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# Shifting the 'goal posts': What is the optimal allocation of Super Rugby competition points?

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**Abstract**

Competition points are awarded in sports events to determine which participants qualify for the playoffs or to identify the champion. We use competition points to measure strength in a prediction model and choose competition points to maximise prediction accuracy. This allows us to determine the allocation of competition points that most appropriately rewards strong teams. Our analysis focuses on Super Rugby as the characteristics of this competition closely match our modelling assumptions. We find that the current allocation of competition points is not optimal and suggest an alternative. Our findings have implications for other competitions.



Keywords: Competition points; Nonlinear least squares; Sports predictions

## 1. Introduction

Administrators of sports competitions involving round-robin or group stages typically award competition points in order to rank participants. These rankings are used to determine which competitors advance to the playoffs or identify the overall winner. It is, therefore, important that organisers employ allocation criteria that accurately reflect the strength of participants.

A common allocation method awards a winning team two competition points, zero points to a losing team and one point to each team if a fixture is tied. A variant of this system, as commonly used in football (soccer) tournaments, grants teams participating in a tied match less than half the number of points awarded for a win. Bonus points have recently been introduced to some competitions. In the (North American) National Hockey League a bonus point is awarded to a losing team if overtime or a penalty shootout is required to determine a winner. In some forms of cricket, bonus point are awarded for narrow losses and dominant victories. We concentrate on Super Rugby, where up to two bonus points are offered, as the allocation of points in this competition is more complicated than most others and our modelling framework is well suited to this event. Namely, (a) there is no promotion or relegation, (b) playing rosters are relatively consistent across years, and (c) teams play balanced schedules each year.

The inclusion of bonus points often produces a different hierarchy of teams relative to if bonus points were not included. For example, Super Rugby teams missed out on semi-finals berths even though they recorded more wins (or as many wins and more ties) than at least one semi-finalist in 1996, 2000 and 2006. Despite the influence bonus points can have on the ordering of teams and ultimately the selection of semi-finalists, the appropriateness of the allocation of Super Rugby competition points has not been evaluated. Furthermore, most other rugby competitions have adopted a similar system for allocating competition points, including the Rugby World Cup – reputably the world's third largest sporting event.

We determine the allocation of Super Rugby points that is best at revealing strong teams by constructing strength measures that are built on competition points and choosing competition points to maximise prediction accuracy. Intuitively, maximising prediction accuracy allows us to determine the optimal allocation of competition points as predictions using strength indices built on an allocation of competition points that is not good at revealing strong teams will be less accurate than predictions based on an allocation that is good at identifying strong teams. To our knowledge, this is the first study to determine the optimal allocation of competition points for a sports competition.

This paper has three further sections. Section 2 outlines the salient features of Super Rugby. Our modelling framework and results are set out in Section 3. Section 4 concludes.

## 2. Super Rugby

Rugby is played on a rectangular field with H-shaped goal posts at each end between teams of 15 players per side. (There are two variants of rugby: rugby union and rugby league. It is common to refer to the former as 'rugby' and the latter as 'league'. This convention is followed here.) We make a distinction between game points and competition points. Game points are awarded during a game and competition points – the subject of our investigation – are awarded at the end of a contest depending on the match outcome. Teams earn game points by scoring tries (placing the ball over their opponent's goal line) and kicking goals (kicking the ball from the ground between the goal posts and over the cross bar). A try is worth five points and grants an opportunity to kick a conversion, which, if successful, is worth an additional two points (so seven points can be scored in a single scoring play). Teams can also attempt to kick a goal when they are awarded a penalty (from the position where the infringement occurred) or attempting a drop goal (dropping the ball and kicking it as it hits the ground) in general play. A goal is worth three points. The rules of rugby are set out by the International Rugby Board (www.irb.com).

The Super Rugby competition has been played annually since 1996 by provincial/state sides from Australia, New Zealand and South Africa. Between 1996 and 2005, there were 12 Super Rugby teams (five from New Zealand, four from South Africa and three from Australia) and the competition was known as the Super 12. Two extra teams from Australia and South Africa respectively were added in 2006 and the tournament was renamed the Super 14. The name 'Super Rugby' encompasses both competitions.

Each tournament begins with a round-robin phase where each team plays every other team once. Each team has one bye, so from 1996-2005 each team played 11 games over 12 rounds. The top four teams from this stage qualify for the semi-finals and the two winning semi-finalists contest the final. Hosting rights for the semi-finals and the final are awarded to the team in each contest that gained the highest round-robin ranking. Competition points are awarded at the completion of each match according to several decision rules. A winning team is awarded four points, a losing team zero points and each team earns two points if a match is tied. In addition, bonus points may be awarded for (i) scoring four or more tries, and/or (ii) losing by seven or fewer points. So, a winning team may earn five or four competition points, a team that ties a match may be awarded three or two points, and a losing team may earn two, one or zero points. In total, there are 17 possible pairwise allocations of points per match (5-2, 5-1, 5-0, 4-2, 4-1, 4-0, 3-3, 3-2, 2-2, 2-3, 0-4, 1-4, 2-4, 0-5, 1-5, 2-5).

A bonus point for losing by a small margin was first introduced in New Zealand's National Provincial Championship (NPC) in 1986. At the time a try was worth four (game) points and a bonus point was awarded if a team lost by six points or less. That is, similar to the narrow-loss bonus in Super Rugby, a losing team was awarded a competition point if an additional maximum scoring play (a try plus a conversion) by this team would have tied the game or reversed the match outcome. However, the value of a try was increased from four to five (game) points in 1992 but the minimum losing margin required to earn a narrow-loss bonus was not increased to seven points until 1995. In contrast, a bonus point for scoring four or more tries was introduced to Super Rugby in 1996 to encourage teams to play attacking rugby.

Geographically, Super Rugby franchises are diverse. The time difference between New Zealand and South Africa in 10 hours, travelling between New Zealand and South African cities can take up to 30 hours, and teams based on South Africa's Highveld are around 2000 meters above sea level while most other teams have coastal headquarters. We distinguish four regions – Australia, New Zealand, South Africa-coastal and South Africa-Highveld – to capture geographic diversity.

Evidence of strong home advantage is that between 1998 and 2005 home teams won 61.3% of matches, away teams won 36.6%, and 2.1% of matches were tied. We present further evidence of home advantage by reporting average points scored, average number of tries scored, and average number of try and loss bonus points earned by home and away teams in Table 1. On average, home teams score 6.4 more points and nearly one more try per match than away teams. Home teams earn a try bonus in 42% of matches while the corresponding figure for away teams is 26%. Away teams earn more narrow-loss bonuses on average than home teams (0.18 versus 0.17) but have a greater propensity to lose.

Table 2 reports average net scores (points scored by the home team minus points scored by the away team) for each team when playing at home and indicates each team's regional location. The simple home advantage measure indicates that there is a large variation in home advantage across teams. For example, over the sample period the Brumbies, Crusaders and Highlanders average home net scores were 17.0, 14.8 and 11.6 respectively, while corresponding figures for the Bulls and the Cats are -1.5 and 0.4 respectively.

Home advantage is also likely to depend on distance travelled by the away team. For example, South African teams travelling to New Zealand are likely to experience greater away disadvantage than other teams playing away fixtures in New Zealand. Table 3 presents average home net scores by regional pair. The data reveal that, on average, Australian and New Zealand teams defeat sides from South Africa's Highveld by large margins when playing at home.

## 3. Modelling framework and results

The details of many sports ranking/prediction systems are not available to the public because of their application to sports gambling and/or for proprietary reasons. In ranking techniques in the public domain, most systems are built on the margin of victory and rankings are updated on a weekly basis. Leake (1976) and Stefani (1977, 1980 & 1983) choose rankings to minimise the sum of squared prediction errors, while Bassett (1997) minimises the sum of absolute errors. Clarke and Stefani (1992) and Clarke (1993) update rankings using exponential smoothing techniques. Zuber *et al.* (1985), on the other hand, generate predictions for the National Football League (NFL) by observing a number of team-specific measures (e.g., number of wins, number of yards rushed, and total offensive plays etc). Also for the NFL, Harville (1980) uses mixed linear models to predict outcomes. Prediction models for Australian Rules Football built on individual player data are developed by Bailey (2000) and Bailey and Clarke (2004). Glickman and Stern (1998) use a state-space model. Stefani (1987 & 1998) reviews this literature. To our knowledge, no existing system is built on competition points. In other related literature, Morton (2006) examines home advantage in Southern Hemisphere rugby and Owen and Weatherston (2004) investigate the determinants of attendance at Super Rugby matches.

We use the home team's net score to characterise the outcome of a match and predict match outcomes by regressing net scores on location and net strength variables. Let $i$ denote the home team, $j$ denote the away team, $n$ and $s$ index regions identified in

Table 3, $r$ index rounds and $y$ index years. We specify the following regression equation

$$NSC_{ij,r,y} = \alpha_0 + \boldsymbol{\alpha_1}\mathbf{D_1} + \boldsymbol{\alpha_2}\mathbf{D_2} + \beta.NSTRN_{ij,r,y} + \varepsilon_{ij,r,y} \quad (1)$$

where $NSC_{ij,r,y}$ is $i$'s net score against team $j$ in round $r$ in year $y$; $\alpha_0$ measures base home advantage (applicable to all teams); $\boldsymbol{\alpha_1}$ is a 1x12 vector of team-specific additional home advantage parameters $\{\boldsymbol{\alpha_1} = (\alpha_1^{Blues},...,\alpha_1^{Waratahs})\}$ $\mathbf{D_1}$ is a 12x1 vector of binary variables equal to 1 if a team played a home match, zero otherwise $\{\mathbf{D_1} = (D_{ij,r,y}^{Blues},...,D_{ij,r,y}^{Waratahs})\}$; $\boldsymbol{\alpha}_2$ is a 1x16 capturing additional home advantage when $i$ is located in region $n$ and $j$ is located in region $s$ $\{\boldsymbol{\alpha_2} = (\alpha_2^{NZ,NZ},...,\alpha_2^{SA-Highveld,SA-Highveld})\}$; $\mathbf{D_2}$ is a 16x1 vector of binary variables equal to 1 if a team from region $n$ hosted a team from region $s$, zero otherwise $\{\mathbf{D}_2 = (D_{ij,r,y}^{NZ,NZ},...,D_{ij,r,y}^{SA-Highveld,SA-Highveld})\}$; $NSTRN$ is the net strength of team $i$; $\beta$ captures the influence of $NSTRN$ on $NSC$, and $\varepsilon$ is an error term.

In our estimations described below, we drop one team-specific home advantage parameter ($\alpha_1^{Blues}$) and the four regional home advantage parameters for which $n = s$ to avoid introducing perfect multicolinearity. $NSTRN$ is defined as

$$NSTRN_{ij,r,y} = STRN_{i,r,y} - STRN_{j,r,y} \quad (2)$$

where $STRN$ measures team strength and is a time-varying weighted average of competition points earned per-game in years $y$ and $y$-1. In the first match of each year, the weight on competition points earned in the current season is zero and this weight increases by a constant amount after each game. Specifically, *STRN* is calculated as

$$STRN_{i,r,y} = \lambda_{i,r,y} POINTS_{i,12,y-1} + (1 - \lambda_{i,r,y}) POINTS_{i,r-1,y} \tag{3a}$$

where $POINTS_{i,r,y}$ denotes competition points earned per-match by team *i* in year *y* at the completion of round *r*, and $\lambda_{i,r,y}$ is equal to (11 – $g_{i,r,y}$ )/11 where *g* denotes the number of games played by team *i* prior to round *r* in year *y*. (Even though there is an even number of teams in the competition, there is not a direct correspondence between the number of games played by a team and the round number as each team has one bye each year.)

Noting that competition points are awarded for winning, tieing and losing by seven points or less yields the following expression

$$\begin{aligned} STRN_{i,r,y} = {} & \lambda_{i,r,y}(\theta^{WIN} WIN_{i,12,y-1} + \theta^{TIE} TIE_{i,12,y-1} \\ & + \theta^{LOSS} LOSS_{i,12,y-1}) + (1-\lambda_{i,r,y})(\theta^{WIN} WIN_{i,r-1,y} \\ & + \theta^{TIE} TIE_{i,r-1,y} + \theta^{TRY} TRY_{i,12,y-1} + \theta^{LOSS} LOSS_{i,r-1,y}) \end{aligned} \tag{3b}$$

where $\theta^{WIN}$, $\theta^{TIE}$, $\theta^{TRY}$ and $\theta^{LOSS}$ are competition points awarded for, respectively, winning, tieing, scoring four tries or more, and losing by seven points or less; and $WIN_{i,r,y}$, $TIE_{i,r,y}$, $TRY_{i,r,y}$ and $LOSS_{i,r,y}$ are the average number of matches team *i* has, respectively, won, tied, scored four or more tries in, and lost by seven points or less in year *y* at the completion of round *r*. We replace *r* with 12 when referring to the average number of wins etc in the previous year as there are 12 rounds in each season.

Substituting (2) and (3b) into (1) gives the equation to be estimated, which is presented in the appendix as equation (A.1).

As the optimal allocation of competition points is invariant to multiplication by any positive scalar, we normalise points with respect to $\theta^{WIN}$. That is, we set $\theta^{WIN}$ equal to one and express values for other events attracting competition points relative to the number of competition points awarded for a win.

Our strength measure is well suited to Super Rugby on three grounds. First, there is no relegation or promotion so the same teams play each other each year. Second, probably because rugby has only been professional for just over a decade, most players are local to the province/state they represent and there is not a well-developed transfer market. Indeed, most movements between franchises are by players on the fringe of selection for their 'home' team seeking an opportunity at another franchise. Third, as each competition begins with a round-robin, each team plays a balanced schedule each year and there is a higher probability that a team has played a schedule of average difficulty as the season progresses. Combined, the three characteristics indicate that it is appropriate to measure a team's strength at the start of each year as average competition points earned in the previous year and increase the weight on current year competition points as the season progresses.

We estimate (A.1) using 528 round-robin Super Rugby matches played during the years for which there were no changes in Super Rugby teams, 1998-2005. (Prior to 1998 South Africa entered the top four teams from its premier domestic competition and, as mentioned above, two additional teams were included in Super Rugby in 2006.) We fix all competition points at (normalised) values currently used in Super

Rugby ($\theta^{WIN}$ = 1, $\theta^{TIE}$ = 0.5, and $\theta^{TRY}$= $\theta^{LOSS}$ = 0.25) in our first regression exercise. In this case all components of *NSTRN* are exogenous and (A.1) collapses to (1). We eliminate insignificant home advantage parameters using a general-to-specific methodology with a single search path. Specifically, we start by including all home advantage parameters (except those omitted to avoid introducing perfect multicolinearity) and eliminate the parameter with the lowest *t*-statistic in each subsequent estimation until the highest *p*-value is less than 0.05. We also search for structural breaks in home advantage parameters by allowing values for these parameters to differ pre and post 2002.

We find that all regional home advantage parameters are not significantly different from zero expect those for Australian teams hosting teams from the Highveld ($\alpha_2^{Australia,SA-Highveld}$) and New Zealand teams hosting sides from the same region ($\alpha_2^{NZ,SA-Highveld}$). The results also indicate that additional home advantage parameters are only significant throughout the sample period for the Brumbies ($\alpha_1^{Brumbies}$) and Crusaders ($\alpha_1^{Crusaders}$). The additional home advantage parameter for the Highlanders ($\alpha_1^{Highlanders}$) was also significant but only until the end of 2002. All other home advantage parameters are not significantly different from zero. (The Wald test for the joint significance of omitted home advantage parameters has a *p*-value of 0.924.)

Results from estimating (1) using ordinary least squares (OLS) and only including significant home advantage coefficients are reported in column (a) of Table 4. The estimates reveal that most teams experience an advantage from playing at home equal to 3.42 game points. Home advantage for the Brumbies and the Crusaders, however, against most teams is equal to 12.14 (3.42 + 8.99) and 10.97 (3.42 + 7.55) respectively. Prior to 2003 the Highlanders enjoyed the largest home advantage of all Super Rugby teams (13.34). Turning to the regional home advantage variables, when an Australian team (except the Brumbies) hosts a team from the Highveld home advantage equates to 19.34 (3.42 + 15.92). Meanwhile, New Zealand teams (except the Crusaders and the Highlanders prior to 2003) entertaining Highveld sides benefit by 11.64 (3.42 + 8.22) points. The impact of location is largest when the Brumbies host a Highveld team and assists the Brumbies by 28.33 (3.42 + 8.99 + 15.92) points. Interestingly, the Brumbies win-loss record against Highveld teams in our sample period is 8-0. Given the geographic dispersion of Super Rugby regions, the large impact of location on match outcome is not surprising. As the influence of home advantage is consistent across specifications, we do not discuss these parameters for other estimations.

The positive and significant coefficient on *NSTRN* indicates that our strength measure is a significant determinant of match outcomes. The value for $\beta$ implies that, in the absence of home advantage, a team that wins every match and a collects a try bonus will beat a team that loses every match without earning any bonus points by 16.86 (1.25*13.49) points. Relative to the impact of where the match is played, the strength of the two opponents appears to have a moderate impact on match results. Overall, the model is able to explain about 20% of the variation in the sum of squared net scores and correctly selects the winning team in around two-thirds of matches.

Results from estimating (A.1) using nonlinear least squares (NLS) are presented in column (b). The estimate for $\beta$ indicates that the net average number of wins by the home team is a significant determinant of net scores. Estimates for $\theta^{TIE}$ and $\theta^{TRY}$ are not significantly different from zero, so the average number of ties and the average number of times four or more tries are scored are not significantly correlated with team strength. The estimate for $\theta^{LOSS}$ is only different from zero at a 10% significance level, indicating that the average number of losses by seven or fewer points is a weak determinant of team strength.

The average number of ties may be an insignificant determinant of strength as there has not been enough tied matches to accurately gauge the impact of this event on team strength (only 2.1% of matches were tied). The appropriateness of the try bonus can be questioned on the grounds that it is not uncommon for teams that lose by a large margin to earn a try bonus. For example, in round nine of the 1998 competition the Stormers earned a try bonus even though they lost 24-74 to the Blues. This could be because whether or not a losing team earns such a bonus is largely determined by the attitude of the winning team. For instance, a dominant team may decide to bring on bench players and/or play with less aggression/enthusiasm. Support for this hypothesis is that the average losing margin when defeated teams are awarded a try bonus (13.0) is similar to the average losing margin when beaten sides do not earn a try bonus (14.7). We also regress the losing margin on a binary variable equal to one if the losing team scored four or more tries (and zero otherwise). The $p$-value on the coefficient for the binary variable is 0.420.

Regarding the narrow-loss bonus, perhaps a seven-point margin is not indicative of a close game. After all, such a margin implies that the losing team could earn a narrow-loss bonus if an additional maximum scoring play (a converted try) by this team would have tied the game. In the NPC between 1992 and 1995 teams could only earn a narrow-loss bonus if an additional maximum score by the losing team would have reversed the outcome of the match. So, history suggests that administrators are unsure how to define a narrow loss.

We examine the appropriateness of cut-offs or partitions used for bonus points by estimating (A.1) for a range of alternative combinations of partitions for try and narrow-loss bonuses. Specifically, the minimum losing margin required for a narrow-loss bonus is varied from 1 to 10 and the number of tries needed for a try bonus is altered from 1 to 12. The sum of squared errors is minimised when a try bonus is awarded for scoring eight or more tries and a narrow-loss bonus granted for losing by five or fewer points. The cut-off for the try bonus makes it very unlikely that a losing team will earn such a bonus. (Only winning teams scored eight or more tries in a match in our sample.) The cut-off for the narrow-loss bonus indicates that a defeated team should be awarded such a bonus if at most two additional goals or a converted try by this team are required to reverse the outcome of the match.

Column (c) in Table 4 reports results when these partitions are used. There is a slight improvement in the $R^2$ and the number of correct predictions. The point estimate for $\theta^{TIE}$ suggests that a tie should attract more points than a win, but this estimate is not significantly different from zero. The estimate relating to the try bonus indicates that scoring eight or more tries should attract 1.64 points. Although, unlike the estimate for $\theta^{TIE}$, the estimate for the try bonus relative to number of points awarded for a win is not illogical, such an allocation may be unpalatable to rugby administrators and supporters. In any case, the estimate for $\theta^{TRY}$ is not significantly different from zero, although the $p$-value for this estimate (0.120) is much smaller than the corresponding $p$-value (0.952) in (b).

Turning to the narrow-loss bonus, the results suggest that losing by five or less points should attract almost 90% of the points awarded for a win. Like in (b), $\theta^{LOSS}$ is only different from zero at a 10% significance level but the $p$-value for this estimate improves from 0.059 in (b) to 0.051. The $p$-value for joint significance of $\theta^{LOSS}$ and $\theta^{TRY}$ is 0.098.

Overall, point estimates for competition points awarded for a tie and the two bonuses are higher than interested parties would find agreeable. Consequently, we impose the following constraints when estimating (A.1)

$$\theta^{TIE} \leq \frac{1}{2}(\theta^{WIN} + \theta^{LOSS}) \tag{4.1}$$

$$\theta^{TRY} \leq \frac{1}{2}\theta^{TIE} \tag{4.2}$$

$$\theta^{LOSS} \leq \frac{1}{2}\theta^{TIE} \tag{4.3}$$

The first constraint places an upper limit on the amount of points awarded for a tie. We allow a tie to attract more than half the number of points awarded for a win on the grounds that the most likely alternative outcome to a tie is a narrow loss for one team, and our specification allows teams that tie to share the competition points awarded for a win and a narrow loss. Constraints (4.2) and (4.3) stipulate that bonuses should be less than or equal to half the number of points awarded for a tie, as in the allocation currently used in Super Rugby.

As our model now involves constraints that hold with inequality, we set up the model as a nonlinear programme using the General Algebraic Modelling System (GAMS). The constrained model is solved for alternative combinations of try and narrow-loss partitions using the solver CONOPT. The sum of squared errors is minimised when (4.1) – (4.3) hold with equality and, as in the unconstrained model, bonuses are awarded for scoring eight or more tries and/or losing by five or fewer points.

Results from estimating (A.1) with the appropriate constraints imposed are reported in column (d) of Table 4. As expected, a lower $R^2$ and fewer correct predictions are associated with the constrained model than the unconstrained model, but the model does better on both of these criterion than (a). The *p*-value for the joint Wald test of the appropriateness of the constraints (0.525) indicates that the data cannot reject the restrictions. Overall, the results suggest that an allocation that awards three points for a win, two points for a tie, one point for scoring eight or more tries, and one point for losing by five or fewer points is marginally better at identifying strong teams than the current allocation.

There were 361 try bonuses in our sample but only 27 such bonuses would have been awarded if eight or more tries were required to earn a try bonus. Consequently, rugby administrators may be unhappy with the allocation touted above. We address this concern by specifying a ‘net try’ bonus, where a bonus is awarded when a team scores more than a certain number of tries more than its opponent (or net tries).

Choosing partitions to minimise the sum of squared errors indicates that a try bonus should be awarded if a team scores two or more tries than its opponent, and a narrow-loss bonus granted if a team loses by five points or less. Regression results for this specification are reported in column (e) of Table 5. As in (c), $\theta^{TIE}$ and $\theta^{TRY}$ are insignificant. The point estimate for $\theta^{LOSS}$ (1.05) is unreasonable but this coefficient is only significantly different from zero when the level of significance is greater than 0.075. The *p*-value for the joint significance test of the two bonus coefficients is 0.153.

Column (f) presents results when we impose (4.1) – (4.3) in our net try specification. All constraints hold with equality and the optimal net try partition is three, which results in 151 try bonuses. The *p*-value for the joint test of the constraints is 0.733. There is little difference between our constrained try speciation, (d), and our constrained net try specification, (f), in terms of $R^2$ and the number of correct predictions. However, the unconstrained counterpart to our try specification, (c), produces a higher $R^2$ and lower *p*-values for all net strength parameters than the unconstrained counterpart to our net try specification, (e).

In both specifications (c) and (e) the try bonus is insignificant. This suggests that, after controlling for the number of wins and narrow losses in previous matches, the number of try bonuses earned by a team does not increase that team’s predicted net score. In other words, offering a try bonus encourages teams to play a style of rugby that does not increase the probability of winning. Anecdotal evidence also supports our assertion that the try bonus is not correlated with team strength. In the quarterfinals of the 2007 Rugby World Cup, New Zealand and Australia, two teams heavily favoured to advance to the next round, lost to France and England respectively. Several rugby experts, including Australian coach John Connolly, suggested that the attacking style adopted by the two favourites was partly responsible for the unexpected results. In turn, the incentive structures in place in the competitions that these teams regularly participate in may influence playing styles. Specifically, New Zealand and Australia compete in the Tri-Nations competition where a try bonus point is offered, and France and England participate in the Six Nation tournament, where a try bonus is not offered.

We report results from estimating (A.1) when the try bonus is dropped in column (g) of Table 5. (The optimal narrow-loss partition when the try bonus is dropped remains at five points.) The larger estimate for $\beta$ reveals that the average number of wins has a greater influence on net score than in all other specifications except (c). Additionally, unlike in other specifications, the point estimate for $\theta^{TIE}$ is not irrational and the *p*-value for the significance of $\theta^{LOSS}$ is less than 0.05. In specification (h) we drop the try bonus and impose constraints (4.1) and (4.3). The data cannot reject the constraints (the *p*-value for the joint test of the constraints is 0.584). This is our preferred specification. Interestingly, the data can also not reject the joint test $\theta^{TIE} = 0.5$ and $\theta^{LOSS} = 0.25$ (the *p*-value for this test is 0.437). This suggests that dropping the try bonuses and changing the losing margin required to earn a narrow loss bonus to five points will improve strength accuracy while requiring minimum changes to the current allocation.

*Model predictions*

We compare out-of-sample predictions generated by (h) with those generated by an exponential smoothing model and other predictors to assess the validity of our net strength specification. We examine predictions for 182 round-robin Super Rugby matches played in 2006 and 2007. In our exponential smoothing model, matches are organised in chronological order and the predicted net score between *i* and *j* at time *t* ($PNSC_{ij,t}$) is given by

$$PNSC_{ij,t} = \alpha_0 + \boldsymbol{\alpha_1} \tilde{\mathbf{D}}\mathbf{1} + \boldsymbol{\alpha_2} \tilde{\mathbf{D}}\mathbf{2} + (R_{i,t} - R_{j,t}) \tag{5}$$

where $R_{i,t}$ is the rating of team *i* at time *t* and the elements of $\tilde{\mathbf{D}}\mathbf{1}$ and $\tilde{\mathbf{D}}\mathbf{2}$ equal those for $\mathbf{D_1}$ and $\mathbf{D_2}$, respectively, except the period identifiers (*r* and *y*) are replaced by *t*.

In the exponential smoothing model, *i*'s rating is increased (decreased) if *i* does better (worse) than expected. Specifically, *i*'s rating is updated according to the following equation

$$R_{i,t} = \delta E_{ij,t-1} + R_{i,t-1} \tag{6}$$

where $\delta$ is the smoothing constant and $E_{ij,t}$ is the 'prediction error'.

Following Clarke (1993, p.756) the error function in our exponential smoothing algorithm uses a power function "to reduce the relative errors of matches with large actual or predicted margins, and to increase the weighting across the 'win-loss' boundary." Accordingly,

$$E_{ij,t} = \text{sign}(N\text{SC}_{ij,t}).\left|NSC_{ij,t}\right|^{\rho} - \text{sign}(P\text{NSC}_{ij,t}).\left|PNSC_{ij,t}\right|^{\rho} \quad (7)$$

where $\rho$ is the chosen power. (We also estimate (A.1) using the error specification in (7). The results are similar to those reported in Tables 4 and 5.)

To estimate our exponential smoothing model, we set home advantage parameters not significant in our regression analyses equal to zero and choose values for included home advantage parameters, $\delta$ and $\rho$ to minimise the sum of absolute errors. Clarke (1993) also includes a shrinkage factor to allow for team ratings to regress towards the mean during the off season. We do not include such a provision in our model as the data suggest that the abilities of Super Rugby teams do not exhibit this characteristic. This result probably reflects our earlier observation that players tend not to switch franchises.

The model is a nonlinear programme with discontinuous derivatives and is coded using GAMS and solved using MINOS. Starting values for our exponential smoothing model are generated by subjectively choosing ratings at the end of the 1997 competition and estimating the model using 1998 data. The model is then re-estimated for 1999-2005 data using ratings at the end of the 1998 season as initial ratings.

Predictions for several estimators are presented in Table 6. Selecting the home team to win by the average home net score between 1998 and 2005 correctly identifies the winning team in just over 60% of matches and produces an average absolute error of 13.2. The home selection approach is less accurate than both our preferred regression specification, (h), and the exponential smoothing model, with the latter performing better than the former. As strength indices are updated using a continuous variable in our exponential smoothing model but in a discrete fashion in our regression analysis, perhaps this is not surprising. (We also employ an exponential smoothing model with time-varying home advantage parameters that are team specific. These parameters are updated in a similar way to team ratings, but with a different smoothing constant. This model produces less correct predictions than exponential smoothing model described above.)

We infer bookmakers' head-to-head selections, which are presented in the final column of Table 6, from published odds. Given that bookmakers use a larger information set (player availability, team selection etc) than our models, the relative performance of our predictions, especially when exponential smoothing is used, are pleasing. Overall, the numbers in Table 6 indicate that the predictive power of a model that uses competition points to create strength measures is adequate.

**4. Conclusions**

We determined the allocation of competition points that most appropriately rewards strong teams. We focused on Super Rugby as the allocation of points in this competition is relatively complicated and several features of this tournament fit our modelling strategy.

We found that the bonus awarded for scoring four or more tries is not significantly correlated with team strength and that the bonus for losing by seven or fewer points is only a weak determinant of strength. If competition points are allocated solely to reward strong teams, a try bonus should not be awarded but a bonus should be awarded for losing by five points or less. In addition to distorting league tables, it could be argued that the try bonus encourages teams to play in manner that does not increase the probability of winning. The finding that the (modified) narrow-loss bonus is a significant determinant of team strength suggests that it may be beneficial for other sports competitions to adopt such a bonus, although the different nature of alternative sports may give quite different results.

If a try bonus is included to encourage teams to play attacking rugby, governing bodies may be willing to trade off entertainment against strength accuracy. If rugby administrators wish to continue to offer a try bonus with minimal influence on strength accuracy, two competing specifications are offered. Specifically, a bonus could be awarded for scoring eight or more tries, or, alternatively, a bonus could be granted for scoring three or more net tries. Administrators are likely to prefer the second specification as a larger number of try bonuses are awarded.

Before closing we note that an alternative allocation of competition points may encourage teams to behave differently to that observed in our sample. Although, given the competitive nature of most professional athletes, it seems reasonable to assume that teams wish to win and prefer a narrow loss to a large loss, there are several cases where shifting the ‘goal posts’ may alter teams’ actions. First, a team awarded a kickable penalty near the end of a match and behind by seven points will be more likely to attempt to score a try rather than opting for a shot at goal if a bonus is awarded for losing by seven or fewer points than if a loss by five or less is required. Second, a coach whose team has scored four tries and has a comfortable lead will be less likely to substitute key players if eight or more tries are needed for a try bonus than if only four tries are required.

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**Table 1: Average scores, tries and bonuses, 1998-2005**

| | Home | Away |
|---|---|---|
| Score | 29.7 | 23.3 |
| Tries | 3.4 | 2.6 |
| Try bonus | 0.42 | 0.26 |
| Narrow-loss bonus | 0.17 | 0.18 |

**Table 2: Average home net scores, 1998-2005**

| Team | Net-score |
|---|---|
| Blues (New Zealand) | 9.1 |
| Brumbies (Australia) | 17.0 |
| Bulls (South Africa-Highveld) | -1.5 |
| Cats (South Africa-Highveld) | 0.4 |
| Chiefs (New Zealand) | 4.0 |
| Crusaders (New Zealand) | 14.8 |
| Highlanders (New Zealand) | 11.6 |
| Hurricanes (New Zealand) | 1.8 |
| Reds (Australia) | 6.8 |
| Sharks (South Africa-coastal) | 1.2 |
| Stormers (South Africa-coastal) | 1.4 |
| Waratahs (Australia) | 10.2 |

**Table 3: Average inter- and intra-regional home net scores**

| | Away | | | |
|---|---|---|---|---|
| Home | Australia | New Zealand | SA-coastal | SA-Highveld |
| Australia | 7.0 | 6.9 | 12.0 | 25.9 |
| New Zealand | 6.9 | 4.5 | 8.4 | 17.8 |
| SA-coastal | 0.3 | -1.3 | 5.6 | 7.4 |
| SA-Highveld | -3.2 | 0.1 | 0.7 | 1.9 |

**Table 4: Regression results**

| | (a) | (b) | (c) | (d) |
|---|---|---|---|---|
| Estimation | OLS | NLS | NLS | OLS |
| Try partition | 4 | 4 | 8 | 8 |
| Narrow-loss partition | 7 | 7 | 5 | 5 |
| Constrained | Yes | No | No | Yes |
| $\alpha_0$ | 3.42*** | 3.31*** | 3.47*** | 3.42*** |
| | (0.84) | (0.85) | (0.85) | (0.83) |
| $\alpha_1^{Brumbies}$ | 8.99*** | 9.49*** | 8.32*** | 9.09*** |
| | (2.64) | (2.65) | (2.66) | (2.61) |
| $\alpha_1^{Crusaders}$ | 7.55*** | 7.76*** | 7.33*** | 7.41*** |
| | (2.76) | (2.81) | (2.85) | (2.78) |
| $\alpha_1^{Highlanders}$ (1) | 9.92*** | 10.37*** | 9.10*** | 9.63*** |
| | (2.74) | (2.84) | (2.85) | (2.76) |
| $\alpha_2^{Australia,SA-Highveld}$ | 15.92*** | 15.90*** | 16.58*** | 15.88*** |
| | (3.59) | (3.60) | (3.62) | (3.60) |
| $\alpha_2^{NZ,SA-Highveld}$ | 8.22*** | 8.31*** | 8.87*** | 8.27*** |
| | (2.46) | (2.48) | (2.49) | (2.45) |
| $\beta$ | 13.49*** | 16.26*** | 13.12*** | 15.23*** |
| | (2.56) | (3.32) | (3.10) | (2.65) |
| $\theta^{TIE}$ | 0.50 | 0.88 | 1.26 | 0.67 |
| | - | (0.77) | (0.99) | - |
| $\theta^{TRY}$ | 0.25 | -0.02 | 1.64 | 0.33 |
| | - | (0.26) | (1.06) | - |
| $\theta^{LOSS}$ | 0.25 | 0.57* | 0.89* | 0.33 |
| | - | (0.30) | (0.45) | - |
| $R^2$ | 0.20 | 0.21 | 0.22 | 0.21 |
| Correct predictions | 347 | 352 | 356 | 349 |

*Note:* ***, **, and * denote significance at the 1%, 5% and 10% significance level respectively. Robust standard errors are reported in parentheses. (1) only significant between 1998 and 2002.

**Table 5: Regression results, try bonus based on net tries**

| | (e) | (f) | (g) | (h) |
|---|---|---|---|---|
| Estimation | NLS | OLS | NLS | OLS |
| Net try partition | 2 | 3 | - | - |
| Narrow-loss partition | 5 | 5 | 5 | 5 |
| Constrained | No | Yes | No | Yes |
| $\alpha_0$ | 3.55*** | 3.46*** | 3.34*** | 3.36*** |
| | (0.84) | (0.82) | (0.85) | (0.82) |
| $\alpha_1^{Brumbies}$ | 7.93*** | 8.74*** | 9.24*** | 9.36*** |
| | (2.74) | (2.53) | (2.62) | (2.51) |
| $\alpha_1^{Crusaders}$ | 7.62*** | 7.54*** | 7.52*** | 7.52*** |
| | (2.83) | (2.51) | (2.81) | (2.52) |
| $\alpha_1^{Highlanders}$ (1) | 10.17*** | 9.67*** | 10.21*** | 9.96*** |
| | (2.83) | (3.09) | (2.83) | (3.09) |
| $\alpha_2^{Australia,SA-Highveld}$ | 15.12*** | 15.52*** | 15.90*** | 15.82*** |
| | (3.63) | (3.39) | (3.60) | (3.39) |
| $\alpha_2^{NZ,SA-Highveld}$ | 8.03*** | 8.21*** | 8.47*** | 8.29*** |
| | (2.50) | (2.67) | (2.48) | (2.67) |
| $\beta$ | 11.63*** | 13.76*** | 15.78*** | 15.55*** |
| | (3.68) | (2.54) | (2.79) | (2.95) |
| $\theta^{TIE}$ | 1.21 | 0.67 | 0.88 | 0.67 |
| | (1.10) | - | (0.78) | - |
| $\theta^{TRY}$ | 0.61 | 0.33 | - | - |
| | (0.51) | - | - | - |
| $\theta^{LOSS}$ | 1.05* | 0.33 | 0.71** | 0.33 |
| | (0.59) | - | (0.36) | - |
| $R^2$ | 0.22 | 0.21 | 0.21 | 0.21 |
| Correct predictions | 350 | 349 | 343 | 347 |

*Note:* ***, **, and * denote significance at the 1%, 5% and 10% significance level respectively. Robust standard errors are reported in parentheses. (1) only significant between 1998 and 2002.

**Table 6: 2006-2007 predictions**

| | Home selection | Specification (h) | Exponential smoothing | Bookmakers |
|---|---|---|---|---|
| Correct predictions (%) | 60.4 | 63.7 | 69.2 | 70.0 |
| Mean absolute error | 13.2 | 11.9 | 11.4 | - |

**APPENDIX: The equation to be estimated**

$$
\begin{aligned}
NSC_{ij,r,y} = {} & \alpha_0 + \boldsymbol{\alpha_1 D_1} + \boldsymbol{\alpha_2 D_2} \\
& + \beta.\theta^{WIN}(\lambda_{i,r,y}WIN_{i,12,y-1} + (1-\lambda_{i,r,y})WIN_{i,r-1,y} - \lambda_{j,r,y}WIN_{j,12,y-1} - (1-\lambda_{j,r,y})WIN_{j,r-1,y}) \\
& + \beta.\theta^{TIE}(\lambda_{i,r,y}TIE_{i,12,y-1} + (1-\lambda_{i,r,y})TIE_{i,r-1,y} - \lambda_{j,r,y}TIE_{j,12,y-1} - (1-\lambda_{j,r,y})TIE_{j,r-1,y}) \\
& + \beta.\theta^{TRY}(\lambda_{i,r,y}TRY_{i,12,y-1} + (1-\lambda_{i,r,y})TRY_{i,r-1,y} - \lambda_{j,r,y}TRY_{j,12,y-1} - (1-\lambda_{j,r,y})TRY_{j,r-1,y}) \\
& + \beta.\theta^{LOSS}(\lambda_{i,r,y}LOSS_{i,12,y-1} + (1-\lambda_{i,r,y})LOSS_{i,r-1,y} - \lambda_{j,r,y}LOSS_{j,12,y-1} - (1-\lambda_{j,r,y})LOSS_{j,r-1,y}) \\
& + \varepsilon_{ij,r,y}
\end{aligned}
\tag{A.1}
$$