

Structural Breaks and Broken Trends

(Stock, Handbook of Econometrics)

Breaks in coefficients in time series regression

• TEST FOR A SINGLE BREAK DATE

$$Y_t = \beta_t' X_t + \varepsilon_t$$

- ε_t is a m.d.s w.r.t $\mathcal{F}_{t-1}(\varepsilon_{t-1}, X_{t-1}, \varepsilon_{t-2}, X_{t-2}, \dots)$

- X_t are constant and/or $I(0)$
 $k \times 1$

$$\text{with } E X_t X_t' = \Sigma_x$$

- For convenience $E(\varepsilon_t^2 | \varepsilon_{t-1}, X_{t-1}, \varepsilon_{t-2}, X_{t-2}, \dots) = \underline{\sigma^2}$

- $T^{-1} \sum_{s=1}^{[Td]} X_s X_s' \xrightarrow{P} \Delta \Sigma_x$
 uniformly in Δ for $\Delta \in [0, 1]$

Note that X_{t-1} can include lagged dependent variables as long as they are $I(0)$ under H_0

$$H_0: \beta_t = \beta \quad \forall t$$

$$[H_a: \beta_t = \beta \quad t \leq r \text{ and } \beta_t = \beta + \gamma \quad t > r]$$

* The break date is "r"

* $\gamma \neq 0$

When the potential break date is known, a natural test for a change in β is the Chow (1960) test

$$F_T\left(\frac{r}{T}\right) = \frac{SSR_{1,T} - (SSR_{1,r} + SSR_{r+1,T})}{(SSR_{1,r} + SSR_{r+1,T}) / (T - 2k)}$$

For fixed $\left(\frac{r}{T}\right)$, $F_T\left(\frac{r}{T}\right)$ has an asymptotic χ^2_k

What if $\frac{r}{T}$ is unknown?

* Estimate the break and plug it in $F_T\left(\frac{\hat{r}}{T}\right)$

The distribution of $F_T(\cdot)$ under the null is not the same as if the break were chosen without regard to the data.

* Quandt (1960, JASA) proposed to estimate Γ_B and $\lambda_B = \frac{\Gamma_B}{T}$ by finding the value λ_B which maximizes the Chow or Wald statistic

$$\hat{\lambda}_B = \underset{\lambda_B = \lambda_{\min}, \dots, \lambda_{\max}}{\operatorname{argmax}} F(\lambda_B)_{\gamma=0}$$

i.e., sequentially calculate $F_{\gamma=0}(\lambda_B)$

$$\text{for } \lambda_B = \frac{k+1}{T}, \frac{k+2}{T}, \dots, \frac{T-1}{T}$$

(all possible break dates)

The value λ_B which produces the largest $F_{\gamma=0}(\cdot)$ statistic is denoted by

$$\hat{\lambda}_B$$

Remark:

$$\begin{array}{ccc} \hat{\lambda}_B & \xrightarrow{P} & \lambda_B \\ \text{but } \uparrow & & \\ \hat{\Gamma}_B & \xrightarrow{P} & \Gamma_B \end{array}$$

And what about the test?

$$\underset{\text{Quandt}}{QLR} = \max_{\Gamma = \Gamma_0, \dots, \Gamma_T} F_T\left(\frac{\Gamma}{T}\right)$$

(i) QLR $\xrightarrow{d} \chi^2_{(1)}$

(ii) We use the max to solve the problem of unidentification of γ under H_0

(iii) We use the max because the intuition suggests that this statistic will have power against a change in β even though the break is unknown.

Think on $F_{\gamma=0}(\lambda_B)$ as a function of

$\lambda_B \in [0, 1]$. This is similar to the unit root partial sum process

$X_T(r) = T^{-1} \sum_{t=1}^{[Tr]} \varepsilon_t$

with r a function of $r \in [0, 1]$

Then to find the A-D of QLR we can use the FCLT and CMP.

Let $\tilde{F}_T(r/T) = SSR_{1,T} - (SSR_{1,r} + SSR_{r+1,T})$

and use $y_t = \beta_t' X_t + \varepsilon_t$ to write

$$\begin{aligned}\tilde{F}_T\left(\frac{r}{T}\right) &= -\left(\sum_{t=2}^T X_{t-1} \varepsilon_t\right)' \left(\sum_{t=2}^T X_{t-1} X_{t-1}'\right)^{-1} \left(\sum_{t=2}^T X_{t-1} \varepsilon_t\right) \\ &\quad + \left(\sum_{t=2}^r X_{t-1} \varepsilon_t\right)' \left(\sum_{t=2}^r X_{t-1} X_{t-1}'\right)^{-1} \left(\sum_{t=2}^r X_{t-1} \varepsilon_t\right) \\ &\quad + \left(\sum_{t=r+1}^T X_{t-1} \varepsilon_t\right)' \left(\sum_{t=r+1}^T X_{t-1} X_{t-1}'\right)^{-1} \left(\sum_{t=r+1}^T X_{t-1} \varepsilon_t\right)\end{aligned}$$

$$= -Y_T(1)' V_T(1)^{-1} Y_T(1)$$

$$+ Y_T\left(\frac{r}{T}\right)' V_T\left(\frac{r}{T}\right)^{-1} Y_T\left(\frac{r}{T}\right)$$

$$+ \left[Y_T(1) - Y_T\left(\frac{r}{T}\right)\right]' \left[V_T(1) - V_T\left(\frac{r}{T}\right)\right]^{-1} \left[Y_T(1) - Y_T\left(\frac{r}{T}\right)\right]$$

Where $Y_T(\lambda) = T^{-\frac{1}{2}} \sum_{t=2}^{[T\lambda]} X_{t-1} \varepsilon_t$

$$V_T(\lambda) = T^{-1} \sum_{t=2}^{[T\lambda]} X_{t-1} X_{t-1}'$$

Because ε_t is a m.d.s then X_{t-1}, ε_t is a m.d.s too. Assume additionally

- X_{t-1} has sufficiently limited dependence

- X_{t-1}, ε_t enough moments

Then we can apply a FCLT for m.d.s

$$V_T(\cdot) \Rightarrow \sigma_\varepsilon \sum_x^{\frac{1}{2}} W_k(\cdot)$$

where

$W_k(d) = k$ -dimensional std BMobn

$$= \begin{pmatrix} W_1(\lambda) \\ W_2(\lambda) \\ \vdots \\ W_k(\lambda) \end{pmatrix} \Rightarrow \begin{matrix} \text{independent} \\ \text{univariate} \\ \text{standard} \\ \text{BMobns} \end{matrix}$$

$$V_T(d) \xrightarrow{P} d \Sigma_x \text{ uniformly in } d$$

Then

$$\tilde{F}_T(\cdot) \Rightarrow \sigma_\varepsilon^2 F^*(\cdot)$$

where

$$\begin{aligned} F^*(\lambda) &= -W_k(1)' W_k(1) + \underbrace{W_k(\lambda)' W_k(\lambda)}_{\lambda} \\ &\quad + \underbrace{[W_k(1) - W_k(\lambda)]' [W_k(1) - W_k(\lambda)]}_{1-\lambda} \\ &= \frac{B_k^\lambda(\lambda)' B_k^\lambda(\lambda)}{\lambda(1-\lambda)} \end{aligned}$$

with $B_k^\lambda(\lambda) = W_k(\lambda) - \lambda W_k(1)$

a k -dimensional Brownian Bridge

Because $\tilde{F}_T \Rightarrow \sigma_\varepsilon^2 F^*$ and $SSR_{1,T}/(T-k) \xrightarrow{P} \sigma_\varepsilon^2$
 under the null,

$$\frac{(SSR_{1,r} + SSR_{r+1,T})}{T-2k} \xrightarrow{P} \sigma_\varepsilon^2$$

 uniformly in r .

Thus

$$F_T \Rightarrow F^*$$

From the CMP

$$QLR \Rightarrow \sup_{\lambda \in [\lambda_0, \lambda_1]} \left\{ \frac{B_k^M(\lambda)' B_k^M(\lambda)}{\lambda(1-\lambda)} \right\}$$

Note that for a fixed $\bar{\lambda}$, $F^*(\bar{\lambda}) \Rightarrow \chi^2$

<u><u>k=1</u></u>	QLR _{5%}	8.85
	$\chi^2_{5\%, 1}$	3.84

k=10	QLR _{5%}	27.03
	$\chi^2_{5\%, 10}$	18.3

The A.D.s obtained so far have to be modified if

(*) ε_t is serially correlated

(**) X_t contains $I(1)$ or trended regressors

Trended regressors

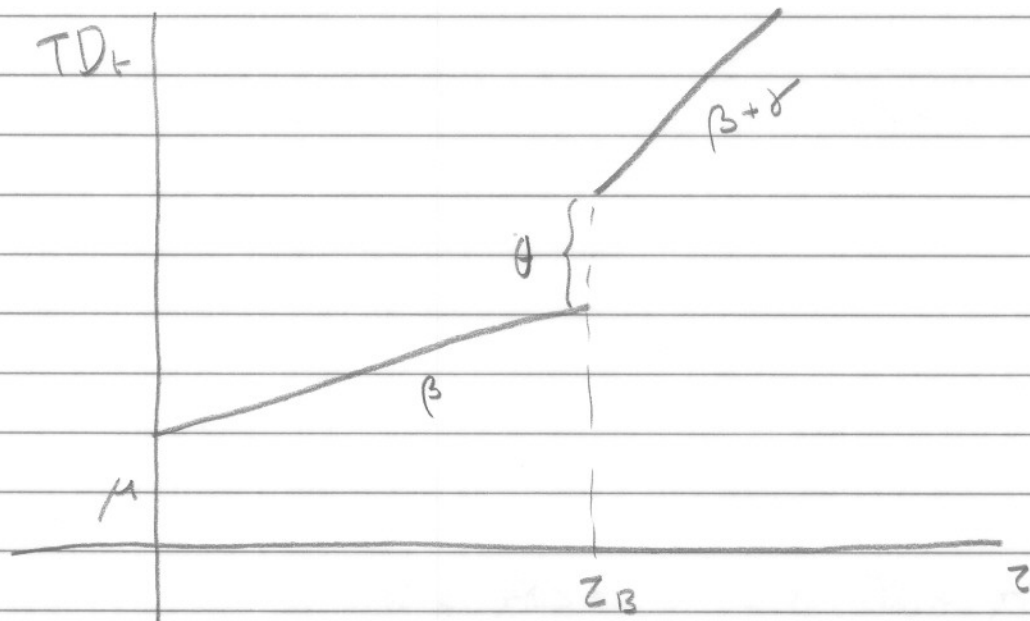
$$Y_t = \mu + \theta DU(\tau_B)_t + \beta t + \gamma DT(\tau_B)_t + \sum_{j=1}^p c_j Y_{t-j} + \varepsilon_t \quad \varepsilon_t \sim WN(0, \sigma^2)$$

where

$$DU(\tau_B)_t = \begin{cases} 1 & t > \tau_B \\ 0 & \text{otherwise} \end{cases}$$

$$DT(\tau_B)_t = \begin{cases} t - \tau_B & \text{if } t > \tau_B \\ 0 & \text{otherwise} \end{cases}$$

$$TD_t = \mu + \theta DU(z_B)_t + \beta t + \gamma DT(z_B)_t$$



There are two possibilities for the no-structural change models

$$(1) H_0^1: \theta = 0, \gamma = 0 \text{ and } Y_t \sim I(0)$$

$$(2) H_0^2: \theta = 0, \gamma = 0 \text{ and } Y_t \sim I(1)$$

In each case we compute

$$QLR = \max_{\lambda_B \in [\lambda_{\min}, \lambda_{\max}]} F(\lambda_B) \quad \theta = \gamma = 0$$

Vogelang (1997) shows that the AD of QLR is different in cases (1) and (2).

Trend Breaks and tests for autoregressive unit roots

Shift in mean $d_t = \beta_0 + \beta_1 I(t > r)$

Shift in trend $d_t = \beta_0 + \beta_1 t + \beta_2 (t-r) I(t > r)$

Now we can run the DF test with these broken trends in the regression:

$$\Delta y_t = d_t + \alpha y_{t-1} + \varepsilon_t$$

* Test for $\alpha = 0$ vs $\alpha < 0$
assuming we know the break date

* We can test for $\alpha = 0$ vs $\alpha < 0$
with the break date unknown

$$t_{DF}^{\min} = \min_{\delta \in [\delta_0, \delta_T]} \hat{t}^d(\delta)$$

where

$$\hat{t}^d(\delta) = \frac{T^{-1} \sum_{t=2}^T \Delta y_t^d(\delta) y_{t-1}^d(\delta)}{\left\{ (\hat{\sigma}^d)^2(\delta) T^{-2} \sum_{t=2}^T (y_{t-1}^d(\delta))^2 \right\}^{\frac{1}{2}}}$$