Short Course on Football Analytics

Lecture 1:
Intro and current issues of football analytics

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Why I am here

- Sports Analytics is my academic hobby
  - Started with Dimitris Karlis as phd students back in 1998
- First paper in 2000 with Dimitris for fun in "*Student*"
- Seminal paper on 2003 on Bivariate Poisson models

Why I am here

2nd paper in 2003

The Statistician (2003)
52, Part 3, pp. 381–393

Analysis of sports data by using bivariate Poisson models

Dimitris Karlis

Athens University of Economics and Business, Greece

and Ioannis Ntzoufras

University of the Aegean, Chios, Greece

[Received November 2001. Final revision April 2003]

Summary. Models based on the bivariate Poisson distribution are used for modelling sports data. Independent Poisson distributions are usually adopted to model the number of goals of two competing teams. We replace the independence assumption by considering a bivariate Poisson model and its extensions. The models proposed allow for correlation between the two scores, which is a plausible assumption in sports with two opposing teams competing against each other. The effect of introducing even slight correlation is discussed. Using just a bivariate Poisson distribution can improve model fit and prediction of the number of draws in football games. The model is extended by considering an inflation factor for diagonal terms in the bivariate joint distribution. This inflation improves in precision the estimation of draws and, at the same time, allows for overdispersed, relative to the simple Poisson distribution, marginal distributions. The properties of the models proposed as well as interpretation and estimation procedures are provided. An illustration of the models is presented by using data sets from football and water-polo.

Keywords: Bivariate Poisson regression; Difference of Poisson variates; Inflated distributions; Soccer

Google Scholar (24/5/2021)

Analysis of sports data by using bivariate Poisson models 424 2003
D Karlis, I Ntzoufras
Journal of the Royal Statistical Society: Series D (The Statistician) 52 (3 ...

Introduction

Football/Soccer is the best sport for implementing Science/Statistics/Analytics

- Low number of events (so difficult to predict)
- High uncertainty (so difficult to predict)
- Very popular (because it is difficult to predict?)
- Very profitable (because it is difficult to predict?)
- High Financial Risk of investment (because passion becomes more important than numbers and science) – Professional Teams are usually acting as win-maximizers and not profit-maximizers

Main Topics Quantitative analysis of Football/Sports

- Prediction
- Player Evaluation & Performance analytics
- Physical Metrics of Players in training
- Inline game metrics with wearables
- Scheduling
- Sports Economics & Competitive Balance
- Other (Passing Network Analytics, Referee effects, Red card effect, Home effect, Corruption Analytics, Analysis of substitution times)

Prediction

- Offline (before the game)
- Inline (within the game)

Offline Prediction

Modeling of

- Game Scores
  - Poisson based models and extensions
  - Modeling the difference using the Skellam model
- Final outcome of a game (Win/Draw/Loss)
  - Multinomial regression model
  - Bradley Terry Model

Models for Scores

Models for Counts

- Simple Poisson Model (Maher, 1982; Lee, 1992; Dixon & Coles, 1997, Karlis and Ntzoufras, 2000)
- Bivariate Poisson Model (Karlis & Ntzoufras, 2003)
- Negative Binomial Model (see e.g. Ntzoufras 2009)
- Skellam Model for the goal difference (Karlis & Ntzoufras, 2009)
- Poisson-log-normal random effects model (not the best for football counts; see e.g. Ntzoufras 2009)

Models for Scores

Such models allow us not only to predict a single football game but also (simulation based results)

- Final League reproduction
- Estimate probabilities of wining a league, winning European tickets, or relegation.
- Estimate final rankings
- Estimate results under different scenarios/assumptions (by changing covariates i.e. conditions of the game)

Offline Prediction

Poisson Based models

- Vanilla model: home effect + teams attacking and defensive parameters
- Models with time evolved team parameters (time and form matters!)
- Additional covariates
  - Odds from betting teams (easily accessible – good covariates)
  - Team performance (ingame and before the game)
  - Information about events and formation (team strategy, formation, injuries etc.)
  - Economo-demographic variables (Stability, tradition, Budget, Player Value, Coach Value, Country of origin for European leagues)
  - Prior information (previous games between the teams)
  - Team form (e.g. performance in last 5 games)

Offline Prediction

The simple (vanilla) Poisson model

The model is expressed by

$$
\begin{aligned}
Y_{ij} &\sim \text{Poisson}(\lambda_{ik}) && \text{for } j = 1, 2 \\
\log(\lambda_{i1}) &= \mu + \text{home} + a_{\text{HT}_i} + d_{\text{AT}_i} \\
\log(\lambda_{i2}) &= \mu + a_{\text{AT}_i} + d_{\text{HT}_i} && \text{for } i = 1, 2, \ldots, n,
\end{aligned}
$$

where n = number of games, μ = constant parameter; home = home effect; HT_i and AT_i = home and away teams in i game; a_k and d_k = attacking and defensive effects–abilities of k team for $k = 1, 2, \ldots, K$; and K = number of teams in the data (here $K = 20$).

In full (balanced) round-robin leagues, the parameters can be easily calculated by considering averaged of scored/conceded goals for each team

Offline Prediction

Data for the simple (vanilla) model

- Observations
  - 2 × Number of games (N)
  - Each game will occupy two lines/observations (one for home team and one for away team)
- **Response Variable**: Goals scored by each team in each game
- **Covariates**
  - **Home effect**: Binary for home and away teams (1 for home teams and zero otherwise)
  - **Scoring team**: Categorical factor for the team scoring the number of goals (the corresponding coefficient will estimate the attacking ability of each team)
  - **Team accepting goals**: Categorical factor for the team receiving the number of goals (the corresponding coefficient will estimate the defensive ability of each team).

What can we do with such models

We now can calculate via simulation

- The probability of a specific score
- The probability of a score difference
- The probability of win/loss/draw
- Calculate the probability of winning the league or each position
- Reproduce the league under the model

What if analysis for 2017-18

Super league 2017-2018

#	ΟΜΑΔΑ	ΑΓΩΝΕΣ	ΒΑΘΜΟΙ
1	Α.Ε.Κ.	30	70
2	Π.Α.Ο.Κ.	30	64
3	ΟΛΥΜΠΙΑΚΟΣ	30	57
4	ΑΤΡΟΜΗΤΟΣ ΑΘ.	30	56
5	ΑΣΤΕΡΑΣ ΤΡΙΠ.	30	45
6	Α.Ο. ΞΑΝΘΗ	30	45

- **PAOK -3 points for the game PAOK-AEK (11/3/2018) and lost this game**
- **PAOK also lost the game PAOK-OLYMPIAKOS (25/2/2918) without playing**

What if analysis for 2017-18

Super league 2017-2018

#	ΟΜΑΔΑ	ΑΓΩΝΕΣ	ΒΑΘΜΟΙ
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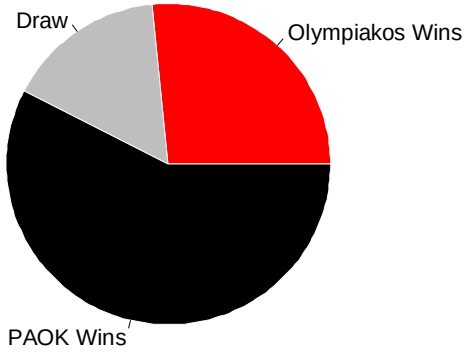
PAOK – OLYMPIAKOS

PAOK Wins 57.5%

Draw 16%

Olympiakos Wins 26.5%



What if analysis for 2017-18

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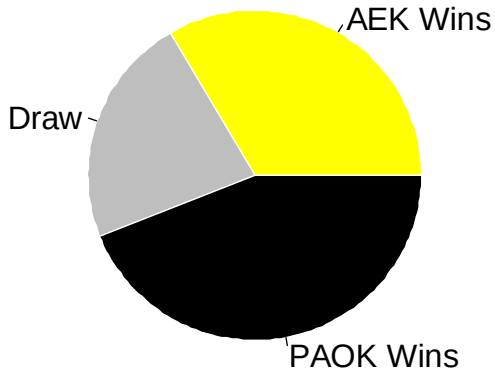
6	Α.Ο. ΞΑΝΘΗ	30	45

PAOK – AEK

PAOK Wins 44.5%

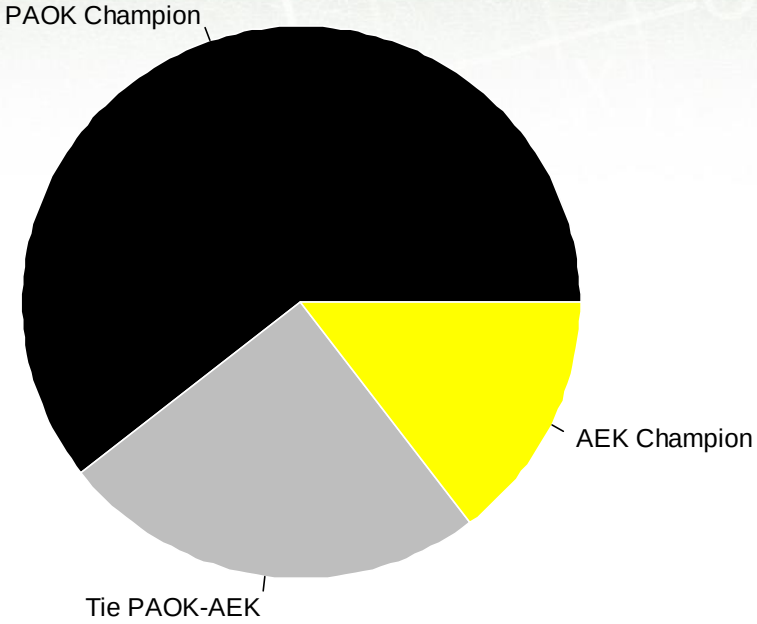
Draw 22%

AEK Wins 33.5%



What if analysis for 2017-18

Super league 2017-2018



Final Result

PAOK Champion 60%

Tie PAOK & AEK 25%

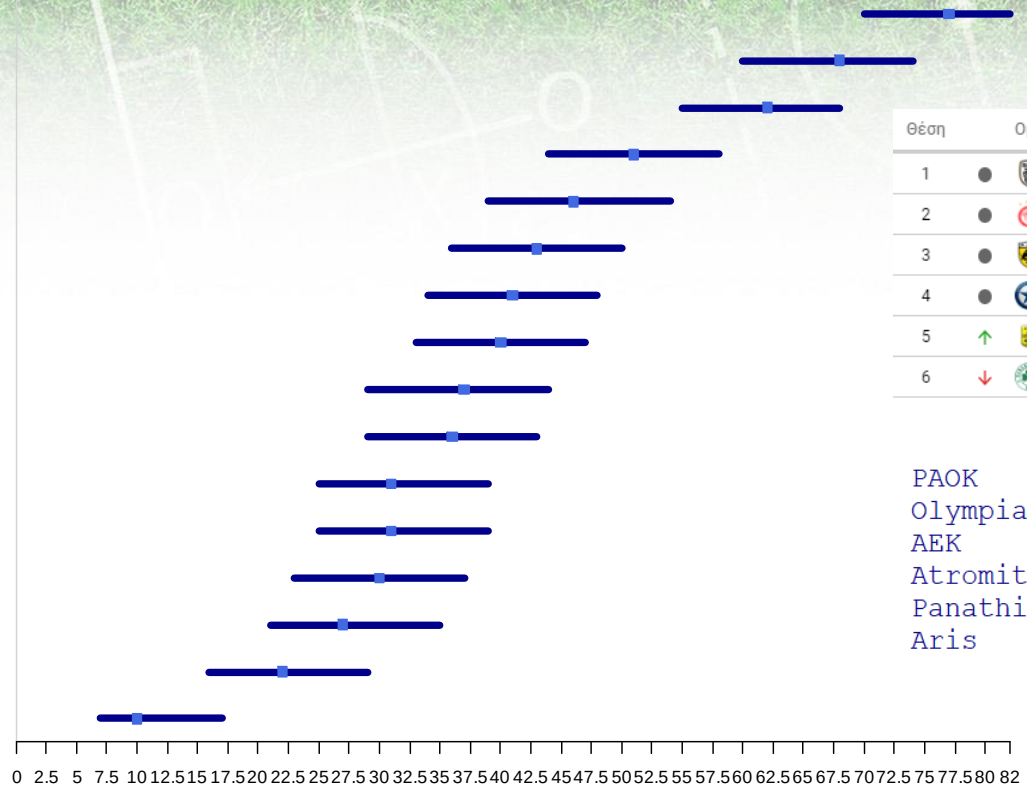
AEK Champion 15%

Who is going to be the champion?

Θέση		Ομάδα	Α	Ν	Ι	Η	ΓΥ	ΓΚ	+/-	ΒΑΘ
1	●	ΠΑΟΚ	19	17	2	0	37	8	29	51
2	●	Ολυμπιακός	19	14	3	2	35	9	26	45
3	●	ΑΕΚ	19	12	4	3	33	8	25	37
4	●	Ατρόμητος	19	9	6	4	28	19	9	33
5	↑	Άρης	19	9	2	8	21	19	2	29
6	↓	Παναθηναϊκός	19	9	7	3	27	16	11	28
7	↑	Παναιτωλικός	19	7	5	7	23	25	-2	26
8	↓	Ξάνθη	19	6	7	6	15	15	0	25
9	●	Πανιώνιος	19	6	4	9	18	29	-11	22
10	↑	Αστέρας Τρίπολης	19	6	3	10	16	22	-6	21
11	↓	Λαμία	19	5	5	9	14	25	-11	20
12	↓	Λάρισα	19	5	5	9	16	23	-7	20
13	↑	ΟΦΗ	19	3	8	8	18	28	-10	17
14	↓	ΠΑΣ Γιάννινα	19	5	2	12	14	29	-15	17
15	●	Λεβαδειακός	19	3	4	12	11	27	-16	13
16	●	Απόλλων Σμύρνης	19	1	3	15	7	31	-24	6

Who is going to be the champion?

PAOK
Olympiakos
AEK
Atromitos
Panathinaikos
Aris
Panetolikos
Xanthi
Asteras Tripolis
Panionios
Lamia
Larisa
OFI Crete
Giannina
Levadeiakos
Apollon



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1	●	ΠΑΟΚ	19	51
2	●	Ολυμπιακός	19	45
3	●	ΑΕΚ	19	37
4	●	Ατρόμητος	19	33
5	↑	Άρης	19	29
6	↓	Παναθηναϊκός	19	28

	2.5%	50%	97.5%
PAOK	70	77	82
Olympiakos	60	68	74
AEK	55	62	68
Atromitos	44	51	58
Panathinaikos	39	46	54
Aris	36	43	50

Who is going to be the champion?

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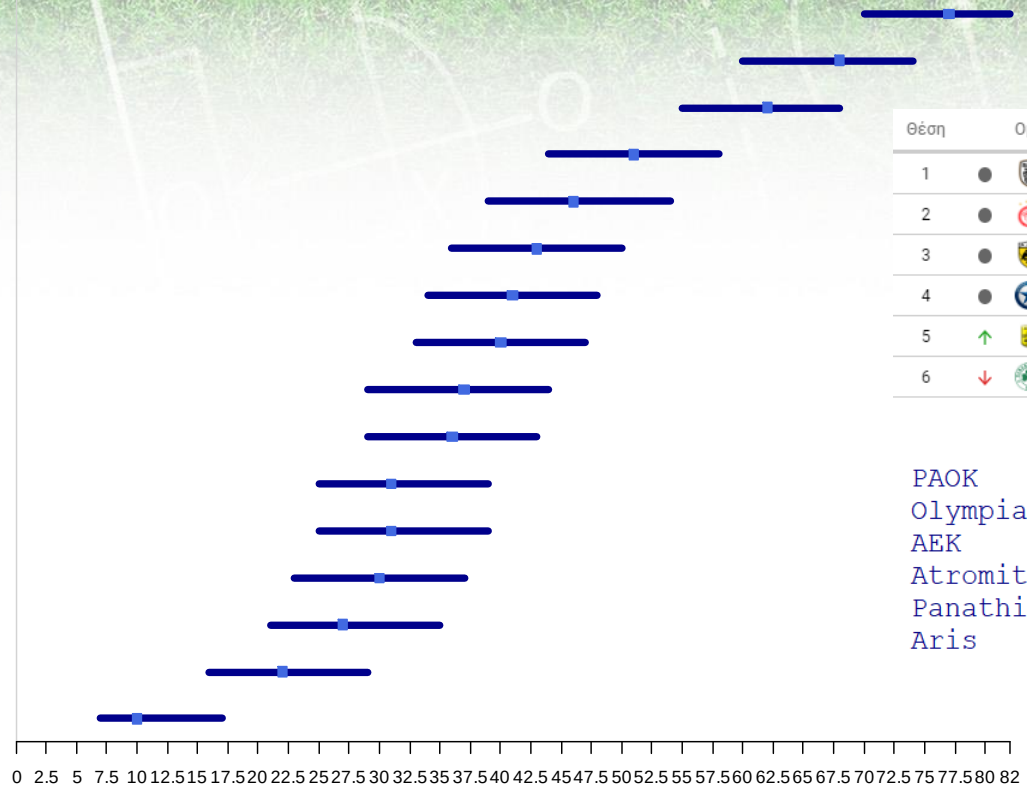

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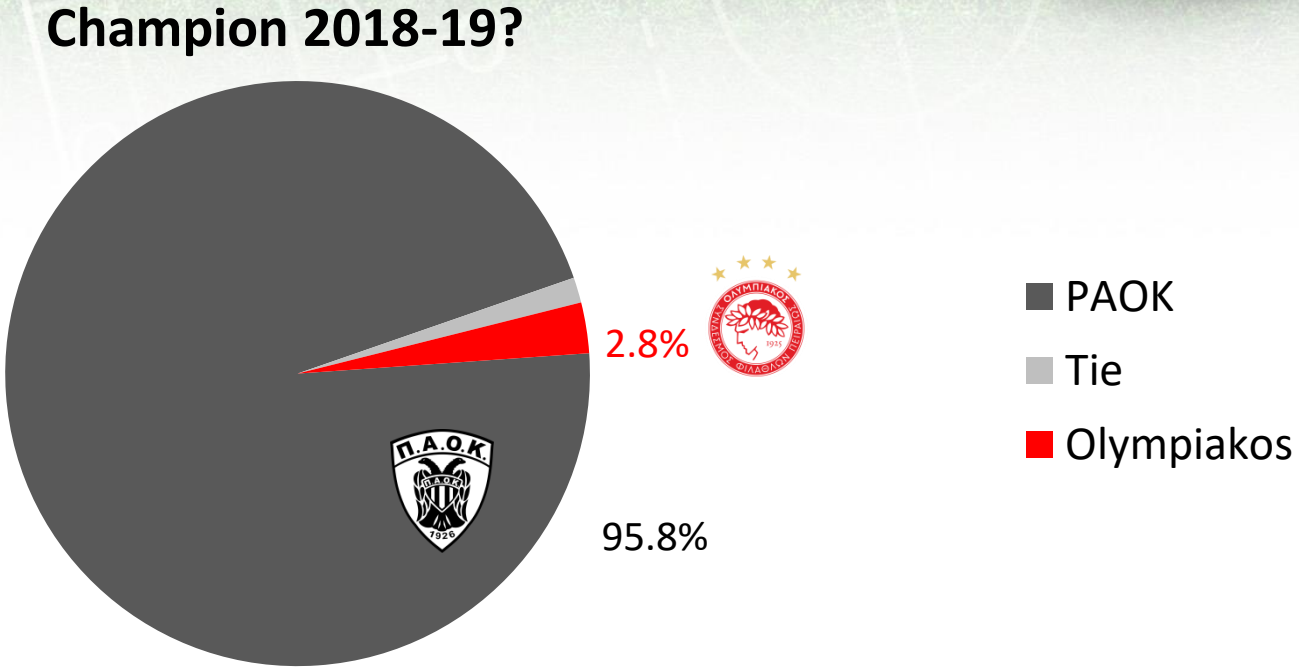
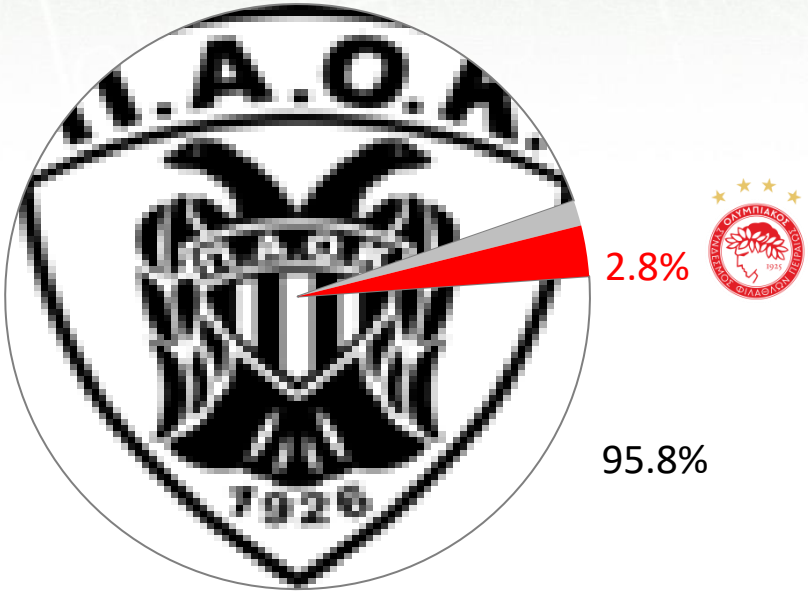
Who is going to be the champion?

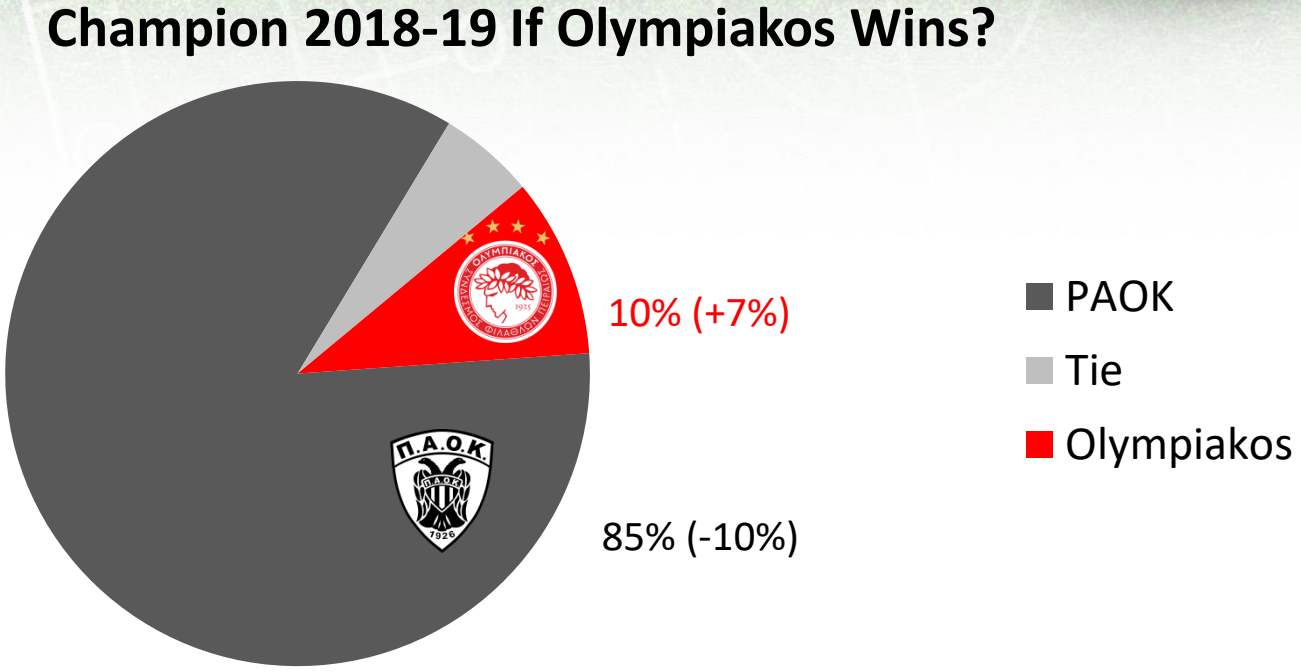


Who is going to be the champion?

Champion 2018-19?



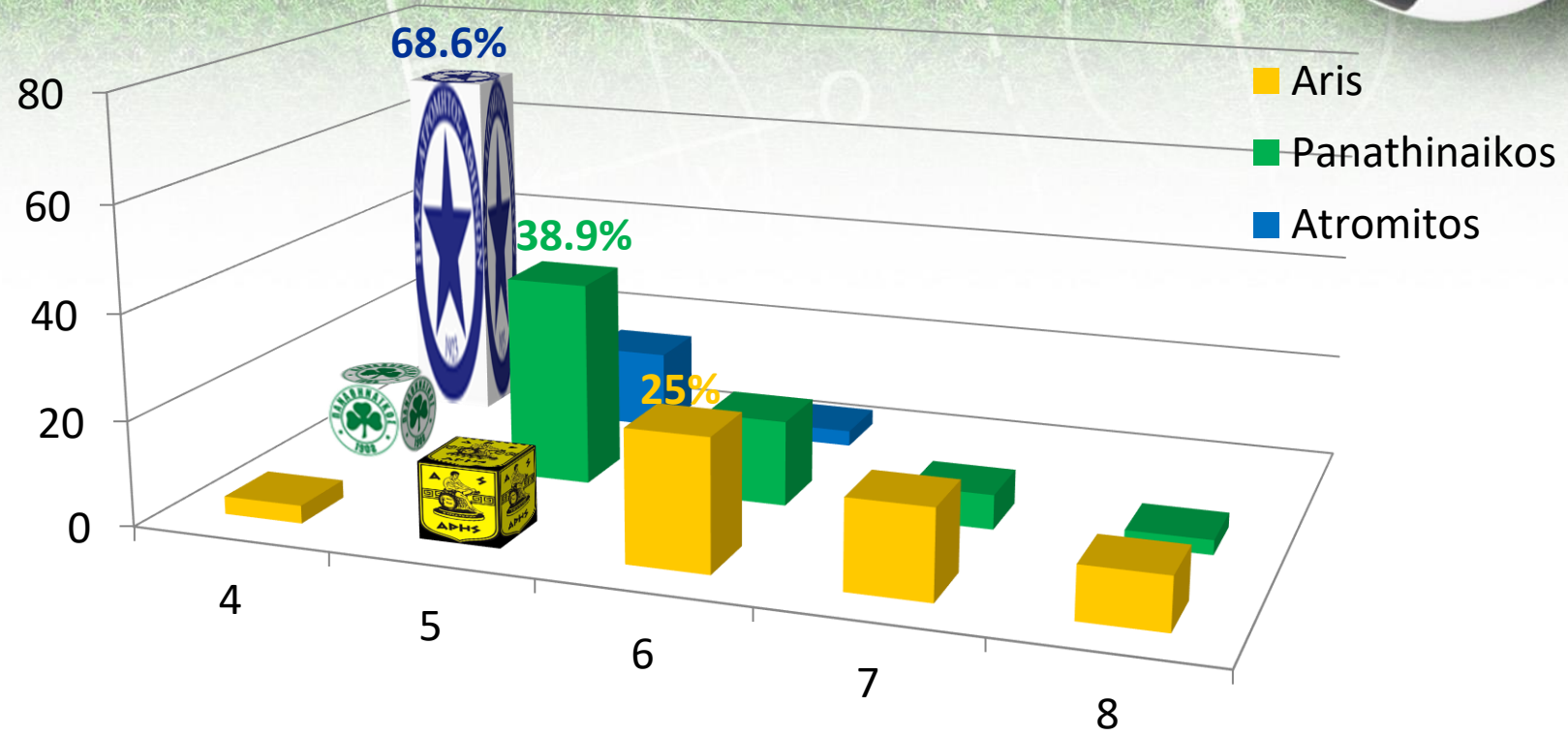
Who is going to be the champion?



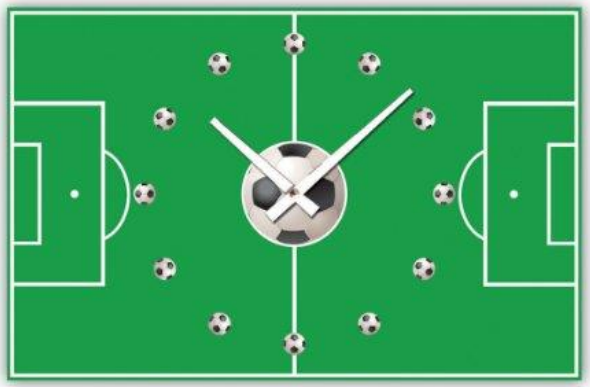
Who is going to be the champion?

Team	2nd	3rd
Olympiakos	79.4%	11%
AEK	11%	81%

Who is going to be the champion?



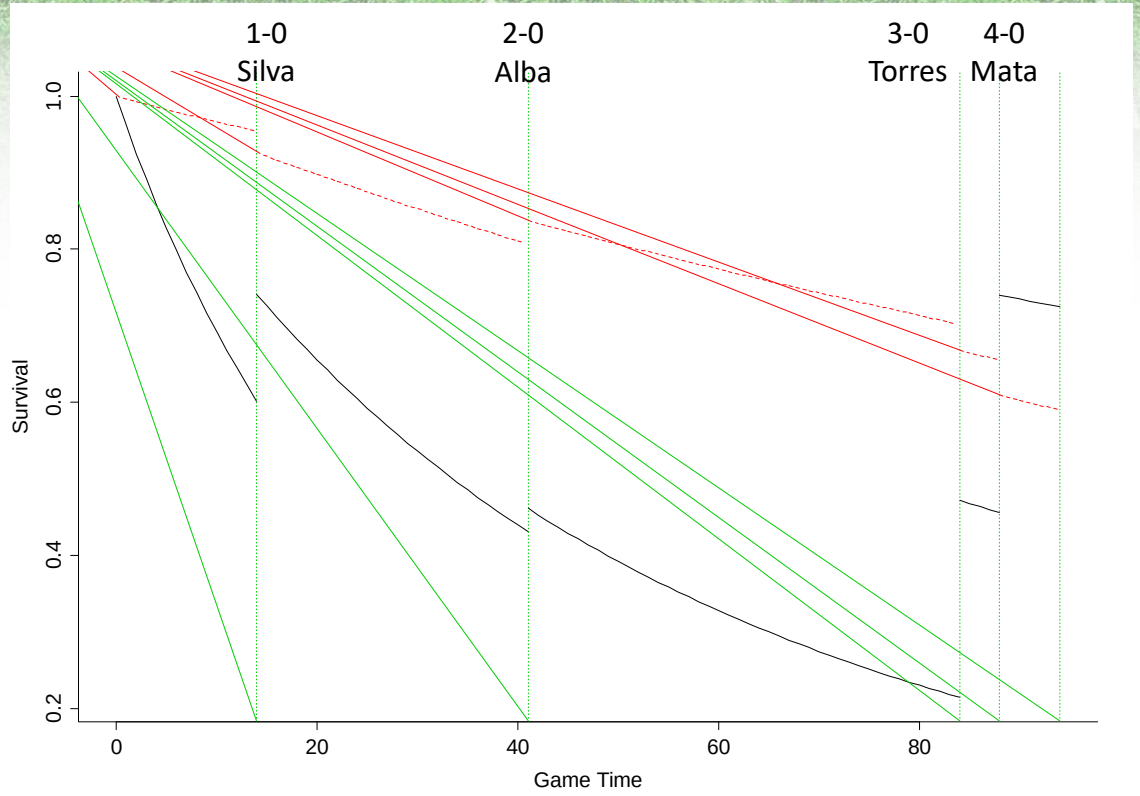
Prediction within the game



Modeling of

- Time to event (goal)
  - Survival analysis based models
    - Dixon & Robinson (1998, *RSSD*)
    - Nevo and Ritov (2013, *JQAS*)
    - Boshnakov, Kharrat, McHale (2017, *Int. J. Forecasting*)
    - Work in progress by our team
- Model the probability of event for short intervals (every 1 or 5 minutes)
  - Using Binomial mixed models for repeated measures

Prediction within the game



EURO 2012 FINAL

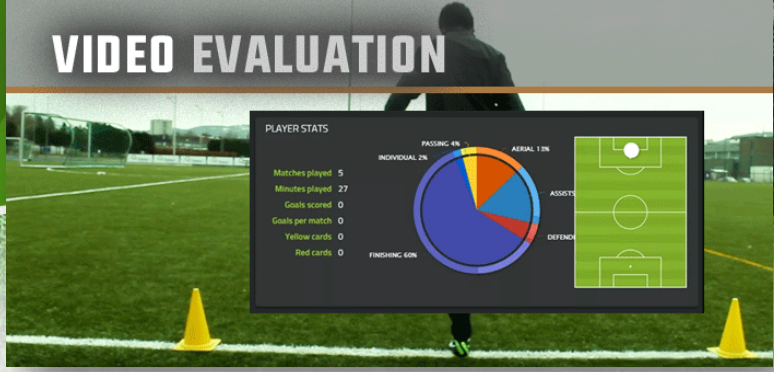
Spain – Italy = 4-0

Survival Inline Plot

(based on a Bayesian Model using posterior medians of the expected arrival times)

From our work in progress with I. Leriou & D. Karlis

Player Evaluation



Aim

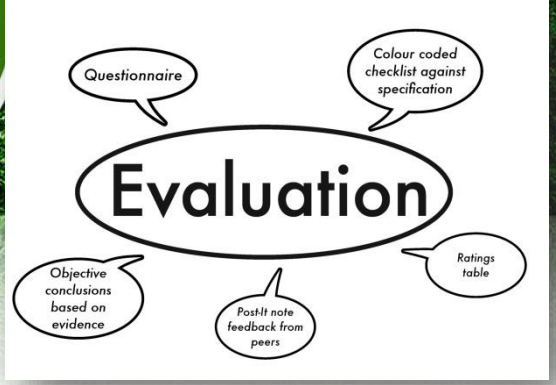
- Estimate the contribution of players in a team
- Rank, identify and reward best players
- Scouting – Early Identification of talents
- Estimate the future performance/value of a Player
- Help the manager to decide the best formation

Player Evaluation

Methods

- Simple approach with binary indicators
- Random effects
- Analysis based on Game Performance Indicators
- Expected Goals (xG) and Expected Assists (xA)
- Player Economic/Marketing Value and performance

Player Evaluation



Methods (2)

- Simple approach with indicators
  - Build a model with indicators whether a players was in the field
  - Binary indicators for players
  - Difficult to build a dataset. Each game should be splitted in multiple lines according to substitution times
- Analysis based on Game Performance Indicators
  - Build a model to identify the importance of each event in the game (goals, shots, steals, passes, speed, stamina, area covered etc.)
  - Use model indicators to build an index of players
  - McHale, Scarf & Folker (2012, *Interfaces*) building different indexes based on different response measures

Player Evaluation

Methods (3)

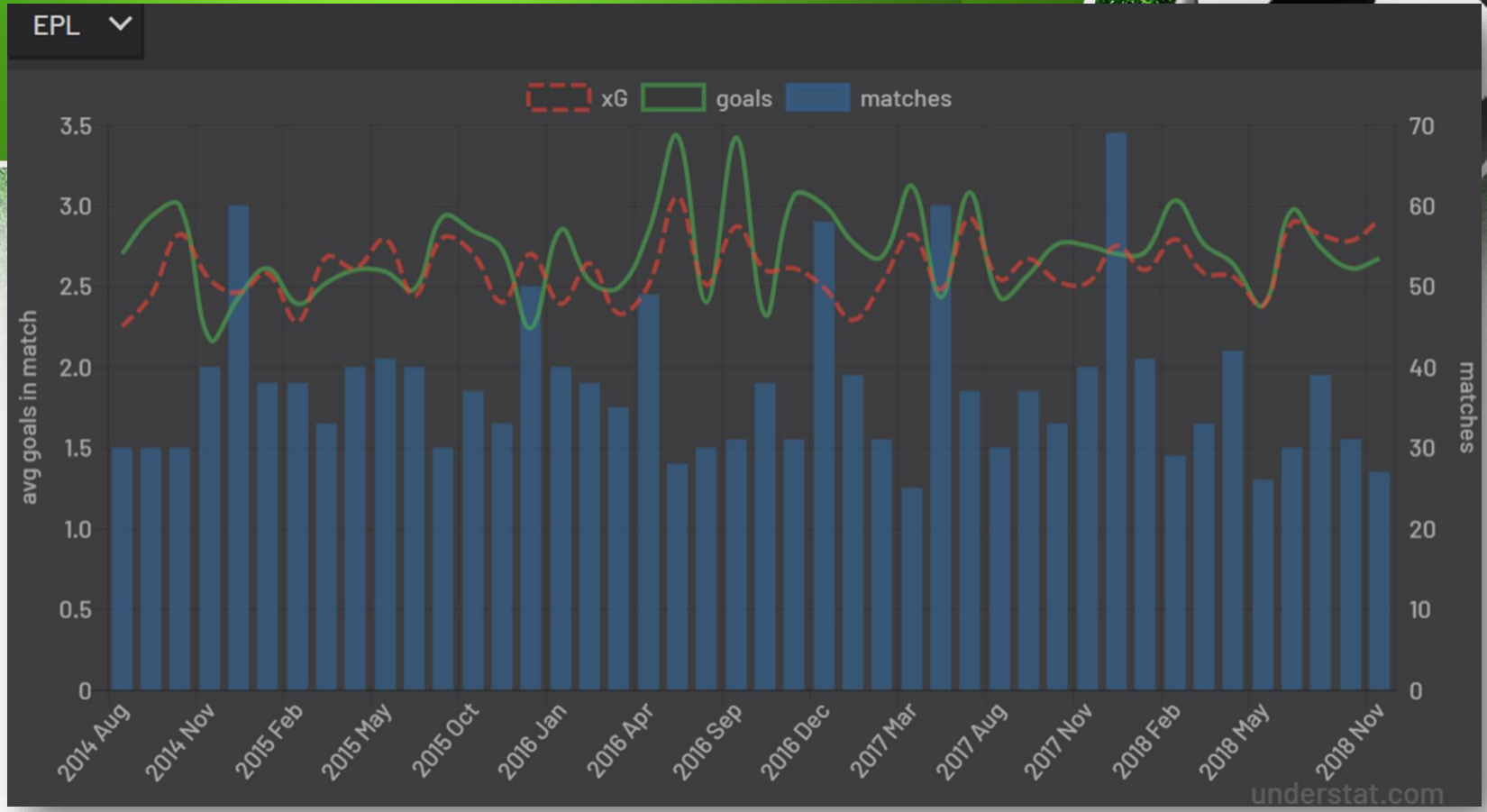
- Random effects
  - Use random effects to identify individual contribution
  - Goal Scoring: McHale & Szczepanski (2014, *JRSSA*)
  - Passing Skills: Szczepanski & McHale (2016, *JRSSA*)
- Player Economic/Marketing Value and performance
  - Saebo & Hvattum (2018, *Journal of Sports Analytics*): *Modelling the financial contribution of soccer players to their clubs*
  - Evaluating the efficiency of the association football transfer market using regression based player ratings (pre-print only)

Player Evaluation

Methods (5)

Expected Goals (xG)

- We model every shot
- Response measure: is the probability of a shot resulting in a goal
- The sum of these probabilities will give the xG of a player and a team
- Similar for assists (xA)
- References:
  - https://www.optasports.com/services/analytics/advanced-metrics/
  - https://understat.com/



Expected Goals (xG): https://understat.com/

Xgoals also in Greek media

xGoals: Η επανάσταση που άλλαξε το ποδόσφαιρο

Τι είναι τα xGoals και γιατί έχουν αλλάξει το ποδόσφαιρο; Το Sport24.gr σας παρουσιάζει τα expected goals, που έχουν βελτιώσει τον τρόπο που βλέπουμε το ποδόσφαιρο, το πώς παίζουν οι ομάδες και αξιολογούνται οι ποδοσφαιριστές. Ο Θέμης Καίσαρης αναλύει την επανάσταση που επιτέλους βάζει το ποδόσφαιρο σε σωστές βάσεις και μας επιτρέπει καλύτερη ανάλυση του παιχνιδιού.

Επιμέλεια: **Θέμης Καίσαρης** Δημοσίευση: 12 Οκτ. 2017 14:40

Mega analysis: Τα xGoals ανοίγουν τα X-Files της Super League

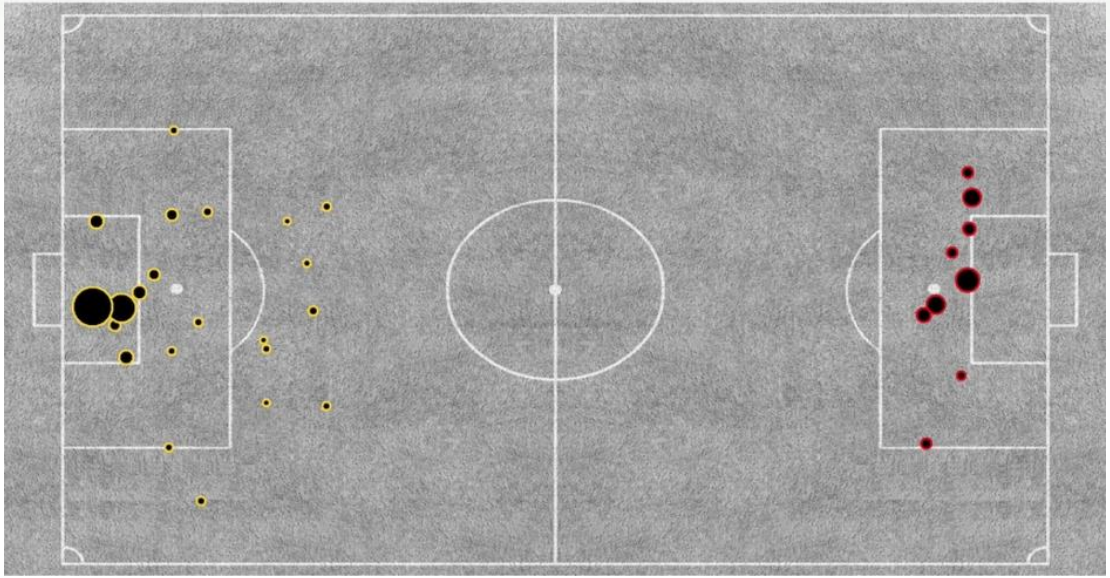
Ποια ομάδα φτιάχνει τις καλύτερες τελικές της Super League και ποια δέχεται τις πιο επικίνδυνες; Ποιοι ξεχωρίζουν στη μάχη του τίτλου και γιατί είναι πίσω ο Ολυμπιακός; Ξεχάστε τα γκολ, το θέμα είναι τα xGoals, που χρησιμοποιούνται για πρώτη φορά στο ελληνικό πρωτάθλημα. Το Sport24.gr και ο Θέμης Καίσαρης σας δίνουν όλες τις απαντήσεις, για όλες τις ομάδες, σε μια UNIQUE ανάλυση.

Επιμέλεια: **Θέμης Καίσαρης** Δημοσίευση: 13 Οκτ. 2017 14:06

https://www.sport24.gr/Columns/longform/xgoals-h-epanastash-poy-allakse-to-podosfairo.4887473.html
https://www.sport24.gr/unique/mega-analysis-ta-xgoals-anoigoyn-ta-x-files-ths-super-league.4889251.html

Xgoals also in Greek media

AEK Athens	24-09-2017	Olympiakos
3	goals	2
22	shots	9
2.75	xG	1.63



Source: https://www.sport24.gr/Columns/longform/xgoals-h-epanastash-poy-allakse-to-podosfairo.4887473.html

Xgoals in American Soccer Analysis website

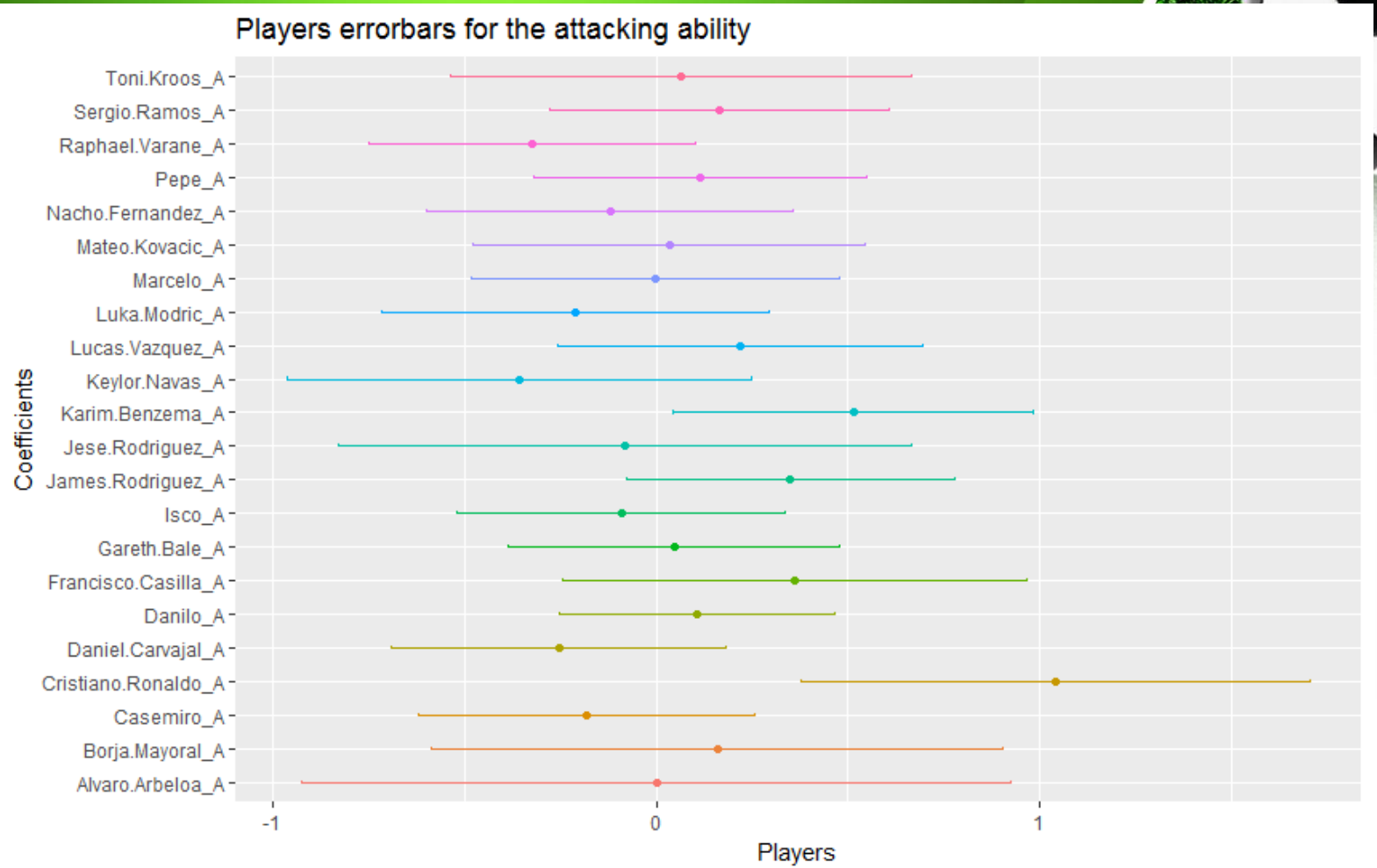
https://www.americansocceranalysis.com/

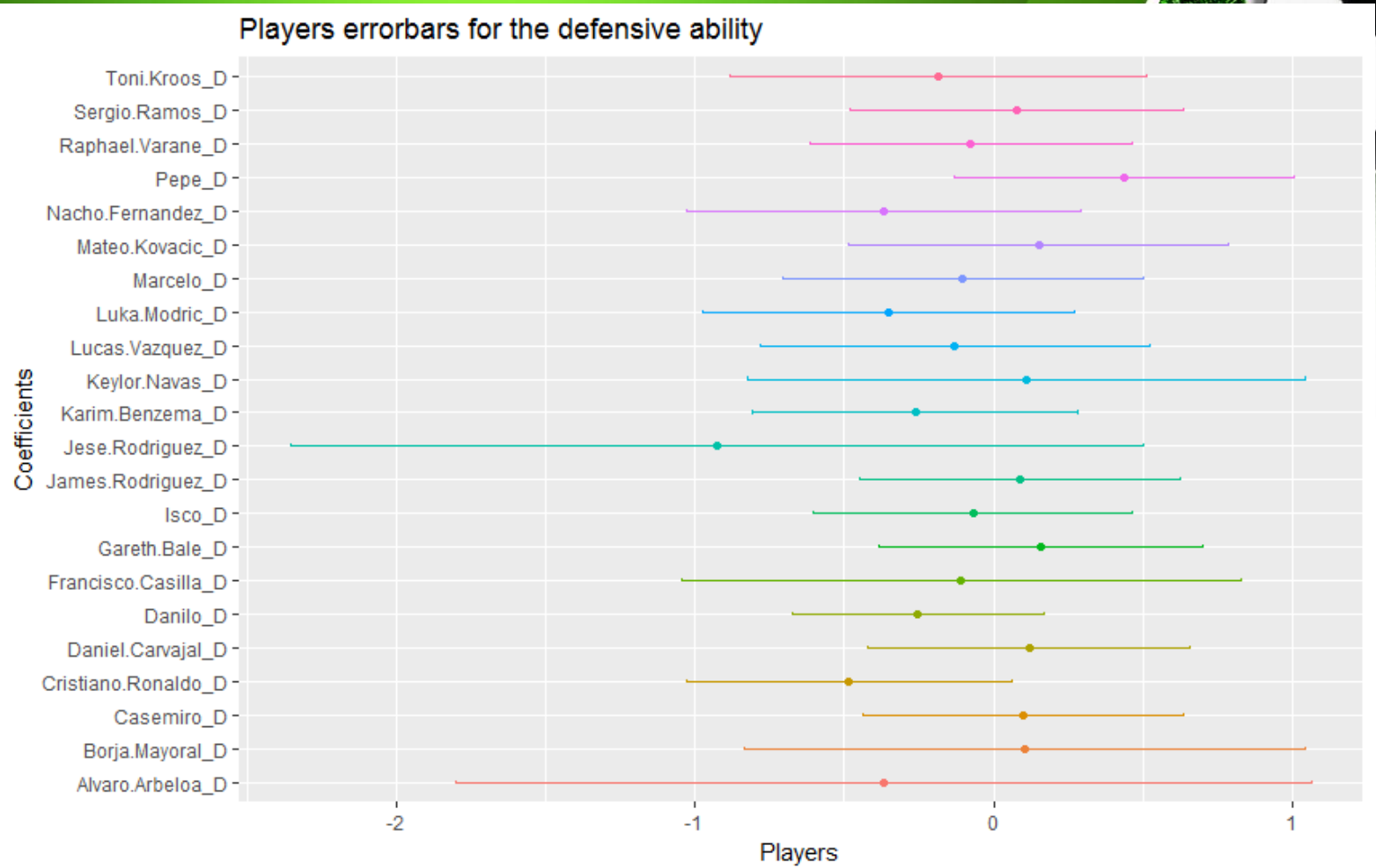
Shooter/Team Model	Estimate	Std. Error	Z-value	P-value)
Intercept	4.172	0.170	24.589	0.000
Distance (log-yds)	-2.353	0.047	-50.056	0.000
Goal Mouth Available (quadratic-yds)	-0.026	0.007	-3.785	0.000
Goal Mouth Available (yds)	0.069	0.019	3.716	0.000
Headed (binary)	-0.648	0.066	-9.746	0.000
Cross (binary)	-0.380	0.061	-6.206	0.000
Through ball (binary)	0.909	0.074	12.292	0.000
Corner (binary)	-0.622	0.064	-9.753	0.000
Free kick (binary)	0.539	0.117	4.592	0.000
Indirect Free kick (binary)	-0.192	0.080	-2.393	0.017
Fastbreak (binary)	0.680	0.106	6.397	0.000
Penalty (binary)	2.735	0.134	20.336	0.000

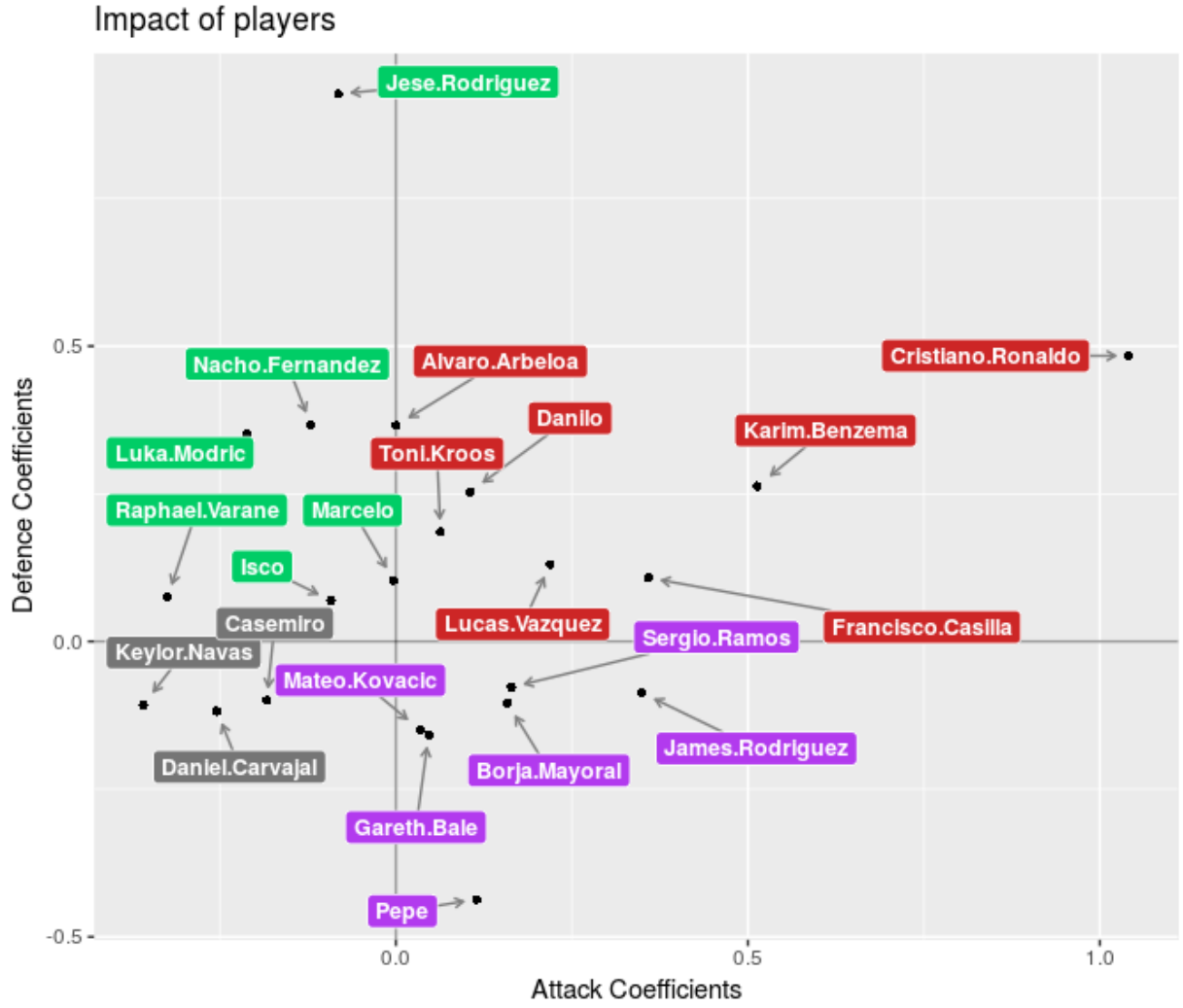
Player Evaluation

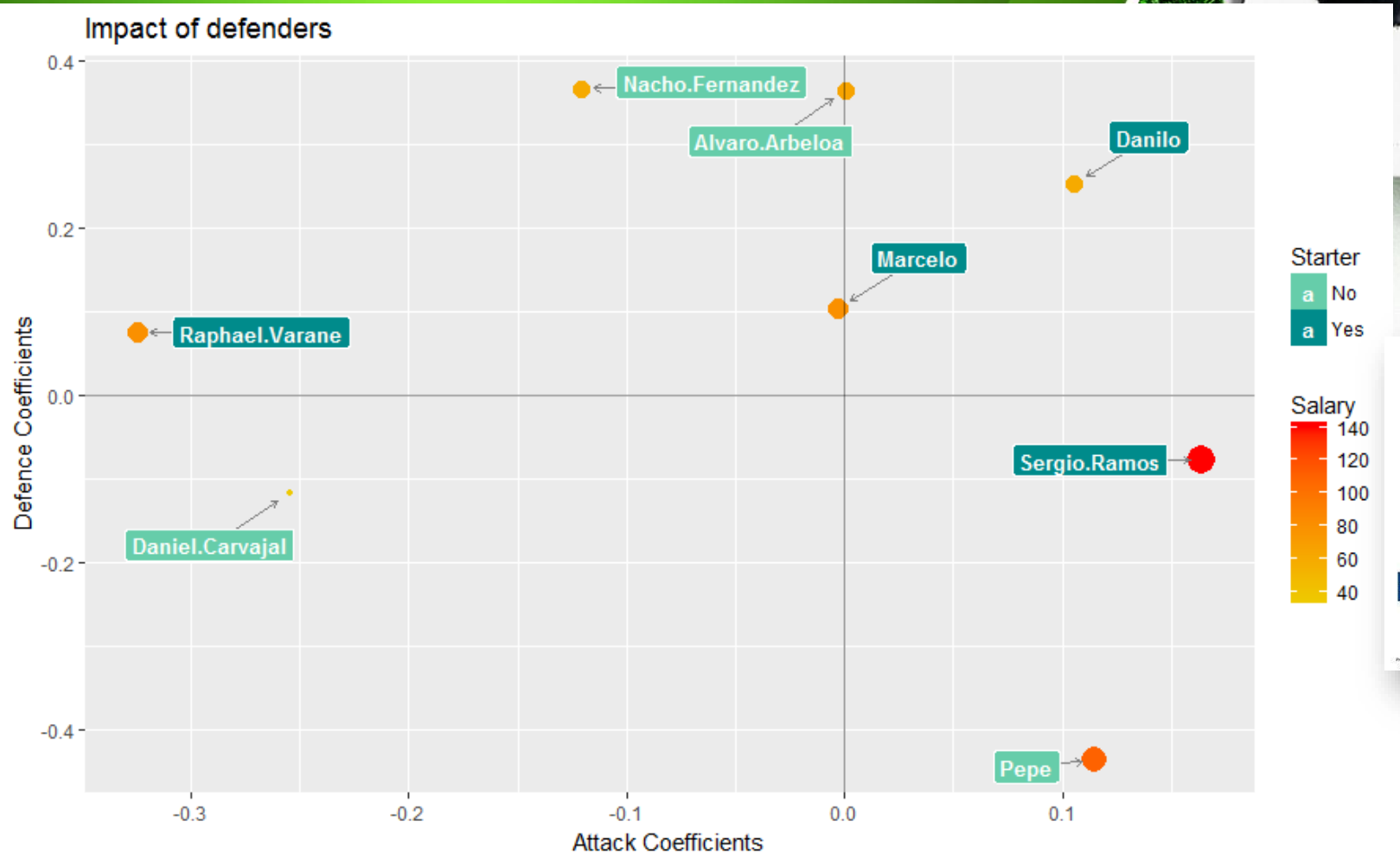
Example of the Simple approach with indicators

- 351 matches of the La Liga Season 2015/2016
- 954 goals (555 goals were scored by home teams, 399 conceded)
- 110 scored by Real Madrid, 34 conceded
- M.Sc. Thesis at AUEB by A. Mourtopallas

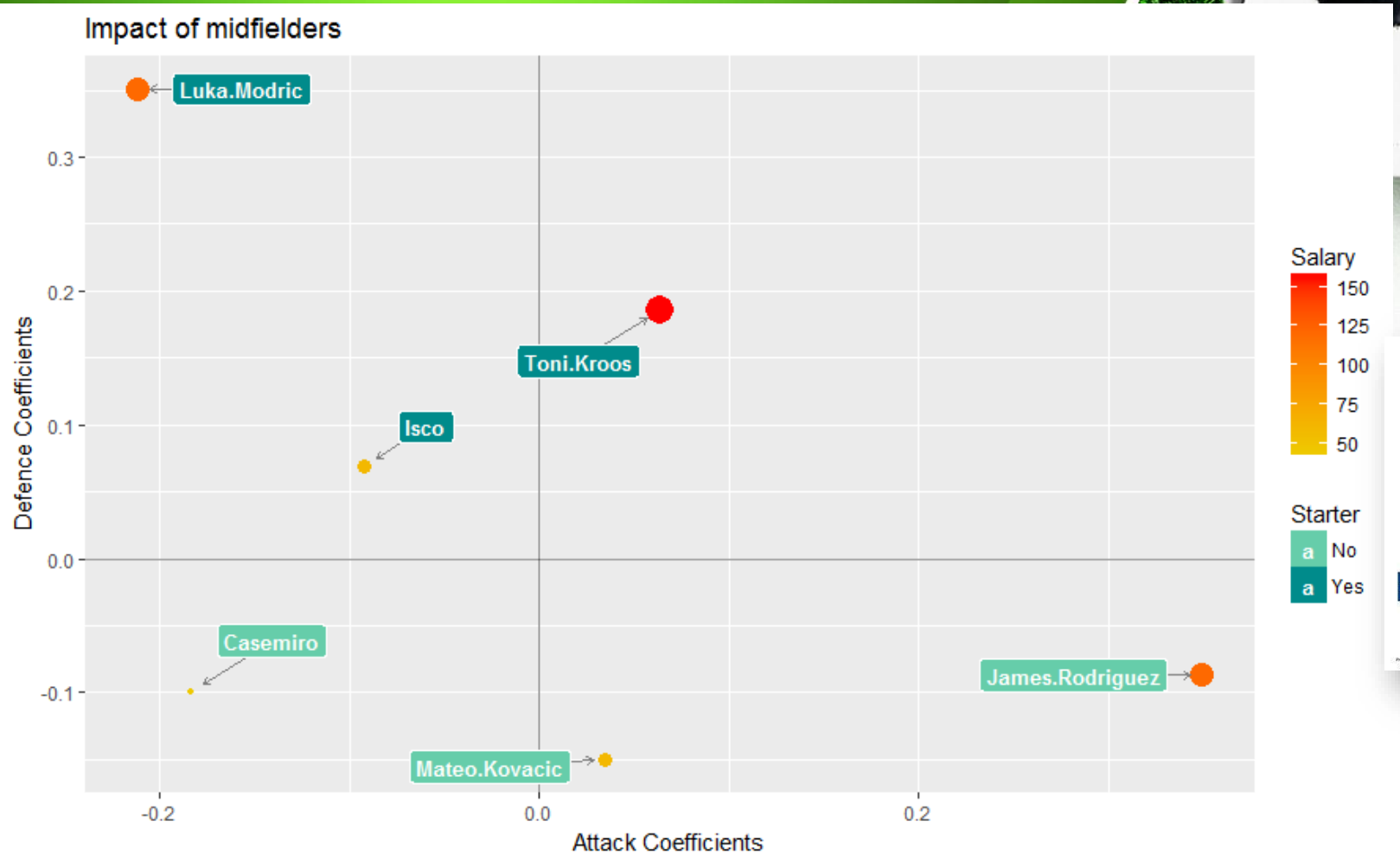

Players errorbars for the attacking ability
Toni.Kroos_A
Sergio.Ramos_A
Raphael.Varane_A
Pepe_A
Nacho.Fernandez_A
Mateo.Kovacic_A
Marcelo_A
Luka.Modric_A
Lucas.Vazquez_A
Keylor.Navas_A
Karim.Benzema_A
Jese.Rodriguez_A
James.Rodriguez_A
Isco_A
Gareth.Bale_A
Francisco.Casilla_A
Danilo_A
Daniel.Carvajal_A
Cristiano.Ronaldo_A
Casemiro_A
Borja.Mayoral_A
Alvaro.Arbeloa_A
Coefficients
-1
0
1
Players


Players errorbars for the defensive ability
Toni.Kroos_D
Sergio.Ramos_D
Raphael.Varane_D
Pepe_D
Nacho.Fernandez_D
Mateo.Kovacic_D
Marcelo_D
Luka.Modric_D
Lucas.Vazquez_D
Keylor.Navas_D
Karim.Benzema_D
Jese.Rodriguez_D
James.Rodriguez_D
Isco_D
Gareth.Bale_D
Francisco.Casilla_D
Danilo_D
Daniel.Carvajal_D
Cristiano.Ronaldo_D
Casemiro_D
Borja.Mayoral_D
Alvaro.Arbeloa_D
Coefficients
-2
-1
0
1
Players

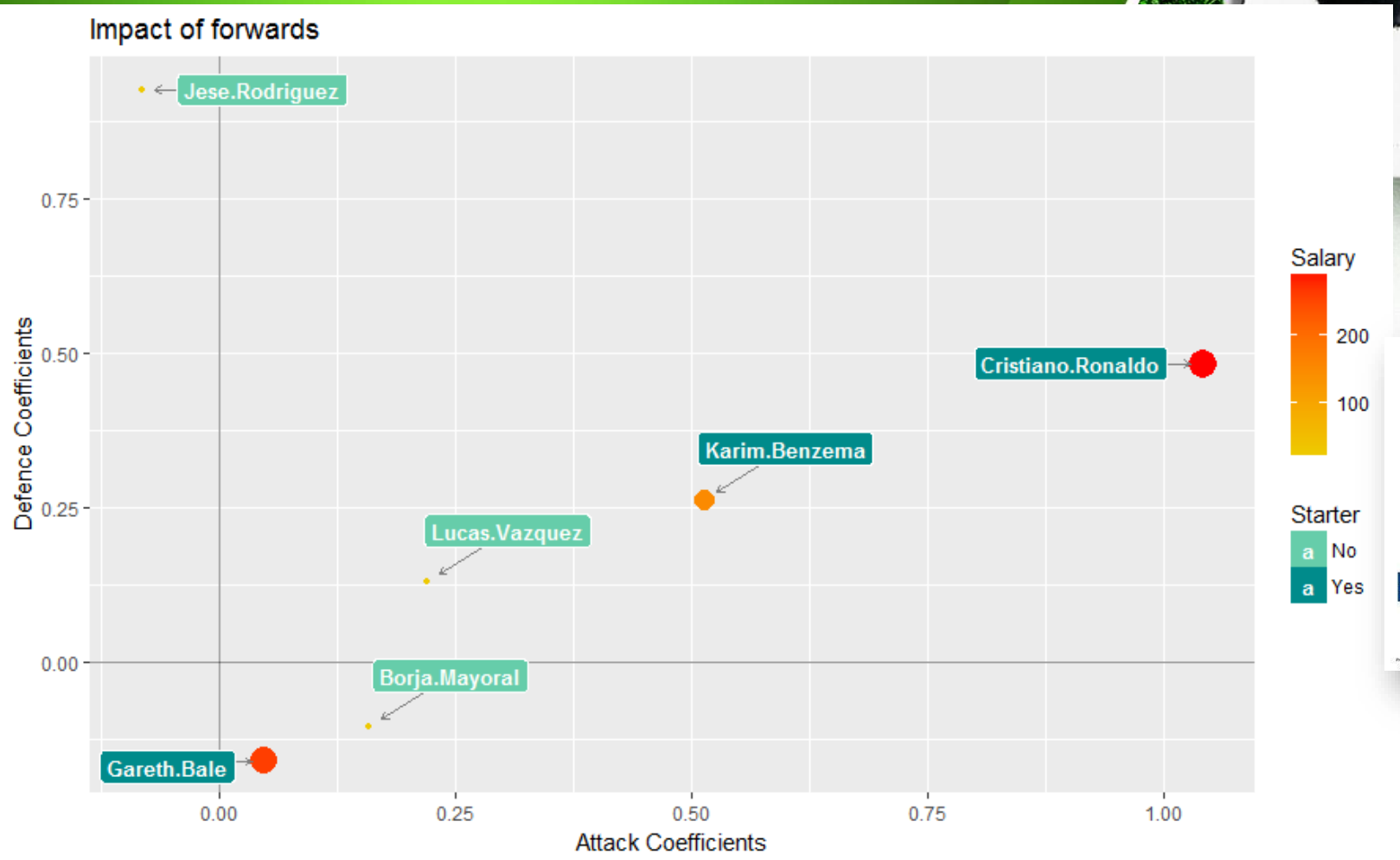

Impact of players
Jese.Rodriguez
Nacho.Fernandez
Alvaro.Arbeloa
Cristiano.Ronaldo
Danilo
Karim.Benzema
Luka.Modric
Toni.Kroos
Raphael.Varane
Marcelo
Isco
Casemiro
Lucas.Vazquez
Sergio.Ramos
Francisco.Casilla
Keylor.Navas
Mateo.Kovacic
James.Rodriguez
Daniel.Carvajal
Borja.Mayoral
Gareth.Bale
Pepe
Defence Coefficients
Attack Coefficients
0.5
0.0
-0.5
0.0
0.5
1.0
Category
Bad at both
Better in attack
Better in defence
Good at both


Impact of defenders
Nacho.Fernandez
Alvaro.Arbeloa
Danilo
Marcelo
Raphael.Varane
Sergio.Ramos
Daniel.Carvajal
Pepe
Defence Coefficients
Attack Coefficients
0.4
0.2
0.0
-0.2
-0.4
-0.3
-0.2
-0.1
0.0
0.1
Starter
No
Yes
Salary
140
120
100
80
60
40

Realmadrid


Impact of midfielders
Luka.Modric
Toni.Kroos
Isco
Casemiro
James.Rodriguez
Mateo.Kovacic
0.3
0.2
0.1
0.0
-0.1
-0.2
0.0
0.2
Defence Coefficients
Attack Coefficients
Salary
150
125
100
75
50
Starter
a No
a Yes

Realmadrid


Impact of forwards
Jese.Rodriguez
Cristiano.Ronaldo
Karim.Benzema
Lucas.Vazquez
Borja.Mayoral
Gareth.Bale
0.75
0.50
0.25
0.00
Defence Coefficients
0.00
0.25
0.50
0.75
1.00
Attack Coefficients
Salary
200
100
Starter
No
Yes
Realmadrid

Real Madrid 2015/16
Player Evaluation

Conclusions

Cristiano Ronaldo is the key player of the team

Tony Kroos' impact is higher than we may presume

Nacho Fernandez improved since last season (very high def contribution)

Lucas Vasquez is a very promising player (contributed positively in both attack and defensive dimensions with low salary)

Gareth Bale performed less than expected (overprized)

Pepe $\Rightarrow$ low defensive contribution – high salary (overprized?)

Metrics for physical improvement and training

Aim

- Improve the physical condition of athletes
- Focus on specific skills and measure them
- Avoid injuries
- Improves the team by optimizing allocated training time

Inline game metrics with wearables

The aim is to measure

- Movement of players in the game
- Speed and coverage
- Physical condition
- Physical and tactics performance

It helps

- Evaluate the performance of players and teams within a game
- The manager to decide formation and substitutions

League and Contest Scheduling

AIM

- Fair scheduling
- Eliminate bias due to the sequence of games
- Strengthen competitiveness (related with next slides)
- Incorporate constraints (incl. other sports, safety issues, other events, tv requirements etc.)

HOW?

- Using Operational Research and optimization methods
- Hybrid search methods
- Validate using simulation methods from Statistical models

Competitive Balance

- A balanced league increases the interest of the fans and improves the athletic product
- The notion of a balanced league is not yet very well defined
  - Equal Strength between all teams? or
  - Equal Strength between best teams (or the teams with the highest number of fans?)

Sports Economics & Competitive balance

What league do we want to see?

- All fans like the fact that a weaker team occasionally wins a game or a league
- May neutral fans follow the weakest team

e.g. Greece in Euro 2004

But

- They do not like their team to loose
- They like or they are willing to pay an expensive ticket to see a final with high ranked and expensive teams

e.g. Bayern-Barcelona

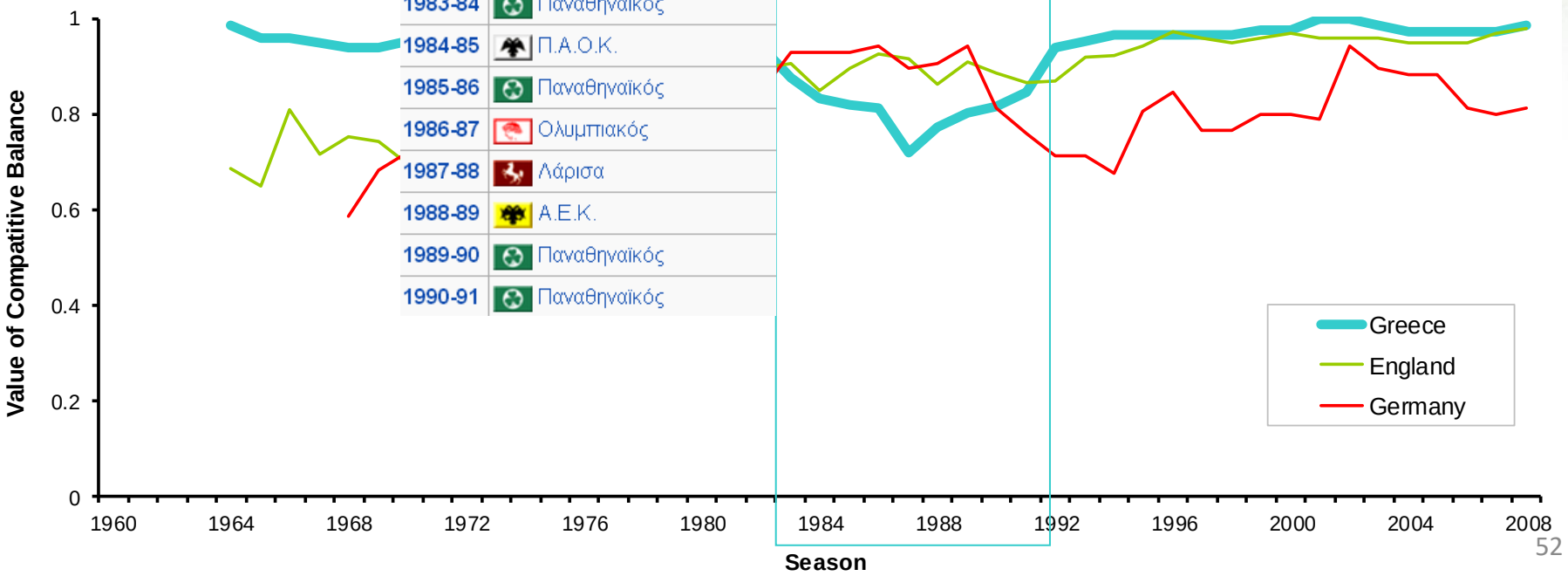
Competitive balance in Greek League

Joint work with V.Manasis

1991-92	Α.Ε.Κ.	2000-01	Ολυμπιακός
1992-93	Α.Ε.Κ.	2001-02	Ολυμπιακός
1993-94	Α.Ε.Κ.	2002-03	Ολυμπιακός
1994-95	Παναθηναϊκός	2003-04	Παναθηναϊκός
1995-96	Παναθηναϊκός	2004-05	Ολυμπιακός
1996-97	Ολυμπιακός	2005-06	Ολυμπιακός
1997-98	Ολυμπιακός	2006-07	Ολυμπιακός
1998-99	Ολυμπιακός	2007-08	Ολυμπιακός
1999-00	Ολυμπιακός	2008-09	Ολυμπιακός

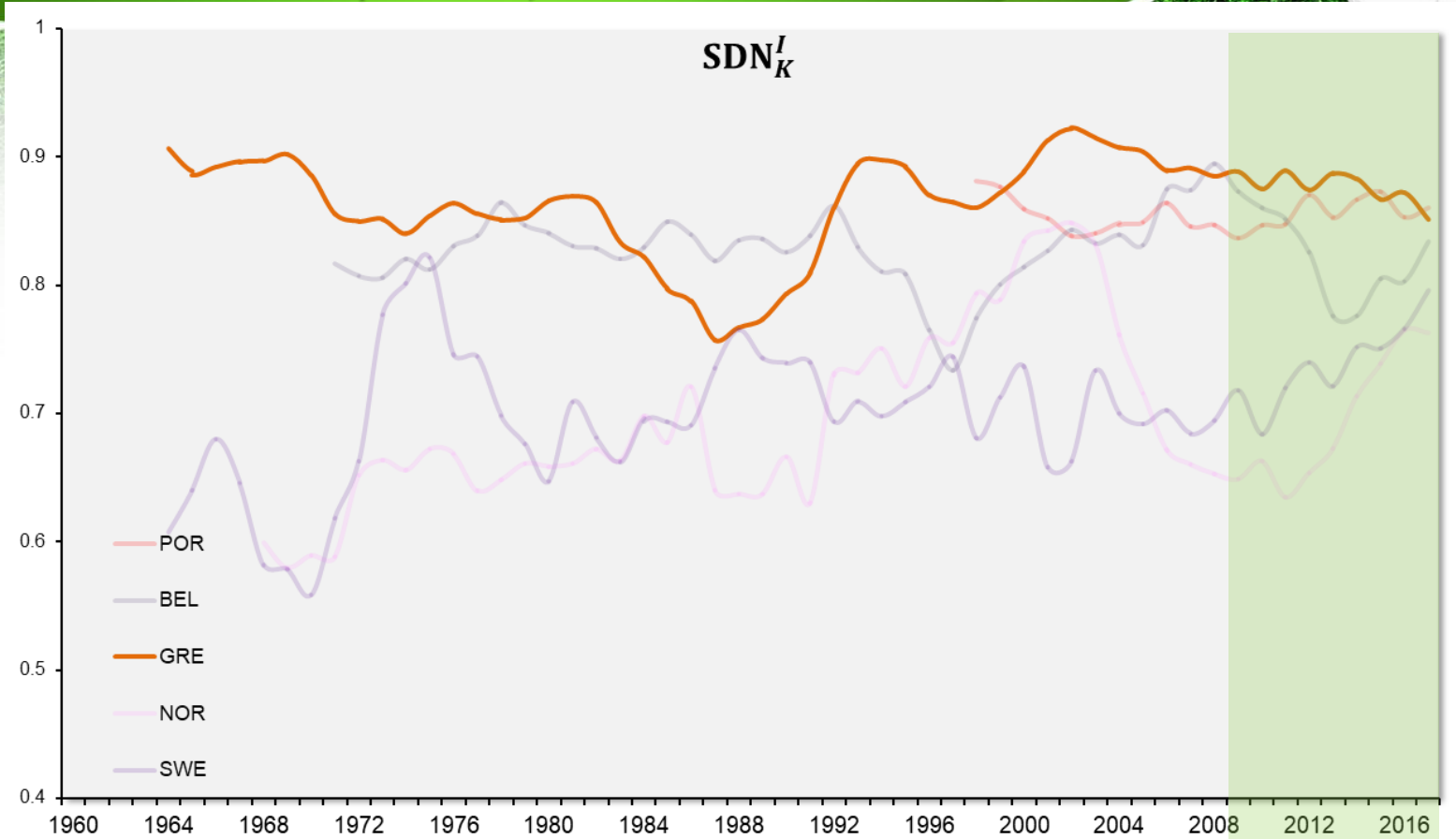
Moving Averages of lag five for DN_1 (Champion) from 1959-20

1983-84	Παναθηναϊκός
1984-85	Π.Α.Ο.Κ.
1985-86	Παναθηναϊκός
1986-87	Ολυμπιακός
1987-88	Λάρισα
1988-89	Α.Ε.Κ.
1989-90	Παναθηναϊκός
1990-91	Παναθηναϊκός



What about the last decade in the Greek League?

Source: SAW2019 presentation of V.Manasis



ManU won 13 out of 17 leagues for the period 1992-2009 and it was not ranked in lower position than 3rd.

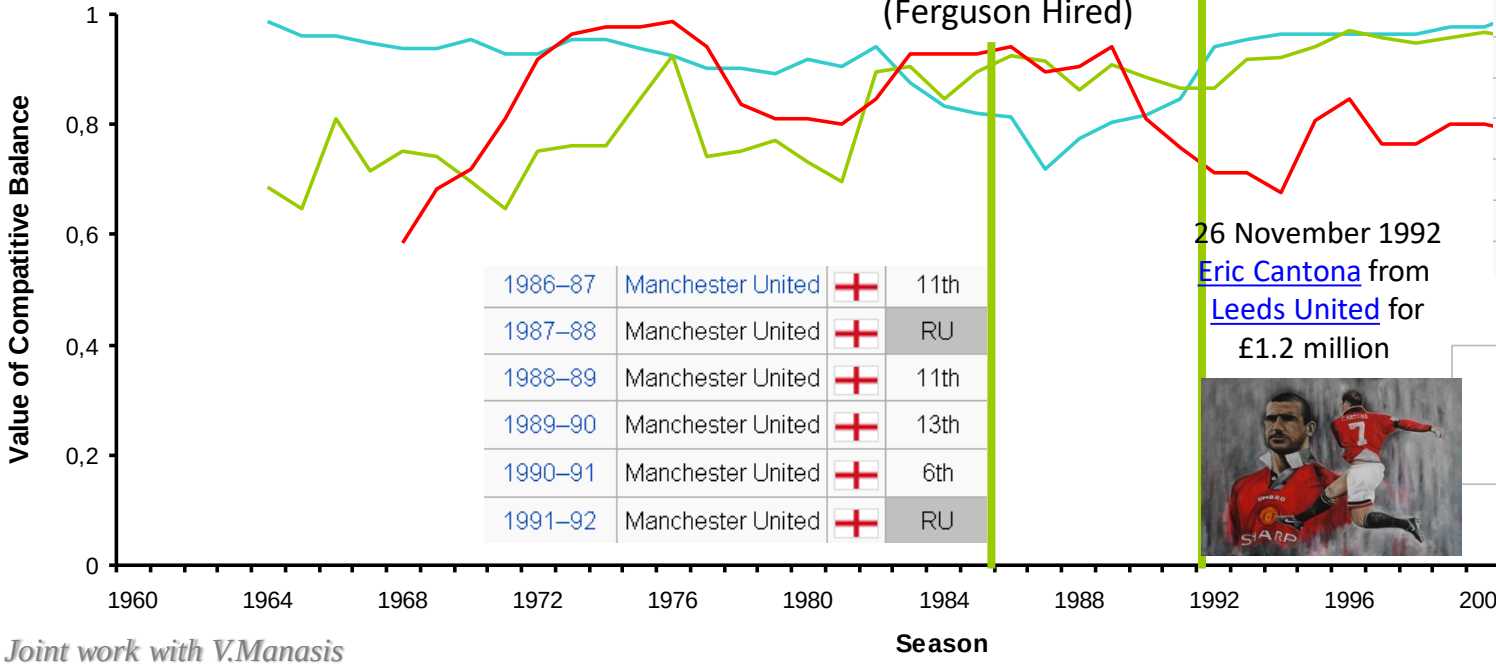
Competitive balance in Premier League

3 cases in England ⇒ promoted team ⇒ won the championship:

Ipswich (1961) & Nottingham (1997) & Leicester (2015-16 – not in the Figu

Joint work with V.Manasis

Moving Averages of lag five for *DN 1* (Champion) from 1959-2008



1986–87	Manchester United		11th
1987–88	Manchester United		RU
1988–89	Manchester United		11th
1989–90	Manchester United		13th
1990–91	Manchester United		6th
1991–92	Manchester United		RU

1992–93	Manchester United		W
1993–94	Manchester United		W
1994–95	Manchester United		RU
1995–96	Manchester United		W
1996–97	Manchester United		W
1997–98	Manchester United		RU
1998–99	Manchester United		W
1999–2000	Manchester United		W
2000–01	Manchester United		W
2001–02	Manchester United		3rd
2002–03	Manchester United		W
2003–04	Manchester United		3rd
2004–05	Manchester United		3rd
2005–06	Manchester United		RU
2006–07	Manchester United		W
2007–08	Manchester United		W
2008–09	Manchester United		W

Joint work with V.Manasis

Premier League after 13 games of the 2015/16 season (when Leicester won)

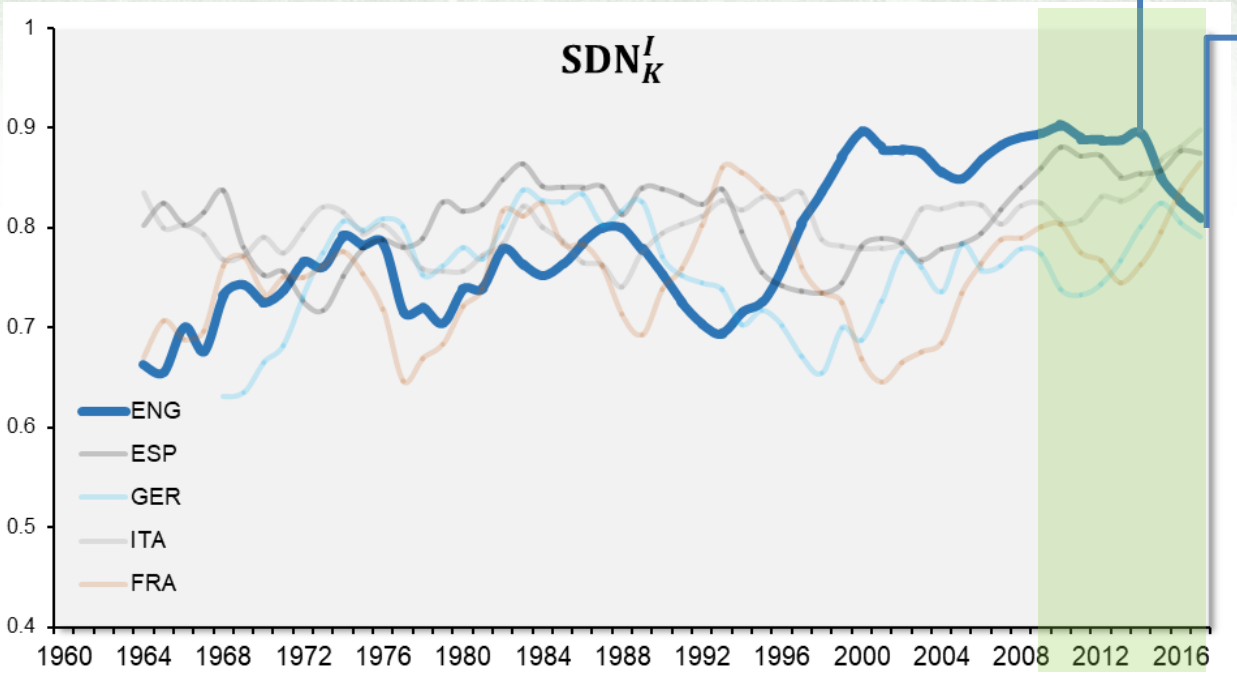
TEAM	P	W	D	L	GD	PTS
Leicester City	13	8	4	1	8	28
Manchester United	13	8	3	2	10	27
Manchester City	13	8	2	3	14	26
Arsenal	13	8	2	3	12	26
Tottenham Hotspur	13	6	6	1	13	24
West Ham United	13	6	3	4	4	21
Everton	13	5	5	3	8	20
Southampton	13	5	5	3	5	20
Liverpool	13	5	5	3	2	20
Crystal Palace	13	6	1	6	1	19
Stoke City	13	5	4	4	-1	19
West Bromwich Albion	13	5	2	6	-5	17
Watford	13	4	4	5	-2	16
Swansea City	13	3	5	5	-4	14
Chelsea	13	4	2	7	-6	14
Norwich City	13	3	3	7	-8	12
Newcastle United	13	2	4	7	-12	10
Sunderland	13	2	3	8	-12	9
Bournemouth	13	2	3	8	-13	9
Aston Villa	13	1	2	10	-14	5

Premier League after 13 games of the 2015/16 season

What about the last decade in Premier League?

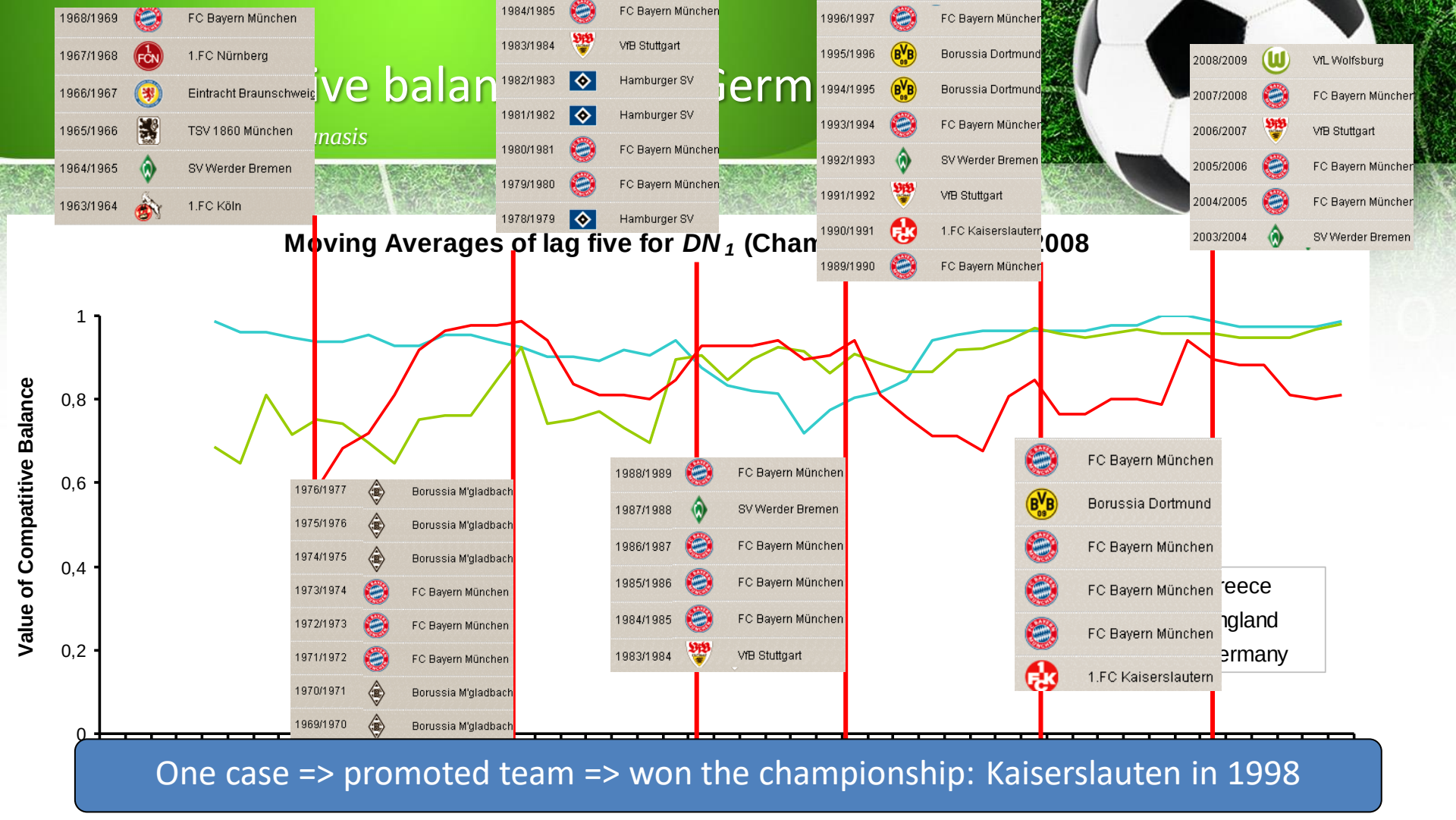
Source: SAW2019 presentation of V.Manasis

Credits: Manasis (2018) Sports Analytics Workshop Presentation



Last Championship for UND Retirement of Ferguson

2006–07	Manchester United (16)
2007–08	**Manchester United**[3] (17)
2008–09	**Manchester United**[4] (18)
2009–10	**Chelsea** (4)
2010–11	Manchester United (19)
2011–12	Manchester City (3)
2012–13	Manchester United (20)
2013–14	**Manchester City**[4] (4)
2014–15	**Chelsea**[4] (5)
2015–16	Leicester City
2016–17	Chelsea (6)
2017–18	**Manchester City**[4] (5)


1968/1969 FC Bayern München
1967/1968 1.FC Nürnberg
1966/1967 Eintracht Braunschweig
1965/1966 TSV 1860 München
1964/1965 SV Werder Bremen
1963/1964 1.FC Köln
1984/1985 FC Bayern München
1983/1984 VfB Stuttgart
1982/1983 Hamburger SV
1981/1982 Hamburger SV
1980/1981 FC Bayern München
1979/1980 FC Bayern München
1978/1979 Hamburger SV
1996/1997 FC Bayern München
1995/1996 Borussia Dortmund
1994/1995 Borussia Dortmund
1993/1994 FC Bayern München
1992/1993 SV Werder Bremen
1991/1992 VfB Stuttgart
1990/1991 1.FC Kaiserslautern
1989/1990 FC Bayern München
2008/2009 VfL Wolfsburg
2007/2008 FC Bayern München
2006/2007 VfB Stuttgart
2005/2006 FC Bayern München
2004/2005 FC Bayern München
2003/2004 SV Werder Bremen
Moving Averages of lag five for DN 1 (Chan
008
Value of Compatitive Balance
1
0,8
0,6
0,4
0,2
0
1976/1977 Borussia M'gladbach
1975/1976 Borussia M'gladbach
1974/1975 Borussia M'gladbach
1973/1974 FC Bayern München
1972/1973 FC Bayern München
1971/1972 FC Bayern München
1970/1971 Borussia M'gladbach
1969/1970 Borussia M'gladbach
1988/1989 FC Bayern München
1987/1988 SV Werder Bremen
1986/1987 FC Bayern München
1985/1986 FC Bayern München
1984/1985 FC Bayern München
1983/1984 VfB Stuttgart
FC Bayern München
Borussia Dortmund
FC Bayern München
FC Bayern München
FC Bayern München
FC Bayern München
1.FC Kaiserslautern
reece
ngland
ermany
One case => promoted team => won the championship: Kaiserslauten in 1998

Sports Economics & Competitive balance

How to design Knockout Tournaments?

- Do we support the stronger or the weakest teams?

We do not wish to see

- **many** strong teams to be disqualified early
- Two weak or not popular teams in the final

We do wish to see

- **Some** strong teams to be disqualified early
- Some weak teams to qualify further against all odds

Sports Economics & Competitive balance

In round-robin contests (National leagues)?

- Do we support the stronger or weakest teams?
- Small or large leagues?
- Playoffs?
- Give more money to strong teams (reward) or to weak teams (balance)?
- What about promotion/relegation rules (refreshes the interest or just recycles bad teams?)

We do wish to see

- A large enough group of teams to be close and compete for the championship
- A large enough group of teams to be close and compete for European tickets

We do not wish to see

- A team having big margin of points from all the rest (so the champion is known early)
- Teams with low number of points so they are not competitive (early relegation)
- Teams with economic problems

Sports Economics & Competitive balance

For UEFA Champions League

- Does it need improvement?
- Not metrics to measure balance
- Big discussion of how to reward teams and share income
- Closed or Open League?
- How many teams from each National League/Country
- The current income share and reward system destroys the balance in National teams in second ranked leagues like Greece.

Home sweet home

- Home effect/advantage is well established in
  - «Καφενείον» discussions

  - Data based Studies

- Pollard (1986)

  ⇒ relatively stable in English League from 1888!

  ⇒ ~**64%** of the points from home teams for 1970-1981

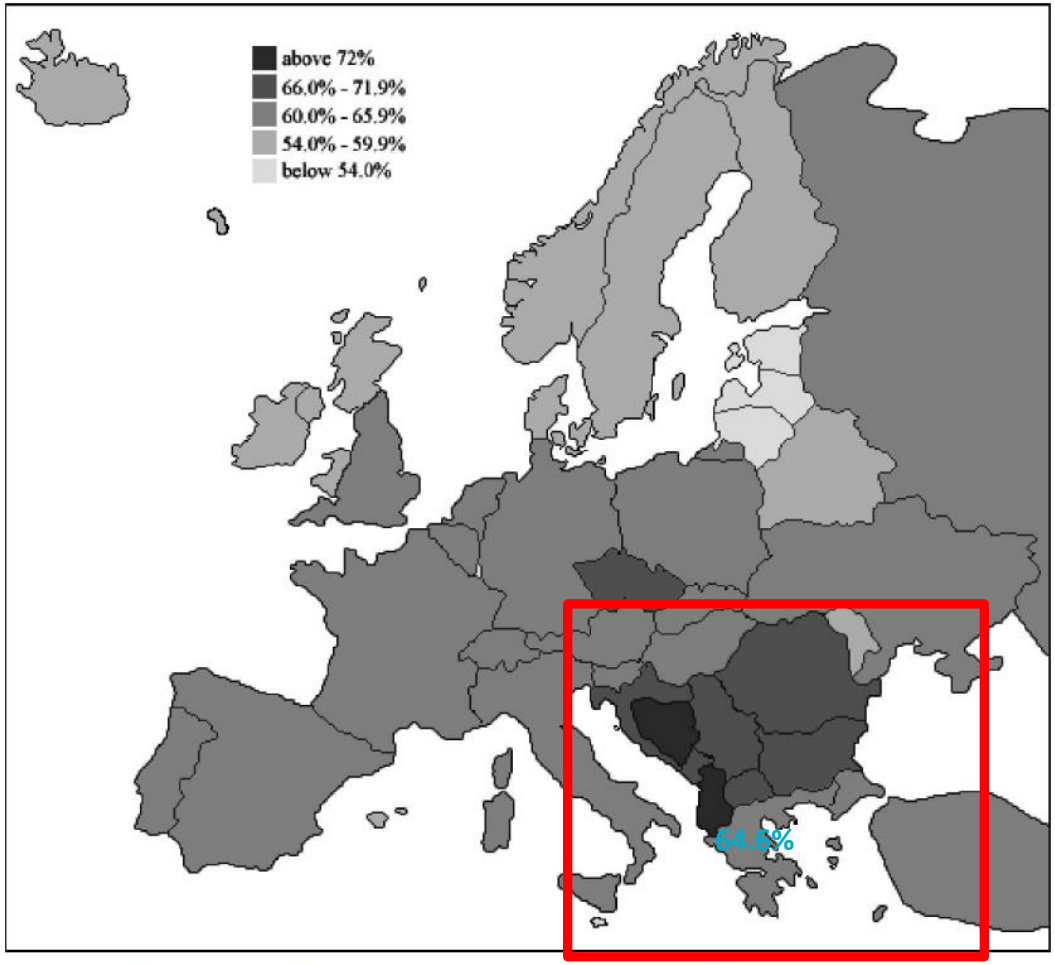


Figure 1. Map of Europe showing home advantage in the national league of each country.

Home effect estimates (% points won) for **1998-2004**

Source: Pollard (2006). Journal of Sports Sciences

Home effect in Super league

+24% (2017-18)

+53% (2018-19)

This is Balkans!

Home effect **+10%**

Home sweet home

- Home effect is stronger in 2nd division leagues compared to 1st division
- Home effect is lower/smaller in derbies (reported in various studies)

Leite & Pollard (2018). Ger J Exerc Sport Res.

Journal of Sports Sciences, September 2007; 25(11): 1185 – 1194

Referee bias contributes to home advantage in English Premiership football

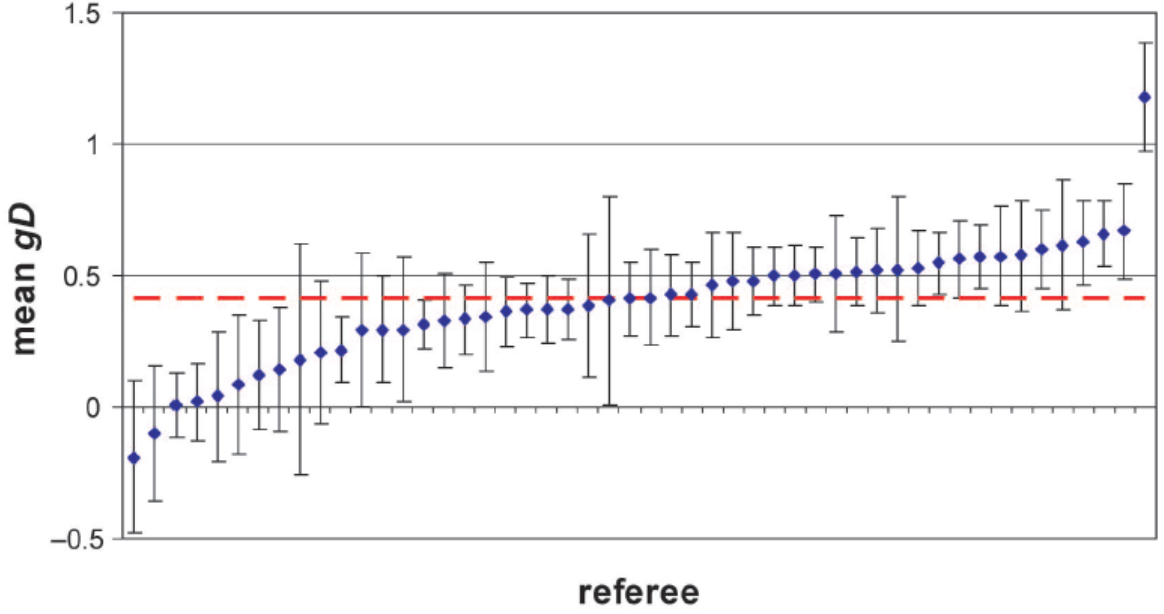


Figure 1. Mean home advantage in terms of goal differential for each of the 50 referees included in the analysis (diamonds) after controlling for team ability and crowd size compared to the league-wide average home advantage (dashed line). Error bars represent standard errors.

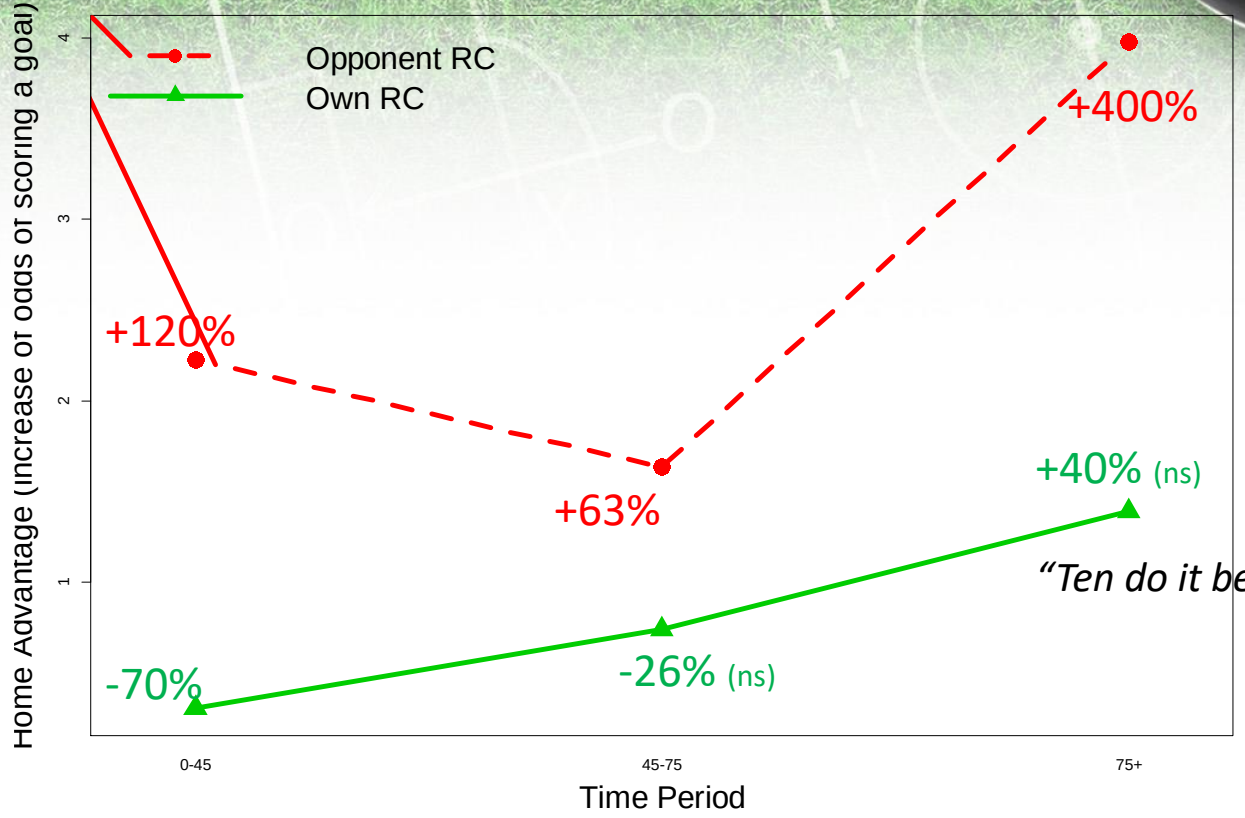
Home effect (goal difference) in Super league

+0.43 (2017-18)

+0.39 (2018-19)

FunStats & Facts – The Red Card Effect

Cerveny, Ours, Tuijl (2018). Empirical Economics



"Ten do it better" myth

FunStats & Facts - **Jersey Color Effect!**

The effect of black uniforms

- Significant in American Football (NFL) and Hockey (NHL)
- Not in Association Football? (At least not in Turkey!)

Perceptual and Motor Skills

0.703 Impact Factor
5-Year Impact Factor 0.826
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Assessing Whether Black Uniforms Affect the Decisions of Turkish Soccer Referees: Is Finding of Frank and Gilovich's Study Valid for Turkish Culture?

M. Şefik Tiryaki

First Published February 1, 2005 | Research Article
https://doi.org/10.2466/pms.100.1.51-57

Article information

Altmetric 1

Abstract

Frank and Gilovich (1988) found that teams with black uniforms were penalized by referees more than other teams that did not wear black uniforms in the U.S. National Football League (NFL), and the U.S. National Hockey League (NHL). This finding was examined for the referees in the Turkish Premier Soccer League (TPSL) for the soccer teams wearing or not wearing black uniforms during actual games. 30 male referees' (ages 22–45 years, M = 34.8) decisions were analyzed in a total of 2,142 Turkish premier soccer league games

FunStats & Facts - **Jersey Color Effect!**

Contents lists available at ScienceDirect

Psychology of Sport and Exercise

journal homepage: www.elsevier.com/locate/psychsport

Short communication

The impact of uniform color on judging tackles in association football

Bjoern Krenn*

- **Red jersey** judged more harshly than the rest for tackles from behind
- "We revealed that tackles from behind were judged more harshly against players dressed in red than against those dressed in blue, green and yellow"
- (the effect is merely significant – p.value=0.07)
- Significant difference vs. blue

FunStats & Facts - **Jersey Color Effect!**

Perceptual and Motor Skills

0.703 Impact Factor
5-Year Impact Factor 0.826
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Color of Soccer Goalkeepers' Uniforms Influences the Outcome of Penalty Kicks

Iain A. Greenlees, Michael Eynon, Richard C. Thelwell

First Published August 1, 2013 | Research Article | Check for updates

https://doi.org/10.2466/30.24.PMS.117x14z6

Article information

Altmetric 11

Abstract

This study examined the proposition that competing against red-clad opponents hinders the performance of soccer (football) athletes. 40 experienced players took 10 penalty kicks against a goalkeeper wearing a black jersey and, 1 week later, took 10 penalty kicks against a goalkeeper wearing either a red, green, blue, or yellow

- **RED Color** is the right color for a **goalkeeper** to catch a penalty!!!
- "Players facing red-clad goalkeepers scored on fewer penalty kicks than those facing either blue- or green-clad goalkeepers, but no differences in expectancy of success emerged. "

FunStats & Facts - **Jersey Color Effect!**

Routledge
Taylor & Francis Group

Journal of Sports Sciences

ISSN: 0264-0414 (Print) 1466-447X (Online) Journal homepage: https://shapeamerica.tandfonline.com/loi/rjsp20

Red shirt colour is associated with long-term team success in English football

Martin J. Attrill , Karen A. Gresty , Russell A. Hill & Robert A. Barton

To cite this article: Martin J. Attrill , Karen A. Gresty , Russell A. Hill & Robert A. Barton (2008) Red shirt colour is associated with long-term team success in English football, Journal of Sports Sciences, 26:6, 577-582, DOI: 10.1080/02640410701736244

FunStats & Facts - **Jersey Color Effect!**

International Journal of Sport and Exercise Psychology, 2014
Vol. 12, No. 1, 10–18, http://dx.doi.org/10.1080/1612197X.2012.756230

Routledge
Taylor & Francis Group

The home advantage over the first 20 seasons of the English Premier League: Effects of shirt colour, team ability and time trends

Mark S. Allen[a]* and Marc V. Jones[b]

[a]*Department of Applied Science, London South Bank University, London, UK;* [b]*Centre for Sport, Health and Exercise Research, Staffordshire University, Stoke-on-Trent, UK*

(*Received 3 July 2012; final version received 22 October 2012*)

FunStats & Facts - **Jersey Color Effect!**

The Guardian

Wearing red helps you win

Tim Radford, *science editor*

Thu 19 May 2005 11.45 BST

Red is the tint for winners. When all else is equal, a sporting strip of scarlet is enough to tip the balance, British scientists report in Nature today.

Almost on the eve of an FA Cup final clash between two teams that both normally sport a red strip, Russell Hill and Robert Barton of the University of Durham have identified a new variable for sporting tipsters and a new challenge for the athletics authorities: red seems to confer an advantage.

"Our results suggest that the evolutionary psychology of aggressive competition is likely to be a fertile field for further investigation," they report. "The implication for regulations governing sporting attire may also be important."

Redness indicates anger, testosterone and male aggression in humans, mandrills and sticklebacks. In experiments, red leg bands have helped ringed birds win a higher place in the pecking order. Red plays a big role in signalling superiority throughout the animal world.

The two scientists decided to investigate the role of red in human contests. They ignored Team Ferrari, with its special tint, and Manchester United and Arsenal's blood-red combat kits, and focused on the sports where the colours are randomly assigned. They examined the outcomes in boxing, tae kwon do, Graeco-Roman and freestyle wrestling, the contact sports of the 2004 Olympics, where contestants were randomly given either red or blue outfits. If colour had nothing to do with it, then the number of red and blue winners should be evenly matched.

FunStats & Facts - **Jersey Color Effect!**

- Man. UND
- Arsenal
- Liverpool

FunStats & Facts - **Jersey Color Effect!**

Color Psychology in Football: The Effect of Shirt Color on a Team's Performance in the Dutch Eredivisie

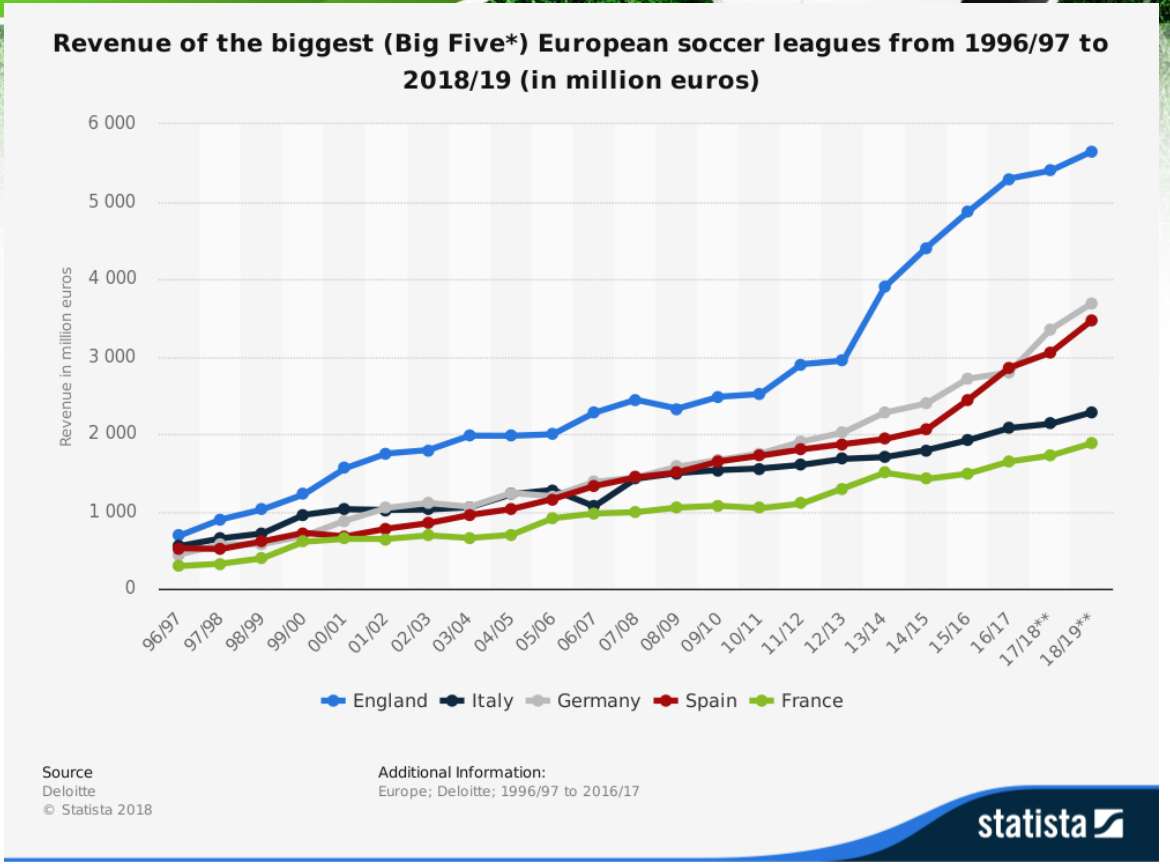
Rosenbaum and Rubin (1983). The found result in this paper is that red colored teams have an advantage in earning points per game and scoring goals relative to getting goals against. These results can have very important implications for club policy makers who want to change the club colors or for people who want to start up a new football team. According to the results, they should choose the color red as the major color for their home shirts.

- **RED** is still important
- Found in Dutch football
- Not in German League
- Also in other sports (handball, Australian football).
- Be careful! Strongly Counfounded with Jerseys of top teams
- What about Greek Football? Is Red Jersey Important?

Ajax Home KIDS Jersey 2018 / 2019

FunStats & Facts

Which league is the wealthiest?



Who was the best player for 2018 (Jan 2019)?

Lars Magnus Hvattum

Professor of Quantitative Logistics

Molde University College

Molde University College
Specialized University in Logistics

Who was the best player for 2018 (Jan 2019)?

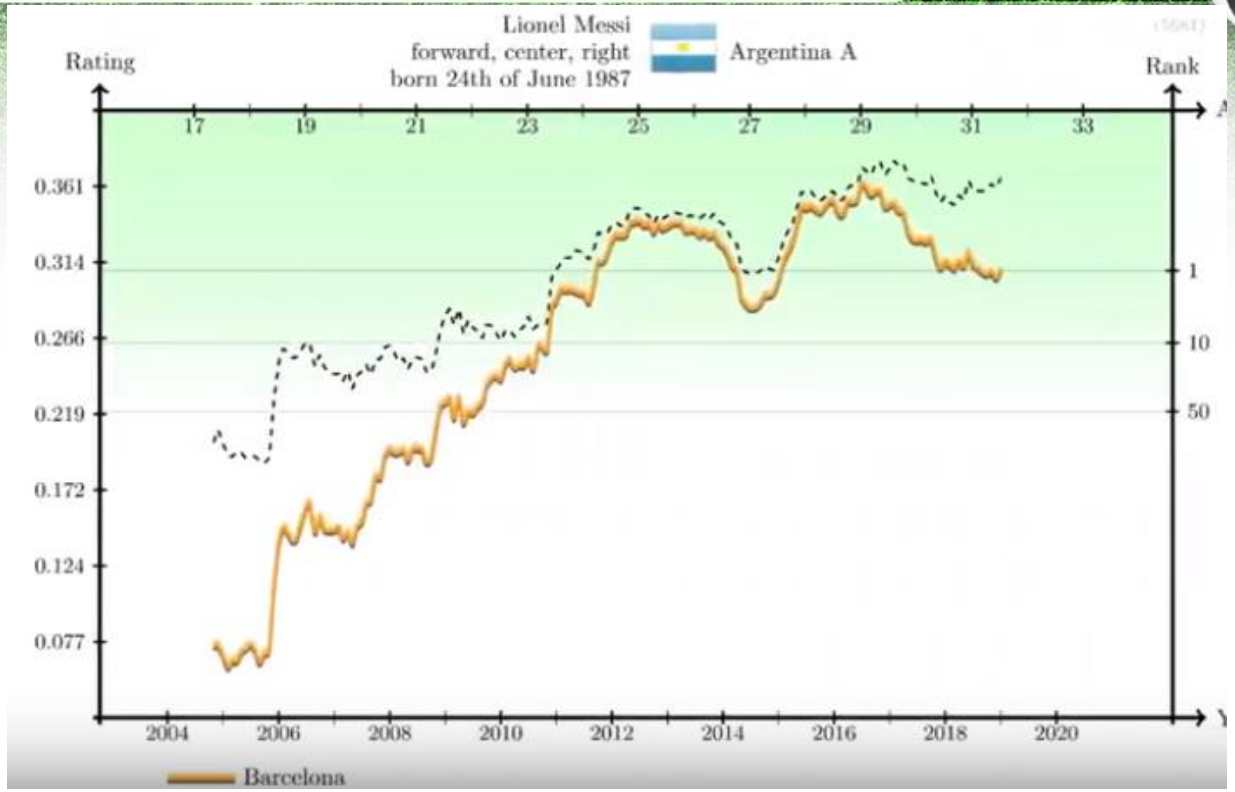
https://gaming.youtube.com/watch?v=jLfACAC4V-I&feature=share

Who was the best player for 2018 (Jan 2019)?

	1	Lionel Messi	31		F	Barcelona	53278	0.365	0.308
↑	2	Neymar	26		F	Paris Saint-Germain	20897	0.313	0.305
↓	3	Thomas Müller	29		F	Bayern München	36226	0.319	0.298
↑	4	Sadio Mané	26		F	Liverpool	22828	0.304	0.297
↑	5	Mohamed Salah	26		F	Liverpool	21439	0.283	0.278
↑	6	David Alaba	26		DM	Bayern München	27614	0.282	0.277
↑	7	Bernardo Silva	24		MF	Manchester City	16382	0.278	0.273
↓	8	Robert Lewandowski	30		F	Bayern München	38539	0.303	0.266
↓	9	Luis Suárez	31		F	Barcelona	39495	0.325	0.264
↓	10	Thiago Alcántara	27		M	Bayern München	17819	0.272	0.263

https://gaming.youtube.com/watch?v=jLfACAC4V-I&feature=share

Who was the best player for 2018 (Jan 2019)?

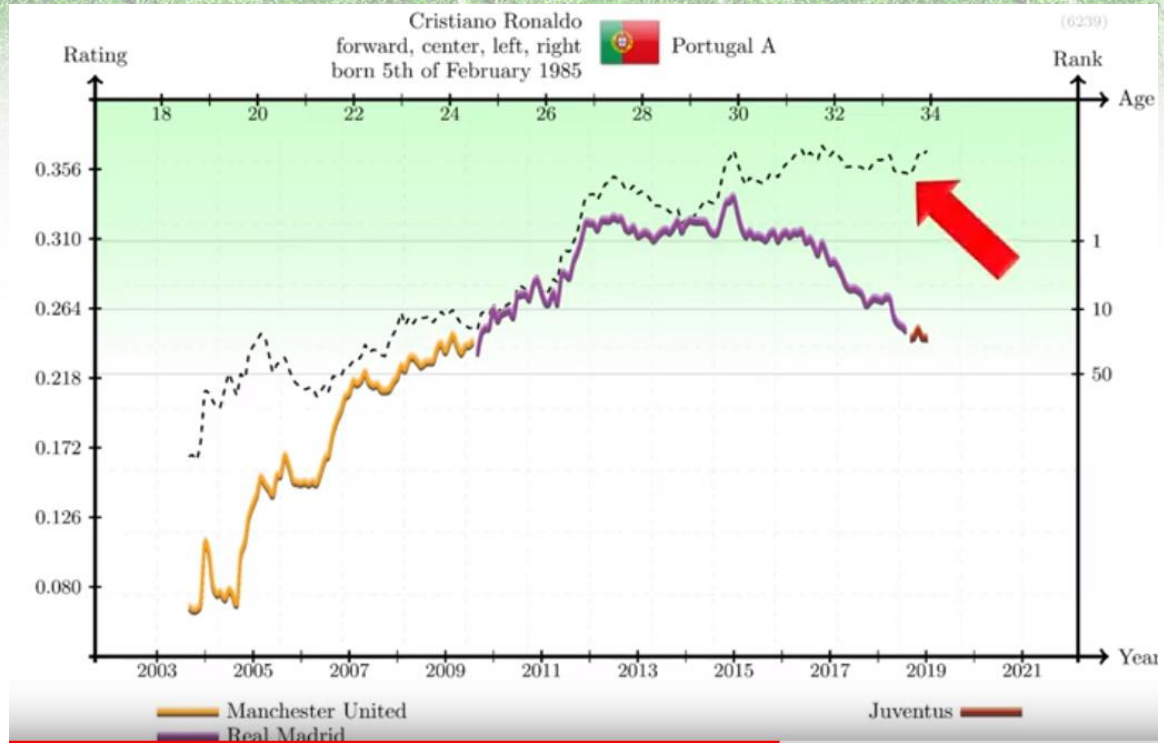


https://gaming.youtube.com/watch?v=jLfACAC4V-I&feature=share

Who was the best player for 2018 (Jan 2019)?

https://gaming.youtube.com/watch?v=jLfACAC4V-I&feature=share

What about Ronaldo?

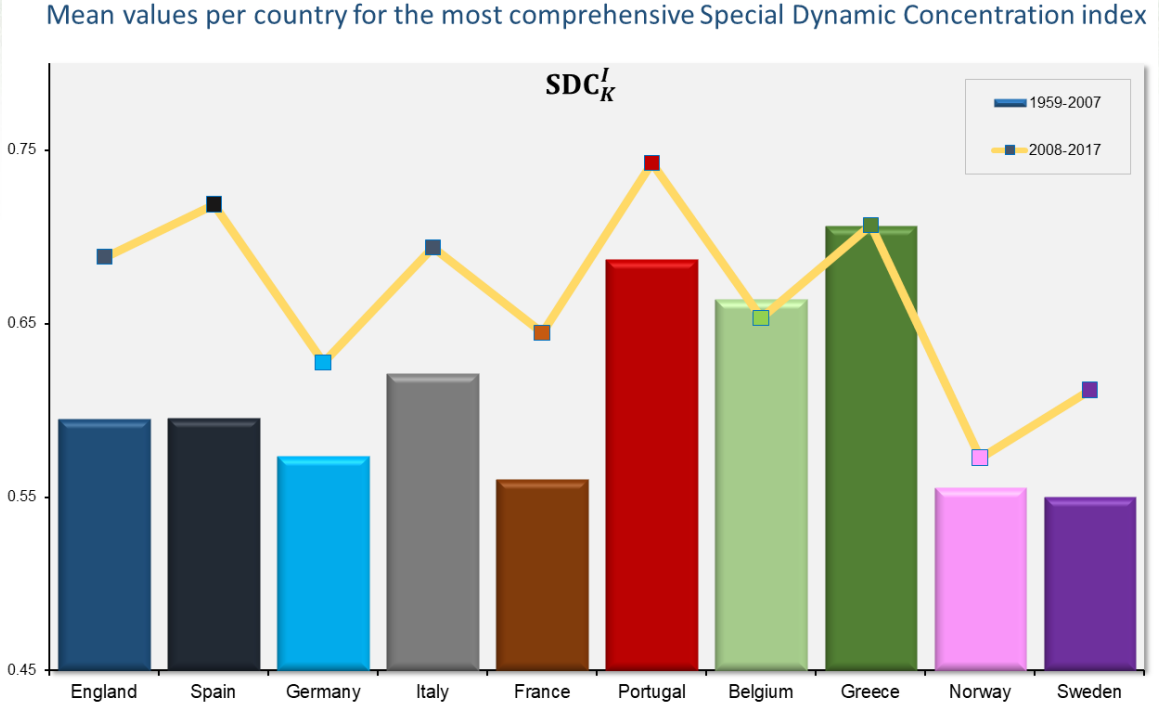


- *Position 23 from 9 (June 2018)*
- *Only player over 33 at top30*
- *Peak rating ⇑*
- *Current rating ⇓ due to*
  - *Age*
  - *Transfer*

https://gaming.youtube.com/watch?v=jLfACAC4V-I&feature=share

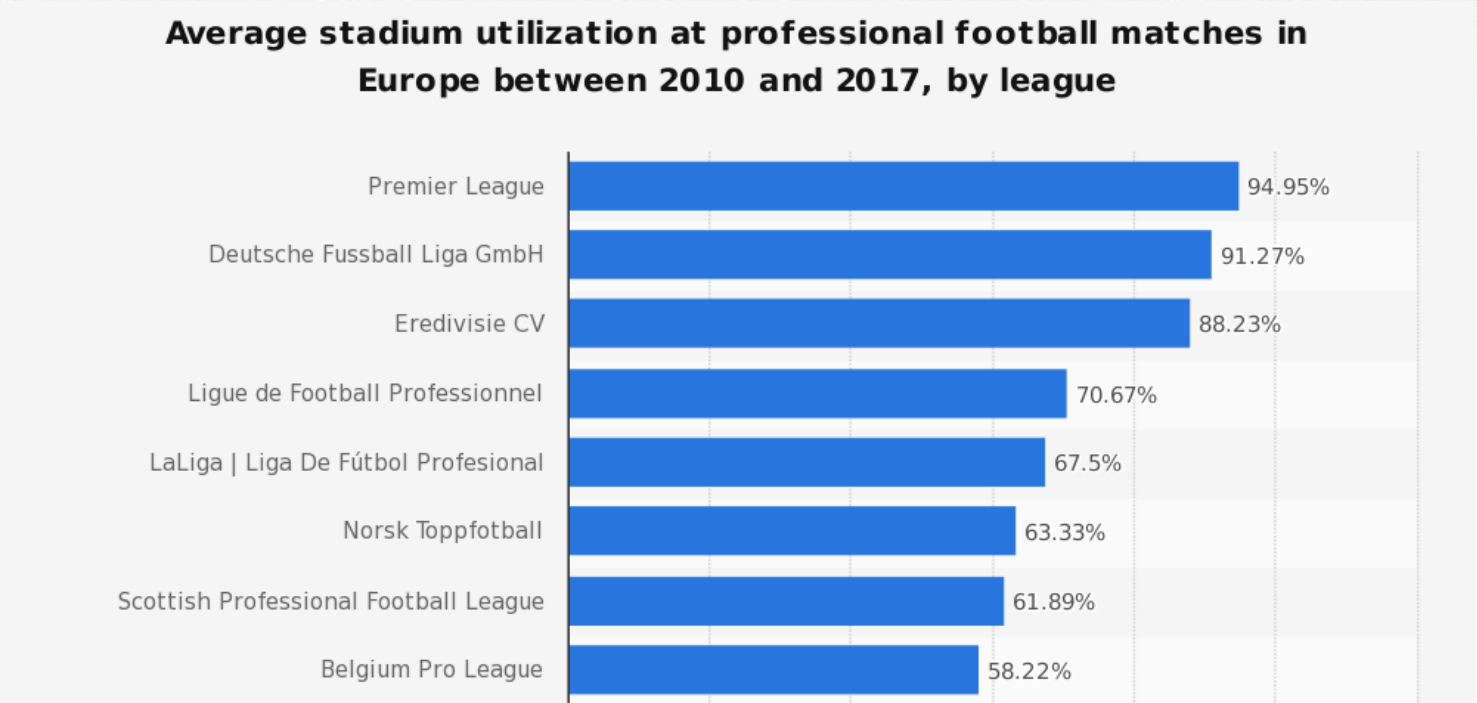
Is the Greek Super League the worst?

Mean values per country for the most comprehensive Special Dynamic Concentration index



FunStats & Facts

Is the Greek Super League the worst?



FunStats & Facts

Celebrating can be Dangerous

More than 1 in 20 soccer injuries are caused by celebrating goals on the pitch.

In the Turkish league a study found that almost 6% of the injuries were caused by goal celebrations.

American Journal of Sports Medicine, 2005, pp. 1237–1240
Picture from FACTSLIDES: https://www.factslides.com/s-Soccer

Concluding remarks

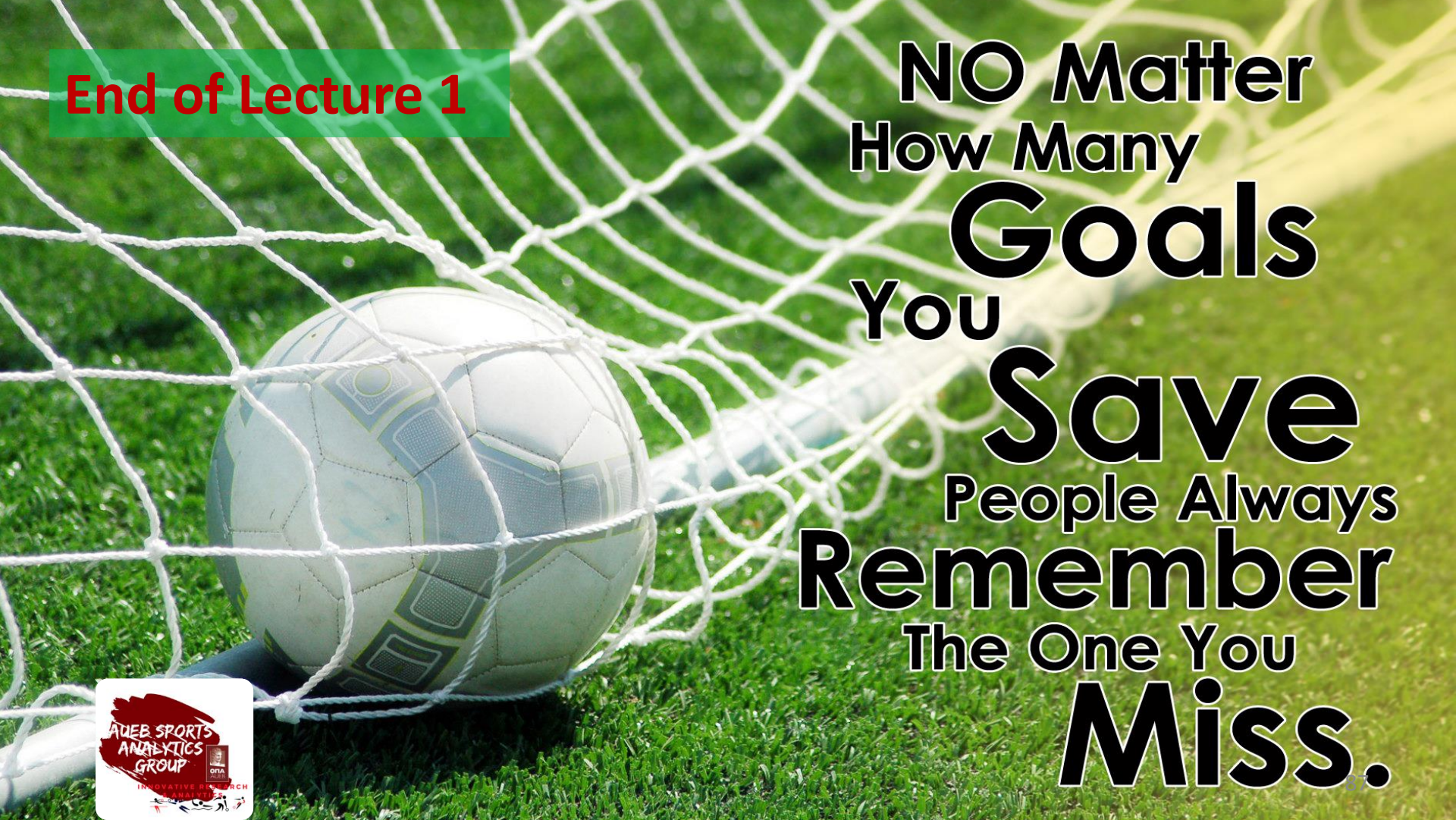
To conclude with

- **Prediction** is important for fans (in terms of betting) ⇒ increases profits of bet companies and interest for the sport product (in macro perspective)
- **Inline prediction** is important for fans (in terms of betting) ⇒ increases profits of bet companies and interest for the sport product (Media – TV, Radio, Internet).

Concluding remarks

- **Player performance and evaluation** $\Rightarrow$ Of main interest for: the fans (Player Ranking), Teams (Scouting, Future Performance and Value), Companies (Sponsoring), Players (A lot of money from all previous), Coaches/Managers (Selection of better players)

- **Physical Measurements** (Training and Games): It is related with player evaluation. Main value to help managers/coaches to improve their teams. In macro perspective also the teams financial position is also improving.

- **Scheduling and Competitive Balance**: More Fair and Balanced contests lead to better product and more profit.

End of Lecture 1