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Do Prediction Markets Aid Defenders in a Weak-Link Contest?

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Abstract: Laboratory experiments have demonstrated that prediction market prices weakly aggregate the disparate information of the traders about states (moves) of nature. However, in many practical applications one is attempting to predict the move of a strategic rival. This is particularly important in aggressor-defender contests. This paper reports an experiment where the defender may have the advantage of observing a prediction market on the aggressor's action. The results of the experiments indicate that: the use of prediction markets does not increase the defender's win rate; prediction markets contain reliable information regarding aggressors' decisions that is not being exploited by defenders; and the existence of a prediction market does not alter the behavior of the aggressor whose behavior is being forecast.

Keywords: Information Aggregation, Prediction Markets, Weak-Link Contests, Colonel Blotto
JEL: C7, C9, D7, D8, G1

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1. Introduction

Prediction markets have gained popularity in recent years as a means of aggregating diversely held information. Chen and Plott (2002) implement prediction markets for sales forecasts at Hewlett-Packard Corporation (HP) and report that these markets outperform more traditional statistical forecasts. Cowgill et al. (2009) document that internal prediction markets at Google perform well for forecasting new office openings, launch dates, etc. Other effective prediction markets include those for movie box office receipts (Pennock et al. 2001), election outcomes (Berg et al. 2003), outbreaks of contagious diseases (Polgreen et al. 2007) and slaughtered cattle (Gallardo 2009). Still there remain many more applications where prediction markets could be utilized, but are not (see Wolfers and Zitzewitz 2004). For example, Hahn and Tetlock (2005) propose using prediction markets to set monetary policy. After the terrorist attacks of September 11, 2011, Policy Analysis Markets (PAM) were proposed by the Defense Advanced Research Projects Agency, but these markets were not implemented due to concerns raised by members of Congress (Pearlstein 2003; Wyden and Dorgan 2003).

A common, but generally inaccurate, concern for prediction markets is that they can be easily manipulated (see Deck and Porter 2013 for a review). Deck et al. (2013) demonstrate that prediction markets can be manipulated, but it is under extreme conditions when traders only get returns from manipulation and have a large bankroll. The other main concern in many countries including the United States involves the ambiguous legal status of prediction markets, due to resemblance with gambling. Prior to halting operations in March 2013, Intrade.com operated public prediction markets on a wide range of future events, including politics, economics, and entertainment, but had spun off the now defunct TradeSports.com which focused exclusively of forecasting the outcome of sporting events years earlier. In Arrow et al. (2008) a group of 22 prominent scholars called for government policies, especially gambling laws, to be relaxed in order for decision makers to better utilize prediction markets.

Concerns of manipulation and gambling are largely mitigated with internal prediction markets, where only members within an organization can participate using token money given to them (as opposed to Intrade where the general public traded shares using money out of their own pockets). The markets at HP were only open to employees in the fields of marketing and finance (Chen and Plott 2002). The proposed PAM markets were to be open only to those inside the defense community. Trades on Google's internal market are denoted in Goobles (Cowgill 2009). Absent the two main concerns of manipulation and gambling, it is easy to see why there are many advocates for increased reliance on prediction markets given their demonstrated success in a variety of settings (see for Wolfers and Zitzewitz 2004).

Despite the rhetoric around prediction market success, these markets are typically quite noisy in the laboratory. As discussed in a recent survey by Deck and Porter (2013), average prices in a period tend to be too high on average and over a series of trading periods the variance in average prices tends to be too small in comparison to full information aggregation. Nonetheless, closing prices contain useful information as they correlate positively – although weakly – with the prices that should prevail when information is aggregated, at least after the traders have gained market experience. Even such imperfect prediction markets can provide useful information to market observers (see Oprea et al. 2007). However, unlike previous laboratory experiments where the forecasted event is exogenously determined through a known process, in many naturally occurring settings the activity that is being forecasted involves strategic uncertainty in a game. For example, one can imagine a firm using a prediction market to forecast which market segments a rival is going to target with its advertising budget. The goal is not simply to aggregate this information, but to use the information in allocating the firm's own advertising budget. The same situation would have arisen in the PAM markets where the forecasted activity would have involved the calculated actions of terrorists who were attempting to hide their actions from those in the defense community.

Predicting strategic behavior raises two issues for prediction markets that may be absent in other settings such as those that have been studied in the laboratory. The first is that the type of behavior that is being forecast may change due to the existence of the prediction market. The second is that traders may be more likely to rely upon their own intuition or bias about what the forecasted behavior is likely to be rather than focusing on their private information. For example, a trader forecasting a rival's advertising efforts in a particular market may be subject to a confirmation bias and overweight their prior belief that the rival is going to invest heavily on a certain market segment. A defense analyst may ignore private information suggesting one target is unlikely to be attacked out of a conviction that it is the obvious choice of target.

The current paper explores the effectiveness of internal prediction markets where the forecasted event is a strategic choice in a game between the market observer and the party whose action is being forecasted. Formally, the game is modeled as a weak-link contest, a type of game that has received considerable behavioral and theoretical attention recently (see Dechenaux et al. 2012 and Kovenock and Roberson 2010 for comprehensive reviews of the respective literatures). The paper is organized as follows. The next section discusses background details. Section 3 describes the experimental design and Section 4 provides the behavioral results. A final section offers a concluding discussion.

2. Background Discussion

Contests have been used to study a variety of topics: lobbying (Krueger, 1974; Tullock, 1980; and Synder 1989), patent races (Fudenberg et al., 1983; Haris and Vickers, 1985, 1987), and military strategy (Borel, 1921; Borel and Ville, 1938; Gross, 1950; Gross and Wagner, 1950 and Freidman, 1958). The essential components of a contest are that each player makes an unrecoverable investment in the hopes of earning a prize, the allocation of which depends in part on the set of realized investments. One common approach is the so called all-pay auction where the party investing (or bidding) more wins with certainty.

One can extend a single all-pay auction to a contests where the ultimate winner depends on combinations of outcomes in individual subcontests. Many sporting champions are determined by playing a best of five or best of seven series. New products often involve a series of patents rather than a single patent. Firms often compete with each other in multiple markets. Terrorists have many possible targets. The classic Colonel Blotto game (Borel 1921) is a multi-contest game where the two militaries simultaneously allocate discrete numbers of soldiers among different battlefields. A battle is won by the military with more troops present and the war is won by the military that wins the most battles.

Despite the relatively simple set up, Colonel Blotto style games are quite complex (see Hart 2008 for solutions to symmetric games). Other recent work in the area has allowed for asymmetric budgets, an opportunity cost of resources, continuous investment, and non-majority win rules (see Kvasov, 2007; Laslier, 2002; Laslier and Picard, 2002; Roberson, 2006; Szentes and Rosenthal 2003a, b). Clark and Konrad (2007) and Golman and Page (2009) consider a setting where one side needs to win every battle to win the war while the other side only needs a single victory. This structure where the whole game is lost if a single subcontest is lost is referred to as a weak-link game drawing on the analogy that a chain is only as strong as its weakest link. In the laboratory, Avrahami and Kareev (2009) examine Colonel Blotto games with symmetric and asymmetric budgets. The results are qualitatively consistent with the theoretical predictions. Cinar and Goksel (2012) also report aggregate behavior in Blotto games that is consistent with the theoretical predictions (see also Arad 2012; Arad and Rubinstein 2012; Chowdhury, et al. 2013).

What has not received much attention in the contest literature is sequential all pay auctions, weak link or otherwise. The reason is that the solution is obvious and favors the last mover. However, if a successful prediction market that was completely aggregating information were in operation, the simultaneous move game would essentially become an uninteresting sequential game that could be dominated by the contestant who observed the prediction. Thus, Colonel Blotto games are exactly where one would want to implement a prediction market. Further, given the clear effect a functioning prediction market should have, this is an ideal environment for exploring prediction markets for strategic actions.

Another advantage of the discrete weak-link contest for the purpose of this paper is that the strategy space lends itself well to the types of exogenous environments that have been used to study prediction markets. The classic information aggregation experiment by Plott and Sunder (1988) involved three possible states of the world where each traders was informed of one of the unrealized states in such a way that the market as a whole had complete information. Anderson and Holt (1997) and Hung and Plott (2001) consider a world with only two states; but in which traders only observe a noisy signal of the realized state. With only two possible states a single state specific asset can capture all of the relevant information. Again the behavioral results were that prices do a reasonable job of aggregating information. The reported success of prediction markets should not be construed to mean that prices are typically correct in the laboratory (see Manski 2006 and Gjerstad 2005 for a theoretical discussion of the divergence in beliefs and equilibrium prices). In the lab, prices are often too high but absent active manipulation market observers are typically able to take this bias into account to some degree when interpreting market behavior (Oprea, et al. 2007; Deck, et al. 2013). Given the previous success and the operational simplicity of prediction markets with only two states as in Anderson and Holt (1997) and Hung and Plott (2001), the contest used in the current paper is restricted to two battlefields. Following Plott and Sunder (1988), the market participants as a whole have complete information, which is achieved by each trader in the market observing one of the discrete units that the player whose actions are being forecasted has available to allocate.

3. Experimental Design

The experiment involves two interconnected pieces: a weak-link contest game and a prediction market. These two components are described in detail separately and then the specific treatments and procedures that were used are presented. For ease of exposition, the setting is described in a manner consistent with the proposed PAM markets where there is an aggressor and a defender. During the experiment, neutral terms such as first mover and second mover were used for the contest, although the prediction market was framed as a market with traders who could buy and sell shares.

3.1 Weak-Link Contest Setup

The aggressor has a budget of 5 tokens to allocate discretely between two subcontests, *A* and *B*. The defender has 6 tokens to allocate between the two subcontests. In each subcontest, whoever invests the most wins and ties are broken in favor of the defender. However, the defender must win both subcontests to win the overall contest, while the aggressor only needs to win one subcontest to win the overall contest. The winner of the overall contest claims a prize, *P*. Since there is no opportunity cost associated with the tokens, each player will always bid her entire endowment and thus strategies are completely identified by the number of tokens bid on *A*.

By design, the weak-link structure of the contest is such that the aggressor has a distinct advantage. While there are multiple mixed strategy Nash equilibria for this simultaneous move game (and no pure strategy equilibrium), each one is such that the aggressor wins with two-thirds probability and the defender wins with one-third probability. Because the game played between the aggressor and the defender is constant sum, it can be expressed by a 6 × 7matrix A where the entry a_{ij} denotes the payoff to the defender if the aggressor invests i-1 tokens in A and the defender invests j-1 tokens in A. The payoff to the aggressor is 2 minus the payoff to the defender. The iterated elimination of weakly dominant strategies yields the reduced game

$$A' = \begin{array}{c} \\ 0 \\ 2 \\ 3 \\ 5 \end{array} \begin{array}{c} \begin{array}{ccc} 1 & 3 & 5 \end{array} \\ \begin{bmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{bmatrix} \end{array}.$$

The defender (aggressor) is the column (row) player and the heading is the number of tokens invested in A. Because investing 2 and investing 3 tokens in A are equivalent for the aggressor, the aggressor is indifferent between any linear combination of these two strategies. Therefore, the game can be reduced further to a 3 × 3 matrix with 2 on the diagonal and 0 off the diagonal. Form here, it is straight forward to show that in equilibrium the defender will randomize by investing 1, 3 or 5 tokens in A, each with probability one third. There is a continuum of equilibrium strategies for the aggressor, all of the form invest 0 tokens in A with probability one third, 5 tokens with probability one third, 2 tokens probability λ and 3 tokens with probability $\frac{1}{3}$ - λ for $\lambda \in [0, \frac{1}{3}]$.

If the defender could perfectly observe the action of the aggressor, then the defender would win the game with certainty in equilibrium – the aggressor would be indifferent among all actions and the defender could simply match the aggressor. Thus, this game provides a setting where a prediction market that fully aggregates information should have a dramatic effect. Of course, a prediction market may only provide a noisy signal. Consider the reduced game, A', where the aggressor invests 0, invests 5 or invests 2 or 3 tokens in A and the defender receives a noisy signal, $\sigma(\alpha)$, of the aggressor's action α that takes on the values "low" and "high." The low signal informs the defender that the aggressor's action was not 5, and high informs the defender that the aggressor's action was not 0. Specifically, let $\sigma(0)$ = low, $\sigma(5)$ = high, and $\sigma(2 \text{ or } 3)$ = low with probability ½ and high with probability ½. If p_0, p_{2-3}, and p_5 denote the probability that the aggressor invests 0, 2 or 3, or 5 tokens in A, respectively, then the probability that the aggressor invested 0 tokens in A conditional on observing a low signal is $\frac{p_0}{p_0+.5p_{2-3}}$; the probability the aggressor invested 2 or 3 tokens conditional on observing a low signal is $\frac{.5p_{2-3}}{p_0+.5p_{2-3}}$; and the probability the aggressor invested 5 tokens conditional on observing a low signal is 0. Similarly, the probability that the aggressor invested 0 tokens in A conditional on observing a high signal is 0; the probability the aggressor invested 2 or 3 tokens conditional on observing a low signal is $\frac{.5p_{2-3}}{p_5+.5p_{2-3}}$; and the probability the aggressor invested 5 tokens conditional on observing a low signal is $\frac{p_5}{p_5+.5p_{2-3}}$. The Bayesian Nash equilibrium is for p_0 = 0.25, p_{2-3} = 0.5, and p_5 = 0.25 and for the defender to invest 1 token in A with probability ¼ and invest 3 tokens in A with probability ¾ if the signal is "low" and to invest 3 tokens in A with probability ¾ and invest 5 tokens in A with probability ¼ if the signal is "high." In this game with a noisy signal the defender wins with a probability of ½. Also, the aggressor is less likely to engage in extreme behavior (investing 0 or 5 tokens in A) than when there is no signal. As a result, the defender is also less likely to engage in extreme behavior (investing 1 or 5 tokens in A).

3.2 Prediction Market Setup

A market consists of five traders, each endowed with cash holdings of 500 lab cents, the market's currency. Every trader observes a signal that is either "A" or "B", thus collectively the five traders know the total number of "A" signals. Traders can buy and sell shares whose value in lab cents is equal to the percentage of "A" signals observed (that is a share is worth 100 × the number of "A" signals / 5). Traders buy and sell shares via a double auction market for two minutes and with their cash holdings changing accordingly. A trader is not endowed with shares, but can hold a short position so long as his cash endowment is sufficiently large to cover the maximum possible value of the share.[1] At the end of trading, the total number of "A" signals is revealed to the traders and the value a trader's outstanding shares is added to his experiment earnings along with his ending cash holdings.

3.3 Treatments and Procedures

To explore the impact of prediction markets on decisions of contestants, we conducted two main treatments of contests with and without prediction markets, referred to as "No

[1] Deck, et al. (2013) demonstrate by comparison to Oprea, et al. (2007) that this procedure as opposed to providing an endowment of shares does not impact market performance in similar settings.

Market" and "With Market." We also collected data from prediction markets where the signals were exogenous.

Contests without Prediction Markets: In the "No Market" contest treatment, twelve fixed pairs of subjects completed the simultaneous version of the contest game described above. To maintain anonymity among subjects, several pairs participated in the experiment at the same time. Each pair played the contest 23 times, including three practice rounds and 20 salient rounds with P = \$2. As demonstrated by Chowdhury et al. (2013), the fixed matching protocol leads to mixing behavior that is more consistent with theoretical prediction in Blotto style games. After each contest, both players were informed of the rival's action as well as the outcome. A copy of the instructions for the contest game is included in the appendix.

Contests with Prediction Markets: The "With Market" contest treatment also had twelve fixed aggressor – defender pairs playing the contest game for 3 practice periods and up to 20 salient periods depending on time. The first mover aggressor made her decision, then the traders in the prediction market each received a signal identifying a distinct token invested by the aggressor. For example, if the aggressor invested 3 tokens in A then three traders observed A signals and 2 observed B signals, thus the signals are endogenous to the game and reflect a strategic choice by the aggressor. Before making her own decision, the second mover defender could not observe aggressor's decision but could observe trading in the prediction market. The defender observed the prediction market (bids, asks, and acceptances) in real time using the same interface as the traders. The defenders had two computers at their workstation – one running the contest and one running the prediction market as if the defender was a trader who had no money and could not trade. For each of the aggressor – defender pairs where the defender could observe a prediction market, in some periods the paired aggressor was also able to observe the market in real time just as the defender did. The aggressors were also seated at workstations with two computers. In the periods where the aggressor could not observe the prediction market, a web browser popped up on the aggressor's screen so that she could surf the web for two minutes while the market was in operation. The website automatically disappeared when the trading market closed. Each aggressor either observed the market for the first 10 periods and then did not observe it for the remainder of the contests *or* the order was reversed. Half of the sessions were run in each order and the defender and traders knew when the aggressor could and could not observe the trading market. Ultimately, the observability of the market by the aggressor had no impact on outcomes. Hence, in the results that are presented in the next section, data from both public and private markets are pooled.

Markets with Exogenous Signals: Prior to the start of the contest, traders went through a sequence of ten paid trading markets where the number of A signals was *exogenously* determined. Thus, this portion of the experiment can be compared to other prediction market experiments, although it does mean that the results for markets predicting *endogenous* strategic behavior are conditioned on having experienced traders in the markets; something that is expected to facilitate information aggregation. Prior to the practice market, subjects were given instructions (see appendix), completed a comprehension quiz, and participated in an unpaid practice market. Traders were in a fixed group for the entire experiment, as is typical in prediction market studies. Further, each group of five traders was always connected to the same fixed aggressor – defender pair in the endogenous periods, although there were always multiple groups running concurrently to maintain anonymity. This type of familiarity between the traders and defender is reflective of naturally occurring internal prediction markets.

Contestants Have Trader Experience: The subjects who would later serve as the contestants (aggressor or defender) first went through the market directions, practice period and the ten exogenously determined token allocation trading periods, so that they would better understand the market feedback they were observing during the contest phase of the experiment. In fact, the future contestants and the subjects who would continue to be traders did not know that there would be any contestants until after the ten initial markets were completed.[2] After the last exogenous signal market, all subjects in the session were informed of how the contest game worked and how the aggressor's actions would determine the information in the market (directions are included in the appendix).

3.4 Summary Information and Payments

All sessions were completed at the Economic Science Institute at Chapman University. Subjects, none of whom had participated in any related studies, were drawn from a database of undergraduate volunteers. The experimental design is summarized in Table 1.

[2] When prediction markets were run, 21 subjects entered the lab. They were randomly and anonymously grouped into three groups of 5 and two groups of 3. Those in a group of 5 remained in that group as traders for the entire time they were in the lab. Those in a group of three were informed that there were only three active traders in their market and that one of the inactive traders was shown an A token and the other was shown a B token so that the active traders as a whole still held complete information about a five token. Subjects in a group of three became contestants. When aggressor-defender pairs were formed, care was taken to ensure that the two subjects had been in different groups of three during the exogenous trading phase of the experiment. Further, both groups of three contained at least one person who would become an aggressor and at least one who would become a defender.

Table 1. Experimental Design

	No Market	With Market
Number of Aggressor - Defender Pairs	12	12
Prediction Market	None	5 Traders
Number of Subjects in a Observational Unit	2	7
Total Number of Subjects	24	84
Number of Periods		
Exogenous Signal Markets	-	10
Contests /Endogenous Signal Markets	20	17-20*
Total Number of Paid Contests	240	228
Total Number of Exogenous Signal Markets	-	120
Total Number of Endogenous Signal Markets	-	228

* Due to time constraints, one session of three groups lasted 17 periods and one session with three groups lasted for 19 periods instead of the planned 20. The other sessions lasted for 20 periods.

Subjects for the no market contest treatment were recruited for one hour. At the end of the experiment, these contestants were privately paid their cumulative earnings in cash and dismissed from the experiment. The average salient payment for this treatment was $20 by construction and each subject was also paid $7 for showing up on time. Subjects in the sessions with prediction markets were recruited for two and half hours. All trader earnings were converted into $US at the rate of 500 lab cents = US$1, a rate that was common knowledge throughout the experiment. At the end of the experiment, subjects were paid their earnings privately in cash and dismissed from the experiment. The average salient earnings for subjects in these sessions was $29.00, which was in addition to a $7 payment for showing up on time. The per period average earnings was the same for every period in every condition of the experiment.

4. Results

The data consist of choices in 468 contests and 348 prediction markets. Table 2 provides basic summary statistic of behavior in different conditions.

Our results are organized around three main questions:

1. Do prediction markets perform differently when the information being forecast reflects strategic decisions rather than being non-strategic exogenously determined?
2. Do prediction markets aid defenders in winning the contest?
3. Do aggressors in contests behave differently when they know there is an informed prediction market forecasting their decisions?

Table 2. Summary Statistics of Behavior in Experiment

Contest Comparison

	Defender Win Rate	Fraction of Extreme Aggressor Actions	Average A Tokens by Defender	Average A Tokens by Aggressor
No Market	.354	.454	3.275	2.575
With Market	.395	.570	3.127	2.333

Market Comparison

	Average Trade Volume	Average Number of Excess Bids	Average Closing Price
Exogenous	10.4	.142	58.846
Endogenous	7.877	-.772	50.340

4.1 Prediction Market Performance with Exogenous and Endogenous Information

To examine whether prediction markets perform differently when the information is exogenous or an endogenous strategic action, we investigate three key outcome variables: the closing price, the excess bids, and the number of contracts.[3] Market closing prices are often used instead of average contract prices because the trading process gathers and refines information over the course of the trading period. In the last half of the exogenous signal markets, the closing prices and the true values of the assets averaged 59.84 and 40 respectively, and the correlation between the average closing and the true asset value was $\rho = 0.162$, consistent with the level of information aggregation in previous lab experiments (see e.g., Deck et al. 2013). Excess bids are defined as the number of unfulfilled standing bids minus the number of unfulfilled standing asks in a market period. Previous research has found that this measure contains useful information for making inference in asset markets (see Smith et al. 1988; Caginalp et al. 2000). In particular, excess bids indicate buying pressure and thus undervalued assets, while excess asks (i.e., excess bids being negative) suggest selling pressure and overvalued assets. The third measure is the number of contracts or trade volume, which is a standard measure of market activity.

Table 3 reports GLS regressions on each of the three market outcome variables described above. The estimation reported in this table, and others throughout the paper, allow for random effects for the observational unit although similar conclusions are found using observational unit clustered standard errors instead. The first regressor in Table 3, "*endogenous,*" takes the value 1 if the signals received by traders are based on the actual

[3] Sixteen of the markets with endogenous signals and one market with exogenous signals had no trades. In these cases the closing price was taken to be the average of the lowest standing ask and highest standing bid when the market closed. In one instance there was no standing ask when the market closed and the closing price was calculated based upon an assumed ask of 100.

strategic decisions of the aggressor, and is 0 if signals are exogenously generated. The second regressor "value" is the true value of the asset.

Result 1. *Prediction market performance differs when signals are determined by strategic human decision makers rather than being exogenously determined.*

Evidence. The *Endogenous* variable is negative and significant in all three columns of Table 3 indicting that closing prices, excess bids and trade volumes are all lower in the endogenous signal markets.[4] As one would expect, value has a positive and significant impact on the closing price – the more the asset is worth, the greater the price. However, the coefficient being smaller than 1 suggests that the effect is much smaller than it would be when closing price fully reflects the true value. The small positive slope on *Value* combined with the positive and significant constant term in the first regression indicates closing prices tend to be too high on average, although they are below the true value when the true value is high and thus there is less variability in asset prices than in the true value. This is consistent with previous prediction market experiments. The second regression reveals that the number of excess bids correlates with the true value as well. When the value is high, there are more people placing unfulfilled bids whereas when the price is low there are relatively more unfulfilled offers to sell. This too is consistent with previous prediction market experiments. The number of contracts, on the other hand, does not vary with the asset's value. This finding is important because it indicates that the traders were not liquidity constrained when the asset value was high.

Table 3. Performance of Prediction Market

Dependent Variable	Closing Price	Excess Bids	Trade Volume
Endogenous	-11.221***	-1.268**	-2.732***
	(2.208)	(0.502)	(0.502)
Value	0.181***	0.058***	-0.004
	(0.028)	(0.006)	(0.007)
Constant	51.974***	-2.159***	10.555***
	(2.832)	(0.603)	(1.317)
Observations	348	348	348

Notes: All columns are General Least Squares regressions with random effects at the aggressor-defender pair level. In parentheses are standard errors. *, **, and *** indicate significant at 10%, 5%, and 1% levels, respectively.

[4] Similar results are found if OLS with standard errors clustered at the session level are used. If lagged values of the dependent variables are included, these lagged values are significant but the other conclusions remain unchanged except that *Endogenous* is no longer significant for *Excess Bids*.

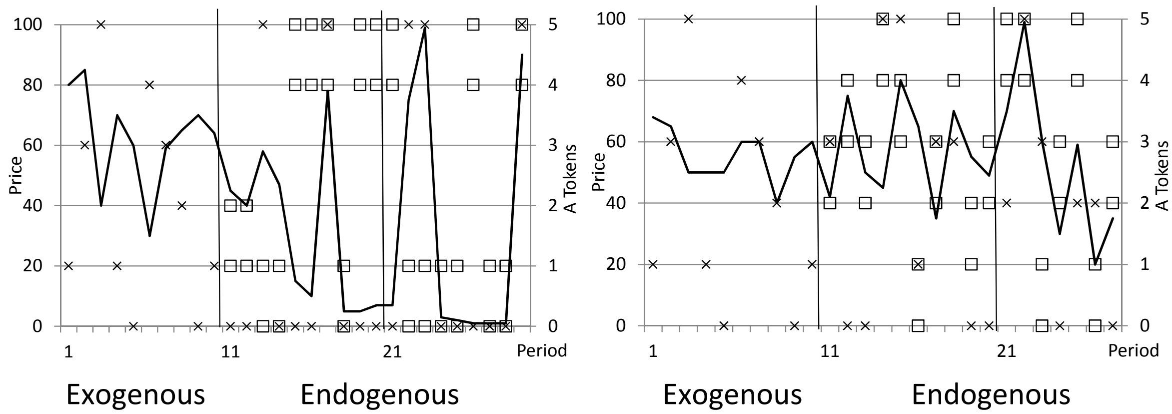
4.2 The Usefulness of Prediction Markets for Defenders

Figure 1 shows details of two aggressor-defender pairs in the prediction market treatment. This figure highlights the heterogeneity across aggressors, which is captured by the asset value after the initial 10 exogenous value periods (shown as × in the figure). The figure also reveals the heterogeneity within aggressors as they vary their number of A tokens over time. While Figure 1 only shows two aggressors, all of the aggressors in the experiment varied their behavior in unpredictable ways. In the session shown in the left panel of Figure 1, the aggressor always makes an extreme choice, investing either 0 or 5 tokens in A. In these cases the prediction markets appear to work well, as shown by the solid lines representing closing market prices. Of course, this performance could be facilitated by traders learning that the aggressors only take extreme actions. In the session shown in the right panel of Figure 1, the aggressor makes extreme and moderate choices and interpretation of what is happening in the prediction market is more difficult. Figure 1 also shows the actions of the defender. Given the structure of the game, the defender wins if he has the same number of A tokens as the aggressor or one more A token than the aggressor. Thus, there are two choices by the aggressor for which the defender could win given the defender's choice – essentially these are the defender's guesses about the aggressor's action. These choices are denoted by □ in the figure with the top one being the number of A tokens selected by the defender. If the defender won a particular contest the × will appear inside the □. If the aggressor won then × will not appear inside the □. As an example, consider the last period in the session on the left. In this period the aggressor selected 5 A tokens and thus the share value was 100. The closing price was 90 and as a result the defender selected 5 A tokens. The defender won this contest.

Table 4 provides two regression results designed to evaluate market and defender performance. The first looks at the degree to which the market provides useful information about the behavior of aggressors. That is, the estimation indicates what market information, if any, a defender *should use* to make inference about an aggressor's actions. The second regression in Table 4 reveals the market information that defenders *actually use* to make their decisions when a prediction market is in operation. The econometric results lead to the following result.

Result 2. *Prediction markets contain useful information regarding aggressor decisions, but defenders fail to extract the information. Specifically, defenders should use closing prices and excess bids, but only rely on closing price.*

Figure 1. Prediction Markets: Asset Value, Aggressor's A Tokens, Closing Prices, and Defender's Guess of Aggressor Behavior



– Closing Prices (left axis), × Aggressor's A Tokens (right axis) and Asset Value (left axis), □ Aggressor Choices for which the Defender will win (i.e. the Defender's guess as to what the Aggressor did), the top one of which is the Defender's A Tokens. If the × appears inside the □ then the defender won the contest. Otherwise the aggressor won the contest.

Table 4. Prediction Market Information that Defenders Should and Do Use

	Should Use	Actually Use
Dependent Variable	Number of Tokens Aggressor Invested in A	Number of Tokens Defender Invested in A
Closing Price	0.023***	0.015***
	(0.005)	(0.005)
Excess Bids	0.149***	0.007
	(0.020)	(0.020)
Trade Volume	0.001	0.017
	(0.021)	(0.021)
Constant	1.292***	2.286***
	(0.337)	(0.341)
Observations	228	228

Notes: All columns are General Least Squares regressions with random effects at the aggressor-defender pair level. In parentheses are standard errors. *, **, and *** indicate significant at 10%, 5%, and 1% levels, respectively.

Evidence. The positive and significant coefficients for closing price and excess bids reported in the left column of Table 4 indicate that both of these market measures provide information about aggressor behavior, consistent with previous prediction market experiments. However, the estimation in the right column of Table 4 reveals that defenders are using information from closing price, as the coefficient is positive and significant. However, they are not using excess bids, as the coefficient is not significant.

As discussed above, there is heterogeneity in terms of how well prediction markets perform. This heterogeneity could be driven in part by the performance of the traders who are in the market and by the type of strategies that an aggressor uses. A defender, who has observed a market that does not accurately aggregate information, may begin to ignore the market altogether while a defender whose market is highly accurate may rely on it heavily. To explore this possibility, the prediction markets are split into two equal sized groups. The prediction quality is measured by the average deviation of closing price from the asset value in the first 10 periods of endogenous signals. Groups of traders whose average deviation is smaller than the median are considered to be *Accurate*. The other half of the trading groups are called *Inaccurate*. As summarized in Table 5, the analysis of what information defenders should use and do use is conducted separately for the *Accurate* and *Inaccurate* groups from period 11 onward.

Table 5. Prediction Market Information that Defenders Should and Do Use by Market Type

	Should Use		Actually Use	
Market Type	Accurate	Inaccurate	Accurate	Inaccurate
Dependent Variable	Number of Tokens Aggressor Invested in A		Number of Tokens Aggressor Invested in A	
Closing Price	0.023**	0.017**	0.031***	0.013
	(0.010)	(0.008)	(0.011)	(0.009)
Excess Bids	0.063**	0.229***	-0.033	-0.002
	(0.030)	(0.040)	(0.033)	(0.049)
Trade Volume	0.012	0.015	0.067	0.051
	(0.042)	(0.042)	(0.046)	(0.045)
Constant	1.658***	1.487**	1.279*	1.650***
	(0.617)	(0.626)	(0.680)	(0.631)
Observations	54	54	54	54

Notes: All columns are General Least Squares regressions with random effects at the aggressor-defender pair level. In parentheses are standard errors. *, **, and *** indicate significant at 10%, 5%, and 1% levels, respectively.

The estimation in Table 5 reveals two interesting points. The first is that defenders who observe *Inaccurate* markets stop paying attention to those markets, as evidenced by the lack of significance in any of the market measures in the fourth column of the table. In contrast, defenders who observe *Accurate* markets do make use of the closing prices from those markets. The second interesting pattern from Table 5 is that *Inaccurate* markets nonetheless provide useful information, as evidenced by the positive and significant coefficients on closing price and excess bids. Not surprisingly, the relative importance of excess bids compared to closing prices is greater with *Inaccurate* markets than with *Accurate* markets.

Having established that the prediction markets do provide information about aggressor choices and that defenders use this information, at least when the market they are observing has been accurate, the analysis turns to the impact that the existence of a prediction market has on defender win rates in the weak-link contest. As reported in Table 2, in the absence of prediction markets defenders won 35% of the contests, not substantially different from the theoretical prediction. When prediction markets were available, defenders won 40% of the contests, an insignificant change in the direction predicted for a defender with a noisy signal of aggressor behavior.[5] However, Figure 1 suggests that prediction markets might be more effective when aggressors make extreme choices (investing 0 or 5 tokens in A) and in fact they are. This is formalized in Result 3.

Result 3. *Having access to a prediction market does not improve the defender's chance of winning overall, but it does help the defender when the aggressor makes an extreme action.*

Evidence. The first column of Table 6 provides econometric support for the overall result, as the coefficient for having a prediction market is not significant. The similarity between the observed and predicted defender win rate is evidenced by the constant term not being different from 33.33%. To explore the possibility that markets are differentially helpful in different circumstances, the second column of Table 6 includes an indicator variable for *Extreme Aggressor Action*. In this specification, the coefficient of *With Prediction Market* variable indicates that defender win rates are unaffected by the presence of a prediction market when the aggressor makes a moderate choice (i.e. placing at least one token in A and B). The coefficient of *Extreme Aggressor Action* suggests that in the absence of a prediction market, aggressors improve their chances of winning by engaging in extreme behavior; however, this is offset by the presence of a prediction market according to the interaction term. The third column of Table 6 shows that even the defenders who have the most accurate markets are not able to win the contest more often than their counterparts.[6] Fortunately for the defenders, having an inaccurate market does not impact their win rate as shown in the fourth column of the table, a result that is not surprising given that these traders have learned to ignore the market.

[5] If attention is restricted to the first period of contest behavior, the defender win rate is 42% in both treatments.
[6] This comparison is based on outcomes from contest 11 through the end of the experiment because the trader groups classified as being accurate were based on the first 10 contests.

Table 6. The Effect of Observing a Prediction Market on Defender Win Rate

	All Markets		Accurate Markets	Inaccurate Markets
With Prediction Market	0.041 (0.045)	-0.042 (0.064)	-0.005 (0.098)	0.018 (0.108)
Extreme Aggressor Action		-0.145** (0.063)		
With Prediction Market × Extreme Aggressor Action		0.175* (0.090)		
Constant	0.354*** (0.031)	0.420*** (0.042)	0.350*** (0.055)	0.350*** (0.061)
Observations	468	468	174	174

Notes: All columns are General Least Squares regressions with random effects at the aggressor-defender pair level. In parentheses are standard errors. *, **, and *** indicate significant at 10%, 5%, and 1% levels, respectively.

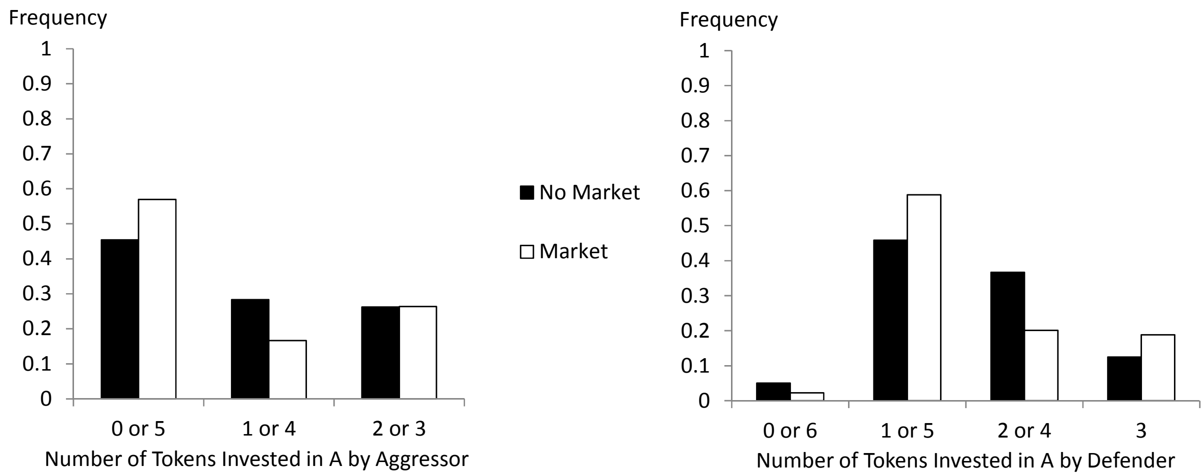
4.3 The Impact of Prediction Markets on Aggressor Strategy

If there is no prediction market, then aggressors should randomize by investing 0, 2 or 3, or 5 tokens in A with equal probability. Figure 2 shows the behavior of aggressors by treatment taking into account the symmetry in the game.[7] As shown in Figure 2, in the absence of a prediction markets aggressors invest 1 or 4 tokens with positive probability. The result of this is that aggressors do not make extreme investments as often as they should nor do they make balanced investments as frequently as they should. However, they do make extreme investments about twice as often as they make balanced investments.

With a perfectly functioning prediction market, the choice of the aggressor is irrelevant, but as described in section 3, if the market provides noisy information to the defender then the aggressor should engage in extreme behavior less frequently. From Figure 2 it appears that the presence of a prediction market leads the aggressor to engage in extreme behavior more frequently (see also Table 2), while not changing the frequency of balanced choices. However, this change is not significant, providing the basis for the final result.

[7] Examining disaggregated data suggests that behavior is broadly symmetric for both aggressors and defenders.

Figure 2. Contest Decisions by Treatment



Result 4. The presence of a prediction market does not alter the behavior of Aggressor.

Evidence. That aggressors do not change their behavior is supported by GLS regression analysis with aggressor-defender pair level random effects, where the dependent variable is whether or not the aggressor's action was extreme (investing 0 or 5 tokens in A) and the explanatory variables were a constant and a binary variable indicating the existence of a prediction market. The p-value for the existence of a market was 0.247.

Figure 2 also shows defender behavior with and without a prediction market. Because the defender has an extra token and wins ties, investing 0 or 6 tokens in A is a dominated strategy for the defender and Figure 2 indicates that defenders understood this and almost always avoided placing all of their tokens in the same subcontest. However, defenders do invest 2 or 4 tokens in A quite frequently, despite the theoretical prediction that they would not.

5. Discussion

Prediction markets are becoming a broadly accepted tool for aggregating disparate pieces of information. Such markets have been used to predict a wide range of future outcomes, from the probability of extra-terrestrials making contact with earthlings (on Intrade.com) to the likelihood that a Hollywood movie set to be released years in the future will be a success (on HSX.com). These markets are also used by business for far more mundane forecasts of market conditions and rival behavior, which are then used to make strategic choices for the firm. However, much of the academic research investigating prediction markets has relied upon studies where the information being forecasted is non-strategic.

In this paper we report the results of a controlled laboratory experiment in which players are competing in a strategic weak-link styled contest. Absent a prediction market, the contest is designed to heavily favor one of the players and this pattern is indeed what we observe behaviorally. However, a successful prediction market should turn the tide in favor of the other player. Ultimately, we do not find evidence that the disadvantaged player was able to use the prediction market to gain the upper hand. This failure appears to be at least partly due to the contestants not making full use of the information in the markets, specifically information contained in excess bids.

Our results yield several important insights about using prediction markets to forecast endogenously created strategically valuable information. The first insight is that market performance in terms of prices, excess bids, and trade volume differ when the predicted information is from a non-strategic exogenous source versus when it is from an endogenous strategic choice. The second insight from our experiments is that while prices in prediction markets contain information, decision makers ignore other information, namely excess bids, from the market at their own peril. Ceteris paribus, the more unfulfilled bids in the market the greater the forecast should be adjusted up from the price with the reverse holding for excess asks. A third finding of the paper is that the existence of a prediction market does not alter the strategic behavior of the party whose action is being predicted. Such a pattern is potentially beneficial in practice because it would suggest that when a market is created, traders could rely on past experience whereas if the predicted behavior changed with the existence of a market then traders drawing from past experience could be detrimental. Of course, all of our results are contingent on the structure of the action being forecasted and the way that information is presented. One key piece of our design is that the market traders as a group had perfect information and each person had a unique piece of information. This differs from the setting in which each trader is receiving say an independent noisy signal about the action being predicted. In such settings having more traders typically results in better market performance as there is more actually more information. In our setting having more traders could actually be problematic as the additional traders would have to be either uninformed or receiving redundant information.

Our work demonstrates that the creation of a prediction market is not a panacea. Having a prediction market is not sufficient for decision makers to make good choices: what to take from a prediction market is not self-evident. Consumers of prediction market information need to be sufficiently sophisticated and trained to be able to fully exploit the advantages of having such markets. Of course, contestants who know they are facing more sophisticated rivals may adjust their own behavior which could in turn influence market performance. We believe that this is an important avenue for future research as more and more organizations begin to implement prediction markets as inputs to important strategic decisions.

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Appendix: Subject Instructions

Text of Directions for Contest with No Prediction Market

Page 1.

This is an experiment in the economics of decision making. You will be paid in cash at the end of the experiment based upon your decisions, so it is important that you understand the directions completely. Therefore, if you have a question at any point, please raise your hand and someone will assist you. Otherwise we ask that you do not talk or communicate in any other way with anyone else. If you do, you may be asked to leave the experiment and will forfeit any payment.

Page 2.

The experiment is broken into a series of rounds. Each round you can earn $2 dollars. At the end of the experiment you will be paid your cumulative earnings.

You will be randomly and anonymously matched with someone else in the experiment and will interact with that person every round. Each round, one of you will earn $2 and the other will earn $0. The process used to determine who earns the money in a round is described on the following pages.

Page 3.

There are two items available each round: item A and item B.

There are also two types of people in this activity: First Movers and Second Movers. You will be a First (Second) Mover, but it is important that you understand both roles.

First Movers earn $2 if they claim *either* item A *or* item B. Second Movers have to claim *both* item A *and* item B to earn $2.

To claim an item each person places a bid on the item using their tokens for that round. Whoever bids more tokens for an item claims it. There is no cost for the tokens and both people must use all of their tokens each round.

First Movers have 5 tokens and Second Movers have 6 tokens. Bids must be in integer amounts, but the Second Mover has an additional 0.5 tokens automatically bid on each item so a tie can never occur.

Your role, the number of tokens and the amount of money available is the same every round. No participant knows how many rounds there will be nor will anyone ever know with whom they were interacting.

Page 4.

Here is an example of how bidding in a round might look.

Suppose the First Mover places a bid of 4 for item A and 1 for item B.

If the Second Mover places a bid of 5 for item A and 1 for item B, then the Second Mover's total bid for item A is 5.5 and 1.5 for item B. In this case, the Second Mover claims both items and thus the Second Mover earns $2 while the First Mover earns $0.

If instead the Second Mover places a bid of 6 for item A and 0 for item B, then the Second Mover's total bid for item A is 6.5 and 0.5 for item B. In this case, the Second Mover claims item A, but the First Mover claims item B and thus the First Mover earns $2 while the Second Mover earns $0.

Alternatively, if instead the Second Mover places a bid of 3 for item A and 3 for item B, then the Second Mover's total bid for item A is 3.5 and 3.5 for item B. In this case, the Second Mover claims item B, but the First Mover claims item A and thus the First Mover earns $2 while the Second Mover earns $0.

Page 5.

First Movers make their decisions before Second Movers do, but Second Movers do not observe the choices of the First Mover prior to making their own decisions. After each round, you will observe the amount each person bid for each item and your earnings for the round.

Page 6

To summarize

> You have been assigned the role of First (Second) Mover and will retain that role throughout the experiment.
>
> Each round you or the person you are matched with will earn $2.
>
> First Movers must claim either item A or item B to earn the money
>
> Second Movers must claim both item A and item B to earn the money
>
> Items are claimed by bidding tokens and whoever bids the most tokens for an item claims it.

First Movers have 5 tokens and Second Movers have 6 tokens plus an extra 0.5 tokens for each item.

Directions for Trading Markets

Instructions

This is an experiment in market decision making. You will be paid in cash for your participation at the end of the experiment. Different participants may earn different amounts. What you earn depends on your decisions and the decisions of others. All money amounts are denoted in lab cents, which will be converted into $US at the rate of 500 lab cents = $1 US.

The experiment will take place through the computer terminals at which you are seated. If you have any questions during the instructions, raise your hand and a monitor will come by to answer your question. If any difficulties arise after the experiment has begun, raise your hand, and someone will assist you.

There will be several market rounds in this experiment. Each market round is separate, although your payoff will be the cumulative sum of your earnings in each market round.

You will be a **Trader** interacting with the same 4 other Traders every round.

There are 5 "tokens" each round that can be either A tokens or B tokens. Before a market round, each **Trader** will observe a different token, so each token is observed by exactly one **Trader**.

Traders can trade "Shares" that are worth either 0, 20, 40, 60, 80, or 100 cents. The actual value of a share in a market round is determined by the percentage of A tokens in a given round. If there are 3 A tokens, and thus 2 B tokens, then the value of a share is 60 cents as 3/5 = 60% of the tokens are A tokens.

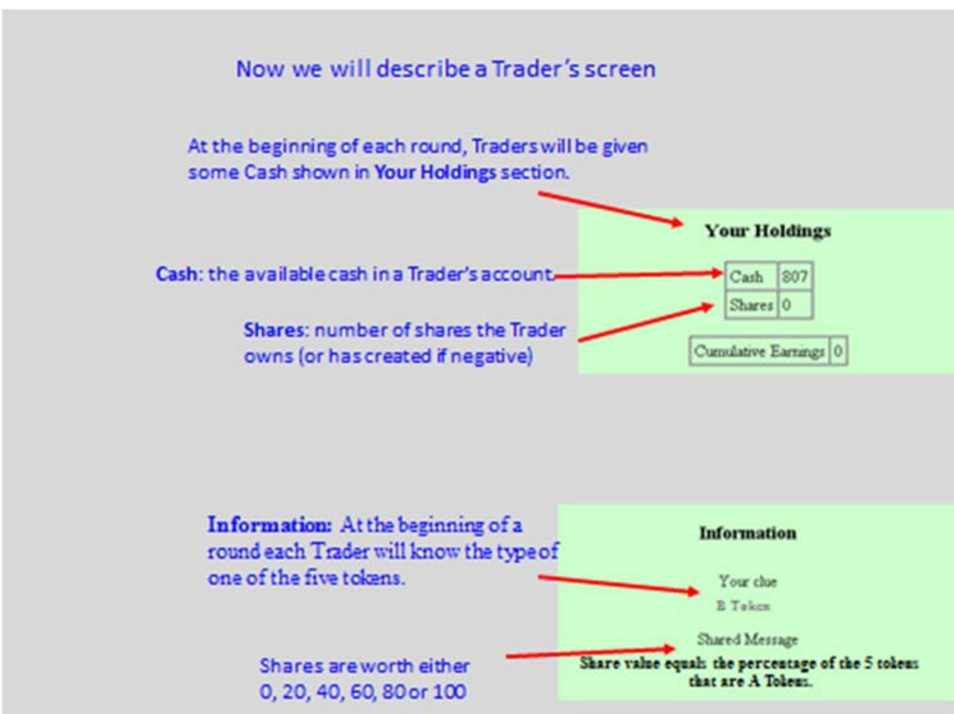
Notice that a share has the same value to every **Trader**. However, this value will only be revealed at the end of the round.

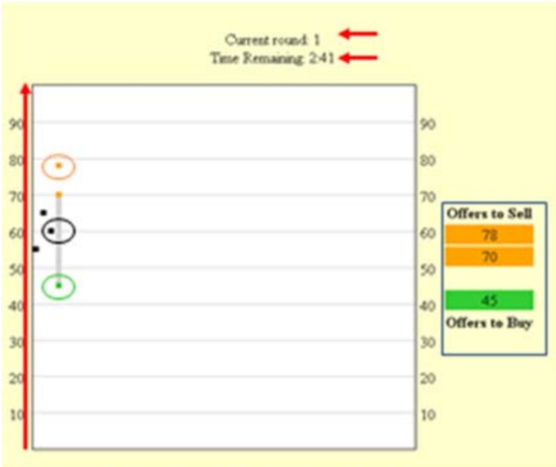
For the first several rounds, the number of A tokens will be determined randomly. The number of B tokens is always 5 minus the number of A tokens. Once the number of A and B tokens is determined, each trader will be randomly assigned one of the five tokens to observe.

Later in the experiment, some of you will participate in a different activity and for the rest of you the way the number of A and B tokens is determined will change, but you will receive additional directions when that change occurs. Nothing you do in this part of the experiment will impact the number of A and B tokens in the second part of the experiment or who is selected to do the other activity.

Each round, **Traders** will start with 500 in "Cash" and can buy or sell shares if they wish. If a **Trader** buys a share, she pays the buying price of the share. If she holds the share until the end of the round then she earns the value of the share. If she sells a share that she bought previously during the round, she will receive the selling price but will not receive the value of the share at the end of the round.

If a Trader does not have a share, but still wishes to sell, she can create a share. Creating a share is identical to selling an existing share except that the seller will have to pay the buyer the value of the share. In order to make sure the seller creating a share can cover the value at the end of the round, the computer automatically takes 100 cents from the **Trader** and puts it into a reserve account to cover payment. So to create a share a **Trader** must have 100 in cash after adding the selling price, which the seller receives. Any money held in the reserve account that is not paid to the owner of the share is given back to the trader who sold the share after the round ends.





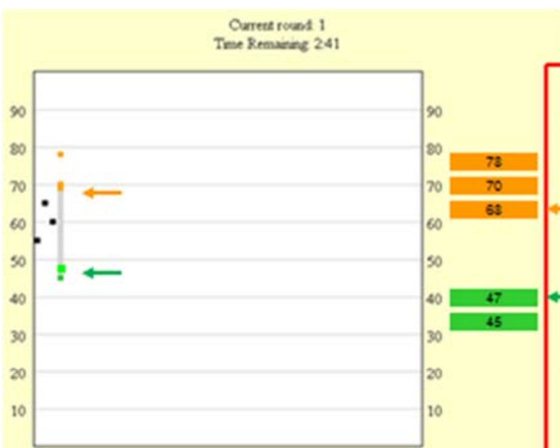
During every round, Traders can buy or sell shares from one another by making offers to buy or to sell.

The existing offers are shown on the **Market Graph** to the left.

On top of the graph, the **Current round** is shown.
Below that, the **Time Remaining** for the trading round is shown. Each round lasts two minutes.
The vertical axis lists the **Price** for the offers.

Every time someone makes an offer to **buy** a share, a **GREEN** dot will appear on the graph to the left.
Every time someone makes an offer to **sell**, an **ORANGE** dot will appear on the graph to the left.
Once a **trade** is actually made, the trade will be shown as a **BLACK** dot in the graph.

Offers are also listed on the **Market Book** to the right of the graph.



The top right section of the screen is the **Orders** box.

To enter a **New Order** to buy or to sell, Traders type in the price at which they would like to buy, or sell, in the appropriate **Submit New Order** box and click the **Buy** or **Sell** button to submit the order.
Once the order is entered, the offer will be updated on both the **Market Book** and the **Market Graph**.

Suppose a Trader wants to place an order to buy, it must be higher than the current best offer to buy, which is now 45. Say, the Trader wants to buy at 47, she types in 47 and clicks buy.
Suppose a Trader wants to place an order to sell, it must be lower than the current best offer to sell, which is now 70. Say, the Trader wants to sell at 68, she types in 68 and clicks sell.

To accept an existing offer from another participant, a Trader can click the Buy or Sell button in the **Immediate Order** section above. The Immediate Order section shows the best prices to buy, or sell, that are currently available on the market.

By clicking on the **Sell** button, a Trader **sells** at the listed price.

The current best offer to buy is 45, if a Trader clicks Sell, she sells a share at the price of 45 immediately.
Her shares go to -1 (she is short a share).
Her cash holdings will initially increase by 45, but her cash will then decrease by 100 as money is put in reserves to cover the share. The net change in her cash is +45(price) -100 (in reserves) = -55.
If a share turns out to be valued at less than 100, the extra reserves will be given back to her.

By clicking on the **Buy** button, a Trader **buys** at the listed price.
The current best offer to sell is 70. If a Trader clicks Buy, she immediately buys a share at a price of 70 (and 100 in reserves is returned to cash).

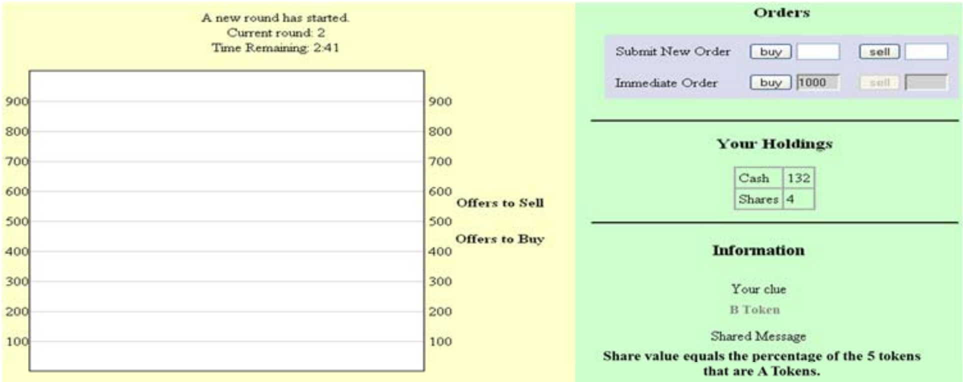
Whenever a Trader enters new offers to buy, or sell, she will have those offers appear as **Buttons** below the order box.

A Trader's outstanding offers to buy cannot exceed her cash holding; her outstanding offers to sell cannot exceed her ability to meet the reserves holdings.

Therefore, a Trader may have to delete offers under **"Cancel Orders"**.

By clicking on these buttons, a Trader can take them off of the market.

Suppose a Trader clicks on the bid button 25, she will remove it from the market.



The share earnings each round will be added to the cash account of the holder. This amount is how much a Trader earns in a given round.

A Trader's earnings will accumulate each round.

Her cash and shares do not carry over to the next round.

Summary of Experiment for Traders

1. Traders will be given an initial amount of Cash and can create shares. The value of a share in lab cents is equal to the percentage of tokens that are A tokens (out of a total of 5 tokens).

2. Each period, Traders will observe one of the 5 tokens and each trader will observe a different token.

3. Traders can submit offers to BUY shares and offers to SELL shares. If a Trader creates a share by selling a share when she does not have one, she will have to set 100 in a reserve account to make sure she can cover the payment to the share's owner.

4. Trades can make trades by buying at the current lowest offer to sell or selling at the current highest offer to buy.

A short quiz will appear on your screen in a moment. The purpose of this is to make sure everyone understand how the experiment works and how payoff are determined.

After everyone completes the quiz, there will be an unpaid practice round to familiarize everyone with the program.

Directions about Contest for Prediction Market Traders

Page 1.

In the next part of the experiment, you will continue trading in a market just like you have been doing so far with the same people. However, others in the lab have been randomly selected to begin doing a different activity.

Starting in the next trading round, the number of A tokens will be determined by what someone in the new activity decides to do as opposed to having been determined randomly as before. Once the number of A tokens is determined, market trading will proceed as before and your payoff each round will be determined in the same way that it was before.

The remainder of these directions explains the new activity. If you have a question at any point, please raise your hand and someone will assist you. Otherwise we ask that you do not talk or communicate in any other way with anyone else. If you do, you may be asked to leave the experiment and will forfeit any payment.

Page 2.

The new activity is also broken into a series of rounds. For the new activity, two people have been randomly and anonymously matched with each other and will continue to interact with each other for the remainder of the experiment. Each round, one of the two people will earn $2 and the other will earn $0. At the end of the experiment each will be paid their cumulative earnings. The process used to determine who earns the money in a round is described on the following pages.

Page 3.

There are two items available each round: item A and item B.

There are also two types of people in this activity: First Movers and Second Movers.

First Movers earn $2 if they claim *either* item A *or* item B. Second Movers have to claim *both* item A *and* item B to earn $2.

To claim an item each person places a bid on the item using their tokens for that round. Whoever bids more tokens for an item claims it. There is no cost for the tokens and both people must use all of their tokens each round.

First Movers have 5 tokens and Second Movers have 6 tokens. Bids must be in integer amounts, but the Second Mover has an additional 0.5 tokens automatically bid on each item so a tie can never occur.

Roles, the number of tokens and the amount of money available is the same every round. No participant knows how many rounds there will be nor will anyone ever know with whom they were interacting.

Page 4.

Here is an example of how bidding in a round might look.

Suppose the First Mover places a bid of 4 for item A and 1 for item B.

If the Second Mover places a bid of 5 for item A and 1 for item B, then the Second Mover's total bid for item A is 5.5 and 1.5 for item B. In this case, the Second Mover claims both items and thus the Second Mover earns $2 while the First Mover earns $0.

If instead the Second Mover places a bid of 6 for item A and 0 for item B, then the Second Mover's total bid for item A is 6.5 and 0.5 for item B. In this case, the Second Mover claims item A, but the First Mover claims item B and thus the First Mover earns $2 while the Second Mover earns $0.

Alternatively, if instead the Second Mover places a bid of 3 for item A and 3 for item B, then the Second Mover's total bid for item A is 3.5 and 3.5 for item B. In this case, the Second Mover claims item B, but the First Mover claims item A and thus the First Mover earns $2 while the Second Mover earns $0.

Page 5.

First Movers make their decisions before Second Movers do, but Second Movers do not observe the choices of the First Mover prior to making their own decisions. The number of tokens the First Mover chooses to bid on A determines the number of A tokens (out of 5) in your market. Second Movers will observe the trading in your market before placing their bids. After each round, the First and Second Movers will observe the amount each person bid for each item and their earnings for the round. The same First Mover will determine the number of A tokens in your market every round and your market will be observed by the same Second Mover every round.

Page 6.

To summarize

You will continue to trade in a market as before.

The number of A tokens out of 5 used to determine the value of a share is set by the First Mover's token bid on A and market trading is observed by the Second Mover.

Each round either the First Mover of the Second Mover will earn $2.

First Movers must claim either item A or item B to earn the money

Second Movers must claim both item A and item B to earn the money

Items are claimed by bidding tokens and whoever bids the most tokens for an item claims it.

First Movers have 5 tokens and Second Movers have 6 tokens plus an extra 0.5 tokens for each item.