

15. Properties of Least Squares

Spring 2021

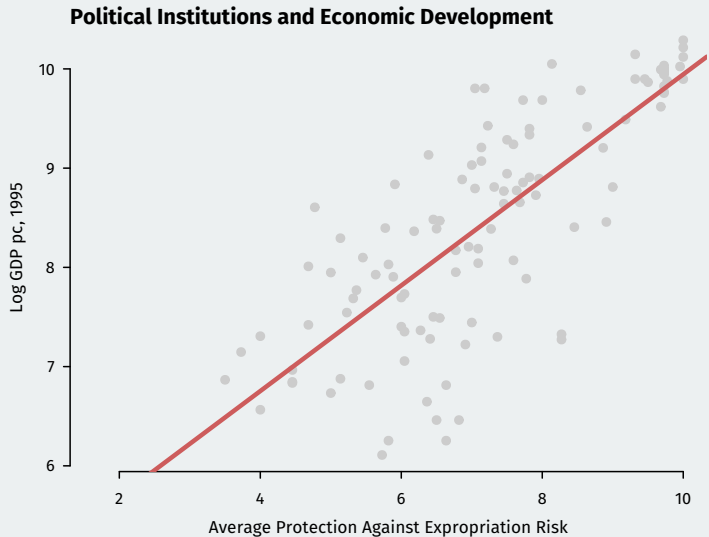
Matthew Blackwell

Gov 2002 (Harvard)

Where are we? Where are we going?

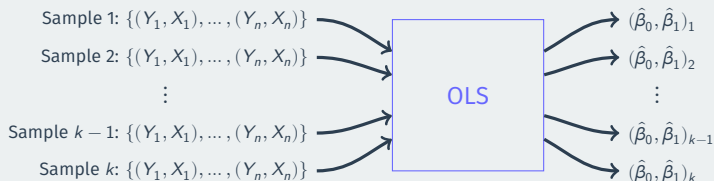
- Before: learned about CEFs and linear projections in the population.
- Last time: OLS estimator, its algebraic properties.
- Now: its statistical properties, both finite-sample and asymptotic.

Acemoglu, Johnson, and Robinson (2001)



Sampling distribution of the OLS estimator

- OLS is an estimator—we plug data into and we get out estimates.

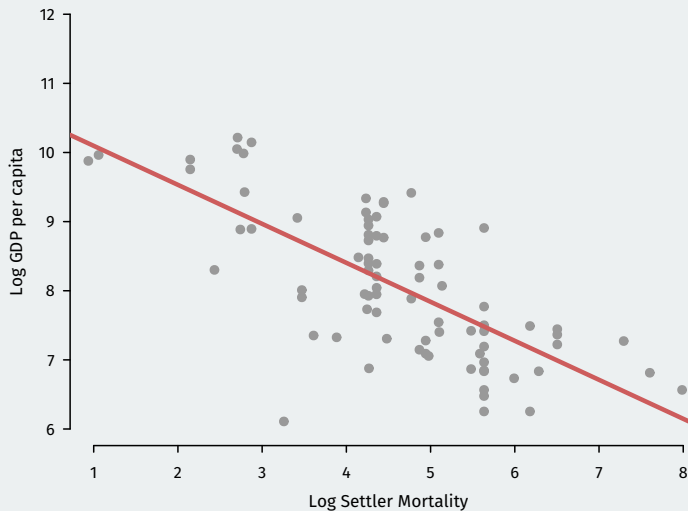


- Just like the sample mean or sample difference in means
- Has a sampling distribution, with a sampling variance/standard error.

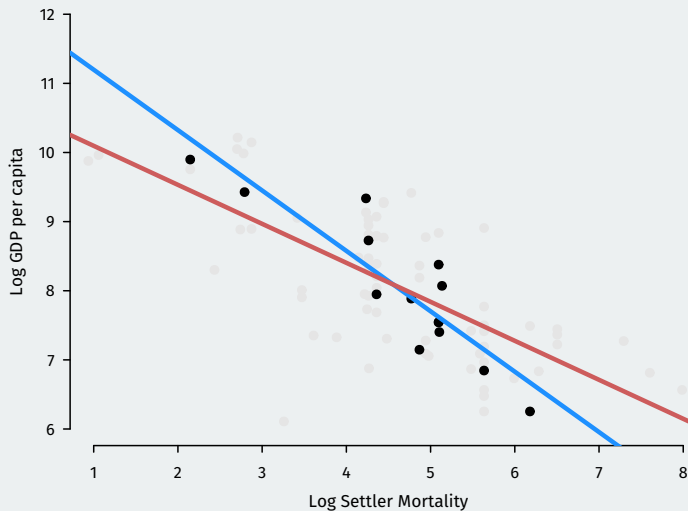
Simulation procedure

- Let's take a simulation approach to demonstrate:
 - Pretend that the AJR data represents the population of interest
 - See how the line varies from sample to sample
1. Draw a random sample of size $n = 30$ with replacement using `sample()`
 2. Use `lm()` to calculate the OLS estimates of the slope and intercept
 3. Plot the estimated regression line

Population Regression



Randomly sample from AJR



Big picture

- We want finite-sample guarantees about our estimates.
 - Unbiasedness, exact sampling distribution, etc.
- But finite-sample results come at a price in terms of assumptions.
 - Unbiasedness: CEF is linear.
 - Exact sampling distribution: normal errors.
- Asymptotic results hold under much weaker assumptions, but require more data.
 - OLS consistent for the linear projection even with nonlinear CEF.
 - Asymptotic normality for sampling distribution under mild assumptions.
- Focus on two models:
 - **Linear projection model** for asymptotic results.
 - **Linear regression/CEF model** for finite samples.

1/ Linear projection model and Large-sample Properties

Linear projection model

- We'll start at the most broad, fewest assumptions

Linear projection model

1. For the variables (Y, \mathbf{X}) , we assume the linear projection of Y on \mathbf{X} is defined as:

$$Y = \mathbf{X}'\boldsymbol{\beta} + e$$

$$\mathbb{E}[\mathbf{X}e] = 0.$$

2. The design matrix is invertible, so $\mathbb{E}[\mathbf{X}_i\mathbf{X}_i'] > 0$ (positive definite).

- Linear projection model holds under **very** mild assumptions.
 - Remember: not even assuming linear CEF!
 - Implies coefficients are $\boldsymbol{\beta} = (\mathbb{E}[\mathbf{X}\mathbf{X}'])^{-1}\mathbb{E}[\mathbf{X}Y]$
- What properties can we derive under such weak assumptions?

A very useful decomposition

$$\hat{\beta} = \left(\frac{1}{n} \sum_{i=1}^n \mathbf{x}_i \mathbf{x}_i' \right)^{-1} \left(\frac{1}{n} \sum_{i=1}^n \mathbf{x}_i Y_i \right) = \beta + \underbrace{\left(\frac{1}{n} \sum_{i=1}^n \mathbf{x}_i \mathbf{x}_i' \right)^{-1} \left(\frac{1}{n} \sum_{i=1}^n \mathbf{x}_i e_i \right)}_{\text{estimation error}}$$

- OLS estimates are the truth plus some estimation error.
- Most of what we derive about OLS comes from this view.
- Sample means in the estimation error follow the law of large numbers:

$$\frac{1}{n} \sum_{i=1}^n \mathbf{x}_i \mathbf{x}_i' \xrightarrow{p} \mathbb{E}[\mathbf{x}_i \mathbf{x}_i'] \equiv \mathbf{Q}_{\mathbf{xx}} \quad \frac{1}{n} \sum_{i=1}^n \mathbf{x}_i e_i \xrightarrow{p} \mathbb{E}[\mathbf{x}_i e_i] = \mathbf{0}$$

- $\mathbf{Q}_{\mathbf{xx}}$ is invertible by assumption, so by the continuous mapping theorem:

$$\left(\frac{1}{n} \sum_{i=1}^n \mathbf{x}_i \mathbf{x}_i' \right)^{-1} \xrightarrow{p} \mathbf{Q}_{\mathbf{xx}}^{-1} \implies \hat{\beta} \xrightarrow{p} \beta + \mathbf{Q}_{\mathbf{xx}}^{-1} \cdot \mathbf{0} = \beta,$$

Consistency of OLS

Theorem (Consistency of OLS)

Under the linear projection model and i.i.d. data, $\hat{\beta}$ is consistent for β .

- Simple proof, but powerful result.
- OLS consistently estimates the linear projection coefficients, β .
 - No guarantees about what the β_j represent!
 - Best linear approximation to $\mathbb{E}[Y \mid \mathbf{X}]$.
 - If we have a linear CEF, then it's consistent for the CEF coefficients.
- Valid with no restrictions on Y : could be binary, discrete, etc.
- Not guaranteed to be unbiased (unless CEF is linear, as we'll see...)

Central limit theorem, reminders

- We'll want to approximate the sampling distribution of $\hat{\beta}$. CLT!
- Consider some sample mean of i.i.d. data: $n^{-1} \sum_{i=1}^n g(\mathbf{X}_i)$. We have:

$$\mathbb{E} \left[\frac{1}{n} \sum_{i=1}^n g(\mathbf{X}_i) \right] = \mathbb{E}[g(\mathbf{X}_i)] \quad \text{var} \left[\frac{1}{n} \sum_{i=1}^n g(\mathbf{X}_i) \right] = \frac{\text{var}[g(\mathbf{X}_i)]}{n}$$

- CLT implies:

$$\sqrt{n} \left(\frac{1}{n} \sum_{i=1}^n g(\mathbf{X}_i) - \mathbb{E}[g(\mathbf{X}_i)] \right) \xrightarrow{d} \mathcal{N}(0, \text{var}[g(\mathbf{X}_i)])$$

- If $\mathbb{E}[g(\mathbf{X}_i)] = 0$, then we have

$$\sqrt{n} \left(\frac{1}{n} \sum_{i=1}^n g(\mathbf{X}_i) \right) = \frac{1}{\sqrt{n}} \sum_{i=1}^n g(\mathbf{X}_i) \xrightarrow{d} \mathcal{N}(0, \mathbb{E}[g(\mathbf{X}_i)g(\mathbf{X}_i)'])$$

Standardized estimator

$$\sqrt{n}(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}) = \left(\frac{1}{n} \sum_{i=1}^n \mathbf{x}_i \mathbf{x}_i' \right)^{-1} \left(\frac{1}{\sqrt{n}} \sum_{i=1}^n \mathbf{x}_i e_i \right)$$

- Remember that $(n^{-1} \sum_{i=1}^n \mathbf{x}_i \mathbf{x}_i')^{-1} \xrightarrow{p} \mathbf{Q}_{\mathbf{X}\mathbf{X}}^{-1}$ so we have

$$\sqrt{n}(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}) \approx \mathbf{Q}_{\mathbf{X}\mathbf{X}}^{-1} \left(\frac{1}{\sqrt{n}} \sum_{i=1}^n \mathbf{x}_i e_i \right)$$

- What about $n^{-1/2} \sum_{i=1}^n \mathbf{x}_i e_i$? Notice that:
 - $n^{-1} \sum_{i=1}^n \mathbf{x}_i e_i$ is a sample average with $\mathbb{E}[\mathbf{x}_i e_i] = 0$.
 - Rewrite as \sqrt{n} times an average of i.i.d. mean-zero random vectors.
- Let $\boldsymbol{\Omega} = \mathbb{E}[e_i^2 \mathbf{x}_i \mathbf{x}_i']$ and apply the CLT:

$$\left(\frac{1}{\sqrt{n}} \sum_{i=1}^n \mathbf{x}_i e_i \right) \xrightarrow{d} \mathcal{N}(0, \boldsymbol{\Omega})$$

Asymptotic normality

Theorem (Asymptotic Normality of OLS)

Under the linear projection model,

$$\sqrt{n}(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}) \xrightarrow{d} \mathcal{N}(0, \mathbf{V}_{\hat{\boldsymbol{\beta}}}),$$

where,

$$\mathbf{V}_{\hat{\boldsymbol{\beta}}} = \mathbf{Q}_{\mathbf{XX}}^{-1} \boldsymbol{\Omega} \mathbf{Q}_{\mathbf{XX}}^{-1} = (\mathbb{E}[\mathbf{X}_i \mathbf{X}_i'])^{-1} \mathbb{E}[e_i^2 \mathbf{X}_i \mathbf{X}_i'] (\mathbb{E}[\mathbf{X}_i \mathbf{X}_i'])^{-1}$$

- $\hat{\boldsymbol{\beta}}$ is approximately normal with mean $\boldsymbol{\beta}$ and variance $\mathbf{Q}_{\mathbf{XX}}^{-1} \boldsymbol{\Omega} \mathbf{Q}_{\mathbf{XX}}^{-1} / n$
- $\mathbf{V}_{\hat{\boldsymbol{\beta}}} / n$ is the **asymptotic covariance matrix** of $\hat{\boldsymbol{\beta}}$
 - Square root of the diagonal of $\mathbf{V}_{\hat{\boldsymbol{\beta}}} / n$ = standard errors for $\hat{\beta}_j$
- Allows us to formulate (approximate) confidence intervals, tests.

Estimating OLS variance

$$\mathbb{V}[\hat{\beta}] = \frac{1}{n} \mathbf{V}_{\hat{\beta}} = \mathbf{Q}_{\mathbf{X}\mathbf{X}}^{-1} \mathbf{\Omega} \mathbf{Q}_{\mathbf{X}\mathbf{X}}^{-1}$$

- Estimation of $\mathbf{V}_{\hat{\beta}}$ uses plug-in estimators.
 - Replace $\mathbf{Q}_{\mathbf{X}\mathbf{X}}^{-1} = \mathbb{E}[\mathbf{X}_i \mathbf{X}_i']$ with $n^{-1} \sum_{i=1}^n \mathbf{X}_i \mathbf{X}_i' = \mathbb{X}'\mathbb{X}/n$.
 - Replace $\mathbf{\Omega} = \mathbb{E}[e_i^2 \mathbf{X}_i \mathbf{X}_i']$ with $n^{-1} \sum_{i=1}^n \hat{e}_i^2 \mathbf{X}_i \mathbf{X}_i'$
- Putting these together:

$$\begin{aligned}\hat{\mathbb{V}}[\hat{\beta}] &= \frac{1}{n} \left(\frac{1}{n} \mathbb{X}'\mathbb{X} \right)^{-1} \left(\frac{1}{n} \sum_{i=1}^n \hat{e}_i^2 \mathbf{X}_i \mathbf{X}_i' \right) \left(\frac{1}{n} \mathbb{X}'\mathbb{X} \right)^{-1} \\ &= (\mathbb{X}'\mathbb{X})^{-1} \left(\sum_{i=1}^n \hat{e}_i^2 \mathbf{X}_i \mathbf{X}_i' \right) (\mathbb{X}'\mathbb{X})^{-1}\end{aligned}$$

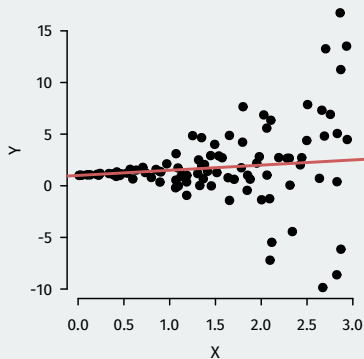
- Straightforward to show this is consistent: $n\hat{\mathbb{V}}[\hat{\beta}] \xrightarrow{p} \mathbf{V}_{\hat{\beta}}$.
- Square root of the diagonal of $\hat{\mathbb{V}}[\hat{\beta}]$: **heteroskedasticity-consistent (HC) SEs**

Homoskedasticity

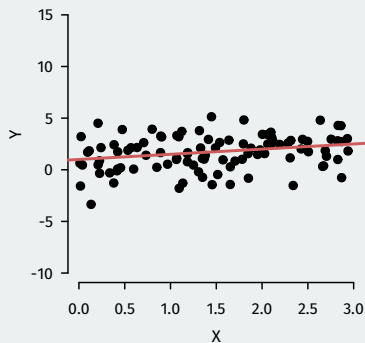
Assumption: Homoskedasticity

The variance of the error terms is constant in \mathbf{X} , $\mathbb{E}[e^2 | \mathbf{X}] = \sigma^2(\mathbf{X}) = \sigma^2$.

Heteroskedastic



Homoskedastic



Consequences of homoskedasticity

- Homoskedasticity implies $\mathbb{E}[e_i^2 \mathbf{X}_i \mathbf{X}_i'] = \mathbb{E}[e_i^2] \mathbb{E}[\mathbf{X}_i \mathbf{X}_i'] = \sigma^2 \mathbf{Q}_{\mathbf{X}\mathbf{X}}$
- Simplifies the expression for the variance of $\sqrt{n}(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta})$:

$$\mathbf{V}_{\hat{\boldsymbol{\beta}}}^0 = \mathbf{Q}_{\mathbf{X}\mathbf{X}}^{-1} \mathbb{E}[e_i^2] \mathbf{Q}_{\mathbf{X}\mathbf{X}} \mathbf{Q}_{\mathbf{X}\mathbf{X}}^{-1} = \sigma^2 \mathbf{Q}_{\mathbf{X}\mathbf{X}}^{-1}$$

- Estimated variance of $\hat{\boldsymbol{\beta}}$ under homoskedasticity

$$s^2 = \frac{1}{n-k} \sum_{i=1}^n \hat{e}_i^2 \quad \hat{\mathbf{V}}^0[\hat{\boldsymbol{\beta}}] = \frac{1}{n} s^2 \left(\frac{1}{n} \sum_{i=1}^n \mathbf{X}_i \mathbf{X}_i' \right)^{-1} = s^2 (\mathbb{X}'\mathbb{X})^{-1}$$

- LLN implies $s^2 \xrightarrow{P} \sigma^2$ and so $n\hat{\mathbf{V}}^0[\hat{\boldsymbol{\beta}}]$ is consistent for $\mathbf{V}_{\hat{\boldsymbol{\beta}}}^0$

Notes on skedasticity

- Homoskedasticity: strong assumption that isn't needed for consistency.
- Software: almost always reports $\hat{V}^0[\hat{\beta}]$ by default.
 - e.g. `lm()` in R or `reg` in Stata.
- Separate commands for HC SEs $\hat{V}[\hat{\beta}]$
 - Use `{sandwich}` package in R or `, robust` in Stata.
- If $\hat{V}^0[\hat{\beta}]$ and $\hat{V}[\hat{\beta}]$ differ a lot, maybe check modeling assumptions (King and Roberts, PA 2015)
- Lots of “flavors” of HC variance estimators (HC0, HC1, HC2, etc).
 - Mostly small, ad hoc changes to improve finite-sample performance.

Inference with OLS

- Inference is basically the same as any asymptotically normal estimator.
- Let \widehat{V}_{β_j} be the estimated SE for $\hat{\beta}_j$.
 - Square root of j th diagonal entry: $\sqrt{[\widehat{V}[\hat{\beta}]]_{jj}}$
- Hypothesis test of $\beta_j = \beta_0$:

$$\text{general t-statistic} = \frac{\hat{\beta}_j - \beta_0}{\sqrt{\widehat{V}_{\beta_j}}} \quad \text{“usual” t-statistic} = \frac{\hat{\beta}_j}{\sqrt{\widehat{V}_{\beta_j}}}$$

- Use same critical values from the normal as usual $z_{\alpha/2} = 1.96$.
- 95% (asymptotic) confidence interval for $\hat{\beta}_j$:

$$[\hat{\beta}_j - 1.96\widehat{V}_{\beta_j}, \hat{\beta}_j + 1.96\widehat{V}_{\beta_j}]$$

- Software often uses t critical values instead of normal (we'll see why).

2/ Inference for Multiple Parameters

Inference for interactions

$$\mathbb{L}[Y|\mathbf{X}] = \beta_0 + X\beta_1 + Z\beta_2 + XZ\beta_3$$

- **Partial** or **marginal** effect of X at Z : $\frac{\partial \mathbb{L}[Y|\mathbf{X}]}{\partial X} = \beta_1 + Z\beta_3$
- Estimate it by plugging in the estimated coefficients: $\frac{\partial \widehat{\mathbb{L}[Y|\mathbf{X}]}}{\partial X} = \hat{\beta}_1 + Z\hat{\beta}_3$
- What if we want the variance of this effect for any value of Z ?

$$\mathbb{V}\left(\frac{\partial \widehat{\mathbb{L}[Y|\mathbf{X}]}}{\partial X}\right) = \mathbb{V}[\hat{\beta}_1 + Z\hat{\beta}_3] = \mathbb{V}[\hat{\beta}_1] + Z^2\mathbb{V}[\hat{\beta}_3] + 2Z\text{cov}[\hat{\beta}_1, \hat{\beta}_3]$$

- Use the estimated covariance matrix:

$$\hat{\mathbb{V}}\left(\frac{\partial \widehat{\mathbb{L}[Y|\mathbf{X}]}}{\partial X}\right) = \hat{V}_{\beta_1} + Z\hat{V}_{\beta_3} + 2Z\hat{V}_{\beta_1\beta_3}$$

Tests of multiple coefficients

$$\mathbb{E}[Y|\mathbf{X}] = \beta_0 + X\beta_1 + Z\beta_2 + XZ\beta_3$$

- What about a test of no effect of X ever? Involves 2 coefficients:

$$H_0 : \beta_1 = \beta_3 = 0$$

- Alternative: $H_1 : \beta_1 \neq 0$ or $\beta_3 \neq 0$
- We would like a test statistic that is large when the null is implausible.
 - Compare model fit when we do and do not impose the null hypothesis.

Restricted and unrestricted models

- Estimates and SSR from **unrestricted model** (alternative is true):

$$\widehat{Y}_i = \widehat{\beta}_0 + X_i \widehat{\beta}_1 + Z_i \widehat{\beta}_2 + X_i Z_i \widehat{\beta}_3 \quad SSR_u = \sum_{i=1}^n (Y_i - \widehat{Y}_i)^2$$

- Estimates and SSR from **restricted model** (null is true):

$$\widetilde{Y}_i = \widetilde{\beta}_0 + Z_i \widetilde{\beta}_2 \quad SSR_r = \sum_{i=1}^n (Y_i - \widetilde{Y}_i)^2$$

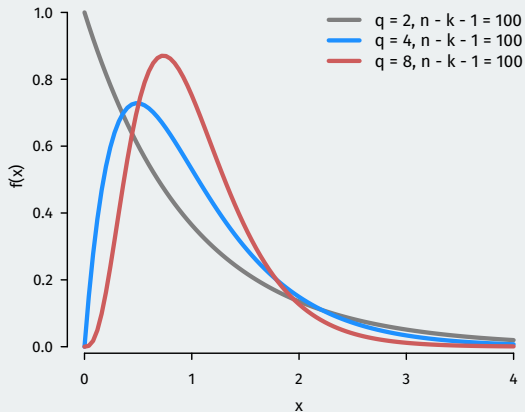
- If the null is true, we'd expect SSR_u to not be much bigger than SSR_r .
 - SSR mechanically increases even if you add noise, but not that much.

$$F = \frac{(SSR_r - SSR_u)/q}{SSR_u/(n - k - 1)}$$

- Components:
 - $(SSR_r - SSR_u)$: increase in residual variation dropping β_1, β_3
 - q = number of restrictions (numerator degrees of freedom)
 - $n - k - 1$: denominator/unrestricted degrees of freedom
- Intuition:
$$\frac{\text{increase in prediction error}}{\text{original prediction error}}$$
- Under the null, F is just sampling noise!
- Asymptotic distribution of F :

$$\frac{(SSR_r - SSR_u)/q}{SSR_u/(n - k - 1)} \xrightarrow{d} F_{q, n-(k+1)}$$

F distribution



- Ratio of two χ^2 (Chi-squared) distributions

F-test steps

1. Choose a Type I error rate, α .
 - Same interpretation: rate of false positives you are willing to accept
2. Calculate the rejection region for the test (one-sided)
 - Rejection region is the region $F > c$ such that $\mathbb{P}(F > c) = \alpha$
 - We can get this from R using the `qf()` function
3. Reject if observed statistic is bigger than critical value
 - Use `pf()` to get p-values if needed.
 - When applied to a single coefficient, equivalent to a t-test.

F statistic for all variables

- **“The” F-test:** null of all coefficients except the intercept being 0.
- In that case, the restricted model is just:

$$Y = \beta_0 + e$$

- And the estimate here would just be sample mean ($\hat{\beta}_0 = \bar{Y}$)
- The SSR_r then would just be the total sum of squares in Y :

$$SSR_r = SST = \sum_{i=1}^n (y_i - \bar{y})^2$$

- Often reported with regression output.

Multiple testing

- Separate t-tests for each β_j : α of them will be significant by chance.
- Illustration:
 - Randomly draw 21 variables independently.
 - Run a regression of the first variable on the rest.
- By design, no effect of any variable on any other.

Multiple test example

```
noise <- data.frame(matrix(rnorm(2100), nrow = 100, ncol = 21))
summary(lm(noise))
```

```
##
## Coefficients:
##      Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.028039   0.113820  -0.25  0.8061
## X2          -0.150390   0.112181  -1.34  0.1839
## X3           0.079158   0.095028   0.83  0.4074
## X4          -0.071742   0.104579  -0.69  0.4947
## X5           0.172078   0.114002   1.51  0.1352
## X6           0.080852   0.108341   0.75  0.4577
## X7           0.102913   0.114156   0.90  0.3701
## X8          -0.321053   0.120673  -2.66  0.0094 **
## X9          -0.053122   0.107983  -0.49  0.6241
## X10          0.180105   0.126443   1.42  0.1583
## X11          0.166386   0.110947   1.50  0.1377
## X12          0.008011   0.103766   0.08  0.9387
## X13          0.000212   0.103785   0.00  0.9984
## X14          -0.065969   0.112214  -0.59  0.5583
## X15          -0.129654   0.111575  -1.16  0.2487
## X16          -0.054446   0.125140  -0.44  0.6647
## X17          0.004335   0.112012   0.04  0.9692
## X18          -0.080796   0.109853  -0.74  0.4642
## X19          -0.085806   0.118553  -0.72  0.4713
## X20          -0.186006   0.104560  -1.78  0.0791 .
## X21          0.002111   0.108118   0.02  0.9845
## ---
## Signif. codes:
##  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.999 on 79 degrees of freedom
## Multiple R-squared:  0.201, Adjusted R-squared: -0.00142
## F-statistic: 0.993 on 20 and 79 DF, p-value: 0.48
```

Multiple testing gives false positives

- 1 out of 20 variables significant at $\alpha = 0.05$
- 2 out of 20 variables significant at $\alpha = 0.1$
- Exactly the number of false positives we would expect.
- But notice the F-statistic: the variables are not **jointly** significant

3/ Linear Regression Model and Finite-sample Properties

Standard linear regression model

- Standard textbook model: **correctly specified linear CEF**
 - Designed for finite-sample results.

Assumption: Linear Regression Model

1. The variables (Y, \mathbf{X}) satisfy the the linear CEF assumption.

$$Y = \mathbf{X}'\boldsymbol{\beta} + e$$

$$\mathbb{E}[e \mid \mathbf{X}] = 0.$$

2. The design matrix is invertible $\mathbb{E}[\mathbf{X}\mathbf{X}'] > 0$ (positive definite).

- Basically this assumes the CEF of Y given \mathbf{X} is linear.
- We continue to maintain $\{(Y_i, \mathbf{X}_i)\}$ are i.i.d.

Properties of OLS under linear CEF

- Linear CEFs imply stronger finite-sample guarantees:

1. **Unbiasedness:** $\mathbb{E}[\hat{\beta} \mid \mathbb{X}] = \beta$

2. **Conditional sampling variance:** let $\sigma_i^2 = \mathbb{E}[e_i^2 \mid \mathbf{X}_i]$

$$\mathbb{V}[\hat{\beta} \mid \mathbb{X}] = (\mathbb{X}'\mathbb{X})^{-1} \left(\sum_{i=1}^n \sigma_i^2 \mathbf{x}_i \mathbf{x}_i' \right) (\mathbb{X}'\mathbb{X})^{-1}$$

- Useful when linearity holds by default (discrete X in experiments, etc)

Linear CEF under homoskedasticity

- Under homoskedasticity, we have a few other finite-sample results:
3. **Conditional sampling variance:** $\mathbb{V}[\hat{\beta} \mid \mathbb{X}] = \sigma^2 (\mathbb{X}'\mathbb{X})^{-1}$
 4. **Unbiased variance estimator:** $\mathbb{E} [\hat{\mathbb{V}}^0[\hat{\beta}] \mid \mathbf{X}] = \sigma^2 (\mathbb{X}'\mathbb{X})^{-1}$
 5. **Gauss-Markov:** OLS is the best linear unbiased estimator of β (BLUE). If $\tilde{\beta}$ is a linear estimator,

$$\mathbb{V}[\tilde{\beta} \mid \mathbb{X}] \geq \mathbb{V}[\hat{\beta} \mid \mathbb{X}] = \sigma^2 (\mathbb{X}'\mathbb{X})^{-1}$$

- For matrices, $\mathbf{A} \geq \mathbf{B}$ means that $\mathbf{A} - \mathbf{B}$ is positive semidefinite.
- A matrix \mathbf{C} is p.s.d. if $\mathbf{x}'\mathbf{C}\mathbf{x} \geq 0$.
- Upshot: OLS will have the smaller SEs than any other linear estimator.

Normal regression model

- Most parametric: $Y \sim \mathcal{N}(\mathbf{X}'\boldsymbol{\beta}, \sigma^2)$.
 - Normal error model since $e = Y - \mathbf{X}'\boldsymbol{\beta} \sim \mathcal{N}(0, \sigma^2)$.
- Rarely believed, but allows for exact inference for all n .
 - $(\hat{\beta}_j - \beta_j)/\widehat{\text{se}}(\hat{\beta}_j)$ follows a t distribution with $n - k$ degrees of freedom.
 - F statistics follows F distribution exactly rather than approximately.
- Software often implicitly assumes this for p-values.
- With reasonable n , asymptotic normality has the same effect.