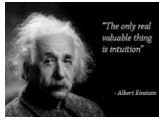


# Structural Equation Models



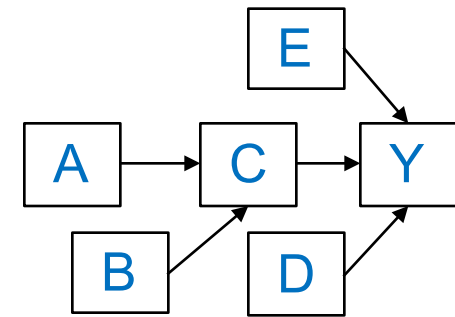
# Structural Equations: Intuition

- In depth coverage of structural equation modeling is beyond the scope of this class, but we discuss a few issues here
- When some variable are highly correlated but business rationale suggests that they belong in a model, the relationship among variables in the model is probably “structural”
- This simply means rather than having a single predictor model, we have a group of inter-related models in which the outcome variable in some models are predictors of other models, e.g.:

$$(1) C = \beta_{0C} + \beta_A A + \beta_B B + \varepsilon$$

$$(2) Y = \beta_{0Y} + \beta_C C + \beta_D D + \beta_E E + \varepsilon$$

- A, B → **“direct”** effect on **C** ( $\beta_A, \beta_B$ )
- C, D, E → **“direct”** effect on **Y** ( $\beta_C, \beta_D, \beta_E$ )
- A, B → **“indirect”** effect on **Y** ( $\beta_A * \beta_C, \beta_B * \beta_C$ )



# Structural Equations Models (SEM)

- **SEM** is a **complex** topic; It is discussed here as an **FYI**
- In some cases, you can use **OLS** to model **SEM**, only **if**:
  - The model is “**non-recursive**” – i.e., all arrows in the model go in **1 direction** → **posterior** variables are **not predictors** of anterior **variables**
  - The model is estimated “**hierarchically**” – i.e., all **predictors** in the **prior** models are **included** in **posterior** models, to test all possible paths. The example above would be modeled:
    - (1)  $C = \beta_{0C} + \beta_A A + \beta_B B + \varepsilon$  (same)
    - (2)  $Y = \beta_{0Y} + \beta_A A + \beta_B B + \beta_C C + \beta_D D + \beta_E E + \varepsilon$
- If  $\beta_A, \beta_B$  are **significant** in (2), the structural model is **wrong**
- If  $\beta_A, \beta_B$  are **significant** in (1) but **not** in (2) the model is **right**
- There are various **SEM methods** (e.g., Lisrel, PLS) which **estimate** the multiple model equations **jointly**





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