Field Experiments on the Effects of Reserve Prices in Auctions: More Magic on the Internet

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First Version: October 1995

This Version: February 2005

Abstract

I present experimental evidence on the effects of minimum bids in first-price, sealed-bid auctions. The auction experiments manipulated the minimum bids in a preexisting market on the Internet for collectible trading cards from the game *Magic: the Gathering*. I examine a number of outcomes, including the number of participating bidders, the probability of sale, the levels of individual bids, and the auctioneer's revenues. The benchmark theoretical model is one with symmetric, risk-neutral bidders with independent private values. The results verify a number of the predictions concerning equilibrium bidding. Many bidders behave strategically, anticipating the effects of the reserve price on others' bids.

[1] Department of Economics, the University of Arizona. I gratefully acknowledge financial support from the National Science Foundation via grants SBR-9811273 and SES-0094800. I wish to thank Michael Urbancic, Marius Hauser, and Mary Lucking for their research assistance, and Skaff Elias for product information about *Magic: the Gathering*. I am grateful to participants in the IO Workshop at MIT, the Russell Sage Foundation Workshop in Behavioral Economics, the North American Summer Meetings of the Econometric Society, and seminars at CalTech and the University of Michigan for their comments. I would also like to thank Editor Rob Porter, two anonymous referees, J.S. Butler, Rachel Croson, Elton Hinshaw, Dan Levin, Kip King, Preston McAfee, John Morgan, Jennifer Reinganum, John Siegfried, Mike Urbancic, and especially Glenn Ellison for invaluable advice and constructive criticism.

1 Introduction

There has been considerable theoretical work on the effects of minimum bids (or reserve prices) in auctions, but little empirical work. This paper represents an attempt to fill this gap. I report experimental tests of the theory of reserve prices in first-price, sealed-bid auctions, using field experiments in a preexisting market. The experimental data verify the predictions of the theoretical model developed by Vickrey (1961) and extended by Riley and Samuelson (1981). In particular, bidders exhibit sophisticated strategic reactions to changes in reserve prices, as predicted by the theory. In addition, I present empirical results on the relationship between mean revenues and the minimum-bid level.

Empirical studies of auctions can be divided into laboratory experiments and field-data studies. Dozens of laboratory experiments have tested different predictions of auction theory (Kagel (1995)). Empirical work using field data, is more limited in testing theory, because of data restrictions (Hendricks and Paarsch (1995)). My methodology is a hybrid of the laboratory and traditional field research; hence the term "field experiment." In Lucking-Reiley (1999), I used a similar methodology to test revenue equivalence of auction formats.

Neither laboratory nor field studies have focused much attention on the levels of reserve prices.[2] A few studies of eBay auctions, such Bajari and Hortacsu (2003), include the effects of minimum-bid levels in their regression results, but this is not the main focus of their work. By systematically varying reserve-price levels, I confirm several predictions of auction theory: increasing the reserve price decreases the number of bids received and the probability of selling the good, and increases revenue for goods which are actually sold. Perhaps most interesting is the result that that bidders react strategically to the existence of reserve prices, as predicted by

[2] McAfee, Quan, and Vincent (2002) and Paarsch (1997) are primarily concerned with reserve prices, and both contain empirical work (on real estate auctions and timber auctions). Both make normative predictions, using data on auction outcomes in order to predict optimal reserve prices for the auctioneer. In contrast, I investigate a positive question: do reserve prices result in the effects predicted by theory?

Bayesian Nash equilibrium theory.

The paper is organized as follows. Section 2 reviews the testable implications of the effects of reserve prices in auctions, based mainly on Riley and Samuelson (1981). Section 3 describes the history and institutional details of the marketplace for collectible trading cards, where these field experiments took place. Section 4 describes the two experimental designs used in this study, along with a demographic description of the experimental subjects. Section 5 describes the results of the experiments, and the paper concludes with a brief summary and suggestions for future research.

2 Theoretical Background

There is a large theoretical literature on reserve prices in auctions (Wilson (1992) and McAfee and McMillan (1987a)), but little of it focuses on testable predictions. In this section, I review the testable implications of the earliest and simplest model of auctions, due to Vickrey (1961), which assumes independent private values (IPV)[3] and an exogenous number of bidders.[4] I do this because of the simplicity of the model, for which the implications of reserve prices were first considered in detail by Riley and Samuelson (1981). Although more general models are available, I focus on this classic model as a first step in the empirical investigation of the effects of reserve prices, to examine the basic model's predictive power. It is an open question whether more complicated models perform better in some circumstances.

In the model of Riley and Samuelson (1981), the effects of reserve prices are relatively straightforward. Setting an optimal reserve price allows the auctioneer to extract a bit of

[3] Many recent theories of auctions have focused on the affiliated-values model proposed by Milgrom and Weber (1982), where individuals' values for the good may be privately uncertain, with signals of uncertain value that are correlated among bidders. For a theory of reserve prices in an auction with affiliated values, see Levin and Smith (1996).

[4] Samuelson (1985), Levin and Smith (1996), and McAfee, Quan, and Vincent (2002) present models of auctioneers' reserve prices in auctions with an endogenous number of bidders. In such models, bidding is costly, and therefore bidders must decide whether or not to participate. Reiley (2005) uses experimental data to examine such models.

additional profit from the highest bidder, above and beyond the profits that would result merely from competition between bidders. In effect, a minimum bid represents a take-it-or-leave-it offer from the auctioneer to the highest bidder.[5]

If N bidders' valuations are drawn independently from a distribution function with CDF $F(v)$, and if the auctioneer holds a first-price, sealed-bid auction with reserve price r, then the symmetric Bayesian Nash equilibrium to the bidding game involves each bidder submitting a bid according to the following bid function:

$$b(v;r) = \begin{cases} v - \dfrac{1}{F(v)^{N-1}} \displaystyle\int_r^v F(u)^{N-1} du, & v \geq r \\ 0, & v < r \end{cases} \tag{1}$$

We can also consider the impact of the reserve price r on the auctioneer's revenue.[6] The expected revenue $R(r)$ to the auctioneer is equal to the expected bid of the bidder with the highest valuation for the good, if there is at least one bid. Riley and Samuelson (1981) derived the following expression for this quantity:

$$R(r) = \int_r^\infty b(v;r) \cdot N \cdot F(v)^{N-1} f(v) dv = N \cdot \int_r^\infty [vF'(v) + F(v) - 1] F(v)^{N-1} dv \tag{2}$$

For example, suppose that bidders' valuations are distributed according to a uniform distribution on [0,1]. Then the bid function is:

$$b(v;r) = \begin{cases} \dfrac{N-1}{N} v + \dfrac{r^N}{Nv^{N-1}}, & v \geq r \\ 0, & v < r \end{cases} \tag{3}$$

With zero reserve, the bid function is linear with slope equal to *(N-1)/N*. With reserve price $r > 0$, a bidder submits no bid unless his value v exceeds r, in which case his bid is again

[5] The auctioneer may instead use an implicit, or secret, reserve price. The highest bidder still wins the item only if he exceeds the amount of the reserve, though he does not know in advance what this reserve price is.

[6] I focus on revenues instead of auctioneer *profits*, which are identical to revenues only if the auctioneer has zero salvage value for the goods. I focus instead on revenues because of their easy measurability. Computing expected profits requires an estimate of my salvage value for the goods, which is necessarily arbitrary.

increasing in the number of bidders. Furthermore, this bid lies above the zero-reserve bid function for all valuations $v \geq r$.

The auctioneer's expected revenue, from equation 2, is given by:

$$R(r) = \frac{N-1}{N+1} + \left(1 - \frac{2N}{N+1} r\right) r^N \tag{4}$$

The optimal reserve price $r = 0.5$ is independent of the number of bidders.[7] The gains to setting an optimal reserve price become very small as N increases. For example, an increase in the reserve price from zero to its optimal value, increases revenue by 25 percent when $N = 2$, but only by 0.78 percent when $N = 5$. For larger N, competition between bidders creates high rents for the auctioneer, which begins to swamp the revenue effect of the reserve price.

The most basic general predictions are that increasing the reserve price should (1) reduce the number of bidders who submit bids, by screening out those bidders with low valuations, (2) reduce the probability of the good's being sold, and (3) increase the revenue earned on a good, conditional on its being sold. A fourth, more subtle prediction depends on the presence of strategic behavior by bidders: that $b(v;r + \Delta r) > b(v;r)$ for all $v > r + \Delta r$, or that an increase in the reserve price will cause a strict increase in the bid for a given bidder. From 1, $\partial b/\partial r = \left[F(r)/F(v)\right]^{N-1} > 0$ for all $v > r$. In Bayesian Nash equilibrium a bidder realizes that an increase in the reserve price will increase the bids of the other bidders who choose to remain in the auction, and therefore will increase his own optimal bid level as well. Finally, we might expect the revenue curve to be more steeply sloped above the optimal reserve than below, as

[7] The fact that the optimal reserve level is independent of the number of bidders turns out to be a general result of the IPV model, for any value distribution $F(v)$, as proven by Riley and Samuelson (1981). The result follows directly from differentiating equation 2 with respect to r, using Leibniz' rule:

$$\frac{dR}{dr} = N \cdot F(r)^{N-1}\left[1 - F(r) - r \cdot f(r)\right].$$

Setting this expression equal to zero yields an expression for the optimal reserve price that is independent of the number of bidders. This may or may not be a global optimum, depending on the distribution of values $F(v)$. The revenue curve has a unique optimum if and only if the equation $vF'(v) + F(v) - 1 = 0$ has only one root. This is satisfied for any distribution with a monotone hazard rate, which is a condition often assumed for convenience by theorists.

expected revenues fall off with the reduced probability of sale.

3 Institutional Background

This paper uses data collected from field experiments with online auctions for cards from the game *Magic: the Gathering*.[8] Introduced in 1993, the game of Magic casts players as dueling wizards, whose individual decks of cards represent their libraries of magic spells. Successive editions of the game introduced over a thousand new card types, some more rare than others, sold in random assortments. Players and collectors developed various trading mechanisms for obtaining desired cards from each other, the most interesting of which took place on the Internet. Although the World Wide Web was not yet in common use at the time, a number of auctions and other trades took place via a text-based newsgroup devoted to discussions of the game. As this newsgroup became overwhelmed by auctions and other offers to trade, a second newsgroup was created exclusively as a marketplace.[9] The marketplace became one of the highest-volume discussion groups on the Internet, with over 6,000 messages a week, during the period of this study.[10]

In my analysis, I make use of a list of reference prices known as the Cloister price list.[11] A trader named Cloister Bell wrote a program to search the marketplace newsgroup for each instance of each card name (with some tolerance for misspellings) and gather data on the prices posted next to each card name in the newsgroup messages. It then computed trimmed means, standard deviations, quantiles, and so on, and automatically posted these data on the Internet for public view. The Cloister prices were recomputed each week, with archives of previous weeks made publicly available. Each card's price on the list represents the trimmed mean of hundreds (or thousands) of individual observations. Such observations may have come from auctions in

[8] For additional details and further work on *Magic* auctions, see Lucking-Reiley (1999) and Reiley (2005).
[9] The primary newsgroup was <rec.games.deckmaster>, while the newsgroup dedicated to trading was <rec.games.deckmaster.marketplace>, which was later renamed to <rec.games.trading-cards.marketplace>.
[10] Source: *Top 40 Newsgroups in Order by Traffic Volume*, April 1995.
[11] Black (1995).

progress (perhaps with low opening prices), from consummated trades, or from advertised prices too high to actually result in trades. Despite the variability of the underlying observations, a number of people found the trimmed-mean Cloister prices to be a reliable measure of card value: I frequently observed traders using the Cloister list as their standard price reference.[12]

Presaging the development of eBay and other online-auction Web sites, The email-based market for *Magic* cards presaged the amazing variety of ecommerce now accepted as commonplace and quotidian. At the time, the *Magic* card market also provided a novel means to run controlled experimental auctions in the field rather than in the laboratory.[13] Since in any given week there were dozens of auctioneers holding *Magic* auctions on the Internet, an experimenter could be a "small player" who did not significantly perturb the overall market.

One of the strengths of this study is the subject pool. The bidders in these experiments had diverse demographic backgrounds,[14] but shared an intense interest in the auctioned items, making them representative subjects for a test of auction theory. This research project used only limited-edition cards, whose relative scarcity it was thought would attract more buyer interest as well as fetch a higher and larger range of prices.

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[12] Scholars occasionally claim that the existence of potential resale value (as is the case with *Magic* cards) automatically implies that bidder valuations have a common-value (CV) component, rather than having independent private values (IPV). However, recent theoretical work by Haile (1999, 2003) demonstrates that resale opportunities do not automatically put auctions into the common-value category. Bidding strategies with resale can be essentially different from standard theories of auctions with either IPV or CV. Furthermore, the important strategic considerations with resale have to do with the resolution of uncertainty about the item's resale value after the initial auction, but in this market one might argue that resale market opportunities are relatively well known before bidding occurs. Finally, many of the bidders in Magic card auctions are primarily interested in the cards for their own use, rather than for resale. Cards are available for sale at a variety of sources, with considerable price dispersion across sellers. Because people have different access to information on card prices, and different values for the amount of time it takes to search for a bargain, we might realistically expect the effective valuation for the good, a "valuation net of search cost," to vary from bidder to bidder. For these reasons, the IPV model seems a plausible approximation to the truth, and certainly a good benchmark.

[13] Of course, this also meant giving up some of the useful controls of the laboratory environment. For example, I could not observe the bidders' valuations or ensure common knowledge of the number of bidders or the distribution of values. In a field experiment, one cannot verify many of the underlying assumptions of a theory; instead one checks whether the predictions of the theory hold true.

[14] For more detailed demographic information about the bidders, see Reiley (1996), available on request. The bidders, from all over the United States and several foreign countries, included college students, professional engineers, government employees, and military personnel.

4 Experimental Procedure

Two distinct experimental designs are used in this paper. The first examines the effects of a binary variable: whether or not minimum bids were used. By auctioning the same cards twice, once with and once without minimum bids, the design exploits within-card variation to find the effects of the treatment variable on bidding behavior. The second design investigates the effects of a continuous variable: the reserve price level (expressed as a fraction of the Cloister reference price). The across-card variation provides information that can be used to test predictions about the shape of the revenue curve $R(r)$ as a function of the reserve price level.

4.1 Within-Card Experiments

The first part of the data collection consisted of two pairs of auctions. Each of the four auctions was a sealed-bid, first-price auction of several dozen individual *Magic* cards.[15] This simultaneous auction of many different goods at once was the norm for *Magic* card auctions on the Internet, and therefore natural for the bidders.

Each auction lasted one week, from the time the auction was announced to the deadline by which all bids had to be received. I announced each auction to potential bidders via two channels. First, I posted three announcements to the appropriate Internet newsgroup. For each auction, I posted three newsgroup messages spaced evenly over the course of the auction. Second, I solicited some bidders directly via personal email messages. My mailing list for direct solicitation was comprised of people who had already demonstrated their interest by participation in previous Magic card auctions.

The paired-auction experiment proceeded as follows. First, I held a zero-minimum-bid auction for 86 different cards (one of each card in the Antiquities expansion set). The subject line of the announcement read “Reiley's Auction #4: ANTIQUITIES, 5 Cent Minimum, Free

[15] A few of the auction items I denote as “cards” were actually groups of cards: either a sealed pack of out-of-print cards, or a set of common cards bundled together.

Shipping!" so that potential bidders might be attracted by the unusually low (essentially zero) minimum bid per card.[16] After the one-week deadline for submitting bids had passed, I identified the highest bid on each card. To each bidder who had won one or more cards, I emailed a bill for the total amount owed.[17] After receiving a winner's payment via check or money order, I mailed them their cards.[18]

I also emailed a list of the winning bids to each bidder who had participated in the auction, whether or not they had won cards, as an attempt to maintain my reputation. I did not give the bidders any explicit information about the number of people who had participated in the auction, or the number who had received email invitations to participate.

One week after the end of the first auction, I ran the second auction in the paired experiment, this time with reasonably high minimum bid levels on each of the same 86 cards. The minimum bid levels for each card were set at 90 percent of the standard (trimmed-mean) Cloister price.

This contrast in minimum bid levels (zero versus 90 percent of the Cloister price list) was the key difference between the two auctions.[19] By keeping other conditions identical between the two auctions, I attempted to isolate the effects of minimum bids on potential bidders' behavior. One condition that could not be kept identical, unfortunately, was the time period during which the auction took place. Because the two auctions took place two weeks apart, there were

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[16] A 5-cent minimum is effectively no minimum, since the auction rules required all bids to be in integer multiples of a nickel.

[17] Although the standard practice in this marketplace is for auctioneers and other card sellers to charge buyers for postage and/or handling, I did not do so. I wanted bidders to bid independently, as much as possible, on each of the cards in which they were interested. Someone interested in one card might bid higher on a second card in the same auction than they would if the cards were auctioned independently, as incremental postage costs are lower if more than one card is acquired. In addition, some of the cards had low Cloister values, and I wanted to avoid having the card values be swamped by the cost of shipping. For example, if a bidder won a single card for 20 cents and then had to pay a fixed 50-cent shipping charge on top of that, the amount of useful information which could be derived from her bid would be suspect.

[18] A small number of winning bidders failed to pay. In all, I received payment for 90 percent of the cards sold, constituting 89 percent of the reported revenue in the within-card auctions. Almost all of the "deadbeat" bidders were those who won only a single card, and who explained that they had originally hoped to win more cards, and didn't feel it was worth it to complete the transaction. Out of 170 winning bidders in the eight auctions, only eight won multiple cards but failed to pay. Since none of the unpaid cards had high winning bids, I assume that all bids were made in good faith, and do not exclude any from the analysis.

[19] The only other differences between the two were that they ran during different seven-day periods, the subject line of announcement for the 90% Cloister minimum price auction omitted the phrase "5 Cent Minimum," and some changes were made to the advertising mailing list (see footnote 23).

potential differences between them that might have affected bidder behavior. First, the demands for the cards (or the supplies by other auctioneers) might have changed systematically over time, which is a realistic possibility in such a fast-changing market as this one.[20] Second, the results of the first auction may have affected the demand for the cards sold in the second auction.[21]

To control for temporal variations, I simultaneously ran the same experiment in reverse order, using a different sample of cards. This second pair of auctions each featured the 78 cards in the Arabian Nights expansion set, with minimum bids present in the first auction but absent in the second. Just as before, minimum bids were set at 90 percent of the Cloister market price level. The first auction in this pair began three days after the start of the first auction in the previous pair, so that the auctions in the two experiments overlapped.[22] I used a larger mailing list for my email announcement in this pair of auctions (232 people) than I had for the previous pair of auctions (50 people), with the first mailing list being a subset of the second mailing list.[23] Also, the Arabian Nights cards in the second pair (median reserve price $8.36) were more valuable than the Antiquities cards used in the first pair (median reserve price $4.41). Otherwise, all other conditions were identical between the two pairs of auctions.[24]

Table 1 reports the number of participating bidders, the number of bids received, and the

[20] For example, certain cards from the Arabian Nights expansion set increased in value by a factor of ten during their first year out of print. Cloister prices were stable during the month in which this experiment was conducted.

[21] For example, suppose that a bidder is anxious to obtain a Guardian Beast card for her deck, and her valuation is much higher than that of the other bidders. She may win the card in the first auction, and have no demand for that card in the second auction. If this is the case for most cards, the highest-value bidders are screened out in the first auction, and we might expect to see lower revenues in the second auction.

[22] This timing was designed in part to make sure I had time to process bids and announce results in a timely manner; two auctions ending the same day might have been more work than I could handle. In subsequent research, I have taken advantage of eBay to conduct more carefully controlled experiments, where treatment and control auctions start and end the same day. eBay also makes it easy to recruit sufficient bidders without having to maintain private mailing lists as I did here. See Katkar and Reiley (2004).

[23] I added a large number of names to my mailing list when a new list of names became available to me; it was important to me (for both financial and experimental reasons) to maintain a large number of participating bidders. Many of the additions turned out not to be interested; they were subsequently dropped (see footnote 26). The number of invited bidders was not a variable of primary interest in this study.

[24] A sample auction announcement is posted at:
http://uaeller.eller.arizona.edu/~reiley/papers/MoreMagicAuctionRules.pdf

total payments received from winning bidders for the four sets of auctions.[25] Note two key points. First, "real money" was involved in the auction transactions. Of the 73 different bills I sent to winning bidders over the course of the experiment, the median payment amount for each auction was between $10 and $24. A few individual payments exceeded $100. Second, in each auction there are many winning bidders. The number of winning bidders in each auction ranges from 6 to 27, and the fraction of bidders who win at least one card is between 40 percent and 86 percent. In each auction, the median number of cards won by each winner is between 2 and 3.5, while the maximum number of cards won by a single bidder ranges from 12 to 26. Except in Auction AR, no winner won more than 29 percent of the cards sold in any single auction. (In Auction AR, only 7 people submitted bids, 6 of whom won at least one card, and 39 of the cards went unsold.) The biggest spender paid $316.50 (or 41%) of the total revenue of $774.75 in Auction BA, despite winning less than 15 percent of the cards - evidently, she was interested only in high-value cards.

In my statistical tests below, I will be assuming independence of observations across cards. This is a weakness of the analysis, because some bidders might be interested in winning groups of cards that they find to be complementary to each other for collecting or game play, but I have no way to measure such complementarities in bidder values. The best I can do is to note that no single bidder ever determines the winning prices for all cards in an auction.

4.2 Between-Card Experiments

A second set of experiments was designed to examine the effects of changes in the *level* of the reserve price, rather than merely changes in the *existence* of reserve prices. Four first-price, sealed-bid auctions took place, each with a one-week timeframe for the submission of bids. Each was a simultaneous auction of 99 different items, this time with no overlap of items

[25] Table 1 and the text refer to the auction sets by the following abbreviations: AA – *A*ntiquities (*A*bsolute), AR – *A*ntiquities (*R*eserve), BA – Ara*b*ian Nights (*A*bsolute), and BR – Ara*b*ian Nights (*R*eserve).

between auctions, and each card had a posted reserve price. Just as before, each auction was announced via three posts to the relevant newsgroup, as well as via email to a list of bidders.[26]

In each of the first two auctions, nine cards were auctioned at a minimum bid of 10 percent of the Cloister price, nine at 20 percent, nine at 30 percent, and so on, up to 110 percent of the Cloister price. After noticing interesting results in these two auctions at relatively low and relatively high reserve prices, I increased the number of observations in these regions. Therefore, the third and fourth auctions auctioned equal numbers of cards at reserve levels of 10, 20, 30, 40, 50, 100, 110, 120, 130, 140, and 150 percent of the Cloister price.[27]

The variation in reserve prices was designed to investigate how bidder behavior and auction revenue would change, and to calculate the revenue-maximizing reserve price level. Normalizing by the Cloister price makes cross-card comparisons feasible. Besides the exceptions noted above, all experimental protocols and bidder instructions were identical to those in the auctions described in section 4.1.

Summary statistics for the between-card auctions are given in Table 2. The average reserve price varied slightly from auction to auction, from 60 percent to 85 percent. Each auction had dozens of bidders and hundreds of bids on individual cards. The number of people receiving email invitations to participate declined with each successive auction, due to recipients asking to be removed from my mailing list, but the number of interested participants should be similar. The data from the between-card auctions are not directly comparable to that those the within-card auctions, because the size and composition of the pool of participating bidders changed and six months passed. Very few bidders participated in both experiments; most of the bidders in the between-card experiment were new recruits. Table 2 also displays some aggregate statistics on

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[26] For this series of auctions, the bidder pool was larger. As stated before, I added new bidders to my mailing list over the course of the research program (by contrast, within any single experiment I tried to hold the potential bidder pool constant).

[27] I made some errors in computing the minimum bid levels in these auctions, so the numbers were not quite equal. Some cards were mistakenly assigned reserve levels of 60 percent and 90 percent, but this does not compromise the integrity of the data.

revenue, including the total Cloister value of all the cards in each auction and the total revenue earned on cards sold. The four auctions generated revenues close to the total Cloister value of the cards, and only 13 percent of the cards were not sold.

5 Results

In the first subsection below, I consider two basic predictions: whether the number or bids and the probability of sale decline with the reserve price. I then examine whether a reserve price increases revenues conditional on a sale, and then consider the effects on unconditional expected revenues. Finally, I test the prediction that bidders react strategically to reserve prices, and raise their bids.

5.1 Number of bids and probability of sale

Higher reserve prices ought to reduce both the number of bidders and the probability of selling the item, because they screen out low-value bidders. These predictions do not require bidders to act strategically; they require only that bidders participate at low reserve prices but stop participating at higher reserve prices. Note that while these predictions should be satisfied under most bidding strategies, it is also possible that the predictions could be violated. For example, some bidders might not bid in auctions where the reserve prices are low, if they assume that none of the items are valuable enough to bother with. Data have not previously been available to test even these basic predictions.

In the within-card experiment, the number of bids declined with the imposition of reserve prices, as shown in Table 1. In experiment A, the imposition of nonzero minimum bids reduced the number of participating bidders from 19 to 7, and the number of individual card bids from 565 to 71. Similarly, the imposition of minimum bids in experiment B lowered the number of participating bidders from 62 to 42, and the number of submitted bids from 1583 to 238.

The probability of sale also decreased when reserve prices were imposed. As shown in Table 1, all cards were sold in the auctions without minimum bids (Auctions AA and BA). When nonzero reserve prices were imposed (Auctions AR and BR), the number of cards sold declined from 86 to 47, and from 78 to 74, respectively. The effect was greater for the thin bidder pool in experiment A, in Auction AR.

The between-card auctions allow me to measure how outcomes vary with different levels of the reserve price. One may think of the cards as having been assigned to one of fifteen discrete "bins," each of which represents a different reserve level.[28] There are at least 16 observations in each bin, so it is possible to estimate the number of bidders and the probability of sale as a non-parametric function of the reserve price *r*, by regressing the auction outcome variable on a set of bin dummies (denoted by 10%RES through 150%RES). In the absence of other regressors, this would be equivalent to computing the mean of the dependent variable in each of the fifteen bins. These regressions also include as control variables the Cloister value of each card (CLOISTER) and a set of dummy variables (R1, R2, R3, R4)[29] for the four auctions.[30] The results of the regressions are reported in Table 3. The dependent variables are NUMBIDS, the number of bids received on a given card, and SOLD, an indicator variable for whether the auction resulted in a sale or not.

The results for NUMBIDS confirm that the number of bids is a monotonically decreasing function of the reserve price level, particularly for reserve prices between 10 percent and 70 percent of Cloister value. The coefficients decline from 9.8 at a reserve price of 10 percent down to 1.0 at a reserve price of 70 percent.[31] At higher reserve-price levels, all bin coefficients have point estimates less than 1.0 and are insignificantly different from each other at the 5-percent

[28] When rounding was necessary in order to satisfy my requirement that all minimum bids be in even multiples of 5 cents, I always rounded down to the nearest nickel. Thus, the 10-percent bin contains cards whose reserve prices were less than or equal to 10 percent of Cloister value, the 20-percent bin contains cards whose reserve prices were between 10 percent and 20 percent of Cloister value, and so on.

[29] Auction dummy R4 is the omitted category in the regression results.

[30] The Cloister value is relevant if more valuable cards attract more bidder interest. The auction dummies are potentially relevant because of the simultaneous auction of sets of cards; for example, an auction with ten $10 cards might attract more bidders than an auction with only six $10 cards, so that the same fifty-cent card might attract more bidders if it were included in the former auction than in the latter.

[31] When CLOISTER is evaluated at its mean value, this indicates that in the base auction R4, there are an average of 10.7 bidders at reserve levels of 10 percent, and 2.1 bidders at reserve levels of 70 percent.

level of significance. The slope of $n(r)$ is negative, as predicted.[32]

The empirical probability of sale similarly is a decreasing function of the reserve-price level. The results of a linear-probability model, with SOLD as the dependent variable, are reported in Table 3.[33] The table shows that the base probability of sale is decreasing in the reserve price, from 0.95 for the 10 percent reserve bin to 0.49 for the 140 percent reserve bin. The decline in the coefficient point estimates is not monotonic in the reserve price, but the standard errors are large enough that one cannot reject for any pairwise comparison of bins (except one)[34] the hypothesis that the larger reserve price bin has a coefficient less than or equal to the coefficient for the bin at the smaller reserve price. The coefficients on the first four bins *are* pairwise significantly greater than the coefficients on the last four bins, indicating a decline in the probability of sale as the reserve price increases.[35]

5.2 Auction revenue conditional on sale

Next, I consider the prediction that reserve prices increase revenue on those goods that are sold, beginning with the within-card experiments. Table 1 contains a row labeled "Revenue

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[32] The Cloister value of the card also has a positive and significant coefficient, indicating that more bidder interest is generated by more expensive cards. This makes sense for a market in which the transaction cost of purchasing a $10 card is a negligibly small fraction of the card value, but where the 32-cent cost of mailing a check for a 50-cent card may discourage bidder interest. The coefficients on the auction dummies indicate that that Auctions R1 and R2 had significantly more participation than did Auctions R3 and R4. This may reflect the fact that the average reserve prices in the first two auctions were lower than in the latter two auctions. That is, bidders appear to have been more likely to bid in on a particular card set if there were more potential bargains available.

In another specification, not reported here, I added a set of interaction terms that allowed the coefficient on Cloister value to be different for each reserve-price bin level. The results were qualitatively the same as in the specification reported in Table 5, with the additional result that the Cloister value significantly influences the number of bidders only when the reserve price is low. The interaction coefficients were positively and statistically significant (at the 5-percent level) only for 10%RES through 60%RES, but insignificantly different from zero for 70%RES through 150%RES. Thus, a valuable card at a low reserve price attracted more bids than did a cheap card at a low reserve price, but the same was not necessarily true at high reserve prices.

[33] In addition to the linear-probability model, I also tried a probit specification. The probit had the disadvantage that I was unable to identify a full set of bin-dummy coefficients, because some of the bins contained no unsold cards and therefore their indicator variables were perfectly correlated with SOLD. Instead of including a full set of dummy variables, I included the normalized reserve-price level as a single regressor. The results were qualitatively the same as in the linear-probability model, as the reserve-price level had a coefficient significantly less than zero at the 5-percent level.

[34] The exception is 150%RES, which had a large number of sold cards (12 of 18). See the end of section for a discussion of this anomaly.

[35] The control variables produce results qualitatively the same as in the NUMBIDS specification, though the standard errors are larger in the SOLD specification.

from twice-sold cards," which reports the total revenue earned on the set of cards sold in both auctions. In both experiments, the cards sold under reserve prices earned more than their matches did in the absence of reserve prices. In card set A the aggregate difference was $44.85, while in card set B it was $25.55. The mean percentage difference between a card's revenue in the reserve auction and revenue in the absolute auction is statistically significantly greater than zero for the set of twice-sold cards (t = 5.4 for card set A, 3.3 for card set B).

Additional evidence comes from the between-card experiments. Table 4 displays the results of a nonparametric (binned) regression, with the same regressors as in Table 3. The dependent variable is REV/CLO, the revenue as a fraction of the Cloister value of that card;[36] the sample is restricted to those 345 cards (out of a total of 396) whose auctions resulted in sale. The point estimates do not increase monotonically, but the standard errors are large enough that for any pair of bins, one cannot reject the hypothesis that the bin with the larger reserve price has a larger revenue coefficient than the bin with the smaller reserve price. By contrast, one can reject all the pairwise hypotheses that the coefficient on any one of the four largest reserve bins is less than or equal to the coefficient on any of the four smallest reserve bins. This verifies that, as predicted, a higher reserve price trades off a decreased number of bids and decreased probability of sale in exchange for higher revenues conditional on sale.

5.3 Unconditional expected auction revenue

Now I consider the effects of reserve prices on revenue, unconditional on sale. This is a topic of considerable importance for auctioneers. In within-card experiment A (Antiquities cards), minimum bids had a negative effect on revenue (see Table 1). Auction revenue per card was $3.40 without minimum bids, but only $2.73 with minimum bids, and the difference is significant (t = -5.27). However, in experiment B (the Arabian Nights cards), minimum bids had a slight positive effect, causing revenue per card to rise from $9.93 to $10.05, which is not

[36] Where revenue is zero if card not sold.

statistically significant (t = 1.03). The inconsistency between the two experiments may be due to the ordering of the auctions. In each experiment, the revenue was higher in the first auction in the pair, suggesting that demand for the second copy of any given card may be lower than demand for the first copy. Also, more bidders were invited to experiment B, so the result is also consistent with the theoretical prediction that reserve prices should have less of an effect on auction revenues as the number of participating bidders increases.

Overall, reserve prices in the within-card experiments had some tendency to reduce auction revenues.[37] What could have caused this effect? One possible explanation is that the reserve prices might high enough screen out the highest-valuation bidder, and cause many cards to go unsold. On the other hand, I tried to choose my reserve prices to be similar in level to those used by other auctioneers in this market, which casts some doubt on this explanation.[38] Note that in measuring revenues rather than profits, I am ignoring the salvage value of the unsold cards. If the salvage value of the unsold cards were 29% or more of Cloister value, then the reserve auctions in the experiments would be generating higher profits than the absolute auctions.[39]

The between-card experiments allow me to trace out the entire shape of the expected-revenue curve, rather than evaluating it in two places. I regress the normalized revenue per card, REV/CLO, on the reserve-price bin dummies and the control variables used previously. The results are reported in Table 4. The major features of the results are that the expected revenue starts at approximately 80 percent of Cloister value for low (20 to 50 percent) reserve price levels, increases to approximately 100 percent of Cloister value for intermediate (80 to 110

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[37] The two t-statistics reported in the previous paragraph are independent standard-normal random variables, so their sum is a normal random variable with mean zero and variance 2. Therefore, to test the joint null hypothesis that revenues are equal across auction formats, an appropriate standard-normal test statistic is the sum of the two t-statistics divided by the square root of 2. That aggregate test statistic is t = -2.99 in this case, indicating that reserve prices had a statistically significant negative effect on revenues.

[38] Some auctioneers chose to run absolute auctions, with zero minimum bids, but those auctions with nonzero minimum bids tended to be around 90 percent of Cloister value on average.

[39] After completing the experiment, I visited a local card dealer to see how much he would be willing to pay me on the spot for my batch of unsold cards, without my having to do any additional work to shop around for buyers. His answer was approximately 20% of their Cloister value, so my absolute auctions probably earned slightly more actual profit than my reserve auctions.

percent) reserve price levels, and then declines to approximately 90 percent of Cloister value for very high (120 to 140 percent) reserve price levels. The additional control variables (Cloister value, auction dummies) are statistically insignificant.[40] The mean normalized revenue per card is significantly higher for cards with reserves of 80 to 110 percent (118 observations), than for cards with reserves of 10 to 50 percent (166 observations, t = 3.13), and not quite significantly higher than for cards at reserves of 120 to 150 percent, (72 observations, t = 1.80).

How do the results compare with the revenue curve predicted by the theory? It is difficult to test the general theory here, because the shape of the revenue curve depends on the unobserved value distribution $F(v)$. Since a monotone hazard rate condition on $F(v)$ is often assumed for convenience, we can check that assumption by asking whether revenue curve is nondecreasing for all reserve prices less than the optimal one. The data suggest that this prediction may be violated, as the point estimates *decline* from reserve prices of 10 percent to reserve prices of 40 percent. However, this decline is not statistically significant; one cannot reject the hypothesis that the revenue curve is flat over the first four bins (F = 1.02). Still, the downward slope of the point estimates is intriguing; additional data would be useful. Perhaps very low reserve prices might attract more participation (relative to moderate reserve prices) even by high-value bidders, which would translate into increased revenues.[41]

At a reserve of 150 percent of Cloister price, mean revenues are high: a normalized revenue value of 1.17, compared with a value of 0.81 at a reserve price of 140 percent. (At a reserve price of 150 percent, only 6 of 18 cards went unsold, compared with 9 of 16 cards at 140

[40] An additional specification, not reported here, also included a set of interaction terms between the reserve-bin dummies and the Cloister price, but none of these coefficients are individually statistically significant, nor did they affect the other qualitative results.

[41] In Riley and Samuelson, the number of potential bidders is fixed, and the reserve price reduces the number of actual bidders by screening out the low-valuation bidders. But minimum bids may also eliminate high-valuation bidders, at the time of the bidder's entry decision (the decision of whether or not to prepare a bid at all). See the models with endogenous entry of bidders of Engelbrecht-Wiggans (1987, 1992) and McAfee and McMillan (1987b). Eliminating minimum bids could be a profit-maximizing strategy (particularly if the auctioneer's outside option value for the good is low). A no-minimum strategy would open up the possibility for losses on some goods, but it may induce more bidders to participate.

percent.) This indicates that the revenue curve $R(r)$ has two local maxima, and the optimal reserve price is actually at 150 percent or more of the Cloister value. However, this difference is not statistically significant at the 5-percent level. Post-experiment interviews revealed that at least one bidder used the minimum bid levels as approximate signals of the cards' value; this could explain why cards continued to sell even at such high reserve prices. It would be interesting to know whether some bidders consistently behave in this manner, in violation of the standard theory of rational bidding.

5.4 Strategic bidding behavior

The most interesting results of this paper concern the levels of individual bids. Recall that in the theoretical model, $\frac{\partial b}{dr} > 0$ for a bidder with $v > r$. This prediction is borne out in the bid data reported in Figures 1 and 2, which show the distributions of the bid amounts received in the four within-card auction treatments. Imposing reserve prices does not raise bid levels merely *to* the level of the reserve, but rather *above* the level of the reserve, as predicted. Imposing 90 percent reserve prices increases the number of bids placed at 100, 110, 120, and even 130 percent of Cloister value.

A total of 2,457 individual bids were placed on the cards in the four auctions. Of these, 2,148 occurred in no-minimum auctions; 309 occurred in auctions with reserve prices. Although the total number of bids was lower in the presence of reserve prices, the number of bids exceeding 90 percent of Cloister value was *greater*. The number of bids equal to the reserve price increased from 7 to 69 when reserve prices were added, and the number strictly greater than the reserve price increased from 162 to 240. This supports the theory's prediction that $\frac{\partial b}{dr} > 0$ for bidders whose valuation is greater than the reserve.

On the other hand, the increase in the number of bids exactly equal to the reserve price (from 7 in the absolute auctions to 69 in the reserve auctions) seems inconsistent with the theory. The bid function (1) implies that only a bidder with valuation $v = r$ should bid exactly the reserve price, which is an event of probability zero if the distribution of valuations is continuous. The discrete bid grid is one explanation for the increase in the number of bids at the reserve level. However, this explanation is unlikely to be the whole story, because most of the reserve-price bids were large compared to the bid increment of $0.05. Only 25 of the 69 bids were for amounts less than $2.50, so most reserve-price bids were at least 50 times the amount of the bid increment. The median reserve-price bid was $6.60. This indicates that some bidders behaved naively regarding reserve prices. Of the 46 unique[42] bidders in auctions AR and BR, 18 submitted at least one bid equal to the reserve.[43] Most of the bidders tended to bid strictly above the reserve price in the reserve auctions.

I also compare the pairs of bids of those bidders who bid on both copies of the same card. Four bidders submitted a total of 22 such pairs of bids in experiment A, and 17 bidders submitted 88 pairs in experiment B. The mean difference between reserve-auction bids and absolute-auction bids, as a fraction of the posted reserve price, was a statistically significant 14.88% ($t = 4.58$).[44] Of the 110 observations where the same bidder bid on the same card in both auctions, 70 of them had higher bids in reserve auctions,[45] 35 were lower under reserve prices, and 5 were the same.[46] The bids that were lower may be accounted for by random bidding errors or random

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[42] Three bidders bid in both auctions AR and BR.

[43] Only seven bidders had all their bids exactly equal to the reserve: one with nineteen bids, one with six bids, and five bidders with one bid each. For those bidders who submitted both types of bids, the reserve bids were for lower amounts (mean $4.72, standard error $0.92, 40 bids) than the above-reserve bids (mean $8.58, standard error $1.14, 64 bids), indicating that rounding probably affected these bids.

Only nine bidders submitted more than half of their bids above the reserve (and six of these submitted only a single bid). These nine bidders appear to have been naive. It is possible that they were used to bidding in English auctions rather than sealed-bid auctions, and bid at the minimum bid amount because they expected to have the opportunity to raise their bid later.

[44] This t-statistic assumes independence of all 110 observations. A more conservative approach is to assume that each bidder generates only one independent observation. Taking each bidder's mean difference to be the unit of observation and equally weighting each bidder, the overall mean difference falls to 7.2%, and the t-statistic falls to 1.22.

[45] Of the 70 increases described above, 28 increased up to the reserve price, while 42 increased above the reserve price.

[46] Under the (questionable) assumption that all 110 observations are independent, I can reject the null hypothesis the bid difference is equally likely to be positive as negative ($z = 2.97$).

changes in bidders' valuations. A few bidders systematically bid lower in reserve auctions: 3 of the 21 bidders accounted for 21 of the 35 observations. Thus, most individual bidders in the within-card auctions behaved consistently with the prediction and bid higher in the presence of a reserve price.

Table 5 reports data from the between-card experiments. Each row denotes a reserve price bin (0.1 through 1.5 times Cloister value); the number of cards per bin ranges from 16 to 39. Each column denotes a reference bid level; the cells of the table report the average number, per card, of bids greater or equal to this reference level. For example, the first cell of the table shows that for cards with a reserve price level of 0.1 (that is, 10 percent of Cloister value), there were an average of 11.4 bids received per card auctioned. The cell immediately to the right excludes bids which were less than 20 percent of Cloister value; here the average number of bids falls to 9.7, implying that just under 2 of 11 bids on average for these cards fell between 10 percent and 20 percent of Cloister value. The next cell on the right shows that the number of bids per card falls to 6.8 if bids less than 30 percent of Cloister value are excluded, and so on. Cells on the diagonal of the table show the total number of bids greater than or equal to the reserve price, while cells to the right of the diagonal show the number of bids greater than or equal to even higher levels.

Within any given column of Table 5, the number of bids received is an increasing function of the reserve price. For example, in the "bids $\geq$ 0.4" column, we see that the number of bids received at levels greater than or equal to 40 percent of Cloister price increases as the reserve price increases. There are 4.4 such bids received per card auctioned at a reserve price of 0.1, 4.8 bids per card at a reserve price of 0.2, 6.2 bids per card at a reserve price of 0.3, and 9.1 bids per card at a reserve price of 0.4. This is consistent with the sort of strategic behavior predicted by the theory: the reserve price can cause bidders to raise their bids even when the reserve is not binding. For example, raising the reserve price from 0.2 to 0.3 increases not only the number of bids submitted at prices of 0.3, but also the number of bids at prices of 0.4 (in this case, from 4.8 bids to 6.2 bids on average). This phenomenon is generally true down each of the columns of the table, although the effect appears only in the last several rows of each column. For example, increasing the reserve price from 0.2 to 0.3 has very little effect on the number of bids submitted at levels of 1.5 or more.

These differences in the empirical bid distribution appear to be statistically significant for the most part, though it is not clear what the single best summary statistic should be. For example, in comparing auctions with a reserve price of 0.1 to auctions with a reserve price of 1.0, the number of bids greater than or equal to 1.1 increases from 0.333 to 1.179 bids per card, which is a statistically significant difference (t = 3.318). For each different column of the table, one can similarly compare the first row to the next-to-last row, and find that the point estimate of the difference is always positive (that is, the number of bids greater than or equal to X is always higher with a high reserve price, of just under X, than it is for a low reserve price, of 0.1). These differences are individually statistically significant for each of columns 0.5 through 1.2, with t-statistics ranging from 2.73 to 4.48. In columns 0.3 and 0.4, the differences are statisically insignificant (t = 0.68 and 1.63, respectively), because small reserve prices have relatively small effects on the magnitudes of large bids.[47] In columns 1.3 and 1.4, the differences are again individually insignificant (t = 1.49 and 1.36), because very few bids can be generated at levels of 1.3 or 1.4 times Cloister price or more, no matter how high the reserve.[48] Thus, every column of the table indicates point estimates consistent with the type of strategic bidding behavior predicted by the theory, with statistically significant differences for the vast majority of columns

[47] This is predicted by the theory. See, for example, equation 3.

[48] Furthermore, the experimental design generated fewer observations for reserve prices greater than 1.1, which also increases the standard errors of these estimates of the mean number of bids. Note, however, that the difference in column 1.5 turns out to be statistically significant (t = 2.19), indicating significantly higher numbers of bids of at least 1.5 times Cloister price when $r = 1.4$ than when $r = 0.1$.

(particularly those where the theory would predict the observed differences to be greatest).[49]

Just as in the within-card experiments, the between-card experiments also generated a substantial amount of bidding exactly equal to the reserve price. Of a total of 2217 bids submitted in the four auctions, 563 were equal to the posted reserve price; these bids were submitted by 50 of the 119 participating bidders. Twenty bidders had more than half of their submitted bids equal to the reserve price. In these auctions, there were more low card values than in the within-card experiments: 358 of the 563 reserve-price bids were for amounts less than $2.50, indicating that some reserve-price bidding may have been due to rounding. Overall, the evidence from the experiments suggests that while some bidders react naively to reserve prices, the majority of bidders behave as predicted.

6 Conclusion

This study uses field experiments to explore the effects of reserve prices in a preexisting auction environment. By auctioning real goods in the nascent online market for *Magic* cards, I have combined the traditional experimental methods of the laboratory with the field-data collection common in IO studies. While not every variable could be observed or controlled (such as the bidders' values for each good), I did hold constant all of the relevant variables in each of the environments except for the treatment variables: the existence and level of reserve prices.

The first result of this paper is that auction theory accurately predicts a number of important features of the data. Holding all else constant, implementing reserve prices (1) reduces the

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[49] An aggregate test of all thirteen point estimates being jointly equal to zero would have much higher power than any of the individual tests. Such a test would almost certainly reject the null, given that each of the point estimates had the same sign. Unfortunately, I do not know how to compute a valid aggregate test statistic. If each of the thirteen t-statistics were an independent standard-normal random variable (see footnote 42), an aggregate standard-normal test statistic would equal the average of the thirteen t-statistics multiplied by the square root of thirteen, which in this case would yield t = 10.16. However, this procedure is not valid, because these t-statistics are not in fact independent (while the rows of Table 5 are independent of each other, the columns within a row are not, and each individual test involves subtracting an observation in the first row).

number of bidders, (2) increases the frequency with which goods go unsold, and (3) increases the revenues received on the goods conditional on their having been sold. Second, the empirical shape of the expected revenue curve is roughly consistent with examples from the theory. Some intriguing potential anomalies appear at both low and high reserve prices, but neither is statistically significant in this data set. Finally, perhaps the most subtle and interesting result is that bidders appear to behave strategically in the presence of reserve prices, just as predicted by the theory. Though a few bidders appear to react naively to reserve prices, most high-value bidders apparently raise their bids to be strictly above the reserve, as if they correctly anticipate that rival bidders will also raise their bids in the presence of posted minimums.

This paper suggests some interesting lines of research. First, it would be useful to reproduce these experiments in a laboratory setting, where bidder valuations can be observed and controlled. Second, it would be useful to experiment with the number of invited bidders as a treatment variable. Riley and Samuelson (1981) predict that the optimal reserve price is independent of the number of potential bidders *N*, while Samuelson (1985) and Levin and Smith (1996) predict that the optimal reserve declines with *N*.[50] By manipulating the number of invited bidders as a treatment variable, an experiment could investigate this and other questions about the different effects of reserve prices in thick versus thin markets.

[50] Riley and Samuelson (1981) assume an exogenous number of bidders, while Samuelson (1985) and Levin and Smith (1996) assume endogenous, costly entry. The results of the present paper provide some weak evidence against all three of these theories. In the within-card experiment, it appeared that 90% of Cloister value was higher than optimal, particularly for the experiment (A) with the lower number of invited bidders. By contrast, the between-card experiments, with a large number of invited bidders, had an optimal reserve in the range of 80% to 110% of Cloister price. One possible interpretation is that the optimal reserve price is increasing in the number of bidders. However, these results are merely suggestive, and not at all conclusive (for example, the experiments took place at different points in time). A new experiment could be designed to provide a cleaner test of this hypothesis.

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Table 1: Summary statistics for within-card experiments.

	Auction AA	Auction AR	Auction BA	Auction BR
Minimum bids?	No	Yes	No	Yes
Card set	Antiquities	Antiquities	Arabian Nights	Arabian Nights
Start date	Fri, 24 Feb	Fri, 10 Mar	Tue, 14 Mar	Tue, 28 Feb
End date	Fri, 3 Mar	Fri, 17 Mar	Tue, 21 Mar	Tue, 7 Mar
Number of items for auction	86	86	78	78
Number of items sold	86	47	78	74
Revenue from twice-sold cards	$189.90	$234.75	$758.25	$783.80
Total auction revenue	$292.40	$234.75	$774.75	$783.80
Total number of bids	565	71	1583	238
Total number of bidders	19	7	63	42
from email invitations	12	5	44	35
from newsgroup announcements	7	2	19	7
Number of email invitations sent	52	50	232	234
Number of winners	15	6	25	27
Winner/bidder ratio	78.9%	85.7%	40.3%	64.3%
Cards per winner:				
Max	25	26	12	18
as share of total sold	29.1%	55.3%	15.4%	24.3%
Min	1	1	1	1
Mean	5.7	7.8	3.1	2.7
Median	3	3.5	2	2
Payment per winner:				
Max	$70.00	$129.40	$316.50	$128.00
as share of total	23.9%	55.1%	40.9%	16.3%
Min	$3.00	$0.70	$1.05	$2.55
Mean	$19.49	$39.13	$30.99	$29.03
Median	$10.50	$23.68	$13.15	$13.00

Table 2: Summary statistics for the between-card experiments.

	Auction R1	Auction R2	Auction R3	Auction R4
Card set	Artifacts	Black	White	Blue
Start date	Tue, 3 Oct	Fri, 6 Oct	Fri, 20 Oct	Mon, 23 Oct
End date	Tue, 10 Oct	Fri, 13 Oct	Fri, 27 Oct	Mon, 30 Oct
Number of items for auction	99	99	99	99
Number of items sold	98	92	77	78
Mean reserve level	60%	60%	85%	81%
Total number of bids	798	652	366	401
Total number of bidders	57	55	46	38
Number of email invitations sent	532	523	512	489
Total Cloister value	345.83	271.55	285.87	224.89
Total auction revenue	338.45	282.65	260.95	219.25

Table 3: Least-squares regressions of number of bids and probability of sale, regressed on reserve-price-level bins.

	Dependent variable:	
	NUMBIDS	**SOLD**
10%RES	9.8043 (0.8411)	0.9564 (0.0585)
20%RES	8.0201 (0.8318)	0.9592 (0.0578)
30%RES	5.8973 (0.8390)	0.9032 (0.0583)
40%RES	6.0878 (0.9411)	0.9444 (0.0654)
50%RES	3.3543 (0.8433)	0.8430 (0.0586)
60%RES	2.8973 (1.2013)	0.8727 (0.0835)
70%RES	1.0484 (1.2039)	0.9247 (0.0837)
80%RES	-0.2924 (1.1799)	0.8602 (0.0820)
90%RES	-0.0082 (1.0153)	0.8647 (0.0706)
100%RES	-0.1592 (0.8430)	0.7599 (0.0586)
110%RES	0.2704 (0.8389)	0.8478 (0.0583)
120%RES	0.3449 (1.0775)	0.5415 (0.0749)
130%RES	0.4758 (1.1379)	0.5468 (0.0791)
140%RES	0.3371 (1.0762)	0.4880 (0.0748)
150%RES	0.5464 (1.0770)	0.6533 (0.0748)
R1	3.3535 (0.6898)	0.0075 (0.0035)
R2	2.1689 (0.6887)	0.0784 (0.0479)
R3	-0.1215 (0.6285)	0.0235 (0.0479)
CLOISTER	0.3867 (0.0501)	-0.0085 (0.0437)
R^2	0.4935	0.2249
Number of observations	396	396

Table 4: Least-squares regression of normalized revenues (REV/CLO), both conditional and unconditional on sale.

Variable	Sold Cards Only	All Cards
10%RES	0.9433 (0.0964)	0.8852 (0.1167)
20%RES	0.8709 (0.0955)	0.8164 (0.1154)
30%RES	0.8890 (0.0977)	0.7959 (0.1165)
40%RES	0.8324 (0.1066)	0.7588 (0.1306)
50%RES	0.9552 (0.1012)	0.7950 (0.1170)
60%RES	1.1133 (0.1397)	0.9667 (0.1170)
70%RES	0.9357 (0.1372)	0.8352 (0.1671)
80%RES	1.2035 (0.1370)	1.0367 (0.1638)
90%RES	1.1365 (0.1205)	0.9729 (0.1409)
100%RES	1.2489 (0.1074)	0.9573 (0.1170)
110%RES	1.2421 (0.1025)	1.0560 (0.1164)
120%RES	1.3264 (0.1575)	0.7271 (0.1495)
130%RES	1.5364 (0.1648)	0.8530 (0.1579)
140%RES	1.6498 (0.1683)	0.8166 (0.1494)
150%RES	1.7700 (0.1463)	1.1682 (0.1495)
R1	-0.0060 (0.0057)	0.1524 (0.0957)
R2	0.0598 (0.0815)	0.0448 (0.0956)
R3	-0.0045 (0.0824)	-0.0212 (0.0826)
CLOISTER	-0.0125 (0.0799)	0.0032 (0.0872)
R^2	0.1974	0.0511
Number of observations	345	396

Table 5: Number of bids received, as a function of the bid amount.
This reports the mean number of bids received per card in each reserve-price bin, with std. dev. of the mean in italics.

Reserve Price	Observed bids at amounts greater than or equal to a price level of:														
	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1.0**	**1.1**	**1.2**	**1.3**	**1.4**	**1.5**
0.1	11.436	9.667	6.769	4.410	3.231	1.949	1.256	0.923	0.590	0.436	0.333	0.282	0.256	0.256	0.231
	1.349	*1.206*	*0.893*	*0.632*	*0.529*	*0.382*	*0.246*	*0.206*	*0.136*	*0.115*	*0.106*	*0.090*	*0.088*	*0.088*	*0.078*
0.2		10.111	7.694	4.778	3.472	2.528	1.833	1.111	0.667	0.583	0.417	0.361	0.333	0.278	0.250
		1.187	*1.023*	*0.733*	*0.525*	*0.476*	*0.407*	*0.232*	*0.191*	*0.175*	*0.115*	*0.114*	*0.105*	*0.086*	*0.083*
0.3			8.314	6.200	3.343	2.200	1.514	0.943	0.686	0.543	0.286	0.257	0.114	0.086	0.086
			0.965	*0.901*	*0.545*	*0.395*	*0.308*	*0.201*	*0.191*	*0.161*	*0.120*	*0.111*	*0.055*	*0.048*	*0.048*
0.4				9.115	6.962	4.154	2.692	1.808	1.115	0.692	0.385	0.115	0.077	0.077	0.077
				1.380	*1.262*	*1.015*	*0.695*	*0.571*	*0.361*	*0.227*	*0.167*	*0.085*	*0.053*	*0.053*	*0.053*
0.5					6.118	4.882	2.706	1.529	1.059	0.794	0.500	0.441	0.324	0.265	0.206
					0.896	*0.794*	*0.471*	*0.344*	*0.257*	*0.218*	*0.195*	*0.190*	*0.162*	*0.136*	*0.125*
0.6						6.150	4.250	1.950	1.050	0.700	0.500	0.350	0.350	0.250	0.200
						1.047	*0.852*	*0.432*	*0.285*	*0.219*	*0.185*	*0.109*	*0.109*	*0.099*	*0.092*
0.7							5.438	3.313	1.750	0.625	0.375	0.250	0.188	0.188	0.125
							0.671	*0.546*	*0.470*	*0.301*	*0.180*	*0.112*	*0.101*	*0.101*	*0.085*
0.8								3.650	2.100	1.100	0.500	0.350	0.300	0.150	0.150
								0.519	*0.390*	*0.216*	*0.154*	*0.109*	*0.105*	*0.082*	*0.082*
0.9									3.440	2.400	1.000	0.400	0.320	0.160	0.120
									0.566	*0.436*	*0.271*	*0.141*	*0.111*	*0.075*	*0.066*
1.0										2.256	1.179	0.564	0.256	0.179	0.128
										0.293	*0.232*	*0.183*	*0.080*	*0.072*	*0.066*
1.1											2.606	1.485	0.485	0.424	0.212
											0.351	*0.258*	*0.180*	*0.151*	*0.084*
1.2												2.053	1.421	0.947	0.842
												0.883	*0.777*	*0.789*	*0.735*
1.3													1.800	0.900	0.600
													0.639	*0.464*	*0.373*
1.4														1.278	0.722
														0.311	*0.211*
1.5															1.375
															0.554

Figure 1: Distribution of bids in Antiquities auctions.

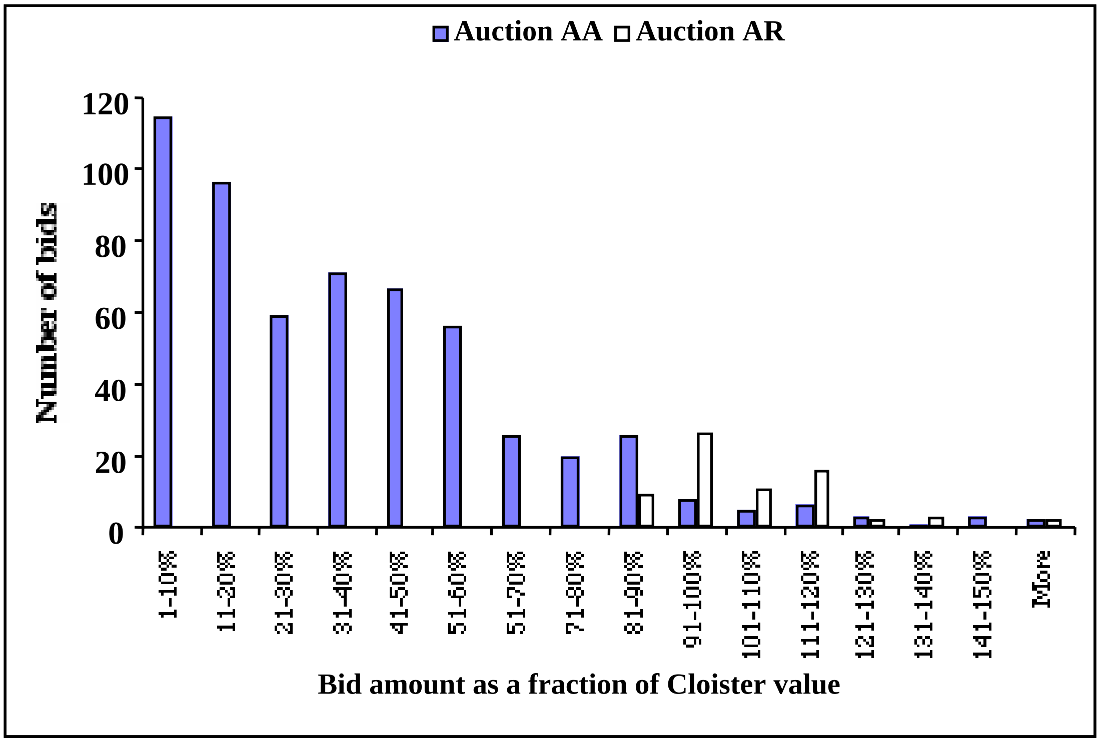

Figure 2: Distribution of bids in Arabian Nights auctions.