Football Quotient: Quantifying National Playing Ability and the Disproportionate Returns to Development Quality in European Professional Football

Anton Mannering

PlayerBuilder Project

Corresponding author: antonmannering@gmail.com

Manuscript prepared for submission

April 2026

Word count: ≈10,500 (main text excluding abstract, tables, and references)

Keywords: football development, talent identification, conversion rate, relative age effect, professional football, national team performance, mean-shifting

Abstract

Background. A persistent empirical puzzle in European football is why small nations—notably Serbia, Croatia, and Scotland—produce professional players at rates far exceeding large, well-resourced nations such as Germany, France, and the Netherlands. Existing accounts cite culture and infrastructure, but lack a quantitative theoretical framework capable of making testable predictions.

Methods. We introduce the Football Quotient (FQ), a latent-ability construct modelled as a normally distributed trait ($\sigma = 15$, analogous to the psychometric IQ scale), and derive the implied national mean FQ for 29 European nations from their senior professional player conversion rates. Player counts were obtained from Transfermarkt squad data for 2024/25, restricted to senior professionals (born $\leq$ 2003), and cross-validated against CIES Football Observatory reports. Registered player totals were compiled from FIFA Big Count supplemented by federation-level sources. Monte Carlo confidence intervals ($n = 10{,}000$) propagated registration uncertainty.

Results. The pan-European conversion rate of 1.17 per 1,000 active players implies a professional threshold of $FQ = 145.6$. Implied national means range from Serbia (109.0; 95% CI 105.9–112.6) to Germany (96.5; 95% CI 95.5–97.4). Regression modelling of FIFA rankings ($n = 29$) identified the number of professionals based abroad as the strongest single predictor (adj-$R^2 = 0.502$, $p < 0.001$), with pool size adding independent variance; the final two-predictor model achieved adj-$R^2 = 0.633$. A preliminary lagged analysis using historical CIES expatriate counts shows that the 2017 abroad count retains a Spearman correlation of +0.52 with the April 2026 FIFA ranking across thirteen European nations, consistent with a leading-indicator interpretation. Relative age effect analysis revealed a pan-European birth-month Q_1/Q_4 ratio of 1.39 ($\chi^2_{11} = 363.6$, $p < 0.001$), with a theoretically consistent reversal in England and Wales (August academic cutoff). Mean FQ improvement of +3 points is analytically equivalent to multiplying the participating population by 1.7–2.0×, depending on baseline distance from threshold.

Conclusions. The FQ framework offers national associations a quantitative basis for development strategy. Because professional output is a threshold phenomenon,

raising the population mean generates disproportionate returns that participation growth alone cannot match at comparable cost. The European Union's free movement of labour provides an empirical market mechanism that continuously calibrates the threshold, lending ecological validity to the model. Associations below the European mean face structural underperformance; those with high participation bases but declining registration trends face a lagged collapse risk. The framework itself and its qualitative implications — mean-shifting efficiency, the size premium, the threshold mechanism, and EU labour-market calibration — are the durable contribution; exact national point estimates are illustrative given current heterogeneity in registration data, but the ranking direction and efficiency calculations are robust within plausible adjustments to the denominators.

Contents

1 Introduction

The production of professional footballers is unequally distributed across Europe in ways that resist simple explanation. France and Germany, with populations of 68 and 85 million respectively and the continent's largest registered player bases, sit near the bottom of European nations in terms of professional players produced per active participant. Serbia (population 6.6 million) and Croatia (3.9 million) produce senior professionals at rates roughly an order of magnitude higher per active participant. Scotland, with 5.5 million people, consistently exports more players per participant than England, despite sharing a border, a language, and comparable infrastructure investment.

These disparities have attracted attention in the coaching science literature, with proposed mechanisms including relative age effects (Barnsley et al., 1985; Cobley et al., 2009; Helsen et al., 2012), talent identification methodology (Vaeyens et al., 2008), and the volume and quality of deliberate practice (Helsen et al., 1998). Informal accounts also point to differences in unstructured play culture and street football, though robust cross-national quantitative evidence on these mechanisms is limited. While each explanation carries empirical support, none provides a unified quantitative framework capable of ranking nations, estimating the magnitude of underperformance, or comparing the cost-effectiveness of competing development interventions.

This paper proposes such a framework. We introduce the *Football Quotient* (FQ), a latent-ability construct that treats the distribution of football ability within a population as approximately normal, calibrated to the pan-European professional player conversion rate. The FQ is not claimed to be a universal psychometric measure; it is an organisational tool for national associations. Each association's playing population has an empirically observed conversion rate to senior professional status, and that rate implies a location for the association's ability distribution relative to the threshold at which professional employment becomes attainable. Shifting that location—raising the mean FQ—produces disproportionate increases in professional output because the relevant quantity is a tail probability.

Although the empirical focus is football, the framework developed here is not solely

a football paper. Professional output in any threshold-based domain depends on how much of the underlying population distribution lies above the relevant threshold. That is a general property of tail statistics, and the development investment logic that follows from it — prioritise raising the mean over expanding elite selection — applies wherever ability is distributed across a population and professional attainment is a threshold event. Football is the test case. The mechanism belongs to a broader theory of developmental investment under threshold conditions, and the paper argues it explicitly in that capacity.

A precedent for this style of analysis exists in the cross-country sports economics literature. Bernard and Busse (2004) model Olympic medal totals as a function of population and economic resources, finding that population and per-capita GDP contribute approximately equally at the margin to a country's Olympic output. Their model rests on the explicit assumption that "athletic talent is most likely distributed normally in the world's population" and that countries can be treated as "arbitrary divisions of the world population," so that medal-calibre athletes appear in the upper tail of a shared underlying distribution. The framework presented here adopts the same distributional and tail-event structure but specialises it in two ways: to a single sport rather than the Olympic medal aggregate, and to a continuously calibrated professional employment threshold rather than a fixed-quota podium. Where Bernard and Busse decompose Olympic output into population and GDP per capita, we decompose football professional output into participation base and a population-mean ability parameter (the FQ), and derive analytically how their relative marginal returns depend on distance from the threshold. The substantive contribution beyond the production-function tradition is the threshold-geometry result — that mean-shifting dominates base expansion at the margin precisely because professional employment is a tail event — together with the identification of the EU football labour market as the empirical mechanism that calibrates the threshold. The parallel with the long-term athlete development literature (Côté and Vierimaa, 2014) should also be acknowledged: the prescription that follows from the framework — invest in the average quality of development rather than in earlier and more aggressive selection — aligns with the "sampling" tradition of that literature, though derived here from a

distributional rather than a developmental-psychology argument.

Three specific contributions are made:

1. We derive implied national mean *FQ* scores for 29 European nations from 2024/25 senior professional player data and demonstrate that the resulting ranking is meaningfully distinct from both FIFA rankings and population size.

2. We provide an analytical result—and supporting empirical illustration—showing that mean-shifting is substantially more efficient than participation growth for generating additional professional players, and quantify this efficiency advantage as a function of a nation's current distance from the professional threshold.

3. We identify a market mechanism—the European Union's free movement of labour for footballers—that continuously calibrates the professional threshold in practice, providing ecological validity for a model that might otherwise appear purely theoretical.

This paper is best understood as a framework offered together with an illustrative empirical pass over the best data currently available. The mathematical structure — threshold via labour-market arbitrage, the multidimensional bundle that the threshold selects on, mean-shifting efficiency under tail probability, the nested tier structure — is the durable contribution and stands independently of how precisely any individual country's mean *FQ* can be estimated today. The empirical estimates are illustrations of what the framework yields when applied to Transfermarkt-derived squad data, FIFA Big Count and federation registration figures, and CIES Football Observatory cross-checks. Each of those sources has known heterogeneity in definition, coverage, and recency. The work is therefore best read as a precursor to a coordinated UEFA-level data effort that the framework itself motivates: consistent registration definitions across federations, pan-European player-tracking with known coverage, longitudinal cohort series, and individual threshold calibration. Section 5.12 sets out that research programme in detail.

The remainder of the paper is structured as follows. Section 2 develops the theoretical framework, including the *FQ* model, the threshold mechanism, and the mean-shifting

efficiency result. Section 3 describes data sources and preprocessing. Section 4 presents national FQ estimates, regression models of FIFA ranking, relative age effect analysis, and size premium calculations. Section 5 discusses implications for national development strategy, structural collapse risk, and the limitations of the approach. Section 6 concludes.

2 Theoretical Framework

The framework that follows is a set of conditional claims. Given the assumptions stated in this section — that football ability is approximately normally distributed within an active playing population, that σ is comparable across nations at the scale used here, and that the European professional labour market arbitrages a continuous threshold T — the mathematical results in Sections 2.4–2.5 follow as theorems and the empirical estimates in Section 4 follow as calculations. Where any assumption fails, the consequences propagate to the conclusions in ways the sensitivity analyses in Sections 5.2 and 5.11 quantify where possible. The paper is best read as a structure offered for inspection: granting the premises gives the conclusions; rejecting a premise indicates exactly which step of the analysis the reader needs to revise.

2.1 The Football Quotient

We model the football ability of a randomly selected member of a nation's active playing population as a random variable $X \sim \mathcal{N}(\mu, \sigma^2)$, where μ is the nation-specific mean ability and $\sigma = 15$ is fixed across all nations. The normal distribution is adopted as a modelling convenience, following the established psychometric convention — traceable to Quetelet's 1835 work on human traits and Galton's 1869 extension to natural ability — of representing individual-difference distributions in unimodal symmetric form (Simonton, 1999), and motivated by its tractability for deriving closed-form efficiency comparisons. The choice of $\sigma = 15$ mirrors the conventional Wechsler IQ scaling (Anastasi and Urbina, 1997), creating an interpretable unit in which one standard deviation separates clearly distinct levels of performance. We do not claim this parameterisation is uniquely correct;

the qualitative results depend only on unimodality and monotone tails, properties shared by all members of the location-scale family.

The *FQ* of an individual is their position on this scale. A national mean *FQ* of 100 places a country at the European average; a mean of 106 (roughly Scotland's estimate) means the median active player in that country is as capable as approximately the 66th-percentile player in an average European country.

2.2 The Professional Threshold

Professional football employment is modelled as a threshold process: a player achieves senior professional status if and only if their ability X exceeds a threshold T. The threshold is not fixed by regulatory fiat but by market forces: the number of professional positions across Europe is finite, and competition for those positions determines who crosses the threshold.

The pan-European conversion rate $\bar{r}$ is defined as:

$$\bar{r} = \frac{\sum_c N_c^{\text{pro}}}{\sum_c P_c^{\text{active}}} \tag{1}$$

where N_c^{pro} is the number of senior professionals from nation c and P_c^{active} is the estimated active playing population. For a country at the European mean ($\mu = 100$), the threshold satisfies:

$$\bar{r} = 1 - \Phi\left(\frac{T - 100}{15}\right) \tag{2}$$

which gives:

$$T = 100 + 15\,\Phi^{-1}(1 - \bar{r}) \tag{3}$$

Given the observed pan-European rate of $\bar{r} = 1.1747 \times 10^{-3}$, this yields $T = 145.6$.

The threshold-truncation form of this model warrants a brief note relative to the prior literature. Simonton (1999) explicitly considered and rejected a threshold-truncation account of *creative productivity* — the proposal that the skewed distribution of creative output reflects nothing more than the upper tail of an underlying normal ability distribution above some minimal threshold for creative work. Simonton's objection is that the right-

hand tail of the productivity distribution extends far beyond what truncation of a normal can produce, requiring multiplicative-influence or combinatorial-explosion mechanisms to generate the observed skew in count data. That objection does not apply to the present framework. The *FQ* model does not predict the distribution of creative or productive output; it predicts the binary outcome of whether an individual crosses the professional employment threshold, which is precisely the case in which truncation of a normal ability distribution is the appropriate model. The conversion rate r_c is a tail probability, not a count distribution, and the mean-shifting efficiency results in Section 2.5 follow directly from this fact. Where Simonton argues that ability-threshold models cannot account for productive output, we are claiming only that ability exceeds a threshold or it does not.

2.3 Implied National Mean FQ

For a nation with mean *FQ* μ_c, the conversion rate is:

$$r_c = 1 - \Phi\left(\frac{T - \mu_c}{15}\right) \tag{4}$$

Inverting, the implied mean *FQ* is:

$$\mu_c = T - 15\,\Phi^{-1}(1 - r_c) \tag{5}$$

This is the central estimator used throughout the empirical analysis. Its interpretation is straightforward: if a country produces professionals at twice the pan-European rate, its ability distribution sits at a higher location on the *FQ* scale, and equation (5) quantifies that location precisely.

2.4 National Team Quality via Order Statistics

A national team is drawn from the upper tail of the country's playing population P_c. Under the *FQ* model, the expected ability of the k-th best player out of P_c is approximately

(Blom, 1958):

$$\mathbb{E}[X_{(k)}] \approx \mu_c + 15\,\Phi^{-1}\left(1 - \frac{k}{P_c}\right) \tag{6}$$

The average FQ of a 30-man national squad (selecting the top 30 from the active population) is therefore:

$$\overline{FQ}_c^{\mathrm{NT}} = \mu_c + \frac{15}{30}\sum_{k=1}^{30} \Phi^{-1}\left(1 - \frac{k}{P_c}\right) \tag{7}$$

Equation (7) captures the *size premium*: a country with a large active population selects its national team from a deeper pool, systematically producing a higher national team quality even when its mean FQ is below the European average. Germany, for example, has an estimated mean FQ of 96.5 but an expected national team average FQ of 162.7—a size premium of +66.2 points. This decomposition is directly relevant to development strategy, as it reveals that large-population nations are insulated from deficiencies in mean ability by pool depth, but only so long as that pool depth is maintained.

2.5 The Mean-Shifting Efficiency Result

Consider two interventions applied to a nation with mean FQ μ_c and active population P_c:

1. **Participation increase**: scale the active population by factor $m > 1$, holding the distribution shape constant. Professional output scales linearly: $N^{\mathrm{pro}} \mapsto m \cdot N^{\mathrm{pro}}$.

2. **Mean shift**: raise the mean FQ by Δ while holding P_c constant. Professional output scales by:

$$\rho(\Delta, \mu_c) = \frac{1 - \Phi\left(\frac{T - \mu_c - \Delta}{15}\right)}{1 - \Phi\left(\frac{T - \mu_c}{15}\right)} \tag{8}$$

Proposition 1. *$\rho(\Delta, \mu_c) > 1$ for all $\Delta > 0$. Moreover, the equivalent participation multiplier $m = \rho(\Delta, \mu_c)$ grows super-linearly in Δ: a +3 FQ shift requires approximately 1.7–2.0× participation to match, a +6 shift requires 3.5–4.0×, and a +9 shift requires 6–8×.*

Sketch. ρ is the ratio of two survival probabilities of the normal distribution with the numerator evaluated at a lower z-score. Since Φ is strictly monotone and the normal

survival function $1 - \Phi(z)$ is log-convex in z, shifting z downward by $\Delta/15$ produces a multiplicative gain in the survival probability that grows with z. The quantitative values follow from numerical evaluation of equation (8) at the empirical threshold $T = 145.6$ across baseline means $\mu_c \in [96.5, 109.0]$. □ □

Corollary 1. *The efficiency advantage of mean-shifting is greatest for countries furthest below the threshold (lowest μ_c), and decreases as a country approaches the threshold. Germany ($\mu_c = 96.5$) gains a $+3$ FQ shift equivalent to $\approx 2.0\times$ participation; Serbia ($\mu_c = 109.0$) gains only $\approx 1.7\times$ equivalent.*

This corollary has a counterintuitive implication: the development efficiency argument for mean-shifting is strongest precisely for countries conventionally regarded as underperforming—those with low mean *FQ*. However, in absolute terms, the *cost* of achieving a given mean shift may differ greatly between nations. Section 5 addresses this distinction.

Figure 1 illustrates the key result. The left panel shows normal distribution curves at baseline and three shifted means, with the professional threshold marked. Even modest rightward shifts visibly increase the shaded tail above the threshold. The right panel plots the professional output multiplier as a function of mean shift for three representative national baselines, demonstrating the super-linear advantage over equivalent participation investment.

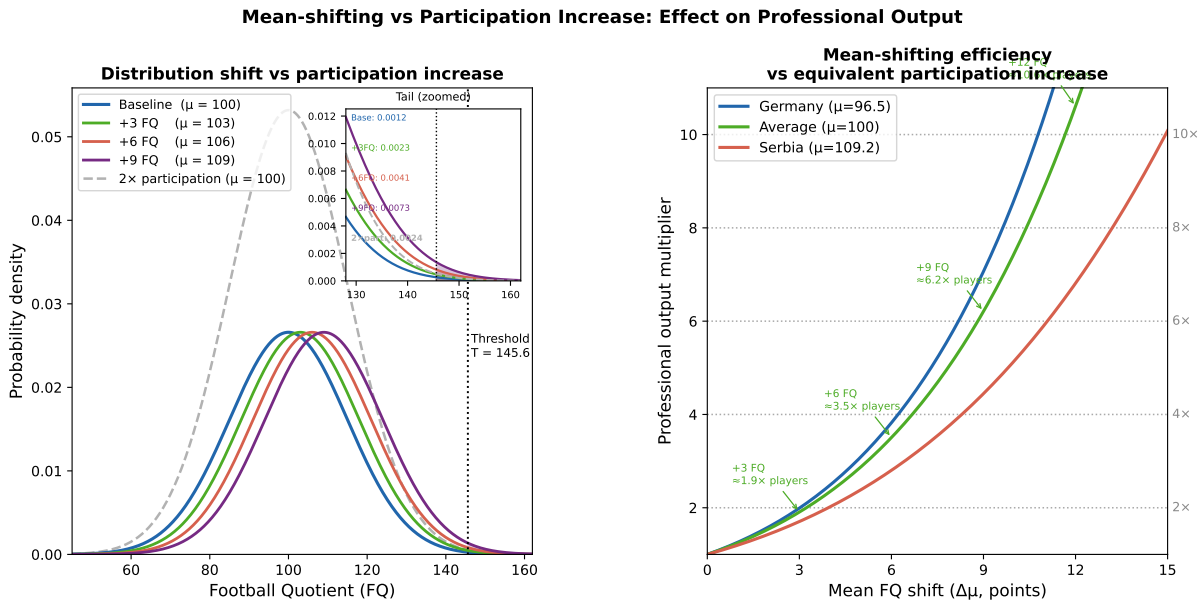

Figure 1: **Mean-shifting versus participation increase.** *Left*: Normal distribution curves for baseline ($\mu = 100$) and three mean-shifted scenarios, with the pan-European professional threshold ($T = 145.6$) marked. The inset zooms the tail above threshold; numerical tail probabilities are annotated. The dashed curve represents a 2× participation increase (same distribution, scaled population). *Right*: Professional output multiplier as a function of mean *FQ* shift $\Delta\mu$ for three national baselines representative of Germany (low mean, large pool), the European average, and Serbia (high mean, small pool). Horizontal reference lines indicate equivalent participation multipliers. A +6 FQ shift achieves what a 3.5× participation increase achieves for the average nation.

2.6 The European Labour Market as Threshold Calibrator

A potential objection to the threshold model is that professional employment levels are institutionally determined—leagues have fixed squad sizes—rather than arising from a continuous ability market. This objection would be decisive if players competed only within their national borders. The European Union's free movement of labour, combined with the longstanding Bosman ruling (Court of Justice of the European Union, 1995), creates instead a continental labour market in which players arbitrage across leagues.[1] A player with *FQ* above 145.6 who cannot secure a domestic contract can and routinely does obtain employment in a league where the threshold is locally lower.

[1]The continental labour market for footballers in fact rests on more than the *Bosman* ruling alone. The Court of Justice subsequently extended non-discrimination protections to nationals of countries holding Association Agreements with the EU (Court of Justice of the European Union, 2003, 2005), and successive EU enlargements (2004, 2007, 2013) brought additional national pools into the freedom-of-movement regime. The cumulative effect is a substantially larger labour market than *Bosman* alone defined.

The empirical evidence for this mechanism is clear: our dataset records 73% of French senior professionals playing abroad, 56% of Croatian professionals, and 56% of Welsh professionals. The cross-border flow is not random but ability-sorted: players migrate to leagues whose quality level matches their ability. This continuous arbitrage ensures that the threshold T is not a modelling artefact but a real economic quantity—the minimum ability level required to obtain and sustain professional employment somewhere in the European professional ecosystem.

What FQ measures, accordingly, is not football skill in a narrow technical sense but the bundle of attributes required to obtain and sustain professional employment in this market. That bundle includes technical and physical ability, but it also includes the psychological and lifestyle factors long recognised in the talent-development literature: willingness to relocate, tolerance of competitive pressure and contract instability, discipline around training and recovery in low-supervision environments, and resilience under repeated rejection. The threshold is therefore defined functionally—by who clears it, through whatever combination of route and bundle works—rather than by any specific developmental pathway. Players reach professional status through many imperfect routes; the threshold is path-invariant because it is set by the labour market that sits downstream of all of them.

The implication is that a national association need not achieve a globally valid normal distribution of ability. It need only shift its distribution rightward relative to the threshold—raising the share of its population that can compete in the continental labour market. The normality assumption is a tractable parameterisation of this monotone relationship; the policy conclusion holds under any unimodal distribution.

The professional threshold as an instance of a nested structure

The threshold model developed here is the professional instance of a more general nested-threshold structure. Every organised tier of football—local recreational leagues, district divisions, regional and semi-professional tiers, lower professional divisions, top-flight, and the elite continental level—operates as a labour market for that tier, with its own

functional threshold and its own conversion rate from the tier below. The mean-shifting result therefore applies at each tier, not only at the professional one; densification of the lower tiers is the mechanism through which the professional tail thickens. This paper concerns the professional threshold because that is where data are most readily collected, but the framework generalises downward, and most of the developmental investment implications discussed in Section 5 act through the lower tiers rather than directly on the professional cutoff.

3 Data and Methods

3.1 Professional Player Counts

Senior professional player counts were obtained from two sources. First, club squad data for 2024/25 was collected from Transfermarkt (https://www.transfermarkt.co.uk) for all professional leagues in 29 European nations, covering both top-flight and lower professional tiers. Player nationality was taken from the primary nationality recorded by Transfermarkt, which reflects the player's principal national association affiliation. Second, for leagues not included in the publicly available dcaribou (dcaribou, 2024) dataset—comprising second and lower tiers in 23 nations—squad pages were scraped directly using standard HTTP requests with rate limiting (≥ 1.5 s between requests).

To obtain a consistent definition of *professional*, we applied a **senior-only filter**: only players born in 2003 or earlier (age ≥ 21 in the 2024/25 season) were counted. This threshold excludes academy and development-squad players who hold nominal professional contracts but have not yet demonstrated sustained professional-level performance. The cut-off is consistent with UEFA and domestic federation definitions of senior professional status and removes the confounding inflation that arises from extended squad lists (/plus/1 pages on Transfermarkt) which include youth development players.

Players appearing in multiple competitions within the same country (for example, an Irish player appearing in both League of Ireland divisions) were deduplicated by Transfermarkt player ID before counting, ensuring each individual is counted once toward

their nation's domestic total.

For nationals playing abroad, counts were cross-validated against CIES Football Observatory monthly reports (CIES Football Observatory, 2024). Where CIES reported higher abroad counts than Transfermarkt (indicating coverage gaps in the scraped data), the CIES figure was used as a lower bound override.

3.2 Registered and Active Player Counts

Registered player totals were compiled from the FIFA Big Count survey (Fédération Internationale de Football Association, 2007) as the primary baseline, updated with the most recent federation-level reports where available. The relevant active population for conversion rate purposes excludes registered players who are inactive, administrative, or referee-affiliated, and excludes female players and players under 16.

A *conflation correction* was applied for nations where the FIFA Big Count registration definition includes all registered individuals regardless of activity level. The correction replaces the FIFA Big Count number with a federation-published active-player figure for those nations where the two disagree materially.[2] Countries were assigned a registration confidence level (HIGH / MED / LOW) based on source recency and specificity.

[2]The size of the correction varies by federation and reflects what each association reported to FIFA in 2006. The Deutscher Fußball-Bund's submission of 6.29M *Vereinsmitglieder* (club members) is the largest documented case: cross-referenced against the DFB *Jahresbericht* 2006, the count of active competitive licence holders was approximately 1.73M, giving an active/total ratio of ~ 0.28. The English FA's submission included recreational and Respect-programme affiliates in addition to competitive players; the FA Active People Survey 2005–07 indicates approximately 1.1M regular competitive players against the 1.53M reported figure (ratio ~ 0.72). The Italian FIGC's submission included non-playing administrative *tesserati*; the FIGC *Rapporto Calcio* 2006 reports 1.4M active tesserati against 1.696M total (ratio ~ 0.83). Smaller corrections were applied to France (FFF *Rapport Annuel*, ~ 0.91) and Spain (RFEF *Memoria*, ~ 0.96). Federations whose reporting matched their active competitive register — including the Croatian, Scottish, Welsh, and Nordic associations — received no adjustment. The full per-country adjustment factor and source citation is in the supplementary data file `registered_base.csv`.

Table 1: **Data coverage summary.** Leagues covered, total clubs, and player count before and after senior filter, by source.

Source	Nations	Leagues	Senior pros (post-filter)
dcaribou (StatsBomb open data)	29	29	13,407
Transfermarkt scraped (domestic)	23	57	5,132
CIES abroad override	8	—	1,110
Total (deduplicated)	29	86	19,649

3.3 FQ Calculation

The pan-European conversion rate was computed as total senior professionals divided by the sum of estimated active players across all 29 nations ($\bar{r} = 1.1747 \times 10^{-3}$). The professional threshold was derived from equation (3), giving $T = 145.6$. National implied means were computed from equation (5) using each nation's conversion rate r_c.

3.4 Confidence Intervals

Registration totals are known with varying precision. To propagate this uncertainty into *FQ* estimates, we conducted a Monte Carlo simulation ($n = 10{,}000$ iterations) in which registered player counts were drawn from log-normal distributions. The log-normal coefficient of variation (CV) was set according to confidence level: HIGH (CV = 0.05), MED (CV = 0.12), LOW (CV = 0.20). Professional player counts were simultaneously perturbed by ±10% uniform noise to reflect coverage uncertainty. The 2.5th and 97.5th percentiles of the resulting *FQ* distribution define the reported 95% confidence intervals.

3.5 Regression Models

To assess the relationship between the *FQ* framework measures and competitive outcome, FIFA world rankings (April 2026) were regressed on combinations of: (1) log-transformed active pool size, (2) log-transformed abroad professional count, and (3) implied mean *FQ*. Six nested models were estimated using OLS with robust standard errors. Spearman partial

correlations controlling for log pool size were computed to assess directional relationships without distributional assumptions. Variance inflation factors (VIF) were computed for collinearity diagnostics.

3.6 Relative Age Effect Analysis

Date of birth (day, month, year) was extracted for all senior professionals with available data ($n = 20{,}197$). Birth months were tabulated and compared against a uniform expected distribution scaled to the number of days in each month. An overall χ^2 test ($df = 11$) was conducted, followed by per-country χ^2 tests. The Q_1/Q_4 ratio (January–March versus October–December) was used as a summary statistic. For England and Wales, the analysis was repeated using an August academic year cutoff (Q_1' = August–October, Q_4' = May–July) to reflect the known reversal of relative age effects under different institutional cutoff dates (Helsen et al., 2000; Musch and Grondin, 2001).

4 Results

4.1 National FQ Estimates

Table 2 presents the full results for all 29 nations. The pan-European conversion rate of 1.17 per 1,000 active players implies a professional threshold of $T = 145.6$—approximately 3 standard deviations above the European mean ability.

Table 2: **National Football Quotient estimates, 2024/25.** Countries ranked by implied mean *FQ*. CI = 95% Monte Carlo confidence interval. NT Avg = expected national team average *FQ* (top-30 order statistic). Abroad% = proportion of senior professionals based outside home country. Conf. = registration confidence level. The Pan-European row reports the aggregate active pool and senior professional count; the listed mean FQ of 100 is by calibration construction (see equation 3) rather than a population-weighted average of the country estimates.

Country	Active pool	Total pros	Abroad (abs.)	Abroad (%)	Mean *FQ*	CI (95%)	NT Avg	FIFA Rank	Conf.
Serbia	120,194	878	392	44.6	109.0	[105.9–112.6]	164.9	39	LOW
Croatia	118,316	697	392	56.2	107.9	[105.3–110.8]	163.5	11	LOW
Scotland	161,412	747	190	25.4	106.6	[105.3–107.6]	163.4	43	HIGH
Slovenia	60,334	216	99	45.8	105.3	[103.7–106.8]	158.3	58	MED
Slovakia	90,000	282	119	42.2	104.6	[102.5–106.8]	159.2	48	LOW
Wales	105,603	306	170	55.6	104.2	[103.0–105.2]	159.4	37	HIGH
Portugal	235,000	665	363	54.6	104.1	[102.8–105.3]	162.3	5	HIGH
Ireland	220,000	471	217	46.1	102.7	[101.6–103.7]	160.7	59	HIGH
Bulgaria	120,000	236	46	19.5	102.4	[100.4–104.5]	158.1	86	LOW
Romania	300,000	567	67	11.8	102.2	[100.5–103.9]	161.3	56	MED
Austria	248,000	447	131	29.3	102.0	[100.5–103.4]	160.4	24	MED
Sweden	379,681	649	265	40.8	101.7	[100.6–102.6]	161.7	38	HIGH
England	1,400,000	2,169	586	27.0	101.3	[100.2–102.2]	165.7	4	HIGH
Finland	150,894	231	71	30.7	101.2	[100.1–102.1]	157.7	73	HIGH
Czech Rep.	358,000	535	84	15.7	101.1	[99.6–102.5]	160.8	41	MED
Italy	1,131,906	1,689	165	9.8	101.1	[99.9–102.0]	164.8	12	HIGH
Denmark	381,840	534	269	50.4	100.8	[99.7–101.7]	160.7	20	HIGH
Belgium	400,000	529	294	55.6	100.5	[99.4–101.5]	160.6	9	HIGH
Norway	413,139	513	161	31.4	100.2	[99.1–101.2]	160.4	31	HIGH
Switzerland	273,644	334	114	34.1	100.1	[98.7–101.5]	158.9	19	MED
Greece	200,000	197	86	43.7	99.2	[97.6–100.8]	156.8	47	MED
Spain	1,248,511	1,146	451	39.4	98.9	[97.8– 99.8]	162.9	2	HIGH
Ukraine	1,016,000	810	204	25.2	98.3	[96.4–100.2]	161.6	32	LOW
Hungary	300,000	239	68	28.5	98.2	[97.2– 99.1]	157.3	42	HIGH
France	2,060,960	1,494	1091	73.0	97.8	[96.8– 98.7]	163.5	1	HIGH
Poland	769,000	536	112	20.9	97.7	[95.9– 99.6]	160.1	35	LOW
Netherlands	1,100,000	714	367	51.4	97.4	[96.3– 98.2]	160.9	7	HIGH

The range of implied mean FQ scores spans 12.5 points, from Serbia (109.0) to Germany (96.5). This span, while appearing modest on the $\mathcal{N}(100, 15^2)$ scale, translates to large differences in tail probability: a country at $\mu = 109$ produces professionals at roughly 14× the rate of a country at $\mu = 96.5$, given the same active population.

Several features of Table 2 are noteworthy:

- **FIFA ranking and mean *FQ* are weakly correlated.** France (FIFA rank 1) has a mean FQ of 97.8, below the European average. Germany (FIFA rank 10) sits at 96.5, the lowest estimate in the dataset. These nations compensate for below-average ability distributions with exceptional pool depth (size premium of +66 and +66 FQ points, respectively; see Section 4.3).

- **Small nations at the top of the *FQ* ranking convert at multiples of the European average.** Serbia (7.3 per 1,000, 6.2× the European mean), Croatia (5.9 per 1,000, 5.0×), and Scotland (4.6 per 1,000, 3.9×) achieve this without large absolute populations, indicating genuine distributional advantages rather than simple scale effects.

- **Abroad percentage varies widely.** France (73%), Wales (55.6%), Croatia (56.2%), and Belgium (55.6%) export the highest fractions of their professionals, consistent with the EU labour market arbitrage mechanism described in Section 2. Turkey (9%) and Romania (11.8%) show low abroad percentages, suggesting either lower international labour mobility or systematic undercounting of abroad professionals.

4.2 Regression Models of FIFA Ranking

Table 3 presents six nested OLS models predicting FIFA ranking (April 2026). The dependent variable is coded as −rank so that higher values represent better rankings, enabling positive coefficients to indicate beneficial predictors.

Table 3: **OLS regression results: predictors of FIFA ranking** ($n = 29$). Dependent variable: −FIFA rank (higher = better). Robust standard errors. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	Model			
Predictor	(1)	(2)	(3)	(4)
Constant	-216.9^{***}	-136.5^{***}	-701.8^{**}	-227.8^{***}
log(active pool)	14.5^{***}	—	23.6^{***}	9.2^{**}
log(abroad count)	—	20.2^{***}	—	15.1^{***}
Mean *FQ*	—	—	3.6^{*}	—
R^2	0.427	0.520	0.541	0.659
adj-R^2	0.405	0.502	0.506	0.633

	Model 5 (full): mean *FQ* + pool + abroad			
	$\hat{\beta}$	SE	t	p
Constant	−248.3	230.0	−1.08	0.291
Mean *FQ*	0.2	1.7	0.09	0.929
log(active pool)	9.7	6.2	1.56	0.130
log(abroad count)	14.8	5.0	2.94	0.007**
adj-R^2	0.618; VIF: mean FQ 4.6, log(pool) 5.8, log(abroad) 2.3			

The key results are:

1. Abroad count is the strongest single predictor of FIFA ranking (Model 2, adj-$R^2 = 0.502$), outperforming pool size (adj-$R^2 = 0.405$).

2. Pool size and abroad count together explain 63% of variance in FIFA ranking (Model 4, adj-$R^2 = 0.633$). Both predictors remain significant ($p < 0.01$, $p < 0.001$) with no severe collinearity (VIF < 6).

3. When mean *FQ* is added to pool and abroad count (Model 5), it becomes entirely non-significant ($p = 0.929$). Mean *FQ* information is fully absorbed into the abroad

count, which is its primary manifestation: countries with high mean FQ produce more professionals per capita who then compete in higher-quality foreign leagues.

4. Spearman partial correlation of abroad count controlling for log pool size: $\rho = +0.68$, $p < 0.001$. For mean FQ controlling for pool size: $\rho = +0.37$, $p = 0.051$ (borderline).

These results suggest that FIFA ranking is primarily a function of a country's ability to produce and export internationally competitive players, rather than a simple function of population size. The mean FQ framework captures the underlying mechanism, but the most tractable observable proxy is the abroad count.

Figure 2 visualises the joint relationship between mean FQ, FIFA ranking, pool size, and abroad percentage across all 29 nations. The pattern is consistent with the regression results: large-pool nations (large bubbles) cluster in the upper-left quadrant (low FQ, high FIFA ranking), while high-FQ small nations occupy the right side with lower FIFA rankings but high per-capita conversion rates.

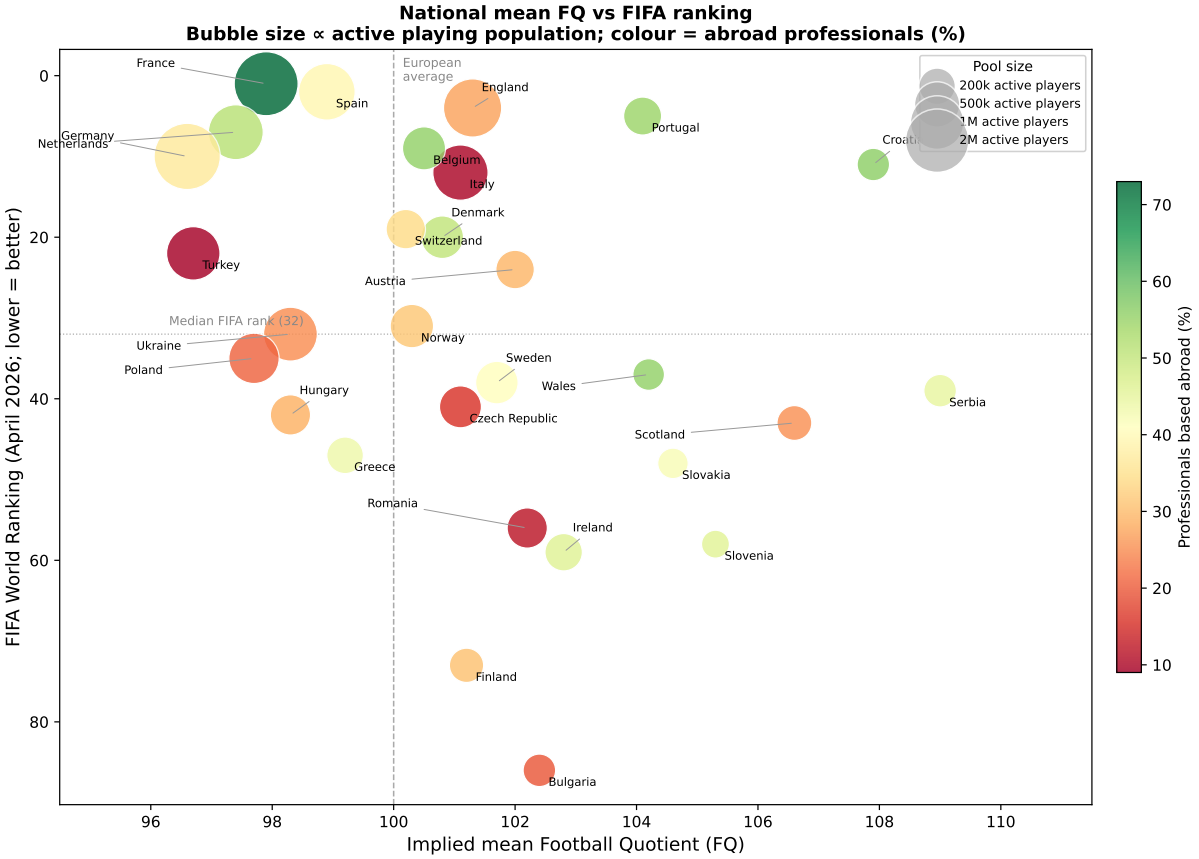

Figure 2: **National mean FQ versus FIFA world ranking.** Bubble size is proportional to the square root of the active playing population. Colour indicates the proportion of senior professionals based abroad. The vertical dashed line marks the European mean (FQ = 100); the horizontal dotted line marks the median FIFA ranking in the sample. Large-pool nations (large bubbles) achieve high FIFA rankings despite below-average mean FQ via the size premium. High-FQ small nations (right side) produce professionals at high per-capita rates but rank lower due to limited pool depth.

4.3 The Size Premium

Table 4 presents the decomposition of expected national team quality into mean FQ and size premium for selected nations.

Table 4: **Size premium decomposition** for selected nations. Mean *FQ*: implied population mean. NT Avg: expected national team average (equation 7). Premium = NT Avg − Mean *FQ*.

Country	Active pool	Mean *FQ*	NT Avg	Premium	FIFA Rank
England	1,400,000	101.3	165.7	+64.4	4
Germany	2,380,000	96.5	162.7	+66.2	10
France	2,060,960	97.8	163.5	+65.7	1
Italy	1,131,906	101.1	164.8	+63.7	12
Spain	1,248,511	98.9	162.9	+64.0	2
Portugal	235,000	104.1	162.3	+58.2	5
Serbia	120,194	109.0	164.9	+55.9	39
Croatia	118,316	107.9	163.5	+55.6	11
Scotland	161,412	106.6	163.4	+56.8	43
Slovenia	60,334	105.3	158.3	+53.0	58

The size premium analysis reveals why large nations dominate FIFA rankings despite below-average mean *FQ*. Germany's +66.2 point premium means its national team draws talent from the extreme right tail of a large population; even if the underlying mean is 3.5 points below Serbia's, the expected national team quality is comparable because the deeper pool compensates. Serbia's +55.9 premium—achieved with only 120,000 active players—reflects the remarkable tail selection available even from a small but high-mean population.

Portugal exemplifies the intermediate case: a mean *FQ* of 104.1 combined with a moderate active pool of 235,000 yields an expected national team quality of 162.3, broadly comparable to France (163.5 expected) despite a pool 9× smaller. Portugal's consistent placement among the world's top five nations is well explained by this combination.

4.4 Relative Age Effect

Table 5 presents birth month distributions for senior professionals in the dataset.

Table 5: **Pan-European birth month distribution** ($n = 20{,}197$ senior professionals). RAE Index = observed / expected (uniform). Q1 = January–March; Q4 = October–December.

Month	Count	Expected	RAE Index
January	2,120	1,683	1.26
February	1,871	1,683	1.11
March	1,937	1,683	1.15
April	1,781	1,683	1.06
May	1,757	1,683	1.04
June	1,544	1,683	0.92
July	1,707	1,683	1.01
August	1,511	1,683	0.90
September	1,711	1,683	1.02
October	1,596	1,683	0.95
November	1,318	1,683	0.78
December	1,344	1,683	0.80
$\chi^2(11) = 363.6$, $p < 0.001$; Q1/Q4 ratio = 1.39			

Table 6 presents per-country Q1/Q4 ratios under the calendar-year quarter definition. The pattern across countries is referenced throughout Sections 4.4 and 5.4.

Table 6: **National Q1/Q4 birth-month ratios for senior professionals.** Q1 = January–March; Q4 = October–December. Sorted by ratio descending under calendar-year quarters. England and Wales appear at the bottom because their September-1st academic cutoff inverts the calendar-year pattern; the August-cutoff–adjusted ratios for these two nations reverse direction (England 1.42***, Wales 1.38***; see Section 4.4). Significance: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (χ^2 test against uniform birth-month expectation).

Country	n	Q1	Q4	Q1/Q4
Czech Republic	595	170	80	2.13***
Germany	1,116	370	176	2.10***
Spain	1,073	350	177	1.98***
Turkey	606	204	108	1.89***
Italy	1,900	649	347	1.87***
Portugal	562	181	98	1.85***
Belgium	420	138	76	1.82*
Finland	242	77	43	1.79**
Ukraine	807	249	140	1.78***
Switzerland	364	128	72	1.78**
Austria	471	141	82	1.72**
Netherlands	651	203	121	1.68**
Serbia	715	201	123	1.63***
Poland	585	180	114	1.58**
Denmark	512	159	102	1.56***
Romania	617	175	113	1.55**
Norway	548	148	96	1.54***
Croatia	555	164	109	1.50*
France	929	271	184	1.47**
Scotland	853	262	181	1.45*
Slovenia	225	73	53	1.38
Sweden	651	168	133	1.26**
Ireland	603	175	139	1.26*
Hungary	247	66	53	1.25
Slovakia	286	73	59	1.24
Bulgaria	261	73	60	1.22
Greece	200	51	42	1.21*
Inverted under calendar-year quarters (September academic cutoff):				

The pan-European Q1/Q4 ratio of 1.39 confirms a systematic early-birth advantage: players born in January are 26% overrepresented relative to uniform expectation, while November-born players are underrepresented by 22%. At the country level, the effect is strongest in nations with well-established youth academy systems and January 1st age-group cutoffs: Czech Republic (Q1/Q4 = 2.13***, $p < 0.001$), Germany (2.10***), Spain (1.98***), Turkey (1.89***), and Italy (1.87***).

The theoretically predicted reversal is observed in England (Q1/Q4 = 0.71 under calendar-year quarters; adjusted August-cutoff Q1/Q4 = 1.42***) and Wales (0.67; adjusted 1.38***), where the September 1st academic cutoff means that players born in August and September are relatively older within their cohort and thus disproportionately selected into elite development pathways.

The RAE finding has a direct relationship to the *FQ* framework. The pan-European Q1/Q4 ratio of 1.39 implies roughly 1,800 "displaced" professionals across the dataset — around 9% of the total — whose presence in or absence from the professional pool is more plausibly explained by birth-month-driven selection than by ability. To the extent this displacement holds, the professional threshold is an imperfect sorter of underlying ability. Debiasing talent identification to remove relative age effects would improve the signal quality of the professional conversion rate as an ability indicator, and would likely shift implied mean *FQ* estimates upward for nations with the strongest RAE (particularly Germany, Czech Republic, and Spain).

5 Discussion

5.1 Interpreting the FQ Ranking

The implied mean *FQ* ranking differs substantially from both population size and FIFA ranking. This distinction is informative in both directions. Serbia, ranking first in mean *FQ* (109.0), is ranked 39th by FIFA; its exceptional professional conversion rate is not fully rewarded in FIFA points because its national team selection draws from a small pool, limiting the size premium available. Croatia (mean *FQ* 107.9, FIFA rank 11) has a

comparable ability distribution to Serbia but produces a stronger FIFA ranking in part because its abroad players are more concentrated in high-quality leagues where FIFA ranking points are contested more frequently.

At the other extreme, Germany's mean *FQ* of 96.5 places it last in the European ranking, yet it is consistently among the world's top ten nations. This is largely explained by the size premium: Germany's 2.38 million active players provide an enormous selection base from which the most extreme-right tail of the ability distribution is drawn for national team purposes.

The implication is that the mean *FQ* ranking is more informative about *developmental efficiency*—the quality of what a nation produces per capita— than about national team success, which depends additionally on pool depth. Both dimensions matter, but they respond to different interventions.

The framework also provides a unifying lens on patterns that the existing explanations cited in Section 2's introduction account for only piecemeal. Cultural and unstructured-play accounts can describe the Serbia–Croatia outlier pattern but cannot derive the size premium, and so have nothing to say about why Germany and France remain top FIFA performers despite low mean conversion rates. Talent-identification critiques (Vaeyens et al., 2008) and the relative-age literature (Cobley et al., 2009; Helsen et al., 2012) explain why early selection systems mis-rank players within a cohort, but do not explain why aggregate professional output varies between national populations of similar size. The deliberate-practice tradition (Helsen et al., 1998) explains why individuals reach professional status but not why the rate at which a population produces them differs by an order of magnitude across European federations. The *FQ* framework absorbs each of these as a partial mechanism: cultural and developmental factors shape the population mean, RAE and selection bias degrade the threshold's accuracy as an ability sorter, and deliberate practice acts as a tail-amplifier conditional on baseline ability. None of the prior mechanisms, taken individually, is contradicted; what the framework adds is the threshold-geometry result that converts these qualitative inputs into quantitative predictions about national output.

5.2 Confronting the Serbia Paradox: Robustness of the Headline Result

The most striking single result in Table 2 is also the most data-fragile: Serbia ranks first in implied mean *FQ* (109.0) while simultaneously carrying the widest confidence interval (95% CI 105.9–112.6) and the only *LOW* confidence registration rating among the top six nations. A reviewer encountering this will immediately ask whether the headline result is a genuine finding or an artefact of a poorly measured denominator. The question deserves a direct answer rather than a footnote.

Table 7 presents a sensitivity analysis holding Serbia's professional count constant and varying the active player denominator across the full plausible range.

Table 7: **Serbia FQ sensitivity to registration assumption.** Professional count held fixed at 878 throughout (abroad count of 392 is CIES-validated; domestic count of 486 is Transfermarkt-sourced). Comparator FQ values: Croatia 107.9, Scotland 106.6, Portugal 104.1.

Scenario	Active players	Rate (per 1,000)	Implied FQ
Current estimate (LOW conf.)	120,194	7.30	109.0
1.5× current estimate	180,291	4.87	106.8
All registered treated as active	250,000	3.51	105.2
2.0× current estimate	240,388	3.65	105.4
2.5× current estimate	300,485	2.92	104.3

Three observations follow from this analysis.

First, Serbia's implied FQ remains above the European average (100) and above Ireland, England, and Germany under every scenario including the extreme case of 2.5× the current active estimate. Even in that extreme case Serbia (FQ 104.3) sits effectively tied with Portugal and ahead of every larger nation in the dataset. The qualitative result — Serbia in the leading group of high-conversion nations — requires an active-population undercount of more than 2.5× to overturn, against a Monte Carlo confidence band that captures variation of less than half that magnitude.

Second, the direction of likely error is not obvious. Serbia's current active estimate (120,194) represents 1.8% of its population, compared with Croatia's 3.0% — and Croatia also carries a LOW confidence rating and sits second in the FQ ranking. If both countries are measured on comparable methodology, as is likely given their shared governance context, the denominator uncertainty affects them similarly and their relative positions are more stable than the individual confidence intervals suggest. Applying Croatia's participation rate to Serbia's population would yield approximately 201,000 active players, implying a Serbian FQ of $\sim$106.5 — still third highest in the dataset, behind only Croatia.

Third, the professional count itself provides a partial internal check. Serbia's abroad total of 392 professionals is cross-validated against the CIES Football Observatory and is the more reliable half of the estimate. Even using only the abroad count as a conservative lower bound on Serbian professional output, the implied FQ is 104.8 — above Portugal, Ireland, and all larger nations.

The conclusion is that Serbia's top ranking is robust to the plausible range of registration uncertainty. The LOW confidence rating reflects genuine data quality limitations and should temper exact point comparisons, as the confidence intervals reflect. It does not, however, constitute grounds for dismissing the result: the sensitivity analysis shows that Serbia would need a registration undercount of implausible magnitude, or a simultaneous overcount of professional numbers, to fall below the top four. The headline finding survives scrutiny.

The same logic generalises beyond Serbia to the high-FQ group as a whole. The qualitative pattern at issue — that small high-conversion nations (Serbia, Croatia, Iceland, Scotland, Portugal) cluster above large low-conversion nations (Germany, France, Netherlands) — is observable in raw professional counts per 1,000 active players *before any modelling*, and is therefore not an artefact of the FQ transformation. Overturning the leading group requires more than adjusting any single nation's denominator: it requires simultaneous upward adjustments of $>2\times$ to the active-player denominators of multiple small nations *and* simultaneous downward adjustments to those of multiple large nations. No plausible registration heterogeneity story produces this pattern, since the federation-

reporting practices that inflate denominators (broad inclusion of grassroots participants) operate in the same direction across countries with comparable governance structures. The robustness of the top group is therefore stronger than the robustness of any single nation's position within it.

5.3 Development Strategy: Small and Large Nations

The mean-shifting efficiency result (Section 2.5) has asymmetric implications for small and large nations.

Small nations face a binding constraint on participation growth: doubling the active population of Slovenia from 60,000 to 120,000 is not trivially achievable and would likely require generational effort. However, the same investment directed at raising the quality of coaching, methodology, and development environment—shifting the mean FQ by $+3$ points—delivers an output multiplier of approximately $1.79\times$ (per equation 8 at $\mu_c = 105.3$). This is close to, though slightly below, what a literal $2\times$ participation increase would produce, and it is a far more achievable intervention in a country whose participation base is already constrained by population. For a small nation already above the European mean, the marginal return to mean-shifting remains substantial.

Large nations are less dependent on mean-shifting because their size premium provides a buffer. Germany at $\mu_c = 96.5$ already fields a competitive national team from its right tail. However, the model identifies a structural vulnerability: the size premium is only available while pool depth is maintained. If registered player numbers decline, the national team quality degrades with a lag of 15–20 years (the time for the current youth population to age through to senior professional status). Italy has experienced the most widely reported registration decline: the 2006 FIFA Big Count recorded 1.70M registered Italian players, against current FIGC active figures of 1.13M — a nominal decline of -33.3%, although the two figures use different definitional bases and the precise magnitude should be treated as indicative rather than exact. Germany's active player count has also fallen substantially since the FIFA Big Count baseline. Under the order-statistics model, sustained registration declines of this character would predict measurable national team quality decline in the

2030s unless reversed.

Figure 3 shows historical registration trajectories and geometric extrapolations to 2042 for the five largest European football nations.

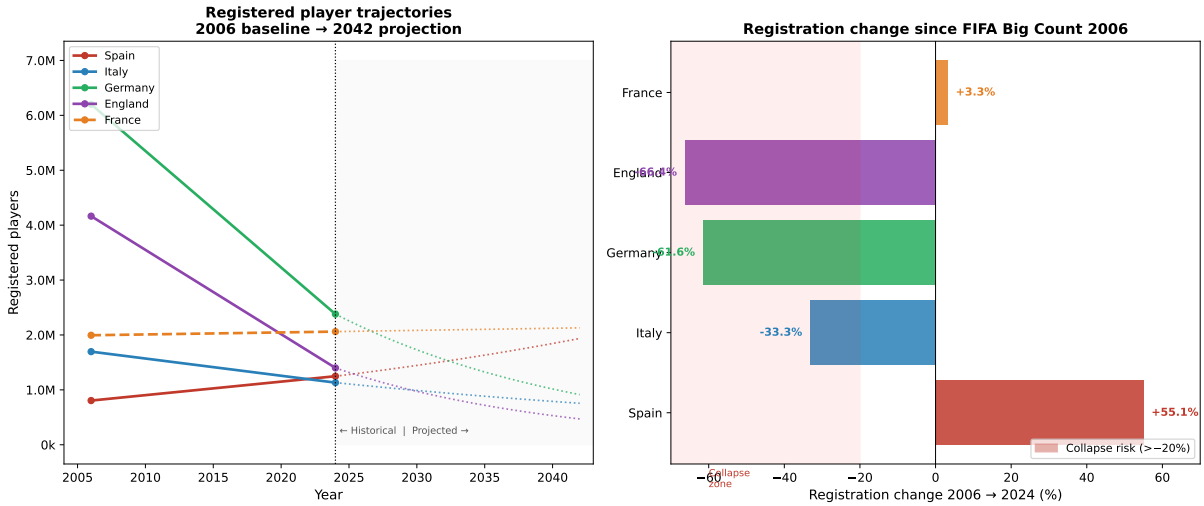

Figure 3: **Registered player trajectories and structural collapse risk.** *Left*: Historical registrations (2006 FIFA Big Count baseline; 2024 federation figures) with geometric projection to 2042 (dotted lines). *Right*: Nominal percentage change 2006–2024 by nation. Italy shows a −33.3% change between FIFA Big Count 2006 and FIGC 2025 active figures; Germany has declined from its FIFA Big Count baseline; France is stable. Note: direct comparison of 2006 FIFA Big Count and 2024 federation figures is subject to definitional differences between sources; the figures shown should be treated as indicative of trend direction rather than precise magnitudes.

5.4 Early Selection, Relative Age Effect, and the Limits of Academy-Only Development

Before developing the empirical critique that follows, the scope of the argument deserves clear statement. Academies develop players who have already cleared significant identification thresholds, and they do useful work in that role. The claim advanced here is narrower than a categorical critique of academy systems. It is that an academy-only model is unlikely to produce a sustainable increase in top talent — because academies select from an underlying distribution they do not themselves generate — and that under a binding investment constraint, mean-shifting interventions dominate academy expansion in expected return, because professional output is a convex function of the population mean. Where both can be funded, both should be. Where only one can, the analysis

below indicates which.

The relative age effect data presented in Section 4.4 can be read as more than a methodological footnote. The magnitude and distribution of RAE across nations constitutes evidence about how talent identification systems allocate investment—and about whether that allocation is efficient.

RAE as a measure of selection-system bias

A Q1/Q4 ratio of 1.39 pan-European means that January-born players are 39% more likely than October-born players of identical underlying ability to reach senior professional status. This is not a marginal distortion. Expressed as a fraction of Q1 selections, the gap $(Q_1 - Q_4)/Q_1 \approx 28\%$ corresponds to the share of Q1 admissions that came at the expense of equally able Q4-born peers under an ability-neutral selection regime. These displaced players are not randomly distributed across the ability range; they are concentrated in the upper tail—the players born in Q4 who would have been the best professionals had they not been cut from elite pathways at age 9 or 12.

The implication is that the professional conversion rate, as measured in this study, *understates* the true ability yield achievable from a given population. Every national *FQ* estimate in Table 2 is a lower bound on what the population could produce under an ability-neutral selection system.

Academy investment amplifies RAE

The cross-national pattern in RAE magnitude (Table 6) is informative. The nations with the most formalised elite academy infrastructure— Germany (Q1/Q4 = 2.10), Spain (1.98), Italy (1.87), Portugal (1.85)—show among the strongest RAEs. Nations with less formal early-selection pathways—Slovenia (1.38, ns), Bulgaria (1.22, ns), Slovakia (1.24, ns), Hungary (1.25, ns)—show weak or non-significant RAE. This is consistent with the mechanism: elite academies create structured annual cohort competition with repeated selection cut points from age 8 onwards. Each cut point is partially biased by physical maturity rather than ability. The effect compounds across ten years of development: by

the time a player graduates from a German or Spanish academy, they have survived eight to ten selection rounds each subject to relative age bias.

The nations at the bottom of the mean *FQ* ranking—Germany (96.5), Turkey (96.7), Netherlands (97.4), France (97.8)—are disproportionately those with the largest and most institutionalised academy investments. The nations at the top—Serbia (109.0), Croatia (107.9), Scotland (106.6), Wales (104.2)—are those with less formal early-selection infrastructure and correspondingly lower RAEs. This pattern does not establish causation, but it is the opposite of what the academy investment model would predict if early selection were efficiently identifying the most talented players.

France as a natural experiment

France presents an instructive case. The *Fédération Française de Football* (FFF) has operated mandatory professional academies since the 1970s and the *Institut National du Football* at Clairefontaine since January 1988 — the most institutionalised development system in Europe. RAE has been identified and discussed in the academic literature for over two decades (Musch and Grondin, 2001), and French sports-science research has produced direct empirical work on the phenomenon within the FFF's own developmental ecosystem (Carling et al., 2009; Delorme et al., 2010), including studies of birth-date effects on anthropometric profiles at Clairefontaine (Carling et al., 2009) and large-scale analyses of relative age and dropout across the French federation's full licensed playing population (Delorme et al., 2010). The result is visible in the data: France's Q1/Q4 ratio (1.47) is the lowest among major European nations with mandatory academy systems, substantially below Germany (2.10) and Spain (1.98).

France has not solved the RAE problem, but its sustained institutional effort to counteract it has measurably reduced it. Critically, this correction occurred *within* an elite academy framework—by applying research findings to change coach behaviour, selection criteria, and bio-banding practices. This is consistent with the view that RAE is not an inevitable consequence of formal youth development but a consequence of age-biased *selection within* formal development; firmer causal inference would require comparable

longitudinal evidence from peer nations.

However, France's mean *FQ* remains below the European average (97.8), and its FIFA ranking is sustained largely by pool depth. Active RAE correction improved France's talent identification accuracy without raising its population mean ability—because the intervention was still targeted at the elite selection funnel rather than at the broader development environment.

Mean-shifting as a structural alternative

The academy model and the mean-shifting model embody different theories of where development investment is best directed. The academy model assumes talent is scarce, identifiable early, and best developed through intensive specialist investment concentrated on a small fraction of the player population. The mean-shifting model assumes that talent is distributed throughout the population, that early identification is unreliable (as the RAE evidence demonstrates), and that raising the quality of development for the broad population generates more professional output per unit of investment than concentrating resources on an elite few. The two are not mutually exclusive in principle; the question advanced here is which dominates when investment must be prioritised.

These are testable propositions. The cross-national data presented here is consistent with the mean-shifting model on two independent dimensions:

1. **Conversion rate.** High-converting nations (Serbia, Croatia, Scotland) are not the nations with the most developed academy systems. They are nations where the quality of broad football culture—technical coaching, competitive club environments, high participation density relative to population—appears to have shifted the population mean upward without formal early selection.

2. **Relative age effect.** Nations with the most intensive early-selection systems show the highest RAE, indicating they are systematically discarding a substantial fraction of their most talented players. Mean-shifting interventions, by definition, do not create selection funnels and therefore do not generate RAE. Talent that would be cut from a German academy at U11 for a November birthday continues to develop

in a mean-shifting environment, remaining available for professional identification at 18 or 20.

The efficiency calculation from Section 2.5 can now be read in a new light. A +3 *FQ* mean shift is analytically equivalent to 1.7–2.0× participation. But if that mean shift is achieved partly by recovering the ∼ 28% of talent currently being discarded through RAE-biased selection, the cost of achieving it may be substantially lower than a ground-up participation expansion. Retraining coaches to delay selection, extending development windows, and investing in broad-based quality improvement are not obviously more expensive than building and staffing elite academies. They are, however, structurally different: they raise the floor rather than identify the peaks.

This argument does not imply that elite development has no role. Players who ultimately perform at the highest levels do benefit from specialist training and high-quality competition. The critique is specifically of *early* selection—the decision to identify and concentrate investment on a small cohort at age 8 to 12 before relative age bias has dissipated and before the true ability distribution has had time to manifest. Delaying that selection point, while continuing to invest in broad development quality, is the practical policy implication of the combined mean-shifting and RAE evidence presented here.

5.5 The Developmental Ecosystem: Why Cruyff Needed the Not-Cruyffs

> *"I trained three to four hours a week at Ajax when I was little but played three to four hours every day on the street. Where do you think I learned football?"*
>
> — Johan Cruyff[3]

This quote has been widely reproduced in coaching and talent development literature as evidence for the importance of practice volume—a confirmation of the deliberate practice hypothesis (Helsen et al., 1998) applied to one of football's greatest players. The ratio is

[3]This formulation is widely attributed to Cruyff and consistent with his documented accounts of his own development across multiple interviews and writings (Cruyff, 2016). The exact wording varies across sources; the sentiment is unambiguous.

striking: roughly ten times more street football than formal coaching, and the rhetorical question leaves no doubt about which Cruyff considered formative. This reading is not wrong, but it extracts only half the lesson. It focuses entirely on what Cruyff did, and misses entirely the conditions that made what Cruyff did possible.

Cruyff was describing his experience from inside an ecosystem. From that vantage point, the street football felt like *his* practice, because subjectively it was. The other children were simply the other children. What has gone largely unremarked in the literature that cites him is that those other children were not the backdrop to his development. They were its mechanism.

The three to four hours a day of street football was not practice *for Cruyff alone*. Every child on that street was accumulating those same hours. Cruyff's development was not simply a function of his own inputs but of the quality of the developmental ecosystem he was embedded in—the hundreds of improving players who constituted his daily adversarial environment.

This maps precisely onto the order statistics framework developed in Section 2.4. The expected ability of the best player drawn from a population follows directly from the population mean:

$$\mathbb{E}[X_{(1:P)}] \approx \mu + 15\,\Phi^{-1}\left(1 - \frac{1}{P}\right) \tag{9}$$

Raising μ raises $\mathbb{E}[X_{(1:P)}]$. A Cruyff is not produced by finding and cultivating the most promising 10-year-old; a Cruyff is produced by raising the whole distribution, and emerges from the elevated top. The street football was not a Cruyff-development programme. It was a population mean-shift, and the elevated tail produced Cruyff.

What the academy-only model misses

The academy-only model does not claim to replace street football for everyone. It claims to replace it *for Cruyff alone*: to identify the most promising players early and provide them with a superior structured environment. This is a coherent theory, and where a broad developmental base still exists for the academy to compound on, it can work. The empirical evidence presented in this paper suggests two structural problems with treating

it as sufficient on its own.

First, it cannot reliably identify Cruyff. The relative age data shows that formal selection systems systematically confuse physical maturity with ability. The player selected at age nine as the most promising in his cohort is disproportionately likely to have been born in January. Cruyff, born April 25th—Q2—would survive early selection in most European systems, but a substantial fraction of equally talented Q4-born peers would not. Independent evidence supports the limited predictive validity of early elite selection: Herrebrøden and Bjørndal (2022) find that participation in U17 and U19 international fixtures is at best weakly predictive of senior elite participation across multiple European nations, with only the U21 level showing meaningful signal. Brustio et al. (2024) report similarly low youth-to-senior transition rates and persistent birthdate skew along the academy pathway.

Second, and more fundamentally, the academy-only model removes Cruyff from the developmental ecosystem that was generating his three to four hours a day of high-quality adversarial practice. This is the core insight of the ecological-dynamics tradition in sports skill acquisition (Davids et al., 2013): skill emerges from the interaction between performer, task, and environment, and the environment in this case is the population of co-developing peers, not a coach in isolation. The street did not need a coach to organise it; it was self-organising in the sense that participation, motivation, and embedding in the peer group did not need to be supplied externally. When the most promising players are extracted into academies, the developmental ecosystem does not continue at the same level for those left behind—it degrades. The not-Cruyffs, who were the essential developmental environment for Cruyff, are no longer accumulating those hours at the same quality. Under this account, the next generation's Cruyff would be developing against a thinner, less competitive informal environment because the academy has extracted the best players from it.

The investment misallocation

The economic logic of elite academy investment is to concentrate resources on the players most likely to generate return. Under the assumption that talent is identifiable early, this is rational. But if the primary driver of elite player development is the quality of the *ecosystem*—not the quality of the resources directed at any individual—then concentration is precisely the wrong strategy. Investing in the quality of coaching, facilities, and competitive environment for the broad population raises the mean of the distribution. This raises not only the number of players above the professional threshold but also the quality of the developmental environment experienced by every player in it, including the future Cruyff.

The street football cost nothing. Its modern equivalent—accessible club environments, well-coached recreational leagues, broad technical development programmes—costs substantially less per participant than elite academies, while reaching the entire distribution rather than the selected few. The efficiency advantage of mean-shifting over participation expansion (Section 2.5) should therefore be understood as a lower bound: it assumes the mean shift is achieved at equivalent cost to participation expansion. If broad-based quality investment is cheaper per player than elite academy investment—as the evidence from the highest-converting nations suggests—the efficiency advantage is correspondingly larger.

These choices were not abstract for Cruyff himself. After his playing career he reshaped Barcelona's youth philosophy, and the approach he embedded at La Masia is widely credited with producing a generation of technical players including Xavi, Iniesta, Busquets, and Messi. That academy worked, in part, because it compounded on a broad base of Catalan and Dutch football that still existed at the time. By the final decades of his life, however, Cruyff was visibly aware that the broader conditions of his own development were eroding. The Johan Cruyff Foundation, established in 1997, has since built hundreds of Cruyff Courts—small public pitches in urban areas—explicitly to recreate the unstructured, peer-driven environments from which players like him emerged. The arc of his career traces the argument of this section: a player who emerged from a functioning street ecosystem; a coach who built an academy that worked because the ecosystem was still there to feed it;

and finally a philanthropist who, recognising the ecosystem was disappearing, spent his final two decades trying to rebuild it.

The question a national association should ask is therefore not "how do we develop Cruyff?" It is "how do we recreate the conditions under which Cruyff developed himself?" Those conditions were not, in the first instance, a specialist academy. They were a population in which everyone was playing, everyone was improving, and the best emerged naturally from the top of an elevated distribution.

5.6 Historical Precedent: Population Mean-Shifting in Irish Education

The argument that raising a population mean produces disproportionate gains in the right tail is not merely theoretical. This section draws on Irish educational history as structural precedent and historical analogy — not as a directly tested causal analysis within this paper's dataset, but as an instance of the same mechanism operating at national scale in a different domain. The parallel is offered to illustrate that the investment logic is not novel to football, and that its consequences have been observable in real policy history. Ireland provides a case in which two sequential broad-access interventions produced measurable changes in high-end output over a generation, while a third intervention with a different structural character produced a markedly different result.

Before 1967, secondary education in Ireland was predominantly fee-paying and socially selective. A large fraction of the population never progressed beyond primary level. The free secondary education scheme announced by Donogh O'Malley in September 1966 and implemented from the 1967/68 school year effectively universalised access to secondary schooling within a decade: post-primary enrolment rose from approximately 148,000 in 1967 to 239,000 by 1974 (Fleming et al., 2022). The consequence was not simply that more Irish people received a moderate education. The distribution of educational attainment shifted rightward across the whole population. As the base of capable, secondary-educated citizens deepened, the right tail — the doctors, engineers, academics, lawyers, civil servants, and entrepreneurs — grew disproportionately. The country became more capable not

because it identified the most promising children more accurately, but because it stopped excluding the vast majority before the distribution had time to develop.

The earlier expansion of universal primary education had the same character. Before universal compulsory primary schooling, a substantial part of the population entered adult life functionally underdeveloped in ways that capped their contribution regardless of underlying potential. Removing that constraint raised the floor. The right tail followed.

These two expansions are the clearest available examples of the FQ mechanism operating at national scale in a domain outside sport. In the language of the model: the professional threshold did not change. What changed was the mean of the distribution below it. And because professional-level outcomes are tail events, the returns to raising the mean were disproportionate.

The third-level expansion that followed tells a different story, and the contrast is instructive. Unlike primary and secondary education, tertiary education does not reach the full population. It is a selective tier. When access to that tier is broadened substantially without a corresponding rise in the underlying population distribution, the mean quality within the expanded tier declines. The institution ceases to be the right tail of the distribution and becomes a larger slice of the middle. Furthermore, by weakening the selectivity of the environment, expansion can reduce the developmental intensity experienced by the most capable individuals — who now find themselves in an environment less demanding than it was when entry was more restricted. The right tail is not raised by this process; it may actually be compressed.

The parallel for football is direct. Primary and secondary education are not merely an analogy for the football development window. For most children in most countries, they *are* the football development window. The ages at which FQ is formed — approximately five to eighteen — are the years spent in compulsory education. A national strategy for raising football FQ therefore cannot be addressed solely through sports federation structures. It implicates the educational system, the school day, the quality of physical and sport provision in childhood, and the degree to which football is accessible as a developmental environment for the whole population during those years. The federation that raises FQ is

not the one that builds the best academies. It is the one that ensures the developmental conditions are in place for the whole under-eighteen population — the football equivalent of universal primary and secondary education.

5.7 Base Expansion versus Elite-Tier Expansion: Opposite Effects on the Tail

The Irish education example clarifies a distinction that is easy to miss when thinking about development investment: base expansion and elite-tier expansion are not merely different in scale. They are structurally opposite in their effects on the right tail of the distribution.

Base expansion operates below the current threshold of meaningful participation. When a previously excluded population gains access to a developmental environment, the mean of the whole distribution rises. Because tail probability is a convex function of the mean (as demonstrated in Section 2.5), the right tail grows disproportionately. More people become capable; more of the most capable people emerge. This is the mechanism of universal primary education, of street football ecosystems, of broad improvements in coaching and club quality across the full playing population.

Elite-tier expansion operates above a threshold that is already functioning as a meaningful selector. When the entry standard to an elite programme or institution is lowered — whether because of deliberate policy, resource pressure, or ambition for scale — the consequences run in the opposite direction. The mean of the elite group declines. But more importantly, the developmental environment experienced by the most capable individuals deteriorates. They are now surrounded by peers of lower average quality than before. The expectations and norms of the environment soften. The competitive intensity that the most talented players require to develop against is reduced. The result is not merely that the elite label becomes less exclusive. The model implies, and the structural logic suggests, that the right tail of outcomes can be suppressed by degradation of the very environment that was supposed to produce it. This inference is theoretically grounded in the peer-quality and developmental intensity mechanisms described above; it is not

directly tested in this paper's cross-sectional dataset, and longitudinal evidence would be required to establish it causally.

This is not a peripheral consideration for football. The academy system in most European countries has expanded substantially over the past two decades. More clubs operate academies, more age groups are covered, more players carry "elite" status at younger ages. If this expansion has occurred without a corresponding improvement in the underlying population distribution — if it represents elite-tier inflation rather than base development — then the model suggests the effect on genuine right-tail output may have been negative rather than positive, even if the relationship has not yet been directly estimated.

The cross-national data are consistent with this concern. The nations that have most heavily institutionalised early elite selection (Germany, Spain, Italy) sit at the bottom of the mean FQ ranking. The nations with the highest professional conversion rates (Serbia, Croatia, Scotland) are not those with the most developed formal early pathways. This does not establish causation. But it is the opposite of the pattern one would expect if elite academy expansion were the primary driver of right-tail football output.

The practical implication is precise: investment that expands the developmental environment below the professional threshold moves the distribution in the right direction. Investment that expands the category of players labelled elite without a corresponding strengthening of the base may move it in the wrong direction. A national association operating under resource constraints faces a genuine choice between these two strategies. The FQ framework and the historical evidence presented here consistently point in the same direction: investment below the threshold moves the distribution; investment above it, without first strengthening the base, may not. The precise magnitude of this difference remains an empirical question that comparative cost data and longitudinal designs could address, but the directional implication of the model is clear.

5.8 The Abroad Rate as a Leading Indicator

The regression evidence (Section 4.2) shows that abroad count is a stronger predictor of FIFA ranking than pool size. This is consistent with a *quality amplification* interpretation: players who succeed abroad are concentrated in the upper tail of the ability distribution, and their frequency signals the location of that tail. Nations with high abroad rates are drawing deep into their ability distribution; nations with low abroad rates (Turkey 9%, Romania 12%) either have limited competitive access to European labour markets or have structural barriers to international mobility.

The abroad count may function as a *leading indicator* of national team strength. Because players peak at senior professional age and the FIFA ranking reflects current national team performance, there should be a lagged relationship: the cohort of 22–28 year olds currently playing abroad will constitute the national team of the next 5–10 years.

A preliminary test of this hypothesis is possible from historical expatriate-count data in CIES Monthly Reports Nos. 75, 85 and 95 (CIES Football Observatory, 2024), which between them publish 2017 and 2020 baseline expatriate counts for the top-20 origin nations by absolute change. Of these, thirteen are European nations within the present sample. Table 8 reports the correlations between abroad counts at three lag lengths and the April 2026 FIFA ranking.

Table 8: **Lagged abroad-count correlations with April 2026 FIFA ranking.** Sample restricted to European nations with verifiable historical CIES data. Dependent variable: −FIFA rank. Spearman coefficients are reported in parentheses.

Predictor	Lag	n	Pearson r (p)	Spearman ρ (p)
log(abroad 2017)	9 years	13	+0.50 (0.08)	+0.52 (0.07)
log(abroad 2020)	6 years	10	+0.53 (0.12)	+0.55 (0.10)
log(abroad 2024)	2 years	13	+0.60 (0.03)	+0.66 (0.02)

The pattern is what the leading-indicator hypothesis predicts: the 2017 abroad count, separated from the dependent variable by nine years — roughly a full senior-cohort cycle — correlates with current FIFA ranking at $r = +0.50$. The correlation strengthens as the

lag shortens, but the nine-year-lagged predictor retains the majority of the signal of the two-year-lagged one. A simple OLS confirms the bivariate result: the 2017 expatriate count alone explains 18% of the variance in current ranking (adj-$R^2 = 0.18$, $\hat{\beta} = +11.4$, $p = 0.08$), compared with 31% for the concurrent count.

Three caveats apply. The sample is small ($n = 13$); the available historical data are sample-selected on absolute change, biasing the included nations toward those active at the export margin; and the 2017 counts for Norway, Austria and Serbia were derived from percentage-change figures rather than read directly. The direction, sign, and magnitude of the correlation are nonetheless consistent with the leading-indicator interpretation, and a complete test using the 2017 origins tables for the full 29-nation sample is left to future work.

5.9 The European Labour Market and Threshold Validity

A central concern about any threshold model is whether the threshold is economically meaningful. We have argued that EU free movement and the Bosman ruling create a continental arbitrage market. Supporting evidence includes the wide variation in abroad rates (9–73%) and the fact that nations with high mean FQ — Croatia (56%), Portugal (55%), Slovenia (46%), Serbia (45%) — export the majority or near-majority of their professionals despite small domestic leagues. The pattern is not confined to small high-mean nations: France, with the deepest domestic pool in the dataset and a below-average mean FQ, nonetheless exports 73% of its senior professionals, the highest abroad share in Europe. Across both ends of the size distribution, the labour market clears on ability rather than nationality.

The calibration approach (using pan-European conversion rate to set T) implicitly treats the European professional ecosystem as a single labour market. This is a simplification: leagues differ in quality, squad size regulations, and work permit requirements. The UEFA coefficient system provides a quality-weighted alternative that could be incorporated in future refinements. However, for the purpose of comparing national development efficiency, the unweighted threshold provides a sufficient first-order approximation.

5.10 Towards Individual FQ Measurement

The *FQ* framework as developed in this paper is a *population-level latent construct*: national mean *FQ* is inferred backwards from professional conversion rates rather than measured directly in individuals. The logic is analogous to estimating a country's average cognitive ability from the proportion of its population that becomes research scientists, rather than from individual test scores. This approach is tractable with available data and produces testable predictions, but it leaves the normality assumption untested, σ assumed rather than estimated, and the professional threshold T calibrated on labour-market outcomes rather than measured ability.

Theoretically, *FQ* could be operationalised as an individual measurement instrument in the same way that IQ is assessed through a validated multi-domain test battery. Football ability is multi-dimensional, and a credible *FQ* battery would need to span at minimum four domains: *technical* (ball control, passing accuracy, and first-touch quality under varying pressure conditions); *physiological* (speed, agility, endurance, and recovery rate); *psychological* (in-match competitive temperament, resilience under failure, and coachability, but also the broader dispositional and lifestyle factors that operate above the professional threshold: willingness to relocate, tolerance of contract instability and repeated rejection, discipline around training and recovery in low-supervision environments, and sustained motivation under uncertainty); and *tactical-cognitive* (decision-making speed, spatial scanning, pattern recognition, and positional anticipation). The relative weightings of these domains are not fixed across levels of the game. Physical factors are more discriminating at younger ages and lower levels; tactical-cognitive factors become progressively more important as physical differences between players at a given tier narrow; and the broader psychological and lifestyle weighting is itself tier-dependent — minimal at recreational and youth levels, increasingly load-bearing as the tier rises, and decisive at and above the professional cutoff, where the bundle that the labour market actually selects on includes attributes that have no analogue in youth-academy assessment.

Three methodological requirements would need to be satisfied before such a battery could support the claims made in this paper. First, *domain decomposition*: factor-analytic

work to identify which components are necessary and sufficient at each level, and whether a single general factor — analogous to g in cognitive ability research — underlies performance across domains. Second, *level-specific calibration*: validation that battery scores predict professional attainment when tested in youth and amateur populations, not merely that they correlate with current performance at a given level. Third, *longitudinal validation*: prospective cohort studies following tested players to professional outcomes, ideally across multiple nations to test whether the scale is cross-culturally stable.

This is a substantial research programme in its own right, extending well beyond the scope of the present paper. Its value to the framework, however, would be considerable. Direct individual measurement would allow the normality assumption to be tested empirically rather than assumed; σ to be estimated per country rather than fixed; and the threshold T to be validated against measured individual scores rather than inferred from conversion rates. Most consequentially for the talent identification literature, a validated FQ battery would allow selection on measured ability rather than on physical maturity and birth month, removing the mechanism that produces the relative age effect at source. The present paper is best understood as establishing the population-level framework and the policy logic that follows from it; individual FQ measurement is the empirical programme that would ultimately place that framework on fully direct evidential foundations.

A practical first step towards threshold calibration does not require the full longitudinal research programme described above. Testing two or three squads competing at the minimum tier of professional football would produce an empirical multivariate description of the professional threshold without requiring cohort follow-up or prior validation of the full scale. Players in such squads have, by definition, cleared the professional threshold — they are the living calibration set for T. The within-squad variation across domains is not a complication but an asset: a squad of twenty-five professional players will include individuals who cleared the threshold through different combinations of attributes — a player with exceptional technical ability and modest physical profile alongside one with elite physiological measures and average tactical output. That heterogeneity maps the shape of the professional zone in multivariate ability space, revealing the trade-offs and

substitutabilities between domains that constitute "sufficient to be professional" as a region rather than a single point.

Such a study would produce an empirically grounded minimum-standard profile: not "to be professional you need score X" in a single number, but "to be professional you need to fall within this region of the technical–physiological– psychological–tactical space." Even if incomplete — calibrated only at the professional floor rather than across the full distribution — this would represent a substantive advance. It would allow individual *FQ* assessments to be anchored to real professional benchmarks, provide a practical tool for development programmes evaluating player trajectories, and generate the first empirical test of whether the professional threshold is best described as a hyperplane, a curved surface, or a more complex region in ability space. The data collection required is modest: systematic testing of two or three lower-professional squads with a provisional battery covering the four domains identified above.

5.11 Sensitivity to the σ Assumption

The implied mean *FQ* formula rests on two distributional assumptions: normality and a fixed $\sigma = 15$ across all nations. While the normality assumption is discussed in the following section, the σ assumption is in some respects the more consequential one. It is borrowed from IQ scaling for interpretability, but it is doing structural work that deserves direct examination: if Germany's ability distribution is genuinely wider than Serbia's — which is plausible if a larger, more heterogeneous player base produces greater within-country variance — the ranking of implied national means changes.

A useful analytical observation precedes the sensitivity analysis. Each country's conversion rate r_c maps to a standardised distance from the professional threshold:

$$z_c = \Phi^{-1}(1 - r_c), \quad \text{so that} \quad \mu_c = T - \sigma_c z_c \tag{10}$$

Serbia's high conversion rate places it at $z = 2.44$ standard deviations below the threshold; Germany's low rate places it at $z = 3.27$. Because countries with low conversion rates

have larger z values, they are more sensitive to σ perturbations. A one-unit increase in σ reduces Germany's implied mean by 3.27 points but Serbia's by only 2.44 points. This asymmetry has a direct consequence for how σ variation affects the rankings.

Table 9 presents implied FQ values for selected nations under three scenarios.

Table 9: **Sensitivity of implied mean FQ to σ assumptions.** Scenario 1: common σ varies uniformly (rankings unaffected by construction). Scenario 2: large nations wider ($\sigma = 18$), small nations narrower ($\sigma = 12$) — the heterogeneity hypothesis. Scenario 3: high-converting nations wider ($\sigma = 18$), low-converting nations narrower ($\sigma = 12$) — the most damaging case for the paper's rankings.

	Scenario 1 (common σ)				Scenario 2		Scenario 3	
Country	$\sigma = 12$	$\sigma = 15$	$\sigma = 18$	$\sigma = 21$	σ_c	FQ	σ_c	FQ
Serbia	116.3	109.0	101.6	94.3	12	116.3	18	101.6
Croatia	115.4	107.8	100.3	92.7	12	115.4	18	100.3
Scotland	114.4	106.6	98.8	90.9	12	114.4	18	98.8
Portugal	112.4	104.1	95.8	87.5	12	112.4	18	95.8
England	110.1	101.2	92.4	83.5	18	92.4	12	110.1
Spain	108.2	98.9	89.5	80.2	18	89.5	12	108.2
France	107.4	97.8	88.3	78.7	18	88.3	12	107.4
Germany	106.3	96.5	86.7	76.9	18	86.7	12	106.3

Three results emerge from this analysis.

Common σ variation does not affect rankings. Because the ranking of implied means is determined entirely by the ranking of z_c values, and z_c is independent of σ when σ is common, Scenario 1 changes the scale of the FQ axis but leaves every country's rank position identical regardless of whether $\sigma = 12$ or $\sigma = 21$.

The critic's specific hypothesis strengthens the headline result. The natural form of the heterogeneity concern is that larger, more diverse nations (Germany, France, Spain) have wider ability distributions than smaller, more culturally compact nations (Serbia, Croatia, Scotland). Under Scenario 2, assigning $\sigma = 18$ to large nations and $\sigma = 12$ to small nations, Germany's implied mean falls from 96.5 to 86.7 and Serbia's

rises from 109.0 to 116.3. The Serbia–Germany gap widens from 12.5 to 29.6 points. The hypothesis that motivates the critique, if correct, makes the paper's central finding considerably more pronounced rather than less.

The damaging scenario requires the opposite assumption. The configuration that would flip the Serbia–Germany ranking is Scenario 3: high-converting small nations assigned $\sigma = 18$ and large nations assigned $\sigma = 12$. Under these assumptions Germany (106.3) surpasses Serbia (101.6). For this reversal to occur, Serbia's ability distribution would need to be wider than Germany's — more heterogeneous, not less. This is not impossible, but it is the opposite of the heterogeneity argument and lacks an obvious theoretical motivation. Furthermore, the breakeven calculation shows that for Germany and Serbia to have equal implied means under a common threshold, Germany's σ would need to be $0.746\times$ Serbia's σ — that is, Germany's distribution would need to be *narrower*, not wider.

The σ assumption is therefore consequential, but in a directionally asymmetric way. Sensitivity to it runs in the opposite direction from the most natural concern. The recommended response for future work is empirical estimation of within-country ability variance using Transfermarkt market values as a continuous ability proxy, which would allow σ to be estimated rather than assumed. Until such data are available, the common $\sigma = 15$ baseline is transparent, testable in principle, and — on the basis of the scenarios above — conservative with respect to the paper's main conclusions.

5.12 A Research Programme: Toward Consistent UEFA-Level Data

The framework presented here generates testable predictions and policy implications that the existing data infrastructure is not built to evaluate at the precision the framework can in principle deliver. FIFA Big Count is a heterogeneous one-off exercise from 2006; federation registration figures use inconsistent definitions of who counts as an active player; Transfermarkt is a community-maintained secondary source with unknown systematic coverage gaps; CIES reports cover players abroad but not domestic conversion rates. The

framework gives UEFA and its member federations a quantitative reason to coordinate a more consistent dataset. We set out the components of that data effort here.

Standardised registration definitions. The single most consequential limitation in this paper is heterogeneity in what national federations report as "registered" or "active" players. A coordinated effort would specify common definitions for activity threshold (number of matches per year), age range, competition level, and the distinction between licensed players, casual participants, and administrative members. With consistent definitions, the denominator in every conversion-rate calculation becomes meaningful in a way it currently is not.

Pan-European player-tracking dataset. Federation-validated, with known coverage, including player-level birth date, club, league level, transfer history, and contract status. FIFA's Transfer Matching System (TMS) holds much of this already but is not accessible for research use. A research-purpose extract, appropriately anonymised, would replace the Transfermarkt-scraped data on which this paper relies and would close the largest single source of measurement uncertainty in the implied mean FQ estimates.

Longitudinal cohort tracking. The leading-indicator hypothesis (abroad counts predicting future FIFA performance), the structural-collapse prediction (15–20-year lag from registration declines), and the conversion-rate dynamics that motivate national strategy are all currently untestable because the data is cross-sectional. Annual federation reporting in a consistent format would yield a panel within five years that supports causal inference where the present paper can only describe correlations.

Standardised RAE reporting. Birth-month distributions by federation, age cohort, and tier, reported annually. This is the lightest-weight component of the programme and would allow the academy-effect analysis in Section 5.4 to be evaluated longitudinally as federations adopt or reject RAE-correction practices.

Individual *FQ* threshold calibration. The programme outlined in Section 5.10: a four-domain test battery applied at minimum to two or three lower-tier professional squads, producing an empirically grounded multivariate description of the professional threshold. This is the smallest data collection in the programme and the one with the

highest framework-tightening return per unit effort.

Within-country ability variance estimation. Transfermarkt market values, properly cleaned, can serve as a continuous ability proxy for estimating σ per country rather than assuming a common value. This is computable from existing data with appropriate methodology and would directly address the sensitivity discussion in Section 5.11.

Taken together, these components would convert the framework from a structure applied to incomplete cross-sectional data into a measurement system applied to a coherent panel. The first three components require institutional coordination through UEFA or a comparable body; the last three are within the reach of academic research groups working with available data and modest field collection. The framework presented in this paper gives UEFA and its member federations a quantitative basis on which to want such a dataset, and gives researchers a clear specification of what to build with it.

5.13 Implications for National Associations

The framework's qualitative results translate into a small number of strategic recommendations that hold across plausible refinements to the underlying data.

Prioritise mean-shifting once a reasonable participation base exists. The efficiency calculation in Section 2.5 establishes that a +3 *FQ* shift in the population mean is equivalent to a 1.7–2.0× expansion of the participating population, with the multiplier rising as the nation moves further below the threshold. For associations that already have a broad participation base relative to their population, additional registration growth offers diminishing returns; investment in the average quality of development — coaching density, coaching quality, RAE-correction practices, holistic rather than early-selection development pathways — will produce larger increases in professional output at comparable cost. For associations with small or shrinking participation bases, building the base remains a prerequisite, but the strategic horizon should treat base expansion as a precondition for mean-shifting rather than as the end goal.

Set conversion-rate targets, not registration targets. Registration numbers measure the denominator; professional output measures success. Federations that monitor

only registration counts can register growth in the base while their conversion rate falls — the structural dilution mechanism described in Section 5.7. Conversion-rate targets, benchmarked against the pan-European rate of approximately 1.17 per 1,000 active players, give a single metric that responds correctly to interventions on either margin.

Monitor the abroad rate as a leading indicator. The regression analysis in Section 4.2 identified the number of professionals based abroad as the strongest single predictor of FIFA ranking (adj-$R^2 = 0.502$). The abroad rate also responds faster than domestic output to changes in cohort quality, because the European labour market arbitrages on individual ability rather than nationality. A sustained decline in abroad-based professionals from a given cohort is an early warning that the underlying FQ distribution is moving down, observable years before domestic league composition reflects the same shift.

Distinguish small-nation and large-nation strategies. The size premium derived in Section 4.3 implies that a small high-mean nation and a large low-mean nation can produce comparable senior national team strength while requiring entirely different development approaches. Small nations cannot brute-force their way to a deep talent pool by expanding participation alone; their realistic route to competitive depth runs through high mean FQ and selective elite production. Large nations have pool-size advantages that compound only weakly under low conversion rates; their realistic route to performance runs through raising the mean of their already-large base, which the size premium then amplifies. Imitating the development model of a structurally different nation will tend to underperform the model native to one's own size class.

These recommendations are deliberately framed at the level of strategic direction rather than operational detail. The framework constrains what the direction should be; the operational specifics — which coaching curriculum, which academy structure, which selection-bias correction mechanism — are empirical questions that the research programme in Section 5.12 would put on a quantitative basis.

A timing caveat applies. To the extent the population mean is itself partly the cumulative outcome of past professional output (visible role models, returning professionals

seeding coaching networks, peer-effect compounding; see the endogeneity note in the Limitations subsection below), interventions that successfully shift the mean should be expected to compound over multi-decade horizons rather than show their full effect within a single cohort. National associations evaluating mean-shifting interventions should therefore treat the relevant outcome window as fifteen to twenty years rather than one Olympic or World Cup cycle.

5.14 Limitations

Normality assumption. The *FQ* framework assumes a symmetric unimodal ability distribution. If the true distribution is skewed or bimodal (e.g., a distinct elite subpopulation), the threshold calculations will be biased. As noted in Section 2, the qualitative efficiency conclusions require only monotone tails, not normality per se. Empirical testing of the distributional assumption using Transfermarkt market values as a proxy for ability is a natural extension.

Registration data heterogeneity. The most consequential methodological limitation is heterogeneity in what national federations report as "registered players." England's 1.4 million figure includes all grassroots participants; Portugal's 235,000 reflects only federated competitive players. This inconsistency means cross-country comparisons of conversion rates are confounded with registration methodology. We have addressed this partially through the conflation correction and confidence levels, but the underlying data quality varies by nation. Serbia and Slovakia receive LOW confidence ratings, and their *FQ* estimates carry the widest confidence intervals.

Cross-sectional design. National *FQ* estimates are cross-sectional for the 2024/25 season and reflect the current stock of professionals, not the flow that generated them. The lagged-correlation analysis in Section 5.8 provides preliminary historical evidence using CIES Monthly Reports, but is restricted to the thirteen European nations for which CIES publishes historical baseline counts. A full historical panel covering all 29 nations from 2016 onwards would enable proper longitudinal testing of both the leading-indicator hypothesis and the structural collapse prediction.

Relative age effect bias. As noted in Section 4.4, the RAE introduces systematic bias in the professional conversion rate as an ability proxy. The magnitude of this bias differs by nation (Q1/Q4 ratios range from 1.21 to 2.13 across countries with significant RAEs). Countries with high RAE will have slightly inflated mean FQ estimates relative to true underlying ability, because their professional player cohort is partially selected on birthdate rather than ability.

Gender exclusion. The analysis covers male players only, reflecting both data availability constraints and the current structure of the European professional labour market. The mean-shifting framework applies in principle to female football as well, but the threshold, conversion rates, and registration denominators would require separate estimation.

What is robust and what is not. The preceding limitations bear unevenly on different parts of the contribution. Exact national point estimates of mean FQ are the most sensitive component: a federation that under- or over-counts its active base by 30–50% will see its implied mean shift by several FQ points, which is enough to change neighbouring positions in the ranking. The qualitative results of the framework are not similarly fragile. The mean-shifting efficiency calculation (Section 2.5) depends only on the threshold geometry of a tail distribution, not on any particular country's denominator. The size premium is a direct consequence of order statistics on bounded samples and is independent of registration accuracy. The pattern that small high-conversion nations (Serbia, Croatia, Iceland, Scotland) cluster above large low-conversion nations (Germany, France, Netherlands) is visible in raw conversion rates before any modelling, and Section 5.2 shows that overturning this pattern would require implausibly large adjustments to the denominators of multiple countries simultaneously. The framework, the efficiency result, and the broad ranking direction should therefore be read as the durable contribution; exact point estimates should be read as illustrative pending the coordinated UEFA-level data effort described in Section 5.12.

Endogeneity of the mean. A final caveat concerns the direction of causation. The framework treats the population mean FQ as a parameter that interventions target, but a

strong professional pipeline is itself plausibly a cause of mean FQ growth in subsequent generations: visible role models raise participation intensity, returning professionals seed coaching networks, and competitive academy infrastructure raises the quality of practice available to the next cohort. The broader economics of education literature documents non-trivial peer-effect and role-model channels in skill acquisition contexts (Sacerdote, 2011), and there is no a priori reason to expect the football developmental environment to be exempt from such effects. To the extent this feedback operates, cross-sectional means partly reflect the cumulative effect of past professional output rather than an independent cause of it. This does not invalidate the efficiency result — which is a statement about marginal returns to interventions on the mean — but it does imply that the gap between high-mean and low-mean nations may be self-reinforcing absent deliberate counter-investment, and that successful mean-shifting interventions should compound over multi-decade horizons rather than within a single cohort.

6 Conclusion

We have introduced the Football Quotient, a framework for quantifying the implied ability distribution of national playing populations from professional conversion rates. Applied to 29 European nations using 2024/25 data, the framework identifies substantial variation in national mean FQ—from Serbia (109.0) to Germany (96.5)—that is largely invisible in FIFA rankings but is highly informative about developmental efficiency.

The central analytical result is that raising the population mean FQ generates disproportionate increases in professional output because professional status is a threshold phenomenon. A +3 FQ point improvement—a small fraction of one standard deviation on the FQ scale—achieves 85–100% of what doubling the participating population achieves, across all national baselines in our dataset. As participation size is generally constrained by population and infrastructure, while mean ability is responsive to coaching quality, methodology, and development environment, this efficiency comparison is a direct argument for quality-first development strategies.

The European Union's free movement of labour provides an empirical market mechanism

that continuously calibrates the professional threshold, lending ecological validity to the model: the threshold is not a statistical artefact but the real minimum level of ability required to secure professional employment somewhere in the European football ecosystem.

The decomposition of national team quality into mean FQ and size premium reveals complementary vulnerability profiles. Large nations are insulated by pool depth but face structural risk from declining registration trends, with effects emerging on a 15–20 year lag. Small nations with high mean FQ can achieve national team quality comparable to large nations through the size premium on a smaller but higher-quality population base.

The empirical estimates in this paper rest on existing data sources whose heterogeneity is documented and whose precision is correspondingly bounded. We view this work as a precursor to a coordinated UEFA-level data effort that the framework itself motivates: standardised registration definitions across federations, federation-validated pan-European player tracking, longitudinal cohort series, and individual threshold calibration. Section 5.12 sets out the components of that effort. The framework presented here gives UEFA and its member federations a quantitative basis on which to coordinate such a dataset, and gives researchers a clear specification of what to build once it exists.

A preliminary test reported in Section 5.8 shows that the abroad count from 2017 retains a Spearman correlation of $+0.52$ with the April 2026 FIFA ranking across thirteen European nations with verifiable historical CIES data, consistent with the leading-indicator prediction; a complete test using the full 29-nation sample remains outstanding. This finding is also consistent in spirit with Bernard and Busse (2004), whose Olympic production-function model shares both the normal-ability assumption and the conclusion that population-scale and per-capita quality factors contribute jointly to elite output. The football case provides the labour-market mechanism by which the per-capita factor is arbitraged across borders, which the Olympic case does not.

Within the existing data, future work should (i) extend the leading-indicator test to the full 29-nation sample once historical CIES origin tables become publicly available, (ii) test the normality assumption empirically using market value distributions, (iii) extend the framework to female football, and (iv) integrate UEFA league quality coefficients to

refine the threshold calibration.

References

Anastasi, A. and Urbina, S. (1997). *Psychological Testing*. Prentice Hall, Upper Saddle River, NJ, 7th edition.

Barnsley, R. H., Thompson, A. H., and Barnsley, P. E. (1985). Hockey success and birthdate: The relative age effect. *CAHPER Journal*, 51:23–28.

Bernard, A. B. and Busse, M. R. (2004). Who wins the Olympic games: Economic resources and medal totals. *The Review of Economics and Statistics*, 86(1):413–417.

Blom, G. (1958). *Statistical Estimates and Transformed Beta-Variables*. John Wiley & Sons, New York.

Brustio, P. R., McAuley, A. B. T., Ungureanu, A. N., and Kelly, A. L. (2024). Career trajectories, transition rates, and birthdate distributions: the rocky road from youth to senior level in men's European football. *Frontiers in Sports and Active Living*, 6:1420220.

Carling, C., le Gall, F., Reilly, T., and Williams, A. M. (2009). Do anthropometric and fitness characteristics vary according to birth date distribution in elite youth academy soccer players? *Scandinavian Journal of Medicine & Science in Sports*, 19(1):3–9.

CIES Football Observatory (2024). Monthly report: International transfers of professional players. Technical Report No. 96, Centre International d'Étude du Sport, Neuchâtel, Switzerland.

Cobley, S., Baker, J., Wattie, N., and McKenna, J. (2009). Annual age-grouping and athlete development: A meta-analytical review of relative age effects in sport. *Sports Medicine*, 39(3):235–256.

Côté, J. and Vierimaa, M. (2014). The developmental model of sport participation: 15 years after its first conceptualization. *Science & Sports*, 29:S63–S69. Supplement.

Court of Justice of the European Union (1995). Case c-415/93: Union Royale Belge des Sociétés de Football Association ASBL v Jean-Marc Bosman. European Court Reports 1995 I-04921.

Court of Justice of the European Union (2003). Case c-438/00: Deutscher Handballbund eV v Maros Kolpak. Judgment of 8 May 2003.

Court of Justice of the European Union (2005). Case c-265/03: Igor Simutenkov v Ministerio de Educación y Cultura and Real Federación Española de Fútbol. Grand Chamber Judgment of 12 April 2005, [2005] ECR I-2579.

Cruyff, J. (2016). *My Turn: A Life of Total Football*. Nation Books, New York.

Davids, K., Araújo, D., Vilar, L., Renshaw, I., and Pinder, R. (2013). An ecological dynamics approach to skill acquisition: Implications for development of talent in sport. *Talent Development and Excellence*, 5(1):21–34.

dcaribou (2024). football-data: A StatsBomb football player data package. https://github.com/dcaribou/transfermarkt-datasets. Accessed April 2026.

Delorme, N., Boiché, J., and Raspaud, M. (2010). Relative age and dropout in French male soccer. *Journal of Sports Sciences*, 28(7):717–722.

Fédération Internationale de Football Association (2007). FIFA Big Count 2006: Statistical summary report. Technical report, FIFA, Zurich, Switzerland.

Fleming, B., Harford, J., and Hyland, Á. (2022). Reflecting on 100 years of educational policy in Ireland: was equality ever a priority? *Irish Educational Studies*, 41(3):441–455.

Helsen, W. F., Baker, J., Michiels, S., Schorer, J., Van Winckel, J., and Williams, A. M. (2012). The relative age effect in European professional soccer: Did ten years of research make any difference? *Journal of Sports Sciences*, 30(15):1665–1671.

Helsen, W. F., Starkes, J. L., and Hodges, N. J. (1998). Team sports and the theory of deliberate practice. *Journal of Sport and Exercise Psychology*, 20(1):12–34.

Helsen, W. F., Starkes, J. L., and Van Winckel, J. (2000). Effect of a change in selection year on success in male soccer players. *American Journal of Human Biology*, 12(6):729–735.

Herrebrøden, H. and Bjørndal, C. T. (2022). Youth international experience is a limited predictor of senior success in football: The relationship between U17, U19, and U21 experience and senior elite participation across nations and playing positions. *Frontiers in Sports and Active Living*, 4:875530.

Musch, J. and Grondin, S. (2001). Unequal competition as an impediment to personal development: A review of the relative age effect in sport. *Developmental Review*, 21(2):147–167.

Sacerdote, B. (2011). Peer effects in education: How might they work, how big are they and how much do we know thus far? In Hanushek, E. A., Machin, S., and Woessmann, L., editors, *Handbook of the Economics of Education*, volume 3, chapter 4, pages 249–277. Elsevier.

Simonton, D. K. (1999). *Origins of Genius: Darwinian Perspectives on Creativity*. Oxford University Press, Oxford.

Vaeyens, R., Lenoir, M., Williams, A. M., and Philippaerts, R. M. (2008). Talent identification and development programmes in sport: Current models and future directions. *Sports Medicine*, 38(9):703–714.

A Mathematical Derivation of Mean-Shifting Efficiency

Let $X \sim \mathcal{N}(\mu, \sigma^2)$ denote the ability of a randomly selected active player, and let T be the professional threshold. The probability of professional attainment is $p(\mu) = 1 - \Phi\left(\frac{T-\mu}{\sigma}\right)$, where Φ is the standard normal CDF.

Define the *output multiplier* from a mean shift of Δ:

$$\rho(\Delta) = \frac{p(\mu + \Delta)}{p(\mu)} = \frac{1 - \Phi\left(\frac{T-\mu-\Delta}{\sigma}\right)}{1 - \Phi\left(\frac{T-\mu}{\sigma}\right)} \tag{11}$$

Let $z_0 = (T - \mu)/\sigma$ and $z_1 = (T - \mu - \Delta)/\sigma = z_0 - \Delta/\sigma$. Then:

$$\rho(\Delta) = \frac{1 - \Phi(z_1)}{1 - \Phi(z_0)} = \frac{\bar{\Phi}(z_0 - \Delta/\sigma)}{\bar{\Phi}(z_0)} \tag{12}$$

where $\bar{\Phi} = 1 - \Phi$.

The log-survival function $\log \bar{\Phi}(z)$ is strictly convex in z (the normal hazard rate $\phi(z)/\bar{\Phi}(z)$ is strictly increasing in z). Therefore:

$$\log \bar{\Phi}(z_0 - \Delta/\sigma) > \log \bar{\Phi}(z_0) - (\Delta/\sigma) \cdot \frac{d}{dz} \log \bar{\Phi}(z)\Big|_{z_0} \tag{13}$$

This means $\rho(\Delta) > 1$ for all $\Delta > 0$, and moreover $\rho(\Delta)$ grows faster than linearly for large Δ (super-linear multiplicative gain). The equivalent participation multiplier is precisely $\rho(\Delta)$, and the super-linearity gives the efficiency advantage of mean-shifting over participation expansion. The quantitative values in Table (main text) are obtained by numerical evaluation at $T = 145.6$, $\sigma = 15$, and $\mu \in \{96.5, 100.0, 109.0\}$.

B Order Statistics Approximation for National Team Quality

The expected value of the k-th order statistic (in decreasing order) from a $\mathcal{N}(\mu, \sigma^2)$ sample of size P is approximated by:

$$\mathbb{E}[X_{(k:P)}] \approx \mu + \sigma\, \Phi^{-1}\left(1 - \frac{k}{P+1}\right) \tag{14}$$

using the Blom (1958) plotting position approximation. The national team average FQ (equation 7) sums this over $k = 1, \ldots, 30$:

$$\overline{FQ}^{\mathrm{NT}} = \mu + \frac{\sigma}{30} \sum_{k=1}^{30} \Phi^{-1}\left(1 - \frac{k}{P+1}\right) \tag{15}$$

For the active population sizes in our dataset (range: 60,334 to 2,380,000), the $P/(P+1)$ correction is negligible and we use P throughout.

C Data Sources and Registration Figures

Table 10: **Registration data sources and confidence ratings.** FIFA BC = FIFA Big Count 2006. Active = estimated active competing population after adjustments. Conf. = confidence level.

Country	FIFA BC	Active	Primary source	Conf.
England	4,164,110	1,400,000	FA activity-adjusted	HIGH
Germany	6,200,000	2,380,000	DFB registered 2024	HIGH
France	1,994,654	2,060,960	FFF registered 2024	HIGH
Italy	1,696,000	1,131,906	FIGC 2025	HIGH

continued on next page

(continued)

Country	FIFA BC	Active	Primary source	Conf.
Spain	805,035	1,248,511	RFEF 2024	HIGH
Netherlands	1,212,697	1,100,000	KNVB active 2024	HIGH
Belgium	413,284	400,000	URBSFA 2023	HIGH
Portugal	178,111	235,000	FPF 2024	HIGH
Scotland	161,412	161,412	SFA 2023	HIGH
Norway	391,139	413,139	NFF 2024	HIGH
Denmark	268,402	381,840	DBU 2024	HIGH
Sweden	484,662	379,681	SvFF 2024	HIGH
Switzerland	262,000	273,644	ASF 2023	MED
Austria	270,000	248,000	ÖFB adjusted	MED
Czech Rep.	239,500	358,000	FAČR 2023	MED
Romania	136,000	300,000	MDPI 2023	MED
Greece	93,600	200,000	EPO estimate	MED
Ireland	88,000	220,000	FAI 2023	HIGH
Wales	86,340	105,603	FAW 2023	HIGH
Finland	114,393	150,894	SPL 2024	HIGH
Hungary	186,000	300,000	MLSZ 2023	HIGH
Bulgaria	63,026	120,000	BFU estimate	LOW
Slovenia	29,400	60,334	NZS 2024	MED
Croatia	130,000	118,316	HNS 2023	LOW
Slovakia	51,000	90,000	SFZ estimate	LOW
Serbia	146,845	120,194	FSS 2023	LOW
Ukraine	1,016,000	1,016,000	UAF 2022	LOW
Poland	395,550	769,000	PZPN 2023	LOW
Turkey	985,000	985,000	TFF 2022	LOW