

Asymmetric Information and Bidding Behavior in Failed Bank Auctions

George & Shoukry (2024)

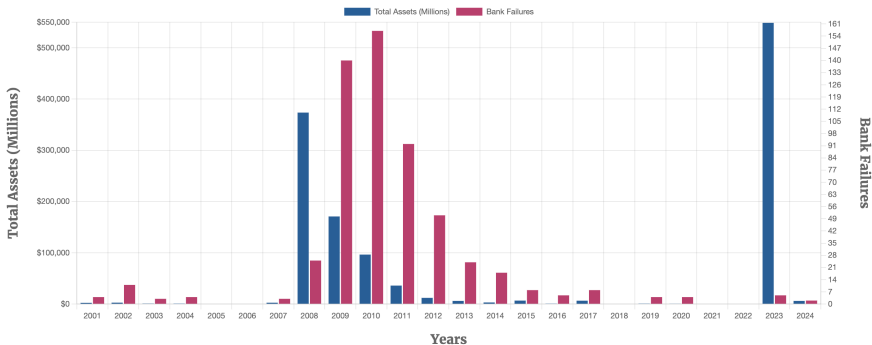
Discussion by Filippo Cavaleri¹
University of Chicago

March 22, 2025

¹Please send comments and suggestions to fcavaler@chicagobooth.edu.

Motivation and research question

- **Question:** What is the most efficient way to resolve bank failures?
 \Rightarrow 568 bank failures since 2001; some of them very salient, e.g. SVB.
- Auctions? However, information asymmetries can lead to inefficient allocations.

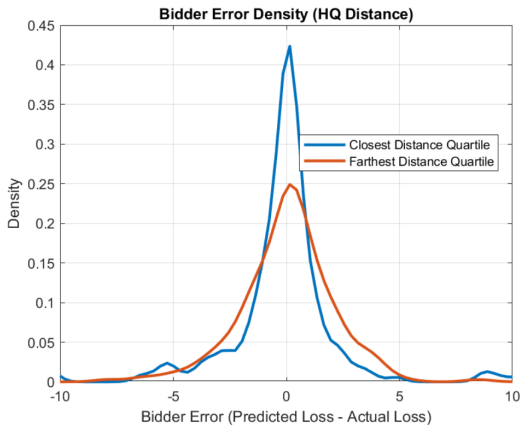


Summary and contribution

- Substantial information asymmetries across bidders in failed bank auctions.
⇒ Asymmetry driven by geographic distance; not so much by portfolio similarity.
- Dispersion in prediction errors higher for distant bidders.
- More distant bidders also tend to underpredict post-auction losses.
- Winner's curse: bidders who underpredict experience larger post-auction losses.
- Data: confidential data on post-auction asset performance and scoring rule.
⇒ Improvement over existing work where both features are not directly observable.
- Methodology: nonparametric relation between bids and (predicted) losses.
⇒ Machine learning: random forest; double ML; double residual kernel.

Main result: dispersion of prediction errors increases with distance

FIGURE 5. Error Density by Proximity (Headquarter Distance)



Comment 1: bidders asymmetry

- **Theory:** symmetric FPA efficient; asymmetries can lead to inefficient allocation.
- Two asymmetry sources in interdependent value auctions: **signals** and **values**.
⇒ Better information or higher valuations (or both)? Important for auction design.
- Given **bids** and **characteristics**; model extracts e_{ij} ; assumes L_i the same for all j .
⇒ The (observable!) loss would have been the same had someone else won the auction.

$$\hat{L}_{ij} = L_i + e_{ij}$$

$$b_{ij} = F(\hat{L}_{ij}) + G(x_{ij}) \implies L_i = F^{-1}(b_{ij} - G(x_{ij})) - e_{ij}$$

Comment 1: bidders asymmetry

- **Theory:** symmetric FPA efficient; asymmetries can lead to inefficient allocation.
- Two asymmetry sources in interdependent value auctions: **signals** and **values**.
⇒ Better information or higher valuations (or both)? Important for auction design.
- Given **bids** and **characteristics**; model extracts e_{ij} ; assumes L_i the same for all j .
⇒ Suppose instead that the loss $L_i = \bar{L}_i + \eta_{ij}$ depends on the winner's actions.

$$\hat{L}_{ij} = \bar{L}_i + \eta_{ij} + e_{ij}$$

$$b_{ij} = F(\hat{L}_{ij}) + G(x_{ij}) \implies L_i = F^{-1}(b_{ij} - G(x_{ij})) - e_{ij} - \eta_{ij}$$

- Unless $\eta_{ij} \subseteq x_{ij}$, residual r_{ij} conflates asymmetries in valuations and information.

Comment 1: bidders asymmetry

- **Theory:** symmetric FPA efficient; asymmetries can lead to inefficient allocation.
- Two asymmetry sources in interdependent value auctions: **signals** and **values**.
⇒ Better information or higher valuations (or both)? Important for auction design.
- Given **bids** and **characteristics**; model extracts e_{ij} ; assumes L_i the same for all j .
⇒ Suppose instead that the loss $L_i = \bar{L}_i + \eta_{ij}$ depends on the winner's actions.

$$\hat{L}_{ij} = \bar{L}_i + \eta_{ij} + e_{ij}$$

$$b_{ij} = F(\hat{L}_{ij}) + G(x_{ij}) \implies L_i = F^{-1}(b_{ij} - G(x_{ij})) - e_{ij} - \eta_{ij}$$

- Unless $\eta_{ij} \subseteq x_{ij}$, residual r_{ij} conflates asymmetries in valuations and information.
- Is the heterogeneity in valuation quantitatively relevant? *Probably yes*.
⇒ Agarwal et al. (2014): differences in regulation; Granja, Matvos & Seru (2017): balance sheet complementarities; Allen, Clark, Hickman & Richert (2023); ...
- **Suggestion:** *Clarify if heterogeneity in valuations/skills quantitatively matters; what is the relation between level and dispersion of prediction errors?*

Comment 2: asymmetric information and bidding behavior

- Main result: dispersion of e_{ij} higher for more distant bidders.
⇒ Information asymmetries grow with distance, likely because of heterogeneity in access to soft information (Granja, Matvos & Seru (2014)).

Comment 2: asymmetric information and bidding behavior

- Main result: dispersion of e_{ij} higher for more distant bidders.
⇒ Information asymmetries grow with distance, likely because of heterogeneity in access to soft information (Granja, Matvos & Seru (2014)).
- **Theory:** with information asymmetries, equilibria are rarely symmetric.
⇒ A classic example is Engelbrecht-Wiggans, Milgrom & Weber (1983).
- The functional relation between predicted loss and bids varies across bidders.

Comment 2: asymmetric information and bidding behavior

- Main result: dispersion of e_{ij} higher for more distant bidders.
⇒ Information asymmetries grow with distance, likely because of heterogeneity in access to soft information (Granja, Matvos & Seru (2014)).
- **Theory:** with information asymmetries, equilibria are rarely symmetric.
⇒ A classic example is Engelbrecht-Wiggans, Milgrom & Weber (1983).
- The functional relation between predicted loss and bids varies across bidders.
- In the data, does bidding behavior depend on geographical proximity to target?
⇒ Multiple multi-dimensional bids; contractual provisions; participation frequency.
- Imposing the same functional relation F across all bidders could be too restrictive.

Comment 2: asymmetric information and bidding behavior

- Main result: dispersion of e_{ij} higher for more distant bidders.
⇒ Information asymmetries grow with distance, likely because of heterogeneity in access to soft information (Granja, Matvos & Seru (2014)).
- **Theory:** with information asymmetries, equilibria are rarely symmetric.
⇒ A classic example is Engelbrecht-Wiggans, Milgrom & Weber (1983).
- The functional relation between predicted loss and bids varies across bidders.
- In the data, does bidding behavior depend on geographical proximity to target?
⇒ Multiple multi-dimensional bids; contractual provisions; participation frequency.
- Imposing the same functional relation F across all bidders could be too restrictive.
- **Suggestion:** *Explore how distance influences different dimensions of bidding. Divide bidders in two groups based on distance and estimate F separately.*

Policy implications: how to improve allocative efficiency?

- Information asymmetries suggest that auction allocations might be inefficient.
⇒ Costly for FDIC: buyers with the highest valuation do not necessarily win.

Policy implications: how to improve allocative efficiency?

- Information asymmetries suggest that auction allocations might be inefficient.
⇒ Costly for FDIC: buyers with the highest valuation do not necessarily win.
- **Policy 1: better disclosure?** For example targeted marketing, scoring rule,...
- However: soft information and budget constraints challenging to overcome.
⇒ Soft information hard to acquire in a timely manner; the best buyer might be financially constrained, regardless of information ([Granja et al. \(2017\)](#)).

Policy implications: how to improve allocative efficiency?

- Information asymmetries suggest that auction allocations might be inefficient.
⇒ Costly for FDIC: buyers with the highest valuation do not necessarily win.
- **Policy 1: better disclosure?** For example targeted marketing, scoring rule,...
- However: soft information and budget constraints challenging to overcome.
⇒ Soft information hard to acquire in a timely manner; the best buyer might be financially constrained, regardless of information ([Granja et al. \(2017\)](#)).
- **Policy 2: resale** may improve efficiency; gains from trade after dust settles.
- Current provisions limit resale; assets may end up being stuck with worse buyers.
⇒ Anti-flipping provisions; constraints on branch closures; share loss agreement.
- Is a contract granting the FDIC a percentage of future resale profits feasible?

Policy implications: how to improve allocative efficiency?

- Information asymmetries suggest that auction allocations might be inefficient.
⇒ Costly for FDIC: buyers with the highest valuation do not necessarily win.
- **Policy 1: better disclosure?** For example targeted marketing, scoring rule,...
- However: soft information and budget constraints challenging to overcome.
⇒ Soft information hard to acquire in a timely manner; the best buyer might be financially constrained, regardless of information ([Granja et al. \(2017\)](#)).
- **Policy 2: resale** may improve efficiency; gains from trade after dust settles.
- Current provisions limit resale; assets may end up being stuck with worse buyers.
⇒ Anti-flipping provisions; constraints on branch closures; share loss agreement.
- Is a contract granting the FDIC a percentage of future resale profits feasible?
- **Suggestion:** *Explore the best way to mitigate inefficiencies from information asymmetries: better disclosure or promote future resale?*

Other minor points

- Multiple bids, likely because of scoring rule uncertainty (Allen et al. (2023)).
⇒ Bidders do not know ex-ante which of their bids is the best bid: their other bids may provide additional information about the uncertainty they face.
- FDIC typically sets a reserve price; cost of directly repaying insured deposits.
⇒ How does that impact bidding behavior and which bidders win the auction?
- Winner's curse not an equilibrium outcome: rational bidders account for it provided they play equilibrium strategies. Are bidders playing best responses?
- How do the estimated bid functions compare to benchmarks, e.g. IPV, CV?

Outlook and conclusion

- Very nice and interesting paper; I learned a lot!
 - Main result: dispersion in prediction errors increase with geographic distance.
 - Novel data on failed bank auctions: **scoring rule** and ex-post **asset-level losses**.
-
- **Suggestion 1**: disentangle asymmetries in information versus valuations.
 - **Suggestion 2**: explore how information asymmetries impact bidding behavior.
-
- Policy implications: disclosing more or promoting resale? **Open question**.