

## Heuristics: Where does normality of $\varepsilon$ come from?

- Poincare: “Everyone believes in the *Gaussian* law of errors, the experimentalists because they think it is a mathematical theorem, the mathematicians because they think it is an experimental fact.”
- Gauss (1809) worked backwards to construct a distribution of errors for which the least squares is the maximum likelihood estimate (“the most probable estimate”). Hence normal distribution is sometimes called Gaussian.
- Central limit theorem justification: De-Moivre-Laplace, Liapunov, Levy, Khinchin, and Lindeberg (no Gauss here). In econometrics, Haavelmo, in his “Probability Approach to

Econometrics", *Econometrica* 1944, was a prominent proponent of this justification.

- Under the CLT justification, the errors  $\varepsilon_i$  are thought of as a sum of a large number of small and independent elementary errors  $v_j$ , and therefore will be approximately Gaussian due to the central limit theorem considerations.

- If elementary errors  $v_j, j = 1, 2, \dots$  are i.i.d. mean-zero and  $E[v_j^2] < \infty$ , then for *large*  $N$

$$\varepsilon_i = \sqrt{N} \left[ \frac{\sum_{j=1}^N v_j}{N} \right] \approx_d N(0, E v_j^2),$$

as follows from the CLT.

- However, if elementary errors  $v_j$  are i.i.d. symmetric and  $E[v_j^2] = \infty$ , then *for large*

$n$  (with additional technical restrictions on the tail behavior of  $v_j$ ).

$$\varepsilon_i = N^{1-\frac{1}{\alpha}} \left[ \frac{\sum_{j=1}^N v_j}{N} \right] \approx_d \text{Stable}$$

where  $\alpha$  is the largest finite moment:  $\alpha = \sup\{p : E|v_j|^p < \infty\}$ . This follows from the CLT proved by Khinchine and Levy. The Stable distributions are also called sum-stable and *Pareto-Levy* distributions.

- Densities of symmetric stable distributions are “bell-shaped” but have thick tails which behave approximately like power functions  $x \mapsto \text{const} \cdot |x|^{-\alpha}$  in the tails, with  $\alpha < 2$ .
- Another interesting side observation: If  $\alpha > 1$ , the sample mean  $\sum_{j=1}^N v_j/N$  is a converging statistic, if  $\alpha < 1$  the sample mean  $\sum_{j=1}^N v_j/N$  is a diverging statistics.

- References: Embrechts et al. *Modelling Extremal Events*