A Hedonic Model of Player Wage Determination from the Indian Premier League Auction[#]

Liam J. A. Lenten, Wayne Geerling[*] and László Kónya

School of Economics and Finance

La Trobe University

Version Prepared for Seminar, University of Canterbury,

Department of Economics, 1 May 2009

Abstract

A range of cross-sectional models are estimated with a view to establishing the factors that determine the valuation of professional athletes in a highly-specialised sport, with an application to cricket's Indian Premier League (IPL). We distinguish between personal characteristic and playing ability factors, and with respect to the former, between ability in different forms of the sport. We find a number of interpretable variables that have explanatory power over auction values, while decomposition according to batting and bowling specialisations produces very different results depending on the use of either Test or One-Day International (ODI) variables. There is also sufficient evidence of inefficient bidding, insofar that overbidding was somewhat correlated with players with higher realised values.

JEL Classifications: C21, D44, L83

Keywords: Demand for Sport, Cricket, Auctions, Cross-section Models, Labour Demand

---

[#]Earlier versions of this paper were presented at: (i) Economics Society of Australia (Tasmanian Branch), Hobart, 18 March 2009; and (ii) the Staff Developmental Workshop, School of Economics and Finance, La Trobe University, 23 April 2009. The authors would like to thank the various participants of the seminar and workshop for their comments and suggestions, as well as Ray Stefani and Michael Smiddy.
[*]Contact details: School of Economics and Finance, La Trobe University, Victoria, 3086, AUSTRALIA. Tel: + 61 3 9479 1148, Fax: + 61 3 9479 1654. E-mail: w.geerling@latrobe.edu.au

1. Introduction and Previous Literature

The inaugural Indian Premier League (IPL) Season of 2008 marked arguably the biggest business revolution in the sport of cricket in the 130-year formal history of the game. Its formation was an attempt to capitalise on the financial windfall being generated by the explosive growth in demand arising from the new, shorter form of the game (known as 'Twenty20') in just the last few years at the expense of the traditional Test Match format (see Lenten, 2008), as can be seen in table 1 at international level and even more so in table 2 at domestic level. However, it was also a response by the game's governing body in India, the Board of Control for Cricket in India (BCCI), to mitigate the threat posed by the rival and non-sanctioned Indian Cricket League (ICL). As a measure of the financial optimism surrounding the IPL concept, in January 2008, the eight franchises were auctioned for a combined total of USD724 million, while the 10-year broadcast rights were sold for USD1,026 million (plus regional rights).

As a new league, several design features had to be established. One such feature was the method of allocating players to teams. The IPL decided to conduct a player auction, held on 20 February 2008 in Mumbai, whereby the winning bid essentially represents the player's wage for the tournament. Such an auction represents an extremely rare opportunity to measure the true value (marginal revenue product) of labour of professional athletes in the sports industry. This is because none of the usual rigidities, typically present in the players' labour market that exist in ongoing leagues (for a description, see Rosen and Sanderson, 2001), were present in this case.[1] However, it is worth noting that the sports economics literature is rich with

[1] Measuring true marginal revenue product is even more problematic in individualistic sports, due to the commonality of rank-order tournaments, and the associated fixed prize money allocation rules. See Leeds (1988) or Ehenberg and Bognanno (1990) for an outline of some of the associated issues.

contributions that utilise player wage data, but usually with a specific application, see Khan (2000) for a general overview. More specific examples include testing the link between wage expenditure and (on-field) success, such as Berri, Schmidt and Brook (2006), or whether wage discrimination exists in certain leagues (see Bodvarsson and Brastow, 1998; Hill, 2004; or the very recent evidence of Goddard and Wilson, 2009).

Therefore, the purpose of this study is to estimate a hedonic model of player wages arising from this one-off auction process.[2] We wish to use player career statistics at the time of the auction to identify a set of playing traits are valued most highly by teams (the *Moneyball*-style setting of Lewis, 2003). However, we also wish to consider other observable personal characteristics that may have some material effect on the players' valuations – characteristics that determine a player's 'marketability' distinctive from their playing talent. The use of such modelling to identify determinants of auction values in sport is not uncommon – see Parsons and Smith (2007), who undertake such an exercise for thoroughbred yearling sales in horse racing. However, such markets are typically largely unrestricted, unlike the IPL auction case. Therefore, we also wish to consider the role of restrictions on the auction in terms of limits on squad composition and overall player expenditure, in an attempt to observe how player valuations are distorted by such restrictions.

Furthermore, within the sports economics field, the quantity of academic work focussing on the distinctive nuances of international cricket is minimal, a deficiency that this paper hopes to remedy. While a general commentary on the economics of

[2] It is important to note that while further auctions would be planned for future seasons, such auctions would largely involve only new or 'uncapped' players, while there would also be a transfer 'window' (like those in European football leagues) in which existing players could transfer from one IPL franchise to another prior to the commencement of the new season.

cricket is outlined by Preston (2006), other studies have tended to be quite specific in nature, such as those by Brooks, Faff and Sokulsky (2002); Bhattacharya and Smyth (2003); and Allsop and Clarke (2004).

The structure of this paper proceeds in the following manner. Section 2 provides a detailed description of the rules and restrictions of the auction, making possible some inferences based on what auction theory would say about the outcomes involved. Section 3 outlines the data and the econometric modelling used, which leads to section 4, where the results are presented and discussed in detail. Section 5 concludes on a general note.

2. Background on the 2008 IPL Auction

The eight franchises each bid for a maximum of eight foreign (non-Indian) players from a pool of 89 who had been contracted to the BCCI.[3] There were two exceptions to the bidding process:

i) The IPL placed 'icon' status on five marquee Indian players who were not up for auction;

ii) Each franchise could only select a maximum of two Australian players (owing to a clause in a contract with Cricket Australia).

Prior to the first auction, the BCCI laid down a number of guidelines for each franchise which regulated the following: salary cap, the size and composition of each squad and the use of icon players (explained in the following paragraph). Since the teams had to effectively construct a squad of players, the auction can be classified as a

[3] To be eligible for a BCCI contract, foreign players required a 'No Objection Certificate' from their country's governing body. Since the 18 April-1 June IPL season clashed with the English County Championship season (as well as a tour by New Zealand), the England and Wales Cricket Board (ECB) refused to release their players. Subsequently, there were no English players signed in the first auction, although non-international regular Dimitri Mascarenhas was bought in the second auction.

multi-unit auction, with the restrictions outlined above, plus the requirement of a sufficient depth of playing talent in each of the game's specialisations – batting, bowling and wicket-keeping. However, the teams would later have additional opportunities to complete their squad through further player allocation processes (which were themselves subject to a range of restrictions).

Each franchise had a maximum of USD5 million to spend in the first players' auction, hence the auction also involved a budget constraint (there was also a minimum salary cap of USD3 million, which proved to be non-binding). The amount of the winning bid (determined in an English-style setting) became the player's salary and this figure was included in the salary cap. Icon players were to be paid 15 per cent more than the next highest paid player in their respective franchises, creating affiliated values in the auction process. Under-22 players from the BCCI were remunerated with a minimum annual salary of USD20,000, while the remaining players (Indian or overseas) were offered a base of USD50,000, effectively creating 'reserves' for these players.

The guidelines on squads reconciled the profile and talent of overseas players with a need to encourage franchises to promote the game among India's young cricketers. While each squad was restricted to a quota of eight foreign players, four at most could be in any given starting line up. The BCCI mandated that a minimum of four local players from both 'catchment areas' and the BCCI under-22 pool be included in each franchise. The BCCI awarded 'icon' status to the following players: Sachin Tendulkar, Rahul Dravid, Sourav Ganguly and Yuvraj Singh, and (after lobbying from Delhi) Virender Sehwag, making the franchise a monopsony in the market for that player's labour.[4] Each player had to represent the city in which they are based.

Prior to the auction, players were divided into six categories based on their skills, with the 'marquee' players on top (to be auctioned in the first round). The categories were: opening batsmen, middle-order batsmen, pace bowlers, spin bowlers, all-rounders and wicketkeepers. The nature of the auction was sequential - chits with players' names were selected from a bowl and franchisees given the opportunity to bid for them. If no-one bid for a player at reserve initially, that chit would be kept separately (the player relegated to a reserve pool to be auctioned later) and the bidding for the other players continued.

The auction itself was carried out over eight rounds with an additional round for players in the reserve pool, making the auction multi-stage. Seventy-five players received bids: Mohammad Yousuf (Pakistan) and Ashwell Prince (South Africa) were the only overseas players not to receive bids at reserve (hence missing out on playing altogether). A total of USD36.78 million was spent (at an average of just under USD500,000 per player). Including the premiums for the 'icon' players, the total wage bill amounted to nearly USD42 million. By country of origin: India 25, Australia 13, Sri Lanka 11, South Africa 10, Pakistan 7, New Zealand 5, West Indies 3, Zimbabwe 1. According to specialty: 17 all-rounders were chosen, 10 wicket-keepers, 25 bowlers and 23 batsmen.

[4] VVS Laxman was later added to the list but then voluntarily opted out of his icon status to give his franchise more money to bid for players.

Despite the salary cap restriction of USD5 million, five franchises were allowed ultimately to exceed this figure (Chennai, Delhi, Hyderabad, Mohali and Mumbai), while Kolkata nudged USD6 million. Players unavailable for part of the tournament due to being on national duty (mainly Australian players) were paid on a pro-rata basis, thereby reducing the expenditure of franchises below USD5 million. Therefore, while the budget constraint proved to be binding (as it is in most professional sports where it is used), it could be argued that the league faced credibility problems in its enforcement.

The IPL conducted a second players' auction on 11 March, involving an additional list of 28 players who were available.[5] This included 14 from India's under-19 player list.[6] As noted above, the salary cap of USD5 million was a major constraint to at least half of the franchises. Jaipur was the only franchise to spend below the minimum threshold of USD3 million in the first auction, and hence were able to take full opportunity to add to its squad. IPL officials decided to relax the rule on overseas players and allow each franchise the option of picking up a ninth overseas player because some players were unavailable for the entire season and two of the players contracted by the IPL before the first auction were still available.[7]

In summary, the various rules and restrictions, as well as the general dynamics and characteristics of the auction created a very unusual auction framework, necessitating the consideration of numerous modelling issues. These issues are outlined in the following section.

---

[5] Only one player (James Hopes) sold for more than USD150,000 in the second auction, compared to only three of the 80 players in the first auction selling for less than this figure.
[6] These players were allocated according to a draft system.
[7] Bangalore, Jaipur and Kolkata each exercised this option.

3. Modelling Issues

3.1 Data Set

Our data set comprises of the 80 players for whom the bidding price resulted in a 'sale'. The player characteristic and career statistic data were collated from the CricInfo website at: http://www.cricinfo.com/, the latter being compiled over two weekends in March 2008 and backdated to 19 February wherever necessary. Discretionary judgement was required in constructing some binary variables, such as player specialisation and international team status variables, and for some players, the values of these variables may differ slightly between Tests and ODIs.

Since the aim of this research is to model player valuation in the IPL, the key variable is *VALUE*, the player's auction value in USD. We considered the following potentially important explanatory variables:

PAGE: player's age in years on 20 February 2008;

NIND, *NAUS*, *NRSA*, *NSRL*, *NOTH*: dummy variables for the players' nationality (1 for Indian, Australian, South African, Sri Lankan and all other nationalities, respectively, and 0 otherwise);

SBAT, *SBWL*, *SWKT*, *SALR*: dummy variables for players regarded primarily as batsmen, bowlers, wicket-keepers and all-rounders, respectively;

FLDR: a dummy variable for (outfield) players that have stand-out fielding ability;

XFTR: an 'X-Factor' dummy variable for players that have qualities that may generate extra value independent of playing ability (aura, looks, marketability, etc);

RETD: a dummy variable indicating the player had retired from international duties prior to the commencement of the IPL season;

IREG, *IYTD*, *IMSC*: dummy variables indicating the players are considered regular, yet-to-debut and miscellaneous (all other), respectively, in their respective international sides;

ICON: a dummy variable indicting that the player belongs to an IPL side that has an 'icon' player;

CAPT: a dummy variable indicating captaincy experience (defined as national side captaincy on at least two occasions);

FORM: a dummy variable indicating that a batsman/wicket-keeper (bowler) had a higher (lower) batting (bowling) average in 2007 than in his entire playing career – for all-rounders, both conditions are required;

MTCH: number of matches played;

BTIN, *RUNS*: the numbers of innings batted and runs scored;

HSCR: highest score;

BTAV: batting average;

BLSF: number of balls faced;

BTSR: batting strike rate;

C100, *H050*: the numbers of centuries and half-centuries scored;

FOUR, *SIXS*: the numbers of fours and sixes scored;

BWIN, *BLBD*, *RUNC*, *WKTS*: the numbers of innings bowled in, balls bowled, runs conceded and wickets taken, respectively;

BWAV, *BWSR*: the bowling average and strike rate, respectively; *ECON* is the economy rate;

05WI, *10WM*: the numbers of occasions a bowler took at least five or ten wickets in a (long-form) innings or in a match, respectively;

B4WK, *B5WK*: the numbers of occasions a bowler took at least four and five wickets in a (one-day) match;

TW20, *T20I*: the numbers of Twenty20 matches played at domestic or international levels, and on international level only.

Some of the playing statistics and variables are not uniform in different forms of the game. In these cases, superscripts indicate the relevant game form.

As regards the functional form of our hedonic regression model, we assume that it is log-lin, that is the dependent variable is the logarithm of *VALUE* but otherwise the model is linear in the independent variables, except *PAGE*. In this case we allow for a quadratic relationship assuming that up to a certain point higher age implies player improvement/development and hence value, but thereafter it becomes a liability as inevitable athletic decline sets in. All in all, we consider 57 potentially important explanatory variables. Their sample means, standard deviations, largest and smallest values are shown in columns 2-5 of table 3.

In table 4, we assign the explanatory variables to a number of distinct groups, categorised by the broad athletic trait described by the statistic. The first two categories are based on identifiable characteristics (henceforth IC), and the remaining categories on career statistics (CS). This partition is displayed in column 6 of table 3. Note that it is not a one-to-one relation, as certain variables fall into more than one category.

Finally, the last column of table 3 exhibits the expected signs of the relationships between *VALUE* and individual explanatory variables. While we have no expectation of most nationality and specialisation variables (nor *ICON* for that matter), we do expect to observe a premium for Indian players and perhaps all-rounders because of their versatility. We would expect to see premiums for strong fielders, international regulars, 'X-Factor' players (by definition), form players, players with captaincy experience, and those who have played more Twenty20 matches; while expecting discounts for retired players, or those yet-to-debut internationally. In terms of career statistics, all batting variables are defined such that 'more is better', therefore, we would expect to see positive estimates across the board; whereas with bowling, we would expect negative estimates only for statistics framed in terms of runs conceded per unit (specifically *RUNC*, *BWAV*, *ECON* and *BWSR*).

3.2 Model Specification and Estimation

Given the large number of potentially important explanatory variables, serious multicollinearity is most likely in a regression model containing all or most of them. In order to study this possibility, we calculated pairwise correlation coefficients between the possible pairs of independent variables and also between ln(*VALUE*) (henceforth *value*) and each independent variable.[8] We found 42 pairs of independent variables exhibiting extremely strong correlation, i.e. above 0.9 in absolute value - not surprising, since some variables are definitionally linear combinations of other variables. What is even more important, the highest correlation coefficient between *value* and any of the independent variables is only 0.345 (with *XFTR*) and close to one-quarter of all pairs of independent variables have stronger relationships.

In the light of these findings it was not surprising that our first regression with all possible independent variables could not be estimated due to near singularity. To

[8] Given the enormity of the correlation matrix, it is not reported here but is available on request.

avoid serous multicollinearity, we had to reduce the number of independent variables. Consequently, it was necessary to perform automatic variable selections with stepwise regressions. For each group of players (i.e. all, batters, bowlers) and forms of the game (i.e Test and ODI) we experimented with the stepwise forwards and swapwise selection methods. The stepwise-forwards procedure starts with a regression including just a constant term and then in each step augments the model with the variable that has the lowest *p*-value in the latest regression and removes each variable whose *p*-value is high, both compared to some stopping criterion. The swapwise selection method is similar to the stepwise-forwards method, but this time the decision rule to add a variable or to swap an 'inside' variable with an 'outside' variable is based on the potential increment in R^2. In four out of six cases the stepwise-forwards procedure led to reasonable and similar specifications to the swapwise method, but in the other two cases the swapwise results turned out to be superior.

Our preferred models were subjected to four standard tests: the *F*-test of overall significance, (F); the Jarque and Bera (1980) test for normality of the residuals, (N); White's (1980) heteroscedasticity (χ^2) test without cross terms, (W); and Ramsey's (1969) regression specification error test with two fitted terms, $(RESET)$. Each model passed the *F*, *N* and *RESET* tests, but two failed the White test. In these latter cases we rely on White's heteroscedasticity-consistent standard errors. We also calculated the Durbin-Watson *d*-statistic (DW) for each preferred model from the residuals ordered according to increasing values of the dependent variable.

4. Results

The results are summarised in table 5. Overall, the various models produce some intriguing results. With only one exception, all models explain over 60 per cent of the variation in *value* and variables from most categories appear as significant in most models, with the exception of the FP category. The most frequently appearing variables are *NIND*, *XFTR* and *TW20*, each appearing in five models out of six, suggesting strong evidence of value premiums for Indian players, those with an X-Factor characteristic, and those with more experience in this specific form of the game. The home player bias is arguably the most predictable result (presuming that management decisions reflect perceived fan preferences), and is consistent with numerous other studies, such as Kanazawa and Funk (2001) and Foley and Smith (2007), but in direct contrast to the findings of Wilson and Ying (2003). Furthermore, virtually all significant coefficient estimates are of the anticipated sign, except for AC-category domestic variables, which may be attributable to non-Test regulars (generally less valuable players) playing more domestic matches, allowing them to accumulate more 'contribution' at that level.

Initially, two models were estimated for all 80 players purchased in the auction – one using Test (and Domestic) career statistics and the other using ODI statistics, as it is not clear *a priori* which set of statistics contain more information about the player's ability to perform in the IPL and hence which set bidders will give greater weight to. Since the volume of Twenty20 matches played up to February 2008 is thin, it is inadvisable to use career statistics in that form of the game, rather we use simply the number of games played, as any (albeit limited) experience at Twenty20 would be considered potentially valuable.

The Test Model results (ignoring factors mentioned already as being standard) indicate, *inter alia*, that players who had retired already from playing Tests were valued less, reflecting their reduced match conditioning. Players signed with teams containing an icon player also received higher bids. A player's propensity to hit sixes (less common in Tests) when batting is a strong positive indicator of the value of big-hitting ability. For bowling, ability to take wickets is valued at Test level, but the analogous domestic coefficient estimate is significantly negative, possibly due to interaction with the Test wickets term. The sign on bowling average is negative but positive for strike rate, suggesting that better bowlers are valued more highly, but combined with a higher strike rate means that such bowlers are also more economical.

For the ODI model, *PAGE* becomes significantly negative, consistent with the observations of commentators that Twenty20 is '…a young man's game', however, $PAGE^2$ is not significant. In addition to the Indian premium, there is also a premium for Australian and South African players reflecting recent strong performance of these international teams. Also, one-day experience in terms of number of matches played) and number of sixes hit are also both significant.

With a mix of batting and bowling statistics evident in the full sample, the next question to address is that of whether more precise estimates can be obtained by splitting the sample into batting and bowling specialisations. For the former, we include only records for which either *SBAT*=1 or *SWKT*=1, on the assumption that wicket-keepers are still heavily valued for their batting skills. Here, bowling variables are ignored completely, since most batsmen have bowled a small amount during their career, thus possibly creating distortions in the results if they were left in. For this reason, all-rounders are excluded since they are valued heavily on their bowling as well. However, for bowling regressions (requiring either *SBWL*=1 or *SALR*=1 for inclusion), batting variables are still included. The reason for this is that even a specialist bowler may still have some additional value if they have an ability to play a 'cameo' role when they are required to bat with a few overs still remaining in an innings.

For the selected batting group, the Test model is really the only model in which most of the significant variables are career statistics as opposed to identifiable characteristics. Total test runs scored proves to be significant, but so are both domestic average and number of centuries scored, covering elements of categories *AB*, *AC* and even *FP* for batsmen. Interestingly, the identifiable characteristics take over in the ODI model for batsmen. Fielding prowess becomes significant (thought to make a larger difference to the outcome in shorter forms of the game), as well as experience in the form of number of ODI appearances.

In the models for bowlers, it is seen that some batting variables prove to still be significant. For the Test model, an Australian premium arises once again (perhaps due largely to Shane Warne and Glenn McGrath), while players retired from or yet to play tests are valued at a discount. Like before, two significant domestic variables (matches and strike rate) are not the anticipated sign, whereas $BWSR^{T}$ and $05WI^{T}$ demonstrate the value of taking wickets more frequently and the ability to take big hauls. When batting, bowlers who have greater ability are valued higher, even though their ability to score quickly is clearly not, as evidenced by the signs on the $BTAV^{\mathrm{T}}$ and $BTSR^{\mathrm{T}}$ terms.

With respect to diagnostics, it is seen in table 5 that there is some evidence of positive serial correlation (based on increasing *value*). While this typically implies model misspecification, we argue that there is an underlying interpretation – that of bidder irrationality. Figure 1 plots a solid line of (increasing) fitted values according to the geometric mean of USD player values from each of the models (this will be an average of four of the six models for each player).[9] We identify and label three outliers outside the approximate 95 per cent confidence interval – Mohammad Kaif and Kumar Sangakkara above, and Scott Styris below.[10]

While not so evident in the averages, there nevertheless appears to be strong evidence of underbidding (overbidding) at the bottom (top) end of the player pool, demonstrating a Winner's Curse for 'star' players, especially if they underperform in the tournament *ex-post*. When players are ordered instead with respect to actual valuations, we find that 28 out of the 40 less expensive players were underbid according to our mean valuations, whereas only 14 of the more expensive 40 players were underbid, (this difference is significant at the one per cent level of a χ^2-distributed difference of means test). At a cursory glance, figure 1 also seems to suggest that the greatest absolute percentage valuation errors occur in the mid-range of the market.

[9] The use of a mean value for this comparative exercise is on the grounds that the various models differ quite markedly, and do not always include the same sample of players.
[10] Shahid Afridi is also labelled and worthy of a special mention – he is just inside the lower-bound interval, and a bigger outlier than the other three in terms of absolute (as opposed to logarithmic) value.

Such behaviour in the sports industry is not unheard of, due to the existence of ‘superstar effects’ – see Matthews, Sommers and Peschiera (2007) for an illustration in women’s golf with respect to the distribution of prize money in tournaments. While in this particular case, our sample is also drawn from the upper-tail of the population, the outcome may be driven largely by the various restrictions placed on the auction referred to earlier, as the true valuations of players cannot be revealed completely within this framework. Specifically, it is likely that the budget constraint may have limited expenditures on the ‘lesser-lights’, since bidding for ‘star’ players, for which bidding was most highly competitive, was concentrated heavily in the earlier rounds of the auction.

Finally, in contrasting the use of Test versus ODI models, when the full sample is used, it is difficult to separate the models purely on the basis of the measures of fit or information criteria. This tells us that bidders were well informed about players’ abilities in both forms of the game in trying to assess their suitability for Twenty20 cricket. This makes sense, for while Test cricket is a longer form of the game, and is hence likely to reveal more of a player’s true qualities, ODIs much more closely resemble Twenty20 matches.

However, in the player specialisation decompositions, we see an interesting development. The fit and information criteria measures show that for batsmen, ODI stats may be given slightly more weighting in assessment, whereas Test information is given more weighting for bowlers. Such an observation is consistent with the apparent consensus of cricket commentators, who note that the scope for a single bowler to determine the outcome of a Twenty20 match is limited compared to that of a single batman. Thus, perhaps ODI data is more useful in assessing batters because of the similarity of the formats, whereas assessors fall back on Test data for bowlers as a general indication of true ‘quality’.

5. Conclusion

We have undertaken a formal evaluation of the determinants of the marginal revenue product of professional cricketers, as established by an auction with a very unique range of characteristics that can allow us to make inferences on the effect of such restrictions on price. The problem is a very appealing one for numerous reasons, among them that the IPL is arguably the biggest revolutionary concept in the game’s history; the auction is a very rare opportunity to measure athletes’ valuations in this way; and the free availability of player data.

Our most compelling findings are as follows: our six models have strong explanatory power for cross-sectional models; that variables from most defined categories appear as significant in most models; and that most of our significant estimates are of the anticipated sign. The variables most commonly appearing to have a material bearing on player value are the existence of Indian-player and X-Factor premiums, as well as a positive relation with previous Twenty20 experience (number of games). Furthermore, the presence of serial correlation is interpretable as evidence of overbidding for star players and underbidding for lesser players. Finally, ODI statistics seem to provide more informational content about batsmen than Test statistics, while the inverse is true for bowlers.

There is great potential for future work in auction theory to model this auction (with its unique set of attributes) in a formal setting, with a view to considering whether the findings are consistent with those presented here, as well as those from classic works in sports economics, most notably the seminal Fort and Quirk (1995) model. Nevertheless, while not comparable directly with results from any future auctions, the results could be used by the various IPL franchises, along with other information, to approximate ‘fair’ valuations for players in future seasons, to mitigate the incidence of overbidding.

Table 1: Number of International ICC-Sanctioned Cricket Matches by Type, 1993-2008 (Not Counting Cancelled or Abandoned Matches)

Calendar Year	Tests	ODIs	Twenty20
1993	36	82	0
1994	38	98	0
1995	40	60	0
1996	28	127	0
1997	44	115	0
1998	45	108	0
1999	43	154	0
2000	46	131	0
2001	55	120	0
2002	54	145	0
2003	44	147	0
2004	51	128	0
2005	49	107	3
2006	46	160	9
2007	31	191	38
2008	47	126	29

Source: http://www.cricinfo.com/

Table 2: Number of Domestic-Level Matches by Type in All 10 Test-Playing Countries, 2000-2008 (Not Counting Cancelled or Abandoned Matches)

Calendar Year	Long-Form	Limited Overs	Twenty20
2001	773	665	0
2002	693	847	0
2003	731	669	48
2004	633	649	70
2005	604	626	159
2006	598	584	168
2007	680	615	236
2008	615	612	262

Source: http://www.cricinfo.com/

Table 3: Descriptive Statistics

Variable	Mean	Std. Dev.	Maximum	Minimum	Category	Sign
ln(*value*)	12.983	0.647	14.221	11.513	NA	
PAGE	28.700	4.811	38.000	19.000	PC	*
$PAGE^2$	846.55	278.15	1,444.0	361.00	PC	-
NIND	0.363	0.484	1.000	0.000	PC	+
NAUS	0.163	0.371	1.000	0.000	PC	?
NRSA	0.125	0.333	1.000	0.000	PC	?
NSRL	0.138	0.347	1.000	0.000	PC	?
NOTH	0.213	0.412	1.000	0.000	PC	?
$SBAT^T$	0.388	0.490	1.000	0.000	CC	?
$SBAT^O$	0.350	0.480	1.000	0.000		
$SBWL^T$	0.338	0.476	1.000	0.000	CC	?
$SBWL^O$	0.338	0.476	1.000	0.000		
SWKT	0.113	0.318	1.000	0.000	CC	?
$SALR^T$	0.163	0.371	1.000	0.000	CC	+
$SALR^O$	0.200	0.403	1.000	0.000		
$FLDR^T$	0.100	0.302	1.000	0.000	CC	+
$FLDR^O$	0.113	0.318	1.000	0.000		
$XFTR^T$	0.113	0.318	1.000	0.000	CC,PC	+
$XFTR^O$	0.138	0.347	1.000	0.000		
$RETD^T$	0.088	0.284	1.000	0.000	CC	-
$RETD^O$	0.088	0.284	1.000	0.000		
$IREG^T$	0.475	0.503	1.000	0.000	CC	+
$IREG^O$	0.550	0.501	1.000	0.000		
$IYTD^T$	0.125	0.333	1.000	0.000	CC	-
$IYTD^O$	0.025	0.157	1.000	0.000		
$IMSC^T$	0.313	0.466	1.000	0.000	CC	0
$IMSC^O$	0.338	0.476	1.000	0.000		
ICON	0.625	0.487	1.000	0.000	NA	?
$CAPT^T$	0.225	0.420	1.000	0.000	CC	+
$CAPT^O$	0.250	0.436	1.000	0.000		
$FORM^T$	0.313	0.466	1.000	0.000	CC	+
$FORM^O$	0.350	0.480	1.000	0.000		
$MTCH^T$	47.913	43.098	146.00	0.000	EX	+
$MTCH^O$	132.23	107.48	413.00	0.000		
$BTIN^T$	73.938	67.085	237.00	0.000	EX	+
$BTIN^D$	191.05	121.08	571.00	18.000		
$RUNS^T$	2,416.9	2,937.5	11,782	0.000	AC	+
$RUNS^D$	6,548.9	6,149.1	26,277	58.000		
$RUNS^O$	2,752.7	3,531.6	16,088	0.000		
$HSCR^T$	127.95	103.68	380.00	0.000	FP	+
$HSCR^D$	176.81	95.539	380.00	23.000		
$HSCR^O$	86.350	57.602	189.00	0.000		
$BTAV^T$	26.653	18.668	78.143	0.000	AB	+
$BTAV^D$	33.823	15.145	60.059	7.273		
$BTAV^O$	23.735	13.885	55.429	0.000		

$BLSF^{T}$	4,207.0	5,444.0	23,582	0.000	AB,EX	+
$BLSF^{O}$	3,437.4	4,397.4	18,839	0.000		
$BTSR^{T}$	43.479	21.695	86.131	0.000	EE	+
$BTSR^{O}$	72.325	21.726	116.67	0.000		
$C100^{T}$	5.488	8.853	39.000	0.000	AB,AC,FP	+
$C100^{D}$	15.625	19.543	80.000	0.000		
$C100^{O}$	3.888	7.314	41.000	0.000		
$H050^{T}$	10.963	14.009	51.000	0.000	AB,AC,FP	+
$H050^{D}$	30.200	28.666	99.000	0.000		
$H050^{O}$	15.325	21.735	87.000	0.000		
$FOUR^{T}$	284.91	341.49	1,245.0	0.000	AB,AC	+
$FOUR^{O}$	265.51	369.11	1,758.0	0.000		
$SIXS^{T}$	15.600	20.541	100.00	0.000	AB,AC	+
$SIXS^{O}$	37.575	54.026	247.00	0.000		
BWIN	45.213	65.611	273.00	0.000	EX	+
$BLBD^{T}$	4,795.8	9,167.6	40,705	0.000	AB,EX	+
$BLBD^{D}$	10,787	14,874	74,830	0.000		
$BLBD^{O}$	3,341.9	4,520.7	16,364	0.000		
$RUNC^{T}$	2,261.7	4,028.5	17,995	0.000	AC	-
$RUNC^{D}$	5,183.2	6,611.4	34,449	0.000		
$RUNC^{O}$	2,522.7	3,239.9	11,206	0.000		
$WKTS^{T}$	78.713	158.65	723.00	0.000	AC	+
$WKTS^{D}$	191.11	275.42	1,319.0	0.000		
$WKTS^{O}$	85.663	118.01	459.00	0.000		
$BWAV^{T}$	27.899	24.480	105.63	0.000	AB	-
$BWAV^{D}$	34.132	23.918	187.00	0.000		
$BWAV^{O}$	26.709	25.429	151.00	0.000		
$ECON^{T}$	2.602	1.837	13.000	0.000	EE	-
$ECON^{D}$	3.146	1.024	7.588	0.000		
$ECON^{O}$	4.078	2.988	18.000	0.000		
$BWSR^{T}$	54.195	45.565	210.00	0.000	AB	-
$BWSR^{D}$	65.304	42.851	330.00	0.000		
$BWSR^{O}$	32.186	28.541	150.00	0.000		
$05WI^{T}$	3.825	9.900	62.000	0.000	AB,AC,FP	+
$05WI^{D}$	9.063	18.047	114.00	0.000		
$10WM^{T}$	0.775	2.719	20.000	0.000	AB,AC,FP	+
$10WM^{D}$	1.613	4.496	32.000	0.000		
B4WK	2.125	3.421	13.000	0.000	AB,AC,FP	+
B5WK	0.938	1.716	8.000	0.000	AB,AC,FP	+
TW20	13.975	9.445	45.000	0.000	FY	+
T20I	5.838	4.465	15.000	0.000	FY	+
N	80					

Note: the sample size is 80 for all variables. For playing statistics and variables not uniform in different forms of the game, ^{T} indicates Tests; ^{D} indicates first-class/domestic (long-form); and ^{O} indicates ODIs. *Sign* refers to the expected sign of the relationship between *value* and a particular independent variable, (*) indicates expected sign to be '+' if $PAGE^2$ enters the model, and '-' if it does not.

Table 4: Categories to Which Variables are Assigned

Identifiable Characteristics (IC)	Code	Career Statistics (CS)	Code
Personal characteristics	PC	Ability (mean-driven)	AB
Cricketing characteristics	CC	Experience	EX
		Accumulated contribution	AC
		Expeditiousness/economy	EE
		Freak performances	FP
		Familiarity	FY

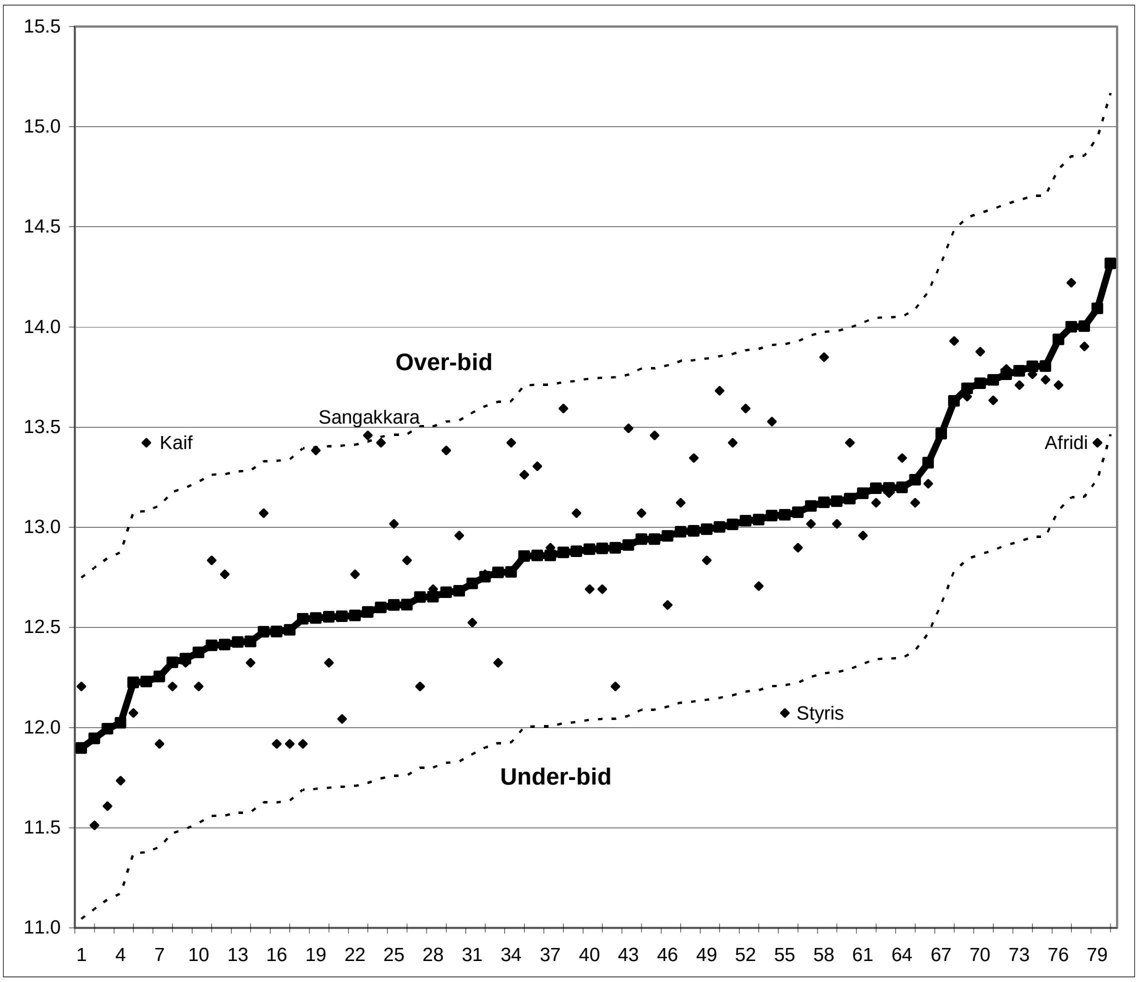
Note: ‘freak performances’ is the possibility that such performances create a ‘halo effect’ in the minds of bidders.

Table 5: Regression Results for Tests and ODIs

	Overall Test	Overall ODI	Batting Test	Batting ODI	Bowling Test	Bowling ODI
C	11.660^{a}	13.421^{a}	10.838^{a}	11.705^{a}	12.229^{a}	12.816^{a}
PAGE		-0.064^{a}				
NIND	0.706^{a}	0.854^{a}	0.816^{a}	1.006^{a}	0.577^{a}	
NAUS		0.552^{a}			0.557^{a}	
NRSA		0.349^{c}				
NSRL						-0.716^{a}
NOTH						-0.415^{b}
FLDR				0.438^{b}		
XFTR	0.848^{a}	0.698^{a}		0.731^{b}	0.600^{a}	0.406^{b}
RETD	-0.729^{a}				-0.570^{c}	
IREG						0.388^{b}
IYTD					-1.671^{a}	
ICON	0.213^{b}					
$MTCH^{O}$		0.004^{a}		0.003^{a}		
$MTCH^{D}$					-0.005^{a}	
$RUNS^{T}$			9.1×10^{-5b}			
$BTAV^{T}$					0.035^{a}	
$BTAV^{D}$			0.036^{a}			
$BTSR^{T}$					-0.018^{a}	
$C100^{D}$			-0.030^{a}			
$FOUR^{O}$						0.001^{b}
$SIXS^{T}$	0.012^{a}					
$SIXS^{O}$		0.015^{a}				
$WKTS^{T}$	0.004^{a}					
$WKTS^{D}$	-0.002^{a}					
$BWAV^{D}$	-0.032^{a}					
$BWSR^{T}$					-0.016^{a}	
$BWSR^{D}$	0.021^{a}				0.030^{a}	
$05WI^{T}$					0.036^{a}	
TW20	0.036^{a}	0.021^{a}	0.025^{a}	0.029^{a}	0.026^{b}	
R^2	0.630	0.607	0.626	0.661	0.747	0.528
$\overline{R}^2$	0.577	0.569	0.558	0.606	0.634	0.464
AIC	1.235	1.221	1.435	1.311	1.095	1.374
SC	1.562	1.460	1.731	1.573	1.644	1.620
F	11.770^{a}	15.876^{a}	9.193^{a}	12.076^{a}	6.639^{a}	8.276^{a}
N	0.570	0.955	0.629	0.556	0.726	0.226
W	9.632	16.152^{a}	3.658	2.946	23.778^{b}	6.536
RESET	0.304	0.286	2.072	0.147	1.465	1.134
DW	1.194^{a}	1.307^{b}	1.389^{b}	2.539	0.938^{a}	0.999^{a}
n	80	80	40	37	40	43
Method	*SF*	*SWMIN*	*SF*	*SF*	*SWMAX*	*SF*

Note: ^{a}, ^{b} and ^{c} indicate significance at 1%, 5% and 10% levels based on two-tail *t*-tests. *AIC* and *SC* denote the Akaike (1973 and 1977) and Schwarz (1978) Information Criterion, respectively; and *n* is the sample size. *SF* refers to stepwise-forwards regression with p =0.1 stopping criterion for both forwards and backwards. *SWMIN* and *SWMAX* refer to swapwise regressions based on min and max R^2 increment, respectively.

Figure 1: Rank-Fitted (Thick Line) with Approximate 95 Per Cent Confidence Intervals (Dashed Line) and Actual (Scatter Plots) Auction Values



References

Akaike, H. (1973), "Information Theory and an Extension of the Maximum Likelihood Principle", in *2nd International Symposium on Information Theory*, eds Petrov, B. N. and Csaki, F., Akadémiai Kiadó, Budapest, pp. 267-281.

Akaike, H. (1977), "On Entropy Maximization Principle", in *Applications of Statistics*, ed. Krishniah, P. R., North Holland, Amsterdam, pp. 27-41.

Allsop, P. E. and Clarke, S. R. (2004) "Rating Teams and Analysing Outcomes in One-Day and Test Cricket", *Journal of the Royal Statistical Society (Series A)*, 167 (4), 657-667.

Berri, D. J., Schmidt, M. B. and Brook, S. L. (2006), *The Wages of Wins: Taking Measure of the Many Myths in Modern Sport*, Stanford University Press, Stanford.

Bhattacharya, M. and Smyth, R. (2003), "The Game is Not the Same: The Demand for Test Match Cricket in Australia", *Australian Economic Papers*, 42 (1), 77-90.

Bodvarsson, O. B. and Brastow, R. T. (1998), "Do Employers Pay for Consistent Performance?: Evidence from the NBA", *Economic Inquiry*, 36 (1), 145-160.

Brooks, R. D., Faff, R. W. and Sokulsky, D. (2002) "An Ordered Response Model of Test Cricket Performance", *Applied Economics*, 34 (18), 2353-2365.

Ehenberg, R. G. and Bognanno, M. L. (1990), "Do Tournaments Have Incentive Effects?", *Journal of Political Economy*, 98 (6), 1307-1324.

Foley, M. and Smith, F. H. (2007), "Consumer Discrimination in Professional Sports: New Evidence from Major League Baseball", *Applied Economics Letters*, 14 (13), 951-955.

Fort, R. and Quirk, J. (1995), "Cross-Subsidisation, Incentives, and Outcomes in Professional Team Sports Leagues", *Journal of Economic Literature*, 33 (3), 1265-1299.

Goddard, J. and Wilson, J. O. S. (2009), "Racial Discrimination in English Professional Football: Evidence from an Empirical Analysis of Players' Career Progression", *Cambridge Journal of Economics*, 33 (2), 295-316.

Hill, J. R. (2004), "Pay Discrimination in the NBA Revisited", *Quarterly Journal of Business and Economics*, 43 (1-2), 81-92.

Jarque, C. M. and Bera, A. K. (1980), "Efficient Test for Normality, Heteroscedasticity and Serial Independence of Regression Residuals", *Economics Letters*, 6 (3), 255-259.

Kanazawa, M. T. and Funk, J. P. (2001), "Racial Discrimination in Professional Basketball: Evidence from Nielsen Ratings", *Economic Inquiry*, 39 (4), 599-608.

Khan, L. M. (2000), "The Sports Business as a Labour Market Laboratory", *Journal of Economic Perspectives*, 14 (3), 75-94.

Leeds, M. A. (1988), "Rank-Order Tournaments and Worker Incentives", *Atlantic Economic Journal*, 16 (2), 74-77.

Lenten, L. J. A. (2008), "Is the Decline in the Frequency of Draws in Test Match Cricket Detrimental to the Long Form of the Game?", *Economic Papers*, 27 (4), 364-380.

Lewis, M. M. (2003), *Moneyball: The Art of Winning an Unfair Game*, W.W. Norton, New York.

Matthews, P. H., Sommers, P. M. and Peschiera, F. J. (2007), "Incentives and Superstars on the LPGA Tour", *Applied Economics*, 39 (1-3), 87-94.

Parsons, C. and Smith, I. (2007), "The Price of Thoroughbred Yearlings in Britain", *Journal of Sports Economics,* 9 (1), 43-66.

Preston, I. (2006), "The Economics of Cricket", in *Handbook on the Economics of Sport,* eds Andreff, W. and Szymanski, S., Edward Elgar, Cheltenham and Northampton, pp. 585-593.

Ramsey, J. B. (1969), "Tests for Specification Errors in Classical Least-Squares Regression Analysis", *Journal of the Royal Statistical Society (Series B),* 31 (2), 350-371.

Rosen, S. and Sanderson, A. (2001), "Labour Markets in Professional Sports", *Economic Journal*, 111 (469), F47-F68.

Schwarz, G. (1978), "Estimating the Dimension of a Model", *Annals of Statistics*, 6 (2), 461-464.

White, H. (1980), "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity", *Econometrica*, 48 (4), 817-838.

Wilson, D. P. and Ying, Y.-H. (2003), "Nationality Preferences for Labour in the International Football Industry", *Applied Economics*, 35 (14), 1551-1160.