

Week 9 : Regression in Time Series

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9.1

Regressing Stationary TS

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9.1.1 OLS and GLS

From week 2 p.28,

OLS

- From model

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

- Minimizes sum of squares, $(\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})'(\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})$,
-

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}.$$

GLS

- Minimizes weighted sum of squares,

$$(\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})'\boldsymbol{\Gamma}_n^{-1}(\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})$$

•

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}'\boldsymbol{\Gamma}_n^{-1}\mathbf{X})^{-1}\mathbf{X}'\boldsymbol{\Gamma}_n^{-1}\mathbf{Y}.$$

If \mathbf{X} is non-random, we have $E(\hat{\boldsymbol{\beta}}) = \boldsymbol{\beta}$ and

$$V(\hat{\boldsymbol{\beta}}) = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\boldsymbol{\Sigma}\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}.$$

For OLS, $\boldsymbol{\Sigma} = \sigma^2\mathbf{I}$, and

$$V(\hat{\boldsymbol{\beta}}) = \sigma^2(\mathbf{X}'\mathbf{X})^{-1}.$$

For GLS, $\boldsymbol{\Sigma} = \boldsymbol{\Gamma}_n$, and

$$V(\hat{\boldsymbol{\beta}}) = (\mathbf{X}'\boldsymbol{\Gamma}_n^{-1}\mathbf{X})^{-1}.$$

It can be shown that GLS estimator is the best linear unbiased estimator of $\boldsymbol{\beta}$. Therefore, GLS is better than OLS, but we need $\boldsymbol{\Gamma}_n$.

Iterative Regression Scheme

1. Compute OLS. Get residuals.
2. Fit ARMA model to the residuals by Gaussian Maximum Likelihood.
3. Using the fitted model, calculate $\mathbf{\Gamma}_n$. Go back to the original series, compute GLS.
4. Repeat from 2).

9.1.2 Regressing TS to TS

Sometimes, you want to model your TS linearly dependent on other time series.

- Sales depends on Global Economy
- Utility Demand depends on Temperature
- Level of toxin depends on local industry production

In that case, your Model is that the time series of interest X_t , has linear relationship with your independent series B_t , plus stationary noise. In the vector notation,

$$\begin{aligned} X_t &= \boldsymbol{\beta} \mathbf{B}_t + Y_t \\ Y_t &\sim ARMA \end{aligned}$$

where x_t contains the "explanatory" TS.

In scalar notation,

$$X_t = a + bB_t + Y_t \quad Y_t \sim ARMA$$

where x_t contains the "explanatory" TS.

Example

See TS-09_R.txt

9.1.3 ARMAX model

ARMAX(2,1) is the model

$$Y_t = \beta \mathbf{x}_t + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + e_t + \theta_1 e_{t-1}$$

Don't confuse this with additive model

$$K_t = \beta \mathbf{x}_t + Y_t$$

$$Y_t \sim ARMA(2,1)$$

If we write ARMAX using backwards operator,

$$Y_t = \beta \mathbf{x}_t + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + e_t + \theta_1 e_{t-1}$$

$$\Phi(B)Y_t = \beta \mathbf{x}_t + \Theta(B)e_t$$

$$Y_t = \frac{\beta \mathbf{x}_t}{\Phi(B)} + \frac{\Theta(B)}{\Phi(B)} e_t$$

which is very hard to interpret.

Currently, there is no package that directly deal with ARMAX model.

9.2

Cointegration

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9.2.1 Cointegration and Spurious correlation

Notation:

$X_t \sim I(1) \quad := \quad X_t \text{ is integrated series of order 1}$

$= \quad \nabla X_t \text{ is stationary}$

e.g. If X_t is ARIMA(2,1,2), then $X_t \sim I(1)$.

Cointegrated Relationship

Two $I(1)$ series have linear relationship?

$$W_t \sim I(1)$$

$$U_t = a + bW_t + Y_t$$

where Y_t is a stationary series.

Cointegration

Many Economic Theory implies cointegrated relationship

- Money Demand Model
- Permanent Income Model
- Unbiased Forward Rates Hypothesis
- Fisher Equation

What to do?

$$W_t \sim I(1)$$

$$U_t = a + bW_t + Y_t$$

Just regress W_t on U_t . It should give you \hat{a} and \hat{b} .

Spurious correlation

Now imagine two $I(1)$ series

$$W_t = W_{t-1} + e_t \quad e_t \sim WN(0, 1)$$

$$U_t = U_{t-1} + v_t \quad v_t \sim WN(0, 1)$$

These two RW have nothing to do with each other. So if you model relationship between these two as

$$U_t = a + bW_{t-1} + Y_t,$$

you should not find \hat{a} and \hat{b} significant, at least most of times, because in true relationship, $a = 0$ and $b = 0$.

However, if we regress W_t on U_t , we get what's called spurious correlation.

Example

See TS-09_R.txt