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Colin Cannonier

Belmont University
Bibhudutta Panda
Wabash College
Sudipta Sarangi
Louisiana State University

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Department of Economics
Louisiana State University
Baton Rouge, LA 70803-6306
http://www.bus.lsu.edu/economics/

# Strategic Convergence in Cricketing Formats* 

Colin Cannonier ${ }^{\dagger}$<br>Bibhudutta Panda ${ }^{\ddagger}$<br>Sudipta Sarangi ${ }^{\text {§ }}$

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#### Abstract

Using data for 2008-2009, we determine winning strategies for the game in two different formats: 50 -over one-day internationals and 20 -over games from the Indian Premier League and Twenty 20 Internationals. We find that attacking batting and defensive bowling outperform all other strategies in determining the probability of winning in both formats despite the thirty over difference between them. Moreover, in both versions of the game, good fielding turns out to be an important complement to these two strategies. We speculate that this will have implications for the future of cricket, especially for the popularity of formats and the composition of teams.


Keywords: Cricket, Match Results, IPL, ODI, T20I

[^0]
## 1 Introduction

The conventional game of cricket has gone through many transformations to keep up with changing times. Today several formats co-exist, ranging from the gentlemen's version of the five-day Test match to the one-evening, fast-paced twenty-over format called Twenty20 (T20). Modern society, as reflected in attendance at games, has been creating pressure to adopt shorter, result-oriented versions of the game. In 1971, the 50-over one-day international (ODI) games were introduced to the cricket playing nations and quickly became popular. In 2003, the English Cricket Board introduced an even shorter 20 -over version, Twenty 20 , in its inter-county competition which became an immediate success owing to its shorter length and non-stop action. Other test-playing nations quickly followed suit and in 2007 the International Cricket Council (ICC) organized the first T20 International World Cup, adding further momentum to the popularity of this format.

Following India's victory in the inaugural T20 International World Cup, the Board of Control for Cricket in India (BCCI) decided to establish a T20 cricket league in India known as the Indian Premier League (IPL) along the lines of the English Premier League. Teams in the IPL owned by wealthy Indian businessmen and stars from Bollywood, were allowed to choose players from a pool of international and regional players through a bidding system with a cap on the amount any team can spend on player acquisition. ${ }^{1}$ The inaugural competition took place in early 2008 between eight teams competing on a "home" and "away" basis, with top four teams making it to the semi finals. ${ }^{2}$ The winner of the competition was decided in a final match between the two winning teams from the semifinals. The huge commercial success of this league through advertising, media campaign, satellite and TV rights, ticket sales, along with a big dash of Bollywood glamor has added new value to the league's brand. This success of T20 and the IPL in particular have the potential to alter the future of the game.

Popular opinion suggests that the outcome of the shorter versions of the game is determined primarily by batting performance. In fact it is often claimed that in T20 batting alone carries the day. The objective of this paper is examine the veracity of this assertion. We use data from ODI and T20 games where T20 comprises of IPL and 20-over international (T20I) matches to study this issue. Our objective is to determine the optimal winning strategies in both formats and speculate about

[^1]its implications for the future of cricket. We use a production function approach to determine the outcome of a cricket game as a function of batting, bowling, fielding and other relevant inputs. We divide the batting and bowling strategies into three categories based on intent: (1) where the specific intent is to score as many runs while batting or to capture as many wickets while bowling (attacking), (2) where the strategy is to limit or curtail the number of runs the opposing team scores or to limit the number of wickets lost while batting (defensive) and (3) a combination or mix of attacking and defensive (average). Using a conditional logit estimation, we order the different strategies in terms of their ability to create victories for the team. We find that attacking batting is the winning strategy for both ODI and T20 games. Interestingly, even a difference of thirty overs or 180 deliveries does not affect the optimal batting strategy in the two different formats of the game. Moreover, the optimal bowling strategy is also the same for the two different formats of the game. Aggressive batting which consists of scoring boundaries, emerges as the next best strategy in both formats followed by average batting. Defensive bowling stands out as the best strategy in ODI and T20I. Though the strength of bowling strategies change in IPL as we change the combinations of batting and bowling strategies, the optimal strategy is defensive bowling combined with attacking batting. Broadly speaking, we find a strategic convergence between both formats where the optimal strategic combination for any team is attacking batting and defensive bowling. Fielding plays an important role in improving the odds for winning in both formats, if a team adopts the optimal strategy combination. Further, other inputs such as toss and home team advantage do not play an important role in affecting the odds for winning. Based on our findings, we hypothesize what direction cricket may take in the future.

We now provide a brief overview of the relevant literature starting with the seminal paper by Schofield (1988). He uses the production function approach to estimate the outcome of two different formats in English county cricket: the three-day County Championship and the limited over John Player league in the seasons of 1981-83. The author finds attacking batting has greater importance in both formats, while the strength of bowling inputs differ across formats. Attacking bowling has greater importance in the three-day format, while defensive bowling emerges as a key factor for winning limited over games. Bairam, Howells and Turner (1990) extend this approach to include the longer format of first-class cricket games played in Australia and New Zealand. Using a Box-Cox general transformation function, they find attacking batting and attacking bowling as the best strategy combination to maximize the probability of winning in New Zealand cricket. By contrast, winning probabilities are maximized using a mix of attacking batting and defensive bowling in Australia.

Brooks et al. (2002) extend the production function approach to the longer format of test cricket. This paper methodologically differs from the previous papers as it uses an ordered response model to accommodate the presence of a qualitative dependent variable in contrast to the Ordinary Least Squares (OLS) used in other papers. It finds average batting and average bowling intents to be the optimal mix for most of the test playing nations, with the model correctly predicting $71 \%$ of the cricket outcomes.

Besides batting and bowling inputs, researchers have also studied the impact of other important factors such as toss and home team bias on the match results in cricket. We briefly mention some of these studies. de Silva and Swartz (1997) find evidence of home team advantage in ODIs, but they fail to find similar evidence for effect of the toss advantage. Bhaskar (2009) finds significant advantage for a team that wins the toss and opts to bat first in a day-night ODI match. On the contrary, a team which decides to bat first after winning the toss in the day matches has a significant disadvantage. Dawson et al. (2009) find that the toss outcome combined with the decision to bat first increases the probability of winning by $31 \%$ in day-night ODI matches.

## 2 Empirical Framework

The contribution of batting, bowling and fielding inputs to a team's ability to win games within the production function approach has been widely explored in the sports economics literature. ${ }^{3}$ This approach expresses a team's winning ability as a function of batting, bowling and fielding inputs:

$$
\begin{equation*}
W i n(W)=f(\text { Batting }, \text { Bowling, Fielding }) \tag{1}
\end{equation*}
$$

It is assumed that a team has to choose from a set of attacking, defensive and average strategies for each input. These can vary with the format of the game or even with the identity of the rival team.

Each input measure depends on a set of observable and unobservable factors. Examples of unobservable factors include player ability and form, captaincy skills, coaching skills and team management skills. While ability and form is player-specific, coaching, captaincy and management skills can be viewed as a set of think-tanks that are primal in devising the strategies for the team for a given game. Observable factors may include toss outcomes, home team bias and weather conditions. For example, although the toss outcome is merely decided by flipping a coin with a $50 \%$ probability of winning for

[^2]each team and does not directly affect any input measures, it provides a comparative advantage to the team winning the toss in choosing its strategies given the pitch, outfield and weather conditions. Similarly, playing at home can provide an impetus to the input strategies given the familiarity with pitch conditions and home crowd support.

It is important to take a specific note of the fielding input given its exclusion in the abovementioned studies. It can be argued that the choice of different types of fielding strategies is exclusive of bowling strategies, but the outcome is clearly dependent since the measures of efficient bowling depend to a large extent on fielding performance. Further, in the shorter format of the game, run rate is an important variable making good fielding an important issue for winning. Since our goal is to determine whether or not a good fielding side increases its chances of winning, we include this variable in our empirical model. ${ }^{4}$

The literature is divided over the choice of the empirical methodology for estimating the model discussed above with the construction of the dependent variable being the cause of debate. Schofield (1988) and Bairam et al. (1990) focus on first-class cricket where teams play each other on a seasonal basis, and present the output and input measures relative to the seasonal averages. Since the output variable (expressed as a percentage of games won or points scored) is a continuous one, they estimate the model using OLS. On the other hand, Brooks et al. (2002) who use data from international test cricket where teams do not play each other on a seasonal basis, estimate an ordered response model in which the dependent variable is a categorical variable taking values based on win, loss or draw. In our data set, though the IPL tournament is played on a seasonal basis; the ODI and T20I competitions are scheduled in advance in the ICC's Future Tours Programme. Hence, we opt for a logit model using a binary dependent variable based on the win or loss outcome of the game.

The latent variable model can be expressed as

$$
\begin{equation*}
y_{j}^{*}=x_{j} \beta+e_{j} \tag{2}
\end{equation*}
$$

where $e_{j}$ has a standard logistic distribution independent of $x_{j}$, with $e_{j} \sim\left(0, \frac{\pi^{2}}{3}\right)$, and $y^{*}$ is the unobserved latent variable indicating a team's chances of winning. The vector of explanatory variables comprising batting, bowling and fielding inputs along with variables related to toss and home team advantage are represented by $x_{j}$ while $\beta$ is the matrix of parameters to be estimated. Given $y^{*}$ is

[^3]unobserved, what we really observe is whether a team has won $(=1)$ or not $(=0)$ where:
$$
y=1 \text { if } y^{*}>0 \text { and } y=0 \text { if } y^{*} \leq 0
$$

So, given the explanatory variables, the logit model can be represented as

$$
\begin{equation*}
P\left(y_{j}=1 \mid x_{j}\right)=P\left(y_{j}^{*}>0 \mid x_{j}\right)=\frac{e^{x_{j} \beta}}{1+e^{x_{j} \beta}}=\Lambda\left(x_{j} \beta\right) \tag{3}
\end{equation*}
$$

where $\Lambda($.$) is the cumulative distribution function for a standard logistic distribution.$
Further, it should be noted that each match/game generates a pair of observations in the data set: one for the winning team and the other for the loosing team. This involves an one-to-one matching between the two choices. It stands to reason that within each pair, the outcomes of a match are linearly dependent and hence the error terms are correlated. So, we estimate a "Conditional (Fixed-Effect) Logit" model with "match/game" as the grouping variable which accounts for this correlation due to fixed effects (different intercept across matches) in the model.

## 3 Data

We collect individual game-specific information from the ESPN-owned CRICINFO website (http: //www.espncricinfo.com//) for all IPL, T20I and ODI matches for 2008 and 2009. Our dataset comprises 276 ODI, 77 T20I and 118 IPL games that took place during 2008 and 2009. For each game, we obtain data on batting, bowling, fielding and other related inputs for each team. The dependent variable is binary and equals one whenever a team wins a game and zero otherwise. Each match generates two observations where the observations are stacked by one team's batting, bowling and fielding performance followed by the other team's performance along with other related variables.

The batting and bowling variables are constructed following the studies already mentioned. The set of constructed batting variables are the number of runs a team scores on average for each wicket it loses in a game ( $R P W$ ), number of runs scored by a team for each over bowled ( $R P O$ ) and number of fours and sixes hit by a team in a game (BOUND). While $R P W$ may be thought of as an "average" batting strategy (a combination of attacking and defensive) where a team accumulates runs without losing too many wickets, RPO and BOUND depict "attacking" and "aggressive" batting strategies, respectively reflecting quicker accumulation of runs. Similarly, the set of bowling variables comprise the following: the number of runs scored by the opposition for each wicket taken (ORPW) reflecting an average bowling strategy, the number of overs bowled per wicket ( $O B P W$ ) reflecting an attacking
strategy where a team intends to dismiss the opposition quickly, and the number of runs scored by the opposition per over bowled (ORPO) reflecting a defensive strategy where a team tries to slow down the opposition team's run accumulation. The fielding variable (Fielding) is the sum of dismissals due to catches, run-outs and stumpings. Other independent variables include dummy variables reflecting whether a team played at home (Home), whether a team won the toss (Toss) and whether a team batted first (Bat1).

## $<$ Insert Tables 1 and 2 here>

Tables 1 and 2 show the summary statistics for ODI and T20 matches, and for IPL and T20I, respectively. As is evident from both tables, there are no significant differences in the outcomes between ODI and T20 matches or between IPL and T20I. With respect to independent variables, the batting inputs are significantly different between ODI and T20 as well as between IPL and T20I. In Table 1, the average value for $R P W$ is higher for ODIs as a team needs to bat for a longer innings without getting out in order to maximize its runs or to defend the target set by the opposition. On the other hand, the mean value for $R P O$, a measure of attacking batting strategy, is clearly higher for the shorter format consisting of T20I and IPL games given that there is a higher premium on accelerated scoring. In the case of $B O U N D$, the average number is higher for ODIs. This is due, in large part, to the significantly higher number of fours scored in boundaries compared to T20. The other constituent, sixes, is significantly higher for T20. Since ORPW (ORPO) is the opposition team's $R P W$ ( $R P O$ ), the mean values are very similar to those shown under batting inputs. Meanwhile, $O B P W$, an attacking bowling strategy is higher for ODIs with a bowling team having an entire 50 overs at its disposal to bowl out the opposition as opposed to the 20 overs in the T20 format. The results in Table 2 illustrate that all of the batting inputs in IPL matches are statistically significantly larger than those of T20Is. This is not necessarily surprising since league-level games such as the IPL allow for the possibility of exceptional pooling of talent from across the world. Moreover the higher financial incentives also can influence performance. For the fielding variable, while we find no difference between the T20I and IPL, there is a significant difference between ODI and T20. One can argue that since in T20 runs are scored at much faster pace, fielding plays a lesser role in T20. With respect to other variables, there is generally no difference between ODI and T20 matches or between IPL and T20I. There is one exception, in which there is a statistical difference in Home matches between ODI and T20. This is because the documented mean value of 0.251 under T20 is smaller than usual as a result of 2009 IPL matches (which constitutes a portion of the T20 matches) played at neutral venues in South Africa.

## 4 Results

Our objective is to find the different combinations of batting and bowling strategies that increase the $\log$ odds of winning in different formats of the game. Our results therefore are not specific to a team, but identify different winning combinations of batting and bowling strategies that a team can adopt based on the format. The estimated conditional logit coefficients for different combinations of batting and bowling strategies as well as fielding and other factors are presented in Tables 3-5 for ODI, T20I and IPL respectively. We include year fixed-effects to separate out any existing qualitative changes in a team between 2008 and 2009. We discuss and compare the importance of each input across different formats below.

## <Insert Table 3 here>

Batting Strategies Table 3 reports the estimated coefficients for ODIs. The coefficients for all the three batting strategies enter at the $1 \%$ significance level in the regression and have the expected signs. Among the three batting strategies, $R P O$ has the strongest impact on the log odds of winning. Given the fact that ODI is a limited over format, a team needs to set a target as large as possible for the opposition if it bats first, or chases the target set by the opposition if it bats second by accumulating runs at a faster pace, hence attributing an important role to run rate or $R P O$. The impact of the aggressive batting strategy $B O U N D$ follows $R P O$. In the recent times, the international teams have adopted more attacking intent in the limited over format, hence attributing an increasingly important role to BOUND (fours and sixes) to accumulate runs. ${ }^{5}$ Though ODI is a limited over format, a team still needs to bat through the entire 50 overs to amass a large total score or chase the target without losing all its wickets. Therefore, it can be argued that though $R P O$ and BOUND emerge as superior strategies in ODI, there is still a role for the average batting strategy $R P W$, as a team needs to accumulate runs without losing too many wickets. However, $R P W$ is more important than BOUND in conjunction with an attacking bowling strategy $O B P W$. This is indicative of the fact that a game where the winning bowling strategy is attacking bowling for each team, each batting team needs to adopt an average batting strategy to restrict the fall of wickets while scoring. Our results are similar to Schofield (1988) who found that $R P O$ is more important than $R P W$ for winning matches in the

[^4]limited over John Player League in English county cricket. ${ }^{6}$

## $<$ Insert Tables 4 and 5 here>

Tables 4 and 5 report the estimated coefficients for T20I and IPL matches, respectively. As before, all three strategies enter significantly with the expected signs in both sets of regressions. Similar to the ODIs, RPO clearly emerges as the best strategy in affecting the log odds of winning. ${ }^{7}$ As T20 is a stripped-down version of the limited over format, a team has fewer overs at the crease and so the best strategy is to accumulate runs at a faster rate by adopting an attacking strategy. $R P W$ has the lowest impact with BOUND exerting greater influence on the log odds of winning. It appears that a team needs to adopt an aggressive batting strategy to enhance its $R P O$ given the fewer number of overs allotted for hitting boundaries. However, the importance of keeping wickets cannot be discounted as $R P W$ enters significantly in the regressions. In summary, $R P O$ emerges as the best strategy followed by BOUND and RPW as the second and third best strategies in both formats and in both international and club level games.

Bowling Strategies A team needs both attacking and defensive bowlers in its bowling portfolio. This is evident from the fact that $O R P W$ which is a combination of both attacking and defensive bowling intent enters significantly with the expected signs regardless of batting strategies in the case of ODI, T20I and IPL in tables 3, 4 and 5 respectively. Though it is intuitive to argue that a team needs both attacking and defensive bowling strategies, our goal is to determine the relative importance of defensive and attacking strategies for different formats. In Table 3, the measure of defensive bowling ORPO emerges as the best approach for improving the log odds of winning for ODI. While attacking bowling is important, given the length of the ODI innings, this result suggests restricting the opposition to a lower score by adopting a defensive strategy. This conclusion echoes the finding of Schofield (1988) who shows the relatively greater importance of defensive bowling in the limited over John Player leagues from English county cricket. ${ }^{8}$

[^5]Similar to ODI, the defensive strategy ORPO emerges as a clear winner for T20I irrespective of the chosen batting strategy. However, the relative importance of attacking and defensive strategies to a team varies as it changes its batting strategy in the IPL. This can be inferred from Table 5. Attacking bowling $O B P W$ carries more weight when a team also simultaneously opts for the average batting strategy $R P W$ in IPL. Conversely, defensive bowling ORPO emerges as the best strategy if the team chooses an attacking batting strategy or an aggressive batting strategy in IPL. The following argument supports these findings. In a game where the winning bowling strategy is attacking bowling for each team, each batting team needs to adopt an average batting strategy to restrict the fall of wickets while scoring. On the contrary, if the winning batting strategy is attacking batting, the optimal bowling strategy that needs to be followed is defensive bowling which serves to restrict run accumulation by the opposition.

Optimal Strategy It can be inferred from Table 3 that attacking batting and defensive bowling clearly emerge as the optimal strategic combination for a team in ODI. An interesting point to note is that regardless of the batting strategy, defensive bowling is always an optimal strategy. Though we get a similar clear picture for T20I, the optimal strategy combination of attacking batting and defensive bowling enter at a lower level of significance in the estimated model. The optimal combination for IPL is also attacking batting and defensive bowling. However in this 20 -over league, we find that the optimal bowling strategy is no longer independent of the batting strategy. Thus, there is a clear convergence of optimal strategies across both formats of the game and in the international and professional league-level T20 formats. This has implications for marginal player selection. Given the optimal strategy combination, a team would opt for an attacking batsman who can serve as an additional bowler (preferably defensive) if it has the option to choose another player. ${ }^{9}$

Fielding Our paper contributes to this strand of literature by including the fielding input as an additional explanatory variable in the model. Though Schofield (1988) considers fielding an important input in determining the success of a team, he does not test it explicitly due to lack of data. We construct a proxy for fielding by summing dismissals due to catches, run-outs and stumpings. It can be argued that a team with a better fielding side will not only be successful in dismissing players from catches, run-outs and stumpings, but also in restricting run accumulation by the opposition. Since our optimal strategies are attacking batting and defensive bowling, we will focus on the importance

[^6]of fielding in combination with both of these strategies. The fielding variable enters significantly with the expected positive sign in column (6) of Tables 3 and 4 for ODI and T20I, respectively. However, the strength and the significance of the fielding variable reduces for IPL in column (6) of Table 5. Recall, one possible reason is that in mean terms there is no difference in fielding between IPL and T20I. In fact, it is slightly lower for IPL and this can be explained in part by the fact that teams are composed of players who often do not have the opportunity to spend considerable time practising as a team. Given that runs scored in IPL are significantly higher, it might explain the fact that the fielding variable loses its explanatory power.

Other Inputs Additionally, we test the importance of toss and the presence of home team advantage. As discussed previously, winning the toss can provide comparative advantage to a team in choosing its strategies given the pitch, outfield and weather conditions. Similarly, there may be advantages to the home team due to the familiarity to home conditions and support from the home crowd. However, there is conflicting evidence in the literature regarding the advantages from winning the toss. While de Silva and Swartz (1997) do not find any evidence of an advantage from winning the toss in ODI, Dawson et al. (2009) find that winning the toss and batting first increases the probability of winning in a day-night ODI. Our empirical exercise does not provide any support for the importance of toss. Similarly, we do not find any evidence that winning the toss and batting first improves winning probabilities. ${ }^{10}$ Further, we do not find any evidence for home team advantage, unlike the findings reported in de Silva and Swartz (1997).

### 4.1 Predicting Outcomes: An Illustration

## $<$ Insert Table 6 here $>$

In this section we will provide both in-sample and out-of sample predictions (using 2010 data) for our optimal strategy combination. Note that due to the nature of the estimation for this problem, our predictions can at best be viewed as indicative and no more than an illustration. Table (6) reports the predictions for the optimal strategy combination using the conditional (fixed-effect) logit model. For comparison purposes, we also report the predictions using the logit estimates. The first two columns in the table refer to the in-sample predictions using the data for 2008-2009 and the last two columns

[^7]refer to the out of sample predictions using 2010 data. ${ }^{11}$
We begin with two specific observations on our choice of models. Recall, in our sample each game/match generates a pair of outcomes: one team wins while the other does not. It stands to reason that within each pair, the outcomes of a match are linearly dependent and hence the error terms are correlated. Therefore, the model chosen must account for correlation due to fixed effects (different intercept across matches) as well as correlation with other covariates in the model. The conditional logit is designed to address these issues and is thus preferred to the ordinary logit model. Under these conditions, the conditional logit produces more accurate and efficient estimates. Although some variant of the conventional logit model may be used (for example, adding match dummies as covariates in the model), this process relies on having extremely large data sets.

Second, the results in the table above were derived from post-estimation procedures after estimating each model. However, in both models, the post-estimation procedures make the rather restrictive assumption that the estimated model has no fixed effects (i.e. the intercept is the same across all observations). This assumption is inherent in the standard logit model which, as already pointed, will provide less efficient estimates. In terms of prediction we find that in many instances the logit model outperforms the conditional logit model. This may partly be due to the fact that although the logit model does not include match fixed-effects, it does incorporate team fixed-effects through the team dummies. ${ }^{12}$ While the absence of accurate predictions clearly indicates a compromise, nevertheless, we feel this exercise is instructive.

From the table note that both the conditional and unconditional models successfully predict more than $80 \%$ of the outcomes for ODIs for 2008-2009. However, the prediction for 2010 is lower between $63 \%-67 \%$ for both models. One possible explanation for the low out-of-sample predictions may be related to greater variation in team quality arising from a number of factors related to coaching, team composition, leadership such as captaincy and the increased participation of other teams over time. Indeed, there is greater evidence of this in T20I where the predictive results are quite similar to those from ODIs. In the case of T20I, our out-of-sample period, 2010, witnessed an influx of smaller teams like Afghanistan, Zimbabwe, Ireland, and Kenya with a substantial number of matches being played between them. ${ }^{13}$ Therefore the limited in-sample observations involving these teams may help explain

[^8]the low predictive power for the out-of sample. Further, the lower percentage of successful prediction for 2010 can also be attributed to the changing team qualities over years. However, the in-sample predictions for T20I yield different results in conditional and unconditional models. While the logit model predicts $90 \%$ of the outcomes, the conditional model only predicts $55 \%$ of the outcomes. It can be recalled that while the logit controls for team fixed-effects by using team dummies, the conditional logit does not, hence results in lower prediction of outcomes. Contrast these results with those of the IPL where both models correctly predict 90 percent of the in-sample outcomes on average. The average out-of-sample predictions improve to about 95 percent! Recall that in IPL the teams are constructed through auctions where the primary (and perhaps, the only) goal is to win; as opposed to national teams competing in ODIs and T20Is where other goals such as rebuilding the team with younger players (thus compromising quality) may be important. For the first three years of the IPL, the teams retained their core players, so that team composition and quality remained relatively stable over the period.

## 5 Coda: Is One-day Out?

The recent growth of the T20 format can be attributed to its shorter time span, the thrill of nonstop action and the emergence of the cash rich IPL. In this paper, we exploit a production function approach to determine the outcome of a cricket game as a function of batting, bowling, fielding and other variables. Using data on ODI and T20 games from IPL and T20I, the paper determines the optimal combination of strategies for winning games and finds that they are similar for both formats.

Our empirical results indicate that a team's best winning strategy is a combination of attacking batting and defensive bowling. In other words, this means that while batting a team should be committed to scoring as many runs in the fewest possible overs (i.e. maximizing RPO). This approach to batting should be combined with a defensive bowling tactic aimed at limiting the amount of runs the opposition team scores in a given number of overs (i.e. minimizing ORPO). In part, this can be achieved (not surprisingly) through exceptional fielding.

With this strategic convergence between the 50 -over and 20 -over formats and the growing popularity of T20 cricket, it is possible to speculate about some future directions of the game. Although both limited over formats are driven by batting oriented performances, the attacking intent in T20 is supported by aggressive batting, hence adding more action, excitement and popularity to the T20 format. The presence of Bollywood stars and entertainment is a major draw for the IPL games. This
has clearly made a dent in the viewership and popularity of the longer format of the game (see for instance Raghunath, 2009). Given its popularity and significant monetary benefits, players will also possibly prefer the shorter format. Since this opportunity is missing in the 50 -over format and the required skill set is no different, it will also be an easy transition for the players. Our implication is clearly supported by a recent survey conducted on 45 overseas players by the Federation of International Cricketers' Association (FICA) where $40 \%$ of players indicated a preference to play in the IPL over their country, while $32 \%$ of the respondents reported they could retire prematurely in order to keep playing unconditionally in these lucrative leagues. ${ }^{14}$ While test cricket has remained robust to the threats of ODI and T20 cricket, the prognosis for ODI in light of the emergence of T20 is unclear. In fact, in a recently published interview the well known English cricketer Graeme Swann displayed his inclination in completely eliminating or reducing the length of the 50 -over format. ${ }^{15}$ However, some may argue that both ODIs and Test cricket will continue to exist for the purists who will prefer formats where players can demonstrate finer talents, though there might be fewer games available to watch. Moreover, since the majority of the ICC's revenues currently derive from ODIs, their decline in importance will not be immediate, but it is hard to speculate about how fast this might occur. One might also conjecture that in the future, cricketing nations will have specialized teams for the different formats. In fact, there is evidence that different national squads are chosen for test cricket and ODIs. Due to the considerably more aggressive nature of T20, this will lead to very different squads for test cricket and T20 and somewhat dissimilar squads for the two shorter formats.

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Table 1: Summary Statistics for ODI and T20 for 2008-2009

| Variable | Variable Definition | IPL | T20I |
| :---: | :---: | :---: | :---: |
|  |  | $\begin{gathered} \text { Mean } \\ \text { (Std. Dev.) } \end{gathered}$ | $\begin{gathered} \text { Mean } \\ \text { (Std. Dev.) } \end{gathered}$ |
| Win | Equals one if team wins | $\begin{gathered} \hline 0.483 \\ (0.501) \end{gathered}$ | $\begin{gathered} \hline 0.474 \\ (0.501) \end{gathered}$ |
| RPW | Runs scored per wicket lost | $\begin{gathered} 34.164 \\ (29.452) \end{gathered}$ | $\begin{gathered} 25.614^{* * *} \\ (16.561) \end{gathered}$ |
| RPO | Runs scored per overs faced | $\begin{gathered} 7.940 \\ (1.505) \end{gathered}$ | $\begin{gathered} 7.401^{* * *} \\ (1.777) \end{gathered}$ |
| BOUND | Number of boundaries (fours and sixes) per innings | $\begin{aligned} & 17.517 \\ & (6.517) \end{aligned}$ | $\begin{gathered} 14.651^{* * * *} \\ (6.307) \end{gathered}$ |
| ORPW | Opposition runs scored per wicket taken | $\begin{gathered} 34.101 \\ (29.507) \end{gathered}$ | $\begin{gathered} 25.614^{* * *} \\ (16.561) \end{gathered}$ |
| OBPW | Overs bowled per wicket taken | $\begin{gathered} 4.138 \\ (3.119) \end{gathered}$ | $\begin{aligned} & 3.417^{* *} \\ & (2.252) \end{aligned}$ |
| ORPO | Opposition runs per over bowled | $\begin{gathered} 7.918 \\ (1.574) \end{gathered}$ | $\begin{gathered} 7.401 * * * \\ (1.777) \end{gathered}$ |
| Fielding | Sum of catches, stumpings and run outs per innings | $\begin{gathered} 4.428 \\ (2.271) \end{gathered}$ | $\begin{gathered} 4.566 \\ (1.869) \end{gathered}$ |
| Home | Equals one if team plays at home | $\begin{gathered} 0.237 \\ (0.426) \end{gathered}$ | $\begin{gathered} 0.273 \\ (0.447) \end{gathered}$ |
| Toss | Equals one if team wins the toss | $\begin{gathered} 0.483 \\ (0.501) \end{gathered}$ | $\begin{gathered} 0.494 \\ (0.502) \end{gathered}$ |
| Bat1 | Equals one if team bats first | $\begin{gathered} 0.483 \\ (0.501) \end{gathered}$ | $\begin{gathered} 0.494 \\ (0.502) \end{gathered}$ |
| Observations |  | 236 | 154 |
| Notes: Statistical levels of significance, based on the difference between means of the two groups, are as follows: |  |  | ** indicates |


|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Win | Win | Win | Win | Win | Win | Win | Win | Win |
| RPW | $\begin{gathered} \hline 0.167^{* * *} \\ (0.031) \end{gathered}$ | $\begin{gathered} \hline 0.153^{* * *} \\ (0.021) \end{gathered}$ | $\begin{gathered} \hline 0.191^{* * *} \\ (0.027) \end{gathered}$ |  |  |  |  |  |  |
| RPO |  |  |  | $\begin{gathered} 1.432^{* * *} \\ (0.294) \end{gathered}$ | $\begin{gathered} 0.983^{* * *} \\ (0.199) \end{gathered}$ | $\begin{gathered} 2.938^{* * *} \\ (0.804) \end{gathered}$ |  |  |  |
| BOUND |  |  |  |  |  |  | $\begin{gathered} 0.217^{* * *} \\ (0.032) \end{gathered}$ | $\begin{gathered} 0.147^{* * *} \\ (0.022) \end{gathered}$ | $\begin{gathered} 0.204^{* * *} \\ (0.031) \end{gathered}$ |
| ORPW | $\begin{gathered} -0.136^{* * *} \\ (0.024) \end{gathered}$ |  |  | $\begin{gathered} -0.165^{* * *} \\ (0.031) \end{gathered}$ |  |  | $\begin{gathered} -0.176^{* * *} \\ (0.027) \end{gathered}$ |  |  |
| OBPW |  | $\begin{gathered} -0.556^{* * *} \\ (0.111) \end{gathered}$ |  |  | $\begin{gathered} -0.669^{* * *} \\ (0.125) \end{gathered}$ |  |  | $\begin{gathered} -0.737^{* * *} \\ (0.124) \end{gathered}$ |  |
| ORPO |  |  | $\begin{gathered} -1.909^{* * *} \\ (0.316) \end{gathered}$ |  |  | $\begin{gathered} -3.255^{* * *} \\ (0.878) \end{gathered}$ |  |  | $\begin{gathered} -1.664^{* * *} \\ (0.222) \end{gathered}$ |
| Fielding | $\begin{aligned} & -0.006 \\ & (0.106) \end{aligned}$ | $\begin{gathered} 0.123 \\ (0.106) \end{gathered}$ | $\begin{gathered} 0.386^{* * * *} \\ (0.117) \end{gathered}$ | $\begin{gathered} 0.065 \\ (0.108) \end{gathered}$ | $\begin{gathered} 0.194^{* *} \\ (0.099) \end{gathered}$ | $\begin{gathered} 0.526^{* * *} \\ (0.096) \end{gathered}$ | $\begin{gathered} 0.053 \\ (0.119) \end{gathered}$ | $\begin{gathered} 0.188^{* *} \\ (0.093) \end{gathered}$ | $\begin{gathered} 0.554^{* * *} \\ (0.087) \end{gathered}$ |
| Home | $\begin{aligned} & -0.141 \\ & (0.337) \end{aligned}$ | $\begin{aligned} & -0.077 \\ & (0.315) \end{aligned}$ | $\begin{aligned} & -0.008 \\ & (0.361) \end{aligned}$ | $\begin{aligned} & -0.221 \\ & (0.272) \end{aligned}$ | $\begin{aligned} & -0.169 \\ & (0.236) \end{aligned}$ | $\begin{gathered} 0.112 \\ (0.260) \end{gathered}$ | $\begin{aligned} & -0.253 \\ & (0.335) \end{aligned}$ | $\begin{aligned} & -0.137 \\ & (0.255) \end{aligned}$ | $\begin{gathered} 0.153 \\ (0.269) \end{gathered}$ |
| Toss | $\begin{aligned} & -0.242 \\ & (0.539) \end{aligned}$ | $\begin{gathered} 0.094 \\ (0.517) \end{gathered}$ | $\begin{aligned} & -0.216 \\ & (0.555) \end{aligned}$ | $\begin{aligned} & -0.249 \\ & (0.576) \end{aligned}$ | $\begin{aligned} & -0.250 \\ & (0.473) \end{aligned}$ | $\begin{aligned} & -0.317 \\ & (0.520) \end{aligned}$ | $\begin{gathered} 0.176 \\ (0.519) \end{gathered}$ | $\begin{gathered} 0.107 \\ (0.428) \end{gathered}$ | $\begin{gathered} 0.333 \\ (0.447) \end{gathered}$ |
| Bat1 | $\begin{gathered} 0.109 \\ (0.584) \end{gathered}$ | $\begin{gathered} 0.697 \\ (0.480) \end{gathered}$ | $\begin{gathered} 0.653 \\ (0.670) \end{gathered}$ | $\begin{gathered} 0.021 \\ (0.580) \end{gathered}$ | $\begin{gathered} 0.350 \\ (0.453) \end{gathered}$ | $\begin{gathered} 0.208 \\ (0.612) \end{gathered}$ | $\begin{gathered} 0.278 \\ (0.529) \end{gathered}$ | $\begin{gathered} 0.460 \\ (0.455) \end{gathered}$ | $\begin{gathered} 0.674 \\ (0.478) \end{gathered}$ |
| Toss*Bat1 | $\begin{gathered} 0.568 \\ (0.912) \\ \hline \end{gathered}$ | $\begin{aligned} & -0.075 \\ & (0.778) \\ & \hline \end{aligned}$ | $\begin{gathered} 0.072 \\ (0.972) \\ \hline \end{gathered}$ | $\begin{gathered} 0.497 \\ (1.014) \\ \hline \end{gathered}$ | $\begin{gathered} 0.387 \\ (0.783) \\ \hline \end{gathered}$ | $\begin{gathered} 0.151 \\ (0.871) \\ \hline \end{gathered}$ | $\begin{aligned} & -0.829 \\ & (0.855) \\ & \hline \end{aligned}$ | $\begin{array}{r} -0.444 \\ (0.743) \\ \hline \end{array}$ | $\begin{aligned} & -1.019 \\ & (0.798) \\ & \hline \end{aligned}$ |
| Observations | 522 | 522 | 528 | 528 | 528 | 534 | 528 | 528 | 534 |
| Pseudo $R^{2}$ | 0.808 | 0.752 | 0.808 | 0.724 | 0.617 | 0.762 | 0.720 | 0.618 | 0.638 |

Table 3: Conditional-Logit Results from ODI Games

|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Win | Win | Win | Win | Win | Win | Win | Win | Win |
| RPW | $\begin{gathered} \hline 0.111^{* * *} \\ (0.036) \end{gathered}$ | $\begin{gathered} \hline \hline 0.110^{* * *} \\ (0.029) \end{gathered}$ | $\begin{gathered} \hline \hline 0.165 * * * \\ (0.050) \end{gathered}$ |  |  |  |  |  |  |
| RPO |  |  |  | $\begin{gathered} 0.734^{* * *} \\ (0.217) \end{gathered}$ | $\begin{gathered} 0.493^{* * *} \\ (0.167) \end{gathered}$ | $\begin{aligned} & 1.941^{*} \\ & (1.048) \end{aligned}$ |  |  |  |
| BOUND |  |  |  |  |  |  | $\begin{gathered} 0.231^{* * *} \\ (0.071) \end{gathered}$ | $\begin{gathered} 0.162^{* * *} \\ (0.054) \end{gathered}$ | $\begin{gathered} 0.321^{* * *} \\ (0.092) \end{gathered}$ |
| ORPW | $\begin{gathered} -0.073^{* * *} \\ (0.027) \end{gathered}$ |  |  | $\begin{gathered} -0.156^{* * *} \\ (0.039) \end{gathered}$ |  |  | $\begin{gathered} -0.147^{* * *} \\ (0.051) \end{gathered}$ |  |  |
| OBPW |  | $\begin{aligned} & -0.380 \\ & (0.269) \end{aligned}$ |  |  | $\begin{gathered} -0.849^{* * *} \\ (0.290) \end{gathered}$ |  |  | $\begin{gathered} -0.905^{* * *} \\ (0.336) \end{gathered}$ |  |
| ORPO |  |  | $\begin{gathered} -0.683^{* * *} \\ (0.250) \end{gathered}$ |  |  | $\begin{gathered} -1.870^{* *} \\ (0.952) \end{gathered}$ |  |  | $\begin{gathered} -0.944^{* * *} \\ (0.356) \end{gathered}$ |
| Fielding | $\begin{aligned} & 0.243^{*} \\ & (0.146) \end{aligned}$ | $\begin{gathered} 0.344^{* *} \\ (0.136) \end{gathered}$ | $\begin{gathered} 0.319^{* *} \\ (0.151) \end{gathered}$ | $\begin{aligned} & 0.282^{*} \\ & (0.161) \end{aligned}$ | $\begin{gathered} 0.429^{* * *} \\ (0.165) \end{gathered}$ | $\begin{gathered} 0.702^{* *} \\ (0.349) \end{gathered}$ | $\begin{gathered} 0.159 \\ (0.167) \end{gathered}$ | $\begin{aligned} & 0.291^{*} \\ & (0.157) \end{aligned}$ | $\begin{gathered} 0.584^{* * *} \\ (0.211) \end{gathered}$ |
| Home | $\begin{aligned} & -0.053 \\ & (0.615) \end{aligned}$ | $\begin{gathered} 0.015 \\ (0.631) \end{gathered}$ | $\begin{aligned} & -0.092 \\ & (0.585) \end{aligned}$ | $\begin{aligned} & -0.246 \\ & (0.605) \end{aligned}$ | $\begin{aligned} & -0.142 \\ & (0.581) \end{aligned}$ | $\begin{aligned} & -0.289 \\ & (0.722) \end{aligned}$ | $\begin{gathered} 0.019 \\ (0.667) \end{gathered}$ | $\begin{gathered} 0.001 \\ (0.657) \end{gathered}$ | $\begin{gathered} 0.224 \\ (0.583) \end{gathered}$ |
| Toss | $\begin{gathered} 0.106 \\ (0.712) \end{gathered}$ | $\begin{gathered} 0.124 \\ (0.670) \end{gathered}$ | $\begin{gathered} 0.618 \\ (0.827) \end{gathered}$ | $\begin{gathered} 0.210 \\ (0.681) \end{gathered}$ | $\begin{gathered} 0.228 \\ (0.631) \end{gathered}$ | $\begin{gathered} 1.467 \\ (1.163) \end{gathered}$ | $\begin{gathered} 0.199 \\ (0.719) \end{gathered}$ | $\begin{gathered} 0.134 \\ (0.629) \end{gathered}$ | $\begin{gathered} 1.010 \\ (0.835) \end{gathered}$ |
| Bat1 | $\begin{gathered} 0.208 \\ (0.809) \end{gathered}$ | $\begin{gathered} 0.241 \\ (0.780) \end{gathered}$ | $\begin{gathered} 0.732 \\ (0.729) \end{gathered}$ | $\begin{gathered} 0.091 \\ (0.738) \end{gathered}$ | $\begin{gathered} 0.052 \\ (0.729) \end{gathered}$ | $\begin{gathered} 1.240 \\ (1.399) \end{gathered}$ | $\begin{aligned} & -0.283 \\ & (0.997) \end{aligned}$ | $\begin{aligned} & -0.307 \\ & (0.857) \end{aligned}$ | $\begin{aligned} & -0.023 \\ & (0.688) \end{aligned}$ |
| Toss*Bat1 | $\begin{gathered} 0.567 \\ (1.251) \\ \hline \end{gathered}$ | $\begin{gathered} 0.618 \\ (1.175) \\ \hline \end{gathered}$ | $\begin{aligned} & -0.568 \\ & (1.304) \\ & \hline \end{aligned}$ | $\begin{gathered} 0.531 \\ (1.069) \\ \hline \end{gathered}$ | $\begin{gathered} 0.670 \\ (1.028) \\ \hline \end{gathered}$ | $\begin{aligned} & -1.529 \\ & (2.163) \\ & \hline \end{aligned}$ | $\begin{gathered} 0.535 \\ (1.155) \\ \hline \end{gathered}$ | $\begin{gathered} 0.868 \\ (0.968) \\ \hline \end{gathered}$ | $\begin{aligned} & -0.922 \\ & (1.262) \\ & \hline \end{aligned}$ |
| Observations | 150 | 150 | 150 | 150 | 150 | 150 | 150 | 150 | 150 |
| Pseudo $R^{2}$ | 0.567 | 0.540 | 0.621 | 0.597 | 0.511 | 0.739 | 0.574 | 0.508 | 0.593 |
| Note | The num | s in pare | hesis repre | nt the ro | t standard | rrors. * | $\mathrm{p}<.1,{ }^{* *} \mathrm{p}<.05,{ }^{* * *} \mathrm{p}<.01$ |  |  |

Table 4: Conditional-Logit Results from T20I Games

|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Win | Win | Win | Win | Win | Win | Win | Win | Win |
| RPW | $\begin{gathered} \hline \hline 0.093^{* * *} \\ (0.021) \end{gathered}$ | $\begin{gathered} \hline \hline 0.129^{* * *} \\ (0.022) \end{gathered}$ | $\begin{gathered} \hline 0.123^{* * *} \\ (0.028) \end{gathered}$ |  |  |  |  |  |  |
| RPO |  |  |  | $\begin{gathered} 1.182^{* * *} \\ (0.243) \end{gathered}$ | $\begin{gathered} 0.756^{* * *} \\ (0.118) \end{gathered}$ | $\begin{gathered} 3.257^{* * *} \\ (0.990) \end{gathered}$ |  |  |  |
| BOUND |  |  |  |  |  |  | $\begin{gathered} 0.239^{* * *} \\ (0.037) \end{gathered}$ | $\begin{gathered} 0.154^{* * *} \\ (0.026) \end{gathered}$ | $\begin{gathered} 0.320^{* * *} \\ (0.058) \end{gathered}$ |
| ORPW | $\begin{gathered} -0.109^{* * *} \\ (0.032) \end{gathered}$ |  |  | $\begin{gathered} -0.159^{* * *} \\ (0.038) \end{gathered}$ |  |  | $\begin{gathered} -0.151^{* * *} \\ (0.027) \end{gathered}$ |  |  |
| OBPW |  | $\begin{gathered} -1.434^{* * *} \\ (0.298) \end{gathered}$ |  |  | $\begin{gathered} -0.923^{* * *} \\ (0.241) \end{gathered}$ |  |  | $\begin{gathered} -0.965^{* * *} \\ (0.187) \end{gathered}$ |  |
| ORPO |  |  | $\begin{gathered} -0.807^{* * *} \\ (0.227) \end{gathered}$ |  |  | $\begin{gathered} -3.221^{* * *} \\ (1.090) \end{gathered}$ |  |  | $\begin{gathered} -1.330^{* * *} \\ (0.275) \end{gathered}$ |
| Fielding | $\begin{aligned} & -0.136 \\ & (0.153) \end{aligned}$ | $\begin{gathered} 0.002 \\ (0.154) \end{gathered}$ | $\begin{gathered} 0.498^{* * *} \\ (0.102) \end{gathered}$ | $\begin{aligned} & -0.137 \\ & (0.187) \end{aligned}$ | $\begin{gathered} 0.096 \\ (0.164) \end{gathered}$ | $\begin{aligned} & 0.220^{*} \\ & (0.132) \end{aligned}$ | $\begin{aligned} & -0.178 \\ & (0.160) \end{aligned}$ | $\begin{gathered} 0.031 \\ (0.145) \end{gathered}$ | $\begin{gathered} 0.321^{* * *} \\ (0.118) \end{gathered}$ |
| Home | $\begin{gathered} 0.513 \\ (0.533) \end{gathered}$ | $\begin{gathered} 1.024^{* *} \\ (0.520) \end{gathered}$ | $\begin{gathered} 1.020^{* *} \\ (0.500) \end{gathered}$ | $\begin{gathered} 0.473 \\ (0.572) \end{gathered}$ | $\begin{gathered} 0.534 \\ (0.637) \end{gathered}$ | $\begin{gathered} 0.306 \\ (0.690) \end{gathered}$ | $\begin{gathered} 0.618 \\ (0.459) \end{gathered}$ | $\begin{gathered} 0.641 \\ (0.523) \end{gathered}$ | $\begin{gathered} 0.545 \\ (0.598) \end{gathered}$ |
| Toss | $\begin{aligned} & 0.709^{*} \\ & (0.372) \end{aligned}$ | $\begin{gathered} 1.728^{* * *} \\ (0.504) \end{gathered}$ | $\begin{gathered} 1.079^{* * *} \\ (0.395) \end{gathered}$ | $\begin{gathered} 0.614 \\ (0.542) \end{gathered}$ | $\begin{gathered} 0.491 \\ (0.518) \end{gathered}$ | $\begin{gathered} 0.154 \\ (0.408) \end{gathered}$ | $\begin{gathered} 0.624 \\ (0.463) \end{gathered}$ | $\begin{gathered} 0.482 \\ (0.457) \end{gathered}$ | $\begin{gathered} 0.450 \\ (0.315) \end{gathered}$ |
| Bat1 | $\begin{gathered} 0.143 \\ (0.371) \end{gathered}$ | $\begin{gathered} 1.011 \\ (0.817) \end{gathered}$ | $\begin{gathered} 0.498 \\ (0.779) \end{gathered}$ | $\begin{aligned} & -0.425 \\ & (0.499) \end{aligned}$ | $\begin{aligned} & -0.300 \\ & (0.468) \end{aligned}$ | $\begin{aligned} & -0.644 \\ & (0.647) \end{aligned}$ | $\begin{aligned} & -0.743 \\ & (0.487) \end{aligned}$ | $\begin{aligned} & -0.531 \\ & (0.460) \end{aligned}$ | $\begin{aligned} & -0.856^{*} \\ & (0.508) \end{aligned}$ |
| Toss*Bat1 | $\begin{array}{r} -0.053 \\ (0.219) \\ \hline \end{array}$ | $\begin{aligned} & -0.726 \\ & (0.962) \end{aligned}$ | $\begin{aligned} & -0.647 \\ & (0.797) \\ & \hline \end{aligned}$ | $\begin{gathered} 0.186 \\ (0.688) \\ \hline \end{gathered}$ | $\begin{gathered} 0.355 \\ (0.554) \end{gathered}$ | $\begin{aligned} & -0.229 \\ & (0.650) \end{aligned}$ | $\begin{gathered} 0.338 \\ (0.593) \\ \hline \end{gathered}$ | $\begin{gathered} 0.461 \\ (0.505) \\ \hline \end{gathered}$ | $\begin{gathered} 0.002 \\ (0.459) \\ \hline \end{gathered}$ |
| Observations | 222 | 222 | 225 | 225 | 225 | 228 | 225 | 225 | 228 |
| Pseudo $R^{2}$ | 0.582 | 0.557 | 0.521 | 0.475 | 0.381 | 0.645 | 0.418 | 0.339 | 0.427 |

Table 5: Conditional-Logit Results from IPL Games

Table 6: Prediction Based on Optimal Strategy Combination

|  | In-Sample |  | Out-of-Sample |  |
| :--- | :---: | :---: | :---: | :---: |
|  | Clogit | Logit | Clogit | Logit |
|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ |
| ODI | 80.80 | 92.64 | 63.38 | 66.67 |
| T20I | 55.19 | 90.28 | 60.29 | 58.82 |
| IPL | 83.47 | 95.18 | 93.33 | 98.33 |

Note: The reported numbers refer to the percentage of observations correctly predicted for each match outcome.


[^0]:    *We would like to thank Areendam Chanda, Rajnish Kumar, David Paton, Abhinav Sacheti and Arabinda Sarangi for their insightful comments on the paper.
    ${ }^{\dagger}$ College of Business Administration, Belmont University, Nashville, TN 37212. Email: colin.cannonier@belmont.edu
    ${ }^{\ddagger}$ Department of Economics, Wabash College, IN 47933. Email: pandab@wabash.edu
    ${ }^{\S}$ Corresponding author: Department of Economics, Louisiana State University, Baton Rouge, LA 70803. Email: sarangi@lsu.edu

[^1]:    ${ }^{1}$ In order to give the league an international flavor and more importantly, to improve the quality of domestic regional players, the rules of the IPL allow each team to have a maximum of 4 overseas players in its starting XI.
    ${ }^{2}$ The eight teams are Bangalore Royal Challengers, Chennai Super Kings, Delhi Daredevils, Hyderabad Deccan Chargers, Jaipur Rajasthan Royals, Kolkota Knight Riders, Mohali Punjab Kings XI, and Mumbai Indians. Two new teams, Kochi Tuskers Kerala and Pune Warriors, were added to the league in the 2011 edition.

[^2]:    ${ }^{3}$ See for instance Schofield (1988), Bairam et al. (1990) and Brooks et al. (2002).

[^3]:    ${ }^{4}$ Bairam et al. (1990) suggest possible collinearity for the exclusion of fielding. In our data we also verify that there is no evidence of multicollinearity with the inclusion of both bowling and fielding inputs.

[^4]:    ${ }^{5}$ Among the listed 391 highest innings totals in ESPN-CRICINFO, approximately $50 \%$ innings are scored post July, 2005 after the introduction of field restrictions in terms of "Powerplays" and approximately $30 \%$ are scored between 2008-2011 (ESPN-CRICINFO Statsguru). This provides evidence for the adoption of an increasingly attacking intent in the limited over format in recent times.

[^5]:    ${ }^{6}$ For a comparison across different formats of the game, see also Schofield (1988), who finds that $R P O$ is more important than $R P W$ in three-day County championship. Bairam et al. (1990) provide similar evidence from domestic first-class cricket matches in Australia and New Zealand. By contrast, Brooks et al. (2002) attribute an important role to $R P W$ in determining the winner in test cricket.
    ${ }^{7}$ In conjunction with a defensive bowling strategy $O R P O$, though $R P O$ emerges as a dominant strategy with a higher coefficient than $R P W$ and $B O U N D$ in T20Is, the variable only enters significantly at the $10 \%$ level as opposed to the $1 \%$ level.
    ${ }^{8}$ Schofield (1988) attributes greater importance to attacking bowling in the case of the longer format county championship. On the contrary, Brooks et al. (2002) find greater importance for average bowling strategy for most of the countries in the five-day international test cricket.

[^6]:    ${ }^{9}$ In a joint significance test of relative importance of attacking batting and defensive bowling, we fail to reject the null hypothesis of equality of strength in all the three cases of ODI, T20I and IPL.

[^7]:    ${ }^{10}$ We also run additional regressions similar to Dawson et al. (2009) by dropping the dummies for toss and batting first and introducing the interaction of the dummies for toss and bat first and toss and bowl first. Those results do not provide any additional insights.

[^8]:    ${ }^{11}$ The dataset for 2010 is also constructed using the individual game-specific information from the ESPN-owned CRICINFO website.
    ${ }^{12}$ On a cautionary note, we wish to emphasize that despite its better predictive power, the logit model will provide inaccurate estimates.
    ${ }^{13}$ For Zimbabwe of course this should be considered as a re-entry.

[^9]:    $\sqrt[14]{4}^{\text {Times of India, June 03, } 2011}$
    ${ }^{15}$ http://www.espncricinfo.com/england/content/story/542139.html

