# QUANTIFYING THE EVOLUTION OF FIRST-CLASS RUGBY IN NEW ZEALAND

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# Structural changes to a competition affects the competitiveness of the competition

**DOT Sport** delivers innovative, relatable, data-driven insights to create winning strategies.

Apply cutting edge machine learning to minimise human bias and maximise use of big data.

We have helped a range of sporting organisations win with data over the last 20 years ranging from: *National Governing Bodies*, *Sport Franchises*, to *Academic* and *Commercial* entities.

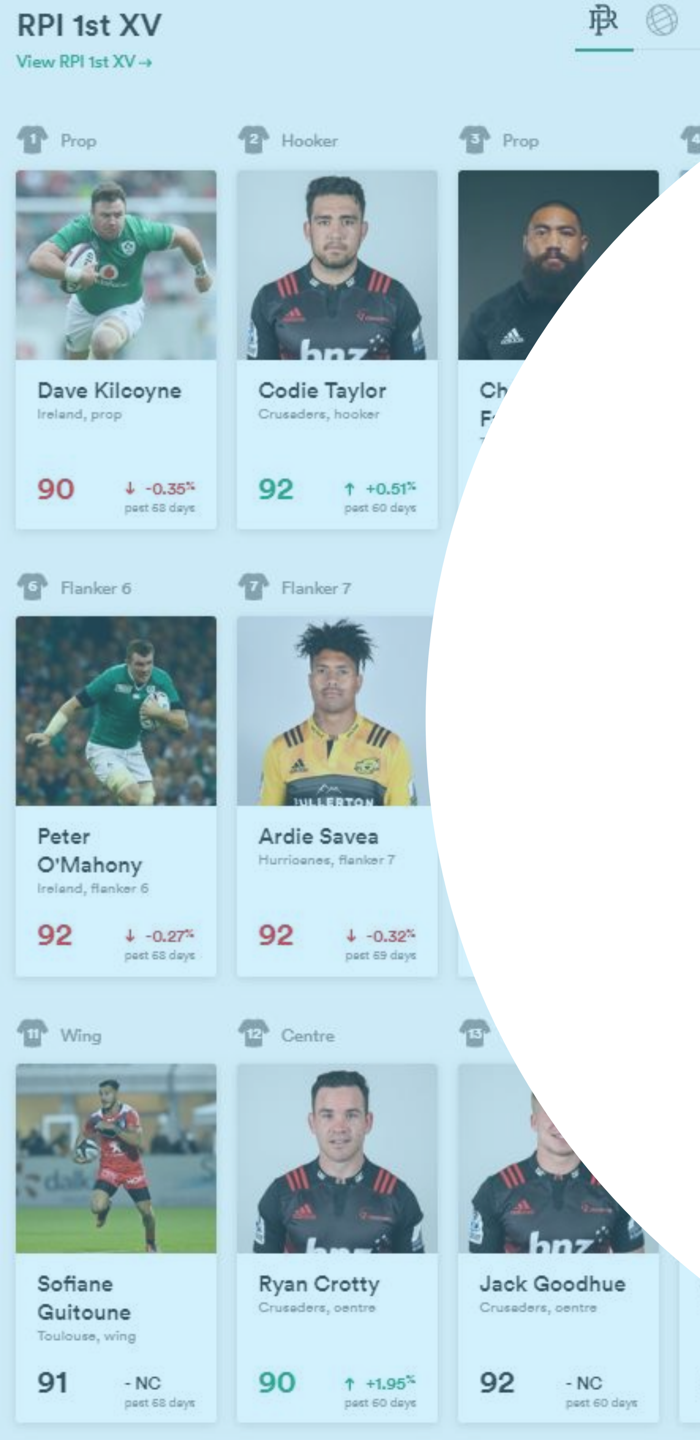
We have explored numerous sports, ranging from *Cricket* and *Rugby* through to *Golf* and Y*achting*.

**BUT,** the intent is always the same – *how to create winning performances*.

- **Rugby union**, commonly known in most of the world simply as **rugby**, is a contact team sport which originated in England in the first half of the 19th century.

- It is based on running with the ball in hand. A game is between two teams of 15 players using an oval-shaped ball on a rectangular field with H-shaped goalposts at each end.


https://www.youtube.com/watch?v=_43F2RsHHL0&t=101s




# WHAT IS RUGBYPASS?

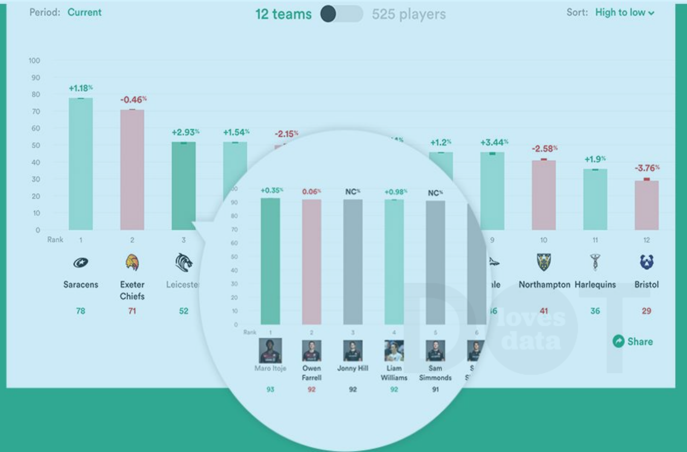
[https://index.rugbypass.com/](https://index.rugbypass.com/)

DOT built a revolutionary rugby rating system based upon individual skill executed in real time

What makes it different? The approach is all about winning, and the contribution to winning.

Winning a game is about winning moments

Parsimonious models align with perception and results are readily interpretable

# New Zealand Rugby

**New Zealand's first-class domestic rugby has gone through many structural and divisional changes over the last 30 years**

- Since 1976 there have been 5 major competition changes and 3 divisional changes.
- New Zealand rugby ushered in professionalism in 1995.

***Structural changes alongside socio-demographic changes such as urban drift have changed the competitiveness of these competitions over time*.**

# QUANTIFY HOW STRUCTURAL CHANGES TO A SPORTS COMPETITION AFFECT COMPETITIVNESS

# <u>HYPOTHESIS</u>

In balanced competitions, the Elo update function needs to be a larger value to update the ratings more quickly to maintain predictivity of the rating system

# WHAT IS *K*?

- Parameter $k$ is a learning rate and can be tuned to achieve optimal predictive performance
- Measures how a team or players rating is impacted by a winning or losing result
- Controls the sensitivity of change in ratings to new match results
- Changes in $k$ across seasons and competitions can be interpreted to understand the underlying mechanics of domestic first-class rugby
- Use the update function, $k$, as a descriptive measure to indicate the impact of latent structural changes in top-flight domestic first-class rugby in New Zealand
- As we hypothesise that $k$ can be used to determine structural changes in a competition, we need to detect statistically significant changes

# SECONDARY OBJECTIVES

1

**Optimise** ***k to produce the predictive ratings of match outcome***

2

***Introduce a ratings deviation to the Elo framework***

## ELO

$$r_i \rightarrow r_i + k\left[y_i - L\left(\frac{r_i - r_j \pm h}{B}\right)\right]$$

$$L(x) = \frac{1}{1+e^{-x}} \text{ and } B = \frac{400}{\ln(10)} \approx 173.7$$

- Lack of a reliability measure for the point estimate and update parameter *k*
- Measures how a winning or losing result impacts the ratings
- Rating remains unchanged for as long as a player remains inactive
- Simply, easy to calculate formula

## GLICKO

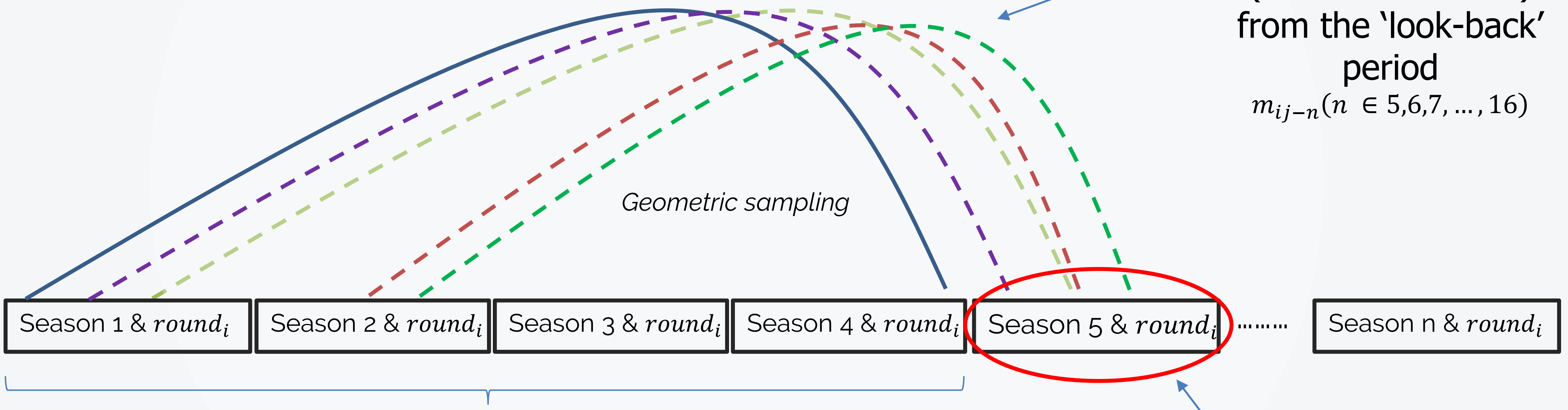
$$r' = r + \frac{1}{\frac{1}{RD^2} + \frac{1}{D^2}} \sum_{j=1}^{m} g(RD_j)\left(s_j - E\left(s|r, r_j, RD_j\right)\right)$$

$$RD = min\left(\sqrt{RD_0^2 + c^2 t}, 350\right)$$

- Glicko ratings incorporates a reliability measure to evaluate the confidence for its predictions
- Indicates a player's expected performance with a 95% confidence
- No *"park the bus"* approach – RD decreases after a game, but slowly increases over-time of inactivity
- Complex calculation requires a computer program

# MODIFIED ELO FRAMEWORK

Time-series geometric sampling (set of $x$ matches) from the 'look-back' period
$m_{ij-n}(n \in 5,6,7,\dots,16)$



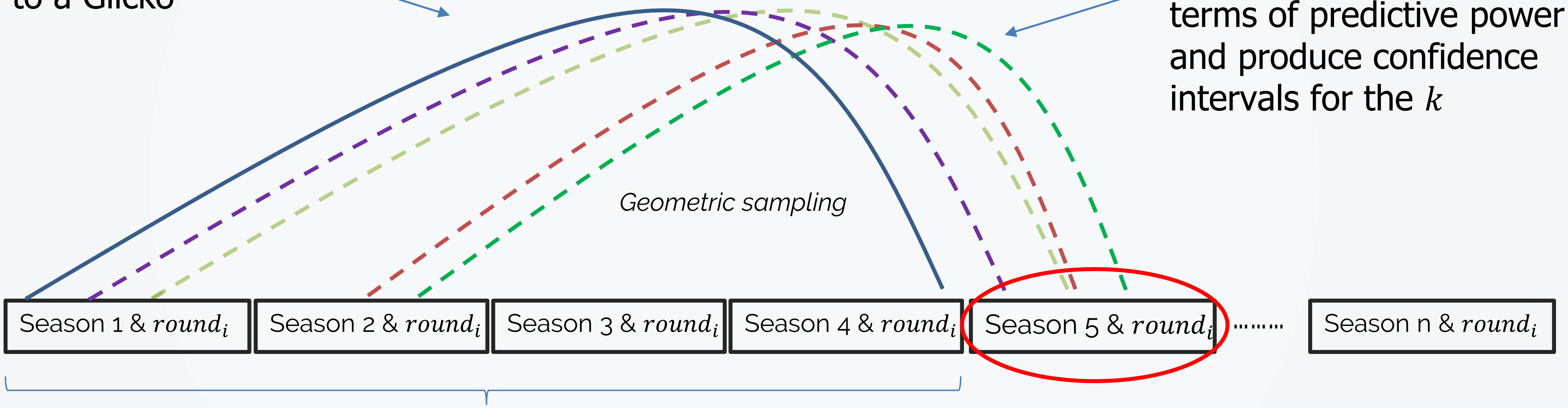

$m_{ij}$ - season-round

Randomly sample without replacement a range of $k$ parameters from a uniform distribution; $k \sim Uni[15, 200]$

# MODIFIED ELO FRAMEWORK cont….

Compare the predictive power of the Elo method to a Glicko model

Bootstrap the top 50 $k's$ in terms of predictive power and produce confidence intervals for the $k$




- Optimise $k$ using log-loss evaluation metric
- $K$ – identify the parameter that produces the greatest predictive power for the sampled ‘look-back period

# INITIAL RATINGS AND HOME GROUND ADVANTAGE

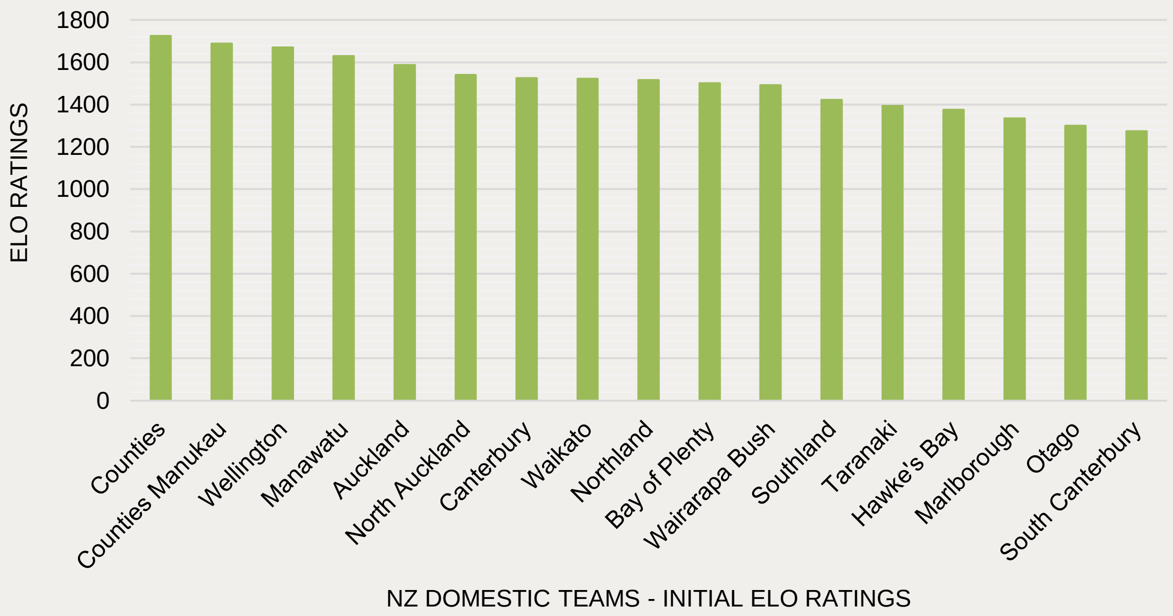
- Initial ratings are set to a mean value of 1500 before evolving the ratings over some training set of matches, eventually reaching equilibrium.
- Set the initial rating equal to a set of static initial ratings $\left\{r_i^{(0)}\right\}$ minimising a log-loss function.
- This is a constrained optimisation problem, where the mean rating is constrained to 1500

$$\min_i \left[ y - logistic\left(\frac{r_h - r_A \pm h}{B}\right)\right]^2 \qquad s.t. \frac{\sum_i (r_i)}{n} = 1500$$

- The constant *h* is optimised simultaneously with the initial ratings.

$$SS\left(\left\{r_i^{(0)}\right\}; h\right) = \sum_R \left[ y_i - L\left(\frac{r_i^{(0)} - r_j^{(0)} \pm h}{B}\right)\right]^2 \qquad s.t. \frac{\sum_i (r_i)}{n} = 1500$$

# HOME GROUND ADVANTAGE ≈ 42



# MODEL VALIDATION AND RESULTS

# VALIDATION AND APPLICATION: WHAT WE FOUND?

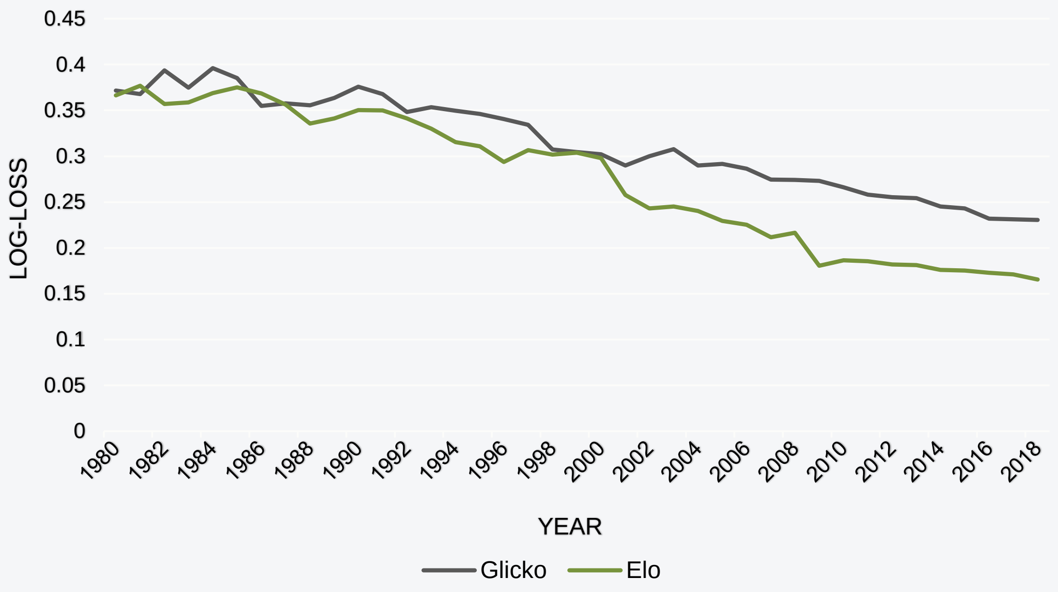



*Figure 1: Log-loss Elo vs. Glicko*

| PROPORTION OF CORRECT FORECASTS | | |
|---|---|---|
| **YEAR** | **ELO** | **GLICKO** |
| 1980- 1984 | 0.842 | 0.807 |
| 1985- 1989 | 0.858 | 0.808 |
| 1990- 1994 | 0.883 | 0.819 |
| 1995- 1999 | 0.869 | 0.829 |
| 2000- 2004 | 0.89 | 0.828 |
| 2005- 2009 | 0.899 | 0.837 |
| 2010- 2014 | 0.897 | 0.84 |
| 2015- 2018 | 0.895 | 0.858 |

*Figure 2: Proportion of correct forecasts*

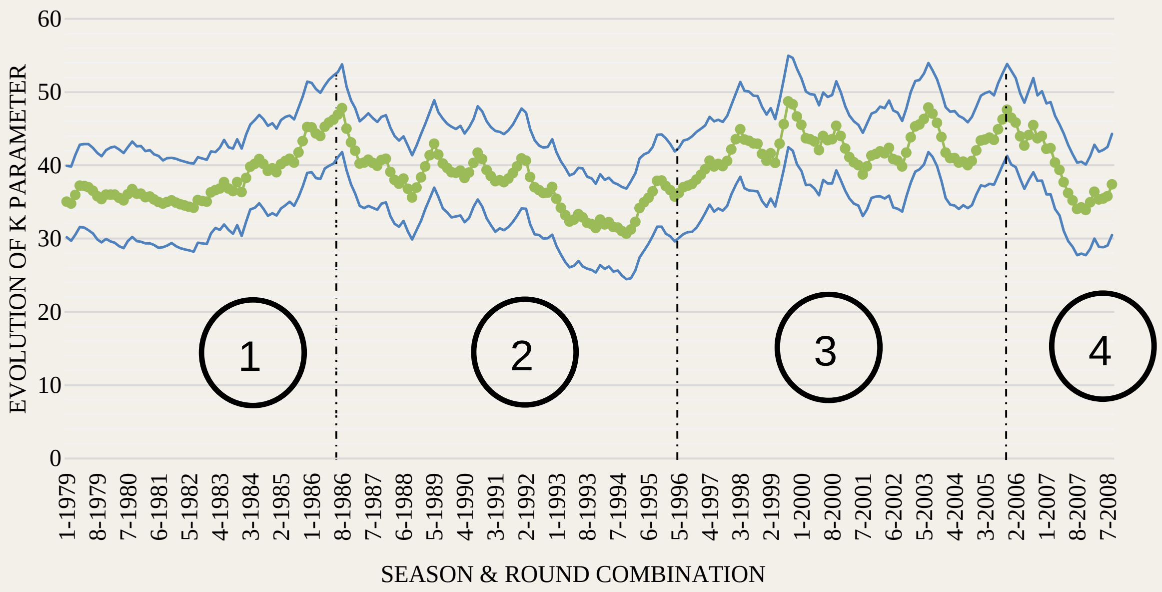



*Figure 3: Evolution of k*

# QUANTIFYING FIRST-CLASS RUGBY EVOLUTION

The optimal $k$ appears quite noisy. Consequently, applying an EWMA (weight = 0.2) removes some noise. This identifies the latent structures of the competition.

There are several structural events influencing the evolution of top 1st class Rugby in New Zealand.

A substantial shift in the nature of the competition, with $k$ becoming increasingly large from 1982-1985.

In 1985, the second tier which was an intra-Island competition was restructured into a 2nd and 3rd division, with promo/ releg.

Between 1985-1996, $k$ tends to decrease. Interesting period for NZ rugby following the 1st world cup and ushering in professionalism.

Interesting, $k$ began to increase, following the introduction of professionalism.

# DISCUSSION AND CONCLUSION

- Several structural events influenced the evolution of top tier first class in New Zealand
- $k$ decreases following any major restructure of the competition
- $k$ describes a competitions structural change and helps determine shifts in competition competitiveness
- Useful for monitoring tiered competitions where either grading, promotion or relegation is involved
- Evolution of $k$, 1982-1985, coincides with the 1$^{st}$ major structural change
- Statistically significant shifts in $k$ following the introduction of professionalism in 1996
- Modified Elo > [out-of-box] Glicko model
- Avg. validation period (7 rounds) for obtaining the optimal $k$

# WHAT NEXT AND THE IMPLICATIONS?

Tune and optimise Glicko parameters

Implement framework to domestic RugbyPass competitions

Are there any practically significant difference between predictive power?

New Zealand Rugby – affect of structural changes on competition

Following any major restructure of the competition, $k$ decreases

Implement as an extension to the RugbyPass system

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