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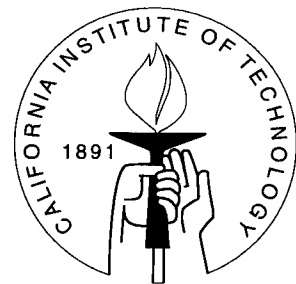
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IS THERE A WINNER'S CURSE IN THE MARKET
FOR BASEBALL PLAYERS? EVIDENCE FROM THE FIELD

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Abstract

A winner's curse exists in common value auctions when bidders fail to fully account for the fact that the winning bidder's valuation of the object is an upward-biased estimates of its true (unknown) value. Previous studies have reported mixed evidence for a winner's curse in oil lease auctions, corporate takeovers, auctions for failed banks, and in many experiments. In this paper we search for a winner's curse in the 1990 negotiations for free agent baseball players. Free agents are overpaid, relative to direct estimates of the revenue impact of their performance, by about 50% on average. A control sample of non-free agent players, in contrast, are overpaid by only 1%. However, proper adjustment for the winner's curse requires bidders to bid less when the variance of an object's value is lower; and salaries are lower for players with more variable previous performances. Taken together, the data show a large winner's curse but the curse is not due to teams mistakenly paying more for high-variance players.

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I. INTRODUCTION

In a common value auction for an object of uncertain value, the bidder who is most optimistic about the object's value is likely to bid highest and get the object. A "winner's curse" exists if bidders fail to fully account for the fact that winners are more optimistic than losers, and consequently bid too much (relative to the Nash equilibrium which adjusts for the curse). The main purpose of this investigation is to look for a winner's curse in one kind of naturally occurring data -- salaries of Major League Baseball players.

A winner's curse is most likely in an open market for the services of ballplayers, in which the player is free to contract with any team. This condition is met in the case of Major League Baseball *free agents*. Free agents are players who have at least six years of seniority and whose contracts have expired. By the labor/management agreement in force in baseball during the time when this study was conducted, such players had complete freedom to contract with any ball club. A complete description of the organization, structure and history of the market for ballplayers' services can be found in Scully (1989).

Standard economic theory predicts that when a worker is hired, his salary should not exceed the marginal revenue product of labor he provides. Because the number of units of labor (offensive production) provided by a baseball player is stochastic in any season, if ballclubs are risk-neutral then salary will equal the revenue impact of the player's expected productivity. Thus, economic theory states that free agent salaries should be proportional to expected performance, and no greater than expected marginal product. But bidding for free agents is like a common value auction, and bidders are vulnerable to the *winner's curse* (e.g., Capen, Clapp and Campbell, 1971). The winner's curse predicts that the auction winner (the player's new club) will overpay for the player's services.

This study compares these two predictions in two ways. First, we calculate the expected marginal product of free agents and compare it to salaries, to see if they are paid more than they are worth. We find that free agents are overpaid (relative to other players who are not free agents), which provides the most direct evidence of a winner's curse in bids. Second, we determine whether the winning bids for free agents are (on average) appropriately sensitive to uncertainty. Optimal bidding requires that bidders bid less when player values are more uncertain. Bids for free agents are lower when the agents' values are more uncertain. Optimal bidding also requires that teams bid less when there are more bidders, but there are no reliable field data on the number of teams n bidding on a player. In a companion paper, we designed laboratory experiments to closely resemble natural markets for free agents to measure the effect of n on bids. The experimental data show that

subjects do adjust bids downward for value uncertainty, as actual teams do, but also show that subjects bid more, not less, when there are more bidders, making the winner's curse worse. (Analyses done on naturally occurring data, repeated for the experimental data, also serve as an unusual check on the external validity of the experiment.)

Why study baseball?

Readers may wonder whether baseball is like other labor markets and, hence, worth studying in search of a winner's curse. In fact, there are several advantages to studying baseball free agency.

In most industries using skilled labor, it is virtually impossible to determine how an individual worker's productivity affects the bottom line. In baseball, by contrast, individual performances are easily observed (by millions!), extensive productivity statistics exist, and good data are available on both workers' salaries and firm revenues. The performance of a baseball team can also be characterized fairly accurately as the sum of the performances of the individual players. This is not the case in many other industries, where complementarities are large so a worker's marginal product is hard to measure.

Baseball is a large industry. Gross receipts in 1990 were estimated to be over \$1.3 billion. In 1993, six players earned at least \$5 million annually and at least one hundred players made \$3 million or more. The incentives for firms to behave in a profit-maximizing manner, and avoid the winner's curse, are high.

Also, baseball decisions are intensely scrutinized in the sports media, and ex-post performance data provide feedback about quality of decisions. The data we analyze come from the fifteenth year of baseball free agency. If a winner's curse is found in owners' bids, then it has persisted after several years of feedback and learning opportunities.

II. PREVIOUS RESEARCH ON THE WINNER'S CURSE

The winner's curse results from a judgment error which can only arise in auctions for objects which have an element of uncertain "common value" to all bidders. To establish a basic framework, we use the terminology of McAfee and McMillan (1987). Assume there is a single seller and n bidders in an auction. In an independent private values (IPV) auction, for each bidder i , a valuation v_i is drawn from a distribution F_i . The F_i distributions are common knowledge but the values v_i are private knowledge (and statistically independent). An example of this type of auction is the sale of a work of art which all of the bidders intend to display at home (i.e. the purchase is not intended as an investment for later resale).

In a common values (CV) auction, the item to be sold has a single objective value for all bidders, but this true value is unknown. An example is oil companies bidding on offshore tracts which contain unknown amounts of oil that are about equally valuable to all bidders. Call the object's value V . Each bidder has a guess as to what V is. These guesses v_i , $i=1, \dots, n$, are independent draws from some distribution $H(v_i/V)$, where H is assumed to be common knowledge.

Thus, the underlying distribution of value guesses is common to all bidders, but the guesses v_i are privately known.

Most auctions have elements of both the IPV and CV models. For example, suppose dealers plan to resell antiques they bid on at an unknown market price, but dealers differ in their ability to re-sell the object. Then the market price is a common value and their resale ability is a private value. If firms value a takeover target differently because of firm-specific complementarities, and also are unsure of the target's basic economic worth, there is both private value (from complementarities) and common value (from the target's uncertain worth).

The more general "affiliated values" (AV) model has IPV and CV as special cases (Milgrom and Weber, 1982). In the AV model, x_i is the private signal received by bidder i about the value of the object. Let $x = (x_1, \dots, x_n)$. Let $s = (s_1, \dots, s_m)$ be a vector of variables that describe the quality of the item for sale; some components of s may be known to the seller, but none are known to any of the buyers. Bidder i 's valuation of the item is $v_i(s, x)$, a function of all the signals available to the bidders (x) and of the factors which determine the true quality (s). Roughly speaking, the vector (s, x) is affiliated if there is a positive correlation among the v_i . When $m = 0$ and $v_i = x_i$, this reduces to the IPV model. When $m = 1$ and $v_i = s$, this reduces to the CV model.

Comparative static results can be derived from analysis of equilibrium bidding in these auctions. As the variance of the valuations v_i rises in any of the models, bids should decrease. This is true in IPV auctions because the high bidder wants to bid just slightly more than the second-highest valuation, and the gap between the first- and second-highest valuations grows with the variance of valuations. In CV auctions, as value variance grows, the expected amount by which the highest value exceeds the true value grows too. So bidders in CV auctions should hedge more, bidding a smaller fraction of their value estimate, as variance grows.

The effect of an increase in the number of bidders (n) on bids is different in the IPV and CV models. In the IPV model, as n rises the winning bidder should bid more because the expectation of the value of the second high bidder grows (and, recall, the winning bidder wants to just outbid the second-highest bidder). In the CV model the effect is opposite: As n rises, the expected amount by which the highest valuation exceeds the true value grows. Anticipating this, bidders should hedge more from their value estimates, bidding less when n is higher.¹ If this counter-intuitive effect is not understood by the participants in a CV auction, then the winner may pay more than is prescribed by the Nash equilibrium bidding strategy. The result is the winner's curse (see, e.g., Cox and Isaac, 1984).

¹ Harrison (1990) shows in his Equation (9) on page 124 that "the magnitude of the winner's curse" equals the product of the standard deviation of the estimation error and the expected first order statistic of the valuations. Increases in n cause increases in the first order statistic of valuations.

A. Field Evidence

The winner's curse has been analyzed in many contexts besides baseball salaries, including offshore oil leases, initial public offerings, and corporate control.

a. Outer Continental Shelf (OCS) oil leases

The term "winner's curse" was coined by Capen, Clapp, and Campbell (1971). They documented low returns oil companies earned from Gulf of Mexico oil leases bought at auction and suggested low returns were due to a key feature of CV auctions:

"In competitive bidding, the winner tends to be the player who most overestimates true tract value... it is true (or I assume it so) that one's evaluations are correct on the average -but it is not true that one's evaluations on the tracts he wins are correct on the average." (p. 643)
(italics in original)

Other authors have drawn different conclusions from more sophisticated analyses. Gilley and Karels (1981) noted that not all companies bid on all available tracts. They allow "zero bids" (nonparticipation) in a probit two-stage least squares analysis of bids from the 1976 Baltimore Canyon sale. A misspecified one-stage OLS model showed that bids increased with n but the two-stage probit analysis founds bids fell with n (consistent with equilibrium bidding). This study suggests bidders avoided the winner's curse.

Gilley, Karels, and Leone (1986) replicated the earlier findings on Baltimore Canyon leases, but found that bidders were not sensitive to n in an earlier 1974 Texas Gulf sale. They suggest that the widespread experience of those bidders with Texas Gulf drilling (70 of 72 firms had experience) reduced the uncertainty about tract values, reducing the potential for winner's curse and making insensitivity to n fairly harmless.

Hendricks, Porter, and Boudreau (1987) studied the same data Capen et al did (OCS leases in the Gulf of Mexico in the 1950's and 1960's). They broke the data into two categories: sales of *wildcat* wells, with unknown geological properties, and sales of *drainage* tracts, which are adjacent to tracts on which a deposit has already been discovered. Informed bidders (owners of neighboring tracts) won more than half the drainage tract auctions, and "average net profits on all drainage tracts won by uninformed firms are zero." They also found that average net profits for tracts with many bidders (for more) were negative. Both findings suggest winner's curse.

To explain these data, Hendricks and Porter (1988) modelled the drainage sale as a problem of asymmetric information. Since informed bidders will bid on "good" tracts only, the uninformed will win only the "bad" tracts. In equilibrium, the uninformed must make profits on the good tracts they win to compensate for expected losses on the bad tracts. Thus, good tracts sell at a discount (giving positive profits to the informed) and the uninformed earn zero expected profits, driving them to indifference regarding participation in the whole process. The evidence is consistent with this model, because (p. 874):

"The neighbor firm won 62 percent of the tracts that it bid on... its share of the tract value [subsequent profits] was approximately 44 percent, which was considerably higher than the 23 percent average firm share on wildcat tracts. The average net profit of non-neighbor winners was virtually zero. It was positive on tracts which received a neighbor bid, and it was significantly negative on tracts which received no neighbor bid."

Because all these results are consistent with rationality and equilibrium bidding (given firms' asymmetric information), it seems that adverse selection, rather than the winner's curse, explains OCS profit levels.

Hoffman, Marsden, and Saidi (1991) examined the same OCS data, but noted that many oil companies made joint bids with others on individual tracts. Bidding together, firms can pool information (reducing the variance of valuation error) and perhaps also "educate one another about the need to discount bids". Joint bidders did earn greater returns. These returns seem attributable to information sharing because the same companies earned more by bidding jointly than by bidding alone. (Interestingly, eight major companies were barred from being co-bidders on any future joint bids in 1975.)

This stream of careful research shows that while there may be a winner's curse reflected in oil lease bids (and subsequent low returns), there are other plausible explanations.² It is difficult to conclude that the low profits on oil leases are necessarily a result of failing to understand the winner's curse.

b. Pricing of Initial Public Offerings (IPOs)

Many studies show that initial public offerings (IPOs) of common stock are systematically underpriced, resulting in substantial increases immediately after stocks become traded. Average discounts of the initial offer price of up to 22% in the US have been noted by many authors (e.g., Ibbotson, 1975). Dawson (1987) shows similar results from Asia.

A prominent explanation for IPO underpricing is that information asymmetry among investors creates a potential winner's curse (Rock, 1986). The argument is very similar to Hendricks and Porter's (1988) model of oil lease bidding.

A key feature of IPO markets is that investment banks underwrite an offering by fixing a

² Returns from OCS leases may be low for reasons other than errors in strategic bidding. Hendricks and Kovenock (1989), study a two period model of competing companies leasing neighboring tracts. They prove that an equilibrium exists where both companies overinvest in their tracts by both engaging in the fixed cost of exploratory drilling, instead of one firm doing so and the other getting the positive externality of seeing the result. That is, firms may not be overbidding as the winner's curse predicts, but failing to coordinate on who incurs certain fixed costs, running total costs up and profits down.

price and quantity of shares. Investors must request shares. If too many shares are requested the available shares are rationed to investors. Since informed investors know something about the likely after-market price of the offering, and only request shares of IPOs they expect to rise in price, uninformed investors who apply for every IPO get stuck with lots of shares of bad companies and few shares of good ones. If uninformed investors anticipate this adverse selection, firms must underprice their IPOs to compensate uninformed investors for being adversely selected against.

The asymmetric-information model has been tested with data from London (Levis, 1990) and Singapore (Koh and Walter, 1989), where data on subscriptions and allocations are available. As the asymmetric-information theory predicts, uninformed investors' returns are about equal to risk-free rates of return, and IPOs which are more heavily subscribed rise more in price in the aftermarket. The results are consistent with the theory that investors are aware of a winner's curse and are compensated for it.

c. Corporate Takeovers

Studies of corporate takeovers repeatedly show that the joint gains from a takeover go entirely to the acquired firm's stockholders (see Jensen and Ruback, 1983). Roll (1986) advanced the hypothesis that "hubris" causes acquiring firms to ignore the winner's curse.

Varaiya (1988) tested Roll's idea by examining 91 acquisitions made between 1974 and 1983. Those data show that buyers' gains were highly negative, target company gains were highly positive, and total gains were insignificantly positive. He also found more direct support for the existence of a winner's curse because overpayment was larger when there was more uncertainty about the target's value (measured by variance of analysts' earnings estimates). A weak test found no increase in overpayment when there were multiple bidders.

d. Other Studies

Giliberto and Varaiya (1989) studied 219 auctions of failed banks to other financial institutions during the period from 1975 through 1985. Their results show that bidders do not generally adjust their bids in a way that reflects understanding of the winner's curse.

Brannman, Klein, and Weiss (1987) studied seven different types of auctions, including bond underwriting, offshore oil, and timber. Their idea was to see whether the best prediction of winning bids was made by the first order statistic as predicted in CV auctions without adjusting for winner's curse, the second order statistic which is normative behavior in an IPV auction, or $1/n$ which is normative if the winner's curse is understood and adjusted for.³ In all seven markets, the $1/n$ measure proved worst, indicating that the markets are either IPV in nature (which seems unlikely) or bidders fail to deal with the winners curse properly.

³ Wilson (1977) showed that expected profits in equilibrium in a CV auction are proportional to $1/n$. Holding the true value of the item constant, raising n should therefore raise the winning bid in proportion to $1/n$.

Gaver and Zimmerman (1977) studied construction bids made on BART (San Francisco's Bay Area Rapid Transit system) contracts. Since these are contracts where the low bidder wins, proper adjustment for the winner's curse dictates that bids should rise with an increase in n . These authors found the opposite.

Overall, it is hard to conclude that the winner's curse is always a serious problem in naturally-occurring markets. Instead, the data indicate that there are venues where the curse is well-understood and largely avoided (IPOs), others where it clearly victimizes winning bidders (construction bids and failed banks) and others where its presence is unclear (oil leases, takeovers).

B. Laboratory Evidence

Many laboratory experiments have been designed to determine whether bidders understand and appropriately compensate for the winner's curse in CV auction settings. The stylized facts are that bidders do not initially adjust for the winner's curse (they are especially insensitive to changes in n). They also gradually adjust over time, but never adjust sufficiently.

a. "Pennies" Auctions

Bazerman and Samuelson (1983) conducted classroom auctions for large quantities of various tokens (pennies, nickels, small (2 cent) paper clips, and large (4 cent) paper clips). Subjects could view a jar filled with tokens, to form a personal estimate of the total value of the jar's contents. Bidders knew the number of other bidders, and the winning bidder earned the total token value minus the winning bid.

These early results are striking. While the average bid significantly understates the total token value, the average winning bid resulted in a loss to the bidder. If the variance of bids is used as a proxy for the variance of value estimates made by the bidders, they found that bidders are not bidding lower when values are mere uncertain. Bids were also independent of n , contrary to theory.

b. Kagel, Levin, et al.

An impressive series of experiments by Kagel, Levin and colleagues have used the following basic design: Players are told the endpoints V_L and V_H of a uniform distribution from which the underlying common value of the object to be auctioned, V , is drawn. After V is drawn (and observed only by the experimenters), each player is then given a signal s_i which is drawn from the uniform distribution $[V-\epsilon, V+\epsilon]$, where ϵ is known to subjects and is one of the experimental treatment variables. The high bidder earns $V-b$, where b is the winning bid; all others earn zero. The risk-neutral Nash equilibrium (RNNE) conditions of this game were derived by Wilson (1977) and yield a bidding function (for signals S_i in the range V_L to V_H) of:

$$(1) \quad b(S_i) = S_i - \epsilon + \left(\frac{2\epsilon}{n+1}\right) e^{-\left(\frac{n}{2\epsilon}\right)[S_i - (V_L + \epsilon)]}$$

Kagel and Levin (1986) ran groups of varying size through anywhere from 18 to 32 periods of this design. Each player was given a starting cash balance. Feedback in the form of the value V , and gains and losses was given after each round. All experiments used experienced subjects (i.e. subjects had participated in this type of design before).

In most groups, bidders bid above the Nash equilibrium bid and earned less than they could. In small groups ($n=3,4$) profits were positive, but bidders in large groups ($n=6,7$) averaged negative profits. Bidders bid less when ϵ was larger (as the Nash theory prescribes).

Kagel, Levin, Battalio, and Meyer (1989) replicated these results. Subjects began making negative profits, then learned to bid less and earn positive profits, but still bid more than the Nash prediction. They also found that giving more complete feedback after each round (including all bidders' private signals and bids) did not help much.

Lind and Plott (1991) ran a clever experiment designed to address the unusual criticism (Hansen and Lott, 1991) that overbidding in Kagel and Levin's experiments was caused solely by near-bankrupt subjects, who realized they would not have to pay the experimenter if they lost their entire stake. In Lind and Plott's experiments, subjects were given an object to sell. The subject who made the lowest offer sold their item and collected the asking price. The other subjects received the item's value. In this auction, a "seller's curse" will cause subjects to bid too low, leaving money on the table; but the curse cannot cause bankruptcy. They replicated the Kagel & Levin results-- a winner's curse existed but shrank with experience-- but also pointed out that no clear alternative model fit the data better than the Nash bidding model.

Dyer, Kagel, and Levin (1989) used the standard design and compared the performance of undergraduate student subjects with executives in construction contracting businesses (who routinely bid for construction projects in CV-type auctions). The executives behaved much like students, exhibiting a strong winner's curse which was diminished, but not eliminated, by experience.

Since these executives remain in business (they are not consistently losing money), Dyer et al conclude that they may have learned to avoid the winner's curse in construction bidding but do not generalize their knowledge to the laboratory auctions. The idea that executives have adapted, but not learned, implies that when their business environment changes the winner's curse can strike afresh. (For example, if new competitors start bidding, bidders who bid more to beat the new competition will suffer a larger winner's curse.)

III. BASEBALL SALARIES

There are many scholarly articles about baseball salaries. This subsection reviews and critiques the findings of these studies, especially those relevant to free-agency.

Most studies of baseball salaries are focussed on calculations of a ballplayer's economic contribution to club profits, or Marginal Revenue Product (MRP). Many of these studies examine

how changes in the bargaining agreement between management and labor changed ballplayers' pay. Three papers test for a winner's curse directly.

Scully (1974) pioneered MRP calculation for major league players, in order to see whether baseball's reserve clause held player salaries down. Until a 1976 Supreme Court decision stopped the practice, the reserve clause gave a player's current team an exclusive option to renew the player's contract. Ballplayers could not shop for the best offer.

Scully's idea was to measure the revenue generated by a ballplayer's performance and compare it to salary, calculating a rate of monopsonistic exploitation. He did this using a two-equation model. The first equation predicted team winning percentage as a function of team performance variables. The second equation predicted team revenue based upon team winning percentage, demographics and other factors. After determining a player's contribution to team performance, these two equations can be used to determine the change in club revenue that resulted from the player. He concluded that ballplayers were paid only 10-12% of their MRP in 1968-69.

This creative early work has some shortcomings. He uses only 148 salary observations (over a two-year period). Two independent variables in the first wins equation have perfect rank-order relationships with the dependent variable (and hence, with each other). Scully ignores concession revenue and "charged" players a pro-rated share of team overhead to compute the players' net MRP (rather than treating overhead as a fixed cost, incorporated in a constant in the revenue equation).

Many authors have extended or modified the two-equation MRP model. Medoff (1976) added a product substitute variable in the revenue equation (presence of other sports teams), allowed the wins-equation and revenue-equation errors to be correlated (to capture omission of a common predictor), and used data from 1973-4. He estimated players were paid 45% of MRP.

Cassing and Douglas (1980) wrote a widely-cited paper claiming to demonstrate a winner's curse in baseball free agency. Free agency began after the Supreme Court struck down the reserve clause in 1976. Cassing and Douglas conclude that the winner's curse existed in the first crop of free agents (1977 and 1978), because they calculate that the average free agent is overpaid by 20%, and 28 of 44 are overpaid (significant at $p=.04$ by a sign test). Our work is partly motivated by shortcomings in their work.

Two features of their tests deserve a further look. First, they took Scully's club revenue figures from 1968-9 and simply adjusted them for inflation to produce 1977-78 figures. But since attendance at ballgames rose 97% during that period, while the CPI rose only 76%, this procedure probably biases revenue estimates downward, which could easily account for the 20% gap between apparent revenues and salaries.

Second, Cassing & Douglas base their MRP calculations on the free agent's lifetime statistics, but pay in year t should be compared with subsequent performance in year t rather than

lifetime performance. If free agents improve with age, or play better after being signed than before, this misspecification will understate the revenue boost from the free agent and make it appear that teams have paid too much. Raimondo (1983) also adjusted the Scully and Medoff MRP numbers for inflation but correctly compared salaries with same-year performance. He found that the median free agent was slightly underpaid, by 5%.

Somers and Quinton (1982) looked at the same 1977 data as Cassing & Douglas. They added variables for expansion teams and a win-percentage-by-population interaction, and compared 1977 salaries with same-year performance. Then only 6 of 14 free agents appear to be overpaid (and only 4 are overpaid by more than 10%).

Bruggink and Rose (1990) re-estimated the modified Scully equations in order to determine how club owners' collusive behavior in 1985-86 affected the monopsonistic rate of exploitation of ballplayers. (The owners were convicted of collusion and assessed damages of \$280 million.) They included concession revenue (as a constant fraction of gate revenues) and found that collusion reduced free agent salaries from between 27% and 47%. The results of Hoffman et al, on joint bidding for oil leases suggest that collusion by owners is a way to minimize the winner's curse, by pooling information and reducing n . Hence, apparent collusion could be taken as prima facie evidence that a curse existed before the collusion began. (Our companion experimental results show a similar phenomenon: Cursed winners simply quit bidding until n falls low enough to support positive profits.)

All this research leaves unanswered the question of whether a winner's curse exists in baseball free agency. The biggest effect is reported by Cassing & Douglas-- free agents are overpaid by 20%-- but all later analyses show no substantial overpayment.

In fact, clearly establishing a curse this way is nearly impossible. Even if players are underpaid (relative to MRP), teams may be bidding more than the Nash bids and, hence, suffering from a winner's curse but not losing money. And even if players appear to be overpaid, the apparent overpayment may be due to model misspecification (particularly omission of revenue sources, interactions of star players with other players, etc.).

We attack the problem from two new angles. First, we estimate the two Scully equations for wins and revenue to calculate free agent MRP, and do the same for non-free agent players. Then we can judge whether free agents are more overpaid than non-free agents. (Since bidding for free agents is by definition more vigorous than renegotiations for regular players, we only expect a winner's curse overpayment in the free agent market.) This comparison controls for many kinds of misspecification, like missing revenue sources and risk-aversion or collusion among owners (which can keep all salaries down).

Second, we examine the sensitivity of bids to uncertainty about players' values. If free agents appear to be overpaid, and bids respond in the wrong direction to uncertainty, a stronger case

for existence of winner's curse can be made.

IV. DATA, MODELS, AND RESULTS

The Appendix describes the data we use in some detail. The most controversial measure is probably player performance. To measure performance we use Bill James' "Runs Created" (RC) measure. The formula for RC is:

(2)

$$RC = \frac{(H + BB - CS)(TB + 0.55 * SB)}{(AB + BB)}$$

where, H is hits, BB are walks, CS are times caught stealing, TB is total bases on hits (singles plus 2 times doubles plus 3 times triples plus 4 times homeruns), SB are stolen bases, and AB are official at-bats.

Some variables used by others are omitted from this model. Some are omitted because they are functions of the dependent measure; the others are not included because we have found them to be insignificant in predicting the dependent measure. Insignificant demographic variables include latitude and longitude (outside the Midwest), league (National vs. American), stadium age or size, number of baseball teams in the city, number of All Star players on the team, and simple measures of the team's racial composition.

A. Salaries and MRPs: Are players overpaid?

Both of the models to be investigated are discussed below. For each, the theory is developed, the model and hypotheses are stated mathematically and results are discussed.

Failure to adjust for a potential winner's curse implies that the auction winner will pay more than the equilibrium price for the item auctioned. The magnitude of this overpayment is a function of the number of bidders and the distribution of valuations. In the field, we can not know what this distribution truly is. However, assuming teams are profit-maximizing and not risk-seeking, the average winning bidder ought to pay no more than MRP.

We have changed the basic Scully model into one which accurately describes the problem as an affiliated values auction. Our model is:

(3)
$$\text{Wins} = \alpha_0 + \alpha_1 \text{Offense} + \alpha_2 \text{Pitching} + \alpha_3 \text{Errors}$$

(4)
$$\text{Revenue} = \beta_0 + \beta_1 \text{WtWins} + \beta_2 \text{Population} + \beta_3 \text{WtWins} * \text{Population} + \gamma X$$

and

Our measure of offense and pitching are Runs Created (RC) and Base Runners Allowed per 9 Innings (hits plus walks). In the revenue equation, the WtWins term represents "weighted wins", the best linear predictive balance between this and last years' victory totals.⁴ The previous year's wins should be predictive of early season attendance (and hence revenue). The WtWins*Population interaction term gives this model an affiliated values flavor, as each team has a different marginal value of victory, but player marginal product of labor across teams remains perfectly correlated. X represents a vector of demographic variables⁵ which are unimportant but statistically significant.

The hypothesis that ballplayers are overpaid is:

H1₀: Salary > MRP, where:

$$MRP = RC * \alpha_1 * (\beta_1 + \beta_3 \text{Population}) + \gamma_2/4 * (\# \text{ of MVP years})$$

The right-hand side of this equation is a player's estimated marginal revenue product of labor. Their production (RC) times α_1 is their contribution to their team's wins. This number times $(\beta_1 + \beta_3 \text{Population})$ is the impact of this season's performance on this and next year's team revenue. The $\gamma_2/4 * \text{MVP}$ term represents gate draw revenue generated by the player (MVP is the sum of four 0/1 variables, one for each year in 1987-1990; γ_2 is from Equation (4)). Table 1 contains descriptive statistics for the variables used to compute MRP.

Table 1
Descriptive Statistics for MRP Factors

	RC	Population (Millions)	# MVP Years
Mean	38.44	3.47	0.16
(std. dev.)	33.84	2.25	0.51
Median	34	2.48	0
Maximum	134	8.86	2
Minimum	0	1.33	0

⁴ WtWins equals 84.17% of 1990 wins plus 15.83% of 1989 wins.

⁵ Included in X are SUN, MVP, and MIDWEST. SUN is the percentage of time that the sun shines on the team's home field (This equals zero for teams that play in non-retractable domes, under the assumption that fans enjoy sitting in open sunshine in cities with nonretractable domes lessens the fit of the model to a significant degree.) MVP is the number of players on the team who were top MVP vote-getters 3 seasons ago. These players generate revenue by their presence; they are gate draws. MIDWEST is a 0/1 variable indicating whether the team's home is in the American Midwest.

Table 2
Estimated Wins Equation (3)

	Coef.	Estimate	F Value	p-Values	R ² =.755	n=26
Constant	α_0	803.7				
RC	α_1	0.5824	15.83	.001		
H&BB	α_2	-53.39	30.71	.000		
Err	α_3	-0.3973	1.29	.269		

Table 3
Estimated Revenue Equation (4)

	Coeff.	Estimate	F Value	p-value	R ² =.838	n=26
Constant	β_0	-40.89				
Win	β_1	0.0986	10.65	.004		
Pop	β_2	12.99	13.79	.001		
Win*Pop	β_3	-.0231	11.24	.003		
Sun	γ_1	.1440	13.24	.002		
MVP	γ_2	4.774	28.94	.000		
Midwest	γ_3	-4.380	7.04	.016		

Regression estimates are presented in Tables 2 and 3. First note that the coefficient β_3 is significantly negative. This means that, contrary to baseball wisdom, an incremental victory (and thus a free agent) is worth more to a small city team than it is to a big city team. We can reconcile this counter-intuitive result as follows: *ceteris paribus*, a small city team has more empty seats for a game than does a large city team. Thus, the potential change in revenue for incremental wins is higher for small city teams. The fact that 18 of the 32 free agents in 1990 signed with smaller-than-median-sized teams lends some support to this idea.

The fact that β_3 is negative means the linear revenue model has a major flaw: As population grows, at some point the value of $(\beta_1 + \beta_3 \text{Population})$, and thus MRP, becomes negative. Unfortunately, this cross-over happens at a relatively low population level, a city size of 4.282 million inhabitants for the Table 3 figures. If this number were much higher, we could ignore the problem. However, six of the free agents play in cities large enough⁶ that their MRP is less than zero.

We must therefore adopt a more realistic model of revenue. Of the class of models constructed so that the marginal value of victory never falls below zero, the model found which best predicts revenues is:

⁶ New York City's population is 8.547 million, Los Angeles' is 8.863 million. The New York Yankees and Los Angeles Dodgers signed one free agent each. The New York Mets signed no free agents in 1990. Philadelphia's population is 4.857 million; they signed two free agents in 1990, as did Detroit (population of 4.382 million).

$$(5) \quad \text{Revenue} = \beta_0 + \beta_1 \frac{\text{Win}}{\text{Population}} + \beta_2 \text{Population} + \gamma X$$

The results of this regression are reported in Table 4.

Table 4
Regression Results for Revenue Equation (5)

	Coeff.	Estimate	F-value	p-value	R ² =.783 (n=26)
Constant	β_0	-3.300			
Win/Pop	β_1	0.03905	4.27	.0520	
Pop	β_2	2.765	11.54	.0029	
Sun	γ_1	.1312	7.96	.0106	
MVP	γ_2	5.445	27.35	.0001	
Midwest	γ_3	-5.143	7.74	.0115	

This model is more realistic than (4), and only slightly lower in R². Using estimates for equations (3) and (5), we calculate the MRP of a ballplayer as: $(RC * \alpha_1 * \beta_1) / \text{Population} + \gamma_2$ (number of MVP years.) The results are reported in Table 5. Of the 32 free agents in 1990, 7 were underpaid and 25 were overpaid ($p < 0.003$ by sign test). The average free agent created \$604,678 in value and was paid \$934,115, for an average return of -35.27%. This average loss of \$329,437 with a standard error of \$133,865 generates a T-value of 2.46 for $n=32$, which is significant (two-tailed) at the $p=0.02$ level.

Alternately, we can ask how many of the free agents' salaries differ from MRP by one or two standard errors⁷. The answer is that four are underpaid by at least a standard error, and twenty are overpaid by at least one standard error. Three are underpaid by two standard errors and thirteen of the thirty-two are overpaid by two standard errors.

The ballplayers who were not free agents are a control group for this study. For them, player salary should equal player MRP. Indeed, for the 103 players who signed contracts prior to the 1990 season who were not free agents, the average value created was \$704,317 and the average salary was \$712,023. These players are paid almost exactly their marginal revenue product.

⁷ The standard error of the predicted value of player productivity is calculated by first determining the square of the standard error for each observation in the revenue equation (5). These values are the variances of predicted revenues for each team. If we assume that all of this error is attributable to player-related factors and that player productivity is homoscedastic we can divide this value by 24 (each club had 24 players in 1990) to obtain player productivity variances for each player on a given team. The square roots of these values are the standard errors of player performance for each team. Because all team revenue predictive error is ascribed to player-related factors, what is repeated here are actually upper bounds on standard errors. The table reports the player standard error of revenue for the team that each free agent played for. The standard errors for the two players who played for two teams each during 1990 (C. Martinez and K. Phelps) are calculated by weighting the player standard errors for each of those two teams by the percentage of his total productivity that the player generated for that team.

Table 5
Ex-Post Analysis of Worth: 1990 Free Agents

Name	Salary	Value Created	Standard Error	Difference	Return
P. O'Brien	150,000	414,946	(311,734)	264,946	177%
D. Parker	1,200,000	2,727,027	(195,190)	1,527,027**	127%
R. Henderson	2,250,000	4,218,261	(188,270)	1,968,261**	87%
W. Backman	400,000	541,724	(188,619)	141,724	35%
C. Maldonado	825,000	1,055,715	(196,523)	230,715*	27%
G. Pettis	703,333	887,800	(268,005)	184,467	26%
R. Yount	3,200,000	4,008,897	(195,190)	808,897**	25%
W. Wilson	800,000	638,965	(206,916)	-161,034	-20%
T. Kennedy	850,000	538,760	(209,218)	-311,239*	-36%
T. Phillips	866,667	420,367	(207,530)	-446,299**	-51%
D. Anderson	500,000	212,668	(209,218)	-287,331*	-57%
K. Hrbek	2,100,000	821,420	(331,887)	-1,278,579**	-60%
M. Wilson	1,125,000	415,652	(241,652)	-709,347**	-63%
F. Lynn	650,000	218,491	(203,991)	-431,508**	-66%
D. Collins	225,000	65,134	(210,540)	-159,865	-71%
K. Bass	1,250,000	354,447	(209,218)	-895,552**	-71%
T. Pena	1,700,000	396,052	(265,279)	-1,303,947**	-76%
F. White	1,150,000	261,394	(206,916)	-888,605**	-77%
C. Martinez	700,000	149,829	(189,236)	-550,170**	-78%
L. Moseby	1,400,000	295,814	(207,530)	-1,104,185**	-78%
C. Castillo	550,000	73,835	(331,877)	-476,164*	-86%
H. Brooks	1,366,667	182,177	(292,393)	-1,184,489**	-86%
K. Oberkfell	625,000	82,645	(309,333)	-542,354*	-86%
B. Buckner	200,000	23,763	(265,279)	-176,237	-88%
M. Hall	1,100,000	106,429	(256,309)	-993,570**	-90%
K. Phelps	825,000	76,423	(190,333)	-748,576**	-90%
N. Esasky	190,000	16,048	(243,647)	-173,951	-91%
S. Lake	340,000	28,093	(189,302)	-311,906*	-91%
K. Hernandez	1,750,000	111,781	(196,523)	-1,638,218**	-93%
J. Shelby	500,000	5,131	(292,393)	-494,868*	-98%
T. Francona	150,000	0.00	(195,190)	-150,000	-100%
T. Lawless	250,000	0.00	(241,652)	-250,000*	-100%

*-Underpaid by 1 std error

** - Overpaid by 1 std error

** - Underpaid by 2 or more std errors

** - Overpaid by 2 or more std errors

Diagnostic tests of residuals from equations (3) and (5) suggest the underlying assumptions of the model are not violated. First, their error terms are not correlated ($p=0.63$). Neither equation was found to be heteroscedastic. The studentized range of the residuals was 4.035, (equation 3) and 4.762 for equation (5), consistent with normality at about the $p=0.09$ level.

It is possible that clubs intentionally pay too much for free agents. This would be the case if these free agents, when added to the club, interacted in significant ways with players already on the team. If this is true then the club productivity equation (3) expressed above is incomplete and allowances for these synergies would have to be made. This question can be addressed in two ways: by examining the predictive ability of equation (3) and by testing the relationship between team revenue and overpayment for free agents.

Equation (3) predicts Major League Baseball club productivity as a function of the individual production levels of its players. If players can create profit synergies in certain combinations with each other then (3) may be misspecified. The R^2 of 75.5% leaves some room for the addition of other powerful independent variables. If player productive complementarities exist at all, we might expect that they would occur for teams that win often but need an extra player to become dominant, or when a team is poor but the addition of another player would make them competitive. That is, the added number of wins associated with an increment in player productivities might be U-shaped, rather than linear form. To test this, we ran the regression (3) in three additional ways: adding $\text{Log}(RC)$, RC^2 and $1/RC$ as independent variables. None of these nonlinearities were significant.

The models assume that a club's profit falls if it overpays for free agents. This implies that the residuals of the club revenue equation (5) will be positively correlated with the amount they overpay for free agents, which is the fifth column of Table 5. On the other hand, if productive complementarities exist clubs are not in fact overpaying, but are (rationally) underpaying their free agents. In this case this correlation should be significantly negative. When the gross profit associated with each of the free agents in Table 5 is allocated to his club, and these amounts are compared to the clubs' revenue residuals from equation (5), we obtain a correlation coefficient of 0.148($p=0.47$). This provides no evidence of production synergies.

B: Are Bids Sensitive to Uncertainty?

To adjust for the winner's curse, the bidders must decrease their bids as either the estimation variance or n grows. Using this test directly addresses the potential confounds to the winner's curse discussed earlier, in section I.

We next examine the following regression equation:

$$(6) \quad \text{Salary}_{1990} = \alpha_0 + \alpha_1 RC_{1989} + \alpha_2 RC_{1988} + \alpha_3 RC_{1987} + \alpha_4 \sigma^2_{RC} + \alpha_5 \text{FREE} + \alpha_6 \sigma^2_{RC} \text{FREE} + \alpha_7 \text{Seniority}$$

In this model, the dependent variable is the base salary of each ballplayer (free agent or not) who signed a contract between the 1989 and 1990 seasons, RC represents performance (Runs Created), σ^2_{RC} represents the historical variance of performance, and FREE is a dummy variable which equals 1 for free agents, zero otherwise. The coefficients α_1 , α_2 , and α_3 represent pay for expected performance, α_4 is the coefficient of risk aversion, α_5 is the "premium" for free agency, α_6 is the adjustment for performance variance predicted by the winner's curse theory, and α_7 is a seniority premium. The proxy used for performance variance (σ^2_{RC}) is the variance of the last two years' productivities (RC_{1989} and RC_{1988}).⁸

If the winner's curse is accounted for by bidders then we should see:

$$H2_0: \alpha_6 < 0$$

Table 8: Regression Results from test of Hypothesis 2, Equation (6)

	Coeff.	Estimate	F	p-value	$R^2=.739$	$n=273$
Constant	α_0	-344512	40.45	.000		
RC_{1989}	α_1	8134.8	78.39	.000		
RC_{1988}	α_2	4871.2	21.97	.000		
RC_{1987}	α_3	4611.1	29.86	.000		
Variance	α_4	88.328	1.45	.230		
FREE	α_5	195581	6.55	.011		
Var*FREE	α_6	-879.32	6.52	.011		
Seniority	α_7	30675	32.71	.000		

This test of H2 shows that the sign of α_6 is significantly negative, indicating that owners do bid less for higher-variance free agents. Residuals are approximately normal (studentized range is 5.40) and there is some heteroscedasticity with respect to σ^2 but correcting for it does not alter the estimate of α_6 or its t-statistic much.⁹

⁸ Three proxy measures of performance variance are statistically significant predictors of salary. They are: variance of the last two years' productivities, the absolute difference of the last two productivities, and the coefficient of variation of the last two productivities (p-levels of .02, .05, and 0.2 respectively). When the variance, sum of absolute differences, or coefficient of variation of the previous three years' RC measures are used, no significance is found. The variance proxy is used here because it is the one most commonly reported in research of this type.

⁹ The error terms of this regression are heteroscedastic in the terms RC_{1989} , σ^2 , and seniority. The first and third are of no real consequence, but the heteroscedasticity in σ^2 is troublesome. The problem is eliminated by adding the term: $\alpha_8(\sigma^2_{RC})^2$ to Equation (6). In this model, $\alpha_4 = -247.77$ (p-level = 0.127), $\alpha_8 = 0.250$ (p-level = 0.021), and most importantly, α_6 remains significantly negative, $\alpha_6 = -700.41$ (p-level = 0.046). The major conclusion, that the adjustment for performance variance is made in the correct direction, remains. The studentized range of regression residuals is 5.40, which is not significantly different from the range for a normal distribution.

Owners of Major League ballclubs also show slight risk-seeking (α_4 is positive) but that can not be differentiated from risk-neutrality (α_4 is insignificantly different from zero). Therefore, the source of overpayment is not a failure to understand that you should bid conservatively on uncertain-value objects. This is consistent with the literature reported above, which usually concludes that bidding is sensitive to changes in performance variance in the right direction.

This finding fits common sense as well. Since both common and private value auctions require optimizing bidders to lower bids as variance rises, even if bidders mistake this common value auction for a private value auction they will still respond correctly to changes in the variance of value.

V. CONCLUSIONS

We believe that the various results presented are pieces of a coherent whole, and that the gestalt picture depicts a world where the winner's curse is a very real and costly phenomenon. The field data show that free agents are overpaid, but bidders adjust correctly for variance in performance. One possible explanation for this is that bidders do not adjust correctly for changes in n . Our companion experimental research finds precisely this mistake.

The experiments also demonstrated that bidders do not learn to bid correctly; instead, they learn not to bid when n is large. This finding matches the field data well. On the two occasions when Major League Baseball club owners have been known to collude, they did not collude on bid levels, but, they colluded to reduce the number of bidders. They did so in the late 1870's by creating the Reserve Clause, which bound a player to a club for life (or any club that he was traded or sold to). One hundred years later, after the Reserve Clause had been struck down by a federal arbitrator, owners once again had to bid competitively for the services of ballplayers. As these costs rose, they colluded again, with the intent of keeping n low. Thomas T. Roberts, a baseball arbitrator concluded that they had conspired to be anti-competitive, stating that nothing in the history of free agency explained "the sudden and abrupt termination of all efforts to secure the services of free agents from other clubs. They surely had a value at some price and yet no offers were advanced". Roberts fined the owners over \$100 million. The owners were eventually fined a total of over \$280 million for collusive behavior over a three year period.

Were the owners colluding to avoid the winner's curse, or simply to garner excess profits? Clearly, the collusion was motivated by a consensus that wages were too high. Earlier in this paper, we discussed misspecification of the production function as a potential explanation for the apparent winner's curse. If this happens, management believes that a unit of productivity is more valuable to the company than it actually is. If this were the case, owners would have tried to determine the value of free agents and would have colluded to limit pay offers to this level. That is not what happened. Owners colluded to limit n , a result consistent with our experiments and with the hypothesis that the winner's curse and problems with bid competitiveness were the sources of systematically high pay offers.

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Appendix: Data sources

City population data are found in two sources. American population data for metropolitan areas are found in the Statistical Abstract of the United States (1991). The numbers used are the 1990 survey counts for geographic areas defined as MSAs and PMSAs.¹⁰ Canadian population data were found in the Canada Year Book 1990 (1990). The most recent (1987) definitions of 1990 Canadian Census Metropolitan Areas are used.¹¹ No adjustment is made for cities with two teams; the actual city population is a better predictor than any adjusted value is.

Player performance data used by this research can be found in Total Baseball, edited by Thorn and Palmer (1991), who calculate all the measures we require. We use Bill James' "Runs Created" (RC) as our measure of offensive productivity; Harder (1991) has shown this measure to be better calibrated to salaries than a common alternative, slugging average. This measure is also naturally additive across players to create a team-level total RC. The formula for Runs Created is shown in text equation (2).

The salary data used come from various issues of USA Today, The National (a daily sports newspaper), and wire service stories. Conversations with a baseball agent indicate that though these data are occasionally (up to 20% of the time) incorrect, the errors are probably unbiased. Players included in the analysis are those who had signed major league contracts after the end of the 1989 season and before the start of the 1990 season. The salaries used are base salaries, exclusive of incentive clauses. This will tend to understate pay, thus making it harder to discover an overpayment indicating winner's curse. In the future, it may be interesting to check for interaction between the presence of incentive clauses and parameters of the auction (particularly RC and σ^2).

Club revenue data are taken from the July 9, 1991 issue of Financial World. This issue estimated gate, media, and stadium revenue for all professional sports teams. Because these numbers are independently derived, as opposed to the historical methods¹², our regressions should have lower R²'s than past ones estimated by others (and do). Financial World assured us that their audit methods are both extensive and correct. Their complete research database containing all the data used in their audit is available, but the cost is prohibitive and the complete data are probably unnecessary.

10 MSAs are (essentially) isolated cities and their immediate surroundings. PMSAs are the appropriate subdivisions of multiple city consolidations (CMSA). For example, the Kansas City MO-KS MSA was used, this area is part of no CMSA. The Philadelphia PA-NJ PMSA numbers were also used; Philadelphia is part of the Philadelphia-Wilmington-Trenton PA-NJ-DE-MD CMSA.

11 The definition of a Census Metropolitan Areas is: "Built up areas of 100,000 population or more and adjacent municipalities linked by travel to work patterns". This definition matches the US usage of "MSA" fairly well.

12 Historically, concession revenue has been estimated as a constant fraction of gate revenue. Thus, total revenue consisted of two perfectly correlated elements. Our estimates are more accurate, and because they are not internally perfectly correlated, noisier.

Weather was measured by averaging the historical percentage of sunny days (from Ruffner and Bair, 1987) from April through September for each US Major League city. (This is a better predictor than other measures, like longitude and latitude.) For Canadian cities, data from the closest US city was used (Burlington, VT for Montreal and Buffalo, NY for Toronto).