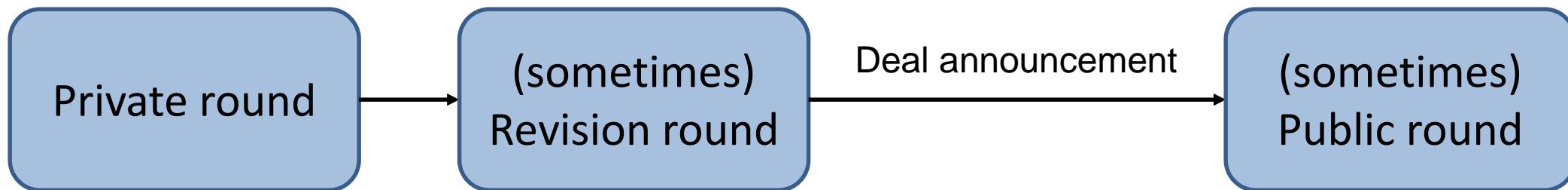


Model details

Real life complication: there may be several rounds of formal offers



To *illustrate* the model, consider a deal completed in the private round.

(Log) **target valuations** $v_{i,j}$ in deal i for bidder j are

$$v_{i,j} = \log b_{i,j} + X'_{i,j}\beta + \varepsilon_{i,j}$$

- Valuations and prices per share are in percentages of target market value

Model details, continued

(Log) **target valuations** $v_{i,j}$ in deal i for bidder j are

$$v_{i,j} = \log b_{i,j} + X'_{i,j}\beta + \varepsilon_{i,j}$$

Impose cross-bidder constraints on realizations of $\varepsilon_{i,j}$:

- If bidder 1 is the **winner** ($W_{i,1} = 1$), then
 - $v_{i,1} \geq v_{i,j}, j > 1$: the offer, including terms, is better than rival offers
 - $v_{i,1} \geq v_{i,0}$: the offer is better than standalone target value (which may be different from its market price)
 - N_i inequalities in a deal with N_i bidders
- If bidder $j > 1$ is the **loser** ($W_{i,j} = 0$), then
 - $v_{i,j} \leq v_{i,1}$; in robustness checks also impose $v_{i,1} \geq v_{i,0}$
 - Losing bidders are unranked among themselves

[Two rounds](#)

Model estimation

We estimate the model via **Gibbs sampler (MCMC)**. In each iteration k :

- Sequentially draw $\boldsymbol{v}_{i,j,k} = \log \mathbf{b}_{i,j} + \mathbf{X}'_{i,j} \boldsymbol{\beta}_{k-1} + \boldsymbol{e}_{i,j,k}$, $e_{i,j,k} \sim \text{TruncN}(0, \sigma_{\varepsilon,k-1}^2)$
 - E.g., if $v_{i,1,k}$ for winner is drawn first, $v_{i,1,k} \geq v_{i,j,k-1}$ and $v_{i,1,k} \geq v_{i,0,k-1}$ truncate $e_{i,1,k}$
- Estimate distributions of $\hat{\boldsymbol{\beta}}$ and $\hat{\sigma}_{\varepsilon}$ via OLS $\boldsymbol{v}_{i,j,k} = \log \mathbf{b}_{i,j} + \mathbf{X}'_{i,j} \boldsymbol{\beta} + \boldsymbol{\varepsilon}_{i,j,k}$
- Draw $\boldsymbol{\beta}_k$ and $\sigma_{\varepsilon,k}$ from these distributions to be used in the next iteration
- ...
- Analyze distributions of 50,000 iterations of $\boldsymbol{\beta}_k$ and $\sigma_{\varepsilon,k}$

Why Bayesian?

- Alternatively, can maximize the joint likelihood of all target decisions $W_{i,j}$ with respect to $\boldsymbol{\beta}$ and σ_{ε}
 - This is very computationally intensive: e.g., for a deal with 5 formal bidders, need to calculate the likelihood of a complex shape in a 6D probability space

Appendix: measurement error problem in simulations

Simulate 250 deals:

- Each deal i has between 2 and 5 bidders: typical in formal rounds of bidding
- Bidders offer prices $b_{i,j} = 1.3 + N(0, 0.4^2)$: typical offer premiums
- $X_{i,j}$ is a 0/1 dummy: e.g., due diligence closing condition
- True target valuations are $v_{i,j} = b_{i,j} + \frac{0.1}{\beta_1} X_{i,j} + N(0, \frac{0.25^2}{\sigma_\varepsilon})$

	$\widehat{\text{Const}}$	95% conf. int.	$\widehat{\beta}$	95% conf. int.	$\widehat{\sigma}_\varepsilon$
OLS w/o constant			-0.971	[-1.047, -0.895]	
OLS with constant	-0.990	[-1.030, -0.950]	0.019	[-0.038, 0.075]	
Model			0.099	[0.023, 0.179]	0.248

[Back](#)