Information Aggregation and Belief Elicitation in Experimental Parimutuel Betting Markets

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Abstract

This paper studies the impact of belief elicitation on informational efficiency and individual behavior in experimental parimutuel betting markets. In one treatment, groups of eight participants, who possess a private signal about the eventual outcome, play a sequential betting game. The second treatment is identical, except that bettors are observed by eight other participants who submit incentivized beliefs about the winning probabilities of each outcome. In the third treatment, the same individuals make bets and assess the winning probabilities of the outcomes. Market probabilities more accurately reflect objective probabilities in the third than in the other two treatments. Submitting beliefs reduce the favorite-longshot bias and making bets improves the accuracy of elicited beliefs. A level-$k$ framework provides some insights about why belief elicitation improves the capacity of betting markets to aggregate information.

KEYWORDS: Parimutuel betting; Information aggregation; Favorite-longshot bias; Elicited beliefs; Level-$k$ reasoning; Experiment.

JEL CLASSIFICATION: C72; C92; D82.

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1 Introduction

Parimutuel betting markets are of considerable empirical importance.\(^1\) They are also of interest in the economics and finance research communities because they are simple financial markets (Sauer, 1998; Vaughan Williams, 1999). In parimutuel win-betting markets, individuals bet money on an outcome, such as a horse winning a race. If the horse wins they get to keep their bet as well as share, net of any market maker’s costs, of all the money placed on losing horses, with the other winners. Individuals are betting against one another in a situation where the odds change over the course of the betting period. Therefore, parimutuel, like financial, markets are characterized by uncertainty about future payoffs as well as by investors who may have access to some private information, the history of trades, and a statistic which reflects the market price information, namely the current odds. The fact that the uncertainty is resolved unambiguously at the time the outcome is realized facilitates the measurement of the informational efficiency of the market. Indeed, numerous field studies on horse race betting, beginning with Griffith (1949), have attempted to evaluate the extent to which betting markets are efficient (see Vaughan Williams, 2005, chap. 2 and 3 for extensive reviews). The evidence suggests that insiders can earn above-average returns, and thus the market may be considered informationally inefficient (see, for example, Schnytzer and Shilony, 1995).

In this paper we use experimental methods to investigate some factors that may influence the informational efficiency of parimutuel betting markets. The markets we study are sequential, in the sense that bettors take turns in making bets, and have the sequence of prior bets available to them when they make their choices. We take advantage of the fact that experiments allow the researcher to vary one aspect of the betting environment or process, while keeping all other aspects the same, and thus permit isolation of the effect of one element on market efficiency. Our results show that the elicitation of bettors’ beliefs about the outcome probabilities significantly affect their behavior and improves the information aggregation capacity of the market.

There is some prior experimental evidence that the elicitation of incentivized beliefs does influence behavior in other contexts, but the results are mixed. For example, in social dilemmas Croson (2000) finds that belief elicitation reduces cooperation, while Gächter and Renner (2010) observe that it increases cooperation. On the other hand, Nyarko and Schotter (2002) and Costa-Gomes and Weizsacker (2008) find no or weak effects of belief elicitation on actions, and Rutström and Wilcox (2009) find that belief elicitation affects behavior for only one of the two players in an asymmetric game. One way in which incentivized beliefs

\(^1\)Betting turnover on horse racing in the United States alone in 2005 was approximately 14 billion US dollars (International Federation of Horseracing Authorities, http://www.horseracingintfed.com).
can influence actions is in creating the ability for players to use the payoffs from submission of beliefs to hedge the actions they take in the game itself. Blanco, Engelmann, Koch, and Normann (2010), in a study focused on this issue, find that incentives to use beliefs to hedge influence behavior when hedging opportunities are very transparent, but that they do not affect behavior in other games. The hedging problem can be overcome if beliefs of observers rather than of players are elicited. However, Palfrey and Wang (2009) find that beliefs of observers and players are very different, and that player forecasts are the more biased of the two.

A few studies have measured beliefs in settings related to ours. Dominitz and Hung (2009) elicit beliefs in the context of an information cascade experiment. The structure of the game is similar to a parimutuel betting market but payoff externalities are absent: Individuals receive private information about which one of two possible outcomes is likely to occur and must publicly state, sequentially, which outcome they believe will be realized. Dominitz and Hung (2009) report that players’ forecasts are biased in the sense that subjects often fail to change them in response to the decisions of other players, and extreme beliefs are widely reported. Nevertheless, belief elicitation does not have a systematic effect on decisions. In the context of asset markets, Smith and Williams (1988) and Haruvy and Noussair (2007) find that traders’ future price predictions reflect historical trends and do not anticipate future price changes, but that belief elicitation does not, in itself, affect market behavior.

There is reason to believe that belief elicitation might exert an effect on betting decisions in parimutuel markets. In a sequential betting market, the inputs to a rational bettor’s decision are (1) an estimate of the probability of each outcome, which one calculates using one’s own private signal and the informational content of prior bettors’ decisions, and (2) the payoff of each of the options, as captured in the odds of each outcome. However, betting options are typically expressed purely in terms of betting odds or payoffs conditional on each outcome. If poor decisions occur because insufficient attention is paid to outcome probabilities, belief elicitation may increase the weight the outcome probabilities receive in the bettor’s decision process, relative to the odds, and thereby affect bettors’ behavior and the information aggregation performance of the market. That probability information is neglected in favor of payoff information is suggested from the favorite-longshot bias widely observed in racetrack betting, in which market odds tend to make it more profitable to bet on favorites than on longshots.²

Experimental methods have been successfully applied to the study of parimutuel betting markets in an active ongoing literature. Plott, Wit, and Yang (2003) present the first experimental evidence on the capacity of parimutuel betting markets to aggregate informa-

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²For recent references see, for example, Ottaviani and Sørensen (2008, 2010) and Snowberg and Wolters (2010).
tion. They study a setting in which asymmetrically informed individuals could place bets on outcomes by making purchases from a market maker in several markets operating in continuous time. They find that the market aggregates information effectively in simple environments, but that it is less effective as the environment becomes more complex, and that a small favorite-longshot bias exists. The structure of our market is simpler, and is related to that studied experimentally in Drehmann, Oechssler, and Roider (2005) and in Cipriani and Guarino (2005) (differences are detailed in Section 2.1). Both Drehmann et al. (2005) and Cipriani and Guarino (2005) observe widespread contrarian behavior, which is suboptimal betting on the longshot and against one’s private information, distorting market prices and generating a favorite-longshot bias.

Our experiment consists of three different treatments, which are described in detail in Section 2. In all treatments, subjects observe private signals about the probability that each of two a priori equally likely events has occurred. Subject sequentially make bets on one of the two possible outcomes. A winning bet yields a return that is decreasing with the proportion of subjects who have bet on the winning outcome. In the Bet treatment, subjects make bets only. In the ObsPred treatment, there are two groups of subjects: bettors and observers. Bettors make bets while observers submit beliefs about the probabilities of each outcome based on the betting data they have observed. In the BetPred treatment, the same subjects submit both bets and beliefs. In both ObsPred and BetPred, belief statements are not made public. That is, no subject observes at any time the beliefs any other subject has submitted.

We compare the three treatments with regard to the extent to which the final market odds reflect information aggregation. Measuring the difference between the Bet and BetPred treatments allows us to consider whether requiring bettors to submit beliefs leads to more successful information aggregation. Comparison of belief statements in treatments ObsPred and BetPred allows us to investigate whether making bets affects the accuracy of stated beliefs about outcome probabilities. Contrasting bets in treatments Bet and ObsPred reveals whether bettors’ decisions change when they know that others observe them. We use a level-k approach (Stahl and Wilson, 1994, Crawford and Iriberri, 2007) to study how the treatment manipulations induce a change in individual behavior. The implications of the level-k model for betting decisions in our market are discussed in Section 3.

Our results are reported in Section 4. We find that the market’s capacity to aggregate information is better when bettors are themselves required to submit beliefs, in BetPred, than in the other two treatments. The favorite-longshot bias, a phenomenon observed in treatments Bet and ObsPred, is reduced when beliefs are elicited from bettors in BetPred. The comparison between the ObsPred and BetPred treatments also reveals that placing bets improves the accuracy of belief statements. The level-k model suggests a greater incidence
of strategic reasoning on the part of bettors when they are also required to submit beliefs.

2 Experimental design and procedures

2.1 The sequential parimutuel betting game

Our setting is an extension of Bikhchandani, Hirshleifer, and Welch’s (1992) specific model of information cascades, with the additional feature that market prices, the odds on each outcome, exist and are updated after each individual makes his bet. An alternative extension of the information cascade setting has been considered by Avery and Zemsky (1998). In the simplest version of their model, they assumed efficient prices and showed that herding is not possible, since an efficient market price always separates people with favorable and unfavorable information about the security so that the former always buy and the latter always sell. However, the return of each player also depends on his expectation about the behavior of later participants in parimutuel betting markets which drastically complicates the analysis.

Consider a horse race with two horses called A and B. There is a finite set $N \equiv \{1, \ldots, 8\}$ of bettors. Each bettor is endowed with one unit of money which he is required to wager on one of the horses. In other words, each bettor $i \in N$ chooses $s_i \in \{A, B\}$, where A or B consists of betting one unit of money on horse A or horse B, respectively. Bets are made sequentially with bettor $i$ denoting the $i$th bettor in the sequence. Each bettor observes the betting decisions of all previous individuals before making his choice. Let $s^i = (s_1, \ldots, s_i) \in \{A, B\}^i$ denote a history of bets up to and including bettor $i$’s bet. Bettors are not permitted to cancel their bets after they are made. A priori, each state of nature in $\{\theta_A, \theta_B\}$ is equally likely where $\theta_A$ stands for “horse A wins the race” and $\theta_B$ stands for “horse B wins the race”.

For any history of bets $s^i$ and any horse $H \in \{A, B\}$, let $h(s^i) = |\{j \in \{1, \ldots, i\} : s_j = H\}|$ be the number of bettors who bet on horse $H$, and let $\overline{H}$ denote the horse other than $H$. Given a history of bets $s^i$, $O_H(s^i) = \overline{h}(s^i)/h(s^i)$ denotes the current odds against horse $H$.

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3Experimental tests of Avery and Zemsky’s simple model have confirmed that the presence of a flexible price prevents herding. In Drehmann et al. (2005), the price is automatically set equal to the level that would result if the market maker infers the private information of bettors from their bets, when such inference is possible, and prices each outcome fairly given this information. Thus, it is always optimal for each bettor to bet in accordance with his private information, and drawing inferences from the sequence of prior bets is not necessary. Cipriani and Guarino (2005) consider three treatments that differ in the pricing rule that the market maker uses and in the information available to bettors. In one treatment, prices are independent of betting history. In the other two treatments, prices are set as in Drehmann et al.’s (2005) study, but the treatments differ in the availability of the prior betting history.
which are left unspecified in case no bet has been placed on horse $H$. Bettors’ payoffs are determined by the final odds. If bettor $i$ bets on horse $H$ and horse $H$ wins the race then his payoff equals the final odds against horse $H$ plus 1 ($\frac{\bar{h}(s^H)}{h(s^H)} + 1$). If bettor $i$ bets on horse $H$ and horse $\overline{H}$ wins the race then he receives 0 payoff, losing his stake.

Before making his decision, each bettor $i$ receives a private signal $q_i \in \{q^A, q^B\}$ that is correlated with the true state of nature. Conditional on the state of nature, bettors’ signals are independent, identically distributed, and satisfy

$$
\Pr(q_i = q^A | \theta_A, q_j) = \Pr(q_i = q^A | \theta_A) = \pi \in (1/2, 1)
$$

$$
\Pr(q_i = q^A | \theta_B, q_j) = \Pr(q_i = q^A | \theta_B) = 1 - \pi,
$$

for all $i, j \in N, i \neq j$. Using Bayes’ rule, bettor $i$’s beliefs after he has received his private information but before he has observed any market activity are given by $\Pr(\theta_H | q_i = q^H) = \pi$ and $\Pr(\theta_H | q_i = q^{\overline{H}}) = 1 - \pi, H = A, B$.

### 2.2 Procedures

The experiment was conducted in twelve sessions at the laboratory for experimental economics (LEES) in Strasbourg University, France. 176 subjects, who had no previous experience with economic experiments on betting, were recruited for participation in the study. All sessions were conducted in French. Table 1 contains the number of sessions, participants, bets placed and beliefs stated in each treatment. The experiment consists of three treatments, the Bet, ObsPred, and BetPred treatments, with four sessions conducted under the conditions of each treatment. The treatments shared several important features in the manner and timing with which they were conducted. Each session consisted of 20 repetitions of the sequential betting game described in Section 2.1, in which there are eight betting periods in each repetition. Each betting period consisted of a turn of one designated individual to submit a bet. We will use the term round to refer to a repetition of the game and the term period to refer to a subject’s turn to bet within a round. The same sequences of private signals was used for every group in all of the treatments and they were randomly generated.

At the beginning of each session, subjects were instructed on the rules of the game and the use of the computer program with written instructions. These were read aloud by an assistant. A short questionnaire and one dry run followed.\(^5\) Afterwards, the twenty rounds

\(^4\)Odds stated at race tracks are usually reported as $\frac{\bar{h}(s^i)}{h(s^i)}$ to 1.

\(^5\)In each session, subjects read the instructions on their own, listened to the assistant reading the instructions aloud, and answered a questionnaire. The questionnaire mainly checked subjects’ understanding of the calculation of earnings. Subjects who made mistakes in answering the questionnaire were paid the minimum compensation of 3 euros and were replaced by subjects who were randomly selected among those who made
of the sequential betting game that constituted the experiment took place. Communication between the subjects was not allowed. Each session was between 90 and 135 minutes in duration.

The three treatments differed in terms of whether participants made bets, predictions, or both. In the Bet treatment, individuals made bets on which one of two possible outcomes would be realized. As Table 1 shows, each session consisted of eight individuals, yielding a total of 32 participants. Each session consisted of 20 rounds in which each individual made a bet, yielding a total of 640 bets made under the conditions of the Bet treatment.

The ObsPred treatment differed from the Bet treatment in that, of the sixteen subjects who participated in each session, eight submitted bets, and the eight others observed the bets and submitted predictions. They did so after every bet in the session, and the predictions specified a probability that each of the possible outcomes would be the actual outcome. The belief elicitation process is described in Section 2.2.2. This yields 640 bets, as in the Bet treatment, as well as 5120 predictions, one from each of eight predictors, for each of eight bets, submitted in each of twenty rounds, in each of four sessions.

In the BetPred treatment, the same individuals made bets, and submitted predictions after observing their own and other players’ bets. Thus there are, as in the ObsPred treatment, 640 bets and 5120 predictions.

### 2.2.1 The betting process

Each round involved the following sequence of events. At the beginning of a round, a random choice was made between color A (state $\theta_A$) and color B (state $\theta_B$), with a probability of choosing color A equal to 1/2. Subjects were not made aware of the color that was chosen until the end of the round. Different colors were used in each round to be assigned to no mistakes on the questionnaire. Thus, in each session, all subjects who were retained for participation in the remainder of the experiment had made no mistakes on the questionnaire.

<table>
<thead>
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<th></th>
<th>Bet</th>
<th>ObsPred</th>
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<td>Periods per round</td>
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<td>5120</td>
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Table 1: Number of sessions, subjects, bets, and belief statements in each treatment.
the two identifying letters, in order to reduce the likelihood that subjects believed that a dependence existed across rounds. Subjects were then chosen in random order, which differed from round to round, to bet one Experimental Currency Unit (ECU) on either color A or B. Before making his bet, each subject observed the current returns and received a private signal correlated with the correct color. Private signals were not made public at any time. The probability that any signal was correct was equal to \( \pi = 3/4 \) for all bettors (this probability was public information), and each bettor’s signal was drawn independently. On subjects’ computer screens, the signal took the form of a ball drawn from an urn containing 4 balls, three “correct” balls and one “incorrect” ball. At the end of each round, the final odds, the winning color, the payout from a bet on each color, and the subject’s own earnings were displayed on his computer screen.

In all sessions the same random draws were used so that the same signals were assigned to the same positions in the sequence of bettors in each round. However, the draws differed between rounds within a given session.

2.2.2 The elicitation of beliefs

Subjects that did not make bets in \( \text{ObsPred} \) were asked before each period to state beliefs about the likelihood that A, as well as B, was the true state in the round. At the time they made their assessments, they had the current odds and the history of previous bets, in the current round, available. Before making his assessments in period \( i \), exactly one of the observers received the same private signal as bettor \( i \). Each observer received exactly one signal in each round. Each observer reported his beliefs in period \( i \) by keying in a vector \( \mu_i = (\mu_i^A, \mu_i^B) \), indicating his belief about the probability that the color randomly chosen at the beginning of the round was A or B.\(^7\)

Subjects’ assessments were rewarded on the basis of a quadratic scoring rule function. In period \( i \), the payoff when color \( j \in \{A, B\} \) was the outcome and \( \mu_i \) was the reported belief vector was given by euro \( .15(1 - (\mu_i^k)^2) \) with \( k \in \{A, B\}, k \neq j \). Thus, if color A was the true state, the greater the weight the subject placed on B, the more that was subtracted from his endowment of .15 euros. The worst possible prediction, placing all weight on the incorrect outcome, yielded a payoff of 0. It can be easily demonstrated that this reward function provides an incentive for risk-neutral subjects to reveal their true beliefs about the probability that each color was chosen.\(^8\)

\(^6\)The belief that the probability of an event decreases when it has occurred recently, even though the probability of the event is objectively known to be independent across trials, is called the gambler’s fallacy. For more discussion of the gambler’s fallacy in parimutuel markets see Terrell (1994).

\(^7\)In the experiment, subjects entered \( \mu_i^A \) and \( \mu_i^B \) as numbers in the interval \([0, 100]\), which were described as percentages.

\(^8\)Belief elicitation using a quadratic scoring rule is widely employed in experimental economics (see for
In the BetPred treatment, each participant, in addition to making bets in his designated period, reported his beliefs in each period about the likelihood that each color was the true state, in an identical manner to ObsPred.

2.2.3 Subjects’ earnings

In the Bet and ObsPred treatments, three of the twenty rounds were chosen at random at the end of the session to count toward bettors’ earnings. Subjects received six euros for each ECU they won during that subset of rounds. In BetPred, only two of the twenty rounds counted toward subjects’ earnings. This difference between BetPred and the other treatments was due to the fact that belief submission provided another source of earnings in BetPred, and payments were set with the intention to roughly equalize per hour average earnings across treatments. Average earnings from betting equaled 18 euros in the Bet and ObsPred treatments, and 12 euros in the BetPred treatment. In ObsPred, only belief submissions counted toward observers’ earnings. Average earnings from belief submissions equaled 17.76 and 20.37 euros in ObsPred and BetPred, respectively.

3 Level-\textit{k} betting and research hypotheses

The sequential parimutuel betting game described in Section 2.1 is a well-defined multistage game, and in principle, Nash or sequential equilibria can be identified. However, this is an intractable exercise due to the enormous number of strategy profiles and the difficulty in computing expected final odds. Equilibrium strategies cannot be computed using backward reasoning as in dynamic, perfect information games, nor forward as in games without payoff externalities (as, for example, in information cascade games). More importantly, the generic existence of multiple sequential equilibria means that equilibrium predictions are typically indeterminate (see Koessler, Noussair, and Ziegelmeyer, 2008).

In this section, we derive predictions for our sequential parimutuel betting game by example Nyarko and Schotter, 2002). Offerman, Sonnemans, van de Kuilen, and Wakker (2009) show how proper scoring rules can be generalized to modern theories of risk and ambiguity, and can become valid under risk aversion and other deviations from expected value. They also report experimental results suggesting that it is desirable to correct subjects’ reported probabilities elicited with scoring rules if only a single large decision is paid, but that this correction is unnecessary with many repeated decisions and repeated small payments.

\footnote{At the end of the session, the assistant randomly drew the rounds that counted toward participants’ earnings. Cubitt, Starmer, and Sugden (1998), in a systematic investigation of whether the random lottery incentive procedure distorts behavior, find that random lottery designs yield behavior no different from one-shot games.}

\footnote{In none of the rounds randomly selected for payment did all eight subjects bet on the wrong horse, which would have led to no payment for the round.}
relying on the non-equilibrium level-$k$ ($L_k$) model introduced by Stahl and Wilson (1994). This type of model is often used as a predictive model in experimental studies (see, e.g., Crawford and Iriberri, 2007). The idea is similar to the notion of rationalizability, but instead of considering all possible strategy profiles at the initial level of reasoning ($L_0$), it specifies the exact strategy at this level. Then, the $L_1$ strategy is simply a best response to the $L_0$ strategy profile, the $L_2$ strategy is a best response to the $L_1$ strategy profile, and so on. This generically yields unique predictions for the profile of bets, once the behavior of $L_0$ agents is specified. The level-$k$ model predicts betting in accordance with one’s own signal, but also herding, betting on the favorite and against one’s own signal, and contrarianism, betting on the long shot and against one’s own signal, depending on the precision of bettors’ signals.

$L_0$ represents the starting point of a bettor’s strategic thinking. A reasonable $L_0$ specification in our game assumes that a $L_0$ type bets in agreement with his own signal whatever the history of bets. This strategy is referred to as truthful $L_0$ in Crawford and Iriberri (2007). Then, a $L_k$ type, for $k = 1, 2$, maximizes his expected payoff while assuming that all other bettors use the $L(k - 1)$ strategy. We confine attention to $L_1$ and $L_2$ types since in most games the experimental evidence suggests that more sophisticated types are comparatively rare. As we show below, the characterization of $L_1$ and $L_2$ strategies is already rather complex, and we must rely on numerical computations.

### 3.1 Level-1 strategy

$L_1$ types assume that other players bet according to their signals. Accordingly, and for a given history of previous bets $s^{i-1} \in \{A, B\}^{i-1}$, a $L_1$ type endowed with signal $q_i \in \{q^A, q^B\}$ believes that horse $A$ wins the race with probability

$$
\mu^{L_1}(\theta_A \mid s^{i-1}; q_i) = \left[ 1 + \frac{\pi^{a(s^{i-1})+1-I_A(q_i)} (1 - \pi)^{a(s^{i-1})+I_A(q_i)}}{\pi^{a(s^{i-1})+I_A(q_i)} (1 - \pi)^{b(s^{i-1})+1-I_A(q_i)}} \right]^{-1},
$$

where $I_A(q^A) = 1$ and $I_A(q^B) = 0$.

$L_1$ types believe that their own bets (as well as their predecessors’ bets) do not influence future bets (this feature is not true for higher levels of reasoning). Hence, the probabilities assigned by a $L_1$ type to the realization of the profile $s_f = (s_{i+1}, \ldots, s_8) \in \{A, B\}^{8-i}$ of

\[\text{An alternative} L_0 \text{specification assumes uniform random bets, independent of the private signal. Given the parametrization of the betting game used in our experimental sessions involves a high quality of private information ($\pi = 3/4$), this alternative specification seems less appealing.}\]
future bets conditionally on the realized state of nature is given by
\[ \Pr_{L_1}(s^f | \theta_A) = \pi^{a(s^f)} (1 - \pi)^{b(s^f)} \quad \text{and} \quad \Pr_{L_1}(s^f | \theta_B) = (1 - \pi)^{a(s^f)} \pi^{b(s^f)}. \]

The expected conjectured payoff when the \( L_1 \) type bets on horse \( A \) is
\[ \mu_{L_1}(\theta_A | s^{i-1}; q_i) = \sum_{s^f \in \{A,B\}^{8-i}} \Pr_{L_1}(s^f | \theta_A) \frac{8}{a(s^{i-1}, s^f) + 1}, \]
and similarly when the \( L_1 \) type bets on horse \( B \). Therefore, for a given history \( s^{i-1} \), \( L_1 \) types endowed with signal \( q_i \) bet on horse \( A \) if
\[ \frac{\mu_{L_1}(\theta_A | s^{i-1}; q_i)}{\mu_{L_1}(\theta_B | s^{i-1}; q_i)} \geq \sum_{s^f \in \{A,B\}^{8-i}} \frac{\Pr_{L_1}(s^f | \theta_B)}{\Pr_{L_1}(s^f | \theta_A)}. \]

In words, \( L_1 \) types bet on horse \( A \) if the ratio between the probabilities of state \( \theta_A \) and state \( \theta_B \) is greater than the ratio between the conjectured payoff of betting on horse \( B \) (conditionally on the realization of state \( \theta_B \)) and that of betting on horse \( A \) (conditionally on the realization of state \( \theta_A \)). (The optimal) \( L_1 \) strategy has no closed-form solution because the ratio of conjectured payoffs (the RHS of Equation (1)) takes a particularly complex form. It is however easy to observe that the likelihood ratio (the LHS of Equation (1)) equals
\[ \left( \frac{\pi}{1 - \pi} \right)^{a(s^{i-1}) - b(s^{i-1}) + I_A(q_i)}, \]
so it increases with the signal’s quality \( \pi \) and with the difference \( a(s^{i-1}) - b(s^{i-1}) \). Since the ratio between the conjectured payoffs is bounded above by 8, a \( L_1 \) type bets on horse \( A \) (resp. \( B \) \textit{whatever his signal} as soon as the number of observed \( A \) bets sufficiently exceeds (resp. lags) the number of observed \( B \) bets. Said differently, \( L_1 \) types herd in our betting game when there is a clear favorite (and the precision of signals is not arbitrarily close to 1/2).\footnote{In betting games with sufficiently low signal qualities, the likelihood ratio tends to 1 which implies that \( L_1 \) types adopt a contrarian behavior whenever their signal is in accordance with the majority of previous bets.}

With the parametrization used in our experimental sessions (\( \pi = 3/4 \)), numerical computations show that the \( L_1 \) strategy consists in herding if and only if there is an observed majority of at least 2 bets, and betting according to the signal otherwise.\footnote{The computational code and the summary of \( L_1 \) and \( L_2 \) predictions for all possible histories are available in the online supplementary material.} Consequently, about 25 percent of all possible (non-final) histories of bets lead \( L_1 \) types to herd. Contrar-
ianism is completely absent.

Table 2 displays the predicted bets for the signal profiles used in the experiment. For each round, the first row shows the sequence of eight signals, and the second row shows the sequence of eight $L_1$ bets. For example, in round 12, the fifth $L_1$ type bettor observes history $BBBB$ and herds, and, in round 20, the fourth $L_1$ type bettor observes history $AAA$ and herds. The last column reports the winning horse. In most rounds, all $L_1$ bets are identical as $L_1$ types exhibit a strong tendency to follow predecessors without realizing that most of the observed bets are uninformative. Herding is less prevalent among $L_2$ types, as detailed below.

### 3.2 Level-2 strategy

$L_2$ types assume that other players follow the $L_1$ strategy. Consequently, $L_2$ types do not interpret each bet as a signal favoring the corresponding horse. Additionally, $L_2$ types may observe histories of bets that are incompatible with their conjecture. For example, the sequence of bets $AAAB$ is not compatible with the $L_1$ strategy for $\pi = 3/4$ since a $L_1$ bettor is supposed to herd after any history with a majority of at least 2 bets. For simplicity, we assume that $L_2$ types believe that bets inconsistent with the $L_1$ strategy stem from $L_0$ bettors. Continuing with the previous example, $L_2$ types believe that the first two bettors’ signals are $q^A$, the third bettor’s signal is either $q^A$ or $q^B$, and the fourth bettor’s signal is $q^B$.

Given the observed bets and their signal, $L_2$ types assign winning probabilities to horse $A$ and $B$, they compute the conjectured payoffs of betting on horse $A$ or $B$, and they choose to bet on horse $A$ if the likelihood ratio between state $\theta_A$ and state $\theta_B$ is greater than the ratio between the conjectured payoff of betting on horse $B$ (conditionally on realized state $\theta_B$) and the conjectured payoff of betting on horse $A$ (conditionally on realized state $\theta_A$). The computation of winning probabilities and conjectured payoffs is much more involved for $L_2$ than for $L_1$ types as past bets are not always truthful and $L_2$ types believe that current bets influence future bets.

With the parametrization used in our experimental sessions ($\pi = 3/4$), numerical computations show that herding is much less prevalent among $L_2$ types than among $L_1$ types. About 14 percent of all possible (non-final) histories of bets lead $L_2$ types to herd. In particular, $L_2$ types always follow their signal in the first four periods, and they never herd in the absence of bets on the longshot. Any history which leads $L_2$ types to herd also leads $L_1$ types to herd. Only two histories of bets induce contrarianism, history $AAAABBBB$ and $BBBBAAA$, the former when $L_2$ types are endowed with signal $q^A$ and the latter when they are endowed with signal $q^B$. $L_2$ types bet according to their signal in all 218 remaining
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Table 2: Level-k predictions in the 20 experimental rounds (herding in bold).
histories. Overall, the (optimal) $L_2$ strategy generates a greater percentage of truthful bets than the $L_1$ strategy ($218/255 \approx 85\%$ against $191/255 \approx 75\%$). Sequences of bets generated by the $L_2$ strategy for the signal profiles used in the experiment are shown in the third row of Table 2 for each round. For example, in round 12, the fifth $L_2$ type bettor observes history $BBAB$ and herds whereas, in round 20, the fourth $L_2$ type bettor observes history $AAA$ and bets according to own signal.

There are two reasons why herding is less frequent with $L_2$ types than with $L_1$ types. First, $L_2$ types believe that only the first few bets are informative in a long sequence of identical bets. For example, if history $BBB$ is observed, $L_1$ and $L_2$ types believe that there are three and two informative bets respectively. The ratio of state probabilities is therefore much smaller for $L_1$ types than for $L_2$ types, which induces the former to herd but not the latter. Second, $L_2$ types herd less often because they anticipate full herding by future bettors if they bet on the favorite. For instance, consider the history $BB$. The ratio of state probabilities is $1/3$ for the third bettor whatever its type because the first two bets are always assumed informative. But $L_2$ types do not herd here because they anticipate that if they do then all future bettors herd which induces the ratio of conjectured payoffs to be very small. The ratio of conjectured payoffs is larger for $L_1$ types who believe that future bets follow private signals whatever their own bet.

3.3 Research hypotheses

The level-$k$ model yields some ways to assess the extent of strategic sophistication in our data and to make comparisons between treatments. First, and most importantly, contrarian betting is (almost always) inconsistent with all levels of sophistication, including $L_0$. We therefore equate contrarianism with the absence of strategic reasoning which most likely results from the attempt to obtain abnormally large payoffs in disagreement with both private and public information (ruling out the peculiar belief that predecessors bet against their signal). At first glance, it might seem that contrarian betting is unlikely to appear in our data, but in fact, it has been widely observed in previous experimental studies of similar betting markets (Drehmann et al., 2005; Cipriani and Guarino, 2005). Second, $L_0$ betting can be distinguished from higher level betting whenever bettors fail to herd though $L_1$ and $L_2$ strategies specify herding. Betting in accordance with one’s own signal when many previous bets point in the opposite direction clearly indicates a low level of sophistication, whatever the reason for neglecting the public information.

We hypothesize that bets are consistent with a greater level of strategic sophistication in $BetPred$ than in the other two treatments. The intuition underlying our first hypothesis is that requiring bettors to report beliefs forces them to evaluate the probabilities of each
outcome which in turn encourages them to pay attention to the informational content of previous bets. Consequently, bettors are less likely to focus entirely on payoffs or their private information in *BetPred* than in the other two treatments.

**Hypothesis 1.** Contrarianism and bets that are consistent with $L_0$ but not with $L_1$ and $L_2$ are less common in *BetPred* than in *Bet* and *ObsPred*.

A betting market is successful in aggregating the information held diversely by individual bettors if the market’s assessment of the winning outcome coincides with the assessment obtained by pooling all bettors’ information. Clearly, bettors’ level of strategic sophistication influences the capacity of parimutuel betting markets to aggregate information. Contrarian betting decreases informational efficiency because it shifts the market’s assessment in the opposite direction of the bettors’ information. Similarly, a betting market with many $L_0$ types poorly aggregates information because many late bettors follow their private information no matter how strong the accumulated evidence in the opposite direction. In fact, the aggregate assessment of a large betting market populated only by $L_0$ types is close to $\pi$ whereas the assessment obtained by pooling all bettors’ information is close to 1. On the contrary, a betting market mainly populated by $L_1$ and $L_2$ types quite successfully aggregates information because only herding hampers the aggregation of information. And though it is clearly detrimental when triggered too early, herding might close the gap between the market’s assessment and the assessment obtained by pooling all bettors’ information. We therefore hypothesize that a greater level of strategic sophistication is conducive to more successful information aggregation.\(^\text{14}\)

**Hypothesis 2.** Information aggregation is greater in *BetPred* than in *Bet* and *ObsPred*.

Our third hypothesis concerns belief statements. Symmetrically to the positive feedback that belief statements are supposed to have on bets, we hypothesize that making bets improves belief statements meaning that the latter are more accurate in *BetPred* than in *ObsPred*.

**Hypothesis 3.** Elicited outcome probabilities are closer to objective probabilities in *BetPred* than in *ObsPred*.

4 **Results**

We first compare the capacity of parimutuel betting markets to aggregate bettors’ private information in our three treatments. Alternative baselines can be used to assess information

\(^{14}\text{The derivation of the relationship between the betting market’s informational efficiency and the distribution of types is beyond the scope of this paper.}\)
aggregation in parimutuel betting markets, and most of them make assumptions about bettors’ behavior and rationality.\textsuperscript{15} Since the existing literature has not delivered yet standard game-theoretical predictions for the betting markets we consider, we compare our treatments with the help of an informational efficiency benchmark that does not require any behavioral assumptions. We compare the market’s aggregate assessment of the likelihood that horse $H$ will win, the final \textit{market probability}, with horse $H$’s final \textit{objective probability} of winning. The final market probability that horse $H$ will win is calculated from the final odds whereas horse $H$’s final objective probability of winning is obtained by the pooling of all information given to the bettors. The conventional view is that, if betting markets were strongly informationally efficient, these probabilities would coincide. Moreover, if the fraction of money bet on each horse is equal to its objective probability then expected payoffs are equalized across horses, even for insiders who would have access to all the information privately held in the market.\textsuperscript{16}

Given a history of bets $s^i$, the current market probability that horse $H$ wins is a function of the current odds against horse $H$ and is given by $1/(O_H(s^i) + 1) = h(s^i)/i$. The final market probability that horse $H$ wins is given by $h(s^8)/8$, and can be viewed as the bettors’ support for horse $H$’s winning if one considers each bet as a vote to win. Obviously, odds and market probabilities are equivalent measures of the bettors’ evaluation of horses’ winning chances. Given a vector of private signals $q^i = (q_1, \ldots, q_i)$ up to and including bettor $i$’s signal, the current objective probability that horse $H$ wins is given by $\Pr(\theta_H \mid q^i)$. The final objective probability that horse $H$ wins is given by $\Pr(\theta_H \mid q^8)$, and corresponds to the posterior probability that horse $H$ wins given the information distributed among all bettors. The objective probability is a benchmark against which market probabilities in the different treatments will be compared to determine the distance from perfect aggregation of information.\textsuperscript{17}

Figure 1 plots the time path of horse $A$’s objective and market probability for each round of the experiment. A separate time series is provided for each of the three treatments for each round, and the data are averaged over the four sessions within each treatment. There are several general patterns apparent at first glance. In all treatments the winning horse is usually the favorite at the end of the betting process, as the final market probability typi-

\textsuperscript{15}See, for example, Vaughan Williams (1999).

\textsuperscript{16}Alternatively, one may compare the market probability with the corresponding \textit{posterior} probability held by an outsider who can observe the whole sequence of bets (see, for example, Ottaviani and Sørensen, 2010, in a simultaneous betting market game). However, the computation of posterior probabilities requires the existence of theoretical bets. See also Plott et al. (2003) for other benchmarks.

\textsuperscript{17}\textit{Perfect} information aggregation is impossible in our markets due to the small number of bettors and the binary action space. However, the benchmark is still relevant to compare informational efficiency across treatments.
cally implies the same favorite as the final objective probability. The only exceptions are in rounds 6 and 12 for Bet, and rounds 6, 11, and 19 for the ObsPred and BetPred treatments. The final market probability in the BetPred treatment is usually (in 15 of 20 rounds) closer to the final objective probability than in each of the other treatments, suggesting better information aggregation in BetPred. There does not seem to be a systematic difference with respect to information aggregation between the Bet and ObsPred treatments, as average final market probabilities in ObsPred are closer to objective probabilities than in Bet for 12 of 20 rounds.

Result 1 supports our second hypothesis.

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The final objective probability of the winning horse is always at least 9 times greater than the final objective probability of the losing horse. Indeed, in any given round, the number of correct signals exceeds by at least 2 the number of incorrect signals.
Result 1 (Information aggregation)  *Elicitation of beliefs of bettors increases the information aggregated in the market in the sense that odds are more consistent with objective probabilities.*

*Support:* For each of the three treatments, in each of the four sessions, we compute the absolute difference between the final market probability and the final objective probability in each of the 20 rounds (per round absolute prediction error). The difference averaged over sessions and rounds equals .210 in BetPred, .286 in ObsPred, and .299 in Bet. The difference in the BetPred treatment is the smallest and is similar to the difference averaged over rounds for the L1 strategy (.205) and the L2 strategy (.216). Moreover, the average difference for each of the four sessions in BetPred is lower than the average difference for any of the four sessions in either Bet or ObsPred. Thus, a conservative rank-sum test, using each session as an observation, rejects the hypotheses at the 5 percent level that (a) treatments Bet and BetPred, and (b) treatments ObsPred and BetPred, aggregate the same amount of information. A similar test for a difference between treatments Bet and ObsPred is insignificant at conventional levels. (Our conclusions remain valid if we use per round squared prediction error instead of per round absolute prediction error.)

A well documented deviation from parimutuel betting market efficiency is the so called favorite-longshot bias, according to which the final market probability that the favorite will win is lower than its final objective probability. This indicates that a bettor placing a bet at the final odds would have a higher expected payoff betting on the favorite than on the longshot. The extent of the favorite-longshot bias in our experiment, and the difference between treatments, is summarized in Result 2.

Result 2 (Favorite-longshot bias)  *Market odds are consistent with a favorite-longshot bias in the Bet and ObsPred treatments. The bias is reduced when beliefs of bettors are elicited.*

*Support:* The objective probability of one of the horses being the outcome equals at least 0.9 by the end of every round. Since there are eight players and the market probability equals the ratio of bets for and against an outcome, the final market probabilities are always divisible by 1/8, so that market probabilities equal to 1 or 7/8 in favor of the objective favorite do not necessarily indicate a deviation from the objective probability, but any market probability of .75 or lower on the objective favorite is consistent with a favorite-longshot bias. This occurs in 78.75% of markets in the Bet treatment, 68.75% in ObsPred, and only 43.75% in BetPred. The total number of instances consistent with a favorite-longshot bias for each of the four sessions in BetPred is lower than the total number of such instances for any of the four sessions in either Bet or ObsPred. Thus, a conservative rank-sum test, using each
session as an observation, rejects the hypotheses at the 5 percent level that (a) treatments Bet and BetPred, and (b) treatments ObsPred and BetPred, exhibit the same extent of favorite-longshot bias. A similar test for a difference between treatments Bet and ObsPred is insignificant at conventional levels.

We now turn to individual behavior and we show that hypothesis 1 is largely supported.

**Result 3 (Effect of belief elicitation on individual bets)** Belief elicitation significantly reduces the incidence of contrarianism. Failures to herd, despite the fact that L1 and L2 strategies include herding, are significantly less common in the BetPred treatment than in the Bet treatment, and weakly significantly less common in the BetPred treatment than in the ObsPred treatment.

**Support:** We observe 58, 64, and 20 deviations from the level-k model in the Bet, ObsPred, and BetPred treatment respectively (a theoretical bet in a given period is computed given the actual history of bets and there are 640 betting decisions per treatment). Most deviations correspond to contrarian bets which implies that, in line with our first research hypothesis, contrarianism is drastically reduced in BetPred compared to the other two treatments.19 According to one-sided Mann-Whitney tests using session-level statistics, contrarianism is significantly less present in BetPred than in Bet and ObsPred (p-values = 0.014), but no significant difference is observed between Bet and ObsPred (p-value > 0.25). We also hypothesized that the elicitation of beliefs leads bettors to herd more consistently with the L1 and L2 strategies but we find less support for this second part of hypothesis 1. According to one-sided Mann-Whitney tests using session-level statistics, significantly fewer failures to herd are observed in BetPred than in Bet (p-value = 0.043), weakly significantly fewer failures to herd are observed in BetPred than in ObsPred (p-value = 0.057), and no significant difference is observed between Bet and ObsPred (p-value > 0.25). Finally, we note that no significant difference is observed between any of our three treatments in terms of incorrect herding (herding that is inconsistent with the level-k model).

We now consider the accuracy of belief statements. Figure 2 plots the average20 time path of horse A’s objective probability compared to the average stated belief in ObsPred and BetPred. Given a vector of private signals \(q^i = (q_1, \ldots, q_l)\) up to and including bettor \(i\)’s

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19An actual bet against one’s own signal is considered consistent with contrarianism also in the absence of a longshot, e.g. in period 1, but the same conclusions hold if we restrict ourselves to bets on longshots. Incidentally, we observe 1, 1 and 2 histories which would lead L2 types to bet in a contrarian way in the Bet, BetPred, and ObsPred treatment respectively, but in all four cases the actual bet is in agreement with the private information.

20Because in each period only one subject among the eight who state their beliefs is endowed with a private signal, in order to make fair comparisons between the stated belief and the objective probability of horse A, we compute the average objective probability in period \(i\) as \((7 \Pr(\theta_A | q^{i-1}) + \Pr(\theta_A | q^i))/8.\)
signal, the current objective probability that horse $H$ wins is given by $\Pr(\theta_H | q^i)$. The final objective probability that horse $H$ wins is given by $\Pr(\theta_H | q^8)$, and corresponds to the posterior probability that horse $H$ wins given the aggregate information distributed to all bettors. It is evident from the figure that the differences between the two treatments are considerable. Stated beliefs at the end of period 8 in $BetPred$ are on average closer to the objective probability than in $ObsPred$ in all 20 rounds. Average beliefs in $ObsPred$ are closer to 1/2, an equal probability on each outcome, than in $BetPred$ in 17 of 20 rounds. The exceptions are rounds 6, 11, and 19, the only ones in which the final market probabilities yield an incorrect prediction in a majority of markets and on average. The findings are summarized as Result 4.

![Figure 2: Objective probability and stated beliefs in $ObsPred$ and $BetPred$, averaged across sessions.](image)

**Notes:**
- Objective probability:
- Average beliefs in $ObsPred$:  
- Average beliefs in $BetPred$.

**Result 4 (Effect of placing bets on accuracy of beliefs)** *Submitting bets improves the accuracy of belief statements.*

**Support:** Table 3 shows the average value of the absolute difference between the average
stated belief and the objective probability in ObsPred and BetPred in each session. The average difference for each of the four sessions of bettors that participated in BetPred is lower than the average absolute differences for any session in ObsPred, whether all periods or only the final periods are used in the calculation. Thus, a conservative rank-sum test, using each session as an observation, rejects the hypothesis at the 5 percent level that belief statements have identical accuracy in treatments ObsPred and BetPred. In addition, subjects’ stated beliefs in BetPred lead to earnings from predictions that are 14.68% higher than those in ObsPred. If the comparison between treatments is restricted to instances in which the previous sequences of bets and private signals are identical, the difference in earnings is 10.46%.

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Table 3: Average absolute difference, in terms of probability of outcome, between belief statements and objective probability, each session, all rounds.

As we report in Result 5 below, we also observe that when the beliefs are submitted by the same individuals who make the bets, the beliefs are closer to reflecting the market probabilities. This may not be surprising since when predictors and bettors are different individuals, as in ObsPred, they might have different opinions.

**Result 5 (Consistency between bets and stated beliefs)** Submitting bets in addition to beliefs improves the consistency between betting data and stated beliefs.

**Support:** We measure the degree of consistency between the betting data and the stated beliefs using the average absolute difference between an individual’s stated beliefs and the market probabilities. All four sessions in BetPred have smaller average absolute differences than any session in ObsPred. Thus, a rank-sum test using each group as an observation, rejects the hypothesis at the 5 percent level that the degree of consistency between stated beliefs and market probabilities in ObsPred and BetPred are equal.
5 Conclusion

The data support our three research hypotheses. Betting patterns reflect greater information aggregation under BetPred, in which bettors themselves state beliefs, than in the other two treatments. The BetPred treatment is characterized by much less contrarian behavior. Because contrarian behavior involves betting on the longshot, BetPred exhibits a much smaller favorite-longshot bias than the other two treatments.

The elicitation of beliefs appears to make probability information more prominent. This, in turn, discourages an overemphasis on the attractive return associated with a longshot during the decision process, and more emphasis on the low probability of the outcomes that yield high payouts. It leads to fewer bets on longshots, which can be measured as a reduction in contrarian behavior. However, it also appears that under BetPred, belief elicitation allows players to assess, and to use, the information contained in the sequence of bets. Because they must make a prediction after each bet, players have more direct incentives to deduce and to use the information content of each bet. This is consistent with more herding in cases predicted by L1 and L2 strategies in BetPred than in the other two treatments.

We also find that betting decisions are no better when subjects are observed than when they are not observed, indicating that common knowledge of the fact that beliefs are being elicited based on bettors’ behavior, is insufficient to improve their decisions. Bettors must be submitting their own beliefs to lead to improved betting decisions. Stated beliefs are more accurate, as well as more consistent with market activity, when the agents submitting beliefs are also placing bets. The positive feedback between bets and belief statements operates in both directions. The comparison between the level of information aggregation in the Bet and BetPred treatments shows that making belief statements improves bets. Similarly, the comparison between belief statements in ObsPred and BetPred reveals that making bets improves belief statements.

Experimental economists have found that eliciting beliefs of subjects is a useful methodological tool for theory testing or for gaining insight into human decision making. Manski (2004) argues that, more generally, applied economic research can benefit from combining choice data with self-reports of expectations, elicited in the form of subjective probabilities, to predict behavior. Our results suggest yet another use for belief elicitation procedures, as potential instruments to improve economic outcomes, in this case a market’s capacity to aggregate information. Of course, our results come from a highly stylized laboratory environment, and it is an open question whether similar results would be observed in the field.
Acknowledgments

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