many models can be estimated around linear regressions: the framework remains simple, but the modeling is more complex. ➔ modeling choices must be made
- Can improve the performance of "classical" models, they do not replace them.
  (Study of $\sim$ 30 forecasts models: in-sample and out-of-sample errors always reduced with state space models)
- Models sometimes complex to implement (especially state-space) ➔ `tvCoef` can help (InseeFrLab/tvCoef)

See workshop for complete example: https://aqlt.github.io/AteliertvCoef/

Thanks for you attention

TODO for `tvCoef`: be able to handle AR-X models.

https://github.com/InseeFrLab/tvCoef