Banking System Fragility and Resolution Costs

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Workshop on Banking and Financial Stability at the Central Bank of Chile

September 12, 2024

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- The FDIC **resolves** insolvent institutions: put up for auction
- It typically **loses money** on these transactions
  - Cost to *Deposit Insurance Fund* during GFC was over $90 billion (25% of failed bank assets)
    - Resulting deficit (-$20.9 billion) covered by:
      (i) borrowing from the U.S. Treasury
      (ii) increasing assessment rates
    - Generates **distortions** & affects lending when the system is in turmoil

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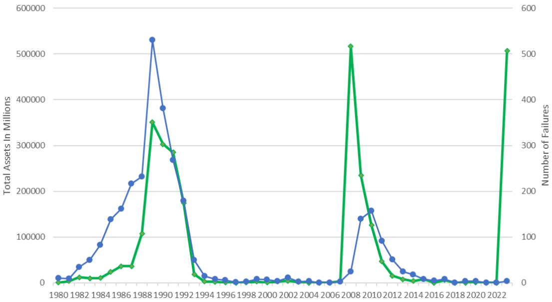

Many failures are clustered together in crises

- Potential buyers may be less able to pay, increasing resolution costs

Monetary Tightening Crisis Spring 2023

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- **Concern in Spring 2023:** Many other banks might be **at-risk** too!

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2. Structurally estimate costs to FDIC of resolving at-risk banks
   - Use FDIC data on bank failures during GFC
   - Value distributions estimated with methodology of Allen et al. (ReStud 2023)
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   - Extend to model entry process that endogenously determines the number of bidders
3. Simulate impact of different eligibility criteria and/or macroeconomic shocks
   - Increase competition by removing size and health restrictions

Empirical exercise and preview of results

1. Validate our approach using failures from 2017-2023 (for which costs/format are known)
   - Predicted average loss of 17.92% of failed bank assets
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   1. Identify 185 / 247 at-risk banks using Jiang et al. (2023) approach
   2. Estimate total resolution cost would be over **$105 billion** (including four actual failures)
      - Approaching the $128 billion in the FDIC's deposit insurance fund!
      - High cost estimate largely explained by lack of competition
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3. Counterfactuals suggest that eliminating size or health restrictions could lower these costs
   - During crises resolution costs can spiral as the set of unconstrained bidders shrinks

Institutional Background

FDIC Resolution Process

- Primary resolution method: **Purchase & Assumption** transaction
  - Troubled institution (physical assets, investment portfolios, customer deposit accounts) auctioned off to *large* and *healthy* banks

- Procedure:
  1. Bank's regulator informs the FDIC of pending failure
  2. Can close a bank that is
     - ☐ Critically undercapitalized
     - ☐ Assets less than obligations to creditors
  3. FDIC determines liquidation value of bank
  4. Establishes *eligible bidder* list based on participation constraints
  5. A subset sign NDA to learn the basic info, get access to virtual data room (*potential bidders*)
  6. A subset of the potential bidders become *actual bidders* by performing costly due diligence/merger valuation and submitting P&A bids
  7. FDIC selects least-cost bid or liquidates

FDIC Participation Constraints

- FDIC participation constraints:
  - Size restrictions:
    - Assets at least twice as large as those of failing bank
  - Health restrictions, require satisfactory:
    - Tier 1 leverage capital ratio
    - CAMELS ratings
    - Compliance rating
    - Bank holding company composite rating
    - Community Reinvestment Act rating
    - Anti-money laundering record

Key features of the auction process

1. Bidding is multidimensional
   - Cash (continuous)
   - Four discrete components (loss share, partial bank, nonconforming, value appreciation instrument): 16 possible *packages*
2. FDIC's mandate is to resolve the failing institution at the *lowest cost*
3. Algorithm for calculating the least-cost bid is proprietary
   - Uncertain (from bidders' perspectives) auction-specific scoring rule
4. Banks permitted to submit multiple bids in the same auction

Dataset

- **Data:** mostly gathered from FDIC website ◂ Summary Stats
  - Failed bank list and resolution cost
  - Full summaries for ALL bid proposals
    - ☐ See bid proposals matched to identities of winner and low-cost loser

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- **2009-2013 Sample:** 322 auctions
  - Characteristics of failed and bidding banks (SOD, Call Reports)
- **2017-2023 Sample:** 20 auctions
  - Characteristics of failed banks (SOD, Call Reports)
  - Resolution costs to FDIC for 20 auctions
- **Monetary tightening / CRE Samples:** 185 + 62 auctions
  - Characteristics of Modern banks (SOD, Call Reports)

Framework for Forecasting Resolution Costs

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- Approach:
    - GFC-era data: estimate a multi-stage entry and bidding model
    - 2017-2023 data: validate model's ability to forecast actual resolution costs
    - Contemporary data: forecast resolution costs of hypothetical failure wave
        - *At-risk* banks: e.g., Problem-bank list or banks at risk during a modern crisis
        - *Bidder-eligible* banks: criteria – (i) financial health, (ii) size relative to failed bank

Stage 1: Post-Failure Bank Merger Valuations – Conditional on Entry

- **Structurally estimate the underlying preferences of banks for failed institutions and different components**
  - Model of merger valuations based on Allen et al. 2023
  - Generalize existing empirical auction methods:
    - Setup similar to *pay-as-bid package auction*
    - Bids can be on any subset of packages
  - Extend combinatorial auction techniques - Cantillon & Pesendorfer (2007)
    - C&P extend Guerre, Perrigne and Vuong (2000) FOC approach to the case of package bidding for dissimilar objects
    - We extend further to deal with uncertainty over scoring rule

Stage 1: Empirical Strategy (GPV)

- Classic techniques pioneered by Guerre, Perrigne, and Vuong (*Econometrica*, 2000)
- GPV setting: Single-object first price auction with N symmetric bidders, valuations v_i
- Bidder i's (reduced-form) problem:

$$\max_{b_i} \pi_i(v_i, b_i) = [v_i - b_i]G(b_i)$$

where

$$G(b_i) = Prob(\max_{\ell \neq i} b_\ell \leq b_i) = Prob(b_i \text{ is the winning bid})$$

- Which yields the following expression for valuations in terms of observables:

$$v_i = b_i + \frac{G(b_i)}{g(b_i)}$$

Stage 1: package auctions with noisy scoring rule

- This approach is more complicated in our setting:
  - Multiple first order conditions (one for each package):
    - Hold with equality for packages bid on
    - Inequalities otherwise
  - Construction of G (prob. of winning) more complicated
    - Unknown set of asymmetric competitors
    - Unknown scoring rule
    - Multiple bidding – own bid is in G
  - But simpler combinatorial setting than C&P:
    - Only one winner possible

Stage 1: package auctions with noisy scoring rule

- Failed Banks (auctions) indexed $j = 1, \ldots, J$
- Bidders (healthy banks) indexed $i = 1, \ldots, N_j$
  - $N_j \sim \pi(N|\boldsymbol{Z}_j)$ unobserved to individual bidders
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- Bidder i draws private valuation for AS-IS takeover contract:
  - $\overline{V}_{ij} \sim F_{\overline{v}}(\overline{V}_{ij}|\mathbf{W_{ij}}, \mathbf{Z_j})$ (where $\boldsymbol{W}_{ij}$ is bidder observables)

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- Package-Specific Valuations depend on component switches:

$$
\begin{aligned}
v_{ijk} \quad &= \quad \bar{v}_{ij} + v_{ij}^{LS} d_k^{LS} + v_{ij}^{NC} d_k^{NC} + v_{ij}^{PB} d_k^{PB} + v_{ij}^{VAI} d_k^{VAI} + \boldsymbol{D}_k \boldsymbol{\lambda} \\
& \quad d_k^s = \mathbf{1}\left[\text{switch } s \text{ on in } k^{th} \text{ package}\right], \; k = 1, \ldots, 16 \\
& \quad \boldsymbol{D}_k \boldsymbol{\lambda} \text{ accounts for switch complementarity}
\end{aligned}
$$

Stage 1: Bidding behavior

- Bidders choose an optimal package portfolio L_{ij}^*, and bid profile $\boldsymbol{b}_{ij}^*$ to solve:

$$\max_{L_{ij}}\left\{\max_{\boldsymbol{b}_{ij}\in\mathbb{R}^{16}}\sum_{k\in L_{ij}}(v_{ijk}-b_{ijk})G(b_{ijk}|L_{ij},\boldsymbol{b}_{ij}^{-k},\boldsymbol{X}_j)\right\}$$

$$G(b_{ijk}|L_{ij},\boldsymbol{b}_{ij}^{-k},\boldsymbol{X}_j)\equiv\Pr\left[\text{win } k^{th} \text{ package with } b_{ijk}\;\middle|\; L_{ij},\,\boldsymbol{b}_{ij}^{-k},\boldsymbol{X}_j\right]$$

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- FOC (GPV inversion), for each k:

$$v_{ijk} = b_{ijk} + \frac{G(b_{ijk}|L_{ij}, \boldsymbol{b}_{ij}^{-k}, \boldsymbol{X}_j) + \sum_{k'\in L_{ij},\, k'\neq k} (v_{ijk'} - b_{ijk'}) \frac{\partial G(b_{ijk'}|L_{ij}, \boldsymbol{b}_{ij}^{-k}, \boldsymbol{X}_j)}{\partial b_{ijk}}}{g(b_{ijk}|L_{ij}, \boldsymbol{b}_{ij}^{-k}, \boldsymbol{X}_j)}$$

(For packages not bid on: Similar but inequality)

◂ Model assumptions

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4. Finally, we can project
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5. So, **with α, β we know merger valuations as functions of $\boldsymbol{X}_{ij} = \boldsymbol{Z}_j \otimes \boldsymbol{W}_{ij}$**,
   - (i.e., balance-sheet info. for failed banks and bidders)

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  - Total # of potential bidders is: $N^p \sim \psi(n|\overline{N}_j)$
- Potential bidder i doesn't know precise merger value $\overline{V}_{ij}$ when deciding on entry
  - Requires costly due diligence/merger valuation analysis to learn
  - Inputs by accountants, lawyers, finance experts, consultants, executives, etc...
- Idiosyncratic entry cost $\eta_i \sim H_\eta(\eta|\boldsymbol{Z}_j)$
  - Must incur cost η_i to learn $\overline{V}_{ij}$, become ***actual bidder***

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- Potential bidder i enters auction j if expected surplus exceeds entry cost:

$$S_{ij} \equiv E\left[surplus \middle| \boldsymbol{W}_{ij}, \boldsymbol{Z}_j\right] \qquad (unconditional\ on\ winning)$$

$$= E\left[\sum_{k=1}^{K} (V_{ijk} - b^*_{ijk}(\overline{V}))Pr\left[win\ contract\ k \middle| \boldsymbol{b}^*_{ij}(\overline{V})\right] \middle| \boldsymbol{W}_{ij}, \boldsymbol{Z}_j\right] \geq \eta_i,$$

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- This entry process generates distributions of actual bidders $N \sim \pi(N|\boldsymbol{Z}_j)$ and surpluses S
  - *Known from STAGE 1 estimation*

Stage 2: Identification

Key assumptions:

1. *Entry Costs* η_i *are independent of* $\overline{V}_{ij}$ (and also $\boldsymbol{W}_{ij}$ for simplicity)
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2. *At least one of the following is true:*

   (*i*) *EITHER* $\max\{Supp(\eta)\} < \max\{Supp(S_{ij})\}$

   - Maximal entry costs are lower than maximal merger surplus.

   (*ii*) *OR* $\lim_{\overline{N}\to 1} p(y_\ell, \overline{N}) = 1$ for each $l = 1, \ldots, L$

   - FDIC ramps up proactive marketing efforts when eligible bidder pool becomes small.

Stage 2: Identification

Identification: *Entry model primitives $H_\eta(\eta)$, $p(y_1, \overline{N}_j)$, and $p(y_2, \overline{N}_j)$ are uniquely pinned down from observables $(\mathcal{E}_{ij}, s_{ij}, y_{ij}, \overline{N}_j)$ for each eligible bank i in auction j (where $\mathcal{E}_{ij} = 1$ means i enters auction j).* Formal proof

1. Expected surplus s_{ij} is known from STAGE 1 estimation.

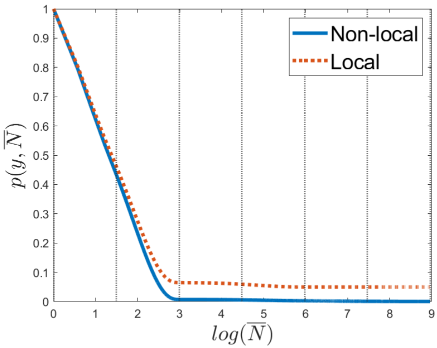
2. Model implies that entry probabilities, given $\overline{N}$, y_ℓ, and s can be characterized as

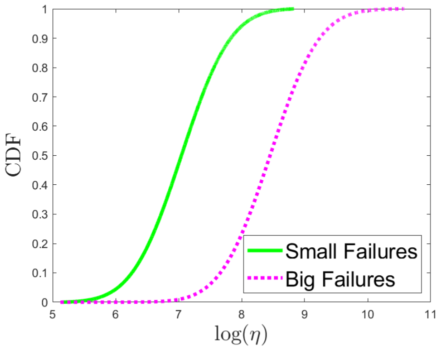
$$Pr(\mathcal{E} = 1 | \overline{N}_j, s, y_\ell, \boldsymbol{Z}_j) = H_\eta(s|\boldsymbol{Z}_j) p(y_\ell, \overline{N}_j), \quad l = 1, 2.$$

   - *The left-hand side is raw data; right-hand side is model.*

3. Estimation is Maximum Likelihood

Entry Model Estimates





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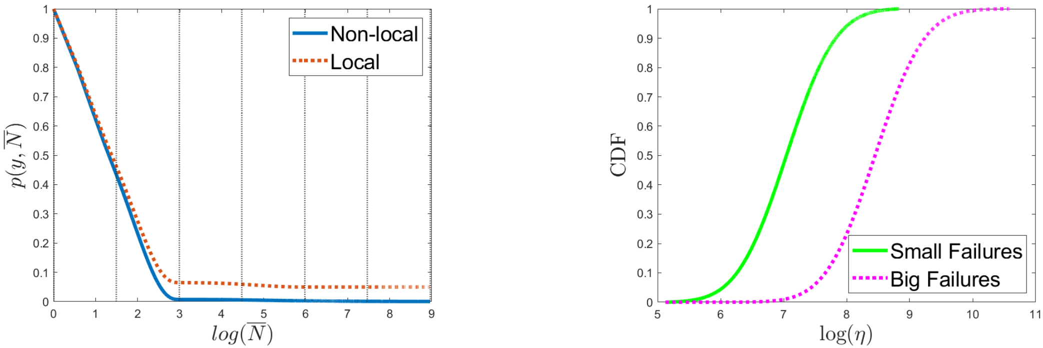

- Median Entry Costs:
  - \$1.1M / \$4.6 conditional on entry (for small / large failures)

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   - This gives $\overline{N}_j$ and a pool of eligible $\boldsymbol{W}_{ij}$'s

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   - This gives $\overline{N}_j$ and a pool of eligible $\boldsymbol{W}_{ij}$'s
3. Then, for each at-risk bank j, use model estimates *(from GFC-era data)* to repeatedly:

   (*i*) Simulate entry decisions
   - This implies distribution of actual bidders $\pi(N|\boldsymbol{Z}_{ij})$
   - Also implies distribution of merger values $\overline{V}_{ij}$

   (*ii*) Simulate optimal bids $(L_{ij}^{*}, \boldsymbol{b}_{ij}^{*})$ for each entrant i in auction j

   (*iii*) Determine winner, final resolution costs for at-risk bank j

Empirical Implementation: Simulation of Contemporary Banking Crises

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   - This implies a pool of $\boldsymbol{Z}_j$'s (most likely failure candidates)

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   (ii) Simulate optimal bids $(L^*_{ij}, \boldsymbol{b}^*_{ij})$ for each entrant i in auction j

   (iii) Determine winner, final resolution costs for at-risk bank j

4. Average resolution costs across simulations Assumptions

Model validation

Validation: failures from 2017-2023

Forecast cost of 20 failures from 2017-2023 for which resolution cost/sale format known

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Forecast cost of 20 failures from 2017-2023 for which resolution cost/sale format known

- Model predicts:
  - \$26.42 billion cost vs. \$36.5 billion actual
  - Average 17.92% of failed bank assets vs. 19.81% actual
  - Predicted/realized losses correlation of 0.53 and significant at 5%

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  - \$26.42 billion cost vs. \$36.5 billion actual
  - Average 17.92% of failed bank assets vs. 19.81% actual
  - Predicted/realized losses correlation of 0.53 and significant at 5%
- Compare to naive OLS predictions: $\hat{c}_{ijk} = \boldsymbol{X}_{ij}\gamma$ (γ estimated on GFC data)
  - Average loss 25.85%
  - Correlation of -0.01, not significant

Our method captures changes in costs resulting from strategic bidding behavior as the set of participants and macroeconomic conditions shift over time

- Naive approach can't account for changes in participation in 2017-2023

Resolving a Contemporary Banking Crisis: Monetary Tightening / CRE

Identifying at-risk banks using Jiang et al (2023) approach

- For each US bank calculate its *Insured Deposit Coverage ratio*:

$$\textbf{IDC ratio} = \frac{\text{Marked-to-market Assets} - \text{Uninsured Deposits} - \text{Insured Deposits}}{\text{Insured Deposits}}$$

- Market values of assets estimated using data on traded indexes in real estate, US Treasuries
  - By the first quarter of 2023, the rate increase resulted in 9% decline in marked-to-market value of the median bank's assets

- A bank is classified as *at-risk* if its IDC ratio would be negative in the event 50% of its uninsured deposits ran.

  $\rightarrow$ 185 such banks ◂ Bidder Sum Stats

Expected Auction Outcomes

	Mean	StDev
Costs ($Millions)	378.7	1935.7
Costs (%FBAssets)	18.41	2.29

- Takeaways:
  - Average resolution cost: $379 million (vs. $135 million per failure during GFC)
  - Total cost for resolving 185 at-risk banks: $70 billion (plus $35 billion for four 2023 failures)
    - Approaches the $128 billion in the Deposit Insurance Fund

Expanding the bidder pool

- Elevated cost driven by difficulty finding banks able to participate and willing to submit bids $>$ FDIC's liquidation value
  - Only 1.54 bidders on average
- Investigate impact of size & health constraints on resolution costs
  - Size: allow bidders to offer on banks of any size
  - Health: allow even unhealthy banks to participate (not a policy CF!)
- Investigate bidder options:
  - How would resolution costs change if FDIC allowed LS or PB bidding?

Expected Auction Outcomes

	Mean	StDev
Costs ($ millions)		
Current rules	378.7	1935.7
Relaxing solvency & size	232.3	1369.0
Relaxing solvency	398.6	2344.4
Relaxing size	255.0	1469.6
Costs (%FBA)		
Current rules	18.41	2.29
Relaxing solvency & size	14.38	3.39
Relaxing solvency	17.19	2.61
Relaxing size	15.53	3.06

- Takeaways:
  - Relaxing Both: ↑ nbr bidders to 2.60, ↓ costs to $232M/bank
  - Relaxing solvency: ↑ nbr bidders to 1.79, ↑ costs to $398M/bank
  - Relaxing size: ↑ nbr bidders to 2.22, ↓ costs to $255M/bank

How Do Constraints Impact Purchasers?

Table: Impact on Average Auction Winner Traits

	Size ($B)	Same-Zip (%)	T1
Current rules	109.01	15.88	10.39
Relaxing solvency & size	49.99	17.72	10.89
Relaxing Solvency	106.3	18.34	9.91
Relaxing Size	48.6	12.80	11.83

- Takeaways:
  - Relaxing Both: $\uparrow$ capitalization and local overlap, $\downarrow$ size
  - Relaxing size: $\downarrow$ size, $\downarrow$ local network overlap
  - Relaxing solvency: $\uparrow$ local overlap, small $\downarrow$ size
  - SVB: size constraint removed, cost $16.2B $\sim$ actual $20B

Imposing bans on purchases by local banks

	Mean	StDev
Costs ($ millions)		
Whole bank	379	1935.7
Banning Local Sales	410.1	1983.3
Costs (%FBA)		
Whole bank	18.41	2.29
Banning Local Sales	19.80	2.26

Impact on Winner Traits			
	Size ($B)	Same-Zip (%)	T1
Whole Bank	109.01	15.88	10.39
Banning Local Sales	29.22	0	10.63

CRE crisis

	Mean	StDev
Costs ($ millions)		
Whole bank	319.83	1636.2
Relaxing solvency & size	194.13	1188.2
Relaxing solvency	341.59	2042.1
Relaxing size	263.46	1708.1
Costs (%FBA)		
Whole bank	18.30	2.14
Relaxing solvency & size	14.12	3.30
Relaxing solvency	17.08	2.43
Relaxing size	15.29	3.00

Impact on Average Winners Traits

	Size ($B)	Same-Zip (%)	T1
Whole Bank	108.08	16.6	10.35
Relaxing solvency & size	49.6	17.98	10.90
Relaxing Size	105.2	13.36	11.82
Relaxing Solvency	49.9	18.78	9.89

Conclusion

Conclusion

- We develop a framework to estimate the costs to the FDIC of resolving *at-risk* banks
  - Superior to regression model out of sample: captures changes in buyer health
  - 2023 Crisis: The cost of resolving these banks would be over $105 billion
    - Approaches the $128 billion in the FDIC's deposit insurance fund!
    - Our CFs suggest that eliminating size or health restrictions could lower these costs
  - During crises resolution costs can spiral as the set of unconstrained bidders shrinks
- Tool allows the FDIC to estimate costs in real-time, understand the impact of macroeconomic conditions, & evaluate costs of participation constraints,

Additional Slides

Least-cost resolution example

Cost = transactions equity + asset discount - deposit premium + expenses

- Deposits: \$1 million
- Loans outstanding \$500,000; book value only \$250,000
- Cash on hand: \$500,000
- total assets = loan outstanding + cash = \$750,000
- Transaction equity = 750,000-1,000,000 = (\$250,000)

- Bid: asset discount of \$120,000, deposit premium of \$100,000

Transfer from FDIC to winning bank = \$250,000 + \$120,000 - \$100,000 + expenses.

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FDIC Bid Summaries

Bid Summary

Legacy Bank, Scottsdale, AZ
Closing Date: January 7, 2011

Bidder	Type of Transaction	Deposit Premium/ (Discount) %	Asset Premium/ (Discount) $(000) / %	SF Loss Share Tranche 1	SF Loss Share Tranche 2	SF Loss Share Tranche 3	Commercial Loss Share Tranche 1	Commercial Loss Share Tranche 2	Commercial Loss Share Tranche 3	Value Appreciation Instrument	Conforming Bid	Linked
Winning bid and bidder: Enterprise Bank & Trust, Clayton, Missouri	Nonconforming all deposit whole bank with loss share (1)	1.00%	$ (9995)	80%	80%	NA	80%	80%	NA	Yes	No	N/A
Cover - Commerce Bank of Arizona, Tucson, Arizona	All deposit whole bank with loss share	0.25%	$ (21975)	75%	75%	N/A	75%	75%	N/A	No	Yes	N/A
Other bid	All deposit whole bank with loss share	1.00%	$ (9525)	80%	80%	N/A	80%	80%	N/A	No	Yes	N/A
Other bid	All deposit whole bank with loss share	0.25%	$ (21475)	80%	80%	N/A	80%	80%	N/A	No	Yes	N/A
Other bid	All deposit whole bank with loss share	0.00%	$ (22000)	80%	80%	N/A	80%	80%	N/A	No	Yes	N/A
Other bid	Nonconforming Whole Bank P&A (2)	0.00%	$ (41679)	N/A	N/A	N/A	N/A	N/A	N/A	No	No	N/A

(1) Deemed nonconforming due to cap placed on Value Appreciation Instrument
(2) Deemed nonconforming since bid excluded all OREO.

Other Bidder Names:

Commerce Bank of Arizona, Tucson, Arizona
Enterprise Bank & Trust, Clayton, Missouri
SouthWest Bank, Odessa, Texas
Wedbush Bank, Los Angeles, California

Summary Statistics

Variable	GFC-Era Mean	GFC-Era 10-90 Interval	Validation Sample Mean	Validation Sample 10-90 Interval	Contemporary At-Risk Sample: Monetary Mean	Monetary 10-90 Interval	CRE-Crisis Mean	CRE-Crisis 10-90 Interval
#Failed/At-Risk Banks	322	–	20	–	185	–	62	
Tot. Assets ($M)	827	[64, 1348]	26743	[39, 154480]	1811	[53,1953]	750	[78,1895]
Tot. Depos. ($M)	702	[60, 1262]	23139	[34, 136450]	1673	[50,1710]	685	[73,1658]
Ins. Depos. ($M)	630	[55, 1207]	3359	[31, 9179]	1533	[43, 1353]	571	[66,1431]
Core Depos. (%)	77	[56, 95]	88	[61, 100]	94	[85, 100]	92	[83,100]
CRE (%)	25	[10.43, 43.31]	13	[1, 32]	9	[0,20]	15	[5,28]
C&I (%)	8.00	[1.52, 17.37]	12	[1, 26]	4	[0,8]	4	[4,9]
CNSMR (%)	1.52	[0.10, 3.71]	2	[0, 6]	3	[0,6]	2	[1,5]
SFR (%)	18.41	[3.71, 35.71]	22	[3, 49]	32	[6,62]	23	[10,46]
ARE (%)	59.90	[44.87, 74.27]	64	[36, 93]	81	[60,98]	83	[65,97]
ROA	-6.81	[−12.90, −1.72]	-2.3	[−7.3, 1.5]	0.7	[0.2,1.3]	0.9	[0.45,1.69]
Tier 1 Ratio	1.17	[−1.79, 3.58]	5	[1, 9]	9	[2,13]	9	[7,12]
NA (%)	10.97	[4.35, 19.44]	5.7	[0, 14]	0.32	[0,0.77]	0.21	[0,0.6]

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Model assumptions

- Bidders have IPV for absorbing the failed bank's depositors, liabilities, and assets into their own businesses
  - Heterogeneous synergies between bidder and failed-bank assets and depositor base
  - Limited resale opportunities
  - Ex-ante symmetry of information about ex-post value
- Independence Across Auctions
  - No learning
  - No complementarities
  - No dynamic capacity constraints

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Estimation/Identification Overview

Step 1: Estimate G (prob. of winning)

(*i*) Recover Distribution of least-cost scoring rule

$$c_{ijk} = b_{ijk} + \epsilon_j d_{ijk}^{LS}(\%LS) + \kappa_j d_{ijk}^{NC} + \nu_j d_{ijk}^{PB}(\%PB) + \psi_j d_{ijk}^{VAI} + \delta_{ij} + u_j$$

- Estimation: Auction-specific scoring rule weights $(\epsilon_j, \kappa_j, \nu_j, \psi_j)$ assumed normally distributed
- Identification: Observe cost equation for the winning bid; Inequality for all losing bids

(*ii*) Construct weighted bootstrap sample of offers from bidders in similar auctions to determine probability a given bid wins (Hortacsu & McAdams, 2010)

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Estimation/Identification Overview

- **Step 2:** Backing out private values
  - GPV-type inversion to get package-specific $\hat{v}_{ijk}$
  - Specify component-specific valuation as a function of observed traits of bidder & failed bank: $v_{ij}^{s} = \boldsymbol{X}_{ij}\beta^{s}, \; s = LS, NC, PB, VAI$
  - Use panel structure from multiple bids to estimate FE model

$$\hat{v}_{ijk} = \overline{v}_{ij} + \boldsymbol{X}_{ij}\boldsymbol{\beta}\boldsymbol{d}_{k} + \xi_{ijk}, \; i = 1, \ldots, N_j, \; j = 1, \ldots, J$$

STAGE 2: Identification

Identification: *Entry model primitives* $H_\eta(\eta)$, $p(y_1, \overline{N}_j)$, *and* $p(y_2, \overline{N}_j)$ *are uniquely determined by observables* $(\mathcal{E}_{ij}, s_{ij}, y_{ij}, \overline{N}_j)$ *for each eligible bank* i *in auction* j *(where* $\mathcal{E}_{ij} = \mathbb{1}$ *means* i *enters auction* j*).*

1. Expected surplus s_{ij} is known from STAGE 1 estimation.

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1. Expected surplus s_{ij} is known from STAGE 1 estimation.
2. Model implies that entry probabilities, given $\overline{N}$, y_ℓ, and s can be characterized as $Pr(\mathcal{E}=1|\overline{N}_j, s, y_\ell) = H_\eta(s)p(y_\ell, \overline{N}_j), \quad l = 1, 2.$
   - *The left-hand side values of the above equation are known from raw data.*

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   - *The left-hand side values of the above equation are known from raw data.*
3. by either part of Assumption 2, we can isolate entry costs: $\frac{Pr(\mathcal{E}=1|\overline{N}_j, s, y_\ell)}{Pr(\mathcal{E}=1|\overline{N}_j, \eta^{max}, y_\ell)} = \frac{H_\eta(s)}{H_\eta(\eta^{max})} = H_\eta(s)$ (via (i)) and/or $Pr(\mathcal{E} = 1 | 1, s, y_\ell) = H_\eta(s)$ (via (ii)).

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4. Either way, can use $\frac{Pr(\mathcal{E}=1|\overline{N},s,y)}{H_\eta(s)} = p(y, \overline{N})$ to trace out consideration probabilities. □

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Key Assumption

Valuation process is the same for modern-era banks and GFC-era banks:

- Bidder/Failed Bank traits interact to determine values in the same way

Key drivers of baseline values: Assets, Deposits, Insured Deposits, ROA (Allen et al., 2023)

1. Deposit franchise valuations similar across periods
   - Customers' elasticities of deposits wrt rates haven't increased (Schnabl, 2023)
   - Deposit Betas similar to last crisis (Kang-Landsberg et al, 2023)
2. Loan portfolio valuations similar over time
   - Balance-sheet complementarities (Granja et al., 2017) being stable over time
3. Pricing models stable
   - Condition on a wealth of observable balance-sheet characteristics

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Bidding Banks

Variable	Constrained Mean	Constrained 10-90 Interval	Unconstrained Mean	Unconstrained 10-90 Interval	Local Ban Mean	Local Ban 10-90 Interval
Tot. Assets ($B)	134	[0.3, 1219]	46.9	[0.08, 9.78]	28.8	[0.3,199.2]
Tot. Deposits ($B)	94	[0.3, 840]	39.6	[0.07, 8.37]	21.1	[0.2,172.7]
Uninsured Deposits (%)	35.68	[14, 63]	28.8	[10.4, 50.8]	32.6	[13.6, 54.1]
CRE (%)	17.0	[1.8, 31.0]	13	[1, 32]	18.5	[4.3,34.9]
C&I (%)	10.5	[8.2, 21.9]	8.3	[1.5, 16.4]	8.8	[1.5,18.3]
CNSMR (%)	5.4	[0.0, 11.7]	3	[0, 7.1]	3.6	[0.0,8.4]
SFR (%)	12.8	[2.1, 25.3]	17	[3, 34]	15.3	[4.8,27.5]
NA (%)	0.29	[0.0, 0.6]	0.3	[0, 0.9]	0.34	[0,0.82]
ROA	1.25	[0.58, 1.84]	1.08	[0.37, 1.8]	1.14	[0.4,1.8]
Tier 1 Ratio	10.14	[7.62, 13.13]	11.0	[7.6, 14.2]	10.7	[8.1,14.1]
Leverage	10.43	[7.84, 13.45]	11.1	[7.8, 14.4]	10.9	[8.3,14.6]
IDC Ratio	7.84	[7.62, 13.16]	21.8	[−0.1, 19.7]	17	[0.0,30.9]
Losses	8.02	[3.52, 12.48]	10.6	[4.8, 17.0]	9	[4.7,12.7]
Insolvent	0	[0, 0]	0.35	[0, 1]	0	[0,0]

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