Optimizing football squad selection: A multi-objective approach to transfer strategy under budget constraints

(AUEB Sports Analytics Workshop & Conference 2026)

Soudeep Deb

Indian Institute of Management Bangalore
Bannerghatta Road, Bengaluru 560069, India.
Email: soudeep@iimb.ac.in.

May 4, 2026

Outline

1. Motivation
2. Methodology Overview
3. Modeling player ratings
4. Modeling transfer fees
5. Optimization Framework
6. Competitive bidding strategy
7. Concluding remarks

Collaborators

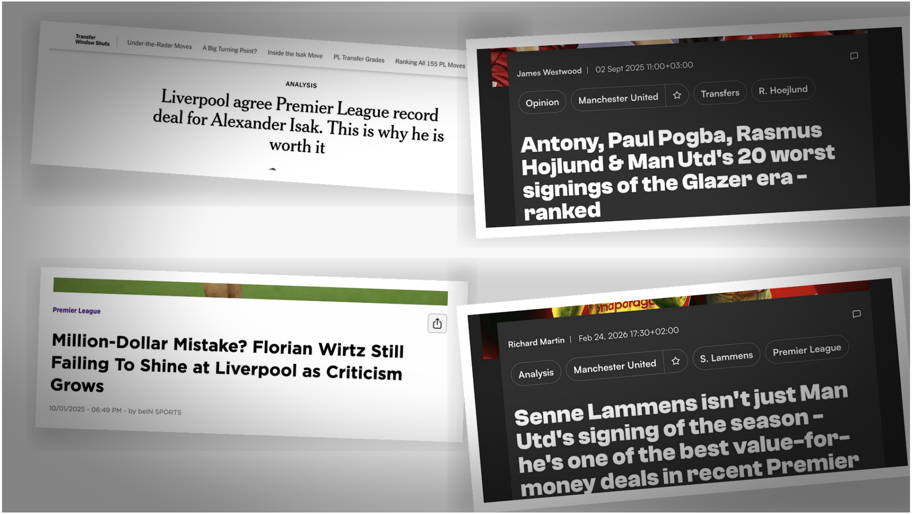
Tathagata Basu
Research Associate
Newcastle University

Rishideep Roy
Lecturer
Univ of Essex

Outline

1. Motivation
2. Methodology Overview
3. Modeling player ratings
4. Modeling transfer fees
5. Optimization Framework
6. Competitive bidding strategy
7. Concluding remarks

It’s always on the news



Introduction and motivation

- Football transfers are high-stakes, time-bound, and uncertain decisions: clubs buy and sell players to reshape squads.
- The transfer market is not only a pricing task; it is a decision problem:
  - predict future contribution (sporting value),
  - predict transfer fees (financial cost),
  - optimize squad composition under constraints.
- Player mobility is high across Europe: average tenure at a club is roughly 1.87–2.56 years.

Auctions, drafts, and transfers

Auctions

- Centralized bidding, Budget and time constraints.
- Requires dynamic valuation and strategy.

Drafts

- Sequential allocation by rules.
- Planning and forecasting.
- Multi-stage decision structure.

Transfers (our focus)

- Decentralized negotiations and clauses.
- Multiple objectives: performance, cost, risk.
- Competition can arise for the same target player.

What the literature has done

- **Player valuation and fee prediction:** regression, multilevel models, and ML using player traits and performance; some benchmark against crowd valuations. (Müller et al, 2017; Franceschi et al., 2024)
- **Economic view of fees:** bargaining and surplus-sharing perspectives that explain why observed fees may differ from productivity measures.(Carmichael et al., 1999; Campa, 2022)
- **Investment and uncertainty:** recent work frames transfers as risky projects with uncertain sporting and financial returns. (Tunaru et al., 2005; Follert & Gleißner, 2024)

What the literature has done

- **Player valuation and fee prediction:** regression, multilevel models, and ML using player traits and performance; some benchmark against crowd valuations. (Müller et al, 2017; Franceschi et al., 2024)
- **Economic view of fees:** bargaining and surplus-sharing perspectives that explain why observed fees may differ from productivity measures.(Carmichael et al., 1999; Campa, 2022)
- **Investment and uncertainty:** recent work frames transfers as risky projects with uncertain sporting and financial returns. (Tunaru et al., 2005; Follert & Gleißner, 2024)
- **Research gap:** studies focus on valuation accuracy for individuals; fewer provide an integrated, constraint-aware decision model.

How this paper contributes

1. Two predictive models grounded in club/league structure
   - next-season rating forecast using linear mixed effects,
   - transfer fee forecast using linear mixed effects on log(fee).
2. A multi-objective optimization framework
   - jointly balances quality, expected cost, and risk,
   - chance constraint for budget feasibility,
   - operational constraints: squad size, positional composition, retention, profit, transfer-count.
3. Competitive layer (extension)
   - embeds optimal transfer decisions in an independent private-value bidding setting with reserve to reason about contested targets.

Outline

1. Motivation
2. Methodology Overview
3. Modeling player ratings
4. Modeling transfer fees
5. Optimization Framework
6. Competitive bidding strategy
7. Concluding remarks

Workflow

- **Step 1: rating model.** Forecast $\hat{R}_{ic_0,s+1}$ for all candidate players (counterfactual rating at the focal club c_0).
- **Step 2: fee model.** Forecast $\widehat{Y}_{i,c\to c_0,s}$ for buying targets and the expected selling prices for current-squad players.
- **Step 3: optimization.** Choose $x_i \in \{0,1\}$ (buy/sell decisions) to maximize quality while controlling expected cost and risk, subject to budget and squad constraints.
- **By-product:** Under optimal recommendations, analyze competitive bidding strategy

Key notations

- Teams $\mathcal{C}$, focal team $c_0 \in \mathcal{C}$; players indexed by $i \in [N]$.
- Decision variable $x_i \in \{0, 1\}$ indicates whether player i is selected in the proposed squad.
- Ratings: $R_{ics} \in \mathbb{R}$ for player i, club c, season s.
- Transfer fee for move $c \to c'$ after season s: $Y_{i,c \to c',s}$.
- Log-fee: $Z_{i,c \to c',s} = \log Y_{i,c \to c',s}$.

Outline

1. Motivation
2. Methodology Overview
3. Modeling player ratings
4. Modeling transfer fees
5. Optimization Framework
6. Competitive bidding strategy
7. Concluding remarks

Modeling player value via ratings

- Goal: forecast counterfactual rating if player i joins c_0 in season $s+1$.
- Linear mixed-effects structure:

$$R_{ics} = \mu_{ics} + u_{(c_{s-1} \to c_s)} + u^{\text{cur}}_{\ell(c_s)} + u^{\text{last}}_{\ell(c_{s-1})} + \varepsilon_{ics}.$$

- Fixed effects in μ_{ics} include: age (quadratic), anthropometrics, position, last-season rating, team context, position-group strength/depth, transfer history, same-team, same-nationality.
- Random effects: origin–destination corridor, current league, last league.

Out-of-sample rating prediction for the focal club

- For candidate player i at club c_0 in season $s+1$, form features $\boldsymbol{x}_{ic_0,s+1}$ using information at end of season s:

$$\hat{R}_{ic_0,s+1} = \boldsymbol{x}_{ic_0,s+1}^{\top}\hat{\boldsymbol{\beta}} + \hat{u}_{(c_s \to c_0)} + \hat{u}^{\mathrm{cur}}_{\ell(c_0)} + \hat{u}^{\mathrm{last}}_{\ell(c_s)}.$$

- If corridor $(c_s \to c_0)$ is unobserved, we shall set $\hat{u}_{(c_s \to c_0)} = 0$ (marginal forecast).
- These $\hat{R}_{ic_0,s+1}$ are the inputs for squad optimization.

Key insights

- **Age profile is nonlinear**: ratings exhibit diminishing returns, supporting a prime-age focus in transfer planning.
- **Strong persistence**: last season's rating is the dominant predictor.
- **Context matters**: higher team quality and positional strength are strongly associated with higher individual ratings, reinforcing the need for squad-level (not player-by-player) optimization.
- **Depth has benefits**: team depth is positively associated with ratings, motivating position-specific constraints in the optimizer.
- **Mobility penalty signal**: more prior transfers are associated with slightly lower subsequent ratings, suggesting adaptation/instability costs that the optimization can treat as an additional risk.

Results

Type of feature	Variable	Estimate	Standard error	df	t-score	p-value
General	Intercept	-1.917^{***}	0.325	18937.944	−5.891	0.000
Player's information	Age (scaled)	0.595^{***}	0.039	37674.916	15.414	0.000
	Age squared (scaled)	-0.111^{***}	0.007	37718.784	−15.409	0.000
	Position (goalkeeper)	-0.955^{**}	0.308	38847.782	−3.099	0.002
	Position (defender)	-0.964^{**}	0.308	38848.973	−3.127	0.002
	Position (midfielder)	-0.940^{**}	0.308	38849.489	−3.050	0.002
	Position (forward)	-0.920^{**}	0.308	38848.768	−2.985	0.003
	Height	0.027	0.018	36548.747	1.494	0.135
	Weight	0.002^{***}	0.000	37059.602	7.684	0.000
	Last season's rating	0.303^{***}	0.005	38868.384	64.854	0.000
	Number of times transferred	-0.004^{**}	0.001	31245.512	−2.923	0.003
	If same team as last season	−0.002	0.003	1125.488	−0.722	0.471
	Playing in the birth country	-0.007^{*}	0.003	33711.504	−2.025	0.043
Team's information	Overall quality	0.258^{***}	0.021	2172.625	12.211	0.000
	Quality in same position	0.723^{***}	0.011	35233.229	67.075	0.000
	#players in same position	0.004^{***}	0.001	28287.721	5.412	0.000

Outline

1 Motivation

2 Methodology Overview

3 Modeling player ratings

4 Modeling transfer fees

5 Optimization Framework

6 Competitive bidding strategy

7 Concluding remarks

Transfer fee model I

- Transfer fees are strictly positive.
- Heavy right tail in empirical data.
- Linear structure becomes tractable on log scale.
- Define the key response variable as

$$Z_{i,c\to c',s} = \log Y_{i,c\to c',s}$$

Transfer fee model II

- Linear mixed effects with buyer/seller heterogeneity:

$$Z_{i,c\to c',s} = \nu_{i,c\to c',s} + b_{c'}^{\text{buy}} + b_{c}^{\text{sell}} + \epsilon_{i,c\to c',s}.$$

- $\nu_{i,c\to c',s}$ includes player characteristics, recent performance, career rating, and market/team context.
- Random intercepts capture systematic mark-ups and discounts by buying and selling clubs.
- A similar framework was adopted by McHale & Holmes (2023).

Transfer fee model: mean structure

Mean term $\nu_{i,c \to c',s}$ is additive in:

- **market trend:** t_s (captures inflation in fees),
- **biographical:** age (quadratic), height, weight, position,
- **quality:** career rating CR_{is} and most recent rating R_{ics},
- **recent performance:** matches, goals, assists, shots, passing accuracy, cards, clearances, interceptions,
- **market context:** club depth and club strength, purchasing and selling patterns of the buyer and the seller league.

Transfer fee model: buyer and seller heterogeneity

- Buyer and seller clubs exhibit persistent, unobserved effects:
  - some clubs systematically pay premiums,
  - some clubs systematically extract higher prices as sellers.
- We capture this via random intercepts:

$$b_{c'}^{\mathrm{buy}} \sim \mathcal{N}(0, \sigma_{\mathrm{buy}}^2), \qquad b_c^{\mathrm{sell}} \sim \mathcal{N}(0, \sigma_{\mathrm{sell}}^2), \qquad \epsilon_{i,c \to c',s} \sim \mathcal{N}(0, \tau^2).$$

- Interpretation:
  - $b_{c'}^{\mathrm{buy}} > 0$: buyer c' tends to overpay relative to observables,
  - $b_c^{\mathrm{sell}} > 0$: seller c tends to command higher fees.

Transfer fee prediction for planning

- For a prospective move $c \to c_0$, form the feature vector $\boldsymbol{w}_{i,c\to c_0,s}$.
- Predicted log-fee:

$$\widehat{Z}_{i,c\to c_0,s} = \boldsymbol{w}_{i,c\to c_0,s}^{\top}\hat{\boldsymbol{\theta}} + \hat{b}_{c_0}^{\text{buy}} + \hat{b}_{c}^{\text{sell}}.$$

- If buyer or seller has no support in training data, set the corresponding random effect to 0 (marginal forecast).
- To obtain a fee on the original scale:
  - baseline point forecast: $\widehat{Y}_{i,c\to c_0,s} = \exp(\widehat{Z}_{i,c\to c_0,s})$,
  - log-normal mean correction (if desired): $\widehat{\mathbb{E}}(Y) = \exp(\widehat{Z} + \frac{1}{2}\hat{\tau}^2)$.
- These predicted fees feed directly into the optimization.

Key insights

- **Market inflation is real**: positive time trend captures systematic fee growth over seasons, so planning needs an inflation adjustment.
- **Lifecycle pricing is concave**: age enters nonlinearly, implying peak pricing around prime years and depreciation thereafter.
- **Roles are different submarkets**: forwards (and to a lesser extent midfielders) command a premium.
- **Long-run quality anchors prices**: career rating is a strong driver of fees, while short-run performance signals refine pricing at the margin.
- **Context calibrates cross-league deals**: league-specific effects shift price levels materially, which is essential when comparing targets across leagues in the squad optimization.

Results I

Type of feature	Variable	Estimate	Standard error	t-score	p-value
General	Intercept	-17.213^{***}	2.141	-8.039	0.000
	Linear trend	0.067^{***}	0.012	5.628	0.000
Player's overall characteristics	Age (scaled)	2.141^{**}	0.744	2.877	0.004
	Age squared (scaled)	-0.620^{***}	0.150	-4.140	0.000
	Position (forward)	0.440^{***}	0.115	3.825	0.000
	Position (midfielder)	0.194^{*}	0.079	2.466	0.014
	Position (goalkeeper)	0.319	0.197	1.623	0.105
	Height	1.376^{**}	0.518	2.653	0.008
	Weight	0.001	0.004	0.361	0.718
	Career rating	1.566^{***}	0.128	12.245	0.000

Results II

Type of feature	Variable	Estimate	Standard error	t-score	p-value
Player's performance in last season	Rating	-0.319^{*}	0.136	-2.357	0.019
	Game-time	0.018^{***}	0.003	6.049	0.000
	Goals	0.408	0.341	1.197	0.231
	Goal contributions	0.152	0.264	0.575	0.566
	Penalty accuracy	-0.540	0.695	-0.776	0.438
	Shots	0.163^{***}	0.043	3.783	0.000
	Passing accuracy	0.022^{***}	0.005	4.165	0.000
	Cards	0.105	0.155	0.675	0.500
	Clearance	-0.004	0.020	-0.184	0.854
	Interception	-0.065	0.043	-1.495	0.135

Results III

Type of feature	Variable	Estimate	Standard error	t-score	p-value
Leagues and teams in last season	Median selling price (seller league)	0.166^{***}	0.019	8.891	0.000
	Median buying price (buyer league)	0.059^{***}	0.010	5.867	0.000
	#players in same position (seller)	−0.008	0.014	−0.618	0.537
	#players in same position (buyer)	0.001	0.012	0.118	0.906
	Quality in same position (seller)	−0.099	0.197	−0.504	0.614
	Quality in same position (buyer)	0.121	0.199	0.608	0.543
	Overall quality (seller)	0.745^{*}	0.301	2.476	0.013
	Overall quality (buyer)	−0.191	0.199	−0.960	0.337

Outline

1. Motivation
2. Methodology Overview
3. Modeling player ratings
4. Modeling transfer fees
5. Optimization Framework
6. Competitive bidding strategy
7. Concluding remarks

Optimization: objective and decision variables

- **Decision**: $x_i \in \{0, 1\}$ selects the proposed squad from $\mathcal{P}$.
- **Inputs**: predicted rating R_i and predicted fee Y_i.
- Consider the following key terms:

$$\text{cost} = \sum_{i \in \mathcal{P} \setminus \mathcal{P}_{c_0}} x_i \, \mathbb{E}(Y_i) + \sum_{i \in \mathcal{P}_{c_0}} (1 - x_i)\big(\mathbb{E}(Y_i) - r_i\big),$$

$$\text{risk} = \sqrt{\sum_{i \in \mathcal{P} \setminus \mathcal{P}_{c_0}} x_i \, \text{Var}\,(Y_i)}, \ \text{quality} = \sum_{i \in \mathcal{P}} x_i R_i.$$

- We focus on the objective

$$\mathcal{F} = -\big(\lambda_1 \,\text{cost} + \lambda_2 \,\text{risk}\big) + \lambda_3 \,\text{quality}.$$

Budget feasibility via chance constraint

- Total spend must stay within transfer budget $B_{\max}$ with high confidence:

$$\Pr\left(\sum_{i \in \mathcal{P} \setminus \mathcal{P}_{c_0}} x_i Y_i \leqslant B_{\max}\right) \geqslant 1 - \alpha.$$

- Deterministic approximation used in the solver:

$$\mathbb{E}\left(\sum_{i \in \mathcal{P} \setminus \mathcal{P}_{c_0}} x_i Y_i\right) + z_\alpha \sqrt{\mathrm{Var}\left(\sum_{i \in \mathcal{P} \setminus \mathcal{P}_{c_0}} x_i Y_i\right)} \leqslant B_{\max}.$$

- Additional constraints: squad size, position minima/maxima, retention, profit, transfer-count, exposure constraints.

Constraints in practice

Squad and sporting constraints

- total squad size $\leqslant \overline{k_{\text{tot}}}$
- position-wise minimum
- maximum number of GK
- retain $\geqslant \underline{k_{\text{retain}}}$ current players
- average age does not increase
- average rating does not decrease

Financial and market constraints

- chance constraint on total spend
- max no of transfers $\leqslant \overline{k_{\text{transfer}}}$
- min profit from sales $\geqslant \underline{\text{profit}}$
- brand exposure constraints
- optional rules: must-buy / must-sell / no-sale list

Solving the constrained optimization

Fitness function:

$$\mathcal{F}_\beta(x) = \Big[-\big(\lambda_1\,\mathrm{cost} + \lambda_2\,\mathrm{risk}\big) + \lambda_3\,\mathrm{quality} \Big] - \beta \sum_{k=1}^{K} \max(0, \mathrm{Constraint}_k),$$

- We use a genetic-algorithm solver with a penalty formulation.
- K equals the number of constraints.
- $\beta \gg 0$ discourages infeasible solutions
- Outputs: the algorithm provides recommended squad, buy list, sell list, and implied cost/risk profile.

Key insights from the algorithm output

- Improved predicted squad ratings for most EPL clubs.
- Budget-respecting transfer portfolios.
- Identifies:
  - undervalued targets
  - overvalued sell candidates
- Demonstrates portfolio-level decision advantage.

Results: Squad metrics

Clubs (2018/19)	Squad (2019)	Est. Squad	Rating (2019)	Est. Rating	Avg Cost	Est. Cost
Manchester City (MNC)	21	25	6.74	7.19	185	150
Chelsea (CHE)	26	24	5.77	6.83	167	121
Manchester United (MNU)	25	30	6.43	6.48	163	82
Liverpool (LIV)	23	27	6.30	6.87	143	111
Arsenal (ARS)	22	27	6.17	6.67	98	72
Everton (EVE)	23	22	6.42	6.75	95	24
Leicester City (LEI)	21	24	6.50	6.73	73	60
Southampton (SOU)	22	26	6.13	6.23	70	35
West Ham United (WHU)	26	30	6.27	6.72	66	46
Tottenham Hotspur (TOT)	24	30	6.25	6.78	65	48
Newcastle United (NEW)	26	27	6.47	6.70	65	39
Watford (WAT)	25	23	**6.64**	**6.57**	53	30
Crystal Palace (CRY)	22	23	6.36	6.58	46	12
Bournemouth (BOU)	24	26	6.41	6.41	45	16
Wolverhampton Wanderers (WOL)	18	23	**6.69**	**6.67**	38	24
Fulham (FUL)	26	24	5.79	6.48	38	11
Brighton & Hove Albion (BHA)	21	24	5.76	6.68	37	14
Burnley (BUR)	21	23	6.68	6.68	31	11
Huddersfield Town (HUD)	29	25	5.12	6.11	23	7

Results: Players to be sold

Team	Player	Position	Transferred (2019)	Expected Price	Last Season Rating
Chelsea	Eden Hazard	Forward	Yes	208	7.68
Manchester United	Romelu Lukaku	Forward	Yes	80	7.29
Liverpool	Sadio Mane	Forward	**No**	76	7.27
Manchester City	**Bernardo Silva**	Midfielder	No	59	6.79
Leicester City	Harry Maguire	Defender	Yes	54	7.08
Manchester City	Riyad Mahrez	Forward	**No**	53	7.28
Tottenham Hotspur	Kieran Trippier	Defender	Yes	44	7.04
Southampton	Mario Lemina	Midfielder	Yes	32	6.93
Manchester United	Chris Smalling	Defender	Yes	31	7.24
Manchester City	Fabian Delph	Midfielder	Yes	29	7.16
Liverpool	**Andrew Robertson**	Defender	No	28	7.02
Southampton	Pierre Emile Hojbjerg	Midfielder	**No**	27	6.61
Newcastle United	Salomon Rondon	Forward	Yes	26	6.77
West Ham United	Andy Carroll	Forward	Yes	26	6.69
Crystal Palace	Aaron Wan-Bissaka	Defender	Yes	24	7.52
Liverpool	Jordan Henderson	Midfielder	**No**	23	6.95
Everton	Kurt Zouma	Defender	Yes	23	7.12

Outline

1. Motivation
2. Methodology Overview
3. Modeling player ratings
4. Modeling transfer fees
5. Optimization Framework
6. Competitive bidding strategy
7. Concluding remarks

Scope and motivation I

- In many transfers, multiple clubs target the same player, so the final fee reflects strategic competition, not just predicted market value.
- Clubs have asymmetric willingness-to-pay (financial strength, sporting objectives), motivating an asymmetric first-price auction framework.
- Sellers may reject the highest bid due to uncertainty and negotiation, so we model a random reserve price and allow a no-sale outcome.
- Football-specific frictions matter: inter-club relationships may affect deals, captured through a bid-dependent acceptance function.

Scope and motivation II

- Goal: translate **contested target** situations into an equilibrium-based tool for expected price, win probability, and negotiation dynamics.
- We take inspirations from the works of Lebrun (1999); Li & Perrigne (2003); Kotowski (2018).

Bidding setting for a contested target

- When multiple clubs target the same player, fees reflect strategic bidding and asymmetric budgets.
- Model the situation as an asymmetric first-price auction with independent private valuations:

$$\log S_c \sim \mathcal{N}(\mu_c, \sigma_c^2), \qquad c \in \mathcal{C}^i.$$

- Each club uses an increasing bid function $b = \kappa_c(s)$ (inverse $\psi_c = \kappa_c^{-1}$).
- Goal: characterize equilibrium bids and translate them into win probabilities and expected fees for planning.

Seller behaviour: random reserve and affinity

- Seller uncertainty is captured via a random reserve price:

$$\log \rho \sim \mathcal{N}(\mu_{c_0}, \sigma_{c_0}^2), \qquad H(b) = \Pr(\rho \leqslant b).$$

- Club-specific deal frictions are captured via bid-dependent acceptance $p_c(b) \in [0, 1]$.
- Buyout clause is modelled by truncation at υ_{thresh}:

$$\hat{H}(b) = \min\left\{\frac{H(b)}{H(\upsilon_{\text{thresh}})}, 1\right\}, \qquad \hat{p}_c(b) = \min\left\{\frac{p_c(b)}{p_c(\upsilon_{\text{thresh}})}, 1\right\}.$$

- This admits no-sale outcomes and captures rivalry/relationship effects.

Equilibrium characterization (main result)

- Probability that club c outbids rivals at bid b:

$$G_c(b) = \prod_{j \neq c} F_j(\psi_j(b)).$$

- Probability of a completed sale to club c at bid b:

$$q_c(b) = \hat{p}_c(b)\hat{H}(b)G_c(b).$$

- Expected utility for valuation s:

$$U_c(b; s) = (s - b)\, q_c(b).$$

- Bayes–Nash equilibrium yields an FOC and an ODE system for $\psi_c(b)$, enabling numerical solution of bidding strategies under asymmetry, random reserve, and affinity.

Theoretical results

Proposition 1

Suppose $p_c(\cdot)$ and $\psi_c(\cdot)$ are continuously differentiable function on $(0, \upsilon_{\text{thresh}}]$. Then, in an interior pure-strategy equilibrium under risk neutrality,

$$\frac{1}{s-b} = \frac{p_c'(b)}{p_c(b)} + \frac{h(b)}{H(b)} + \sum_{j \neq c} \frac{f_j(\psi_j(b))}{F_j(\psi_j(b))} \psi_j'(b).$$

Proposition 2

Suppose $p(\cdot)$ and $\psi_c(\cdot)$ are continuously differentiable in the interval $[b_{\min}, \upsilon_{\text{thresh}}]$ with $p(b), \psi_c(b) > 0$. Then, we get the following system of ODEs, for all c,

$$\psi_c'(b) = \frac{1}{(C-1)} \frac{F_c(\psi_c(b))}{f_c(\psi_c(b))} \left[\sum_{j \neq c} \left(\frac{1}{\psi_j(b) - b} - \frac{p_j'(b)}{p_j(b)} \right) \right.$$
$$\left. - (C-2) \left(\frac{1}{\psi_c(b) - b} - \frac{p_c'(b)}{p_c(b)} \right) - \frac{h(b)}{H(b)} \right].$$

Extension: Bidding in multiple rounds

- Negotiation is modeled as a multiple-round game with the possibility of no-sale.
- In each round, clubs bid, the seller observes the highest bid, then accepts or rejects.
- A rejection updates beliefs about the reserve price, so later rounds become more competitive.
- Buyers update participation by truncating to types that could bid above the last rejected maximum.
- Each round produces an updated equilibrium (solved numerically) with a small bid-gap for stability.

Example: set of players with multiple suggested clubs

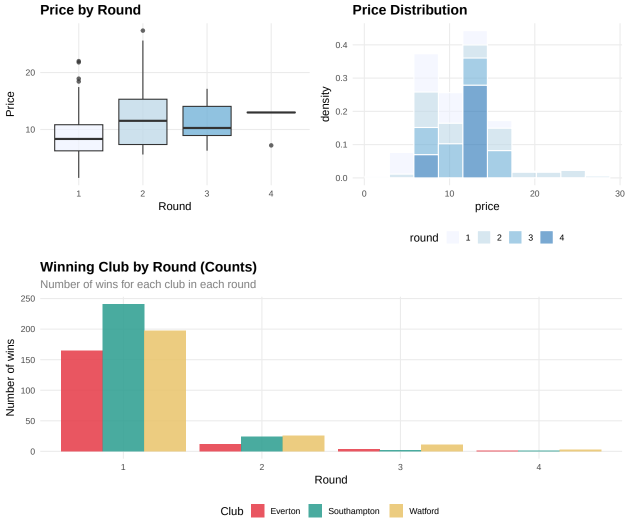
Players	EVE	ARS	CHE	WHU	SOU	MNC	WAT	FUL	TOT	BHA	NEW
M. Almiron	6.1	–	–	–	9.9	–	7.7	–	–	–	–
N. Eliasson	5.4	–	–	–	–	12.6	6.8	–	–	–	–
S. Olivarez	–	–	6.3	4.5	4.7	–	3.5	–	–	–	3.6
S. Hutchinson	–	–	7.9	–	–	–	–	3.1	–	2.8	–
A. Traore	–	–	–	–	–	11.5	6.0	4.1	6.6	–	5.9

Case study of Miguel Almiron I

Analysis for Miguel Almiron

- Total 3 clubs are interested
- Signal for Everton $\mathcal{LN}(1.2, 1.1^2)$
- Signal for Southampton $\mathcal{LN}(1.7, 1.1^2)$
- Signal for Watford $\mathcal{LN}(1.5, 1.1^2)$
- Newcastle United's valuation $\mathcal{LN}(1.5, 1.1^2)$
- Affinity for the three clubs is proportional to $2.7, 4.3, 3.4$

Case study of Miguel Almiron II



Outline

1. Motivation
2. Methodology Overview
3. Modeling player ratings
4. Modeling transfer fees
5. Optimization Framework
6. Competitive bidding strategy
7. Concluding remarks

Key takeaways

- A transfer window can be planned as a multi-objective decision problem: quality, expected cost, and risk.
- Mixed-effects models give club- and league-aware forecasts for both ratings and fees.
- The optimization layer converts forecasts into actionable buy/sell recommendations under realistic constraints.
- Competitive pressure for contested targets can be incorporated to refine expected cost and success probability.

Future scope

- Add richer uncertainty: injuries, minutes forecasts, and scenario-based budget stress tests.
- Extend constraints: wages, amortization, registration rules, and multi-window planning.
- Improve price modeling with contract details and deal structure (add-ons, sell-on clauses).
- Calibrate the bidding layer using observed rival interest and seller affinity signals.

References I

- Campa, D. (2022). Exploring the market of soccer player registrations: An empirical analysis of the difference between transfer fees and estimated players' inherent value. Journal of Sports Economics, 23(4), 379-406.
- Carmichael, F., Forrest, D., Simmons, R. (1999). The labour market in association football: who gets transferred and for how much?. Bulletin of Economic Research, 51(2), 125-150.
- Follert, F., & Gleißner, W. (2024). A decision model to value football player investments under uncertainty. Management Decision, 62(13), 178-200.
- Franceschi, M., Brocard, J. F., Follert, F., Gouguet, J. J. (2024). Determinants of football players' valuation: A systematic review. Journal of Economic Surveys, 38(3), 577-600.
- Kotowski, M. H. (2018). On asymmetric reserve prices. Theoretical Economics, 13(1), 205-237.

References II

- Lebrun, B. (1999). First price auctions in the asymmetric N bidder case. International Economic Review, 40(1), 125-142.
- Li, T., & Perrigne, I. (2003). Timber sale auctions with random reserve prices. Review of Economics and Statistics, 85(1), 189-200.
- McHale, I. G., Holmes, B. (2023). Estimating transfer fees of professional footballers using advanced performance metrics and machine learning. European Journal of Operational Research, 306(1), 389-399.
- M΄uller, O., Simons, A., Weinmann, M. (2017). Beyond crowd judgments: Data-driven estimation of market value in association football. European Journal of Operational Research, 263(2), 611-624.
- Tunaru, R., Clark, E., Viney, H. (2005). An option pricing framework for valuation of football players. Review of financial economics, 14(3-4), 281-295.

Thank you!

Contact: soudeep@iimb.ac.in
Webpage: https://soudeepd.github.io/