Resolving Failed Banks: Uncertainty, Multiple Bidding, & Auction Design

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Workshop in memory of Art Shneyerov

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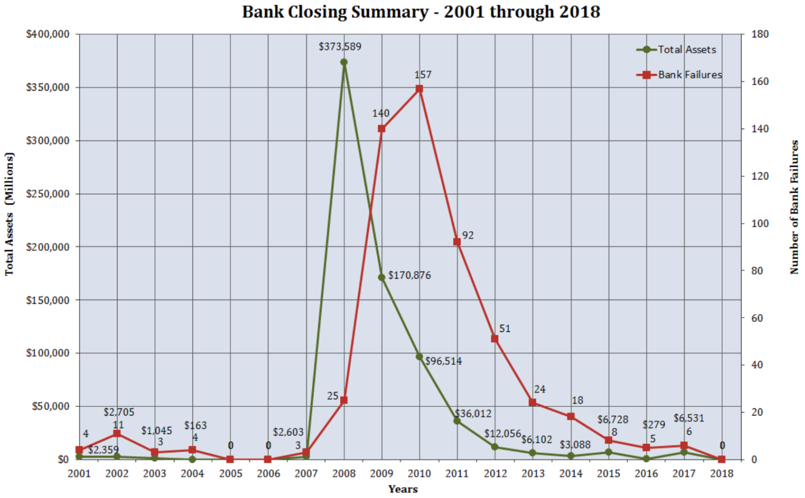
Preliminary and incomplete. The views in this paper do not reflect those of the Bank of Canada.

Motivation

- U.S. banking industry much more fragmented than in other countries
  - At the start of the crisis, over 8,000 institutions insured by the Federal Deposit Insurance Corporation (FDIC)
- Occasionally, banks' balance sheets deteriorate and they **become insolvent**
  - During crisis **510** banks failed
  - These banks had combined assets of over $700 billion

Motivation – Bank Failures



Source: FDIC

Motivation – Cost to FDIC

- FDIC **resolves** insolvent banks using an opaque non-judicial, administrative process
  - The failed bank is put up for auction
- The FDIC typically **loses money** on these transactions
  - Cost to *Deposit Insurance Fund* (DIF) during crisis was over $70 billion
    - Represents an average loss of about 25% of failed bank assets
  - Losses during crisis were so extensive that DIF turned negative in 2009 (-$20.9 billion)
    - FDIC must then either (i) increase assessment rates, (ii) levy special assessments on the industry, or (iii) borrow from the U.S. Treasury

Motivation – Resolution process

- Key features of the auction process:
  - FDIC permits banks to bid a $ amount, and specify other components (ex. loss share, partial bank)
    - Four components: so 16 possible *packages*
  - FDIC's mandate is to resolve the failing institution at the *lowest cost* possible (FDIC Improvement Act 1991)
  - Algorithm for calculating the least-cost bid is proprietary
    - Bidders uncertain as to how bids for different packages will be ranked
    - Multidimensional auction with unknown scoring rule
    - Allows for flexibility on the part of the FDIC
- Observation: some banks submit multiple bids in the same auction
  - Bids are for different packages

Research questions

- What impact does uncertainty have on outcomes?
  - **Uncertainty effect**: Bidders that value the failed bank highly have incentive to shade less
- What impact does multiple bidding have on costs?
  - **Substitution effect**: Shade more, since packages are substitutes
  - **Competition effect:** Shade less because *number* of bids increased

Specific questions:

- Can we improve the efficiency of the resolution process the FDIC uses to allocate failing banks?
  - ☐ Should the FDIC reveal the method for calculating the costs of a bid and remove uncertainty in these auctions?
  - ☐ If not, should the FDIC forbid multiple bidding?

Empirical approach

Use FDIC data summarizing bidding behavior:

1. Structurally estimate the underlying preferences of banks for failed institutions and different components
    - Setup similar to *pay-as-bid package auction*:
        - Dissimilar objects auctioned, bids can be on any subset of packages
    - Follow 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
2. Perform counterfactual experiments
    - Eliminate uncertainty
    - Eliminate multiple bidding

Institutional Background

Institutional background

Resolution process:

- Objective:
  - Turn failed bank's assets into cash in the *least costly manner*
- Procedure:
  1. Bank's regulator informs the FDIC of pending failure
  2. Can close a bank that is
     - Critically undercapitalized according to FDIC's 5-point scale
     - Assets less than obligations to creditors
  3. FDIC determines liquidation value of bank
  4. Puts together marketing strategy including list of potential buyers
     - Condition (chartered, good CAMELS rating...)
     - Business plan
     - Geographic location
  5. Interested bidders given access to virtual data room with info so that they can conduct due diligence
  6. Bidders submit proposals
  7. FDIC selects least-cost bid or liquidates

Dataset

- Data gathered from the FDIC website
  - Failed bank list
  - Bid summaries
    - For every auction: Bids, and information on all components
  - Cost to deposit insurance fund
  - Characteristics of failed bank and bidding banks
- Main sample: 297 auctions (2009-2013)
  - 123 with multiple bidding
- Restricted sample: 177 auctions
  - Need to be able to identify bidder associated with each bid to estimate valuations (1, 2, and 3 bidder auctions)
  - 25 with multiple bidding

FDIC Bank Failure List

Bank Name	City	ST	CERT	Acquiring Institution	Closing Date	Updated Date
Covenant Bank & Trust	Rock Spring	GA	58068	Stearns Bank, N.A.	March 23, 2012	March 21, 2014
New City Bank	Chicago	IL	57597	No Acquirer	March 9, 2012	October 29, 2012
Global Commerce Bank	Doraville	GA	34046	Metro City Bank	March 2, 2012	June 26, 2014
Home Savings of America	Little Falls	MN	29178	No Acquirer	February 24, 2012	December 17, 2012
Central Bank of Georgia	Ellaville	GA	5687	Ameris Bank	February 24, 2012	March 21, 2014
SCB Bank	Shelbyville	IN	29761	First Merchants Bank, National Association	February 10, 2012	February 19, 2015
Charter National Bank and Trust	Hoffman Estates	IL	23187	Barrington Bank & Trust Company, National Association	February 10, 2012	March 25, 2013
BankEast	Knoxville	TN	19869	U.S. Bank, N.A.	January 27, 2012	December 7, 2015
Patriot Bank Minnesota	Forest Lake	MN	34823	First Resource Bank	January 27, 2012	November 13, 2017
Tennessee Commerce Bank	Franklin	TN	35296	Republic Bank & Trust Company	January 27, 2012	March 21, 2014
First Guaranty Bank and Trust Company of Jacksonville	Jacksonville	FL	16579	CenterState Bank of Florida, N.A.	January 27, 2012	July 11, 2016
American Eagle Savings Bank	Boothwyn	PA	31581	Capital Bank, N.A.	January 20, 2012	February 21, 2018
The First State Bank	Stockbridge	GA	19252	Hamilton State Bank	January 20, 2012	March 21, 2014
Central Florida State Bank	Belleview	FL	57186	CenterState Bank of Florida, N.A.	January 20, 2012	June 6, 2016
Western National Bank	Phoenix	AZ	57917	Washington Federal	December 16, 2011	February 5, 2015
Premier Community Bank of the Emerald Coast	Crestview	FL	58343	Summit Bank	December 16, 2011	February 19, 2018
Central Progressive Bank	Lacombe	LA	19657	First NBC Bank	November 18, 2011	February 5, 2015
Polk County Bank	Johnston	IA	14194	Grinnell State Bank	November 18, 2011	August 15, 2012
Community Bank of Rockmart	Rockmart	GA	57860	Century Bank of Georgia	November 10, 2011	March 21, 2014
SunFirst Bank	Saint George	UT	57087	Cache Valley Bank	November 4, 2011	August 9, 2017
Mid City Bank, Inc.	Omaha	NE	19397	Premier Bank	November 4, 2011	April 16, 2018
All American Bank	Des Plaines	IL	57759	International Bank of Chicago	October 28, 2011	February 21, 2018
Community Banks of Colorado	Greenwood Village	CO	21132	Bank Midwest, N.A.	October 21, 2011	January 2, 2013
Community Capital Bank	Jonesboro	GA	57036	State Bank and Trust Company	October 21, 2011	January 6, 2016
Decatur First Bank	Decatur	GA	34392	Fidelity Bank	October 21, 2011	March 21, 2014

FDIC Bid Summaries

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
Winning bid and bidder: Enterprise Bank & Trust, Clayton, Missouri	Nonconforming all deposit whole bank with loss share (1)	1.00%	$ (9,995)	80%	80%	NA	80%	80%	NA
Cover - Commerce Bank of Arizona, Tucson, Arizona	All deposit whole bank with loss share	0.25%	$ (21,975)	75%	75%	N/A	75%	75%	N/A
Other bid	All deposit whole bank with loss share	1.00%	$ (9,525)	80%	80%	N/A	80%	80%	N/A
Other bid	All deposit whole bank with loss share	0.25%	$ (21,475)	80%	80%	N/A	80%	80%	N/A
Other bid	All deposit whole bank with loss share	0.00%	$ (22,000)	80%	80%	N/A	80%	80%	N/A
Other bid	Nonconforming Whole Bank P&A (2)	0.00%	$ (41,679)	N/A	N/A	N/A	N/A	N/A	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

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iscount)	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
	$ (9,995)	80%	80%	NA	80%	80%	NA	Yes	No	N/A
	$ (21,975)	75%	75%	N/A	75%	75%	N/A	No	Yes	N/A
	$ (9,525)	80%	80%	N/A	80%	80%	N/A	No	Yes	N/A
	$ (21,475)	80%	80%	N/A	80%	80%	N/A	No	Yes	N/A
	$ (22,000)	80%	80%	N/A	80%	80%	N/A	No	Yes	N/A
	$ (41,679)	N/A	N/A	N/A	N/A	N/A	N/A	No	No	N/A

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Offer submissions

An offer by a bank includes a dollar amount:

1. **Deposit Premium** (%)
2. **Asset Discount** (level)

} = Pricing terms (bid)

Offer also specifies whether components switched on/off:

3. **Loss Share (LS)**
   =1 if FDIC agrees to share in future losses of the failed bank (80%)
4. **Non-Conforming (NC)**
   =1 if bid is non-conforming
5. **Partial Bank (PB)**
   =1 if bidder agrees to take only part of bank, specifies assets bidder agrees to take
6. **Value Appreciation Instrument (VAI)**
   =1 if bidder grants the FDIC a warrant to purchase interest in the bidder's stock

Model

Modeling approach

- Recall: Guerre, Perrigne and Vuong, 2000 (GPV)
  - FOCs for optimal bidding written as a function of observables
    - Function of bids rather than unobserved valuations
- Setup:
  - N symmetric bidders have valuations $V_i \sim F$
  - Let $\beta(V)$ denote symmetric bidding function
  - Bidder's problem:

$$\begin{aligned}\max_{b_i} \pi_i(V_i, b_i) &= [V_i - b_i] Prob(b_i > \max_{j \neq i} \beta(V_j)) \\ &= [V_i - b_i] F[\beta^{-1}(b_i)]^{(n-1)}\end{aligned}$$

  - First order condition (after rearranging):

$$\beta'(V_i) = (V_i - \beta(V_i))(n-1)\frac{f(V_i)}{F(V_i)}$$

Modeling approach

- Define:

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

- Rewrite bidder i's problem as:

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

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

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

Multidimensional auctions with noisy scoring rule

- Borrow from Cantillon and Pesendorfer (2007) who extend GPV approach to package auctions for dissimilar objects
  - Our case: 16 possible packages
- Setup:
  - N bidders draw IID baseline valuation for full bank: $\overline{V}_i \sim F_{\overline{V}}(\overline{v}_i)$
  - Conditional on full bank valuation, also have valuations V_{ik} for each package k
    - IID from $F(\cdot|\overline{V}_i, \boldsymbol{X}_i)$ where and X_i are bidder and auction observables
  - Valuation V_{ik} depends on the specific package:

$$v_{ik} = \bar{v}_i + v_{i,LS} d^k_{LS} + v_{i,NC} d^k_{NC} + v_{i,PB} d^k_{PB} + v_{i,VAI} d^k_{VAI}$$

  - where $v_{i,s}$ are valuations for switch $s = \{LS, NC, PB, VAI\}$
  - where d^k_s indicates that switch s is turned on in package k

Bidding behavior

- Strategies: $(L_i, \boldsymbol{o}_i)$
  - L_i = set of *meaningful* offers to submit
  - Offer vector: $\boldsymbol{o}_i = (o_{i1}, \ldots, o_{i,16})$, with $o_{ik} = (b_{ik}, \boldsymbol{d}_k)$
    - $b_{ik} \in \mathbb{R}$ is a premium
    - $\boldsymbol{d}_k \in \{0,1\}^4$ is a full set of switches
    - $\{k : b_{ik} > \underline{b}_k\} = L_i$
    - $\underline{b}_k$ guarantees a loss
- Allocation is determined by the minimum cost
  - FDIC's cost calculation is *ex-ante* unknown

Bidders choose their L and $\boldsymbol{o}$ to solve

$$max_{L,\boldsymbol{o}} \sum [(V_{ik} - b_{ik})] G(b_{ik} | \boldsymbol{d}_k, L_i, \boldsymbol{o}_i)$$

- $G(b_{ik} | \boldsymbol{d}_k, L_i, \boldsymbol{o}_i)$ = Win Probability of offering premium b_{ik} on k^{th} package, given other own bids

First Order Conditions

For each $k \in L_i$:

$$(V_{ik} - b_{ik}) \frac{\partial G(b_{ik} | \boldsymbol{d}_k, L_i, \boldsymbol{o}_i)}{\partial b_{ik}} + \sum_{k' \in L_i,\ k' \neq k} (V_{ik'} - b_{ik'}) \frac{\partial G(b_{ik'} | \boldsymbol{d}_{k'}, L_i, \boldsymbol{o}_i)}{\partial b_{ik}} = G(b_{ik} | \boldsymbol{d}_k, L_i, \boldsymbol{o}_i)$$

For each $k \notin L_i$:

$$(V_{ik} - \underline{b}_k) \frac{\partial G(\underline{b}_k | \boldsymbol{d}_k, L_i, \boldsymbol{o}_i)}{\partial \underline{b}_k} + \sum_{k' \in L_i,\ k' \neq k} (V_{ik'} - b_{ik'}) \frac{\partial G(b_{ik'} | \boldsymbol{d}_{k'}, L_i, \boldsymbol{o}_i)}{\partial \underline{b}_k} \leq G(\underline{b}_k | \boldsymbol{d}_k, L_i, \boldsymbol{o}_i)$$

GPV Inversion

For $k \in L_i$:

$$V_{ik} = b_{ik} + \frac{G(b_{ik}|\boldsymbol{d}_k, L_i, \boldsymbol{o}_i) + \sum_{k' \neq k}(V_{ik'} - b_{ik'})\frac{\partial G(b_{ik'}|\boldsymbol{d}_{k'}, L_i, \boldsymbol{o}_i)}{\partial b_{ik}}}{\frac{\partial G(b_{ik}|\boldsymbol{d}_k, L_i, \boldsymbol{o}_i)}{\partial b_{ik}}}$$

For $k \notin L_i$:

$$V_{ik} \leq \underline{b}_k + \frac{G(\underline{b}_k|\boldsymbol{d}_k, L_i, \boldsymbol{o}_i) + \sum_{k' \neq k}(V_{ik'} - b_{ik'})\frac{\partial G(b_{ik'}|\boldsymbol{d}_{k'}, L_i, \boldsymbol{o}_i)}{\partial \underline{b}_k}}{\frac{\partial G(\underline{b}_k|\boldsymbol{d}_k, L_i, \boldsymbol{o}_i)}{\partial \underline{b}_k}}$$

Estimation and Identification

Estimation

- Objective: Estimate Valuations (including and component values)
- Method:
  - Like in GPV we observe the offer: $b_{ik}, \boldsymbol{d}_k$
  - Use GPV inversion
  - Need to compute G: the probability that a given offer wins in an auction
    - Challenges: (i) uncertain scoring rule, (ii) uncertainty over set of competitors, (iii) multiple bidding

Estimation steps

- **Step 1:** Compute G:
  i. Estimate by maximum likelihood the FDIC's least-cost scoring rule in order to estimate the probability that each offer wins in a simulated auction
  ii. Construct a weighted bootstrap sample of offers from bidders in *similar* auctions to determine prob of winning (additional details)

  For step 1 use data from all 297 auctions

- **Step 2:** Estimate package-specific $\hat{V}_{ijk}$ (or bounds) using GPV inversions given above.

  For step 2 use restricted sample (where we can identify all bidders)

Step 1.i: Estimation of the least-cost scoring rule

$$\begin{aligned} \text{transfer}_{i,j} &= bid_{i,j} + u_j + 1(LS_{i,j} = 1)(\epsilon_j) + 1(VAI_{i,j} = 1)(\psi_j) \\ &+ 1(NC_{i,j} = 1)(\kappa_j) + 1(PB_{i,j} = 1)(\nu_j) + \gamma_{i,j} \end{aligned}$$

- Estimation via Tobit MLE (additional details)
  - We observe the cost associated with the winning bid – equation holds with equality
  - Provides a bound for all other bids.

- Units: % of tot. assets

- $bid_{i,j}$: amount transferred on close
  - u_j and $\gamma_{i,j}$ assumed normally distributed

- $\epsilon, \psi, \kappa, \nu$: individual component shocks
  - Assumed normally distributed

Step 2: Estimation of package-specific $\hat{V}_{ijk}$

- Estimation Equation:

$$\hat{V}_{ijk} = X_{i,j}\beta d_k + \bar{V}_{ij} + \epsilon_{ijk}$$

- Tobit type setup:
  - If package k is not bid on, only know that V_{ijk} is less than some bound given by inversion
  - Otherwise V_{ijk} pinned down
- Estimate 17 parameters (a constant and a multiplier on observable traits) for each V_{is} and a $\bar{V}_i$ for each bidder
  - $V_{i,s}$ fully described by traits and ϵ_{ijk} represents sampling noise
- Selection problem: For each auction and number of bids chosen, calculate a probability of selection into the observed set and re-weight by this in the likelihood

Estimation Results

Least-cost scoring rule estimates

	Estimate	Standard Error
Common mean	-0.5208	0.680
Common Sd	**10.498*** **	0.700
Conforming mean	**-6.974*** **	1.000
Conforming Sd	**22.505*** **	1.011
Partial mean	**57.390*** **	1.008
Partial Sd	**20.746*** **	0.999
VAI mean	**3.521*** **	0.997
VAI Sd	0.185	2.746
Loss Share Mean	**-12.077*** **	0.887
Loss Share Sd	0.011	1.002
Idiosyncratic Sd	**7.480*** **	0.841
Observations	1126	
Pseudo R-squared	0.7285	

Least Cost Scoring Rule Estimates

1. Using **Loss Share** equivalent to additional Asset Discount of 11.9 percent of failed bank assets
2. Bids for **Partial Bank** request large payments in the bid amount from the FDIC, but FDIC retains assets they can sell, positive shock
3. **Non-Conforming** involves a wide range of modifications, big standard deviation
4. **VAI** has small positive increase on ranking of the bid

Distance Value Shifters

	Non-Conforming	Loss Share	PB	VAI
Constant	-54.109***	76.769***	-118.235***	5.850***
	(4.012)	(3.757)	(4.274)	(1.755)
Same Zip	3.752*	33.327***	-19.937***	14.303***
	(2.078)	(3.195)	(3.450)	(3.792)
Pairwise Average Distance	13.008***	-1.918***	-10.123***	5.850***
	(1.426)	(0.476)	(1.126)	(1.755)
Squared Pairwise Average Distance	-0.732***	-0.045	0.596***	-0.409***
	(0.097)	(0.036)	(0.072)	(0.173)
Portfolio Percentage Difference				
Commercial Real Estate	1.095***	-0.541***	-0.473***	1.081***
	(0.178)	(0.104)	(0.147)	(0.241)
Commercial and Industrial	1.637***	-0.727***	-3.114***	1.665***
	(0.299)	(0.159)	(0.305)	(0.349)
Consumer	1.013***	0.310	-0.767***	4.718***
	(0.214)	(0.182)	(0.228)	(0.312)
Residential	-0.841***	1.387***	1.402***	-2.442***
	(0.187)	(0.156)	(0.195)	(0.488)
Observations	4224			
R Squared	0.27			

Traits Value Shifters

	Non-Conforming	Loss Share	PB	VAI
Bidder Traits				
log Total Assets	-1.573***	3.639***	9.508***	-12.966***
	(0.415)	(0.333)	(0.400)	(1.078)
Tier 1 ratio	-2.000***	-0.292***	0.257**	0.772***
	(0.192)	(0.074)	(0.119)	(0.141)
Percentage CRE	-0.627***	-1.559***	-1.593***	1.342***
	(0.101)	(0.094)	(0.083)	(0.190)
Percentage CI	-1.283***	-1.894***	-0.938***	2.192***
	(0.244)	(0.135)	(0.163)	(0.484)
ROA Bidder	10.769***	13.652***	-3.084***	17.366***
	(1.176)	(2.196)	(0.620)	(2.517)
Failed Traits				
ROA Failed	-0.981***	-14.873***	-0.075	-0.590**
	(0.158)	(0.737)	(0.125)	(0.239)
Core Deposits Failed	-0.259***	-0.108***	0.395***	-0.209***
	(0.041)	(0.029)	(0.042)	(0.069)
Percentage CRE	-0.302***	0.805***	0.456***	-0.473***
	(0.048)	(0.039)	(0.066)	(0.133)
Percentage CI	-0.375	0.679***	0.560***	0.556
	(0.207)	(0.103)	(0.151)	(0.414)
Observations	4224			
R Squared	0.27			

Valuation Estimation Results

- Close bidder: Loss share better, PB worse, VAI better.
  - Benefit of nonconforming increasing in distance.
- Bigger Bidder: Loss share better, PB better, VAI worse
- Failed Bank Specialized in CRE: Loss share better, PB better
- Bidder specialized in CRE: Loss share worse, PB worse

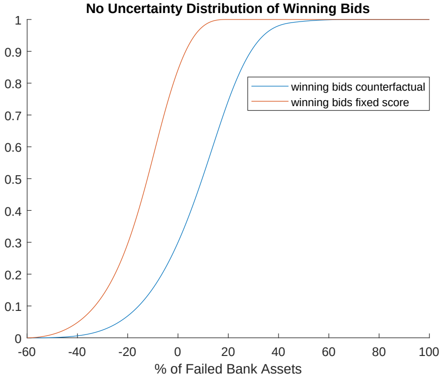
Counterfactual Experiments

Counterfactual Experiments

- Recall our questions:
  - Should the FDIC reveal the method for calculating the costs of a bid and remove uncertainty in these auctions?
  - If not, should the FDIC forbid multiple bidding by the same bidder?
- So we consider two sets of counterfactuals:
  - Eliminate uncertainty
  - Eliminate multiple bidding
- Approach
  - To eliminate uncertainty, set the score function at the mean of the estimated shock distributions

Eliminating Uncertainty

Winning Bids



Counterfactual Experiments–Results

- In restricted sample of 177 auctions loss to FDIC is \$18 billion
  - Eliminating uncertainty: loss falls to \$2.5 billion
  - Loss falls to \$1 billion if number of bids=number of bidders

Conclusion

Conclusion

- We study the impact of uncertainty in the scoring rule on outcomes in auctions for failed banks in the US
- Uncertainty in the scoring rule leads to multiple bidding on the part of banks
- Our findings suggest that eliminating uncertainty would reduce the loss experienced by the FDIC by $85 million per failed bank
  - This translates to a reduction in losses of $15.5 during the crisis (2009-2013)
  - Loss falls to $1billion if number of bids=number of bidders
- Still to do: CF that eliminates multiple bidding but keeps uncertainty
- Now that we have this model, can think about other policy questions (although may need to model entry)

Step 2: Construct a sample of bids from similar bidders in similar auctions

- Objective: Create bootstrapped sample of auctions taking bids more frequently from similar auctions
- Which auctions are similar?
  - Take Failed Bank Traits: (lat, long, size, percentage cre, capitalization)
  - Calculate the single dimensional Principle Component projection of these traits
  - Kernel weights for each auction relative to each other one in the space of the single dimensional projection.

Constructing the sample

- Draw sets of possible competitors
  - Number of competitors drawn from the distribution of number of competitors in similar auctions
  - Opposing bids drawn from the distribution of bids in similar auctions
- Integrate over the uncertainty in the scoring rule to get the probability of winning against the set of opposing bids in each fake auction
- Average the win probability over the simulated auctions
- For Multiple Bidders their other bids are always present when calculating probability a given bid wins

BACK

Identification of the least-cost scoring rule

- Distribution of $u_j + \gamma_{i,j}$: identified from when all other indicators are zero, since we observe the bid and the cost for the winner
- Variance of $\gamma_{i,j}$: identified from when all the indicators are zero, by the probability a bid with a smaller premium is the winner
  - Assume: $\gamma_{i,j}$ is mean zero normal.
- Other shock distributions: identified by turning on indicators one at a time. Observe convolution of turned-on indicator distribution with the u_j distribution (known).

Estimation of the least-cost scoring rule

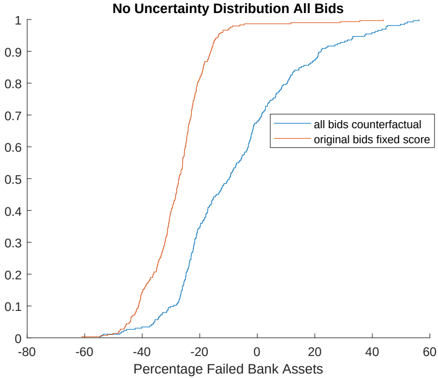
- Assume normality and compute the probability that:
  - The winning score is equal to the reported cost $\hat{c}_{winner} = cost_j$
  - The scores of all other bidders are worse
- Choose the parameters that maximize the probability of the observed costs and rankings

$$\int \int \int \int \int f_{\gamma_w}(cost - \hat{c}_{winner}) F_{\gamma_o}(cost - \hat{c}_{others}) dF_{\psi} dF_{\epsilon} dF_{v} dF_{\kappa} dF_{u}$$

BACK

Eliminating Uncertainty

Actual number of bids, but with a unique bidder for each – All Bids



Eliminating Uncertainty

Actual number of bids, but with a unique bidder for each – Winning Bids