Model details

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

Private round → (sometimes) Revision round $\xrightarrow{\text{Deal announcement}}$ (sometimes) Public round

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

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

- 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

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

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

- If bidder 1 is the ***winner*** ($W_{i,1} = 1$), then
  - $\boldsymbol{v_{i,1} \geq v_{i,j}, j > 1}$: the offer, including terms, is better than rival offers
  - $\boldsymbol{v_{i,1} \geq v_{i,0}}$: 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
  - $\boldsymbol{v_{i,j} \leq v_{i,1}}$; 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 $\boldsymbol{v_{i,j,k} = log\, b_{i,j} + X'_{i,j}\beta_{k-1} + e_{i,j,k}}$, $e_{i,j,k} \sim \text{Trunc}N\left(0, \sigma^2_{\varepsilon,k-1}\right)$
  - E.g., if $v_{i,1,k}$ for winner is drawn first, $\boldsymbol{v_{i,1,k}} \geq \boldsymbol{v_{i,j,k-1}}$ and $\boldsymbol{v_{i,1,k}} \geq \boldsymbol{v_{i,0,k-1}}$ truncate $e_{i,1,k}$
- Estimate distributions of $\hat{\beta}$ and $\hat{\sigma}_\varepsilon$ via OLS $\boldsymbol{v_{i,j,k} = log\, b_{i,j} + X'_{i,j}\beta + \varepsilon_{i,j,k}}$
- Draw β_k and $\sigma_{\varepsilon,k}$ from these distributions to be used in the next iteration

  …

- Analyze distributions of 50,000 iterations of β_k and $\sigma_{\varepsilon,k}$

Why Bayesian?

- Alternatively, can maximize the joint likelihood of all target decisions $W_{i,j}$ with respect to β 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 $v_{i,j} = b_{i,j} + \underbrace{\mathbf{0.1}}_{\beta_1} X_{i,j} + N(0, \underbrace{\mathbf{0.25}}_{\sigma_\varepsilon}{}^2)$

	$\widehat{\text{Const}}$	95% conf. int.	$\hat{\beta}$	95% conf. int.	$\hat{\sigma}_\varepsilon$
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

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