Economics can be distinguished from other social sciences by the belief that most (all?) behavior can be explained by assuming that agents have stable, well-defined preferences and make rational choices consistent with those preferences in markets that (eventually) clear. An empirical result qualifies as an anomaly if it is difficult to "rationalize," or if implausible assumptions are necessary to explain it within the paradigm. This column will present a series of such anomalies. Of course, "difficult" and "implausible" are judgments, and others might disagree with my assessment. Therefore, I invite readers to submit brief explanations (within the paradigm or otherwise) for any of the anomalies I report. To be considered for publication, however, proposed explanations must be falsifiable, at least in principle. Future topics for this column will come from as many fields of empirical economics as possible. Readers are invited to suggest topics by sending a note with some references to (or better yet copies of) the relevant research. The address is: Richard Thaler, c/o Journal of Economic Perspectives, Johnson Graduate School of Management, Malott Hall, Cornell University, Ithaca, NY 14853.

Introduction

Economists have given great attention to stock markets in their efforts to test the concepts of market efficiency and rationality. Yet wagering markets are, in one key
respect, better suited for testing market efficiency and rationality. The advantage of wagering markets is that each asset (bet) has a well-defined termination point at which its value becomes certain. The absence of this property is one of the factors that has made it so difficult to test for rationality in the stock market. Since a stock is infinitely lived, its value today depends both on the present value of future cash flows and on the price someone will pay for the security tomorrow. Indeed, one can argue that wagering markets have a better chance of being efficient because the conditions (quick, repeated feedback) are those which usually facilitate learning. However, empirical research has uncovered several interesting anomalies. While there are numerous types of wagering markets, legal and otherwise, this column will concentrate on racetrack betting and lotto-type lottery games.¹

**Racetrack Betting Markets**

The “market” at the racetrack convenes for about 20–30 minutes during which time participants place bets on any number of the six to twelve horses in the upcoming race. In a typical race, participants can bet on each horse, either to win, place or show (as well as “exotic” bets which depend on the combined outcomes of two or more horses). The horses that finish the race first, second or third are said to finish “in-the-money.” All participants who have bet a horse to win realize a positive return on that bet only if the horse is first, while a place bet realizes a positive return if the horse is first or second, and a show bet realizes a positive return if the horse is first, second or third. There is a separate “pool” of money kept for each type of bet. Payoffs are determined in a “parimutuel” fashion, which means that the winning bets divide the money wagered on losing bets, less transactions costs.² The transactions costs consist of a fixed percentage \( t \), which includes the “track take” and “breakage,” the additional cost incurred because all returns per dollar bet are rounded down to the nearest five or ten cents. These transactions costs are substantial, typically in the range of 15–25 percent depending on the type of wager and the locale.

The proportion of the money in the win pool that is bet on any given horse can be interpreted as the subjective probability that this horse will win the race. By summing over many races, one can check what proportion of the horses with subjective probabilities between, say, .2 and .25 actually won races. The results of this analysis are impressive. Horses rated by the crowd as most likely to win (the “favorites”) do win most often (about 1/3 of the time), and the correlation between subjective and objective probabilities is very high.³ Apparently the bettors in these markets have considerable expertise.

¹A future column may address other betting markets, such as NFL betting. Authors of recent papers on this topic are requested to send copies to Thaler.
²Since payoffs depend only on the final odds, bettors do not know potential payoffs when they bet. In Britain and some other places bookies accept bets on a fixed odds system where bettors are promised a certain payoff if their horse wins.
³See, for example, the studies by Weitzman (1965), Rosett (1965), Ali (1977), and Snyder (1978).
Does the high correlation between subjective and objective probabilities imply that the racetrack market is efficient? That depends on the definition of market efficiency. If we assume for the moment that all bettors are expected value maximizers with rational expectations, then two definitions of market efficiency seem appropriate.

**Market efficiency condition 1 (weak).** No bets should have positive expected values.

**Market efficiency condition 2 (strong).** All bets should have expected values equal to \((1 - t)\) times the amount bet.

While the racetrack may be surprisingly efficient, there is substantial evidence that both of these conditions are violated. The most robust anomalous empirical regularity is called the favorite-longshot bias. Specifically, the expected returns per dollar bet increase monotonically with the probability of the horse winning. Favorites win more often than the subjective probabilities imply, and longshots less often. This means that favorites are much better bets than longshots. Indeed, extreme favorites, those with odds of less than 3-10 (that is, with a greater than 70 percent chance to win) actually have positive expected values, in violation of condition 1.

Figure 1 (taken from Ziemba and Hausch, 1986) illustrates the favorite-longshot bias using data from most of the previously published studies (including over 50,000 races). Expected returns per dollar bet are plotted for horses at various market odds, using a transactions costs assumption of \(t = 15.33\) percent, which applies in the state of California. The horizontal line indicates the point at which returns are the expected \(0.8467 = (1 - t)\). This occurs at odds of about 9-2 (that is, about a 15 percent probability of winning). For odds above 18-1 there is a steep drop in the expected return, with returns falling to only 13.7 cents per dollar wagered at 100-1. This implies that the typical 100-1 shot has real odds of about 730 to 1! Below 3-10 expected returns are positive, with returns of about 4-5 percent for the shortest odds horses. (This is partially explained by the $1.05 per dollar minimum payoff at nearly all U.S. tracks.) Although such overwhelming favorites are too rare to get very excited about, other profitable betting strategies are discussed below.

Another test of market efficiency is to compare the payoffs of equivalent bets. For example, most tracks offer a “daily double” bet which requires bettors to select the winners of the first two races. Suppose a bettor is considering buying a daily double ticket on horse \(A\) in the first race and \(B\) in the second race. Then an alternative betting strategy (called a parlay) would be to bet on \(A\) in the first race, and, if \(A\) wins, bet the proceeds on \(B\) to win the second race. Efficiency requires that the daily double payoff on \(A\) and \(B\) be the same as the parlay on \(A\) and \(B\). This proposition has been tested by Ali (1979) and by Asch and Quandt (1987). The conclusion from these tests seems to be that daily double and parlay bets are priced reasonably efficiently relative to each other, though bettors should prefer the daily double because it offers lower transactions costs.

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4 Risk neutrality seems like a sensible initial assumption since most bettors probably wager a small portion of their total wealth. Other assumptions will be considered in the commentary section.

5 Probabilities at the racetrack are traditionally quoted as “odds.” If a horse has odds of “\(x\) to 1” then the implicit probability the horse will win is \((1 - t)/(x + 1)\).
A similar test is possible using exacta betting in which a bettor must correctly pick the first and second place horses in the correct order. Just as the relative amounts bet on different horses in the win pool can be used to calculate implicit forecasts of the probability of winning, similar calculations for the exacta can be made using the so-called Harville (1973) formula. If $q_i$ is the probability that horse $i$ wins, then it is assumed that the probability that horse $i$ is first and horse $j$ is second is $q_iq_j/(1 - q_i)$. (Similarly, the probability that horse $i$ is first, $j$ is second, and $k$ is third is $q_ik_j/(1 - q_i)(1 - q_i - q_j)$.) Asch and Quandt (1987) used the Harville formula to compare the subjective probability of winning implied by the betting in the win pool and the exacta pool. They found that the public did not bet in a mathematically consistent fashion. The implicit probabilities of winning for a given horse were often very different in the two pools.

**Betting Strategies**

Betting strategies at the track, as at the stock market, come in both fundamental and technical varieties. Fundamental strategies commonly are based on publicly available information used to “handicap” races. A bettor using a fundamental or

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6 The Harville formulas are quite accurate considering how little data they require. However, they tend to overestimate the probability that a low-odds horse will finish exactly second or third. More accurate estimation formulas are derived in Stern (1987), but these require data on all the horses in the race.
handicapping strategy attempts to determine which horses, if any, have probabilities of winning (or placing or whatever) that exceed the market-determined odds by an amount sufficient to overcome the track take. Technical systems require less information and use only current betting data. Bettors using a technical system attempt to find inefficiencies in the market and bet on such "overlays" when they have positive expected value. Most academic research has concentrated on the latter strategies.

Hausch, Ziemba and Rubinstein (1981) (HZR) develop and test a strategy for betting in the place and show markets. They use the amounts bet in the win pool and the Harville formulas to calculate the probabilities of placing and showing for each horse based on the betting in the win pool. Using these methods they are able to identify horses that are underbet to place or show. The basic idea is to compare the proportion of the win pool bet on horse \( i \) with the amount of the place or show pool bet on horse \( i \). If, for example, 40 percent of the bets in the win pool are on horse \( i \), but only 15 percent of the bets in the place pool are bet on horse \( i \), then it is profitable to bet on horse \( i \) to place. Such profitable betting opportunities typically occur 2 to 4 times per racing day. Empirical studies on two seasons of racing data indicate that significant returns on the order of 11 percent per bet are possible in the place and show markets. This violates weak market efficiency. Moreover, publication of the system does not appear to have eliminated the profitable betting opportunities. At the recent 1987 Breeders' Cup races there were five "system" bets during the racing day. As luck would have it, all five bets paid off.

Ziemba and Hausch (1986) also developed similar techniques to identify and exploit inefficiencies in the exacta markets. The most frequent profitable bets have the favorite in second position. Their plots of the probability of winning and coming in second versus odds as shown in Figure 2, show that short odds horses have a substantial probability of coming in exactly second. The betting public might easily underestimate this chance. The other common profitable wagers are derived from the extreme favorite-longshot bias. Betting extreme favorites in the first position can thus yield profitable bets. The public wagers a considerable amount on these super horses, but not as much as they should. Combinations of longshots are almost never a good exacta wager; such bets typically return 10 to 30 cents on the dollar.

Asch, Malkiel and Quandt (1984, 1986) and Asch and Quandt (1986) investigated whether a drop in the odds late in the betting period might reflect inside information and thereby point to wagers that may have positive expected returns.
Common racetrack folklore suggests that the smart money is bet late. This is borne out by Asch, Malkiel and Quandt (1982) using data at various points in the betting cycle from 729 races at the Atlantic City Race Course. They found that for winning horses the final odds tend to be lower than the “morning line odds” (predicted odds by the track handicapper), whereas for horses finishing out of the money the final odds are much higher than the morning line odds. The later in the betting period, the more pronounced is the effect for the winners. The final odds for winners are 96 percent of the morning line odds, but for the money bet during the last eight minutes, the marginal odds are 82 percent of the morning line, and in the last five minutes they drop further to 79 percent. The final odds for losers are about 1.5 times the morning line odds. Asch and Quandt (1986) develop a logit model of the probability of winning, using the change in the odds during the last few minutes as one of the independent variables. The logit model is then used to search for profitable investment strategies. They could not find any profitable bets in the win pool, but they did find some in the place and show pools. Apparently, place and show betting on favorites whose odds have fallen in the last few minutes yields small profits. This is consistent with the Ziemba and Hausch (1987) results suggesting inefficiencies in the place and show pools.

Asch and Quandt (1986) argue that this occurs because the smart money bettors want to withhold any information that their bets might convey. This implies that the public will bet more on a horse if the odds are lower than expected: an upward sloping demand curve! But if bettors have reservation odds for each horse, then they will also bet more on a horse if the odds are higher than expected. Probably the betting public contains a mixture of people using each strategy.
Cross Track Betting

A recent development in race track betting is the opportunity for bettors to wager at their home track on major thoroughbred races being run at another track. Cross track betting raises new and interesting questions about market efficiency. While arbitrage is made difficult by the high transactions costs and the absence of public telephones inside most race tracks, rational expectations would seem to imply that the odds at every track would be approximately the same. In fact, they frequently vary dramatically. For example, in the 1986 Kentucky Derby, the winner Ferdinand paid $16.80 for $2 at Hollywood Park in California where he had run often and was well known. He paid $37.40 at Aqueduct in New York, $79.60 at Woodbine in Toronto, $63.20 at Hialeah in Florida, and $90.00 at Evangeline in Louisiana.

While pure arbitrage may be difficult, profitable betting strategies are possible. Hausch and Ziemba (1987) have developed an optimal betting model for cross track betting under the assumption that final odds at all tracks are known in time to compute and place bets at each track. The essence of the system is to assume that the home track odds are accurate (after correcting for the favorite-longshot bias) and then to select a combination of bets at other tracks to exploit the inefficiencies. If the discrepancies in the odds at the various tracks are large enough (as they have been at some races), it is even possible to create a genuine arbitrage opportunity by betting on every horse at the track where the odds are best. Unfortunately, in the absence of a sophisticated communications system, these strategies are likely impractical (and possibly illegal). However, a Chicago commodities trader has developed and profitably used a workable one-track system using a portable television at the cross track. The bettor views the home odds when they are flashed on television, and then searches for overlays at the cross track.

Lotto Games

Lottery games date at least to biblical days. Israel was divided among the seven tribes by lot. Christ’s robe was given to a lottery winner so it would not have to be cut. The Sistine chapel and its paintings were supported by lotteries. The Italian lottery has been running continuously since 1530. Lotteries are played in over 100 countries. Lotteries arrived in North America with the Pilgrims, and they were used to partially fund the new schools such as Harvard, Princeton and Yale. Later they were used to pay off debts of notables such as Thomas Jefferson. Extreme corruption led to their demise in the late 19th century, and they were banned in the United States and Canada. They resurfaced in 1964 in New Hampshire. In Canada they arrived to repay the debts from Expo 1967 in Montreal. Since then there has been explosive growth in popularity and sales. However, with an expected return of between 40 and 60 cents on the dollar, they are usually a poor investment for the rational investor.

Even with such low payout rates, it is possible to obtain positive expected value bets in lotto games. This occurs because not all numbers are equally popular with the public. The possibility of exploiting this pattern was first formalized by Chernoff.
(1980) (and tested by some of his students) in the context of the Massachusetts
numbers game. In this game the object is to pick a number from 0000 to 9999. If your
number is drawn, then you share a portion of the total pool. A subsidiary prize is
awarded if three numbers match. Chernoff found that certain numbers were unpopu-
lar: those with 0's, 9's, and to a lesser extent 8's. His theoretical analysis suggested that
there were combinations with positive expected values, inducing some of his students
to bet systematically on the “good” numbers. However, the students did not fare very
well. First, over time the unpopular numbers became less advantageous, due to a
combination of learning and simple regression. Second, they fell victim to the dreaded
“gambler’s ruin.” The students’ bankroll was not sufficient to wait out the time needed
to have enough hits to generate substantial profits. Finally, they were unlucky: the
unpopular numbers came up less often than would be expected.

The game that has attracted the most attention in North America is Lotto 6/49
or some similar variant. In this game one chooses six of forty-nine numbers and if they
all match then one wins the jackpot. Lesser prizes are awarded for three to five
matches. The probability of selecting the winning combination in this game is 1 in
13,983,816: if you play twice a week you can expect to win in 134,360 years, a long
time horizon even for a rational economist!

Two features make the game interesting for the rational investor. First, as in the
numbers game, some numbers are more popular than others. Second, if the grand
prize is not won in a given drawing, it is carried over to the next week. Thus prizes can
be enormous.11 Ziemba and his co-workers (1986) have been studying whether these
factors can produce favorable investment opportunities. Several estimation methods
have been used to calculate the best numbers: simple counts of the frequency with
which the numbers are picked, a regression of the log of payoffs on the winning
numbers, and a sophisticated constrained maximum likelihood model. All lead to the
same conclusion, namely that 15 to 20 of the numbers are quite unpopular. Moreover,
the precise numbers are virtually the same from year to year. While there has been
some learning over the years, so that these numbers are not quite as unpopular as they
used to be, the unpopular numbers tend to remain unpopular. In fact, there are
thousands of combinations of numbers that have expected returns over $1 even when
there is no carryover. The expected value of betting the best numbers increases with the
carryover and converges to about $2.25 per $1 for very large pools. The best numbers
tend to be high numbers (non-birthdays) and those ending in 0's, 9's and 8's.

According to the regression model, the twelve most unpopular numbers are 32, 29, 10,
30, 40, 39, 48, 12, 42, 41, 38, and 18 which tend to be 15 percent to 30 percent less
popular than average. Using the marginal approach (those numbers chosen two
standard deviations less than average), one finds the nineteen most unpopular

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11In the U.S. lottery prizes are often announced using the accounting methods favored by university fund
raisers and agents for professional athletes, namely undiscounted nominal dollars. The present value of the
prize after taxes is typically about one-third of the announced value. In Canada, however, prizes are paid in
cash and incur no Canadian tax liability.
numbers to be 40, 39, 20, 30, 41, 38, 42, 46, 29, 49, 48, 32, 10, 47, 1, 37, 28, 34 and 45. These numbers have edges from 26.7 percent down to 3.2 percent. The most popular number is 7, which is selected nearly 50 percent more often than the average number.

The question remains—can you make money in the lotto games playing the unpopular numbers? While you can achieve an expected value of $2 per dollar bet, there may not be any arbitrage opportunity available. Consider a hypothetical carnival game with one million spokes. You pay $1 for a number between 1 and 1 million, and you get $2 million if your choice comes up. While you have an edge, the chance of winning is so small that you probably will go bankrupt before winning the jackpot. To analyze this problem one needs to have an adequate model of growth of wealth versus security of wealth. MacLean, Ziemba and Blazenko (1987) have developed such a model to investigate questions such as: Can a dynasty enhance its long-term wealth playing lotto games? The answer is that it can. With sufficiently small wagers it can increase its initial stake of, say, $10 million by tenfold before losing $5 million with probability arbitrarily close to one, but this process takes thousands of years even if they play all over the world. For one lotto game it will take them millions of years. A more interesting question for most of us is: Can a group or single investor use the unpopular numbers to become rich? This is even more difficult, especially if one wants low risk. It is easy to bankroll, as the optimal wager can be as low as 10 cents per week for one of ten syndicate members, but these aspiring millionaires are most likely to be residing in a cemetery when their distant heirs finally reach the goal. It is still best to play unpopular numbers—they have an edge and you will win 3 to 7 times the usual prizes should you hit—but you will expect to play a very long time before winning.

One of the most attractive aspects of lotto games is that the portion of the pool designated for the jackpot is carried over to the next draw when no one wins the jackpot. Indeed it is the prospect of winning a huge jackpot that is the main driving force behind the tremendous interest and sales of lotto tickets. Does it ever pay to buy all the numbers and hence “steal the pot”? Two conditions are necessary for this to be profitable. Roughly speaking these are: (1) a large carryover (in 6/49, $7.7 million); and (2) “not very many” tickets sold. While these conditions are unlikely to obtain, there are cases that can and have arisen in minor lotto games in Canada and elsewhere where it actually would have been a reasonable idea to buy the pot. It is important to stress, however, that even if the right conditions arose, buying the pot would entail enormous transactions costs since the tickets must be bought and redeemed one by one, and, you would have to hope that no one else tried to buy the pot at the same time (see Ziemba et al., 1986, for details). Similar situations sometimes arise in exotic racetrack betting such as the “pick six” (pick the winners of six consecutive races) and related exotic bets. Substantial carryovers can exist in these pools, and making large wagers or actually buying the pot can be profitable. In fact, there are at least two major syndicates that actually try to do this, one of which made over $1 million last year.
Commentary

Racetrack betting

The racetrack betting market is surprisingly efficient. Market odds are remarkably good estimates of winning probabilities. This implies that racetrack bettors have considerable expertise, and that the markets should be taken seriously. Nevertheless, two robust anomalies are present: the favorite-longshot bias, and the inefficiencies of the place and show markets. How can these anomalies be explained?

Quandt (1986) has offered the following argument regarding the favorite-longshot bias (see also Rosett, 1965). The fact that bettors make wagers that are known to have negative expected value implies that they must be “locally” risk seeking. This implies that the usual risk-return relationship will be reversed. In equilibrium, investments (bets) with high variance will have lower average returns than investments with low variance. While this argument is logically consistent, we feel that it is not a satisfactory explanation of the observed behavior. The crucial issue is whether the inference that bettors are risk-seeking is a reasonable one to draw from the fact that they are at the track betting.

What does it mean to be “locally risk seeking”? Recognizing that most racetrack fans, including themselves, purchase insurance, Asch and Quandt (1986) suggest that the utility of wealth function may have the shape proposed by Friedman and Savage (1948), namely concave below the current wealth level and convex above it. While this assumption can explain why racetrack bettors also purchase insurance, it is surely not an adequate explanation for bettors’ other behavior such as investing. We venture a guess that when it comes to retirement saving, Professors Asch and Quandt would not be willing to accept a lower mean return in order to obtain a higher level of risk. Indeed, having read their coauthor’s book on the stock market (Malkiel, 1985) we guess that when it comes to investing, many racetrack bettors display concave utility functions. Thus the term “locally risk seeking” may apply to racetrack bettors, but only if the term “locally” refers to physical location rather than wealth level!

It is true that racetrack fans go to the track to bet—watching a horse race is just not that much fun if you do not have a rooting interest. The real question is to what extent we can explain racetrack betting with the assumptions of rational expectations, expected utility maximization, and a convex utility of wealth function. Consider some stylized facts about racetrack bettors: First, most bring a stake that represents a small portion of their wealth. The average amount bet per person in 1985 was about $150 for the day. The median is surely lower. Second, they allocate that stake over the

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12 The more basic question is whether individuals display a consistent “trait” that can be captured in an index of risk aversion or risk seeking. Psychologists have found that most such traits are highly context specific, and risk taking is no exception. As Paul Slovic (1972, p. 795) has commented: “Although knowledge of the dynamics of risk taking is still limited, there is one important aspect that has been fairly well researched—that dealing with the stability of a person’s characteristic risk-taking preferences as he moves from situation to situation. Typically, a subject is tested in a variety of risk-taking tasks involving problem solving, athletic, social, vocational, and pure gambling situations. The results of close to a dozen such studies indicate little correlation, from one setting to another, in a person’s preferred level of risk taking.”
course of the betting day, intending to bet on nearly every race, unless they run out of money before the day ends. Third, groups of friends that attend the track together rarely bet among themselves, although they could thereby guarantee a zero sum game for the group and increase variance as much as they wanted. Are these facts consistent with maximization of a convex utility of wealth function?

Another fact that is difficult to explain within this framework is the tendency (first pointed out by McGlothlin, 1956) for the favorite-longshot bias to become more pronounced for the last couple of races of the day. Most observers (McGlothlin, 1956; Kahneman and Tversky, 1979; Asch and Quandt, 1986) seem to agree on the cause. Bettors on average are losing toward the end of the day. They would like to go home a winner, but do not want to risk losing much more money. Therefore, they bet on longshots in an attempt to break even for the day. Notice that this behavior is hard to explain within a Friedman-Savage framework. Why should a reduction in wealth increase the tendency for risk seeking?

We feel that a more promising way of modeling race track betting (and other gambling behavior) is to introduce the concept of mental accounting (Kahneman and Tversky, 1984; Thaler, 1985). The key assumption of mental accounting is that people adopt mental accounts and act as if the money in these accounts is not fungible. To get the feel of mental accounting, consider another thought experiment. A set of identical twins Art and Bart (with identical wealth levels) is at the race track, contemplating their bets for the last race of the day. Art has lost $100 betting so far, though he has another $100 in cash with him. Bart is even in the betting so far, but between races he read the financial page in the newspaper and discovered that a stock in which he holds 100 shares went down one point the previous day.

Notice that both twins have lost $100, and thus any wealth-based explanation of their betting behavior must predict that they will make similar bets. However, in a mental accounting formulation, Art is behind in the race track account while Bart is even; thus they might well bet differently. (See Thaler and Johnson (1986) for evidence consistent with this view.) Once the concept of mental accounting is introduced, then it becomes much easier to understand how an individual can be risk neutral or risk seeking at the racetrack but risk averse with respect to retirement savings.

As for the favorite-longshot bias, many behavioral factors are probably at work for different reasons. (1) Bettors might overestimate the chances that the long shots will win. (2) As in Kahneman and Tversky's (1979) prospect theory, bettors might overweight the small probability of winning in calculating the utility of the bet. (3) Bettors may derive utility simply from holding a ticket on a longshot. After all, $2 is a cheap thrill. (4) It is more fun to pick a long shot to win than a favorite. It is hard to claim much credit for predicting that a 1-5 favorite will win (much less place or show), but if a 20-1 longshot comes through, considerable bragging rights will have been earned. (5) Some bettors may choose horses for essentially irrational reasons, like the horse's name. Since there is no possibility of short sales, such bettors can drive the odds down on the worst horses, with the "smart money" simply taking the better bets on the favorites.
The fact that the place and show pools seem to be less efficient than the win pool is also an interesting observation. One important factor may simply be that these bets are more complicated. For example, the payoff to a bet to show depends not only on the chance the horse will be in the money, but also on which other horses are in the money and how much has been bet on each. (The greater is the share of the money that has been bet on the horses finishing in the top three positions, the smaller is the payoff.) Bettors might prefer simple bets to complicated bets, or they might simply have difficulty determining when an attractive bet occurs in place and show pools.

One important conclusion we draw from this analysis is that modeling gambling behavior is complicated. Bettors' behavior seems to depend on numerous factors such as how they have done in earlier races, and which bets will yield the best stories after the fact. We should emphasize that these complications apply with equal force to investment behavior. As Merton Miller has said (1986, S467), "[to many individual investors] stocks are usually more than just the abstract 'bundle of returns' of our economic model. Behind each holding may be a story of family business, family quarrels, legacies received, divorce settlements, and a host of other considerations almost totally irrelevant to our theories of portfolio selection. That we abstract from these stories in building our models is not because the stories are uninteresting but because they may be too interesting and thereby distract us from the pervasive market forces that should be our principal concern." While we sympathize with Miller's self-control problem—we also find the stories irresistibly interesting—we feel that to understand the market forces one must enrich the models to incorporate more than the "bundle of returns." Even professional portfolio managers seem more concerned with beating the S & P index than with maximizing returns. In fact, we suspect that portfolio managers trailing the market in the 4th quarter may behave much like the racetrack bettors who bet on longshots when behind at the end of the day.

Lotteries

What can economic theory say about lotteries? Given the dreadful payout rates, one prediction might be that no one will purchase lottery tickets. However, it is easy to rationalize the purchase of a lottery ticket by saying that for a dollar purchase, the customer is paying 50 cents for a fantasy. That's a pretty good deal. The existence of popular and unpopular numbers is more difficult to rationalize. It seems that economic theory yields the following paradoxical prediction: No one will choose the most popular numbers.

To understand this phenomenon it is useful to point out that lotteries in North America did not become popular until New Jersey introduced a game which allowed players to choose their own numbers. The popularity of this feature seems to be explained by what psychologist Ellen Langer (1975) has called "the illusion of control." Even in purely chance games, players feel they have a better chance to win if they can control their own fate, rather than have it determined by purely "chance" factors. For example, Langer found that subjects in her experiments were more

\[13\] For a similar example in the finance literature, see Elton, Gruber, and Rentzler (1982).
reluctant (charged a higher price) to give up a lottery ticket they had selected themselves, than one selected at random for them.

A news story provides a vivid example of the illusion of control (and the confusion of skill and chance). One year, the winner of the Christmas drawing for the Spanish National Lottery, the “El Gordo,” was interviewed on television. He was asked: “How did you do it? How did you know which ticket to buy?” Our winner replied that he had searched for a vendor who could sell him a ticket ending in 48. “Why 48?” he was asked. “Well, I dreamed of the number seven for seven nights in a row, and since seven times seven is 48…”

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14 This example is cited in a forthcoming book on decision making by Jay Russo and Paul Schoemaker. We are grateful they shared it with us.


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