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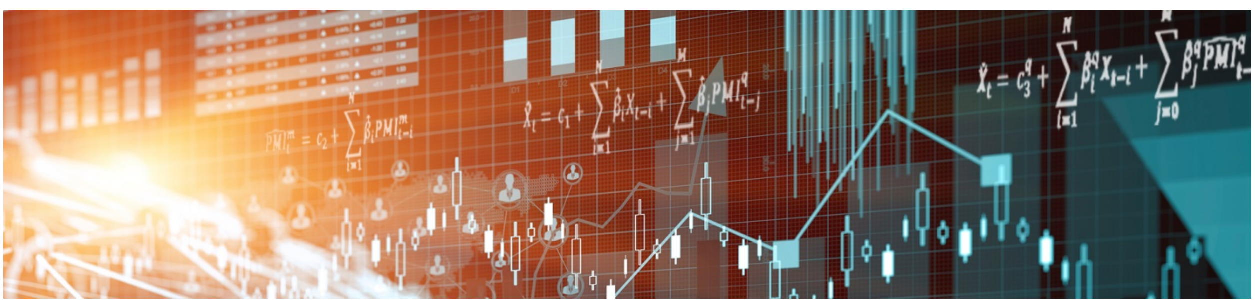
Resolving Failed Banks: Uncertainty, Multiple Bidding & Auction Design



by Jason Allen, Robert Clark, Brent Hickman and Eric Richert

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Resolving Failed Banks: Uncertainty, Multiple Bidding & Auction Design

by

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Abstract

The Federal Deposit Insurance Corporation (FDIC) resolves insolvent banks using an auction process in which bidding is multidimensional and the rule used to evaluate bids along the different dimensions is proprietary. Uncertainty about the scoring rule leads banks to simultaneously submit multiple differentiated bids. This resolution mechanism typically results in considerable losses for the FDIC—$90 billion during the financial crisis. The objective of this paper is to see whether the mechanism could be improved. To do so, we propose a methodology for analyzing auction environments where bids are ranked according to multiple attributes chosen by bidders, but where there is uncertainty about the scoring rule used to evaluate the different components of the bids. Using this framework, which extends structural estimation techniques for combinatorial auctions, and FDIC data summarizing bids, we back out the underlying preferences of banks for failed institutions. With these we perform counterfactuals in which we eliminate uncertainty and/or multiple bidding. Our findings suggest that the FDIC could reduce the cost of resolution by around 17 percent by announcing the scoring rule before bidding begins.

Bank topics: Financial institutions; Econometric and statistical methods
JEL codes: C57, D44, G21

1 Introduction

In response to the global financial crisis, regulators have taken steps to increase financial stability by minimizing the risks associated with *too-big-to-fail* and by developing more effective resolution processes in cases of bank failure. In the U.S., bank resolution is the purview of the Federal Deposit Insurance Corporation (FDIC). The most common resolution method is a Purchase & Assumption transaction, in which the FDIC auctions off failing institutions to healthy banks. These auctions typically result in a cash transfer from the FDIC to the acquiring institution. During the financial crisis the number and size of failures were so elevated that the FDIC's Deposit Insurance Fund lost nearly $90 billion (Davison and Carreon (2010)). Faced with losses, the FDIC must (i) increase insurance premiums to healthy banks, (ii) levy special assessments, or (iii) borrow from the U.S. Treasury. These actions can introduce distortions into the banking system and the broader economy and are particularly problematic in the middle of a banking crisis.[1] Furthermore, the auction outcomes might have implications for local market structure and for market power for banking services, since a failing bank's market share is effectively transferred to the auction winner.

This paper examines the incentives induced by the FDIC's current resolution mechanism in order to determine (i) the mechanism's role in explaining losses, (ii) whether it could be improved, and (iii) its impact on local market structure. The current resolution process has the following key features. First, the FDIC permits bidding to be multidimensional. Healthy banks are encouraged to submit bids consisting of a continuous dollar value for the assets and liabilities of the failed bank, and four discrete components of the acquisition agreement. For example, a bank can specify that its bid includes a loss-sharing provision whereby the FDIC shares in future losses (all components are described in detail in Section 2). The resulting setting is a scoring auction where the FDIC makes trade-offs between the dollar component and the discrete components of each bid.

The second feature is uncertainty about how the FDIC evaluates multidimensional bids, that is, uncertainty over the scoring rule in each auction. Since the passage of the FDIC Improvement Act in 1991, the FDIC is required to select the least-cost bid (subject to a systemic risk exemption), so long as it is superior to their estimated cost of liquidation. Importantly, however, the algorithm used to select the lowest-cost bidder is proprietary. This results in cross-auction variation in the scoring rule. Therefore, from a bidder's perspective there is uncertainty regarding how the FDIC evaluates the different bid components.[2]

[1] There is an extensive literature on the bank lending channel and the impact of bank failures on local markets. See, for example, Bernanke (1983) and Ashcraft (2005).

[2] Conversations with regulators and with banking industry insiders confirmed that there is indeed uncertainty over the FDIC's scoring rule from the perspective of acquiring banks.

Finally, uncertainty over how the FDIC scores bids gives banks an incentive to submit multiple bids for the same failing institution. Since they do not know the relative weights the FDIC places on the different components of each bid, banks can submit multiple bids to protect against different eventualities. Importantly, bidding is sealed and simultaneous, so multiple bidding occurs in these auctions because of uncertainty about the scoring rule and not as a reaction to changes in information availability.

We are interested in quantifying the impact of uncertainty about the least-cost rule on auction outcomes. Uncertainty about how bids are scored influences bidding behavior, including whether prospective buyers engage in multiple bidding. Uncertainty introduces noise into the auction process such that the probability of winning a given auction depends, to some extent, on randomness. The implications of this fact may be heterogeneous across bidders. For instance, from the perspective of high-valuation bidders, the auction might seem more competitive than it otherwise would, since randomness could favor the component(s) chosen by lower-valuation bidders. We call this the *noise effect*, and it will generally lead to less bid shading (i.e., more aggressive bidding) among high-valuation bidders and more bid shading among low-valuation bidders. For its part, multiple bidding generates two conflicting incentives. First, the increased number of bids stemming from multiple bidding could make an auction appear more competitive—since each bidder now best responds to a larger number of outside bids—leading to a reduction in bid shading. We label this the *competition effect*. Alternatively, multiple bidding can lead to increased bid shading if bidders internalize the effect of each of their bids on their other own bids, since only one bid can be the winner. We refer to this as the *substitution effect*. One of our empirical objectives is to quantify these different effects on bidder behavior.

To do so, we develop a methodology for analyzing auction environments where the auctioneer ranks bids according to multiple attributes chosen by bidders, but where there is uncertainty about the weight placed on the different components of the bid. This setting extends the environments considered in Takahashi (2018) and Krasnokutskaya et al. (2018). Like us, Krasnokutskaya et al. (2018) allow for uncertainty about the scoring rule; however, in their setting the non-price components of the bid are set exogenously. In our context, bidders make choices over all components of the bid without knowing how the FDIC weights each one. In Takahashi (2018), bidders choose price and quality, but there is uncertainty over how the latter will be evaluated. Weights on price and quality are known, but each bidder receives an individual-specific shock to quality. This is in contrast to our setting, where, due to regulation, there is no concern that components will be evaluated differently across bidders, but weights across components are unknown to all bidders. Moreover, in both Krasnokutskaya et al. (2018) and Takahashi (2018), bidders are only allowed to bid once, while in many environments featuring uncertainty bidders are allowed to make multiple submissions.[3]

[3] Greve (2011) models a multidimensional auction where agents compete in price and quality and

We develop a structural model of bidding to recover healthy banks' underlying valuations for failing banks and each of the different components of the acquisition agreement. Since bidding is multidimensional, we cannot apply standard techniques for recovering valuations. Instead, we note that the decision to bid on each of the components is discrete and that the sum of decisions across components plus the continuous dollar portion of the bid can together be thought of as a "package." With this perspective, we draw on the combinatorial auctions literature and employ a similar modeling approach to Cantillon and Pesendorfer (2006b), who extend the first-order-condition method developed by Guerre et al. (2000) (henceforth GPV) to the case of package auctions. In Cantillon and Pesendorfer (2006b) bus routes are auctioned off and bidders can place bids for single routes or combinations thereof (i.e., packages). They show that one can estimate bidder valuations in this environment by using the first-order condition(s) for optimally chosen bids. Rather than bids being characterized by a single first-order condition, there is a set of first-order conditions, one for each possible package. These hold with equality for packages that are bid on, and are inequalities otherwise. Our setting is similar except that there can be only one winner of each auction and bidders are uncertain about the scoring rule.

In our setup, healthy banks can make one or more bids for a failing bank. Heterogeneous bidders each have a (one-dimensional) private signal about the value of taking over the failing bank on an *as-is* basis. Conditional on their private bank valuation, a bidder receives a private signal from a known distribution for the value of turning on each of the four components. Given this combined information, bidders derive a valuation for each possible package and then decide optimally on which bundle of packages to bid. As in GPV, we use a bidder's first-order conditions to link observed bids with the unobserved private values for each package; in order to do so, we need an estimate of the win probability. This is complicated in our setting for three reasons. The first is the uncertainty over the scoring rule. The second is that bidders submit multiple bids and know the other bids that they themselves submit. Finally, bidders are uncertain about the set of competitors. To overcome the first of these complications, we estimate the scoring rule. To address the second two, we adapt the techniques of Hortaçsu and McAdams (2010) for resampling from bids made in similar auctions. Using the estimated scoring rule, we can rank resampled bids to determine the probability of winning with a given bid.

Using this approach and publicly available data from the FDIC summarizing bidding behavior, we estimate private valuations for failing institutions. With these in hand,

the weights placed by the auctioneer on quality are unknown. The result is an excessive amount of quality. There is also a large literature on multidimensional scoring auctions, but this literature assumes no uncertainty over the scoring rule. See, for example, Che (1993), Branco (1997), Asker and Cantillon (2008), Asker and Cantillon (2010), Athey and Levin (2001), Bajari et al. (2014), and Bajari and Lewis (2011).

we can compute bidders' optimal strategies under alternative scoring rules and conduct counterfactuals to estimate the impact of scoring-rule uncertainty on auction outcomes. We estimate the FDIC's reduction in losses under the counterfactual scenario that it announces its particular least-cost scoring rule before bidding begins (thereby removing uncertainty). We are further able to isolate the *substitution* effect of multiple bidding. For this we construct a counterfactual in which multiple bidding is forbidden, but where the number of bids is kept constant (i.e., we suppose each bid is associated with a separate bidder). The sets of acquirers that win the failing banks under these alternative scoring rules can also be compared. This allows us to understand how uncertainty can act as a subsidy towards certain types of acquirers based on their size, portfolio, or locations.

In the auctions that we consider the FDIC reports losses of over $20 billion. Eliminating uncertainty about the scoring-rule (we set the weights in the rule equal to their means) decreases the loss suffered by the FDIC by about 17%. Eliminating multiple bidding but keeping the number of bidders constant allows us to quantify the substitution effect, which turns out to represent about 50% of the total change.

Although on average uncertainty is bad from the FDIC's perspective, we find that for low-cost failures the noise effect can actually dominate the substitution effect, with high-valuation bidders engaging in less bid shading to protect against bad shocks. This is not the case for high-cost failures. The value to the FDIC of maintaining uncertainty on the scoring rule therefore depends on the characteristics of the failed bank.

We also compare the set of winners under the current regime to the set that arises under regimes without uncertainty or multiple bidding. Given the amount of heterogeneity in preferences across packages, ex ante there might be concern that the current rule favors certain banks and results in less competition than would a more transparent rule. However, we find that removing uncertainty leads to only small changes in the traits of auction winners and therefore in market structure. The main reason for this is that uncertainty impacts the amount of bid shading, but not the identity of the winners. Having a transparent rule would lower FDIC costs by decreasing bid shading by high-valuation bidders, but not by altering the distribution of winners.

In addition to the literature on multidimensional auctions mentioned above, our study is also related to an extensive literature on bank failures, mostly focused on the Savings and Loan (S&L) crisis and the wave of bank failures of the 1980s and early 1990s (see for instance James and Wier (1987), James (1991), and Cochran et al. (1995), to list only a few), but increasingly centered on the more recent set of failures following the global financial crisis (see for instance Granja (2013), Igan et al. (2017), Granja et al. (2017), Kang et al. (2015), and Vij (2018)). None of these papers explicitly model the auction process to determine whether it could be improved.

2 Institutional details

Most years feature few, if any, bank failures. However, in periods of crisis the number of bank failures can become elevated. During the S&L crisis of the 1980s, nearly 1,300 financial institutions failed. Our focus is on the most recent crisis, during which 510 banks failed between 2007 and 2014. The combined assets of failed banks during the crisis were over $700 billion, and FDIC losses totalled nearly $90 billion.

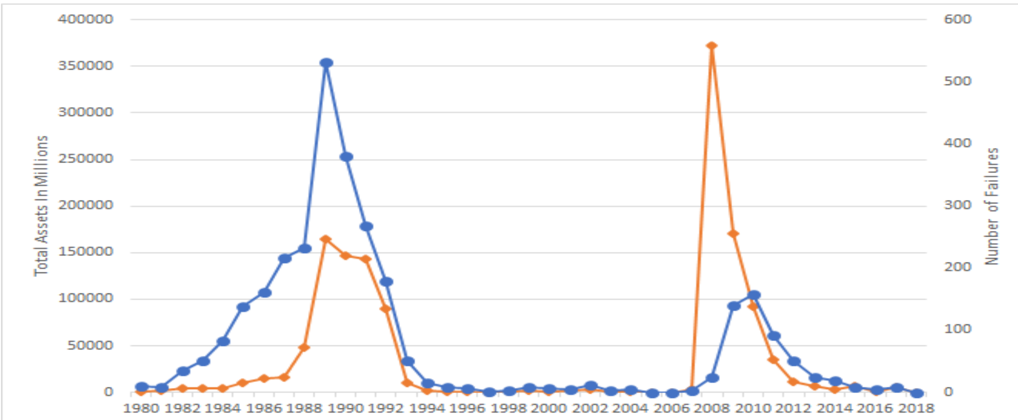


Figure 1: U.S. bank failures since 1991

This graph plots the number (blue, round) and size (orange, diamond) of U.S. bank failures between 1991 and 2018.

The current rules governing the resolution of failing banks were established in 1991 with the Federal Deposit Insurance Corporation Improvement Act (FDICIA). The enactment followed the S&L crisis and the subsequent undercapitalization of the FDIC. Prior to 1991, the FDIC was able to employ discretion when reviving/selling/liquidating failing banks. Today, the resolution process is more transparent and the FDIC is required to resolve troubled institutions at the *lowest cost possible*.[4]

Details on the resolution process can be found in FDIC (2014). In summary, a troubled bank's regulator first informs the FDIC of pending failure. The FDIC then determines the bank-liquidation value, generates a list of potential buyers who will be invited to evaluate the failing institution, and decides on the set of assets that will be included when each of the discrete components is activated. 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. The resulting list usually numbers in the hundreds. From this list, typically over half will *look* at what is being offered. Finally,

[4]Guidelines are provided in the rules of the FDICIA, outlined in OCC (2001). Troubled banks are those that are critically undercapitalized or have assets less than obligations. See Shibut (2017).

a small subset (almost always fewer than 10) will conduct due diligence either in person or through the FDIC's virtual data room (VDR).[5] Subject to confidentiality agreements, the documents available in the VDR provide detailed financial and legal information regarding the target institution's loans, deposits, general ledger, and operations. Potential bidders are provided an opportunity to do their own due diligence as well as to view research conducted by the FDIC. The VDR also provides auction-specific information about the packages. Participants do not observe who has been invited to the VDR.

Valuation of assets is done by both the FDIC and potential bidders. Asset uncertainty arises due to market timing, asset type, loan underwriting standards of the failed bank, and loan performance. We assume that the FDIC and bidders are equally uncertain about asset quality.[6] The FDIC estimates a liquidation value for the failing institution. Liquidation can be undertaken by the FDIC if it estimates this 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 and disposing of assets (deposit payout). Although liquidation is not the norm, since resolution costs are typically lower through an auction, the liquidation value can be thought of as the FDIC's reserve price. This price is typically not revealed. Potential bidders do, however, know the distribution of liquidation values, which we plot in Figure 2. We incorporate this distribution of losses into our analysis in Section 6.

2.1 Bidding

Bids made by healthy banks at the auction stage specify a continuous dollar component for the value of assets and liabilities of the failed bank, and four other discrete components of the acquisition agreement: (i) loss share (LS), (ii) nonconforming (NC), (iii) partial-bank purchase (PB), and (iv) value appreciation instrument (VAI).

2.1.1 The four discrete components of bids

Loss sharing: A loss-share agreement is one where the bidder assumes only a fraction of future losses on specific asset classes. In its *Resolutions Handbook*, the FDIC lists the following main reasons for favoring loss share: (i) it lowers risk for the acquiring institution, (ii) it reduces the FDIC's need for immediate funding, and (iii) assets remain

[5]According to the FDIC, a typical auction has, on average, 380 banks invited to participate. Roughly, 200 banks "look" at what is being offered, 4 to 5 conduct due diligence, and 3 to 4 place bids.

[6]A failing bank's assets are stratified by class (single-family residential, commercial real estate, commercial loans, etc.), and loans are then sampled from each category. Cumulative losses of all loans in the sample are estimated assuming that they are held to maturity. The FDIC also produces a market value for each asset, which is its estimate of the secondary market cash value.

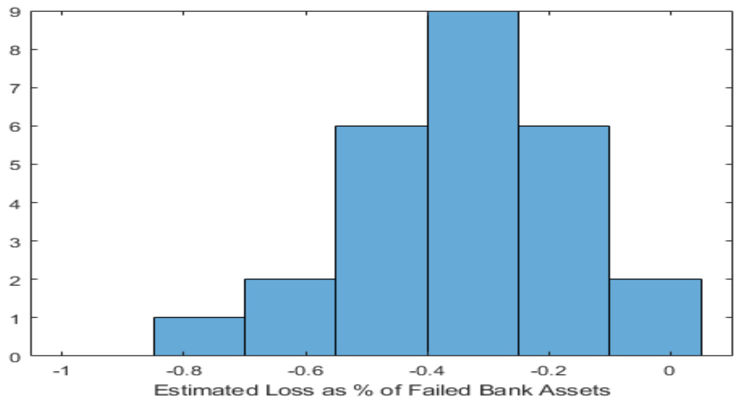


Figure 2: Loss in deposit payout

Data on estimated losses from insured deposit payouts are provided by the FDIC. In all auctions the bids are compared against the estimated cost of an insured deposit payout as part of the least-cost test. The direct estimated cost is divided by the total assets of the failed bank plotted on the x-axis. The y-axis represents the empirical frequency from a total of 26 resolutions by insured deposit payout.

in the private sector. The cost to the acquiring institution is increased oversight and reporting.[7] For the most part, loss-sharing agreements conformed to an FDIC-proposed rule where the FDIC takes 80% of losses and the acquirer takes 20% up to a threshold, after which the split was 95% and 5%.[8] The FDIC shares in recoveries in the same percentages. In our full sample (322 auctions) we observe 864 bids that include loss share, and a loss-share bid wins 65% of the time.

Nonconforming: A bid is considered nonconforming if it stipulates adjustments to the criteria set out by the FDIC in its marketing strategy. Because of the obligation to resolve at the least cost, these bids must nevertheless be considered by the FDIC (if they can be priced). Nonconforming bids are most often combined with an LS agreement or occur when a potential acquirer carves out certain assets that they do not wish to buy. Some examples of discrete options include the exclusion of brokered deposits, the exclusion of other real estate assets, or the inclusion of a branch-purchasing option. A total of 349 bids in our sample are nonconforming, and a nonconforming bid won 20% of the time.

[7]One might be concerned that awarding loss share would induce greater risk taking on loans covered by loss share. Implicitly we are assuming that the FDIC internalizes this when estimating the value of loss share and also why there are increased oversight and strict reporting requirements. Related, we might be concerned that removing uncertainty about the loss-share valuation could lead to adverse selection. We would be missing this positive impact of uncertainty in our estimation.

[8]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 5 in Appendix B shows that, despite the permitted flexibility, in most cases banks bid according to the original 80/20 rule.

Partial bank: In a modified or partial-bank (PB) agreement a bidder proposes to buy only certain assets (as well as all deposits). The FDIC Handbook explicitly states that it encourages auction participants to purchase the maximum amount of a failed institution's assets. The composition of the PB option is determined prior to the auction by the FDIC as part of its marketing strategy. Typically, riskier assets such as non-performing loans, development and construction loans, land, and owned real estate (ORE) are excluded from the sale. Assets that are not acquired at auction have to be liquidated by the FDIC following the auction. Figure 3 presents a histogram of the percentage of assets acquired in a PB bid. There is substantial variation across auctions. In our sample, fewer than 10% of auctions include a PB bid, and a PB bid won 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 exercise 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 VAI format depends on bidder size and public-listing status, but is calculated using standard formulas (Barragate et al. (2011)). We abstract from differences in VAI characteristics across auctions. There are 89 VAI bids in the full sample, and 6% of the winning bids include VAI.

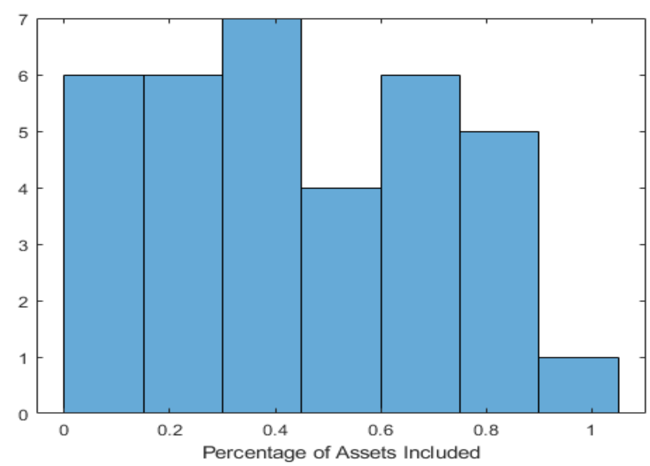


Figure 3: Partial-bank acquisitions

Histogram of the percentage of a failed bank's assets acquired in partial-bank bids

2.1.2 Packages

Table 1 presents the frequencies with which we observe each package. In nearly 16% of cases we observe only a cash bid for the assets and deposits, with no components switched on. By far the most common active component is loss sharing, often by itself. There are two package options that we never observe, each involving a combination of PB and VAI.

By offering bidders options, the FDIC hopes to attract competitive bids from banks that would otherwise not be interested/able to compete for the whole bank. This expansion can make an auction more competitive and lead to lower costs. To see how, consider an example where a bidder has a high value for the deposit franchise but does not want to acquire assets that might contribute risk to their portfolio. If restricted to bidding on the whole bank, the institution may have to ask for a large amount of cash to be able to maintain their capitalization. With partial bank, they can exclude some riskier assets, thus minimizing the impact on their risk-weighted capital, allowing them to bid more aggressively.

Table 1: Probability of observing different packages

This table provides the observed frequency of each package ranked by frequency, in all 322 auctions and in auctions with multiple bidding (MB) and without (No MB). Columns sum to 100%.

Package				Percent of Bids		
Nonconforming	Loss Share	Partial Bank	VAI	All	MB	No MB
No	Yes	No	No	42.79	38.05	56.66
No	No	No	No	15.60	16.49	13.00
Yes	Yes	No	No	12.69	14.16	8.36
Yes	No	No	No	8.51	10.99	1.24
No	No	Yes	No	3.86	2.22	8.67
Yes	No	Yes	No	2.76	3.07	1.86
Yes	Yes	No	Yes	2.76	3.38	0.93
No	Yes	Yes	No	4.96	5.07	4.64
No	Yes	No	Yes	3.62	3.91	2.79
Yes	Yes	Yes	No	0.95	0.74	1.55
Yes	No	No	Yes	0.55	0.74	0.00
No	Yes	Yes	Yes	0.55	0.63	0.31
No	No	No	Yes	0.24	0.32	0.00
Yes	Yes	Yes	Yes	0.16	0.21	0.00
No	No	Yes	Yes	0.00	0.00	0.00
Yes	No	Yes	Yes	0.00	0.00	0.00

2.2 The least-cost rule

The method for calculating the cost of a bid is described in Cowan and Salotti (2015) and the FDIC *Resolutions Handbook*. The basic formula is presented in equation (1). A positive value represents a loss (cost) to the FDIC. The first step is for the FDIC to calculate the transaction equity, or the difference in book value between the set of liabilities and assets included in the bid. The asset and deposit premiums are then added.[9] Finally, receivership expenses are included.

$$\begin{aligned}\text{Cost} &= \text{Takeover Bid} + \text{Expenses}\\ &= \text{Transaction Equity} + \text{Asset premium} + \text{Deposits premium} + \text{Expenses}.\end{aligned} \tag{1}$$

In order to illustrate how the cost rule works, consider a simple example where a failed bank has $1,000,000 of deposits and has issued $500,000 worth of outstanding loans, but, due to unforeseen circumstances, their book value is now only $250,000. Finally, the bank has $500,000 of cash remaining from its deposits, meaning that its total assets amount to $750,000 and its total liabilities amount to $1,000,000 (i.e., its obligations to depositors). Assume, for simplicity, that an acquisition agreement is executed on an as-is basis. *Transaction Equity* is the difference between assets and liabilities, which must be paid out by the FDIC in order to make the acquiring bank whole, relative to the book value of the failed bank's assets. In this example, that would be $250,000. Suppose the acquiring bank were only willing to assume the failed bank's loans at a dollar value of $130,000; this would imply an *Asset Discount* (an additional cash infusion from the FDIC) in the amount of $120,000. Suppose further that the acquiring bank were willing to pay a *Deposit Premium* of $100,000 in order to acquire the failed bank's depositors as its new customers, and that the FDIC accumulates internal resolution administrative *Expenses* of $25,000. Therefore, the FDIC's total costs in this simple example would be

$$\$295,000 = \$250,000 + \$120,000 - \$100,000 + \$25,000.$$

The LS, NC, PB, and VAI components all induce shifts in the set of assets/deposits used in the cost formula. Bidders are aware of the structure of the scoring rule given in equation (1), which is an accounting relationship between bids and costs. We assume that bidders know the distribution of possible shifts to the FDIC's cost stemming from each of the components as it operates through the set of assets/deposits. What is unknown to bidders is the auction-specific realization of the size and direction of the shift, and therefore the impact of bidding with each component on the FDIC's costs. This is the source of uncertainty. For instance, the FDIC's willingness to enter into LS or VAI agreements—which imply constraints on its future operations—may vary over time. Moreover, different

[9] The deposit premium is submitted as a percentage, which is translated into a dollar amount by dividing by 100 and multiplying by assumed deposits.

configurations of the discrete components can alter the administrative expenses borne by the FDIC by introducing complexity into the acquisition agreement—e.g., time required by its lawyers and accountants. These two examples could result in uncertainty if bidders are unaware of the FDIC's current and/or expected future operational constraints and/or human resources cost structure.

3 Data

We study bank failures from 2009 to 2013 using publicly available auction information. Our sample period starts in 2009, since that is when the FDIC began making bid data available. It ends in 2013 because of the diminished number of failures starting at this time, and a move by the FDIC towards offering optional loan pools and linked bids.[10]

For each auction, the FDIC releases a summary of bids, which includes information on the cash transfer component and each of the discrete components.[11] The bid summaries provide the identity of the winning and cover (second-highest) bidders as well as a list of bank names for all other bids, but do not specify the names associated with each bid. The FDIC also releases their estimate of the cost to the Deposit Insurance Fund on the date of the auction from the transaction. This information is available only for the winning bid, but we know that other bids did not win the auction and therefore were deemed costlier by the FDIC.

The full sample includes 322 auctions. In 153 of these at least one bidder submits multiple bids. In total, 359 healthy banks bid in at least one of the 322 auctions, generating 814 unique bidder-failure pairs and 1,269 bids. We also construct a restricted sample, since in order to estimate and identify valuations, we must be able to identify bidders, and bidder identities are revealed only for the two best bids in each auction. Therefore, to estimate valuations we restrict attention to all auctions featuring one or two bidders, and to three-bidder auctions where we can link bidders and bids. Our restricted sample contains 193 auctions, 42 of which involve some multiple bidding.

[10] Auctions are linked when they have the same closing date and the FDIC allows bidders to express complementarities in preferences across them. Since this introduces a combinatorial problem across and within auctions, and because of the additional choice involved in scheduling the auctions under this rule, we drop these cases. Loan pools allow healthy banks to bid for deposits and cash, cash equivalents, and marketable securities but also bid on pools (groups) of loans. Bids are submitted and evaluated separately for each loan pool, and bidders have the option to link bids on different pools to their bid for the institution. As in the case of linked auctions, this allows bidders to express a wider set of complementarities, but substantially complicates the analysis.

[11] See Appendix B for one example of a bid summary sheet.

3.1 Summary statistics

Table 2 presents summary statistics for the full sample. Table 11 in Appendix B provides the same information for our restricted sample. We match the auctions data with bank balance-sheet information from quarterly call reports (SDI), and location information from the annual summary of deposits (SOD). Our balance-sheet and physical-distance measures were constructed as in Granja et al. (2017). We present characteristics of the failed banks in the top panel. Bidder characteristics are provided in the second panel, while the third compares failing banks to bidders. We also highlight some auction characteristics and point to several measures of market concentration that are meant to capture the degree of competition in the market for loans and deposits. The set of bidders for which we report traits includes only the actual bidders at auction.

The main takeaways from Table 2 are the following. First, failing banks are relatively small and bidders are relatively large. Failing banks also have much larger real-estate loan portfolios than do bidders, with the portfolios of the former being on average close to 60% and for the latter about 48%. In addition, the Tier 1 capital ratio for failing banks is very low—close to 1, compared to bidders for whom, on average, it is above 15. Also, not surprisingly, the return on assets (ROA) for failed banks is negative, whereas bidders have healthy ROA. There is also heterogeneity in the distances between the branch networks of failed and healthy banks, where the pairwise branch distance ranges from 20 miles at the 10th percentile to 838 miles at the 90th.

In our sample the average bidder participated in 2.4 auctions, while the 90th percentile participation rate was 4 auctions. Therefore, even though there are many auctions, most healthy banks participate in very few. This is different than in procurement or securities auctions, where the same bidders are observed repeatedly. In our sample of auctions there are, on average, 3.96 bids per auction. The average cost of resolution to the FDIC is approximately $98 million per failure or 24% of failing banks' assets.

We also present information on the structure of the market (HHI) in which the failure occurs, and the impact of the acquisition on concentration. To do this we calculate the average percentage change in concentration across markets where the failed bank is active. If both the failing bank and the acquirer are active in a county, then concentration will increase, while in cases where the acquisition permits the acquirer to enter a new market, concentration remains unchanged. At the county level, the average impact of a bidder winning the auction is an increase in concentration levels of roughly 4.39% in the deposit market and roughly 3.59% as measured by branch presence. The impact on the loan market is an increase in concentration of about 0.3%.

Table 2: Summary statistics

We report balance-sheet information for failed banks and bidders separately using data from the SDI for the quarter pre-failure. SDI labels are in parentheses. Variables include *Total Assets (asset), Total Deposits (dep), Insured Deposits (depins)*. Variables *Commercial Real Estate (lnrenses), Commercial and Industrial (lnci), Consumer (lncon), Single-Family Residential (lnreres), All Real Estate (lnre)* are the shares of lending in each sector. *Core Deposits* is the share of total funding that is stable. *ROA* is return on assets and measures profitability. *Tier 1 Ratio*, is a measure of financial health. *Book Value Equity* is the difference between the total assets and the total liabilities as a percentage of failed-bank assets as of the quarter before failure. The portfolio percentage 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. Multiple bidding is an indicator if an auction featured more bids than bidders. The cost to the FDIC is the estimated loss from the press release data made on the date of failure. The bid premium is the transfer amount calculated using equation 1 divided by the total assets of the failed institution. HHI is calculated for both deposits and branches. The loan HHI is calculated using information on mortgage lending from the HMDA data set. A total of 88 failed banks and 72 bidders did not have any lending to report under HMDA.

	N	Mean	SD	P10	P50	P90
Failed Bank Traits						
Total Assets ($ Millions)	322	628.39	1944.55	48.86	193.44	1009.15
Total Deposits ($ Millions)	322	531.85	1561.12	45.77	181.64	919.61
Insured Deposits ($ Millions)	322	478.50	1322.45	41.88	167.29	915.48
Commercial Real Estate (%)	322	24.59	12.37	10.43	23.31	43.31
Commercial and Industrial (%)	322	8.00	6.79	1.52	6.18	17.37
Consumer (%)	322	1.52	2.16	0.10	0.80	3.71
Single-Family Residential (%)	322	18.41	13.21	3.71	16.34	35.71
All Real Estate (%)	322	59.90	12.34	44.87	60.83	74.27
Core Deposits (%)	322	77.37	15.56	56.09	79.00	94.74
ROA	322	-6.81	6.95	-12.90	-5.04	-1.72
Tier 1 Ratio	322	1.17	3.46	-1.79	1.48	3.58
Book Value Equity (%)	322	13.93	15.24	-0.29	11.25	31.82
Bidder Traits						
(Avg. over participated auctions)						
Total Assets ($ Millions)	359	13900	122000	171.94	725.54	8791.93
Total Deposits ($ Millions)	359	9841	83700	147.05	587.23	6638
Insured Deposits ($ Millions)	359	5575	42200	121.88	481.89	5221
Commercial Real Estate (%)	359	20.75	11.03	7.92	19.66	33.98
Commercial and Industrial (%)	359	9.99	7.07	3.29	8.51	18.81
Consumer (%)	359	3.39	4.72	0.30	1.70	8.36
All Real Estate (%)	359	48.23	14.32	30.84	47.96	65.63

Continued on next page

continued from the previous page	N	Mean	SD	P10	P50	P90
Single-Family Residential (%)	359	17.18	11.95	5.94	14.51	30.86
ROA	359	1.34	2.00	0.17	1.01	3.01
Tier 1 Ratio	359	15.46	8.13	10.69	13.51	21.70
Nbr of Auctions participated in	359	2.40	3.43	1.00	1.00	5.00
Portfolio % Differences						
Commercial Real Estate	814	10.65	9.40	1.57	8.04	23.74
Commercial and Industrial	814	6.21	5.96	0.82	4.40	14.38
Consumer	814	3.03	5.09	0.15	1.21	7.72
Single-Family Residential	814	9.68	9.84	1.21	6.92	20.94
All Real Estate	814	15.31	11.63	2.21	12.93	32.34
Avg. Pairwise Distance (miles)						
	814	306.88	412.78	20.39	140.01	838.49
Auction characteristics						
Number of Bids	322	3.96	3.79	1.00	3.00	8.00
Multiple Bidding	322	0.48	0.50	0.00	0.00	1.00
Cost to FDIC ($ Millions)	322	134.25	347.78	9.00	41.60	77.64
Bid Premium	1269	-0.24	-0.26	-0.76	-0.14	-0.04
% Δ in HHI from Acquisition						
Branches						
Zip Code	217	11.79	12.38	2.11	9.07	24.36
County Code	360	3.59	7.19	0.00	0.55	11.60
Deposits						
Zip Code	217	11.45	16.41	0.13	4.91	31.73
County	360	4.39	10.83	0.00	0.25	1.17
Loans						
County	262	0.30	1.52	0.00	0.00	0.47

3.2 Multiple bidding

From Table 2 we can see that in 48% of auctions, at least one bank submits multiple bids. Table 3 examines multiple bidding in more detail. In panel A we plot the number of bidders against the number of bids per auction. In approximately one third of auctions there is only one bidder and one bid, but even in single-bidder auctions there are multiple instances with two bids. In panel B we present the number of bidders against the number of bids per auction in our restricted sample of auctions, which we use to estimate valuations.[12] Restricting attention to auctions in which all identities are known narrows the maximum number of bidders to three.

Table 3: Number of bidders and bids per auction

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.

Panel A	Nb. Bids										
Nb. 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

3.3 Independence across auctions

In the model developed in Section 4, we assume independence across auctions. This would be problematic if there were (i) learning across auctions, (ii) complementarities across auctions, or (iii) banks had capacity constraints, in the sense that winning one auction limited future participation. Regarding learning, since the impact of each of the discrete components is different across auctions, bidders could never learn the exact scoring rule even if they participated in multiple auctions. It is possible, though, that bidders are initially uncertain about the distribution of cost shifts stemming from each component, in which case they might learn this over time. There is some evidence from pre-FDICIA

[12] We can also proceed by attempting to match the identities of the remaining bidders using an unsupervised assignment algorithm. We do not allow bidders to place bids dominated by one of their existing bids and group together any bids with identical asset premiums. When none of these rules applies, random assignment is used. This results in 75% of the bids being non-randomly matched to a bidder. Performing the estimation on this sample produces similar results to the restricted sample.

auctions consistent with learning. Zhang (1997) showed that repeat bidders faced reduced competition in the auctions where they won, made lower bids, and were more likely to have positive abnormal returns in the days just after winning, which he interprets as evidence of learning. Regarding complementarities, when multiple banks are closed on the same day, the FDIC often allows *linked bidding* so that bidders can express connections. This suggests the existence of within-period complementarities. We drop auctions with linked bidding, and therefore need only be concerned about complementarities across closing dates. Finally, 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 suggests that small, local bidders may be capacity constrained.

In Appendix C we discuss these concerns in further detail and test for the presence of any of these sources of dependence. Table 12 presents regression results demonstrating that learning, complementarities over time, and strategic bidding due to capacity constraints are not features of the auctions we study and so we do not incorporate them into our model.

4 Model

In this section we develop a structural model of bidding that allows us to recover healthy banks' underlying valuations for failing banks and each of the different components of the acquisition agreement. Bidding is multidimensional, so standard techniques for recovering valuations cannot be applied. Instead, we note that the decision to bid on each of the components is discrete and that the sum of decisions across components plus a bid's continuous portion can together be thought of as a "package". With this perspective, we draw on the combinatorial auctions literature and employ a similar modeling approach to Cantillon and Pesendorfer (2006b), who extended the nonparametric method of Guerre et al. (2000) to handle package bidding.[13]

Our setting has several unique characteristics relative to standard combinatorial auctions. All bids must involve taking on all the deposits of the failed bank. As a result, there can only be one winner in each auction. This greatly simplifies the combinatorial problem. On the other hand, our problem is more complicated because our bidders are subject to an auction-specific, noisy scoring rule, which shifts the auctioneer's utility of allowing a winner under different configurations of the acquisition agreement.

Our setup is the following. Failed banks vary by a vector of characteristics $\boldsymbol{Z}_j$, and bidders vary according to some observable traits denoted by $\boldsymbol{W}_i$. There are N_j asymmetric bidders, indexed by i, who participate in the auction for a particular failed bank j.

[13] See also Cantillon and Pesendorfer (2006a).

However, N_j is not observed by bidders at the time when they formulate their bids, so from the perspective of their decision process it is a random variable. Note also that the bidders in the auction are asymmetric in the sense that they all have different characteristics $\boldsymbol{W}_i$, but they do not observe the characteristics of their competitors prior to bidding. Rather, they are aware of the distribution of bidder characteristics, $F_{\boldsymbol{W}}(\boldsymbol{W})$.

From the auctioneer's perspective, the auction-to-auction variation in total number of bidders N_j is characterized by probability mass function $\pi_N(n|\boldsymbol{Z}_j)$, but from bidder i's perspective, conditional on itself being part of the auction, the number of its competitors is a slightly different random variable, $M_j \equiv N_j - 1$, which has probability mass function $\pi_M(m|\boldsymbol{Z}_j) = \pi_N(m+1|\boldsymbol{Z}_j)\frac{(m+1)}{\mathrm{E}[N|\boldsymbol{Z}_j]}$.[14]

Conditional on observables, bidders draw privately known valuations for the full bank (in absence of any discrete components of the acquisition agreement) as *iid* realizations from the following distribution:

$$\overline{V}_{ij} \sim F_{\overline{v}}(\overline{V}_{ij}|\boldsymbol{X}_{ij}),$$

where $\boldsymbol{X}_{ij}$ contains both $\boldsymbol{Z}_j$ and $\boldsymbol{W}_i$, as well as interaction terms. In what follows we drop the "j" subscript for the auction unless needed for additional clarity. Conditional on the full bank valuation, $\bar{v}_i$, each bidder has valuation v_{ik} for acquiring the failed bank under package k:

$$v_{ik} = \bar{v}_i + v_i^{LS}d_k^{LS} + v_i^{NC}d_k^{NC} + v_i^{PB}d_k^{PB} + v_i^{VAI}d_k^{VAI}, \tag{2}$$

where v_i^s is the valuation for switch $s \in \{LS, NC, PB, VAI\}$ and d_k^s indicates that switch s is turned on in package k. The switches are loss share (LS), nonconforming (NC), partial bank (PB), and value appreciation instrument (VAI). We assume that the switch valuations follow a joint distribution $(V_i^{LS}, V_i^{NC}, V_i^{PB}, V_i^{VAI}) \sim F_s(\cdot,\cdot,\cdot,\cdot)$, and that package-specific valuations are additive in the discrete switch components.[15]

For each auction, the FDIC draws a baseline reservation value $R \sim F_R(\cdot)$ representing its cost of directly reimbursing depositors without holding an auction for the failed bank's assets. It also draws an auction-specific $\Gamma \in \mathbb{R}^4$ as an *iid* (across auctions) realization from a joint distribution $F_\Gamma(\cdot|\boldsymbol{Z}_j)$, representing its evaluation of the impact of each discrete component on its cost structure. This can be thought of as its expected future losses from an LS-agreement in the case of loss share, the value of selling the remaining assets in separate loan sales for PB, the value of the VAI option, and/or the difference in expected losses due to a nonconforming modification.

[14] This subtle fact was proven by Myerson (1998). Bodoh-Creed et al. (2019) were the first to incorporate it into a structural model of Poisson games.

[15] In principle we can allow for switch valuations v_i^s and $v_i^{s'}$ to interact with each other. While implementing our estimator we experimented with this more general form and found that the data did not support a meaningful role for interaction terms.

We denote the set of bids offered by bidder i by $\boldsymbol{o}_i = \{(b_{i1}, \boldsymbol{d}_1), \ldots, (b_{i16}, \boldsymbol{d}_{16})\}$, where $b_{ik} \in \mathbb{R}$ is the dollar component of the bid stemming from the asset/deposit premium, and $\boldsymbol{d}_k \in \{0,1\}^4$ is the set of switches associated with package k. Denote $L_i = \{k : b_{ik} > \underline{b}_k\}$ the set of meaningful bids, where $\underline{b}_k$ is a cutoff point for the k^{th} package, below which no bid on that package can result in a win. The notation L_i is convenient because it allows us to keep track of meaningful bids, rather than all bids. Finally, let $\boldsymbol{b_i} = (b_{i1}, \ldots, b_{i16})$ denote the vector of dollar components of each bid, with $b_{ik} = \underline{b}_k$ for $k \notin L_i$.

The failed bank is allocated to the healthy bank offering the least-cost bid, evaluated according to the rule defined in equation (1). We restrict the least-cost rule to be linear in bids and auction characteristics and rewrite it as follows:

$$c_{ik} = b_{ik} + \Gamma_k \boldsymbol{d}_k + \delta_{ik} + u. \tag{3}$$

The δ_{ik} term is a bid-specific shock representing the FDIC's evaluation of package k for bidder i in auction j.[16] The second error term u_j represents the auction-level unobserved cost component, which includes expenses for the FDIC incurred during liquidation.

The bidder's information set includes the distribution of baseline valuations, the distribution of switch valuations, the distribution of FDIC reservation values, the distribution of FDIC component weights, and the probability that a rival bidder shows up with a given set of traits. In other words, bidders do not know the exact weights in the scoring rule. This is the source of uncertainty.

Given the information that they have, and their other own bids, for each package k bidder i derives a win probability function $G(b_{ik}|L_i, \boldsymbol{b}_i) \equiv \Pr[win\ with\ k|b_{ik}, L_i, \boldsymbol{b}_i]$. More specifically, in order for bidder i to win with a bid b_{ik} on package k, several things have to happen at once: b_{ik} must imply a lower resolution cost than (i) the (ex ante unknown) reserve price r, (ii) i's own bids on packages other than k, and (iii) all bids submitted by all other bidders (whose types and actions are ex ante unknown to player i). Moreover, whether or not (ii) and (iii) happen is a function of three separate factors: (a) the realization of the number of competitors, (b) their competitors' observables and private-value draws, and (c) the realized FDIC component weights Γ.

Once bidders infer the equilibrium win probability function, they choose their profile of continuous bids $\boldsymbol{b_i}$ to solve:

$$\max_{\boldsymbol{b_i}} \sum_{k \in L_i} (v_{ik} - b_{ik}) G(b_{ik}|L_i, \boldsymbol{b}_i). \tag{4}$$

[16]For example, δ_{ik} could capture the FDIC's belief that selling to bidder i (as opposed to bidder $i' \neq i$) under package k could improve the future value of the failed bank's assets under an LS agreement or VAI.

The first-order conditions are the following. For each $k \in L_i$ we have:

$$(v_{ik} - b_{ik})\frac{\partial G(b_{ik}|, L_i, \boldsymbol{b}_i)}{\partial b_{ik}} + \sum_{k' \in L_i,\, k' \neq k} (v_{ik'} - b_{ik'})\frac{\partial G(b_{ik'}|, L_i, \boldsymbol{b}_i)}{\partial b_{ik}} = G(b_{ik}|L_i, \boldsymbol{b}_i),$$

while for each $k \notin L_i$ we have:

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

Given the FOCs we can invert bids into values as in Guerre et al. (2000). For $k \in L_i$:

$$v_{ik} = b_{ik} + \frac{G(b_{ik}|L_i, \boldsymbol{b}_i) - \sum_{k' \neq k}(v_{ik'} - b_{ik'})\frac{\partial G(b_{ik'}|L_i, \boldsymbol{b}_i)}{\partial b_{ik}}}{\frac{\partial G(b_{ik}|L_i, \boldsymbol{b}_i)}{\partial b_{ik}}}, \tag{5}$$

and for $k \notin L_i$:

$$v_{ik} \leq \underline{b}_k + \frac{G(\underline{b}_k|, L_i, \boldsymbol{b}_i) - \sum_{k' \neq k}(v_{ik'} - b_{ik'})\frac{\partial G(b_{ik'}|, L_i, \boldsymbol{b}_i)}{\partial \underline{b}_k}}{\frac{\partial G(\underline{b}_k|L_i, \boldsymbol{b}_i)}{\partial \underline{b}_k}}. \tag{6}$$

4.1 Existence

Existence of an equilibrium of this game is assured using arguments similar to those from Lemma 1 in Cantillon and Pesendorfer (2006b) but with the addition of scoring-rule uncertainty, which simplifies the argument of the proof by eliminating the possibility of mass points in the bid distribution.

Theorem 1. *Consider the private value combinatorial first-price auction with package constraints described above with an unknown reserve price and scoring-rule uncertainty. If, in any equilibrium in which bidders bid at or below their valuations, the following conditions hold, then an equilibrium exists:*

1. *bidders are indifferent about the way in which ties that occur with positive probability are resolved,*
2. *bidders' expected equilibrium payoffs are continuous at their equilibrium bids,*
3. *there are no mass points in the distribution of equilibrium bids.*

A proof of this theorem is presented in Appendix D.

4.2 Model discussion

We are interested in understanding the impact of multiple bidding and uncertainty on bidding behavior. In the Introduction we described three influences on bidding behavior arising in our setting. Multiple bidding generated a *substitution effect* and *competition effect*, while uncertainty led to a *noise effect*.

In general, bidders will not be indifferent between winning with each of the bids they submit. Rather, each bidder submits the set of meaningful bids that maximizes their expected profits. Moreover, this set will not usually consist of bids for each of the packages. To fix ideas, consider the problem of a bidder deciding whether to place a meaningful bid on an additional package. An additional bid will strictly increase a banks' probability of winning, but will *lower* its probability of winning with any of its existing bids, one of which may yield higher profits. This can be seen in the second term of the numerator of equation (5). This term is not present in the first-order conditions of a standard first-price auction. It is always negative, generating additional shading, which leads to a *substitution* effect. The larger it is, the larger the difference between the valuation and bid. This argument, however, does not account for the adjustment through G, which is an equilibrium object and depends on the strategies employed.

Also built directly into G is the *competition* effect. The increased number of bids stemming from multiple bidding could make an auction appear more competitive, with bidders now best responding to a larger number of rival bids. Holding fixed the average level of each bid, a larger number of them will naturally tend to reduce bid shading. Of course, as described above, the substitution effect reduces the mean value of each competitor's submitted bids, such that the overall effect on bid shading is ambiguous.

For the *noise* effect, if one bid is ranked above another in bid space, it may still lose due to randomness if bids correspond to different packages. Holding packages and bidder identities fixed, the greater the continuous difference between the bids, the higher the probability that the higher bid will win. Bidders can gauge this probability using the distribution of F_Γ, which may lead them to shade more or less, and will be captured in the function G.

Changes in the information structure may also impact the set of acquirers. Consider an auction with two bidders, one large national player, and one smaller competitor that previously competed locally with the failed bank. The local competitor may not be in a position to acquire all of the assets of the failed bank. Therefore, the local bank is only interested in bidding with a PB option. The national bank, on the other hand, might have a low value for acquiring the additional assets, leading it to favor the partial bank as well, but is sufficiently capitalized to consider bidding without it. Assuming that banks correctly anticipate their opponents' traits (up to the private-value draw), the national bidder knows the local bidder prefers a PB bid. If the FDIC announces the rule, and it is favorable to PB bids, the national bank joins the local bank to bid for the partial bank, increasing the direct competition. However, if the FDIC announces a rule that is unfavorable to PB, the national bidder faces less competition and can offer a low price. In this way, institutional traits can affect the set of acquirers and FDIC losses.

5 Identification

In this section we describe our identification approach. Our first challenge is that the FDIC's proprietary algorithm for computing its least-cost scoring rule is not publicly observed and varies across auctions. Therefore, our first step is to show that the distribution of the scoring rule can be identified from the available observables. Then, we apply similar arguments as in Cantillon and Pesendorfer (2006b) to show that the valuation distributions of bidders' private information are identified, or set identified for packages where they do not place bids. Finally, we show that our additively separable valuation structure allows us to separately identify baseline valuations from component-specific valuations.

5.1 Least-cost scoring rule

Recall from our discussion of equation (1) the basic structure of the least-cost calculation. With this, the functional form for equation (3) can be rewritten it as follows:

$$\begin{aligned} \text{cost}_{ijk} &= b_{ijk} + \mathbf{1}(LS_{ijk}=1)(\%LS_j)(\epsilon_j) + \mathbf{1}(VAI_{ijk}=1)(\psi_j) \\ &+ \mathbf{1}(NC_{ijk}=1)(\kappa_j) + \mathbf{1}(PB_{ijk}=1)(\%PB_j)(\nu_j) + \delta_{ijk} + u_j, \end{aligned} \tag{7}$$

where $\mathbf{1}(\cdot)$ is an indicator function. In order to achieve identification of the stochastic least-cost scoring model, it is sufficient to impose a single parametric restriction on the distribution of the bidder-package-specific shock, while leaving the remaining shock distributions unrestricted:

Assumption 1. *The bidder-package-specific shock δ_{ijk} follows a mean-zero normal distribution $\Phi(\delta; 0, \sigma^2_\delta)$, with variance σ^2_δ.*

Assumption 2. *The least-cost scoring rule shocks δ_{ijk}, u_j, ϵ_j, ψ_j, κ_j, and ν_j are pair-wise independent.*

Theorem 2. *Under Assumptions 1 and 2, the bidder-package shock variance σ^2_δ and the distributions of the remaining shocks $u_j, \epsilon_j, \psi_j, \kappa_j, \nu_j$ from the least-cost scoring rule are semi-parametrically identified from the published resolution cost of the winning takeover bid, without functional form restrictions on the distributions of $u_j, \epsilon_j, \psi_j, \kappa_j$, or ν_j.*

A formal proof is in Appendix D; however, the intuition is straightforward. Consider the set of single-bid auctions that specify no discrete component. In this case, the only uncertainty when trying to map observed bids to observed losses stems from $u_j + \delta_{ijk}$. Therefore, the distribution of this convolution is identified from single-bid auctions. We then make use of auctions with multiple bids having the same switches turned on, but different dollar amounts to compare the probability that bids with different-sized bid premiums win. For any difference in bid premiums, we observe from raw data across multiple auctions the probability that the winning bid beats any other bid with the same switch configuration $Pr(bid_1 + \delta_{1jk} \geq bid_2 + \delta_{2jk})$. This is equivalent to the probability that the difference of the bid-specific unobserved evaluation shocks is smaller than the difference in bid amounts. Thus the distribution of the difference $\delta_{ijk} - \delta_{ljk}$ is also observed. Unfortunately, this does not allow for nonparametric identification of the distribution of δ. Therefore, we assume δ has a mean-zero normal distribution, allowing us to identify its variance from the distribution of the differences. Standard deconvolution techniques can then be applied to recover the distribution of u. As for the component-shock distributions ϵ, ψ, κ, and ν, similar logic holds by applying deconvolution techniques to subsamples of auctions where the winning bid varies from some losing bid by a single discrete component.

5.2 Valuation distribution

To recover the distribution of bidders' underlying valuations, we impose the following assumtpion.

Assumption 3. *Component utilities satisfy* $v^s_{ij} = v^s(\boldsymbol{X}_{ij}) = \boldsymbol{X}_{ij}\boldsymbol{\beta}^s$*, for each* $s \in \{LS,\ PB,\ NC,\ VAI\}$*. Moreover, component utilities enter* v_{ijk} *in an additively separable way as in equation (2).*

Theorem 3. *Under Assumption 3,* $\boldsymbol{\beta}^{LS}$*,* $\boldsymbol{\beta}^{PB}$*,* $\boldsymbol{\beta}^{NC}$*,* $\boldsymbol{\beta}^{VAI}$*, and the distribution of* $\overline{v}$ *are identified from observed bids and bidder identities, without a priori restrictions on the distribution of* $\overline{v}$*.*

For convenience we will define a component utility matrix $\boldsymbol{\beta} \equiv [\boldsymbol{\beta}^{LS}\ \boldsymbol{\beta}^{PB}\ \boldsymbol{\beta}^{NC}\ \boldsymbol{\beta}^{VAI}]$. The basic inversion result of GPV showed how a bidder's private value could be directly recovered from knowledge of the distribution of opposing bids and their own bid, seen as a best response to the former. Using a similar strategy, we can recover a package-specific valuation v_{ijk} for each bidder that submits a non-trival bid, since the win probability function $G(b_{ijk}|L_i, \boldsymbol{b}_{ij})$ can be derived from observables. A final challenge arises from measurement error: in practice, when estimating the component utility parameters $\boldsymbol{\beta}$ with a finite sample of data, the econometrician does not observe actual bidder-package valuations but, rather, estimated pseudo-valuations $\hat{v}_{ijk}$.

$$\begin{aligned}\hat{v}_{ijk} &= v_{ijk} + \xi_{ijk} \\ &= \overline{v}_{ij} + \boldsymbol{X}_{ij}\boldsymbol{\beta}\boldsymbol{d}_k + \xi_{ijk},\end{aligned} \tag{8}$$

where ξ_{ijk} derives from finite sample variability in previous stages of estimation. However, in order to separately identify each bidder's baseline valuation and their discrete component valuations v^s_{ij}, $s \in \{LS,\ PB,\ NC,\ VAI\}$, we take advantage of the within-bidder panel structure of multiple bids submitted by the same bidder, while treating $\overline{v}_{ij}$ as a bidder fixed effect. Note that $\hat{v}_{ijk}$ converges in probability to the true value v_{ijk} as the number of auctions in the sample approaches infinity. This is a useful fact, since the within-bidder panel length is small, being bounded above by the number of unique packages (2^4).

5.3 FDIC reserve price distribution

While the auction-specific reserve price is not observed, the distribution of the losses from deposit payouts is. The deposit payout occurs in auctions where the FDIC cannot find any interested participants or receives no satisfactory bids. This is the outside option for the auctioneer, i.e., their reserve price. This distribution is directly observed and so is nonparametrically identified.

6 Estimation

As in GPV we observe participants' sets of bids, $\boldsymbol{o}_i$; therefore, we can retrieve valuations as a function of bids and the probability that a given bid wins (G). There are a number of challenges, however, for estimating bidder valuations in our case. For the estimation of the win probability, (i) the scoring rule is unknown, (ii) there is uncertainty about the set of asymmetric competitors a bidder faces, and (iii) the FDIC allows multiple bidding. Moreover, valuations are only observed for packages that are bid on, and the valuations for different packages are related for a given bidder. We take a three-step approach to address these challenges. First, we estimate the parameters of the least-cost scoring rule. Next, we estimate G and compute package-specific valuations, and finally, we decompose each package-specific valuation into component-specific and baseline pieces.

6.1 Least-cost rule

For tractability in estimating the parameters of the least-cost scoring rule, we impose the additional assumption that the component shocks $u, \psi, \epsilon, \kappa, \nu$ are normally distributed, each with their own mean $(\mu_u, \mu_\psi, \mu_\epsilon, \mu_\kappa, \mu_\nu)$ and variance parameters $(\sigma_u^2, \sigma_\psi^2, \sigma_\epsilon^2, \sigma_\kappa^2, \sigma_\nu^2)$. Let $\boldsymbol{\theta}$ represent a vector containing the set of parameters to be estimated, including the means and variances above, and the variance of the bidder-package-specific shock σ_δ^2.

The first challenge we encounter is a missing data problem. Although we model the LS and PB options as discrete from the 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.[17] 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 in two scenarios. These occur when the winner turns PB or LS 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.[18] 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 will abstract from the missing information problem in our subsequent discussion of the estimator.

We take a simulated maximum likelihood approach by solving for the parameters of the least-cost scoring rule that maximize the probability that winning bids lead to their respective observed costs and that they dominate their respective competing bids. Formally, the problem is to maximize the likelihood function given by

$$\begin{aligned}\max_{\boldsymbol{\theta}} \prod_{j=1}^{J} \int_u \int_\epsilon \int_\kappa \int_\nu \int_\psi \phi \left[(c_j^T - \hat{c}_j^{winner}); 0, \sigma_\delta^2 \right] \\ \times \prod_{i=1}^{I_j} \prod_{k \in L_{ij}} \Phi \left[(c_j^T - \hat{c}_{ijk}); 0, \sigma_\delta^2 \right]^{1-w_{ijk}} dF_\psi dF_\nu dF_\kappa dF_\epsilon dF_u,\end{aligned} \tag{9}$$

where c_j^T is the observed cost in the j^{th} auction; $\hat{c}_{ijk}$ is the cost assigned to i's bid on package k (according to equation (7)), holding fixed a value of $(u, \epsilon, \kappa, \nu, \psi)$ but excluding the bidder-package-specific shock δ_{ijk}; $\hat{c}_j^{winner}$ is an analogous quantity for the winning package bid; w_{ijk} is a dummy variable indicating whether bidder i won auction j with a bid on package bid k; I_j is the number of bidders at auction j.

[17]As discussed in Section 2.1.1 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).

[18]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.

Simulated integration is used because the component shocks are constant for all bids within an auction but occur in various combinations depending on the set of packages for which opposing bids are received. The resulting analytic integral is therefore too complicated in settings with many bidders and a variety of packages. This equation can also be estimated while allowing a variety of control variables to shift the means or variances; results are similar. We use 5,000 simulated draws, which are held fixed during run time, and standard errors are calculated using the empirical Hessian estimator.

6.2 Win probabilities

The second step of estimation concerns win probabilities, $G(\cdot)$. To control for heterogeneity across auctions as well as bidder asymmetry, we apply a resampling approach similar to the one used by Hortaçsu and McAdams (2010). Intuitively, the win probability is the likelihood of encountering a set of competitors with lower bids than one's own, so we resample repeatedly from the set of all competitors across all failed bank auctions in the data set. However, our sampling procedure needs to account for possible selection on observables, which may arise if bidder characteristics are correlated with the characteristics of the failed bank up for auction. Therefore, we adopt a weighted resampling estimator wherein, for a given auction, win probabilities are estimated from a sample where bidders from similar auctions are more likely to appear.

The win probability function also depends on the scoring rule and the ex ante unknown reserve price, which behaves much like an additional competing bid. Holding fixed each resampled set of competitors, we simulate repeatedly from the distribution of the reserve price r and from the distributions of the scoring rule shocks. For each of these, we compute a binary variable indicating whether a fixed bid $(b, \boldsymbol{d})$ would have won. After resampling repeatedly from sets of competitors (using sample weights), and simulating repeatedly from the reserve price and shock distributions, we are able to compute empirical win frequencies at various levels of bids b and at various switch configurations $\boldsymbol{d}$.

A final challenge is to cope with the fact that bidders do not observe the number or characteristics of their competitors prior to bidding.[19] Hickman et al. (2017) show that identifying the probability mass function of the number of a bidding bank's competitors, M_j, is sufficient to achieve identification of the win probability function in private values auctions. This idea is manifest in our resampled estimator through simulation from the empirical distribution $\pi_M(m_j|\boldsymbol{Z}_j)$. This is useful because we are able to directly observe $(N_j, \boldsymbol{Z}_j)$ pairs in our data, from which we can consider the distributions of competitors as known objects.

[19] Previous theory work has explored bidding in auctions with unknown competitors (McAfee and McMillan (1987) and Harstad et al. (1990)).

To summarize, the four steps of our resampling procedure are the following:

1. For a given $(b_k, L, \boldsymbol{b}, \boldsymbol{Z})$ quadruple, and for $t = 1, \ldots, T$, simulate an *iid* draw m_t from the empirical distribution of competitors $\hat{\pi}_M(\cdot|\boldsymbol{Z})$, where T is a pre-specified number of *outer* simulations.

2. Perform weighted resampling (with replacement) of m_t draws from the set of all bidders across the data set. Each sampled bidder is stored with its complete set of observed bids $\{L_{ti}\}_{i=1}^{m_t}$.

3. Holding t fixed, perform *inner* simulation as follows for $h = 1, \ldots, H$, where H is the number of prespecified inner simulations:

   (a) Simulate *iid* draws from the distribution of reserve prices to get $\{r_{th}\}_{h=1}^{H}$.

   (b) For each h, simulate from the bidder-package-specific shock distribution to get a sample $\{\delta_{thk}\}_{k\in L}$ for the own bids paired with b_k, and $\{\{\delta_{thik}\}_{k\in L_{ti}}\}_{i=1}^{m_t}$ for simulated competitor bids.

   (c) Simulate from the FDIC component weight shock distributions to get a sample $\{(u_{th}, \epsilon_{th}, \kappa_{th}, \nu_{th}, \psi_{th})\}_{h=1}^{H}$.

4. For each t and h pair, use the information in the h^{th} inner simulation to compute the FDIC resolution cost associated with b_k, the costs associated with other own bids in $\boldsymbol{b}$, and the costs associated with each of the m_t resampled competitor bid sets. Finally, compute a full set of binary outcomes w_{th}, indicating whether in simulation (t, h) the bid b_k (on the k^{th} package) won the auction (by being the FDIC's lowest-cost option), and calculate $\widehat{G}(b_k|L, \boldsymbol{b}, \boldsymbol{Z}) = \sum_{t=1}^{T}\sum_{h=1}^{H}\frac{w_{th}}{TH}$.

Note that an equivalent way to think about $\widehat{G}$ described above is that it represents the CDF of the distribution of the lowest competing cost.[20] With this intuition in mind, it follows that a similar process can be used to obtain an estimate of the derivative of G, $g(b_k|, L, \boldsymbol{b}, \boldsymbol{Z})$. We use boundary-corrected kernel density estimation with the resampled draws to obtain an estimate $\widehat{g}$ so as to avoid the need for sample trimming.[21]

6.2.1 Practical issues

There are many potential observable bank-specific covariates that could be of interest to healthy banks when deciding to participate in an auction and in forming their valuation.

[20]Specifically, one could have computed a sample consisting of the lowest simulated competing cost for each (t, h) pair and then represented $\widehat{G}$ as the empirical CDF of this sample.

[21]One problem with this approach is that for the highest and lowest draws the observations come mainly from one side, decreasing the estimated probability at these points. This can be corrected for using boundary correction methods as in Hickman and Hubbard (2015).

We want to develop a set of weights that reflects how informative the behavior of bidders in auction A is for the expected behavior of bidders in auction B. To overcome a curse of dimensionality in the construction of the resampling weights, we first use a principal components dimension reduction approach based on traits. The results are given in Table 10 of Appendix B. Denoting the p^{th} principal component by PC_p, the percentage of the total variance explained by PC_1 is roughly 30%, while PC_2 and PC_3 account for 19% and 14%, respectively. PC_1 seems to represent capitalization and bank performance, while PC_2 and PC_3 represent the size and area of portfolio concentration.

We compute weights for our resampling scheme in the following way. First, using only the first principal component, for each auction j we compute sample weights by centering a Gaussian kernel over PC_{1j} and choosing bandwidth h_1^p according to Silverman's optimal bandwidth rule. Sampling weights for all other auctions j' are then computed as

$$\omega_{j,j'} = \omega^1_{j,j'} = \phi\left(\frac{PC_{1j'} - PC_{1j}}{h_1^p}; 0, 1\right)$$

and then normalized to sum to one.[22]

Before the resampling estimator is used, however, we must first estimate the reserve price. In all of the resampling equations we include the FDIC as a bidder, where they draw a random reserve price as their submitted bid. The reserve price distribution is estimated using the auctions where no sale occurred and deposits were paid out. This is always the default outside option for the FDIC. This distribution is plotted in Figure 2. Since we always observe the cost of deposit payout when it occurs, this distribution is directly identified. The empirical distribution is plugged in to the estimation directly. Note that under our counterfactual scenarios, this (secret) reserve price distribution will remain fixed. Finally, recall that earlier we assumed away measurement error arising from the fact that the amount of assets included (covered) in a PB (LS) agreement is not always observed. In these cases, for the estimation of the win probability we fix the percentage of assets included at the average percentage from the auctions where it is observed.[23]

[22]In order to test for sensitivity to different sample weighting schemes, we also experimented with computing normalized kernel function weights relative to the first three principal components. The resulting sample-weight formula was as follows:

$$\omega^p_{j,j'} = \phi\left(\frac{PC_{pj'} - PC_{pj}}{h_p^p}; 0, 1\right), \quad p = 1, 2, 3; \qquad \omega_{j,j'} = \frac{\omega^1_{j,j'} + \omega^2_{j,j'} + \omega^3_{j,j'}}{\sum_{j' \neq j} \sum_{p=1}^{3} \omega^p_{j,j'}}.$$

After estimating baseline pseudo-values using only PC_1, call them $\widehat{v}^1_{ijk}$, and then re-estimating pseudo-values using the first three principal components in this expanded way, call them $\widehat{v}^3_{ijk}$, we found that our results were very close. The correlation between the two estimates was 0.94 and that regressing $\widehat{v}_{ijk}$ on $\widehat{v}^{PC_3}_{ijk}$ resulted in an R^2 of 0.88. Given the higher computational cost of the expanded method using the first three principal components, we opted for the method using only PC_1 as our baseline specification.

[23]This "error" is observed by the bidder but not the econometrician; therefore, ideally an expectation

6.3 Decomposition of values

Once G is estimated, solving the system of equations (5)-(6) is relatively simple. This solution gives a set of pseudo-valuations for each package with a bid as well as bounds for valuations on all packages not bid on. Moving forward, we follow the convention of denoting both our estimated pseudo-value levels (using equation (5) for packages that are bid on) and our estimated pseudo-value bounds (using equation (6) for packages that are not bid on) as $\widehat{v}_{ijk}$.

In order to compute counterfactuals in the absence of uncertainty later on, we need to learn each bidder's exact value for each package. To do so, we estimate the component utility matrix $\boldsymbol{\beta}$ and the distribution of bidder-specific fixed effects, $\bar{v}_{ij}$. We rely on equation (8), but recall that the left-hand side (i.e., bidder-package pseudo-values $\widehat{v}_{ijk}$) is only observed for packages that are actually bid on; for packages that are not bid on, (8) becomes an inequality. Recall also from above our assumption that the error term ξ_{ijk} represents sampling variability in pseudo-values derived from the estimated win probability function $\widehat{G}$.[24] This assumption means that there is no censoring problem in the error distribution as in a usual Tobit model, as these errors are not observed by the bidders and do not influence their choices. This also means that even with our fixed "panel length" (i.e., there are only 16 possible packages to bid on within each bidder), the parameters in $\boldsymbol{\beta}$ can be consistently estimated since the noise in our estimate $\widehat{G}$ becomes smaller as the number of auctions in the sample increases.

We estimate the parameters in $\boldsymbol{\beta}$ and $\overline{v}_{ij}$ using a GMM approach, where the inequality is used as an over-identifying moment condition (Moon and Schorfheide (2009)).

$$\arg\max_{\boldsymbol{\beta}, v_{ij}} \sum_{j=1}^{J} \sum_{i=1}^{N} \sum_{k=1}^{16} \left(\widehat{v}_{ijk} - \overline{v}_{ij} - \boldsymbol{X}_{ij}\boldsymbol{\beta}\boldsymbol{d}_k\right)^2 \max\left\{\mathbf{1}(k \in L_i), \mathbf{1}\left(\widehat{v}_{ijk} - \overline{v}_{ij} - \boldsymbol{X}_{ij}\boldsymbol{\beta}\boldsymbol{d}_k < 0\right)\right\}. \tag{10}$$

In the objective function above, the final multiplicative term determines how the inequality information is incorporated into the objective function. Whenever we have level information for any pseudo-value $\widehat{v}_{ijk}$, the first indicator function equals one and the corresponding residual is included in the objective function. For a particular value of $(\boldsymbol{\beta}, \overline{v}_{ij})$ and for pseudo-values where we only have bound information, if the argument for the second indicator function is non-negative, then the corresponding inequality is satisfied

would be taken over the estimated valuations calculated given the possible draws of this unobserved share, but this is computationally demanding. Point estimates calculated using the integration are similar to the main specification for both the baseline valuations and component shifts.

[24] After estimating equation (8), we find that the variance of ξ_{ijk} accounts for only 13% of the total variation in estimated pseudo-values $\widehat{v}_{ijk}$. We believe this relatively low number lends credibility to our assumption that the error term in equation (8) represents sampling variability in pseudo-values derived from the estimated win probability function $\widehat{G}$.

and both indicator functions take on a value of zero such that the relevant residual is omitted from the objective function. On the other hand, if the argument of the second indicator function is negative, then the corresponding bound is violated for that given value of $(\boldsymbol{\beta}, \overline{v}_{ij})$, and we add a relevant squared residual term to the objective function. In this way our estimator finds a best fit relative to the equality information, while also minimizing violations of the bound information.

Following the estimation of equation (8), we want to understand the traits of a bidder that influence the baseline valuation $\overline{v}_{ij}$. In order to obtain these correlations, we regress the estimated baseline valuations on bidder traits:

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

7 Results

We start by presenting our estimates of the least-cost scoring rule. We then highlight how different discrete components are valued depending on bank characteristics. Finally, we present two counterfactual exercises to separately decompose the roles of uncertainty and multiple bidding on auction outcomes.

7.1 Least-cost scoring rule estimation

Our estimates of equation (7) are presented in Table 4 for three different specifications. We estimate the mean and variance parameters associated with the discrete components and the common shock, as well as the variance of the idiosyncratic shock. In specifications (2)-(3) we allow the LS and PB means to be linear functions of observable traits and location and year effects. We do not have a sufficient number of bids with NC and VAI to allow for this additional flexibility. Specifications (2) and (3) also include quarter fixed effects on the auction-specific mean. Estimation is based on the 322 auctions in our full sample. In total there are 1,267 observations.[25]

We concentrate our analysis on column (1), which we use to construct our win probability measure. Results are qualitatively similar across the other specifications. The coefficients can be interpreted in terms of percentage asset discount. The coefficient on LS is -29.8. Recall from equation (7) that this shock is interacted with the actual percentage of assets covered by the loss-share agreement. Therefore, by multiplying -29.8 by the average percentage of assets specified by the FDIC in our sample (74%), we get an average percentage asset-discount equivalent of 22.05 using LS. The coefficient associated

[25]Results are similar if we estimate the least-cost rule based on the restricted sample and available upon request.

with the LS standard deviation indicates there is a substantial amount of uncertainty in the FDIC's valuation of this component.

Table 4: Scoring rule estimates

This table presents estimates for the least-cost scoring rule (equation 7) based on the 322 auctions in our sample. There are 1,267 observations. The last row reports McFadden's R-squared. Column (2) included Florida and Georgia fixed effects and year fixed effects for 2009, 2010, and 2011–2013 grouped together interacted with individual packages. See Table 2 for definitions and summary statistics on the included variables. Statistical significance: $***p<0.01, **p<0.05, *p<0.1$.

	(1)		(2)		(3)	
Variables	Param.	SE	Param.	SE	Param.	SE
Common (u) Mean						
Constant	-4.406***	1.269	-0.4327	0.9816	-0.356	1.061
Book value of Equity			-0.945***	0.038	-0.955***	0.033
Quarter Fixed Effects	No		Yes		Yes	
Common (u) Sd	19.562***	0.574	5.333***	0.741	5.128***	0.926
PB (ν) Mean						
Constant	42.872***	3.932	68.763***	8.312	73.033***	1.7086
% CRE			-0.061	0.0639	-0.635	0.271
% CI			-0.220	0.1513		
% NA			-0.099	0.1288		
T1 ratio					-0.234	1.017
Year and State FE	No		Yes		No	
PB (ν) Sd	23.954***	7.559	8.071***	5.812	15.951***	6.287
LS (ϵ) Mean						
Constant	-29.828***	1.726	-21.108***	1.451	-22.533***	1.214
% CRE			-0.815***	0.314	-0.066***	0.051
% CI			-0.154	0.434		
% NA			1.031***	0.361		
T1 Ratio					0.301	0.261
Year and State FE	No		Yes		No	
LS (ϵ) Sd	11.506***	1.057	0.741	1.956	0.717	1.773
NC (κ) Mean	-6.128***	2.138	-6.018***	1.448	-5.916***	1.261
NC (κ) Sd	20.206***	1.107	17.799***	1.890	18.062***	1.709
VAI (ψ) Mean	-2.212	1.670	-3.810***	1.451	-3.598***	1.214
VAI (ψ) Sd	3.244	2.158	0.4203	3.778	0.028	3.023
Idiosyncratic (δ) Sd	3.52***	0.449	8.268***	0.441	8.318***	0.529
R^2	0.1282		0.2137		0.2106	

The coefficients for the mean and standard deviation of PB can be interpreted similarly. The coefficient on the mean is 42.87, and the average share of assets included in PB transactions as specified by the FDIC is 68%, such that the average percentage asset-discount equivalent to using PB is -29.15. At first glance the fact that the asset-discount equivalent to PB is negative might seem surprising since one would assume that the FDIC has a preference for selling the bank whole. However, a PB bid results in a large transfer to the bidder at closing, as they assume the same amount of liabilities but fewer assets. The size of the transfer increases through the transaction equity term one for one with the excluded loan volume. The coefficient on PB therefore represents the FDIC resale value for the retained set of loans relative to book value, and these tend to be high-risk loans.

An NC bid is equivalent to a 6.13% discount of total assets. The coefficient on the standard deviation of NC is 20.2%, suggesting that these bids involve a wide range of modifications and generate a lot of uncertainty. Note also that the use of VAI does not have a large impact on bid rankings. Finally, note that we estimate the auction-specific common-shock mean discount to be 4.41% with a standard deviation of 19.56%. This term represents the receivership expenses of the auction, which Bennett and Unal (2015) find to be 4.5% on average with a standard deviation of 9%.

7.2 Valuation estimation

We next highlight the way that banks' observable characteristics shift their valuations of the whole bank and the four discrete components.

The left-hand panel of Table 5 reports estimates of equation (8). We allow the valuation of each component to be shifted by (i) an indicator for whether the branch networks of the bidding and failed banks overlap in at least one zip code (Same zip), (ii) the average pairwise distance between all pairs of branches (Distance), (iii) an average over the difference in percentage concentrations of lending in various loan categories for the bidding and failed banks (Portfolio), (iv) the log of total assets of the failed bank (Size), (v) the bidding bank's Tier 1 capitalization (Tier 1), (vi) the portfolio similarity in commercial real estate (%CRE), and (vii) deposit concentration (HHI).

We find evidence that LS is more attractive for larger failures. This could be because the additional monitoring and reporting costs associated with LS may outweigh the insurance benefits for smaller failures, or because larger institutions are more complex, such that a less complete evaluation of the books is possible in the limited time before the sale. The value of a PB agreement is negative for all bidders but becomes greater as the size of the failed bank increases. This suggests that bidders for smaller failures are more willing to take on all the failed bank's assets. PB is also more attractive when banks are in the same zip code and have more similar portfolios. Better capitalized bidders also are less inclined to use partial bank. The value of nonconforming bids is greater in larger failures and for banks in different zip codes. VAI is more valuable for smaller failed banks and for cases where the banks' networks do not overlap and where their portfolios are different.

We also consider the correlations of bidder traits with their estimated baseline valuations for the whole bank with no options (equation (11)). These results are presented in the right-hand side panel of Table 5. When we do this, we consider distance, size, capitalization, CRE portfolios, and impact of the sale on market structure. Bidders' valuations are positively correlated with the potential increase in deposit market concentration that would result from a given bidder acquiring the bank and therefore positively related to the value that it has for the failed bank. Once we have controlled for the market structure change, being in the same zip code actually has a negative impact on valuations. This would seem to reflect a desire to use failures to expand geographically.[26] Larger failures and more CRE lending are associated with higher valuations. We also find that portfolio similarity has a positive effect on valuations.

7.3 Counterfactual experiments

We are interested in quantifying the role of uncertainty and multiple bidding on bid shading and on the set of acquirers. We consider three counterfactuals. In the first we eliminate strategic multiple bidding. In the second, we eliminate uncertainty, which, as a side effect, removes bidders' incentives to engage in multiple bidding. In addition to these two main counterfactuals, we also consider the case where bidders' only discrete option is loss share.

To eliminate strategic multiple bidding, we compute equilibrium strategies maintaining uncertainty and holding fixed the number of bids and the set of packages that we observe in the data, but preventing bidders from internalizing the effect of each of their bids on their other bids' win probabilities. In practice, this is equivalent to assuming that each bid is associated with a distinct bidder, such that the substitution effect is eliminated but the competition and noise effects remain active.

The scoring rule maps bids into costs. We estimate the distribution of the shock components in this mapping, but the auction-specific draw of the rule is unknown. When calculating the costs that result from the chosen bids in the counterfactuals, we impose the mean scoring rule on every auction. To avoid confounding the three effects of interest with the change to the mean rule, we then compare the counterfactual results to the cost of the winning bid when the set of original bids is evaluated according to the mean rule.

[26] A number of papers have studied the geographic diversification motives of banks. See, for example, Rose (1995), Acharya et al. (2006), Deng and Elyasiani (2008), and Aguirregabiria et al. (2016).

This implies that the substitution effect can be calculated as the difference between the costs of the actual bids and the bids chosen under the assumption of no multiple bidding where both sets of costs are evaluated according to the mean scoring rule.

In the second counterfactual we remove uncertainty by setting the score function at the mean of the estimated shock distributions and supposing that bidders know this rule. Eliminating uncertainty shuts off all three effects: noise, competition, and substitution.

In the third counterfactual we force all bidders to use loss share (in addition to the continuous-bid component). This is similar to reducing uncertainty over all components in that it removes the incentive for multiple bidding and the noise effect. It concentrates all the bids in one package, which increases the perceived level of competition amongst bidders.

To compute the optimal strategy, we cycle through the bidders, updating the best response sequentially until the bidders are best responding to the equilibrium $\hat{G}$ function, calculated given the other bidders' strategies. An additional step is required to choose the packages for the no-uncertainty counterfactual. The optimal package for a given bidder can be calculated by comparing a bidder's v^s to Γ_s as announced by the FDIC. Note that the problem of computing the equilibrium in the general combinatorial auction is very difficult, since there are many combinations of packages on which to bid. We therefore restrict the set of counterfactuals to those for which the set of competitive bids L_i can be calculated before the joint solution of strategies and the distribution of opposing bids.[27]

7.3.1 Counterfactual costs

Table 6 provides point estimates from the three counterfactual experiments. Recall that our focus is on the restricted sample of 192 bank failures for which we can identify bidders. For these experiments we also drop the auction of Colonial Bank (Montgomery, Al.) because it is so much larger than all the other failures in the sample and therefore would receive too much weight in our levels results (this is not a problem for all of our earlier results, which are presented as percentage of assets).

The actual cost to the FDIC of resolving the remaining 191 failures was \$23.81 billion (\$124 million per failure). Using instead the mean scoring rule, we estimate this cost to be \$19.16 billion (\$99.79 million per bank). Using the mean scoring rule therefore slightly underestimates the cost to the FDIC. From column (3) we can see that eliminating uncertainty, which also removes the incentive for multiple bidding, lowers the cost to the FDIC relative to bids at the mean scoring rule by \$3.26 billion (17%) to \$15.90 billion. To

[27] In the counterfactual without uncertainty, bids include any components that they value more than the cost shift announced by the FDIC. For the no-multiple-bidding counterfactual, bids are made on the same set of packages, which allows us to isolate the substitution effect. In the loss-share-only counterfactual, we restrict to the loss-share-only package.

cover these additional costs would require an increase in the deposit insurance assessment rates of about 3 cents per 100 dollars of insured deposits.[28]

From column (4) we can see that the cost to the FDIC when strategic multiple bidding is removed is \$17.52 billion. From this we can determine that the substitution effect is \$1.64 billion (=\$19.16 billion - \$17.52 billion).[29] The combined impact of noise and competition is therefore \$1.62 billion (=\$3.26 billion - \$1.64 billion). In other words, the benefit of eliminating uncertainty comes almost evenly through a reduction of the substitution effect and the noise/competition effect. Bidders shade more when they can bid multiple times, since their bids compete against each other and they can take advantage of different auction-specific scoring-rule shocks. Noise also encourages bidders lower in the valuation distribution to shade more, hoping that a good shock will allow them to win anyway. These findings suggest that this noise effect overwhelms the competition effect, although we cannot separately identify these two factors.

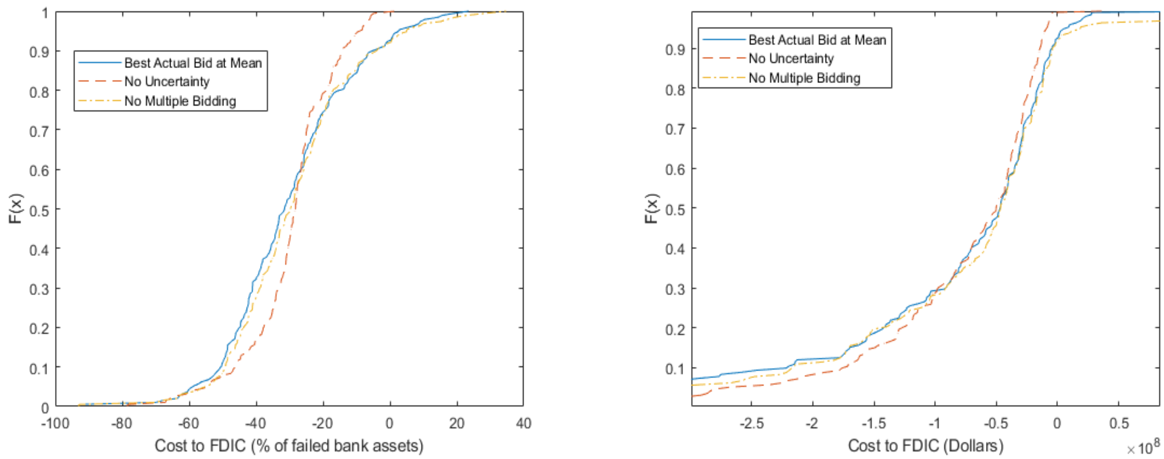
In column (5) we show the results from allowing only loss share. This leads only to a small benefit to the FDIC relative to column (3). The reason is the following: both policies increase the perceived level of competition. Low-value bidders have to bid more aggressively since there is no longer the benefit from uncertainty. As a result, high-value bidders are also more aggressive. As we show in Section 7.3.2, both policies ultimately have little impact on who wins the auction. The policies, instead, result in less bid shading.

Noise in the scoring rule introduces uncertainty in the level of bids. On the one hand, high-value bidders are close to the upper bound on bids, so favorable shocks to them provide little benefit. On the other hand, negative shocks could result in a loss to a lower-value competitor receiving a large positive shock, pushing the high-value bidder to shade less. Figure 4, Panel A, which plots the distribution of winning bids at the mean scoring and the two (main) counterfactual distributions, illustrates this phenomenon: the red dashed line (no uncertainty) is to the left of the solid blue line (winning bids at the mean scoring rule) at the top of the distribution. This can also be seen by comparing the counterfactual results for the different percentiles in Table 6.

From Panel A of Figure 4 it is not clear what is the total effect on costs from eliminating uncertainty, since the results are in terms of percentage of failed-bank assets. Therefore, without knowing the size of the failed banks in each part of the distribution, we cannot say anything about costs. To get a better sense of the cost impact, Panel B plots the distributions of the failure costs to the FDIC in dollar terms. It is clear that the area between the actual and counterfactual distributions is bigger at the bottom than at the

[28]The current baseline assessment rates range from 1.5 cents to 40 cents, see `https://www.fdic/gov/deposit/insurance/calculator.html`, accessed August 1, 2019.

[29]Recall that the restricted sample features fewer auctions with multiple bidding than the main sample. The estimated savings from removing multiple bidding reported here, therefore, are likely conservative.



Panel A Panel B

Figure 4: Distribution of winning bids for different scenarios
This figure plots, in Panel A, the distribution of winning bids as percentages of the failed bank's assets when bids are evaluated at the mean scoring rule (solid blue), and under the no-uncertainty counterfactual (dashed red) and no-multiple-bidding counterfactual (dash-dotted yellow). Panel B plots the distribution of winning bids in terms of dollar cost to the FDIC.

top, such that the total cost to the FDIC falls under the counterfactual of no uncertainty. Going back to Panel A, this means that the lower part of the counterfactual distribution of percentage of failed-bank assets (i.e., before its crossing with the factual distribution) includes more large failures.

Uncertainty is beneficial from the FDIC's point of view in small-bank auctions because the noise effect dominates the substitution effect. These auctions feature more bidders and valuation distributions with longer and fatter upper tails. As a result, the role of high-valuation bidders is magnified; they engage in less bid shading to protect against bad shocks. Note that the FDIC's earlier experiences with failures during the Savings and Loans crisis involved primarily very small institutions. As a result it had no opportunities to learn about the impact of uncertainty on resolution costs for large banks. In contrast, the recent crisis featured many larger failures, and for these the noise effect can actually operate in the opposite direction such that, overall, uncertainty is bad from the FDIC's point of view.

7.3.2 Counterfactual set of acquirers

Having shown that uncertainty is costly to the FDIC, we next evaluate the impact of removing uncertainty on the types of banks that win the auctions. The valuations for different packages depend on the bidder and failed bank observed traits, so the announcement of a scoring rule may either reduce or increase the asymmetries across bidders. This may shift the set of winners towards bidders with preferences for packages that the FDIC penalizes less heavily. Table 7 shows the packages that bidders choose under no uncertainty, compared to the original set of choices. In the counterfactual scenario, bidders switch on nonconforming less often, such that the package choice most commonly observed under uncertainty (conforming, no PB, no VAI, LS) is selected even more frequently. This is not surprising, since bidders with low valuations can no longer hope to benefit from a favorable shock by choosing a less common package.

Table 8 shows the impact of removing uncertainty on the mean and median traits of the winning bidders. Removing uncertainty has little effect on the size of the winning bank, but does lead to a slight increase in the distance between the failed bank and winning bidder. There is little impact of uncertainty in terms of commercial real estate and loan portfolios. Finally, we investigate the impact of the removal of uncertainty on the change in market concentration (HHI). Post-financial crisis, there has been renewed interest in market concentration for deposits and the relationship between the deposit and loan markets. In particular, there has been a substantial increase in market concentration in banking in the last decade. See, for example, Egan et al. (2017), Egan et al. (2016) and Aguirregabiria et al. (2018). Here we are interested in the role of auction uncertainty in explaining part of this increase. We do not find large changes in the concentration from eliminating uncertainty about the scoring rule. The main reason is that the winning bidder in the counterfactual is only rarely different than in the actual auction. The result is that uncertainty impacts bid shading, but not the winners.

8 Conclusion

This paper proposes a methodology for analyzing auction environments where bids are ranked according to multiple attributes chosen by bidders, but where there is uncertainty about the weight placed on the different components of the bid. We apply our approach to the resolution of failing banks in the U.S. We look at the role of auction uncertainty and multiple bidding in determining the allocation and revenues raised by the FDIC. The estimates indicate that the FDIC's secret scoring rule and requests for multiple bids are effective at increasing the competition that bidders face in these auctions, but overall, uncertainty is costly to the FDIC. The set of bidders that wins the auctions is fairly stable under the current rule and when uncertainty is removed. The size, distance, and balance-sheet traits of the median winner are comparable under the two rules, and the mean size and post-auction increase in market structure decrease only slightly when uncertainty is removed. However, removing uncertainty leads to less bid shading by large acquirers when acquiring large failing banks, and therefore removing uncertainty can lower the cost of resolution.

Table 5: Value shifters

This table provides estimates of the relationship between bidder and failed bank traits on bidder valuations of failing banks. The LHS panel reports results from the estimation of equation (8), while the RHS panel presents results for equation (11). Our first measure of distance is an indicator variable equal to 1 if the acquirer and failing bank have branches in the same zip code. Our second measure of distance is the average pairwise kilometers between all pairs of branches. In terms of balance sheet, we measure the distance between the acquirer and the acquired bank's portfolio shares for various loan categories. % Δ CRE is the difference of concentration in CRE of the bidding and failed bank. Bidder capitalization is measured by the Tier 1 capital ratio. Size captures the log of total assets of the failing bank. We also include the average change in deposit-HHI in zip codes where the failed bank is active that would result from the acquisition by a particular bidder. The estimates for LS, PB, NC, and VAI along with a set of fixed effects are estimated jointly, while the parameters in the column $\bar{v}$ are from a regression of these traits on the estimated bidder-auction fixed effects. Standard errors are computed via bootstrap over the estimated sampling variability from the estimation of the scoring function and the resampling estimation.

	Component valuations			Baseline valuations		
Package	Variable	Param.	SE	Variable	Param.	SE
Loss Share	Same Zip	-0.3398	0.542	Same Zip	-5.304***	0.617
	Portfolio	0.0382	0.048	Portfolio	-0.218***	0.0420
	Size	2.381***	0.226	Size Failed	7.205***	0.435
	Tier 1	0.0233	0.028	Tier 1	-0.0192	0.030
	Constant	-6.518***	2.605	Distance	-0.114***	0.0027
	Average	23.221		% Δ CRE	0.108***	0.009
PB	Same Zip	3.571***	1.139	Delta HHI	6.158***	1.349
	Portfolio	-0.788***	0.061	Constant	-91.464***	0.083
	Size	4.950***	0.9293	Year FE	Yes	
	T1	-0.282***	0.0259	State(FL,GA)	Yes	
	Constant	-82.05***	10.515			
	Average	-30.65				
NC	Same Zip	-1.368***	0.520			
	Portfolio	-0.011	0.0579			
	Size	1.213***	0.195			
	T1	0.028	0.018			
	Constant	-22.376***	2.398			
	Average	-7.47				
VAI	Same Zip	-4.263***	0.754			
	Portfolio	0.254***	0.063			
	Size	-0.565***	0.326			
	T1	0.051***	0.0138			
	Constant	0.677	4.349			
	Average	-4.724				
	N	4432			277	

Table 6: Impact of uncertainty and multiple bidding on FDIC costs

This table shows the impact of removing (i) uncertainty of the least-cost rule and (2) multiple bidding. Column (1) is data. Column (2) provides an estimate of losses using bids at the scoring rule. Column (3) looks at the impact of removing uncertainty. Column (4) is the impact from removing multiple bidding. Column (5) removes uncertainty by limiting the discrete options to only loss share. The numbers in parentheses are the cost to the FDIC as a fraction of the failed banks' assets. The auction of Colonial Bank, Montgomery Al is dropped.

	Actual	Bids at Scoring Rule	No Uncertainty	No Multiple Bid	LS Only
Total	-23.8119	-19.1596	-15.8982	-17.516	-15.084
Mean	-124.02	-99.7897	-82.8031	-91.2294	-78.56
P10	-315.86	-193.318	-127.18	-178.656	-163.06
	(-47.69)	(-39.81)	(-36.56)	(-47.56)	(-42.10)
P50	-47.5	-40.6387	-37.7784	-37.7717	-46.86
	(-26.12)	(-25.83)	(-21.08)	(-25.16)	(-25.30)
P90	-4.48905	-10.94	-10.386	1.677217	-13.23
	(-4.08)	(-15.65)	(-7.92)	(2.43)	(-12.30)

Table 7: Probabilities for different packages change with uncertainty

This table lists the observed frequency of each package in the subsample of auctions from which we compute the counterfactual, and the frequency with which that package is bid on in the counterfactual with no uncertainty. The packages are ranked by popularity.

Package				Percent of Bids	
Nonconforming	Loss Share	Partial Bank	VAI	Original	No Uncertainty
No	Yes	No	No	42.70	48.65
No	No	No	No	15.60	39.19
Yes	Yes	No	No	12.69	0.00
No	Yes	Yes	No	8.51	11.15
No	No	Yes	No	3.86	0.68
Yes	No	Yes	No	2.76	0.34
No	Yes	No	Yes	2.76	0.34
Yes	No	No	No	4.96	0.00
Yes	Yes	Yes	No	3.62	0.00
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	0.00
Yes	No	Yes	Yes	0.00	0.00

Table 8: Removing uncertainty can lead to different winners

This table shows the impact of removing uncertainty on the type of winners at auction.

	Mean		Median	
	Actual	No Uncertainty	Actual	No Uncertainty
Size	8.590	7.773	1.325	1.407
% CRE	21.872	22.759	22.937	22.937
% CI	9.660	9.483	8.887	8.991
Distance	429.051	475.924	203.281	222.088
Tier 1 Capital	16.199	15.721	13.996	14.036
Δ HHI Assets County	0.0283	0.0275	0.000	0.000
Δ HHI Deposits Zip	0.0061	0.0076	0.000	0.000
Δ HHI Deposits County	0.0458	0.0428	0.0370	0.0365
Δ HHI Branches Zip	0.0046	0.0057	0.000	0.000
Δ HHI Branches County	0.0252	0.0238	0.0191	0.0185

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A Data Source

Table 9: Source and variable description

The table presents the description of the raw variables used in our analysis. The variable name corresponds to the name in the original data set and the definitions of the variables are those provided by the FDIC, subject to some editing to conserve space. The data in the Statistics on Depository Institutions is extracted by the FDIC from banks' Quarterly Call Reports. The Summary of Deposits provides location and branch-level information. Additional Latitude/Longitude Information is filled in by zip code using data from `https://www.census.gov/geo/maps-data/data/gazetteer.html`

Variable	Description	Source
asset	The sum of all assets owned by the institution including cash, loans, securities, bank premises, and other assets. Excludes off-balance-sheet accounts.	SDI
ore	Total other real estate owned on a consolidated basis. Includes direct and indirect investments in real estate. The amount is reflected net of valuation allowances.	SDI
liabeq	Total liabilities, limited-life preferred stock and equity capital.	SDI
liab	Deposits and other borrowings, subordinated notes and debentures, limited-life preferred stock and related surplus, trading account liabilities and mortgage indebtedness.	SDI
dep	The sum of all deposits including demand deposits, money market deposits, other savings deposits, time deposits, and deposits in foreign offices.	SDI
coredep	Definition was changed in March 2011. Core deposits held in domestic offices now includes total domestic office deposits minus (1) time deposits of more than $250,000 held in domestic offices, (2) brokered deposits of $250,000 or less held in domestic offices. Prior to March 2010, core deposits were calculated as follows: Total domestic office deposits minus time deposits of $100,000 or more held in domestic offices.	SDI
naasset	Total assets, which are no longer accruing interest. Total assets include real estate loans, installment loans, credit cards and related loans, commercial and all other loans, lease financing receivables, debt securities and other assets	SDI
rbc1aaj	Tier 1 (core) capital as a percent of average total assets minus ineligible intangibles. Tier 1 (core) capital includes common equity plus noncumulative perpetual preferred stock plus minority interests in consolidated subsidiaries less goodwill and other ineligible intangible assets. The amount of eligible intangibles (including mortgage servicing rights) included in core capital is limited in accordance with supervisory capital regulations. Average total assets used in this computation are an average of daily or weekly figures for the quarter.	SDI

continued on next page

Variable	Description	Source
rbc1rwaj	Tier 1 (core) capital as a percent of risk-weighted assets as defined by the appropriate federal regulator for prompt corrective action during that time period.	SDI
bkclass	A classification code assigned by the FDIC based on the institution's charter type, charter agent, Federal Reserve membership status and its primary federal regulator.	SDI
lnlsgr	Total loans and lease financing receivables, net of unearned income.	SDI
lnre	Loans secured primarily by real estate, whether originated by the bank or purchased.	SDI
lnrenres	Nonresidential loans, excluding farm loans, primarily secured by real estate held in domestic offices. Loans secured by real estate as evidenced by mortgages or other liens on nonfarm nonresidential properties, including business and industrial properties, hotels, motels, churches, hospitals, educational and charitable institutions, dormitories, clubs, lodges, association buildings, homes for aged persons and orphans, golf courses, recreational facilities, and similar properties.	SDI
lnreres	Total loans secured by 1-4 family residential properties (including revolving and open end loans) held in domestic offices.	SDI
lnci	Commercial and industrial loans. Excludes all loans secured by real estate, loans to individuals, loans to depository institutions and foreign governments, loans to states and political subdivisions, and lease financing receivables.	SDI
lncon	Loans to individuals for household, family, and other personal expenditures including outstanding credit card balances and other secured and unsecured consumer loans.	SDI
zipbr	The Zip code associated with the physical address of the branch.	SOD
brnum	Numerical reference to identify a branch office within one institution.	SOD
charter	Identifies whether an institution is federally or state chartered.	SOD
depsumb	Branch office deposits as of June 30.	SOD
sims_lat	The lattitude of the branch's physical location.	SOD
sims_lon	The longitude of the branch's physical location.	SOD
stnumbr	The FIPS number of the state in which the branch is physically located.	SOD
stalp	The state abbreviation of the location of the institution's headquarters.	SOD
cntynumb	County number that corresponds to the county in which the branch is located.	SOD

B Additional Tables and Figures

Table 10: Principal component failed bank traits

The table presents the estimated coefficients from a principal component analysis. 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)* are the percentage commercial real estate (lnrenres), and commercial and industrial (lnci), respectively, of the total loans and leases (lnlsgr). *Tier 1 Capital Ratio (Tier 1 Ratio)* is the Tier 1 risk-based capital ratio, (rbc1rwaj). *Leverage Ratio* is the core capital (leverage) ratio (rbc1aaj). *NPL Ratio* is the sum of assets 90 days past due (p9asset) and the nonaccruing assets (naasset) as a share of the total loans and leases. *OREO Ratio* is other real estate owned (ore) divided by total assets. All these variables are then standardized by subtracting their mean value then dividing by their standard deviation.

	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
%ORE	-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

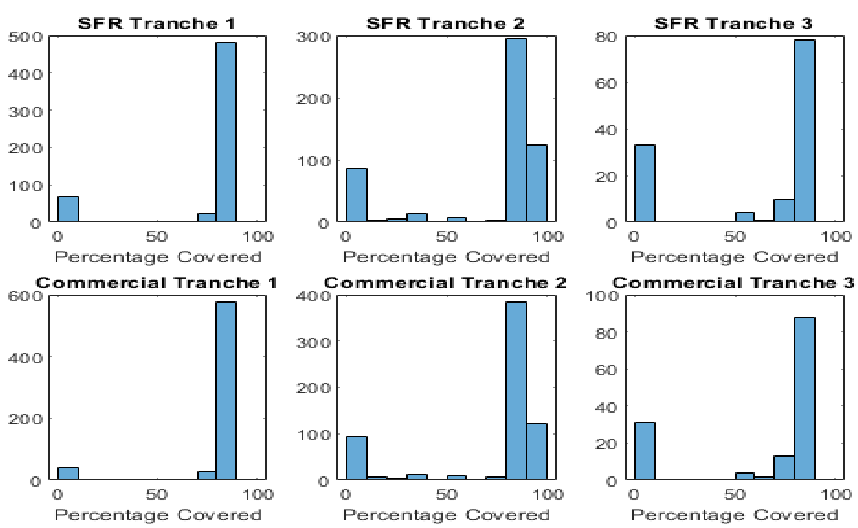

Figure 5: Loss-sharing agreements
Loss-share agreements for single-family residential mortgages (SFR) and commercial assets during our sample period. The y-axis is the number of bids made, with the percentages on the x-axis.

Bank Name	City	ST	CERT	Acquiring Institution	Closing Date	Updated Date
Jasper Banking Company	Jasper	GA	16240	Stearns Bank N.A.	July 27, 2012	January 29, 2019
Second Federal Savings and Loan Association of Chicago	Chicago	IL	27986	Hinsdale Bank & Trust Company	July 20, 2012	January 3, 2018
Heartland Bank	Leawood	KS	1361	Metcalf Bank	July 20, 2012	January 29, 2019
First Cherokee State Bank	Woodstock	GA	32711	Community & Southern Bank	July 20, 2012	October 6, 2017
Georgia Trust Bank	Buford	GA	57847	Community & Southern Bank	July 20, 2012	February 6, 2019
The Royal Palm Bank of Florida	Naples	FL	57096	First National Bank of the Gulf Coast	July 20, 2012	March 21, 2014
Glasgow Savings Bank	Glasgow	MO	1056	Regional Missouri Bank	July 13, 2012	August 19, 2014
Montgomery Bank & Trust	Ailey	GA	19498	Ameris Bank	July 6, 2012	January 29, 2019
The Farmers Bank of Lynchburg	Lynchburg	TN	1690	Clayton Bank and Trust	June 15, 2012	August 8, 2016
Security Exchange Bank	Marietta	GA	35299	Fidelity Bank	June 15, 2012	November 26, 2018

Figure 6: 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 7: 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.

Table 11: Summary statistics restricted sample

This table provides descriptive statistics of our restricted sample. We report balance sheet information for failed banks and bidders separately using data from the SDI for the quarter pre-failure. SDI labels are in parentheses. Variables include *Total Assets (asset), Total Deposits (dep), Insured Deposits (depins)*. Variables *Commercial Real Estate (lnrenses), Commercial and Industrial (lnci), Consumer (lncon), Single-Family Residential (lnreres), All Real Estate (lnre)*, are the shares of lending in each sector. *Core Deposits* is the share of total funding that is stable. *ROA* is return on assets and measures profitability. *Tier 1 Ratio*, is a measure of financial health. The portfolio percentage 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. Multiple bidding is an indicator if an auction featured more bids than bidders. The cost to the FDIC is the estimated loss from the press release data made on the date of failure. The bid premium is the transfer amount calculated using equation 1 divided by the total assets of the failed institution. HHI is calculated for both deposits and branches. The loan HHI is calculated using information on mortgage lending from the HMDA data set. Eighty-eight failed banks and 72 bidders did not have any lending to report under HMDA.

	N	Mean	SD	P10	P50	P90
Failed Bank Traits						
Total Assets ($ Millions)	193	576.12	1961.18	48.86	191.85	1181.17
Total Deposits ($ Millions)	193	492.594	1576.12	45.77	181.64	919.61
Insured Deposits ($ Millions)	193	434.65	1275.35	44.85	164.30	915.48
Commercial Real Estate (%)	193	24.13	11.84	10.26	22.46	41.46
Commercial and Industrial (%)	193	7.73	6.69	1.17	6.06	17.39
Consumer (%)	193	1.65	2.30	0.08	0.88	3.92
Single-Family Residential (%)	193	18.55	13.27	3.03	17.12	37.49
All Real Estate (%)	193	61.00	11.52	48.43	61.73	74.24
Core Deposits (%)	193	74.94	15.03	53.73	76.59	92.94
ROA	193	-7.48	7.67	-12.96	-5.69	-1.87
Tier 1 Ratio	193	1.08	3.39	-1.77	1.47	3.50
Bidder Traits						
(Avg. over participated auctions)						
Total Assets ($ Millions)	123	5973.8	1960	158.45	837.73	1340
Total Deposits ($ Millions)	123	4352	1360	125.90	666.43	9466
Insured Deposits ($ Millions)	123	3015	8577	108.12	539.73	7507
Commercial Real Estate (%)	123	22.85	12.28	7.21	21.31	39.69
Commercial and Industrial (%)	123	9.36	5.74	3.06	8.86	16.51
Consumer (%)	123	2.33	2.65	0.19	1.51	5.81
All Real Estate (%)	123	50.30	14.43	33.12	50.90	67.84
Single-Family Residential (%)	123	17.34	13.08	3.28	15.60	30.86
ROA	123	1.57	2.46	-0.06	1.07	3.82
Tier 1 Ratio	123	15.46	8.13	10.69	13.51	21.70

Continued on next page

continued from the previous page	N	Mean	SD	P10	P50	P90
Nbr of Auctions attended	343	2.40	3.43	1.00	1.00	5.00
Portfolio % Differences						
Commercial Real Estate	277	9.63	8.24	1.45	7.34	21.08
Commercial and Industrial	277	5.73	5.28	0.76	4.08	12.92
Consumer	277	2.36	3.21	0.13	1.32	5.79
Single-Family Residential	277	9.93	10.31	1.19	6.34	23.36
All Real Estate	277	15.31	11.43	2.21	13.57	31.86
Avg. Pairwise Distance (km)						
	277	487.62	736.13	26.16	206.81	1417.32
Auction characteristics						
Number of Bids	193	1.76	1.04	1.00	1.00	3.00
Multiple Bidding	193	0.16	0.363	0.00	0.00	1.00
Cost to FDIC ($ Millions)	193	137	347.55	10.96	48.0	329.0
Bid Premium	340	-0.13	0.30	-0.53	-0.07	0.15
% Δ in HHI from Acquisition						
Branches						
Zip Code	76	9.47	9.79	2.13	6.37	17.27
County Code	128	2.84	6.60	0.01	0.41	6.82
Deposits						
Zip Code	76	8.88	14.04	0.06	4.21	25.01
County Code	128	3.517	9.70	0.00	0.23	6.11
Loans						
County	92	0.25	0.71	0.00	0.01	0.85

C Testing for Independence Across Auctions

In Section 4 we assumed independence across auctions. This would be problematic if there were (i) learning across auctions, (ii) complementarities across auctions, or (iii) banks had capacity constraints, in the sense that winning one auction limited future participation. In an attempt to test for the presence of dependence across the auctions we study, we estimate two sets of regressions. We first consider a logit regression in which the dependent variable is an indicator that takes the value of 1 for winning bids. If bidders learn the scoring rule over time, we expect that increased experience should mean a bidder is more likely to win. If capacity constraints are present, bidders should bid less aggressively following a winning bid. Winning tightens the capacity constraints, leaving bidders only able to acquire only at a low price. In the case of complementarities, we expect to see more aggressive bidding following a win as the value of the subsequent acquisition is increased. Since these effects are potentially offsetting, we exploit variation in the tightness of the constraint across bidders and attempt to isolate capacity effects by comparing large bidders to poorly capitalized bidders. We then run separate regressions to look at the relationship of experience on the amount bid. Except for learning, which may reduce the amount bid as bidders learn to manipulate their package choice, the expected signs are the same. Results are presented in Table 12. In all specifications the number of participants is controlled for, producing a mechanical effect where the probability of winning is decreasing in the number of bidders.

Looking first at the logit regressions, the results from column (1) suggest that, in contrast to Zhang (1997), experience is negatively correlated with the win-probability of a bank. One possible explanation is that in the pre-FDICIA period studied in Zhang (1997) the FDIC had discretion to rank offers and might have favored more experienced bidders. 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. 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.

Table 12: Effect of experience on bidding competition

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, PC, 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.

Variables		Winner		Bidder premium	
	(1)	(2)	(3)	(4)	(5)
Experience	-0.0716***	-0.0751			
	(0.0140)	(0.0832)			
Experience pre-win			-0.0315	0.0129	0.0113
			(0.168)	(0.008)	(0.00764)
Experience post-win			-0.0474	-0.00424	-0.00361*
			(0.0473)	(0.00352)	(0.00196)
Nbr bidders	-0.570***	-1.539***	-1.517***	-0.00914	-0.00948
	(0.0507)	(0.212)	(0.209)	(0.00847)	(0.00840)
Large		-0.782		-0.0133	
		(0.671)		(0.0302)	
Large x Experience		0.0591		0.00198	
		(0.0838)		(0.0843)	
Low Capital		-0.277		0.0242	
		(0.466)		(0.0211)	
Low Capital x Experienced		-0.148		-0.0178**	
		(0.170)		(0.00763)	
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

D Additional Proofs

Proof of Theorem 1: Equilibrium Existence. Define Γ as a vector containing the FDIC's draws of $\epsilon, \psi, \kappa, \nu$ and $\boldsymbol{d}_k$ the vector of indicators taking a value of 1 if the component is included in package k. Define q_k as follows:

$$q_k \equiv max_{t \neq k}\{R, b_{-it} + \Gamma_t d_t + \delta_{-i,t}, b_{it} + \Gamma_t d_t + \delta_{it}\} - \Gamma_k \boldsymbol{d}_k - \delta_k^i. \tag{12}$$

We need to show that q_k has no mass points or kinks that can induce mass points, in the optimal bidding strategies. This is trivial compared to Cantillon and Pesendorfer (2006b) since we have assumed normally distributed bid-specific shocks. As in Cantillon and Pesendorfer (2006b), the game satisfies the conditions of Jackson et al. (2002) and an equilibrium exists. □

Proof of Theorem 2: Least-cost Identification. Consider the set of bids for whole bank, no loss share, conforming, and no VAI. The distribution of $\delta_2 - \delta_1$ is observed from the probability $Pr(b_1 + \delta_1 \geq b_2 + \delta_2) = Pr(b_1 - b_2 \geq \delta_2 - \delta_1)$, which we know from the observed auction results, and bid levels b.

Rewriting in terms of the characteristic functions gives:

$$Z(t) = \phi_y(t) = E[\exp(it(X))\exp(itX)] = \phi_x(t)\phi_x(t). \tag{13}$$

However, there are many $\phi_x(t)$ that could give the same Z(t), so we do not have nonparametric identification. Consider, as an example, $x_1 \sim N(\mu_1, \sigma_1^2)$ and $x_2 \sim N(\mu_2, \sigma_2^2)$ with $\mu_1 \neq \mu_2$. Using equation (13), we get $Z_1 = e^{(it(\mu_1-\mu_1)-\frac{\sigma_1^2+\sigma_1^2t^2}{2})}$ and $Z_2 = e^{(it(\mu_2-\mu_2)-\frac{\sigma_2^2+\sigma_2^2t^2}{2})}$. It is clear that for any μ_1, μ_2 this Z is the same, and therefore the mean is not identified.

We assume normality, and mean zero for the distribution of δ. Then because the distribution of the difference is observed, σ is identified.

Now consider all *as-is* winning bids. For these bids we observe their b and the resulting cost estimate. This means that the distribution of $u_j + \delta_{i,j}$ is observed from the sample of single-bid auctions. We represent that as $J(\cdot)$. Let m(t) denote the characteristic function of J and l(t) the characteristic function of the distribution of u. It must be that $l(t) = m(t)e^{\frac{\sigma^2t^2}{2}}$, and l(t) is identified.

Now consider all the winning bids with one additional component. Without loss of generality, let the bid only include loss share. Then, the distribution of $u_j + \gamma_{ij} + \epsilon_j$ is observed. Call the characteristic function for this new observed distribution $q(t)$ and for ϵ $r(t)$. Then $q(t) = l(t)r(t)$, and since q is observed from the data and l is observed, we can solve for a unique $r(t)$. □

Proof of Theorem 3: Identification. By Theorem 1, there exists an equilibrium in this game, and the equilibrium is monotone in bidders' private information within a given package. Therefore, by Theorem 1 in Cantillon and Pesendorfer (2006b), the v_ijk of the player for a given package is observed if they bid on it. For the packages where they do not bid, we observe only a bound. We impose the form in Equation 8, and this gives a standard regression formula with bidder-level fixed effects $\overline{v}$. Multiple bidding allows us to identify the fixed effects along with the β terms in this model as per usual arguments. $\square$