PLAYER INJURIES AND PRICE RESPONSES IN THE POINT SPREAD WAGERING MARKET

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Abstract

This paper studies the response of point spreads to a readily observed event: the absence of a key player due to injury. The analysis is thus similar to an event study, with the added feature that the mean price response is compared with the mean effect of the injuries on actual outcomes (game scores). The analysis in this paper can thus be viewed as a test of event study methods using a market where the simplicity of the financial contract makes such a test feasible. Yet, though the contract is simple, the injuries themselves create problems, since many of them are partially anticipated events. In the case of basketball injuries, an empirical model of the probability of player participation can be estimated and used in conjunction with a model of efficient pricing to interpret the relation between point spreads and scores. The pricing model yields numerous implications that are consistent with the data. Hence, the good news is that the relation between point spreads and scores during injury events is consistent with efficient pricing. The exercise tests and lends credence to the importance of partial anticipation as an important factor in interpreting abnormal returns when the ex ante probability of an event differs substantially from zero.

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1. Introduction

This paper studies the point spread wagering market for professional basketball games. Its primary concern is the wagering market's response to a series of events: injuries to star basketball players. In colloquial terms, the paper seeks to determine if the absence of a Larry Bird or a Magic Johnson (perennial stars in this sample) is efficiently priced. Injuries were chosen for this study because the absence of a key player is arguably the single most important factor affecting game scores, and thus prices in this market.

Contracts in the point spread betting market are quite simple, in that the value of a wager is determined once and for all by the outcome of a single game. This contrasts with the value of most financial assets, which are affected by a continuum of events and anticipations at multiple horizons. The relative simplicity of wagering markets enables a sharper focus on the relation between events, market prices, and outcomes. For the most part however, the literature on wagering markets has failed to exploit this possibility. There are many papers which evaluate the profitability of various betting rules, or that test for statistical biases in reduced form regressions, but few papers focus directly on the relation between events, prices, and outcomes.

The analysis of injury events in the wagering market enables us to address an important question: do changes in market prices precipitated by events accurately reflect changes in the distribution of outcomes? Event studies generally presume that the answer is yes: abnormal returns measured therein are used to draw inferences about the consequences of changes in regulation, corporate governance, and other factors. These studies are valuable precisely because direct measurement of the event's impact on earnings is difficult. But the difficulty of measurement also makes it difficult to directly test the event study method itself.

This paper uses a point spread pricing model to provide such a test based on injury events to star basketball players. A sample of 700 games missed by star players over a six year period provides an opportunity to confront this model with a sequence of repeated events. We can therefore carefully evaluate the performance of the point spread market as an mechanism which puts a price on the event of interest. In fact, the paper shows that point spreads are biased predictors of game scores during injury events. The question then becomes whether this bias reflects inefficient pricing, or alternatively, a combination of the event-generating process and the empirical approach employed by the event study method.

The definition of an injury event is guided by the central question of this study, namely, is the absence of a star basketball player efficiently priced in the point spread betting market? Hence, an injury event consists of a game missed by a star player. Although this appears to be a natural definition, it creates problems since many games missed due to injury are neither surprises nor perfectly anticipated. Partial anticipation of player absences can create bias in point spread forecast errors, much in the way that estimates of value changes due to takeover activities contain a negative bias due to sample selection and partial anticipation (Malatesta and Thompson, (1985) and Bhagat and Jefferis, (1991)).

A unique feature of this study is the means by which the bias problem is resolved. By studying the nature of injury spells to basketball players, we learn how to form a sub-sample free of selection bias. In addition, knowledge of the injury process can be incorporated into a simple pricing model. The model implies that biases in the primary sample will vary in predictable ways as an injury spell progresses. Finally, the pricing model can be used to extract the market's estimate of the participation probability of an injured player. This estimate is quite close to the estimate obtained from a duration analysis of the injuries.

In each case, we find that the point spread response to injury events is consistent with efficient pricing. Hence, the primary question addressed in the paper is answered in the affirmative: price changes accurately reflect changes in the distribution of outcomes. Yet proper interpretation of these price changes required detailed knowledge of the event generating process. Without such knowledge, interpretations of event study returns can be misleading, as Malatesta and Thompson (1985) and Bhagat and Jefferis (1991) have argued.

The analysis begins with a brief description of the wagering market and the data. Section 3 documents the essential facts on the nature injury spells. These are used to construct a model of efficient point spreads in Section 4. Section 5 describes an estimation procedure which enhances our ability to test the model, and subsequently conducts the tests.

2. The Point-Spread Market for Professional Basketball Games

2.1 Efficient Point Spreads

A point spread wager is defined by the following example. Suppose the Hawks are favored by 5 points over the Bulls. Let PS = 5 represent this 5 point spread, and define DP as the actual score difference; that is, points scored by the Hawks less points scored by the Bulls. A point spread wager is a bet on the sign of (DP - PS). Bets on the Hawks pay off only if DP - PS > 0, i.e. if the Hawks outscore the Bulls by more than the 5 point spread. Bets on the Hawks lose if DP - PS < 0. Bets on the Bulls pay off / lose in the opposite circumstances and bets on both teams are refunded if DP - PS = 0.

Winning bets pay off at odds of 1 to (1 + t), where t can be thought of as a transactions cost which covers the bookmaker's costs of operation. A winning wager of $1 therefore returns $(1 + 1/(1+t)). Standard terms in the Las Vegas market set t at 10 cents on the dollar.

Consider a strategy that places bets on a chosen team under a specific set of conditions. Without loss of generality, define the DP and PS ordering by subtracting the opponent's points from the points scored by the chosen team. The probability that a bet is a winner is p = [prob(DP - PS) > 0]. In addition, the probability that the bet is a loser is p' = [prob(DP - PS) < 0], and the probability of the bet being refunded is p_0 = [prob(DP - PS) = 0] = 1 - p - p'.

Efficient point spreads deny the existence of a profit opportunity to any strategy. Specifically, the expected return to a $1 wager must be non-positive:

(1) $$p(1 + 1/(1+t)) - (1 - p_0) <= 0.$$

A similar requirement holds for p', which is the probability that the opposing team beats the spread. Combining these yields bounds for the probability of a winning wager:

(2) $$(.5 - p_0/2) / (1 + t/2) <= p <= (.5 - p_0/2)(1 + t) / (1 + t/2).$$

This result is simplified if the commission is assumed to be zero. Then $p = .5 - p_0/2$. Since the probabilities sum to 1, p = p'. Hence, [prob(DP - PS) > 0] = [prob(DP - PS) < 0], which is satisfied only if PS is the median of the distribution of DP.

Provided that the ex ante distribution of DP is symmetric, then PS = E(DP) is also implied, and the point spread can be said to be an unbiased forecast of the score difference of the game. The ex post distribution of the forecast errors (DP - PS) will then be symmetric with a mean of zero. Hence the null hypothesis implied by efficient point spreads under these conditions is that the mean forecast error is zero:

(3) $$H^0: \text{MFE(PS)} = 0$$

which is a standard test that is often performed in point spread studies.[1]

These restrictions on efficient point spreads are weakened when non-zero transactions costs are recognized. Assuming that $p_0 = 0$ for convenience and setting t = .10, p is bounded by p å (.4762,. 5238), which restricts PS to being within a precise distance of the median of DP.[2] Inspection of (2), above, indicates that the distance from the median allowed by the no profit opportunity condition shrinks to zero as t approaches zero.

In sum, an efficient point spread is the median of the distribution of score differences in the absence of transactions costs. For symmetric distributions, (3) is implied, and efficient point spreads are the optimal forecast of the score difference. Given symmetry and positive transactions costs, failure to reject (3) is consistent with efficient pricing of point spreads.[3]

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[1] The symmetry condition is rarely examined however, and in some cases this is critical (baseball over/under wagers are an example). If the ex ante distribution is not symmetric, then the distribution of the forecast errors will be skewed. In this case the mean forecast error will not be zero even when PS = median (DP), and hence a test of (3) is inappropriate.

[2] Tryfos et al (1984) were the first to systematically examine this bound.

[3] Rejection of (3) would motivate consideration of transactions costs. For example, the simple betting rules proposed in Vergin and Scriabin (1978) are re-evaluated by Tryfos et al. (1984), who use statistical tests which explicitly recognize the transaction costs. The conclusion that these rules are profitable is overturned by these tests.

2.2 Point Spreads and Scores: The Data

The data are based on a sample of 5636 games played over six consecutive seasons beginning in 1982. The point spreads are those prevailing in the Las Vegas Market at 5PM Eastern time on the day the game is played.[4] Define DP_{tij} as the difference in the score of a game at t, and PS_{tij} as the point spread's prediction of this differential, where the ordering is obtained by subtracting the visiting team's (team j) points from the home team's (i) points.[5]

Figures 1a-1c depict the distributions of the point differences, spreads, and forecast errors. A glance at the distributions show no obvious asymmetry; and the data pass formal tests of the hypothesis that the distributions are symmetric.[6] Since the symmetry property is accepted, tests based on expected values can be used to test the proposition that point spreads are efficient forecasts of the difference in scores of NBA games.

Alternative ways of defining the score difference ordering exists. Indeed. the hom-visitor ordering is a simple transformation of the ordering displayed in daily newspapers, in which the point difference is defined by subtraction of the points scored by the underdog from those of the favorite. A recent series of papers considers the implications of the score difference ordering (Golec and Tamarkin,

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[4] The point spread data are from Bob Livingston's <u>The Basketball Scoreboard Book</u>. There were 943 games played in each of the six seasons. Point spreads were not offered for some games. The scores were obtained from the <u>Sporting News Official NBA Guide</u>.

[5] Henceforth subscripts are dropped except where needed.

[6] The skewness coefficients $m_3/m^{3/2}_2$ are .02 (.05) and .10 (.05) for the point difference and forecast error distributions, respectively (m_3 and m_2 are the 3rd and 2nd moments of the distribution, with standard errors of the coefficients in parentheses). This coefficient is zero for a normal distribution, which is the usual standard of comparision.

1991 and Dare and McDonald, 1996, and Sauer, 1998) for simple tests of efficient pricing. In light of this discussion we examine these tests under all partitions of the favorite-underdog/home-visitor partitions of the sample.

Table 1.A examines the median condition for each sub-sample. The right-most column in the Table lists the proportion of winning bets realized by a strategy of betting on the team listed first in the score difference. Betting on the home team yields a winning percentage of 50.6% over the six year period, whereas betting on the favorite wins 50.3% of the time. Only in the case of pick 'em games in which betting on the home team wins just 47.7% of bets, is the proportion near the efficient bound (.4762, .5238), hence this simple test is consistent with efficient pricing (test statistics are not applicable since the proportions are inside the bound).

Table 1.B presents the sample means and standard deviations for the point differential (DP), point spread (PS), and the forecast error (DP - PS) under each ordering. The right-most column lists the t-statistic for testing the hypothesis the point spread is an unbiased forecast; i.e. H^0: E(DP - PS) = 0. In the case of home underdogs, it appears that the point spread is biased as the mean of DP - PS = .96 (t=2.91). Betting on home underdogs is not profitable however, as seen in Table 1.A (wins/bets = .508). Hence, one infers that this latter result is a violation of the symmetry condition for this sub-sample and not a rejection of efficiency.

3. Point Spreads and Injury Spells: The Data

3.1 The Sample of Injury Games

We now examine the forecast errors of point spreads when important players are unable to participate in a contest. A sample of star players was compiled for each of the six seasons by reference to the previous year's performance standings in the Official NBA Guide. The top twenty leading scorers and rebounders were recorded, as were members of the All-Star team. The games missed by these players in the subsequent year constitute the sample of injury games for analysis. This procedure creates a sample of 273 injury spells encompassing 700 missed games.[7]

3.2 Bias In the Forecasts

For this analysis, the score ordering is defined by subtracting the opponent's points from the points of the team with the injured player. The forecast error then, is the observed score differential for the game less the point spread (similarly defined). The mean forecast error of the spread for the 700 game sample is -1.28 points (t=2.87). Point spreads for injury games therefore contain significant bias. Teams with injured players do worse, by more than a point on average, than predicted by the point spread. As far as previously documented biases in point spreads go, this is quite large.

There are two possible explanations for this bias. A conjecture motivated by the behavioral

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[7] In one case the player checked in to a drug rehabilitation clinic and missed several games. Although this is not an injury in a precisely defined sense, these games were retained in the injury game sample for the purposes of simplicity of definition. If a game is missed, it is assumed to be an injury game. Differences in injury severity and so on are not commonly divided by bright lines, so we adopt a simple definition here as well.

school might go as follows. Bookmakers trade mostly with a relatively uninformed, unsophisticated clientele (since on average the clientele must lose). These bettors are not up to date on the status of injured players, so bookmakers do not fully adjust prices for injury games. Had one known that the player was destined to miss the game, betting against the team with the injured player would represent a profit opportunity.

An alternative hypothesis is that the bias stems from (rational) partial anticipation of the player's absence from the game. If there is some chance ex ante that the player might participate in the game, the mean forecast error of -1.28 points is affected by selection bias even if the point spread is efficient. The following example illustrates the point. Suppose there is a 50% chance (ex ante) that the player will miss the game. With the player, team i is expected to win by 4 points; without him, by 2 points. If so, the efficient point spread would be 3 points. On average then, his team wins by 2 points when he misses the game, but the spread is 3, which delivers the bias.

There are thus two competing explanations for the point spread bias. The remainder of the paper explores implications of the partial anticipation explanation, in which profit opportunities are absent. We begin by studying the injuries themselves.

3.3 Injury Spells in the NBA

When the casual sports fan thinks of injured athletes, famous cases of incapacitating injuries, such as a broken leg (Tim Krumrie in the 1989 Super Bowl, Joe Theisman on Monday Night Football) or broken ankle (Michael Jordan in 1985) come to mind immediately. Yet these are relatively infrequent occurrences. Far more common are the nagging injuries such as muscle pulls and ligament sprains which could either heal or deteriorate between contests. Professional athletes continually play with taped ankles and thighs, knee braces, finger splints, wrist casts, flak jackets, etc. Indeed, many games at the professional level are contested by the "walking wounded."[8]

This is relevant to the analysis because it is nagging injuries which cause uncertainty over participation. This uncertainty exists not only for the general public, but also for team trainers and the players themselves. Indeed the classic injury situation occurs when the team announces that a player is on a "day-to-day basis." It is not uncommon for the player to announce that he is fit and ready to play, while team officials state otherwise. Whether or not an injured player will participate is often determined by his response during the pre-game warmup, only moments before the game begins.[9]

Table 2 tabulates information on injury spell durations for the full sample of 263 injuries. Most spells are short: 75.5% of those not yet censored last for 3 games or less.[10] For the first three games, the probability of returning in each subsequent game, i.e. the hazard, is in the .30-.40 range. For injuries that preclude participation for more than 3 games, the hazard is much lower, in the .10-.20 range.

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[8] There is ample evidence in newspaper reports to support this. One example is the sequence of hamstring injuries to World B. Free in 1985. Free is quoted in the Cleveland Plain Dealer of 11/21/85: "I had the left one for about two weeks but I didn't say anything. Then I had put too much pressure on the right one and hurt it.... Things like that happen ...."

[9] For example, consider the following remark of Clemson University's sports information director, referring to star running back Terry Allen: "It's the classic case of not knowing if he can play until he warms up (Greenville News, Oct. 21, 1989)." Allen suited up, but didn't play. He returned to the lineup later in the season.

[10] Censored spells are those terminated by the end of the season rather than a return to action.

The data on spell lengths suggest a fairly simple message: if a player hasn't missed many games, his chances of returning in the next game are fairly high. On the other hand, if he has missed more than a few games, his chances of returning in the next game are quite low. This suggests two broad classes of injuries. In the much larger class the player may return to the lineup at any time. We classify these as nagging injuries that require an uncertain amount of rest for recuperation. More serious injuries can be incapacitating, completely ruling out a quick return to action. These injuries comprise the second, less common class.

To take a closer look at nagging injuries, Table 2.B tabulates spell lengths and return probabilities for spells lasting 5 games or less. Almost half of these spells terminate after just 1 game. Of spells that continue, slightly more than half terminate after the second game; the hazard is a bit greater following the third. On the assumption that the hazard rate for this sub-sample is constant, its maximum likelihood estimate is 0.513, with a standard error of .032.[11] A rate of .50 would yield a cumulative return rate of 75% by the second game, 87.5% by the 3rd, and 93.75% by the 4th. These are quite close to the actual return rates of 76.9%, 92.0%, and 95.0%.[12] Hence, for nagging injuries

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[11] The technique is described in Kiefer (1988), esp. pp. 662-3. Since the sample used was defined by excluding spells of six games or longer, this estimate is biased upward. This exclusion is the only practical means of separating incapacitating from nagging injuries. The bias induced is very slight however, since only .0312 of the sample would be expected to incur spells of six games or more if the return probability were indeed 0.5. As a means of evaluating the bias, an estimate of the hazard was calculated by treating all 5 game spells (there are only 8 such games in the 219 game sample) as censored at four games, i.e. as being of length >= 4 games rather than 5. The estimate obtained is .505 (std error=.036), virtually the same as that reported in the text.

[12] In contrast, the return rates implied by p=.4 {.64, .784, .870} are consistently below that observed. The rates given by p=.6 {.84, .914, .956} are slightly above that observed for the 2nd game, but close to the mark for the 3rd and 4th games.

(spells of short duration), we assume the probability of returning in the n+1st game, having missed n games thus far, is about 0.5.

4. Participation Uncertainty and Efficient Point Spreads Surrounding Injury Spells

Explaining the ex post bias by appealing to participation uncertainty is straightforward. Testing this explanation yields insight into its credence, and can be achieved by imposing a simple probability structure on the injury process. This structure differs according to whether the injury is nagging (yielding a short spell) or incapacitating (yielding a long spell). We begin with the case of nagging injuries.

Assume that participation in games reveals information about the soundness of a player. Playing informs the market that the player is relatively sound, whereas not playing informs the market that the player is currently unsound. For simplicity, we assume that the participation probability, given that the player participated in the previous game, is 1.[13] Based on the evidence in Section II, we assume that the probability of playing conditional on having missed the previous game is 0.5.

These assumptions apply to nagging injuries; the onset of these spells is unexpected, and there is a positive probability of terminating the spell in each subsequent game. In contrast, incapacitating injuries are likely to be observable (a broken leg for example). Thus, the onset of long spells will be anticipated, and expected to continue for some time. Hence for long spells we assume that the participation probability is 0.

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[13] This is obviously untrue, but is a convenient way of imposing the condition that this probability is the same for players on both teams. Nagging injuries are a factor on both sides of the score.

The following notation is used to develop the model's implications.

p = probability (ex ante) that the player participates

DP = DP_{tij}; the difference in points scored on date t between teams i and j, where the ordering defines team i as having the injured player

PS = PS_{tij}; the market point spread with the ordering defined as for DP

PSPLAY = PS|play; the point spread conditional on the player participating (p=1)

PSNOT = PS|not play; PS conditional on p=0

In an efficient market, PSPLAY = E(DP|play), and PSNOT = E(DP|not play). The efficient unconditional point spread for injury games, PS^*, is thus given by:

$$PS^* = p\ PSPLAY + (1-p)PSNOT. \qquad (1)$$

A construction which will be important in testing some of the propositions that follow is the estimated "change" in the point spread. This is defined as the difference between the market point spread, and the point spread that would be in effect assuming the injured player were to participate. This defines

$$DIFF = PS - PSPLAY. \quad (2)$$

We now use the model to describe the evolution of the point spread bias as an injury spell progresses. p = 1 for the first game of short spells. Thus, the player's initial absence is a surprise, which leads to the first proposition.

Proposition 1: For the first game of short spells, PS^* = PSPLAY, and therefore DIFF = 0.

Given that the player does not participate in games during the spell, the expected outcome is E(DP|not play) = PSNOT. Since the efficient point spread incorporates a non-zero probability of participation, it is a biased forecast (ex post), which is proposition 2.

Proposition 2: The forecast errors of an efficient point spread are biased for games missed during short injury spells.

This can be tested by calculating MFE(PS), which is predicted to be the difference between the expected outcome and the point spread. Thus, $MFE(PS) = PSNOT - PS^* = p[PSNOT - PSPLAY] < 0$.

This proposition explains the point spread bias which we have already documented, provided that p is non-zero. We can be more precise however. The value of the player to the team is measured by the loss in output due to his absence. This defines

$$\text{LOSS} = E(\text{DP}|\text{not}) - E(\text{DP}|\text{play}) = \text{PSNOT} - \text{PSPLAY}$$

in an efficient market. Our study of injury durations indicated that $\text{prob}(\text{play}_t|\text{not}_{t-1}) = 0.5$. Hence we can sharpen this proposition for games 2-n of an injury spell.

Proposition 3: In games 2-n of an injury spell, the point spread adjustment (DIFF) will equal half the value of the injured player.

Hence the mean forecast error will be 50% of the value of the player: $\text{MFE(PS)} = .5 \cdot \text{LOSS}$. Obtaining a measure of LOSS along with MFE(PS) allows us to infer the market's estimate of p.

The analysis used above is symmetric in the sense that it applies not only during the injury spell, but in the game when the player returns to the lineup. Thus, when the player returns to the lineup, the bias is reversed, since the expected outcome given participation is PSPLAY, and $p < 1$.

Proposition 4: The bias for the return game is $\text{PSPLAY} - \text{PS}^* = (1-p)[\text{PSPLAY} - \text{PSNOT}] > 0$.

If $p = 0.5$ and constant throughout the spell, the return game bias is simply the mirror image of the injury game bias. We also predict that $\text{DIFF} < 0$, as above.

Once a player returns to the lineup after a short spell, p subsequently returns to 1.0. We thus have

Proposition 5: After the initial return game, PS^* = PSPLAY. Hence, we expect DIFF = 0, and the absence of forecast bias.

Long spells involve more serious injuries. By distinguishing long from short spells, we develop two additional propositions. These stem from the assumption that the injury produces no uncertainty regarding the player's status (p = 0).

Proposition 6: For long spells, PS^* = PSNOT, and thus DIFF = PSNOT - PSPLAY = LOSS.

Since p = 0, the expected forecast error is E(DP|not play) - PSNOT = 0. Efficient point spreads thus display no ex post bias for long spells.

Recall the assumption that incapacitating injuries are observed by the market when they happen. Hence, p = 0 for the first game.

Proposition 7: For the first game of long spells, PS^* = PSNOT.

Thus, DIFF = LOSS, and PS^* is unbiased. This proposition stands in contrast to its counterpart for short spells.

The model in this section provides us with an array of predictions about the behavior of point spreads during injury spells. Not only does it imply the ex post bias, it predicts the magnitude of the bias, and differences in the bias over the duration of the spell and across different types of injuries. Testing some, though not all, of these predictions requires knowledge of E(DP|play), or PSPLAY in an efficient market. Since wagering opportunities on NBA games are normally offered only on the day of the game, PSPLAY is not observed in situations where injuries are involved. It turns out however, that a simple statistical technique provides very accurate estimates of PSPLAY, enabling tests of all 7 propositions.

5. Empirical Analysis of the Nagging Injury Hypothesis

The propositions are tested in section 5.3. Section 5.1 presents the basis for estimating PSPLAY, and section 5.2 examines its statistical properties. This analysis shows that PSPLAY can be estimated with considerable precision.

5.1 A Method for Estimating PSPLAY

The method we use is like that of an event study, which requires an estimate of the expected return in order to compute an abnormal return. The former can be calculated using regression estimates of the parameters in the market model. Brown and Warner (1985) have studied the statistical properties of this method, and conclude that its estimates of abnormal returns are reasonably precise, with desirable statistical properties. This is so despite the fact that the market model is a very poor conditional predictor of stock returns. *In sample*, the average R^2 of Brown and Warner's market model regressions was .10.

We can do much better with point spreads *out of sample*. The technique we use is motivated by the following. Suppose that the outcome of a game -- the difference in score -- is determined by luck, the home court advantage, the relative ability of the two teams, and idiosyncratic factors. Then score differences can be thought of as being generated by the following:

$$DP = g(c_{i,} S_i, -S_j, e, w). \qquad (3)$$

S_i and S_j are measures of the ability of teams i and j at full strength, c_i is the home court advantage of team i, and e and w are random components. Each variable is assumed to be calibrated in terms of points (scoring). We assume that w is "luck" that cannot be anticipated, whereas e includes idiosyncratic factors (matchup problems, length of road trip, injured players, etc) that may be known. It is assumed that e and w are uncorrelated with the teams' abilities. Based on section I, we assume that PS = E(DP), and further, that g is a simple additive function. Thus

$$PS = c_i + S_i - S_j + e \qquad (4)$$

Recall that the object of this exercise is to obtain an estimate of PSPLAY, the point spread that would be observed if the injured player was expected to play. Since S_i and S_j are team abilities at full strength, PSPLAY can be constructed if they, along with c_i, are known. We estimate them using the following regression:

$$PS_{tij} = S_{hi}\, d_{hi} - S_{vj}\, d_{vj} + B\, I_{tij} + e'. \qquad (5)$$

The estimation procedure uses the 20 games for each team played prior to each injury spell.[14] d_i is a dummy variable which takes on the value of 1 when team i is the home team, and d_j is 1 when team j is the visitor. S_{hi} and S_{vj} are the coefficients of the team dummies, and are interpreted as the ability indexes. Since S_{hi} and S_{vi} differ, this specification embeds a team specific home court advantage (c_i) in the model. I_{tij} is the difference in the number of injured players. Since we have this data, it is included in the regression to keep the estimates of S_{hi} and S_{vj} free of omitted variable bias, which would otherwise occur if point spreads in the estimation period were affected by the absence of an injured player. e' is the idiosyncratic error term which remains after account is taken of observable injuries. Out of sample estimates of PSPLAY can be obtained by subtracting the visiting strength of team j from the home strength of team i:

$$PSPLAY = S_{hi} - S_{vj}.$$

5.2 The Accuracy of PSPLAY

Before using PSPLAY, we check the model's ability to predict point spreads -- for non-injury games -- out of sample. There are three criteria:

(1) What percentage of the variation in point spreads is explained by out of sample predictions from the model?

[14] Diagnostic checks indicated that 10 game samples yielded accurate estimates as well. Hence, for injury spells commencing in the 11th through 20th game of each season, the maximum available number of pre-injury games was used. Summary statistics for regressions using samples of the first 10 and 20 games of the 1982 season are presented in Appendix A.

(2) What are the characteristics of the distribution of the forecast errors PS-PSPLAY?

(3) Is there a discernable difference between the ability of actual and estimated point spreads to predict game outcomes?

For each of the six seasons, the model was successively re-estimated using samples including the most recent 20 games for each team. Out-of-sample forecasts (PSPLAY) were then generated for the next 5 games. This procedure yielded 3567 predicted point spreads for non-injury games over the six year period.

The variance of actual point spreads for these games is 31.4 points. The residual variance of the forecast error, PS-PSPLAY, is 4.2. Hence, *out of sample*, the model explains more than 85% of the variation in point spreads. This is almost an order of magnitude greater than what market models used in event studies achieve *in sample*.

The distribution of the forecast errors PS-PSPLAY, is depicted in Panel A of Figure 2. The mean of the distribution is -0.003, with standard deviation of 2.06. Less than a quarter of the forecast errors are more than 2 points away from zero. The distribution is thus concentrated on a narrow interval around zero, as it must be if we are to use the model to predict what point spreads would be in the absence of an injury. In contrast, observe the distribution of PS-PSPLAY for games which players miss due to injury, in Panel B of Figure 2. This distribution is clearly shifted to the left of its non-injury counterpart. Evidently, the method is precise enough to portray changes in the point spread due to observable factors such as injuries.

Returning to non-injury games, since the actual and predicted point spreads are very close to each other, it therefore follows that their ability to forecast game outcomes is similar. Indeed, for each of the six years, the mean forecast errors of PS and PSPLAY (and their variance) are virtually identical. PSPLAY is thus an accurate and unbiased predictor of point spreads. We can therefore employ it in tests of the injury bias model.

5.3 Empirical Tests of the Partial Anticipation Hypothesis

The model of section 4 implies differences in point spread bias depending on whether the spell was long or short, and whether the game is the first game of the spell, in the middle of the spell, or upon the player's return to the lineup. In order to make a sharp distinction, long spells are defined as those lasting 10 or more games, and short spells as those lasting five games or less.

Table 3 presents summary statistics on the forecast errors by game. Panel A lists the results for short spells, and panel B for long spells. In addition, Panel C tabulates results for the five game sequence (for all spells) beginning with the game when the player returns. Column 1 provides the mean forecast error of the actual point spread (PS), which is used to examine the market's ex post bias. The loss to the team due to the absence of the injured player is LOSS = E(DP) - PSPLAY. The mean forecast error of PSPLAY is thus our estimate of LOSS, which is tabulated in column 2. In Column 3 is DIFF, the difference between the actual spread and PSPLAY.

One can see immediately from inspection of panel B that for long spells, the hypothesis of no bias cannot be rejected. For short spells, the model predicts bias for games 2-N, and furthermore that .5@LOSS = MFE(PS). Indeed, MFE(PS) is negative, and is .56 LOSS, quite close to the predicted value. Hence, the ex post bias in the point spread provides an estimate of the return probability (.56) which closely approximates the conditional return probability observed in the sample.

The model fares less well in its implications for the first game of the injury spells. The point spread response for short spells, measured by DIFF, is significantly lower for game 1 than in subsequent games, as expected. Yet the spread does drop by a point (t=6.08), indicating that the model omits information that is factored into point spreads. Note however that teams with injured players suffer a significantly lower LOSS (-2.06 vs -3.83 points) in game 1 than in subsequent games. This indicates that the surprise hypothesis has some merit, as the opposing team is unable to take complete advantage of the player's absence in the first game of the injury spell.[15]

When players return to the lineup, the forecast error of the first game is positive (0.73), but not significant (t=0.92), and DIFF remains significantly negative (-0.89, t=5.88). These results are in rough accord with proposition 4.[16] The forecast errors of the point spread thereafter are not statistically different from zero (MFE(PS) = -0.01, t = 0.01), as implied by proposition 5.

On three counts the model performs quite well. The point spread is unbiased for long injury spells, where the selection bias problem stemming from partial anticipation is not relevant. In the middle

[15] Teams attempt to keep certain injuries secret for exactly this reason. A recent example is the New York Giants' secrecy concerning an injury to quarterback Phil Simms' throwing hand, suffered in practice prior to an 1990 NFL playoff game. Advance knowledge can suggest successful strategies to the opponent.

[16] The magnitude of the bias (in absolute value) is less in the return game than during the spell, indicating that the return probability may increase with spell duration. The difference in bias can be traced to a decline in DIFF of 0.78 points (t=3.23) in the return game relative to games 2-N of the spell. Note that this decline is sharply reduced (to 0.40 points, t=1.37) if one compares the last game in a short spell to the return game. Recall also that the data on the actual injuries hint of an increasing hazard for nagging injuries, which seems reasonable.

of short injury spells, point spreads contain an estimate of a player's return to action that is quite close to that implied by a duration analysis of the injury spells. Finally, point spreads for games played after the player's return are unbiased. The model fares less well in the transition games surrounding the injury spells, most likely due to the stark probability structure that is assumed.

6. Conclusion

This paper began with what was expected to be a simple exercise: analyzing the response of market prices to a sample of repeated events. In the wagering market, this exercise encompasses not just events and price changes, but the outcomes themselves, enabling a comparison between price changes and outcomes that is generally infeasible with stock prices. Hence the findings of this exercise provide a small piece of evidence on the efficiency of price responses to changes in information that is difficult to replicate in other settings.

Point spreads are biased predictors of game scores during injury events, which is potential evidence of inefficient pricing in the wagering market. An alternative explanation is based on the idea that many injuries are partially anticipated. A pricing model which combines empirical features of player injuries with the selection method for determining injury games predicts variations in the ex post bias which are consistent with both the data and efficient pricing. The bottom line is that price responses in the wagering market contain efficient estimates of the value of an injured player.

Extracting this signal from a sample of injury games is, unfortunately, somewhat tricky. As with other events of interest in financial economics, one needs to develop knowledge specific to the class of the event being studied before interpreting the forecast error. This creates a problem. Explanations of apparently inefficient pricing for a class of events reduce to story-telling exercises unless the stories can be tested. Sorting through the relevant details that are potentially relevant to each class of event can take many papers and many years, as indicated by various takeover puzzles (Malatesta and Thompson, 1985, Bhagat and Jefferis, 1991).

In this paper we develop such a story using facts about injury durations in the NBA. A model that makes use of these facts has testable implications for the behavior of the ex post forecast bias across and within injury spells. These implications are easily tested, and are generally consistent with the data. Although this is good news for event studies -- price responses to injury events are efficient -- these results highlight the problems involved in obtaining accurate estimates of value from price changes when the ex ante probability of an event is not well known.

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Point Spreads and Score Differences in the NBA, 1982–1988

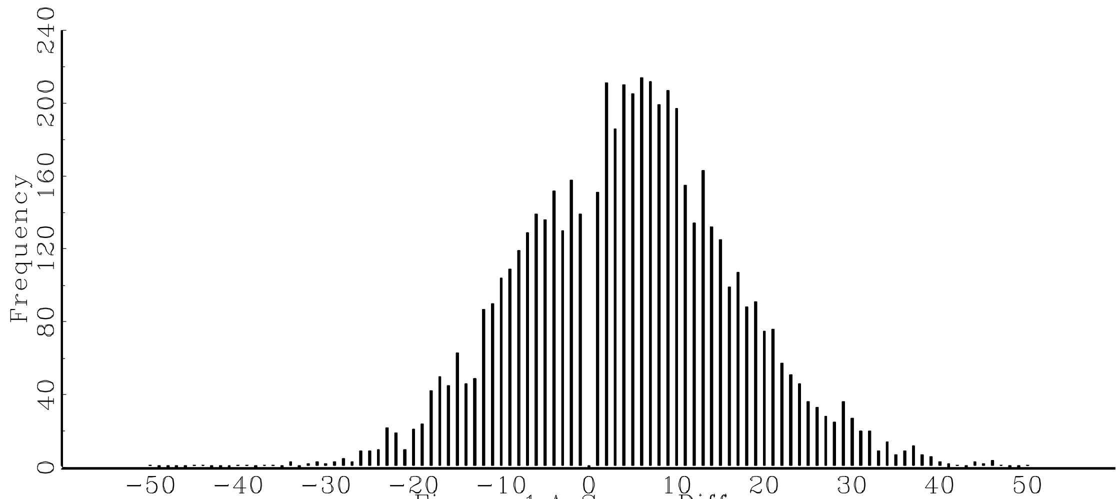

Figure 1.A Score Differences

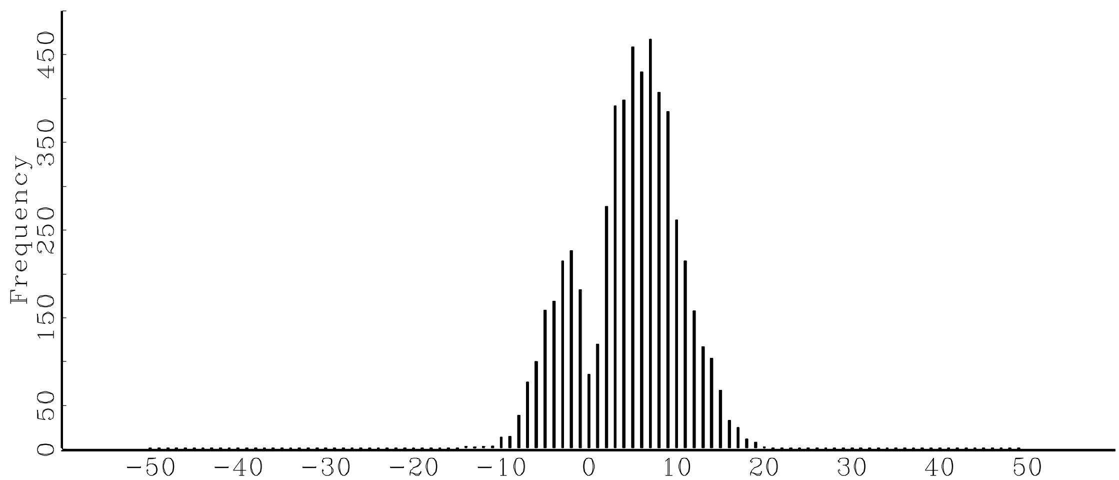

Figure 1.B Point Spreads

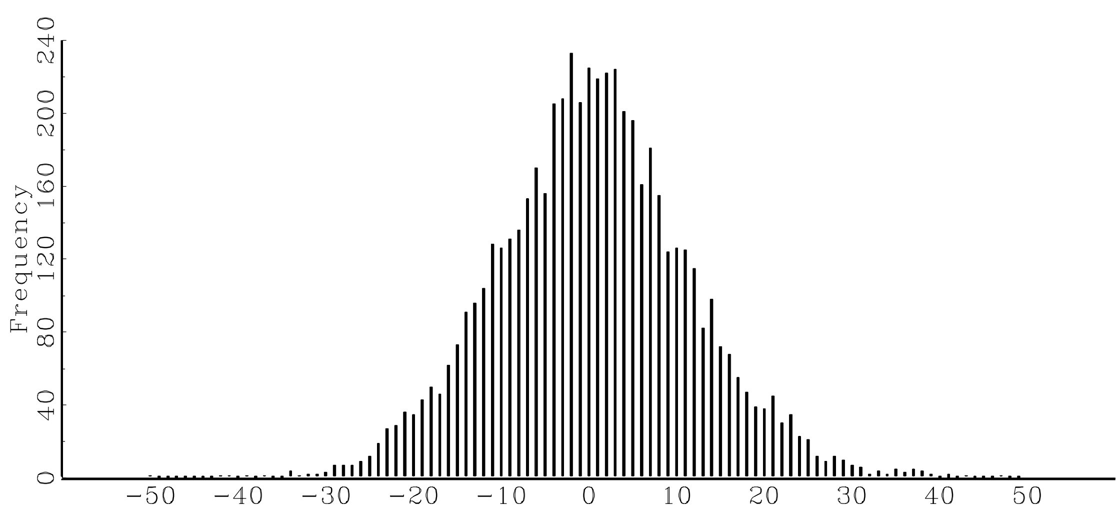

Figure 1.C Forecast Errors

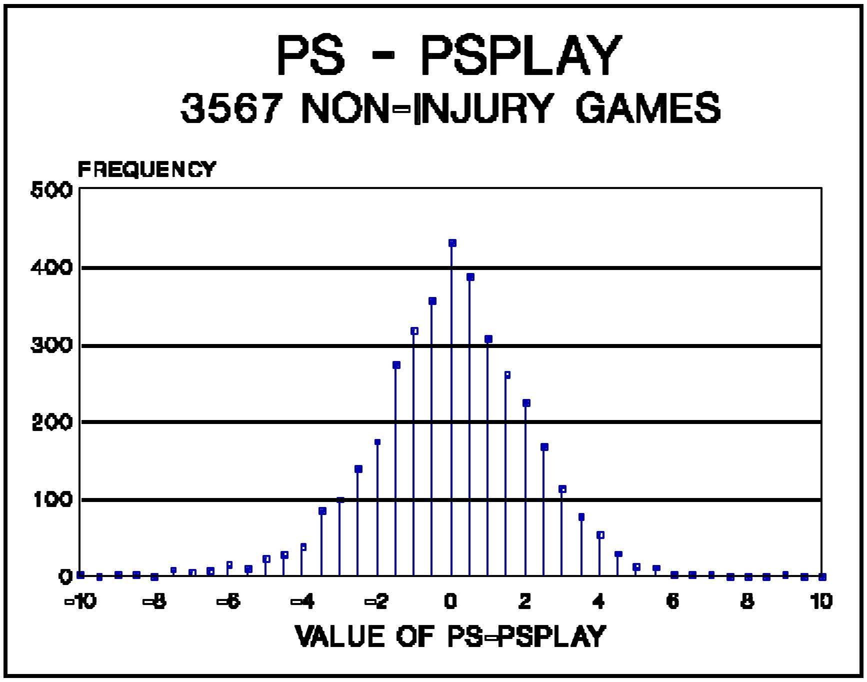

Figure 2.A

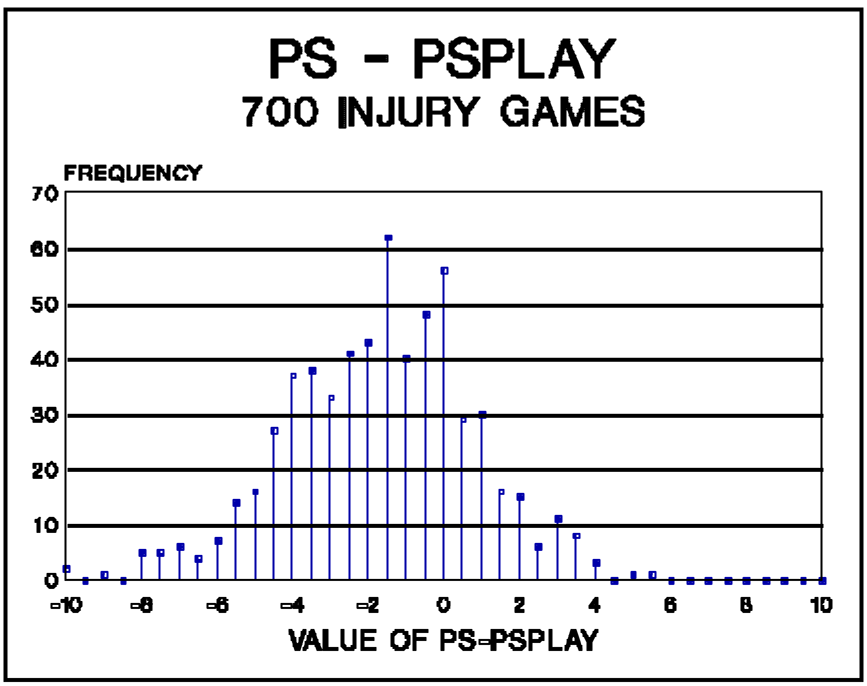

Figure 2.B

Notes to figures 2A and 2B: The horizontal axes of these distributions are the magnitude of the difference between the actual point spread and the predicted point spread of the statistical model. Figure 2A is constructed by using the statistical model (estimated on a 20 game sample) to forecast 5 games ahead, and sequentially updating for each of the six seasons. Figure 2B displays the distribution of the error in predicting point spreads when players are injured.

Table 1
Score Differences and Point Spreads for NBA Games

A. Sample Frequencies

Differencing Method/ Sample Partition	Games	Bets	Wins	Ties	Wins/Bets
A1. Home-Away					
All Games	5636	5510	2789	126	.506
Home Favorites	4341	4243	2148	98	.506
Home Underdogs	1209	1181	600	28	.508
Pick 'em Games	86	86	41	0	.477
A2. Favorite-Underdog	5550	5424	2729	126	.503

B. Sample Means and Standard Deviations

Differencing Method/ Sample Partition	DP	PS	DP-PS	t-stat
B1. Home-Away				
All Games	4.62 (12.42)	4.38 (5.59)	0.24 (11.15)	1.62
Home Favorites	6.87 (11.82)	6.81 (3.62)	0.06 (11.07)	0.37
Home Underdogs	-3.09 (11.74)	-4.05 (2.30)	0.96 (11.45)	2.91
Pick 'em games	-0.91 (10.58)	0.00 (0.00)	-0.91 (10.58)	-0.79
B2. Favorite-Underdog	6.05 (11.83)	6.21 (3.56)	-0.16 (11.16)	1.06

Notes to Table 1: (i) Sample Characteristics. The sample encompasses all regular season NBA games played in the six seasons from 1982-83 through 1987-88. Score differences were obtained from the annual edition of the *Sporting News NBA Guide*. Point spreads were obtained from *The Basketball Scoreboard Book*. These point spreads are those prevailing in the Las Vegas market about 2.5 hours prior to the start of play (5 PM Eastern time on a typical night). No point spread is reported for 22 games during this period, which reduces the sample from 5658 (all games played) to 5636 (all games with point spreads).

(ii) Panel A. This panel lists the number of games, bets (the number of games in which DP … PS, which are ties), and the number of bets won by wagering on the team in the first position of the score difference. Wins/Bets is the sample estimate of p, the proportion of such bets won. Since this proportion always lies inside the bounds given by (2), no test statistic is required to evaluate this implication of efficient pricing.

(iii) Panel B. Standard deviations are given in parentheses. The t-statistic tests the null hypothesis that the mean forecast error (DP - PS) is zero. Although the null is rejected in the case of home underdogs, the failure to reject efficient pricing in panel A for this partition indicates that the rejection in B is caused by a departure from the symmetry assumption.

Table 2.a

Injury Spell Durations and Hazard Rates

Spell Length	Frequency	Censored	At risk	Hazard	Cumulative return rate
1	105	16	263	.3992	.3992
2	51	2	142	.3592	.6316
3	29	0	89	.3258	.7551
4	6	2	60	.1000	.7796
5	7	1	52	.1346	.8148
6	8	1	44	.1818	.8512
7	6	1	35	.1714	.8797
8	5	0	28	.1786	.9042
9	5	0	23	.2174	.9250
10	0	1	18	.0000	.9250
11	4	1	17	.2353	.9456
12	1	0	12	.0833	.9538
13	1	0	11	.0909	.9580
14	1	0	10	.1000	.9622
15	1	1	9	.1111	.9664
16	1	0	7	.1429	.9747
17	1	0	6	.1667	.9789
18	1	0	5	.2000	.9831
19	0	0	5	.0000	.9831
20	0	0	5	.0000	.9831

TABLE 2.B

HAZARD RATES FOR NAGGING INJURIES

Spell Length	Frequency	Censored	At risk	Hazard	Cumulative return rate
1	105	16	219	.4795	.4795
2	51	2	98	.5204	.7685
3	29	0	45	.6444	.9204
4	6	2	16	.3750	.9502
5	7	1	8	.8750	.9950

Notes to Table 2: Frequency is the number of injury spells terminated after an absence of n games, where n is given in the spell length column. Censored observations are terminated by the end of the season rather than a return to action. Hence hazard is frequency/(at risk-censored); the cumulative return rate incorporates censored spells in a similar manner.

Table 3
Forecast Errors of Point Spreads by Game Missed

A. Injury Spells of 5 Games or less
(Absolute value of t-statistics in parentheses)

	MFE(PS)	DP-PSPLAY (LOSS)	PS-PSPLAY (DIFF)	N
Game 1	-1.03	-2.06	-1.03	185
	(1.18)	(2.35)	(6.08)	
Games 2-n	-2.16	-3.83	-1.67	145
	(2.25)	(3.91)	(9.38)	

B. Injury Spells of 10 or More Games

	MFE(PS)	DP-PSPLAY (LOSS)	PS-PSPLAY (DIFF)	N
Game 1	3.08	0.92	-2.15	14
	(1.39)	(0.43)	(3.22)	
Games 2-n	-0.56	-2.20	-1.64	193
	(0.70)	(2.66)	(9.53)	

C. Forecast Errors of Point Spreads upon Return
(All Injury Spells)

	MFE(PS)	DP-PSPLAY (LOSS)	PS-PSPLAY (DIFF)	N
Game 1	0.73	-0.16	-0.89	207
	(0.92)	(0.43)	(5.88)	
Games 2-5	-0.01	-0.17	-0.17	778
	(0.01)	(0.40)	(1.98)	

Notes to Table 5: This table calculates forecast errors according to the sequence of the games missed by the injured player. Game 1 is the first game of the injury spell for games missed, etc. Panel C tabulates the statistics for the first five games after completion of the injury spell.

MFE(PS) is the mean forecast error of the market point spread. LOSS is the average of DP - PSPLAY, i.e. a measure of the effect of the player's absence (or lack of it in panel C) on the game. DIFF is average of PS - PSPLAY; i.e. the point spread reaction in the market to the injury situation.

Appendix

1982 Season

Observations: 230 R-sq: 0.969

Variable	Estimate	t-value
HAWKS	-3.334359	-6.139491
CELTICS	2.910794	4.645186
BULLS	-6.229776	-11.396556
CAVS	-11.091149	-20.562050
MAVS	-4.196604	-7.130448
NUGGETS	-4.830953	-8.943902
PISTONS	-4.356497	-7.775327
WARRIORS	-6.065996	-9.978129
ROCKETS	-11.510297	-17.661852
PACERS	-6.846988	-11.348433
CLIPPERS	-8.742780	-15.109341
LAKERS	3.052869	5.209969
BUCKS	0.430284	0.773051
NETS	-3.712991	-6.807746
KNICKS	-6.676410	-11.700208
SIXERS	2.710749	5.012054
SUNS	-2.643456	-4.196462
BLAZERS	-2.265396	-4.150938
KINGS	-3.759032	-6.027770
SPURS	-2.050936	-3.536199
SONICS	1.049140	1.616020
JAZZ	-8.272100	-15.026895
BULLETS	-3.932458	-6.694430
HO-HAWKS	0.866018	1.428633
HO-CELTI	6.213943	11.137314
HO-BULLS	-1.819314	-3.059896
HO-CAVS	-9.438899	-16.256515
HO-MAVS	-2.065136	-3.323394
HO-NUGGE	0.512874	0.821924
HO-PISTO	-1.133018	-1.886866
HO-WARRI	-1.040707	-1.787460
HO-ROCKE	-8.786952	-15.468773
HO-PACER	-3.798072	-6.649878
HO-CLIPP	-5.959837	-10.205729
HO-LAKER	7.183994	12.348228
HO-BUCKS	3.482937	6.311453
HO-NETS	0.121674	0.197153
HO-KNICK	-3.169490	-5.575937
HO-SIXER	6.855646	11.335485
HO-SUNS	2.692941	4.853336
HO-BLAZE	0.825848	1.364113
HO-KINGS	-0.813232	-1.422055
HO-SPURS	1.410239	2.455259
HO-SONIC	4.058689	7.286932
HO-JAZZ	-5.331165	-8.976392