Estimation of the Magnitude of Victory in One-Day Cricket

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Abstract

The Duckworth-Lewis method is steadily becoming the standard approach for resetting targets in interrupted one-day cricket matches. In this paper we show that a modification of the Duckworth-Lewis resource table can be used to quantify the magnitude of a victory in one-day matches. This simple and direct application is particularly useful in breaking ties in tournament standings and in quantifying team strength.

Keywords: one-day cricket matches, estimation, weighted least squares, Gibbs sampling.

1. Introduction

There are four possible outcomes in one-day cricket matches:

(1) the team batting first can win in a non-abandoned match

(2) the match can end in a tie

(3) the match can be abandoned

(4) the team batting second can win in a non-abandoned match

In the first case, the run differential between the two teams is a sensible measure of the magnitude of victory. In the second case, which is rare in practice, the tie itself indicates that there is zero magnitude of victory. In the third case, either the game is declared null or one of the teams is declared the winner. In the latter event, a projected score is determined for the team batting second, and again, magnitude of victory can be assessed by calculating the run

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differential. However, in the fourth case, the magnitude of victory is unclear because the match terminates as soon as the team batting second scores more runs than the team batting first even though the team batting second may have remaining wickets and overs.

Why should we care about quantifying the magnitude of victory? Without such quantification, statistical analyses are typically based on binary data corresponding solely to wins and losses. For example, de Silva and Swartz (1997) estimate the effect of the home team advantage in one-day international (ODI) cricket matches using logistic regression. It is a generally accepted statistical principle that data is valuable and that one should not "waste" data by needless summarisation. Therefore, by quantifying the magnitude of victory in one-day cricket matches, future statistical modelling can better utilise the information contained in matches. Quantifying the magnitude of victory may aid in assessing team strength, determining betting strategies, breaking ties in tournament standings, etc.

How can we quantify the magnitude of victory? The Duckworth-Lewis method (Duckworth and Lewis, 1998a, 1998b) is steadily becoming the standard approach for resetting targets in interrupted one-day cricket matches. At the time of writing, the Duckworth-Lewis method has been adopted for various competitions by the Zimbabwe Cricket Union, the England and Wales Cricket Board, New Zealand Cricket, and the International Cricket Council (ICC). It is noteworthy that the method was used in the 1999 World Cup of Cricket. Very simply, the Duckworth-Lewis method is based on the recognition that at the beginning of a match, each side has a number of resources available (typically 50 overs and 10 wickets). When a match is shortened, the resources of one or both teams is depleted and the two teams usually have different resources for their innings. In this case, to be fair, a revised target for the team batting second must be set. The determination of this target is known as the Duckworth-Lewis method.

In Section 2, we show that a simple application of the Duckworth-Lewis resource table can be used to quantify the magnitude of victory in one-day cricket matches. A modification to the Duckworth-Lewis resource table is made in Section 3 to improve the estimation procedure for the applications considered in this paper. In Section 4, we provide an example whereby a three-way tie could have sensibly been broken using our approach. Section 5 uses existing data and the modified Duckworth-Lewis resource table to model the strength of ICC nations in ODI cricket matches. A short summary and discussion are then given in Section 6. Related details are available from the papers presented by de Silva, Pond and Swartz (2000) and Allsopp and Clarke (2000) at the Fifth Conference on Mathematics and Computers in Sport.

2. Quantifying the Magnitude of Victory

The Duckworth-Lewis resource table (see Table 1) was devised to improve "fairness" in interrupted one-day matches. The resource table is based on the principle that resources are diminished in a shortened match and that targets should be reset according to the resources available. Duckworth and Lewis (1998a) obtained the entries in the resource table using statistical methods based on historical match data. For a brief introduction to the Duckworth-Lewis method, see the CricInfo website (http://www.cricket.org).

Our problem, as stated in Section 1, is to quantify the magnitude of victory when the team batting second wins in a non-abandoned match. Using the Duckworth-Lewis resource table, this is a straightforward task. We determine the resource percentage remaining, R, relative to a standard 50-over match. We then solve $(100 - R)E/100 = A$ for E, where E is the number of effective runs and A is the actual number of runs scored. With effective runs, an effective run differential can then be calculated to quantify the magnitude of victory.

Consider the simplest situation where the team batting first scores X runs and either uses all of its wickets or uses all of its overs. The team batting second then wins by scoring $Y > X$ runs based on a certain number of wickets used and overs used. One then consults the Duckworth-Lewis resource table to determine the resources remaining $R = b_1$ for the team batting second. It follows that the effective number of runs by the team batting second is $E = 100Y/(100 - R)$.

In the most general scenario, a team starts and stops batting n times. When they start batting on the i-th occasion they have a_i resources available according to Table 1, and similarly, when they stop batting they have b_i resources remaining. Therefore, the team has used $\sum_{i=1}^{n}(a_i - b_i)$ resources relative to a standard 50-over match and has $R = 100 - \sum_{i=1}^{n}(a_i - b_i)$ resources available. For example, consider a 50-over match where 10 overs are played and 1 wicket is lost. A rain delay occurs and the inning is shortened to 20 remaining overs which are then played out. In this case, $a_1 = 100.0$, $b_1 = 84.5$, $a_2 = 56.7$ and $b_2 = 0.0$.

The simplicity of the approach is part of its appeal. Further, we note that in any shortened match, we may want to scale the number of runs as described above so that they are comparable to a standard 50-over match.

3. Assessing the Adequacy of the Estimation Procedure

We begin by making the assumption that on average, the team batting first is no different (i.e. neither better nor worse) than the team batting second. To partially test this assumption, we consider the 797 full 50-over ODI matches that have taken place over the 10 year period from 1991 through September 2000. In these matches, the team batting first won slightly more than half the time (407 matches) and tied 14 times. Using the two-tailed Binomial test of H : Prob(team batting first wins) = 1/2, we obtain the p-value .28. The assumption is also supported by an empirical study (de Silva and Swartz, 1997) which shows that the result of the coin toss has no impact on the outcome of a match.

Therefore, under the above assumption, we would expect the distribution of the actual run differentials to be the same as the distribution of the effective run differentials if the effective run differentials are estimated adequately. If the distributions differ, this suggests a difficulty with the estimation of the effective run differentials.

To compare the distribution of the actual run differentials with the distribution of the effective run differentials, we consider the 783 non-tied matches described above. We divide these matches into two groups; the first group consists of the 407 matches where the team batting first wins and the second group consists of the 376 matches where the team batting second wins.

For the first group, we calculate the actual run differential for each match and construct the associated empirical distribution function (ecdf). For the second group, we use the methodology described in Section 2 to obtain the effective run differential for each match and then construct the corresponding ecdf. In Figure 1(a), the two ecdfs are superimposed and we see that the effective run differentials have a much longer right tail than the actual run differentials. To a lesser extent, we also observe a longer left tail for the effective run differentials.

How might we explain the poor performance of the Duckworth-Lewis resource table in this application and how can the estimation procedure be improved? Duckworth and Lewis (1998a) are not explicit about the data used in the construction of the resource table. However, one may presume that the Duckworth-Lewis data concerned teams that used up all of their resources in a given match. In this application, we obtain an effective run differential for teams that have not used up all of their resources (i.e. matches where the team batting second wins).

We conjecture that when the team batting second wins and has an extremely large effective run differential, this is partly due to the team having played unusually well. If batting were allowed to continue until either the wickets or overs were exhausted, we would not expect the team to maintain the same pace, and therefore the resources available should be somewhat smaller than those given in the Duckworth-Lewis resource table. On the other hand, when the team batting second wins by a small effective run differential, we conjecture that the match has been close and that the team batting second has been playing cautiously. In this case, if batting were allowed to continue until either the wickets or overs were exhausted, we would expect the team to play more aggressively, and therefore the resources available should be somewhat larger than those given in the Duckworth-Lewis resource table.

We let R denote the resources available according to the Duckworth-Lewis resource table. Our goal then is to find a modified resource percentage $R_{\text{mod}}(R)$ which assigns fewer resources when many are available and more resources when few are available. We do this by minimizing the Cramer-von Mises statistic

$$C(a1, a2) = \int (F_1(x) - F_2(x))^2 \; dx$$

where F_1 is the ecdf of the actual run differentials and F_2 is the ecdf of the effective run differentials based on the modified resource percentage $R_{\text{mod}} = (a_1 + a_2 R)R$. Based on a grid search, we obtain the optimal value

$$R_{\text{mod}} = (1.183 - .006R)R. \tag{1}$$

In Figure 1(b), the ecdfs F_1 and F_2 are superimposed and we observe that there is good agreement in the distributions. Hence, for the remainder of the paper, whenever an effective run differential is calculated, it will be based on the modification (1). To put R_{mod} into perspective, it assigns the modified resource percentages 0%, 11.2%, 21.3%, 30.1%, 37.7% and 44.2% when the Duckworth-Lewis table gives 0%, 10%, 20%, 30%, 40% and 50% respectively.

4. An Example Concerning Ties

To illustrate the method, we take the Asia Cup played in Sharjah, UAE, 1995, as an example. This tournament featured India, Sri Lanka, Pakistan and Bangladesh in 50-over matches with the top two teams advancing to the championship final. After the initial round, Bangladesh had no wins and three losses. The remaining teams each had two wins and one loss. Under the three-way tie, India and Sri Lanka advanced to the finals based on superior run rates.

It is widely accepted that run rates can be unfair. We will use our method to calculate an effective run differential for each game, and use a net run differential to decide which teams should advance. The relevant details of the initial round matches involving India, Sri Lanka and Pakistan are given in Table 2. In the first match, Pakistan has a differential of 97 runs over India. In the second match, India had lost only two wickets in 33 overs plus one out of six balls when it exceeded Sri Lanka's run total. Therefore, in a 50-over match, India had 16.83 of its overs left. Interpolating from Table 1, India had 48.17% of its resources remaining which yields 43.06% under the modification (1). Therefore, we calculate India's effective runs E by solving $(100 - 43.06)E/100 = 206$. This gives India 362 effective runs and an effective run differential of $362 - 202 = 160$ over Sri Lanka. A similar calculation in the third match gives Sri Lanka an effective run differential of 109 over Pakistan.

Putting these results together, India has $160 - 97 = 63$ net runs, Sri Lanka has $109 - 160 = -51$ net runs and Pakistan has $97 - 109 = -12$ net runs. Therefore, our approach would have advanced India and Pakistan to the championship final rather than India and Sri Lanka. We note that the same conclusion is reached when the matches involving Bangladesh are included in the calculation.

5. An Example Concerning the Modelling of Team Strength

There are special features of ODI cricket that have an impact on the statistical analysis of team strength. For example, ICC nations do not play against one another frequently in ODI competitions, and therefore, a strength analysis based solely on the current year's data would not yield trustworthy results. For example, in 2000, New Zealand scheduled only 20 ODI matches; 5 versus the West Indies, 6 versus Australia, 3 versus Zimbabwe and 6 versus South Africa. Fortunately, a compensating factor is that cricketers typically have lengthy careers (c.f. rugby), and it is therefore reasonable to assume that the relative strength of the ICC nations does not change dramatically from year to year. A strength analysis then, ought to consider matches from previous years. Finally, another complicating feature in the statistical analysis of team strength, and a premise of this paper is that the magnitude of victory in matches is not adequately expressed by the actual run differential.

The data used in this analysis are the results of full 50-over ODI matches involving the nine nations of the ICC. Although the analysis could be extended to include shortened matches, there are relatively few of these (e.g. 5.1% of matches in ODI tournaments in 2000). Also, it seems preferable to restrict our analysis to full 50-over matches where strategies are constant. There are 546 such matches over the six year period beginning January 1995 through September 2000, the results of which are available from the "Archive" link at the CricInfo website.

As in Section 4, a run differential is calculated for every match. For matches in which the team batting first wins, the run differential is simply the actual run differential. For matches in which the team batting second wins, the run differential is calculated by subtracting the actual runs of the team batting first from the effective runs of the team batting second obtained via modification (1) of the Duckworth-Lewis resource table. We let indices $i, j = 1, \ldots, 9$ correspond to the nine ICC nations and let $k = 0, \ldots, 9$ correspond to the site of a match where $k = 0$ refers to a neutral site. Following Pond (1999), we consider the model

$$d_{ijk} = \tau_i - \tau_j + \gamma_{ijk} + \epsilon_{ijk} \tag{2}$$

where the response variable d_{ijk} is the run differential (i.e. team i minus team j) for a match at site k, τ_i is a measure of strength for the i-th team such that $\sum_{i=1}^{9} \tau_i = 0$, γ_{ijk} is the home field advantage such that

$$\gamma_{ijk} = \begin{cases} \gamma & \text{if } k = i \\ -\gamma & \text{if } k = j \\ 0 & \text{otherwise} \end{cases}$$

and the ϵ_{ijk} are independent and identically distributed Normal$(0, \sigma^2)$ errors. This 10-parameter model is taken over all 546 matches. It is sensible as the determination of team strength takes into account not only victories and losses, but also the magnitude of the victories and losses, the strength of the opponent and the site of the match. We note that the inclusion of the error term ϵ_{ijk} gives us a stochastic model so that when two teams play again at the same site, we would not necessarily have the same result. The constraint $\sum_{i=1}^{9} \tau_i = 0$ provides identifiable parameters and the interpretation that on average, team i is better than team j by $\tau_i - \tau_j$ runs at a neutral site.

To give more emphasis to recent matches, we consider a weighted least squares approach. Model A assigns linear weights; weight 1 to every match in 2000, weight 5/6 to every match in 1999, weight 4/6 to every match in 1998, etc. Model B assigns geometric weights; weight 1 to every match in 2000, weight 1/2 to every match in 1999, weight 1/4 to every match in 1998, etc. Model C considers only recent data by assigning weight 1 to the 87 completed matches in the year 2000 and weight 0 to all remaining matches. Thus model B represents a compromise between models A and C; it considers matches from the distant past but does not assign much importance to these matches.

The models are fitted with S-Plus and the results are given in Table 3 along with the Yehhai ranking points obtained from www.yehhaicricket.com. We observe an ordering for the ICC nations where for example, under models A and B, Australia is the strongest team and Zimbabwe is the weakest. The estimated parameters can be used to forecast the outcomes of matches. For example, under model B, should South Africa play India in Johannesburg, we would expect South Africa to win by $16.7 - (-7.5) + 18.0 = 42.2$ runs. This is one of the advantages of the proposed models over standard rankings such as those given by the Yehhai points. With the Yehhai points, one cannot meaningfully assess how much better one team is than another. We also observe that the home field advantage γ is significant in ODI matches under all three models. Finally, note that the error σ is somewhat large; this highlights the variability in cricket matches, where unlike sports such as rugby, a considerably weaker team has a realistic chance at upsetting a stronger team. A consequence of this is that the model fit diagnostic R^2 is somewhat low for all three models.

A troubling aspect of the weighted least squares approach is that the choice of weights is arbitrary yet it has a considerable impact on inferences. For example, under model A, Sri Lanka is not nearly as strong as suggested by model C. We also note that model C which is based on matches from the current year yields undesirably large standard errors for the parameter estimates. To account for the uncertainty of the weighting and to allow the data to determine the appropriate weights, we consider and endorse a Bayesian analysis. We retain the assumptions in (2) and introduce the n_l-dimensional vector y_l which consists of the data d_{ijk} corresponding to the year $l = 1995, \ldots, 2000$. We also introduce the weight parameter $w \geq 1$ whereby the variance of d_{ijk} in a given year is $1/w$ times the variance in the previous year. Letting $[A \mid B]$ denote the conditional distribution of A given B and assuming conditional independence of the data, we obtain the 11-dimensional posterior distribution

$$[\tau, \gamma, \sigma, w \mid y] \propto \left(\prod_{l=1995}^{2000} [y_l \mid \tau, \gamma, \sigma, w] \right) \cdot [\tau, \gamma, \sigma, w] \qquad (3)$$

where $[y_l \mid \tau, \gamma, \sigma, w] \sim \text{Normal}_{n_l}[X_l\beta, \sigma^2 w^{2000-l} I]$, $\beta = (\tau'\gamma)'$, X_l is the design matrix determined by (2) and the standard default for $[\tau, \gamma, \sigma, w]$ is given by the improper prior $1/\sigma$. We refer to this as model D.

Given the complexity of the posterior distribution (3), our goal is to simulate from it so that marginal posterior characteristics can be estimated. We do this using the Gibbs sampling algorithm which is an iterative approach to simulation from a target distribution. Gibbs sampling has been successfully used in many Bayesian applications (Gelfand and Smith, 1990). Our implementation requires that we generate variates from the full conditional distributions $[\tau, \gamma \mid \cdot]$, $[\sigma^2 \mid \cdot]$ and $[w \mid \cdot]$. Sampling from the first two full conditionals is straightforward as it is easy to show that

$$[\tau, \gamma \mid \cdot] \sim \text{Normal}_9[(\sum_{l=1995}^{2000} X_l' X_l / w^{2000-l})^{-1} (\sum_{l=1995}^{2000} X_l' y_l / w^{2000-l}),\ \sigma^2 (\sum_{l=1995}^{2000} X_l' X_l / w^{2000-l})^{-1}]$$

$$[\sigma^2 \mid \cdot] \sim \text{Inverse Gamma}[(\sum_{l=1995}^{2000} n_l/2) - 1/2,\ \sum_{l=1995}^{2000} \frac{1}{2w^{2000-l}} (y_l - X_l\beta)'(y_l - X_l\beta)]$$

However, the distribution $[w \mid \cdot]$ is non-standard with a density proportional to

$$g(w) = w^{\sum_{l=1995}^{1999}(l-2000)n_l/2} \exp\{\sum_{l=1995}^{1999} \frac{-1}{2\sigma^2 w^{2000-l}}(y_l - X_l\beta)'(y_l - X_l\beta)\}$$

truncated on $w > 1$. We therefore "imbed" a Metropolis step in the Gibbs sampler (see Gilks, Richardson and Spiegelhalter, 1996) using an Exponential(1.0) proposal density truncated on $w > 1$. This is a convenient choice as the variates w can be generated via inversion.

In Table 4, we present the posterior means and posterior standard deviations for the parameters in model D. We note a striking similarity with the τ and γ estimates from model A and some improvement in the model error σ. The expected posterior weight $E(w \mid y) = 1.32$ indicates that a match from 2000 is weighted $1.32^5 \approx 4$ times as heavily as a match from 1995; this corresponds with our intuition.

Naturally, our inferences are only as good as our model, and one of the assumptions of the Bayesian model D is that d_{ijk} has the same mean in years $l = 1995, \ldots, 2000$. This, is of course tempered by the fact that the variance of d_{ijk} is decreasing by a factor of $1/w$ in each additional year. Whereas we are comfortable with this assumption based on extensive exploratory analysis of the yearly match results, one should not simply extend the data arbitrarily far back in time. For then, the mean of certain d_{ijk} would certainly not be constant and the model would be in error. As an example, we present the results of model E in Table 4 where model E is identical to model D except that the data includes the 701 matches from January 1993 to Sept 2000 (i.e. two additional years). Although most of the estimates in models D and E are comparable, we note that model E assigns considerably more strength to the West Indies. It is widely accepted that the West Indies is not as strong as they were in the early 90's and this suggest that its mean has changed. We also note that σ is increased in model E and that w is unreasonably small. All of these signs point to the fact that we have gone too far back in time with model E.

The simulation procedure is particularly useful for predictive inference (i.e. betting). Consider then a future match between Australia (i.e. $i = 1$) and New Zealand (i.e. $j = 7$) in Auckland. Using the Bayesian model (3), we generate parameters $\tau_1, \tau_7, \gamma, \sigma, w$ from the posterior using Gibbs sampling and then generate d_{177} from the Normal(μ, σ^2) distribution where $\mu = \tau_1 - \tau_7 - \gamma$. Our predictive inferences are then based on the set of generated d_{177} values. For example, the estimated probability that Australia defeats New Zealand is given by the proportion of the generated d_{177}'s that exceed zero. This turns out to be .69 for model D.

6. Summary and Discussion

This paper considers the use of a modification of the Duckworth-Lewis resource table to quantify the magnitude of victory in one-day cricket matches.

For breaking ties in tournaments (Section 4), an appeal of the approach is its simplicity. A simple approach is more likely to be adopted in one-day cricket tournaments. The issue of fairness is also an advantage of the approach; it is well documented that the current practice of run-rate comparisons can be extremely unfair.

For rating team strength as described in Section 5, there are clearly a variety of models that can be considered. For example, one may introduce different covariates, transform variables and propose different match weightings. However, fundamental to all models is the use of the run differential d_{ijk} proposed in this paper. For without d_{ijk}, we are limited to binary data (i.e. wins/losses) for which the estimation of team strength is less efficient. Whether you are a handicapper or simply interested in supporting your home team, the estimation of team strength in ODI cricket is a fascinating topic.

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Table 1: Abbreviated version of the Duckworth-Lewis resource table. The table entries indicate the percentage of resources remaining in a match with the specified number of wickets lost and overs available.

	Wickets Lost									
Overs Left	0	1	2	3	4	5	6	7	8	9
50	100.0	92.4	83.8	73.8	62.4	49.5	37.6	26.5	16.4	7.6
40	90.3	84.5	77.6	69.4	59.8	48.3	37.3	26.4	16.4	7.6
30	77.1	73.1	68.2	62.3	54.9	45.7	36.2	26.2	16.4	7.6
20	58.9	56.7	54.0	50.6	46.1	40.0	33.2	25.2	16.3	7.6
19	56.8	54.8	52.2	49.0	44.8	39.1	32.7	24.9	16.2	7.6
17	52.3	50.6	48.5	45.8	42.2	37.2	31.5	24.4	16.1	7.6
16	49.9	48.4	46.5	44.0	40.7	36.1	30.8	24.1	16.1	7.6
10	34.1	33.4	32.5	31.4	29.8	27.5	24.6	20.6	14.9	7.5
5	18.4	18.2	17.9	17.6	17.1	16.4	15.5	14.0	11.5	7.0
1	3.9	3.9	3.9	3.9	3.9	3.8	3.8	3.7	3.5	3.1
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Table 2: Summary of the relevant initial round matches involving India, Sri Lanka and Pakistan in the 1995 Asia Cup as described in Section 4. We let Team 1 denote the team batting first and Team 2 denote the team batting second. Runs, wickets and overs refer to the number of runs scored, the number of wickets used and the number of overs used in a match. An asterisk denotes the winner of a match. ARD and ERD denote the actual run differential and the effective run differential respectively.

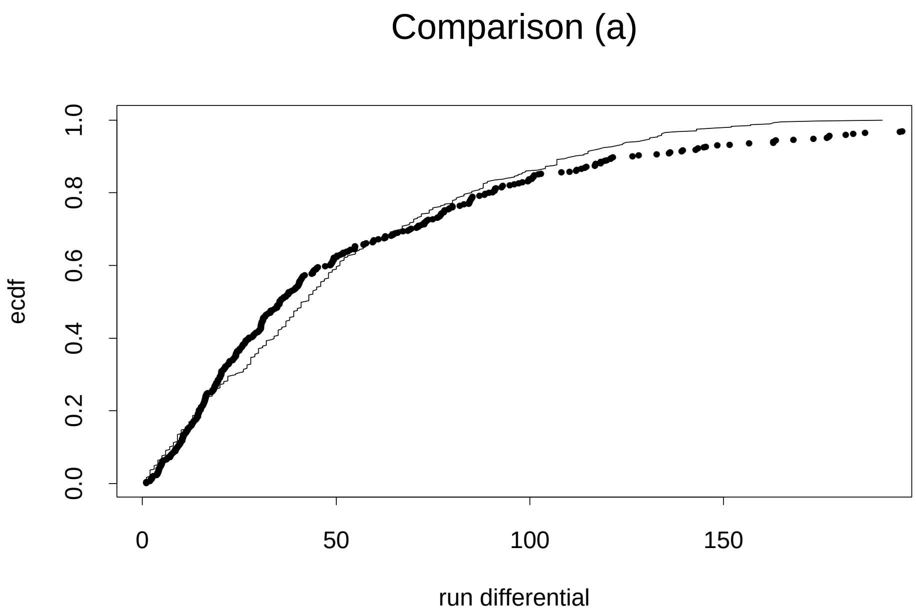
Date	Team 1 (Runs/Wickets/Overs)	Team 2 (Runs/Wickets/Overs)	ARD	ERD
Apr 07	Pak (266/9/50)*	Ind (169/10/42.4)	97	97
Apr 09	SL (202/9/50)	Ind (206/2/33.1)*	4	160
Apr 11	Pak (178/9/50)	SL (180/5/30.5)*	2	109

Table 3: The estimated model parameters and the Yehhai points as described in Section 5. The teams are listed according to relative strength as given by model A.

Parameter (τ_i)	Model A Est (Std Err)	Model B Est (Std Err)	Model C Est (Std Err)	Yehhai Points
Australia	26.2 (5.5)	32.4 (5.6)	27.2 (15.0)	62.5
South Africa	23.1 (5.5)	16.7 (5.4)	1.2 (12.3)	27.0
Sri Lanka	7.9 (6.0)	13.3 (6.5)	40.3 (21.4)	39.5
Pakistan	7.3 (5.0)	7.2 (5.1)	-6.3 (12.3)	-1.0
England	6.5 (7.0)	12.9 (7.2)	36.0 (19.3)	14.0
India	-4.0 (5.3)	-7.5 (5.5)	-38.0 (16.0)	-28.0
New Zealand	-11.8 (6.4)	-14.0 (6.7)	-11.0 (18.6)	11.5
West Indies	-16.8 (6.3)	-24.2 (6.2)	-27.4 (16.3)	-10.0
Zimbabwe	-38.4 (6.1)	-36.8 (6.1)	-22.0 (15.5)	-44.5
home field (γ)	16.8 (3.9)	18.0 (3.9)	20.6 (9.4)	
standard deviation (σ)	56.0	42.5	69.9	
R^2 diagnostic	.15	.18	.29	

Table 4: The posterior means and posterior standard deviations of the parameters in the Bayesian models of Section 5.

Parameter (τ_i)	Model D Mean (Std Dev)	Model E Mean (Std Dev)
Australia	24.1 (4.1)	19.4 (4.0)
South Africa	22.1 (4.1)	20.8 (4.0)
Sri Lanka	6.6 (4.4)	2.5 (4.2)
Pakistan	6.9 (3.7)	7.8 (3.4)
England	4.7 (5.1)	0.7 (5.3)
India	-3.8 (3.9)	-1.6 (3.9)
New Zealand	-11.6 (4.7)	-11.7 (4.4)
West Indies	-15.0 (4.6)	0.2 (4.5)
Zimbabwe	-34.0 (4.5)	-38.1 (4.8)
home field (γ)	15.6 (2.8)	13.6 (2.8)
standard deviation (σ)	39.7 (1.5)	54.3 (2.2)
weight factor (w)	1.32 (.05)	1.05 (.03)



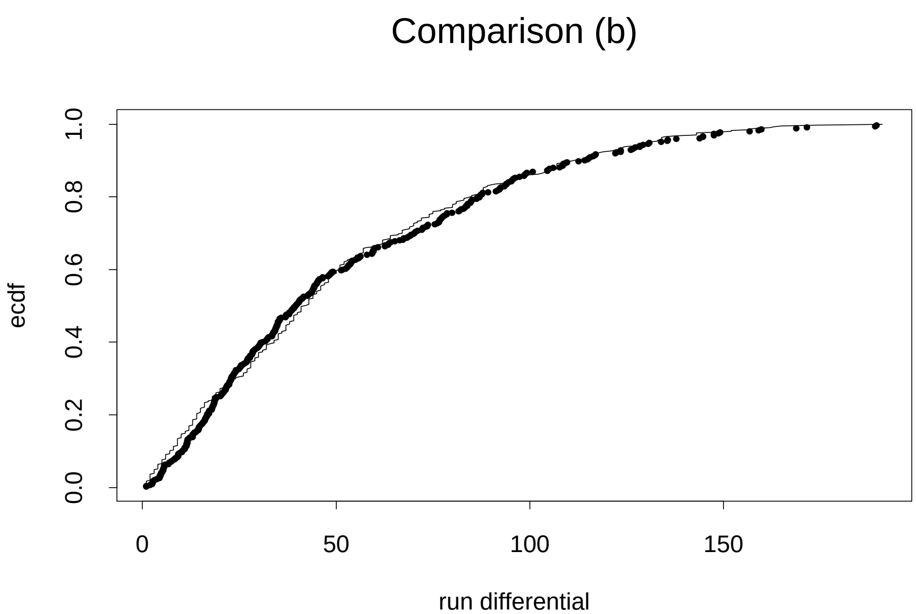


Figure 1: A comparison of the empirical distribution functions of the run differential when the team batting first wins (—) and when the team batting second wins (...). In (a), the Duckworth-Lewis resource table is used. In (b), the modification R_{mod} in (1) is used.