What is the most competitive sport?

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We present an extensive statistical analysis of the results of all sports competitions in five major sports leagues in England and the United States. We characterize the parity among teams by the variance in the winning fraction from season-end standings data and quantify the predictability of games by the frequency of upsets from game results data. We introduce a mathematical model in which the underdog team wins with a fixed upset probability. This model quantitatively relates the parity among teams with the predictability of the games, and it can be used to estimate the upset frequency from standings data. We propose the likelihood of upsets as a measure of competitiveness.

What is the most competitive team sport? We answer this question via a statistical survey of game results [1–4]. We relate *parity* with *predictability*, and propose the likelihood of upsets as a measure of competitiveness.

We studied the results of all regular season competitions in 5 major professional sports leagues in England and the United States (table I): the premier soccer league of the English Football Association (FA), Major League Baseball (MLB), the National Hockey League (NHL), the National Basketball Association (NBA), and the National Football League (NFL). NFL data includes the short-lived AFL. We considered only complete seasons, with more than 300,000 games in over a century [5].

The winning fraction, the ratio of wins to total games, quantifies team strength. Thus the distribution of winning fraction measures the parity between teams in a league. We computed $F(x)$, the fraction of teams with a winning fraction of x or lower at the end of the season, as well as $\sigma = \sqrt{\langle x^2\rangle - \langle x\rangle^2}$, the standard deviation in winning fraction. Here $\langle\cdot\rangle$ denotes the average over all teams and all years using season-end standings. For example, in baseball where the winning fraction x typically falls between 0.400 and 0.600, the variance is $\sigma = 0.084$. As shown in figures 1 and 2a, the winning fraction distribution clearly distinguishes the five leagues. It is narrowest for baseball and widest for football.

league	years	games	$\langle$games$\rangle$	σ	$\boldsymbol{q}$	$q_{\rm model}$
FA	1888-2005	43350	39.7	0.102	**0.452**	0.459
MLB	1901-2005	163720	155.5	0.084	**0.441**	0.413
NHL	1917-2004	39563	70.8	0.120	**0.414**	0.383
NBA	1946-2005	43254	79.1	0.150	**0.365**	0.316
NFL	1922-2004	11770	14.0	0.210	**0.364**	0.309

TABLE I: Summary of the sports statistics data. Listed are the time periods, total number of games, average number of games played by a team in a season ($\langle$games$\rangle$), variance in the win-percentage distribution (σ), measured frequency of upsets ($\boldsymbol{q}$), and upset probability obtained using the theoretical model ($q_{\rm model}$). The fraction of ties in soccer, hockey, and football is 0.246, 0.144, and 0.016, respectively.

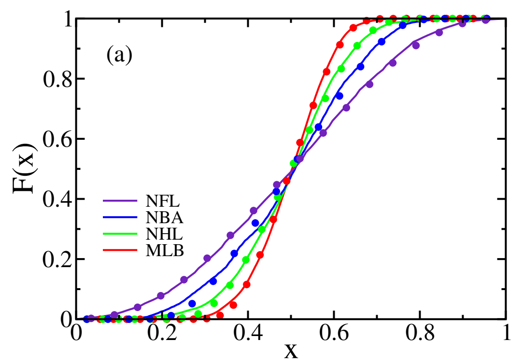

FIG. 1: Winning fraction distribution (curves) and the best-fit distributions from simulations of our model (circles). For clarity, FA, that lies between MLB and NHL, is not displayed.

Do these results imply that MLB games are the most competitive and NFL games the least? Not necessarily! The length of the season is a significant factor in the variability in the winning fraction. In a scenario where the outcome of a game is completely random, the total number of wins performs a simple random walk, and the standard deviation σ is inversely proportional to the square root of the number of games played. Generally, the shorter the season, the larger σ. Thus, the small number of games is partially responsible for the large variability observed in the NFL.

To account for the varying season length and reveal the true nature of the sport, we set up mock sports leagues where teams, paired at random, play a fixed number of games. In this simulation model, the team with the better record is considered as the favorite and the team with the worse record is considered as the underdog. The outcome of a game depends on the relative team strengths: with the "upset probability" $q < 1/2$, the underdog wins, but otherwise, the favorite wins. Our analysis of the nonlinear master equations that describe the evolution of the distribution of team win/loss records shows that σ decreases both as the season length increases and as games become more competitive, i.e., as q increases [6]. In a hypothetical season with an infinite number of games,

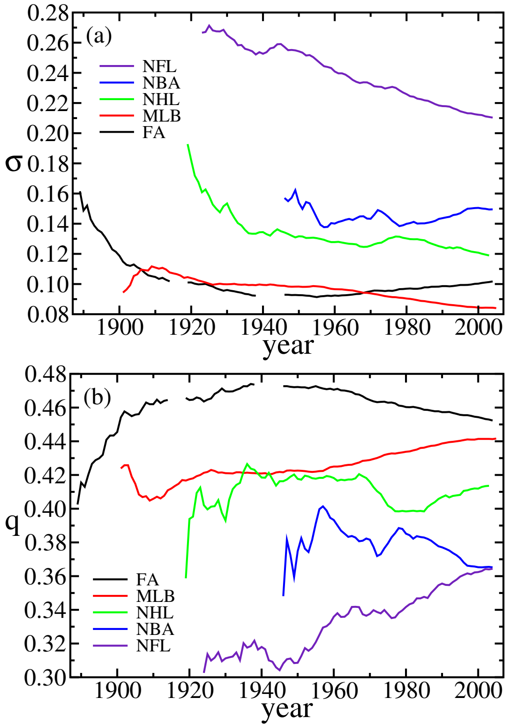

FIG. 2: (a) The cumulative variance in the winning fraction distribution (for all seasons up to a given year) versus time. (b) The cumulative frequency of upsets q, measured directly from game results, versus time.

the winning fraction distribution is uniform in the range $q < x < 1 - q$ and as a result, $\sigma = (1/2 - q)/\sqrt{3}$.

We run Monte Carlo simulations of these artificial sports leagues, with sport-specific number of games and a range of q values. We then determine the value of q that gives the best match between the distribution $F(x)$ from the simulations to the actual sports statistics (figure 1). Generally, we find good agreement between the simulations results and the data for reasonable q values.

To characterize the predictability of games, we followed the chronologically-ordered results of all games and reconstructed the league standings at any given day. We then measured the upset frequency q by counting the fraction of times that the team with the worse record on the game date actually won (table I). Games between teams with no record (start of a season) or teams with equal records were disregarded. Game location was ignored and so was the margin of victory. In soccer, hockey, and football, ties were counted as 1/2 of a victory for both teams. We verified that handling ties this way did not significantly affect the results: the upset probability changes by at most 0.02 (and typically, much less) if ties are ignored.

We find that soccer and baseball are the most competitive sports with $q = 0.452$ and $q = 0.441$, respectively, while basketball and football, with nearly identical $q = 0.365$ and $q = 0.364$, are the least. There is also good agreement between the upset probability $q_{\rm model}$, obtained by fitting the winning fraction distribution from numerical simulations of our model to the data as in figure 1, and the measured upset frequency (table I). Consistent with our theory, the variance σ mirrors the bias, $1/2 - q$ (figures 2a and 2b). Tracking the evolution of either q or σ leads to the same conclusion: NFL and MLB games are becoming more competitive, while over the past 60 years, FA displays an opposite trend.

In summary, we propose a single quantity, q, the frequency of upsets, as an index for quantifying the predictability, and hence the competitiveness of sports games. We demonstrated the utility of this measure via a comparative analysis that shows that soccer and baseball are the most competitive sports. Trends in this measure may reflect the gradual evolution of the teams in response to competitive pressure [7], as well as changes in game strategy or rules [8].

Our model, in which the stronger team is favored to win a game [6], enables us to take into account the varying season length and this model directly relates parity, as measured by the variance σ with predictability, as measured by the upset likelihood q. This connection has practical utility as it allows one to conveniently estimate the likelihood of upsets from the more easily-accessible standings data. In our theory, all teams are equal at the start of the season, but by chance, some end up strong and some weak. Our idealized model does not include the notion of innate team strength; nevertheless, the spontaneous emergence of disparate-strength teams provides the crucial mechanism needed for quantitative modeling of the complex dynamics of sports competitions.

We thank Micha Ben-Naim for assistance in data collection and acknowledge support from DOE (W-7405-ENG-36) and NSF (DMR0227670 & DMR0535503).

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