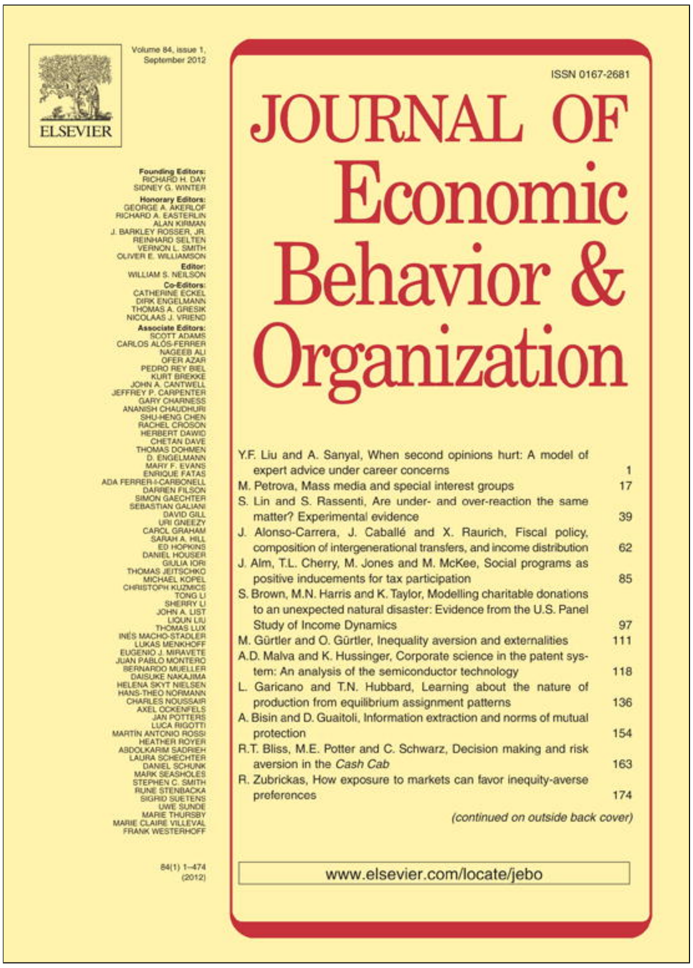

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Irrationality and beliefs in a laboratory asset market: Is it me or is it you?

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ABSTRACT

This paper reports on an experiment designed to examine individual and market outcomes with a mixture of rational and non-rational traders. Using values elicited via auctions, we measure a specific form of irrationality: the tendency to overweight high payoff, low probability events, or probability judgment error. Subjects are classified by their tendency to exhibit errors, as well as their beliefs regarding whether others will make errors. Subjects then participate in a series of double auction markets. The results indicate that both probability judgment error and beliefs about other subjects' susceptibility to probability judgment error have significant impact on individual and market outcomes.

1. Introduction

Both economists and psychologists have demonstrated that economic decision-makers do not always behave as rational agents, and it seems plausible to suppose that in market environments there may be a mixture of some rational and some non-rational individuals. If so, agents' beliefs concerning the rationality of other agents could have a critical effect on both price determination and the welfare of market participants. Blanchard (1979) considered an extreme case, a theoretical speculative bubble, where prices are inefficient even though all agents are rational. More recently, Camerer et al. (2004) developed a cognitive hierarchy theory of games, where players can "believe, incorrectly and overconfidently, that the other participants are not doing as much thinking as they themselves are. In these situations, the players are not in equilibrium because some players' beliefs are mistaken" (Camerer et al., 2004, p. 863)). Behavioral game theorists have demonstrated that models incorporating levels of reasoning can explain data from laboratory games.[3] This paper describes an experiment designed to look at individual rationality and beliefs about the rationality of others in the context of an experimental asset market. We study prices and trading performance in an asset market with a mixture of rational and non-rational traders.

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[3] See Camerer (2003) for a review of this literature.

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The specific form of irrationality we investigate is probability judgment error related to high payoff, low probability outcomes.[4] Previous research reports that subjects tend to overweight high payoff, small probability events (Ackert et al., 2006) and that asset price bubbles are associated with such probability judgment errors (Ackert et al., 2009). First, we measure whether individual traders are prone to such probability judgment error. Our subjects bid to purchase two types of assets in a series of auctions. We measure the difference in bids for an asset with a low probability of high payout and another whose dividend distributions are nearly identical. The "truncated" asset pays the same large dividend with the same probability as does the "lottery" asset, but the number of large dividend payouts is limited. Despite this limitation, the risk-neutral values of the two assets are almost identical and, thus, any difference in valuation indicates probability judgment error. While participating in these auctions, subjects are also asked to predict the results of similar auctions for both the truncated and the lottery asset. We use differences in predicted prices for these assets as a measure of subjects' beliefs about other subjects' probability judgment errors. Finally, all subjects are asked to participate in a multi-period experimental asset market for a third lottery asset. Our asset market is based on the Smith et al. (1988) design, which is well-studied and often produces inefficient pricing.

In markets with diverse traders, some traders may believe that others have mistaken expectations. Those they trade with may or may not actually fall prey to irrationality. Still others may make rational decisions and expect that everyone else will, as well. Our analysis consists of first classifying subjects according to two criteria: whether they are prone to making probability judgment errors and whether they believe other subjects make these errors. Mispricing in the double auctions is then related to the number of subjects in each group. We find that the belief that others are subject to probability judgment errors fuels mispricing. We also compare subjects' profits and trading activity across groups. We find that expected profits are lowest and trading activity is highest for subjects who make probability judgment errors, but predict that other subjects do not make this error. If we can interpret these subjects as being overconfident, our findings are consistent with the theoretical prediction that overconfident agents trade more and earn less.

The remainder of the paper is organized as follows. Section 2 contains a brief review of related research studies. Section 3 presents the experimental design. Experimental results are reported in Section 4 and 5 concludes.

2. Background

Three strands of previous research are especially relevant to our study. There is a large body of literature pertaining to experimental asset market bubbles, another set of studies relating to level of reasoning, and finally a number of overconfidence experiments. We discuss each of these strands in turn.

2.1. Laboratory asset market bubbles

Experimental economists have discovered a particular laboratory asset market structure in which prices bubble and crash regularly. Smith et al. (1988) designed an experimental asset market where subjects trade an asset that pays a random dividend each period for a finite number of periods. Because all subjects know the number of periods and the probability distribution governing dividends, the asset's expected value is very easy to calculate. Even so, Smith, Suchanek, and Williams regularly observe mispricing in the form of asset price bubbles.[5] They hypothesize that their observations are examples of speculative or rational bubbles. Such bubbles may arise if some rational subjects believe that others are not rational. In this scenario, one of the rational subjects may knowingly purchase the asset for a high price (relative to risk-neutral value) if he/she believes that the asset can be sold later at an even higher price to one of the irrational subjects. Even if all of the subjects are rational, the belief that there are irrational subjects can be enough to generate bubbles.

Lei et al. (2001) modify the Smith, Suchanek, and Williams design by incorporating a no speculation treatment. They eliminate the opportunity to speculate by allowing participants to be either only buyers or only sellers of the asset. But Lei, Noussair, and Plott still obtain bubbles, and so conclude that the ability to speculate is not necessary for bubble formation. Their bubbles are not speculative bubbles, but are instead the result of actual irrational behavior. Lei, Noussair, and Plott suggest that trader confusion is the source of the irrationality.

Ackert et al. (2009) design an experiment to further link irrationality and bubbles. They create an environment where some subjects will likely exhibit irrational behavior. Decision researchers (see Camerer (1995) for a survey) have found that subjects frequently misjudge the probabilities of very unlikely events. Ackert, Charaput, Deaves, and Kluger incorporate low probability events into the Smith, Suchanek, and Williams market structure by allowing subjects to trade two assets. The first asset is a "lottery" asset, that is, an asset with a very small chance of paying the bearer a large payoff.[6] The dividend each period has a .02 probability of paying the holder $20. Since there were ten periods, there was a very remote chance that the

[4] Researchers have investigated a variety of forms of irrationality. See, for example, Duh and Sunder (1986), Camerer (1987), Ganguly et al. (2000), Kluger and Wyatt (2004), Budescu and Maciejovsky (2005), Fehr and Tyran (2005), and Asparahouva et al. (2007).

[5] Since then, there have been hundreds of laboratory experiments based on this design. See Davis and Holt (1993) and Kagel and Roth (1995) for introductions to this literature.

[6] Ackert et al. (2006) report that traders will pay higher prices for an asset having lottery characteristics (i.e., a claim on a large, though unlikely, payoff) in a bubble market environment.

asset would pay $200. The second asset was a truncated version of the lottery asset. This truncated asset was identical to the lottery asset except that it could only pay a maximum of three dividends. Since the chance of more than three dividends is very small, the expected values of the lottery asset and the truncated lottery asset differ by much less than a penny.

Ackert, Charaput, Deaves, and Kluger measure irrationality, specifically probability judgment error, as the difference between the market prices of the lottery and the truncated assets. They find an association between the existence of bubbles and probability judgment error. Our study uses a similar technique to measure probability judgment error, however we also elicit values from individual subjects. Our purpose is to study the mechanism through which rational and irrational subjects interact in a laboratory setting where mispricing is common.

2.2. Level of reasoning

In 1936 Keynes likened professional investment to a beauty contest in which a decision maker attempts to pick the face that others judge to be the prettiest, rather than the one he himself finds most attractive (Keynes, 1936). This insight has had a lasting impact in finance because it suggests that theorists should recognize that beliefs about others' beliefs affect asset prices, and not simply beliefs about future cash flows.[7] Theorists (Camerer et al., 2004) have developed models featuring levels of reasoning, where agents who use higher order reasoning choose a best response based on his or her beliefs about what others believe.

Experimentalists have investigated depth of reasoning in the laboratory and in larger scale samples of newspaper and magazine readers (Nagel, 1995; Bosch-Domenech et al., 2002). In the basic laboratory beauty contest, players pick a number in the interval [0,100]. The winner of the game is the player who picks the number closest to the mean selection of all multiplied by p, where $p < 1$ and is common knowledge. The Nash equilibrium is that all players select zero. By examining choices over rounds, researchers have studied how people reason over steps. The results indicate that people employ different levels of reasoning, with some behaving randomly and others behaving more strategically. Newspaper contests allow larger and more diverse subject pools than is practical in a laboratory setting. Interestingly, researchers conclude that the final choices of those who use higher order beliefs depended on their confidence in the ability of others to also use higher order beliefs (Bosch-Domenech et al., 2002). Recent research using eye-tracking technology gives additional insight into the strategies people use in evaluating potential responses. Muller and Schwieren (2011) find that the level of reasoning may be higher than what first seems apparent as people adjust their choices based on beliefs about the actions of others.

In our experiment, we measure whether subjects are prone to probability judgment error and whether they believe other subjects fall prey to such error. If a subject incorrectly assesses the values of two nearly identical assets, performance will suffer. At the same time, how a subject views the reasoning process of others will also affect his or her trading decisions. We investigate market outcomes and the decisions of market participants when traders are classified based on the rationality of their decisions as well as their assessments of the rationality of others.

2.3. Overconfidence

An overconfident person overestimates the probability of his preferred hypothesis (Griffin and Tversky, 1992). Thus, overconfidence is a behavioral bias resulting from self-deception. That people are often overconfident is long recognized and empirically documented (Barber and Odean, 2001; Fischhoff et al., 1977; Odean, 1998).

Researchers have recognized several forms of overconfidence.[8] Overconfidence may result from miscalibration or the tendency to overestimate the precision of private information. Researchers also note that overconfident people believe they are "better than average" or more skilled than others. Third, researchers recognize that overconfidence may arise when a person is overly optimistic about the future.

Can this behavioral bias persist in a market environment? It seems logical that in the long-run overconfident traders will disappear if their irrationality leads to the accumulation of trading losses. However, overconfident traders can survive in some models (Benos, 1998; Hirshleifer and Lou, 2001). In other research, Lichtenstein and Fischhoff (1980) show that overconfident people can learn to improve calibration with intensive feedback on their performance. In our design, participants receive no feedback on their performance until the conclusion of the experiment. Thus, incorrect valuations could be persistent because traders do not have the opportunity to learn. We examine whether the composition of the market, in terms of rational and irrational traders, has an impact on pricing.

Empirical studies of overconfidence have also linked excessive trading and lower earnings to overconfidence (Barber and Odean, 2001; Glaser and Weber, 2007; Grinblatt and Keloharju, 2009). By measuring probability judgment error, we can examine the performance of irrational traders. Further, measuring beliefs about others' susceptibility to such errors, allows us to identify overconfident traders. We conjecture that subjects making the probability judgment error, while believing that others do not make the error, are likely to be overconfident. Using this intuition, we examine the impact of overconfidence on profits and trading in our asset markets.

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[7] For an example of a model of asset pricing that incorporates higher order expectations see Allen et al. (2006). In this model, public information actually pushes price away from fundamental value because traders are overly sensitive to shared information.

[8] See Hirshleifer (2001) and Ackert and Deaves (2010) for a review of overconfidence.

Table 1
Expected values for both the lottery asset and the truncated asset.

Periods remaining	Lottery asset	Truncated asset
12	$4.80000	$4.79856
11	$4.40000	$4.39856
10	$4.00000	$3.99856
9	$3.60000	$3.59856
8	$3.20000	$3.19856
7	$2.80000	$2.79856
6	$2.40000	$2.39861
5	$2.00000	$1.99867
4	$1.60000	$1.59877
3	$1.20000	$1.19894
2	$0.80000	$0.79919
1	$0.40000	$0.39953

The lottery asset has a 0.02 probability of paying $20 each period for twelve periods. The truncated asset is identical except that it may only pay a maximum of three dividends. Defining a success as a payout if the asset were not truncated, the truncated asset values are calculated as: prob(zero prior successes)[20 * prob(one future success) + 40 * prob(two future successes) + 60 * prob(three or more future successes)] + prob(one prior success)[20 * prob(one future success) + 40 * prob(two or more future successes)] + prob(two prior success)[20 * prob(one or more future successes)].

3. Experimental design

Our experiment features three different types of assets, a non-traded lottery asset, a non-traded truncated asset, and a traded lottery asset.[9] Each trading session consists of twelve periods, and each period contains two phases. In the first phase one share of each of the non-traded assets is sold via second price auctions. Subjects are also asked to make some price predictions in this phase. The second phase is a double auction in which the traded asset can be exchanged. We first describe these assets, and then our market procedures.

All assets pay a random dividend each period for twelve periods. The lottery assets both pay a dividend each period based on a random draw from an opaque jar containing 100 chips numbered 1 through 100. If a chip numbered 1 through 98 is drawn, the payout is zero, but, if a chip numbered 99 or 100 is drawn, the payout is $20. A trader who acquires one share in period 1 and holds it until the conclusion of the session could receive $240, though this is a near-zero probability event.

The truncated asset is very similar to the lottery asset except that its total payoff is limited. A truncated asset pays $20 when a chip numbered 99 or 100 is drawn only if the asset has previously paid fewer than three $20 dividends. Thus, the maximum cumulative payoff from holding a truncated share is $60. All dividend draws are cross-sectionally and intertemporally independent, i.e., there are separate, independent draws to determine the dividends for shares of the traded lottery asset, the non-traded lottery asset and the truncated asset.

The risk-neutral values of the lottery and truncated assets are virtually identical. The expected values for both assets are shown in Table 1. The expected value for the truncated asset is the relevant value for a trader in our design, where all dividend draws are made at the end of the sessions. With all twelve dividends remaining, the expected values differ by only 0.00144. With fewer dividends remaining, the expected values diverge only slightly.[10]

Our experiments differ from most previous asset market bubble studies in that all dividend draws for all assets occurred at the conclusion of trading in each session.[11] With potentially high payouts, it is important to minimize the potential for wealth effects. A dividend payoff will result in a large injection of cash into the economy, which may by itself promote bubbles (see Caginalp et al., 1998). As well, other possible behavioral biases such as the house money effect, or the law of small numbers may, if present, make data interpretation problematic.

3.1. Conduct of sessions

The experiment includes ten sessions, each of which required two and one-half to three hours. Each session has twelve subjects, recruited from the undergraduate student body of a large state university.[12] All participants were inexperienced in that none had participated in an earlier session. On arrival, subjects were provided with a set of instructions, included in the online Appendix. They were informed that their compensation for participation would include profits accrued in the two phases of each period during the session. An experimenter read the instructions aloud as participants followed along.

[9] In the instructions, and during the experiment, the assets are always referred to as Asset A, Asset B, and Asset C, respectively.

[10] We cannot be certain that probability judgment error is responsible for observed price differences. It is also possible that nonstandard preferences, such as those described in cumulative prospect theory, can explain the difference between untruncated and truncated asset prices. However, we think cumulative prospect theory is a less plausible explanation because of the magnitude of the price differences observed in the experiment. Even an individual who values skewed assets is unlikely pay very much more for the lottery asset if he or she is presented with and understands the probabilities associated with the two assets.

[11] Smith et al. (2000) examine how the timing of dividend payments impacts the formation of asset price bubbles. As we describe subsequently, our results are consistent with their findings.

[12] Our sample includes 74 women and 46 men, of whom 45 are business majors and 75 are non-business majors.

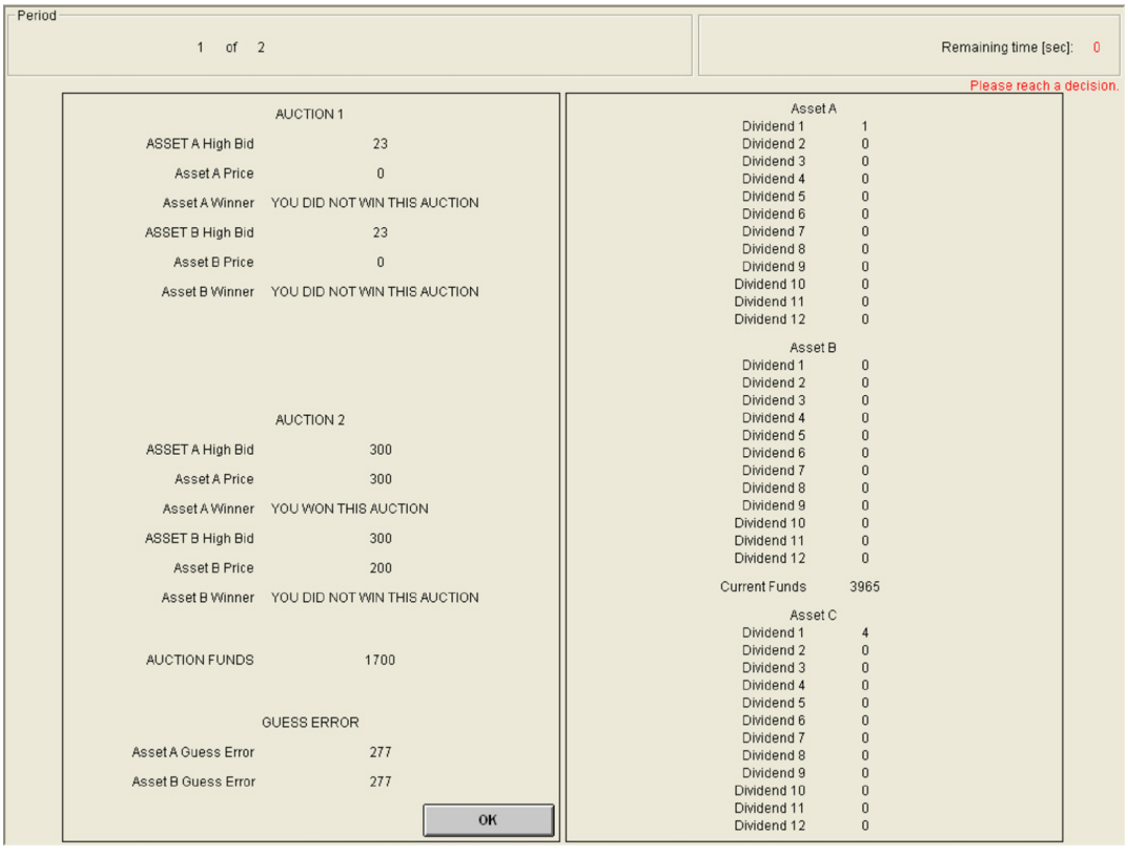

Fig. 1. Summary screen. A summary screen was displayed for subjects at the conclusion of trading in each period of the double auction market.

Then an experimenter provided an extensive recap, while addressing all procedural and technical questions. Before period one began, participants were each given $5 in cash and asked to bid on a candy bar in order to gain experience with second price auctions.

3.2. *Second price auctions and prediction task*

After the candy bar auction the first period began. Both auctions and trading were computerized and implemented using a program written for this experiment using the z-Tree programming environment available from Fischbacher (2007). Initially, subjects received an endowment of $20 that was used to finance purchases in the second price auctions for the non-traded assets. Funds remaining carried across periods for use in subsequent second price auctions and participants kept any balance remaining at the end of the session.

Each period, the twelve subjects were split into two groups of six and each group participated in separate second price auctions for a single share of the non-traded lottery and the non-traded truncated assets. Group membership was randomly determined each period so it was unlikely that they bid against the same set of participants across periods. As well, group membership was anonymous. Subjects knew only the group to which they were assigned. They were not told the identities of other subjects in either group.

At the same time as the bids were collected, subjects also predicted the highest bid price for each asset in the other auction. Subjects were compensated for better predictions of the bids in the other second price auction. Their guess errors, computed as the difference between the highest bid price and their prediction, were summed across periods. At the end of the session, participants earned $30 less their total guess errors.

3.3. *Double auctions*

Before receiving any feedback on the results of the second price auctions, the second phase of the period began. Participants were endowed with three shares of the traded lottery asset and given a loan of $40 that was repaid at the end of the experiment. The cash loan was used to finance purchases of the traded asset only and these funds were isolated from those available for the second price auctions. The trading institution was a computerized double auction. All trading periods lasted 3 min.

At the end of the second phase of each period, a participant's current position was privately displayed on his or her computer screen. The summary screen, shown in Fig. 1, included the highest price in each second price auction and whether the participant purchased an asset, second price auction funds remaining, cumulative guess errors, current funds available in the double auction market for the traded lottery asset, and the total number of dividends to be received at the end of the experiment for the traded lottery asset, and both non-traded assets.

3.4. Dividends and payments

Recall that the dividends for all of the assets were determined at the conclusion of each session by a series of random draws, with replacement. After the dividends were determined, participants computed their final cash balance and then completed a post-experiment questionnaire designed to collect demographic information as well as participants' thoughts on the experiment. In addition to their earnings from the auctions, subjects received $5 for completion of the post-experiment questionnaire and $5 if they arrived to the experiment on time. If a trader's profit in one phase was negative, earnings were reduced dollar for dollar. After completion of the experiment, subjects were paid in cash, with the median total compensation over all sessions being approximately $35. The maximum subject payout was $431, and the minimum was $20.[13]

4. Results

The first question we analyze concerns the prevalence of probability judgment errors amongst our subjects. We measure each subject's probability judgment error using the difference between his or her bids for the lottery and the truncated shares. We measure a subject's belief concerning other subjects' probability judgment errors using the difference between his or her predictions for the lottery and the truncated shares. Subjects are then assigned into four groups according to whether they make the error and/or whether they believe others make the error. The next step is to analyze the data from the double auctions. We observe mispricing of the shares of the traded lottery asset and study the association between mispricing, probability judgment errors, and beliefs about probability judgment errors. Finally, we look for differences in profits and in trading activity among our subject groups.

4.1. Probability judgment error

The summary data for the bids and for prices of all of the assets featured in our design are reported in Table 2 in cents.

The average bids for both the non-traded lottery shares, as well as the median prices for the traded lottery shares are presented by session for each of the twelve periods. Average predictions for the non-traded lottery asset, as well as the differences in bids and prediction between the non-traded lottery and truncated assets are also included in Table 2. Prices for all types of shares often diverge greatly from their expected values.

Table 2 also shows that probability judgment error is common. The "Bid NT Lottery–NT Truncated" is the difference between subjects' bids for the non-traded assets, averaged over subjects. This difference is often large, and in several instances is well over $1.[14] Similarly, the "Guess NT Lottery–NT Truncated" is the difference between subjects' predictions for the high bids for the non-traded assets in the second-price auctions, averaged over subjects. This difference is also usually positive and often large, indicating that many subjects' believe that at least some of the other auction participants are prone to the probability judgment error.

To normalize our measures, we define %Bid as the difference between a subject's bids for the lottery and the truncated assets as a fraction of the average of the subject's bids for these assets:

$$\%\text{Bid} = \frac{\text{Bid}_{\text{lottery}} - \text{Bid}_{\text{truncated}}}{(\text{Bid}_{\text{lottery}} + \text{Bid}_{\text{truncated}})/2} \tag{1}$$

Similarly, %Guess is:

$$\%\text{Guess} = \frac{(\text{Guess}_{\text{lottery}} - \text{Guess}_{\text{truncated}})}{(\text{Guess}_{\text{lottery}} + \text{Guess}_{\text{truncated}})/2} \tag{2}$$

Table 3 contains %Bid and %Guess for each subject averaged over the 12 periods of their session, and further confirms that probability judgment errors are common.

To formally test for probability judgment error, Wilcoxon signed-rank tests on the null hypothesis that the subject's %Bid equals zero are performed for each subject. Prior to these tests some bids were omitted. First, we excluded observations for which one or both of the bid prices were zero. Second, we recognized that constraints on funds available could have been binding, thus impacting a participant's ability to bid in the second price auctions.[15] To incorporate this potential constraint, we classified a subject as constrained if the subject had auction funds less than (4/3) times the expected values (EV) of both

[13] One lucky subject held nineteen shares of the traded asset when the payout was $20 per share.

[14] Recall that bids and predictions are reported in cents so that 100 = $1.

[15] If a subject purchased one of the non-traded assets at an inflated price during a prior second-price auction, he or she may not have had enough money to bid aggressively in subsequent auctions. To avoid situations where subjects had uncollectible negative earnings, our computer program did not allow subjects make bids in excess of their auction cash balances.

Table 2
Average asset prices by session and period.

	Period	1	2	3	4	5	6	7	8	9	10	11	12
Session	Expected Value	480	440	400	360	320	280	240	200	160	120	80	40
	Bid NT Lottery	433	479	428	464	414	353	306	209	213	156	122	91
	Guess NT Lottery	544	524	543	572	566	515	445	394	399	324	278	261
A	Bid NT Lottery–NT Truncated	95	54	4	126	32	47	58	32	57	−1	18	−12
	Guess NT Lottery–NT Truncated	−10	−35	7	53	48	55	32	24	−2	24	2	29
	Traded Lottery	434	387	378	336	329	294	234	262	300	247	217	212
	Bid NT Lottery	372	461	458	390	394	365	285	302	210	190	139	100
	Guess NT Lottery	611	983	470	504	496	421	470	380	375	314	233	175
B	Bid NT Lottery–NT Truncated	7	9	10	33	60	55	26	55	13	7	10	−4
	Guess NT Lottery–NT Truncated	23	259	26	50	88	14	33	28	−54	−13	−16	−35
	Traded Lottery	216	178	156	175	169	173	170	170	169	167	170	157
	Bid NT Lottery	220	353	332	337	256	184	167	163	130	103	70	46
	Guess NT Lottery	283	373	435	470	371	336	275	237	219	180	122	97
C	Bid NT Lottery–NT Truncated	8	4	32	63	0	13	7	20	1	−18	4	5
	Guess NT Lottery–NT Truncated	17	39	33	38	−22	27	−6	10	28	6	−8	0
	Traded Lottery	196	238	216	190	180	165	162	177	163	123	104	39
	Bid NT Lottery	265	238	284	225	217	231	253	191	165	168	167	153
	Guess NT Lottery	335	402	334	344	295	301	321	309	204	212	179	212
D	Bid NT Lottery–NT Truncated	32	44	14	−1	29	28	78	25	13	19	26	39
	Guess NT Lottery–NT Truncated	33	30	18	12	35	27	54	29	−3	1	5	35
	Traded Lottery	284	267	212	287	262	267	315	298	329	271	267	242
	Bid NT Lottery	195	224	292	309	352	313	269	294	235	202	161	112
	Guess NT Lottery	379	454	378	477	389	790	355	337	373	320	257	284
E	Bid NT Lottery–NT Truncated	27	17	2	29	28	34	25	80	38	38	18	−10
	Guess NT Lottery–NT Truncated	3	18	49	20	−101	104	32	51	41	73	15	79
	Traded Lottery	207	305	276	316	331	289	245	231	229	175	168	239
	Bid NT Lottery	285	294	333	334	238	175	147	105	99	98	76	64
	Guess NT Lottery	358	504	487	480	482	363	311	231	183	138	110	91
F	Bid NT Lottery–NT Truncated	83	2	−5	64	40	−9	13	4	11	21	23	−6
	Guess NT Lottery–NT Truncated	51	12	1	40	37	12	9	8	8	3	8	4
	Traded Lottery	225	228	188	187	189	189	190	179	158	137	106	49
	Bid NT Lottery	306	509	440	343	402	326	243	251	187	185	124	125
	Guess NT Lottery	517	542	575	642	631	587	515	413	392	337	260	225
G	Bid NT Lottery–NT Truncated	−30	68	26	−36	84	49	53	44	1	31	24	37
	Guess NT Lottery–NT Truncated	43	11	0	24	58	23	53	−2	4	−5	−2	4
	Traded Lottery	230	87	372	321	339	341	298	242	217	192	153	138
	Bid NT Lottery	429	408	382	320	351	304	254	199	158	121	101	89
	Guess NT Lottery	599	780	578	465	483	435	348	329	268	201	192	169
H	Bid NT Lottery–NT Truncated	166	39	24	20	38	14	33	32	16	−7	7	15
	Guess NT Lottery–NT Truncated	148	240	112	5	47	−8	24	−13	8	2	−2	11
	Traded Lottery	181	165	171	151	145	143	134	133	138	138	134	118
	Bid NT Lottery	317	383	361	332	433	356	255	260	266	219	250	140
	Guess NT Lottery	501	593	467	453	467	538	472	388	353	359	366	411
I	Bid NT Lottery–NT Truncated	−16	86	37	24	74	72	2	24	18	33	43	−70
	Guess NT Lottery–NT Truncated	44	35	11	45	40	34	40	39	27	9	26	56
	Traded Lottery	437	426	441	473	474	463	475	447	484	481	480	465
	Bid NT Lottery	413	435	488	402	419	311	262	250	235	188	136	118
	Guess NT Lottery	535	575	608	616	628	578	476	397	359	280	301	154
J	Bid NT Lottery–NT Truncated	91	87	148	171	93	−6	58	47	118	94	69	−4
	Guess NT Lottery–NT Truncated	72	98	46	116	104	115	79	21	74	27	59	21
	Traded Lottery	101	128	120	118	109	110	107	110	112	113	114	86

The average bids across subjects in the second price auction for the Non-traded Lottery asset are in the Bid NT Lottery row. The average predictions for the Non-traded Lottery asset are in Guess NT Lottery. Both bids and price predictions are reported in cents. Bid NT Lottery–NT Truncated is the average difference in bids between the Non-traded Lottery and Non-traded Truncated assets. The average difference in predictions is in the row labeled Guess NT Lottery–NT Truncated. Finally, Traded Lottery contains the average transaction price for the Lottery asset in the double auctions.

Table 3
Percentage bid and guess differences.

Subject	%Bid	%Guess	Class	Subject	%Bid	%Guess	Class
A1	−2.7%	10.5%*	Guess	D1	10.3%	9.4%*	Guess
A2	0.5	0.0	No Error	D2	22.5**	18.9**	Both
A3	23.2*	18.8*	Both	D3	−1.7	−2.8	No Error
A4	−1.3	1.5	No Error	D4	13.7	−3.6	No Error
A5	14.9**	16.3**	Both	D5	34.4**	13.7**	Both
A6	3.3	1.9	No Error	D6	17.8*	−7.8	Bid
A7	20.9**	3.4	Bid	D7	4.8	8.6	No Error
A8	1.1	0.3	No Error	D8	−0.1	7.4**	Guess
A9	20.9	29.7	No Error	D9	−1.9	−1.1	No Error
A10	2.6	7.0	No Error	D10	38.4**	8.3**	Both
A11	2.8	−1.2	No Error	D11	20.0	40.3**	Guess
A12	−1.8	−13.4	No Error	D12	5.6	3.3	No Error
All A	6.8**	6.3%**		All D	13.5%**	7.9%**	
B1	2.4%*	−0.4%	Bid	E1	−5.6%	35.9%*	Guess
B2	29.8**	5.7**	Both	E2	5.1**	7.7**	Both
B3	19.2*	18.8*	Both	E3	4.5	9.9	No Error
B4	−8.7	9.1**	Guess	E4	62.8**	29.2**	Both
B5	0.1	−3.1	No Error	E5	−4.4	0.0	No Error
B6	0.2	8.4	No Error	E6	9.3**	0.2**	Both
B7	0.0	0.0	No Error	E7	21.7*	20.9**	Both
B8	103.5	−2.0	No Error	E8	−23.4	41.5**	Guess
B9	−24.3	85.6**	Guess	E9	22.9**	20.4**	Both
B10	4.2**	2.3*	Both	E10	−17.9	−23.1	No Error
B11	−59.4	−37.0	No Error	E11	39.0*	−28.8	Bid
B12	19.3	−1.6	No Error	E12	−1.0	−26.8	No Error
All B	3.1%*	7.1%**		All E	9.8%**	8.5%**	
C1	0.8%	0.0%	No Error	F1	−13.5%	−9.9%	No Error
C2	−0.1	−1.4	No Error	F2	8.0	2.6	No Error
C3	10.5*	−2.6	Bid	F3	2.3	10.1	No Error
C4	0.0	0.0	No Error	F4	−0.3	8.3**	Guess
C5	−8.0	6.3	No Error	F5	−13.6	−11.5	No Error
C6	−12.6	−2.2	No Error	F6	52.5*	13.8	Bid
C7	1.4	9.3**	Guess	F7	0.0	0.0	No Error
C8	13.1*	2.4	Bid	F8	−5.0	−2.4	No Error
C9	23.6**	9.9*	Both	F9	21.6**	21.3**	Both
C10	40.3	14.2*	Guess	F10	13.6*	15.5*	Both
C11	16.2	17.2*	Guess	F11	47.8	40.1**	Guess
C12	0.0	1.1	No Error	F12	0.0	−1.3	No Error
All C	5.3%**	4.5%**		All F	7.2%**	4.6%**	
G1	70.9%	3.3%	No Error	I1	10.3%*	34.7%**	Both
G2	0.0	29.5	No Error	I2	0.0	0.0	No Error
G3	38.7*	−33.0	Bid	I3	12.2**	10.3**	Both
G4	6.9**	3.8*	Both	I4	9.7	13.2**	Guess
G5	−1.5	0.0	No Error	I5	9.1	6.6**	Guess
G6	29.4	−4.1	No Error	I6	−15.2	−37.6	No Error
G7	11.6	8.3**	Guess	I7	3.8**	9.8**	Both
G8	2.9	9.4	No Error	I8	35.2**	13.0**	Both
G9		7.0*	Both	I9	20.3*	10.5*	Both
G10	−12.5	−14.7	No Error	I10	2.1	6.7*	Guess
G11	−15.4	8.3	No Error	I11	4.2	−5.5	No Error
G12	9.5*	16.0**	Both	I12	−2.7	−0.6	No Error
All G	8.2%**	3.0*		All I	7.1%**	8.1%**	
H1	6.9%	8.0%	No Error	J1	20.3%	15.2%	No Error
H2	15.8*	−15.6	Bid	J2	57.4**	80.0	Bid
H3	13.8**	11.8**	Both	J3	59.9**	33.5**	Both
H4	−16.8	−0.8	No Error	J4	59.0*	39.0**	Both
H5	−38.3	13.4**	Guess	J5	0.8	1.5	No Error
H6	22.9**	25.2**	Both	J6	−8.4	15.8**	Guess
H7	0.0	6.6*	Guess	J7	0.0	25.1**	Guess
H8	10.9	20.7	No Error	J8	−2.7	6.7	No Error
H9	1.1	1.5	No Error	J9	38.4*	17.8**	Both
H10	36.1**	−10.7	Bid	J10	18.3*	29.6**	Both
H11	20.3*	4.3	Bid	J11	0.0	0.0	No Error
H12	57.6*	24.6**	Both	J12	−2.5	20.1**	Guess
All H	7.7%**	7.4%**		All J	21.3%**	15.2%**	

%Bid is the difference in bids between the Non-traded Lottery and Non-traded Truncated assets expressed on a percentage basis: %Bid = (Bid NT Lottery–Bid NT Truncated)/((Bid NT Lottery + Bid NT Truncated)/2). %Guess is the analogous percentage difference in the price predictions. Both %Bid and %Guess are averages by subject over the twelve periods. The asterisks show the result of a Wilcoxon SR test with the null hypothesis that %Bid (or %Guess) equals zero. One asterisk signifies that the relevant null can be rejected at the 10% level. Two asterisks signify rejection at the 5% level. Each subject is then classified according the result of the Wilcoxon tests using the 10% level.

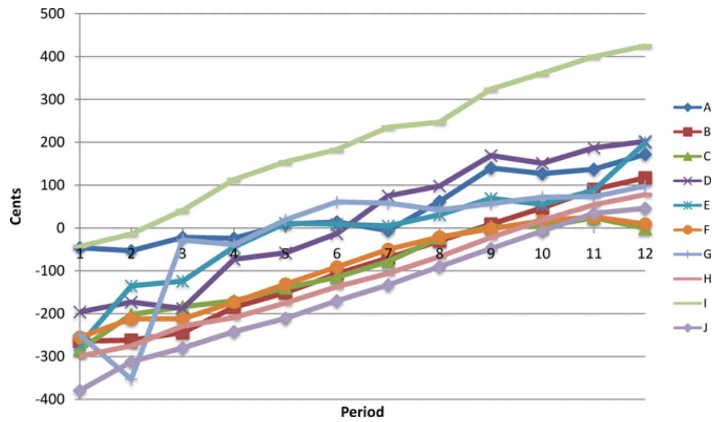

Fig. 2. Lottery asset mispricing. The figure shows the difference between the average prices by period for the traded lottery asset and the expected value of the asset by period. The expected value of the lottery asset is $4.80 in period one. The expected value declines by forty cents per period.

assets for the period.[16] An asterisk in Table 3 indicates that the null is rejected in favor of the one-tailed alternative that the subject's %Bid is greater than zero at the 10% significance level. Two asterisks indicate that the null is rejected at the 5% level. Similar results concerning the subject's %Guess are also presented in Table 3.

Subjects are then classified by whether they are prone to probability judgment errors, whether they think others are subject to these errors, or both. Subjects who make probability judgment error as determined by the 10% Wilcoxon test on %Bid are labeled "Bid Error." "Guess Error" subjects are those who believe others make probability judgment error based on the 10% Wilcoxon test on %Guess. Thus, four groups, "Bid Only", "Guess Only", "Both" and "No Error" are possible.

The "No Error" group consists of subjects who do not make the probability judgment error, and predict that others do not make the error as well. The most subjects, 55 of 120, fall into this category. The "Both" group includes 31 subjects who both make the error, and believe that others make the error. The "Guess Only" category consists of subjects who do not make the probability judgment error, but believe that others do make the error and includes 22 subjects. These subjects are reminiscent of the "rational speculators" of Smith et al. (1988). "Bid Only," the last group, contains 12 subjects who make the probability judgment error, yet still predict that others do not make the error.

We hypothesize that the behavior of the "Bid Only" subjects is consistent with overconfidence for the following reasons. Being a "Bid Only" makes sense only if a subject does not believe that the probability judgment error is actually an error. "Bid Only" subjects incorrectly value the assets, yet they realize that others understand that the two assets have similar values. So "Bid Only" subjects believe the lottery asset is more valuable than the truncated asset despite believing that other subjects do not share their opinion. Maintaining an incorrect valuation estimate and disregarding the opinions of other subjects describes the behavior of an overconfident agent.

The data indicate that making the bid error and the guess error are correlated. The correlation between "Bid Error" and "Guess Error" is 0.26, which is significant at $p < 0.0001$ (for classifications using either 5 percent or 10 percent levels). Fisher's exact test rejects the null hypothesis that the probability of a subject being classified as making the guess error is the same for those classified as making bid errors as for those without bid errors. Subjects who make probability judgment errors are more likely to believe that other subjects also make the errors.[17]

4.2. Pricing of the traded lottery asset

Table 2 contains the average prices by period for the traded lottery asset in our double auction markets. While we do see clear mispricing, we do not observe the typical bubble and crash pattern observed in previous studies. We often observe relatively constant prices across periods, which means that price deviations from fundamental value are increasing over time. Fig. 2 plots the difference between the average price each period and the fundamental value, computed as the expected dividend per period ($0.40) times the number of periods remaining. For example, the expected value of the asset is $4.80 in period 1. Fig. 2 illustrates that mispricing is consistently increasing over the course of most of the ten sessions.

To allow comparison across assets, Fig. 3 shows asset mispricing for each type of asset by period, averaged across sessions. For the Traded Lottery asset, the graph shows the difference between the average transaction price per period and the expected value. For the bids (guesses) for both the truncated and non-truncated asset, the graph shows the difference between the average of the bids (guesses) across subjects during each period's second-price auction phase less the asset

[16] We assessed the sensitivity of the results to the specification of the budget constraint by varying the classification for constrained. Results are similar to those reported subsequently in the paper with 2, 1.5, and 1.33 times the EV of both assets.

[17] Recall that in the instruction phase of the experiment, subjects bid on a candy bar to illustrate bidding in a second price auction. It is possible that the winners of the candy bar auction behaved differently subsequently because they "won" the candy bar. We identified the candy bar auction winners and compared their error classifications with the full sample. "Bid Error" and "Guess Error" frequencies were similar to those in the full sample.

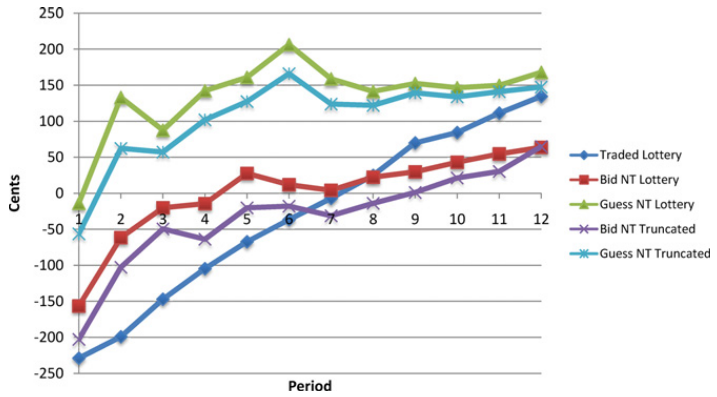

Fig. 3. Average asset mispricing. The figure shows asset mispricing for each type of asset by period, averaged across sessions. The expected value of the lottery asset is $4.80 in period one. The expected value declines by forty cents per period. For the Traded Lottery asset, the graph shows the difference between the average transaction price per period and the expected value. For the bids (guesses) for both the truncated and non-truncated asset, the graph shows the difference between the average of the bids (guesses) across subjects during each period's second-price auction phase less the asset expected value.

Table 4
Mispricing of the traded lottery asset.

Session	Average price deviation	Average absolute price deviation	Average scaled price deviation	Average absolute scaled price deviation
A	45.9	61.9	0.66	0.70
B	−81.0	127.8	0.12	0.69
C	−93.8	98.8	−0.23	0.29
D	13.8	143.8	0.75	1.06
E	−18.5	94.4	0.46	0.71
F	−91.3	100.8	−0.20	0.31
G	22.4	84.0	0.42	0.55
H	−116.7	143.1	−0.12	0.62
I	216.1	216.1	2.09	2.08
J	−148.8	164.6	−0.30	0.62
Average	−25.2	123.5	0.37	0.76

This table reports statistics that measure the extent of mispricing in the double auction market for the traded lottery asset. The average price deviation is the average across periods of the differences between the average trading price and the risk-neutral value in each period. Average scaled price deviation averages across periods the differences between the median price and the risk neutral value normalized by the risk-neutral value. Absolute deviations are computed in a similar manner, but use the absolute differences between the median trading price and the risk-neutral value in each period.

expected value. From the figure we see that subjects expect others to price the asset higher than they themselves are willing to pay, i.e., guesses exceed bids. We also observe that mispricing for all assets generally increases over time. Thus, instead of becoming better calibrated with experience, our subjects push prices farther from fundamental value. This observation likely results from the design choice to conduct all dividend draws at the conclusion of the experiment.

To provide further insight into pricing in our markets, we compute measures of mispricing. Table 4 reports summary statistics used to detect the presence of positive price bubbles in the double auction markets. The average price deviation is the average across periods of the differences between the average trading price and the risk-neutral value in each period. Average scaled price deviation averages across periods the differences between the median price and the risk neutral value normalized by the risk-neutral value. Absolute deviations are computed in a similar manner, but use the absolute differences between the median trading price and the risk-neutral value in each period. High average price deviations would suggest that trades occur at prices far from fundamental values. For our markets, we actually observe average underpricing in many markets.

Our results are quite different from those typically reported in the literature for such experimental bubbles markets. Perhaps most startling is the relative absence of the typical price run-up and crash pattern. A possible reason for this result may be our procedural decision to pay all dividends at the end of the double auction market. Experiments by Smith et al. (2000) provide support for this conjecture. Their goal was to examine the effect of dividend timing on the production of price bubbles. In one of their treatments, a single dividend was paid to those holding the asset at the end of the trading horizon. They report that a bubble appeared in only *one of ten* single dividend markets, which suggests that dividend timing has an important role in generating over-pricing.

Even though the typical bubble pattern is not observed, we do observe significant mispricing in many of the sessions. In order to shed light on the relationship between market mispricing and the number of irrational traders and their types, we examine the correspondence between mispricing and error groups. The results are reported in Table 5 where mispricing of the traded lottery asset is measured using the average absolute scaled price deviation, or the absolute value of the percentage

Table 5
Correspondence between mispricing of the Traded Lottery asset with error group.

Session	Lottery asset average absolute scaled price deviation	%Bid	%Guess	No Error	Both	Bid Only	Guess Only
A	0.70	6.8	6.3	8	2	1	1
B	0.69	3.1	7.1	6	3	1	2
C	0.29	5.3	4.5	6	1	2	3
D	1.06	13.5	7.9	5	3	1	3
E	0.71	9.8	8.5	4	5	1	2
F	0.31	7.2	4.6	7	2	1	2
G	0.55	8.2	3.0	7	3	1	1
H	0.62	7.7	7.4	4	3	3	2
I	2.08	7.1	8.1	4	5	0	3
J	0.62	21.3	15.2	4	4	1	3
Average	0.76	9.0	7.3	5.5	3.1	1.2	2.2

Mispricing of the traded lottery asset is measured using the average absolute scaled price deviation, which is the absolute value of the percentage difference between the median traded lottery asset price and the risk neutral value, averaged across periods. Sessions are sorted from according to the degree of lottery asset mispricing. %Bid is the measure of probability judgment error constructed from subjects' bids for the assets sold in the second price auctions. %Guess is our measure of beliefs concerning others' susceptibility to probability judgment error. The remaining columns are based on a one-tailed Wilcoxon SR test with the null hypothesis that a subject's %Bid (or %Guess) equals zero. The value in the "No Error" column is the number of subjects where the null that %Bid = 0 and %Guess = 0 cannot be rejected with a 10% significance level. "Guess Only" is the number of subjects where the null of %Guess = 0 can be rejected, and %Bid = 0 cannot be rejected, and "Both" counts the number of subjects where both nulls (%Bid = 0 and %Guess = 0) can be rejected.

Table 6
Correspondence between mispricing of the Traded Lottery asset with subjects' errors.

Independent variable	*a*	*b*
Number of subjects who make only the bid error.	−0.49	−0.30
Bid Only[a]	(0.02)	(0.44)
Number of subjects who make only the guess error	−0.74	0.41
Guess Only	(0.15)	(0.48)
Number of subjects who make the bid error	−2.12	1.21
Bid Only + Both	(0.06)	(0.11)
Number of subjects who make the guess error	−3.19	1.69
Guess Only + Both	(<.01)	(<.01)
Number of subjects who make both errors	−1.37	0.93
Both	(<.01)	(0.01)
Number of subjects who make either or both errors	−3.25	1.53
Bid Only + Guess Only + Both	(0.07)	(0.11)

Regressions relating the lottery asset average absolute scaled price deviation to the number of subjects making bid and/or guess errors.
Ln(Average absolute scaled price deviation) = $a + b$ Ln(Independent variable) + e.
Estimated regression coefficients are shown in columns *a* and *b* with *p*-values below in parentheses. The *p*-values for the slope coefficients are for tests of the null hypothesis that subjects errors do not affect pricing.
[a] Session with no Bid only subjects is not included.

difference between the median traded lottery asset price and the risk neutral value, averaged across periods. The session with greatest mispricing is session I. %Bid is the measure of probability judgment error constructed from subjects' bids for the assets sold in the second price auctions. %Guess is our measure of beliefs concerning others' susceptibility to probability judgment error. The remaining columns are based on a one-tailed Wilcoxon signed-rank tests with the null hypothesis that a subject's %Bid (or %Guess) equals zero. The value in the "No Error" column is the number of subjects where the null that %Bid = 0 and %Guess = 0 cannot be rejected with a 10 percent significance level. "Guess Only" is the number of subjects where the null of %Guess = 0 can be rejected, and %Bid = 0 cannot be rejected, and "Both" counts the number of subjects where both nulls (%Bid = 0 and %Guess = 0) can be rejected.

Nonlinearity of the measure of mispricing, the average absolute price deviation, makes inference based on the results reported in Table 5 somewhat muddy, though there seems to be greater numbers of irrational subjects with probability errors in sessions with greater mispricing. To provide a clearer picture we perform additional analysis of the relationship between mispricing and error groups.

Table 6 reports the results of regressions of the lottery asset average absolute scaled price deviation on an independent variable measuring the number of subjects making errors. Because of the nonlinear nature of the variables, we use a logarithmic transformation, as follows:

$$\text{Ln(Average absolute scaled price deviation)} = a + b \quad \text{Ln(Independent variable)} + e \tag{3}$$

We repeat the regressions several times redefining the independent variable as the number of subjects who make only the bid error, number of subjects who make only the guess error, total number of subjects who make the bid error, total number of subjects who make the guess error, number of subjects who make both errors, and number of subjects who make

Table 7
Expected profits by subject classification.

Session	No Error	Both	Bid Only	Guess Only
Panel A: Average expected profits by session				
A	0.6	82.5	155.0	−325.0
B	25.8	−796.7	915.0	660.0
C	57.5	36.0	−568.0	251.7
D	−841.0	440.0	460.0	808.3
E	−880.3	1,127.4	−738.0	−689.0
F	−105.0	210.0	−1,523.0	919.0
G	−13.6	−195.0	30.0	650.0
H	340.3	1,068.0	−1,465.0	−85.0
I	184.5	59.0		−344.3
J	−685.0	−269.5	−365.0	1,394.3

No Error	Both	Bid Only	Guess Only	*F* statistic
Panel B: Average expected profits across sessions				
−158.0	226.6	−549.8	375.7	3.1 (0.03)

The expected profit from a purchase is the expected asset value minus the price. For sales, expected profit is the price minus the expected asset value. For each subject, expected profit is totalled over all transactions made. Each subject is classified as making the bid error only, the guess error only, neither or both using Wilcoxon signed-rank tests. Panel A of the table reports subjects' total expected profit for each session, averaged by subject classification. Panel B of the table reports the results of a test of the null hypothesis that expected profits are the same across subject error classifications, with the *p*-value below in parentheses.

either or both errors. Coefficients of the regressions are shown in columns *a* and *b* of Table 6. The *p*-values for the coefficients are shown under the coefficients in parenthesis.

The results reported in Table 6 indicate that mispricing is most significantly correlated with the total number of subjects in the Guess only plus Both categories. These subjects all believe that other subjects make the probability judgment error, (where the Guess subjects do not make the error themselves, and the Both subjects do make the error). When the independent variable is defined as the total number of subjects who make the guess error (Guess only + Both) we find significance at $p \leq 0.01$. However, if the independent variable is only the number of subjects who make both errors (Both), we still find significance at $p = 0.01$. We cannot fully disentangle the contribution of the Bid Error and the Guess Error because the tendencies to make these errors are correlated.

4.3. Profits and trading activity

Finally, we examine whether the performance of traders varies across error categories. First we examine expected profits by subject error classification.

The expected profit from a purchase is the expected asset value minus the price and for sales expected profit is the price minus the expected asset value. For each subject, we sum expected profit over all transactions made. Each subject is classified as making the bid error only, the guess error only, neither or both using Wilcoxon signed-rank tests as explained earlier. Then, subjects' expected profit totals are averaged by subject classification. Average expected profits by session are reported in Panel A of Table 7. Panel B of Table 7 tests the null hypothesis that expected profits are the same for each subject error classification. The *F*-statistic reported in Panel B rejects this null. On average, "Bid Only" subjects accrue negative profits, whereas "Both" and "Guess Only" subjects accumulate positive earnings.[18]

Table 8 contains a similar analysis studying the number of transactions made by each subject classification. As before, each subject is classified as making the bid error only, the guess error only, neither or both, using Wilcoxon signed-rank tests. Subjects' trading volumes are averaged by subject classification and reported by session in Panel A of Table 8. Although "Bid Only" subjects trade more often, the *F*-test does not indicate that the number of transactions differs significantly across subject classifications. Bonferroni paired comparisons do not indicate significant differences in trading activity across error types, though "Bid Only" subjects trade more than the other groups.[19]

[18] This *F*-test, and the others reported in this section, use each subject as a single observation and therefore assume that subjects' profits (transactions and quote frequencies) are independent. We also used paired *t*-tests to compare average profits across subject groups using each session as a single observation. This is more conservative since independence across subjects is not assumed, but has the drawback that we only have ten observations. The paired *t*-test indicates that the "Guess Only" subjects earned significantly more than the other subject groups ($p < 0.10$). However, the paired *t*-tests do not support differences in transactions at standard significance levels.

[19] We also examined whether other demographics variables interacted with probability judgment errors. We cross-tabulated bid and guess errors by age, gender, education, as well as other information collected in the post-experiment questionnaire. Wilcoxon–Mann–Whitney tests did not indicate any significant pattern in the data for any demographic variable.

Table 8
Transactions by subject classification.

Session	No Error	Both	Bid Only	Guess Only
Panel A: Average transactions by session				
A	7.3	6.0	7.0	5.0
B	3.5	5.3	5.0	4.0
C	9.8	12.0	9.5	6.0
D	8.0	4.3	8.0	5.7
E	11.8	12.6	15.0	6.5
F	7.3	3.0	16.0	5.5
G	6.1	3.0	2.0	4.0
H	7.5	16.7	12.3	6.5
I	7.0	7.0		5.7
J	6.0	10.0	5.0	15.0

No Error	Both	Bid Only	Guess Only	*F* statistic
Panel B: Average transactions across sessions				
7.1	8.3	9.5	6.7	0.94 (0.43)

Each subject is classified as making the bid error only, the guess error only, neither or both using Wilcoxon signed-rank tests. Panel A of the table reports subjects' trading volume for each session, averaged by subject classification. Panel B of the table reports the results of a test of the null hypothesis that trading volumes are the same across subject error classifications, with the *p*-value below in parentheses.

5. Conclusions

Although laboratory asset markets have provided important insights into asset pricing, our understanding of how individual behaviors impact market outcomes is limited. This paper has identified and documented one channel through which market prices reflect irrational expectations. Some people overweight high payoff, low probability outcomes which leads to asset prices that deviate from fundamental value. Other "rational speculators" do not make this judgment error, consistent with the intuition of Smith et al. (1988). These rational traders predict that others will fall prey to judgment errors and, because they themselves do not, they are able to excel at generating trading profits.

Our paper also integrates simpler aspects of level-of-reasoning intuition into an experimental asset market. Ho et al. (1998) suggest that decision-making models should include a mixture of traders, including naïve decision-makers who simply behave adaptively and those with more sophisticated, higher reasoning. Experimental studies of games, such as the beauty contest, illustrate that levels of reasoning models can explain subjects' strategies. Our results demonstrate that this remark can apply to experimental asset markets as well.

In order to understand the effects of differing levels of rationality and beliefs about rationality in experimental markets, experimental researchers must devise ways to measure errors and beliefs. Our paper is a first step in this direction. We measure probability judgment errors by eliciting values for two assets that differ slightly. The lottery asset has a very small chance of very large payoffs, but the truncated asset does not. We measure beliefs by asking subjects to predict the outcomes of second-price auctions for each of these non-traded assets. Subjects then trade a third type of asset in a standard double auction.

We group subjects according to whether they make probability judgment errors, and/or believe that other subjects make such errors. We find that the composition of subjects in our markets affects informational efficiency, and that one group, the "Bid Only" subjects, earns less and trades more. The "Bid Only" subjects, who make the error, but believe that others do not, can be thought of as overconfident in the context of our experimental asset markets. Another group, the "Guess Only" subjects, believes that others will make judgment errors and are able to turn this expectation into superior profits.

In experimental and real world markets, we have experienced prices that tend to bubble high above reasonable valuations and subsequently crash. The dot.com bubble in the U.S. stock market is one noteworthy example. Price deviations unrelated to changes in value are of great concern to policymakers, practitioners, and investors. Our research shows that, at least in one specific experimental environment, the likelihood and magnitude of mispricing appears to be linked to both the incidence of probability judgment errors and to subjects' beliefs about the existence and magnitude of other subjects' judgment errors.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jebo.2012.03.014.

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