EC331
Research in Applied Economics

A Hedonic analysis of the Determinants of Indian Player Valuations in the 2011 Indian Premier League

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ABSTRACT

This paper examines the determinants of bid prices of cricket players in the Indian Premier League (IPL) 2011 tournament using international and IPL data. The hedonic model estimated is founded on the theory that experience, performance and qualitative attributes are the primary characteristics assessed by IPL franchises when appraising a cricketer; particular emphasis will be placed on Indian players, the most represented nationality in the dataset. In addition to specific international performance statistics, ICC player ranking data is also used to define two alternative performance specifications. The regression analysis covers two techniques; firstly Ordinary Least Squares but also Tobit estimation due to evidence of sample selection bias. This study finds that players who have previously participated in the IPL are valued more than players with any type of international experience. Furthermore, performance in Test cricket is found to be highly significant for Indian batsmen while the economy rate is the most influential statistic for bowlers, with even greater premiums estimated for Indian bowlers. Shortcomings in the empirical strategy limit the wider inference of the results although the expansion of the hedonic methodology in this paper can be used in future research.

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1. INTRODUCTION

The Indian Premier League (IPL), a Twenty20[1] cricket tournament, was launched in 2008 with the backing of both the Board of Control for Cricket in India (BCCI) and the International Cricket Council (ICC). Each participating team is centred on an Indian city and bought as a business franchise. The IPL is structured such that teams play each other in a round-robin group stage; the top four teams progress to a round of eliminators from which two emerge as finalists. An 'English' auction system allocates players to teams in a sequential, sealed-bid process. Players are auctioned in groups based on speciality with a successful bid dependent on a player's reserve (base) price[2] being matched or exceeded. Each bid represents the annual wage a team is willing to offer a player in a three-year contract. The most important rules imposed on the auction process are listed below:

- Up to ten non-Indian players are allowed in each squad
- There must be at least four catchment-area players[3]
- Four players must be under-22 years old
- Franchises can retain up to four players between the 2010 and 2011 IPL seasons
- Franchises must spend a minimum of US$3.3 million and a maximum of US$9 million[4] on player contracts

The IPL has revolutionised cricket, raising the profiles of many professional cricketers while simultaneously generating strong appeal from investors, audiences and media firms alike. The auction provides a rare opportunity to measure more precisely the determinants of cricketers' wages. All pre-existing player contracts expired prior to the 2011 tournament, thus each triennial renegotiation year, coupled with the free availability of player data, provides an opportune backdrop to facilitate such a study. Players that represent 'value for money', or an attractive rate of return, are crucial to the franchise model of creating a profitable and successful team. Therefore, it is in the interests of both players and franchises to understand the factors that drive valuations, especially when on-field performance is an essential but not comprehensive component.

2. LITERATURE REVIEW

Literature analysing the wages of sportsmen has a long history, the majority of which focus on American sports. Scully's seminal works on Major League Baseball stand out in particular while Jones and Walsh (1988) and Idson and Kahane (2000) are but a few who have analysed North American ice hockey. In a perfectly competitive labour market, standard microeconomic theory suggests that wages are equal to marginal revenue product (MRP). Scully (1974) concludes that a baseball player's MRP is determined by the effect his performance contribution to the team has on ticket sales. Parallels can be drawn between baseball and cricket given that both sports share the principle of one side 'hitting' and the other 'throwing' a ball. Nonetheless, performance is not the sole determinant of player salaries, Scully (1973) and Kahn (2000) highlight that racial discrimination could also play an important role.

[1] The shortest format of cricket in which each side faces 20 overs of bowling
[2] An IPL committee set base prices at one of the following levels: $20,000, $50,000, $100,000, $200,000, $300,000 or $400,000
[3] The catchment area is defined around the city in which they are based
[4] The upper bound was US$5 million before 2011

Considering that for the first time in cricket's history player salaries are transparently available through the IPL auction,[5] a limited range of literature is unsurprising. Bhattacharya and Smyth (2003), Hynds and Smith (1994) and Chapman et al. (1987) all explore attendance for Test cricket while Paton and Cooke (2005) instead examine English county cricket. Aside from attendance, Barr and Kantor (2004) evaluate different performance metrics to assess the quality of batsmen.

Hedonic price analysis outlines a set of observable attributes that drive demand.[6] Rastogi and Deodhar (2009) apply this approach to the IPL's inaugural season. Similar to findings in baseball, the authors conclude that age and nationality are significant determinants of player wages. More specifically, the auction rules led to premiums for younger players, under-22 years old, and Indian players. The paper recognises but ignores international player rankings while the lack of econometric testing could be a serious cause for concern.

Karnik (2010) proposed a similar model around the foundation that performance is determined by runs scored for batsmen and wickets taken for bowlers. However, the ratios created to measure performance are ambiguously defined and it remains unclear whether they represent one particular year or career statistics. Considering Karnik was interested in the difference between bid and base prices, the dependent variable should arguably have been the premium and not the auction price. Lenten et al. (2012) build on Karnik's model by capturing the current form and captaincy experience of a player as well as identifying 'X' factor players and standout fielders. The problematic measurability of the latter two variables, coupled with issues of multicollinearity limit the interpretability of their results. The authors also find evidence of underbidding (overbidding) at the bottom (top) end of the player pool, implying a Winner's Curse for 'star' players. Intangible factors such as media value and fan popularity may account for this effect.

Boorah and Mangan (2011), Dalmia (2010) and Karnik (2010) all consider measures to evaluate the return on investment when purchasing cricketers, however the proposed performance indices are largely unconvincing. Even though Karnik is the most persuasive, IPL data from only the first two seasons has been considered rendering his conclusions premature. Swartz (2011) and Chakraborty et al. (2012) both advocate alternatives to the current auction system and outline the distortionary impact of auctioning complementary players in a single-item, sequential manner. The former favours a draft, akin to American sports, while the latter recommend bidding on bundles of players in a combinatorial auction mechanism.

Parker et al. (2008) neatly tie together concepts from auction theory such as private, and common, value uncertainty to find expected premiums for younger and Indian cricketers, in addition to evidence of a Winner's Curse, the potential for irrational exuberance[7] and the impact of player speciality. The paper emphasises its own limitations in terms of measuring intangibles, including media value and fielding, but also analysing just one year of IPL data.

The only paper to model sample selection is that of Karnik (2013) who uses a Heckman selection model to build on the methodology proposed in Karnik (2010). The simplistic analysis of runs scored and wickets taken, as sole performance indicators, ignores the importance of averages[8] (consistency) and strike rates[9] (effectiveness) that the literature

[5] Assuming no undisclosed perks or out-of-contract transfers between players and franchises
[6] Further details in Appendix A1
[7] Defined as a "heightened sense of speculative fever" (Boorah and Mangan, 2011, p. 268)
[8] The average measures the number of runs scored per dismissal (batsmen), or the number of runs conceded per wicket (bowlers)
[9] The strike rate captures the number of runs per ball (batsmen), or balls per wicket (bowlers)

emphasises as particularly relevant for Twenty20 cricket. Moreover, minimal justification is given for the use of the base price as an exclusion restriction.

Research on the IPL has predominantly focused on international cricket data; Karnik (2013) is the first to combine both international and IPL performance. Nonetheless, still no consensus has been reached on the best performance measures to adopt. Furthermore, the auction rules impose a distinct bias towards 'home-grown' Indian players, that has caused over 40% of all players in the IPL 2011 to be Indian,[10] but the precise characteristics and measures that drive their valuations have yet to be explored. This paper attempts to address all of the issues outlined above.

3. DATA ANALYSIS

A cross-sectional dataset was created for the purposes of this paper. It covers 340 cricketers, 115 of which were bought in the 2011 auction. An additional 12 players were retained,[11] for whom prices were estimated based on the amount subtracted from the overall auction purse of each franchise.[12] Data definitions and summary statistics for key variables can be found in Tables B1 and B2. Uncapped domestic players received the lowest bids while Gautam Ghambir, an Indian international cricketer, represents the upper bound at $2,400,000. The chosen dependent variable is the natural logarithm[13] of the auction price in 2011, '*lap11*', which encompasses all 127 of the aforementioned players.

All performance statistics were taken from cricinfo's statistical database 'statsguru' (Cricinfo, 2014), which also provides information on qualitative player attributes (such as age, nationality and speciality) and IPL 2011 auction prices. Wikipedia (2013) is the only comprehensive source that details 2011 base prices but only for players that were bought in the auction;[14] a breakdown is shown in Figure B1.

In the literature, age is typically included as a proxy for ability; this paper instead analyses the effect of the auction rule for players under the age of 22, captured by the variable '*young*'. Experience can also reflect underlying ability as well as being desirable itself. Parker et al. (2008), Depken and Rajesekhar (2010) and Lenten et al. (2012) find evidence of a positive relation between experience and the auction price. The first column of Table 1 supports this claim; the strongest correlation is found between the pairing of IPL experience ('*iplexp*') and '*lap11*', at 53%.

Table 1: Correlation between the auction price and measures of experience

Correlation Matrix					
	LAP11	IPLEXP	T20MAT	ODIMAT	TESTMAT
LAP11	**1**				
IPLEXP	**0.5329**	1			
T20MAT	**0.2533**	0.1185	1		
ODIMAT	**0.161**	0.3572	0.528	1	
TESTMAT	**0.1354**	0.3415	0.3739	0.8766	1

[10] See Figure B3
[11] Namely: H Singh, JA Morkel, KA Pollard, M Vijay, MS Dhoni, SK Raina, SK Warne, SL Malinga, SR Tendulkar, SR Watson, V Kohli and V Sehwag
[12] Cricinfo (2011)
[13] Using the natural logarithm ensures a normally distributed dependent variable.
[14] Base prices should be assigned to all players registered for the 2011 auction, regardless of whether they were bought or not

The dataset includes twelve different nationalities of which nine were represented in the 2011 tournament (Figures B2 and B3, respectively). Notably 47% of the overall dataset, and 41% of all players in the 2011 tournament, were Indian. The dummy variable '*Ind*' takes the value one if a player is of Indian nationality and zero otherwise; its interactions with various experience and performance measures form the main variables of interest in this paper. The breakdown of player specialities in the IPL is representative of the sample as a whole (Figures B4 and B5); approximately one-third are bowlers, one-third batsmen and the rest either all-rounders or wicket-keepers.

The dataset includes performance measures for all three formats of international cricket and the first three seasons of the IPL.[15] In general, higher batting statistics (e.g. ODI batting average) mean better performance; therefore a positive relation with player valuations would be expected (Figure B6). The opposite is true of bowling statistics (e.g. Test economy rate), implying a negative correlation (Figure B7). A good fielder contributes by not only taking catches and assisting in run-outs but also through preventing runs being scored therefore a positive relationship with the auction price would be anticipated. In addition, the ICC rank the top 100 batsmen and bowlers in international cricket[16] and these raw player ratings have been included in the dataset.

4. METHODOLOGY

The methodology chosen is centred on the hedonic model proposed by Parker et al. (2008)[17,18]:

$$lap11_i = f(experience, qualitative\ attributes, performance)_i + bp11_i + \varepsilon_i$$

where,
$lap11_i$ = natural logarithm of the IPL 2011 auction price
$experience$ = career experience in Twenty20s, One Day Internationals, Tests and the IPL
$qualitative\ attributes$ = age, nationality and speciality
$performance$ = a range of performance statistics for batting, bowling and fielding across all three international formats and the IPL
$bp11_i$ = player base price in IPL 2011 auction
ε_i = estimated error of the model

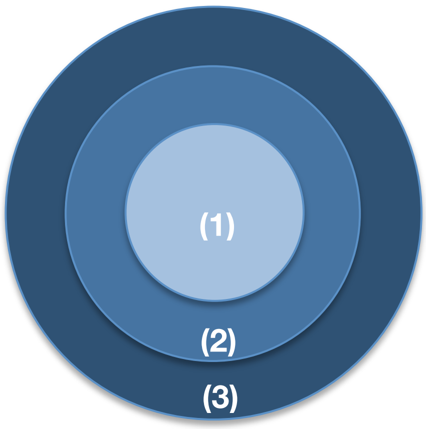
The equation is estimated using Ordinary Least Squares (OLS). All explanatory variables are classified under one of the above categories and have been chosen with care in view of potential multicollinearity between performance measures. In particular, ICC ranking data runs the risk of multicollinearity with raw performance statistics, thus two alternative specifications will be analysed. Qualitative attributes, experience and IPL performance are assumed to be exogenous and feature in both specifications.

As previously mentioned, only a subset of the full dataset participated in the IPL 2011. Using Figure 1, Type (1) includes all the players who were bought in, or retained for, the 2011 auction. Type (2) players were auctioned but remained unsold and thus did not

[15] Calculated as career performance statistics up to and including 31st December 2010
[16] The ranking is based on the number of runs scored/ wickets taken, current form, relative performance and the quality of opposition, although the precise details and aggregation methods are not publicly disclosed
[17] See Appendix A1
[18] Parker et al. (2008) did not investigate the base price while different experience and performance statistics have been chosen in this paper

participate in the competition. Finally, Type (3) relates to players that were neither involved in the auction nor the tournament itself[19]. Solely analysing the 127 players of Type (1) could possibly lead to a sample selection bias. Therefore, 213 players of Types (2) and (3) have been added to the dataset.[20]

Figure 1: Layers of Sample Selection



Consequently the dependent variable, '*lap11*', is left-censored[21] to include the full sample of players. There are two alternatives when considering OLS estimation of censored data, either the whole sample can be examined or only players of Type (1) for whom auction prices are reported. Regardless of whichever is chosen, Gujarati (2011) points out that the conditional mean of the error term would be nonzero and the error terms correlated with the regressors. Therefore, OLS estimation would be both biased and inconsistent.

The Tobit model uses Maximum Likelihood Estimation (MLE) to accommodate the censored data and can be applied to the dataset in the following way:

$$Let\ Y_i = \begin{cases} Y_i^* & if\ lap11 > 0 \\ 0 & if\ lap11 \leq 0 \end{cases}$$

$$where\ \ Y_i^* = f(experience, qualitative\ attributes, performance)_i + bp11_i + \varepsilon_i$$

The variable Y_i^* is only observed for Type (1) players. It is for these observations that the determinants of the auction price will be estimated and interpreted.

The Heckman model analysed by Karnik (2013) is an alternative approach for censored data. The author defines selection and outcome equations on the same set of explanatory variables using the base price as an exclusion restriction.[22] One criticism would be that the allocation of base prices is likely correlated to performance: renowned international cricketers warrant higher brackets while uncapped players are typically given the lowest base prices. Secondly, base price data on unsold players is not available which limits its effectiveness as an exclusion restraint. Given these limitations, and the lack of another feasible exclusion constraint, the Tobit model is preferred with the base price included as an independent variable.

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[19] Notably, no Pakistani players have participated in the IPL since 2008 due to political differences between India and Pakistan

[20] The inclusion criteria involved a minimum experience of five International Twenty20 matches as well as either Test, ODI or IPL experience

[21] '*ap11*' is left-censored at a value of 1 so that its natural logarithm, '*lap11*', takes the value of zero if censored or at the positive value corresponding to an auction bid; further details on censored regressions can be found in Appendix A2

[22] This refers to the unique variable that only affects selection but not the outcome of the model

5. RESULTS

5.1. ICC Specification

Along with Parker et al. (2008), this is one of the first papers to use ICC ranking data to measure performance. The results from OLS estimation of the ICC specification can be found in the first column of Table 2. Each coefficient can be directly interpreted as the marginal effect of that particular variable at the mean of the dependent variable. All regressors are either individually or jointly significant at the 10% level.

A number of control variables are used in the model, most of which relate to the qualitative attributes of players or the auction rules, such as the '*young*' variable. The focus of this paper is on Indian players and the characteristics that drive their valuations thus coefficients on other, statistically significant, nationalities will not be directly interpreted. The negative coefficient found on the variable '*ind*' may be an initial cause for concern however, considering the numerous interactions with performance and experience measures, its interpretation may be less informative.

It is estimated that all-rounders ('*all*') warrant valuations that are 160% more, ceteris paribus, than any other speciality type. Even though the magnitude of the coefficient is quite remarkable, Parker et al. (2008) similarly conclude that all-rounders are prized assets particularly for their versatile ability to influence a match through batting, bowling and fielding. A more puzzling result is that Indian all-rounders ('*indall*') are worth less, on average, than all-rounders of any other nationality. In fact, some of the highest bids in the auction were for Indian all-rounders, namely Yusuf Pathan ($2,100,000) and Yuvraj Singh ($1,800,000). Indian all-rounders may not be valued for the classification itself but rather the skills and attributes they offer. Therefore, the desirable aspects could have been captured by the interactions with individual performance and not the '*indall*' estimate.

IPL experience ('*iplexp*') is found to be highly significant at the 1% level with each additional IPL match estimated to raise player value by 17%; Figure C1 further supports the regression analysis. Thus franchise owners are happy to reward players who have previously participated in the IPL with higher annual wages. For Indian players, ODI experience ('*indodimat*') is also highly regarded but not to the same extent as IPL experience.

ICC rankings are designed to reward the best performing players so positive coefficients for these variables would be expected. A ten-unit increase in a player's ODI bowling rank ('*odibowlrank*') or Twenty20 batting rank ('*t20batrank*') is estimated to raise his worth by 3% or 2% respectively. Furthermore, the largest premium is found for the Test batting rank of an Indian player ('*indtestbatrank*') where a ten-unit rise inflates his auction price by 20%, ceteris paribus; an effect that is highly significant at the 1% level. The IPL and international Twenty20 formats both involve 40 overs of cricket so the latter would have been expected to provide the most relevant information, however Twenty20 rankings have only been recently introduced which may lessen their reliability.

Finally, the results for career IPL performance reconcile some of the relationships hypothesised in the data analysis. A one-unit reduction in a player's IPL career bowling average ('*iplbowlav*') is estimated to raise his value by 2.9% whereas an additional fielding dismissal, for an Indian cricketer ('*indipldis*'), elevates his worth by 36%.

Table 2: ICC Specification (Full Results)

Variable	OLS Model	Tobit Model	Tobit (Marginal Effects)
YOUNG	0.697	1.975	0.704
	(0.550)	(1.466)	
IND	**-2.358*****	-6.969***	**-2.311**
	(0.602)	(2.285)	
AUS	**3.146*****	7.463***	**3.220**
	(0.769)	(1.794)	
SA	**1.997****	5.573***	**2.313**
	(0.845)	(1.933)	
SRI		5.563**	**2.342**
		(2.327)	
NZ		4.351*	1.749
		(2.237)	
ALL	**1.596****	3.838***	**1.409**
	(0.688)	(1.253)	
INDALL	**-2.409****	-6.705***	**-1.735**
	(0.966)	(2.499)	
ODIMAT	**-0.015****	-0.044***	**-0.015**
	(0.007)	(0.016)	
INDODIMAT	**0.034****	0.079***	**0.026**
	(0.015)	(0.029)	
TESTMAT	-0.001	-0.007	-0.002
	(0.019)	(0.047)	
INDTESTMAT	**-0.121*****	-0.271***	**-0.090**
	(0.037)	(0.093)	
TESTBATRANK	-0.001	-0.004	-0.001
	(0.002)	(0.004)	
INDTESTBATRANK	**0.020*****	0.045***	**0.015**
	(0.004)	(0.009)	
ODIBOWLRANK	**0.003****	0.006**	**0.002**
	(0.001)	(0.002)	
T20BATRANK	0.002*	0.006*	0.002
	(0.001)	(0.003)	
INDT20BATRANK	**-0.017*****	-0.039***	**-0.013**
	(0.005)	(0.009)	
IPLEXP	**0.174*****	0.355***	**0.118**
	(0.037)	(0.067)	
IPLBOWLAV	**-0.029****		
	(0.015)		
INDIPLBOWLAV	**0.064*****		
	(0.020)		
IPLECON		-0.347***	**-0.115**
		(0.121)	
INDIPLECON		0.780***	**0.259**
		(0.224)	
IPLDIS	**-0.224*****	-0.420***	**-0.140**
	(0.061)	(0.124)	
INDIPLDIS	**0.362*****	0.748***	**0.248**
	(0.068)	(0.152)	
BP11	**0.000*****	0.000***	**0.000**
	(3.2×10^{-6})	(6.4×10^{-6})	
CONST	**1.283****	-6.523***	
	(0.535)	(1.66)	
SIGMA		6.416***	
		(0.357)	
R^2	0.73		
PSEUDO R^2		0.25	
NO. OF OBSERVATIONS	340	340	

* Represents significance at the 10% level, ** at the 5% level, *** at the 1% level.
OLS & Tobit Dependent Variable = *lap11*
Robust standard errors in parentheses

The results from Tobit estimation are shown in the second column of Table 2 with the resulting marginal effect[23] in the third column. At first glance, there appears to be little difference between the marginal effects from the OLS and Tobit models. For variables that are statistically significant in both, the coefficients are of identical sign. To generalise further, for variables included in both models, the Tobit estimations show a greater degree of statistical significance while smaller marginal effects.

A few distinctions are worth noting. Two additional nationality dummy variables were found to be statistically significant and warrant premiums. The effect of an additional IPL fielding dismissal, for an Indian player, is 11% lower than the, 36%, OLS prediction. Lastly, the IPL economy rate (‘*iplecon*’), and not the bowling average, is found to be highly significant at the 1% level.

5.2. Raw Performance Specification

A summary of the main results for the raw performance specification can be found in Table 3 with the full results in Table C1. Fittingly, the control variables yield consistent results with the ICC specification. IPL experience continues to be statistically significant at the 1% level although there is 6% difference between the OLS and Tobit estimates.

The investigation of raw performance measures reveals some interesting results. Parker et al. (2008) and Karnik (2010) find ODI batting strike rate to be insignificant while Rastogi and Deodhar (2009) suggest that higher strike rates raise player valuations. This paper supports the latter claim with the variable ‘*indodibatsr*’ statistically significant at the 1% level, but only for Indian players. Furthermore, Test cricket appears to play the most influential role in the pricing of Indian batsmen. A possible justification could be that Test cricket reveals the ‘true characteristics’ of a batsman while the ODI and Twenty20 formats are more easily susceptible to anomalies. A one-unit increase in strike rate (‘*indtestbatsr*’) is estimated to raise valuations in both the OLS and Tobit models by 11% and 8% respectively; Figure C2 graphically supports the regression analysis. Likewise, an additional Test hundred (‘*indtesthun*’) is expected to inflate prices by 50% (OLS) or 12% (Tobit).

Moving on to bowling measures, in the OLS model an additional ODI five-wicket haul (‘*indodifive*’) or ODI fielding dismissal (‘*indodidis*’) is found to boost valuations for Indian players while a reduction in Test bowling strike (‘*indtestbowlsr*’) has the same effect. Considering these effects are insignificant under Tobit estimation could imply that their importance is limited to players who participated in the IPL 2011 auction but not when a wider selection of cricketers can be chosen. A key finding in the Tobit model is that economy rates are the dominant performance statistic for bowlers in general, especially the IPL economy rate. For Indian players in particular, a one-unit decrease in ODI (‘*indodiecon*’) or Test economy rate (‘*indtestecon*’) is estimated to improve their price, on average, by 74% and 68% respectively.

[23] The marginal effect is calculated as the expectation of ‘*lap11*’ for each explanatory variable given that the individual has not been censored; see Appendix A3

Table 3: Summarised results of Raw Performance Specification

Variable	OLS Model	Tobit Model	Tobit (Marginal Effects)
IPLEXP	**0.161*****	0.289***	**0.096**
	(0.036)	(0.053)	
IPLECON		-0.437***	**-0.145**
		(0.116)	
INDODIBATSR	**0.055*****	0.140***	**0.046**
	(0.015)	(0.030)	
INDODIECON		-2.225***	**-0.737**
		(0.750)	
INDODIFIVE	**3.252*****		
	(1.021)		
INDODIDIS	**0.037*****		
	(0.012)		
INDTESTBATSR	**0.111*****	0.235***	**0.078**
	(0.028)	(0.057)	
INDTESTHUN	**0.501*****	0.352**	**0.117**
	(0.077)	(0.172)	
INDTESTBOWLSR	**-0.185*****		
	(0.041)		
INDTESTECON		-2.062**	**-0.683**
		(0.924)	
BP11	**0.000*****	0.000***	**0.000**
	(2.47×10^{-6})	(4.59×10^{-6})	
NO. OF OBSERVATIONS	340	340	

* Represents significance at the 10% level, ** at the 5% level, *** at the 1% level.
OLS & Tobit Dependent Variable = *lap11*
Robust standard errors in parentheses

6. DIAGNOSTIC TESTS AND LIMITATIONS

Robust standard errors have been used in all models due to evidence of heteroskedasticity. For OLS, this is investigated using the Breusch-Pagan test, in which the null hypotheses of homoskedasticity can be unambiguously rejected. For both Tobit specifications, the final regressions are tested on several sub-samples of the dataset to observe whether the estimated standard errors change significantly; this is found to be the case. All aforementioned tests are displayed in Table D1. In the ICC specification, there appears to be minimal evidence of sample selection bias, notwithstanding the censored data means OLS is biased and inconsistent. Meanwhile, Tobit estimation is inefficient in the presence of heteroskedasticity[24], thus it is difficult to conclude which model is preferable. There is greater evidence of selection bias in the raw performance specification supporting the use of the Tobit model in this case. For consistency, both Tobit models will be classed as ‘preferred’ models however this is by no means authoritative.

One potential cause for the heteroskedasticity could be model misspecification, which can be tested using the Ramsey RESET test in OLS estimation.[25] From Table D2, the null hypotheses of no omitted variables can also be unambiguously rejected thus the estimated effects may be biased. There are a myriad of performance variables that could have been considered, however data availability limits such analysis and the likelihood of a correctly specified model. A noteworthy omission is media value. Parker et al. (2008), Rastogi and Deodhar (2009) and Lenten et al. (2012) all allude to the impact

[24] The implications of heteroskedasticity in Tobit models are discussed in Appendix A3

[25] The results for the RESET test can be extrapolated to include both Tobit models, in the absence of explicit testing, with the rationale remaining consistent.

of a player exogenous to his cricketing abilities. IPL franchises generate income through advertising and ticket sales; therefore high-profile celebrity cricketers can boost both revenue streams, implying their value would exceed the amount hedonically estimated. The lack of holistic measures for leadership ability and fielding further restrain the capabilities of this framework.

The base price exhibits strong statistical significance yet meaningless marginal effect in all estimated models; this could denote potential endogeneity. Table D3 details the testing on both 'preferred' models. A strong positive correlation is found between the estimated errors and the base price, which suggests that the estimated effects are likely biased in all models. Furthermore, it could explain the incorrect signs on some estimated coefficients such as ODI economy rate ('*odiecon*') or ODI experience ('*odimat*'). Unfortunately the usual procedures to correct for endogeneity cannot be applied due to the lack of an exogenous, relevant instrument. In light of this, future research could use information on base price criteria and allocation methods to estimate a reduced form model with two separate regressions for the base price and the auction price.

Finally, the estimated wages for retained players could be another source of bias. Simply discarding these 12 observations would also lead to bias because the estimates are in the upper-tail of the distribution of auction prices. The generalised residuals from the full sample and those excluding the retained players are highly correlated in both 'preferred' models (c. 90%).[26] Therefore, there is some unmodeled common factor that affects both retained and non-retained players. All things considered, the results outlined should be interpreted with caution, heeding the limitations in the methodology.

7. EXTENSIONS AND ROBUSTNESS CHECKS

In order to validate the stability of the estimated effects, five extensions were run on the 'preferred' models with the results displayed in Tables E1 and E2. Overall, the estimates on the key variables do no change significantly while statistical significance is typically maintained, implying the results are relatively robust. As an initial test South African players, the third most represented nationality in the 2011 competition, were removed from the regression with results displayed in Column (1).

The most limiting check only examines players with international experience. From Column (2) it can be generalised that even though most estimated effects are smaller in magnitude, likely due to the constriction of the dataset from 340 to 220 observations, the correct signs on coefficients and statistical significance are maintained.

In Column (3), the '*leadership*' variable measures the number of international matches a player has captained. All forms of international experience are consequently dropped due to multicollinearity. In both cases, leadership is highly significant but carries a negative sign much like the '*odimat*' variable. The sign reversal could be attributed to endogeneity while its statistical significance likely stems from being the only remaining measure of international experience.

Finally, dropping '*all*' and '*indall*' to the default, it is investigated whether a premium exists for batsmen, Column (4), or bowlers, Column (5), over all other speciality types. In the ICC specification, a premium is found on Indian batsmen at the 10% level while in

[26] Refer to Table D4

the Tobit model an even greater mark-up is estimated for Indian bowlers, at the 5% level. Nonetheless, the aforementioned effects are comparatively less robust and statistically significant than the premiums for all-rounders in both specifications.

8. CONCLUDING REMARKS

The main aim of this paper was to investigate the factors that are most influential in determining the valuation of Indian cricketers in the IPL. Contrary to popular belief, performance in Test cricket is found to have the strongest impact on the bid price of Indian batsmen. On the other hand, the evidence suggests that the economy rate is the bowling statistic most valued by franchises, with even greater premiums possible for Indian bowlers. Akin to the literature, the auction rules continue to artificially inflate the value of '*young*' and Indian players. Finally, the paper finds evidence that a higher ICC ranking is likely to increase a player's bid price while IPL experience is an invaluable attribute that is prized above all other types of experience.

Unfortunately the chosen methodology was not fit for purpose, particularly with reference to the inclusion of the endogenous base price variable. The likely biased estimations limit the interpretability and wider scope of the results found. Nevertheless, the main contribution of this paper may not lay in the results per se, but in the expansion of the hedonic approach for measuring performance, including two separate specifications, as well as finding sufficient evidence of sample selection.

Additional base price data would allow for the variable to be analysed correctly, a Heckman or reduced form model are two possibilities. Further information on retained players would facilitate an examination of the strong correlation found in Table D4 and the best approach to model the effect. On a final note, investigating more accurate measures of fielding, captaincy and media value would enable the researcher to capture the 'true value' of a cricketer.

9. APPENDICES

Appendix A

A1: Hedonic price analysis

Hedonic price analysis stems from revealed preference theory. It assumes that utility is not derived by the consumption of a good but the underlying characteristics of that particular good. In this regard, the market price is the sum of the prices consumers are willing to pay for each desirable characteristic[27]:

$P(x) = p(x_1, x_2, \ldots, x_n)$

This methodology can be used to estimate the constituents of demand for a good. The demand function for a cricket player can fundamentally be derived from his batting and bowling ability, which reflect the two innings played in every game of cricket. To comply with the economic theory, each estimated model must include at least one bowling and one batting measure. Experience and qualitative attributes further reveal information about a cricketer's ability and thus are also included in the hedonic analysis (as described in the Methodology on page 6).

A2: Censored data and regressions

Censored data occurs when the responses of a variable are only available for a certain range (Wooldridge, 2010). For example, if responses are positive when the variable is observed but exhibit a value of zero, or a missing value, when there is no response then the data is said to be "left-censored" (as is the case for this paper). The most common example of left-censoring would be the female labour market in which wages are only recorded for women in employment. In general, uncensored data only considers women with positive wages whereas censored regression models (such as the Tobit) impose a lower limit on the dependent variable to extend the data to include all individuals.

A3: Caveats with the Tobit model

Interpretation of the Tobit model is not as simple as OLS. A unit change in any variable has two effects:

1) $\mathrm{Pr}(Y_i > 0|x_i)$: The effect on the probability that Y_i^* is actually observed, and
2) $\mathrm{E}(Y_i|Y_i > 0, x_i)$: The effect on the mean value of the observed dependent variable given that the observation is not censored

The interest of this paper lays in the determinants of player wages given that they participated in the IPL auction suggesting the second effect is most relevant. Therefore, the marginal effects reported in all Tobit regression tables relate to this particular interpretation.

Issues in specification further highlight differences between the OLS and Tobit estimation methods. In an OLS setting, the estimators may not be efficient but remain consistent in the presence of heteroskedasticity. This means that it affects the testing of hypothesis, and thus the statistical significance of variables, but the coefficients remain robust. However, Wooldridge (2012) points out the assumption of homoscedasticity is crucial to the Tobit model, if it does not hold then it is difficult to know what the MLE is estimating. Furthermore, if the error term is heteroskedatic, the estimated effects are neither consistent nor efficient (Gujarati, 2011). In this case it is important to determine the cause of the heteroskedasticity and whether it can be resolved. The use of robust standard errors or the logarithmic transformation of the dependent variable are two possible solutions but their impact would be limited if the functional form of the model is inappropriate.

[27] Sources: Rosen (1974) and Rastogi and Deodhar (2009)

Appendix B

Table B1: Data Definitions

Variable	Definition
AP11	IPL auction price 2011
LAP11	Natural logarithm of '*ap11*'
BP11	The base (reserve) price of a player in the IPL 2011 auction
AGE	The age of the player, measured in years, on 31st December 2010
ODIMAT	Total number of One Day International (ODI) matches played
TESTMAT	Total number of Test matches played
TESTBATRANK	ICC Test batting rank (raw measure)
ODIBOWLRANK	ICC ODI bowling rank (raw measure)
T20BATRANK	ICC Twenty20 batting rank (raw measure)
IPLEXP	Total number of IPL matches played
IPLBOWLAV	IPL career bowling average
IPLECON	IPL career economy rate
IPLDIS	IPL career fielding dismissals (the number catches and stumpings)
T20BATAV	International Twenty20 batting average
T20BOWLSR	International Twenty20 bowling strike rate
ODIBATAV	ODI batting average
ODIBATSR	ODI batting strike rate
ODIBOWLAV	ODI bowling average
ODIECON	ODI economy rate
ODIFIVE	ODI five-wicket hauls
ODIDIS	ODI fielding dismissals
TESTBATSR	Test batting strike rate
TESTHUN	Number of Test hundreds
TESTBOWLAV	Test bowling average
TESTBOWLSR	Test bowling strike rate
TESTECON	Test economy rate
YOUNG	Dummy variable: taking the value 1 if the player is under the age of 22, 0 otherwise
IND	Dummy variable: taking the value 1 if the player is Indian, 0 otherwise
ALL	Dummy variable: taking the value 1 if the player is an all-rounder, 0 otherwise
BAT	Dummy variable: taking the value 1 if the player is a batsman, 0 otherwise
BOWL	Dummy variable: taking the value 1 if the player is a bowler, 0 otherwise
AUS	Dummy variable: taking the value 1 if the player is Australian, 0 otherwise
SRI	Dummy variable: taking the value 1 if the player is Sri Lankan, 0 otherwise
NZ	Dummy variable: taking the value 1 if the player is Kiwi, 0 otherwise
SA	Dummy variable: taking the value 1 if the player is South African, 0 otherwise
INDODIMAT INDTESTMAT INDTESTBATRANK INDT20BATRANK INDIPLBOWLAV INDIPLECON INDIPLDIS INDT20BATAV INDT20BOWLSR INDODIBATSR INDODIBOWLAV INDODIECON INDODIFIVE INDODIDIS INDTESTBATSR INDTESTHUN INDTESTBOWLAV INDTESTBOWLSR INDTESTECON	The following are all interactions terms between the '*Ind*' dummy variable and performance measures, and experience, defined above

Table B2: Summary Statistics*

Variable	Obs.	Mean	Std. Dev.	Min	Max
AP11+	127	612,200	549,700	20,000	2,400,000
LAP11+	127	12.85	1.092	9.903	14.69
BP11+	115	170,300	113,700	20,000	400,000
AGE	340	27.96	4.850	18	41
ODIMAT	340	56.01	85.48	0	441
TESTMAT	340	18.79	34.35	0	172
TESTBATRANK	340	97.99	219.1	0	882
ODIBOWLRANK	340	107.5	215.3	0	727
T20BATRANK	340	90.07	192.6	0	847
IPLEXP	340	11.32	12.70	0	46
IPLBOWLAV	340	15.03	19.63	0	122
IPLECON	340	4.689	4.716	0	21.50
IPLDIS	340	3.874	5.718	0	38
T20BATAV	340	9.114	11.96	0	52
T20BOWLSR	340	7.173	10.31	0	42.50
ODIBATSR	340	47.86	40.71	0	205.4
ODIECON	340	2.339	2.537	0	7.17
ODIFIVE	340	0.3971	1.136	0	10
ODIDIS	340	23.82	51.97	0	472
TESTBATSR	340	23.97	26.44	0	86.97
TESTHUN	340	2.094	6.199	0	50
TESTBOWLSR	340	31.48	47.17	0	296
TESTECON	340	1.227	1.608	0	4.64
YOUNG	340	0.1206	0.3261	0	1
IND	340	0.4735	0.5000	0	1
ALL	340	0.2324	0.4230	0	1
BAT	340	0.3294	0.4707	0	1
BOWL	340	0.3412	0.4748	0	1
AUS	340	0.1412	0.3487	0	1
SRI	340	0.05588	0.2300	0	1
NZ	340	0.0411	0.1990	0	1
SA	340	0.08529	0.2797	0	1

* Rounded to 4 significant figures where appropriate

+ Summary statistics for these variables have been taken before data censoring, as it is more informative

Figure B1

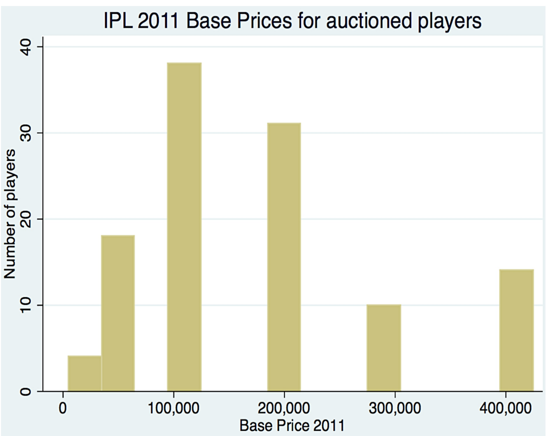


Figure B2

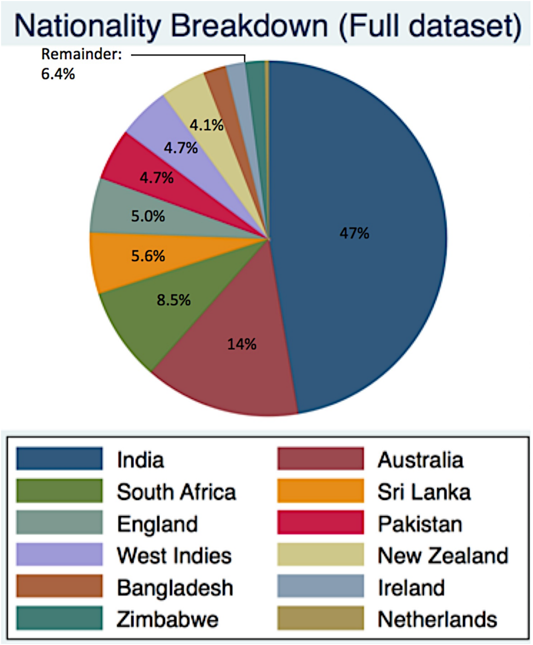


Figure B3

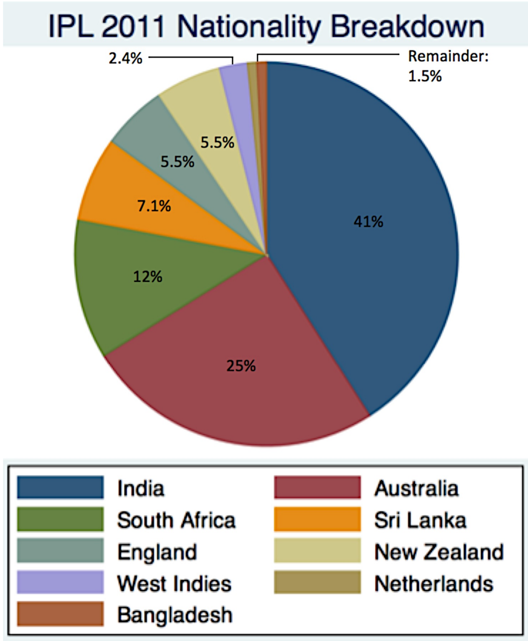


Figure B4

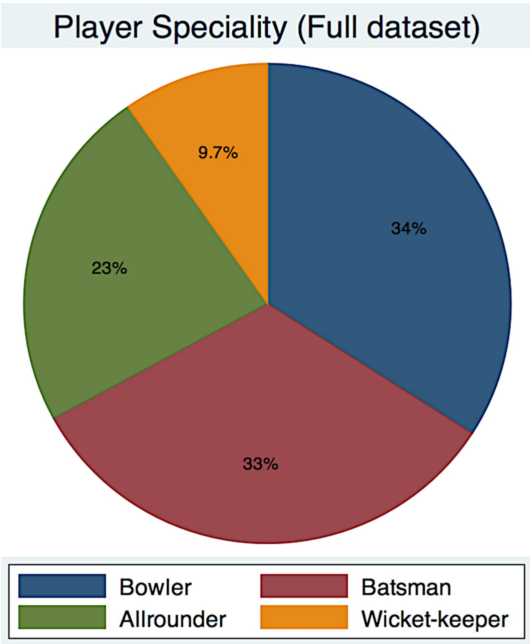


Figure B5

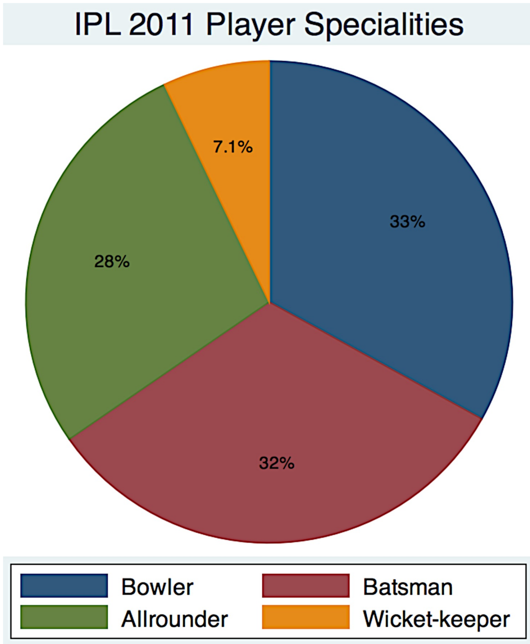
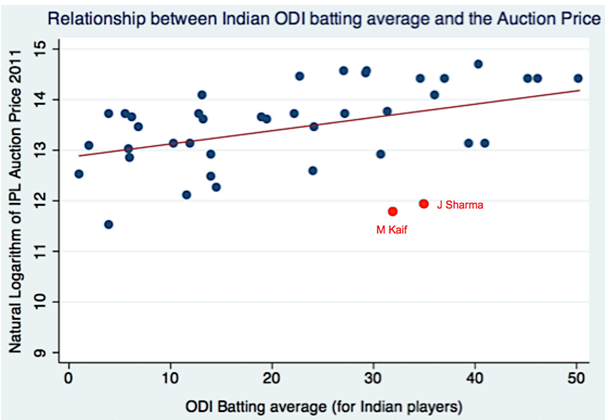
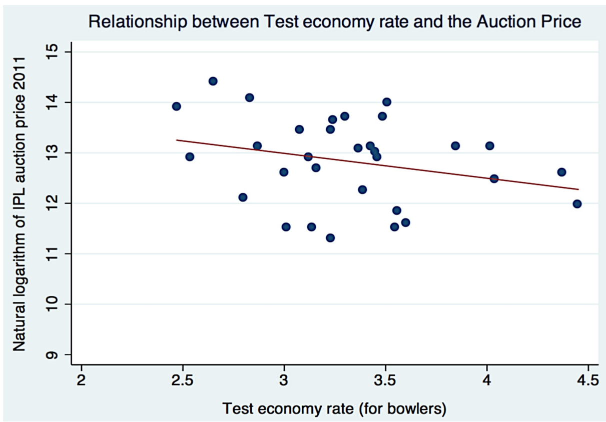


Figure B6*



* With regards to the outliers in red, M Kaif played his last ODI in 2006 while J Sharma has only played 4 ODIs

Figure B7



Appendix C

Figure C1

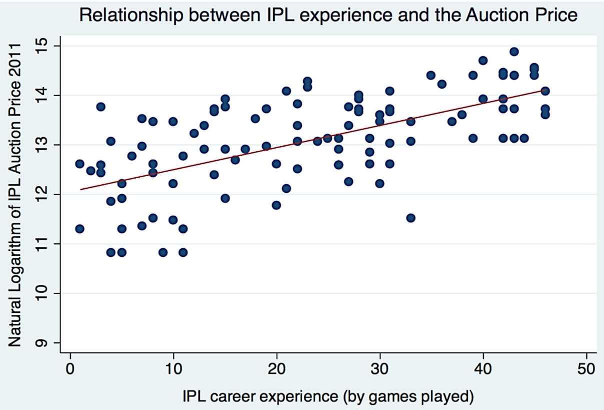
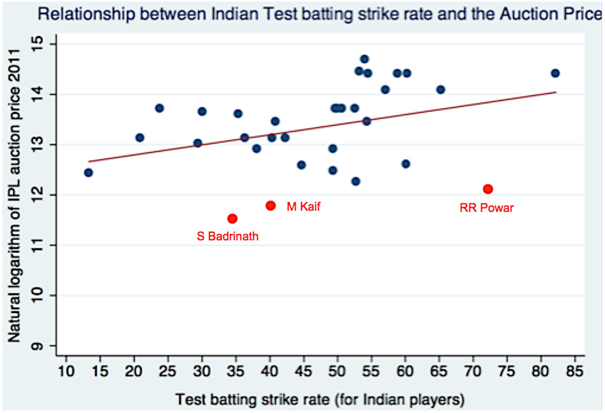


Figure C2*



* The outliers in red were all inconsistent members of the Test team, having only played 17 Test matches between them

Table C1: Raw Performance Specification (Full Results)

Variable	OLS Model	Tobit Model	Tobit (Marginal Effects)
YOUNG	0.907*	2.434*	0.890
	(0.480)	(1.350)	
IND	-1.546	-8.587***	**-2.865**
	(0.993)	(2.797)	
AUS	**2.778*** **	7.458***	**3.307**
	(0.760)	(1.593)	
SA	**1.558*** *	5.651***	**2.410**
	(0.782)	(1.755)	
SRI		6.300***	**2.815**
		(2.245)	
NZ		5.677***	**2.484**
		(2.062)	
ALL	1.132*	3.209**	**1.168**
	(0.678)	(1.375)	
INDALL	**-1.874*** *	-7.752***	**-1.879**
	(0.900)	(2.897)	
ODIMAT	-0.008	-0.043***	**-0.014**
	(0.005)	(0.008)	
INDODIMAT	**-0.060*** **		
	(0.011)		
IPLEXP	**0.160*** **	0.289***	**0.096**
	(0.035)	(0.053)	
IPLECON		-0.437***	**-0.145**
		(0.116)	
INDIPLECON		0.896***	**0.297**
		(0.249)	
IPLDIS	**-0.130*** *		
	(0.057)		
T20BATAV		0.046	0.015
		(0.057)	
INDT20BATAV		-0.208**	**-0.069**
		(0.093)	
T20BOWLSR		-0.009	-0.003
		(0.069)	
INDT20BOWLSR		0.203*	0.067
		(0.105)	
ODIBATSR	0.004	-0.036*	-0.012
	(0.011)	(0.021)	
INDODIBATSR	**0.055*** **	0.140***	**0.046**
	(0.015)	(0.030)	
ODIBOWLAV		-0.088**	**-0.029**
		(0.041)	

INDODIBOWLAV		0.129**	**0.043**
		(0.059)	
ODIECON	**0.330*** **	2.017***	**0.668**
	(0.113)	(0.464)	
INDODIECON		-2.225***	**-0.737**
		(0.750)	
ODIFIVE	-0.375*		
	(0.211)		
INDODIFIVE	**3.273*** **		
	(1.021)		
ODIDIS	-0.001		
	(0.005)		
INDODIDIS	**0.037*** **		
	(0.012)		
TESTBATSR	-0.014	-0.021	-0.007
	(0.015)	(0.032)	
INDTESTBATSR	**0.112*** **	0.235***	**0.078**
	(0.028)	(0.057)	
TESTHUN	**-0.107** **	-0.151	-0.050
	(0.045)	(0.093)	
INDTESTHUN	**0.503*** **	0.352**	**0.117**
	(0.077)	(0.172)	
TESTBOWLAV	0.013		
	(0.031)		
INDTESTBOWLAV	**0.267*** **		
	(0.076)		
TESTBOWLSR	-0.012		
	(0.020)		
INDTESTBOWLSR	**-0.185*** **		
	(0.041)		
TESTECON		-0.561	-0.186
		(0.466)	
INDTESTECON		-2.062**	**-0.683**
		(0.924)	
BP11	**0.000*** **	0.000***	**0.000**
	(2.47×10^{-6})	(4.59×10^{-6})	
CONST	0.971	-5.559***	
	(0.963)	(1.962)	
SIGMA		5.770***	
		(0.317)	
R^2	0.77		
PSEUDO R^2		0.29	
NO. OF OBSERVATIONS	340	340	

* Represents significance at the 10% level, ** at the 5% level, *** at the 1% level.
OLS & Tobit Dependent Variable = *lap11*
Robust standard errors in parentheses

Appendix D

Table D1: Tests for Heteroskedasticity

OLS ICC Specification	*OLS Raw Performance Specification*
Breusch-Pagan / Cook-Weisberg test*	**Breusch-Pagan / Cook-Weisberg test***
Ho: Constant variance (Homoskedasticity)	Ho: Constant variance (Homoskedasticity)
χ^2 Test statistic = 26.97 Probability = 0.0000	χ^2 Test statistic = 24.22 Probability = 0.0000

* The Breusch-Pagan Test was carried out on the normal standard errors of both specifications. The null hypothesis of constant variance, or homoskedasticity, can be unambiguously rejected in both of these cases.

*Tobit ICC Specification**			*Tobit Raw Performance Specification**		
Variable	**Maximum Standard Error**	**Minimum Standard Error**	**Variable**	**Maximum Standard Error**	**Minimum Standard Error**
YOUNG	3.97	1.55	YOUNG	3.76	1.42
IND	7.47	3.48	IND	10.24	3.77
AUS	4.63	2.23	AUS	3.94	2.18
SA	4.12	2.37	SA	4.31	2.37
SRI	6.02	3.18	SRI	6.02	2.69
NZ	7.05	2.65	NZ	5.40	2.58
ALL	2.27	1.88	ALL	2.05	1.88
INDALL	6.50	3.13	INDALL	7.47	3.06
ODIMAT	0.051	0.017	ODIMAT	0.032	0.011
INDODIMAT	0.23	0.033	IPLEXP	0.11	0.063
TESTMAT	0.13	0.039	IPLECON	0.41	0.17
INDTESTMAT	0.67	0.11	INDIPLECON	1.06	0.27
TESTBATRANK	0.015	0.0046	T20BATAV	0.22	0.077
INDTESTBATRANK	0.060	0.013	INDT20BATAV	0.32	0.15
ODIBOWLRANK	0.0050	0.0029	T20BOWLSR	0.20	0.089
T20BATRANK	0.041	0.0049	INDT20BOWLSR	0.51	0.17
INDT20BATRANK	0.037	0.013	ODIBATSR	0.065	0.023
IPLEXP	0.22	0.10	INDODIBATSR	0.085	0.044
IPLECON	0.41	0.20	ODIBOWLAV	0.18	0.045
INDIPLECON	0.82	0.30	INDODIBOWLAV	0.53	0.10
IPLDIS	0.61	0.18	ODIECON	1.74	0.55
INDIPLDIS	0.70	0.35	INDODIECON	4.07	1.29
BP11	0.000013	0.0000070	TESTBATSR	0.10	0.048
CONST	3.69	1.64	INDTESTBATSR	0.14	0.083
			TESTHUN	4.11	0.13
			INDTESTHUN	5.53	0.17
			TESTECON	1.47	0.78
			INDTESTECON	2.29	1.29
			BP11	0.0000096	0.0000065
			CONST	4.78	1.70

* Both final models are tested on seven sub-samples of the dataset; these are defined as follows: players of Indian and Australian nationality, batsmen, bowlers, all-rounders and individuals above and below the mean age in the IPL 2011 tournament. The maximal and minimal normal standard errors are reported above. There is sufficient evidence to suggest that the normal standard errors vary significantly across these sub-samples, thus a null hypotheses of homoskedasticity can be rejected in both cases.

Table D2: Tests for Model Misspecification

OLS ICC Specification	*OLS Raw Performance Specification*
Ramsey RESET test*	**Ramsey RESET test***
Ho: Model has no omitted variables	Ho: Model has no omitted variables
F (3, 315) = 91.98 Probability = 0.0000	F (3, 309) = 104.65 Probability = 0.0000

* The Ramsey Regression Equation Specification Error Test (RESET) test investigates whether non-linear combinations of the explanatory variables have any power in explaining the dependent variable, '*lap11*'. The null hypothesis of no omitted variables can be unambiguously rejected in both cases

Table D3: Tests for Endogeneity of the base price

Regression of generalized residuals on the base price+

	GRESICCNBP	GRESRAWNBP
BP11	0.000***	0.000***
	(3.72×10^{-7})	(3.50×10^{-7})
CONST	-0.194***	-0.218***
	(0.044)	(0.042)
NO. OF OBSERVATIONS	340	340

* Represents significance at the 10% level, ** at the 5% level, *** at the 1% level.

+ The dependent variables are the generalised residuals from the Tobit estimations of the ICC and Raw Performance specifications respectively. In each case, the residuals have been calculated excluding the base price as an explanatory variable. The high statistical significance, at the 1% level, suggests that the base price is highly correlated with residuals from the estimated models. Therefore, a null hypothesis of no correlation between the estimated error and the base price can be rejected in both cases.

Tobit ICC Specification			*Tobit Raw Performance Specification*		
Correlation Matrix*			**Correlation Matrix***		
	GRESICCNBP	GRESICCBP+		GRESRAWNBP	GRESRAWBP+
GRESICCNBP	1		GRESRAWNBP	1	
GRESICCBP+	**0.6143**	1	GRESRAWBP+	**0.6556**	1

+ For these generalised residuals the base price is the dependent variable which is regressed on the same set of explanatory variables as the final models in both specifications, except for the base price itself of course.

* The matrices depict the correlation between the generalised residuals of the 'preferred' models and those when using the base price as the dependent variable, excluding the base price as a regressor in all four cases. The results reinforce the regressions above, which suggest that the base price is an endogenous variable.

Table D4: Correlation between generalised residuals of Retained and Non-Retained players

Tobit ICC Specification			*Tobit Raw Performance Specification*		
Correlation Matrix*			**Correlation Matrix***		
	GRESICCT	GRESICCTNR		GRESRAWT	GRESRAWTNR
GRESICCT	1		GRESRAWT	1	
GRESICCTNR	**0.8986**	1	GRESRAWTNR	**0.8781**	1

* The matrices depict the correlation between the generalised residuals of the final model, '*gresicct*' ('*gresrawt*'), and the generalised residuals when then 12 retained players are removed from the model, '*gresicctnr*' ('*gresrawtnr*') for both specifications. These residuals are found to be highly correlated that would suggest an unmodeled factor is affecting both retained and non-retained players. Therefore, the 12 estimated valuations, for retained players, cannot be removed from the model without changing the estimated effects of all other variables.

Appendix E

Table E1: Robustness checks for Tobit ICC Specification

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
YOUNG	1.815	1.502	2.855*	1.903	1.857
	(1.586)	(1.059)	(1.536)	(1.486)	(1.472)
IND	-6.686***	4.299*	-4.618**	-9.581***	-8.733***
	(2.392)	(2.438)	(2.295)	(2.534)	(2.422)
AUS	7.506***	7.559***	8.652***	7.742***	7.298***
	(1.819)	(1.517)	(1.830)	(1.854)	(1.844)
SRI	5.480**	5.459***	4.796*	4.849**	5.133**
	(2.515)	(1.941)	(2.485)	(2.195)	(2.229)
NZ	4.272*	4.218**	4.036*	3.924	4.088*
	(2.283)	(1.868)	(2.399)	(2.411)	(2.346)
SA		6.689***	7.302***	5.340***	5.727***
		(1.550)	(1.901)	(1.939)	(1.947)
BAT				-2.518	
				(1.571)	

INDBAT				3.862*	
				(2.189)	
BOWL					-1.535
					(1.617)
INDBOWL					2.541
					(2.354)
ALL	4.636***	4.020***	4.035***		
	(1.394)	(0.997)	(1.312)		
INDALL	-7.450***	-7.252***	-6.839**		
	(2.582)	(1.974)	(2.689)		
LEADERSHIP			-0.062***		
			(0.015)		
ODIMAT	-0.052***	-0.039***		-0.038**	-0.037**
	(0.017)	(0.014)		(0.015)	(0.016)
INDODIMAT	0.086***	0.054***		0.072**	0.070**
	(0.029)	(0.020)		(0.029)	(0.030)
TESTMAT	0.016	-0.000		-0.024	-0.023
	(0.049)	(0.038)		(0.044)	(0.046)
INDTESTMAT	-0.291***	-0.188***		-0.248***	-0.255***
	(0.093)	(0.059)		(0.091)	(0.096)
TESTBATRANK	-0.003	-0.001	-0.006*	-0.004	-0.004
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
INDTESTBATRANK	0.044***	0.028***	0.020***	0.044***	0.047***
	(0.009)	(0.006)	(0.006)	(0.009)	(0.009)
ODIBOWLRANK	0.005**	0.004**	0.004	0.005**	0.007***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
T20BATRANK	0.005	0.004*	0.007**	0.007**	0.004
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
INDT20BATRANK	-0.039***	-0.024***	-0.019**	-0.042***	-0.039***
	(0.009)	(0.006)	(0.008)	(0.009)	(0.009)
IPLEXP	0.376***	0.155**	0.295***	0.372***	0.357***
	(0.073)	(0.061)	(0.073)	(0.066)	(0.069)
IPLECON	-0.366***	-0.124	-0.350***	-0.283**	-0.249**
	(0.129)	(0.092)	(0.130)	(0.125)	(0.126)
INDIPLECON	0.792***	0.454**	0.741***	0.717***	0.582**
	(0.233)	(0.192)	(0.219)	(0.230)	(0.231)
IPLDIS	-0.410***	-0.068	-0.627***	-0.474***	-0.426***
	(0.129)	(0.111)	(0.124)	(0.130)	(0.125)
INDIPLDIS	0.713***	0.232*	0.979***	0.780***	0.774***
	(0.157)	(0.128)	(0.154)	(0.149)	(0.155)
BP11	0.000***	0.000***	0.000***	0.000***	0.000***
	(6.88x10^{-6})	(4.89x10^{-6})	(6.56x10^{-6})	(6.41x10^{-6})	(6.52x10^{-6})
CONST	-6.945***	-4.136***	-8.836***	-5.009***	-5.263***
	(1.824)	(1.381)	(1.693)	(1.698)	(1.772)
SIGMA	6.474***	4.886***	6.893***	6.505***	6.540***
	(0.381)	(0.304)	(0.364)	(0.360)	(0.364)
NO. OF OBSERVATIONS	311	220	340	340	340

* Represents significance at the 10% level, ** at the 5% level, *** at the 1% level.
OLS & Tobit Dependent Variable = *lap11*
Robust standard errors in parentheses

Table E2: Robustness checks for Tobit Raw Performance Specification

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
YOUNG	2.445*	2.148*	3.227**	2.540*	2.377*
	(1.436)	(1.208)	(1.305)	(1.322)	(1.317)
IND	-10.216***	-4.300	-7.603***	-11.521***	-10.951***
	(2.835)	(3.640)	(2.773)	(2.773)	(2.941)
AUS	6.702***	6.628***	7.669***	7.517***	7.438***
	(1.576)	(1.370)	(1.702)	(1.646)	(1.600)
SRI	6.263***	5.710***	5.191**	5.877***	6.297***
	(2.375)	(1.994)	(2.256)	(2.175)	(2.243)
NZ	5.730***	5.159***	5.415**	5.671**	5.581***
	(2.113)	(1.846)	(2.179)	(2.202)	(2.137)
SA		6.849***	6.422***	5.529***	5.777***
		(1.413)	(1.786)	(1.790)	(1.764)

BAT				-1.181	
				(1.460)	
INDBAT				3.611	
				(2.211)	
BOWL					-2.688*
					(1.562)
INDBOWL					4.608**
					(2.280)
ALL	4.214***	4.394***	3.381**		
	(1.496)	(1.145)	(1.424)		
INDALL	-8.747***	-9.248***	-8.011**		
	(2.928)	(2.303)	(3.155)		
LEADERSHIP			-0.036***		
			(0.012)		
ODIMAT	-0.044***	-0.033***		-0.044***	-0.043***
	(0.008)	(0.006)		(0.008)	(0.008)
IPLEXP	0.301***	0.188***	0.241***	0.291***	0.304***
	(0.057)	(0.047)	(0.054)	(0.052)	(0.051)
IPLECON	-0.416***	-0.165*	-0.456***	-0.386***	-0.422***
	(0.128)	(0.098)	(0.126)	(0.126)	(0.122)
INDIPLECON	0.883***	0.861***	0.862***	0.887***	0.758***
	(0.260)	(0.237)	(0.249)	(0.239)	(0.270)
T20BATAV	0.039	0.030	0.051	0.074	0.011
	(0.062)	(0.049)	(0.062)	(0.062)	(0.067)
INDT20BATAV	-0.206**	-0.068	-0.246**	-0.262***	-0.167
	(0.096)	(0.086)	(0.110)	(0.098)	(0.104)
T20BOWLSR	-0.069	-0.083	-0.080	0.036	0.060
	(0.075)	(0.061)	(0.074)	(0.071)	(0.063)
INDT20BOWLSR	0.262**	0.249**	0.258**	0.114	0.092
	(0.109)	(0.099)	(0.111)	(0.107)	(0.097)
ODIBATSR	-0.050**	-0.072***	-0.042*	-0.041*	-0.038*
	(0.023)	(0.018)	(0.024)	(0.022)	(0.021)
INDODIBATSR	0.154***	0.107***	0.142***	0.132***	0.143***
	(0.031)	(0.029)	(0.032)	(0.031)	(0.032)
ODIBOWLAV	-0.072*	-0.085**	-0.097**	-0.077*	-0.086**
	(0.043)	(0.037)	(0.038)	(0.041)	(0.042)
INDODI	0.114*	0.104*	0.145**	0.116*	0.128**
	(0.060)	(0.058)	(0.058)	(0.064)	(0.062)
ODIECON	1.825***	1.708***	2.271***	1.970***	2.135***
	(0.516)	(0.411)	(0.480)	(0.471)	(0.475)
INDODIECON	-2.051***	-2.236***	-2.464***	-1.914**	-2.443***
	(0.782)	(0.724)	(0.801)	(0.810)	(0.789)
TESTBATSR	-0.007	-0.017	-0.074**	-0.031	-0.027
	(0.033)	(0.026)	(0.034)	(0.032)	(0.032)
INDTESTBATSR	0.223***	0.160***	0.275***	0.270***	0.249***
	(0.059)	(0.050)	(0.057)	(0.055)	(0.058)
TESTHUN	-0.143	-0.105	-0.311***	-0.140	-0.177*
	(0.129)	(0.078)	(0.097)	(0.096)	(0.092)
INDTESTHUN	0.346*	0.309**	0.283	0.291	0.415**
	(0.195)	(0.125)	(0.183)	(0.193)	(0.181)
TESTECON	-0.567	-0.665*	-0.387	-0.677	-0.589
	(0.538)	(0.397)	(0.477)	(0.470)	(0.467)
INDTESTECON	-2.074**	-1.662**	-2.688***	-1.984**	-2.084**
	(0.981)	(0.826)	(1.004)	(0.935)	(0.986)
BP11	0.000***	0.000***	0.000***	0.000***	0.000***
	(4.94×10^{-6})	(3.81×10^{-6})	(4.93×10^{-6})	(4.82×10^{-6})	(4.77×10^{-6})
CONST	-4.209**	0.009	-6.017***	-4.632**	-4.089**
	(2.099)	(1.680)	(2.084)	(1.976)	(2.013)
SIGMA	5.803***	4.682***	6.067***	5.891***	5.858***
	(0.347)	(0.281)	(0.332)	(0.314)	(0.316)
NO. OF OBSERVATIONS	311	220	340	340	340

* Represents significance at the 10% level, ** at the 5% level, *** at the 1% level.
OLS & Tobit Dependent Variable = *lap11*
Robust standard errors in parentheses

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