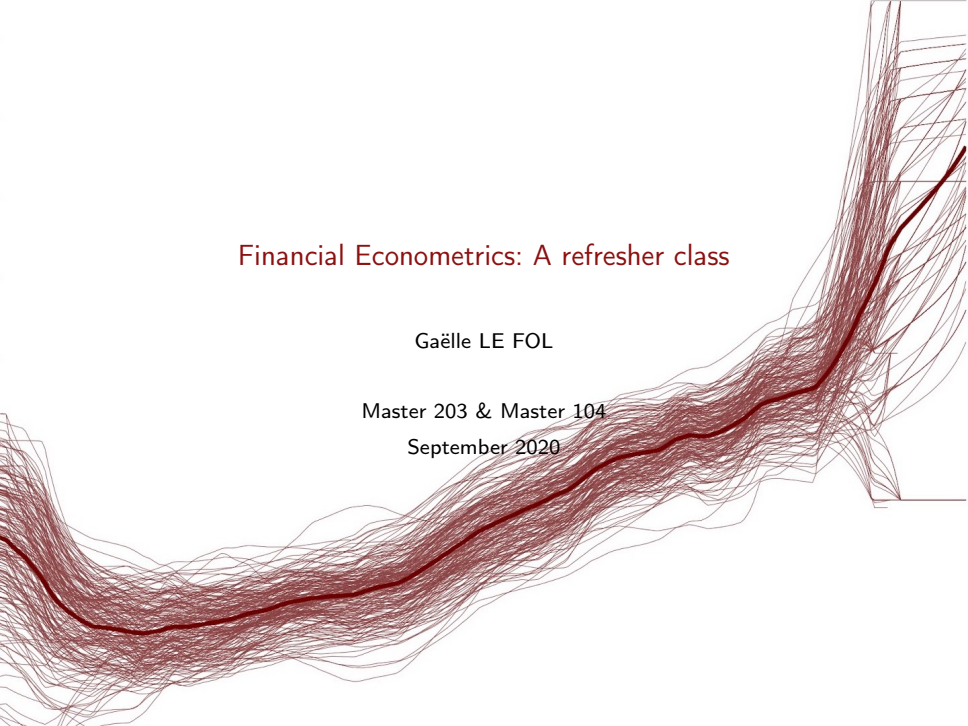


Financial Econometrics: A refresher class

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Introduction

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- Basics in statistics and mathematics

- The data

- Limits, critics & model construction

The classical linear regression model

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- Assumptions

- Properties of the OLS estimator

- Precision and standard errors

- Goodness of fit

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- Distribution of the estimated parameters

- Significativity test

- Confidence interval approach

- The level of significance : choosing α

- The exact level of significance : the p-value

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- Matrix form of the model

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- Estimation of the variance of the errors I

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- Distribution of the estimated parameters

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- Testing simultaneously the estimated parameters

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- Constructing factors and excess returns

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Other assumptions violation and diagnostic tests

- Stochastic regressors and exogeneity

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Appendix & References

- Suppose that the errors are distributed as a normal $\varepsilon \sim N(0, \sigma_\varepsilon^2 \mathbf{I})$ and following equation (42) :

$$\hat{\beta} = \beta + (X'X)^{-1}X'\varepsilon,$$

$\hat{\beta}$ is linear in ε and is normally distributed as a normal $\hat{\beta} \sim N(\beta, \Omega_{\hat{\beta}})$, where $\Omega_{\hat{\beta}} = \sigma_\varepsilon^2 (X'X)^{-1}$ (see equation 45).

- For any $\hat{\beta}_i$ associated to i^{st} explanatory variable x_{it} , we have :

$$\hat{\beta}_i \sim N(\beta_i, \sigma_\varepsilon^2 a_{i+1, i+1}),$$

where $a_{i+1, i+1}$ is the $(i+1)^{st}$ diagonal element of $(X'X)^{-1}$. We have :

$$\frac{\hat{\beta}_i - \beta_i}{\sigma_\varepsilon \sqrt{a_{i+1, i+1}}} \sim N(0, 1).$$

From equation (46), we know :

$$\hat{\sigma}_\varepsilon^2 = \frac{e'e}{T-k-1}.$$

Recall that if $w \sim N(0, \sigma_w^2 \mathbf{I})$ then $\frac{w'w}{\sigma_w^2}$ is distributed as a χ^2 and

$$\begin{aligned}\frac{e'e}{\sigma_\varepsilon^2} &\sim \chi_{T-k-1}^2 \\ \frac{(T-k-1)\hat{\sigma}_\varepsilon^2}{\sigma_\varepsilon^2} &\sim \chi_{T-k-1}^2\end{aligned}$$

Recall that for any $z \sim N(0, 1)$ and $\nu \sim \chi_r^2$, $\frac{z\sqrt{r}}{\sqrt{\nu}} \sim t(r)$. We then have :

$$\frac{\frac{\hat{\beta}_i - \beta_i}{\sigma_\varepsilon \sqrt{a_{i+1, i+1}}} \sqrt{T-k-1}}{\sqrt{\frac{(T-k-1)\hat{\sigma}_\varepsilon^2}{\sigma_\varepsilon^2}}}$$

Finally, we have :

$$\frac{\hat{\beta}_i - \beta_i}{\hat{\sigma}_\varepsilon \sqrt{a_{i+1, i+1}}} \sim t(T-k-1) \quad (47)$$

- Testing the null hypothesis that β_i equals the particular value of β^* :

$$\begin{cases} H_0 : \beta_i = \beta^* \\ H_a : \beta_i \neq \beta^* \end{cases}$$

Under H_0 ,

$$\frac{\hat{\beta}_i - \beta^*}{\hat{\sigma}_\varepsilon \sqrt{a_{i+1,i+1}}} \sim t(T - k - 1)$$

and the decision rule gives :

- ▶ If $\left| \frac{\hat{\beta}_i - \beta^*}{\hat{\sigma}_\varepsilon \sqrt{a_{i+1,i+1}}} \right| \leq t_{p/2}$ we do not reject H_0 that $\beta_i = \beta^*$ at a $100\alpha\%$ significance level.
- ▶ If $\left| \frac{\hat{\beta}_i - \beta^*}{\hat{\sigma}_\varepsilon \sqrt{a_{i+1,i+1}}} \right| > t_{p/2}$ we reject H_0 and $\beta_i \neq \beta^*$ at a $100\alpha\%$ significance level.

The most common test is the significance of the parameters :

- Testing the null hypothesis that $\beta_i = 0$:

Under H_0 ,

$$\begin{cases} H_0 : \beta_i = 0 \\ H_a : \beta_i \neq 0 \end{cases}$$

$$t_{\hat{\beta}_i} = \frac{\hat{\beta}_i}{\hat{\sigma}_{\hat{\beta}_i}} \sim t(T - k - 1) \text{ where } \hat{\sigma}_{\hat{\beta}_i} = \hat{\sigma}_\varepsilon \sqrt{a_{i+1,i+1}}$$

- ▶ If $\left| \frac{\hat{\beta}_i}{\hat{\sigma}_{\hat{\beta}_i}} \right| \leq t_{p/2}$ we do not reject H_0 that $\beta_i = 0$ at a $100\alpha\%$ significance level \iff the variable X_{it} is not significant and does not influence Y_t .
- ▶ If $\left| \frac{\hat{\beta}_i}{\hat{\sigma}_{\hat{\beta}_i}} \right| > t_{p/2}$ we reject H_0 and $\beta_i \neq 0$ at a $100\alpha\%$ significance level \iff the variable X_{it} is significant and does influence Y_t .

- Testing the significance of an isolated parameter corresponds to a Student t-test.
- Testing the significance of several (all) the estimated parameters at the same time corresponds to a Fisher test. Suppose that the parameters are subject to r constraints :

$$R\beta = r,$$

where R is a $(q, k + 1)$ matrix and r a vector of size q . We suppose $q \leq k + 1$ and R to be full rank \iff the constraints are linearly independent.

- ▶ The case where $R = [0 \dots 0 1 0 \dots 0]$ and $r = 0$ corresponds to the previous Student-t test.
- ▶ The case where $R = [0 1 - 1 \dots 0]$ and $r = 0$ corresponds to the test where $\beta_1 = \beta_2$.

- The case where

$$R = \begin{pmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & 1 \end{pmatrix} \text{ and } r = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

corresponds to the test of global significance of the parameters or the model.

$$\begin{pmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & 1 \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

$$\iff \beta_1 = \beta_2 = \dots = \beta_k = 0.$$

Exercise 10 : Test examples

Considering the model

$$y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \dots + \beta_k x_{k,t} + \varepsilon_t, \quad t = 1, \dots, T.$$

give R and r in the following cases :

1. $H_0 : \beta_3 = 1 ; H_a : \beta_3 \neq 1.$
2. $H_0 : \beta_0 + \beta_1 = 1 ; H_a : \beta_0 + \beta_1 \neq 1.$
3. $H_0 : \beta_2 \times \beta_1 = 0 ; H_a : \beta_2 \times \beta_1 \neq 0.$

- Aiming at implementing the previous test, we need to consider two models :
 - ▶ The unconstrained model \mathcal{M}_{uc} corresponds to the regression of the dependent variable on the set of all explanatory variables without imposing any constraint on the parameters.
 - ▶ The constrained model \mathcal{M}_c corresponds to the regression of the dependent variable on a sub-set of explanatory variables that account for the linear constraints on the parameters. **Note that**, we may have to change variables in order to isolate the estimated parameters at the right side of the equal sign for example.
 - ▶ The constrained model \mathcal{M}_c is a special case of the unconstrained model \mathcal{M}_{uc} .
 - ▶ The constrained \mathcal{M}_c and unconstrained \mathcal{M}_{uc} models must be estimated to compute the statistic of the test F .

Testing simultaneously some estimated parameters IV

- The statistic of the test is :

$$F = \frac{(ESS_c - ESS_{uc})/q}{ESS_{uc}/(T - k - 1)} \sim F(q, T - k - 1) \quad (48)$$

- The Fisher test is testing that the relative gap between the two ESS is significant $H_0 : ESS_c - ESS_{uc} = 0$ and thus, that the constraint is statistically justified.

What is the alternative hypothesis of that test ?

- If $F \leq F(q, T - k - 1)$, we do not reject the null hypothesis H_0 . In the contrary case, we reject the null.
- The Student-t test of the significance of β_i can be seen as a Fisher test, where the constrained model reduces to the regression of the dependent variable on a set of explanatory variables including all the explanatory variables but X_{it} . In that case, the Student-t statistic, t -stat is such that $t^2(T - k - 1) = F(1, T - k - 1)$.
- The null hypothesis of the overall significance test of a multiple regression, is $H_0 : \beta_1 = \beta_2 = \dots = \beta_k = 0$.
- The unconstrained model is :

$$\mathcal{M}_{uc} : y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \dots + \beta_k x_{k,t} + u_t, \quad t = 1, \dots, T,$$

- The constrained model is $\mathcal{M}_c : y_t = \beta_0 + u_t$.

Testing simultaneously some estimated parameters V

- We have $\hat{y}_t = \hat{\beta}_0$, $\bar{\hat{y}} = \bar{y} = \hat{\beta}_0$ and $q = k$. Finally,

$$ESS_c = \sum_{t=1}^T (y_t - \hat{y}_t)^2 = \sum_{t=1}^T (y_t - \bar{y})^2 = TSS$$

- Replacing, ESS_c and ESS_{uc} in

$$F = \frac{(ESS_c - ESS_{uc})/q}{ESS_{uc}/(T - k - 1)} \sim F(q, T - k - 1), \quad (49)$$

we get,

$$\begin{aligned} F &= \frac{(TSS - ESS)/k}{ESS/(T - k - 1)} \\ &= \frac{RSS/k}{ESS/(T - k - 1)} \sim F(k, T - k - 1) \\ &= \frac{R^2/k}{(1 - R^2)/(T - k - 1)} \sim F(k, T - k - 1) \end{aligned}$$

where RSS is the regression sum of squares.

- The Student test of the significance of β_i can be interpreted as a Fisher test, where the constraint model resumes to regressing the dependant variable over the set of explanatory variables but x_{it} .

Exercise 11 : Constrained vs unconstrained model

Consider the model

$$y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \beta_3 x_{3,t} + u_t, \quad t = 1, \dots, T$$

Describe the method (set of regressions included) to test $\{\beta_1 = 1; \beta_3 = -1\}$.

- To perform multiple tests,
 - ▶ we estimate the two models \mathcal{M}_c and \mathcal{M}_{nc} and each time, we extract the *ESS*,
 - ▶ we compute the statistic of the test,
 - ▶ we compare it to a critical value of the corresponding distribution,
 - ▶ we reject H_0 whenever the statistic is greater than the critical value (tabulated value).
- Equivalently,
 - ▶ we can calculate the risk of rejecting the true hypothesis (type-I error),
 - ▶ compare it to a risk tolerance level we are willing to bear (α),
 - ▶ we reject H_0 if the p-value is lower than the risk we are willing to bear.

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- The classical APT model explains single stock excess returns by the variations of a market index excess return and other factors. Brooks tries to explain Microsoft monthly returns by unexpected changes of macroeconomics and financial variables.
- File called macro.xls : 325 monthly observations from March 1986 to April 2013. Variables are : Dates, Microsoft stock price, *S&P*500 index value, the consumer price index, an industrial production index, Treasury bill yields with maturities 3 months, 6months, 1 year, 3 years, 5 years and 10 years, a measure of money supply, a consumer credit series, an a credit spread series.

The APT-style model of Brooks II

- Load the file under gretl and construct the returns for the microsoft stock and the *S&P500* index.

```
genr rmsoft = log(Microsoft/Microsoft(-1))
```

- Assuming naive expectations, unexpected changes are obtained as the first difference in any variable of interest. Construct the interesting unexpected changes in the macro and financial variables.

```
genr dcredit = CONSUMER_CREDIT - CONSUMER_CREDIT(-1)
```

- Construct the slope of the yield curve of interest rate

```
genr term = USTBY10 - USTB3M
```

- Construct the risk free rate as the monthly 3 months treasury bill yields.

```
genr mustb3m = USTB3M/12
```

- Construct the excess returns for Microsoft and the *S&P500*.

```
genr ermsoft = rmsoft - mustb3m
```

- Run the appropriate regression.

```
Model APT <- ols ermsoft const ersandp dprod dcredit dinflation  
dmoney dsread dterm
```

- Interpret the output.

The APT-style model of Brooks III

Model APT : OLS, using observations 1986 :05–2007 :04 ($T = 252$)
Dependent variable : ermsoft

| | Coefficient | Std. Error | <i>t</i> -ratio | p-value |
|--------------------|---------------|--------------------|-----------------|---------|
| const | −0.587603 | 1.45790 | −0.4030 | 0.6873 |
| ersandp | 1.48943 | 0.203276 | 7.3271 | 0.0000 |
| dprod | 0.289322 | 0.500919 | 0.5776 | 0.5641 |
| dcredit | −5.58389e−005 | 0.000160491 | −0.3479 | 0.7282 |
| dinflation | 4.24781 | 2.97734 | 1.4267 | 0.1549 |
| dmoney | −1.16153 | 0.713974 | −1.6268 | 0.1051 |
| dspread | 12.1578 | 13.5510 | 0.8972 | 0.3705 |
| rterm | 6.06761 | 3.32136 | 1.8268 | 0.0689 |
| Mean dependent var | −0.420803 | S.D. dependent var | 15.41135 | |
| Sum squared resid | 47480.62 | S.E. of regression | 13.94965 | |
| R^2 | 0.203545 | Adjusted R^2 | 0.180696 | |
| $F(7, 244)$ | 8.908218 | P-value(F) | 9.08e−10 | |
| Log-likelihood | −1017.642 | Akaike criterion | 2051.284 | |
| Schwarz criterion | 2079.520 | Hannan–Quinn | 2062.646 | |
| $\hat{\rho}$ | −0.078198 | Durbin–Watson | 2.156221 | |