Explaining the Favorite–Long Shot Bias: Is it Risk-Love or Misperceptions?

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The favorite–long shot bias describes the long-standing empirical regularity that betting odds provide biased estimates of the probability of a horse winning: long shots are overbet whereas favorites are underbet. Neoclassical explanations of this phenomenon focus on rational gamblers who overbet long shots because of risk-love. The competing behavioral explanations emphasize the role of misperceptions of probabilities. We provide novel empirical tests that can discriminate between these competing theories by assessing whether the models that explain gamblers' choices in one part of their choice set (betting to win) can also rationalize decisions over a wider choice set, including compound bets in the exacta, quinella, or trifecta pools. Using a new, large-scale data set ideally suited to implement these tests, we find evidence in favor of the view that misperceptions of probability drive the favorite–long shot bias, as suggested by prospect theory.

I.   Introduction

The racetrack provides a natural laboratory for economists interested in understanding decision making under uncertainty. The most discussed empirical regularity in racetrack gambling markets is the *favorite–long shot bias*: equilibrium market prices (betting odds) provide biased estimates of the probability of a horse winning. Specifically, bettors value long shots more than expected given how rarely they win, and they value favorites too little given how often they win. Figure 1 illustrates, showing that the rate of return to betting on horses with odds of 100/1 or greater is about −61 percent, whereas betting the favorite in every race yields losses of only 5.5 percent. Betting randomly yields average returns of −23 percent, which, while better than long shots, are negative, as the racetrack takes a percentage of each bet to fund operations.[1]

Since the favorite–long shot bias was first noted by Griffith in 1949, it has been found in racetrack betting data around the world, with very few exceptions. The literature documenting this bias is voluminous and covers both bookmaker and pari-mutuel markets.[2]

Two broad sets of theories have been proposed to explain the favorite–long shot bias. First, neoclassical theory suggests that the prices bettors are willing to pay for various gambles can be used to recover their utility function. While betting at any odds is actuarially unfair, this is particularly acute for long shots—which are also the riskiest investments. Thus, the neoclassical approach can reconcile both gambling and the long shot bias only by positing (at least locally) risk-loving utility functions, as in Friedman and Savage (1948).

Alternatively, behavioral theories suggest that cognitive errors and misperceptions of probabilities play a role in market mispricing. These theories incorporate laboratory studies by cognitive psychologists that show people are systematically poor at discerning between small and tiny probabilities and hence price both similarly. Further, people exhibit a strong preference for certainty over extremely likely outcomes, leading highly probable gambles to be underpriced. These results form an important foundation of prospect theory (Kahneman and Tversky 1979).

Our aim in this paper is to test whether the *risk-love class* of models or the *misperceptions class* of models simultaneously fits data from multiple betting pools. While there exist many specific models of the favorite–long shot bias, we show in Section III that each yields implications for the pricing of gambles equivalent to stark models of either a risk-loving

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[1] For more on the analytical treatment of the track take, see n. 8.

[2] Thaler and Ziemba (1988), Sauer (1998), and Snowberg and Wolfers (2007) survey the literature. The exceptions are Busche and Hall (1988), which finds that the favorite–long shot bias is not evident in data on 2,653 Hong Kong races, and Busche (1994), which confirms this finding in an additional 2,690 races in Hong Kong and 1,738 races in Japan.
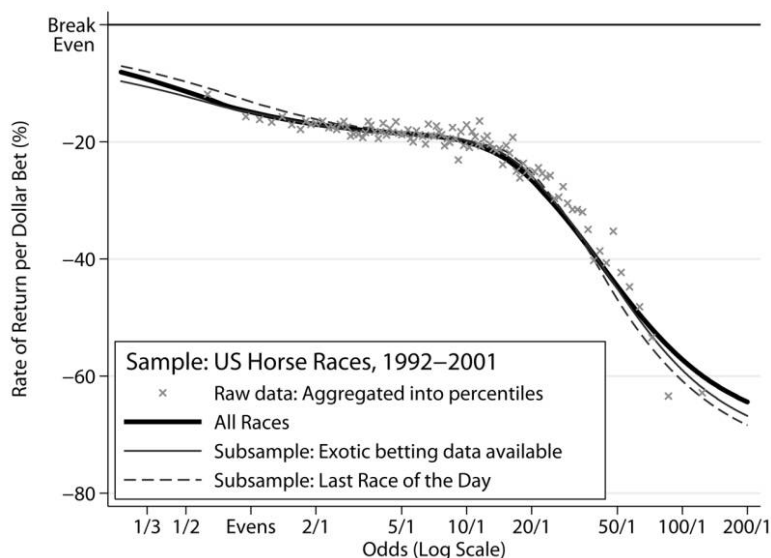
Fig. 1.—The favorite–long shot bias: the rate of return on win bets declines as risk increases. The sample includes 5,610,580 horse race starts in the United States from 1992 to 2001. Lines reflect Lowess smoothing (bandwidth = 0.4).

representative agent or a representative agent who bases her decisions on biased perceptions of true probabilities. That is, the favorite–long shot bias can be fully rationalized by a standard rational expectations expected-utility model or by appealing to an expected wealth-maximizing agent who overweights small probabilities and underweights large probabilities.[3] Thus, without parametric assumptions, which we are unwilling to make, the two theories are observationally equivalent when examining average rates of return to win bets at different odds.

We combine new data with a novel econometric identification strategy to discriminate between these two classes of theories. Our data include all 6.4 million horse race starts in the United States from 1992 to 2001. These data are an order of magnitude larger than any data set previously examined and allow us to be extremely precise in establishing the relevant stylized facts.

Our econometric innovation is to distinguish between these theories by deriving testable predictions about the pricing of compound lotteries (also called *exotic bets* at the racetrack). For example, an *exacta* is a bet on both which horse will come first and which will come second. Es-

[3] Or adopting a behavioral vs. neoclassical distinction, we follow Gabriel and Marsden (1990) in asking, "Are we observing an inefficient market or simply one in which the tastes and preferences of the market participations lead to the observed results?" (885).

sentially, we ask whether the preferences and perceptions that ratio-
nalize the favorite–long shot bias (in win bet data) can also explain the
pricing of exactas, *quinellas* (a bet on two horses to come first and second
in either order), and *trifectas* (a bet on which horse will come in first,
which second, and which third). By expanding the choice set under
consideration (to correspond with the bettor's actual choice set!), we
use each theory to derive unique testable predictions. We find that the
misperceptions class more accurately predicts the prices of exotic bets
and also their relative prices.

   To demonstrate the application of this idea to our data, note that
betting on horses with odds between 4/1 and 9/1 has an approximately
constant rate of return (at −18 percent; see fig. 1). Thus, the misper-
ceptions class infers that bettors are equally well calibrated over this
range, and hence betting on combinations of outcomes among such
horses will yield similar rates of return. That is, betting on an exacta
with a 4/1 horse to win and a 9/1 horse to come in second will yield
expected returns similar to those from betting on the exacta with the
reverse ordering (although the odds of the two exactas will differ). In
contrast, under the risk-love model, bettors are willing to pay a larger
risk penalty for the riskier bet—such as the exacta in which the 9/1
horse wins and the 4/1 horse runs second—decreasing its rate of return
relative to the reverse ordering.

   Our research question is most similar to the questions asked by Jullien
and Salanié (2000) and Gandhi (2007), who attempt to differentiate
between preference- and perception-based explanations of the favorite–
long shot bias using data only on the price of win bets.[4] The results of
the former study favor perception-based explanations and the results of
the latter favor preference-based explanations. Rosett (1965) conducts
a related analysis in that he considers both win bets and combinations
of win bets as present in the bettors' choice set. Ali (1979), Asch and
Quandt (1987), and Dolbear (1993) test the efficiency of compound
lottery markets. We believe that we are the first to use compound lottery
prices to distinguish between competing theories of possible market
(in)efficiency. Of course the idea is much older: Friedman and Savage
(1948) note that a hallmark of expected utility theory is "that the re-
action of persons to complicated gambles can be inferred from their
reaction to simple gambles" (293).

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[4] These papers show that it is theoretically possible to separate these explanations in
win-bet data by comparing the menus of bets offered in different races; however, com-
putational constraints force them to rely on functional form assumptions in their empirical
strategy.

II. Stylized Facts

Our data contain all 6,403,712 horse starts run in the United States between 1992 and 2001. These are official Jockey Club data, the most precise available. Data of this nature are extremely expensive, which presumably explains why previous studies have used substantially smaller samples. The Appendix provides more detail about the data.

We summarize our data in figure 1. We calculate the rate of return to betting on every horse at each odds and use Lowess smoothing to take advantage of information from horses with similar odds. Data are graphed on a log-odds scale so as to better show their relevant range. The vastly better returns to betting on favorites rather than on long shots is the favorite–long shot bias. Figure 1 also shows the same pattern for the 206,808 races (with 1,485,112 horse starts) for which the Jockey Club recorded payoffs to exacta, quinella, or trifecta bets. Given that much of our analysis will focus on this smaller sample, it is reassuring to see a similar pattern of returns.

Figure 2 shows the same rate of return calculations for several other data sets. We present new data from 2,725,000 starts in Australia from the South Coast Database and 380,000 starts in Great Britain from flatstats.co.uk. The favorite–long shot bias appears equally evident in these countries, despite the fact that odds are determined by pari-mutuel markets in the United States, bookmakers in the United Kingdom, and
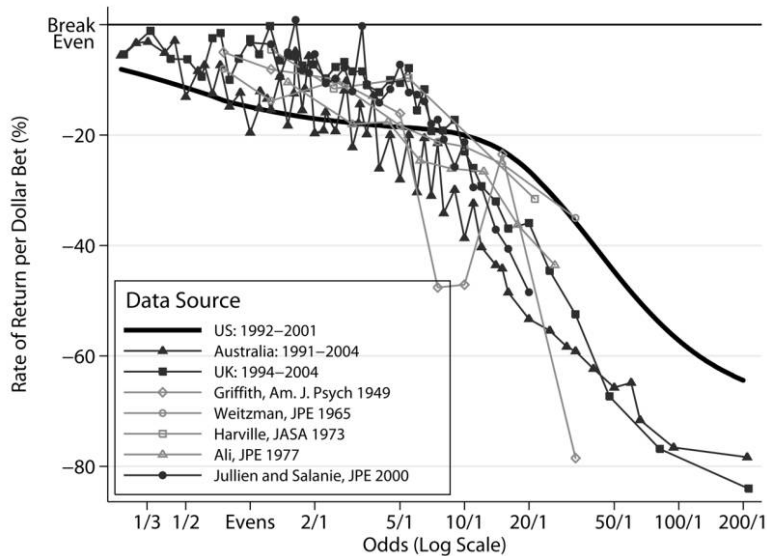

Fig. 2.—The favorite–long shot bias has persisted for over 50 years

bookmakers competing with a state-run pari-mutuel market in Australia. Figure 2 also includes historical estimates of the favorite–long shot bias, showing that it has been stable since first noted in Griffith (1949).

The literature suggests two other empirical regularities to explore. First, Thaler and Ziemba (1988) suggest that there are positive rates of return to betting extreme favorites, perhaps suggesting limits to arbitrage. This is not true in any of our data sets, providing a finding similar to that in Levitt (2004): despite significant anomalies in the pricing of bets, there are no profit opportunities from simple betting strategies.

Second, McGlothlin (1956), Ali (1977), and Asch, Malkiel, and Quandt (1982) argue that the rate of return to betting moderate long shots falls in the last race of the day. These studies have come to be widely cited despite being based on small samples. Kahneman and Tversky (1979) and Thaler and Ziemba (1988) interpret these results as consistent with loss aversion: most bettors are losing at the end of the day, and the last race provides them with a chance to recoup their losses. Thus, bettors underbet the favorite even more than usual and overbet horses at odds that would eliminate their losses. The dashed line in figure 1 separates out data from the last race; while the point estimates differ slightly, these differences are not statistically significant. If there was evidence of loss aversion in earlier data, it is no longer evident in recent data, even as the favorite–long shot bias has persisted.

In the next section we argue that these facts cannot separate risk-love from misperception-based theories. We propose new tests based on the requirement that a theory developed to explain equilibrium odds of horses winning should also be able to explain the equilibrium odds in the exacta, quinella, and trifecta markets separately, as well as the equilibrium odds in exacta and quinella markets jointly.

III.   Two Models of the Favorite–Long Shot Bias

We start with two extremely stark models, each of which has the merit of simplicity. Both are models in which all agents have the same preferences and perceptions but, as we suggest below, can be expanded to incorporate heterogeneity. Equilibrium price data cannot separately identify more complex models from these representative agent models.

A.   The Risk-Love Class

Following Weitzman (1965), we postulate expected utility maximizers with unbiased beliefs and utility $U(\cdot): \mathbb{R} \to \mathbb{R}$. In equilibrium, bettors must be indifferent between betting on the favorite horse A with probability
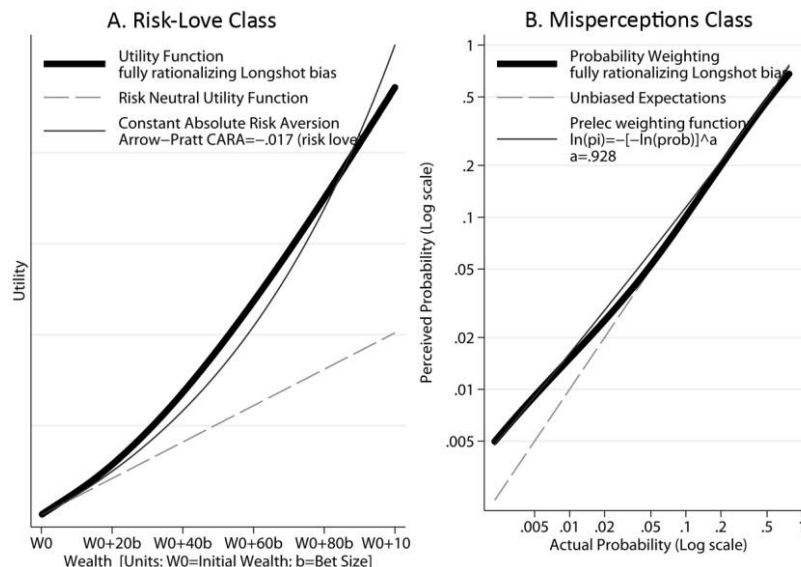
FIG. 3.—The win data are is completely rationalized by both classes

of winning p_A and odds of $O_A/1$, and betting on a long shot B with probability of winning p_B and odds of $O_B/1$:

$$p_A U(O_A) = p_B U(O_B) \tag{1}$$

(normalizing utility to zero if the bet is lost).[5] The odds (O_A, O_B) and the probabilities (p_A, p_B) of horses winning, which we observe, identify the representative bettor's utility function up to a scaling factor.[6] To fix the scale we normalize utility to zero if the bet loses and to one if the bettor chooses not to bet. Thus, if the bettor is indifferent between accepting and rejecting a gamble offering odds of $O/1$ that wins with probability p, then $U(O) = 1/p$. Figure 3A performs precisely this analysis, backing out the utility function required to explain all of the variation in figure 1.

As can be seen from figure 3A, a risk-loving utility function is required to rationalize the bettor accepting lower average returns on long shots, even as they are riskier bets. The figure also shows that a constant absolute risk aversion utility function fits the data reasonably well.

Several other theories of the favorite–long shot bias yield implications that are observationally equivalent to this risk-loving representative

[5] We also assume that, consistent with the literature, each bettor chooses to bet on only one horse in a race.
[6] See Weitzman (1965), Ali (1977), Quandt (1986), and Jullien and Salanié (2000) for prior examples.

agent model. Some of these theories are clearly equivalent—such as that of Golec and Tamarkin (1998), which argues that bettors prefer skew rather than risk—as they are theories about the shape of the utility function. It can easily be shown that richer theories—such as that of Thaler and Ziemba (1988), in which "bragging rights" accrue from winning a bet at long odds, or that of Conlisk (1993), in which the mere purchase of a bet on a long shot may confer some utility—are also equivalent.[7]

B.   The Misperceptions Class

Alternatively, the misperceptions class postulates risk-neutral subjective expected utility maximizers, whose subjective beliefs are given by the *probability weighting function* $\pi(p)$: $[0, 1] \rightarrow [0, 1]$. In equilibrium, there are no opportunities for subjectively expected gain, so bettors must believe that the subjective rates of return to betting on any pair of horses A and B are equal:

$$\pi(p_A)(O_A + 1) \,=\, \pi(p_B)(O_B + 1) \,=\, 1. \tag{2}$$

Consequently, data on the odds (O_A, O_B) and the probabilities (p_A, p_B) of horses winning reveal the misperceptions of the representative bettor.[8]

Note that the misperceptions class allows more flexibility in the way probabilities enter the representative bettor's value of a bet, but it is more restrictive than the risk-love class in terms of how payoffs enter that function. More to the point, without restrictive parametric assumptions, each class of models is just-identified, so each yields identical predictions for the pricing of win bets.

Figure 3B shows the probability weighting function $\pi(p)$ implied by the data in figure 1. The low rates of return to betting long shots are rationalized by bettors who bet as though horses with tiny probabilities of winning actually have moderate probabilities of winning. The specific

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[7] Formally, these theories suggest that agents maximize expected utility, where utility is the sum of the felicity of wealth, $y(\cdot) \colon \mathbb{R} \rightarrow \mathbb{R}$, and the felicity of bragging rights or the thrill of winning, $b(\cdot) \colon \mathbb{R} \rightarrow \mathbb{R}$. Hence the expected utility to a bettor with initial wealth w_0 of a gamble at odds O that wins with probability p can be expressed as

$$E(U(O)) \,=\, p[y(w_0 + O) + b(O)] + (1 - p)y(w_0 - 1).$$

As before, bettors will accept lower returns on riskier wagers (betting on long shots) if $U'' > 0$. This is possible if either the felicity of wealth is sufficiently convex or bragging rights are increasing in the payoff at a sufficiently increasing rate. More to the point, revealed preference data do not allow us to separately identify effects operating through $y(\cdot)$ rather than $b(\cdot)$.

[8] While we term the divergence between $\pi(p)$ and p misperceptions, in non–expected utility theories, $\pi(p)$ can be interpreted as a preference over types of gambles. Under either interpretation our approach is valid, in that we test whether gambles are motivated by nonlinear functions of wealth or probability. In (2) we implicitly assume that $\pi(1) = 1$, although we allow $\lim_{p \rightarrow 1} \pi(p) \leq 1$.

shape of the declining rates of return identifies the probability weighting function at each point.[9] This function shares some of the features of the decision weights in prospect theory (Kahneman and Tversky 1979), and the figure shows that the one-parameter probability weighting function in Prelec (1998) fits the data quite closely.

While we have presented a very sparse model, a number of richer theories have been proposed that yield similar implications.[10] For instance, Ottaviani and Sørenson (2010) show that initial information asymmetries between bettors may lead to misperceptions of the true probabilities of horses winning. Moreover, Henery (1985) and Williams and Paton (1997) argue that bettors discount a constant proportion of the gambles in which they bet on a loser, possibly because of a self-serving bias in which losers argue that conditions were atypical. Because long shot bets lose more often, this discounting yields perceptions in which betting on a long shot seems more attractive.

C. *Implications for Pricing Compound Lotteries*

We now show how our two classes of models—while each is just-identified on the basis of data from win bets—yield different implications for the prices of exotic bets. As such, our approach responds to Sauer (1998, 2026), who calls for research that provides "equilibrium pricing functions from well-posed models of the wagering market." We examine three types of exotic bets:

- exactas: a bet on both which horse will come in first and which will come in second,
- quinellas: a bet on two horses to come in first and second in either order, and
- trifectas: a bet on which horse will come in first, which second, and which third (in order).

We discuss the pricing of exactas (picking the first two horses in order)

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[9] There remains one minor issue: as fig. 1 shows, horses never win as often as suggested by their win odds because of the track take. Thus we follow the convention in the literature and adjust the odds-implied probabilities by a factor of one minus the track take for that specific race, so that they are on average unbiased; our results are qualitatively similar whether or not we make this adjustment.

[10] While the assumption of risk neutrality may be too stark, as long as bettors gamble small proportions of their wealth, the relevant risk premia are second-order. For instance, assuming log utility, if the bettor is indifferent over betting x percent of his wealth on horse A or B, then

$$\pi(p_A) \log (w + wxO_A) + [1 - \pi(p_A)] \log (w - wx) =$$

$$\pi(p_B) \log (w + wxO_B) + [1 - \pi(p_B)] \log (w - wx),$$

which under the standard approximation simplifies to $\pi(p_A)(O_A + 1) \approx \pi(p_B)(O_B + 1)$, as in (2).

TABLE 1
EQUILIBRIUM PRICING OF EXACTA BETS

Risk-Love Class (Risk-Lover, Unbiased Expectations)	Misperceptions Class (Biased Expectations, Risk-Neutral)
$p_A p_{B\|A} U(E_{AB}) = 1$	$\pi(p_A)\pi(p_{B\|A})(E_{AB}+1) = 1$
Noting $p = 1/U(O)$ from (1)	Noting $\pi(p) = 1/(O+1)$ from (2)
$E_{AB} = U^{-1}(U(O_A)U(O_{B\|A}))$ (3)	$E_{AB} = (O_A+1)(O_{B\|A}+1) - 1$ (4)

in detail. Prices for these bets are constructed from the bettors' utility function; indifference conditions, as in (1) or (2); data on the perceived likelihood of the pick for first, A, actually winning (p_A or $\pi(p_A)$, depending on the class); and conditional on A winning, the likelihood of the pick for second, B, coming in second ($p_{B|A}$ or $\pi(p_{B|A})$). Table 1 begins with the fact that a bettor will be indifferent between betting on an exacta on horses A then B in that order, paying odds of $E_{AB}/1$, and not betting (which yields no change in wealth, and hence a utility of one), and derives equilibrium prices of exactas under both classes.

Thus, under the misperceptions class, the odds of the exacta E_{AB} are a simple function of the odds of horse A winning, O_A, and conditional on this, on the odds of B coming in second, $O_{B|A}$. The risk-love class is more demanding, requiring that we estimate the utility function. The utility function is estimated from the pricing of win bets (in fig. 3) and can be inverted to compute unbiased win probabilities from the betting odds.[11]

Our empirical tests simply determine which of (3) or (4) better fits the actual prices of exacta bets. We apply an analogous approach to the pricing of quinella and trifecta bets: the intuition is the same; the mathematical details are described in the appendix of Snowberg and Wolfers (2010).

Note that both (3) and (4) require $O_{B|A}$, which is not directly observable. In Section IV we infer the conditional probability $p_{B|A}$ (and hence $\pi(p_{B|A})$ and $O_{B|A}$) from win odds by assuming that bettors believe in conditional independence. That is, we apply the Harville (1973) formula, $\pi(p_{B|A}) = \pi(p_B)/[1 - \pi(p_A)]$, replacing $\pi(p)$ with p in the risk-love class. This assumption is akin to thinking about the race for second as a "race within the race" (Sauer 1998). While relying on the Harville

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[11] Our econometric method imposes continuity on the utility and probability weighting functions; the data mandate that both be strictly increasing. Together this is sufficient to ensure that $\pi(\cdot)$ and $U(\cdot)$ are invertible. As in fig. 1, we do not have sufficient data to estimate the utility of winning bets at odds greater than 200/1. This prohibits us from pricing bets whose odds are greater than 200/1, which is most limiting for our analysis of trifecta bets.

formula is standard in the literature (see, e.g., Asch and Quandt 1987), we show that our results are robust to dropping this assumption and estimating this conditional probability, $p_{B|A}$, directly from the data.

D.   Failure to Reduce Compound Lotteries

As in prospect theory, the frame the bettor adopts in trying to assess each gamble is a key issue, particularly for misperceptions-based models. Specifically, (4) assumes that bettors first attempt to assess the likelihood of horse A winning, $\pi(p_A)$, and then assess the likelihood of B coming in second given that A is the winner, $\pi(p_{B|A})$. An alternative frame might suggest that bettors directly assess the likelihood of first and second combinations: $\pi(p_A p_{B|A})$.[12]

There is a direct analogy to the literature on the assessment of compound lotteries: does the bettor separately assess the likelihood of winning an initial gamble (picking the winning horse), which yields a subsequent gamble as its prize (picking the second-place horse), or does she consider the equivalent simple lottery (as in Samuelson [1952])? Consistent with (4), the accumulated experimental evidence (Camerer and Ho 1994) is more in line with subjects failing to reduce compound lotteries into simple lotteries.[13]

Alternatively, we could choose not to defend either assumption, leaving it as a matter for empirical testing. Interestingly, if gamblers adopt a frame consistent with the reduction of compound lotteries into their equivalent simple lottery form, this yields a pricing rule for the misperceptions class equivalent to that of the risk-love class.[14] Thus, evidence consistent with what we are calling the risk-love class accommodates either risk-love by unbiased bettors or risk-neutral but biased bettors, whose bias affects their perception of an appropriately reduced compound lottery. By contrast, the competing misperceptions class implies the failure to reduce compound lotteries and posits the specific form of this failure, shown in (4).

This discussion implies that results consistent with our risk-love class are also consistent with a richer set of models emphasizing choices over simple gambles. These include models based on the utility of gambling, information asymmetry, or limits to arbitrage, such as Ali (1977), Shin

[12] Unless the probability weighting function is a power function ($\pi(p) = p^\alpha$), these different frames yield different implications (Aczél 1966).

[13] Additionally, note that (4) satisfies the compound independence axiom of Segal (1990).

[14] To see this, note that identical data (from fig. 1) are used to construct the utility and decision weight functions, respectively, so each is constructed to rationalize the same set of choices over simple lotteries. This implies that each class also yields the same set of choices over compound lotteries if preferences in both classes obey the reduction of compound lotteries into equivalent simple lotteries.

(1992), Hurley and McDonough (1995), and Manski (2006). Any theory that prescribes a specific bias in a market for a simple gamble (win betting) will yield similar implications in a related market for compound gambles if gamblers assess their equivalent simple gamble form. By implication, rejecting the risk-love class substantially narrows the set of plausible theories of the favorite–long shot bias.

IV.   Results from Exotic Bets

Figure 4*A* shows the difference between the predictions for exactas of the risk-love and misperceptions classes, expressed as a percentage of the predictions. This demonstrates that the two classes of models yield qualitatively different predictions. Exotic bets have relatively low probabilities of winning, so under the risk-love class a risk penalty results, yielding lower odds. By contrast, the misperceptions model is based on the underlying simple lotteries, many of which suffer smaller perception biases. The risk penalty becomes particularly important as odds get longer; thus the difference in predictions grows along a line from the bottom right to the top left of figure 4*A*.

To focus on shorter-odds bets, in table 2 we convert the predictions into the price of a contingent contract that pays \$1 if the chosen exacta wins: Price $= 1/(\text{Odds} + 1)$. We test the ability of each class to predict the observed price by examining the mean absolute error of the predictions of both classes (col. 1). We further investigate which class produces predictions that are closer, observation by observation, to the actual prices (col. 3). The explanatory power of the misperceptions class is substantially greater. The misperceptions class is six percentage points closer to the actual prices of exactas (col. 2), an improvement of 6.3/ 34.3 $= 18.4$ percent over the risk-love class.

Figure 4*B* plots the improvement of the misperceptions class according to the odds of the first- and second-place horses. When both horses have odds of less than 10/1, which accounts for 70 percent of our data, the average improvement of the misperceptions class over the risk-love class is 16.8 percent. At long odds (the top and right of the figure) there are clear patterns in the data that are not well explained by either class, leaving room for more nuanced theories of the favorite–long shot bias.

The second and third parts of panel A of table 2 repeat this analysis to see which class can better explain the pricing of quinella and trifecta bets. The intuition is similar in all three cases. Each test, across all three

A. Percentage difference between exacta predictions

B. Percentage Improvement: Misperceptions of Class over Risk-Love Class
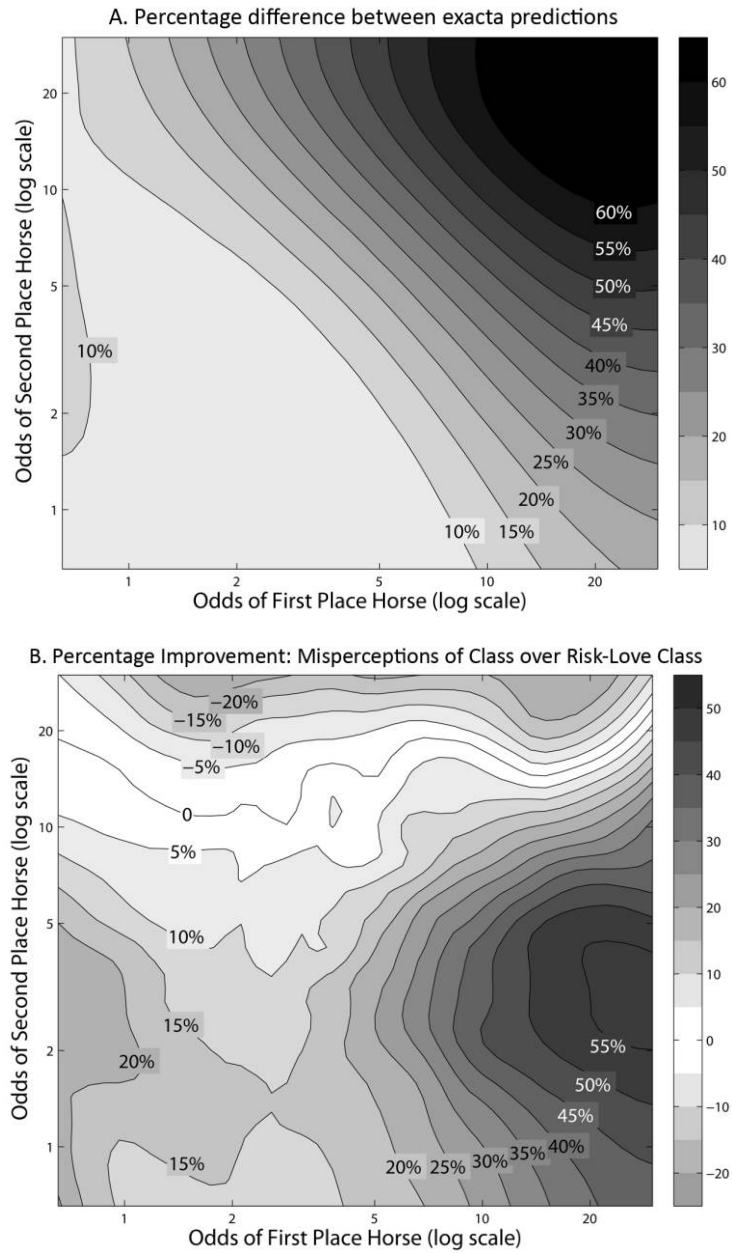

Fig. 4.—Differences between theories

TABLE 2

No Risk-Preference Model Accounts as Well for Win and Exotic Odds Simultaneously as a Misperceptions Model

	Absolute Error: $|Prediction - Actual|$ (1)	Absolute % Error: $|Prediction - Actual|/$ Actual (2)	Which Prediction Is Closer to Actual? (%) (3)
		Test	
	A. Assuming Conditional Independence (Harville 1973)		
		Exacta Bets ($n = 197,551$)	
Risk-love class	.0139	34.3	42.1
Misperceptions class	.0125	28.0	57.9
Risk-love error − misperceptions error	.00137	6.3	
	(.00002)	(.1)	
		Quinella Bets ($n = 70,169$)	
Risk-love class	.0274	39.0	46.0
Misperceptions class	.0258	36.3	54.0
Risk-love error − misperceptions error	.00155	2.7	
	(.00003)	(.2)	
		Trifecta Bets ($n = 137,756$)	
Risk-love class	.00796	100	28.9
Misperceptions class	.00532	57.4	71.1
Risk-love error − misperceptions error	.00264	42.9	
	(.00001)	(.2)	

B. Relaxing Conditional Independence

Exacta Bets ($n = 197{,}551$)

Risk-love class	.0117	33.7	42.9
Misperceptions class	.0109	24.4	57.1
Risk-love error − misperceptions error	.00082	9.3	
	(.00001)	(.1)	

Quinella Bets ($n = 70{,}169$)

Risk-love class	.0240	37.7	48.7
Misperceptions class	.0235	33.8	51.3
Risk-love error − misperceptions error	.00046	3.9	
	(.00002)	(.2)	

Trifecta Bets ($n = 137{,}756$)

Risk-love class	.00650	98.0	30.4
Misperceptions class	.00464	49.0	69.6
Risk-love error − misperceptions error	.00186	49.0	
	(.00001)	(.1)	

NOTE.—Standard errors are in parentheses. Predictions and actual outcomes are measured in the price of a contract that pays \$1 if the event occurs, zero otherwise.

parts, shows that the misperceptions class fits the data better than the risk-love class.[15]

Relaxing the assumption of conditional independence.—Recall that we observe all the inputs to both pricing functions except $O_{B|A}$, the odds of horse B finishing second, conditional on horse A winning. Above we used the Harville formula, which rests on the convenient assumption of conditional independence, to assess the likely odds of this bet. Generally, this provides a reasonable approximation of $p_{B|A}$ and, thus, using (1) and (2), $O_{B|A}$. However, nonparametric techniques provide a better fit.

As a robustness check of the results in panel A of table 2, we now use nonparametrically estimated probabilities $p_{B|A}$. That is, rather than inferring $p_{B|A}$ (and hence $\pi(p_{B|A})$ and $O_{B|A}$) from the Harville formula, we simply apply empirical probabilities estimated directly from the data. That is, our estimate of $p_{B|A}$ reflects how frequently horses with odds of winning O_B actually run second in races in which the winner had odds O_A. This probability is estimated using the nonparametric, multidimensional Lowess procedure of Cleveland, Devlin, and Grosse (1988). We implement this exercise in panel B of table 2, calculating the price of exotic bets under the risk-love and misperception classes, but adapting our earlier approach so that $p_{B|A}$ is derived from the data.[16]

The results in panel B of table 2 are almost identical to those in panel A. For exacta, quinella, and trifecta bets, the misperceptions class has consistently greater explanatory power than the risk-love class.

V.   Simultaneous Pricing of Exactas and Quinellas

Our final test of the two classes of theories relies on the relative pricing of exacta and quinella bets and is more stringent as it considers these bets simultaneously. As before, we derive predictions from each class, and the predictions of the misperceptions class more closely match the data. However, the predictions of the risk-love class exhibit a perverse negative correlation with the data, requiring a more detailed explanation.

Deriving predictions.—The exacta AB (which represents A winning and

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[15] We have also rerun these tests a number of other ways to test for robustness. Our conclusions are unaltered by whether or not we weight observations by the size of the betting pool; whether we drop observations in which the classes imply very long odds; whether or not we adjust the classes in the manner described in n. 8; and different functional forms for the price of a bet, including the natural log price of a $1 claim, the odds, or log odds.

[16] Because the precision of our estimates of $p_{B|A}$ varies greatly, weighted least squares, weighted by the product of the squared standard error of $p_{B|A}$ and p_A, might be appropriate. Additionally, we tried estimating $p_{B|A}$ without using Lowess smoothing. These approaches produced qualitatively identical results.

B coming in second) occurs with probability $p_A \times p_{B|A}$; the *BA* exacta occurs with probability $p_B \times p_{A|B}$. By definition, the corresponding quinella pays off when the winning exacta is either *AB* or *BA* and hence occurs with probability $p_A \times p_{B|A} + p_B \times p_{A|B}$. Each model yields unique implications for the relative prices of the winning exacta and quinella bets and thus unique predictions for

$$\frac{p_A p_{B|A}}{p_A p_{B|A} + p_B p_{A|B}}. \tag{5}$$

This is also the probability that horse *A* wins given that *A* and *B* are the top two finishers.

Table 3 begins by considering the *AB* exacta at odds of $E_{AB}/1$ and the corresponding quinella at $Q/1$. Equations (10) and (11) show that for any pair of horses at win odds $O_A/1$ and $O_B/1$ with quinella odds $Q/1$, each class has different implications for how frequently we expect to observe the *AB* exacta winning, relative to the *BA* exacta. That is, each class gives distinct predictions about how often a horse with win odds $O_A/1$ will come in first, given that horses with win odds $O_A/1$ and $O_B/1$ are the top two finishers.

What do the data say?—As a first test, we regress an indicator for whether the favorite out of horses *A* and *B* actually won—given that horses *A* and *B* finished first and second—on the predictions of each model.[17] In this simple specification, the misperceptions class yields a robust and significant positive correlation with actual outcomes (coefficient = 0.63; standard error = 0.014, $n = 60,288$), and the risk-love class is negatively correlated with outcomes (coefficient = −0.59; standard error = 0.013, $n = 60,288$).

Note that (10) and (11) also yield distinct predictions of the winning exacta even within any set of apparently similar races (those whose first two finishers are at $O_A/1$ and $O_B/1$ with the quinella paying $Q/1$). Thus, we can include a full set of fixed effects for O_A, O_B, and Q and their interactions in our statistical tests of the predictions of each class.[18] The residual after differencing out these fixed effects is the predicted likelihood that *A* beats *B*, relative to the average for all races in which horses at odds of $O_A/1$ and $O_B/1$ fill the quinella at odds $Q/1$. That is, for all races we compute the predictions of the likelihood that the exacta with the relative favorite winning (*AB*) occurs and subtract the baseline $O_A \times O_B \times Q$ cell mean to yield the predictions for each class of model, relative to the fixed effects. The results, summarized in figure 5, are

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[17] In the rare event in which horses *A* and *B* had the same odds we coded the indicator as 0.5.

[18] Because the odds O_A, O_B, and Q are actually continuous variables, we include fixed effects for each percentile of the distribution of each variable (and a full set of interactions of these fixed effects).

TABLE 3

SIMULTANEOUS PRICING OF EXACTAS AND QUINELLAS

	Risk-Love Class (Risk-Lover, Unbiased Expectations)	Misperceptions Class (Biased Expectations, Risk-Neutral)
Exacta	$p_A p_{B\mid A} U(E_{AB}) = 1$ $p_{B\mid A} = \dfrac{U(O_A)}{U(E_{AB})}$ (6)	$\pi(p_A)\pi(p_{B\mid A})(E_{AB}+1) = 1$ $\pi(p_{B\mid A}) = \dfrac{O_A+1}{E_{AB}+1} \Rightarrow p_{B\mid A} = \pi^{-1}\!\left(\dfrac{O_A+1}{E_{AB}+1}\right)$ (7)
Quinella	$[p_A p_{B\mid A} + p_B p_{A\mid B}]\,U(Q) = 1$ $p_{A\mid B} = U(O_B)\left[\dfrac{1}{U(Q)} - \dfrac{1}{U(E_{AB})}\right]$ (8)	$[\pi(p_A)\pi(p_{B\mid A}) + \pi(p_B)\pi(p_{A\mid B})](Q+1) = 1$ $\pi(p_{A\mid B}) = (O_B+1)\left(\dfrac{1}{Q+1} - \dfrac{1}{E_{AB}+1}\right) \Rightarrow p_{A\mid B} = \pi^{-1}\!\left(\dfrac{(O_B+1)(E_{AB}-Q)}{(E_{AB}+1)(Q+1)}\right)$ (9)

Hence, from (1), (6), and (8):

$$\frac{p_A p_{B\mid A}}{p_B p_{A\mid B} + p_A p_{B\mid A}} = \frac{U(Q)}{U(E_{AB})} \qquad (10)$$

Hence, from (2), (7), and (9):

$$\frac{p_A p_{B\mid A}}{p_A p_{B\mid A} + p_B p_{A\mid B}} = \frac{\pi^{-1}\!\left(\frac{1}{O_A+1}\right)\pi^{-1}\!\left(\frac{O_A+1}{E_{AB}+1}\right)}{\pi^{-1}\!\left(\frac{1}{O_A+1}\right)\pi^{-1}\!\left(\frac{O_A+1}{E_{AB}+1}\right) + \pi^{-1}\!\left(\frac{1}{O_B+1}\right)\pi^{-1}\!\left(\frac{(O_B+1)(E_{AB}-Q)}{(E_{AB}+1)(Q+1)}\right)} \qquad (11)$$
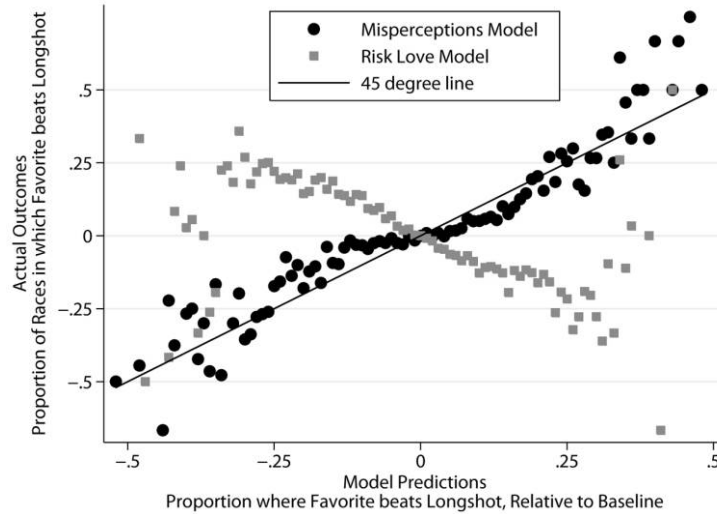
FIG. 5.—Predicting the winning exacta within a quinella: the proportion in which the favored horse beats the long shot, relative to the baseline. The chart shows model predictions from (3) and (4) and actual outcomes relative to a fixed-effect region baseline. For the first-two finishing horses the baseline controls for (*a*) the odds of the favored horse, (*b*) the odds of the long shot, (*c*) the odds of the quinella, and (*d*) all interactions of *a*, *b*, and *c*. The plot shows model predictions after removing fixed effects, rounded to the nearest percentage point, on the *x*-axis and actual outcomes, relative to the fixed effects, on the *y*-axis.

remarkably robust to the inclusion of these multiple fixed effects (and interactions): the coefficient on the misperceptions class declines slightly, and insignificantly, whereas the risk-love class maintains a significant but perversely negative correlation with outcomes. It should be clear that this test, by focusing only on the relative rankings of the first two horses, entirely eliminates parametric assumptions about the race for second place.

Explaining the negative correlation.—Two factors create the perverse negative correlation between the predictions of the risk-love class and the data. First, when the winning quinella is made up of two horses with not too dissimilar odds, the risk-love class predicts that the relative favorite will win with less than a one-half probability whenever it wins and predicts that the relative favorite will win with greater than a one-half probability whenever it loses. Second, as most winning quinellas (and exactas) feature horses with not too dissimilar odds, most of the data are from this range as well, leading to the observed negative correlation.

We discuss the data as if they were generated by misperceptions and explain the resulting negative correlation by emphasizing how the predictions of the risk-love class deviate from misperceptions. To fix ideas,

consider the case in which the relative favorite, A, has win odds of 4/1 and the relative long shot, B, has win odds of 9/1. The data give average exacta odds $E_{AB} = 39/1$ and $E_{BA} = 44/1$ and average quinella odds $Q = 20/1$. These data agree extremely closely with the predictions of the misperceptions class, so when (11) is applied to data from such a race, it makes accurate predictions about $p_A p_{B|A}/(p_A p_{B|A} + p_B p_{A|B})$.[19]

A risk-loving bettor is willing to pay a premium for riskier bets; that is, he is willing to accept lower odds than a risk-neutral bettor as probabilities of winning become small. Figure 1 shows that under the risk-love class, an exacta bet at odds $E_{AB} = 39/1$ has a large risk premium.[20] However, the same figure shows that the rate of return from bets on A and B (with odds of 4/1 and 9/1, respectively) is close to the average rate of return on all bets, implying no risk premium in bets on either horse individually. Thus, according to the misperceptions class (as expressed in [4]), there is no risk premium in the observed odds E_{AB}.

The difference between the risk-love class and the data, namely, that the risk-love class infers there is a risk-premium built into $E_{AB} = 39/1$, leads the risk-love class to predict that AB will occur with a lower than actual probability. Specifically, according to the data underlying figure 1, a risk-loving bettor is willing to accept odds of 39/1 for a bet that wins only one out of 54 times. In contrast, if there was no risk premium, the bet would have odds of 53/1. Conversely, when the risk-lover is told an exacta has odds $E_{AB} = 39/1$, he believes that it has only a one in 54 chance of winning. Or, to put this another way, when the risk-love class is given an exacta with odds $E_{AB} = 39/1$, it predicts that the numerator of (5), $p_A p_{B|A}$, is 0.018 when the probability in the data is much closer to 0.025.

The inferred risk premium is much lower for the quinella than for the exacta, which leads the risk-love class to predict a less than 50 percent chance that the relatively favored horse A will finish first out of A and B. Specifically, as shown in figure 1, the rate of return at $Q = 20/1$ is close to the average, implying almost no risk premium. Thus, the risk-love model will predict the denominator of (5), $p_A p_{B|A} + p_B p_{A|B}$, well at 0.046. However, as shown in the previous paragraph, the prediction for the numerator of (5) is too small, leading to a prediction that A will win ~40 percent of the time if A and B are the top two finishers. But A is the favorite of the two horses ($O_A/1 = 4/1 < 9/1 = O_B/1$) and finishes before B ~60 percent of the time.

If, instead, the relative long shot B wins, the exacta $E_{BA} = 44/1$ is

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[19] We adjust figures in this example slightly so that the discussion can ignore the track take. See n. 8 for more on the analytical treatment of the track take.

[20] The use of the term risk premium here differs slightly from standard usage, where risk premium refers to the higher payoff risk-averse agents will need to accept a risky bet. Here risk-loving agents are willing to pay a premium for a riskier bet.

observed, which leads the risk-love class to predict that there is a lower than 50 percent chance that *B* wins given that *A* and *B* are the top two finishers. Applying the logic above, the risk-love class infers that this price incorporates an even larger risk premium and thus assigns a lower probability to this exacta than to $E_{AB} = 39/1$. In turn, this means that it yields a low probability of horse *B* coming in first, given that *A* and *B* are the top two finishers. However, the risk-love class will make this prediction only when exacta E_{BA} is observed, that is, when horse *B* actually wins the race.

When the left-hand side of the regression that began this discussion takes a value of one, indicating that horse *A* has won out of *A* and *B*, the right-hand side takes a value of 0.4, indicating that the risk-love model predicts a 40 percent chance of *A*'s victory. Conversely, when the left-hand side is zero, indicating that *A* has lost, the right-hand side takes a value of 0.65.

Taken together, these two cases imply that there is a negative correlation between the predictions of the risk-love class and the data when the odds of the top two finishers are 4/1 and 9/1. Moreover, the intuition extends to any case in which the odds of the first two horses are not too dissimilar, which describes almost all the races in our data set. When the odds of the first two horses are more dissimilar, for example, 1/1 and 100/1, then both models correctly predict that the 1/1 horse will almost always win. However, such finishes are so rare that they have almost no impact on the analysis, resulting in the observed negative correlation.

Summary.—The risk-love class fails here because it insists that the same risk premium be priced into all bets of a given risk, regardless of the pool from which the bets are drawn. Yet exotic bets with middling risk—relative to the other bets available in a given pool—do not tend to attract large risk penalties, even if those bets would be very risky relative to bets in the win pool (Asch and Quandt 1987).

These tests show that a model from the risk-love class that accounts for the pricing of win bets yields inaccurate implications for the relative pricing of exacta and quinella bets. By contrast, the misperceptions class is consistent with the pricing of exacta, quinella, and trifecta bets and, as this section shows, also consistent with the relative pricing of exacta and quinella bets. These results are robust to a range of different approaches to testing the theories.

VI. Conclusion

Employing a new data set that is much larger than those in the existing literature, we document stylized facts about the rates of return to betting on horses. As with other authors, we note a substantial favorite–long

shot bias. The term bias is somewhat misleading here. That the rate of return to betting on horses at long odds is much lower than the return to betting on favorites simply falsifies a model in which bettors maximize a function that is linear in probabilities and linear in payoffs. Thus, the pricing of win bets can be reconciled by a representative bettor with either a concave utility function or a subjective utility function employing nonlinear probability weights that violate the reduction of compound lotteries. For compactness, we referred to the former as explaining the data with risk-love, whereas we refer to the latter as explaining the data with misperceptions. Neither label is particularly accurate since each category includes a wider range of competing theories.

We show that these classes of models can be separately identified using aggregate data by requiring that they explain both choices over betting on different horses to win and choices over compound bets: exactas, quinellas, and trifectas. Because the underlying risk or set of beliefs, depending on the theory, is traded in both the win and compound betting markets, we can derive unique testable implications from both sets of theories. Our results are more consistent with the favorite–long shot bias being driven by misperceptions rather than by risk-love. Indeed, while each class is individually quite useful for pricing compound lotteries, the misperceptions class strongly dominates the risk-love class. This result is robust to a range of alternative approaches to distinguishing between the theories.

This bias likely persists in equilibrium because misperceptions are not large enough to generate profit opportunities for unbiased bettors. That said, the cost of this bias is also very large, and debiasing an individual bettor could reduce his or her cost of gambling substantially.

Appendix

Data

Our data set consists of all horse races run in North America from 1992 to 2001. The data were generously provided to us by Axcis Inc., a subsidiary of the Jockey Club. The data record the performance of every horse in each of its starts and contain the universe of officially recorded variables having to do with the horses themselves, the tracks, and race conditions.

Our concern is with the pricing of bets. Thus, our primary sample consists of the 6,403,712 observations in 865,934 races for which win odds and finishing positions are recorded. We use these data, subject to the data-cleaning restrictions below, to generate all figures. We are also interested in pricing exacta, quinella, and trifecta bets and have data on the winning payoffs in 314,977, 116,307, and 282,576 races, respectively. The prices of nonwinning combinations are not recorded.

Owing to the size of our data set, whenever observations were problematic,

we simply dropped the entire race from our data set. Specifically, if a race has more than one horse owned by the same owner, rather than deal with coupled runners, we simply dropped the race. Additionally, if a race had a dead heat for first, second, or third place, the exacta, quinella, and trifecta payouts may not be accurately recorded, and so we dropped these races. When the odds of any horse were reported as zero, we dropped the race. Further, if the odds across all runners implied that the track take was less than 15 percent or more than 22 percent, we dropped the race. After these steps, we are left with 5,606,336 valid observations on win bets from 678,729 races, and 1,485,112 observations from 206,808 races include both valid win odds and payoffs for the winning exotic bets.

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