National Bias of International Gymnastics Judges during the 2013–2016 Olympic Cycle

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Abstract—National bias in sports judging is a well-known issue and has been observed in several sports: judges, in the aggregate, give higher marks to athletes of the same nationality. In this work, we study the national bias of international gymnastics judges during the 2013–2016 Olympic cycle. As opposed to prior work, our analysis leverages the intrinsic variance of the judging error based on the performance level of the gymnasts for each apparatus and discipline. The magnitude of the national bias varies across judges, nations and disciplines. While acrobatics and trampoline do not exhibit any bias, we observe considerable bias by aerobics, artistic and rhythmic gymnasts. In aerobic and artistic gymnastics this bias further increases for the best athletes competing in the finals. On the positive side, we show that judges are unbiased against direct competitors of their own gymnasts. Our approach could easily be applied to other sports that incorporate a judging panel and objective judging guidelines. It could help sports federations and the public at large understand the extent of national bias and identify particularly prone judges or nations.

Keywords: Sports judges, national bias, heteroscedasticity, intrinsic judging variance, gymnastics

I. INTRODUCTION

Judging sports competitions is a challenging task. Despite a myriad of technological advances, judges must assess the performance of athletes live, surrounded by thousands of cheering spectators, and according to hundreds of instructions specified in scoring regulations. These evaluations anoint international champions and Olympic medalists, and all the involved parties – athletes, coaches, fans, officials, sponsors – have a vested interest in having accurate and fair judges.

In this article we focus on the fairness aspect of judging. Fair judges grade every performance as accurately as possible without introducing any subjective biases into their evaluation. There are many well-known biases in sports judging, and in most cases it is impossible to determine whether theses biases are intentional or not. The most studied and discussed bias in sports is national bias. National bias comes in two flavors: judges can favor athletes of the same nationality, and at the same time penalize their close competitors. National bias was shown to exist in many sports including figure skating [1], [2], [7], [8], [6], [9]. Zitzewitz [2] links the appearance of national bias to the selection procedure of judges and shows that in figure skating, national bias increases with the importance of the event. He also reveals vote trading in figure skating, where judges reinforce national bias of other judges, and compensation effects in ski jumping, where judges weaken national bias of other judges.

A. Estimating national bias by modeling the heteroscedasticity of judging errors in gymnastics

Judging in gymnastics and similar sports is a noisy process and does not rely on comprehensive technical assistance. Athletes are evaluated live by panels of judges, and the final scores aggregate the individual marks given by these judges. This aggregation process typically uses the median or the trimmed mean to remove outliers and improve the accuracy of the overall evaluation. Judges within a panel grade the same performance but rarely agree on a single grade. They may have individual preferences and interpret the scoring regulations differently, but more importantly they do not detect the same errors. Even experienced judges with sophisticated cognitive judging strategies and sensorimotor experiences have a low error detection rate [11]. This leads to an inevitable element of subjectivity and randomness in the judging process which introduces a natural variation in the marks given by judges.

This article is the second of a series of three articles on sports judging. In the first article [12], we showed that the variation of the judging error in international gymnastic competitions depends on the intrinsic quality of the performance of the gymnasts: judges are more accurate judging the best athletes than mediocre ones. We modeled and quantified the variance of this judging error very accurately with heteroscedastic random variables for each apparatus and discipline using data from continental and international gymnastic competitions held during the 2013–2016 Olympic cycle. In this work, we integrate and leverage this knowledge of the distribution of the judging error into our national bias model. Contrary to previous regression-based analyses in gymnastics, e.g. by Leskošek et al. [6], this allows us to quantify the national bias not only on a nominal level but also in terms of the natural variation of judging marks. This is essential to evaluate the severity of the bias: the smaller the variance of the scores, the less misjudgement is required to impact the ranking of the gymnasts. After all, a national bias of 0.2 in favor of an athlete...
could provide an improved national bias analysis in all these marks within a finite range. The integration of this behaviour heteroscedastic shape in other sports using judging panels and the variance of the judging error has the same characteristic it is difficult to avoid same-nationality evaluations. 

in all-around finals in artistic and rhythmic gymnastics where steps to further decrease the impact of national bias, especially marks from the judging panels. In the conclusion, we propose to the aggregation mechanisms excluding the worst and best same-nationality judges in the finals whenever possible, and the Fédération Internationale de Gymnastique (FIG) to avoid occur more frequently is a testament to the efforts made by the podium in artistics gymnastics. The fact that this did not happen in all competitions held in 2013) has this national bias modified the podium in artistics gymnastics. The fact that this did not occur more frequently is a testament to the efforts made by the Fédération Internationale de Gymnastique (FIG) to avoid same-nationality judges in the finals whenever possible, and to the aggregation mechanisms excluding the worst and best marks from the judging panels. In the conclusion, we propose steps to further decrease the impact of national bias, especially in all-around finals in artistic and rhythmic gymnastics where it is difficult to avoid same-nationality evaluations.

Note that in the third article of the series [13], we show that the variance of the judging error has the same characteristic heteroscedastic shape in other sports using judging panels and marks within a finite range. The integration of this behaviour could provide an improved national bias analysis in all these sports.

II. JUDGING IN GYMNASTICS

The five main gymnastics disciplines recognized by the Fédération Internationale de Gymnastique (FIG) are artistic gymnastics, rhythmic gymnastics and trampoline, which are Olympic sports, and aerobic gymnastics and acrobatic gymnastics, which have a world championship held every two years. Gymnastics disciplines have different apparatus and competition formats. Acrobatic gymnastics routines are performed in pairs or in groups; men, women and mixed competitions are held. Aerobic gymnastics features individual and group routines; group routines can be mixed or split by gender. Artistic gymnastics is split by gender; men compete on six apparatuses (floor exercise, parallel bars, horizontal bar, pommel horse, still rings and vault) and women compete on four (balance beam, floor exercise, uneven bars and vault). Rhythmic gymnastics is only practised by women; it includes individual routines with one apparatus (ball, club, hoop or ribbon) and group routines with one or two apparatus. Trampoline is split by gender, but men and women compete in the same events: individual and synchronized trampoline, double mini-trampoline, and tumbling.

Gymnastics competitions typically consist of a qualifying round followed by a final regrouping the best qualifiers. A gymnastic routine at the international level is evaluated by panels of judges focusing on the difficulty, artistry and execution components of the performance. The final scores and the rankings of the gymnasts are obtained by aggregating the marks from the judges. The number of panels, the number of judges per panel and the aggregation procedure vary per discipline.

In this article we focus on execution judges in all the disciplines, with the additional inclusion of artistry judges in acrobatic and aerobic gymnastics.\(^1\) After the completion of a routine by the gymnast, each execution judge in the panel grades the performance with a score from 0 to 10 at steps of 0.1. The evaluation of a gymnastics routine is based on precise guidelines specified in the Code of Points of each discipline and apparatus [14], [15], [16], [17], [18], [19]. All the disciplines with the exception of trampoline can include two reference judges who evaluate performances based on the same criteria than execution and artistry panel judges, but with increased weight if they strongly diverge from them.

III. DATA

The data, provided by the FIG\(^2\) and Longines\(^3\) encompasses 21 international and continental competitions held between 2013 and 2016, including the 2016 Rio Olympic Games. Table I shows the size of the dataset by discipline after the following preprocessing. The number of marks depends on the number of performances in the dataset and the size of the judging panels, the latter ranging from four to nine judges. We analyze artistry and execution marks, including those from reference judges, but exclude marks for the difficulty component. We also exclude synchronized trampoline since its panels are not amenable to analysis due to their small size. We assume that national bias is marginal in aborted or poorly executed routines because the risk for a judge of being accused of cheating is not worth the potential benefits. We therefore restrict the dataset to performances with a median panel score of at least 7.0. This excludes 9.9% of the original data points.

Since we are interested in the raw marks reported by judges, we disregard penalties outside their jurisdiction and post-evaluation aggregation. We do not distinguish between reference and regular panel judges, which are all part of a single and enlarged panel for our analysis. This is further justified from our previous work [12] showing that reference and regular panel judges have a similar marking behavior. We also show in [12] that artistry and execution judges in acrobatic and aerobic gymnastics behave similarly.

\(^1\)Besides acrobatic and aerobic gymnastics, the other disciplines do not feature artistry judges.

\(^2\)www.fig-gymnastics.com

\(^3\)www.longines.com
### Methods

We develop our regression model starting with the mathematical essence of judging: the score $s_{p,j}$ of performance $p$ by judge $j$ is expressed as

$$s_{p,j} = \lambda_p + \epsilon_p$$

(1)

where $\lambda_p$ is the unknown true quality of the performance and $\epsilon_p$ is a random error term. In gymnastics, the true performance level $\lambda_p$ is called the control score $c_p$ and typically generated by technical committees using post-competition video reviews. Since the control scores are unavailable for our analysis, we assume that the judging panel is large enough to provide a good approximation of the true performance level. We use the median panel score $c_p \hat{=} \text{med}(s_{p,j})$ as an approximation for $\lambda_p$ to decrease the impact of biased and erratic judges.

Refining this simple model, we consider the general tendency $\mu_j$ of a judge who consistently applies the judging regulations too harshly or too generously. We then include the national bias of a judge in favor of an athlete with the same nationality with the binary variable $I_{SN}$. The extent of the bias is determined by the parameter $\beta_{SN}$ and estimated by the regression model. National bias does also occur by penalizing direct competitors of same-nationality athletes; we integrate this into the model with $I_{COMP}$ and $\beta_{COMP}$. Our improved model becomes

$$s_{p,j} = c_p + \mu_j + \beta_{SN} \cdot I_{SN} + \beta_{COMP} \cdot I_{COMP} + \epsilon_p.$$  

(2)

As done in our first article, we express the distance to the control score $c_p$ in relation to the approximated standard deviation of the judging error $\hat{\sigma}_d(c)$ for discipline $d$. We approximate $\hat{\sigma}_d(c)$ using a weighted least-squares exponential regression using our data. We can derive this approximation by discipline, apparatus, gender, and even by judge. In every gymnastic except trampoline, a single approximation per discipline is sufficient. Figure 1 shows $\hat{\sigma}_d(c)$ as a function of $c$ for all the disciplines except trampoline and Table II shows numerical values for men’s artistic gymnastics. For trampoline, there are significant differences between apparatus, thus we do one regression for $\hat{\sigma}_d(c)$ per apparatus. The results are shown in Figure 2. Note that some curves are below zero for control scores close to 10, but this is extrapolated and there is no scoring data in that range.

This approximation of the judging variability allows to describe the judge specific general error $\mu_j$ and the biases ($\beta_{SN}, \beta_{COMP}$) more precisely. We assume that they have similar properties of heteroscedasticity: intentional and unintentional.

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**Table I. Sample size by discipline.**

| Discipline      | Nb. of routines | Nb. of marks | Nb. of same nationality marks | Nb. of direct competitors |
|-----------------|-----------------|--------------|-------------------------------|---------------------------|
| Acrobatics      | 714             | 4’874        | 257 (5.3%)                    | 843 (17.3%)               |
| Aerobics        | 921             | 6’396        | 200 (3.1%)                    | 757 (11.8%)               |
| Artistics (M)   | 7’120           | 46’748       | 909 (1.9%)                    | 3’006 (6.4%)              |
| Artistics (F)   | 3’545           | 23’515       | 522 (2.2%)                    | 1’694 (7.2%)              |
| Rhythms         | 2’636           | 17’673       | 405 (2.3%)                    | 1’297 (7.3%)              |
| Trampoline      | 1’483           | 7’278        | 343 (4.7%)                    | 833 (11.4%)               |

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Figure 1. Approximated standard deviation of judging error as a function of the control score per discipline.

| $c$   | $\hat{\sigma}_d(c)$ |
|-------|----------------------|
| 7.0   | 0.31                 |
| 7.5   | 0.27                 |
| 8.0   | 0.24                 |
| 8.5   | 0.20                 |
| 9.0   | 0.15                 |
| 9.5   | 0.09                 |

**Table II. Estimated standard deviation of judging error as a function of the control score in men’s artistic gymnastics.**

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**Figure 2.** Approximated standard deviation of judging error as a function of the control score per apparatus in trampoline.

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4One could argue that the control score is still an approximation of the true quality, although a very good one. This is further discussed in [12].

5$\mu_j$ is generally very small, i.e., below 0.02, however for some judges this deviation reaches 0.2 points.
misjudgements are smaller for the best athletes. If the natural variability decreases, any individual divergence away from the remaining panel decreases as well. Being too far off the panel score is very suspicious and is immediately noticed by officials, and is usually unnecessary since a small difference is sufficient to make an impact. We therefore suppose that judges do adapt their scoring behaviour to not stand out, no matter if their bias is intentional or not. We can thus assess the individual general tendency \( \mu_j \) and the national bias \((\hat{\beta}_{SN}, \hat{\beta}_{COMP})\) in terms of the approximated deviation of scores \( \hat{\sigma}_d(c) \). Our model becomes

\[
 s_{p,j} = c_p + (\mu_j + \hat{\beta}_{SN} \cdot I_{SN} + \hat{\beta}_{COMP} \cdot I_{COMP}) \cdot \hat{\sigma}_d(c_p) + \epsilon_p. \tag{3}
\]

To restrict the number of variables in the regression model, we estimate the general judge tendency \( \mu_j \) beforehand as

\[
 \mu_j = E \left[ \frac{s_{p,j} - c_p}{\hat{\sigma}_d(c_p)} \right] \tag{4}
\]

which is the average judging error expressed as a multiple of the natural deviation \( \hat{\sigma}_d(c) \). Since we know \( c_p, \mu_j \) and \( \hat{\sigma}_d(c_p) \), we can group \( c_p, \mu_j \) and \( \cdot \hat{\sigma}_d(c_p) \) together with the reported judge score \( s_{p,j} \) into a single variable. The resulting response variable \( d_{p,j} \) is the judging error corrected for the judge specific tendency and given by

\[
 d_{p,j} = (\hat{\beta}_{SN} \cdot I_{SN} + \hat{\beta}_{COMP} \cdot I_{COMP}) \cdot \hat{\sigma}_d(c_p) + \epsilon_p. \tag{5}
\]

Up to this point we did not specify the distribution of the error term \( \epsilon_p \). Based on our observations in \cite{12}, and as discussed above, the distribution of the judging error for discipline \( d \) is heteroscedastic in \( c_p \) with mean zero and standard deviation approximation as a factor of \( \hat{\sigma}_d(c_p) \). In \cite{12}, we go further and calculate a marking score \( M_f \) for each judge quantifying his/her accuracy as a factor of \( \hat{\sigma}_d(c_p) \). We thus model the judging error of a specific judge \( j \) as a normal random variable with mean zero and variance \( \hat{\sigma}_d^2(c_p) \cdot M_f^2 \). Putting everything together, our final regression model is

\[
 d_{p,j} = (\hat{\beta}_{SN} \cdot I_{SN} + \hat{\beta}_{COMP} \cdot I_{COMP}) \cdot \hat{\sigma}_d(c_p) + \epsilon_p \Rightarrow \epsilon_p \sim N(0, \hat{\sigma}_d^2(c_p) \cdot M_f^2) \tag{6}
\]

and can be solved with a generalized least squared estimator. We can use Eq. \( \ref{6} \) to estimate the national bias \( (\hat{\beta}_{COMP}, \hat{\beta}_{SN}) \) by apparatus, by discipline, by nationality and by judge.

V. RESULTS AND DISCUSSION

A. National bias by discipline

Table \( \ref{3} \) shows the outcome of the general linear model specified by Eq. \( \ref{6} \). The results are split by discipline and stage of the event. While ‘All gymnasts’ encompasses all performances in the dataset, ‘Top 8 finalists’ only includes the top eight gymnasts in the final stage of a competition (apparatus and all-around finals). Because the general linear model includes the functional heteroscedasticity variable \( \hat{\sigma}_d(c) \), the estimated parameters \( \hat{\beta}_{SN} \) and \( \hat{\beta}_{COMP} \) are expressed in relation to \( \hat{\sigma}_d(c) \). For instance, \( \hat{\beta}_{SN} = 0.5 \) means that the bias level in favor of same-nationality gymnasts is half the natural deviation of marks for a specific performance level.

| Discipline      | All gymnasts        | Top 8 finalists     |
|-----------------|---------------------|---------------------|
|                 | Estimate | Std. error | Estimate | Std. error |
| **Acrobatics**  |          |            |          |            |
| \( \hat{\beta}_{SN} \) | 0.04     | (0.06)     | -0.08    | (0.27)     |
| \( \hat{\beta}_{COMP} \) | -0.04    | (0.03)     | -0.04    | (0.08)     |
| **Aerobics**    |          |            |          |            |
| \( \hat{\beta}_{SN} \) | 0.25***  | (0.07)     | 0.50***  | (0.15)     |
| \( \hat{\beta}_{COMP} \) | -0.04    | (0.04)     | -0.01    | (0.06)     |
| **Artistics (M)** |        |            |          |            |
| \( \hat{\beta}_{SN} \) | 0.43***  | (0.03)     | 0.68***  | (0.11)     |
| \( \hat{\beta}_{COMP} \) | -0.02    | (0.02)     | -0.05    | (0.03)     |
| **Artistics (F)** |        |            |          |            |
| \( \hat{\beta}_{SN} \) | 0.28***  | (0.04)     | 0.55***  | (0.13)     |
| \( \hat{\beta}_{COMP} \) | -0.05*   | (0.02)     | 0.02     | (0.04)     |
| **Rhythmic**    |          |            |          |            |
| \( \hat{\beta}_{SN} \) | 0.34***  | (0.05)     | 0.30     | (0.19)     |
| \( \hat{\beta}_{COMP} \) | -0.04    | (0.03)     | -0.09    | (0.06)     |
| **Trampoline**  |          |            |          |            |
| \( \hat{\beta}_{SN} \) | -0.05    | (0.05)     | 0.02     | (0.12)     |
| \( \hat{\beta}_{COMP} \) | -0.06    | (0.03)     | -0.11*   | (0.07)     |

Table III. Regression results by discipline. Estimated parameters \((\hat{\beta}_{SN}, \hat{\beta}_{COMP})\) indicate the national bias in terms of the approximated natural variation of marks \( \hat{\sigma}_d(c) \). To obtain the nominal bias for a given performance quality \( c_p \), multiply the estimated parameter with \( \hat{\sigma}_d(c_p) \).

The results reveal that in aerobic, artistic and rhythmic gymnastics, judges mark same-nationality gymnasts significantly higher than the other panel judges, whereas national bias is not a systemic issue in acrobatic gymnastics and trampoline. In artistic and rhythmic gymnastics in particular, national bias is even more pronounced for finalists than during earlier stages of competitions, in other words judges bend the rules further when it counts. This does not necessarily imply that the nominal bias is higher for the best gymnasts since the natural deviation of judging marks decreases as the performance level improves, but instead that the magnitude of the national bias compared to the other judging errors increases for the best athletes.

The most severe bias appears in men’s artistic gymnastics, where judges give gymnasts of the same country an average bonus of almost half the natural variation, and an average bonus of two thirds the natural deviation for the best finalists. The best men artistic gymnasts in the world typically get marks between 8.5 and 9.5 depending on the apparatus. Using Figure \( \ref{4} \) and Table \( \ref{3} \) the national bias \( \hat{\beta}_{SN} = 0.68 \) for the top men finalists corresponds to a nominal bias of between 0.06 and 0.15 points depending on the apparatus, or 10% of the total deductions of the performance. Considering the narrow gaps between the best gymnasts, this is a worrying result, both in relative and in absolute terms. We point out again that this is for an average judge; the most biased judges are significantly worse!

The results in Table \( \ref{3} \) further show that the penalization of direct competitors of same-nationality athletes is very small in all the disciplines. This negative bias, even when statistically
significant, remains much smaller than the natural variation of marks and therefore has a negligible impact on the final rankings. This is in line with prior research [5], [4].

B. National bias by nationality and judge

We can apply our general linear regression model by nationality and by judge. We first restrict the number of variables by discarding the penalization of direct competitors, which is negligible compared to the positive bias toward same-nationality gymnasts. Figure 3 shows the estimated national bias per country in men’s artistic gymnastics. The distribution is right-skewed around $\beta_{SN} = 0.43$ with a fat right tail corresponding to the most biased countries. The histogram further partitions the countries to differentiate 'large nations' with reliable results from 'small nations' with few data points. The threshold is 15 same-nationality marks. Unsurprisingly, small nations show a larger national bias variance than large nations. We observe the same behavior in women’s artistic gymnastics and rhythmic gymnastics.

| Country       | Nb. of same-nationality marks | Estimated national bias |
|---------------|-------------------------------|-------------------------|
| Japan         | 24                            | 0.916                   |
| Great Britain | 37                            | 0.761                   |
| South Korea   | 50                            | 0.713                   |
| China         | 23                            | 0.667                   |
| Belgium       | 22                            | 0.657                   |

Table IV. Countries with the highest national bias in men’s artistic gymnastics. The list only includes countries with at least 15 same-nationality marks.

Tables V-VI show the ‘large nations’ with the worst estimated national bias in men’s artistic gymnastics, women’s artistic gymnastics, and rhythmic gymnastics, respectively. We have less data in women’s artistic gymnastics and rhythmic gymnastics, thus in both cases we set the threshold for large nations at 10 same-nationality marks instead of 15. Eastern European countries dominate the list in rhythmic gymnastics, whereas Asian countries dominate in artistic gymnastics. South Korea is among the worst three biased countries in all three disciplines.

Table V. Countries with the highest national bias in women’s artistic gymnastics. The list only includes countries with at least 10 same-nationality marks.

| Country     | Nb. of same-nationality marks | Estimated national bias |
|-------------|-------------------------------|-------------------------|
| South Korea | 23                            | 0.822                   |
| Greece      | 10                            | 0.721                   |
| Romania     | 13                            | 0.697                   |
| Bulgaria    | 15                            | 0.689                   |
| Estonia     | 10                            | 0.483                   |

Table VI. Countries with the highest national bias in rhythmic gymnastics. The list only includes countries with at least 10 same-nationality marks.

Figure 3. Estimated national bias by nationality in men’s artistic gymnastics. We distinguish 'large countries' with at least 15 same-nationality evaluations from 'small countries'.

Figure 4. Estimated national bias by judge in men’s artistic gymnastics. We distinguish 'active judges' with at least 5 same-nationality evaluations from other judges.
own gymnasts is insufficient: if they show a large national bias, it is likely that they are prone to other biases as well.

We must point out that it is difficult to infer systemic national bias, or lack thereof, based on the average national bias of a country. To illustrate this, Figure 5 shows the estimated national bias of all the Dutch and South Korean men’s gymnastics judges. Although the two countries have a strikingly different average national bias (−0.12 versus 0.71), one could argue that this is, at least partly, due to the appalling bias of a single South Korean judge.

C. Impact of national bias on rankings

The regular and significant bias in favor of same-nationality gymnasts naturally raises the question of its impact on the competitions’ rankings. We study this further and focus on the apparatus and all-around finals in artistic gymnastics. We apply the scoring aggregation procedure as defined in the Codes of Points [10], [17], and study ranking distortions by calculating the rankings with and without the marks of same-nationality judges. Whenever we observe a same-nationality mark, we discard it and calculate the trimmed mean of the remaining panel marks. If a discarded score comes from a reference judge, the average reference score simply becomes the mark of the second reference judge.

In the apparatus finals, 4 out of 740 performances in our dataset include a same-nationality evaluation. For one of the four gymnasts, the final score of the performance is boosted by 0.267 points due to the national bias of a judge. The FIG and the other athletes were lucky in this instance because the gymnast in question finished last and far behind the other finalists, and this scoring discordance had no effect on the ranking. In most other instances a difference of this magnitude would have improved the position of the gymnast by a few rankings. In this work, we studied the national bias of international gymnastics judges during the 2013–2016 Olympic cycle. The main novelty of our approach over prior work is that we leverage and integrate the natural deviation of judging scores into our national bias regression model. We have shown in [12] that this natural judging error is heteroscedastic and can be accurately modeled with weighted least-squares exponential regressions. This allows us to express national bias as a function of the natural judging error. Intuitively this makes sense: judges are very accurate when evaluating the best gymnasts, thus even a small nominal bias can have a lot of impact on the ranking of the gymnast.

VI. Conclusion and Recommendations

In this work, we studied the national bias of international gymnastics judges during the 2013–2016 Olympic cycle. The main novelty of our approach over prior work is that we leverage and integrate the natural deviation of judging scores into our national bias regression model. We have shown in [12] that this natural judging error is heteroscedastic and can be accurately modeled with weighted least-squares exponential regressions. This allows us to express national bias as a function of the natural judging error. Intuitively this makes sense: judges are very accurate when evaluating the best gymnasts, thus even a small nominal bias can have a lot of impact on the ranking of the gymnast.

We estimate the national bias by discipline, by nationality and by judge, and show important differences between the least- and most-biased judges. National bias has the largest impact in all-around competitions where it is impossible to avoid same-nationality evaluations.

A. Recommendations

The FIG has already taken successful steps to decrease the impact of national bias in gymnastics. We now discuss them and propose additional mitigation measures.

1) Avoid same-nationality judges: The FIG already avoids same-nationality judges in the apparatus finals. This is not possible in all-around finals since they require too many judges.

2) Increase the size of the judging panels: Large panels are more robust because they decrease the impact of outlier marks. Unfortunately, same-nationality judging situations are already difficult to avoid in all-around finals; larger panels will not solve this problem.

3) Get rid of the increased power imparted to reference judges: In [12], we have shown that reference judges, who are hand-picked by the FIG, are not better than regular panel judges. We thus recommended that the FIG merges the execution and reference judges into a larger execution panel where all the judges have the same power. The FIG Technical Coordinator is currently proposing the adoption of our recommendation. This will prevent a biased reference judge from strongly affecting the final scores of the gymnasts due to its increased decision power.

4) Aggregate marks more aggressively: For all-around finals, where same-nationality evaluations are unavoidable, we recommended that the FIG removes more extreme marks from its panels before aggregating them with a (more aggressive) trimmed mean, and even take the median panel mark. Trampoline already uses the median mark for each jump, but doing the same thing for artistic or rhythmic gymnastics routines would result in more ties. The FIG understandably does not like to award ties, but this should not be an issue in all-around finals since the final ranking includes scores from
all the apparatus. Moreover, we believe that awarding two gold medals to gymnasts whose performances are within the margin of error of the best judges is a better outcome than letting a biased judge act as the tiebreaker. Following our recommendation, the FIG Technical Coordinator is currently proposing to trim the best and worst two marks from its execution panels for all the disciplines except trampoline, which already uses the median. The resulting aggregation would be the trimmed mean of the middle three scores in artistic gymnastics, and the trimmed mean of the middle two scores in aerobic, acrobatic and rhythmic gymnastics. This change would apply to all the events, including all-around finals.

5) Track the long-term performance of judges and remove the worst culprits: The FIG recently started using an improved Judge Evaluation Program (JEP) to assess the performance of gymnastics judges. JEP allows longitudinal monitoring of the judges, many of whom are judging for decades. The bias tool in JEP is not as refined as the analysis done in this article, but it should nevertheless make it easier to highlight and get rid of the most biased judges.

B. Future work

Accurate control scores provided by video review post-competitions could allow us to refine our work on national bias. In particular, we could investigate more complex judging behavior in gymnastics such as vote-trading and compensation effects revealed in figure skating and ski jumping. Further analysis should also include the serial positioning of athletes to better understand the bias against direct competitors of same-nationality gymnasts. Before a same-nationality athlete has performed his/her routine, a judge vaguely knows his/her direct competitors. After the routine, it is more clear who the direct competitors are, and how much they should be penalized. We expect to see a dependence of the national bias on the positioning of the gymnasts.

National bias has been investigated in many other sports besides gymnastics. In the third article of this series, we show that the judging error variance in other sports with panels of judges awarding marks within a finite range has a similar heteroscedastic shape. The integration of this behaviour could provide an improved national bias analysis in all these sports.

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