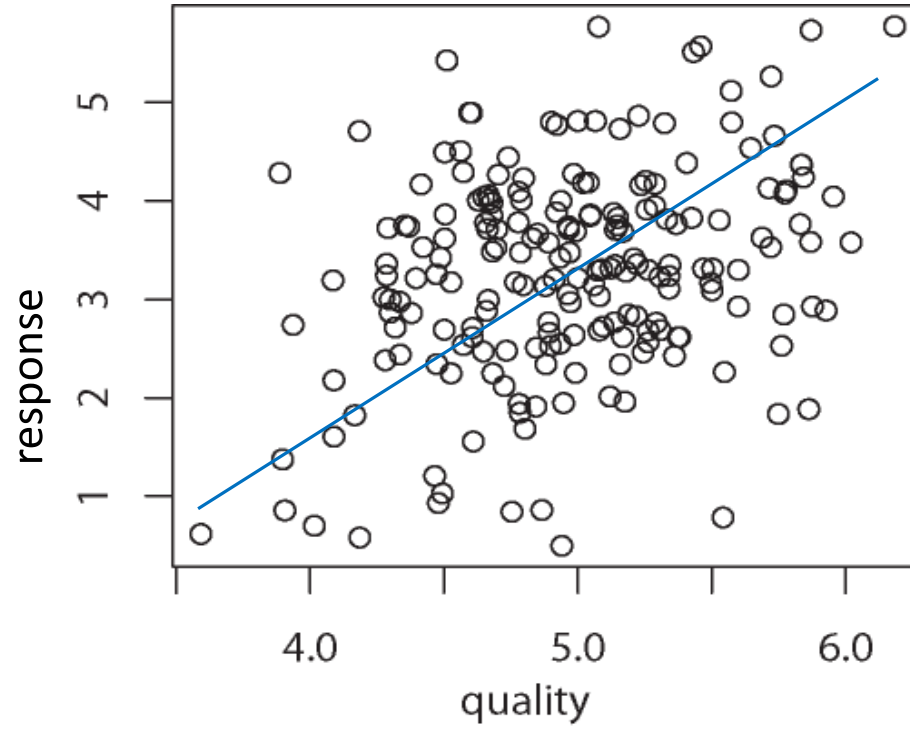


Characterizing Uncertainty:Part 2

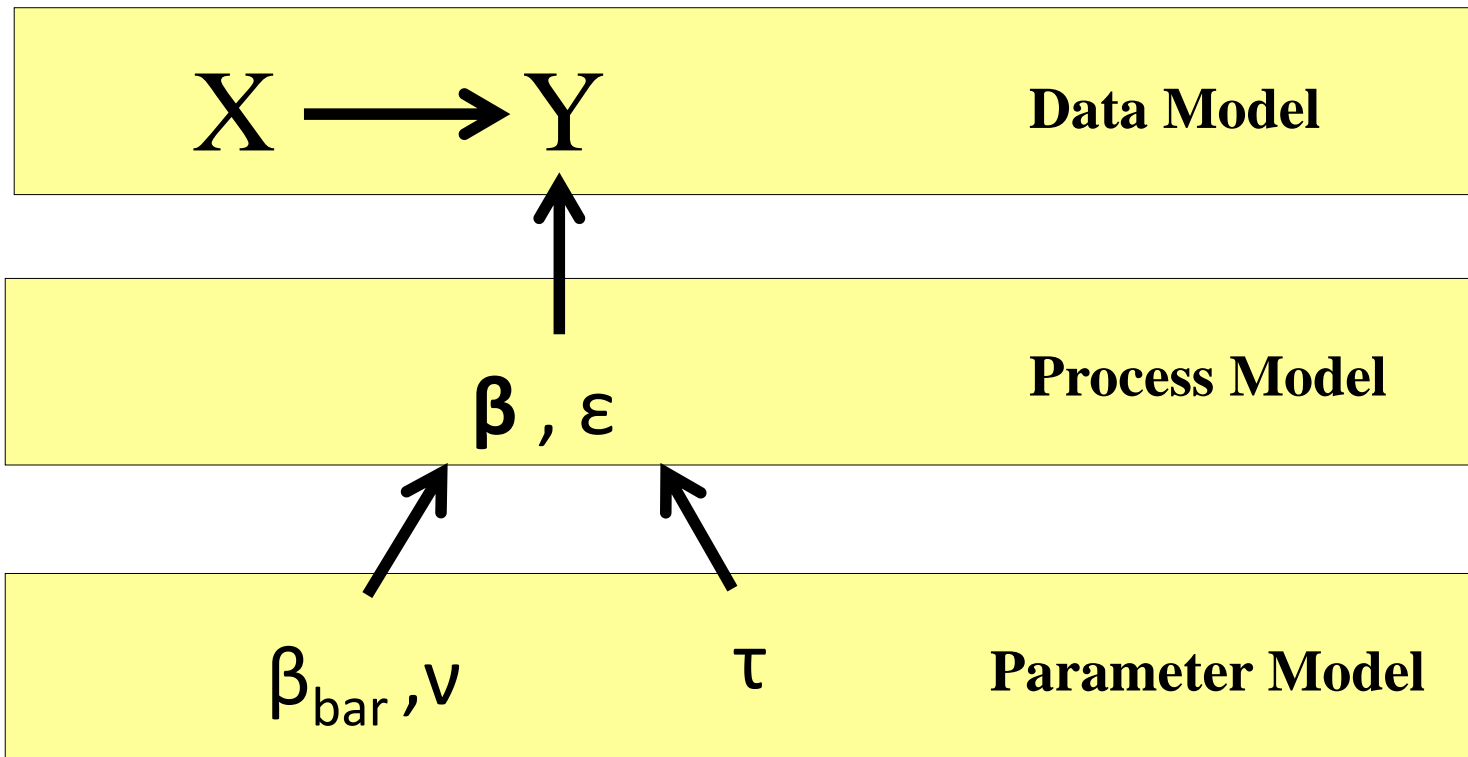
Linear Model

$$y_i \sim \beta_0 + \beta(x_i) + \varepsilon_i$$



Linear Model – Graph Notation

$$y_i \sim \beta_0 + \beta(x_i) + \varepsilon_i$$

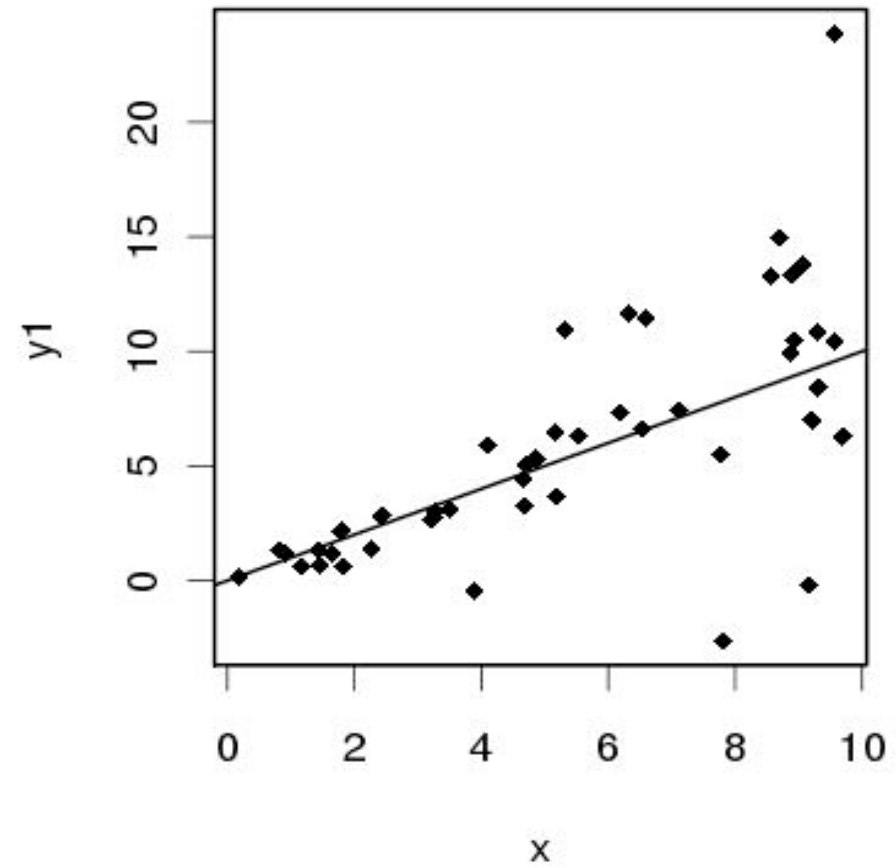
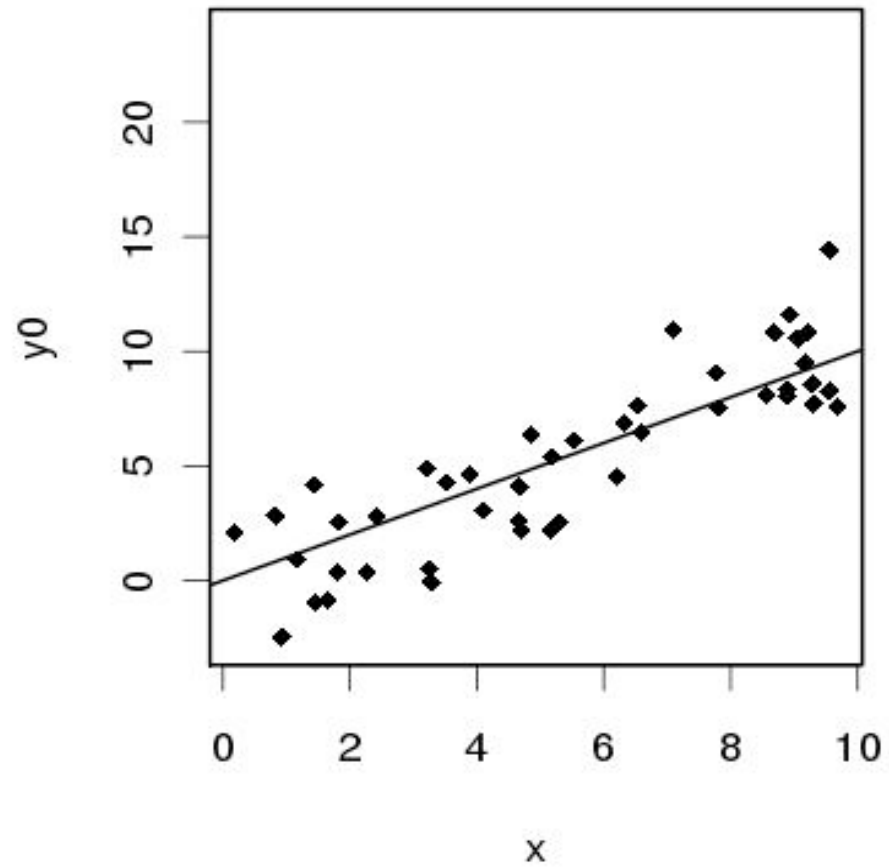


$$\varepsilon_i \sim N(0, \tau)$$
$$\beta \sim N(\beta_{\text{bar}}, \nu)$$

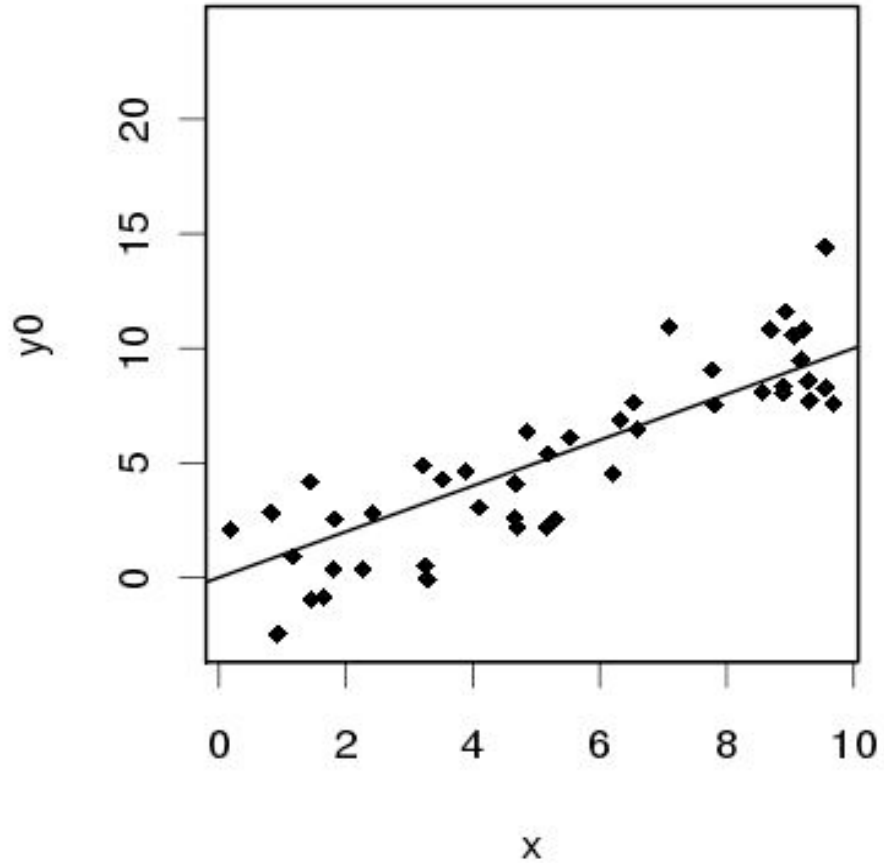
Classic Assumptions of Linear Model:

- Normally distributed error
- Homoskedasticity
- No error in X variables
- Error in Y variables is measurement error
- Observations are independent
- No missing data

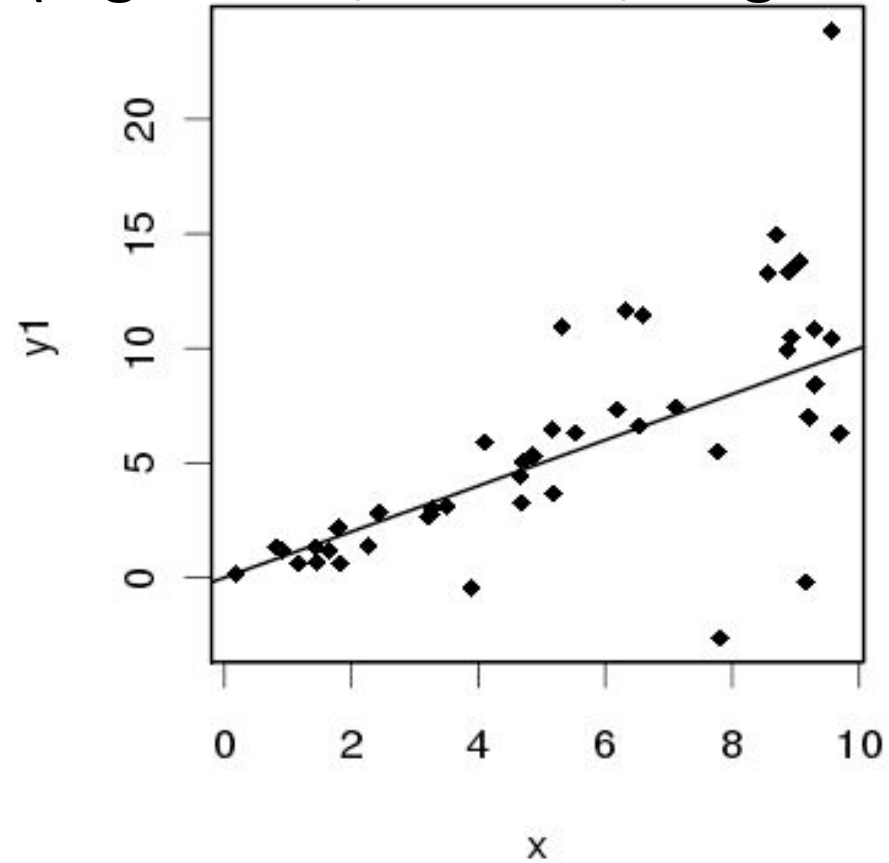
Heteroskedasticity



Heteroskedasticity



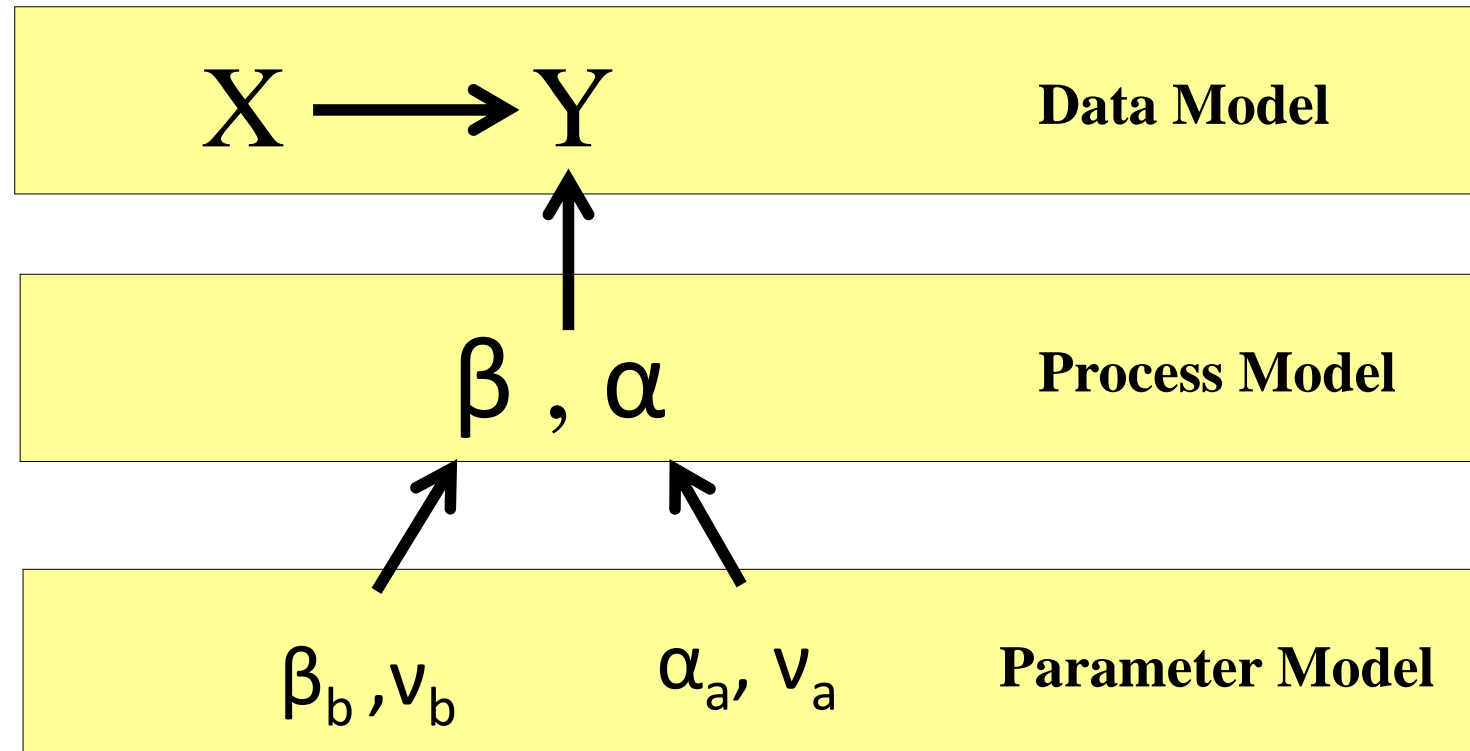
Could use different distribution
(lognormal, Poisson, Neg. Binomial)



Heteroskedasticity

Model the variance:

$$y \sim N(\beta_1 + \beta_2 x, (\alpha_1 + \alpha_2 x)^2)$$

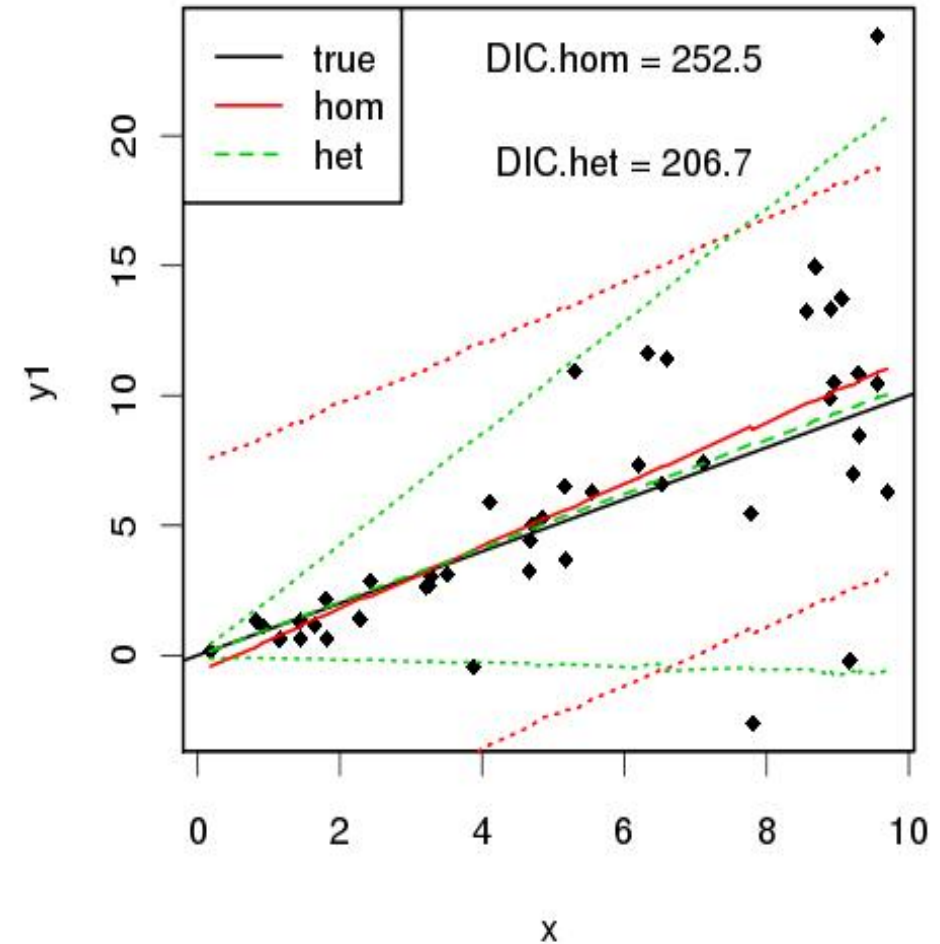
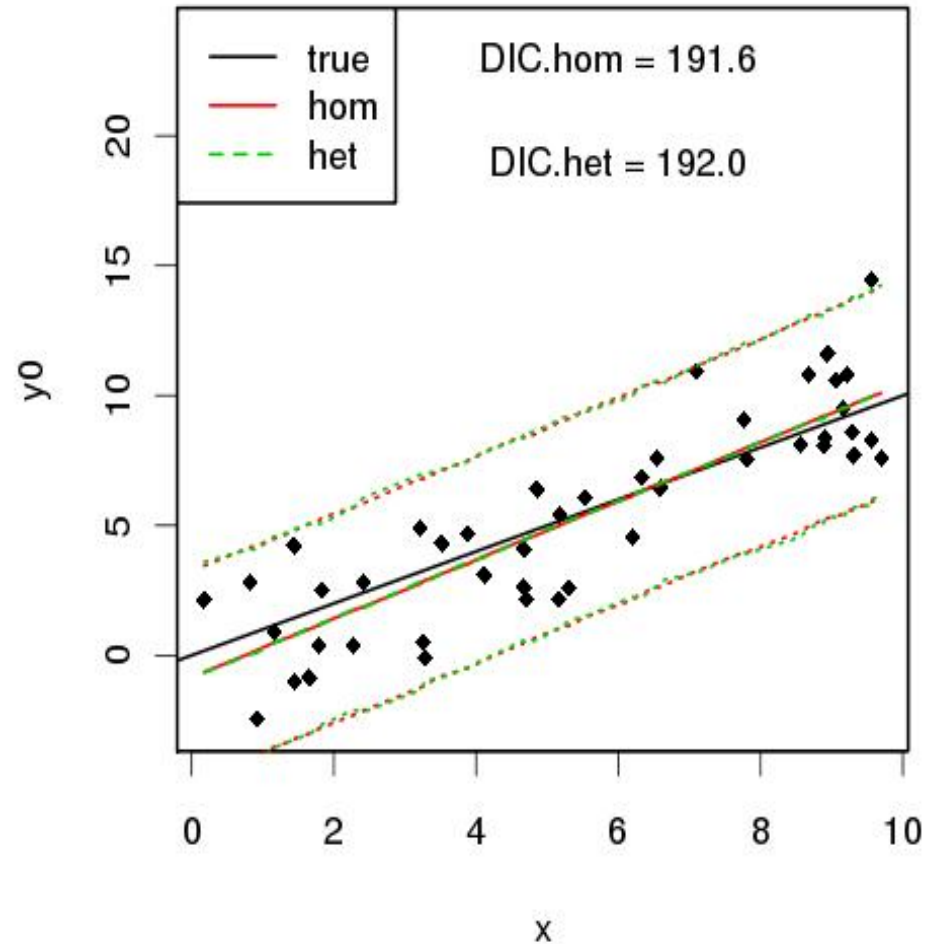


$$\alpha \sim N(\alpha_a, v_a)$$
$$\beta \sim N(\beta_b, v_b)$$

Heteroskedasticity

$$y \sim N(\beta_1 + \beta_2 x, s^2)$$

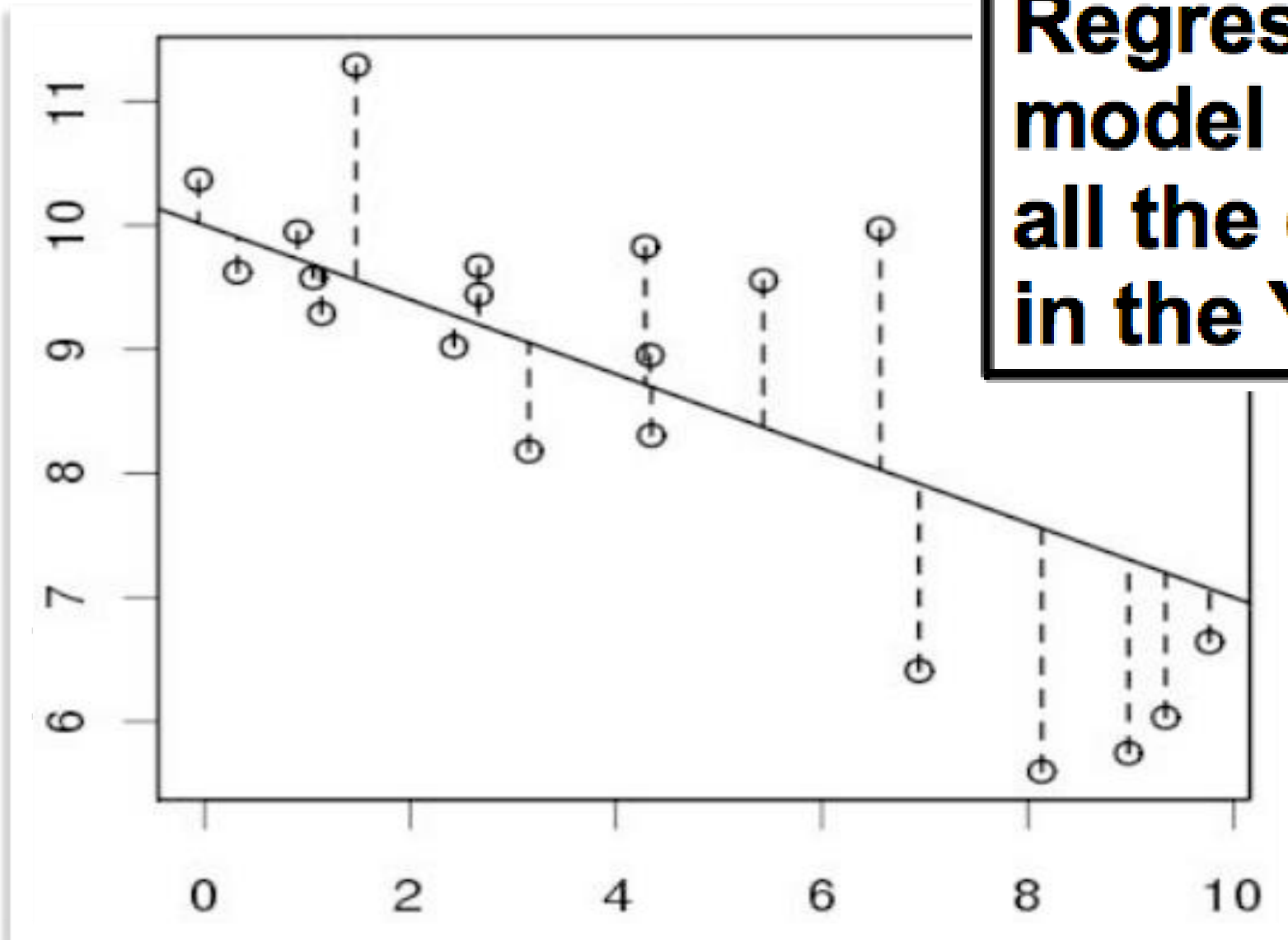
$$y \sim N(\beta_1 + \beta_2 x, (\alpha_1 + \alpha_2 x)^2)$$



Classic Assumptions of Linear Model:

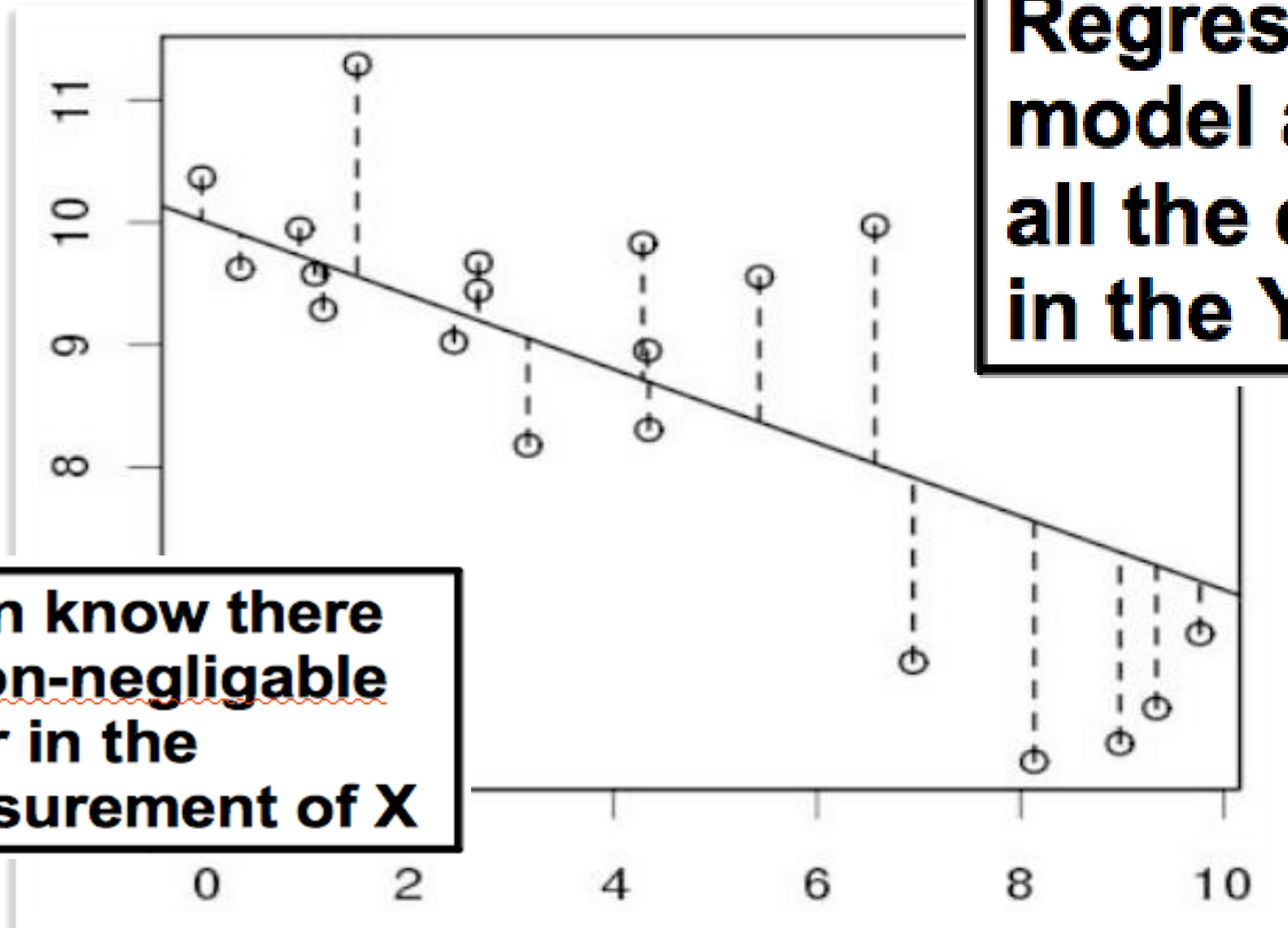
- Normally distributed error
- Homoskedasticity
- **No error in X variables**
- Error in Y variables is measurement error
- Observations are independent
- No missing data

Errors in variables (EIV)



**Regression
model assumes
all the error is
in the Y**

Errors in variables (EIV)



Regression model assumes all the error is in the Y

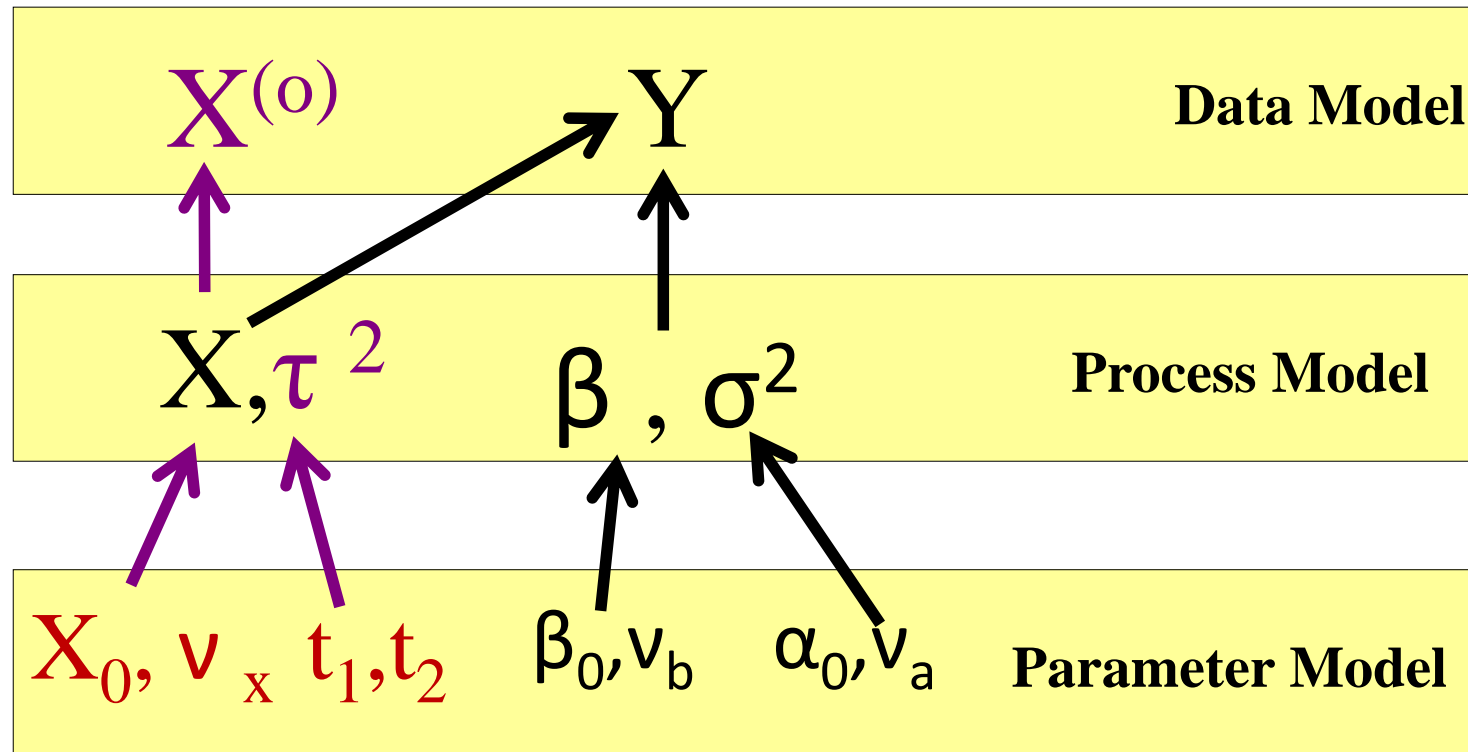
Often know there is non-negligible error in the measurement of X

Errors in variables

Model covariate (X) as random variable

$$Y \sim N(\beta X, \sigma^2)$$

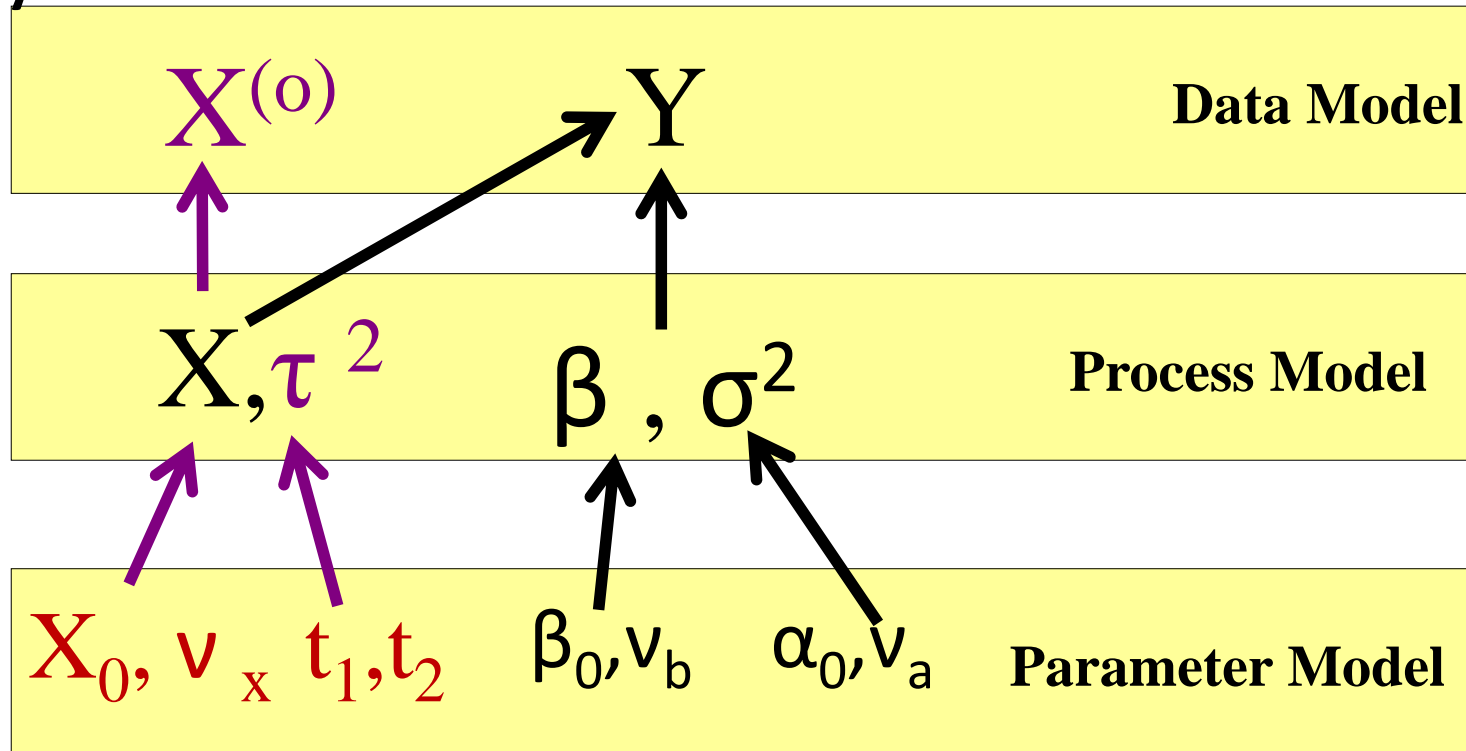
$$X_0 \sim N(X, \tau^2)$$



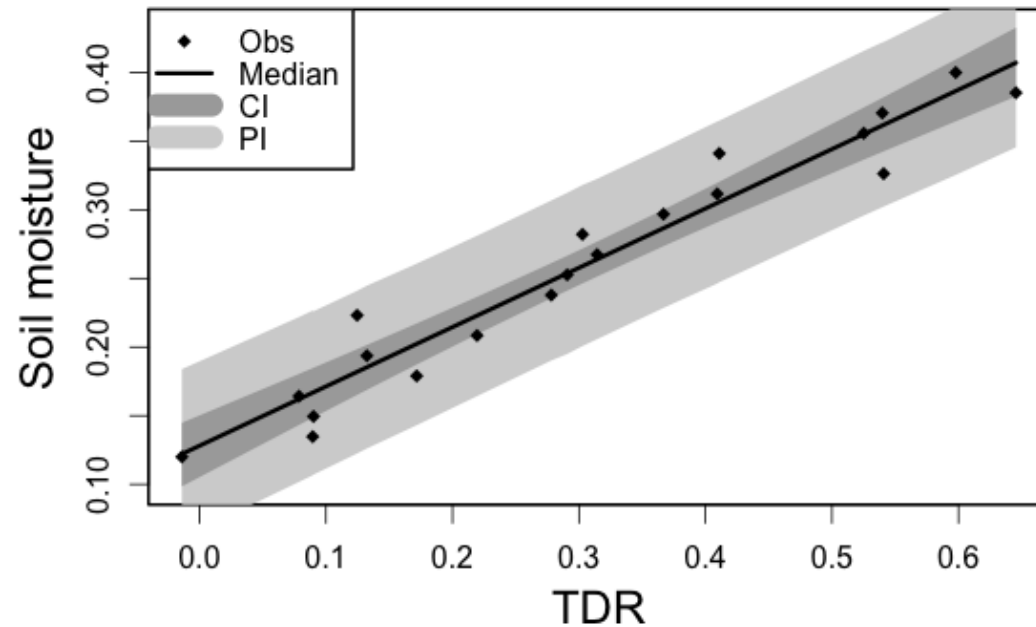
Errors in variables

This model could also be a calibration model - if covariate is proxy measure.

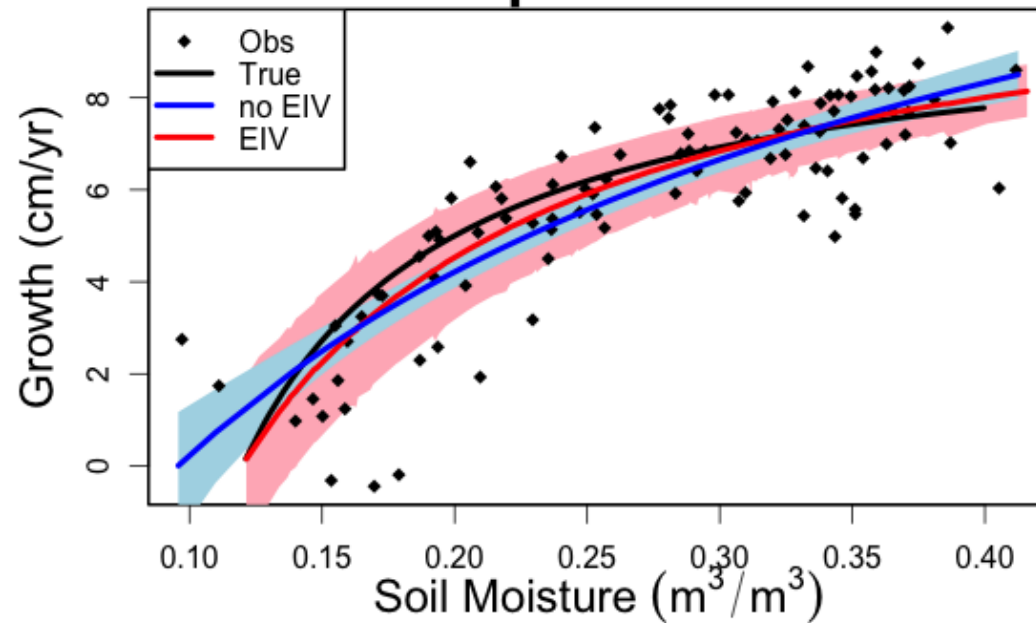
$$Y \sim N(\beta X, \sigma^2)$$
$$X_0 \sim N(X, \tau^2)$$



Calibration



Growth Response to Moisture



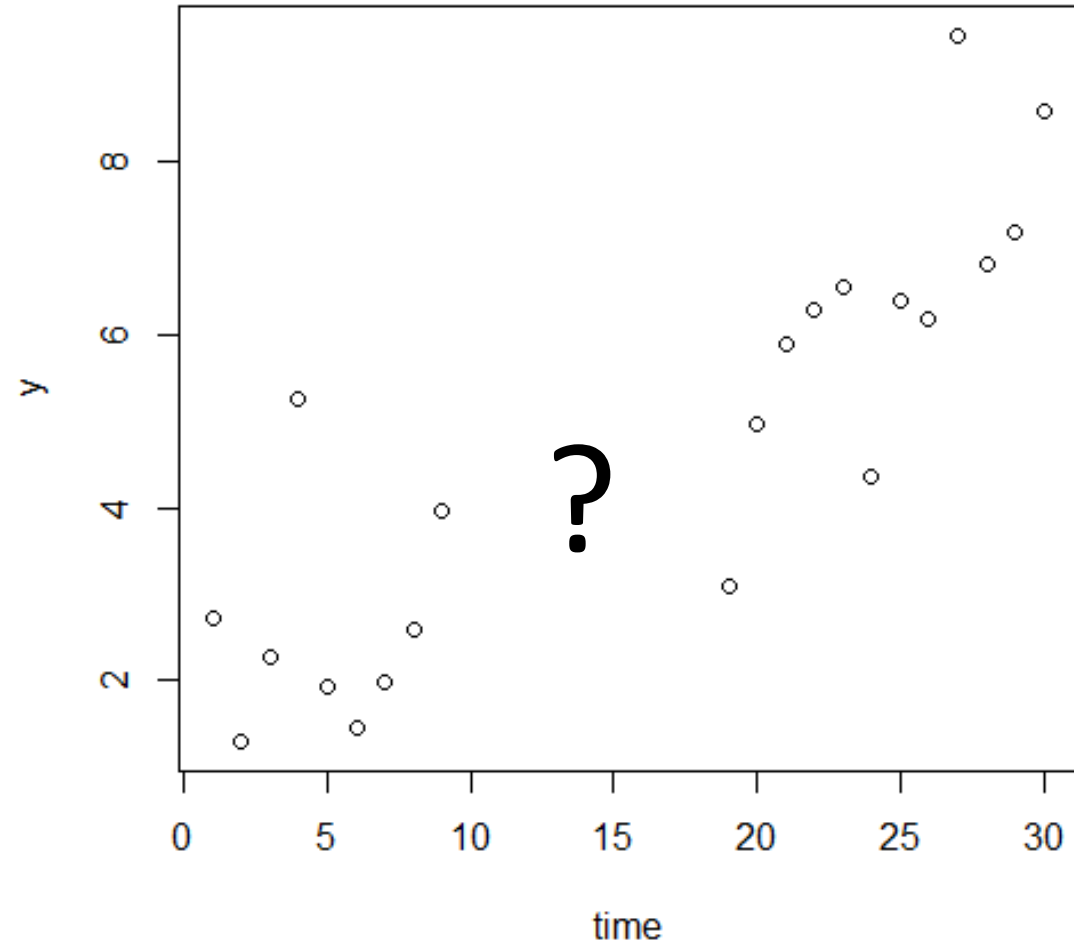
Classic Assumptions of Linear Model:

- Normally distributed error
- Homoskedasticity
- No error in X variables
- **Error in Y variables is measurement error**
- **Observations are independent**
- **No missing data**

Latent Variables

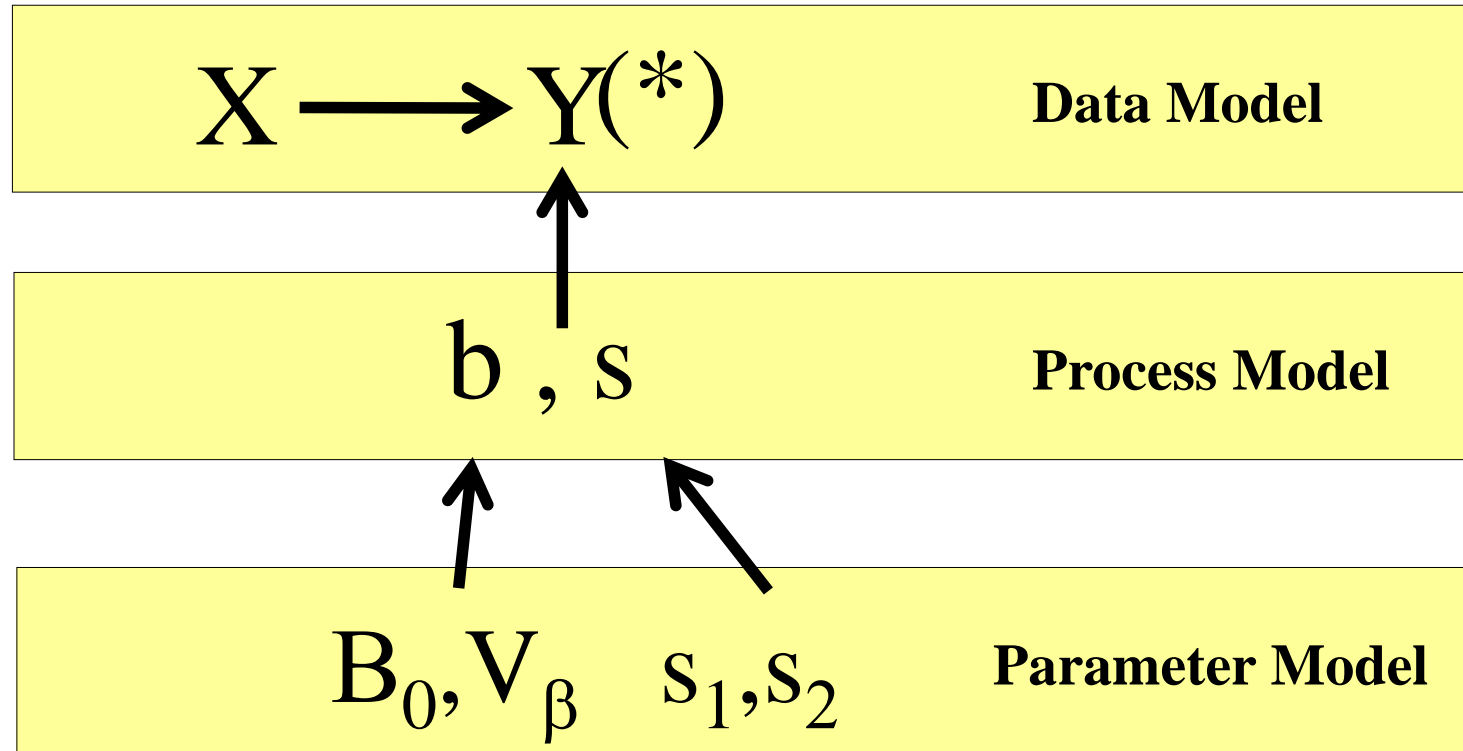
- Any variable not directly observed
 - **Missing data**
 - Variable measured with error
 - Proxy measures

Missing Data

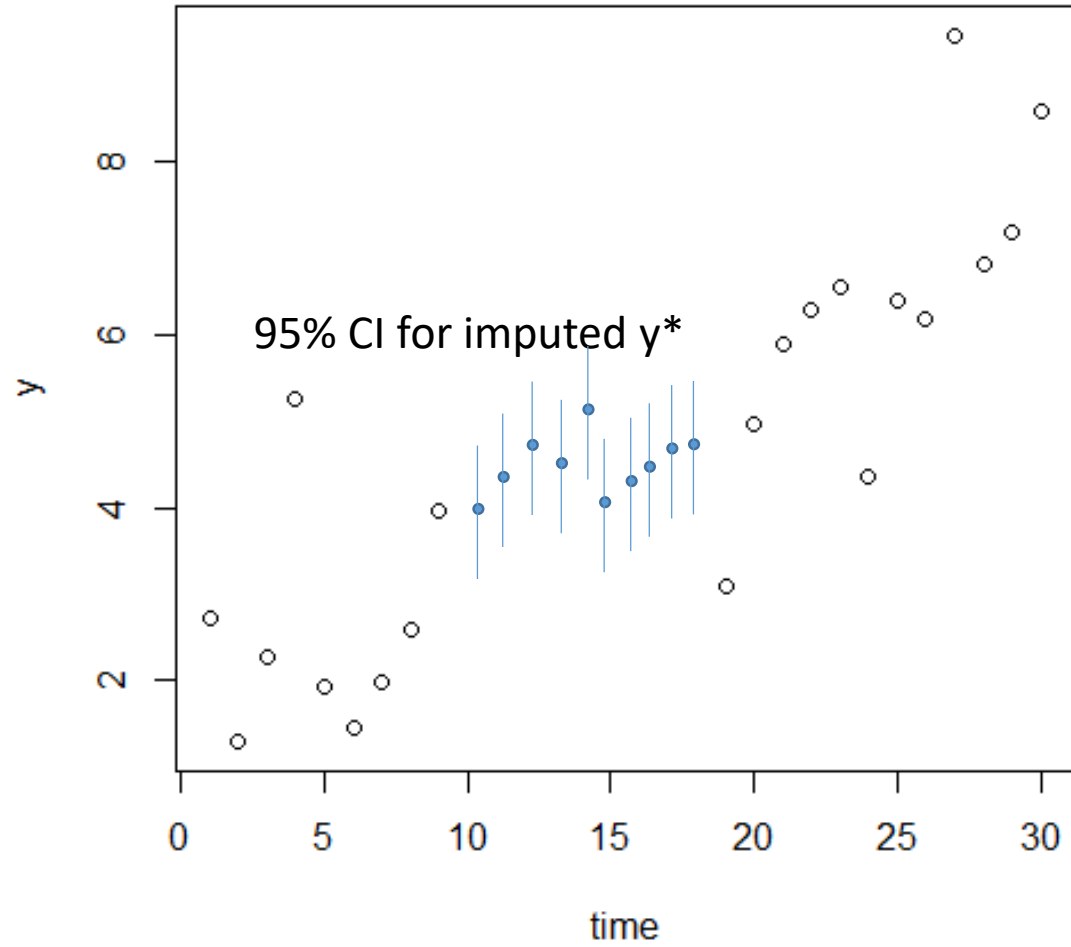


Missing Data Model

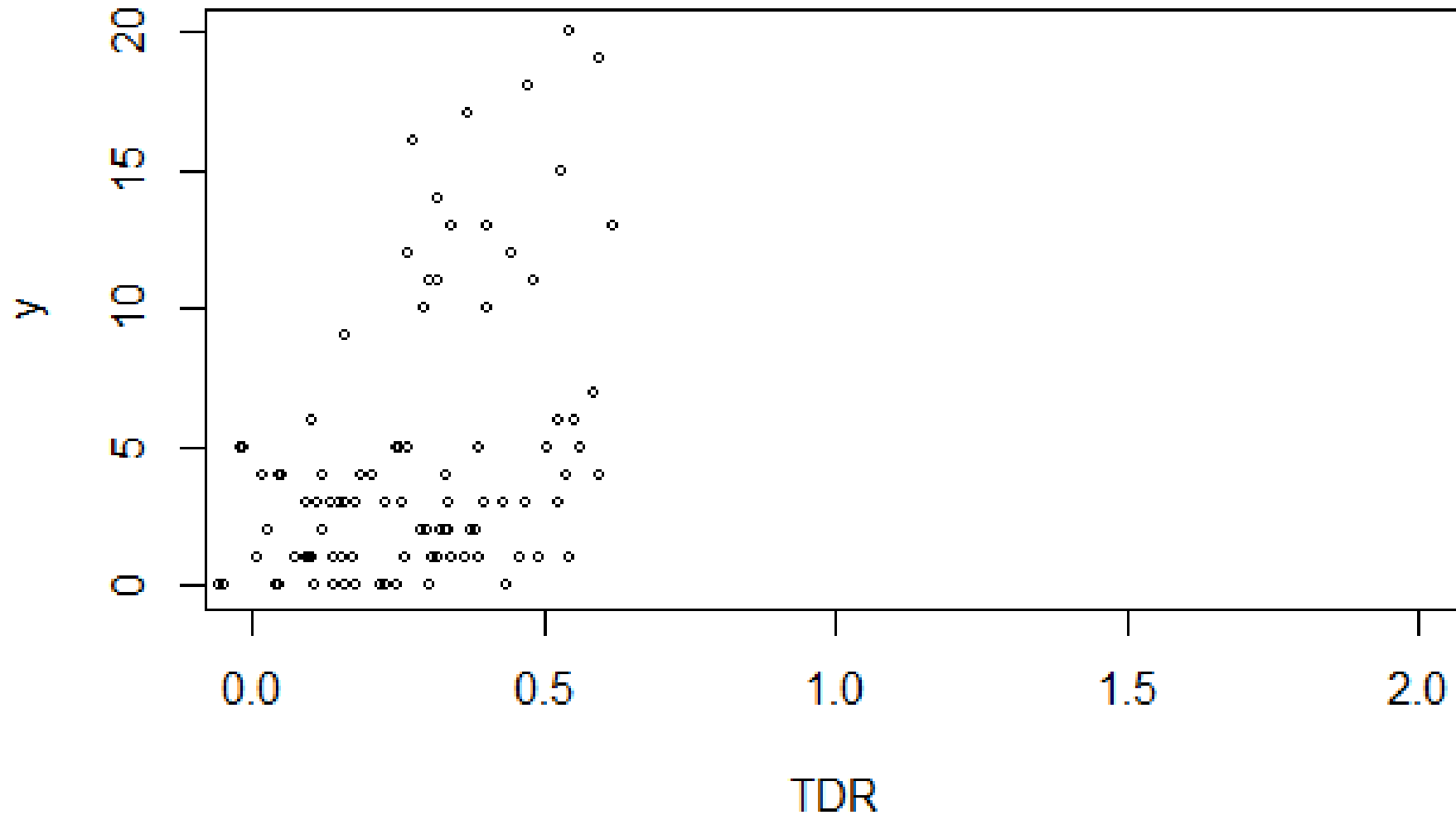
$$y^* \sim N(\beta X, s^2)$$



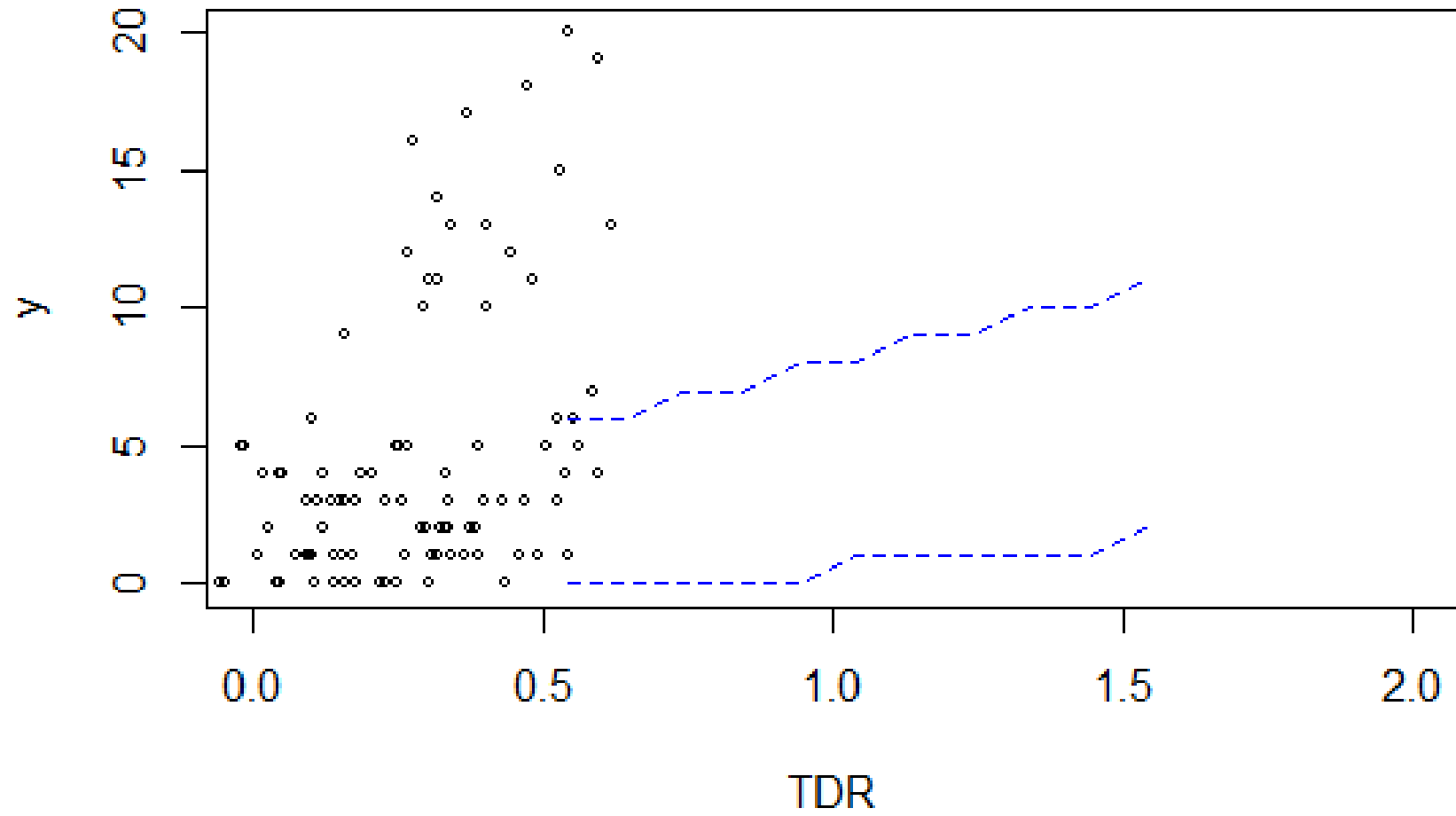
Missing Data



Missing Data



Missing Data



Latent Variables

- Any variable not directly observed

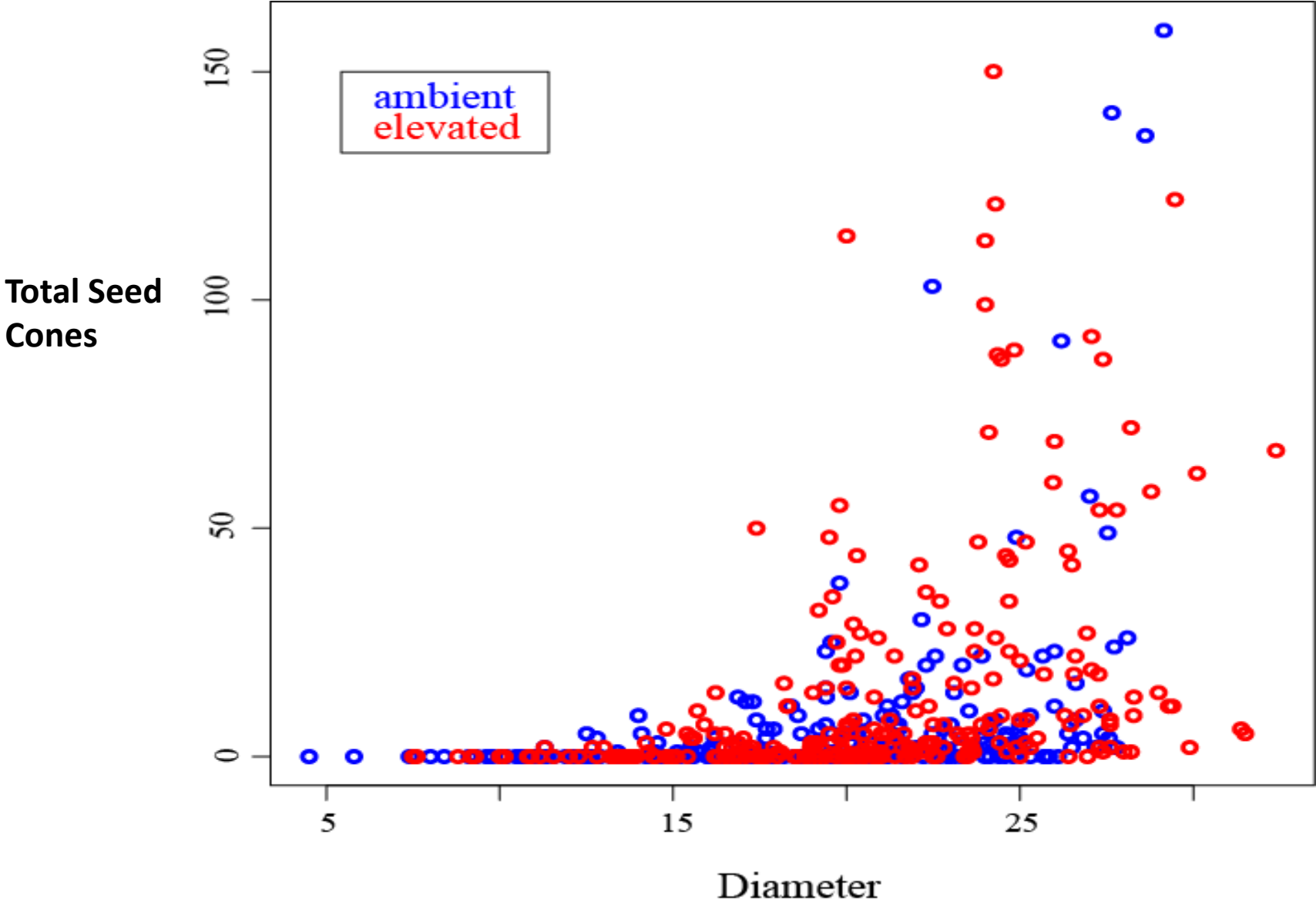
- Missing data

- Variable measured with error (e.g., detection models)

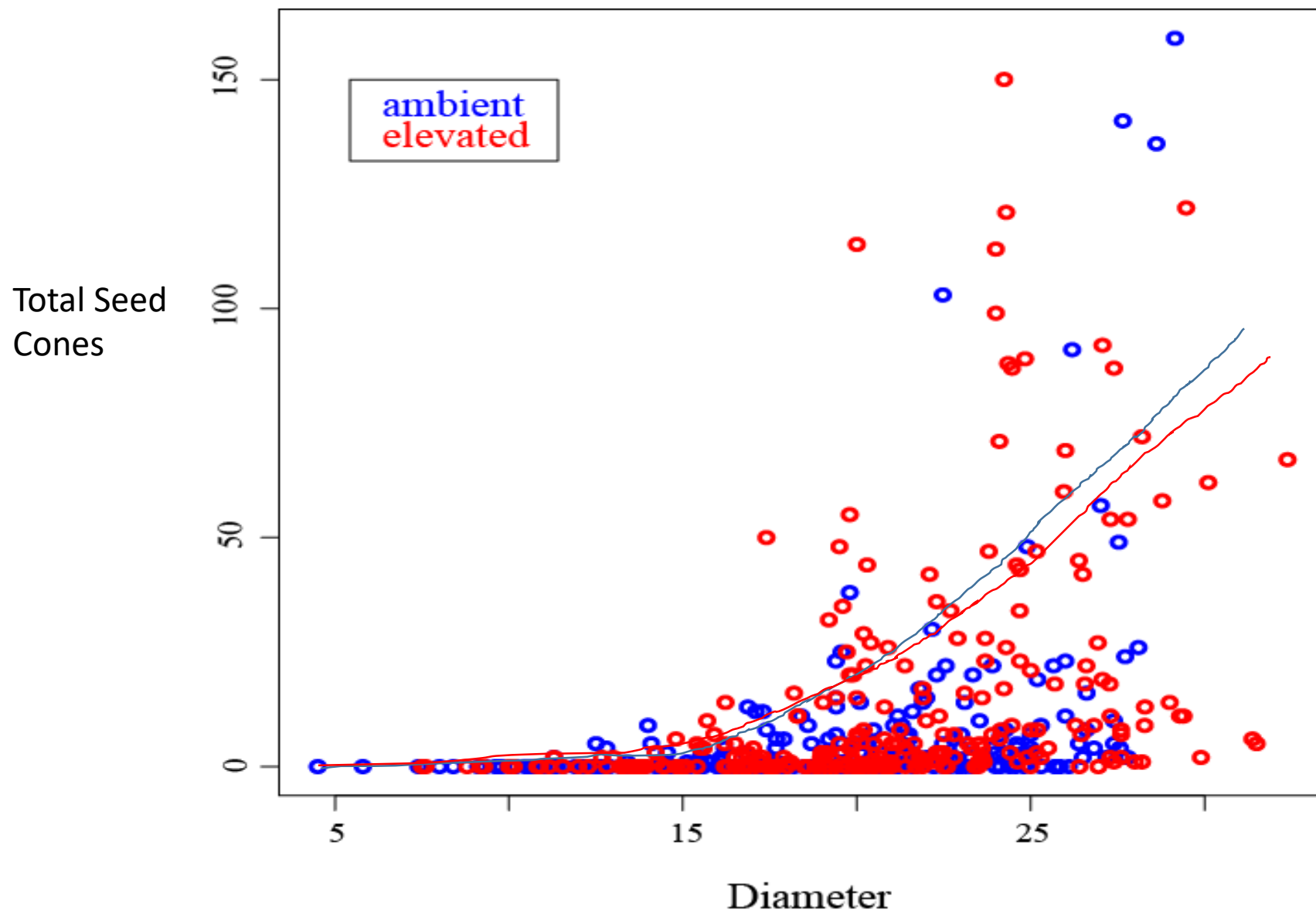
- **Proxy measures –estimating variables never observed**

Fecundity of trees is often related to tree size:

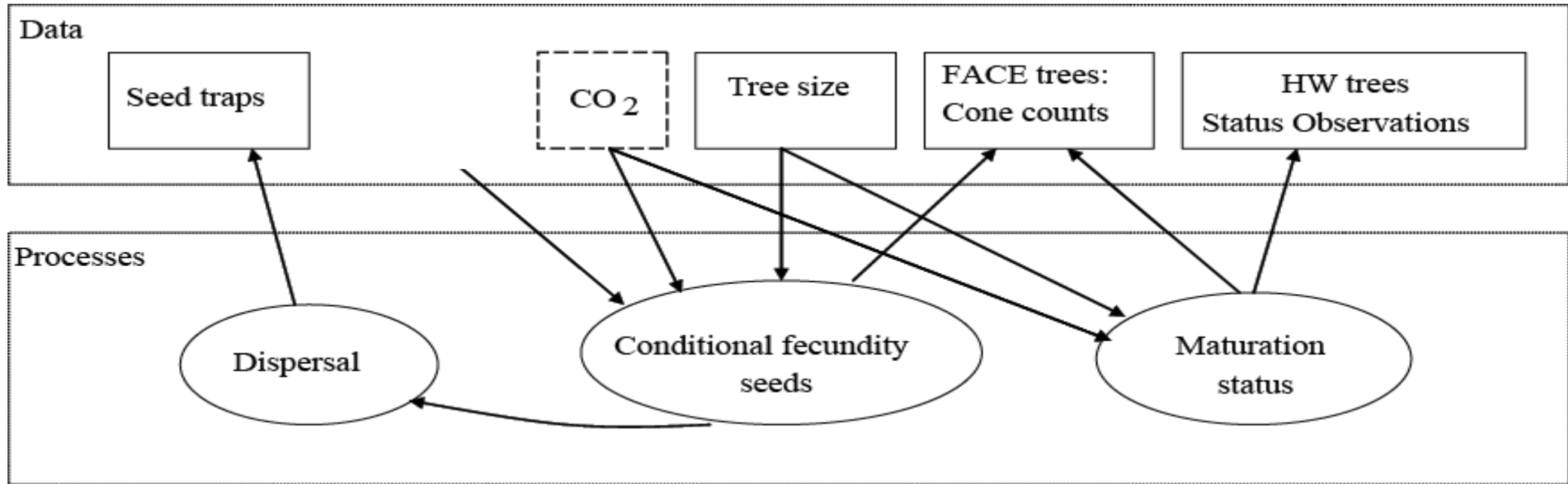
$$\text{seeds} = \text{fxn}(\text{diam})$$



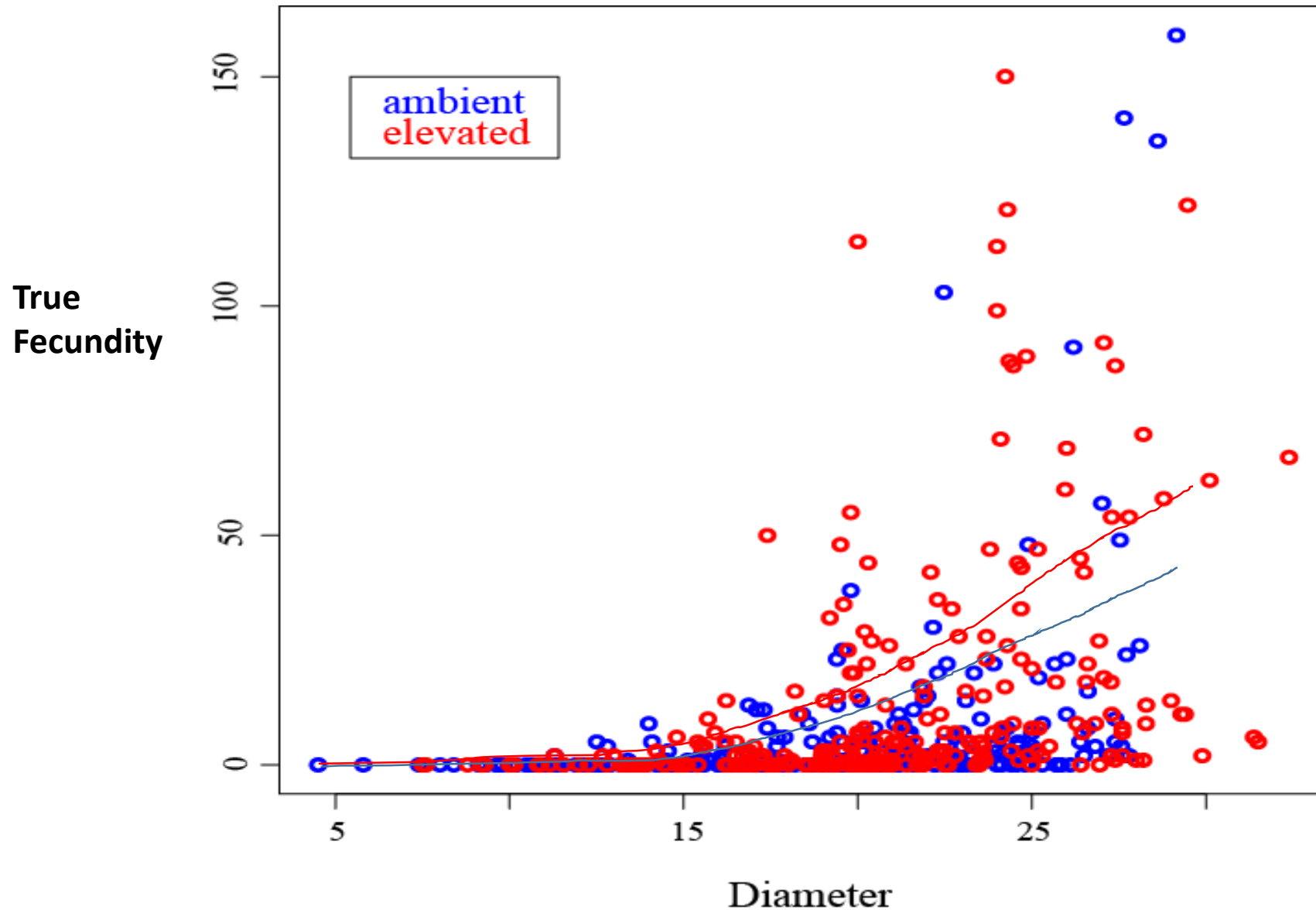
Regression would suggest more cones per diameter for ambient trees (blue line).



Modeling Fecundity



Accounting for tree maturation and fecundity highlight that many large ambient trees produce 0 seeds.



Latent Variables=

when variable of interest is not exactly what you measure

Ignoring variable latency (e.g., modeling a derived response or flawed observation) can lead to incorrect or overconfident conclusions