The Journal of Behavioral Finance
2005, Vol. 6, No. 3, 108–120

Bidding and Overconfidence in Experimental Financial Markets

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Overconfidence is a well-documented phenomenon in psychology. Psychologists define an overconfident individual as one who believes he has more accurate information than he actually does. Recently, behavioral economists have become interested in the implications of trader overconfidence for financial decision-making and the functioning of financial markets. To date, most financial market studies have been analytical in nature. These studies assume that traders are overconfident and model decision-making behavior accordingly.

Rather than assuming the presence of overconfidence, we use experimental bidding data to determine the extent to which trader overconfidence exists, and what variables suggested by previous finance and psychology research relate to it. We find approximately 40% of subjects exhibited overconfidence. Variables that distinguish overconfident bidding from risk-averse and risk-neutral bidding include the traditional financial variables that explain bidding (expected value and standard deviation), non-traditional financial variables, and variables relating to the self-attribution bias and feedback. Contrary to what some analysts have suggested, experience did not reduce overconfidence.

Introduction

Hurricane and earthquake preparedness officials find a growing underestimation of disaster risks by people living on the South Atlantic and Gulf coasts and the west coast of the U.S. The more years that pass without significant earthquakes or hurricanes, the greater the tendency for residents to ignore preparedness instructions and evacuation orders. Compounding the problem, people unfamiliar with the risks continue to move into these areas. People who live in these regions may also bear undue financial risks because they often overlook government-subsidized insurance against earthquakes and floods, hazards not covered under standard insurance policies.

Behaviors like these reflect overconfidence, a well-researched and widely documented phenomenon in psychology that is becoming increasingly relevant in financial decision-making. In broad terms, psychologists and other scholars regard people as overconfident when they believe their traits or abilities are better than they really are. As decision-makers, overconfident individuals assume they have more information or knowledge than they actually do. Overconfidence is such a robust psychological phenomenon that experience is often not sufficient to eliminate its influence. See Barber and Odean [1999] for a broad summary of documented overconfident behaviors and attitudes.

To date, economists have studied overconfidence mostly analytically, not empirically. These studies have addressed whether and how overconfident traders persist in competitive financial markets, and what impact they have on market outcomes. Results suggest that overconfident traders may not only persist in markets, but they may excel to the point of dominating "rational" traders under certain circumstances. At the market level, overconfident traders may significantly affect trading volume, market depth, distribution of wealth, and other outcomes.

The analytical studies rest on the psychological finding that overconfidence is a widespread trait. That is, the authors typically *assume* that traders are overconfident and then model decision-making behavior accordingly using a variety of working definitions of overconfidence. In this paper, we test for the presence of overconfidence empirically.

Based on psychological and economic findings, we identify overconfident behavior by analyzing the manner and determinants of subjects' bids in experimental financial markets. Because we observe bidding behavior over time, we can investigate how bidding is influenced by financial and behavioral variables within a panel data setting. In the end, approximately 40% of the bids reflected overconfidence.

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In the second section, we review scholarly literature relating to bidding behavior and overconfidence as a means of laying a foundation for our empirical approach and analysis. We then describe the experimental design, discuss the econometric analysis and results, and present our conclusions.

Literature Review

The Basis of Bids

Basic financial theory holds that the value of an asset is equal to the present value of its future cash flows, discounted at the appropriate rate of return for the riskiness of the asset. Hence, the possible returns of an asset are moderated by a person's risk preferences in determining the asset's value to a particular individual. When assets are valued in isolation,[1] the relevant return and risk measures are the expected value and the variance of the distribution of the asset's value (Danthine and Donaldson [2002]).

Choice theory derived from these definitions depends on the validity of expected utility (EU) theory and its axioms of rational behavior (von Neumann and Morgenstern [1947]). The validity of the EU axioms has been challenged successfully so often that alternative choice models based on observed behavior have been developed and widely disseminated, e.g., Kahneman and Tversky's [1979] prospect theory.

In addition, Evans [1993] showed that decision-makers in experimental settings preferred a variety of information cues when making different types of capital project decisions. The mean and median payoffs and the standard deviation of the payoff were among the least selected elements of information used to make decisions. Traders more often requested various discrete elements of the distribution, such as the highest possible payoff, the payoff associated with the highest probability, the cost of the project, and the lowest probability associated with a payoff. This may be because some decision-makers were not familiar with the mean and the variance, or their meanings may not have been as clear as the other elements of the distribution. Thus, while we expect the experimental subjects here to use the mean and variance in determining their bids for gambles, they may also prefer other information.

The Nature of Overconfidence

Psychologists have studied overconfidence for decades. In what they generally term calibration studies, subjects are asked to 1) answer factual questions in a variety of subject domains, and/or 2) predict the outcome of an upcoming event. Besides making decisions, subjects estimate the probability (or give odds) that their answers are correct. Psychologists compare the actual rate at which subjects are correct with their predictions of being correct (their confidence). Results indicate that subjects are generally overconfident, i.e., they overestimate their accuracy in answering questions. In one study of this type by Lichtenstein, Fischhoff, and Phillips [1982], subjects who reported 70% confidence were correct only 60% of the time, and subjects who reported 90% confidence were correct 75% of the time.

Many psychologists suggest that overconfidence relates to a person's ability to process information. Fischhoff, Slovic, and Lichtenstein [1977] provide two possible explanations. First, subjects may not use adequate inference processing methods in selecting an answer. They search their experience for information to support one of the possible answers. Once they hit on an answer, they continue to search their experience to further support the initial response or to negate it. At this point, subjects' memory retrieval processes can more easily access information that supports the initial conclusion.

Alternatively, subjects may believe they are selecting the answer directly from their memories, never realizing they are using an inference process. If financial traders place bids in either of these ways, they may first select a bid from a similar past gamble, and then continue to search their memories for information that would justify lowering or raising the bid.

Griffin and Tversky [1992] claim overconfidence originates in people's biased evaluation of evidence. Evidence has two dimensions: strength and weight. Strength refers to the extremity of the evidence (e.g., someone forecasts an event as highly unlikely to occur, or a colleague highly praises a job candidate's talent), while weight refers to the predictive validity of the evidence (e.g., the accuracy of the forecasting model or the credibility of the recommender). Griffin and Tversky suggest that overconfident people tend to focus on the strength of the evidence and then adjust it inadequately for its weight. When strength is high but weight is low, people tend to be overconfident. When strength is low but weight is high, they tend to be underconfident.

Ferraro [2003] finds a link between a person's competence in an area and his overconfidence. Less competent individuals have trouble *judging* their competence, leading them to overestimate their ability—overconfidence.

Bloomfield, Libby, and Nelson [2000], building on the work of Griffin and Tversky [1992], propose that over- and underconfidence may both be explained by how people react to imperfect signals about the reliability of their information. Using experimental evidence, they conclude that investors overweight the reliability of highly unreliable information, and underweight the reliability of highly reliable information. In other words, investors tend to incorrectly moderate their assessment of reliability toward an average.

Other authors cite self-attribution (self-serving) bias to explain overconfidence (e.g., Gervais and Odean [2001]). Self-attribution bias is a well-documented trait that occurs when people attribute their successful outcomes to their own abilities and their failures to external factors. The more successful one has been, the more self-attributing and overconfident one becomes.

Similarly, Hvide [2002] argues that people form pragmatic beliefs based on which beliefs have paid off in the past versus what is literally true (rational) in the present. He demonstrates through an example how overconfidence can lead to higher payoffs. Over time, thought processes that lead to higher payoffs get reinforced (learned), leading to unconscious overconfidence. In bidding, we might expect subjects who have made more money in more transactions to exhibit overconfidence.

Although overconfidence is a robust phenomenon, we find no consensus in the literature on its origin, and, indeed, it probably has many sources. But regardless of source, overconfidence is consistently associated with limitations or biases in information processing. Researchers have found greater overconfidence when experimental subjects perform difficult tasks (Griffin and Tversky [1992]), when they receive slow and noisy feedback (Odean [1998]), when they evaluate information that is relatively abstract rather than specific and distinctive (Kahneman and Tversky [1973]), and when outcomes depend on one's skills relative to competitors (Camerer and Lovallo [1999]).

In the context of bidding, we expect overconfident people to place higher bids on gambles, other things remaining equal. Because financial factors can also reasonably affect bids, we control for them in our statistical analysis. In addition to the financial variables, we investigate how important information processing ability is to overconfidence.

Overconfidence in the Economics Literature

Economists studying overconfidence have had to establish definitions of the phenomenon specific enough to apply to markets. As Hvide [2002] discusses, the psychology literature provides two sometimes interchangeable definitions. In the first, people overestimate their ability. In the second, they see an event as more certain than it really is. In any case, the agent believes he has more accurate information than he really does.

These approaches have led many economists to define overconfidence as an overestimation of the mean and underestimation of the variance of an information distribution. Alternatively, Gervais and Odean [2001] have characterized overconfidence as the biased updating of beliefs, as opposed to a biased distributional estimate. But all studies illustrate that overconfidence can persist because financial markets contain many elements conducive to it—complex tasks, abstract information, slow feedback, and skill-dependent results.

Hvide [2002] criticizes the mean-variance definition of overconfidence, seeing these errors as clearly distinct phenomena. Someone may be overconfident about his ability but underconfident by overestimating the width of the probability distribution. Or he may be overconfident in both dimensions. Hvide's criticism of the mean-variance definition has validity and might logically be expanded.

Barber and Odean [1999] demonstrate how overconfidence affects the performance of individual traders in financial markets. Specifically, they test 1) the *disposition effect* of prospect theory (Kahneman and Tversky [1979]), which predicts that overconfident investors will trade too frequently to maximize wealth and utility, and 2) *regret aversion* (Shefrin and Statman [1985]), which predicts investors will sell their winning stocks but keep their losers. Barber and Odean followed trades from 10,000 randomly selected brokerage accounts, and found that overconfidence led investors to sell winners, hold losers, trade more frequently, and ultimately experience bigger losses. They conclude from investors' extremely aberrant trading behavior that overconfident investors not only misinterpret the precision of their signals, but the nature of the information itself.

For example, overconfident traders may have more trouble determining whether an accounting irregularity means a stock is more or less desirable, or means nothing at all. Moreover, they may be more confident about their own information and their ability to interpret it than they are about the opinions of competing traders.

Several researchers have investigated analytically the extent to which overconfident traders might persist in financial markets and their impact on market outcomes. Traditional financial models imply that rational traders should drive overconfident traders out of the market. But these analytical studies show that overconfident traders can indeed survive in markets, and may even dominate them.

DeLong et al. [1990] define overconfidence as a trader's underestimation of risk. Using analytical markets, they conclude that overconfident traders hold more risky assets in their portfolios than would be predicted to maximize utility, earning them the higher returns associated with higher-risk assets.

Odean [1998] evaluates how markets react to the overconfidence of different participants (price-taking traders, strategic insiders, and market makers). He defines overconfidence as a trader's belief that his information is more accurate than it really is. He shows that overconfident traders trade more frequently than rational traders because the mix of the two groups increases the heterogeneity of beliefs about stock returns. Heterogeneous beliefs are necessary to induce agents to trade. Traders hold underdiversified portfolios as in DeLong et al. [1990]. A higher-risk portfolio, on average, results in higher returns.

Odean [1998] also finds that 1) trading volume increases when market participants are overconfident, 2) markets may have positive serial correlation of returns when overconfident traders underreact to information from rational traders, 3) overconfidence increases market depth, and 4) overconfident traders increase volatility (although overconfident market makers may reduce this effect).

Benos [1998] models a market in which overconfident (aggressive) traders and more cautious traders are aware of each other's existence. Overconfident traders overestimate the precision of their signals of asset value. Benos concludes that overconfident traders may earn higher profits because they are more willing to push market prices higher. Reacting to that behavior, more cautious traders reduce trading demand, giving overconfident traders a first-mover advantage. Similarly, Kyle and Wang [1997] find that informed traders who know they are competing against overconfident traders will reduce their trading to the advantage of the overconfident traders.

In the moderated confidence model advanced by Bloomfield, Libby, and Nelson [2000], a trader assesses signals about the reliability of asset value information. If the trader receives an unbiased yet noisy signal, he tends to underreact to more reliable information and overreact to less reliable information. Experimental market evidence supports the model, revealing that traders who react appropriately to the reliability of information do not trade aggressively enough to offset the biased traders' effects on market prices.

To study the learning of overconfidence, Gervais and Odean [2001] model markets in which risky assets pay dividends. They assume the source of overconfidence is self-attribution bias. A trader receives a signal about the distribution of the dividend. Initially, he does not know his ability to interpret the signal correctly. An overconfident trader will update his beliefs with bias, overweighting his signal interpretation successes and underweighting his failures. Gervais and Odean illustrate that if the model is played infinitely, the trader and market makers will eventually learn the trader's true signal interpretation ability. They demonstrate that frequent, quick, and clear market feedback can reduce overconfidence because it allows traders to learn to judge their abilities more quickly. In this model, overconfident traders earn lower profits, increase trading volume, and increase expected price volatility.

Hirshleifer and Luo [2001] argue that overconfident traders bid more aggressively than rational traders because they overestimate the expected payoff *and* underestimate the variance of their trading strategies. Traders' aggressive bidding makes them better able to exploit any risky profit opportunities and any mispricing caused by liquidity and noise traders. It also earns them higher profits—but at the expense of lower expected utility.

Camerer and Lovallo [1999] studied excess entry into competitive experimental markets. When skill determined who made or lost money, more subjects entered the market, resulting in higher losses. Although subjects understood completely that the total profit to entering the industry was negative, they thought their own profit would be positive. Camerer and Lovallo concluded that business managers entering industries often overestimate the probability that their relative skill will earn them positive returns.

Along with investigating the influence of basic financial variables on overconfidence, we also investigate the role of several important factors in psychological and economic research:

- Information processing ability.
- The nature of the trader's specific task.
- Self-attribution bias.
- Trader experience.
- Market feedback.

To this end, we use panel data generated from the financial experiments described below.

Experimental Design

The experiments incorporated here were designed to investigate betweenness violations of expected utility theory (Evans [1997]), and were based upon those in Camerer [1989]. Subjects were asked to price gambles with identical expected values, offered in groups of three (called trios). Table 1 provides information about the trios. The gambles offered payoffs equal to \$0, \$1.50, and \$3. The trios were designed as a choice between a gamble $G = (P_{Low}, P_{Medium}, \text{and } P_{High})$, and a transformation of G with a 0.20 probability of the middle payoff being shifted evenly to both the low and high payoffs. The repeated shifting of probability from the middle to the extreme payoffs results in trios of gambles with the same expected value.

Each gamble trio was presented on a separate sheet of paper using Camerer's [1989] proportional rectangle design. The probability of each payoff was shown on the vertical axis, and the magnitude of the payoff was shown in proportionally sized rectangles on the horizontal axis. The gamble trios were offered in random order, as were the low-, medium-, and high-risk gambles within a trio.

We used fifth-price sealed-bid auctions for the market-level experiments (see the appendix for a complete

Table 1. *Summary of Gambles*

Trio	Expected Value	Least Risky Gamble, G_{Low}			Medium Risk Gamble, G_{Medium}			Most Risky Gamble, G_{High}		
		P_{Low}	P_{Med}	P_{High}	P_{Low}	P_{Med}	P_{High}	P_{Low}	P_{Med}	P_{High}
1	$2.10	0	0.6	0.4	0.1	0.4	0.5	0.2	0.2	0.6
2	$2.10	0.1	0.4	0.5	0.2	0.2	0.6	0.3	0	0.7
3	$1.50	0	1.0	0	0.1	0.8	0.1	0.2	0.6	0.2
4	$1.50	0.3	0.4	0.3	0.4	0.2	0.4	0.5	0	0.5
5	$0.90	0.4	0.6	0	0.5	0.4	0.1	0.6	0.2	0.2
6	$0.90	0.5	0.4	0.1	0.6	0.2	0.2	0.7	0	0.3

Note: Where low, medium, and high payments are $0, $1.50, and $3, respectively.

set of instructions). At the beginning of the auctions, subjects were endowed with an initial account balance of $10 or $15. Throughout the auctions, their gains and losses were posted against their accounts. For each auction, subjects submitted bids to purchase all the gambles offered in a trio. After the bidding, the market price (the fifth-highest price) for the first gamble in a trio was announced. The buyers were the four subjects who submitted bids greater than the market price.

The gamble was then resolved by randomly selecting a ticket out of a box of 100 numbered from 1 to 100 (representing probabilities). The procedure was repeated for the second and third gambles in the trio. Gains from the transactions increased subjects' account balances; losses decreased them. New bids were then solicited for the next trio of gambles. The six trios of gambles were offered twice, and no trio was repeated until all had been presented once and we had changed the order of gambles in the repetition of the market. Subjects were paid at the end of the experiment.

We conducted fifteen auctions with 109 subjects. Nine of the experiments were comprised only of experienced subjects (those who had participated in previous financial experiments). The 109 subjects made 3,924 total bids during the auction.[2]

Analysis

Panel Data

The experimental design allows us to observe subjects as they make trading decisions over time. Thus, we create a panel data set to analyze trader bidding behavior and its various determinants. For our purposes, panel data offer several advantages. First, they allow a greater number of data points than would be available in a single-period cross-sectional data set. This increases the degrees of freedom and reduces collinearity among the various independent variables hypothesized to influence bidding.

Panel data also allow us to investigate hypotheses that relate specifically to the passage of time. Without multiple observations on subjects over time, we could not readily estimate time-dependent effects such as learning, self-attribution bias, or market feedback. Along these lines, panel data allow greater control for unobserved heterogeneity: subject-specific characteristics that may be obscured cross-sectionally. In other words, we might eventually observe some variation in how traders bid. But we wouldn't know the extent to which that pattern, or any explanation for it, holds over repeated observations or whether it is spurious. See Greene [2003] for a further discussion.

In this setting, some of the independent variables are subject-specific and time-invariant, while others are time-varying. Thus, we formulate the regression model as

$$\text{Bid}_{it} = \alpha + \boldsymbol{X}_{\text{it}}\, \beta + v_i + \varepsilon_{it} \tag{1}$$

where Bid_{it} represents subject i's bid at time t, and $\boldsymbol{X_{it}}$ contains the hypothesized determinants of the bid. The error term v_i captures subject-specific residuals, while ε_{it} captures residuals associated with the panel. The parameter vector $\boldsymbol{\beta}$ is estimated using a random effects generalized least squares method (GLS).

Table 2 gives information about the bids for each gamble. Nearly all the highest quartiles of bids exceed the expected value of the gambles, suggesting a great deal of overconfidence in the bidding. In addition, the mean bids for the gambles across all 109 subjects universally exceed the mean market values across the fifteen markets, implying skewness in the upper bid ranges.

The mean market values, however, lie below the expected values of the gambles. Subjects who bid in the highest quartile stumbled upon a fortuitous strategy of bidding above expected value when the market value was set below the expected value. On average, this aggressive strategy could produce a profit. One may wonder whether these traders are overconfident in process-

Table 2. *Description of Bids in Order Administered*

Gamble	EV of Gamble	Range of Highest 25% of Bids	Range of Lowest 25% of Bids	Mean Bid	Mean Market Value	Expected Gain[1]	Differences in Means[2]
Initial Setting							
1	$1.50	$1.50–$4.00	$0.10–$1.30	$1.44	$1.37	$0.13	$0.07
2	$1.50	$1.54–$4.00	$0.25–$1.25	$1.51	$1.34	$0.16	$0.17
3	$1.50	$1.53–$4.00	$0.00–$1.26	$1.51	$1.34	$0.16	$0.17
4	$0.90	$1.00–$4.50	$ 0.20–$0.75	$1.02	$0.84	$0.06	$0.18
5	$0.90	$0.90–$3.00	$0.10–$0.50	$0.84	$0.64	$0.26	$0.20
6	$0.90	$0.90–$2.50	$0.10–$0.50	$0.81	$0.61	$0.29	$0.20
7	$2.10	$2.24–$4.00	$0.40–$1.37	$1.93	$1.72	$0.38	$0.21
8	$2.10	$2.00–$3.00	$0.00–$1.21	$1.70	$1.54	$0.56	$0.16
9	$2.10	$2.00–$3.00	$0.10–$1.38	$1.73	$1.53	$0.57	$0.20
10	$2.10	$2.05–$4.00	$0.50–$1.50	$1.92	$1.73	$0.37	$0.19
11	$2.10	$2.00–$5.00	$1.00–$1.53	$1.93	$1.70	$0.40	$0.23
12	$2.10	$2.10–$4.99	$0.70–$1.36	$1.90	$1.67	$0.43	$0.23
13	$0.90	$1.00–$3.00	$0.00–$0.53	$0.84	$0.71	$0.19	$0.13
14	$0.90	$0.90–$3.00	$0.10–$0.50	$0.73	$0.53	$0.37	$0.20
15	$0.90	$1.00–$3.50	$0.30–$0.60	$0.92	$0.73	$0.17	$0.19
16	$1.50	$1.60–$3.50	$0.56–$1.16	$1.46	$1.26	$0.24	$0.20
17	$1.50	$1.54–$3.25	$0.45–$1.00	$1.34	$1.09	$0.41	$0.25
18	$1.50	$1.69–$4.00	$0.25–$1.00	$1.51	$1.22	$0.28	$0.29
Repeat Setting							
19	$1.50	$1.70–$3.50	$0.56–$1.35	$1.51	$1.38	$0.12	$0.13
20	$1.50	$1.55–$3.00	$1.00–$1.40	$1.52	$1.45	$0.05	$0.07
21	$1.50	$1.70–$3.00	$0.75–$1.38	$1.54	$1.44	$0.06	$0.10
22	$0.90	$1.00–$3.00	$0.00–$0.50	$0.77	$0.58	$0.32	$0.19
23	$0.90	$1.00–$3.00	$0.10–$0.66	$0.94	$0.80	$0.10	$0.14
24	$0.90	$1.00–$3.00	$0.00–$0.43	$0.82	$0.65	$0.25	$0.17
25	$2.10	$2.24–$5.00	$0.25–$1.51	$1.95	$1.79	$0.31	$0.16
26	$2.10	$2.05–$4.00	$1.00–$1.50	$1.82	$1.68	$0.42	$0.14
27	$2.10	$2.24–$4.00	$1.00–$1.50	$1.91	$1.71	$0.39	$0.20
28	$2.10	$2.25–$4.00	$1.00–$1.54	$1.92	$1.82	$0.28	$0.10
29	$2.10	$2.11–$4.50	$0.80–$1.60	$1.93	$1.80	$0.30	$0.13
30	$2.10	$2.10–$4.00	$1.25–$1.66	$1.99	$1.79	$0.31	$0.20
31	$0.90	$0.97–$1.50	$0.00–$0.51	$0.77	$0.59	$0.31	$0.18
32	$0.90	$1.01–$2.00	$0.40–$0.75	$0.91	$0.82	$0.08	$0.09
33	$0.90	$1.00–$1.60	$0.00–$0.60	$0.84	$0.69	$0.21	$0.15
34	$1.50	$2.00–$3.00	$0.53–$1.40	$1.62	$1.41	$0.09	$0.21
35	$1.50	$1.79–$3.00	$0.50–$1.00	$1.51	$1.30	$0.20	$0.21
36	$1.50	$1.80–$3.01	$0.30–$1.14	$1.59	$1.36	$0.14	$0.23

Note: [1]Difference between expected value of gamble and its mean market value. [2]Difference between the mean bid and the mean market value.

ing information in the gambles (as suggested by psychologists), or in their strategy of bidding against seven other traders, or both. In any case, overconfidence is captured through the higher bid.

Capturing Confidence Types

We constructed two independent dummy variables to capture the confidence type of each subject's bid. The first, D_{over}, is designed to capture overconfident decisions. It is set equal to 1 if the trader's bid in the *previous* period is above the expected value, and 0 otherwise. We specify expected value as the standard against which to define overconfidence because financial theory assumes decision-makers are risk-averse, and the experimental economics literature assumes subjects are risk-neutral (Davis and Holt [1993]). We use the bid value from the previous period to prevent problems associated with endogeneity among explanatory variables.

The second variable, D_{under}, measures underconfidence. It is set equal to 1 if the bid in the *previous* period is below the expected value, and 0 otherwise. Hence, the reference group for these two types of bids consists of bids that are equal to the expected value, i.e., risk-neutral bids.[3] To measure the impact of confidence on bidding, we include interaction terms between the dummy variables and a vari-

Table 3. *Summary Statistics for Variables Used in the Study*

	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Expected Value (EV)	3,924	1.50	0.49	0.90	2.10
Standard Deviation (σ)	3,924	1.03	0.34	0	1.50
Lag D_{over}	3,815	0.40	0.49	0	1
Lag D_{under}	3,815	0.56	0.50	0	1
EV * D_{over}	3,815	0.52	0.70	0	2.10
EV * D_{under}	3,815	0.93	0.89	0	2.10
σ * D_{over}	3,815	0.41	0.55	0	1.50
σ * D_{under}	3,815	0.62	0.57	0	1.50
Highest Payoff	3,924	2.83	0.47	1.50	3.00
Highest Payoff * D_{over}	3,815	1.12	1.41	0	3.00
Highest Payoff * D_{under}	3,815	1.65	1.47	0	3.00
Lowest Payoff	3,924	0.17	0.47	0	1.50
Lowest Payoff * D_{over}	3,815	0.05	0.26	0	1.50
Lowest Payoff * D_{under}	3,815	0.08	0.34	0	1.50
Return, Three-Period Lag	3,594	0.17	0.97	–4.00	6.32
Return * D_{over}	3,594	0.05	0.56	–3.85	5.00
Return * D_{under}	3,594	0.11	0.77	–4.00	6.32
Wealth, Three-Period Lag	3,924	13.28	4.81	0	35.95
Wealth * D_{over}	3,815	5.16	7.00	0	35.95
Wealth * D_{under}	3,815	7.64	7.65	0	35.95
Cumulative Participation, Three-Period Lag	3,597	9.36	7.23	0	33
Participation * D_{over}	3,597	3.46	6.37	0	33
Participation * D_{under}	3,597	5.51	7.07	0	32
Pricing Errors	3,912	0.02	0.37	–4.00	3.00
Pricing Errors * D_{over}	3,803	0.01	0.25	–4.00	3.00
Pricing Errors * D_{under}	3,803	0.01	0.28	–2.92	2.59
Experience	3,924	0.59	0.49	0	1
Experience * D_{over}	3,815	0.23	0.42	0	1
Experience * D_{under}	3,815	0.33	0.47	0	1
Time Period	3,924	18.5	10.4	1	36
Time * D_{over}	3,815	6.45	10.12	0	36
Time * D_{under}	3,815	11.87	12.70	0	36

ety of independent variables, introduced as the regression models are discussed below. Approximately 40% of bids were captured by D_{over}, 57% by D_{under}, and the remaining 3% were risk-neutral. See Table 3 for summary statistics of the variables used.

Incorporating Financial and Dummy Variables to Capture Bid Type

Standard financial theory holds that asset valuation, represented here by the trader's bid, is a function of its mean and standard deviation. Model 1 in Table 4 gives coefficient estimates for this most basic regression model. Each coefficient is statistically significant, as is the Wald chi-square statistic, indicating the overall significance of the model. While the R^2 is only 0.054 overall, the signs of the coefficients are appropriate for a market composed of risk-averse bidders. A higher expected value is associated with a higher bid, and a higher standard deviation is associated with a lower bid.

Model 2 in Table 4 incorporates the lagged dummy variables, D_{over} and D_{under}. Not surprisingly, the coefficients for these high-bid and low-bid dummy variables are positive and negative, respectively. Each coefficient is significant, and the overall R^2 increases to 0.302. The results suggest that, in addition to the traditional financial variables, the behavioral types captured by the dummy variables also affect bidding behavior.

To determine whether the bid types are developed differently using basic financial information, we interact the dummies with expected value and standard deviation. As shown in Model 3 (Table 4), expected value and standard deviation remain significant, with the correct signs for a risk-averse market. D_{over} remains significantly positive, but D_{under} loses significance. This result suggests that the lower bidders do not exist as a distinctive type, in contrast to the higher bidders.

Only one interaction term is significant, the coefficient for expected value interacted with D_{over}, which is negative. This indicates that overconfident bidders as a type bid less on gambles with higher expected values. However, the bidders do not respond significantly to risk (standard deviation), which is contrary to what we expect for a strictly risk-seeking bidder. The overall ef-

Table 4. *Regression Results with Coefficients (in dollars) and P-Values*

	1 Basic Financial Model	2 Basic Financial Model with Dummy Variables	3 Basic Financial Model with Interactions with Dummy Variables	4 Extended Financial Model with Interactions with Dummy Variables	5 Extended Financial Model with Behavioral Variables
Constant	1.653 (0.000)	1.138 (0.000)	1.054 (0.000)	0.560 (0.050)	1.080 (0.004)
Expected Value (EV)	0.140 (0.000)	0.357 (0.000)	0.497 (0.000)	0.296 (0.038)	0.273 (0.072)
Standard Deviation (σ)	–0.437 (0.000)	–0.304 (0.000)	–0.408 (0.002)	–0.787 (0.000)	–0.564 (0.032)
Lag D_{over}		0.447 (0.000)	0.803 (0.001)	0.057 (0.851)	–0.156 (0.690)
Lag D_{under}		–0.235 (0.000)	–0.297 (0.209)	-0.252 (0.401)	–0.682 (0.078)
EV * D_{over}			–0.438 (0.001)	-0.344 (0.018)	–0.346 (0.025)
EV * D_{under}			0.058 (0.671)	0.204 (0.160)	0.223 (0.148)
σ * D_{over}			0.222 (0.114)	0.298 (0.155)	0.188 (0.491)
σ * D_{under}			–0.060 (0.677)	–0.264 (0.212)	–0.526 (0.052)
Highest Payoff				0.401 (0.000)	0.278 (0.031)
Highest Payoff * D_{over}				0.184 (0.123)	0.239 (0.078)
Highest Payoff * D_{under}				0.018 (0.884)	0.153 (0.260)
Lowest Payoff				0.078 (0.644)	0.110 (0.554)
Lowest Payoff * D_{over}				0.243 (0.167)	0.266 (0.169)
Lowest Payoff * D_{under}				–0.379 (0.027)	–0.424 (0.024)
Return, Three-Period Lag					0.036 (0.421)
Return * D_{over}					0.005 (0.917)
Return * D_{under}					–0.035 (0.439)
Wealth, Three-Period Lag					–0.011 (0.368)
Wealth * D_{over}					0.009 (0.493)
Wealth * D_{under}					0.011 (0.395)
Cumulative Participation, Three-Period Lag					0.024 (0.046)
Participation * D_{over}					0.008 (0.527)
Participation * D_{under}					–0.003 (0.821)
Pricing Errors					0.165 (0.300)
Pricing Errors * D_{over}					–0.092 (0.572)
Pricing Errors * D_{under}					–0.123 (0.449)
Experience					–0.094 (0.412)
Experience * D_{over}					0.091 (0.441)
Experience * D_{under}					0.066 (0.572)
Time Period					–0.021 (0.025)
Time * D_{over}					–0.005 (0.634)
Time * D_{under}					0.009 (0.373)
R-Square Within	0.074	0.250	0.294	0.371	0.353
Between	0.000	0.837	0.785	0.821	0.777
Overall	0.054	0.302	0.328	0.383	0.429
Wald Chi-Square	304.23 (0.000)	1414.50 (0.000)	1692.16 (0.000)	2273.90 (0.000)	2343.83 (0.000)
Number of Observations	3924	3815	3815	3815	3585

fect of every \$1 increase in expected value on overconfident bids is equal to the sum of the coefficients for expected value and EV * D_{over}, or \$0.497 – \$0.438 = \$0.059. The impact of expected value on the overconfident bids is very small relative to standard deviation, –\$0.408. Overconfidence in bidding adds \$0.365 to the average bid, calculated as the sum of the coefficients for D_{over} and EV * D_{over}.

Comparing Model 2 to Model 3, D_{over} retains a positive and significant coefficient. Thus, the high-bid type appears to be influenced by individual specific variables related to D_{over} (to be introduced in subsequent models). D_{under} loses significance, indicating that bidding below the expected value does not constitute a distinct confidence type.

Evans [1993] suggests that decision-makers may use alternative financial cues in setting a bid. To examine this possibility here, we add two cues to the regression model that are popular with subjects in Evans' study—the highest and lowest payoff in each gamble and their interaction effects with D_{over} and D_{under}. Results are in Model 4, Table 4.

Expected value uninteracted remains significantly positive, and standard deviation significantly negative. The positive, significant coefficient for highest payoff suggests that larger highest payoffs (higher payoff "ceilings") induce higher bids. While not unreasonable, this result is contrary to basic financial valuation theory, which predicts that only expected value and standard deviation should induce value.

The lowest payoff uninteracted is not statistically significant.

D_{under} and D_{over} lose significance, uninteracted, in Model 4. However, the interaction EV * D_{over} remains significantly negative. The lowest payoff interacted with D_{under} is significantly negative, indicating that bigger lowest payoffs (higher payoff "floors") induce lower bids among underconfident bidders.

Incorporating Non-Financial Behavioral Variables

Previous overconfidence research suggests that behavioral factors unrelated to the financial characteristics of the gambles can further explain bidding variation by certain types. To investigate this, we add several behavioral variables to the model that are identified in the psychology and economics literature. Below, we discuss the motivation and construction of these variables, and consider what the regression model illustrates in light of their inclusion.

Some researchers argue that overconfidence occurs because of the self-attribution bias. This would imply here that the more successful the subject has been in earning money in the experiment, the more overconfident his bids become. We add three variables to capture this effect: return lagged three periods, wealth lagged three periods, and cumulative participation lagged three periods. A trader's return is computed as the rate of return of wealth before the bid is made relative to the \$10 or \$15 the subjects were given at the start of the experiment. Wealth is the cumulative amount of money the subject has, including the initial \$10 or \$15, prior to making the bid. Cumulative participation is the number of times the subject has been one of the top four bidders in the market, and hence eligible to earn a profit or loss when the gamble is resolved. The variables are lagged three periods because subjects made bid decisions in groups of three gambles. The information they would have on their success, or lack thereof, comes three gambles before the current bid.

Previous research has also related overconfidence to faulty information processing. Although our subjects received full information about the gambles, they still likely differ in their ability to interpret or process the information into accurate expected values and standard deviations. The variable pricing errors represent the dollar differences in a subject's bid for a gamble the first and second time it was offered (in the initial and repeated conditions). Subjects who are less consistent with their pricing may lack a systematic way of thinking about bids, which may imply less competence in information processing. Indeed, Ferraro [2003] has linked lower competence to overconfidence empirically.

In this study, however, bigger pricing errors may be related to overconfident bids. The variable is only relevant for the second half of the experiment, because computing the error requires both the initial and repeated bids. We set pricing errors equal to zero for the initial condition. The variable is time-varying in the repeated portion.

According to Gervais and Odean [2001] overconfidence should decrease with experience or feedback, because traders learn from their overconfidence and adjust over time. By contrast, other studies indicate that overconfidence is a deeply ingrained psychological trait that resists experience. To investigate experience here, we incorporate the time-invariant dummy variable experience, equal to 1 if a subject participated in previous financial experiments, and 0 otherwise. To capture feedback, we incorporate the variable time period, a sequential count variable for gambles 1 through 36.

Model 5 in Table 4 incorporates these behavioral variables. As in the previous models, the coefficient for expected value is significantly positive and the coefficient for standard deviation is significantly negative, as one would expect in a risk-averse market. The coefficient for the D_{over} type is statistically insignificant, but the D_{under} type regains significance (at the 7.8% level) even in the presence of the full set of available financial and behavioral variables. The addition of the behavioral variables appears to reveal underconfidence as a distinct type.

The expected value interaction with D_{over} remains negative and significant as in Models 3 and 4. For the first time, a bidder type becomes significant in interaction with standard deviation, as the coefficient for standard deviation and D_{under} emerges as significantly negative. The overall effect of every \$1 increase in the standard deviation on bids by underconfident bidders is –\$1.09 = –\$0.564 – \$0.526. The highest payoff and its interaction with D_{over}-type bids becomes positive and significant, while the lowest payoff interacted with D_{under} is negative and significant.

Only two of the behavioral variables uninteracted emerge as significant, cumulative participation and time period. We find that traders bid significantly more when they have participated more often previously, other factors remaining equal. The positive significance of cumulative participation is consistent with self-attribution, although the coefficient is small (\$0.024). The insignificance of the other two self-attribution bias variables, return and wealth, suggests that self-attribution did not substantially influence bidding in the markets we analyzed.

The time period coefficient shows that in later rounds traders bid about \$0.021 less per period, on average, suggesting that feedback affected their performance. The insignificance of experience and its interaction terms indicates that the experienced traders in our study generally did not bid differently from the inexperienced traders. This result may be consistent with the finding by some psychologists that experience does not reliably reduce overconfidence.

Previous analytical studies of overconfidence derived contradictory results about whether overconfident trading leads to greater or lesser wealth (e.g., Odean [1998] and Gervais and Odean [2001]). We tested for differences in the average ending wealth associated with the D_{over}- and D_{under}-type bids. On average, the amounts were $16.24 and $15.38, respectively. D_{over} ending wealth was significantly higher than D_{under} and risk-neutral ending wealth ($p = 0.005$), while D_{under} was significantly lower than D_{over} and risk-neutral ending wealth ($p = 0.000$).[4]

Discussion and Conclusions

Psychologists have documented extensively the overconfidence phenomenon. According to traditional financial models, in order for markets to function properly, economic agents must make decisions absent such biases. But a growing body of analytical research has shown that overconfident traders may persist in markets and greatly impact market outcomes. In this paper, we have investigated the prevalence and determinants of overconfidence empirically, making use of panel data on traders who participated in an experimental financial market.

We captured overconfident and underconfident bids relative to risk-neutral bids using dummy variables defined on the basis of subjects' actual lagged bidding behavior. Generalized least squares results support the prevalence of overconfidence in market bidding—approximately 40% of bids were overconfident. Traditional financial variables appear to influence only overconfident bids. We find significantly negative interaction terms between expected value and overconfident bids.

The underconfident-type bids (57%) do not appear distinct from simple risk-averse bids in the presence of interactions with only standard financial variables for risk (standard deviation) and return (expected value). Among the non-traditional financial variables studied here, a greater value for the highest possible payoff in a gamble (a higher payoff "ceiling") tended to induce higher bids for all confidence types. A greater value for the lowest possible payoff (a higher payoff "floor") tended only to affect underconfident bids, lowering them.

Introducing behavioral variables to the regression models impacts the results only minimally. Of the three variables included to capture self-attribution bias, only one was statistically significant (cumulative participation) and carried the expected positive sign. This indicates that all subjects (not just overconfident ones) tend to bid more when they have participated more frequently in the past in the resolution of the gamble.

Researchers differ over whether experience should eliminate overconfidence; we found overconfidence impervious to trader experience. However, feedback throughout the experiment tended to reduce all bids, not just over- or underconfident types. Overconfident bid types end the experiment with significantly more wealth than underconfident types.

Psychologists have established the broad role overconfidence plays in human decision-making. Our empirical results suggest that it carries over into financial decision-making. We see that both traditional and non-traditional financial variables are associated with overconfident and underconfident bids. We do not find compelling evidence that self-attribution bias affects overconfidence in the traders we study.

The fact that individual economic decisions don't follow traditional rational models has important implications for market outcomes. This is illustrated by analytical studies on overconfidence, and by anecdotal evidence like the lack of hurricane and earthquake preparedness described in the introduction. Future research may move beyond the use of experimental data, and work to improve practical understanding of the presence and impact of overconfidence.

Acknowledgments

This research is supported by grants to D. Evans from the National Science Foundation (SES 91–22201) and the College of Administrative Science's Mini-Grant Committee of the University of Alabama in Huntsville. Previous versions of this paper were presented at the Public Choice/Economic Science Association meetings in March 2002, and at the Meetings of the Society for the Advancement of Behavioral Economics in July 2003. The authors express their appreciation to Sunny Duddilla for his help in conducting the experiments, and to John Morgan and Fan Tseng for helpful comments in developing the paper.

Notes

1. This is in contrast to the asset's being held in a diversified portfolio, when β in the Capital Asset Pricing Model is the appropriate risk measure.
2. 3,924 prices = 109 subjects × 6 trios of gambles × 3 gambles per trio × 2 for repeated decisions.
3. In light of their construction, these variables represent bid type (or confidence type) rather than trader type. This is because, in principle, a single trader may exhibit either type of behavior over time. Multiple observations on these traders allow us to take advantage of this variation.
4. Averages for wealth throughout the experiment for D_{over} and D_{under} were $12.99 and $13.51, respectively. The differences in average wealth between the bid type and the opposite bid type and risk-averse bids are significant ($p = 0.000$ and $p = 0.022$, re-

spectively). These results are the reverse of ending wealth. Therefore, on average throughout the experiment, wealth for the D_{over} bid type is lower than for the D_{under} bid type, but by the end of the experiment the overconfident bid types achieved greater wealth.

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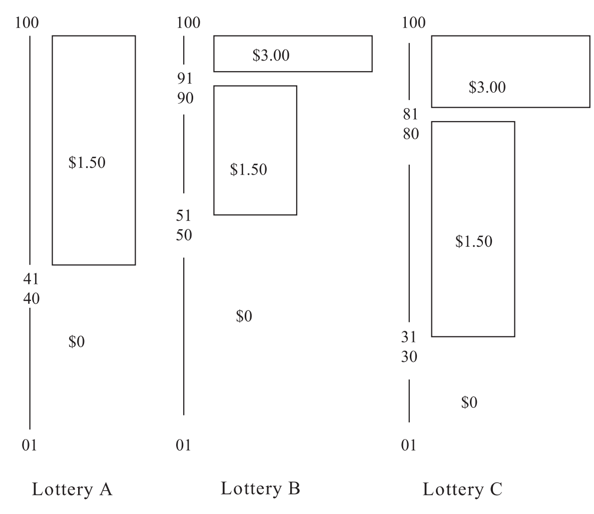
Appendix
Instructions for Fifth-Price Sealed-Bid Buying Auction

We will read the instructions together. If you do not understand the instructions, please ask for assistance. The monitors are here to help you.

This is an experiment in the economics of market decision-making. The National Science Foundation and The University of Alabama in Huntsville have provided funds for the conduct of this research. If you follow the instructions closely and make appropriate decisions, you may make an appreciable amount of money. These earnings will be paid to you in cash at the conclusion of the experiment.

Introduction to Lotteries

You will be making pricing decisions about trios of lotteries. A lottery describes the outcomes of a decision and gives the probability of each outcome. See the lotteries below:



The outcomes of the lotteries above are determined by a random number between 01 and 100. Each of the numbers is equally likely to occur. Look at Lottery A. If a number between 01 and 40 were drawn, you would be paid $0; if any number between 41 and 100 were drawn, you would be paid $1.50.

The height of Lottery A's drawing illustrates the relative likelihood of each payoff. The distance between 01 and 40 is 40% of the total height of the line; the distance between 41 and 100 is 60% of the height of the line.

In Lottery B, if the random number were between 01 and 50, you would be paid $0; if the number were between 51 and 90, you would be paid $1.50; and if the number were between 91 and 100, you would be paid $3. Again, the heights of the lines indicate how likely each payoff is. The distance between 01 and 50 is 50% of the height; between 51 and 90 it is 40%; and between 91 and 100 it is 10%. Lottery C is interpreted in the same fashion as Lotteries A and B.

The widths of the rectangles indicate the size of the payoffs. For a payoff of $0 there is no rectangle, only a line. The $1.50 payoff rectangle is half the width of the $3 payoff rectangle.

General Instructions

In this experiment you will participate in a series of auctions in which you will be given the opportunity to purchase lotteries, which will be played for cash at the end of each auction.

You will be given a starting balance of $10 at the beginning of the experiment. The auction will be repeated fourteen times: two practice auctions (during which no payments will be made), followed by twelve purchase auctions (during which you will earn monetary payments). If you purchase no lotteries during the experiment, you will keep the $10 when you leave. If you purchase lotteries, your earnings will be:

STARTING BALANCE
– PAYMENTS FOR LOTTERIES
+ LOTTERY PAYOFFS

Your earnings will be tallied at the end of each auction. Instructions on how to tally your earnings on the attached **EARNINGS WORKSHEET** will be given shortly. Please note that persons who go bankrupt during any auction will not be allowed to participate in the remaining auctions.

Specific Instructions on the Auctions

You, along with several other individuals participating in the experiment, will take part in several auctions for lotteries. Four lotteries will be sold to four different participants in each auction. In each auction you will be asked to submit bids indicating how much you are willing to pay for each lottery in a trio. To see how the auction works, consider the following example.

Suppose there are eight participants submitting bids for a lottery: Bidder 1, Bidder 2, and so on through Bidder 8. The monitor will sell four of each lottery in a trio during each auction. The first step for each participant is to submit a bid for each lottery. Write your bids on one of the provided bid forms and give the form to the monitor. There will be four buyers for each lottery in each auction, one for each of the four lotteries sold. The buyers will be the four participants who submit the four highest bids. However, the price each buyer actually pays (the *market price*) will be the *fifth* highest submitted bid.

To illustrate the auction process, consider that the eight participants in a *hypothetical* auction submit the following bids:

Bidder 1	$300
Bidder 2	$450
Bidder 3	$295
Bidder 4	$330
Bidder 5	$280
Bidder 6	$455
Bidder 7	$250
Bidder 8	$320

We then order all the bids from highest to lowest as follows:

1st highest bid – $455 by Bidder 6
2nd highest bid – $450 by Bidder 2
3rd highest bid – $330 by Bidder 4
4th highest bid – $320 by Bidder 8
5th highest bid – $300 by Bidder 1
6th highest bid – $295 by Bidder 3
7th highest bid – $280 by Bidder 5
8th highest bid – $250 by Bidder 7

Because the monitor is selling only four of each lottery during each auction, Bidders 6, 2, 4, and 8 are buyers in this auction because they submitted the four highest bids. Bidders 1, 3, 5, and 7 are not buyers as their bids were lower. However, the buyers (Bidders 6, 2, 4, and 8) do not have to pay the bid prices they submitted for the lottery. Instead, each pays the "market price," which is determined by the fifth-highest submitted bid. This market price is the value of the first bid below the lowest bid submitted by a buyer. In this example, the market price is $300, submitted by Bidder 1, who is *not* a buyer in this auction.

During the experiment, we will report only the market price and not identify buyers by number. You will know you are a buyer if your bid is *higher* than the market price. At the end of the experiment you will have the opportunity to reconcile your records with ours.

You should note that no buyer has to pay the bid price he or she submitted unless the lowest buyer's bid and the market price are the same (tied). In the event of a tie at the market price, the buyer (or buyers) will be chosen by having each roll a die. The bidder (or bidders) who rolls the highest number (or numbers) will be declared a buyer (or buyers) and the market price will be the bid submitted by the tied participants. In all cases in which there is not a tie at the market price, buyers will not have to pay their submitted bids.

Some people argue that since you generally do not have to pay the bid price that you submit, it is in your best interest to write down a bid price *exactly equal to the maximum amount you are willing to pay for a lottery.* According to them, you do not want to submit a bid higher than the maximum amount you are willing to pay because the market price might turn out to be more than you are willing to pay. Also, they make the point that you do not gain by submitting a bid lower than the maximum amount you are willing to pay. To support their view, they provide the following example:

Suppose you are willing to pay as much as $400 for a lottery. If the market price turns out to be $300, you can buy a ticket for $300 when you would have been willing to pay as much as $400 ($100 more than the market price). Now, suppose that you thought the market price was going to be $250 and you submitted a bid of $275, even though you would have been willing to pay as much as $400. As a result of not correctly anticipating the market price, you would have lost the opportunity to purchase the lottery for $300 and the opportunity to realize a gain of $100 over the market price. Of course, if you truly would be willing to pay no more than $250, then that is the bid you should submit even if it means that you purchase no lotteries.

You are, of course, free to submit your bids using whatever approach you may wish to use. Keep track of your submitted bids and purchases on your Earnings Worksheet. In each auction period, record your submitted bid in column 3. As soon as the market price is determined, record the market price in column 4, and in column 5 indicate with a Y or N if you are or are not a buyer in the market. In column 6, record the amount spent in that auction: the market price if you purchased a lottery, or $0 if you did not. When the lottery has been resolved (described later), place the lottery payoff in column 2. In column 7 record your net profit (or loss) for that auction period: the lottery payoff (column 2) minus the amount spent (column 6) if you bought a lottery; or $0 if you did not. In column 8 compute your new balance: previous balance plus profits or minus losses. At the end of the experiment, your final balance will be paid to you.

If you are one of the buyers of a lottery, you will get to play the lottery for cash. The monitor will select a ticket from a container to determine your payoff. This container has 100 tickets numbered 01 through 100. The ticket will determine the outcome of the lotteries you buy. To see how you will be paid based on the ticket number, refer back to Lotteries A, B, and C on the first page. If the ticket number were 37, you would win $0 on either Lottery A or Lottery B but $1.50 on Lottery C. If the ticket number were 93, you would be paid $1.50 for Lottery A, but $3 for Lottery B or C.

At the end of the experiment, bring your Earnings Worksheet to the monitor for confirmation and a cash payment. You will sign a receipt. Only one subject should go to the monitor at a time. Please do not talk to other subjects while waiting to be paid.

You will participate in two practice lottery sessions before we begin so that you can test your understanding of the instructions. No money can be earned or lost in the practice period.

You may refer to the instructions at any time.