Modelling netball scores

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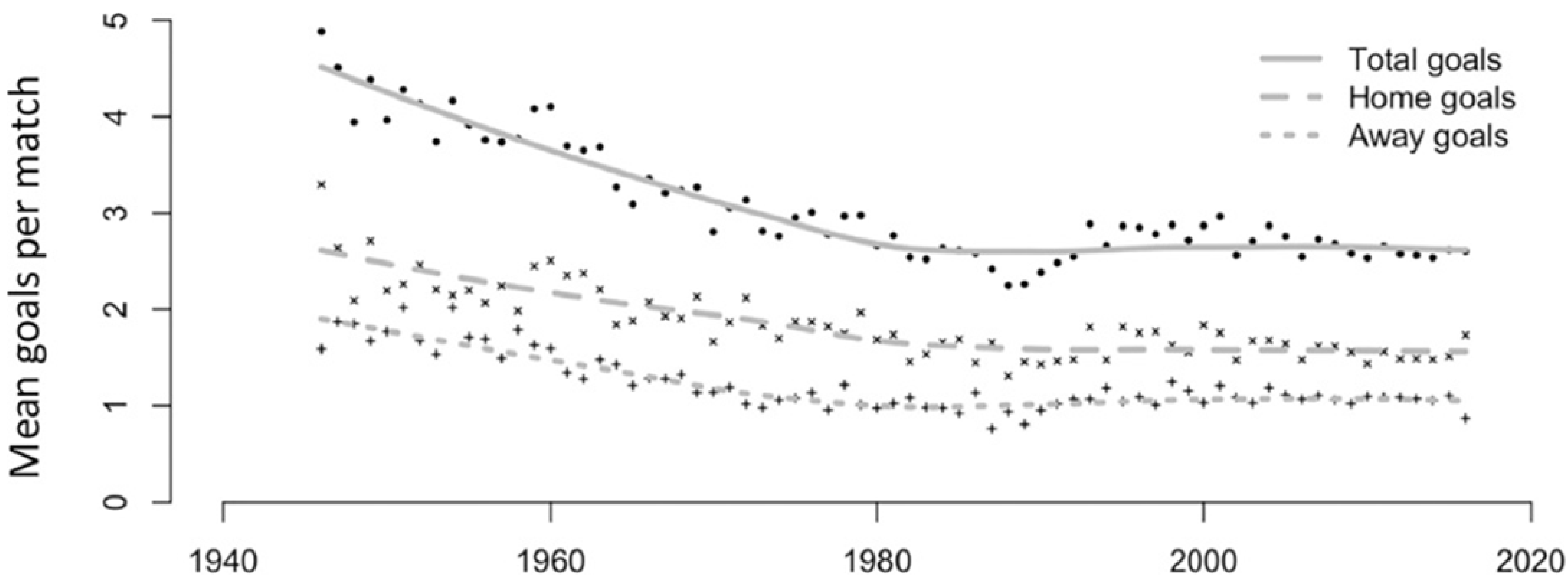
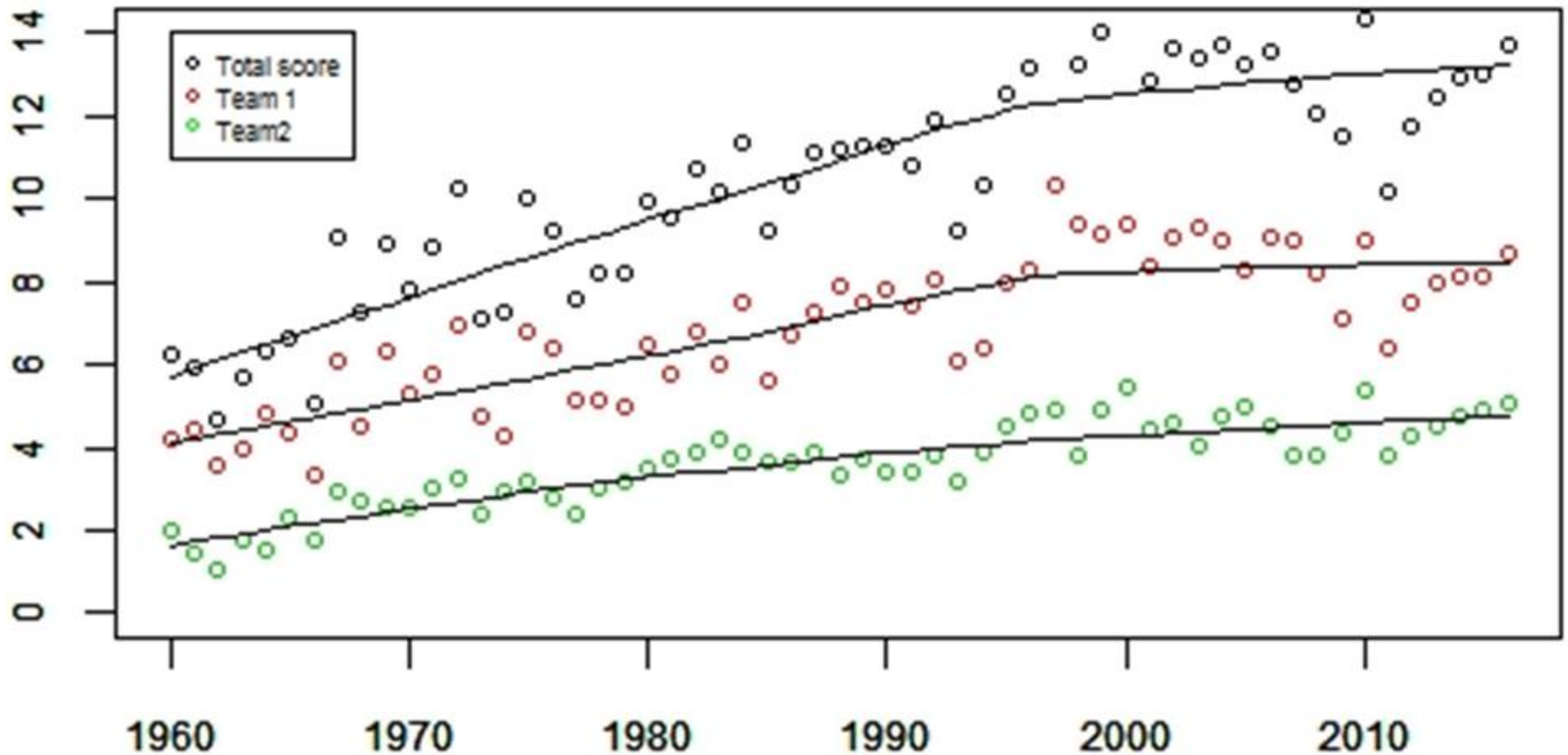
Scoring rates in soccer look like this…Baker and McHale (2018)



Scoring rates in rugby look like this

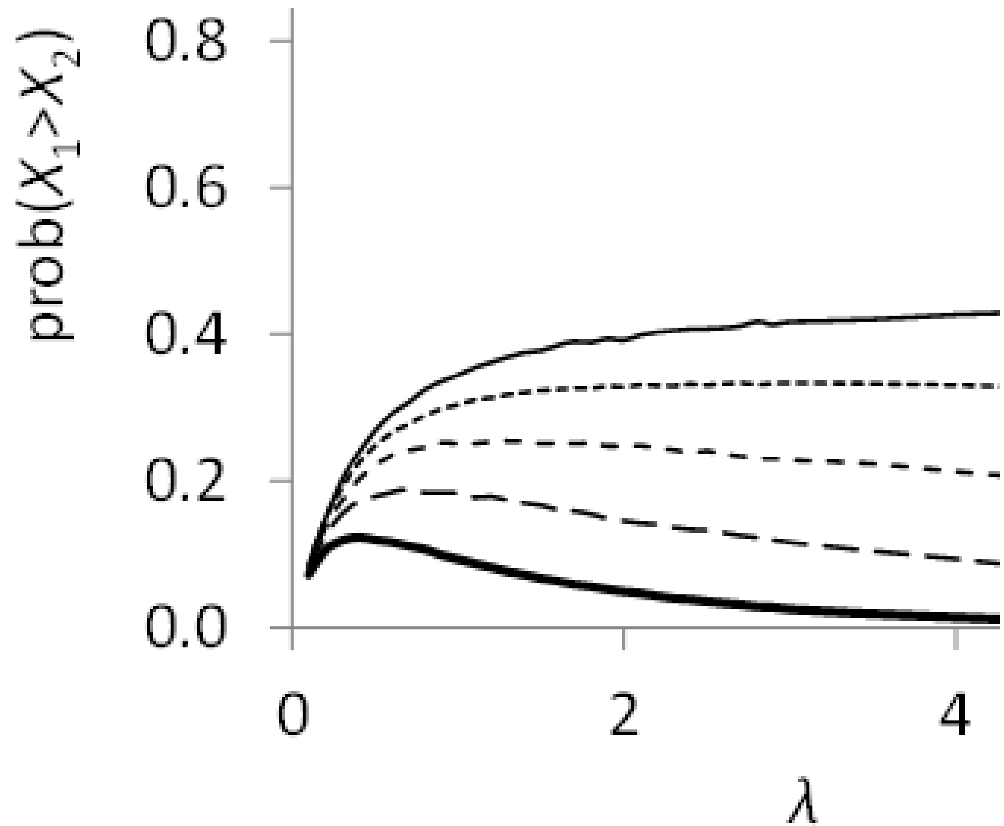


Because scoring rates in rugby are increasing we asked: **what is the relationship between scoring-rate (SR) and outcome uncertainty (OU)?**

In a Poisson-match

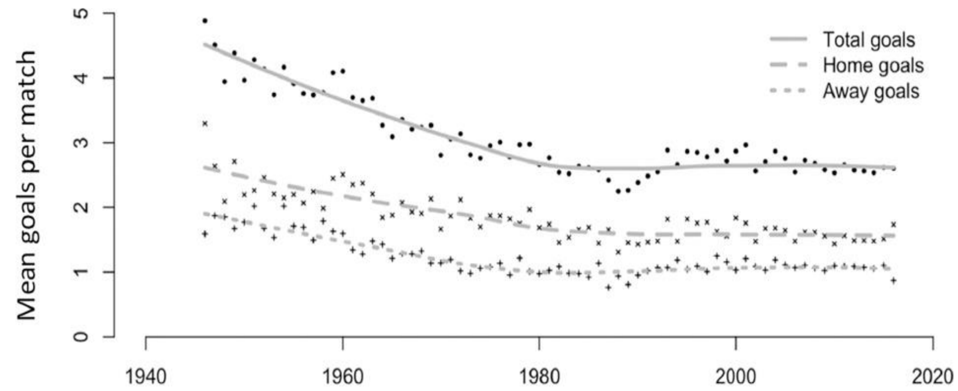
$$X_1 \sim \mathrm{Po}(\lambda) \text{ and } X_2 \sim \mathrm{Po}(\varepsilon\lambda) \text{ independent}$$

the relationship between SR and OU looks like this:

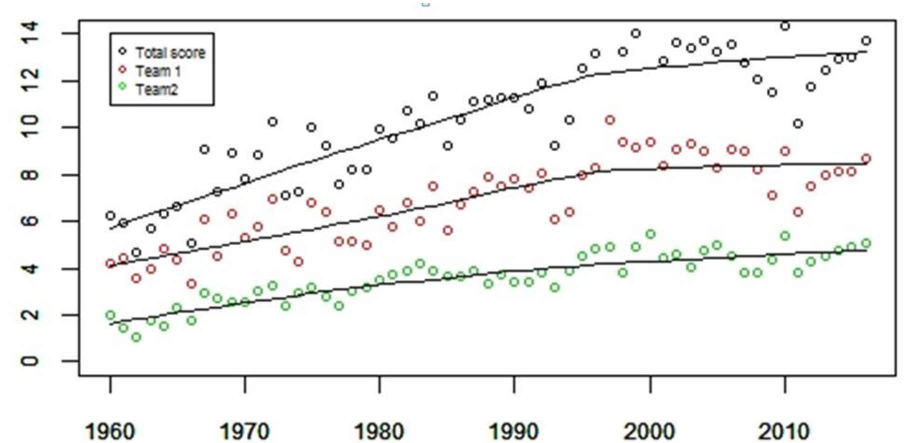


For $X_1 \sim \mathrm{Po}(\lambda)$ and $X_2 \sim \mathrm{Po}(\varepsilon\lambda)$ independent:
$\Pr(X_1 > X_2)$ as a function of λ for various ε
(solid line $\varepsilon = 1$, short dash $\varepsilon = 1.2$, medium dash $\varepsilon = 1.5$, long dash $\varepsilon = 2$, bold solid line $\varepsilon = 3$).

It is well known that soccer scores follow a Poisson-match: international **soccer is a “2-1 Poisson-match”**



Scarf, Parma, McHale (EJOR, 2019) show that **rugby union is an “8-4 Poisson-match”**



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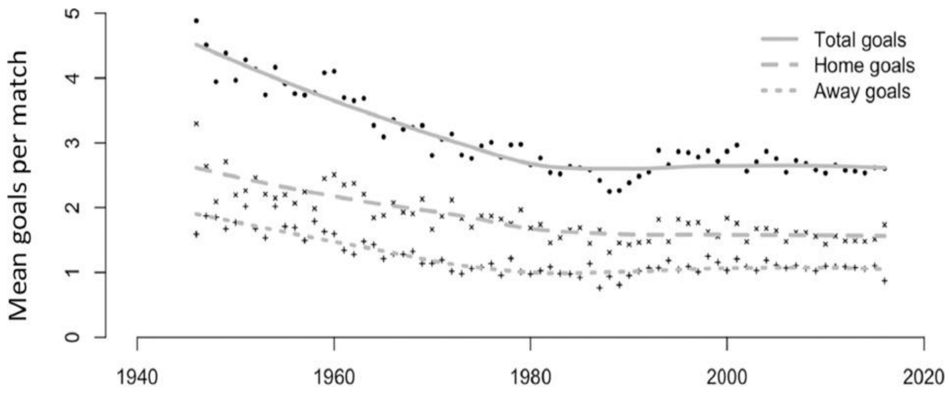
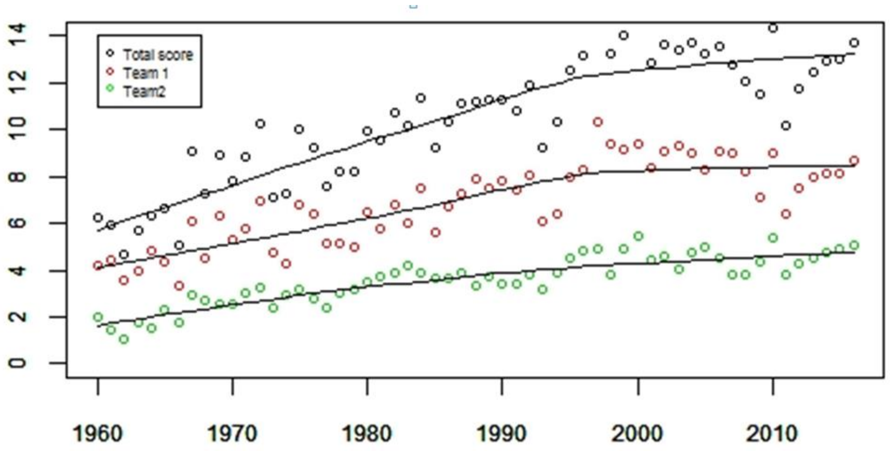
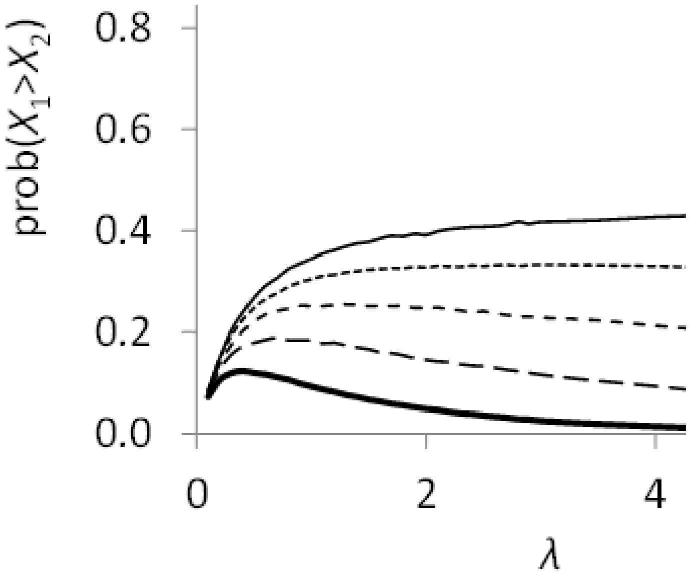


Scarf, Parma, McHale (EJOR, 2019) show that **rugby union is an “8-4 Poisson-match”**...**careful**



It appears then that soccer is OU maximizing, rugby is not (maybe), and **OU in rugby is decreasing**. **Does it matter?**



For $X_1 \sim \mathrm{Po}(\lambda)$ and $X_2 \sim \mathrm{Po}(\varepsilon\lambda)$ independent: $\Pr(X_1 > X_2)$ as a function of λ for various ε (solid line $\varepsilon = 1$, short dash $\varepsilon = 1.2$, medium dash $\varepsilon = 1.5$, long dash $\varepsilon = 2$, bold solid line $\varepsilon = 3$).

Kevin Garside

The material circumstances underpinning this rebirth were created by the avaricious march of the club game, super-rich Champions League clubs siphoning off the talent and producing a competition that recycles the same contenders every year. The Premier League likewise. Predictability is death to sport. Here we had 32 teams who had to make

- A higher level of competitive balance, reflected in more uncertain outcomes, increases match attendances, television audiences and overall interest. This is the *outcome uncertainty hypothesis*.
- Scarf, Parma, McHale (EJOR, 2019) argue that rugby administrators should act to reduce the scoring rate.
- What about other sports? Sports other than soccer and rugby. Netball for example?
- Netball has a very high scoring rate…

The Guardian

Remainder of this talk

- How does outcome uncertainty look in netball?
- Is netball a Poisson-match?
- If netball were a Poisson-match, what would be the chance of a close result?
- What is a good model of the score in a netball match?
- What is the forecasting performance of this model?
- How does OU vs SR look in this model?

Table 5. New Zealand (N) vs Australia (A) in Netball World Cup 2015 final. Final score 55-58. Possession sequences shown (first column), scores (second and third). New Zealand had 56 starts, Australia 57, and there were 58 CPs each. Conversion proportions: $\tilde{p}_{\mathrm{NZ}} = 0.786$ and $\tilde{p}_{\mathrm{Aus}} = 0.807$.

Quarter 1			Quarter 2			Quarter 3			Quarter 4		
N	1	0	N	8	16	A	22	31	N	38	43
A	1	1	A	8	17	N	23	31	A	38	44
N	2	1	N	9	17	A	23	32	N	39	44
A	2	2	AN	10	17	N	24	32	A	39	45
N	3	2	NANANA	10	18	A	24	33	N	40	45
A	3	3	A	10	19	N	25	33	A	40	46
NA	3	4	NA	10	20	A	25	34	N	41	46
A	3	5	A	10	21	N	26	34	A	41	47
NAN	4	5	N	11	21	A	26	35	N	42	47
A	4	6	A	11	22	N	27	35	A	42	48
NA	4	7	N	12	22	A	27	36	N	43	48
A	4	8	A	12	23	N	28	36	A	43	49
NANA	4	9	N	13	23	AN	29	36	N	44	49
A	4	10	A	13	24	N	30	36	A	44	50
N	5	10	NA	13	25	A	30	37	NA	44	51
A	5	11	AN	14	25	NANA	30	38	A	44	52
N	6	11	N	15	25	A	30	39	N	45	52
A	6	12	A	15	26	N	31	39	A	45	53
N	7	12	N	16	26	A	31	40	N	46	53
A	7	13	A	16	27	N	32	40	A	46	54
NA	7	14	N	17	27	AN	33	40	N	47	54
A	7	15	AN	18	27	N	34	40	AN	48	54
NA	7	16	N	19	27	AN	35	40	N	49	54
ANANA	7	16	A	19	28	N	36	40	A	49	55
			N	20	28	A	36	41	N	50	55
			A	20	29	N	37	41	A	50	56
			N	21	29	A	37	42	N	51	56
			A	21	30	NA	37	43	A	51	57
			N	22	30	*AN*	37	43	N	52	57
									AN	53	57
									N	54	57
									A	54	58
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NA	4	7	N	12	22	A	27	36	N	43	48

VITALITY SUPERLEAGUE 2018

Pos	Team	P	W	L	+	-	+/-	GA	Pts
1	Wasps Netball	20	18	2	1232	911	321	1.35	54
2	Loughborough Lightning	20	16	4	1164	957	207	1.22	48
3	Manchester Thunder	19	15	4	1106	946	160	1.17	45
4	Team Bath	19	11	8	961	903	58	1.06	33
5	benecosMavericks	18	10	8	979	912	67	1.07	30
6	Severn Stars	18	8	10	904	883	21	1.02	24
7	Surrey Storm	18	5	13	904	1004	-100	0.90	15
8	UWS Sirens	18	5	13	815	962	-147	0.85	15
9	Team Northumbria	18	3	15	817	1022	-205	0.80	9
10	Celtic Dragons	18	2	16	768	1150	-382	0.67	6

- Netball data

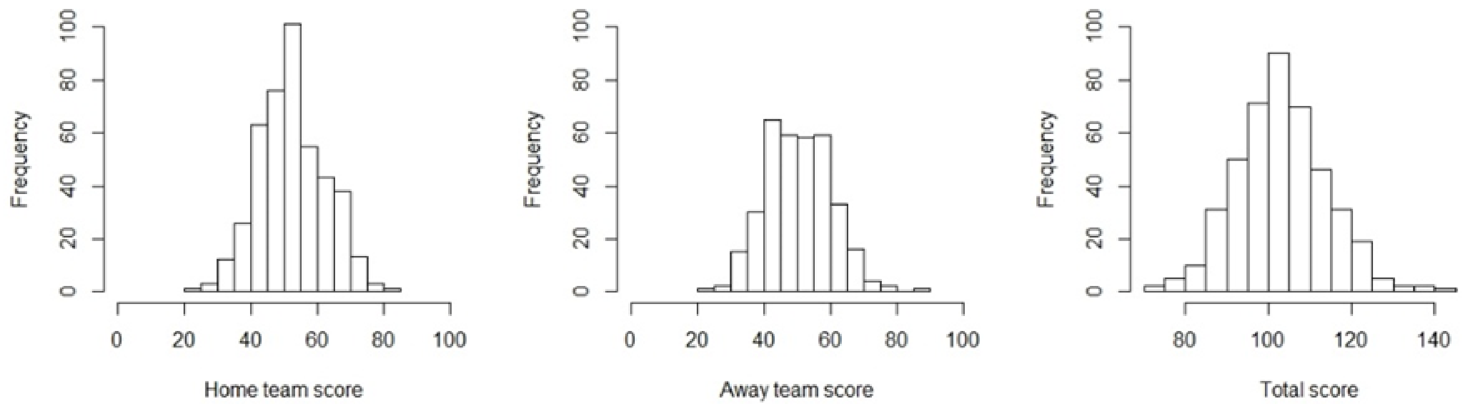

Figure 1. Histograms of scores in UK Superleague 2014-2018

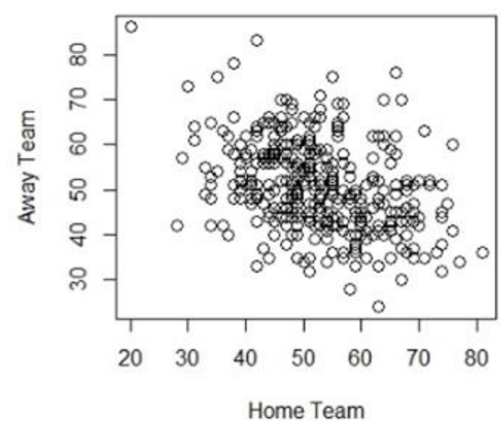

Figure 2. Match scores in UK Superleague 2014-2018

- A bivariate model for netball scores.

- First some rules in brief

Game of four 15 minute quarters

Play starts with a centre pass (CP)

Play ends with a goal or the hooter

The CP alternates regardless of which team scores

- Some observations

Typically, a good team will convert possession into a goal with high probability.

It is critical that a team does not concede possession.

- A bivariate model for netball scores

Score (X_1, X_2)

$2N$ centre passes and $N \sim \mathrm{Po}(\lambda)$ . ...careful

$$X_1 = Y_1 + N - Y_2,$$

$$X_2 = Y_2 + N - Y_1 = 2N - X_1,$$

$Y_1 \sim B(N, p_1)$, $Y_2 \sim B(N, p_2)$ indep.

$$p_1 = 1 - \exp(-\delta\alpha_1 / \beta_2),$$

$$p_2 = 1 - \exp(-\alpha_2 / \beta_1),$$

- A bivariate model for netball scores

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$$p_1 = 1 - \exp(-\delta\alpha_1 / \beta_2),$$
$$p_2 = 1 - \exp(-\alpha_2 / \beta_1),$$

When $p_1 = p_2 = p$, we have

$$\mathrm{corr}(X_1, X_2) = (1 - 2p + 2p^2)/(1 + 2p - 2p^2),$$

$= 1$ when $p = 0, 1$

$= 1/3$ when $p = 1/2$.

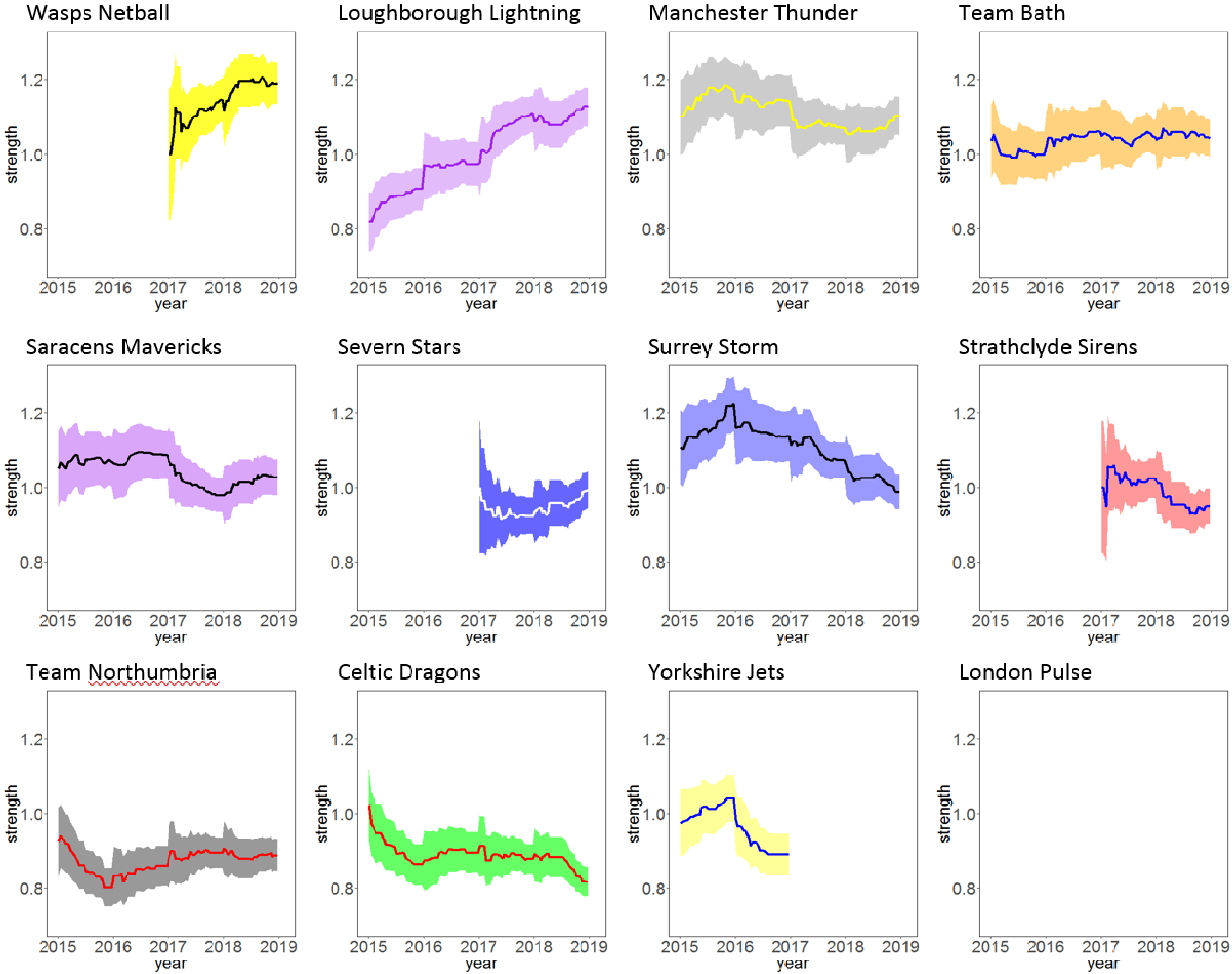

Figure. Ribbon plots of strength estimates $\hat{\alpha}_i$ over time for the fitted binomial-match.

Table. Forecast performance, one-round ahead, out-of-sample, from 2016 onwards.

Model	% correct forecasts	Brier score	Mean Absolute Error
Binomial-match	77.15	.1527	9.22
Poisson-match	76.82	.1525	9.17
Distribution-free	78.48		9.51
Home-win forecast	52.98		--

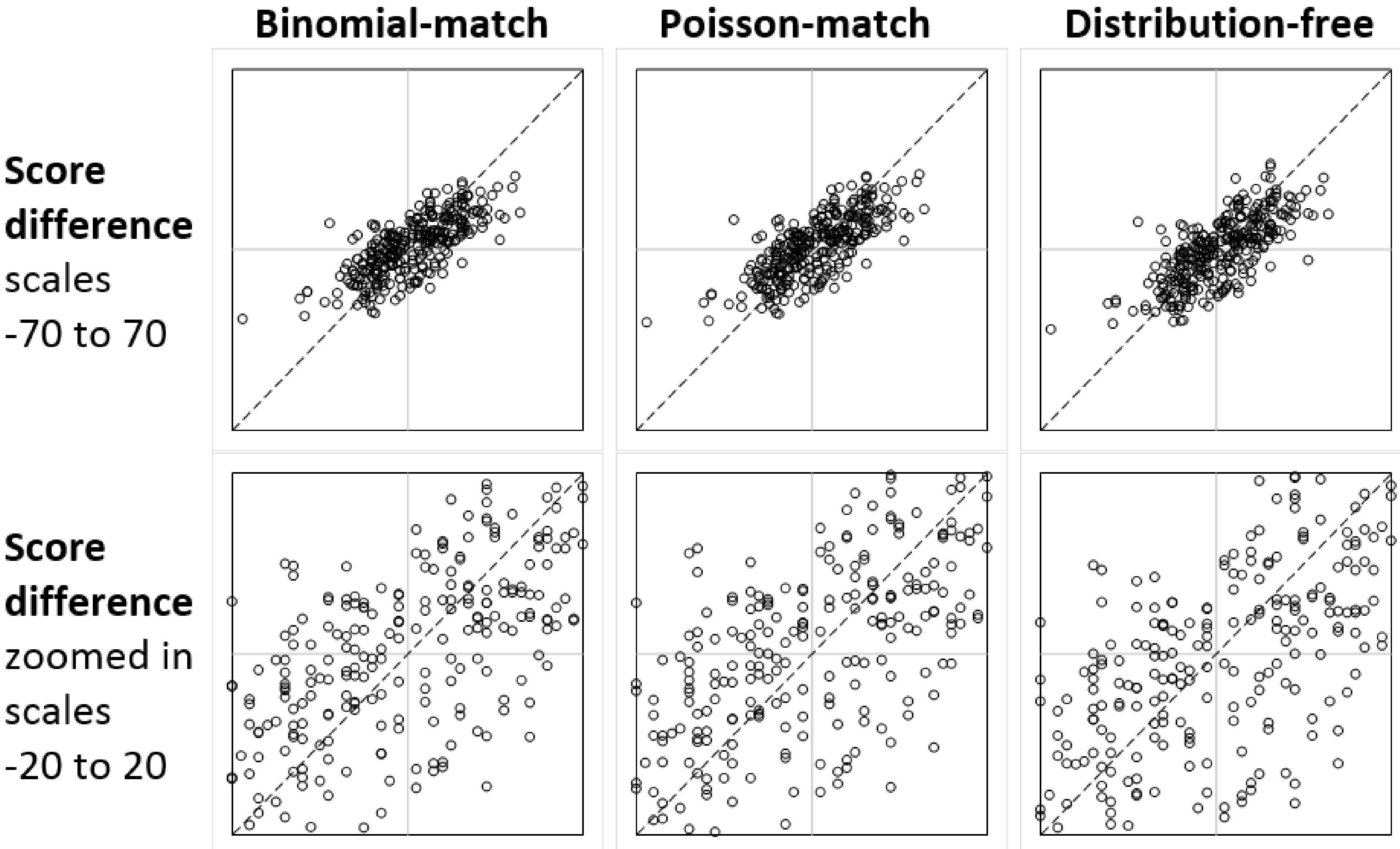

Figure. Forecasts ↑ versus actuals →; dashed line is forecast=actual.

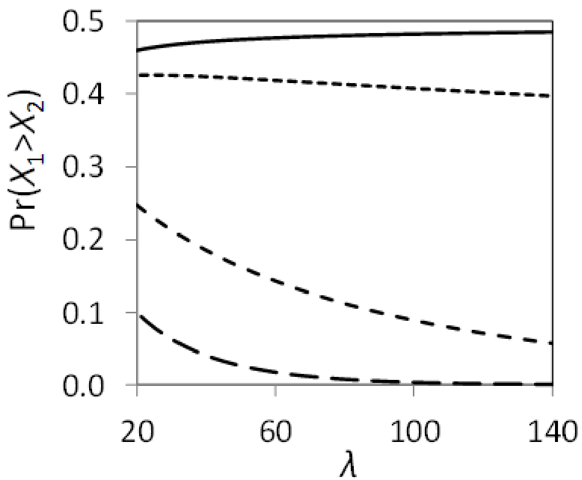

Figure. $\Pr(X_1 > X_2)$ for $X_1 \sim \mathrm{Po}(\mu)$ and $X_2 \sim \mathrm{Po}(\varepsilon\mu)$ independent as a function of the total scoring rate $\lambda = (1+\varepsilon)\mu$ for various ε: solid line $\varepsilon = 1$; short dash $\varepsilon = 1.042$ (equivalent to 3rd strongest plays 2nd strongest); medium dash $\varepsilon = 1.333$ (6th (median team) plays strongest); long dash $\varepsilon = 1.816$ (weakest plays strongest).

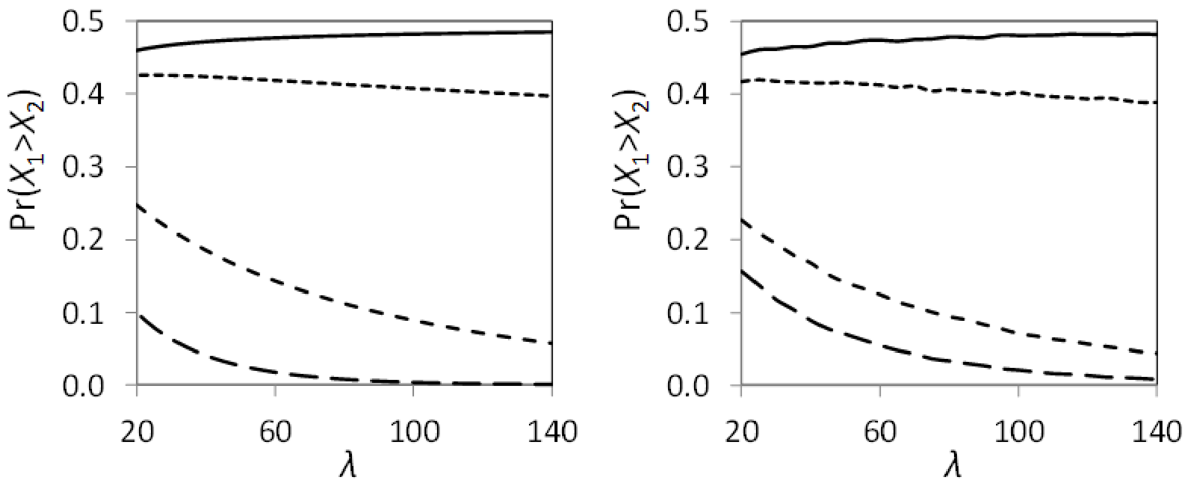

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Table 4: 10,000 simulations of a hypothetical last quarter (Q4) in a binomial-match with total goals in Q4 Poisson distributed with mean 26: proportion of matches that team who start Q4 wins, loses, draws for various $p = p_1 = p_2$ (equal strength teams) and for various match-states at start of Q4 (1-ahead, tied, 1-down)

	$p = p_1 = p_2$	wins	draws	loses	wins/loses
Team starting 1-up	0.6	0.554	0.076	0.370	1.497
	0.7	0.571	0.351	0.079	1.627
	0.8	0.572	0.338	0.090	1.692
Scores tied	0.6	0.469	0.079	0.452	1.038
	0.7	0.466	0.093	0.441	1.057
	0.8	0.476	0.098	0.426	1.117
Team starting 1-down	0.6	0.392	0.079	0.523	0.750
	0.7	0.397	0.085	0.519	0.765
	0.8	0.386	0.097	0.517	0.744

CONCLUSIONS

- binomial-match good for answering Qs about outcome uncertainty (OU), tactics and restart rule-changes
- binomial-match doesn't outperform the Poisson-match on one-step ahead forecasting
- Better models and better strength estimation from possession data

- Further work on outcome uncertainty and its relationship with…
    - *Scoring-rate*
    - *Strength variation*
    - *Restart rules*
- …feeding into better understanding of drivers of consumption of sport…goals, athleticism, stories, tribalism, participation, outcome uncertainty, excitement, suspense, surprises,…