Veconlab Clicker Games:
The Wisdom of Crowds and the Winner's Curse*

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Abstract: We present a classroom-response ("clicker") experiment that illustrates the winner's curse. In the first stage of the experiment, students guess the answer to a numeric question, *e.g.*, the number of pennies in a jar. In the second stage, they bid for a money prize that is a function of the true answer to the question. Even if the distribution of first-stage guesses reflects students' actual beliefs about the answer, the highest bidder in the second stage probably possesses a belief in the upper tail of that distribution. If this person does not comprehend the informational content of winning (*i.e.*, winning implies that his or her guess was among the highest in the class), he or she may bid far too high and lose money, suffering the winner's curse. Because winning becomes an increasingly rare (and informative) event as the number of bidders increases, this exercise can generate an especially dramatic outcome in large classes. Our particular question, guessing the number of marshmallows in a clear container, also challenges students to re-evaluate popular press claims that the average guess from a group is a more accurate predictor than any individual's guess. We further suggest ways to use the data in a simple regression exercise.

Keywords: classroom response system, clickers, classroom game, winner's curse, wisdom of the crowds, selection bias.

Introduction

Participants in a common-value auction should use two pieces of information when forming their bids. The first is their individual perceptions of value. Higher valuations should result in higher bids, because bidders can increase their likelihoods of winning while still enjoying some expectation of profit. The second is the ramification of winning. Winning implies that the winner's perception of value is among the highest in the group, but the highest perceived value is probably not close to the true common value. This fact should lead participants to shade their bids below their perceived values.

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If bidders fail to account for the informational content of winning, they will not perform this second adjustment. The result is a classic "winner's curse": unnecessarily high bids, possibly resulting in negative profits for the winner.

We present a simple two-stage classroom experiment that reveals the winner's curse. To begin, we show students a clear container full of marshmallows. In the first stage, they provide their best guesses about the number of marshmallows in the container, and we promise a small payment to the person whose guess is closest to the truth. In the second stage, students bid for a money prize worth one cent for each marshmallow in the container, and we promise that the winner will be paid the value of the prize minus his or her own bid. After collecting the guesses and bids, we reveal the actual number of marshmallows and the winners of each stage.

In this setting, a student's best estimate of the prize value is one one-hundredth of his or her guess. Most students realize that they should bid some fraction of this amount in order to have a chance of obtaining positive profit, although some do become confused and bid more. The winner tends to be someone with an extremely high guess, and this person usually loses money even when bidding a fraction of his or her guess. The winner's decisions can usually provide a launching point for a discussion of the winner's curse.

One of the most valuable aspects of "thinking like an economist" is to recognize and adjust for selection biases that arise in market interactions. The winner's curse is a vivid example of such a bias: even if students report best guesses in the first stage, the winner of the second-stage auction has probably far overshot the mark and lost money. Hence, this exercise is appropriate for any economics class in which information and selection biases feature prominently, such as finance, behavioral economics, microeconomic principles, and game theory.

In our classes, we have observed a systematic downward bias in average guesses relative to the actual number of marshmallows in a rectangular container. The comparison of guesses with the correct number can initiate a discussion of popular press notions of the "wisdom of crowds."

We conduct this experiment using a classroom-response ("clicker") system for collecting data from students using simple wireless response pads. Several of our colleagues are already using these systems to monitor attendance and give multiple-choice or numeric questions on the fly during lectures. While this experiment could be conducted with pen and paper, the ability to collect guesses and bids from hundreds of students instantaneously saves quite a bit of time.

In this paper, we present two methods of conducting this experiment using a clicker system. The discussion includes the presentation a new website, Veconlab Clickers, that can additionally compile, summarize, and plot the data during class. We provide results from three classroom sessions, and illustrate how they can be used to initiate a discussion about the wisdom of crowds and the winner's curse. We also illustrate how the data can be used in a simple regression exercise to estimate a bid function.

Clicker Systems and Economics Experiments

Before moving to the experiment description, we would like to further emphasize the benefit of using clickers for classroom experiments. Clicker systems allow instructors to engage students in participatory exercises much more easily. Especially in economics and finance, students tend to glaze over when confronted with mathematical models or complicated statistical arguments (Becker and Watts, 1998). This active-learning alternative to "chalk-and-talk" requires students to immediately apply concepts that they encounter in lecture or assigned readings. By presenting simple applications soon after discussion, instructors can provide strong psychological or even grade-based incentives for students to keep up with reading assignments, attend class, and stay alert.

A typical clicker "interlude" contains some multiple-choice or numeric questions. Many of your colleagues in large and small classes have probably already used clickers in this manner, or know someone who does.[1] More recently, some economists have implemented in-class economic interactions via clickers, which are more like classroom experiments. For example, Salemi (2009) collected bids with a clicker system during an in-class auction of a University of California, Santa Barbara "Banana Slug" T-shirt. He reported that the auction results led to a lively class discussion about the formation of individual private values,[2] and how these values can be aggregated into a market demand curve.

In a great irony of the course-assignment process, the instructors most interested in conducting classroom experiments are frequently the ones teaching larger sections of introductory courses. Those who have experienced first-hand the difficulty of coordinating the data collection, analysis, and presentation stages of a classroom experiment with a large number of students are not often tempted to repeat the process. The time requirements for conducting a successful classroom experiment are simply too burdensome in a large class.

The appeal of clickers for the data-collection part of this process is immediately apparent. Clicker pads do not require laptops, power supplies, or high amounts of wireless bandwidth. And, most importantly, they can scale up to hundreds of participants without a perceptible effect on performance. However, a clicker system on its own does not necessarily solve the problem of analyzing data and presenting useful results in a timely fashion, especially if the interaction is at all complex.

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[1] For example, about 1000 principles students and 300 upper-level students at the University of Virginia use clickers in their economics classes.

[2] In one of those auctions, the high bidder needed a birthday present for a friend who attended UCSB. The immediacy of the need and the reduced search costs gave that particular person a very high value for the T-shirt.

We present here two methods of conducting a classroom experiment using a clicker system. In the first (the "spreadsheet method"), the instructor simply imports the collected data into a spreadsheet and plots it. For simple designs, this is a perfectly viable approach, though not without some pitfalls. For example, when collecting bids in an auction, it is not currently possible for a clicker system to enforce numeric bounds on the bids, and so the instructor must be diligent to weed out any spurious responses before plotting the results and announcing winners.[3] In addition, students cannot observe the outcome of their individual actions. If the experiment involves a payoff that is based each student's own actions, individual feedback is critical to the learning experience.

To overcome these limitations, we present a second method of conducting a clicker experiment: the Veconlab Clickers suite of web-based experiments. In this method, the instructor uploads clicker data in real time to a server running the experiment. The server processes these data, performs some consistency checks, computes outcomes, and returns the results to the classroom. Each experiment comes with some pre-packaged instructions and results pages; the latter contain graphs and summary statistics that are available for immediate discussion. In addition, if students register their clickers with the site (free of charge), they can log in after the experiment ends to view the results of their individual decisions. Instructions for setting up a Veconlab Clickers account and a classroom experiment can be found in the Appendix.

The Veconlab Clickers version of the winner's curse experiment requires about 10 minutes of class time to collect and display data. The main determinant of the duration is the amount of time the instructor allots for the class to answer the guess and bid questions. (The data-processing and graphing steps on Veconlab Clickers are nearly instantaneous.) If the instructor adds examples and applications, the discussion of results can easily consume the remainder of a 50-minute class period.

Setup Procedures

Because our version of the experiment involves a question about marshmallows, the instructor will need to construct the container prop before class if he or she wants to replicate it exactly.[4] The necessary materials are several bags of mini-marshmallows and a clear plastic container, the type found in stores with kitchen or craft supplies. The exact

[3] About 5-10% of student responses in our clicker experiments are completely spurious, containing problems like negative bids, outrageous guesses, or non-numeric responses. These types of errors can wreak havoc with the compilation of results if the data are not cleaned first.

[4] Many wisdom-of-crowds-style questions involve a physical prop such as a jar of coins or jelly beans. While we personally prefer this prop for consistency's sake, the instructor should not be discouraged from conducting this exercise if the prop construction seems like too much work. One can easily think of propless questions that fit into this design: "What year was Mozart born?" "What percentage of students have majored in economics at our university in the past decade?" "How many employees does the United Nations have?" The main considerations when choosing a question are scaling the correct number ("True Answer") into a reasonable prize value, and ensuring that the question does not generate guesses that are substantially lower than the correct number. In addition, the instructor may wish to discuss some psychological biases that are more closely related to that question than the ones we provide here.

dimensions of the container are not particularly important, but if you are staring at a bewildering array of containers in a store, you may want a bit of a size hint. The one that we use is 4 inches high, 8 inches wide, and 13 inches long, and costs less than $2.50. The marshmallows will add several dollars to the cost; each 11 oz. bag of the “mini” size contains about 500 marshmallows. We typically use between 1000 and 2000 marshmallows.[5]

The slightly tedious part is to count the marshmallows. Experience has taught us to count out a batch of 50 on a plate, and then dump them into the plastic container. It is also important to keep track of the batches of 50 using a hash count on a slip of paper. When finished counting, the instructor can place this slip into the container: the end of the exercise can be made a little more dramatic if a student volunteer is called upon to open the container and announce actual number..

In class, we use a very brief set of bullet-point instructions to introduce the exercise. When using the spreadsheet method, the instructor should create a presentation slide or equivalent before class. When using Veconlab Clickers, the program automatically generates instructions suitable for projection.

- This exercise has two stages.
- In the first stage, you will **guess the answer** to the following question:

  How many marshmallows are in this box?

  The person closest to the true answer will receive **$5.00**.
- In the second stage, you will **bid for a money prize** that is worth **$0.01 × the true answer**. The highest bidder will win the prize and receive the following payment:

  Payment = $(0.01 × the true answer) – Winning Bid
- The true answer will be revealed at the end. If there are tied winners in either stage, one will be selected at random to receive the payment.

These instructions are relatively generic. The instructor can easily substitute a different question, a different first-stage payoff, and a different second-stage prize conversion factor. Instead of loading the slide with scripts for every possible aspect of the exercise (*e.g.*, the mechanism for breaking ties), we allow students to ask questions about the instructions before proceeding to the guesses.

The exact mechanism for data collection depends upon the clicker system in use. The general strategy is to obtain response data for the two sets of responses in a spreadsheet-like format. In the next section, we present results from one class in which the spreadsheet method was used, and from two classes in which the Veconlab Clickers method was used. We used an *eInstruction* clicker system in the former, and an *iClicker*

[5] Jelly beans are similar in size to mini-marshmallows but are much heavier. Both will go over famously with the students and the administrative staff in your department, particularly if they are eye-catching colors such as Easter-egg pastels. If you do allow anyone to eat them, make sure to keep your hands clean during construction of the prop. (This is probably good advice in any case, because there is always one heedless student who will grab a handful of candy on the way out the door.)

system in the latter. Both systems can generate a file containing response data that is easily imported into a spreadsheet program.

With data for both stages in-hand, the instructor should generate summary statistics and data plots. When using the spreadsheet method, it is best to start with a scatterplot of bids against guesses. Doing so allows for quick identification of any nonsense responses. (Depending on the quality of the data and the size of the class, the instructor may or may not have sufficient time during class to weed out the bad data points.) Some useful statistics are the minimum, maximum, and average guesses and bids, which can be quickly added to scatterplot. The instructor will also need to identify the highest bid and the guess closest to the "True Answer."

When using Veconlab Clickers, the instructor posts a file containing the response data to the Veconlab Clickers server after each question. Posting takes only a few seconds, and the data are automatically cleaned and the winners determined on the fly. After the second set of responses is processed, a page identifying the winners and plotting the guesses and bids is immediately sent back the class.

We should note that it is possible to run this exercise without clickers at all: simply have students write down guesses and bids on sheets of paper. If the instructor has a small class or some teaching assistants, the responses can be compiled into a spreadsheet by hand. Of course, this alternative will almost certainly require two class periods: one for data collection and one for discussion.

In-Class Discussion

To generate interest for the post-experiment discussion, the instructor can show the cover of James Surowiecki's (2004) book, *The Wisdom of Crowds: Why the Many Are Smarter Than the Few*, *and How Collective Wisdom Shapes Business, Economies, Societies and Nations.* The book begins with an account of a guessing contest at an early 20th century English county fair, courtesy of Sir Francis Galton. Spectators were asked to guess the weight of an ox, and the average of their guesses was remarkably close to the ox's actual weight. In fact, the average was a more accurate predictor any of the individual guesses made a group of cattle experts.

Another way to heighten anticipation is to show a short video of a "jelly bean experiment."[6] In a spirit similar to the ox-guessing contest, the interviewer in this clip walks the streets of San Francisco showing a jar of jelly beans to random people. Some people walk by; others stop to guess the number of beans in the jar. The amusing array of sounds and street activities illustrates that the data-collection method in this

[6] The video is titled "Cake on the Wisdom of the Crowds" and is available on YouTube as of the time of writing. A financial-services social-media company (no longer in business) produced the video. Their product enabled people to share their financial portfolios with each other, enabling wisdom-of-crowds-style information aggregation.

experiment does not need to be very formal to be useful. The average guess from this completely unincentivized exercise was better than 95% of the individual guesses.

After the class has seen some background material on the wisdom of the crowds, discussion can begin by selecting a person at random and asking him or her for a guess. Students will probably compare that guess with their own, becoming animated with numbers they find out of line with their expectations. When using the spreadsheet method, the announcement of the actual number can come from a student volunteer who comes to the front of the class and reads the slip of paper in the container. When using Veconlab Clickers, the program will automatically reveal "True Answer" at the end of the exercise.

Next, the instructor should present results. Figure 1 provides a scatterplot of the bids and guesses from a large course in Behavioral Finance at the University of Virginia, and Table 1 presents some summary statistics related to this plot. This exercise generated 201 usable guess/bid pairs, and results were compiled using the spreadsheet method. The data in the table were presented during class, but the scatterplot was not. The container accommodated 1250 marshmallows, but both the average and median guesses were well below this point. About three fourths of the guesses were too low (156 out of 201). One student did guess exactly right, and a few others made guesses of 1200.

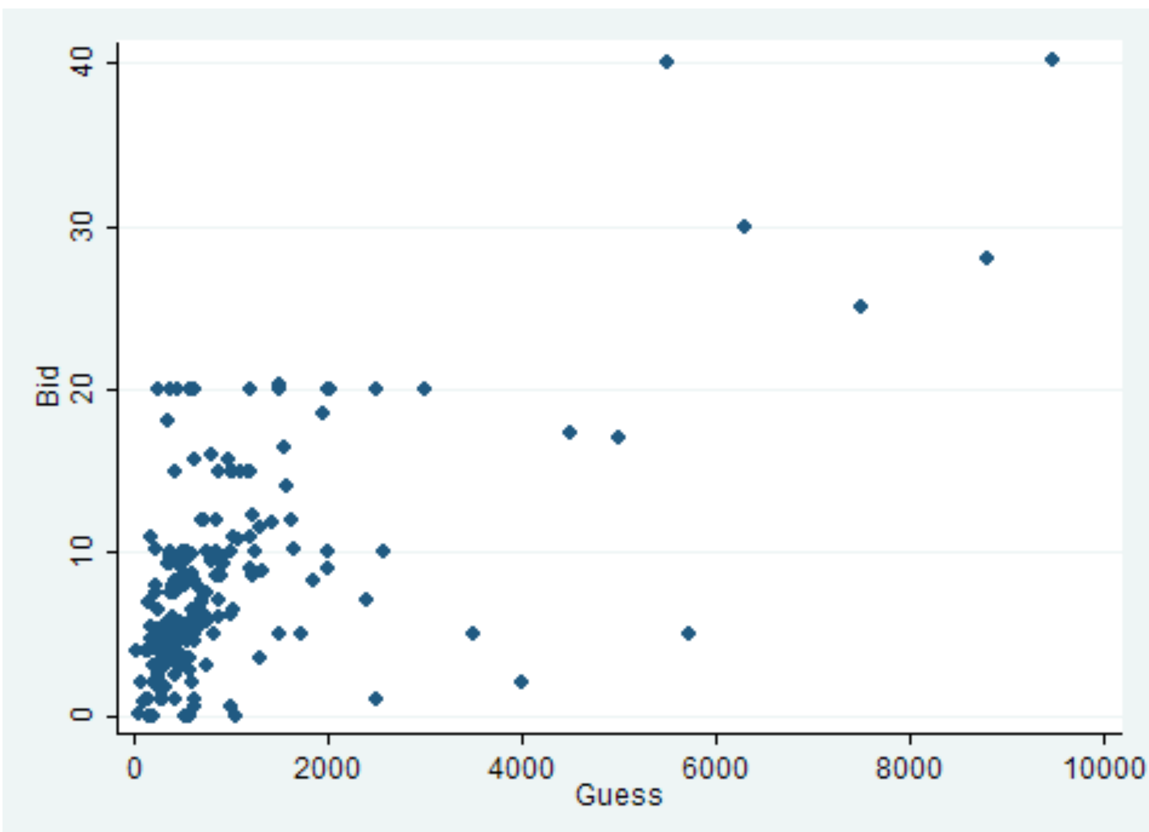
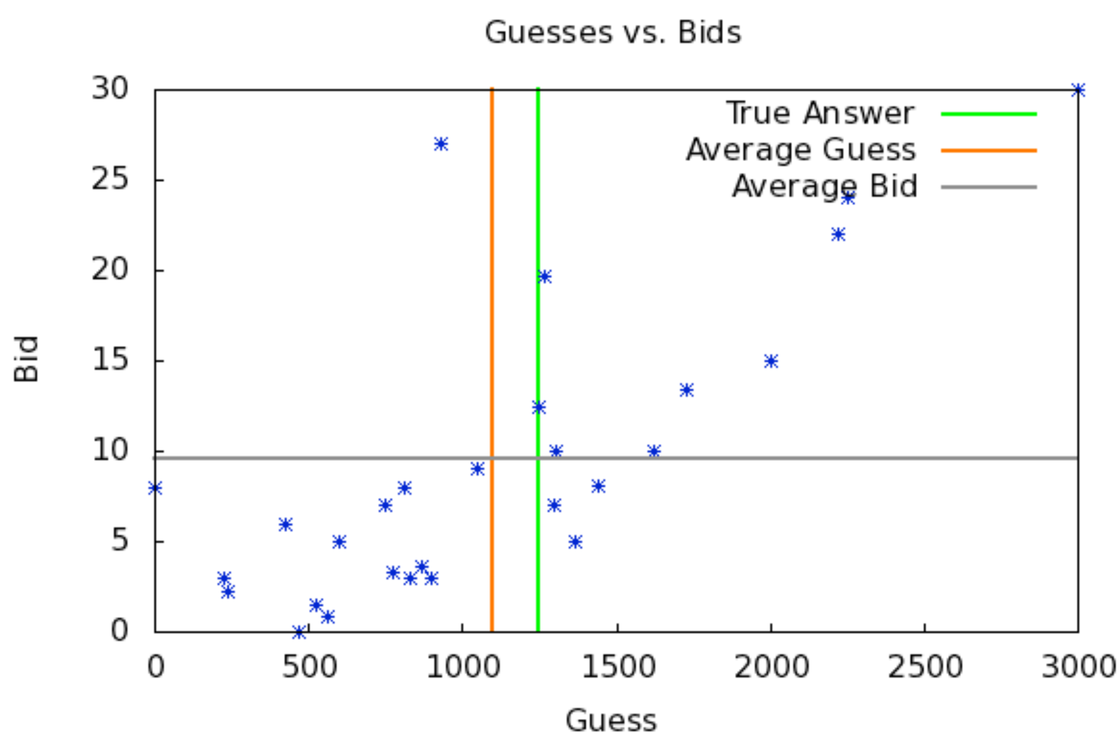


Figure 1. Scatterplot of Bids vs. Guesses (Spreadsheet Method)

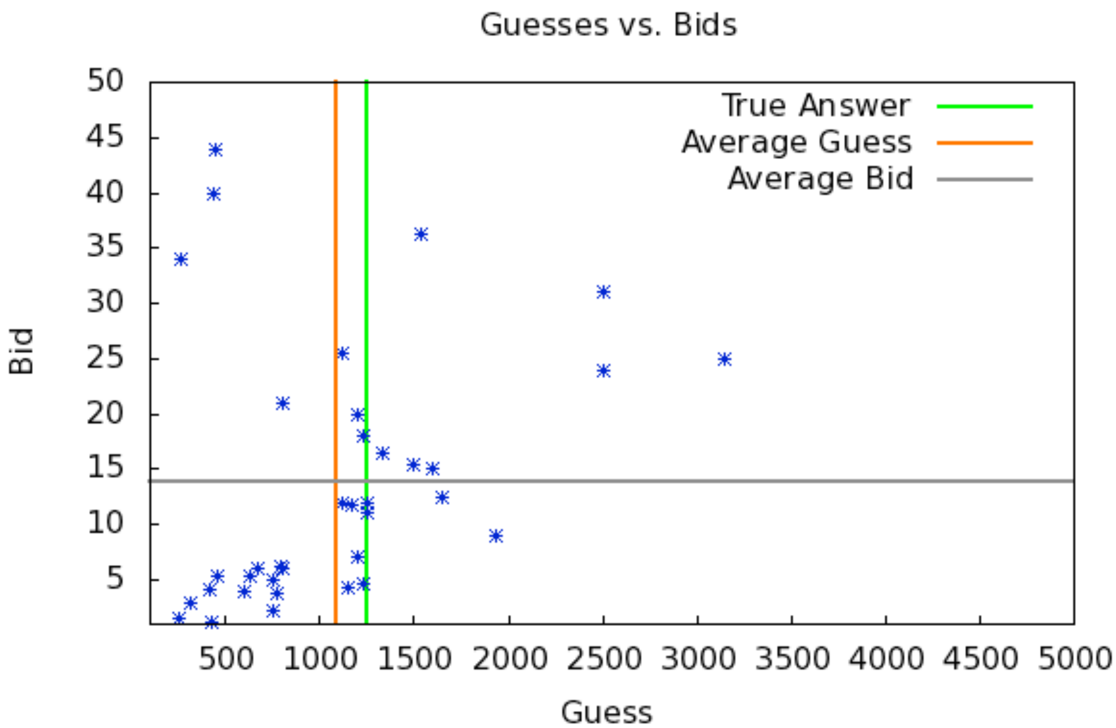
Table 1. Results for 201 Guesses and Bids Using a Container with 1250 Marshmallows

	Average	**Median**	**Maximum**
Guesses	970	550	9,475
Bids	$8.12	$6.00	$40.24

Figure 2 presents two scatterplots of the same experiment conducted in a Coporate Finance class and an Experimental Economics class at the University of Virginia, this time using Veconlab Clickers. These classes are smaller: 28 and 37 students respectively. In each, one student correctly guessed the actual number of marshmallows. The figure contains the exact graphs that were automatically generated by the site upon completion of the exercise, and immediately presented to the class.



(a)



(b)

Figure 2. Scatterplots of Bids vs. Guesses (Veconlab Clickers Method)

In both panels of Figure 2, the average bid is again below the true value of 1250. In the first, one person was convinced that the container had at 3000 marshmallows in it, and bid the full $30 value for the prize.[7] In the second, a few students applied the wrong conversion rate when calculating the prize value, led to bids that were an order of magnitude too high. (This error is immediately obvious in the data: such bids are almost exactly 10 times higher than their corresponding post-conversion guesses, less some bid shading.) Even after accounting for these discrepancies, the highest bid was about $20 above the prize value. Both classes generated a classic winner's curse.

Our experience indicates that the tendency for average guesses to be low is pervasive.[8] [9] On reflection, this may not be such a surprise: the behavioral psychology

[7] The Veconlab Clickers method requires the instructor to submit upper and lower bounds for the bid and guess. This does eliminate some of the most extreme responses that are the least believable, but the instructor should be mindful not to choose bounds that are suggestive of The True Answer. Figure 2(a) indicates that there is still quite a bit of variation in guesses and bids even with the bounds in place, indicating that they were not too informative.

[8] One of the authors (Holt) once asked a group of 12 CEOs attending a workshop on behavioral economics to make simultaneous guesses about the number of jelly beans in a clear plastic rectangular container, with the understanding that all people who were within plus or minus 50 beans would earn $10. There were 550 beans in the container, and the ten guesses were 180, 350, 560, 275, 260, 200, 333, 250, 178, and 395, for an average of 297. Notice that 4 out of 10 (40%) people did better than the crowd average. The remainder

literature is replete with examples of biases, and if individuals are biased, the average will be biased as well. For example, those who rely on their intuition in this exercise may fall prey to a *volume bias* (Raghubir and Krishna, 1999): people automatically perceive tall objects as having higher volume. There is also a kind of *dimensionality bias*: humans tend to perceive a surface in only two dimensions, or at least, may inadequately account for the full impact that a depth calculation adds. People may "anchor" on the most salient dimension and fail to adjust adjust adequately for other less obvious dimensions.

One way to avoid these biases is to employ cognitive calculations that reduce the amount of guessing. One student, for example, admitted that she had formulated her guess by counting the number of marshmallows along three different edges of the container, and multiplying these counts to get a volume in marshmallow units. This method actually yielded a very good prediction, even though she was sitting some distance away from the container.[10]

In an economics class, the instructor should highlight effect of these biases rather than their causes. The most salient effect is the hugely detrimental outcomes in the bidding stage. The class discussion should be driven by a question that requires students to develop their own explanations for the losing winning bid. A glance at the final column of the Table 1 provides one clue. The person in this exercise with the highest guess (9425 marshmallows) also had the highest bid ($40.24, for a prize that only turned out to be worth $12.50).[11] The rate of overbidding was about 10% for those who guessed too low, but it was over 33% for those who guessed too high. Data from the smaller classes presented in Figures 2 and 3 tell a similar story: the winning bidder loses money.[12]

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of the class made guesses in a sequence so that people could hear the guesses of those before them in the sequence. The observed sequence was: 500, 280, 600, 290, 358, 458, 305, 827, 400, 800, 237, 220, with an average of 440 and a median of 379. Note that a sequential setup may induce a bias if there is a tendency to follow the leaders in the sequence (*e.g.*, as in the "information cascade" experiments in Anderson and Holt, 1997). On the other hand, people later in the sequence might be able to incorporate information provided by those earlier in the sequence, which could improve the average.

[9] Surowiecki does qualify his claims with phrases such as "under appropriate conditions" (*i.e.*, with independent guesses), recognizing that crowds can be herded or otherwise persuaded when some people have access to guesses made by others. If individual guesses are independent and systematically unbiased (in the psychological sense), then the wisdom of crowds is an implication of the *law of large numbers*: the average of the guesses converges to The True Answer as the number of guesses increases.

[10] When we have allowed students to handle the container during the guessing stage, they seem to employ the edge-counting strategy quite frequently. To make the exercise harder, we have also used a more irregularly-shaped confection such as candy corn. Performing an edge count with a box of candy corn is not nearly as precise as with marshmallows, because the cone-shaped kernels can fit in several different directions. Students frequently react with surprise when they compute their volume estimates.

[11] We always engage a student who loses money in a discussion of their strategy, but never ask them to pay.

[12] Some high bids may very well be mistakes. For example, we have frequently seen students forget the decimal place in their bids, so that an intended 4.01 gets reported as 401. (Entering a numeric answer on an *iClicker 2* response pad is much like mobile-phone texting, and we are suspicious that the general lack of punctuation in texts is related to this problem.) In addition, some students may not bid a fraction of their guess, but rather a multiple.

After the students determine for themselves the source of the winner's curse, the instructor can introduce them to the term and ask them to provide other examples. The instructor can refer to Thaler (1988) and other references at the end of this paper for additional discussion of the winner's curse.

Another question to pose is whether the winner's curse is more likely to arise with small or large groups of bidders. After taking opinions on the question, the instructor can cite experimental evidence on increasing severity in large groups (see Holt, 2006, Chapter 21). The instructor could also make the same point by looking at subsets of bids (*e.g.*, none of the first 9 bids submitted in the class were above value, but the 10^{th} bid in the observed sequence came in at 2000!). A more statistical argument can be presented by illustrating that the larger number in two guesses is not as likely to be as biased as the largest number in 200 guesses.

A final point to make is that business managers develop rules of thumb to deal with the winner's curse, or else they go out of business (selection effects appear once again). For example, Bob Wilson of Stanford University once recounted the case of a petroleum company that had estimated the value of oil in a tract to be about $200 million. However, those responsible for bidding were considering a bid below $100 million. When Professor Wilson suggested that they raise their bid to increase their chances of winning, he was told that "people who bid that high on a tract like this are no longer in this business." This suggests that the winner's curse may be more likely to arise in situations with less precice information. For example, during the wave of corporate takeovers in the 1980s, the raiders, flush with cash and overconfidence, tended to pay more than market value for target firms. They noticed that stockholders of acquired firms typically made significant profits, but the buyer often ended up gaining little on average.

Using the Data in a Regression Exercise

In auction theory, an optimal bid can sometimes be expressed as a linear function of a bidder's private-value signal. Our exercise does not have nearly enough structure to allow us to find a theoretically-optimal bid function, but we can estimate an empirical bid function that summarizes the average proclivity for participants to shade their bids. Estimating a bid function using data collected in class may be a useful stand-alone exercise in a statistics course, or could be incorporated into post-experiment homework.[13]

Assuming a linear bid function, the regression model to be estimated is

$$Bid = \alpha + \beta \cdot Guess + \varepsilon$$

The instructor can start the discussion by asking for the economic interpretation of α and β. Students should be led into the realization that that α represents the expected bid in

[13] In addition, most spreadsheet programs have built-in slope and intercept formulas for simple regression, which would enable the instructor to add the regression line to the scatterplot during discussion.

the population for a guess of zero marshmallows, and that β represents the bid-shading fraction given a particular guess. After this initial discussion, students should be comfortable asserting that $\alpha = 0$ and $\beta < 0.01$ are reasonable theoretical restrictions.[14] These can both be tested with the regression results.

A more challenging question is to ask for an economic interpretation of ε. Many students will probably give a statistical interpretation, perhaps saying that it is a "random fluctuation." The instructor should encourage students to go a bit deeper than this, asking what actually causes these fluctuations. In this experiment, fluctuations are rooted in individual differences in the amount of bid shading, which could be attributed to a number of factors. For example, some students could be more risk-averse than others, some may be more perceptive of the winner's curse than others, and some may understand the game better than others. In addition, some measurement error could be introduced if students enter their guesses and bids improperly, or if the instructor inaccurately transcribes their responses.

Once the sources of the error term are identified, the instructor can also challenge students to verify that the statistical requirements of the error term are met. For example, do the fluctuations appear to have constant variability over the range of guesses (homoskedasticity)? Is there any reason to believe that the source of the fluctuation is correlated with the guess?[15] Asking these questions in advance of the analysis allows students to build an appropriate level of confidence in the results.

The estimated linear bid function for the scatterplot data in Figure 1 is

$$Bid = \underset{(0.44)}{5.17} + \underset{(0.00027)}{0.003} \cdot Guess$$

The standard errors (in parentheses) indicate that the estimates are precisely measured. The estimated value of 0.003 for β is indeed less than 0.01, and suggests that students shade their bids by about 70% from their guesses on average. However, the fit to individual bids is not all that precise. The R^2 is about 0.4, indicating some substantial heterogeneity in bid shading that is not captured by this linear specification.

These data also generate a statistically non-zero estimate of α, suggesting that the average participant would bid \$5.17 for a prize perceived to be worthless. If a non-zero

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[14] The null hypothesis on β represents the case in which participants bid exactly their estimates of the prize value. The instructor must remember to apply the prize conversion factor when constructing this null hypothesis. In our case, the factor is \$0.01 per marshmallow, and so $\beta = 0.01$ corresponds to bidding the guess. Of course, doing so would yield zero profit, and so we would expect some bid shading to allow for positive profit.

[15] As an example of correlation between the guess and the fluctuation, consider a group of students who talk to each other about their guesses between the two stages of the experiment. (This can occur quite easily in large classes.) Those with the most extreme guesses will probably realize that they are in the tail of the distribution of perceived values, and adjust their guesses substantially downward during the bidding stage to avoid the winner's curse. This adjustment, of course, is unobservable to those running the regression.

α occurs, the instructor should first ask whether it makes sense. Most students will answer negatively, especially if they have previously discussed the theoretical restriction $\alpha = 0$. Some will probably note that a non-zero α generates troublesome predictions only for low guess values. Because guesses near zero are not really on the support of the data, they might then suggest giving limited credence to the estimated bid function for low guesses.

The discussion could take an interesting turn if someone questions whether the bid function is linear. This question offers the opportunity to show students that there is no substitute for visually inspecting the data. For example, the scatterplot in Figure 1 seems to reflect less bid shading for low guesses than for high guesses. A piecewise-linear form might actually fit the data better.[16]

Figure 3. Linear and Smoothed Regression Predictions

[16] There is some experimental evidence that bid functions may indeed be concave. Dorsey and Razzolini (2003) report a pay-as-bid, private-value auction with a uniform distribution of values. In their design, the Nash bid function is linear, with a slope that depends on the number of participants. They observe concave bid functions instead.

For more advanced students in econometrics, this data pattern may offer a good segue into an application of smoothed regression. Smoothed regression performs a locally-weighted regression analysis in the neighborhood of each data point. This estimation method can pick out nonlinearities in data, but it does not generate an explicit β coefficient. Figure 3 plots the predicted values of both the linear and smoothed regression. The two lines are quite similar for guesses above 250 marshmallows or so. Below this level, the linear prediction line moves linearly back towards the intercept, but the smoothed line quickly curves back towards a small bid for a zero guess. This result suggests some for concavity in the bid function for small values.

Another extension that students (and faculty) may find engaging is determining whether students or professors are more aggressive in bidding. More aggressive bidding could lead to a worse bite from the winner's curse. If the instructor can conduct this experiment with some colleagues before class, he or she can combine their data with the student data and run a new regression:

$$Bid = \alpha + \beta \cdot Guess + \gamma \cdot Faculty + \delta \cdot \left(Faculty \times Guess \right) + \varepsilon$$

where *Faculty* is a dummy variable for faculty observations, and *Faculty* $\times$ *Guess* is the interaction between *Faculty and Guess*. For the exercise to be most meaningful, the number of observations should probably be balanced across faculty and students.

Students should be led to realize that the intercept and slope for the student observations are still α and β, but those for faculty are now $\alpha + \gamma$ and $\beta + \delta$. Thus, γ and δ together provide the marginal faculty effects, and the formal test for faculty differences is a joint test of these two variables being equal to zero.[17] More aggressive bidding by faculty would specifically imply $\delta > 0$: for a given guess g, a faculty member would bid $\delta \times g$ dollars more than a student would.

When we have conducted this exercise in smaller classes (with about 20 student and 20 faculty observations), we have seen faculty effects that are economically meaningful but not statistically significant. For example, we once found point estimates suggesting that faculty members were three times as aggressive in bidding than students (without any improvement in their guess quality), but the joint faculty test was not significant. If this occurs, the instructor can sum up with a discussion on how to best interpret regression results in the presence of large but imprecise estimates, a ubiquitous scenario in econometric applications.

[17] This specification is essentially a long form of the Chow test for different regression coefficients in two different groups.

Further Reading

Inspired by his consulting experience, Wilson (1969) first analyzed a model with rational bidders who adjust their bids *in advance* for the fact that winning is an informative event. Bidders in this model, therefore, have positive earnings on average. Capen, Clapp, and Campbell (1971) discussed the winner's curse in the context of bidding for offshore oil leases: "In recent years, several major companies have taken a rather careful look at their record and those of the industry where sealed competitive bidding is the method of acquiring leases. … If one ignores the era before 1950 when land was a good deal cheaper, … the Gulf has paid off at something less than the local credit union." Subjects in laboratory experiments consistently fall prey to the winner's curse, and losses are more common in auctions with larger numbers of participants. (See Kagel and Levin, 2002, for a comprehensive treatment of these research experiments.)

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Appendix: An Introduction to Veconlab Clickers

The Veconlab Clickers website (http://clickers.veconlab.com/) provides a number of clicker experiments that can be used free of charge by the general public. The website coordinates the execution of experiments as well as the management of experiment data for students and instructors. At the time of writing, it performs best with *iClicker* systems, but readers should check the site for a current list of supported systems.

To begin using Veconlab Clickers, an instructor must first establish an account on the site. This is a simple matter of following the "Instructor Login" link from the homepage and proceeding through the registration step. The email address and password provided at registration serve as the instructor's login credentials. At the first login, the instructor must provide a registration code that was sent to this email address. (This provides one layer of defense against spoofing an instructor account.)

After logging in, the instructor is brought to his or her list of courses. Each experiment is affiliated with one course, so a course must be established first in order to proceed further. Establishing a course is a simple matter of providing some identifying information (*e.g.*, the course name and description), start and end dates, and an Enrollment PIN. Students will use this Enrollment PIN if they later choose to register with the site.

After selecting a course, the instructor can set up a new experiment. The experiment presented in this paper is labeled "Auction with Winner's Curse" in the menu of experiments. Setup consists of three stages. In the first, the instructor provides some identifying information, such as the title and date of the experiment. In the second, the instructor selects how many treatments to conduct. A "treatment" in this context represents an iteration of the full exercise (*e.g.*, guesses and bids with a different container of items). In the last stage, the instructor provides the question, the monetary payoff values, and response bounds for guesses and bids for each treatment.

Once setup is complete, the Status page for the experiment appears. This page places all of the information about the experiment at the instructor's fingertips. From here, the instructor can review the instructions, see the results template, download data, and observe how many responses have been posted for each question.

Part of the setup process involves selecting an Experiment PIN code. The experiment will not start unless the Experiment ID (assigned by the site) and Experiment PIN (assigned by the instructor) are provided. Both can be found on the Status page. If the instructor were to have a teaching assistant run the experiment, he or she could provide the assistant with these two pieces of information, instead of full access to the instructor account.

The only in-class technical requirement is a computer that can both project to the class and run the clicker software. To begin the experiment, the person running the exercise should connect the receiver and initiate a completely new set of questions with the software provided by the clicker manufacturer. Next, he or she must follow the "Experiment Login" link from the Veconlab Clickers homepage, and enter the Experiment ID and PIN. The experiment will then start.

The first clicker question in a Veconlab Clickers experiment is always a "sync" question. Its purpose is simply to record the clickers that are participating. Students can enter anything they wish on this question, but they must enter something at this point in order to participate. Latecomers' responses will be rejected.

After collecting data for the sync question, the instructor must upload a file containing the response data to the Veconlab Clickers server. When using an *iClicker* system, this file can be found under the iClicker program folder. The data are located in the following directory: [18]

[iClicker Program Folder]\Classes\[Your Class Name]\SessionData\

The data file is the ".csv" file that was most recently created. (To more easily locate the file, it is helpful to sort the list of files in the directory by date.) This file will hold all of the raw decision data for the experiment.

When a file is uploaded, the Veconlab Clickers site first verifies that it actually contains clicker data. If the file passes all consistency checks, the person running the exercise will be prompted to select one set of responses from that file to use as the input for the current Veconlab Clickers question. The site will automatically suggest a set of responses; as long as no mistakes have been made in collecting the data, this default should reflect the correct set.

Each time student input is needed, the site will present an upload menu that prompts the person running the exercise to post the data. To reiterate, posting the data to the Veconlab Clickers server involves two steps. The first involves uploading the file, and the second involves selecting one set of responses from that file.

After processing the sync question, the site displays the experiment instructions. During setup, the instructor can opt to disable the default instructions, in which case the program will skip this step. The instructor can then supply his or her own instructions at this point.

The person running the exercise next collects the first-stage guesses. After these are provided, the he or she should post the data to the site. The site automatically cleans the data at this point, rejecting any answers that are nonsense or out of bounds.

The final step is the collection of the second-stage bids. These should be posted in the same manner as before.

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[18] "Your Class Name" refers to the class name as specified in the iClicker software. This may or may not be the same name given to the class in Veconlab Clickers.

After processing these two responses, the site will return a summary page listing the winners and graphing the data. Winners can be identified by their clicker IDs. On an *iClicker* response pad, this ID can be found on a sticker on the back. Displaying of this particular results page is also not required; during setup, the instructor can opt to provide his or her own results.

A potentially useful additional step is for students to establish accounts on the Veconlab Clickers site and review the results of the experiment. The process of obtaining a student account is identical to that of instructors, except that students should follow the "Student Login" link from the homepage. After logging in, the student must enroll in the instructor's course using its Course ID and Enrollment PIN. (The instructor should provide these to the class.)

After enrolling in the course, a student can view the results of each experiment that has been conducted in the course, even if he or she did not participate in some of them. The auto-generated instructions and results pages for each experiment are always available to enrolled students. Additionally, a student can view a question-by-question summary of his or her individual decisions and outcomes for experiments in which he or she participated.