Queen's Economics Department Working Paper No. 1422

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

Jason Allen
Bank of Canada

Robert Clark
Queen's University

Brent R. Hickman
Olin Business School, University of Washington

Eric Richert
Princeton University

Department of Economics
Queen's University
94 University Avenue
Kingston, Ontario, Canada
K7L 3N6

7-2022

# RESOLVING FAILED BANKS: UNCERTAINTY, MULTIPLE BIDDING & AUCTION DESIGN

JASON ALLEN[A], ROBERT CLARK[B], BRENT HICKMAN[C], ERIC RICHERT[D]

Abstract. The FDIC resolves insolvent banks using a scoring auction. Although the basic structure of the scoring rule is known to bidders, they are uncertain about how the FDIC makes trade-offs between the different components. Uncertainty over the scoring rule motivates bidders to submit multiple bids for the same failed bank. To evaluate the effects of uncertainty and multiple bidding for FDIC costs we develop a methodology for analyzing multidimensional bidding environments where the auctioneer's scoring weights are unknown to bidders, ex-ante. We estimate private valuations for banks that failed during the great financial crisis and compute counter-factual experiments in which scoring uncertainty is eliminated. Our findings imply a substantial within-sample reduction in FDIC resolution costs of between 29.8% ($8.2Billion) and 44.6% ($12.3Billion). These savings can reduce policy-driven banking sector distortions, since FDIC resolution costs must be covered either through special levies on banks or through loans from the US Treasury.

*Acknowledgements:* The views in this paper do not reflect those of the Bank of Canada. We thank John Asker and Amiyatosh Purnanandam for excellent discussions of our paper. Helpful comments were provided by Rosalind Bennett, Dan Bernhardt, Aaron Bodoh-Creed, Alessandro Gavazza, Hari Govindan, Jean-François Houde, Jakub Kastl, Brad Larsen, David Lucca, Yao Luo, Lynn Shibut, Paulo Somaini, and by participants at seminars and conferences at the FDIC, Columbia, Cornell, LSE, Northwestern, Texas A&M, Tilburg, TSE, UBC, University of Victoria, University of Illinois at Urbana–Champaign, Vanderbilt, Western, the CEA (Banff), NBER SI-IO (2020), and the Workshop in Memory of Artyom "Art" Shneyerov. We are also indebted to Francesca Molinari and four referees for very insightful feedback on improving the substance and exposition of this paper.

[A]Jason Allen - Bank of Canada; Email: jallen@bankofcanada.ca,
[B]Robert Clark - Queen's University; Email: clarkr@econ.queensu.ca,
[C]Brent Hickman - Olin Business School, Washington University in Saint Louis; Email: hickmanbr@gmail.com,
[D]Eric Richert - Queen's University; Email: richerte@econ.queensu.ca.

*Date*: July 2022.

# 1. Introduction

In response to the global financial crisis, regulators have taken steps to increase financial stability by developing more effective resolution processes in cases of bank failure. In the U.S., bank failures are the purview of the Federal Deposit Insurance Corporation (FDIC). The most common resolution method is a Purchase & Assumption (P&A) transaction, in which the FDIC auctions off failing institutions (i.e., their physical assets, investment portfolios, and customer deposit accounts) to healthy banks. Unlike auctions for consumption goods, these are analogous to procurement, since the FDIC (the auctioneer) *pays* the winning bank (the bidder) its bid *for the service* of taking over the failed bank, which includes assuming its depositor liabilities. Thus, these transactions typically result in a net cash transfer from the FDIC to the acquiring institution, and auctions are used as a value-discovery mechanism among healthy banks, to minimize resolution costs.

During the global financial crisis the volume of failures was so elevated that the FDIC's Deposit Insurance Fund lost nearly $90 billion (Davison and Carreon (2010)). Faced with losses, the FDIC must either increase insurance premiums to healthy banks, levy special assessments, and/or borrow from the U.S. Treasury. These actions can introduce distortions into the banking system and impact lending at times when distortionary measures are particularly unwelcome. Furthermore, auction outcomes impact local market power for banking services, since a failed bank's market share is transferred to the winner.

This paper examines incentives induced by the FDIC's resolution mechanism in order to determine its implications for costs and local market structure. The current resolution process has several key features. First, the FDIC permits multidimensional bidding: healthy banks submit bids consisting of a continuous component—a dollar value for the assets and liabilities of the failed bank—and four discrete P&A contract components. For example, a bank can specify that its bid includes a "loss-sharing" provision whereby the FDIC shares in future losses of the failed bank's investment portfolio. A scoring auction is then used to rank multi-dimensional bids in order to determine a winner.

A second feature is uncertainty about the FDIC's scoring rule in each auction.[1] Since the passage of the FDIC Improvement Act (FDICIA) in 1991, the FDIC is required to select the least-cost bid, so long as it is superior to its cost of directly reimbursing depositors. Although the basic structure of the scoring rule is known to bidders, they are uncertain about how the FDIC makes trade-offs between the different components of bids because they are unaware of the FDIC's operational constraints. For example, bidding banks do not know the state

[1] Conversations with regulators and with banking industry insiders confirmed that there is indeed ex-ante uncertainty over the exact weights in the FDIC's scoring rule, from the perspective of acquiring banks.

of FDIC internal opportunity costs, stemming from its backlog of "loss-share" commitments for previous P&A transactions. Moreover, different contract configurations affect internal administrative expenses borne by the FDIC. Thus, bidders view each discrete component in a P&A bid as implying a distribution of possible costs.

Finally, uncertainty over the FDIC's scoring rule motivates bidders to submit multiple bids for the same failed bank. Since they do not know precisely how each component will affect FDIC resolution costs, healthy banks can (and often do) submit multiple bids to hedge against randomness in the allocation rule. While bidders face various sources of uncertainty, the multiple bidding incentive is born of scoring-rule uncertainty in particular.

The cost implications of scoring-rule uncertainty are ambiguous due to various ways in which it influences incentives. For high-valuation bidders, the auction appears more competitive than it otherwise would: with a known scoring rule they would likely win, but scoring uncertainty perturbs win probability in favor of lower-valuation rivals. We call this the *noise effect*, and it spurs more aggressive bidding among high-value bidders. Multiple bidding generates two other conflicting incentives. First, a multiplicity of bids per rival makes an auction appear more competitive, leading to a reduction in bid shading; we label this the *competition effect*. Second, multiple bidding implies a *substitution effect* where increased shading occurs as bidders internalize the business stealing effect of their bids on their own other bids.

In order to evaluate the implications of the FDIC's P&A mechanism and the relative importances of noise, competition and substitution effects, we develop a methodology for analyzing multidimensional bidding environments where the auctioneer's scoring weights are unknown to bidders, ex-ante. The closest paper to ours is Krasnokutskaya et al. (2018).[2] Like us, they allow for scoring-rule uncertainty, but in their setting the non-price components of bids are exogenous and bidders may bid only once. In our context, bidders make endogenous choices over all components of the bid without knowing the FDIC's cost perception for each one. Healthy banks in FDIC auctions are also allowed to submit multiple bids; this introduces additional complexity as they optimize over different portfolios of bids and bid levels.

We develop a structural model of bidding to recover healthy banks' valuations for failing banks under different P&A agreements. We note that unique configurations of the discrete components plus the dollar portion of the bid can together be thought of as a "package." We draw on the combinatorial auctions literature and employ a modeling approach similar to Cantillon and Pesendorfer (2006), who extend methods by Guerre et al. (2000, GPV) to

[2]Greve (2011) models a multidimensional auction where agents compete in price and quality and the weights placed by the auctioneer on quality are unknown. Previous work on scoring auctions with known scoring weights includes Che (1993), Branco (1997), Asker and Cantillon (2008), Asker and Cantillon (2010), Athey and Levin (2001), Bajari et al. (2014), Bajari and Lewis (2011), and Takahashi (2018).

the case of package auctions for multiple bus routes being simultaneously auctioned off. Our setting is similar except that there can be only one winner, and there is randomness in the allocation rule. We contribute methodologically by establishing identification and estimation when the scoring rule is unknown and bidders can place multiple bids. We also shed new light on central market-design concerns in combinatorial auctions with a novel exploration of bid portfolio choice and two primary bidding incentives: competition and substitution effects.

Healthy banks each have an idiosyncratic valuation for taking over the failed bank on an *as-is* basis. Our assumption of private values lends tractability to the model, but it is based on the idea that acquiring banks are primarily concerned with how absorbing the failed bank will contribute to their individual business models, rather than being focused on re-sale. Idiosyncratic values are a reasonable viewpoint to the extent that (*i*) the size and composition of the failed bank's assets (e.g., business vs. consumer loans) complement a bidder's current portfolio, (*ii*) the size and composition of the failed bank's depositor base will affect a bidder's local market share for banking services and credit, and (*iii*) the failed bank's physical locations complement bidders' own existing branch networks.

Given its as-is P&A valuation, a bidder computes package-specific values using adjustments for including each of the four possible discrete contract components, and can submit one or more P&A bids. Although the bidding model is complex, we are able to establish some key equilibrium predictions that have bearing on FDIC resolution costs. Scoring-rule uncertainty creates incentives for bidders to submit multiple bids; when the weights of the scoring rule are known ex-ante, this incentive is absent. The remaining question is whether multiple bidding is good or bad for resolution costs; this is an empirical question that depends on which of the noise, competition, or substitution effects dominate.

We use bid optimality conditions to link observed bids with the unobserved package-specific private values, but to do so we need an estimate of the win probability. This is complicated in our setting for four reasons: (*i*) uncertainty over the scoring rule, (*ii*) multiple bidding and substitution effects, (*iii*) bidders are uncertain about the number of rivals, and (*iv*) bidders selectively enter auctions rather than being randomly assigned to them. To overcome the first of these complications, we directly estimate the scoring rule in a preliminary step. For the other three we adapt a re-sampling estimation approach proposed by Hortaçsu and McAdams (2010) to simulate win probabilities under the stochastic process for the scoring rule, while controlling for selective bidder entry on a rich set of auction-specific observables.

Using FDIC data we estimate private valuations for failed banks and compute counterfactual experiments on the link between scoring-rule uncertainty and auction outcomes. We estimate a substantial reduction in FDIC resolution costs of 29.8% or more under two scenarios where it eliminates scoring uncertainty, either by announcing the scoring weights prior to bidding, or by constraining potential acquirers to bid only on the single most popular package. For context, this amounts to a savings of at least $8.2Billion during our sample period, or at least 45% of the benefit from attracting an additional bidder to the auction (see Bullow and Klemperer (1996)). We compute two other counterfactual equilibria, where the FDIC eliminates scoring uncertainty by constraining potential acquirers to bid only on the second or third most popular packages. These two scenarios produce less advantageous cost predictions than the first two, due to the fact that these options are less valuable to bidders. This results in a strong endogenous shift toward bids less favorable to the auctioneer.

We also execute a series of bidding-incentive decompositions to explain these results. We show that the competition and noise effects work in the auctioneer's favor, while substitution works in the opposite direction and on average dominates the other two channels. Since scoring uncertainty is not detrimental to costs in every auction—i.e., sometimes substitution does not dominate—we also explore a targeted counterfactual scenario that employs a predictive model to assign each auction to different treatment status, based on failed bank observables.

From a market-design standpoint, our findings show how offering bidders choices (takeover contract options in our case) can strongly benefit the auctioneer by effectively inducing shifts in the private value distribution. At the same time, scoring uncertainty can also produce endogenous strategic responses by bidders that are strong enough to wipe out these benefits.

We investigate potential market-concentration effects by comparing sets of winners under the status-quo and counterfactual auction formats. This tells us whether uncertainty acts as an implicit subsidy for certain types of acquirers; the concern being that alternate auction formats may increase local market power. We find that removing uncertainty leads to a similar set of winners on most observable dimensions, except that they are, on average, smaller and geographically closer to the failed bank. However, counterfactual local market concentration rises only very slightly under the more cost-effective auction formats we propose.

Our analysis produces insights on bidding incentives and auction design that are relevant beyond FDIC auctions. First, the competition and substitution effects we study are fixtures of general combinatorial auctions where multiple bidding is also prevalent. Second, financial institutions frequently sell distressed assets such as credit and mortgage debt via auctions with multidimensional bidding and scoring uncertainty (Federal Trade Commission (2013)). Sellers use scoring rules to evaluate multi-dimensional bids, and they often score a buyer's reputation as a debt-collector. Internal seller opportunity costs and preferences over buyer reputation give rise to scoring uncertainty. In North America, bidders in private distressed asset auctions often have the option to include partial acquisition and profit-sharing provisions in a given P&A bid. As of this writing, a centralized European market for non-performing loans is in planning.[3] Third, large-scale asset purchases by central banks (known as quantitative easing) also have parallels to the auctions we study. There, bidders make offers to sell the central bank different bonds and the central bank uses a proprietary scoring-rule to evaluate these offers (Sack (2011)). The Federal Reserve does not announce its scoring weights because doing so would create negative repercussions for the secondary bond market.

Our study is related to an extensive literature on bank failures, mostly focused on the Savings and Loan crisis of the 1980s and early 1990s (e.g., James and Wier (1987), James (1991), and Cochran et al. (1995)), but increasingly centered on the more recent set of failures following the global financial crisis (e.g., Granja (2013), Kang et al. (2015), Igan et al. (2017), Granja et al. (2017), and Vij (2018)). Our work contributes by explicitly modeling, estimating, and evaluating the P&A auction process, and by decomposing private valuations of acquiring banks to shed new light on acquisition incentives.

## 2. Institutional details

Our focus is on the great financial crisis, during which 510 *troubled banks* failed between 2007 and 2014. Troubled banks are defined by the FDIC as being critically undercapitalized or having assets less than obligations (see Shibut (2017)). The combined assets of failed banks during the crisis were over $700 billion, and FDIC losses totalled $90 billion.[4] The current rules governing resolution of failing banks were established in 1991 with the passage of the FDIC Improvement Act. Previously, the FDIC was able to employ discretion when selling/liquidating failing banks, but today there is greater transparency and it is required to resolve bank failures at the *lowest cost possible*. To summarize the FDIC resolution process (see FDIC (2014)), a troubled bank's regulator first informs the FDIC of pending failure. The FDIC then determines the liquidation value of the bank, generates a list of potential acquirers who will be invited to bid (373 on average), and decides on the set of assets that will be included when each of the discrete components is activated. A subset of invitees sign a non-disclosure agreement to *look* at what is being offered (200 on average) and typically 5 to 6 conduct due diligence. Finally, some of those who have chosen to conduct due diligence then submit one or more bids.[5]

---

[3]See https://strapi-images-nplmwebsite.s3.eu-central-1.amazonaws.com/3370e415331b4236afaf0ca496f4e751.pdf.

[4]Earlier crises also featured a large number of failures. For instance, during the S&L crisis of the 1980s and 1990s, nearly 1,300 financial institutions failed. Figure OS.3 (Online Supplement) plots the number and size of bank failures going back to 1980.

[5]The number of solicitations and those who consider purchasing the failed bank are taken from (Heitz 2022).

To construct the list of potential buyers, the FDIC considers well-capitalized banks and subjects them to a size constraint that depends on geographic proximity to the failed bank. Due diligence is conducted either in person or through the FDIC's secured virtual data room (VDR), which provides detailed financial and legal information regarding the failed institution's loans, deposits, general ledger, and operations. The FDIC also computes an estimate of the secondary-market cash value of all failed-bank assets, and reports this information to prospective acquirers. Potential bidders do their own due diligence and view research conducted by the FDIC. Participants do not observe who else has been invited to the VDR.

Based on this we assume that the FDIC and potential bidders have equal information about the assets of the failed institution. The FDIC and potential bidders compute idiosyncratic valuations of the assets. These differ across individuals due to portfolio complimentarities, business lines, market timing, and heterogeneous abilities to manage asset recovery. The FDIC's reservation cost represents a liquidation value; although liquidation is not the norm, it occurs if the FDIC estimates it to be less costly than any of the options presented at the auction. Liquidation involves paying off insured depositors up to the current insured amount (deposit payout) and disposing of assets (See Appendix D.9 for the CDF of liquidation values).

Each auction is for all insured deposits, and, in practice, for most uninsured deposits. Occasionally some uninsured deposits are excluded from the transaction. For instance, brokered deposits are sometimes excluded. Stockholders are wiped out. In most cases general creditors realize little or no recovery out of the proceeds of the sale.

2.1. **The least-cost Resolution Rule.** The method for calculating resolution cost is common knowledge (see Cowan and Salotti (2015) and *FDIC Resolutions Handbook*). First, the FDIC calculates transaction equity, or the difference between asset book value and liabilities. Then asset discounts, deposit premiums, and receivership expenses are added:

$$Cost = Takeover\ Bid + Expenses = Transaction\ Equity + Asset\ Discount - Deposit\ Premium + Expenses. \tag{1}$$

To illustrate the cost rule, consider a simple example where a failed bank has $1,000,000 of deposits and has issued $500K worth of outstanding loans, but due to unforeseen circumstances their book value is now only $250K. The bank has $500K of cash remaining in its vault, meaning that its total assets amount to $750K and total liabilities (i.e., obligations to depositors) amount to $1,000,000. Consider an as-is P&A agreement. *Transaction Equity*, the difference between book value of assets and liabilities, is $250K and must be paid out by the FDIC in order to make the acquiring bank whole. Suppose the acquiring bank bids to assume the failed bank's loans at an asset discount of $120K below book value; i.e., it requests an additional cash infusion from the FDIC beyond Transaction Equity. Suppose further that the acquiring bank bids a *Deposit Premium* of $100K to absorb the failed bank's depositor base, and that the FDIC's internal administrative *Expenses* total \$25K. Therefore, FDIC costs in this example are $Cost = \$250K + \$120K - \$100K + \$25K = \$295K$, and the capital transfer from the FDIC to the acquiring bank totals $\$250K + \$120K - \$100K = \$270K$.

2.2. **Bidding.** Bids by healthy banks determine the values of the four terms on the right-hand side of equation (1). They first specify a continuous dollar amount for combined assets and liabilities of the failed bank; this directly determines the Asset Discount and Deposit Premium terms. Bids also specify four discrete components of the P&A agreement: (*i*) loss share (LS), (*ii*) nonconforming (NC), (*iii*) partial-bank (PB), and (*iv*) value appreciation instrument (VAI), discussed in detail below. These influence the Transaction Equity and Expenses terms in (1). In the model we treat each discrete component as a binary choice by bidders, and we motivate this choice below. For example, from the perspective of a bidding bank, inclusion of a LS provision is binary because the bidder merely chooses whether to stipulate it as part of a given takeover bid, or not. However, *how each discrete contract provision is valued* may vary widely depending on degree of solvency of the bidder and/or failed bank, portfolio and/or geographic complementarities between them, and other factors.

**Loss sharing:** LS agreements have terms specified by the FDIC to insure bidders against future losses on specific asset classes. In its *Resolutions Handbook*, the FDIC lists the following reasons for favoring LS: it lowers risk for the acquiring institution, it reduces the FDIC's need for immediate funding, and assets remain in the private sector. The cost to the acquiring bank is increased oversight and reporting. Terms of LS agreements are specified by the FDIC: it usually takes on 80% of losses up to a threshold, after which the split is 95%/5%, though it has been known to vary the LS terms on occasion (see Online Supplement D.9, Figure OS.5). Bidding banks typically choose only whether to include the specified LS terms in a P&A bid or not. While these terms are not strictly binding, the modal bid is exactly at the FDIC's proposed coverage levels, and the vast majority of bids are tightly packed around these levels: the mean absolute percentage deviation from the FDIC's LS coverage levels is only 0.64%. In our sample, 68% of bids include LS, and these won 65% of the time.

**Partial bank:** In a PB agreement bidders acquire only certain assets (but all deposits by default). In its marketing strategy, the FDIC specifies the set of excluded assets within the PB option prior to bidding. A PB bid typically excludes riskier assets such as non-performing loans, development and construction loans, land, and owned real estate (ORE). According to the FDIC's *Resolutions Handbook*, PB is a strictly binary option for bidding banks; they can only choose to include it or not. Excluded assets are liquidated by the FDIC after the auction. Figure OS.5 (Online Supplement D.9) is a histogram of the fraction of assets acquired in a winning PB bid. There is substantial variation, though a PB bid won only 11% of the time.

**Value appreciation instrument:** A VAI is a warrant that grants the FDIC the right to purchase an amount of common stock at a fixed price, or to receive cash representing the appreciation of the buyer's stock above the exercise price. This allows the FDIC to take advantage of the stock-price increase that typically follows the announcement of an FDIC-assisted acquisition (James and Wier (1987)). The FDIC specifies the exercise price and expiration date, and it stipulates that the VAI quantity is pegged to the financial value of the loss-sharing option it offered (Barragate et al. (2011)). The bidder's only remaining choice is whether or not to include a VAI provision in a given bid. The VAI option was stipulated in 7% of all bids in the sample, including 6% of winning bids.

**Nonconforming:** The FDIC requires P&A terms to be fixed prior to resolution, but a NC bid may specify modifications to the criteria set out in the FDIC's marketing strategy. Because of the obligation to resolve at the least cost, these bids must nevertheless be considered (if they can be priced). NC bids usually involve discrete adjustments to P&A terms offered by the FDIC, but for simplicity and tractability we model NC as a binary choice. For a random sample of 20 auctions where complete NC information was available, 79% of all such bids proposed exclusion of asset classes that differed from the FDIC's offered PB option. Moreover, for the vast majority of these, all NC bids within the same auction in our sample exclude the same asset classes. Other (less common) examples of discrete NC adjustments includ lifting of constraints on asset resale and/or branch network alterations. Overall, 27.5% of bids in our sample were NC, and these won 20% of the time.

2.2.1. *Packages.* Table 1 shows how different packages vary by popularity among bidders, implied resolution costs to the FDIC, and empirical win frequencies. Twelve out of sixteen packages are observed with positive frequency, and by far the most common active component is loss sharing. As-is P&A proposals account for 15.6% of all bids. By offering options, the FDIC hopes to attract bids from banks that might not otherwise be interested/able to compete, such as a bidder with a high value for the deposit franchise but who is reluctant to acquire assets that contribute risk to its portfolio. With the PB option, it can exclude some riskier assets. The three most costly packages for the FDIC are, in descending order, a contract with NC, LS, and VAI provisions, a PB-only contract, and one with NC, LS, and PB. A joint Wald test rejects equality of mean costs under different packages (p-value$< 10^{-16}$).

2.3. **Bidders' Resolution Cost Uncertainty.** The LS, NC, PB, and VAI components affect the Transaction Equity and Expenses terms in equation (1). In our example from Section 2.1, a bid with LS specifying that the FDIC will take on 80% of future losses on 50% of assets, implies that its expected Transaction Equity may increase by up to \$100K (=0.8×0.5×\$250K) in the future. The FDIC's backlog of pending LS commitments shifts

Table 1. Frequencies of Different Packages & Associated Costs (2009–2013)

| Package | | | | Percent of All Bids | | | FDIC Costs (winner only) | | |
|---|---|---|---|---|---|---|---|---|---|
| NC | LS | PB | VAI | All | MB | No MB | Mean | SD | % winning |
| No | Yes | No | No | 42.79 | 38.05 | 56.66 | 23.9 | 8.9 | 49.4 |
| No | No | No | No | 15.60 | 16.49 | 13.00 | 20.8 | 10.6 | 20.5 |
| Yes | Yes | No | No | 12.69 | 14.16 | 8.36 | 26.5 | 10.6 | 8.4 |
| Yes | No | No | No | 8.51 | 10.99 | 1.24 | 22 | 6.6 | 5.6 |
| No | No | Yes | No | 3.86 | 2.22 | 8.67 | 35.6 | 8.7 | 5.3 |
| Yes | No | Yes | No | 2.76 | 3.07 | 1.86 | – | – | 0.0 |
| Yes | Yes | No | Yes | 2.76 | 3.38 | 0.93 | 35.8 | 13.3 | 2.5 |
| No | Yes | Yes | No | 4.96 | 5.07 | 4.64 | 28 | 10.4 | 1.9 |
| No | Yes | No | Yes | 3.62 | 3.91 | 2.79 | 23.4 | 8.4 | 1.9 |
| Yes | Yes | Yes | No | 0.95 | 0.74 | 1.55 | 30.3 | 9.6 | 1.0 |
| Yes | No | No | Yes | 0.55 | 0.74 | 0.00 | 22.4 | 0 | 0.3 |
| No | Yes | Yes | Yes | 0.55 | 0.63 | 0.31 | 22.7 | 12.2 | 1.5 |
| No | No | No | Yes | 0.24 | 0.32 | 0.00 | 13.6 | 14.6 | 0.6 |
| Yes | Yes | Yes | Yes | 0.16 | 0.21 | 0.00 | 42 | 0 | 0.3 |

Ranked package frequencies in all 322 auctions, in auctions with multiple bidding (MB), and without (No MB). The mean and st.dev. of FDIC costs are reported as a percentage of failed bank assets. The last column reports the percentage of auctions that are won with each package. Two packages—(No,No,Yes,Yes) and (Yes,No,Yes,Yes)—were never bid on in our data.

its level of total exposure over time and thus determines its opportunity cost of accepting new LS contracts in the current auction. This internal state of operational constraints is known only to the FDIC, so from the perspective of bidders there is a distribution of possible costs associated with proposing LS as part of a P&A bid. Similar logic applies to the other discrete components. A second source of scoring uncertainty is administrative overhead: the discrete components induce complexity in the P&A contract, altering time requirements by FDIC lawyers and accountants. This implies further uncertainty since bidders are unaware of the FDIC's human resource constraints. Table 1 (last 3 columns) shows that there is substantial variation in FDIC costs both across and within packages. Thus, we model the FDIC's behavior as a scoring auction where the scoring weights represent trade-offs between the continuous dollar component and the four discrete components of a P&A bid, but where the precise values of the weights are unknown to bidders ex-ante.

## 3. Data

We study bank failures from 2009 to 2013 using data from the FDIC website. Our sample period begins when the FDIC began making bid data available, and it ends in 2013 because of a diminished number of failures around then. The total number of auctions during our sample period is 439. After removing auctions with no bidders (26), or with linked bidding (86) or loan pools (5), the full sample in our empirical analysis includes 322 auctions.[6]

[6] Loan pools allow healthy banks to bid on arbitrary groups of loans. Linked auctions involve different banks with the same closing date *and* state, and where the FDIC allows bidders to express preference complementarities. Both cases introduce a (standard) combinatorial element and complicate the analysis. Sample selection may be induced by omitting linked auctions if banks that happen to fail in the same period and state as another bank failure are systematically different, but there is no statistical difference between

For each auction the FDIC website publishes the ex-post resolution cost (from the winning P&A bid) and a detailed summary of bids, including the cash component and each of the discrete components (see Online Supplement E for an example of a bid summary page.) Bid summaries report the winning bid, the *cover bid* (i.e., the most competitive bid submitted by someone other than the winner), and the identities of the winner and cover bidder. They also report all other bids submitted, and the *losing-bid submitter list*, which contains identities of all bidders who submitted at least one losing bid (including the winner and/or cover bidder, if they had non-singleton bid portfolios). One challenge is that bid summaries do not specify the bidder identity associated with bids other than the winning and cover bids. In the next subsection we discuss how we handle this missing data problem.

3.1. **Bidder-Bid Matching.** For 193 auctions (henceforth, the *restricted sample*) we can positively match all bids to a unique bidder identity.[7] For the remaining auctions in the sample, we adopt an unsupervised assignment algorithm to match bidder identities to bids.[8] The simple idea behind it is that each bid submitted by $i$ must have non-trivial win probability *against $i$'s own other bids*, conditional on the distribution of FDIC scoring weights on the four discrete components.[9,10] For example, a bidder would not submit two bids on the same package, as one would surely lose. Moreover, suppose the FDIC is known to have a strong preference against awarding P&A contracts with a LS provision (i.e., it assigns large negative weights to the LS switch, on average). In that case, the same bidder could not have submitted one bid $b_{i1}$ for an as-is P&A contract, and another bid $b_{i2}$ requesting an even larger capital

our main sample (322) and failed banks in linked auctions (86) on eight dimensions: total assets, total deposits, insured deposits, %loans in commercial real estate and/or single-family residential, %core deposits, return on assets, tier 1 capital ratio, or book value of equity. There are two small but statistically significant differences: failed banks in linked auctions had lower %loans to consumers (1.2% vs 1.5%), and lower %loans in commercial & industrial (5.8% vs 8%).

[7]This is possible whenever any of the following are true: $(I)$ the auction has one bidder (112 auctions); or an auction has 2 bidders and either $(II)$ they both submit a single bid (42 auctions), or $(III)$ only one submits multiple bids (15 auctions), or $(IV)$ both bidders submit two bids but one of the third/fourth placed bids is on the same package as either the winner or cover bid (2 auctions); or finally, if there are 3 bidders and either $(V)$ each submits one bid (18 auctions), or $(VI)$ one submits many bids but the winner and cover bidder submit only one bid each (4 auctions). There are other possibilities for a 3-bidder auction to be included; the above cover observed instances in the data. A 2-bidder auction will not be in the restricted sample if, for example, both bidders submit at least 2 bids and bids dominated by the cover bid include packages other than either the winning bid or the cover bid. Auctions with 4+ bidders are never in the restricted sample.

[8]We use the term “unsupervised” in the computer-science sense, meaning our algorithm does not use a training dataset with known outcomes. However, it does incorporate known bidder-bid match information and structure from a model of optimal bidding to resolve ambiguous matches.

[9]Assuming that bidder $i$ chooses to include in its portfolio only bids that win against its other bids with non-trivial probability is equivalent to assuming there is some (potentially small) fixed cost $\zeta$ of submitting each bid. In that case, if a hypothetical bid wins with small enough probability (or never) against $i$'s optimal bid on some package $k$, then $i$ will choose to omit the dominated bid from its bid portfolio. This idea is incorporated into estimation of the empirical model as well (see Section 5.3).

[10]Note also that scoring rule estimation does not require bidder identity information (see Section 5.1).

transfer from the FDIC on a P&A contract with a LS provision only. This would imply $i$'s own other bid $b_{i1}$ beats out $b_{i2}$ with near certainty, since the two differ only by the LS provision and the proposed capital transfer under $b_{i2}$ is worse from the FDIC's perspective.

3.1.1. *Name Matching Algorithm Sketch.* For 129 out of 322 auctions in our sample, there are some bids for which the identity of the submitter is partially ambiguous. Within the $j^{\text{th}}$ auction, the algorithm (see Appendix D.3 for full details) is seeded with known bidder-bid match information described above. Conditional on this information, it computes the set $A_j$ of all possible unique assignments of bids to bidders within the losing-bid submitter list (with each member of the list being assigned at least one bid). The algorithm then applies two key feasibility constraints to compute a set $A'_j$ of candidate assignments where either ($i$) at least one bidder is assigned two different bids on the same package $k$, or ($ii$) at least one bidder is assigned two bids (on different packages) where one beats the other with probability $(1-\psi)$ or more, $\psi > 0$ (we chose $\psi = 0.05$). The within-portfolio win probabilities in constraint ($ii$) are not equilibrium objects, but rather, represent how often one of a bidder's bids beats out its *own other bids*, given scoring shock variation. The set $A'_j$ now contains all bidder-bid assignments that violate the feasibility constraints, and its relative complement, $A_j \setminus A'_j$, is called the *feasible set* for auction $j$. For notational convenience, we define the overall feasible set as $\boldsymbol{A} \setminus \boldsymbol{A}' \equiv A_1 \setminus A'_1 \times \cdots \times A_J \setminus A'_J$. Finally, the algorithm resolves residual match ambiguity by imposing a uniform prior on $\boldsymbol{A} \setminus \boldsymbol{A}'$, and selecting an assignment at random.

3.1.2. *Algorithm Properties, Performance, and Robustness Checks.* In order to better understand the properties of the algorithm, one can think of it as performing two separate (though related) tasks: grouping bids together into portfolios, and matching portfolios to bidders. As for the first task, the precision of the algorithm is aided by aspects of the raw data. If multiple bidding were maximally frequent and bids were uniformly spread across all 16 packages, the algorithm would lean heavily on its random component, whereas if multiple bidding were less frequent and a small set of packages were bid on, the feasibility constraints are more informative. Fortunately, within the FDIC dataset bidders submit an average of 1.5 bids each and the four most popular packages (out of 16) account for 80% of all bids.

Still, as a robustness check we ran a test of the performance of the algorithm within the restricted dataset, where all bidder-bid match information is ex-ante known. In four waves of the test we successively drop elements of the known match information that seeds the algorithm, and then we run the algorithm many times over to see how well it is able to replicate the empirical frequencies of bid portfolios observed in the original dataset. Table OS.1 in Online Appendix D.3 displays results of the test, which confirm that the algorithm does well at appropriately grouping bids into portfolios. Notably, in the final wave of the test we drop *all* bidder-bid-match seed information—forcing the algorithm to lean solely on feasibility constraints to group bids into portfolios—but it still does remarkably well at replicating the empirical frequencies of bid portfolios in the data.[11] Moreover, within the full sample we ran the name matching algorithm on 129 auctions that do not belong to the restricted sample; among these, 22 (17%) have a singleton feasible set, 53 (41%) have feasible sets with cardinality $|A_j \setminus A'_j| < 5$, and and 65 auctions (50%) have $|A_j \setminus A'_j| \leq 10$.[12] These numbers illustrate how informative feasibility constraints ($i$) and ($ii$) are.

We now turn to an evaluation of the second task the algorithm performs, replicating correlations between bid portfolios and bidder covariates. One can think of a given run of the algorithm as producing a single random draw from the (uniform) distribution of the set of feasible match assignments $\boldsymbol{A} \setminus \boldsymbol{A}'$. Accordingly, during model estimation we integrate over the distribution of residual match uncertainty in order to prevent our estimates from being driven by assignment error (see Section 5.4). Still, our assumption of a uniform prior on the feasible set plays a potentially important role.[13] Alternatively, one might imagine a non-uniform sampling of bidder-bid assignments from $\boldsymbol{A} \setminus \boldsymbol{A}'$, where bidders with certain covariates are more or less likely to submit certain portfolios of bids, relative to the uniform prior scenario. In order to probe for this possibility, we estimate an alternative weighting scheme based on correlations between bidder covariates $\boldsymbol{W}_{ij}$ and the propensity to submit bids on each of the 16 individual packages. These correlations can be used to derive an alternate (possibly non-uniform) weighting of bidder-bid matches in the set $\boldsymbol{A} \setminus \boldsymbol{A}'$. We find that the alternate weighting scheme (and results derived from it) is close to our more simple uniform prior on the feasible set (see Online Appendix D.3 and Section 5.4).

3.2. **Summary statistics.** Table 2 presents summary statistics. We incorporate quarterly bank balance-sheet information (FDIC's *Statistics on Depository Institutions* (SDI) dataset), and location information from the FDIC's annual summary of deposits (SOD). Our balance-sheet and physical-distance measures were constructed as in Granja et al. (2017).

There is substantial heterogeneity in failed bank size, with the $10^{\text{th}}$ and $90^{\text{th}}$ percentiles of total asset book value differing by a factor of 20.7. On average, failed banks are relatively small and healthy bidding banks are larger. Failed banks had more exposure to the real

---

[11]To further illustrate this point, consider an equivalent *greedy* (i.e., myopic) version of the algorithm where bids are iteratively assigned to bidder identities, one at a time. The greedy version of the algorithm implemented on our FDIC data set would imply that 76% of all bids in the full sample are non-randomly matched to bidder identities based on prior match information and/or the feasibility constraints.

[12]Cardinality $|A_j \setminus A'_j|$—number of unique feasible bidder-bid assignments—depends on the number of bidders and bids, the configuration of packages bid on, and the dollar values of bids.

[13]Note that the algorithm uses known seed information (e.g., winning and cover bids), and constraints ($i$) and ($ii$) in order to derive the feasible set. Therefore, assuming a uniform prior on the elements of $A_j \setminus A'_j$ *does not* imply purely random assignment of bids into portfolios or of portfolios to bidders.

estate market (especially commercial), and their Tier 1 capital ratio, a standardized index of financial solvency, is close to 1, in contrast to bidding banks for whom the average is above 15. The average return on assets for failed banks is negative, while bidders have healthy, positive ROAs. The mean and standard deviation for pairwise physical distance between a failed bank and a bidding bank are 191 miles and 257 miles, respectively.

In all, 359 healthy banks bid in at least one auction, generating 814 unique bidder-failure pairs and 1,269 bids. The mean bidder participated in 2.4 auctions.[14] Thus, unlike in procurement or securities auctions where the same bidders frequently return, most healthy banks participate in only a few FDIC auctions. There are an average of 3.96 bids per auction, and 2.6 bidders; even in single-bidder auctions there is often multiple bidding. We observe up to 8 bids in auctions with 3 bidders or fewer. The FDIC's mean resolution cost is $134.3 million per failure. We also calculate the average change in market concentration for deposits (post-resolution merger) across markets where the failed bank is active. Increases in market concentration vary widely and average 6% at the county level and 11.5% at the zip-code level, suggesting a possible role for auction design in shaping local market structure.

## 4. Model

Here we develop a model to facilitate structural inference. For comparability across failed bank auctions of different sizes, moving forward we express all continuous bids and resolution costs as percentages of failed-bank total asset book value. A combination of discrete component inclusions plus a bid's continuous portion can be thought of as a "package," but in contrast to standard combinatorial auctions, there can only be one winner in each auction, which simplifies the combinatorial problem. Bidders are subject to scoring uncertainty that randomly shifts the auctioneer's allocation rule from auction to auction.

Failed bank $j$ has traits $\boldsymbol{Z}_j = (Z_{j1}, \ldots, Z_{jK_z})$, and healthy bidding banks have traits $\boldsymbol{W}_{ij} = (W_{ij1}, \ldots, W_{ijK_w})$, where $i = 1, \ldots, N_j$ indexes bidders participating in auction $j$.

**Assumption 1.** *Total participation, $N_j$, and rival traits, $\boldsymbol{W}_j$, $j \neq i$, are unobserved to bidder i prior to bidding, but for all $\boldsymbol{Z}_j$ the conditional distributions of bidder participation $N \sim \pi_N(n|\boldsymbol{Z}_j)$ and rival traits $\boldsymbol{W} \sim F_{\boldsymbol{W}}(\boldsymbol{w}|\boldsymbol{Z}_j)$ are common knowledge, the former has bounded raw moments $E[N^t|\boldsymbol{Z}_j] < \infty$ for all $t \in \mathbb{N}$, and the latter is absolutely continuous.*[15,16]

[14]The largest bidding banks (top 10%) participated somewhat more frequently (3.9 auctions on average), but the probability of winning a given auction does not depend on size. See discussion of Table C.1, specification (2), Appendix C, where the data fail to reject a joint restriction of all size terms (p-value=0.56).

[15]We assume throughout that auction traits $\boldsymbol{Z}_j$ govern bidder selection by numbers *and* types. While the number of bidders $N$ and their types are unconditionally correlated (through their relation to auction covariates), we assume that, conditional on $\boldsymbol{Z}_j$, the number of bidders is independent of bidder types.

[16]For example, if $N$ has bounded support, or if its moment generating function exists (as in the Poisson case), then it would satisfy the bounded raw moments condition.

Table 2. Summary Statistics

| **Bank Characteristics** | **Failed Banks** | | | | **Bidding Banks** | | | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | ***N*** | **Mean** | **StDev** | **10-90 Interval** | ***N*** | **Mean** | **StDev** | **10-90 Interval** |
| Tot. Assets ($Million) | 322 | 628.39 | 1944.55 | $[48.86, 1009.15]$ | 359 | 13,900 | 122,000 | $[171.94, 8791.93]$ |
| Tot. Deposits ($Million) | 322 | 531.85 | 1561.12 | $[45.77, 919.61]$ | 359 | 9841 | 83700 | $[147.05, 6638]$ |
| Ins. Deposits ($Million) | 322 | 478.50 | 1322.45 | $[41.88, 915.48]$ | 359 | 5575 | 42200 | $[121.88, 5221]$ |
| CRE (%) | 322 | 24.59 | 12.37 | $[10.43, 43.31]$ | 359 | 20.75 | 11.03 | $[7.92, 33.98]$ |
| C&I (%) | 322 | 8.00 | 6.79 | $[1.52, 17.37]$ | 359 | 9.99 | 7.07 | $[3.29, 18.81]$ |
| CNSMR (%) | 322 | 1.52 | 2.16 | $[0.10, 3.71]$ | 359 | 3.39 | 4.72 | $[0.30, 8.36]$ |
| SFR (%) | 322 | 18.41 | 13.21 | $[3.71, 35.71]$ | 359 | 17.18 | 11.95 | $[5.94, 30.86]$ |
| ARE (%) | 322 | 59.90 | 12.34 | $[44.87, 74.27]$ | 359 | 48.23 | 14.32 | $[30.84, 65.63]$ |
| ROA | 322 | -6.81 | 6.95 | $[-12.90, -1.72]$ | 359 | 1.34 | 2.00 | $[0.17, 3.01]$ |
| Tier 1 Ratio | 322 | 1.17 | 3.46 | $[-1.79, 3.58]$ | 359 | 15.46 | 8.13 | $[10.69, 21.70]$ |
| Core Deposits (%) | 322 | 77.37 | 15.56 | $[56.09, 94.74]$ | – | – | – | – |
| Book Value Equity (%) | 322 | 13.93 | 15.24 | $[-0.29, 31.82]$ | – | – | – | – |
| Non-Accruing Loans (%) | 322 | 10.97 | 6.52 | $[4.35, 19.44]$ | – | – | – | – |
| Pairwise Failure Dist. (km) | 322 | 2052 | 1042 | $[1135, 4010]$ | – | – | – | – |
| # Auctions participated | – | – | – | – | 359 | 2.40 | 3.43 | $[1, 5]$ |
| # Auctions Won | – | – | – | – | 359 | 0.894 | 1.139 | $[0, 2]$ |
| **Bidder-Failed Bank Comparisons** | | | | | | | | |
| Portfolio %Diff: CRE | 814 | 10.65 | 9.40 | $[1.57, 23.74]$ | | | | |
| Portfolio %Diff: C&I | 814 | 6.21 | 5.96 | $[0.82, 14.38]$ | | | | |
| Portfolio %Diff: CNSMR | 814 | 3.03 | 5.09 | $[0.15, 7.72]$ | | | | |
| Portfolio %Diff: SFR | 814 | 9.68 | 9.84 | $[1.21, 20.94]$ | | | | |
| All Real Estate | 814 | 15.31 | 11.63 | $[2.21, 32.34]$ | | | | |
| Avg. Pairwise Dist. (km) | 814 | 306.88 | 412.78 | $[20.39, 838.49]$ | | | | |
| **Auction Characteristics** | | | | | | | | |
| # of Bids | 322 | 3.96 | 3.79 | $[1, 8]$ | | | | |
| # of Bidders | 322 | 2.60 | 1.72 | $[1, 5]$ | | | | |
| Cost to FDIC ($Million) | 322 | 134.25 | 347.78 | $[9.00, 77.64]$ | | | | |
| Net Transfer Bid | 1,269 | -0.24 | -0.26 | $[-0.76, -0.04]$ | | | | |
| %Δ in County HHI for Deposits | 246 | 5.99 | 4.24 | $[1.05, 10.69]$ | | | | |
| %Δ in Zip-Code HHI for Deposits | 217 | 11.45 | 16.41 | $[0.13, 31.73]$ | | | | |

Balance-sheet information comes from the SDI for the quarter pre-failure. Variables *CRE* (commercial real estate), *C&I* (commercial and industrial), *CNSMR* (consumer), *SFR* (single-family residential), and *ARE* (all real estate) represent shares of lending in each sector. *Core Deposits*: bank deposits comprise core deposits—checking/savings accounts, consumer CDs—and brokered deposits. Core deposits are more stable than brokered deposits because the latter are more sensitive to interest rate fluctuations. *ROA* is return on assets and measures profitability. *Tier 1 Ratio*—equity capital and cash reserves divided by risk-weighted assets—is a standardized measure of solvency that rises as the financial health of a bank becomes more secure. *Book Value Equity* is the difference between the total assets and the total liabilities as a percentage of failed-bank assets. *Non-Accruing Loans* are 90+ days past due as of the auction date. *Pairwise Failure Dist.* is calculated using the average distance over all branch combinations between each pair of failed banks. *Portfolio %Differences* are the absolute value change in portfolio shares for the failed bank and bidder bank in each bidder-failed bank pair. *Average Pairwise Distance* is calculated using the average distance over all branch combinations of the failed and bidding bank. For comparability across auctions, *Net Transfer Bid* is expressed as the transfer amount (from the FDIC to the bidder when negative, vice versa when positive) calculated using equation (1), divided by the total assets of the failed bank.

While $\pi_N(n|\boldsymbol{Z}_j)$ characterizes variation in total participation from the auctioneer's perspective, from bidder $i$'s perspective the number of its competitors is a different random variable, $M_j \equiv N_j - 1$, which has probability mass function $\pi_M(m|\boldsymbol{Z}_j) = \pi_N(m+1|\boldsymbol{Z}_j)\frac{(m+1)}{\mathrm{E}[N|\boldsymbol{Z}_j]}$ (see Myerson (1998)). Assumption 1 is motivated by institutional details of failed-bank auctions: number and identities of rivals are not revealed publicly until after the auction.

Bidding banks draw independent private valuations for acquisitions $\overline{V}_{ij} \sim F_{\overline{V}}(\overline{V}_{ij}|\boldsymbol{X}_{ij})$, where $\boldsymbol{X}_{ij} = (\boldsymbol{Z}_j \otimes \boldsymbol{W}_{ij})$ is shorthand for the Kronecker product of auction and bidder covariates (i.e., allowing for arbitrary interactions). Bidder $i$'s baseline value $\overline{V}_{ij}$ is typically negative, representing the minimal transfer from the FDIC at which it would be willing to take over the failed bank's business, as-is. Each package $k$ is a unique configuration of discrete switches, and each bidder $i$ has valuation $v_{ijk}$ for P&A under package $k \in \mathcal{K} = \{1, \ldots, 16\}$:

$$v_{ijk} = \bar{v}_{ij} + v_{ij}^{LS} d_k^{LS} + v_{ij}^{NC} d_k^{NC} + v_{ij}^{PB} d_k^{PB} + v_{ij}^{VAI} d_k^{VAI} + \boldsymbol{D}_k \boldsymbol{\lambda}, \tag{2}$$

where $v_{ij}^s$ is the valuation for binary switch $s \in \{LS, NC, PB, VAI\}$, $d_k^s$ is an indicator for $s$ being turned on in $k$, $\boldsymbol{D}_k$ is a full set of pairwise switch indicator interactions, and $\boldsymbol{\lambda}$ is a conformable vector of parameters. Switches are LS (loss share), NC (nonconforming), PB (partial bank), and VAI (value appreciation instrument). Switch valuations are independent across bidders $i$ and follow joint distribution $\boldsymbol{S}_{ij} = (V_{ij}^{LS}, V_{ij}^{NC}, V_{ij}^{PB}, V_{ij}^{VAI}) \sim F_{\boldsymbol{S}|\boldsymbol{X}_i}(\boldsymbol{s}|\boldsymbol{X}_{ij})$.

**Assumption 2.** *The distribution of private values $(\overline{V}, \boldsymbol{S})$, conditional (only) on auction traits $\boldsymbol{Z}_j$, is absolutely continuous, with a compact and connected support, and a differentiable density that is strictly positive everywhere on its support. That is, for all $\boldsymbol{Z}_j$*

$$f_{\overline{V},\boldsymbol{S}}(\overline{v}, \boldsymbol{s}|\boldsymbol{Z}_j) = \int_{Supp(F_{\boldsymbol{W}})} f_{\overline{V},\boldsymbol{S}}(\overline{v}, \boldsymbol{s}|\boldsymbol{Z}_j \otimes \boldsymbol{w}) f_{\boldsymbol{W}}(\boldsymbol{w}|\boldsymbol{Z}_j) d\boldsymbol{w}$$

*exists, $f_{\overline{V},\boldsymbol{S}}(\overline{v}, \boldsymbol{s}|\boldsymbol{Z}_j) \in \mathcal{C}^1$, and $f_{\overline{V},\boldsymbol{S}}(\overline{v}, \boldsymbol{s}|\boldsymbol{Z}_j) > 0 \;\; \forall (\overline{v}, \boldsymbol{s}) \in Supp(F_{\overline{V},\boldsymbol{S}}(\overline{v}, \boldsymbol{s}|\boldsymbol{Z}_j))$.*

Assumptions 1 and 2 imply that from each bidder's perspective the distribution of rival types is non-degenerate and well-behaved; in other words, there is non-trivial residual uncertainty on rival P&A valuations after conditioning on auction covariates $\boldsymbol{Z}_j$. Rival traits $\boldsymbol{w}$ are integrated out because they are ex-ante unobservable prior to bidding. In that sense, bidder traits are essentially another variety of private information from a bidder's perspective, but one that is observable (ex-post) to the econometrician in the empirical model. It will sometimes be convenient to denote bidder $i$'s full set of package-specific valuations by $\boldsymbol{V}_{ij} = (V_{ij1}, \ldots, V_{ij16})$. Recall that each package represents a unique set of contract terms for P&A of failed bank $j$, where each $V_{ijk}$ is constructed from the building blocks $\overline{V}_{ij}$, $\boldsymbol{S}_{ij}$, and $\boldsymbol{\lambda}$, according to equation (2). Let $F_{\boldsymbol{V}}(\boldsymbol{v}|\boldsymbol{Z}_j) : \mathbb{R}^{16} \to [0,1]$ denote its joint distribution.

The set of *net transfer bids* submitted by bidder $i$ is $\boldsymbol{b}_{ij} = (b_{ij1}, \ldots, b_{ij16})$, where $b_{ijk} \in \mathbb{R}$ is the dollar component of a P&A bid for contract package $k$. When the net transfer bid $b_{ijk}$

is a negative number it represents a proposed cash transfer to $i$ from the FDIC under the terms of contract $k$; similarly, $v_{ijk}$ represents its indifference transfer under contract $k$. We denote $i$'s portfolio of packages bid on as $L_{ij} = \{k : b_{ijk} > \underline{b}_{jk}\}$, where $\underline{b}_{jk}$ is a *choke point* for the $k^{th}$ package, at which price the FDIC would prefer not to trade. Bids made exactly at or below the choke point win with zero probability, and we refer to them as *trivial bids*. Finally, let $b_{ijk} = \underline{b}_{jk}$ for $k \notin L_{ij}$ (by convention). [17] Finite choke points are common knowledge to bidders. In the context of failed banks they have a concrete legal interpretation: the FDIC's direct depositor reimbursement cost—i.e., failed-bank depositor receipts minus its cash reserves—which by law (FDICIA) places a bound on any permissible P&A agreement.

For each auction, the FDIC also has a private reservation cost $C_{0j} \sim F_{C_0}(c_0)$ representing its internal estimate of directly reimbursing depositors and liquidating bank $j$ without holding an auction. We assume $F_{C_0}$ assigns positive probability to all values above $\min\{\underline{b}_{j1}, \ldots, \underline{b}_{j16}\}$. Intuitively, bidders cannot predict exactly how much better the FDIC can do with a non-auction liquidation over the direct reimbursement option. They assume that it can do anywhere between a lot better and no better, meaning that any bid slightly above the choke price is viewed as winning with at least a small, positive probability.

An auction-specific vector $\mathbf{\Gamma} = [\gamma_j^{LS}, \gamma_j^{VAI}, \gamma_j^{NC}, \gamma_j^{PB}] \in \mathbb{R}^4$ represents the FDIC's evaluation of the impact of each discrete component on its cost structure. The P&A contract is allocated to the healthy bank offering the least-cost bid, evaluated according to:[18]

$$-C_{ijk} = b_{ijk} + \mathbf{\Gamma}_j \boldsymbol{d}_k + \delta_{ijk} + u_j. \tag{3}$$

The right-hand side is FDIC *revenues* $R_{ijk}$ under $i$'s bid on package $k$: recall that $b_{ijk} < 0$ is a proposed transfer from the FDIC to $i$ and revenues are the negative of costs, or $R_{ijk} = -C_{ijk}$. The weights $\mathbf{\Gamma}$ represent (respectively) internal FDIC trade-offs between the LS, VAI, NC, and PB, components, and the dollar component $b_{ijk}$. The term $u_j$ is an unobserved cost shock, including package-independent FDIC expenses incurred in the resolution process.

**Assumption 3.** *The reserve-cost distribution $F_{C_0}$ assigns positive probability to all values above* $\min\{\underline{b}_{j1}, \ldots, \underline{b}_{j16}\}$*. The vector $(\gamma_j^{LS}, \gamma_j^{VAI}, \gamma_j^{NC}, \gamma_j^{PB}, u_j)$ follows an absolutely continuous joint distribution $F_{\mathbf{\Gamma}U}(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB}, u|\boldsymbol{Z}_j)$ with marginal distributions having full support on the real line. The bidder-package shock term $\delta_{ijk} \sim F_\delta(\delta)$ follows an absolutely continuous, unimodal distribution, and is independent across packages $k$, bidders $i$, and auctions $j$.*

[17] Our assumption throughout is that bidders never choose to submit bids that will lose with probability 1.

[18] Regarding interactions among discrete components in equation (3), we regressed ex-post costs on winning bid component dummies and a full set of component interactions. We could not reject the joint exclusion restriction of interactions (p-value=0.935). Thus, for simplicity we omit them from the scoring equation.

A bidder's information set includes auction traits $\boldsymbol{Z}_j$ and various distributions, including $\pi_M(m|\boldsymbol{Z}_j)$, $F_{\boldsymbol{W}}(\boldsymbol{w}|\boldsymbol{Z}_j)$, $F_{\boldsymbol{V}}(\boldsymbol{v}|\boldsymbol{Z}_j)$, $F_{C_0}(c_0)$, $F_{\boldsymbol{\Gamma}U}(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB}, u|\boldsymbol{Z}_j)$, and $F_\delta(\delta)$. A bidder's equilibrium win probability for package $k$, given its bid portfolio and given auction covariates, is $G(b_{ijk}|L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j) \equiv \Pr[i \textit{ wins P\&A contract } k|L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j]$. For $i$ to win on package $k$, three events must occur all at once: $b_{ijk}$ must dominate the (unknown) reserve cost $C_0$ (event $\mathcal{A}$); $b_{ijk}$ must dominate $i$'s own bids on other packages $k' \in L_{ij}$ (event $\mathcal{B}$); and $b_{ijk}$ must dominate bids submitted by all other bidders (event $\mathcal{C}$). More concretely,

$$
\begin{aligned}
&G(b_{ijk}|\boldsymbol{b}_{ij}, L_{ij}, \boldsymbol{Z}_j) = \Pr\Big[-C_0 - \boldsymbol{\Gamma}_j\boldsymbol{d}_k - \delta_{ijk} - u_j \leq b_{ijk}\Big] \\
&\times \prod_{k' \in L_{ij},\, k' \neq k} \Pr\Big[\boldsymbol{\Gamma}_j(\boldsymbol{d}_{k'} - \boldsymbol{d}_k) + (\delta_{ijk'} - \delta_{ijk}) \leq (b_{ijk} - b_{ijk'})\Big|\mathcal{A} \cap \mathcal{B}_{-k'}\Big] \\
&\times \sum_{M=1}^{\infty} \Big(\prod_{n=1}^{M} \prod_{k' \in L_{nj}} \Pr\Big[\boldsymbol{\Gamma}_j(\boldsymbol{d}_{k'} - \boldsymbol{d}_k) + (\delta_{ijk'} - \delta_{njk}) + b_{njk'} \leq b_{ijk})\Big|\boldsymbol{Z}_j, \mathcal{A} \cap \mathcal{B} \cap \mathcal{C}^M_{-nk'}\Big]\Big)\pi_M(M|\boldsymbol{Z}_j),
\end{aligned}
$$

where $\mathcal{B}_{-k'}$ is the sub-event that $b_{ijk}$ beats all of $i$'s other bids $k'' < k'$, $k'' \neq k$, and $\mathcal{C}^M_{-nk'}$ is the sub-event that, conditional on $M$ competitors, $b_{ijk}$ beats all bids $k'' < k'$ by bidders $n' < n$. In the three inequalities, objects known to the bidder are on the right-hand side; unknown random variables are to the left. Due to the scoring rule and competitor equilibrium bids $b_{njk'}$ being functions of rivals' private information which is correlated with $\boldsymbol{Z}_j$ (see Assumption 2), the $\Pr[\cdot]$ terms involve complicated distributions of sums of correlated random variables. The three multiplicative terms above correspond to events $\mathcal{A}$, $\mathcal{B}$, and $\mathcal{C}$, respectively; successive conditioning is due to dependence on overlapping sets of random variables.

Given $G$, bank $i$ chooses its optimal package portfolio $L_i^*$ and associated bid profile $\boldsymbol{b}_i^*$ to solve a (constrained) mixed discrete-continuous-choice decision:

$$
\begin{aligned}
\max_{L_{ij} \in \mathbb{P}(\mathcal{K})} \Big\{ \max_{\boldsymbol{b}_{ij} \in \mathbb{R}^{16}} \sum_{k \in L_{ij}} (v_{ijk} - b_{ijk}) G(b_{ijk}|L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j) \Big\} \\
\textit{subject to} \quad b_{ijk} \geq \underline{b}_{jk}\ \forall k \in L_{ij}, \\
b_{ijk} = \underline{b}_{jk}\ \forall k \notin L_{ij},
\end{aligned}
$$

where $\mathbb{P}(\mathcal{K})$ denotes the powerset of $\mathcal{K}$. For each $k \in \mathcal{K}$ we have the following Karush-Kuhn-Tucker (KKT) conditions:

$$
\begin{aligned}
v_{ijk}\frac{\partial G(b_{ijk}|L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j)}{\partial b_{ijk}} - \Bigg[G(b_{ijk}|L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j) + b_{ijk}\frac{\partial G(b_{ijk}|L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j)}{\partial b_{ijk}} \\
- \sum_{\substack{k' \in L_{ij}, \\ k' \neq k}} (v_{ijk'} - b_{ijk'}) \frac{\partial G(b_{ijk'}|L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j)}{\partial b_{ijk}}\Bigg] + \mu_{ijk} = 0
\end{aligned}
\tag{4}
$$

$$\mu_{ijk}(b_{ijk} - \underline{b}_{jk}) = 0, \quad \mu_{ijk} \geq 0.$$

The first line is the first-order condition (FOC); its first term is the marginal benefit of raising one's net transfer bid on package $k$—i.e., higher win probability—and the bracketed term represents marginal costs—i.e., lower net transfer conditional on winning $k$ and stealing win probability from other own bids on $k' \in L_{ij}$. The last line is a complementary slackness condition. Intuitively, the FOC states that either it must be possible to equate marginal benefits and costs tied to $b_{ijk}$ with an interior solution (given other $k' \in L_{ij}$), in which case $\mu_{ijk}=0$, or else package $k$ must be omitted from $i$'s portfolio $L_{ij}$, in which case $(b_{ijk}-\underline{b}_{jk})=0$.[19]

4.1. **Equilibrium Existence and Model Predictions.** Our solution concept for the auction game defined above is a symmetric Bayes-Nash equilibrium (BNE). A pure-strategy BNE constitutes a mapping from the space of private information into the space of bid portfolios and bid levels $(L_{ij}, \boldsymbol{b}_{ij})$, $\mathcal{BNE}(\boldsymbol{Z}_j) : Supp(F_{\overline{V}}) \times Supp(F_{\boldsymbol{S}}) \longrightarrow \mathbb{P}(\mathcal{K}) \times \mathbb{R}^{16}$, such that, given $\boldsymbol{Z}_j$, each bidder $i$ has no unilateral incentive to deviate from the prescribed choice $\mathcal{BNE}(\overline{v}_{ij}, \boldsymbol{s}_{ij}; \boldsymbol{Z}_j)$, when all other bidders behave similarly. The game is complex, but several key model implications can be established. We demonstrate existence of a BNE by proving characteristics that equilibrium bidding must satisfy (Lemma 1), and then invoking a result by Jackson et al. (2002). What makes existence challenging in auctions is the presence of discontinuous payoffs due to potential ties between bidders.[20] The bidder-package shock $\delta_{ik}$ eliminates the discontinuous payoffs problem, and as Jackson et al. (2002) point out, would imply existence by virtue of familiar classical results. In order to demonstrate that equilibrium existence does not hinge on that minor model component, for the purpose of Lemma 1 and Proposition 1 we consider the more difficult case where $\delta$ is a single point mass at zero. We also discuss other cost-relevant bidding incentives, including selection of one's portfolio, $L_i$, and optimization of bids on packages in that portfolio. Some of these aspects can be proven outright, and some are more difficult but can be numerically verified using model estimates. We discuss key results here and relegate formal proofs to Appendix A.

**Lemma 1.** *In any Bayes-Nash Equilibrium (if one exists), the following must be true:*

*(1)* $b_{ijk} < v_{ijk} \;\; \forall k \in \left\{ l \mid l \in L_{ij},\ v_{ijl} > \underline{b}_{jl} \right\}$;

---

[19]The KKT conditions need not hold for *all* portfolio choices, but only for the *optimal* choice $L^*_{ij}$. E.g., suppose that for some $L_{ij}$ there is no non-negative vector $\boldsymbol{\mu}_{ij} = \{\mu_{ij1}, \ldots, \mu_{ij16}\}$ satisfying (4). Assuming the complementary slackness conditions are true (and the set of excluded bids $b_{ijk} = \underline{b}_{jk}$ implied by $k \notin L_{ij}$), if values of $\boldsymbol{\mu}_{ij}$ which satisfy the FOC involve at least one negative element, then $L_{ij}$ cannot be an optimal portfolio choice. This is because there must be at least one package $k$ which, if added to the portfolio to get $L'_{ij} = L_{ij} \cup \{k\}$ (i.e., dropping the constraint $b_{ijk} = \underline{b}_{jk}$), must make the bidder strictly better off.

[20]For a simple illustrative example, consider an auction with $N=2$, where both bidders submit P&A proposals on the same package $k$. Holding bidder 1's bid $b_{1jk}$ fixed, consider a sequence $\{b_{2jkn}\}_{n=1}^{\infty} \rightarrow b_{1jk}$ of 2's bids approaching $b_{1jk}$ from below. Along the sequence, bidder 1 wins with surety and bidder 2's win probability is zero, whereas in the limit these probabilities abruptly jump to something strictly between zero and one. This discontinuity in the payoff structure of the game implies that traditional fixed-point approaches to equilibrium existence (e.g., (Debreu 1952), (Glicksberg 1952)) do not apply.

*(2)* $G(b_{ijk}|L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j)$ *is strictly increasing in* $b_{ijk}$ *for any non-trivial bid; and*

*(3)* $b_{ijk} = \underline{b}_{jk}$ $\forall k$ *s.t.* $v_{ijk} \leq \underline{b}_{jk}$.

*(4) There are no mass points in the distribution of bids (for proof see Appendix A).*

That is, equilibrium strategies must prescribe strictly profitable non-trivial bids; the win probability on package $k$ must be monotone and continuous in the bid on that package (holding opponents' actions and other own bids fixed); and trivial bids must be submitted on packages where a bidder's valuation is weakly below the package-specific choke point.

**Proposition 1.** *In the private value, first-price, package auction with scoring-rule uncertainty defined above, a symmetric Bayes-Nash Equilibrium exists.*

We relegate a proof of the proposition to Appendix A.[21] Fully characterizing the equilibrium in this model is difficult, but certain revenue-relevant aspects of bidding incentives can be formalized. Bidders are generally not indifferent to winning with each of the bids they submit; rather, they submit a portfolio of non-trivial bids $L_{ij}$ that maximizes their expected surplus. Remark 1 and Proposition 2 below pertain to crucial aspects of portfolio optimization.

**Remark 1.** *Under scoring uncertainty (barring pathological distributions* $F_{\mathbf{V}}$*) bidders engage in multiple bidding with positive probability. On the other hand, with positive probability bidders choose portfolios* $L_i$ *to be a strict subset of all packages* $\mathcal{K}$*, due to a combination of both mechanical package omissions (for* $k$ *such that* $v_{ijk}$ *is too low to facilitate bilateral trade with the FDIC) and elective package omissions (on which bilateral trade is a priori feasible).*

Examples of "pathological" distributions include cases where all private value mass is below the choke points, thus precluding beneficial trade with the FDIC on multiple packages. In other cases there exist more intuitive incentives for multiple bidding: a bidder may insure against scoring rule uncertainty by submitting bids acceptable to itself on multiple packages. The more surprising part of the remark is that banks may not "fully insure" by including all possible packages in the set $L_{ij}$.

There are two reasons for this. First, mechanically, a bidder may have a very low a package-specific valuation. The second and more interesting reason is elective package omissions

[21] While Jackson et al. (2002) establishes BNE existence, it is difficult in our setting to prove the stronger result of existence in pure strategies. In typical single-unit first-price auctions, this is done by showing that the equilibrium strategy must be monotone in private signals, but this logic is complicated by multiple bidding in our setting. However, in estimation we verify numerically that the system of equations in (7) below has rank equal to the cardinality of $L_{ij}$ (i.e., full rank) for all $i$ and $j$, which is consistent with a pure-strategy BNE in the data-generating process. Note, however, that model identification and estimation are unaffected by this question, since equations (7) and (8), which follow from the KKT conditions, must be satisfied by *any* BNE, mixed or pure (recall that in a mixed strategy equilibrium a bidder must be indifferent to all actions in the support of its mixed strategy). Moreover, our main counterfactuals eliminate scoring uncertainty, collapsing the game to a typical first-price auction, where existence of pure-strategy BNE is known.

due to the *substitution effect.* To fix ideas, consider a bidder deciding whether to place a non-trivial bid on an additional package. Adding a new bid to portfolio $L_{ij}$ may increase win probability overall, but will *reduce* its probability of winning with existing bids, one of which may yield higher surplus. Recall also that bidders have strict preference rankings over inclusion/exclusion of different discrete components, so they are not indifferent about the packages (i.e., P&A contract terms) under which they would prefer to win in auction $j$. As an illustration of this point, within the model recovered from the FDIC data it can be shown numerically that 75% of package omissions from the portfolio $L_{ij}$ were elective, with private values $v_{ijk}$ high enough to facilitate mutually beneficial trade with the FDIC (see Section 6). This strong numerical result highlights how substitution effects may play a central role in bid portfolio choice within the model.

Moreover, substitution effects also shape the levels of optimal bids submitted on included packages. This idea is represented by the third term inside the brackets in equation (4): when forming a bid on package $k$, a bidder internalizes the cost of competition from $b_{ijk}$ on its prospects for winning on other packages $k' \in L_{ij}$. This cost depends both on $i$'s likelihood of winning package $k'$ *and* its gross utility of winning $k'$. Since $\partial G(b_{ijk'}|L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j)/\partial b_{ijk} < 0$ (by construction) and $(v_{ijk'} - b_{ijk'}) > 0$ (by Lemma 1), $i$ will respond to the "business stealing" impact of $b_{ijk}$ on its own other bids $b_{ijk'}$ by increasing the wedge between $v_{ijk}$ and $b_{ijk}$.

**Proposition 2.** *In the absence of scoring rule uncertainty, there is no incentive to engage in multiple bidding, provided that the tie-breaking rule places equal weight on all bidders involved in the tie (rather than on all bids involved in the tie, for proof see Appendix A).*

Proposition 2 reduces the primary cost question to whether multiple bidding is good or bad for FDIC resolution costs, on net. While substitution effects work against the auctioneer's interests, another important incentive arising from multiple bidding is the *competition effect* built into the win probability $G$: multiple bidding by competitors forces one to best-respond to a larger number of rival bids. This competitive pressure reduces bid shading and thus works against substitution, so the sign of the overall effect is ambiguous. Although multiple bidding in our setting hinges on scoring noise (since FDIC auctions can have only one winner each), the substitution and competition effects defined here are also fixtures of general combinatorial auctions, where multiple bidding is prevalent.

Finally, the *noise effect* introduces further nuance: by injecting uncertainty into the auction allocation rule, equation (3) shifts the win probability away from high-value bidders, relative to a world where the allocation rule is known. Since this group enjoys the largest conditional surplus to begin with, they can afford to respond by bidding more aggressively (i.e., bid shading less). This tendency is more pronounced when the difference between the winning bid and cover bid is small in expectation. We numerically isolate these conflicting incentives within the estimated model in Section 6.

4.2. **Modeling Choices: Independent Private Values.** In our model we assume bidders have independent private values (IPV) for absorbing the failed bank's depositors, liabilities, and assets into their own businesses. On technical grounds, the IPV assumption lends tractability: bidding incentives and model primitives would be more complex with correlated private values or a common valuation component.[22] However, it is important to have some assurance that the tractable model is a reasonable lens through which to interpret the data. IPV is appropriate if the environment is consistent with (*i*) heterogeneous synergies between bidder and failed-bank assets and depositor base, (*ii*) limited resale opportunities, and (*iii*) ex-ante symmetry of information about ex-post value.

Heterogeneous synergies (*i*): evidence suggests that the charter value of a failing institution depends on the identity of the winner. There are important management idiosyncrasies (Bertrand and Schoar (2003)), regulator differences (Agarwal et al. (2014), Oktay et al. (2015)), heterogeneity of benefits from geographic diversification (Acharya et al. (2006) and Aguirregabiria et al. (2016)), and balance-sheet complementarities (Granja et al. (2017)), that suggest the ongoing value of an institution depends on who owns it.

Limited resale (*ii*): a potential problem with the IPV assumption is that if bidders sell parts of the failed bank on a secondary market, there could be a common element of valuations. In practice, various factors mitigate this concern. First, the FDIC promotes continuity of ownership by imposing a three-year anti-flipping constraint on private equity bidders. Second, it imposes constraints on branch closures in the first year post-acquisition.[23] Third, the FDIC's LS option reduces incentives for bidders to re-sell the failed bank's loan assets by insuring against future losses.

Ex-ante information symmetry (*iii*): as Kastl (2016) points out, the crucial assumption for IPV is that bidders do not have asymmetric information about ex-post values. In our context this seems a reasonable view, given that each bidding bank may access *all* of the failed

[22]E.g., positive identification results are sparse in interdependent values settings. Somaini (2020) focuses on the most general information environment to date, but models simpler first-price auctions without the additional complications in our setting. More recent work by Nguyen (2022) derives positive identification results in the pure common values paradigm under standard first-price auction formats.

[23]For P&A transactions during our sample period, we investigate whether there are any cases where an acquiring bank divested itself of *all* branches of the failed bank before the end of 2015, at least two years (and up to six) post-resolution. We find only three such cases, all of which involve a failed bank with two or fewer branches in its network. One acquiring bank closed one branch of the former failed bank and sold the other within two years post-P&A, and another acquiring bank sold both former failed-bank branches after 14 months post-P&A. In the third case the acquiring bank sold the single branch belonging to the former failed bank, along with nine of its own other branches roughly three and a half years post-P&A. None of these three cases seems to signal re-sale as a primary motivation for P&A.

bank's financial and legal records before the auction occurs. Moreover, for asset classes that do trade on secondary markets (e.g., mortgage-backed securities), bidders in FDIC auctions can condition their bids on publicly-known prices at the time of resolution.

In principle, these ideas suggest that IPV is reasonable for FDIC auctions, though a data-driven evaluation would be more reassuring. We execute two well-known tests of common values (CV) versus IPV (Giliberto and Varaiya (1989) and Haile et al. (2006)) in Appendix B; results from both suggest that our data do not reject IPV, but some caveats apply. The Haile et al. (2006)) test was not designed for a setting with package bidding, and it is not robust to forms of endogenous bidder selection that may be present in our data. Therefore, we execute a third test recently proposed by Hickman et al. (2021), based on conditional correlations among distinct bidders' bids. This procedure is better suited to the FDIC setting with multiple bidding and flexible bidder selection patterns.

We discuss full details in Appendix B, but to fix ideas consider three mutually exclusive models that IPV rules out: affiliated private values (APV), pure common values (CV), and unobserved, auction-specific heterogeneity with independent private values (UHIPV). Unlike IPV (holding $N_j$ fixed), these models imply residual correlation among competitors' bids, after controlling for information available to the econometrician. In APV bids are correlated since private values are correlated. Under CV, ex-post winner utility is a common, unknown quantity, and private information is an unbiased signal of that common value. UHIPV is similar, though the common component is known to bidders (but not the econometrician) and winner utility is a product of an idiosyncratic signal and the common component. In the latter two cases, bids co-move with the common component.

The test procedure begins by regressing $i$'s mean bid (across $k \in L_{ij}$) on the average of her opponents' mean bids, and a set of controls including $\boldsymbol{Z}_j$, a polynomial in $N_j$, and interactions between opponent mean bids and the $N_j$ polynomial.[24] This last set of interactions is crucial due to strategic co-movement that would exist even in an IPV world: all bidders react to increasing competition ($N_j$) with more aggressive bids. The idea behind the test of IPV is simple: after controlling for observable determinants of bidding co-movement by $i$'s mean bid and her opponents' mean bids, if there is residual conditional correlation then the null hypothesis of IPV is rejected in favor of the alternate hypothesis of APV $\cup$ CV $\cup$ UHIPV. We execute this test on our FDIC data (full results are in Appendix B.1): after controlling for bidder selection on $\boldsymbol{Z}_j$ and strategic co-movement of bids with $N_j$, we find no statistically significant conditional correlation between $i$'s mean bid and the mean bids of her competitors

[24]Within the model, bidders do not directly observe $N_j$ but they compute projections $E[N_j|\boldsymbol{Z}_j]$ given observable auction traits $\boldsymbol{Z}_j$. In the test we use ex-post realizations $N_j$ as a proxy for bidder expectations.

in auction $j$. This finding supports the view that our assumption of valuations $\overline{V}_{ij}$ being idiosyncratic and independent is reasonable within the FDIC context.

In a setting such as this, where bidders are bidding on an investment that has an uncertain payoff, there may be some degree of interdependency of valuations in practice. For example, this would be the case if the acquisitions team from one bidding bank is still interested in the assessment of their counterparts at a rival bidding bank after both teams have carefully examined the failed bank's books. We adopt the assumption of private values for tractability reasons and because there are both institutional details and evidence to suggest that the interdependency we abstract from is not a primary concern.

4.3. **Modeling Choices: Independence Across Auctions.** Our assumption of independence across auctions would be problematic if there were (*i*) learning across auctions, (*ii*) complementarities across auctions, or (*iii*) banks had dynamic capacity constraints, so that winning one auction limited future participation. Regarding (*i*) learning, since the impact of each discrete component varies across auctions, bidders cannot learn the exact scoring rule even through repeated participation.[25] Regarding (*ii*) complementarities, when two geographically close banks are closed on the same day, the FDIC allows *linked bidding* so that bidders can express complementary preferences. We drop auctions with linked bidding (see footnote 6), and thus need only be concerned with temporal complementarities. Finally, because of (*iii*) capacity constraints, one might be concerned about auctions within a short period of one another, causing bidders to consider possible outcomes from other auctions when bidding. Granja et al. (2017) show that when local bidders are poorly capitalized, resolution costs increase. Although there are many reasons why bidders may be poorly capitalized, this result could be consistent with small, local bidders being capacity constrained.

In Appendix C (Table C.1) we execute and discuss several regression analyses to probe for these sources of dependence. Briefly, we find that experience, size, and capitalization are not significant predictors of winning, after controlling for $\boldsymbol{Z}_j$ and $N_j$. We also find that experience is not a significant predictor of bidding behavior. These results suggest that the above forms of temporal dependencies are not major concerns in our setting.

## 5. Model Identification and Estimation

Here we discuss identification and estimation of model primitives, including the stochastic least-cost scoring process, the FDIC reserve cost distribution, the distribution of bidders' as-is valuations, and discrete component utility adjustments. Consistent estimation of the win probability $G$ is pivotal to our empirical strategy, and is subject to three challenges: (*i*) the

[25]Even the econometrician cannot derive the specific component weights $(\gamma_j^{LS}, \gamma_j^{VAI}, \gamma_j^{NC}, \gamma_j^{PB})$ in a given auction $j$, though one can identify and estimate their joint distribution (see Section 5.1).

scoring rule is random and unknown, (*ii*) there is uncertainty about the set of competitors a bidder faces, and (*iii*) the FDIC allows multiple bidding. Moreover, valuations are only identified for packages that are bid on, and package-specific values are related for a given bidder. We take a three-stage approach to address these challenges.

5.1. **Stage 1: Scoring Rule and Reserve Cost Distributions.** The FDIC's proprietary scoring rule is not publicly observed and varies across auctions. Therefore, our first challenge is to show that the distribution of the scoring rule is identified and estimable from the available data. For the empirical model, we re-write equation (3) as

$$-C_{ijk} = b_{ijk} + d_k^{LS}(\%LS_j)(\gamma_j^{LS}) + d_k^{VAI}(\gamma_j^{VAI}) + d_k^{NC}(\gamma_j^{NC}) + d_k^{PB}(\%PB_j)(\gamma_j^{PB}) + \delta_{ijk} + u_j, \quad (5)$$

where $\%LS$ ($\%PB$) is the percentage of failed bank assets covered (excluded) under the FDIC's offered loss-share agreement (partial bank option).

**Assumption 4.** *$\delta_{ijk}$ follows a normal distribution $\delta_{ijk} \sim \Phi_\delta(\delta; 0, \sigma_\delta^2)$, with zero mean and variance $\sigma_\delta^2$, and it is independent of the common shock vector $(\gamma_j^{LS}, \gamma_j^{VAI}, \gamma_j^{NC}, \gamma_j^{PB}, u_j)$.*[26]

Two factors in our context support the idea that $\delta_{ijk}$ is independent of bidder identity. First, participation is by invitation only; the vetting process would mitigate concerns that the FDIC has a compelling interest to favor a given bidder. Second, the FDICIA legally precludes considerations other than insuring depositors at the lowest cost. Still, perhaps the FDIC may judge bidding banks on financial stability characteristics, with a desire to minimize current *and* future resolution costs. As a robustness check on Assumption 4, we ran a test for correlation between bidding bank characteristics and fitted $\delta_{ijk}$ shocks; we found no evidence that this was the case (see Online Appendix D.7.2).

**Assumption 5.** *Common scoring shocks are normal $F_{\mathbf{\Gamma}U} = \Phi\left(\gamma_j^{LS}, \gamma_j^{VAI}, \gamma_j^{NC}, \gamma_j^{PB}, u_j; \boldsymbol{\mu}, \mathbf{\Sigma}\right)$ with mean vector $\boldsymbol{\mu} = (\mu_\gamma^{LS}, \mu_\gamma^{VAI}, \mu_\gamma^{NC}, \mu_\gamma^{PB}, \mu_u)$ and $\mathbf{\Sigma}$ being a 5×5 matrix with variances $\sigma_s^2$ on the diagonal and covariances $\sigma_s \sigma_{s'} \rho(s, s')$ on the off-diagonal, $s, s' \in \{LS, VAI, NC, PB, u\}$.*[27]

Assumption 4 is needed for identification, while Assumption 5 is largely for tractability. In Online Appendix D.1 we provide a proof for why the scoring process is identified in order to illuminate how the moments of the raw bid/cost data pin down model components. The proof is based on somewhat weaker restrictions on the joint distribution $F_{\mathbf{\Gamma}U}$: we maintain the Gaussian copula structure while imposing no *a priori* functional forms on the marginal distributions of $(\mathbf{\Gamma}, U)$. The semi-parametric identification argument combines deconvolution methods (using mutual independence of $\delta$) to back out the marginal distributions of the

[26]Additionally, we assume the idiosyncratic shock $\delta_{ijk}$ is independent of bidder $i$'s private information.

[27]We assume throughout that $(\mathbf{\Gamma}, U)$ is conditionally independent of bidders' private information, given $\boldsymbol{Z}_j$. We also estimate a model specification where shock means are functions of auction covariates $\boldsymbol{\mu}(\boldsymbol{Z}_j)$ (see Table 3). This extension induces no appreciable changes to other model estimates or counterfactual results.

common shocks. Intuitively, the three primary sources of identifying variation in the data are (*i*) observed resolution costs (tied to the winning bid), (*ii*) empirical win frequencies of bids on different packages, and (*iii*) comparisons between dollar amounts for winning and losing bids that use different subsets of the discrete components $\{LS, VAI, NC, PB\}$. These comparisons pin down both the marginal distributions of the scoring shocks, as well as the correlations among them. The interested reader is directed to Appendix D.1 for the full technical details of scoring-shock identification.

Within each auction we observe all bids and the FDIC's cost associated with the winning bid. For losing bids we know that associated costs were higher than the cost tied to the winning bid. In order to incorporate both level information (winning bid) and bound information (losing bids) we use a simulated Tobit maximum likelihood approach for estimation:

$$\max_{\{\sigma_\delta,\boldsymbol{\mu},\boldsymbol{\Sigma}\}} \prod_{j=1}^{J} \int\int\int\int\int \prod_{i=1}^{N_j} \prod_{k\in L_{ij}} \phi_\delta \left[(C_j^T - \hat{C}_{ijk}); 0, \sigma_\delta^2\right]^{A_{ijk}} \times \Phi_\delta \left[(C_j^T - \hat{C}_{ijk}); 0, \sigma_\delta^2\right]^{1-A_{ijk}} \times \phi\left(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB}, u; \boldsymbol{\mu}, \boldsymbol{\Sigma}\right) d\gamma^{LS} d\gamma^{VAI} d\gamma^{NC} d\gamma^{PB} du, \tag{6}$$

where $C_j^T$ is the observed cost; $\hat{C}_{ijk}$ is the cost assigned to $i$'s bid on package $k$ holding fixed a realized value of $(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB}, u)$ but excluding the bidder-package-specific shock $\delta_{ijk}$; and $A_{ijk}$ is an indicator for whether bidder $i$ won auction $j$ with a bid on package $k$.

Simulated integration is used because the component shocks are constant for all bids within an auction but occur in various combinations across auctions. The resulting analytic integral is therefore complicated in settings with many bidders and a variety of packages. We use 5,000 simulated draws (held fixed during run time), and standard errors are obtained using the empirical Hessian estimator evaluated at the point estimates. Our estimator can also accommodate $\Phi(\cdot; \boldsymbol{\mu}, \boldsymbol{\Sigma})$ being conditioned on auction covariates $\boldsymbol{Z}_j$.

The reserve cost distribution $F_{C_0}$ is estimated using auctions where no sale occurred, so deposits were paid out and the FDIC liquidated remaining failed bank physical and financial assets. There are 26 such auctions during our sample period. This is the FDIC's default outside option. Since we always observe the cost of deposit payout when it occurs, its distribution is identified and directly estimable from raw data (see Figure OS.4, online supplement).

5.2. **Stage 2: Win Probabilities.** To estimate $G(b_{ijk}|L_i, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j)$ we adapt a re-sampling approach proposed by Hortaçsu and McAdams (2010). $G$ is the likelihood of (*i*) the scoring weights favoring $b_{ijk}$ over one's other bids, (*ii*) $b_{ijk}$ dominating the reserve cost, and (*iii*) $b_{ijk}$ beating competitors' bids. Thus, we repeatedly simulate from the scoring process, the reserve cost distribution, and the sample of competitors across all auctions in the data.

Recall that bidders do not observe the number or characteristics of competitors prior to bidding. Our estimator must account for bidder selection (by number *and* types) on auction characteristics, so we use weighted re-sampling where, for each $j$, competitors from auction $j'$ with $\boldsymbol{Z}_{j'}$ similar to $\boldsymbol{Z}_j$ are more likely to be re-sampled. Bodoh-Creed et al. (2021) show that identifying the distribution of the number of competitors, $M_j$, is sufficient to pin down win probabilities in private value auctions with stochastic participation.[28] This idea is built into our estimator through simulation from the empirical distribution of the number of rival bidders, $\pi_M(m|\boldsymbol{Z}_j)$ using observed $(N_j, \boldsymbol{Z}_j)$ pairs in the data. Our sampling weights also control for selection on unobserved rival bidder types $(\overline{V}, \boldsymbol{S}, \boldsymbol{W})$ (i.e., endogenous entry, based on auction-level observables).[29] Recall from Assumptions 1 and 2 that a given rival's covariates $\boldsymbol{W}$ and rival private signals $(\overline{V}, \boldsymbol{S})$ are unknown to bidder $i$ prior to bidding, but after observing auction covariates $\boldsymbol{Z}_j$, $i$ knows their conditional distributions, $F_{\boldsymbol{W}}(\boldsymbol{w}|\boldsymbol{Z}_j)$ and $F_{\overline{V},\boldsymbol{S}}(\overline{v}, \boldsymbol{s}|\boldsymbol{Z}_j)$. Thus, by constructing sampling weights to sample more frequently competitors from auctions $j'$ with $\boldsymbol{Z}_{j'}$ similar to $\boldsymbol{Z}_j$, we are able to produce a win probability function that replicates bidder $i$'s information set (including both numbers *and* types of competitors it is likely to face) upon observing the covariates $\boldsymbol{Z}_j$ within its own auction $j$.

More formally, fix $(T, I, H) \in \mathbb{N}^3$, and for each auction $j$ and each $(b_{ijk}, L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j)$ quadruple, $i = 1, \ldots, N_j$, repeat $t = 1, \ldots, T$ *outer* simulations as follows:

(1) Simulate an *iid* draw $m_t^*$ from the empirical distribution $\hat{\pi}_M(m|\boldsymbol{Z}_j)$.

(2) Using sample weights $\omega(j, j', \boldsymbol{Z}_j)$ for each $j' = 1, \ldots, J$, place $\lceil I\omega(j, j', \boldsymbol{Z}_j)\rceil$ copies of each bidder from auction $j'$ in a common urn and sample $m_t^*$ bidders from the urn (with replacement). Each sampled bidder $n$'s complete set of observed bids are added to the $t^{\text{th}}$ simulated competitor profile, denoted $\boldsymbol{\chi}_t^* \equiv \{(\boldsymbol{b}_{tn}, L_{tn})\}_{n=1}^{m_t^*}$.

(3) Holding $\boldsymbol{\chi}_t^*$ fixed, perform *inner* simulations as follows for $h = 1, \ldots, H$:
   (a) Simulate *iid* draws $\{C_{0th}^*\}_{h=1}^H$ from the reserve cost distribution $\hat{F}_{C_0}$.
   (b) Simulate from $\Phi_\delta(\delta; 0, \hat{\sigma}_\delta^2)$ to get a sample $\{\delta_{thik'}^*\}_{k' \in L_{ij}}$ for $i$'s own bids, and $\{\{\delta_{thnk'}^*\}_{k' \in L_{tn}}\}_{n=1}^{m_t^*}$ for simulated competitor bids.
   (c) Simulate shocks $\{\gamma_{th}^{LS*}, \gamma_{th}^{VAI*}, \gamma_{th}^{NC*}, \gamma_{th}^{PB*}, u_{th}^*\}_{h=1}^H$ from $\Phi(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB}, u; \hat{\boldsymbol{\mu}}, \hat{\boldsymbol{\Sigma}})$.
   (d) Using the above information for $h$, compute FDIC resolution costs $\{C_{thik'}^*\}_{k' \in L_{ij}}$ for $i$'s bid profile, and costs $\{\{C_{thnk'}^*\}_{k' \in L_{tn}}\}_{n=1}^{m_t^*}$ for sampled competitors.
   (e) Compute and store the lowest competing cost relative to $b_{ijk}$, defined as $\underline{C}_{thik}^* \equiv \min\left\{C_{0th}^*, \min_{k' \neq k}\{C_{thik'}^*\}, \min_{n=1,\ldots,m_t^*}\{\min_{k' \in L_{tn}}\{C_{thnk'}^*\}\}\right\}$.

[28]See Online Appendix D.2 for further explanation on why this result applies to our setting.

[29]Due to data limitations, Krasnokutskaya et al. (2018) parameterized the distribution of bids and the bidder entry process; in our setting we are able to re-sample directly from the conditional empirical distributions (given $\boldsymbol{Z}_j$) of the number of rivals, and rival traits (equivalently, rival bids and bid portfolios).

Note that, due to the sampling weights, in step (2) above the simulated competitor sample $\boldsymbol{\chi}_t^*$ is constructed to replicate the conditional distribution of $(L, \boldsymbol{b})$ pairs, given auction covariates $\boldsymbol{Z}_j$. In equilibrium these conditional $(L, \boldsymbol{b})$ pairs will be generated by a set of rival bidders having numbers $M$ and types $(\overline{V}, \boldsymbol{S}, \boldsymbol{W})$ from the analogous conditional distributions, given $\boldsymbol{Z}_j$. The final win probability estimator is $\widehat{G}(b_{ijk}|L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j) \equiv \sum_{t=1}^{T} \sum_{h=1}^{H} \frac{\mathbf{1}(C^*_{thik} \leq C^*_{thik})}{TH}$. An equivalent view of $\widehat{G}$ is that it represents the survivor function of the random variable $\underline{C}^*_{ik}$. With this in mind, it follows that a similar process can be used to obtain an estimate of the derivative $g(b_{ijk}|L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j)$. We use boundary-corrected kernel density estimation for $\widehat{g}$ so as to avoid the need for sample trimming (see Hickman and Hubbard (2015)).

Some tuning parameters in the procedure must be pinned down. We chose $T = 1,000$ and $H = 500$ to balance numerical stability and computing time. We defer a complete discussion on sampling weights to Online Appendix D.5. Briefly though, $\boldsymbol{Z}_j$ is a rich set of 9 variables describing each failed bank. As a dimension-reduction measure we combine the first principal component of the 9 indicators with a Gaussian kernel function and the familiar Silverman (1986) bandwidth rule to compute sample weights $\omega(j, j', \boldsymbol{Z}_j)$.[30]

5.3. **Stage 3: Private Values.** Following a standard technique pioneered by GPV, we use first-order conditions to reverse-engineer bidders' private valuations from their observable bids and the equilibrium probabilities of winning with those bids. Equation (4) implies:

$$v_{ijk} = b_{ijk} + \frac{G(b_{ijk}|L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j) - \sum_{k' \in L_{ij},\, k' \neq k} (v_{ijk'} - b_{ijk'}) \frac{\partial G(b_{ijk'}|L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j)}{\partial b_{ijk}}}{\frac{\partial G(b_{ijk}|L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j)}{\partial b_{ijk}}}, k \in L_{ij}, \tag{7}$$

$$v_{ijk} \leq \underline{b}_{jk} + \frac{G(\underline{b}_{jk}|, L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j) - \sum_{k' \in L_{ij},\, k' \neq k} (v_{ijk'} - b_{ijk'}) \frac{\partial G(b_{ijk'}|, L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j)}{\partial \underline{b}_{jk}}}{\frac{\partial G(\underline{b}_{jk}|L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j)}{\partial \underline{b}_{jk}}} \quad k \notin L_{ij}. \tag{8}$$

In contrast to GPV, these FOCs include both inequalities and equalities, and they also differ by the presence of the second term in the numerator. Equations (7) and (8) imply a set of pseudo-valuations $\hat{v}_{ijk}$ for each package $k \in L_{ij}$ and pseudo-value bounds $\hat{v}^{ub}_{ijk}$ for $k \notin L_{ij}$. Note that (8) depends on finite lower bounds in bid space for each package; we need to set the level of these package-specific cut-offs. Rather than basing them on choke points (as in the theory model), in the empirical model we define a cut-off probability $\zeta$: a bank considering a bid on package $k$ will omit it from the portfolio $L_{ij}$ if it would result in a conditional win probability below $\zeta$ in equilibrium.[31] $\zeta$ determines the upper bound in equation (8).

[30]Using kernel-based sampling weights in this way implies $\widehat{G}$ is asymptotically equivalent to the *conditional V-statistic estimator* proposed by Hortaçsu and McAdams (2010). Results are very similar (but computing time is much longer) if we use the first 3 principal components instead.

[31]I.e., we specify $G(\underline{b}_{ijk}|L_{ij}, \boldsymbol{b}_{ij}) = \zeta$ in the empirical analog of equation (8). This is equivalent to imposing a positive fixed cost of preparing each bid. These bounds $\underline{b}_{ijk}$ are strictly greater than the choke points,

5.3.1. *Utility Decompositions.* In order to compute counterfactuals in the absence of uncertainty, we need to decompose package-specific valuations $v_{ijk}$ into baseline as-is valuations $\overline{v}_{ij}$ and discrete component utilities. To that end, we adopt the following:

**Assumption 6.** *Component utilities have the form $v_{ij}^s = \boldsymbol{X}_{ij}\boldsymbol{\beta}^s$, $s = LS, PB, NC, VAI$, and they enter $v_{ijk}$ additively as in equation (2).*

For convenience we define $\boldsymbol{\beta} \equiv [\boldsymbol{\beta}^{LS}, \boldsymbol{\beta}^{PB}, \boldsymbol{\beta}^{NC}, \boldsymbol{\beta}^{VAI}]$. When estimating the component utility parameters $(\boldsymbol{\beta}, \boldsymbol{\lambda})$ with a finite sample, the econometrician does not observe actual bidder-package valuations but, rather, estimated pseudo-valuations $\hat{v}_{ijk}$,

$$
\begin{aligned}
\hat{v}_{ijk} &= v_{ijk} + \xi_{ijk} = \overline{v}_{ij} + \boldsymbol{X}_{ij}\boldsymbol{\beta}\boldsymbol{d}_k + \boldsymbol{D}_k\boldsymbol{\lambda} + \xi_{ijk}, \quad k \in L_{ij}, \\
\hat{v}_{ijk}^{ub} &\geq v_{ijk} + \xi_{ijk} = \overline{v}_{ij} + \boldsymbol{X}_{ij}\boldsymbol{\beta}\boldsymbol{d}_k + \boldsymbol{D}_k\boldsymbol{\lambda} + \xi_{ijk}, \quad k \notin L_{ij},
\end{aligned} \tag{9}
$$

where $\hat{v}_{ijk}^{ub} = \underline{b}_{ijk} + \frac{\zeta - \sum_{k' \in L_i,\, k' \neq k} (v_{ik'} - b_{ik'}) \partial \widehat{G}(b_{ik'} | , L_i, \boldsymbol{b}_i) / \partial \underline{b}_{ijk}}{\widehat{g}(\underline{b}_{ijk} | L_i, \boldsymbol{b}_i)}$ is a utility bound for omitted packages derived from equation (8) (see footnote 31), and we assume $\xi_{ijk}$ derives from sampling variability in stages one and two.[32] In order to separately identify as-is values and discrete component valuations we take advantage of the within-bidder panel structure of multiple bids submitted by the same bidder, treating $\overline{v}_{ij}$ as a bidder-auction fixed effect.[33]

Since the error term $\xi_{ijk}$ represents sampling variability in pseudo-values stemming from the estimated win probability function $\widehat{G}$, there is no censoring problem in the error distribution as in standard Tobit models: these errors are not observed by the bidders and do not influence their choices.[34] This also means that even with our fixed panel length of (at most) 16 possible packages, the vector $(\boldsymbol{\beta}, \boldsymbol{\lambda})$ can be consistently estimated since noise in our stage-2 estimate $\widehat{G}$ diminishes as the number of auctions $J \to \infty$.

We estimate component utility parameters $(\boldsymbol{\beta}, \boldsymbol{\lambda})$ and as-is values $\left\{\{\overline{v}_{ij}\}_{i=1}^{N_j}\right\}_{j=1}^{J}$ by GMM with moment equalities and inequalities. Our estimator finds a best fit relative to the equality

leading to a more conservative measure as the restrictions for estimation will be less informative. We set $\zeta = 5\%$ though our results are robust to using nearby values (e.g., $\zeta = 3\%$) instead.

[32] A more general model might allow for random, idiosyncratic switch values $v_{ij}^s$ and $\boldsymbol{\lambda}_i$, but as Cantillon and Pesendorfer (2006) point out, identification would then require that all bidders submit a maximal set of 16 bids in all auctions, which is inconsistent with equilibrium play due to the substitution effect. In Online Supplement D.7.1 we conduct a robustness check for idiosyncratic values of the most popular switch, LS, and we fail to find evidence that our simplified model induces substantial bias.

[33] Estimation of non-separable fixed effects is a challenging econometric problem (e.g., see Chernozhukov et al. (2013)), and is infeasible given our sample size.

[34] After estimating equation (9), we find that the variance of $\xi_{ijk}$ accounts for 8.65% of the total variation in estimated pseudo-values $\widehat{v}_{ijk}$ (for included packages $k \in L_{ij}$). This relatively low number lends credibility to our assumption that the error term in equation (9) represents sampling variability in pseudo-values derived from the estimated win probability function $\widehat{G}(b_{ijk} | \boldsymbol{b}_{ij}, L_{ij}, \boldsymbol{Z}_j)$.

information, while minimizing violations of the bound information:

$$\min_{\beta,\boldsymbol{\lambda},\{\{\overline{v}_{ij}\}_{i=1}^{N_j}\}_{j=1}^{J}} \sum_{j=1}^{J}\sum_{i=1}^{N_j}\sum_{k=1}^{16}\Big\{ \left(\widehat{v}_{ijk} - \overline{v}_{ij} - \boldsymbol{X}_{ij}\boldsymbol{\beta}\boldsymbol{d}_k - \boldsymbol{D}_k\boldsymbol{\lambda}\right)^2 \times \mathbf{1}(k \in L_{ij}) \\ + \left(\widehat{v}_{ijk}^{ub} - \overline{v}_{ij} - \boldsymbol{X}_{ij}\boldsymbol{\beta}\boldsymbol{d}_k - \boldsymbol{D}_k\boldsymbol{\lambda}\right)^2 \times \mathbf{1}\left(k \notin L_{ij} \;\cap\; \widehat{v}_{ijk}^{ub} - \overline{v}_{ij} - \boldsymbol{X}_{ij}\boldsymbol{\beta}\boldsymbol{d}_k - \boldsymbol{D}_k\boldsymbol{\lambda} < 0\right)\Big\}. \tag{10}$$

The final multiplicative term above determines how inequality information is used. For a particular value of the parameters, if the second term inside the indicator function is non-negative for $i$ on some package $k \notin L_{ij}$, then the corresponding inequality is satisfied and no residual is added. Otherwise, the bound is violated for those parameter values and we penalize the objective function by adding a squared residual term. Finally, to understand what factors influence as-is valuations $\overline{v}_{ij}$, we regress them on failed bank and bidder traits:

$$\widehat{\overline{v}}_{ij} = \boldsymbol{X}_{ij}\boldsymbol{\alpha} + e_{ij}. \tag{11}$$

This exercise illuminates how values vary with failed bank and bidder traits, but these estimates have no impact on the counterfactuals, while estimates from equation (10) do.

5.4. **Integrating Over Bidder-Bid Match Uncertainty.** In Section 3.1 we proposed an unsupervised algorithm for resolving ambiguous assignments of bidder identities to bids. Recall that each run of the name matching algorithm can be thought of as producing a single random draw from our assumed uniform prior over the set of feasible assignments $\boldsymbol{A} \setminus \boldsymbol{A}'$. To avoid our results being driven by simulation error, we integrate over the distribution of bidder-bid match uncertainty at the estimation stage as follows. First, we independently run the algorithm $R = 100$ times (with each run indexed by $r = 1, \ldots, 100$) to get many fully-specified feasible data sets, $\mathcal{A}_r \in \boldsymbol{A} \setminus \boldsymbol{A}'$, varying within auctions on some bidder-bid match assignments.[35] Next, we estimate stages 2 and 3 on all 100 data sets (stage 1 is unaffected). Each set of point estimates $\left\{\left\{\{\{\hat{v}_{ijkr}\}_{k=1}^{16}\}_{i=1}^{N_j}\right\}_{j=1}^{J}, \hat{\boldsymbol{\beta}}_r, \hat{\boldsymbol{\lambda}}_r, \{\{\hat{\overline{v}}_{ijr}\}_{i=1}^{N_j}\}_{j=1}^{J}, \hat{\boldsymbol{\alpha}}_r \middle| \mathcal{A}_r\right\}$ is conditional on a single draw, $\mathcal{A}_r$, from the (uniform) distribution of feasible assignments, $\boldsymbol{A}\setminus\boldsymbol{A}'$. Therefore, in a final step for each model parameter common to all $r$, we average over the 100 conditional point estimates to compute unconditional point estimates:[36]

$$\hat{\boldsymbol{\beta}} = \sum_{r=1}^{100} \frac{\hat{\boldsymbol{\beta}}_r}{100}, \quad \hat{\boldsymbol{\lambda}} = \sum_{r=1}^{100} \frac{\hat{\boldsymbol{\lambda}}_r}{100}, \quad \hat{\overline{v}}_{ij} = \sum_{r=1}^{100} \frac{\hat{\overline{v}}_{ijr}}{100}, \; {\scriptstyle i=1,\ldots,N_j,\, j=1,\ldots,J}, \quad \hat{\boldsymbol{\alpha}} = \sum_{r=1}^{100} \frac{\hat{\boldsymbol{\alpha}}_r}{100}. \tag{12}$$

Standard errors are estimated via the bootstrap (see Appendix D.6).

[35] Note that in 89% of auctions in the full sample, the feasible set has cardinality $|A_j \setminus A_j'| \leq 100$, suggesting that 100 draws from the distribution should provide good coverage of the space of residual match uncertainty.

[36] It is important to note that the parameters in (12) are sufficient for computation of counterfactual model equilibria, as they can be used (in conjunction with covariates $\boldsymbol{X}_{ij}$) to fully specify model-predicted package valuations (recall that the error term in equation (9) represents sampling variability).

As a robustness check on our assumption of a uniform prior on the feasible set $\boldsymbol{A} \backslash \boldsymbol{A}'$, we also compute a re-weighted version of equation (12) point estimates (the part of the model most affected by potential mis-specification of the uniform prior). We do this using propensity-score weights (see Appendix D.3.1) derived from correlations between covariates $\boldsymbol{X}_{ij}$ and package submission probabilities. Table OS.2 compares the baseline and re-weighted stage-3 results, and suggests our uniform prior assumption is reasonable: for $\boldsymbol{\beta}$ and $\boldsymbol{\lambda}$ (40 parameters total), re-weighted estimates are statistically no different from baseline estimates.

As a final robustness check, we re-estimate our model and counterfactuals on the restricted sample where all bidder-bid matches are known with certainty. Parameter point estimates are similar (see Online Appendix D.10), suggesting that sample selection plays little role in shaping model estimates. On the other hand, the model produces counterfactual results that qualitatively differ in expected ways, given that the full sample has (not surprisingly) more bidders per auction than the restricted sample (2.6 vs 1.6) and a larger fraction of auctions involving multiple bidding (43% vs 22%).

## 6. Empirical Results and Counterfactuals

6.1. **Least-Cost Scoring Rule Estimates.** Results are presented in Table 3 for two different specifications (see Figure OS.6 in Appendix D.9 for model fit metrics). We estimate the means and variances of the common shocks ($\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB}, u$) and the variance of $\delta$. In specification (2) we include time and location controls, and we allow the means of the two most popular switches to depend on failed bank traits. These are LS and PB, which are both observed often enough for statistical power with additional included controls.

Win probabilities are constructed with specification (1) (results are similar with (2)). Coefficients can be interpreted in terms of percent net asset transfers. Since $\gamma^{LS}$ is interacted with the percentage of assets covered by the LS agreement, multiplying the empirical average of 74% by -30.5 we get a percent asset-transfer equivalent of -22.53. In plain English, for a failed bank with $1Million in assets the FDIC would be indifferent (on average) between a bid stipulating LS but zero net transfer, and an As-Is bid with a net transfer of -$225,300. For PB transactions, $\hat{\mu}_{\gamma}^{PB}$ is 42.6, and the empirical mean share of assets excluded is 32%, so the percent asset-transfer equivalent is $28.97(= 42.6 \times (1 - 0.32))$. For a $1Million bank failure, the FDIC is (on average) indifferent between a bid for a PB agreement with zero net transfer, and an As-Is net transfer bid of $\$92,704$ ($= \$320,000 \times 0.2897$, i.e., a net premium). The relatively large LS and PB standard deviations indicate substantial bidder uncertainty over how the FDIC makes these trade-offs.

The NC and VAI means, directly interpretable as percent net transfers, indicate these two components play much smaller roles, though the high value of $\hat{\sigma}_{\gamma}^{NC}$ implies that the NC switch

Table 3. Least-Cost Scoring Rule Estimates

| | (1) | | (2) | | | (1) | | (2) | |
|---|---|---|---|---|---|---|---|---|---|
| Parameter | Mean | SE | Coeff. | SE | Parameter | SD | SE | SD | SE |
| $\mu_u$ (Common) | | | | | $\sigma_u$ (Common) | 11.665*** | 4.399 | 2.735 | 2.096 |
| Constant | -4.740*** | 1.663 | 0.261 | 1.001 | $\sigma_\gamma^{PB}$ (PB) | 16.840*** | 6.154 | 4.301*** | 1.181 |
| Book Val. | | | -0.940*** | 0.038 | $\sigma_\gamma^{LS}$ (LS) | 9.335*** | 3.696 | 3.066 | 3.500 |
| $\mu_\gamma^{PB}$ (PB) | | | | | $\sigma_\gamma^{NC}$ (NC) | 10.880 *** | 2.669 | 12.787*** | 2.278 |
| Constant | 42.598*** | 4.361 | 60.000*** | 3.670 | $\sigma_\gamma^{VAI}$ (VAI) | 0.003 | 2.887 | 0.374 | 1.034 |
| % CRE | | | -0.078 | 0.058 | $\sigma_\delta$ (Idiosync.) | 3.381*** | 0.415 | 7.475*** | 0.442 |
| % CI | | | -0.201 | 0.128 | | | | | |
| % NA | | | -0.067 | 0.112 | | | | | |
| $\mu_\gamma^{LS}$ (LS) | | | | | | | | | |
| Constant | -30.452*** | 2.026 | -19.915*** | 1.451 | | | | | |
| % CRE | | | -0.554*** | 0.312 | | | | | |
| % CI | | | -0.216 | 0.424 | | | | | |
| % NA | | | 1.146*** | 0.359 | | | | | |
| $\mu_\gamma^{NC}$ (NC) | -5.056*** | 1.374 | -5.521*** | 1.452 | | | | | |
| $\mu_\gamma^{VAI}$ (VAI) | -1.921 | 1.213 | -3.373*** | 1.034 | | | | | |
| McFadden $R_M^2$ | 0.139 | | 0.219 | | | | | | |

Estimates of equation (6) are based on 322 auctions in the full sample (1,267 bid observations). Column (2) includes Florida/Georgia fixed effects and year fixed effects (2011–2013 grouped together) interacted with PB and LS means, and quarter fixed effects interacted with the mean of $u$. See Table OS.6 (online supplement) for estimated shock correlations. The last row is McFadden's R-squared, $R_M^2 \equiv 1 - \mathcal{L}(\boldsymbol{\mu}, \boldsymbol{\Sigma})/\mathcal{L}(\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0)$, where $\mathcal{L}(\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0)$ is the baseline log-likelihood of a model where the mean vector and the variance-covariance matrix are both restricted to be one dimensional, $\boldsymbol{\mu}_0 = \mu[1, 1, \ldots, 1]^\top$ and $\boldsymbol{\Sigma}_0 = \sigma I$. Note that $R_M^2$ values $\geq 0.2$ "represent excellent model fit" (McFadden (1979)), and are typically much lower than traditional $R^2$ values from OLS. Figure OS.6 (online supplement, computed under specification (1)) depicts a more complete analysis of model fit, which is generally good. Statistical significance: $***p<0.01$, $**\,p<0.05$, $*p<0.1$.

is a significant contributor to scoring uncertainty. The auction-specific common-shock mean transfer equivalent is -4.7% with a standard deviation of 11.7%. These largely represent the role of receivership (i.e., administrative) expenses, and are in line with Bennett and Unal (2015) who estimate a mean and standard deviation of 4.5% and 9%, respectively. Finally, the bidder-package shock plays a small, but non-zero role: a one standard deviation shift in $\delta_{ijk}$ accounts for 15% of the impact of including LS in a P&A bid.

6.2. **Valuation Estimates.** Table 4 reports estimates of equations (10) and (11) (see Figure OS.7 in Appendix D.9 for model fit metrics). Discrete component utilities $V_{ij}^s$ depend on seven variables summarizing failed bank and bidder bank traits, plus interactions. These controls were selected to focus on riskiness of absorbing the failed bank's asset portfolio, since offering opportunities for risk management is mainly why the FDIC offers different P&A options.[37] Note, however, that the model allows for bidders to disagree about the value of different P&A contract options if they differ by degree of solvency, asset portfolio composition, or geographic footprint. Failed bank size substantially raises the value of a LS provision. Monitoring and reporting costs associated with LS may outweigh the insurance value for small failures, but

[37]Estimates for $V_{ij}^{LS}$ ($V_{ij}^{PB}$) also control for %LS coverage (%PB assets included) under standard options. In including these two controls, we have a missing regressors problem for %LS and %PB, since this information is not available for all auctions in our data (see Appendix D.4). In such cases we replace the missing regressor values with their conditional expectations, given the values of the other regressors. This approach is in the spirit of standard methods for regression with missing $X$'s surveyed by Little (1992, Section 4.2).

Table 4. Value Shifters

| | **Discrete Component Valuations $V_{ij}^s$ ($\beta^s$)** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $s=$**LS**† | | $s=$**PB**‡ | | $s=$**NC** | | $s=$**VAI** | |
| | Coeff. Est. | SE | Coeff. Est. | SE | Coeff. Est. | SE | Coeff. Est. | SE |
| Same Zip | 0.627 | 0.665 | -1.748** | 0.756 | -0.916 | 0.579 | -2.577 | 1.827 |
| Portfolio Distance | -0.305*** | 0.041 | -0.333*** | 0.073 | 0.073* | 0.042 | 0.099 | 0.111 |
| FB Size | 5.022*** | 0.298 | -1.591*** | 0.320 | 1.096*** | 0.279 | 0.946** | 0.414 |
| Bidder Tier 1 Capital Ratio | 0.093*** | 0.027 | -0.052 | 0.032 | 0.026* | 0.014 | 0.044*** | 0.017 |
| FB %Core Deposits | -0.195*** | 0.016 | -0.424*** | 0.021 | 0.198*** | 0.022 | 0.061 | 0.042 |
| FB ROA | -0.163*** | 0.029 | -0.444*** | 0.040 | 0.039* | 0.021 | 0.185*** | 0.066 |
| FB %Non-Accruing Loans | 0.231*** | 0.043 | -0.082 | 0.055 | 0.042 | 0.034 | 0.167** | 0.066 |
| Constant | -39.809*** | 4.245 | 11.275*** | 4.028 | -33.834*** | 4.153 | -26.222*** | 5.072 |
| Average Value $E[V_{ij}^s]$: | 18.340 | — | -28.313 | — | -3.805 | — | -8.511 | — |

| **Component Interactions ($\boldsymbol{\lambda}$)** | | |
|---|---|---|
| LS×PB | -9.987*** | 0.654 |
| LS×NC | -2.150*** | 0.359 |
| LS×VAI | 1.960** | 0.952 |
| PB×NC | 6.104*** | 0.614 |
| PB×VAI | 0.369 | 1.362 |
| NC×VAI | 3.180*** | 0.643 |

| **Baseline Valuations $\overline{V}_{ij}$ ($\boldsymbol{\alpha}$)** | |
|---|---|
| Variable | Median St.Dev. Effect |
| FB log(Tot. Assets) | 4.464*** |
| FB log(Tot. Deposits) | -3.743*** |
| FB %Core Deposits | 0.115*** |
| FB ROA | 0.210** |
| FB Real Estate Loans Share | -0.130* |
| $E[\overline{V}_{ij}]$: -3.039 | $St.Dev.[\overline{V}_{ij}]$: 31.678 |

Discrete Component valuation numbers and Mean/St.Dev. for Baseline Valuations are expressed as percentage points of failed bank (FB) assets. *Same Zip* is an indicator for FB and Bidder having branches in same zip code. *Portfolio Distance* is the $\ell_1$-distance between FB and Bidder loan portfolio shares in SFR, C&I, CRE, and CNSMR. *Size* is log(Tot. Assets) (by book value) for the FB. Estimates account for 91.4% of total variation in $\widehat{v}_{ijk}$ for included packages (equation (9)).

† LS switch valuation estimates control for % of Loss-Share coverage. Coeff. estimate (std. err.): 11.588 (1.271).

‡ PB switch valuation estimates control for % of Partial Bank Assets included. Coeff. estimate (std. err.): 35.257 (2.465).

Baseline Value $\boldsymbol{\alpha}$ controls: *log(Tot. Assets)* for FB and Bidder; *Tier 1 Capital Ratio* for FB and Bidder; FB *%Non-Accruing Loans*; *Avg. Pairwise Dist.* (km); FB *%Core Deposits* (cubic polynomial); *ROA* for FB and Bidder (cubic polynomial w/interactions); *Same Zip*; *w/in-county %ΔHHI* (deposits); $\mathbb{1}$[*Bidder is new entrant in all FB markets*]; loan portfolio shares in SFR, C&I, CRE, CNSMR, and ARE for FB and Bidder (cubic polynomials w/interactions); *log(Tot. Deposits)* for FB and Bidder (quartic polynomial w/interactions); and *log(Insured Deposits)* for FB and Bidder. *Median St.Dev. Effect* is the median (across FB-Bidder pairs) change in st.dev. units of $\overline{V}_{ij}$ from a one st.dev. change in the relevant control, *all else equal.* Effects not reported were minimal or statistically insignificant. Estimates account for 65.6% of total variation in $\widehat{\overline{v}}_{ij}$.

Statistical significance: $***p<0.01, **\,p<0.05, *p<0.1$.

also, absorbing a larger distressed asset portfolio is simply riskier. From Table 2, a one standard deviation increase in failed bank size entails a quadrupling of total assets, relative to the mean failed bank; all else equal, this would raise the value of a LS provision by 38.6%. Core deposit percentage plays a secondary role: a one standard deviation increase reduces the value of a LS provision by 17.1%. As core deposits rise, the failed bank's capital base becomes less exposed to interest-rate fluctuations, and its overall value is less risky.

The PB option shifts P&A values by a margin of -28.3% of failed bank assets, on average; i.e., bidders generally prefer to acquire all of the failed bank's assets. A one standard deviation increase in core deposit percentage further reduces the value of a PB option by 24.1%. Return on assets and size are the second most dominant factors, each being roughly half as influential as core deposits. Thus, as the failed bank's liquidity becomes less volatile, as yield from its asset portfolio rises, and as the total size of the asset portfolio rises, the value of excluding assets significantly drops. Diversification seems to play a secondary, though non-trivial role as well: bidding banks are less willing to exclude failed bank assets that complement their own existing portfolios (i.e, larger *portfolio distance*) and/or complement their current physical branch network (i.e., *same zip*=1). NC and VAI shift valuations by smaller margins, but for both, failed bank size is an economically important determinant.

For As-Is valuations we regress $\widehat{\widehat{v}}_{ij}$ on 11 failed bank controls and 15 bidder controls, including non-linear effects and flexible interactions. These controls influence a bidder's comprehensive appraisal of absorbing all aspects of the failed bank's business, including not only its asset portfolio, but also its customer base, depositor liabilities (essentially a non-negotiable aspect of P&A) and its physical branch network[38]. Our main finding is that two factors play a dominant role in shaping baseline values: size of the failed bank's asset portfolio and size of its depositor liabilities. Standard deviation increases change baseline value $\overline{V}$ by 4.5 and -3.7 standard deviations, respectively. These two factors are positively correlated—banks require capital (largely from deposits) in order to issue credit—so a simultaneous standard deviation increase in the size of assets and liabilities on net implies a 0.722 median standard deviation rise in As-Is takeover values. In other words, although adding customers to the bidder's business is in some ways a positive (e.g., service fees), the failed bank's depositors are not "new customers" in the traditional sense, since their capital has already been invested by the failed bank. Thus, bidding banks primarily derive benefits from P&A by acquiring financial assets at a discount. For this same reason, three other factors played a secondary role in boosting P&A values during our sample period: stability of the Failed Bank's capital base, return on assets, and limited exposure to the real-estate market.

6.3. **Incentive Decompositions and Counterfactuals.** Our goal is to explore cost implications of scoring uncertainty and multiple bidding. These depend on the complicated interplay of distinct bidding incentives: the competition effect, the substitution effect, and the noise effect. Before turning to our counterfactuals, we first provide context and intuition in the next subsection by numerically characterizing these incentives within the baseline data-generating process (DGP) through a series of off-equilibrium optimal bid calculations. These off-equilibrium calculations illuminate incentive mechanisms that generate counterfactual (equilibrium) cost changes under alternate auction formats.

6.3.1. *Bidding Incentive Decompositions.* First, we isolate the role of the competition effect, i.e., the fact that bids become more aggressive because multiple bidding implies each bidder is best-responding to more rival bids (holding $N_j$ fixed). To do so we hold the average bid value fixed for each of $i$'s competitors, while having $i$ best-respond to only one bid per competitor. Accordingly, we compute an alternate win probability, $\widetilde{G}_i(b_{ijk}|L_{ij}, \boldsymbol{b}_i, \boldsymbol{Z}_j)$, where we repeatedly sample (with replacement) a single bid per competitor (rather than all their bids), thus

[38]For clarity note that this exercise is informative of why healthy banks value failed bank acquisitions, but the $\boldsymbol{\alpha}$ coefficients have no impact on the counterfactuals, whereas the other estimates in Table 4 ($\boldsymbol{\beta}^s, \boldsymbol{\lambda}$) do.

maintaining average within-competitor bid levels. We then re-optimize $i$'s bids on its (fixed) portfolio of packages $L_{ij}$ as a best response to $\widetilde{G}_i$. This is an off-equilibrium optimization because $\widetilde{G}_i$ is not consistent with opponents' portfolio choices; however, differences relative to the DGP isolate the competition effect by characterizing how $i$'s choice $\boldsymbol{b}_{ij}$ would change if it were best-responding to only a single bid per rival, all else equal.

Second, we run singleton-bid calculations to isolate the two-fold role of the substitution effect: on the one hand, $i$'s choice of $b_{ijk}$ is influenced by its choices of bid levels on other included packages $k' \in L_{ij}$, and on the other hand, substitution influences $i$'s choice of which packages to exclude from the portfolio $L_{ij}$ as well. To isolate the substitution effect on included packages $k \in L_{ij}$, we hold the DGP win probability $G(\cdot)$ fixed, and we re-optimize $b_{ijk}$ as a singleton bid, ignoring the presence of other own bids for each package $k \in L_{ij}$.[39] This is an off-equilibrium partial optimization by $i$, but differences relative to the DGP isolate the substitution effect (for included packages) by showing how bid levels $\boldsymbol{b}_{ij}$ would change if $i$ did not internalize the "business stealing" effect of $b_{ijk}$ on its own other bids $k' \in L_{ij}$. Next, for each omitted package $k'' \notin L_{ij}$, we similarly optimize $i$'s would-be singleton bid on $k''$.[40] We then determine whether the resulting singleton bid would have implied a non-trivial win probability $G(b_{ijk''}|\{k''\}) > \zeta$. Once again, this is an off-equilibrium partial optimization by $i$, but if $b_{ijk''}$, submitted as a hypothetical singleton portfolio, would have a meaningful chance at winning, then $i$'s valuation $v_{ijk''}$ would have allowed for bilateral trade between $i$ and the FDIC on package $k''$. In other words, $i$ chose to omit $k''$ from $L_{ij}$ due to its detrimental effect on expected surplus through business stealing from its other bids $k' \in L_{ij}$ (i.e., substitution).

Third, it is difficult to cleanly isolate noise effects within the model, i.e., how allocation-rule uncertainty shifts win probability away from high-value bidders, causing them to bid more aggressively. However, we can partially decompose noise effects by computing optimal bids in two counterfactual worlds with pre-announced common shocks $(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB}, u)$: one where the bidder-specific shock variance, $\sigma_\delta^2$, is the estimated value of 11.4, and one where it is set to zero. We then compute the impact on high-value bidders, defined as those submitting the top 25% of bids. Bidding differences relative to the DGP highlight how incentives change when one source of allocation-rule noise (the bidder-package shock $\delta$) is shut down.

Table 5 displays the results. Under the DGP, average P&A bids were for 85.8 cents on the dollar, with mean conditional surplus at 22.5% of failed bank assets. If we shut down the competition effect, the mean net discount rises by 74%, with average P&A bids of 75.3 cents on the dollar. Thus, having bidders respond to multiple bids per rival creates competitive

[39]I.e., for each package $k \in L_{ij}$ we hold fixed external aspects of $G(b_{ijk}|\boldsymbol{b}_{ij}, L'_{ij}, \boldsymbol{Z}_j)$ (e.g., $\boldsymbol{b}_{-i,j}$, $C_{0j}$, $\sigma_\delta$, $\boldsymbol{\mu}$, $\boldsymbol{\Sigma}$) but we now condition on $i$'s own portfolio including only one package, $L'_{ij} = \{k\}$.

[40]Once again, we hold outside influences on the win probability $G$ fixed and condition on $L_{ij} = \{k''\}$.

Table 5. Bidding Incentive Decompositions

| | DGP | Change: No Competition Effect | Change: No Substitution: Singleton Included Bids | No Substitution: Singleton Omitted Bids (SOBs) | Change*: No $\delta$ Shock (Noise Effect); High Bidders |
|---|---|---|---|---|---|
| Avg. Discount Bid | -14.222 | -10.482 | 2.410 | -28.518 | -1.374 |
| Avg. Cond. Surplus | 22.541 | 10.482 | -2.410 | 20.920 | — |
| % SOBs With Feasible Trade (% Elective Portfolio Package Omissions) | — | — | — | 75.26 | — |
| % SOBs Dominating Within-Bidder Minimum Submitted Discount Bid, DGP | — | — | — | 19.41 | — |
| % SOBs Dominating Within-Auction Avg. Discount Bid, DGP | — | — | — | 20.14 | — |

Column 1 is DGP mean transfer bid and conditional surplus, in percentage units of failed bank assets. Columns 2 and 3 are changes to the DGP numbers after removing *competition* and *substitution* effects. Column 4 is average singleton-bid/conditional surplus for omitted packages, and percentage of omitted bids where bilateral trade with the FDIC was possible. Column 5 is a partial decomposition of the *noise effect*. *Reported changes are for bids above the 75$^{\text{th}}$ percentile with $\sigma_\delta = 0$, relative to a world with $\sigma_\delta = \hat{\sigma}_\delta > 0$ (no scoring uncertainty in either case).

pressure that strongly favors the auctioneer. On the other hand, substitution works against the auctioneer in two separate ways. For included bids, the presence of package $k' \in L_{ij}$ reduces $i$'s chances of winning on package $k$, so $i$ compensates by choosing $b_{ijk}$ to increase conditional surplus (see equation (7)). Shutting down substitution reduces net discounts by 17% relative to the DGP, raising mean takeover bids to 88.2 cents on the dollar. Substitution also shapes $L_{ij}$, as shown in column 4. The average portfolio includes only 1.52 out of 16 possible packages, and we estimate that the substitution effect is responsible for 75.3% of all portfolio package omissions. Thus, substitution also indirectly limits would-be benefits from the competition effect. Off-equilibrium *singleton omitted bids* (SOBs) on excluded packages imply capital transfers that are less favorable to the FDIC, on average, than submitted transfer proposals. However, it is notable that one in five SOBs actually dominate the within-auction average of submitted (equilibrium, often non-singleton) discount bids, and 19% of SOBs by bidder $i$ dominate $i$'s largest submitted capital transfer proposal to the FDIC. This striking result underscores the role of substitution effects in driving both elective omissions of beneficial trade opportunities between bidders and the auctioneer (through optimal portfolio choice), *and* in shaping optimal bid values within non-singleton portfolios.

Finally, although the magnitude of the noise effect (column 5) may appear small, two factors are worth noting: ($i$) it is based only on exclusion of the bidder-package shock $\delta_{ijk}$, which has relatively small variance, and ($ii$) it does not include larger noise effects induced by variation in the scoring weights $(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB})$, since the noise effect from this last source is difficult to cleanly isolate.[41]

[41]For the most part, noise effect incentives are not orthogonal to competition and substitution effects, making them hard to numerically decompose. While announcing a fixed weighting vector $(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB})$ would shut down noise effects from scoring uncertainty, it would also eliminate incentives for multiple bidding (see Proposition 2) and therefore simultaneously shut down competition and substitution effects as well. However, shutting down $\delta_{ijk}$ alone provides a clean (partial) decomposition of one source of noise effect incentives.

6.3.2. *Equilibrium Counterfactual Resolution Costs.* The various decompositions in the previous section showed that the competition and noise effects arising from scoring uncertainty work strongly in the auctioneer's favor, while the substitution effect works strongly against the auctioneer; thus, optimal auction design will largely hinge on which of these forces dominate. With this context in mind, we now compute four counterfactuals to explore cost implications of multiple bidding driven by scoring uncertainty. In the first counterfactual scenario the FDIC announces, prior to bidding, that it will use the mean discrete component weights $E[(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB})]$. We consider a mean scoring rule announcement as a benchmark case because we do not observe the exact scoring rule within each auction in the data. To avoid confounding incentive effects with the implications of a fixed scoring rule, we compare results to resolution costs when the set of original bids is evaluated according to the mean rule as well. We also compute three other counterfactuals where the FDIC eliminates scoring uncertainty by constraining banks to bid only on a single package. These are (*i*) LS Only (the most popular package among bidders within the DGP), (*ii*) As-Is Only (the second most popular package), and (*iii*) LS+PB Only (the third most popular).[42]

All counterfactual policies shut down competition and substitution effects (Proposition 2) and largely mitigate noise effects. The remaining question is, which of these changes will dominate? Since these countervailing forces may offset each other to different degrees depending on failed bank traits and underlying bidder preferences, it is possible that the optimal policy (scoring uncertainty vs none) varies across auctions. Thus, after computing a one-size-fits-all (OSFA) change we use auction-specific cost differences to estimate a predictive Probit model for whether costs under status-quo scoring uncertainty dominate. This model could form the basis of a targeted uncertainty-mitigation policy, which in principle should be weakly better than the analogous OSFA policy. Finally, for comparison to the cost changes in our main counterfactuals, we compute a benchmark hypothetical scenario where the status quo is preserved, but the expected number of bidders is increased by one, which is known to have large impacts on auction revenues (see classic results by Bullow and Klemperer (1996)).[43]

Table 6 reports counterfactual results. After dropping four large outliers, FDIC reported resolution costs for the remaining 318 failures were \$32.7Billion (\$102.8Million per failure).

[42]In all four cases the distributions of the common shock $u$ and bidder-package shock $\delta$ remain unchanged. Note also that changing auction format could potentially make expected outcomes more or less attractive to some bidders. For simplicity we partially abstract from this detail and hold the bidder selection process (as a function of covariates $\boldsymbol{Z}_j$) fixed across the DGP and our counterfactual scenarios.

[43]Note: our four main counterfactuals eliminate multiple bidding and condense the game to a standard first-price auction, which has a unique symmetric equilibrium. The last counterfactual is purely for context: the FDIC already strenuously encourages healthy banks to participate as bidders. See Online Appendix D.8 for details on equilibrium computation. Appendix D.8.1 contains a robustness check where we search for potential multiple equilibria in the add-a-bidder counterfactual; we find no indications of this as a concern.

Table 6. Counterfactual Cost Comparisons Under Mean Scoring Weights

| | ResolutionCost Levels | | Changes in Resolution Costs | | | | |
|---|---|---|---|---|---|---|---|
| | Actual (Data) | Bids at Mean Scoring Rule | Scoring Announcement OSFA (Targeted) | LS Only OSFA (Targeted) | As-Is Only OSFA (Targeted) | LS-PB Only OSFA (Targeted) | One Extra Bidder |
| Total | 32,718 | 27,486 | -12,270 | -8,185 | -1,231 | 6,417 | -18,004 |
| | | | (-12,491) | (-8,894) | (-5,852) | (-5,125) | |
| Mean | 102.890 | 86.435 | -38.585 | -25.740 | -3.871 | 20.181 | -56.737 |
| P10 | 9 | 4.300 | -0.621 | 3.152 | 1.089 | 8.323 | -7.150 |
| P50 | 41 | 38.824 | -10.730 | -0.516 | -3.856 | 23.515 | -6.508 |
| P90 | 257.92 | 185.559 | -47.596 | -24.213 | 24.617 | 73.338 | -16.088 |
| Predicted Frequency Where Status-Quo Uncertainty is Better: | | | 0.094 | 0.594 | 0.358 | 0.783 | — |
| Mean Bidder Switch Value: | | | 2.666 | 18.340 | 0 | -19.96 | — |
| Mean FDIC Switch Value: | | | 1.358 | -22.535 | 0 | 12.146 | — |

Numbers in \$Millions unless otherwise stated. Column 1 is raw cost data; column 2 evaluates winning bids at mean FDIC scoring weights. Columns 3 and 5 remove uncertainty by announcing mean scoring weights. Columns 4 and 6 remove uncertainty by limiting bid choices to a single P&A package (LS provision only). *OSFA* numbers are for "one size fits all" alternatives, and *Targeted* versions have alternate formats imposed according to the predictive model in Table OS.7. Columns 2–7 add $\mu_u$ for comparability. Totals and means exclude 4 outlier failed banks with total assets over \$10Billion. P10, P50, and P90 rows are results for $10^{\text{th}}$ percentile, median, and $90^{\text{th}}$ percentile failed banks by resolution costs. *Mean Bidder Switch Value* is computed as $E\left[\boldsymbol{X}_{ij}\boldsymbol{\beta}\boldsymbol{d}_k + \boldsymbol{D}_k\boldsymbol{\lambda}\right]$ using bidder data and coefficient estimates from Table 4; *Mean FDIC Switch Value* is computed as $E\left[d_k^{LS}(\%LS_j)(\gamma_j^{LS}) + d_k^{VAI}(\gamma_j^{VAI}) + d_k^{NC}(\gamma_j^{NC}) + d_k^{PB}(\%PB_j)(\gamma_j^{PB})\right]$ using Specification (1) of Table 3.

Evaluating costs at the mean scoring rule instead implies \$27.5Billion; our subsequent analysis focuses on differences from this benchmark. From column (3) we see that a OSFA scoring weight announcement lowers total projected resolution costs by 44.6% (\$12.3Billion). The OSFA results from the LS-Only scenario produce a cost reduction of 29.8% (\$8.2Billion).[44] Cost-savings of these magnitudes would be offset by a one-time rebate of deposit insurance assessment fees (to healthy banks) of between 10.25 and 6.81 cents per \$100 of insured deposits. Current annual assessment rates range from 1.5 cents to 40 cents per \$100 of insured deposits.[45] The OSFA counterfactual policies achieve between 68% and 45% of the cost benefits from adding an additional bidder to each auction.

A more targeted approach can potentially produce additional benefits. For each auction $j$ we defined an indicator $SQ_j^*$ equalling 1 if the status-quo resolution cost (with scoring uncertainty) was lower than the counterfactual cost, and 0 otherwise. We then ran a probit regression of $SQ_j^*$ on failed bank covariates.[46] We report the frequency at which status-quo uncertainty is predicted to produce lower costs in the bottom section of Table 6 (see Table OS.7 in Appendix D.9 for probit estimates). For a mean-rule announcement this is true only 9.4% of the time, but for a LS-only auction it is true 59% of the time. However, in both cases

[44]Table OS.8 (Appendix D.9) reports changes under the $10^{\text{th}}$ and $90^{\text{th}}$ percentile scoring rules for comparison.

[45]See `https://www.fdic.gov/deposit/insurance/calculator.html`, accessed April 2021.

[46]Controls included size, total deposits, loan portfolio controls (%CRE. %C&I, %SFR, %CNSMR), %core deposits, %delinquent loans, ROA, Tier-1 capital ratio, % loss-share coverage offered, and % partial bank assets included. The probit estimator places more weight on cases where prediction mistakes are more costly: sampling weights are assigned using the standardized absolute difference between status-quo cost and counterfactual cost (zero difference from the mean recieves a default weight of 1).

Table 7. Counterfactual Impact on Winner Characteristics

| | Mean | | Median | |
|---|---|---|---|---|
| Variable | DGP | Scoring Announcement | DGP | Scoring Announcement |
| Size | 11.744 | 7.913 | 1.829 | 1.430 |
| % CRE | 22.463 | 21.848 | 22.612 | 22.364 |
| % CI | 10.066 | 9.564 | 9.021 | 8.733 |
| Avg. Pairwise Distance (km) | 531.253 | 482.965 | 264.394 | 214.952 |
| Tier 1 Capital | 16.447 | 15.818 | 14.322 | 14.053 |
| %Δ HHI Deposits County | 4.209 | 4.447 | 1.413 | 1.569 |

This table shows the impact of removing uncertainty on the characteristics of winners. Variable definitions are as in Table 2. For comparability, the *DGP* column computes winner identities under the mean scoring rule benchmark (with 1,000 simulations per auction of bidder-package shocks $\delta$); these correspond to the actual winner identities in the raw data 69% of the time. Table OS.10 (Online Supplement) displays similar figures under hypothetical coordinate-wise $10^{\text{th}}$ and $90^{\text{th}}$ percentile scoring weight announcements for comparison.

the targeted uncertainty-mitigation approach produces only modest improvements over the OSFA policy. This implies that when status-quo scoring uncertainty dominates LS-Only, it is only slightly better, but when the opposite is true the difference tends to be large.

The other two counterfactuals render different results. If the FDIC were to allow healthy banks to bid only on the As-Is contract, or only on the LS+PB contract, costs are projected to either improve modestly or get worse. The targeted versions of these policies do significantly better (between 21% and 19% cost savings), but still not as well as a mean scoring rule announcement or a LS-Only auction. The final two lines of Table 6 present preferences over P&A contract terms (net of baseline valuations) from bidders' perspectives and from the auctioneer's perspective, and they provide insight into the stark differences across the four counterfactual auction formats. Both formats that do best have the highest bidder preferences for packages bid on, despite having relatively low auctioneer preferences for P&A contract terms. In fact, the format that does worst for resolution costs (LS+PB) has the highest auctioneer contract preference, but the lowest bidder contract preference. These trends illustrate how offering contract-term options is a powerful way for the auctioneer to motivate bidders to improve its bottom line through endogenous bid-level choice.

This idea is especially salient in the scoring announcement counterfactual, where bidders select a single package from a menu of 16 based on their own preferences, while taking into account the FDIC's preferences encapsulated in the announced switch weights. By contrast, imposing choice restrictions (LS Only, As-Is Only, or LS+PB Only) induces a shift in the effective private value distribution among bidders. Therefore, another way to understand our results is that the relative strengths of competition, substitution, and noise hinge on the shape of the private value distribution. From a market-design perspective, the overall lesson here is that, while scoring uncertainty is generally revenue negative, offering choices to bidders—or at least, prioritizing *their* preferences when restricting choices—is a highly effective means for achieving cost/revenue improvements.

6.3.3. *CF Failed Bank Acquirers.* Post-financial crisis, there has been renewed interest in banking market concentration, particularly for deposits (e.g., see Egan et al. (2017) and Aguirregabiria et al. (2018)). By resolving failed banks through P&A mergers, the FDIC may be indirectly influencing local market structure. To see if our proposed format changes may imply such hidden costs, we report summary statistics on counterfactual winners and county-level HHI for deposits in Table 7. County-level consumer banking markets with failures in our sample are typically fairly competitive or moderately concentrated pre-failure, with mean and standard deviation of HHI being 1,612 and 1,004, respectively.[47] Counterfactual acquiring banks are slightly smaller and have branch networks that are somewhat closer to the failed bank's network. As a result, local markets see a rise in local concentration (4.5% counterfactually vs 4.2% in the DGP), but not by an economically significant margin. Winners under the OSFA scoring-weight announcement are similar to winners in the DGP in terms of loan portfolio composition and financial health.

## 7. Conclusion

This paper evaluates FDIC failed bank auctions. Selling platforms for distressed financial assets are often similarly structured and are becoming more important within national and international banking industries. They employ scoring rules to rank multidimensional bids and often involve an element of scoring uncertainty, as in FDIC auctions. We find that scoring uncertainty creates incentives for bidders to submit multiple bids, and on net, this tendency raises costs (or reduces revenues) by a margin of between 30% and 45%.

More broadly, our framework and methodology highlight the specific incentive channels through which this result obtains: (*i*) the substitution effect, which shapes bid portfolio choices, and whereby a bidder's own multiple bids lead to *less* aggressive bidding, (*ii*) the competition effect, whereby multiplicity of bids submitted by one's competitors spurs *more* aggressive bidding, and (*iii*) the noise effect, which increases competitive pressure specifically on high-value bidders. Although the latter is specific to our failed banks application, the competition and substitution effects we study offer a window into broader market design settings such as general combinatorial auctions where multiple bidding is common. Our application also illustrates how, by offering multidimensional bidding options, the seller may have some latitude to directly mold the distribution of private valuations among bidders. These insights serve to enrich our understanding of market design in several complex, less-understood settings in the modern economy.

[47]For context, The US Department of Justice does not consider a market to be even "moderately concentrated" until "the HHI is between 1,500 and 2,500 points." https://www.justice.gov/atr/herfindahl-hirschman-index

## References


Acharya, V., I. Hasan, and A. Saunders (2006). Should banks be diversified? Evidence from individual bank loan portfolios. *The Journal of Business 79*(3), 1355–1412.

Agarwal, S., D. Lucca, A. Seru, and F. Trebbi (2014). Inconsistent Regulators: Evidence from Banking. *The Quarterly Journal of Economics 129*(2), 889–938.

Aguirregabiria, V., R. Clark, and H. Wang (2016). Diversification of geographic risk in retail bank networks: Evidence from bank expansion after the Riegle-Neal Act. *The RAND Journal of Economics 47*(3), 529–572.

Aguirregabiria, V., R. Clark, and H. Wang (2018). The geographic flow of bank funding and access to credit: Branch networks and local-market competition.

Asker, J. and E. Cantillon (2008). Properties of scoring auctions. *The RAND Journal of Economics 39*(1), 69–85.

Asker, J. and E. Cantillon (2010). Procurement when price and quality matter. *The RAND Journal of Economics 41*(1), 1–34.

Athey, S. and J. Levin (2001). Information and competition in U.S. forest service timber auctions. *Journal of Political Economy 109*(2), 375–417.

Bajari, P., S. Houghton, and S. Tadelis (2014). Bidding for incomplete contracts: An empirical analysis of adaptation costs. *American Economic Review 104*(4), 1288–1319.

Bajari, P. and G. Lewis (2011). Procurement with time incentives: Theory and evidence. *Quarterly Journal of Economics 126*, 1173–1211.

Barragate, B., C. Macdonald, B. Brasser, J. Olson, B. Raphael, and H. Rodman (2011). Value appreciation instruments in FDIC assisted acquisitions. Jones Day Publications.

Bennett, R. and H. Unal (2015). Understanding the components of bank failure resolution costs. *Financial Markets, Institutions & Instruments 24*(5), 349–389.

Bertrand, M. and A. Schoar (2003). Managing with style: The effect of managers on firm policies. *The Quarterly Journal of Economics 118*, 1169–1208.

Bodoh-Creed, A., J. Boehnke, and B. Hickman (2021). How efficient are decentralized auction platforms? *Review of Economic Studies 88*(1), 91–125.

Branco, F. (1997). The design of multidimensional auctions. *RAND Journal of Economics 28*, 63–81.

Bullow, J. and P. Klemperer (1996). Auctions versus negotiations. *American Economic Review 86(1)*, 180–194.

Cantillon, E. and M. Pesendorfer (2006). Combination bidding in multi-unit auctions. *London School of Economics Research Online Monographs 54289*.

Che, Y.-K. (1993). Design competition through multidimensional auctions. *The RAND Journal of Economics 24*(4), 668–680.

Chernozhukov, V., I. Fernandez-Val, J. Hahn, and W. Newey (2013). Average and quantile effects in nonseparable panel models. *Econometrica 81*(2), 535–580.

Cochran, B., L. C. Rose, and D. R. Fraser (1995). A market evaluation of FDIC assisted transactions. *Journal of Banking & Finance 19*, 261–279.

Cowan, A. R. and V. Salotti (2015). The resolution of failed banks during the crisis: Acquirer performance and FDIC guarantees, 2008–2013. *Journal of Banking & Finance 54*, 222–238.

Davison, L. K. and A. M. Carreon (2010). Toward a long-term strategy for deposit insurance fund management. *FDIC Quarterly 4*, 29–37.

Debreu, G. (1952). A social equilibrium existence theorem. *Proceedings of the National Academy of Sciences 38*, 886–893.

Egan, M., A. Hortaçsu, and G. Matvos (2017). Deposit competition and financial fragility: Evidence from the US banking sector. *American Economic Review 107*(1), 169–216.

FDIC (2014). Resolutions Handbook. Technical report. Washington, D.C.

Federal Trade Commission (2013). The structure and practices of the debt buying industry. Technical Report.

Giliberto, S. and N. Varaiya (1989). The winner's curse and bidder competition in acquistions: Evidence from failed bank auctions. *Journal of Finance 44*(1), 59–75.

Glicksberg, I. L. (1952). A further generalization of the kakutani fixed point theorem. *Proceedings of the American Mathematical Society 3*, 170–174.

Granja, J. (2013). The relation between bank resolutions and information environment: Evidence from the auctions for failed banks. *Journal of Accounting Research 51*(5), 1031–1070.

Granja, J., G. Matvos, and A. Seru (2017). Selling failed banks. *The Journal of Finance 72*(4), 1723–1784.

Greve, T. (2011). Multidimensional procurement auctions with unknown weights. *University of Copenhagen Economics Dept. Discussion Papers 11-23*.

Guerre, E., I. Perrigne, and Q. Vuong (2000). Optimal nonparametric estimation of first-price auctions. *Econometrica 68*(3), 525–574.

Haile, P., H. Hong, and M. Shum (2006). Nonparametric tests for common values in first-price sealed-bid auctions. working paper.

Heitz, A. (2022). The long-run effects of losing failed bank auctions. FDIC working paper 2022-01.

Hickman, B., T. Hubbard, and E. Richert (2021). Testing independent private values versus alternative models in auction models. *working paper, Washington University in St. Louis Olin Business School*.

Hickman, B., T. Hubbard, and Y. Saglam (2012). Structural econometric methods in auctions: A guide to the literature. *Journal of Econometric Methods 1*(1), 67–106.

Hickman, B. R. and T. P. Hubbard (2015). Replacing sample trimming with boundary correction in nonparametric estimation of first-price auctions. *Journal of Applied Econometrics 30*(5), 739–762.

Hickman, B. R., T. P. Hubbard, and H. J. Paarsch (2017). Identification and estimation of a bidding model for electronic auctions. *Quantitative Economics 8*(2), 505–551.

Hortaçsu, A. and D. McAdams (2010). Mechanism choice and strategic bidding in divisible good auctions: An empirical analysis of the Turkish treasury auction market. *Journal of Political Economy 118*(5), 833–865.

Hubbard, T., T. Li, and H. J. Paarsch (2012). Semiparametric estimation in models of first-price, sealed-bid auctions with affiliation. *Journal of Econometrics 168*(1), 4–16.

Igan, D., T. Lambert, W. Wagner, and Q. Zhang (2017). Winning connections? Special interests and the sale of failed banks. IMF working paper No. 17/262.

Jackson, M. O., L. K. Simon, J. M. Swinkels, and W. R. Zame (2002). Communication and equilibrium in discontinuous games of incomplete information. *Econometrica 70*(5), 1711–1740.

James, C. (1991). The losses realized in bank failures. *The Journal of Finance 46*, 1223–1242.

James, C. and P. Wier (1987). An analysis of FDIC failed bank auctions. *Journal of Monetary Economics 20*, 141–153.

Kang, A., R. Lowery, and M. Wardlaw (2015). The costs of closing failed banks: A structural estimation of regulatory incentives. *The Review of Financial Studies 28*(4), 1060–1102.

Kastl, J. (2016). Recent advances in empirical analysis of financial markets: Industrial organization meets finance. Working paper.

Krasnokutskaya, E. (2011). Identification and estimation of auction models with unobserved heterogeneity. *The Review of Economic Studies 78*(1), 293–327.

Krasnokutskaya, E., K. Song, and X. Tang (2018). The role of quality in internet service markets. *Journal of Political Economy* (forthcoming).

Li, T., I. Perrigne, and Q. Vuong (2000). Conditionally independent private information in ocs wildcat auctions. *Journal of Econometrics 98*, 129–161.

Little, R. J. A. (1992). Regression with missing xs: A review. *Journal of the American Statistical Association 87*, 1227–1237.

McFadden, D. (1979). Quantitative methods for analyzing travel behaviour of individuals: Some recent developments. In D. Hensher and P. Stopher (Eds.), *Behavioural Travel Modelling*, Chapter 13. Routledge.

Myerson, R. (1998). Population uncertainty and poisson games. *International Journal of Game Theory 27*, 375–392.

Nevo, A. (2003). Using weights to adjust for sample selection when auxiliary information is available. *Journal of Business and Economic Statistics 21(1)*, 43–52.

Nguyen, A. (2022). Information design in common value auction with moral hazard: Application to ocs leasing auctions. *Working Paper, Tepper School of Business, Carnegie-Mellon University*.

Oktay, Akkus, J., A. Cookson, and A. Hortaçsu (2015). The determinants of bank mergers: A revealed preference analysis. *Management Science 62*.

Pinkse, J. and G. Tan (2005). The affiliation effect in first-price auctions. *Econometrica 73*(1), 263–277.

Sack, B. (2011). Implementing the Federal Reserve's asset purchase program. Remarks at Global Interdependence Center Central Banking Series Event. Federal Reserve Bank of Philadelphia, PA.

Shibut, L. (2017). Crisis and response: An fdic history, 2008–2013. Chapter Bank Resolutions and Receiverships. FDIC.

Silverman, B. (1986). *Density Estimation for Statistics and Data Analysis*. London: Chapman & Hall.

Somaini, P. (2020). Identification in auction models with interdependent costs. *Journal of Political Economy 128*(10), 3820 – 3871.

Takahashi, H. (2018). Strategic design under uncertain evaluations: structural analysis of design-build auctions. *The RAND Journal of Economics 49*(3), 594–618.

Vij, S. (2018). Acquiring failed banks. Working paper.

## Appendix A. Technical Proofs

First recall that for Lemma 1 and Proposition 1, we consider the case where $\delta$ is a point mass at zero; otherwise the more difficult discontinuous payoffs problem vanishes.

*Proof of Lemma 1: Equilibrium Bidding Requirements.* For notational ease in this proof we will drop the auction subscript $j$. We first prove part *(1)* of Lemma 1, that equilibrium strategies can only prescribe non-trivial bids strictly below private valuations. Consider bidder $i$'s decision problem of bids on some portfolio, $L_i \in 2^{16}$. Note that on package $k$, any bid $b_{ik} > \underline{b}_k$ wins with nonzero probability because there is positive probability that zero competitors show up and the reserve cost is dominated by $b_{ik}$.

CASE 1: suppose $b_{ik} \geq v_{ik}\ \forall k \in L_i$, and WLOG, suppose further that $k = 1$ is one such package, and $v_{i1} > \underline{b}_1$, which occurs with positive probability. If this is true, then $i$'s expected surplus is weakly negative and $i$ could do strictly better by deviating to a bid profile where $\underline{b}_1 < b_{i1} < v_{i1}$ and $b_{ik} = v_{ik}$ for each $k \in L_i,\ k > 1$. Since a profitable deviation exists under case 1, it follows that any equilibrium strategy must prescribe at least one bid in $L_i$ strictly below the private valuation for the corresponding package.

CASE 2: suppose $L_i$ can be partitioned into two mutually exclusive, non-empty sets, $L_i^p \equiv \{l \mid l \in L_i,\ v_{il} > b_{il}\}$, the "profitable set," and $L_i^{np} \equiv \{k \mid k \in L_i,\ v_{ik} \leq b_{ik}\}$, the "non-profitable set," and let $(\boldsymbol{b}_i^p, \boldsymbol{b}_i^{np}) = \boldsymbol{b}_i$ represent the corresponding partition of $i$'s profile of non-trivial bids. By definition of the scoring auction game, the win probability function must satisfy: $(i)$ $G(\underline{b}_k|L_i, \boldsymbol{b}_i) = 0,\ \forall k$, and $(ii)$ $G(b_{ik}|L_i^p \cup L_i^{np}, (\boldsymbol{b}_i^p, \boldsymbol{b}_i^{np})) < G(b_{ik}|L_i^p, \boldsymbol{b}_i^p),\ \forall k \in L_i^p$.[48] Note that $i$'s expected utility is

$$\sum_{k \in L_i^{np}} (v_{ik} - b_{ik}) G(b_{ik}|L_i, \boldsymbol{b}_i) + \sum_{l \in L_i^p} (v_{il} - b_{il}) G(b_{il}|L_i, \boldsymbol{b}_i) < \sum_{l \in L_i^p} (v_{il} - b_{il}) G(b_{il}|L_i^p, \boldsymbol{b}_i^p),$$

where the inequality follows from the properties of $G$ and the term on the right-hand side represents $i$'s expected utility after dropping all bids in $L_i^{np}$ instead. Since a profitable deviation exists in case 2 also, property *(1)* of the lemma must be true.

For property *(2)* of the lemma, suppose there is a hole in the support of bids for some package $k$, where a positive mass of bidders choose bids at or below $b_k$ and a positive mass choose bids at or above $b_k' > b_k$, but zero mass choose a bid $b_k^* \in (b_k, b_k')$. If that were the case, then bidders within a small neighborhood of $b_k'$ could profitably deviate by switching to a bid of $(b_k - \varepsilon)$ (i.e., with a larger capital transfer), $\varepsilon < b_k' - b_k$: the change would strictly increase their conditional surplus on package $k$ while sacrificing negligible win probability on $k$ (for a small enough neighborhood). At the same time, this deviation would increase chances of winning on other packages $k' \in L_i \setminus k$, which provide positive conditional surplus by property *(1)*. Thus, equilibrium bids must have full support and therefore the strictly increasing property of $G$ must also be true, because for any package $k$ and any two bids $b_{ik} < b_{ik}^*$, if a bid $b_{i'k'}$ by bidder $i'$ on package $k'$ loses to $b_{ik}$ then it must also lose to $b_{ik}^*$, since $b_{i'k'} + \boldsymbol{\Gamma}_{k'} d_{k'} + \delta_{i'k'} < b_{ik} + \boldsymbol{\Gamma}_k d_k + \delta_{ik}$ implies $b_{i'k'} + \boldsymbol{\Gamma}_{k'} d_{k'} + \delta_{i'k'} < b_{ik}^* + \boldsymbol{\Gamma}_k d_k + \delta_{ik}$.

Property *(3)* follows from properties *(1)* and *(2)* since no profitable bids that win with positive probability are possible when $v_{ik} \leq \underline{b}_k$ and the bidder is indifferent between any bids below $\underline{b}_k$. Finally, to prove property *(4)* of the lemma, suppose there is a positive mass of bidders with package-$k$ valuations on the non-empty interval $(v_k, v_k')$ who all choose

[48] This second condition comes from the fact that one's optimal choice of own other bids on packages $k'$ must shift probability away from a given bid on package $k$ since the scoring rule distribution creates positive probability that the auctioneer may prefer awarding takeover contract $k'$ by a significantly wide margin to overshadow any difference between $b_{ik}$ and $b_{ik'}$.

equilibrium bids equal to $b_k^*$.[49] In that case, one of them could profitably deviate to a bid of $b_k^* + \varepsilon$ for some small $\varepsilon > 0$. This would have the effect of over-cutting a positive mass of competitors by an infinitesimal amount that would leave its expected surpluses and win probabilities on its other own bids virtually unchanged for $\varepsilon$ small enough. □

*Proof of Proposition 1: Equilibrium Existence.* First, note that our auction satisfies the definition of an affine game with indeterminate outcomes, as proposed by (Jackson, Simon, Swinkels, and Zame 2002, JSSZ). Their definition of a game of indeterminate outcomes with the affine property entails several components. First, it must have a finite set of players; in our case with probability 1 the game has finite $N_j$ (set of bidding banks, by Assumption 1), and $N$ has finite mean, variance, etc. Second, the game must have a compact type space $\mathcal{T}$, with a well-defined joint distribution over types that is absolutely continuous. In an auction for a failed bank with traits $\boldsymbol{Z}_j$, player types $(\bar{v}_{ij}, \boldsymbol{s}_{ij})$ live on a compact subset of $\mathbb{R}^5$ and follow a probability measure $F_{\overline{V},\boldsymbol{S}}(\overline{V}, \boldsymbol{S}|\boldsymbol{Z}_j)$ which is absolutely continuous (by Assumption 2). Third, the game must have a compact action space, $\mathcal{A}$. For each bidder in a failed bank auction, their actions are chosen from a compact subset of $\mathbb{P}(\mathcal{K}) \times \mathbb{R}^{16}$, since the lowest possible bid on each package $k$ is defined by the package-specific choke point, and the highest possible bid (that is not strictly dominated with probability one) is the upper bound of the support of the value distribution for package $k$. Thus, without loss of generality, we can ignore bids outside this range for each package $k$, and the action space is compact. Fourth, the outcome space of the game, $\Omega$, is the set of all probabilistic assignments of winner status for the failed bank, including scoring-weight variation, but, more importantly, allowing for arbitrary tie-breaking rules to be implemented. Fifth, the game has an outcome mapping $\Theta : \mathcal{A} \rightarrow \Omega$ that is upper-hemi continuous at each action profile $a \in \mathcal{A}$.[50] Sixth, and finally, there is a utility mapping $u : graph\Theta \times \mathcal{T} \rightarrow \mathbb{R}^N$ that is continuous, convex-valued, and affine. In our model of FDIC auctions, players' utilities for a given outcome are $\sum \theta_{ijk}(v_{ijk} - b_{ijk})$ where $\theta_{ik}$ describes the probability that $i$ wins with package $k$, given the entire set of own and opponents actions. These utilities are affine in actions, given that bidders are Von Neumann-Morgenstern utility maximizers, and given the breadth of possible probabilistic divisions of the failed bank due both to scoring-rule variation (when bidders bid on different packages) and to tie-breaking rules (when bidders bid on the same package) allowed for under the outcome mapping $\Theta$.

From this setup, JSSZ then define an augmented version of the original game, which they refer to as its *communication extension*. The communication extension of a game is an alternate game where players choose actions and face ex-post payoffs identically as in the original game, but where they also make simultaneous reports to the auctioneer of their private types in addition to their bid submissions. These type reports then form the basis of an endogenous rule for resolving ties, should two players choose the same action. JSSZ first show that an equilibrium of the communication extension exists. They then establish

[49] Randomness in of $(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB})$ means that a mass point of bids on some alternative package $k' \neq k$ cannot produce a mass point in the distribution of scores faced by a bidder on package $k$.

[50] To see why, it is illustrative to consider a simple example with only two bidders, and with an action profile $a$ such that both submit bids on the same package $k$. If their bids tie, i.e., $a = (b_{1jk}, b_{2jk})$, $b_{1jk} = b_{2jk}$, then $\Theta(a) = \{\theta_{1jk} | \theta_{1jk} = Pr[bidder\ 1\ is\ awarded\ the\ P\&A\ in\ auction\ j],\ \ \theta_{1jk} \in [0,1]\}$ is set-valued and contains all probabilistic divisions of the failed bank between them. Now, for any convergent sequence of action profiles, $\{a_t\}_{t=1}^{\infty} \rightarrow a$, if we choose a convergent sequence $\{b_t\}_{t=1}^{\infty} \rightarrow b$, where $b_t \in \Theta(a_t)$, $\forall t$, then it must be true of the limit that $b \in \Theta(a)$, since $\Theta(a)$ contains all possible probabilistic divisions of the failed bank between players 1 and 2.

that, if players are indifferent to how ties are broken in the communication extension, then its equilibrium must constitute an equilibrium of the original game as well. Thus, since our FDIC auction model satisfies JSSZ's definition of an affine game with indeterminate outcomes, their Theorem 1 applies, so an equilibrium of the communication extension of our package-auction exists. In any equilibrium of the communication extension, the properties proved in Lemma 1 would also have to apply, including part *4.*, that ties only occur with zero probability. Therefore, players in the communication extension game are indifferent about how ties are resolved, including a scenario where the tie-breaking rule is purely random and independent of ex-ante type reports. This version of the communication extension is equivalent to the original package auction game with scoring rule uncertainty, so therefore an equilibrium of the original game must also exist.[51] □

*Proof of Proposition 2: No Multiple Bidding in Absence of Scoring Uncertainty.* Suppose there is no scoring uncertainty, so that the component weights are known to all bidders ex-ante. Consider the auction from bidder 1's perspective and suppose further that it formulates separate bids on multiple packages. In that case the continuous dollar components would have to be chosen so that the cost score for each of its bids is the same, making the FDIC indifferent among them. Otherwise, suppose its bid $b_{1jk}$ on package $k$ results in a cost score $C_{1jk}$ that is strictly greater than its cost score $C_{1jk'}$ from another of its bids $b_{1jk'}$. Then bidder 1 would know with surety that $b_{1jk}$ cannot win the auction; this would be equivalent to omitting a bid on package $k$, violating our supposition of multiple bidding.[52] Therefore, all of bidder 1's bids must imply the same cost score.

With positive probability, player 1 faces at least one other competitor, call it bidder 2. If 2 submits a bid $b_{2jl}$ (on some package $l$) for which the cost score weakly dominates one of player 1's bids then it would weakly dominate *all* of player 1's bids, $C_{2jl} \leq C_{1jk} = C_{1jk'}$. If $C_{2jl} < C_{1jk}$ then player 2 wins outright; if $C_{2jl} = C_{1jk}$ then the tie-breaking rule places weight on each bidder that is independent of the number of bids they each submitted. Either way, player 1 cannot increase its win probability by submitting multiple bids in the absence of scoring uncertainty. Since 1's preferences establish a strict ranking on winning the auction under any of the 16 possible packages, in absence of scoring uncertainty it cannot improve its expected payoffs by submitting multiple bids. □

[51] Importantly, note that JSSZ does not require that bidders be indifferent to how *all* uncertainty is resolved, like, for example, exogenous uncertainty over rival types built into the definition of the original game; they must only be indifferent to resolution of ties within the endogenous tie-breaking rule of the communication extension. Our game is more complex than a traditional single-unit first-price auction, given that there are 16 possible bids that each bidder can submit in a given auction. However, the presence of random scoring variation constitutes an exogenous source of uncertainty (similar to random variation in rival types) built into the definition of the original game, and it actually helps to *mitigate* the discontinuous payoffs problem. For example, if bidder 1 bids $b_{1j1}$ on package 1, and if bidder 2 bids on package 2, then there is no longer any sequence of 2's bids $\{b_{2j2n}\}_{n=1}^{\infty}$ that is guaranteed to produce the abrupt jump in win probability in the limit as $n \to \infty$. This is because the two packages differ by at least one discrete contract component and, holding $b_{1j1}$ fixed, the point at which the two bid levels would effectively tie is a non-degenerate random variable. In that sense, exogenous scoring uncertainty actually smooths out payoff discontinuities across bids on different packages, thus mitigating some of the problem that JSSZ is designed to solve. However, if bidder 1 and bidder 2 both submit bids on package 1, we still have the original problem that existed in the traditional first-price auction, and JSSZ's main result provides a solution for that.

[52] Recall that bidders never submit bids that will lose with probability 1 (see footnote 17).

Table B.1. Relationship between bids and number of bidders

| Giliberto and Varaiya (1989) Test | | | Haile, Hong, and Shum (2006) Test | | |
|---|---|---|---|---|---|
| VARIABLES | log(bid) | Std. Err. | Sample | Test Statistic | P-value |
| Var(bids) | 0.113 | (0.0765) | Full Sample | 0.0330 | 0.9175 |
| # Bidders | -0.0693*** | (0.0231) | Restricted Sample | 0.9484 | 0.2862 |
| Constant | 11.57*** | (0.144) | | | |
| State(FL,GA) | Yes | | | | |
| Year FE | Yes | | | | |
| $R^2$ | 0.077 | | | | |

This table provides estimates of the CV versus IPV tests from Giliberto and Varaiya (1989) (GV89, left panel) and Haile et al. (2006) (HHS06, right panel) on our sample. For GV89, we replicate their specification but replace the fixed effects for the federal reserve districts that were badly hit by the crisis with fixed effects for the states that were badly hit. Var(bids) measures the variance of bids within an auction. *** p<0.01, ** p<0.05, * p<0.1.

## Appendix B. Testing Independent Private Values

Table B.1 (left panel) evaluates the IPV assumption using a test proposed by Giliberto and Varaiya (1989) (GV89). We find that the number of bidders is negatively correlated with the winning bid, which is a necessary but not sufficient condition for private values. Another paper by Pinkse and Tan (2005) points out that this test has the drawback of potentially failing to distinguish between IPV and CV in first-price auctions.

We also perform a test in the spirit of Haile et al. (2006) (HHS06): in an IPV setting bidders' valuations do not depend on their opponents' information, so $N_j$ does not affect expected value, conditional on winning. Unlike GV89, HHS06 uses bidder valuations (not bids), which must be estimated. Under IPV the expected value of winning should be uncorrelated with the number of bidders $N_j$; under the CV alternative it is decreasing. We run the test procedure described in Section 3.1 of HHS06 on estimated full-bank valuations by computing quantile-trimmed means of the estimated values conditional on the number of bidders. The resulting p-value is 0.9175, so we fail to reject the null hypothesis of IPV, though some caveats apply. First, HHS06 was not designed for settings with package bidding like ours, and second, it is not robust to arbitrary forms of bidder selection, such as selection on unobserved types which is present in our DGP.

### B.1. **A New Test.**

We execute a third test recently proposed by Hickman, Hubbard, and Richert (2021), which is better suited to the FDIC setting and free of the limitations of (Giliberto and Varaiya 1989). It is based on detecting conditional correlation among opposing bids. Consider three mutually exclusive models that our IPV assumption rules out: $(I)$ affiliated private values (APV), $(II)$ pure common values (CV), and $(III)$ unobserved, auction-specific heterogeneity (with independent private values, UHIPV). The common thread is that they all imply residual correlation among competitors' bids, after controlling for relevant information available to the econometrician. To see why, consider a generalization of our IPV model that nests the other three as special cases: given $N_j$ bidders in auction $j$, private information regarding the value of an as-is takeover follows conditional distribution $F_{\overline{\boldsymbol{V}}|Y}(\overline{v}_{1,j}, \ldots, \overline{v}_{N_j,j}|y_j, \boldsymbol{Z}_j)$, where $y_j$ follows a well-behaved distribution $Y \sim F_Y(y)$.

In the APV model $Y$ is irrelevant to ex-post utility and bidders' private values $\overline{v}_{ij}$ are correlated,[53] so bids are correlated as well.[54] In the CV model, ex-post as-is utility for the winner is simply $Y_j$ and private information is an idiosyncratic signal $\overline{v}_{ij} = y_j + \varepsilon_{ij}$, $E[\varepsilon_{ij}] = 0$.[55] The UHIPV model is similar, except that the common component is observable to bidders (but not to the econometrician), and ex-post utility of winning for $i$ is $y_j \times \overline{v}_{ij}$.[56] In the latter two cases, as $Y_j$ varies across auctions all bidders' bids co-move with it. By contrast, in the IPV model (conditional on observable $(\boldsymbol{Z}_j, N_j)$), $Y_j$ is irrelevant to ex-post utility and $(\overline{V}_{1,j}, \ldots, \overline{V}_{N_j,j})$ and $Y_j$ are mutually independent.

With this in mind, our test procedure begins with the following predictive regression:

$$\overline{Bid}_{ij} = \theta_0 + \theta_1 \overline{Bid}_{-i,j} + [\boldsymbol{P}_{ij}, \boldsymbol{P}_{-i,j}, \boldsymbol{X}_{ij}, \boldsymbol{N}_j]\boldsymbol{\eta} + \boldsymbol{M}_j \boldsymbol{\tau} + \varepsilon_{ij}, \tag{13}$$

where $\overline{Bid}_{ij} \equiv \sum_{k=1}^{16} b_{ijk} \mathbf{1}(k \in L_{ij}) / \sum_{k=1}^{16} \mathbf{1}(k \in L_{ij})$ is bidder $i$'s mean continuous bid submitted in auction $j$, $\overline{Bid}_{-i,j} \equiv \sum_{l \neq i} \overline{Bid}_{lj} / (N_j - 1)$, $N_j \geq 2$, is the average of within-bidder mean bids across all of $i$'s competitors, $\boldsymbol{P}_{ij} = [P_{i1}, \ldots, P_{i16}]$ is a full set of indicators for which packages $i$ bid on, $\boldsymbol{P}_{-i,j} = [P_{-i,1}, \ldots, P_{-i,16}]$ is a full set of count variables for the number of times $i$'s competitors bid on each package, $\boldsymbol{N}_j = [N_j, N_j^2, \ldots, N_j^k]$ is a vector of polynomial terms for the number of bidders, $\boldsymbol{M}_j = [N_j, N_j^2, \ldots, N_j^k] \times \overline{Bid}_{-i,j}$ contains interactions with the competitor mean bid, $\boldsymbol{\eta}$ and $\boldsymbol{\tau}$ are conformable parameter vectors, and finally, $\varepsilon_{ij}$ is simple prediction error. Now, the null hypothesis of IPV (with no residual unobserved heterogeneity) translates into $H_0 : \theta_1 = 0$, and the alternate hypothesis $H_a : \theta_1 \neq 0$ corresponds to APV $\cup$ CV $\cup$ UHIPV (including mixtures of the three).[57]

Terms involving $\boldsymbol{N}_j$ and $\boldsymbol{M}_j$ control for strategic co-movement that would exist even in an IPV world with varying $N_j$: when the number of competitors rises bidders respond with more aggressive bids (i.e., lower information rents).[58] The $\boldsymbol{M}_j \boldsymbol{\tau}$ term partials out strategic co-movement between $i$'s actions and her opponents' actions when competition becomes more fierce. Since all bidders react to increasing competition in the same direction—revising their bids to be more favorable to the auctioneer—then failing to control for $\boldsymbol{M}_j$ could lead to an apparent correlation between competitors' bids, even under IPV. Finally, the $\boldsymbol{X}_{ij}$ term—which contains auction covariates $\boldsymbol{Z}_j$, bidder covariates $\boldsymbol{W}_{ij}$, and interactions—is needed to control for observable variation in general failed bank value, as well as bidder selection

[53] Alternatively, one might assume private values are correlated with $Y$, but independent of each other conditional on the unknown realization of $Y$. Thus, the role of $Y$ is to induce correlation in the $\overline{V}_{ij}$'s; this model is known as "conditionally independent private values" (CIPV) and was proposed by Li, Perrigne, and Vuong (2000). CIPV is a generalization of IPV and a special case of APV; see Hickman, Hubbard, and Saglam (2012) for further discussion of information structures in empirical auction models.

[54] Hubbard, Li, and Paarsch (2012) showed that monotone equilibrium bidding implies that the bid distribution and private value distribution share a common copula.

[55] A further generalization of CV, the interdependent values model (IV, see Somaini (2020)), is possible: for bidder $i$ ex-post as-is utility is an idiosyncratic function $U_i(Y_j)$, so that there is a common component of valuations and an idiosyncratic component as well. IV would likewise induce conditional correlation among competitors' bids (since all private information is relevant to $i$'s ex-ante expected payoffs) and is therefore covered by our testing procedure as a possible mixture of CV and IPV or APV.

[56] Krasnokutskaya (2011) proposed a version of this model where the $\overline{V}_{ij}$'s and $Y_j$ are independent.

[57] In the empirical model, switch-specific valuation adjustments are assumed to be deterministic, conditional on $\boldsymbol{X}_{ij}$ (Assumption 6 and equation (9)), so conditional idiosyncratic variation in bids stems from $\overline{v}_{ij}$ alone.

[58] We include polynomial terms because this effect is non-linear in the level of competition $N_j$. Within the model, bidders compute projections $E[N_j | \boldsymbol{Z}_j]$ given auction covariates $\boldsymbol{Z}_j$, but in equation (13) we use ex-post realizations of $N_j$ as a proxy for bidders' expectations.

based on failed bank observables. After controlling for observable determinants of bidding co-movement by $i$ and $i$'s opponents, if there is still residual correlation between $\overline{Bid}_{ij}$ and $\overline{Bid}_{-i,j}$, then the null hypothesis of IPV is rejected in favor of the alternate hypothesis; otherwise, we fail to reject IPV.

Table B.2. Detecting Conditional Correlation among Competing Bids

| OUTCOME VARIABLE: $\overline{Bid}_{ij}$ | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| REGRESSORS | Param Est. | St.Dev. | Param Est. | St.Dev. | Param Est. | St.Dev. | Param Est. | St.Dev. |
| $\overline{Bid}_{-i,j}(\widehat{\theta}_1)$ | 0.819*** | (0.021) | -0.049 | (0.183) | -0.191 | (0.277) | -0.212 | (0.192) |
| $N_j \times \overline{Bid}_{-i,j}(\widehat{\tau}_1)$ | — | | 0.439*** | (0.131) | 0.572*** | (0.221) | 0.517*** | (0.137) |
| $N_j^2 \times \overline{Bid}_{-i,j}(\widehat{\tau}_2)$ | — | | -0.062** | (0.028) | -0.100* | (0.054) | -0.078*** | (0.054) |
| $N_j^3 \times \overline{Bid}_{-i,j}(\widehat{\tau}_3)$ | — | | 0.004** | (0.002) | 0.007* | (0.004) | 0.004** | (0.002) |
| Constant$(\widehat{\theta}_0)$ | -1.831 | (1.421) | -5.965*** | (1.416) | -10.830 | (9.379) | 12.834 | (10.153) |
| $\boldsymbol{N}_j$ | no | — | no | — | yes | [0.747] | no | — |
| $\boldsymbol{P}_{ij}$ | yes*** | [0.000] | yes*** | [0.000] | yes*** | [0.000] | yes*** | [0.000] |
| $\boldsymbol{P}_{-i,j}$ | yes*** | [0.000] | yes*** | [0.000] | yes*** | [0.000] | yes*** | [0.000] |
| $\boldsymbol{Z}_j$ | no | — | no | — | no | — | yes** | [0.012] |
| $\boldsymbol{W}_{ij}$(+interactions) | no | — | no | — | no | — | yes | [0.471] |
| State(FL,GA) | no | — | no | — | no | — | yes* | [0.062] |
| Year FE | no | — | no | — | no | — | yes | [0.639] |
| Observations | 723 | $df=693$ | 723 | $df=690$ | 723 | $df=687$ | 723 | $df=662$ |
| R-squared | 0.806 | | 0.832 | | 0.833 | | 0.844 | |

This table provides estimates of our test of the null hypothesis $H_0: \theta_1 = 0$ (IPV) against the alternate hypothesis $H_a: \theta_1 \neq 0$ (APV ∪ CV ∪ UHIPV and/or mixtures of the three). There are 723 bidder-specific observations in auctions with at least two bidders. Standard errors for individual parameter estimates are in parentheses; p-values for joint exclusions of variable groups are in square brackets. Results are robust to inclusion of higher-order polynomial terms in $N_j$. Statistical significance: ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table B.2 displays results for various specifications of equation (13). Specification (1) includes only the bid portfolio controls, and we get a statistically significant conditional correlation between own mean bid and opponent mean bids. However, in specifications (2)–(4), after controlling for $\boldsymbol{M}_j$ the coefficient $\widehat{\theta}_1$ is much smaller and not statistically different from zero. This result is robust to inclusions of failed bank characteristics, bidder characteristics, and state/year fixed effects. These results support our assumptions that correlated private values, common values, and unobserved failed bank heterogeneity are not major concerns in our model of FDIC auctions.

## Appendix C. Testing for Independence Across Auctions

To test for dependence across auctions, we estimate two sets of regressions. We first consider a logit regression in which the dependent variable is an indicator that takes a value of 1 for winning bids. If bidders ($i$) learn the scoring rule over time, then increased experience should mean a bidder is more likely to win. In the case of ($ii$) complementarities, we expect more aggressive bidding following a win as the value of a subsequent acquisition is increased. If ($iii$) winning tightens capacity constraints leading to lower values for following P&A opportunities, bidders should bid less aggressively following a winning bid. These effects are potentially offsetting, so we exploit variation in bidder experience and capacity constraints by comparing large bidders to poorly capitalized bidders.

Table C.1. Effects of Experience and Size on Bidding Competition

| Variables | Winner (Logit) | | | Bidder premium | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Experience | -0.072*** | -0.075 | | | |
| | (0.014) | (0.083) | | | |
| Experience pre-win | | | -0.032 | 0.013 | 0.011 |
| | | | (0.168) | (0.008) | (0.008) |
| Experience post-win | | | -0.047 | -0.004 | -0.004* |
| | | | (0.047) | (0.004) | (0.002) |
| # Bidders | -0.570*** | -1.539*** | -1.517*** | -0.009 | -0.009 |
| | (0.051) | (0.212) | (0.209) | (0.008) | (0.008) |
| Large | | -0.782 | | -0.013 | |
| | | (0.671) | | (0.030) | |
| Large x Experience | | 0.059 | | 0.002 | |
| | | (0.084) | | (0.084) | |
| Low Capital | | -0.277 | | 0.024 | |
| | | (0.466) | | (0.021) | |
| Low Capital x Experienced | | -0.148 | | -0.018** | |
| | | (0.170) | | (0.008) | |
| Component Controls | No | No | No | Yes | Yes |
| Failed-Bank Controls | No | Yes | Yes | Yes | Yes |
| Year FE | No | Yes | Yes | Yes | Yes |
| Bidder Controls | No | Yes | Yes | Yes | No |
| Observations | 1,227 | 305 | 305 | 305 | 305 |

Columns (1)-(3) present results from a Logit regression with dependent variable $Pr(winner = 1)$, while (4)-(5) present results for the dollar component of the bid as a percent of total assets. *Experience* is the number of auctions in which a bidder has participated. *Experience post-win* and *Experience pre-win* interact Experience with indicator variables for whether the bidder has already or not yet won an auction, respectively. *Large* indicates the bidder is above the 75th percentile of all bidders in terms of total assets, and *Low Capital* indicates the bidder's risk-weighted Tier 1 capital ratio is below the 25th percentile. Unreported controls include *%CRE, %CI, %SFR*, and *log(Total Assets)*. Component controls indicate if the bid included LS, PB, VAI, or NC options. Specifications (2)-(5) are limited to the restricted sample. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Results from column (1) suggest that experience has a small, negative correlation with winning. In column (2), while also adding many controls, we aim to separate complementarities and capitalization effects. None of the variables of interest—size, capitalization, or experience—are significant. Column (3) looks at the effects of experience before or after the first time a bidder wins, and the effects on the probability of winning are both negative but are also not significant. Columns (4) and (5) look at the size of bidder premiums (i.e., $deposit\ premium - asset\ discount$): higher bid premiums are associated with more aggressive bidding. The coefficients on experience both pre- and post-winning are not significant. Although not definitive, we do not find substantial effects of experience on bidding behavior. For this reason (in addition to computational complexity) we do not model learning, complementarities over time, or strategic bidding due to capacity constraints.

Appendix D. Supplemental Online Appendix to accompany
*"Resolving Failed Banks: Uncertainty, Multiple Bidding, & Auction Design,"*
by Jason Allen, Robert Clark, Brent Hickman, and Eric Richert

D.1. **Semi-Parametric Identification of the Least-Cost Scoring Rule.** In this section we discuss an alternate identification argument for the stochastic least-cost scoring model that requires independence of idiosyncratic cost shocks $\delta$, but imposes weaker functional form restrictions on the joint distribution of the common shocks $(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB}, u)$. Despite our use of parametric forms in the estimator for computational tractability, this alternate identification argument helps to elucidate how the raw moments in the data pin down the components of the scoring rule process. Recall equation (5), reproduced here for convenience,

$$-C_{ijk} = b_{ijk} + d_k^{LS}(\%LS_j)\gamma_j^{LS} + d_k^{VAI}\gamma_j^{VAI} + d_k^{NC}\gamma_j^{NC} + d_k^{PB}(\%PB_j)\gamma_j^{PB} + \delta_{ijk} + u_j.$$

In order to facilitate discussion on identification we begin by replacing Assumption 5 (joint normality of the common shocks) with the following weaker condition:

**Assumption 7.** *The common shocks $(\gamma_j^{LS}, \gamma_j^{VAI}, \gamma_j^{NC}, \gamma_j^{PB}, u_j)$ have a joint distribution characterized by a Gaussian copula with correlation matrix $\mathbf{\Sigma}$, with 1's on the main diagonal and correlations $\rho(s, s')$, $s, s' \in \{LS, VAI, NC, PB, u\}$ on the off-diagonal.*

By Sklar's theorem we know that a well-behaved joint distribution can be uniquely represented as $F_{\mathbf{\Gamma}U}(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB}, u) = \mathcal{C}\left[F_\gamma^{LS}(\gamma^{LS}), F_\gamma^{VAI}(\gamma^{VAI}), F_\gamma^{NC}(\gamma^{NC}), F_\gamma^{PB}(\gamma^{PB}), F_u(u)\right]$, where $\mathcal{C}$ is a copula function. One can think of a copula as representing the correlation structure among the set of jointly-distributed uniform random variables $(Y_{LS}, Y_{VAI}, Y_{NC}, Y_{PB}, Y_u)$, where $Y_s = F_s(x)$. A Gaussian copula is the one that exists within a joint normal distribution; it stipulates that a full set of pairwise correlations completely characterizes all aspects of random co-movement within the joint distribution.

**Proposition 3.** *Under Assumptions 4 and 7, the bidder-package shock variance $\sigma_\delta^2$ and the joint distribution of the common shocks from the least-cost scoring rule $(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB}, u)$ are semi-parametrically identified from the published resolution costs and bid histories, without functional form restrictions on the marginal distributions of the common shocks.*

The proof of this proposition proceeds through five main steps. First we argue that the distribution of the sum of the auction-specific shock $u_j$ and the bid-specific idiosyncratic shock $\delta_{ijk}$ is identified from the subset of single-bidder auctions where the sole bidder submits only an as-is P&A bid. In the second step, we show that the variance $\sigma_\delta^2$ is identified from observed win probabilities under varying differences $b_{ijk} - b_{i'jk}$, when at least two bidders $i$ and $i'$ bid on the same package $k$. The third step uses a deconvolution argument to separate the known distributions of $(u_j + \delta_{ijk})$ and $\delta_{ijk}$ to identify the distribution of $u_j$. The fourth step identifies the marginal distributions of each component-specific scoring shock by using bids that differ by only that component and a similar deconvolution argument to steps 2 and 3. Finally, in step five we can identify the correlations by leveraging the identity that the variance of the sum of two random variables is the sum of their variances plus twice the covariance. For the entire identification argument we hold fixed a given set of failed bank traits $\boldsymbol{Z}_j$.

**Step 1:** To begin, we consider the subset of auctions with a single bidder submitting a single As-Is takeover bid.[1] In this case, the only uncertainty when trying to map observed bids to observed losses stems from the convolution $(u_j + \delta_{ijk})$.[2] In this set of auctions the scoring rule implies that $C_{ijk} - b_{ijk} = u_j + \delta_{ijk}$, and the left-hand side of that equation is observed. Therefore, the right-hand side is identified from observed costs and bid submissions in the subsample of single-bidder as-is auctions.

**Step 2:** We focus now on the set of auctions with two bids where the losing bid was submitted on the same package that won the auction. In auction $j$, for any difference between bidders $i$ and $i'$ in bids on package $k$ (i.e., with the same switch configuration) we observe from raw data the frequency with which $b_{i'jk}$ beats $b_{ijk}$, which is the same as

$$Pr[b_{ijk} + \delta_{ijk} \leq b_{i'jk} + \delta_{i'jk}] = Pr[\delta_{ijk} - \delta_{i'jk} \leq b_{i'jk} - b_{ijk}].$$

The expression on the right-hand side is the CDF of the difference $(\delta_{ijk} - \delta_{i'jk})$, which is therefore known since the left-hand side can be derived directly from empirical frequencies. By Assumption 4, $\delta_{ijk}$ and $\delta_{i'jk}$ are independent with mean zero and variance $\sigma_\delta^2$, so the variance of their difference (which is known from raw data) is just $2\sigma_\delta^2$. Thus, since $\delta$ is normal with mean zero, its distribution $\Phi_\delta(\delta; 0, \sigma_\delta^2)$ is known as well.

**Step 3:** From steps 1 and 2 the distributions of $\delta$ and the convolution $y \equiv (u + \delta)$ are known. Given that $u$ is independent of $\delta$, we can express the characteristic function of $Y$ as $\Psi_y(t) = E[\exp(ity)] = E[\exp(it(u + \delta))] = \Psi_u(t)\Psi_\delta(t)$, where $\Psi_u$ and $\Psi_\delta$ are the characteristic functions of $u$, and $\delta$, respectively. Thus, we can obtain the marginal density of $u$ as the inverse Fourier transform of the ratio of known characteristic functions $\Psi_y(t)/\Psi_\delta(t)$.

**Step 4:** To identify the marginal distributions of each of the component-shocks $\gamma^s$, $s = LS, VAI, NC, PB$, we iteratively apply a similar argument from steps 2 and 3. For clarity and simplicity of discussion, it will be convenient to restrict attention to subsamples of auctions with two bids, where the winning bid varies from the losing bid by a single discrete component. Although this subsample will not contain all useful identifying variation in the data-generating process, it will be sufficient to show that the dataset as a whole contains requisite variation to uniquely identify the model parameters.

Let us consider identification of the marginal distribution of $\gamma_j^{VAI}$, the shock associated with use of a VAI option.[3] The same argument holds for the other three components. Consider competing bids on package $k_i$ for bidder $i$ and $k_{i'}$ for bidder $i'$, where all discrete components are the same across $k_i$ and $k_{i'}$, except that one includes a VAI provision and the other does not. If $k_i$ includes VAI, then for any difference in bid premiums, we can observe the frequency at which $i'$ beats $i$

$$Pr[b_{ijk_i} + \delta_{ijk_i} + \mathbf{\Gamma}_j \boldsymbol{d}_{k_i} \leq b_{i'jk_{i'}} + \delta_{i'jk_{i'}} + \mathbf{\Gamma}_j \boldsymbol{d}_{k_{i'}}] = Pr[\delta_{ijk_i} - \delta_{ijk_{i'}} + \gamma_j^{VAI} \leq b_{i'jk_{i'}} - b_{ijk_i}],$$

and if $k_i$ excludes VAI we can observe the probability that $i'$ beats $i$

[1] In order for this subset to be non-empty, it must be true that $\pi_N(1) > 0$, and the support $Supp(F_{\overline{V},\boldsymbol{S}})$ must be such that with positive probability each bidder wishes to only submit a single As-Is takeover bid. This can be empirically verified, but for the purpose of this argument, we assume non-emptiness.

[2] The scoring rule shocks are unknown to bidders when choosing to enter and which package to bid on and so this subset is equally likely to include any realization of $u_j + \delta_{ijk}$.

[3] Because scoring shocks are unknown to bidders when forming their bids, and because shocks are independent of their private information, the shocks to VAI in the subsample under consideration (auctions with two bids where the winning and losing bid differ by the VAI switch) have the same distribution as the full sample.

$$Pr[b_{ijk_i} + \delta_{ijk_i} + \mathbf{\Gamma}_j \boldsymbol{d}_{k_i} \leq b_{i'jk_{i'}} + \delta_{i'jk_{i'}} + \mathbf{\Gamma}_j \boldsymbol{d}_{k_{i'}}] = Pr[b_{ijk_i} - b_{i'jk_{i'}} \leq \delta_{i'jk_{i'}} - \delta_{ijk_i} + \gamma_j^{VAI}].$$

This identifies the distribution of $\delta_{ijk_i} - \delta_{i'jk_{i'}} + \gamma_j^{VAI}$. From step 2, the distribution of $(\delta - \delta')$ is known, where $\delta$ and $\delta'$ constitute two independent draws from the distribution $F_\delta$, and by Assumption 4 this difference is independent of $\gamma_j^{VAI}$. As in step 3, a deconvolution argument can be applied: we can express the characteristic function of $y \equiv (\delta - \delta' + \gamma_j^{VAI})$ as $\Psi_y(t) = E[\exp(ity)] = E[\exp(it(\delta - \delta' + \gamma^{VAI}))] = \Psi_{(\delta-\delta')}(t)\Psi_{VAI}(t)$, where $\Psi_{(\delta-\delta')}$ and $\Psi_{VAI}$ are the characteristic functions of $(\delta - \delta')$, and $\gamma^{VAI}$, respectively. Thus, we can obtain the marginal density of $\gamma^{VAI}$ as the inverse Fourier transform of the ratio of known characteristic functions $\Psi_y(t)/\Psi_{(\delta-\delta')}(t)$.

**Step 5:** Finally, the correlation parameters $\rho(s, s')$ can be uniquely pinned down using Assumption 7 and comparisons across bids in auctions with two bidders and two bids, where the winning and losing bids differ by two discrete components. Consider competing bids on package $k_i$ for bidder $i$ and $k_{i'}$ for bidder $i'$, where all discrete components are the same across $k_i$ and $k_{i'}$, except that one includes a VAI provision *and* a LS provision, and the other omits both. If $k_i$ includes VAI+LS then for any difference in bid premiums, we can observe the frequency at which $i'$ beats $i$ as

$$Pr[b_{ijk_i} + \delta_{ijk_i} + \mathbf{\Gamma}_j \boldsymbol{d}_{k_i} \leq b_{i'jk_{i'}} + \delta_{i'jk_{i'}} + \mathbf{\Gamma}_j \boldsymbol{d}_{k_{i'}}] = Pr[\delta_{ijk_i} - \delta_{i'jk_{i'}} + (\gamma_j^{VAI} + \gamma_j^{LS}) \leq b_{i'jk_{i'}} - b_{ijk_i}],$$

and if $k_{i'}$ includes VAI+LS we can likewise observe the frequency at which $i'$ beats $i$ as

$$Pr[b_{ijk_i} + \delta_{ijk_i} + \mathbf{\Gamma}_j \boldsymbol{d}_{k_i} \leq b_{i'jk_{i'}} + \delta_{i'jk_{i'}} + \mathbf{\Gamma}_j \boldsymbol{d}_{k_{i'}}] = Pr[b_{ijk_i} - b_{i'jk_{i'}} \leq \delta_{i'jk_{i'}} - \delta_{ijk_i} + (\gamma_j^{VAI} + \gamma_j^{LS})].$$

Applying similar logic as before, this establishes that the distribution of the sum $(\gamma^{VAI} + \gamma^{LS})$ is known. Since the marginal distributions of $\gamma^{VAI}$ and $\gamma^{LS}$ are also known, these three pieces of information uniquely determine the value of the pairwise correlation parameter $\rho(VAI, LS) = \frac{\text{Cov}[\gamma^{VAI}, \gamma^{LS}]}{\sqrt{\text{Var}[\gamma^{VAI}]\text{Var}[\gamma^{LS}]}}$ through the identity $\text{Var}[\gamma^{VAI} + \gamma^{LS}] = \text{Var}[\gamma^{VAI}] + \text{Var}[\gamma^{LS}] + 2\text{Cov}[\gamma^{VAI}, \gamma^{LS}]$ which has a single unknown, $\text{Cov}[\gamma^{VAI}, \gamma^{LS}]$. Once again, similar logic applies to establish that other pairwise correlations between discrete component shocks are uniquely determined as well. By assumption 7 these pairwise correlations are sufficient to pin down the copula governing the joint distribution of $(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB})$.

For the final four pairwise correlations $\rho(u, s)$, $s \in \{LS, VAI, NC, PB\}$, the sample of final resolution costs tied to winning bids pins them down, provided that we see combinations of enough different switches winning with positive probability. For simplicity of discussion, consider the subsample of auctions with one bidder and a single bid submitted. Restricting attention further to subsamples where a given package $k$ was submitted, note that when the single submitted bid includes the LS provision only, then the distribution of $(\gamma^{LS} + \delta + u)$ is identified from raw data:

$$\Pr[C_{1jk} - b_{1jk} \leq c | (d_k^{LS}, d_k^{VAI}, d_k^{NC}, d_k^{PB}) = (1, 0, 0, 0)] = \Pr[\gamma_j^{LS} + \delta_{1jk} + u_j \leq c].$$

Thus, knowledge of the above CDF allows us to write down the relation

$$\begin{aligned} &Var\Big[C_{1jk} - b_{1jk} | (d_k^{LS}, d_k^{VAI}, d_k^{NC}, d_k^{PB}) = (1, 0, 0, 0)\Big] \\ &\quad = Var[\gamma^{LS}] + Var[\delta] + Var[u] + 2Cov[\gamma^{LS}, u]. \end{aligned} \tag{14}$$

This pins down the covariance between $u$ and $\gamma^{LS}$, since the variance terms on the right-hand side are known from previous steps. By similar logic, the sample of single-bid auctions where the LS and VAI provisions were included imply the relation

$$\begin{aligned} Var\Big[C_{1jk} - b_{1jk} | (d_k^{LS}, d_k^{VAI}, d_k^{NC}, d_k^{PB}) = (1,1,0,0)\Big] \\ = Var[\gamma^{LS}] + Var[\gamma^{VAI}] + Var[\delta] + Var[u] \\ + 2Cov[\gamma^{LS}, \gamma^{VAI}] + 2Cov[\gamma^{LS}, u] + 2Cov[\gamma^{VAI}, u]. \end{aligned} \tag{15}$$

Thus, since the variance terms and the first covariance term on the right-hand side are known, then, provided that both types of single-bid auctions occur with positive probability, equations (14) and (15) uniquely pin down values of $Cov[\gamma^{LS}, u]$ and $Cov[\gamma^{VAI}, u]$.

Extending similar logic to all 15 unique packages with at least one discrete switch on, we have that the remaining set of four pairwise correlations between $u$ and the discrete component shocks are identified, as long as the following system of linear equations

$$\begin{aligned} \sum_s d_2^s 2Cov[\gamma^s, u] &= Var[C_{ij2} - b_{ij2} | k=2] - Var[\delta] - Var[u] - \sum_s \sum_{s'} d_2^s d_2^{s'} Cov[\gamma^s, \gamma^{s'}] \\ \sum_s d_3^s 2Cov[\gamma^s, u] &= Var[C_{ij3} - b_{ij3} | k=3] - Var[\delta] - Var[u] - \sum_s \sum_{s'} d_3^s d_3^{s'} Cov[\gamma^s, \gamma^{s'}] \\ \vdots \qquad & \qquad \vdots \qquad\qquad\qquad \vdots \qquad\qquad\qquad \vdots \\ \sum_s d_{16}^s 2Cov[\gamma^s, u] &= Var[C_{ij16} - b_{ij16} | k=16] - Var[\delta] - Var[u] - \sum_s \sum_{s'} d_{16}^s d_{16}^{s'} Cov[\gamma^s, \gamma^{s'}] \end{aligned} \tag{16}$$

has full rank (i.e., rank 4), where the sums above are over $s, s' \in \{LS, VAI, NC, PB\}$. ■

As a final note, for simplicity of discussion the above identification argument restricted attention to subsamples of auctions (e.g., those with two bidders and two bids) and showed that such subsamples are sufficient to uniquely identify model parameters. In reality, the larger dataset has much more useful identifying variation: in auctions with three or more bidders and/or three or more bids, there will be many winning bid vs. losing bid comparisons differing by 0, 1, 2, 3, or 4 discrete switches that will be informative of the marginal distributions of $\delta$ and/or $(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB}, u)$, and/or the correlations among the last five shocks. In our empirical application, the Tobit Maximum Likelihood Estimator we implement (based on an additional parametric assumption of joint normality) leverages all pairwise bid comparisons available in the data. The identification argument here, on the other hand is intended to demonstrate that the dataset contains sufficient information, in principle, to uniquely determine values of relevant model parameters related to FDIC scoring shocks.

Finally, while Assumption 7 guarantees the identification of the model we implement in our empirical application, it may be possible to maintain identification with further relaxations of the conditions imposes on the copula structure. For example, the system of equations (16) may lead to over-identification, given our restriction to a Gaussian copula structure among the random variables $(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB}, u)$. However, identification in full generality—i.e., characterizing minimal restrictions on the correlation structure which lead to unique model parameters being recoverable from available data—is beyond the scope of this paper.

D.2. **The Bijective Property of Order Statistics Versus Parent Distributions Under Stochastic $N$.** In Section 5.2 we state that, given results proven by Bodoh-Creed et al. (2021) (and also Hickman et al. (2017)), identifying the distribution of the number of competitors, $M_j$, is sufficient to pin down win probabilities in private value auctions with stochastic participation. Here we provide some additional detail to justify this claim within our setting. While Bodoh-Creed et al. (2021) did not consider a setting with multiple bidding, their argument that pinning down the distribution of rival numbers $\pi_M$ is sufficient (together with bid data) to identify a bijective mapping between the parent distribution of rival bids/costs and the win probability (based on order statistics of rival bids/costs) still applies to the current setting.

The idea is the following: Hold some level of competition $m_j$ fixed, and let $G_{\boldsymbol{LB}}(L, \boldsymbol{b}|\boldsymbol{Z}_j)$ denote the parent joint distribution of a given bidder's equilibrium choices of portfolio $L$ and bid profile $\boldsymbol{b}$. Given $m_j$ independent draws from $G_{\boldsymbol{LB}}$ (which is known from raw bid data), one can use the known scoring process and reserve cost distribution (identified in a step discussed previously) to construct the distribution of the lowest order statistic among costs competing with $i$'s own bids, call it $G_{C^*_{-i}|M}(C^*_{-i}|m_j, \boldsymbol{Z}_j)$. However, this distribution applies only in the event that $M = m_j$; the actual distribution of the lowest competing cost to which bidders best respond is a mixture:

$$G_{C^*_{-i}}(c|\boldsymbol{Z}_j) = \sum_{m_j=1}^{\infty} G_{C^*_{-i}|M}(c|m_j, \boldsymbol{Z}_j)\pi_M(m_j|\boldsymbol{Z}_j).$$

Bodoh-Creed et al. (2021) argue that, holding fixed any (potentially infinite-dimensional) parameterization of $\pi_M$ (and also $\boldsymbol{Z}_j$ in the curent context), this relationship implies a bijective mapping between the parent distribution $G_{\boldsymbol{LB}}$ and the unconditional order statistic distribution $G_{C^*_{-i}}$ for each $c$ in the support of $C^*_{-i}$. The main difference between their setting and ours is that we are fortunate to have access to direct observations of $N_j$, whereas Bodoh-Creed et al. (2021) observed only stochastic lower bounds on $N_j$.

Once $G_{C^*_{-i}}$ is known, the only remaining information to account for in determining the win probability function $G(b_{ijk}|L_{ij}, \boldsymbol{b}_{ij}, \boldsymbol{Z}_j)$ in the FDIC context is competition from one's own (known) bids on packages $k' \in L_{ij},\ k' \neq k$.

D.3. **Additional Estimator Details: Name Matching Algorithm.** Recall from Section 3 that the raw bid summaries include the winning bid, the cover bid, all other losing bids, the identities of the winning bidder and the cover bidder, and a complete list of all bidders who submitted at least one losing bid (including the winner and/or cover bidder if they submitted multiple bids). In 129 auctions out of 322 in our sample, there are some bids for which the identity of the submitter is partially ambiguous. We use an unsupervised algorithm to determine possible assignments for these cases. Underpinning the algorithm is a simple idea that each bid submitted by healthy bank $i$ must have non-trivial win probability, given the distribution of FDIC scoring weights, and conditional on other bids submitted by $i$. This implies two key restrictions that substantially narrow the set of possible matches. First, $i$ cannot submit multiple bids on the same package, as this would imply that one must surely lose. Second, $i$ cannot submit two bids if one dominates the other with very high probability.[4] After taking these constraints into account, the algorithm iteratively resolves remaining ambiguous assignments of bids to bidder identities randomly.

[4]For example, suppose the FDIC is known to have a strong preference against awarding P&A contracts with a LS provision, on average. In that case, the same bidder could not have submitted one bid $b$ for an as-is P&A contract and at the same time another bid $b' < b$ on a contract with a LS provision only.

More formally, for each auction $j$ let $\mathcal{I}_j = \{i_1, i_2, \ldots, i_{T_j}\}$ denote the complete list of bidders who submitted at least one losing bid (excluding the cover bid), and let $\mathcal{O}_j = \{O_1, O_2, \ldots, O_{P_j}\}$ denote the complete list of un-matched losing bids, where $O_p = (b_p, \boldsymbol{d}_{k_p}) \in \mathbb{R}^5$ is a complete set of money and non-money bid characteristics, where $k_p \in \{1, 2, \ldots, 16\}$ denotes the package corresponding to net transfer bid $b_p$. Note that the set $\mathcal{I}_j$ may not include the identities of the winner and/or cover bidder, denoted $i^w$ and $i^c$, respectively, if either (or both) of them did not submit multiple bids. Moreover, define a tolerance $\psi > 0$ and two positive integers $Q$ and $q$. For each auction $j = 1, \ldots, J$,

(1) If $\mathcal{I}_j = \emptyset$, or if $|\mathcal{I}_j| = |\mathcal{O}_j| = 1$ (i.e., no ambiguity), then assign losing bid $p = 1$ to bidder $l = 1$ and continue on to auction $j + 1$; otherwise, go to step 2.
(2) If $|\mathcal{I}_j| = |\mathcal{O}_j| > 1$, randomly match each $l \in \mathcal{I}_j$ to a single $p \in \mathcal{O}_j$ and continue on to auction $j + 1$; otherwise, go to step 3.
(3) If $|\mathcal{I}_j| < |\mathcal{O}_j| \leq Q$ and $|\mathcal{I}_j \setminus \{i^w, i^c\}| \leq q$ do the following (otherwise go to step 4):
  (a) First compute the full set $A_j$ of possible candidate assignments of unique bids $O \in \mathcal{O}_j$ to $i \in \mathcal{I}_j$, where $|A_j| = \binom{P_j}{T_j}(T_j!)\left(T_j^{P_j - T_j}\right) = \frac{P_j!}{(P_j - T_j)!}\left(T_j^{P_j - T_j}\right)$. Each assignment, denoted $\mathcal{A}_{ja} = \{\mathcal{O}^a_{i_1}, \ldots, \mathcal{O}^a_{i_{T_j}}\}$, $a = 1, \ldots, |A_j|$, partitions $\mathcal{O}_j$ into $i = 1, \ldots, N_j$ bidder-specific bins $\mathcal{O}^a_{ji} = \{O_{p_1}, \ldots, O_{p_{P_{ji}}}\}$, where each bidder identity $i$ is assigned at least one bid (i.e., $P_{ji} \geq 1$). Initialize set $A'_j = \emptyset$ and eliminate candidates by doing the following for each $a = 1, \ldots, |A_j|$:
    (i) If some $\mathcal{O}^a_{ji} \in \mathcal{A}_{ja}$ contains $(b_p, \boldsymbol{d}_{k_p})$ and $(b_{p'}, \boldsymbol{d}_{k_{p'}})$ where $k_p = k_{p'}$ (that is, if any bidder is matched with two bids on the same package $k$), re-define $A'_j = A'_j \cup \mathcal{A}_{ja}$.
    (ii) Given the known distributions $F_\delta$ and $F_{\boldsymbol{\Gamma}U}$, compute within-$i$ win probabilities for each bid in each assignment, conditional on the full set of bids $\mathcal{O}^a_{ji}$ assigned to each $i$. If $\mathcal{A}_{ja}$ involves at least one $i$ submitting at least one bid with less than $\psi$ probability of winning against $i$'s other bids in $\mathcal{O}^a_{ji}$, re-define $A'_j = A'_j \cup \mathcal{A}_{ja}$.
  (b) Assuming a uniform prior on the remaining feasible assignments $A_j \backslash A'_j$, randomly select one from this set and continue on to auction $j + 1$.
(4) Otherwise, if $|\mathcal{O}_j| > Q$ or $|\mathcal{I}_j \setminus \{i^w, i^c\}| > q$ (so that $|A_j|$ becomes too large to be computationally feasible), do the following:
  (a) Initialize all bidders' individual assignments $\mathcal{O}_{ji} = \emptyset$, except if $i^w \in \mathcal{I}_j$ ($i^c \in \mathcal{I}_j$), in which case the initial configuration of $\mathcal{O}_{ji^w}$ (and/or $\mathcal{O}_{ji^c}$) contains only the winning (cover) bid.
  (b) Define $\mathcal{O}^*_j = \emptyset$, $\mathcal{I}^*_j = \emptyset$ and for each $p^* = 1, \ldots, P_j$ do the following:
    (i) If $|\mathcal{I}_j \setminus \mathcal{I}^*_j| = |\mathcal{O}_j \setminus \mathcal{O}^*_j|$ then randomly match each $l \in \mathcal{I}_j \setminus \mathcal{I}^*_j$ to a single $p \in \mathcal{O}_j \setminus \mathcal{O}^*_j$ and continue on to auction $j+1$. Otherwise, go to step 4(b)ii.
    (ii) Randomly choose one bid $O_{p^*}$ from $\mathcal{O}_j \setminus \mathcal{O}^*_j$ and re-define $\mathcal{O}^*_j = \mathcal{O}^*_j \cup O_{p^*}$.
    (iii) Compute the list $\mathcal{I}^{p^*}_j$ of bidders for whom $O_{p^*}$ is an eligible addition to their current set of bids—i.e., where $\mathcal{O}_{ji}$ does not contain a bid on package $k_{p^*}$ and $\mathcal{O}_{ji} \cup O_{p^*}$ wins against $\mathcal{O}_{ji}$ with more than $\psi$ probability. If $\mathcal{I}^{p^*}_j = \emptyset$, then temporarily (for $p^*$ only) re-define $\mathcal{I}^{p^*}_j$ simply as the set of $i$ such that $\mathcal{O}_{ji}$ does not contain a bid on package $k_{p^*}$.
    (iv) Randomly select $i^* \in \mathcal{I}^{p^*}_j$ and re-define $\mathcal{O}_{ji^*} = \mathcal{O}_{ji^*} \cup O_{p^*}$ and $\mathcal{I}^* = \mathcal{I}^* \cup i^*$.

Table OS.1. Replicating Portfolio Frequencies in Restricted Sample

| Observed Package Portfolios | | | | **Empirical Frequencies** | **Test Wave 1:** Drop Cover ID | | **Test Wave 2:** Drop Cover Bid | | **Test Wave 3:** Drop Winner ID | | **Test Wave 4:** Drop Winner Bid | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Mean | p25-p75 | Mean | p25-p75 | Mean | p25-p75 | Mean | p25-p75 |
| 6 | 7 | 13 | 14 | **1** | 1 | [1, 1] | 1 | [1, 1] | 0.153 | [0, 0] | 0.245 | [0, 0] |
| 7 | 15 | – | – | **6** | 5 | [5, 5] | 5 | [5, 5] | 4.841 | [4, 5] | 4.986 | [4, 6] |
| 13 | 15 | – | – | **6** | 5 | [5, 5] | 5 | [5, 5] | 4.926 | [4, 6] | 6.762 | [6, 7] |
| 1 | 9 | – | – | **1** | 1 | [1, 1] | 1 | [1, 1] | 1.000 | [1, 1] | 1.134 | [1, 1] |
| 9 | 15 | – | – | **1** | 1 | [1, 1] | 1 | [1, 1] | 1.516 | [1, 2] | 1.341 | [1, 2] |
| 11 | 15 | – | – | **4** | 2 | [2, 2] | 2 | [2, 2] | 2.020 | [2, 2] | 3.020 | [3, 4] |
| 7 | 8 | 15 | 16 | **1** | 1 | [1, 1] | 1 | [1, 1] | 1.000 | [1, 1] | 0.568 | [0, 1] |
| 5 | 7 | 9 | 11 | **1** | 1 | [1, 1] | 1 | [1, 1] | 0.211 | [0, 0] | 0.223 | [0, 0] |
| 1 | 3 | – | – | **2** | 1 | [1, 1] | 1 | [1, 1] | 0.659 | [0, 1] | 0.556 | [0, 1] |
| 15 | 16 | – | – | **1** | 1 | [1, 1] | 1 | [1, 1] | 1.000 | [1, 1] | 1.000 | [1, 1] |
| 11 | 13 | – | – | **1** | 0 | [0, 0] | 0 | [0, 0] | 0.000 | [0, 0] | 0.305 | [0, 1] |
| 1 | 3 | 7 | – | **1** | 1 | [1, 1] | 1 | [1, 1] | 0.382 | [0, 1] | 0.276 | [0, 1] |

This table presents results from running the bidder-bid matching algorithm on the restricted data set after dropping some known bidder-bid match information. The first four columns contain package IDs that are observed to occur together within bid portfolios in the data. Single bid portfolios are excluded from the table for brevity, while all multi-bid portfolios are depicted. Column 5 presents the estimated empirical frequencies of these multi-bid portfolios using the restricted sample of 193 auctions (where all bidder-bid information is known with certainty). Test waves successively drop nested sets of known bidder-bid information and run the algorithm to determine portfolio frequencies that it predicts. Test Wave 1 drops information on the identity of the cover bidder, Test Wave 2 also drops the identity of the cover bid, Test Wave 3 also drops the identity of the winning bidder, and Test Wave 4 drops all seed information used by the algorithm, including the identity of the winning bid.

(v) If $p^* < P_j$, increment the index $p^*$ by one and return to step 4(b)i; otherwise, continue on to auction $j+1$.

Note that the within-$i$ win probabilities mentioned above are not equilibrium objects, but, given scoring shock variability, represent how often one of $i$'s bids beats out $i$'s own other bids. In our implementation we chose $\psi = 0.05$. In the above recursion, step (1) applies to situations where there is no match ambiguity. Step 3 is default algorithm behavior, but it is computationally expensive when $T_j$ and/or $P_j$ is even moderately large. In our implementation we chose $Q = 6$ and $q = 1$. Step 4 takes a recursive approach that is more tractable for large values of $Q$ and $q$, and is nearly equivalent to assuming a uniform prior over the set of feasible assignments $A_j \setminus A'_j$ in step (3b).[5]

D.3.1. *Probing Robustness of the Uniform Prior Assumption.* If it is inappropriate to uniformly sample from the feasible set, this may introduce mis-specification error into parameter estimates. To evaluate the relevance of this concern, we re-estimate the parameters of the model using an alternative weighting scheme that makes use of information contained in correlations between bidder-auction covariates $\boldsymbol{X}_{ij}$ and the propensity to submit bids on each of the 16 unique packages. The alternative weighting scheme models the probability that a given bidder $i$ in auction $j$ (with characteristics $\boldsymbol{X}_{ij}$) will submit a bid on package $k$ as

$$w_{ijk} \equiv \Pr\left[i \text{ submits bid on package } k \text{ in auction } j|\boldsymbol{X}_{ij}\right] = \Phi(\boldsymbol{X}_{ij}\boldsymbol{B}_k),\ k = 1, \ldots, 16.$$

Once this probability is known for all $(i, j, k)$ triples, we can then make distinctions between feasible bidder-bid match assignments that are more or less likely, relative to the uniform prior baseline. That is, if one bidder-bid assignment involves matches between bid portfolios and bidder covariates that are more likely than another bidder-bid assignment, then the algorithm

[5]Recursivity of step (4) delivers tractability at a cost of having a small chance that some bids (when $p^*$ is very close to $P_j$) may not be compatible with matching to any bidder, given previous assignments.

Table OS.2. Re-Weighting Stage-3 Parameter Estimates for a Non-Uniform Prior of the Feasible Set of Bidder-Bid Matches

| | Discrete Component Valuations $V_{ij}^{s}$ ($\boldsymbol{\beta}^{s}$) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $s$ =**LS** | | $s$ =**PB** | | $s$ =**NC** | | $s$ =**VAI** | |
| Covariates $\boldsymbol{X}_{ij}$ | Baseline | Re-Weighted | Baseline | Re-Weighted | Baseline | Re-Weighted | Baseline | Re-Weighted |
| Same Zip | 0.626918 | 0.300519 | -1.74838 | -2.2442 | -0.91601 | -1.03797 | -2.57679 | -1.52831 |
| Portfolio Distance | -0.30474 | -0.28489 | -0.3334 | -0.31782 | 0.073329 | 0.078931 | 0.0992 | 0.065608 |
| Size | 5.021852 | 4.967419 | -1.59102 | -1.51461 | 1.096244 | 1.13027 | 0.945617 | 0.856891 |
| Tier 1 Ratio | 0.09251 | 0.063564 | -0.05192 | -0.07989 | 0.026138 | 0.019298 | 0.044335 | 0.045474 |
| % Core Deposits | -0.19537 | -0.209 | -0.42372 | -0.4153 | 0.198137 | 0.182469 | 0.060695 | 0.0696 |
| ROA | -0.16312 | -0.17601 | -0.44444 | -0.42612 | 0.039253 | 0.009328 | 0.18473 | 0.168953 |
| %NA Loans | 0.2306 | 0.227503 | -0.0823 | -0.0683 | 0.041929 | 0.056817 | 0.166497 | 0.143793 |
| % included LS/PB | 11.58817 | 11.96085 | 35.25663 | 33.326 | | | | |
| Constant | -39.8093 | -38.1861 | 11.27483 | 11.14299 | -33.8344 | -33.6813 | -26.2224 | -25.8579 |

| **Component Interactions ($\boldsymbol{\lambda}$)** | Baseline | Re-Weighted |
|---|---|---|
| LS X NC | -2.150 | -1.897 |
| PB X NC | 6.104 | 6.0902 |
| NC X VAI | 3.180 | 3.835 |
| LS X PB | -9.987 | -9.941 |
| LS X VAI | 1.960 | 1.921 |
| PB X VAI | 0.369 | 1.318 |

will select the former with higher probability, rather than both being selected with equal probability, as in the default behavior described above. We compute this weighting scheme at the package-bidder level rather than at the portfolio-bidder level, due to dimensionality and sample-size constraints.

We fit this model using an observed vector $\boldsymbol{Y}_{ij} \in \{0,1\}^{16}$ where each element is a binary variable which takes a value of 1 if bidder $i$ in auction $j$ is known to have submitted a bid on package $k$ in auction $j$, and 0 if bidder $i$ in auction $j$ is known to have omitted a bid on package $k$ from its bid portfolio $L_{ij}$. At most, we would have 16 observations per bidder-auction pair, but for the same reasons that prompted use of the name matching algorithm, we have a missing information problem. Therefore, we only use verifiable outcome information from two sources: the known package submitted by the winning and cover bidders (for all auctions, $y_{ijk}=1$ in both cases), and package omissions for all bidders when bids on package $k$ were never submitted in auction $j$ ($y_{ijk}=0$ in such cases). This introduces nonrandom sample selection—for some $(i,j,k)$ we will not be able to determine whether $i$ submitted a bid on package $k$ or not—but an appropriate selection correction is possible by construction of a set of sampling weights as proposed by Nevo (2003): we use moments from the full sample to weight each available observation by the inverse of its selection probability.

Within the available outcome data, for every auction we know the value of $y_{ijk}$ if no bid is submitted on package $k$ in auction $j$, or if $(i,j,k)$ is the winning or cover bid.[6] In order to pin down the respective selection probabilities of these two events, we estimate two auxiliary models prior to the main probit model. For the first auxiliary model, within each package $k$ we specify the probability of it being omitted by all participants in auction $j$ as

$$Pr\left[\text{bids on package } k \text{ are never submitted in auction} j|\boldsymbol{Z}_j\right] = \Phi(\boldsymbol{Z}_j \boldsymbol{B}_k^{aux}).$$

[6]There are some additional cases where the identities can be positively linked, but we do not use them here for difficulty in deriving their selection probabilities. This amounts to a trade-off of power for tractability.

With the relevant outcome variable and auction covariates observed in every auction, this first auxiliary model is identified and estimated via the standard probit method.

For the second auxiliary model, note that in order for a bidder-bid pair to show up in the sample of winners and cover bidders, it must correspond to one of the top two bids from the respective auction. In other words, it must imply a resolution cost (revenue) that is lower (higher) than the third lowest implied cost in auction $j$, which we denote by $C_j(3\!:\!N_j)$. Letting $\boldsymbol{b}_j^*$ denote all observed bids within auction $j$ (un-linked from submitter identities), we can characterize the probability of a given bid $b_{ijk}$ on package $k$ dominating the third order statistic. That is, we can simulate the distribution of the random variable $C_j(3\!:\!N_j)$, which depends on the submitted dollar bids $\boldsymbol{b}_j^*$ and the joint distribution of FDIC scoring shocks $(\boldsymbol{\Gamma}, \delta)$:

$$\kappa_{ijk} \equiv \Pr\left[b_{ijk} + \delta_{ijk} + \boldsymbol{\Gamma}_j \boldsymbol{d}_{k_i} + u_j \geq -C_j(3\!:\!N_j) \middle| \boldsymbol{b}_j^*\right].$$

Although these probabilities are analytically difficult, we can derive values of $\kappa_{ijk}$ for each winning bid and cover bid by using the known values of all package bids and simulating repeatedly from the estimated distribution of the scoring shocks from Stage 1.

These two auxiliary models allow us to express sample weights $\nu_{ijk}$ as inverse selection probabilities for all $(i,j,k)$ where $y_{ijk}$ is observed as:

$$\nu_{ijk} = \begin{cases} \frac{1}{\Phi(Z_j \boldsymbol{B}_k^{aux})\kappa_{ijk}} & \text{if } i \text{ submits winner or cover bid on } k \text{ in auction } j \\ \frac{1}{1-\Phi(Z_j \boldsymbol{B}_k^{aux})} & \text{if package } k \text{ was never submitted in auction } j. \end{cases} \tag{17}$$

This facilitates the following weighted log-likelihood function for the main probit model of package submission probability as a function of bidder and auction covariates:

$$\mathcal{L}_k(\boldsymbol{B}_k) = \sum_i \left\{\nu_{ijk}(y_{ijk}\log(\Phi(\boldsymbol{X}_{ij}\boldsymbol{B}_k)) + (1-y_{ijk})\log(1-\Phi(\boldsymbol{X}_{ij}\boldsymbol{B}_k)))\right\},\ k = 1,\ldots,16.$$

The resulting probit estimates of $\hat{w}_{ijk} = \Phi(\boldsymbol{X}_{ij}\hat{\boldsymbol{B}}_k)$ can be used to augment the bidder-bid assignment algorithm, in order to test for robustness of the uniform prior assumption. For each simulated assignment of bids to bidders we can calculate the implied likelihood of each (within-auction) simulated assignment

$$\Pr\left[\mathcal{A}_{ja} \in A \backslash A'\right] = \prod_{i=1}^{N_j} \prod_{k \in \mathcal{O}_{ji}^a} w_{ijk}. \tag{18}$$

These composite assignment-specific weights characterize the relative likelihood of each draw from the feasible set $A_j \setminus A_j'$. After normalizing so that they sum to one (across all feasible assignments), we get an alternate (potentially non-uniform) weighting of bidder-bid matches. Summary statistics for these weights are presented in Figure OS.1. For the figure we simulated 1,000 independent runs of the name matching algorithm (with uniform sampling in the final step) and we compute the normalized product weights from equation (18). For each auction in the sample, we then store the maximum computed weight across all 1,000 simulations. This maximum provides a strong check on deviations from the uniform prior assumption: if it were perfectly satisfied, then the maximum should be exactly 1/1,000 for all auctions, and if it were dramatically violated, we should see non-trivial mass at large values (i.e., close to 1). Note that the within-auction maximum across the 1,000 simulations of the name matching algorithm represents extreme behavior (i.e., the worst from the perspective of our uniform-prior assumption), rather than average behavior. The figure plots the histogram of the maximum, and it shows that the estimated alternate weighting scheme conforms closely to our uniform prior on the feasible set. In the vast majority of auctions, the worst behavior across the 1,000 runs of the algorithm is tightly packed near 1/1,000, which is strongly consistent with the uniform prior assumption.

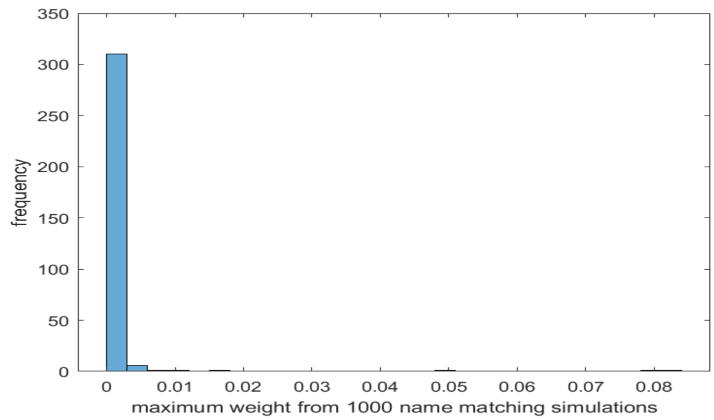



Figure OS.1. Max weight

Max weight across 1000 simulated assignments for each auction in the sample. A uniform prior would imply a weight close to 1/1000 weight on each auction.

Finally we perform a final robustness check to evaluate how differences from the uniform prior might have impacted model parameter estimates. Recall from Section 5.4 that the main estimator integrates across the bidder-bid assignment error by computing point estimates separately for 100 independent runs of the name matching algorithm. This produces 100 sets of point estimates, each conditional on a particular draw from the uniform distribution of feasible assignments, and we compute a simple arithmetic mean of these 100 conditional point estimates (with uniform weighting, see equation (12)) to get unconditional point estimates. With the above probit model, we may consider an alternative specification that replaces the simple arithmetic mean with a weighted average, where the weights account for the probabilities

$$w_r^* \equiv \Pr\left[\mathcal{A}_r = \cup_{j=1}^{J} \mathcal{A}_{jr} \in \boldsymbol{A} \setminus \boldsymbol{A}'\right] = \prod_{j=1}^{J} \prod_{i=1}^{N_j} \prod_{k \in \mathcal{O}_{ji}^r} w_{ijk}.$$

These weights reflect the fact that some of the bidder-bid assignments $\mathcal{A}_r$ will be more (or less) likely to occur than under the uniform prior, once accounting for the available information on correlations between bidder-auction covariates and the propensity to submit a bid on given packages. This implies the following alternative to equation (12) for the common parameters used in counterfactual computation:

$$\hat{\boldsymbol{\beta}} = \frac{\sum_{r=1}^{100} w_r^* \hat{\boldsymbol{\beta}}_r}{\sum_{r=1}^{100} w_r^*}, \quad \hat{\boldsymbol{\lambda}} = \frac{\sum_{r=1}^{100} w_r^* \hat{\boldsymbol{\lambda}}_r}{\sum_{r=1}^{100} w_r^*}. \tag{19}$$

Table OS.2 shows that the baseline and re-weighted estimates are very similar; in fact, taking sampling variability into account, it turns out that for each of the parameters displayed in the table, the re-weighted point estimate falls within the 95% confidence interval of the baseline estimate. This suggests that any mis-specification error introduced by the uniform prior assumption plays a negligible role.

D.4. **Additional Estimator Details: Partial Missing Information on LS and PB.** One challenge we encounter is a missing data problem. Although the LS and PB options are discrete from bidders' perspectives, we want to capture the empirical fact that there is some exogenous variation across auctions in the percentage of assets covered/included for these components.[7] The difficulty is that we only observe the amount of assets included in the PB or covered by the LS agreement when it is part of the winning bid package. As a result, the percentage of assets covered (included) is unobserved when the winner turns LS (PB) off and at least one loser turns that same switch on. We use the observed percentages of assets covered/included under winning bids with LS and/or PB to estimate their distributions, and we correct for missing information, where applicable, by integrating over these distributions.[8] Relative to the ideal dataset where we observe the PB and LS percentages for every auction, this problem leads to lower statistical power but does not introduce bias into our estimates. For simplicity of notation, we abstract from the missing information problem in our main discussion of the estimator. When computing counterfactuals, for cases with missing information on PB/LS, we fix the percentage of assets included at the average percentage from the auctions where it is observed.

D.5. **Additional Estimator Details: Sampling Weights.** In constructing our re-sampling estimator for the win probability function $\widehat{G}(b_{ijk}|\boldsymbol{b}_{ij}, L_{ij}, \boldsymbol{Z}_j)$, we need sampling weights $\omega(j, j', \boldsymbol{Z}_j)$ that reflect how informative the behavior of bidders in auction $j'$ is for the expected behavior of bidders in auction $j$ where $i$ is competing. For each failed bank up for bids in our dataset, we observe nine indicators describing aspects of asset portfolio and financial health. Although it is impossible to formally test for additional selection on other characteristics which are potentially observable to bidders but not to the econometrician, the rich set of observables for each failed bank auction mitigates this concern significantly.

A more salient concern in our case is the curse of dimensionality: conditioning $\widehat{G}$ on a nine-dimensional $\boldsymbol{Z}$ in a fully non-parametric way given our sample size is both computationally and statistically infeasible. To cope with this problem, we compute the sampling weights using a dimension-reduction strategy based on principal components analysis. Specifically, we compute a full set of principal components of the failed bank covariates, denoted $PC_p$, $p = 1, \ldots, 9$. Results are described in Table OS.3. The percentage of total variance explained by the first principal component, $PC_1$, is roughly 30%, while $PC_2$ and $PC_3$ account for 19% and 14%, respectively. $PC_1$ seems to largely represent capitalization and bank performance, while the factor loadings for $PC_2$ and $PC_3$ represent the size and area of portfolio concentration.

We compute sampling weights in the following way. First, using only the first principal component, for each auction $j$ we compute sample weights by centering a standard Gaussian

[7]As discussed in Section 2.2 the FDIC stipulates the nature of the PB option (e.g., excluding commercial loans) so that bidders' only decision is whether or not to bid under the FDIC's offered option. For an LS option, the FDIC typically stipulates the set of assets covered, and an 80% reimbursement on future losses of asset value (relative to book value at time of resolution).

[8]The empirical distribution of the percent of assets included in a PB transaction is indistinguishable from a uniform distribution on $[0, 100]$ under a Kolmogorov-Smirnov test. Therefore, for convenience we model the distribution of PB percentage as uniform, while the distribution of the percent of assets covered by an LS agreement is assumed to follow its empirical distribution.

Table OS.3. Principal component failed bank traits

| | PC1 | PC2 | PC3 | PC4 | PC5 | PC6 | PC7 | PC8 | PC9 |
|---|---|---|---|---|---|---|---|---|---|
| log(Total Assets) | 0.023 | -0.347 | -0.515 | -0.417 | -0.412 | 0.184 | 0.469 | 0.126 | 0.005 |
| %CI | -0.030 | 0.423 | -0.296 | 0.530 | -0.321 | 0.576 | -0.075 | 0.108 | -0.004 |
| %CON | 0.163 | 0.517 | -0.154 | -0.115 | 0.563 | -0.011 | 0.531 | 0.264 | -0.023 |
| %CRE | -0.022 | -0.465 | -0.013 | 0.705 | 0.151 | -0.154 | 0.483 | -0.074 | 0.024 |
| %NPL | -0.214 | -0.397 | -0.246 | -0.076 | 0.609 | 0.512 | -0.304 | 0.064 | 0.001 |
| %OREO | -0.013 | -0.065 | 0.722 | -0.141 | -0.066 | 0.567 | 0.354 | -0.051 | 0.015 |
| ROA | 0.483 | -0.227 | 0.165 | 0.092 | -0.063 | -0.019 | -0.191 | 0.799 | -0.001 |
| Leverage | 0.587 | -0.062 | -0.073 | 0.007 | 0.053 | 0.120 | -0.044 | -0.363 | -0.703 |
| T1 Ratio | 0.589 | -0.022 | -0.090 | -0.012 | 0.068 | 0.113 | -0.054 | -0.347 | 0.710 |
| % of Variance Explained | 29.406 | 18.875 | 14.458 | 10.400 | 8.802 | 7.635 | 6.172 | 3.955 | 0.297 |

The table presents the estimated coefficients from a principal component analysis that serves as a dimension-reduction strategy for our weighted re-sampling estimator of the win probability function $\widehat{G}(b_{ik}|L_i, \boldsymbol{b}_i)$. The variables are *Log Total Assets* which is the log of the asset variable from the SDI data. *%Commercial Real Estate (CRE), %Commercial and Industrial (CI), Consumer* (CON) are the percentage commercial real estate commercial/industrial, and consumer, respectively, of the total loans and leases. *Tier 1 Capital Ratio (Tier 1 Ratio)* is the Tier 1 risk-based capital ratio. *Leverage Ratio* is the core capital ratio. *NPL Ratio* is the sum of assets 90 days past due and the non-accruing assets as a share of the total loans and leases. *OREO Ratio* is other real estate owned divided by total assets. *ROA* is return on assets. Before computing the principal components, all of these variables are then standardized by subtracting their mean value then dividing by their standard deviation.

kernel $\varphi(x; 0, 1)$ over $PC_{1j}$ and choosing bandwidth $h_1^p$ according to Silverman's optimal rule. Sampling weights for all other auctions $j'$ are then computed as

$$\omega(j, j', \boldsymbol{Z}_j) = \omega^1(j, j', \boldsymbol{Z}_j) = \varphi\left(\frac{PC_{1j'} - PC_{1j}}{h_1^p}; 0, 1\right)$$

and then normalized to sum to one. Adopting these as sampling weights for determining the win probabilities that bidders in auction $j$ faced means that the other auctions $j'$ in our dataset are re-sampled at a frequency that is proportional to their similarity (in terms of $PC_1$) to auction $j$. Using sampling weights derived from kernel functions in this way implies our final estimator of the win probability function $\widehat{G}$ is asymptotically equivalent to the *conditional V-statistic* estimator proposed by Hortaçsu and McAdams (2010).

This dimension-reduction strategy based on the first principal component of our set of nine failed bank portfolio indicators leads to a feasible estimator of the win probability function $\widehat{G}$, but a question remains about whether there is additional systematic selection by bidders on failed bank information that is not well-proxied by the first principal component $PC_1$. In order to test for sensitivity to more flexible sample weighting schemes, we also computed normalized kernel function weights relative to the first three principal components.[9] After estimating baseline pseudo-values using only $PC_1$, call them $\widehat{v}_{ijk}^1$, and then re-estimating pseudo-values using the first three principal components in this expanded way, call them $\widehat{v}_{ijk}^3$, we found that our results were very close. The correlation between the two estimates was 0.94 and that regressing $\widehat{v}_{ijk}$ on $\widehat{v}_{ijk}^{PC_3}$ resulted in an $R^2$ of 0.88. Given the similarity of

[9]The resulting sample-weight formula was as follows:

$$\omega^p(j, j', \boldsymbol{Z}_j) = \varphi\left(\frac{PC_{pj'} - PC_{pj}}{h_p^p}; 0, 1\right), \ p = 1, 2, 3; \ \ \omega(j, j', \boldsymbol{Z}_j) = \frac{\omega^1(j, j', \boldsymbol{Z}_j) + \omega^2(j, j', \boldsymbol{Z}_j) + \omega^3(j, j', \boldsymbol{Z}_j)}{\sum_{j' \neq j} \sum_{p=1}^3 \omega^p(j, j', \boldsymbol{Z}_j)}.$$

the results, we opted for the simpler (and computationally less costly) method using only $PC_1$ as our baseline specification.

D.6. **Additional Estimator Details: Stages 2 & 3 Bootstrap Procedure.** Stages 2 and 3 standard errors are estimated via the bootstrap, with re-sampling done 400 times at the auction level. Each bootstrap sample (a list of auction IDs) is applied to various match assignment realizations, which concern only within-auction information. Like the point estimates, each bootstrap estimate is an average across different match assignments. Since 100 estimates per bootstrap sample would be computationally prohibitive, we select a smaller set of 10 representative match assignments (held fixed across all 400 bootstraps). We find this representative set by first ordering each of the 100 independent match assignments $a = 1, \ldots, 100$ from point estimation by the signed $\ell_1$-distance of their conditional estimate vector $[\hat{\boldsymbol{\lambda}}_a, \hat{\boldsymbol{\beta}}_a, \hat{\boldsymbol{\alpha}}_a]$ from the unconditional point estimate $[\hat{\boldsymbol{\lambda}}, \hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\alpha}}] = \sum_{a=1}^{100} [\hat{\boldsymbol{\lambda}}_a, \hat{\boldsymbol{\beta}}_a, \hat{\boldsymbol{\alpha}}_a]/100$. We then select the $5^{\text{th}}$, $15^{\text{th}}$, ..., $85^{\text{th}}$, and $95^{\text{th}}$ percentile match assignments from the ordered list as our representative set. This smaller set of 10 can now serve as a stand-in for the larger set of 100 independent match assignments, thus reducing computation time by a factor of 10.[10]

D.7. **Additional Robustness Checks.**

D.7.1. *Robustness Check: Deterministic Discrete Component Valuations.* In equation (9) we assume that discrete component valuations (and discrete component interactions) are deterministic, conditional on $\boldsymbol{X}_{ij}$, which contains failed bank characteristics $\boldsymbol{Z}_j$, bidding bank characteristics $\boldsymbol{W}_{ij}$, and interactions between the two. A more general model might allow for random, idiosyncratic switch values $v_{ij}^s$ and $\boldsymbol{\lambda}_i$, but as Cantillon and Pesendorfer (2006) point out, this would require that all bidders submit a maximal set of 16 bids in all auctions—which is inconsistent with equilibrium play due to the substitution effect—in order to achieve identification.

A possible implication of this modelling choice is that it might lead to an omitted variable bias problem: unobserved noise in bidders' values of the discrete components like LS are absorbed in the regression error in equation (9), and could be correlated with the baseline valuation $\overline{v}_{ij}$. We construct an informal test for omitted variables in the LS example since it is the most commonly used discrete component. If there is an omitted variable such that the unobserved benefit from loss share is correlated with the regression error in equation (9), these correlations would only influence the estimation of the regression equation through the set of observations where the loss share component is turned on. We can drop all such packages from estimation of stage 3, and estimate baseline values $\overline{v}_{ij}$ for all bidders that place at least one bid on a package without LS.[11] The estimated $\overline{v}_{ij}$'s from the model without loss share are very close to those from the complete model (correlation coefficient=0.913), suggesting that our dimension-reduced model with deterministic switch valuations does not introduce economically important sources of bias.

[10]As a check, we average across the representative set of 10 assignment match point estimates; the result is nearly identical to the point estimates that average across all 100 assignment matches.

[11]More specifically, we estimate an alternate version of the system (9) where all equations and inequalities involving LS are eliminated, and all bids by any bidder which includes LS are dropped. For this exercise, we also retain only those bidders who submit at least one bid on a package not including LS.

D.7.2. *Robustness Check: $\delta_{ijk}$ Independent of Bidder Identity.* As a robustness check on Assumption 4 we ran a test for possible correlation between 3 stability-related bidding bank characteristics

$$\boldsymbol{W}_{ij} = [1,\ tot.\ assets_{ij},\ return\ on\ assets_{ij},\ tier\ 1\ capital\ ratio_{ij}]$$

and the "fitted" shocks $\delta_{ijk}$. The challenge here is that the econometrician does not observe the actual $\delta_{ijk}$ shocks, but we can integrate over their distribution.

Specifically, we start by simulating $(\boldsymbol{\Gamma}_{js}, u_{js}) = (\gamma_{js}^{LS}, \gamma_{js}^{VAI}, \gamma_{js}^{NC}, \gamma_{js}^{PB}, u_{js})$ values, $s = 1, \ldots, 1,000$, for each auction $j$ in the data. Then for each bidder-auction-package-simulation combination we compute $C_{ijks}^{\delta} = -\left(b_{ijk} + \boldsymbol{\Gamma}_{js}\boldsymbol{d}_k + u_{js}\right)$ and fitted shocks $\widehat{\delta}_{ijks} \equiv C_j^* - C_{ijks}^{\delta}$, where $C_j^*$ is the (observed) cost associated with the winning bid in auction $j$. We then regress fitted shocks $\widehat{\delta}$ on $\boldsymbol{W}_{ij}\boldsymbol{\iota}$ via integrated Tobit Maximum Likelihood,

$$(\boldsymbol{\iota}, \widetilde{\sigma}_\delta) = \arg\max \sum_{j=1}^{J} \frac{\sum_{s=1}^{1,000} \log\left[\prod_{i=1}^{N_j} \prod_{k \in L_{ij}} \varphi\left(\widehat{\delta}_{ijks} - \boldsymbol{W}_{ij}\boldsymbol{\iota}; 0, \widetilde{\sigma}_\delta^2\right)^{A_{ijk}} \Phi\left(\widehat{\delta}_{ijks} - \boldsymbol{W}_{ij}\boldsymbol{\iota}; 0, \widetilde{\sigma}_\delta^2\right)^{1-A_{ijk}}\right]}{1,000}$$

where $\boldsymbol{\iota} = [\iota_0, \iota_1, \iota_2, \iota_3]^\top$ is a conformable parameter vector and $\widetilde{\sigma}_\delta$ is an auxiliary parameter for the purpose of the current test only. Finally, we execute a likelihood ratio test of the joint restriction $H_0 : \iota_1 = \iota_2 = \iota_3 = 0$, and find that the data fail to reject the null hypothesis (p-value of 0.996). This suggests that observable characteristics of bidding banks do not enter the scoring equation, and that it is plausible to assume that $\delta_{ijk}$ is distributed independently of bidder identity.

D.8. **Counterfactual Equilibrium Computation.** In two counterfactuals we explore ways for the FDIC to mitigate scoring uncertainty—by announcing scoring rule weights or by only allowing bidders to bid on a P&A contract with the LS switch on and all other switches turned off. In either case, multiple bidding incentives are absent. To compute optimal bids under this scenario, we use Gauss-Seidel iteration, updating bidders' best responses sequentially until each one is best responding to the counterfactual equilibrium win probability function $G$, calculated given the other bidders' strategies. An additional step is required to choose optimal packages (one for each bidder) for the scoring announcement counterfactual. The optimal package for a given bidder can be calculated by comparing a bidder's $v_{ijk}$ to $\boldsymbol{\Gamma}$ as announced by the FDIC, for $k = 1, \ldots, 16$. Intuitively, each bidder will choose its most favored package to win on, subject to the cost in terms of win probability imposed by the scoring rule. More formally, each bidder will elect to bid on package $k_{ij}^* = \arg\max_{k \in \{1,\ldots,16\}} \{v_{ijk} + \boldsymbol{\Gamma}\boldsymbol{d}_k\}$.

Our third counterfactual quantifies the effect (studied by Bullow and Klemperer (1996)) of the presence of one additional bidder (on average) in each auction. The extra bidder counterfactual compares the equilibrium with the distribution of number of opponents in the data to one where this probability mass function is shifted to the right by one. This exercise is meant to provide context to the cost savings numbers for the other two counterfactuals: an additional bidder is known to imply large benefits to the auctioneer in private value auctions. It is not meant as a policy prescription exercise as the other two counterfactuals, given that the FDIC already engages in extensive efforts to encourage participation by healthy banks in its P&A auctions. Computing the equilibrium in this plus-one exercise is challenging, as is equilibrium computation in combinatorial auctions generally, since there are many combinations of packages on which to bid.

To handle this problem, we begin by computing a preliminary set of optimal bids under a scenario where all bidders choose a maximal portfolio of bids, one on every package. By assuming that all bidders submit maximal portfolios of bids, we transform an intractable, high-dimensional, mixed discrete-continuous decision problem to a simpler (though still high-dimensional) continuous decision problem. One technical challenge in this preliminary computation step has to do with a discontinuity in bidders' objective functions. In the model we assume that bids below a choke point cut-off win with zero probability, and therefore are not submitted. In theory, there is a continuous transition of win probability to this cut-off, but in our empirical implementation we use more conservative cutoffs: there we assume that no bidder will choose to submit a bid with a win probability strictly below $\zeta = 0.05$. This more conservative cut-off creates discrete jumps in bidders' profits as they change their bids across the cutoff. To maintain continuity of a bidder's optimization problem, we transform the win probabilities below these cutoffs according the following function:

$$\tilde{G}(b_{ijk}|L_{ij}, \boldsymbol{b}_{ij}) = \begin{cases} 0.05\frac{G(b_{ijk}|L_{ij},\boldsymbol{b}_{ij})^{10}}{0.05^{10}} & \text{if } G(b_{ijk}|L_{ij}, \boldsymbol{b}_{ij}) < 0.05 \\ G(b_{ijk}|L_{ij}, \boldsymbol{b}_{ij}), & \text{otherwise.} \end{cases}$$

Using this transformed win probability function, we apply Gauss-Seidel iteration to update bidders' best responses sequentially (blocks of 8 bidders are performed simultaneously) until each bidders' bid is a best response to the transformed counterfactual equilibrium win probability function $\tilde{G}$.

Once we have this preliminary solution computed, we take additional steps to mitigate the impact of our maximal portfolio assumption and our probability smoothing measure. Using the optimal bids from the first step, we define $L_i$ as the subset of packages for which $G(b_{ik}|L_{ij}, \boldsymbol{b}_{ij}) \geq \zeta$. Finally, we perform a second Gauss-Seidel iteration to allow bidders to re-optimize their bid levels holding fixed their choice of packages $L_i$.

D.8.1. *Probing for Potential Multiple Equilibria: Add-a-Bidder Counterfactual.* For our main counterfactuals—the first where the FDIC announces the mean scoring rule and the second in which the FDIC constrains bidders to a single package choice—there is no multiple equilibria problem as both of these involve scenarios where the complicated scoring-rule auction collapses to a simple 1-dimensional first-price auction.

However in the additional bidder counterfactual we do need to consider the potential for multiple equilibria. We probe for multiplicity by solving for the add-a-bidder equilibrium from multiple different start points. For the baseline solution, we take observed bids as starting values and compute the equilibrium. We then re-compute the equilibrium from six additional restart points. For the first three restart points, we inflate observed bid values by 10%, reduce bid values by 10%, and then we inflate half of all bid values (randomly selected) by 10% and reduce the other half by 10%. For the next three start values we do the same thing, but using an inflation/reduction factor of 20%.

We then compare the results of the multiple restarts to see if the solver seems to be gravitating toward the same solution. Table OS.7 shows that the empirical frequencies of package choices are very similar for all seven solutions, with the possible exception of the "Minus 20%" restart, where several of the least frequently chosen packages have somewhat different empirical frequencies. Some minor differences across the seven equilibrium solutions may be due to relatively inconsequential marginal bids (i.e., those for which bidders are nearly indifferent to their inclusion because of low win probabilities) showing up with different

Table OS.4. Add-a-Bidder CF Package Choice Frequencies: Multiple Restarts

| Packages | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Original | 56 | 15 | 82 | 14 | 19 | 11 | 127 | 19 | 82 | 19 | 170 | 15 | 37 | 13 | 433 | 35 |
| Plus 10% | 68 | 17 | 83 | 18 | 24 | 16 | 130 | 25 | 90 | 24 | 174 | 19 | 42 | 20 | 439 | 42 |
| Mixed 10% | 50 | 15 | 87 | 17 | 20 | 14 | 130 | 22 | 77 | 23 | 169 | 19 | 38 | 15 | 438 | 43 |
| Minus 10% | 64 | 22 | 87 | 23 | 30 | 22 | 136 | 33 | 90 | 30 | 177 | 26 | 47 | 25 | 444 | 48 |
| Plus 20% | 70 | 25 | 89 | 25 | 29 | 24 | 135 | 33 | 96 | 32 | 176 | 27 | 49 | 29 | 439 | 48 |
| Mixed 20% | 39 | 15 | 84 | 17 | 19 | 13 | 130 | 26 | 65 | 23 | 172 | 19 | 39 | 19 | 440 | 38 |
| Minus 20% | 28 | 6 | 87 | 9 | 14 | 7 | 131 | 15 | 49 | 9 | 160 | 9 | 34 | 9 | 443 | 34 |

frequency across the multiple restarts. To probe this issue further, Figure OS.2 presents the empirical CDF of win probabilities for equilibrium bids computed from each of the different starting points. As can be seen from the figure, the seven resulting CDFs of win probabilities are almost indistinguishable. Although we are not aware of a way to definitively prove that the equilibrium is unique, this computation exercise suggests that multiplicity is not a major concern for our add-a-bidder counterfactual.

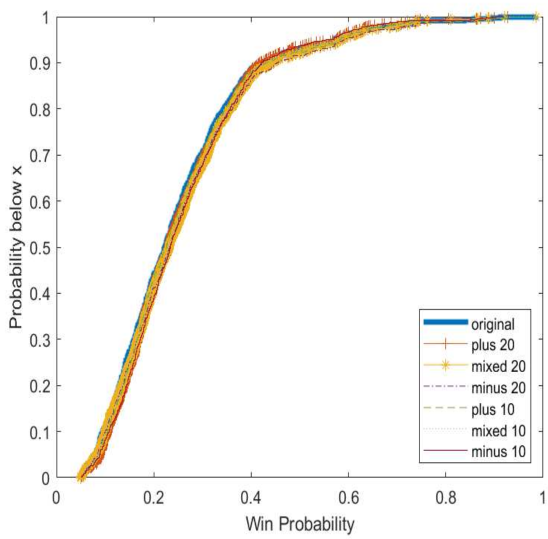



Figure OS.2. Win Probabilities Multiple Restarts

The figure plots the distribution of the win probabilities of each bid submitted in the computed equilibrium.

D.9. **Supplemental Tables and Figures.**

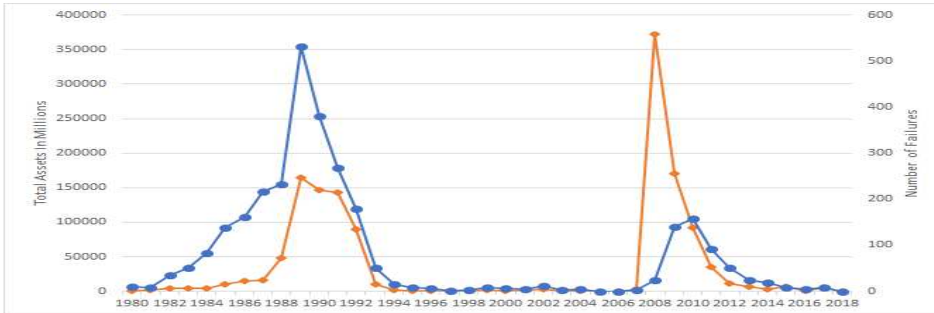



FIGURE OS.3. U.S. bank failures since 1980

This graph plots the number (blue, round) and size (orange, diamond) of U.S. bank failures between 1980 and 2018.

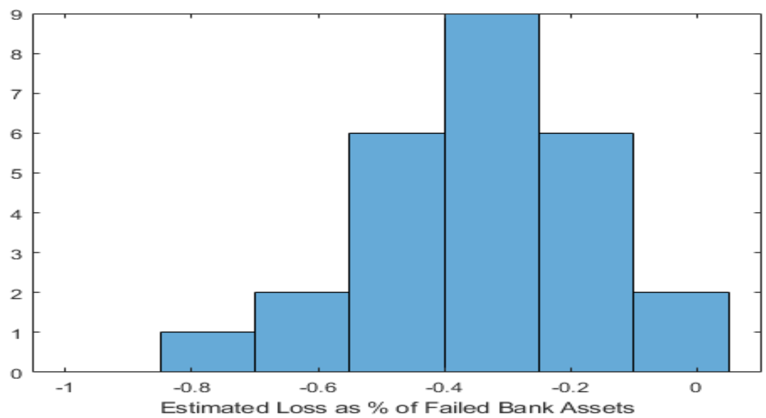


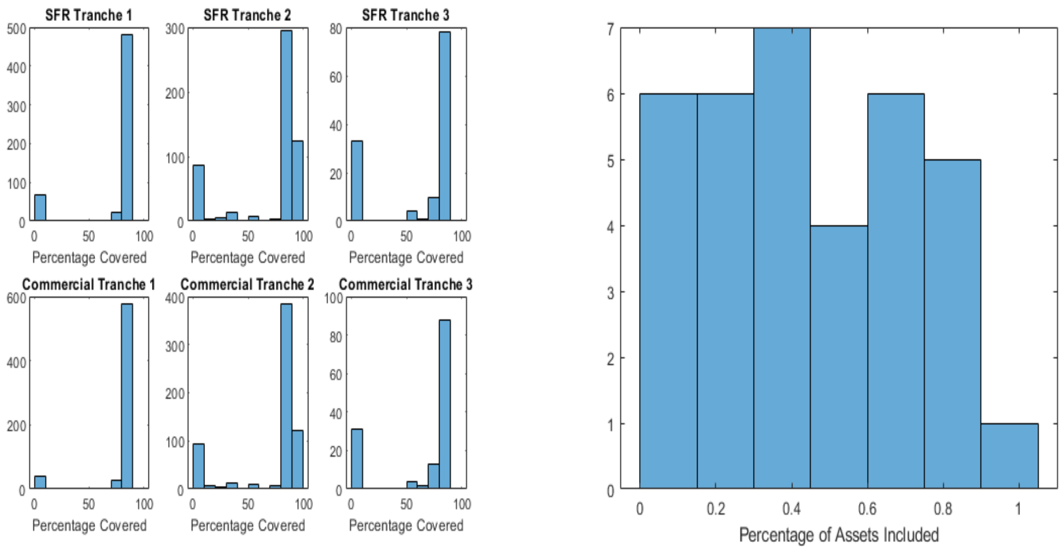

FIGURE OS.4. Loss in deposit payout

Data provided by the FDIC. In all auctions bids are compared to the estimated cost of an insured deposit payout as part of the least-cost test. The direct estimated cost is divided by total assets of the failed bank. The vertical axis is empirical frequencies from a total of 26 resolutions by insured deposit payout.

TABLE OS.5. Number of Bidders and Bids Per Auction

| Panel A | | # Bids | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| # Bidders | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10+ | Total |
| 1 | 104 | 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 113 |
| 2 | 0 | 42 | 13 | 5 | 7 | 1 | 2 | 0 | 0 | 0 | 70 |
| 3 | 0 | 0 | 19 | 16 | 6 | 3 | 4 | 4 | 2 | 4 | 58 |
| 4 | 0 | 0 | 0 | 11 | 10 | 6 | 7 | 2 | 3 | 0 | 38 |
| 5 | 0 | 0 | 0 | 0 | 1 | 4 | 6 | 1 | 2 | 4 | 18 |
| 6 | 0 | 0 | 0 | 0 | 0 | 4 | 1 | 2 | 2 | 4 | 13 |
| 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 2 | 6 | 9 |
| 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 |
| 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 |
| Panel B | | | | | | | | | | | |
| 1 | 103 | 9 | 0 | 0 | 0 | 0 | 0 | | | | 112 |
| 2 | 0 | 42 | 11 | 1 | 3 | 1 | 1 | | | | 59 |
| 3 | 0 | 0 | 18 | 4 | 0 | 0 | 0 | | | | 22 |

We plot the number of bids (horizontal) given a fixed number of bidders (vertical). Panel A is the full sample and Panel B is the restricted sample where we can link all bids with all bidders. Each cell is a count of how many auctions in the data correspond to a given ($\#Bidders, \#Bids$) pair.




(a) loss-share (b) partial bank

FIGURE OS.5. Loss-Share and Partial Bank Acquisitions

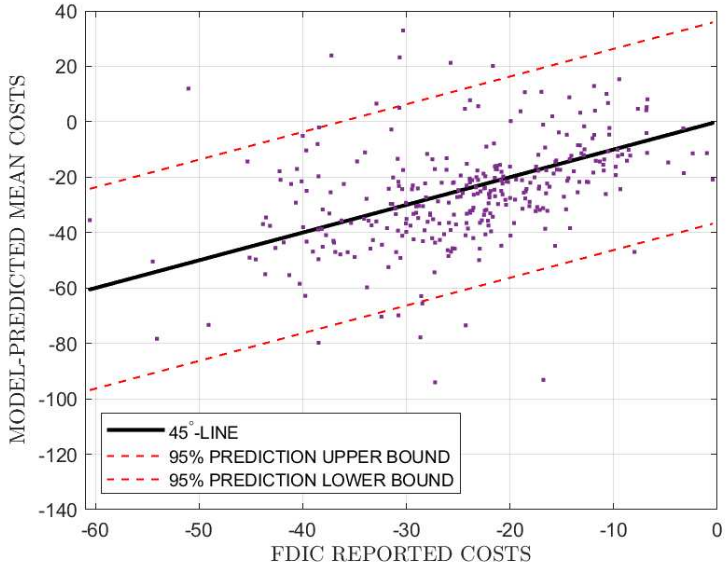
Panel (a) are percentages covered in loss-share agreements for single-family residential mortgages (SFR) and commercial assets during our sample period. The y-axis is the number of bids made, with the percentages on the x-axis. Panel (b) is a histogram of the percentage of a failed bank's assets acquired in partial-bank bids.

TABLE OS.6. Estimated Correlations for Least-Cost Rule Shocks

| COMPONENT | VAI | PB | NC | LS | common |
|---|---|---|---|---|---|
| VAI | 1 | -0.671*** | 0.364 | -0.078 | 0.580*** |
| *std.err.* | | (0.214) | (0.318) | (0.297) | (0.171) |
| PB | | 1 | -0.497* | -0.114 | 0.020 |
| *std.err.* | | | (0.287) | (0.327) | (0.330) |
| NC | | | 1 | -0.547* | 0.025 |
| *std.err.* | | | | (0.303) | (0.369) |
| LS | | | | 1 | -0.276 |
| *std.err.* | | | | | (0.310) |
| common | | | | | 1 |

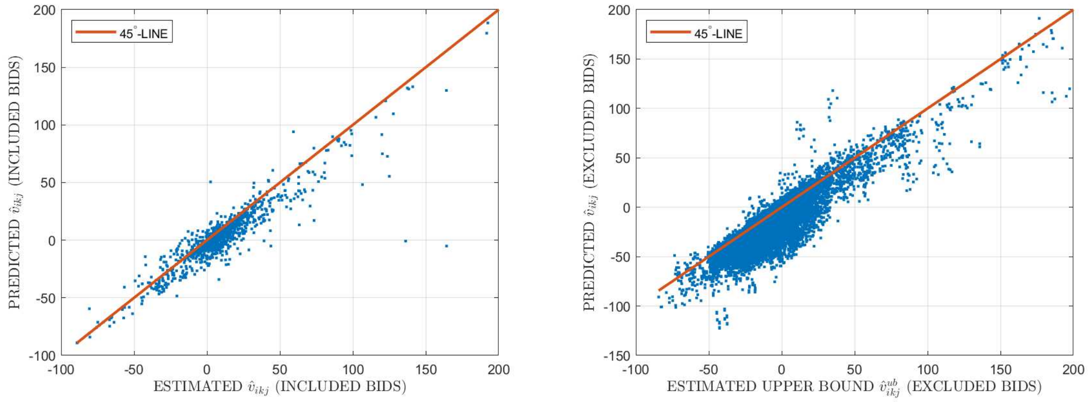
The table reports estimates for correlations $\rho_{s,s'}$, $s, s' \in \{\gamma_j^{LS}, \gamma_j^{VAI}, \gamma_j^{NC}, \gamma_j^{PB}, u_j\}$, where $\gamma_j^{VAI}$ is the scoring rule shock on the VAI switch, $\gamma_j^{PB}$ is the scoring rule shock on the PB switch, $\gamma_j^{NC}$ is the scoring rule shock on the NC switch, $\gamma_j^{LS}$ is the scoring rule shock on the LS switch, and $u_j$ is the auction-specific shock to FDIC costs. Standard errors are reported in parentheses. Statistical significance: $***p<0.01, **\, p<0.05, *p<0.1$.

Figure OS.6. In-sample fit for least-cost estimation




The horizontal axis depicts actual FDIC reported resolution costs (from the winning bid). The value on the vertical axis represents the model-predicted conditional mean resolution cost, given model estimates of the joint distribution of $(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB}, u, \delta)$, and known shock bound information contained in the rankings between the winning bid and all other losing bids. The thick solid line is the 45°-line, and each dot represents one auction. Note that the scatter-plot here would exhibit variation around the 45°-line even in absence of mis-specification error. This is because the residual term $\delta_{ijk} + u_j$ is never observed for the winning bid, and neither is the vector of switch-cost weights, though bounds on the values of $(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB})$ may be derived from the fact that the winning bid produced a cost below the costs tied to all other bids within the same auction. Given the residual prediction error from presence of these six unknown values, one can compute 95% bounds on prediction error, depicted in the plot by thin dashed lines. If the model were devoid of mis-specification error, we would expect to see precisely 5% of scatter-plot points laying outside the prediction bounds. In the figure, the empirical frequency of conditional cost predictions outside the bounds is 5.6%. These two numbers being close provides some assurance that the cost model seems to fit the data fairly well. Moreover, while the figure shows some costs that are significantly overestimated, there is roughly an equal number that are under-estimated, suggesting that the two should balance each other out when computing counterfactual total or mean costs.

Figure OS.7. In-sample fit for valuation estimation




In each of the panels above, the horizontal axis value is the left-hand-side variable in equation (9): this is an equality for package values on included bids in the left-hand panel, and an inequality for bounds on package values on excluded bids in the right-hand panel. The vertical dimension in both panels is the value of the prediction $\overline{v}_{ij} + \boldsymbol{X}_{ij}\boldsymbol{\beta}\boldsymbol{d}_k + \boldsymbol{D}\boldsymbol{\lambda}$. Variation around the 45°-line stems from the error term $\xi_{ijk}$, which accounts for 8.65% of total variation in $\widehat{v}_{ijk}$ for included bids. In the left-hand panel it is expected that the scatter-plot is centered below the 45°-line (since these bidder-package pairs were characterized by valuations below the endogenous cutoff for submitting a non-trivial bid), while some variation above it is possible in finite samples due to $\xi_{ijk}$.

Table OS.7. Targeted Auction Format Probit Results

Outcome Variable: $\mathbf{1}\,[\mathit{Status\ Quo\ Costs} < \mathit{CF\ Costs}]$

| Failed Bank Characteristics | CF: Scoring Announcement Coeff. Est. | SE | CF: LS Only Coeff. Est. | SE | CF: As-is Coeff. Est. | SE | CF: LS-PB Only Coeff. Est. | SE |
|---|---|---|---|---|---|---|---|---|
| Size | -0.224 | 0.732 | -0.032 | 1.164 | -0.496 | 0.684 | -0.274 | 0.669 |
| Tot. Deposits | -0.177 | 0.724 | -0.438 | 1.255 | 0.285 | 0.678 | -0.090 | 0.656 |
| %CRE Loans | 0.043 | 0.096 | 0.160* | 0.092 | -0.027 | 0.102 | 0.190* | 0.099 |
| %C&I Loans | -0.082 | 0.090 | -0.009 | 0.083 | -0.137 | 0.095 | 0.028 | 0.091 |
| %SFR Loans | -0.031 | 0.106 | 0.187* | 0.096 | -0.023 | 0.108 | 0.140 | 0.112 |
| % CNSMR Loans | -0.073 | 0.084 | -0.023 | 0.081 | 0.027 | 0.091 | 0.093 | 0.104 |
| %Core Deposits | -0.378*** | 0.089 | -0.296*** | 0.090 | -0.800*** | 0.107 | 0.022 | 0.093 |
| %NA Loans | -0.106 | 0.110 | -0.446*** | 0.110 | -0.529*** | 0.161 | -0.234** | 0.116 |
| ROA | -0.136 | 0.126 | -0.225* | 0.122 | -0.385* | 0.199 | 0.107 | 0.161 |
| TIER 1 | 0.087 | 0.114 | -0.019 | 0.105 | -0.181 | 0.112 | -0.171 | 0.115 |
| % LS Coverage | 0.040 | 0.072 | 0.008 | 0.080 | 0.116 | 0.072 | 0.044 | 0.089 |
| % PB Assets Incl. | 0.465*** | 0.124 | 0.631*** | 0.136 | 1.200*** | 0.321 | 0.540*** | 0.157 |
| Constant | -0.671*** | 0.079 | 0.020 | 0.075 | -0.423*** | 0.080 | 0.863*** | 0.086 |
| McFadden $R^2_M$ | 0.143 | | 0.179 | | 0.285 | | 0.300 | |

Standardized coefficients are displayed from a Probit model that predicts whether the status quo format with scoring uncertainty will have lower costs than a given counterfactual format—*Scoring Announcement* and *Loss Share Only*, respectively. When coefficient values are positive (negative), an increase in the corresponding covariate makes scoring uncertainty more (less) attractive to the auctioneer. Sample size is $J = 322$ for all regressions. Note that $R^2_M$ values $\geq 0.2$ "represent excellent model fit" (McFadden (1979)), and are typically much lower than traditional $R^2$ values from OLS. Statistical significance: $***p<0.01, **\,p<0.05, *p<0.1$.

## Table OS.8. Cost Comparisons for 10th and 90th Percentile Scoring Rules

| | Resolution Cost Levels: Status Quo Scoring Uncertainty | | | Changes in Resolution Costs | | | |
|---|---|---|---|---|---|---|---|
| | 10th Pctl Scoring Rule | Mean Scoring Rule | 90th Pctl Scoring Rule | Scoring Announcement P10 SR OSFA | Scoring Announcement P90 SR OSFA | LS Only P10 SR OSFA | LS Only P90 SR OSFA |
| Total | -9,437.6 | 27,486 | 64,410 | -27,739 | -20,498 | -2,317 | -14,304 |
| Mean | -29.678 | 86.435 | 202.55 | -87.228 | -64.460 | -7.286 | -44.980 |
| P10 | 37.606 | 185.51 | 457.93 | -27.510 | -144.775 | -0.06 | -99.090 |
| P50 | 1.6223 | 38.478 | 88.153 | -19.478 | -21.526 | 0.73 | -5.130 |
| P90 | -117.16 | 4.308 | 18.453 | -173.099 | -2.090 | 30.578 | 3.278 |

This table depicts the revenue impact of removing uncertainty in the least-cost scoring rule. Column 1 represents baseline bidding under scoring uncertainty, but where the scoring weights are held constant at the (coordinate-wise) 10th percentiles. Columns 2 and 3 are similar, but scoring weights are held fixed at the (coordinate-wise) means (as in Table 6 in the body) and 90th percentiles, respectively. Columns 4 and 5 depict a scoring rule announcement while maintaining bidders' choices of 16 packages to bid on. Columns 6 and 7 limit bidders' package choices to a single P&A package with a loss share provision only. Columns 4–7 represent "one size fits all" counterfactual scenarios where all auctions take the alternate format. Totals and means exclude four large outlier failed banks with total assets over $10Billion each.

## Table OS.9. Counterfactual Package Choice Frequencies

| Package | | | | Percent of Bids | |
|---|---|---|---|---|---|
| Nonconforming | Loss Share | Partial Bank | VAI | DGP | Scoring Announcement |
| No | Yes | No | No | 42.70 | 11.96 |
| No | No | No | No | 15.60 | 56.10 |
| Yes | Yes | No | No | 12.69 | 2.75 |
| No | Yes | Yes | No | 8.51 | 13.88 |
| No | No | Yes | No | 3.86 | 6.70 |
| Yes | No | Yes | No | 2.76 | 0.00 |
| No | Yes | No | Yes | 2.76 | 0.00 |
| Yes | No | No | No | 4.96 | 0.00 |
| Yes | Yes | Yes | No | 3.62 | 3.59 |
| Yes | Yes | No | Yes | 0.95 | 0.00 |
| No | Yes | Yes | Yes | 0.55 | 0.00 |
| Yes | Yes | Yes | Yes | 0.55 | 0.00 |
| Yes | No | No | Yes | 0.24 | 0.00 |
| No | No | No | Yes | 0.16 | 0.00 |
| No | No | Yes | Yes | 0.00 | 5.02 |
| Yes | No | Yes | Yes | 0.00 | 0.00 |

This table lists the observed frequency of each package in the data versus the frequency with which that package is bid on in the counterfactual with a scoring announcement. The packages are ranked by popularity within the DGP.

## Table OS.10. Counterfactual Impact on Winner Characteristics: 10th and 90th Percentile Scoring Rule Announcements

| | Mean | | | Median | | |
|---|---|---|---|---|---|---|
| | 10th Pctl Scoring Rule | Mean Scoring Rule | 90th Pctl Scoring Rule | 10th Pctl Scoring Rule | Mean Scoring Rule | 90th Pctl Scoring Rule |
| Size | 6.476 | 7.913 | 6.661 | 1.430 | 1.430 | 1.633 |
| % CRE | 22.091 | 21.848 | 21.970 | 22.387 | 22.364 | 21.837 |
| % CI | 9.292 | 9.564 | 9.481 | 8.656 | 8.733 | 8.656 |
| Distance | 481.432 | 482.965 | 449.860 | 209.994 | 214.952 | 218.429 |
| Tier 1 Capital | 15.934 | 15.818 | 15.638 | 13.783 | 14.053 | 13.996 |
| %Δ HHI Deposits County | 4.380 | 4.447 | 4.310 | 1.620 | 1.569 | 1.490 |

This table shows the impact of a scoring rule announcement on the characteristics of winners under an announced scoring rule where the shocks $(\gamma^{LS}, \gamma^{VAI}, \gamma^{NC}, \gamma^{PB}, u)$ are at the coordinate-wise 10th percentiles, means, and 90th percentiles. Variable definitions are in Table 2.

Table OS.11. Summary Statistics: Restricted Sample

| Bank Characteristics | Failed Banks | | | | Bidding Banks (avg. over participated auctions) | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | *N* | Mean | StDev | 10-90 Interval | *N* | Mean | StDev | 10-90 Interval |
| Tot. Assets ($Million) | 193 | 576.12 | 1961.18 | $[48.86, 1181.17]$ | 123 | 5973.8 | 1960 | $[158.45, 1340]$ |
| Tot. Deposits ($Million) | 193 | 492.594 | 1576.12 | $[45.77, 919.61]$ | 123 | 4352 | 1360 | $[125.90, 9466]$ |
| Ins. Deposits ($Million) | 193 | 434.65 | 1275.35 | $[44.85, 915.48]$ | 123 | 3015 | 8577 | $[108.12, 7507]$ |
| CRE (%) | 193 | 24.13 | 11.84 | $[10.26, 41.46]$ | 123 | 22.85 | 12.28 | $[7.21, 39.69]$ |
| C&I (%) | 193 | 7.73 | 6.69 | $[1.17, 17.39]$ | 123 | 9.36 | 5.74 | $[3.06, 16.51]$ |
| CNSMR (%) | 193 | 1.65 | 2.30 | $[0.08, 3.92]$ | 123 | 2.33 | 2.65 | $[0.19, 5.81]$ |
| SFR (%) | 193 | 18.55 | 13.27 | $[3.03, 37.49]$ | 123 | 17.34 | 13.08 | $[3.28, 30.86]$ |
| All Real Estate (%) | 193 | 61.00 | 11.52 | $[48.43, 74.24]$ | 123 | 50.30 | 14.43 | $[33.12, 67.84]$ |
| ROA | 193 | -7.48 | 7.67 | $[-12.96, -1.87]$ | 123 | 1.57 | 2.46 | $[-0.06, 3.82]$ |
| Tier 1 Ratio | 193 | 1.08 | 3.39 | $[-1.77, 3.50]$ | 123 | 15.46 | 8.13 | $[10.69, 21.70]$ |
| Core Deposits (%) | 193 | 74.94 | 15.03 | $[53.73, 92.94]$ | – | – | – | – |
| # Auctions participated | — | — | — | — | 343 | 2.40 | 3.43 | $[1, 5]$ |
| **Bidder-Failed Bank Comparisons** | | | | | | | | |
| Portfolio %Diff: CRE | 277 | 9.63 | 8.24 | $[1.45, 21.08]$ | | | | |
| Portfolio %Diff: C&I | 277 | 5.73 | 5.28 | $[0.76, 12.92]$ | | | | |
| Portfolio %Diff: CNSMR | 277 | 2.36 | 3.21 | $[0.13, 5.79]$ | | | | |
| Portfolio %Diff: SFR | 277 | 9.93 | 10.31 | $[1.19, 23.36]$ | | | | |
| All Real Estate | 277 | 15.31 | 11.43 | $[2.21, 31.86]$ | | | | |
| Avg. Pairwise Dist. (km) | 277 | 487.62 | 736.13 | $[26.16, 1417.32]$ | | | | |
| **Auction Characteristics** | | | | | | | | |
| # of Bids | 193 | 1.76 | 1.04 | $[1, 3.00]$ | | | | |
| Cost to FDIC ($Million) | 193 | 137 | 347.55 | $[10.96, 329.0]$ | | | | |
| Bid Discount | 340 | -0.13 | 0.30 | $[-0.53, 0.15]$ | | | | |
| %Δ in County HHI for Deposits | 141 | 5.95 | 4.14 | $[1.16, 10.33]$ | | | | |

This table displays descriptive statistics for the restricted sample of failed bank auctions for which all bids can be positively matched to their respective bidder identities. Balance-sheet information for failed banks and bidders comes from the SDI for the quarter pre-failure. Variables *CRE* (commercial real estate), *C&I* (commercial and industrial), *CNSMR* (consumer), *SFR* (single-family residential), and *All Real Estate* represent shares of lending in each sector. *Core Deposits*: bank deposits comprise core deposits—checking/savings accounts, consumer CDs—and brokered deposits, made to a bank by a third-party broker to increase its liquidity. Core deposits are more stable than brokered deposits because the latter are much more sensitive to interest rate fluctuations. *ROA* is return on assets and measures profitability. *Tier 1 Ratio*, is a measure of financial health. *Portfolio %Differences* are the absolute value change in portfolio shares for the failed bank and bidder bank in each bidder-failed bank pair. *Average Pairwise Distance* is calculated using the average distance over all branch combinations of the failed and bidding bank. *Bid Discount* is the transfer amount calculated using equation (1) divided by the total assets of the failed bank.

### D.10. **Data and Inference on the Restricted Sample.**

## Appendix E. Data Description

As of June 2010, consumer loans were no longer covered in loss-sharing agreements, and bidders were asked to choose a coverage percentage of up to 80% on single-family residential (SFR) and commercial loans. Finally, in September 2010 a three-tier structure for SFR and/or commercial loans was adopted, where bidders chose coverage levels separately for each tier. Figure OS.8 provides an example of the FDIC failed-bank list.

## TABLE OS.12. Value Shifter Estimates: Restricted Sample

| | Discrete Component Valuations $\beta$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **LS** | | **PB** | | **NC** | | **VAI** | |
| | Coeff. Est. | SE | Coeff. Est. | SE | Coeff. Est. | SE | Coeff. Est. | SE |
| Same Zip | -6.489*** | 0.723 | -0.883 | 0.892 | -1.379 | 0.748 | -10.690*** | 2.557 |
| Portfolio | -0.449*** | 0.0798 | -0.194* | 0.106 | 0.097 | 0.085 | 0.286 | 0.298 |
| Size | 8.353*** | 0.391 | 0.509 | 0.333 | 1.024*** | 0.299 | 1.196** | 0.702 |
| Tier 1 | 0.376*** | 0.054 | -0.151*** | 0.036 | 0.033 | 0.021 | 0.015 | 0.043 |
| %Core | -0.034 | 0.028 | -0.177*** | 0.031 | 0.062** | 0.030 | 0.153*** | 0.065 |
| ROA | -0.106*** | 0.030 | -0.178* | 0.059 | 0.300*** | 0.051 | 0.309 | 0.214 |
| %NA | -0.146** | 0.056 | 0.132 | 0.088 | -0.009 | 0.046 | 0.392** | 0.168 |
| Constant | -173.272*** | 7.890 | -27.1099*** | 5.437 | -23.583*** | 4.499 | -64.663*** | 5.987 |
| Average | 28.342 | — | -23.450 | — | -7.830 | — | -36.776 | — |

| **Component Interactions $\lambda$** | | | **Baseline Valuations $\alpha$** | | |
|---|---|---|---|---|---|
| LS×PB | -9.657*** | 0.640 | Same Zip | 7.615 | 6.499 |
| LS×NC | -0.439 | 0.575 | Portfolio | 0.573 | 0.902 |
| LS×VAI | 24.706*** | 5.455 | Size | 1.293 | 2.679 |
| PB×NC | 7.909*** | 0.782 | Tier 1 | -0.036 | 0.236 |
| PB×VAI | 4.772 | 2.987 | %Core | -1.460*** | 0.204 |
| NC×VAI | 3.087** | 1.326 | ROA | 0.407 | 0.419 |
| | | | %NA | -0.540 | 0.474 |
| | | | Distance | -0.843* | 0.409 |
| | | | %ΔCRE | -0.195 | 0.449 |
| | | | ΔHHI | -29.532 | 56.300 |
| | | | Constant | 96.707** | 41.213 |

Balance-sheet information comes from the SDI for the quarter pre-failure. Variables *CRE* (commercial real estate), *C&I* (commercial and industrial), *CNSMR* (consumer), *SFR* (single-family residential), and *All Real Estate* represent shares of lending in each sector. *Core Deposits*: bank deposits comprise core deposits—checking/savings accounts, consumer CDs—and brokered deposits, made to a bank by a third-party broker to increase its liquidity. Core deposits are more stable than brokered deposits because the latter are much more sensitive to interest rate fluctuations. *ROA* is return on assets and measures profitability. *Tier 1 Ratio*—equity capital and cash reserves divided by risk-weighted assets—is a standardized measure of solvency that rises as the financial health of a bank becomes more secure. *Book Value Equity* is the difference between the total assets and the total liabilities as a percentage of failed-bank assets. *Non-Accruing Loans* are 90+ days past due as of the auction date. *Pairwise Failure Dist.* is calculated using the average distance over all branch combinations between each pair of failed banks. *Portfolio %Differences* are the absolute value change in portfolio shares for the failed bank and bidder bank in each bidder-failed bank pair. *Average Pairwise Distance* is calculated using the average distance over all branch combinations of the failed and bidding bank. For comparability across auctions, *Net Transfer Bid* is expressed as the transfer amount (from the FDIC to the bidder when negative, vice versa when positive) calculated using equation (1), divided by the total assets of the failed bank.

† LS switch valuation estimates control for % of Loss-Share coverage. Coeff. estimate (std. err.): 120.4611 (4.567).

‡ PB switch valuation estimates control for % of Partial Bank Assets included. Coeff. estimate (std. err.): 27.758 (4.192).

## Table OS.13. Bidding Incentive Decompositions: Restricted Sample

| | DGP | Change: No Competition Effect | Change: No Substitution: Singleton Included Bids | No Substitution: Singleton Omitted Bids (SOBs) | Change*: No $\delta$; (Noise Effect) High Bidders |
|---|---|---|---|---|---|
| Avg. Discount Bid | -12.348 | -7.870 | 4.336 | -32.691 | -3.657 |
| Avg. Cond. Surplus | 26.221 | 7.870 | -4.336 | 32.142 | — |
| % SOBs w/Trade Feasible | — | — | — | 58.75 | — |
| % SOBs Dominating Avg. Discount Bid, DGP | — | — | — | 20.59 | — |

This table explores removal of incentive channels on bidding. Column 1 lists mean discount value and conditional surplus $(v_{ik} - b_{ik})$ under the DGP, in percentage units of the book value of the failed bank's assets. Columns 2 and 3 display the changes in these numbers, relative to bids submitted under the DGP, after removing the *competition effect* and *substitution effect*, respectively. Column 4 displays the percentage of omitted bids on packages where bilateral trade with the FDIC was possible, as well as averages of bids and conditional surplus for omitted packages under the DGP, in absence of the *substitution effect*. Finally, Column 5 depicts a partial decomposition of the *noise effect*.
*Reported changes in column 5 are for bids above the $75^{\text{th}}$ percentile in absence of scoring uncertainty and the bidder-specific shock $\delta$, relative to a no-scoring-uncertainty counterfactual that includes the bidder-specific shock $\delta$.

## Table OS.14. Counterfactual Cost Comparisons: Restricted Sample

| | Resolution Cost Levels | | Changes in Resolution Costs | | |
|---|---|---|---|---|---|
| | Actual | Bids at Mean Scoring Rule | Scoring Announcement OSFA | LS Only OSFA | One Extra Bidder |
| Total | 23,812 | 19,766 | -5,909 | -3,074 | -18,476 |
| | | | (-6,848) | (-5,957) | |
| Mean | 124.020 | 102.948 | -30.774 | -16.011 | -96.232 |
| P10 | 315.860 | 188.203 | -7.005 | 8.632 | -25.047 |
| P50 | 47.500 | 42.242 | -4.150 | 0.915 | -11.482 |
| P90 | 10.940 | 6.032 | 1.897 | 3.200 | -10.091 |
| Predicted Frequency Where Status Quo Uncertainty is Better: | | | 0.453 | 0.729 | — |
| Mean Bidder Switch Value: | | | 14.884 | 28.342 | — |
| Mean FDIC Switch Value: | | | -2.289 | -22.336 | — |

This table depicts the revenue impact of removing uncertainty in the least-cost scoring rule. Column 1 is data, while column 2 maintains scoring uncertainty but provides an estimate of FDIC resolution costs implied by the mean scoring rule. Column 3 and 5 depict the impact of removing uncertainty by announcing the scoring rule weights prior to bidding. Columns 4 and 6 remove uncertainty by limiting bidders' package choices to a single P&A package with a loss share provision only. The *OSFA* columns represent a counterfactual "one size fits all" scenario where all auctions take the alternate format. The *Targeted* columns represent a counterfactual scenario where alternate auction formats are imposed on a subset of auctions, according to the predictive model in Table OS.15. Totals and means exclude one large outlier failed bank with total assets over $10Billion.

## Table OS.15. Targeted Auction Format Probit Results: Restricted Sample

| Outcome Variable: **1** [*Status Quo Costs* < *CF Costs*] | | | | |
|---|---|---|---|---|
| | CF: Scoring Announcement | | CF: LS Only | |
| Failed Bank Characteristics | Coeff. Est. | SE | Coeff. Est. | SE |
| Size | -2.01 | 1.397 | -0.659 | 1.389 |
| Tot. Deposits | 1.761 | 1.217 | 0.351 | 1.399 |
| %CRE Loans | 0.182 | 0.131 | 0.147 | 0.128 |
| %C&I Loans | 0.035 | 0.121 | 0.182 | 0.123 |
| %SFR Loans | 0.025 | 0.146 | 0.152 | 0.121 |
| % CNSMR Loans | -0.061 | 0.115 | 0.008 | 0.147 |
| %Core Deposits | -0.413*** | 0.132 | -0.270** | 0.101 |
| %NA Loans | -0.603*** | 0.172 | -0.476*** | 0.110 |
| ROA | 0.036 | 0.260 | -0.101 | 0.266 |
| TIER 1 | -0.084 | 0.155 | -0.016 | 0.140 |
| % LS Coverage | -0.203* | 0.117 | -0.308*** | 0.140 |
| % PB Assets Incl. | 0.907*** | 0.254 | 0.904*** | 0.140 |
| Constant | -0.179* | 0.102 | 0.353*** | 0.112 |
| McFadden $R_M^2$ | 0.244 | | 0.280 | |

This table presents coefficients from a Probit model that predicts whether the status quo auction mechanism with scoring uncertainty will have lower costs than a given counterfactual auction format—*Scoring Announcement* and *Loss Share Only*, respectively. When coefficient values are positive (negative), an increase in the corresponding covariate will make scoring uncertainty more (less) attractive to the auctioneer. Sample size is $J=193$ in all regressions. Note that $R_M^2$ values $\geq 0.2$ "represent excellent model fit" (McFadden (1979)), and are typically much lower than traditional $R^2$ values from OLS. Statistical significance: $***p<0.01, **\,p<0.05, *p<0.1$.

| 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 |

FIGURE OS.8. Example of the FDIC failed-bank list

This is an example of what the FDIC provides in terms of failing banks. There is the failing bank and the acquirer. In addition, the date of closing, location information, and the last time information on the acquisition was updated is provided. Information is updated, for example, as the FDIC collects and pays out dividends stemming from the sale of assets. Source: FDIC

**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

**Notes:**

- The winning bidder's acquisition of all the deposits was the least costly resolution compared to a liquidation alternative. The liquidation alternative was valued using valuation models to estimate the market value of the assets. Bids for loss share, if any, were valued using a discounted cash flow analysis for the loss share portfolio over the life of the loss share agreement. If any bids were received that would have been more costly than liquidation they have been excluded from this summary.
- The cover bid is the least costly bid after excluding all bids submitted by the winning bidder.
- The Other Bidder Names and the Other Bids are in random order. There is no linkage between bidder names and bids, except in the case of the winning bid and the cover bid.
- For more information on the bid disclosure policy, see www.fdic.gov/about/freedom/biddocs.html.

Figure OS.9. Example of an FDIC failed-bank bid summary

This is an example of Enterprise Bank & Trusts acquisition of Legacy Bank (AZ). The closing date was January 7, 2011. The list of bidders includes Enterprise Bank & Trust, Commerce Bank of Arizona, SouthWest Bank, and Wedbush Bank. There were 6 bids in total from these 4 bidders. Source: FDIC.