nature human behaviour

LETTERS

https://doi.org/10.1038/s41562-018-0460-y

Prior shared success predicts victory in team competitions

Satyam Mukherjee[1,2,3]*, Yun Huang[4], Julia Neidhardt[5], Brian Uzzi[1,2] and Noshir Contractor[1,2,4,6]

Debate over the impact of team composition on the outcome of a contest has attracted sports enthusiasts and sports scientists for years. A commonly held belief regarding team success is the superstar effect; that is, including more talent improves the performance of a team[1]. However, studies of team sports have suggested that previous relations and shared experiences among team members improve the mutual understanding of individual habits, techniques and abilities and therefore enhance team coordination and strategy[2–9]. We explored the impact of within-team relationships on the outcome of competition between sports teams. Relations among teammates consist of two aspects: qualitative and quantitative. While quantitative aspects measure the number of times two teammates collaborated, qualitative aspects focus on 'prior shared success'; that is, whether teamwork succeeded or failed. We examined the association between qualitative team interactions and the probability of winning using historical records from professional sports—basketball in the National Basketball Association, football in the English Premier League, cricket in the Indian Premier League and baseball in Major League Baseball—and the multiplayer online battle game *Defense of the Ancients 2*. Our results show that prior shared success between team members significantly improves the odds of the team winning in all sports beyond the talents of individuals.

"The idea of star players is a notion everywhere but nonsense in Germany," said the football analyst Hienric Spencer after the dominant performance of Germany in the 2014 FIFA (Fédération International de football Association) World Cup[10]. Spencer's statement questioned the commonly held belief about the association between higher team performance and the presence of highly skilled players in a team[11]. Sports history is, indeed, littered with plenty of instances in which teams with great players have failed. Various factors determine the success of a team. Prior research on team success revealed a positive correlation between cognitive ability and team performance[12], and a link between individual talents of 'core' members of a team and team performance[13]. However, to win in professional sports such as soccer (English Premier League (EPL)), baseball (Major League Baseball (MLB)), basketball (National Basketball Association (NBA)) or cricket (Indian Premier League (IPL)), a team requires not only highly skilled players but also cooperative teammates. A prevalent saying related to the success of a team is "a team is only as strong as its weakest link," enforcing the idea of building teams with close-knit teammates[14].

Within-team relationships may enable more successful collaboration, which is vital for team performance. Information about relations within a team is useful and facilitates teamwork[15,16]. A qualitative, longitudinal field study of three virtual global teams over a period of 21 months found that effectiveness increases if a team has a series of adequate communication incidents[2]. Previous studies have shown that personal relationships and previous collaborations improve the performance of teams with complex tasks[2–5,17–27]. Similarly, the success of sports teams depends on inter-player coordination[6–8]. Earlier studies of player interactions have predicted the individual performance of football players in the 2008 Euro Cup[6], basketball players in the 2010 NBA playoffs[7], cricket matches played between 1877 and 2010[28], and soccer players in the 2014 FIFA World Cup[29]. However, these studies focused on directly observable player coordination activities during the game (for example, passes in football).

Prior collaboration among team members consists of qualitative and quantative aspects that accrue over time[30]. While quantitative aspects measure the number of times individuals collaborated in the past for specific tasks, the qualitative aspect captures the outcome of the task (that is, whether teamwork was a success or failure). Psychological experiments and field research point towards measuring shared wins as a way to understand how teammates learn from experience and provide insights into one another. Positive emotions and psychological states such as pride improve the ability of a person to recall complex information and experiences[31], intricacies about their own behaviour, and to be open to sharing and learning from others. Conversely, negative emotions such as anger, enhance the vulnerability of person to incur losses[31]. A related study measuring instant messaging coordination among teams of financial decision-makers found that negative emotions arise in teams in response to financial losses[32]. Once the negative emotions arise, team members then tend to 'turtle up', and complex cognitions, mindfulness and team communications are reduced. The opposite effects are seen when teams make financial wins.

Building on the earlier research on successful teamwork and work experience, we determine how prior experience of playing together affects the future performance of a team. In this work, we propose that when the goal of a team is to defeat another team, the attributes of team members and their successful prior interactions directly determine the outcome of the team. We investigate the elements of team success in the context of sports by focusing on the successful prior interactions among team members. In other words, when two teams consisting of highly skilled players are competing against one another, what are the chances of the team with greater prior success among its members? In sports and online games, people often play many matches together as part of different teams, and their successful collaborative experiences facilitate relationship building. The number of times they have played with one another

[1]Kellogg School of Management, Northwestern University, Evanston, IL, USA. [2]Northwestern Institute on Complex Systems, Evanston, IL, USA. [3]Indian Institute of Management Udaipur, Udaipur, Rajasthan, India. [4]Department of Industrial Engineering and Management Sciences, Northwestern University, Evanston, IL, USA. [5]Research Division of E-Commerce, TU Wien, Vienna, Austria. [6]Department of Communication Studies, Northwestern University, Evanston, IL, USA. *e-mail: satyam.mukherjee@gmail.com

on teams indicates the strength of their relationship, and the density of the relationship network in a team represents the extent to which the team members have frequently played together. Therefore, we propose the following hypothesis to examine the impact of team relations on team outcomes: when teams with highly skilled players compete, the team with higher successful prior interactions among teammates is more likely to win.

For this study, we collected sports data from the earliest available date for basketball, football, baseball and cricket matches. Our objective was to obtain the prior shared success for a particular season (year) and to the check robustness of the results for another season (year). Specifically, for every sport, we constructed the skills of players and prior shared success based on game statistics between seasons 2002–2003 and 2012–2013 (in the NBA and the EPL) and years 2002–2012 (MLB) and years 2008–2012 (the IPL). We then studied their impacts on team outcomes of sports matches in season 2013–2014 (year 2013). To ensure reliable statistical estimates, we obtained the data of prior shared success within the past 10 years, resulting in an analysis for the season 2013–2014 (year 2013). For the multiplayer online battle game *Defense of the Ancients 2* (*Dota2*), we constructed measurements of players based on the game log in the first week of December 2011 and studied their impacts on 4,357 short matches (up to 30 min) in the following week.

In sports, scores in a match typically measure the performance of a team. In NBA, EPL and MLB games, the team score is the number of points, goals or runs, respectively, a team scores in a contest. In the IPL matches, the 'run rate', that is, the ratio of the number of runs scored to the number of overs (each over being the equivalent of six pitches in baseball) played, measures team performance. For example, if 140 runs are scored in 20 overs, the run-rate score is 7. We chose the difference of the run rate as the dependent variable in IPL matches, since it serves as a surrogate for batting strategy[33]. Compared to sports such as football or basketball, whereby players compete to score simultaneously, in cricket, a team sets a target in the first innings and the opponent team then chases the runs in the second innings. Frequently, the outcome of a contest is decided by the run rate of the team batting second. The fielding captain changes the fielding strategy depending on the run-rates of two teams, and the opponent captain decides whether an aggressive or defensive batting strategy is desirable[33]. In *Dota2*, the number of towers demolished is a meaningful indicator of team performance, since a team needs to destroy the defending towers of the opponent before taking over their stronghold and winning the game.

In each of the five sports, the team with the higher score wins a match. Therefore, we used the difference in the scores of the two teams to measure the outcome of a match. The dependent variable δdv_i^{12} for match i is defined as follows:

$$\delta dv_i^{12} = \text{score}_i^1 - \text{score}_i^2$$

where score_i^1 and score_i^2 are the team scores for Team 1 and Team 2, respectively. For NBA, EPL and MLB games, Team 1 refers to the home team (which hosts the game) and Team 2 to the away team (which is visiting the host). For IPL matches, Team 1 is the team that started batting first, and Team 2 is the second. In *Dota2*, Team 1 and Team 2 indicate the Radiant and Dire teams, respectively, which take different territories of the game map. A positive value of δdv_i^{12} means that Team 1 has a higher score and wins the match.

In Fig. 1 we illustrate a team as a collection of individuals. The relational perspective of teams considers a team as a network of individuals whereby the weight of each connection equals the number of times two players have played together in which they were winners (Fig. 1a). In other words, we counted the number of times a pair of players was part of the same winning team. We measure wins because wins parsimoniously capture the relevant conditions under

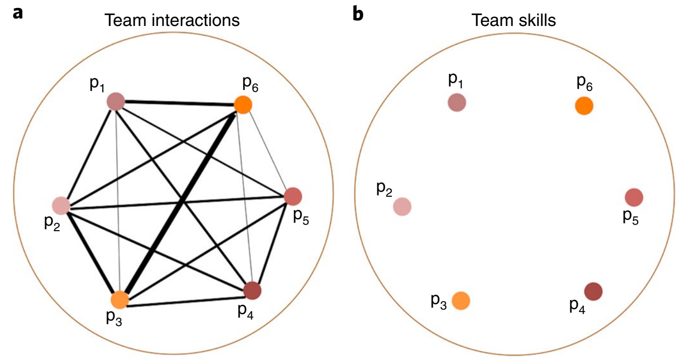

Fig. 1 | Team as an aggregation of players and relationship among players. **a**, The links represent the successful prior repeated interactions among the players, with the thickness of a link being proportional to the number of such interactions. Prior shared success is measured as an average of successful prior repeated interactions. **b**, Every team member possesses individual attributes, such as skills. The colour of the nodes corresponds to thye individual skills of every player. Team skill is measured as the average of individual skills, with stronger teams having a higher average.

which players are likely to recall significant information about the strengths and weaknesses of the opponent and their own effective and ineffective strategies for confronting an opponent. In addition, these states make it more likely for any player to share their insights and to be open to learning from others.

Some teams perform better than others due to the successful relations among team members. For each team, we define the weighted density of its network of past successful interactions (S) of teammates; that is, $S_i = \frac{1}{N_i(N_i-1)} \sum_{k=1}^{N_i} \sum_{j=1}^{N_i} w_{kj}$ where N_i is the number of players a team used in match i, and w_{kj} is the number of matches that team members k and j played together and won in the past. For the season 2013–2014 (year 2013), we checked the number of times two players k and j played successfully between seasons 2002–2003 and 2012–2013 (in NBA and EPL games) and years 2002–2012 (MLB games) and years 2008–2012 (IPL matches). We estimated the number of successful prior interactions only among teammates who played in that particular match. Therefore, each team may have different values of past successful interactions for every match.

The prior shared success variable δS_i^{12} measures the difference of past successful interactions of two teams in a match i as follows:

$$\delta S_i^{12} = S_i^1 - S_i^2$$

where S_i^1 and S_i^2 are the average numbers of past successful interactions in Team 1 and Team 2, respectively. We summarize the dependent variable and the independent variable for all sports in Supplementary Table 1. Given the importance of individual skills in professional sports, we used team skills as a control for the average skills of all team members. Figure 1b illustrates the skills of team members, with nodes coloured according to the different levels of skill. Control variables are defined in the Methods.

Linear regression models were used to examine the impact of prior shared success on the outcome of a match, controlling for the skill factors and team fixed effects. The fixed-effect model is described a follows:

$$\delta dv_i^{12} = \theta_0 + \theta_1 \delta C_{1i}^{12} + \theta_2 \delta C_{2i}^{12} + \theta_3 \delta C_{3i}^{12} + \theta_4 \delta S_i^{12} + \sum_f \gamma_f^1 \text{Team1}_{fi} + \sum_f \gamma_f^2 \text{Team2}_{fi}$$

Table 1 | Descriptive statistics of NBA season 2013–2014 games

	All teams	Home team	Away team	Winning teams	Losing teams
Score	100.94 (11.85)	102.28 (11.86)	99.61 (11.69)	106.34 (10.48)	95.49 (10.56)
BPM	−1.05 (1.03)	−1.05 (1.04)	−1.06 (1.03)	−0.88 (0.99)	−1.23 (1.05)
Points	9.17 (1.54)	9.17 (1.52)	9.16 (1.56)	9.29 (1.45)	9.04 (1.62)
Assists	1.98 (0.44)	1.99 (0.44)	1.98 (0.44)	2.03 (0.42)	1.94 (0.46)
Prior shared success	20.97 (21.66)	21.29 (22.22)	20.62 (21.08)	24.73 (24.49)	17.20 (17.62)
N	2,630	1,315	1,315	1,315	1,315

Data represent mean (standard deviation).

where θ_{0-4} are the coefficients we wanted to estimate, specifically the strength and significance of θ_4. Since the same teams played on multiple occasions in basketball, football, cricket and baseball, the regressions also included sets of fixed effects for each of the teams in these sports for which the binary indicator variables Team1_{fi} equals 1 if *f* played as Team 1 in match *i*, and Team2_{fi} are the indicators for Team 2. We assumed that the fixed effects are different for playing Team 1 or Team 2; for example, playing home or away in NBA, EPL and MLB games, and the team batting first or second in IPL matches. The teams in *Dota2* are one-off, and no team fixed-effects were included in our analysis.

First, we considered a baseline model with the control variable and team fixed effects and estimate their impacts on the match outcome. Next, we added the prior shared success variable to the baseline model and estimate the contribution of team prior shared success by the increase in R^2 and decreases in Bayesian information criterion (BIC) statistics. To estimate the robustness of our findings, we applied logistic (logit) regression models with dependent binary variables being whether Team 1 wins the match. That is

$$\begin{aligned}&\text{logit}(\Pr(\delta dv_i^{12} > 0))\\&= \alpha_0 + \alpha_1 \delta C_{1i}^{12} + \alpha_2 \delta C_{2i}^{12} + \alpha_3 \delta C_{3i}^{12}\\&+ \alpha_4 \delta S_i^{12} + \sum_f \beta_f^1 \text{Team1}_{fi} + \sum_f \beta_f^2 \text{Team2}_{fi}\end{aligned}$$

where α_{0-4} are the coefficients of the control variable, and independent variable, and β_f^{12} are the coefficients of the team fixed effects.

Table 1 shows raw data relationships of all the variables for winning, losing, home and away teams in NBA season 2013–2014. The average winning team score is 106.34 ± 10.48, while the average score of losing teams is 95.49 ± 10.56. As expected, winning teams have a significantly higher score compared with losing teams (Wilcoxon signed-rank test, $z = 10.153$, $P < 0.001$). We also observed that home teams win ~58% of the matches, with the average score of Home teams significantly greater than away teams (Wilcoxon signed-rank test, $z = -6.950$, $P < 0.001$). The difference of average 'box plus/minus (BPM)' is significantly higher for winning teams compared with with losing teams (Wilcoxon signed-rank test, $z = 7.757$, $P < 0.001$). We also observed a higher value of difference of 'average points' (Wilcoxon signed-rank test, $z = 3.876$, $P < 0.001$) and difference of 'average assists' for winning teams (Wilcoxon signed-rank test, $z = 4.365$, $P < 0.001$). The winning NBA teams had a significantly higher value for the number of times their players had previously played in games they won (prior shared success) than the losing teams (Wilcoxon signed-rank test, $z = 10.153$, $P < 0.001$). Conversely, there was no significant difference in prior shared success between home and away teams (Wilcoxon signed-rank test, $z = -0.122$, $P = 0.9030$). Supplementary Table 3 shows the product moment correlation for NBA season 2013–2014 and the higher correlation between the difference of the average of successful past interaction and the difference of team scores. Statistics for EPL season 2013–2014, IPL 2013, MLB 2013 and *Dota2* are presented in the Supplementary Information (Supplementary Tables 2–39). No significant difference in skills was observed between winning and losing teams in EPL 2013–2014 (Wilcoxon signed-rank test; goals: $z = -0.342$, $P = 0.7327$; shots: $z = -0.325$, $P = 0.7451$) and IPL 2013 (Wilcoxon signed-rank test, batting 'strike rate': $z = 0.337$, $P = 0.7363$; bowling 'economy rate': $z = 1.807$, $P = 0.0707$) (Supplementary Tables 4–21). In MLB 2013 matches, difference in 'wins above replacement (WAR)' was significantly higher for winning teams (Wilcoxon signed-rank test, $z = 3.289$, $P = 0.0010$), while there was no significant difference in 'on-base plus slugging (OPS)' between winning and losing teams (Wilcoxon signed-rank test, $z = -1.196$, $P = 0.2316$). Finally, in *Dota2* matches, the difference in average deaths was significantly higher for winning teams than the losing teams (Wilcoxon signed-rank test, $z = -4.867$, $P < 0.001$).

Table 2 illustrates the predictive power of prior shared success in NBA season 2013–2014, EPL season 2013–2014, IPL 2013, MLB 2013, and *Dota2* games. First, we examined the contribution of the skill variables (team skills) on match outcomes. In NBA season 2013–2014, there was no significant association between the following variable on the 'difference of team scores': the difference of (BPM) (d.f. = 1,314, $P = 0.197$, effect size statistic = 0.862, 95% confidence interval (CI) = −0.449 to 2.174); difference of 'mean assists' on difference of team scores (d.f. = 1314, $P = 0.571$, effect size statistic = 0.270, 95% CI = −0.665 to 1.206); and difference of 'mean points' (d.f. = 1314, $P = 0.719$, effect size statistic = 0.477, 95% CI = −2.122 to 3.076). When we added the independent variable (prior shared success) to the baseline model, we observed a modest increase in R^2 from 24.4% to 25.6%, and the BIC decreased from 10,648 to 10,635. Nevertheless, we observed a significant impact of prior shared success on team performance (d.f. = 1314, $P < 0.001$, effect size statistic = 0.126, 95% CI = 0.069 to 0.182). The strength and significance tests of estimated coefficients of the skill variables δC_1, δC_2 and δC_3, suggest that they have no significant impact on the difference of team scores given the impact of prior shared success.

We found a different pattern for football matches played in the EPL. In the EPL season 2013–2014 models, the difference of 'mean goals' scored had a positive effect on the difference of team scores (d.f. = 379, $P = 0.038$, effect size statistic = 0.185, 95% CI = 0.010 to 0.359). Conversely, the difference of 'mean shots' and difference of 'mean assists' had no effect on the difference of team scores (mean shots: d.f. = 379, $P = 0.329$, effect size statistic = 0.066, 95% CI = −0.066 to 0.199; mean assists: d.f. = 379, $P = 0.059$, effect size statistic = −1.157, 95% CI = −2.358 to 0.043). the inclusion of prior shared success resulted in a modest increase of R^2 from 28.4% to 31%, and a reduction in the BIC from 1,660 to 1,652, reflecting an improvement in the model fit to the data. The prior shared success of a team had a positive and significant impact on the difference of team scores (d.f. = 379, $P = 0.001$, effect size statistic = 0.078, 95% CI = 0.033 to 0.122). Interestingly, we also observed a significant

Table 2 | Impact of the prior shared success on the difference of team scores

	NBA 2013–2014		EPL 2013–2014		IPL 2013		MLB 2013		*Dota2*	
Independent variables (prior shared success)										
δ*S* (*P* value) [95% CI]		0.126 (< 0.001) [0.069, 0.182]		0.078 (0.001) [0.034, 0.123]		0.111 (0.003) [0.038, 0.183]		0.083 (< 0.001) [0.069, 0.098]		1.401 (< 0.001) [1.055, 1.746]
Control variables (skills variables)										
	Excl. ind. var.	Incl. ind. var.	Excl. ind. var.	Incl. ind. var.	Excl. ind. var.	Incl. ind. var	Excl. ind.var.	Incl. ind.var.	Excl. ind.var.	Incl. ind.var.
δC_1 (P value) [95% CI]	0.862 (0.197) [−0.449, 2.174]	0.401 (0.546) [−0.901, 1.705]	0.185 (0.038) [0.010, 0.359]	0.231 (0.007) [0.063, 0.399]	0.0001 (0.985) [−0.015, 0.016]	−0.005 (0.565) [−0.022, 0.012]	0.112 (0.281) [−0.091, 0.315]	0.068 (0.492) [−0.127, 0.264]	−4.102 (< 0.001) [−5.430, −2.772]	−4.057 (0.001) [−5.376, −2.736]
δC_2 (P value) [95% CI]	0.270 (0.571) [−0.665, 1.206]	0.470 (0.315) [−0.447, 1.388]	0.066 (0.329) [−0.067, 0.199]	0.088 (0.177) [−0.040, 0.216]	0.344 (0.298) [−0.312, 1.000]	0.325 (0.324) [−0.329, 0.979]	−0.078 (0.938) [−2.040, 1.884]	−0.891 (0.365) [−2.819, 1.038]	2.182 (< 0.001) [0.995, 3.368]	1.144 (0.063) [−0.062, 2.349]
δC_3 (P value) [95% CI]	0.477 (0.719) [−2.122, 3.076]	1.223 (0.354) [−1.366, 3.813]	−1.158 (0.059) [−2.358, 0.043]	−1.358 (0.024) [−2.533, −0.184]	NA	NA	NA	NA	NA	NA
Team fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
R^2	0.244	0.256	0.284	0.310	0.269	0.425	0.064	0.105	0.009	0.023
Prob > *F*	<0.0001	<0.0001	<0.0001	<0.0001	0.021	0.0001	<0.0001	<0.0001	<0.0001	<0.0001
BIC	10,648	10,635	1,660	1,652	336	322	14,270	14,167	40,507	40,453
N_{obs}	1,315	1,315	380	380	74	74	2,422	2,422	4,357	4,357

Prior shared success displays a significant positive effect on the difference in team scores for matches in NBA season 2013–2014. The explanatory power of the independent variable (ind. var.) remains significant when we controllled for the skill variables and team fixed effects ($P<0.001$). The significance of the explanatory power of prior shared success on the difference of team scores was observed consistently in EPL season 2013–2014 ($P=0.001$), IPL 2013 ($P=0.003$), MLB 2013 ($P<0.001$) and *Dota2* ($P<0.001$). Note that for IPL 2013, the dependent variable is the difference of team run-rates. The skill variables were as follows: in NBA games, they were the difference in average BPM (δC_1), the difference in average points (δC_2) and the difference in average assists (δC_3) in the last three seasons; in EPL games, they were the difference in average goals scored (δC_1), the difference in average number of shots, and the difference in average number of assists in the last three seasons; in IPL 2013, they were the difference in average batting strike-rate (δC_1) and the difference in average bowling economy rate (δC_2) in the previous 3 years of Twenty 20 cricket; in MLB 2013, they wre the difference in pitcher (WAR)n (δC_1) and the difference in batting OPS (δC_2); in *Dota2*, they were the difference in the mean death rate (δC_1) and the difference in mean assist rate (δC_2). Interestingly, we also observed a significant effect of the mean death rate on the difference in tower scores in *Dota2* ($P<0.001$). NA, not applicable.

contribution from skill variables δC_1 (d.f. = 379, $P=0.007$, effect size statistic = 0.231, 95% CI = 0.063 to 0.399) and δC_3 (d.f. = 379, $P=0.024$, effect size statistic = −1.358, 95% CI = −2.532 to −0.183).

In the IPL 2013 models, the difference of the mean strike-rate of batsmen and the difference of the mean economy-rate of bowlers had no effect on the difference of team run-rates (mean strike rate: d.f. = 73, $P=0.298$, effect size statistic = 0.0001, 95% CI = −0.015 to 0.016; mean economy rate: d.f. = 73, $P=0.985$, effect size statistic = 0.344, 95% CI = −0.312 to 1.000). The skill variables along with team fixed-effects explained 26.9% of the variance. Once we added prior shared success variable to the baseline model of skill variables, we observed that R^2 increased from 26.9% to 42.5%. There was a significant positive impact of the prior shared success variable on the difference of team run-rates (d.f. = 73, $P=0.003$, effect size statistic = 0.111, 95% CI = 0.038 to 0.183). The BIC in the full model with controls and the prior shared success variable decreased from 336 to 322, suggesting an improvement in the model fit to the baseline model[34].

Next, we tested our hypothesis in baseball games and compared the prediction power of the baseline model with the full model for matches in MLB 2013. Controlling for the skill variable of team members and team fixed effects, we observed that prior shared success of teams displayed a positive and significant association with the difference of team scores (d.f. = 2,421, $P<0.001$, effect size statistic = 0.083, 95% CI = 0.069 to 0.098). Moreover, the with BIC reduced from 14,270 to 14,167 and R^2 increased from 6.4% to 10.5%. Given the positive and significant impact of prior shared success, the impacts of the difference of mean pitching WAR and difference of mean OPS had no significant effect on the difference of team scores (mean pitching WAR: d.f. = 2,421, $P=0.492$, effect size statistic = 0.068, 95% CI = −0.126 to 0.263; mean OPS: df = 2,421, $P=0.365$, effect size statistic = −0.890, 95% CI = −2.819 to 1.037).

Finally, for *Dota2* games, there were significant associations between the skill variables δC_1 and δC_2 and the outcomes of the match. Teams with a lower death rate and a higher mean assist rate than their opponent were more likely to win. However, when the prior shared success variable was included, the effect of the mean assist rate disappeared. Again, prior shared success had a significant positive impact on the outcomes of a match. That is, teams with more successful previous co-play relations than their opponents were more likely to win (d.f. = 4,356, $P<0.001$, effect size statistic = 1.401, 95% CI = 1.055 to 1.746). Once we extended the baseline model, the BIC reduced from 40,507 to 40,453, and R^2 increased from 0.9% to 2.3%. Although the overall explanatory power is quite modest, the results clearly indicate a strong impact of prior shared success of teams.

Table 3 shows the estimates from the logistic model, indicating that the impacts of prior shared success on the probability of winning were robust in all five models. We also measured the overall rate of correct classificationn; first with the control variable model and then comparing the estimates with the full model. For NBA season 2013–2014, the skill variables correctly predicted 69% of the

Table 3 | Impact of prior shared success on the probability of winning

	NBA 2013–2014		EPL 2013–2014		IPL 2013		MLB 2013		*Dota2*	
Independent variables (prior shared success)										
δ*S* (*P* value) [95% CI]		0.021 (< 0.001) [0.009, 0.032]		0.093 (0.007) [0.025, 0.161]		0.210 (0.005) [0.063, 0.356]		0.057 (< 0.001) [0.047, 0.066]		0.114 (< 0.001) [0.084, 0.143]
Control variables (skills variables)										
	Excl. ind. var.	Incl. ind. var.	Excl. ind var.	Incl. ind. var.	Excl. ind. var.	Incl. ind. var.	Excl. ind. var.	Incl. ind. var.	Excl. in. var.	Incl. ind. var.
δC_1 (*P* value) [95% CI]	0.320 (0.018) [0.054, 0.586]	0.251 (0.067) [−0.017, 0.518]	0.234 (0.075) [−0.023, 0.491]	0.302 (0.026) [0.036, 0.568]	0.0008 (0.950) [−0.024, 0.026]	−0.008 (0.621) [−0.039, 0.023]	0.064 (0.195) [−0.032, 0.161]	0.036 (0.475) [−0.063, 0.135]	−0.347 (<0.001) [−0.456, −0.237]	−0.35 (< 0.001) [−0.459, −0.239]
δC_2 (*P* value) [95% CI]	0.034 (0.720) [−0.150, 0.217]	0.062 (0.509) [−0.121, 0.245]	0.007 (0.968) [−0.367, 0.382]	0.087 (0.652) [−0.292, 0.466]	0.017 (0.976) [−1.123, 1.157]	−0.103 (0.868) [−1.318, 1.113]	−0.729 (0.149) [−1.719, 0.261]	−1.322 (0.012) [−2.349, −0.295]	0.182 (< 0.001) [0.086, 0.278]	0.102 (0.043) [0.003, 0.200]
δC_3 (*P* value) [95% CI]	−0.262 (0.322) [−0.780, 0.257]	−0.125 (0.640) [−0.648, 0.398]	−0.586 (0.511) [−2.335, 1.163]	−0.791 (0.388) [−2.586, 1.004]	NA	NA	NA	NA	NA	NA
Team fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
BIC	1922	1915	607	604	163	155	3737	3582	6012	5959
Pseudo-R^2	0.158	0.166	0.17	0.196	0.20	0.32	0.038	0.086	0.013	0.032
Prob > Chi^2	<0.0001	<0.0001	0.0016	0.0010	0.27	0.026	<0.0001	<0.0001	<0.0001	<0.0001
Games correctly predicted (%)	69	71	73	76	71	78	59	65	54	56
N_{obs}	1,315	1,315	380	380	74	74	2,422	2,422	4,357	4,357

Prior shared success displays a significant positive effect on thee match outcome for matches played in NBA season 2013–2014. The explanatory power of the independent variable remained significant when we controlled for the skill variables and team fixed effects ($P < 0.001$). The significant explanatory power of prior shared success the on match outcome was observed consistently in EPL season 2013–2014 ($P = 0.007$), IPL 2013 ($P = 0.005$), MLB 2013 ($P < 0.001$) and online game (*Dota2*). In MLB 2013, we observed significant contributions from the difference in batting OPS on the match outcome ($P = 0.012$). We also observed a significant effect of the difference of mean death rate and difference of mean assist rate on the probability of winning in *Dota2* ($P < 0.001$).

games, while the full model including prior shared success and skills correctly predicted 71% of the games. In EPL season 2013–2014, the skill variables correctly predicted ~73% of the games. The addition of the independent variable to the skill variables increased the percentage of games correctly predicted to ~76%. During IPL 2013, the skill variables correctly predicted 71% of the games, while the independent variable together with the skill variables correctly predicted 78% of the games. In MLB 2013, we observed that the skill variables correctly predict 59% of the games, while the full model correctly predicted 65% of the games. For games played in *Dota2*, the skill variables correctly predict 54% of games, while independent variable and skill variables together predicted 56% of the games. These results suggest that although prior shared success explains the significant variance in the odds of a team winning, these interactions are also dependent on the type of sports. That is, while the increase in explained variance and percentage of correct classification in basketball, football, *Dota2* is modest, we observe a much stronger effect in cricket and baseball.

We performed several analyses to test the robustness of our findings. The effect of prior shared success on team performance was consistent across different sports and over time. We observed that the skill variables pitching WAR and OPS in MLB (Supplementary Tables 40, 43 and 49), the skill variables BPM and assists in NBA season 2012–2013 (Supplementary Tables 44–46), and the skill variables strike rate and economy rate in IPL 2012 (Supplementary Tables 45 and 47) had a significant impact on team performance. However, we also observed that including prior shared success in the model explained the significant variance in the difference of team scores above and beyond the difference of skill variables. This suggests that when teams have similar skill levels in elite-league competitions, differences in skills do not consistently predict match outcome consistently. Prior shared success steadily explains the significant variance in team performance.

Next, we varied the skill variables by aggregating individual statistics in different time windows and estimated the strength and significance of the independent variable (Supplementary Tables 40–49). First, we measured the skill variable for more recent events by aggregating the individual statistics of players in the precceding season for NBA and EPL, and the preceeding year for IPL and MLB. Furthermore, we aggregated the skill variables of players in the past five-seasons (5 years) and conducted additional analyses to assess the robustness of our results (see tables in the Supplementary Information). In the main text, for MLB games, we considered pitching WAR and OPS as skill variables for our models.

We also ran additional analyses with a combination of 'earned run average' and OPS to assess the strength and significance of prior shared success (Supplementary Tables 50–55). The past relationship of in-field players (position at first baseman (1B), second baseman

(2B), third baseman (3B) and shortstop (SS)) in baseball plays a key role in team selection. We tested whether successful past relationships of in-field players had any significant effect on the difference of team scores. Our results showed that there was no significant effect of such prior relations among in-field players in MLB 2013, although a weak effect was observed with logistic models in MLB 2012 (Supplementary Tables 56–61). Evidently, the effect of in-field players is not consistent, the only consistent effect coming from successful past relationships between all the players in the game. Our results reveal that prior experience of successful interactions among team members is important to the success of a team. In four out of five datasets (that is, with the exception of *Dota2*), talent plays the largest role in determining team success: skill variables explain between 6.4% and 28.4% of the variance in team success. The presence of highly talented players in a team does not necessarily guarantee a team's success in a competition, however. In all five datasets, prior shared success explained an additional 1.2–15.6% of the variance in team success, above skill.

Sports enthusiasts believe that individual skill plays an important role in the outcome of competitive games; therefore, individual player performance statistics have been widely used in predicting sports performance in baseball[35]. The common belief of the effect of talent on team success[11] suffered a setback when Germany defeated Brazil in the semifinal of the 2014 FIFA World Cup, setting an example of the triumph of teamwork over individual brilliance. As experts build and maintain teams, the debate between team relations and individual capability is a classical one[9]. Except for anecdotal evidence among sports fans and commentators, the role of prior interactions in team competitions remains unexplored and unclear. Prior successful interactions represent social bonding among team members that facilitates collaboration. Our study explored the impact of prior shared success on the outcomes of competition between sports teams. Compared with prior research on teamwork, we adopted a more nuanced approach by considering the dyadic relationship of teams in team-versus-team competitions. We demonstrated how past successful interactions (prior shared success) significantly improved the odds of a team winning in basketball (NBA), football (EPL), baseball (MLB), cricket (IPL) and online games (*Dota2*).

Our results reveal that prioxperience of successful interactions among team members is critical to tsuccess of a team. The presence of highly talented players in a team does not necessarily guarantee the success of a team in a competition. One possible explanation is that franchise owners in the IPL, and managers in the NBA, MLB and the EPL, select the top available players resulting in teams of similar strength and individual talent. Let us consider the performance of the Kolkata Knight Riders team in the 2008 and 2009 seasons of the IPL, the French national football team in the 2010 FIFA World Cup, the Brazilian football team in the 2014 FIFA World Cup, and Miami Heat in the NBA 2010–2011 season. Indeed, Germany in the 2014 FIFA World Cup did not rely on individuals but demonstrated a better team effort than other teams. In the 2014 FIFA semi-final, the Brazilian national football team had superstars including Neymar da Silva Santos Júnior, David Louis, Maicon Douglas Sisenando, Dante Bonfim Costa Santos and Marcelo Vieira Silva Júnior, yet failed against the better team effort by the German team. Later, in the final match of the 2014 FIFA World Cup, while the Argentine players depended on Lionel Messi, efficient coordination among Thomas Muller, Miroslav Klose and Mario Gotze in the German team resulted in Germany's victory. In IPL 2008, IPL 2009 and IPL 2010, The Kolkata Knight Riders had hired star players such as Ricky Ponting from Australia and Brandon McCullum from New Zealand but still failed to qualify for the quarterfinals. Conversely, the Chennai Super Kings team in the IPL routinely recruited individuals who had played together regularly for the Indian cricket team and dominated. The team won IPL 2010 and IPL 2011, finished as runners-up in IPL 2008, IPL 2012 and IPL 2013, and reached the semifinal in IPL 2009. These examples suggest that n such elite-league competitions, in which all competing teams have highly skilled players on their sides, the difference in skills is possibly not a consistent differentiator for the success of a team. Our analyses suggest that selecting players who have teamed up together successfully in the past increases the odds of a team winning a competition. Prior shared success of a team explains the significant variance in the difference of team scores beyond the difference of average skills of teams.

It is noteworthy that the consistency of our empirical evidence transcends the idiosyncratic characteristics of basketball, baseball, football, cricket and online games. Although our analysis is restricted to sports and online games, it could be extended to other competitive environments.

The positive effects of successful prior interactions on the outcome of competition may provide broader managerial implications for business, politics, academia and creative industries. If repeated positive interactions between team members have a significantly stronger effect than individual expertise, it may be prudent to consider coherence when bringing in new members.

This study advances our understanding of the factors that contribute to the competitive advantage of team. Prior research has focused on the role of individual skills in making teams more competitive. This study demonstrates the competitive advantage derived by a team based on the prior shared success among team members. According to Moneyball, Billy Beane (the general manager of Oakland Athletics) built a successful team on the notion that players work together to increase the probability of scoring runs[36]. The empirical evidence provides guidelines for relation-based incentives in firms, sports franchises and academic laboratories. Rather than solely focusing on the skills of people, company cheif executive officiers, sports coaches and managers should concentrate on the ability of someone to work consistently as part of a team. Prior interactions among team members also help in identifying members who are self-centred; that is, members who are passive in coordinating effectively with other teammates. It remains with the leadership of a team to decide whether to replace such a player or to change tactics while maintaining team productivity. In practice, a coach in football or a captain in cricket looks for the best possible team combinations, even at the cost of excluding some star players. For example, in the 2012 FIFA World Cup Brazil's coach Luiz Felipe Scolari excluded their star player Romário de Souza Faria from the team.

Even though our study has limitations, it has a lot of potential for further research. Our analysis is limited by the macroscopic interactions among the team members. Due to lack of available data we were unable to quantify the intricate details of positive interactions. For example, our study did not capture the football or basketball passes between specific players. One might examine the connection between skills and individual relations in a team. The understanding of who has what skills could be more important than the skill statistics themselves when people need to work together.

The process of discovering the person-specific and team-level skills and knowledge in a group is referred to as transactive memory systems[37,38]. If transactive memory systems can be quantified in sports, they might not only advance our understanding of why prior shared success between team members have large effects but also how those effects can best predict outcomes and be used to value individual talent above and beyond physical talents on the field.

One could argue that in baseball games team members operate independently of each other[39,40] compared to sports such as football, basketball and cricket as well as *Dota2*, where team members have to be more interdependent. Our resultss provide initial evidence of the intricate link between the ability (skill) of a player and interdependent behaviour. For example, in football and basketball, a valuable player is one who can not only score for the team (skill) but also effectively pass the ball, thus maximizing the likelihood of the team winning a contest[41]. A previous study[42] has demonstrated that in EPL, the ball-passing rate between the football players is positively correlated with the number of times they have played together.

This also leads to the question of the 'too much talent effect' in sports; that is "when teams need to come together, more talent can tear them apart"[11]. Future research should explore whether excess talent hurts the interpersonal relationships among team members. For example, talented players may not coordinate effectively with less skilled team members. Another promising area of future research would be to investigate the so-called 'Shane Battier Effect', named for a well-known US basketball player on intra-team relationships. The Battier Effect refers to an interesting phenomenon: Battier's personal statistics for key indicators (points, assists and rebounds) were not phenomenal, but the statistics of his teammates were significantly better when he was on the court than when he was on the bench. Furthermore, the statistics of the opposing teams worsened when he was on court than when he was on the bench. The intuition of individuals making others on their team perform better is widely accepted, but less is known about the specific, potentially network-related mechanisms that explain this phenomenon. Additionally, our prior winning relationships approach indicates the importance of competitive knowledge transfer of individual and team-level capabilities by players who move between teams. The increased use of digital sensor technologies in sports makes it possible for future research to leverage these data to analyse microscopic interactions to further advance our understanding of the impact of team relations on performance.

Methods

Sports and e-Sports data. To test the hypothesis, we used data from four sports (basketball, football, cricket and baseball) and an e-Sport (*Dota2*). The following paragraphs provide a brief description of each dataset.

NBA. A preeminent men's professional basketball league in North America, comprising 30 national-level teams. Our dataset includes the ESPN game statistics of all NBA basketball matches played between seasons 2002–2013 and 2013–2014.

EPL. An English professional league for men's football, comprising 20 clubs. Our dataset includes the ESPN game statistics of all EPL football matches played between seasons 2005–2006 and 2013–2014.

IPL. Known for its short cricket game format (Twenty20), comprises 8 franchise teams (IPL 2008–IPL 2010), 10 franchise teams (IPL 2011) and 9 franchise team (IPL 2012–IPL 2013). Cricket is a popular bat-and-ball game in the erstwhile English colonies, and Twenty20 matches are usually played for 3 hours. Our dataset includes the game statistics of all IPL matches played between 2008 and 2013, as well as international and country-level Twenty20 matches played between 2006 and 2013 from the Cricinfo website, an online information repository of every professional cricket match.

MLB. A professional baseball organization in North America, comprises 30 teams. Our dataset includes the ESPN game statistics of all MLB matches played between 2002 and 2013.

Multiplayer online battle arena game *Dota2*. An e-Sports game, whereby each match has two competing teams, called Radiant and Dire, with five players each. Each player chooses a character, which evolves during a match and can die but revives after a certain period. To win a match, a team has to kill the opponents' characters and destroy their stronghold. Each match starts from the begining, and there is no fixed length. Our dataset includes the game log of all *Dota2* matches in 2011[43].

Control variables—team skills. What are the chances of winning for a team with highly skilled players? Intuitively, one may assume that teams with better players are more likely to win, and that the skills statistics of team members have a significant explanatory power on the outcome of a game. As illustrated in Fig. 1b, the compositional view of teams considers a team as a collection of individuals with attributes or skills. For example, in our case, the skills of a team member refer to his average points and assists in basketball. For each team, the mean statistics over all team members represent the skill factor of the team. Thus, based on the common belief and earlier works on the abilities of the member and team performance[12,13], a team with higher skill statistics is stronger in a competitive environment.

We used the average of individual skill statistics of all team members as the measurement of team skills. For the season 2013–2014 (year 2013), we estimated the skills of players based on their game statistics between seasons 2002–2003 and 2012–2013 (in NBA and EPL) and years 2002–2012 (MLB) and years 2008–2012 (IPL), and in the first week of December 2011 for *Dota2*. The skills statistics are different in different sports. For games played in the NBA, we used BPM, points per game and assists per game as indicators of the skills of players. Unlike basketball, there is not a wealth of individual statistics football[24]. For football matches played in the EPL, we used the number of goals per game, the number of shots per game and the number of assists per game as indicators of the individual skills of a football player. For cricket matches played in the IPL, we used the batting strike rate and the bowling economy rate as quantifiers for the individual performance of players. For a batsman, the batting strike rate is defined as the average number of runs scored per 100 balls faced, while the bowling economy rate is defined as the average number of runs conceded per 6 balls (analogous to 6 pitches in baseball) for a bowler. In matches played in MLB, we used pitching WAR for pitchers and OPS for hitters as the skill variables for baseball players. As a robustness check, we also included the earned run average of pitchers as an indicator of individual skill. For *Dota2*, we used the death rate and the assist rate; that is, the number of times a player was killed divided by his or her total kills and the number of times a player assisted a teammate divided by his or her total kills, respectively. Supplementary Table 1 summarizes the skill statistics used in the different sports. Note that the bowling economy rate, the earned run average the and death rate are negative measures of skills. The lower the bowling economy rate, the better the bowler is in cricket; the lower the earned run average, the better the pitcher is in baseball; and the lower the death rate in *Dota2*, the better the online player.

The compositional variables δC_i^{12} measure the differences in the skill factors of two teams in a match i:

$$\delta C_i^{12} = \text{skill}_i^1 - \text{skill}_i^2$$

where skill_i^1 and skill_i^2 are the team skill measures of Team 1 and Team 2, respectively. In our analysis, we considered the skill of players in the previous 3 years (three seasons). Additionally, we use dummy variables to control for team fixed effects.

Statistical analysis. Exclusion of data points. For IPL 2013, there were 72 games, 2 qualifiers, 1 eliminator and 1 final, resulting in 76 matches. However, 2 games in IPL 2013 did not yield an outcome and were not included, yielding 74 observations. In MLB season 2013, there were are 8 matches that did not have any data from the ESPN MLB webpage (for example, http://www.espn.com/mlb/boxscore?gameId=330916120). Such matches were automatically excluded during data extraction, resulting in 2,422 observations.

Normality and equal variances. Mean and standard deviations of scores, skills and prior successful interactions were calculated for losing teams, winning teams, home teams and away teams in all the sports data. We implemented F-tests for comparing the variances, wherein we failed to reject the null hypothesis of equality of variances for all sports data. We tested the normality hypothesis against the non-normality for every sports data implementing the Shapiro–Francia test. If the normality hypothesis was rejected, we compared the difference of means for losing–winning teams and home–away teams by implementing the Wilcoxon signed rank-test (see Supplementary Tables 2–39 for descriptive statistics). The distributions of skill variables and prior shared success were assumed to be normal (Supplementary Figs. 1 and 2).

Power analysis. No statistical methods were used to pre-determine sample sizes. Our sample sizes were larger than the recommended sample sizes for 80% power and 5% type-I error rate[44].

BIC. The BIC is a criterion for model selection, with preference given to the model with lowest BIC. Formally, the BIC is defined as follows:

$$\text{BIC} = \ln(n)k - 2\ln(L)$$

Where, n is the number of observations, k denotes the number of parameters in the model and L is the maximum value of the likelihood function for the model.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Code availability. Python codes used to generate the skill variables and the independent variable, as well as Stata codes supporting this study, are available at the GitHub repository: https://github.com/smukherjee0305/Skills_Shared_Success_Sports/tree/master/Codes. The Stata codes used for regressions are also provided in the are Supplementary Methods (see Supplementary Information).

Data availability

Raw data of NBA, EPL and MLB games are available from the ESPN website. IPL data are available from the Cricinfo website. Derived data used in the study are available at GitHub: https://github.com/smukherjee0305/Skills_Shared_Success_Sports.

Received: 30 June 2017; Accepted: 27 September 2018;
Published online: 03 December 2018

References

1. Ready, D. A. & Conger, J. A. Make your company a talent factory. *Harvard Business Review* https://hbr.org/2007/06/make-your-company-a-talent-factory (2007).
2. Chudoba, K. & Maznevski, M. Bridging space over time: global virtual team dynamics and effectiveness. *Organ. Sci.* **11**, 473–492 (2000).
3. Skinner, B. The price of anarchy in basketball. *J. Quant. Anal. Sports* https://doi.org/10.2202/1559-0410.1217 (2010).
4. Hackman, J. R. in *Handbook of Organizational Behavior* (ed. Lorsch, J. W.) 315–342 (Prentice-Hall, Englewood Cliffs, 1987).
5. Contractor, N. Some assembly required: leveraging Web science to understand and enable team assembly. *Phil. Trans R. Soc. A* **371**, 20120385 (2013).
6. Duch, J., Waitzman, J. S. & Amaral, L. A. N. Quantifying the performance of individual players in a team activity. *PLoS ONE* **5**, e10937 (2010).
7. Fewell, J. H., Armbruster, D., Ingraham, J., Petersen, A. & Waters, J. S. Basketball teams as strategic networks. *PLoS ONE* **7**, e47445 (2012).
8. Lusher, D., Robins, G. & Kremer, P. The application of social network analysis to team sports. *Meas. Phys. Educ. Exerc. Sci.* **14**, 211–224 (2010).
9. Arrow, H. & Mcgrath, J. E. Membership matters: how member change and continuity affect small group structure, process, and performance. *Small Group Res.* **24**, 334–361 (1993).
10. Sibanda, M. Analysts hail teamwork as Germany rule Brazil. *CAJ News Africa* (14 July 2014).
11. Swaab, R. I., Schaerer, M., Anicich, E. M., Ronay, R. & Galinsky, A. D. The too-much-talent effect: team interdependence determines when more talent is too much or not enough. *Psychol. Sci.* **25**, 1581–1591 (2014).
12. Bell, S. T. Deep-level composition variables as predictors of team performance: a meta-analysis. *J. Appl. Psychol.* **92**, 595–615 (2007).
13. Humphrey, S. E., Morgeson, F. P. & Mannor, M. J. Developing a theory of the strategic core of teams: a role composition model of team performance. *J. Appl. Psychol.* **94**, 48–61 (2009).
14. Yukelson, D. Principles of effective team building interventions in sport: a direct services approach at Penn State University. *J. Appl. Sport Psychol.* **9**, 73–96 (1997).
15. Harrison, D. A., Mohammed, S., Mcgrath, J. E., Florey, A. T. & Vanderstoep, S. W. Time matters in team performance: effects of member familiarity, entrainment, and task discontinuity on speed and quality. *Pers. Psychol.* **56**, 633–669 (2003).
16. Montjoye, Y.-A., de, Stopczynski, A., Shmueli, E., Pentland, A. & Lehmann, S. The strength of the strongest ties in collaborative problem solving. *Sci. Rep.* **4**, 5277 (2014).
17. Joshi, A. & Roh, H. The role of context in work team diversity research: a meta-analytic review. *Acad. Manage. J.* **52**, 599–627 (2009).
18. Cummings, J. N. & Kiesler, S. Who collaborates successfully? Prior experience reduces collaboration barriers in distributed interdisciplinary research. In *Proc. 2008 ACM Conf. Computer Supported Cooperative Work* 437–446 (ACM, 2008).
19. Goodman, P. S. & Leyden, D. P. Familiarity and group productivity. *J. Appl. Psychol.* **76**, 578–586 (1991).
20. Gruenfeld, D. H., Mannix, E. A., Williams, K. Y. & Neale, M. A. Group composition and decision making: how member familiarity and information distribution affect process and performance. *Organ. Behav. Hum. Decis. Process.* **67**, 1–15 (1996).
21. Hinds, P. J., Carley, K. M., Krackhardt, D. & Wholey, D. Choosing work group members: balancing similarity, competence, and familiarity. *Organ. Behav. Hum. Decis. Process.* **81**, 226–251 (2000).
22. Cummings, J. N. & Cross, R. Structural properties of work groups and their consequences for performance. *Soc. Netw.* **25**, 197–210 (2003).
23. Hong, L. & Page, S. E. Groups of diverse problem solvers can outperform groups of high-ability problem solvers. *Proc. Natl Acad. Sci. USA* **101**, 16385–16389 (2004).
24. Guimerà, R., Uzzi, B., Spiro, J. & Amaral, L. A. N. Team assembly mechanisms determine collaboration network structure and team performance. *Science* **308**, 697–702 (2005).
25. Uzzi, B., Mukherjee, S., Stringer, M. & Jones, B. Atypical combinations and scientific impact. *Science* **342**, 468–472 (2013).
26. Balkundi, P. & Harrison, D. A. Ties, leaders, and time in teams: strong inference about network structure's effects on team viability and performance. *Acad. Manage. J.* **49**, 49–68 (2006).
27. Lungeanu, A., Huang, Y. & Contractor, N. S. Understanding the assembly of interdisciplinary teams and its impact on performance. *J. Informetr.* **8**, 59–70 (2014).
28. Mukherjee, S. Complex network analysis in cricket: community structure, player's role and performance index. *Adv. Complex Syst.* **16**, 1350031 (2013).
29. Clemente, F. M., Martins, F. M. L., Kalamaras, D., Wong, P. D. & Mendes, R. S. General network analysis of national soccer teams in FIFA World Cup 2014. *Int. J. Perform. Anal. Sport* **15**, 80–96 (2015).
30. Tesluk, P. E. & Jacobs, R. R. Toward an integrated model of work experience. *Pers. Psychol.* **51**, 321–355 (1998).
31. Dunn, J. R. & Schweitzer, M. E. Feeling and believing: the influence of emotion on trust. *J. Pers. Soc. Psychol.* **88**, 736–748 (2005).
32. Romero, D. M., Uzzi, B. & Kleinberg, J. Social networks under stress. In *Proc. 25th International Conf. World Wide Web* 9–20 (International World Wide Web Conferences Steering Committee, 2016).
33. Scarf, P., Shi, X. & Akhtar, S. On the distribution of runs scored and batting strategy in test cricket. *J. R. Stat. Soc. Ser. A Stat. Soc.* **174**, 471–497 (2011).
34. Raftery, A. E. Bayesian model selection in social research. *Sociol. Methodol.* **25**, 111–163 (1995).
35. Silver, N. *The Signal and the Noise* (Penguin, New York, 2012).
36. Lewis, M. M. *Moneyball: The Art of Winning an Unfair Game* (W. W. Norton & Company, New York, 2003).
37. Liang, D. W., Moreland, R. & Argote, L. Group versus individual training and group performance: the mediating role of transactive memory. *Pers. Soc. Psychol. Bull.* **21**, 384–393 (1995).
38. Lee, J.-Y., Bachrach, D. G. & Lewis, K. Social network ties, transactive memory, and performance in groups. *Organ. Sci.* **25**, 951–967 (2014).
39. Bloom, M. The performance effects of pay dispersion on individuals and organizations. *Acad. Manage. J.* **42**, 25–40 (1999).
40. Halevy, N., Chou, E. Y., Galinsky, A. D. & Murnighan, J. K. When hierarchy wins: evidence from the National Basketball Association. *Soc. Psychol. Personal. Sci.* **3**, 398–406 (2012).
41. McEwan, D. & Beauchamp, M. R. Teamwork in sport: a theoretical and integrative review. *Int. Rev. Sport Exerc. Psychol.* **7**, 229–250 (2014).
42. Grund, T. U. The relational value of network experience in teams: evidence from the English Premier League. *Am. Behav. Sci.* **60**, 1260–1280 (2016).
43. Pobiedina, N., Neidhardt, J., Moreno, M. d C. C., Grad-Gyenge, L. & Werthner, H. On successful team formation: statistical analysis of a multiplayer online game. In *2013 IEEE 15th Conf. Business Informatics* 55–62 (IEEE, 2013).
44. Neter, J., Kutner, M. H., Nachtsheim, C. J. & Wasserman, W. *Applied Linear Statistical Models* (Irwin, New York, 1990).

Acknowledgements

This research was funded by grants from the Northwestern University Clinical and Translational Sciences Institute (NUCATS), the Northwestern University Institute for Complex Systems (NICO), the National Institutes of Health (1R01GM112938-01), the MURI-Defense Advanced Research Projects Agency (grant BAA-11-64), the Army Research Laboratory (grant W911NF-09-2-0053), and the Army Research Office (grant W911NF-14-10686). The funders had no role in study design, data collection and analysis, decision to publish or preparation of the manuscript.

Author contributions

S.M. and N.C. designed the research. S.M., Y.H. and J.N. analysed the data. S.M., B.U., N.C., J.N. and Y.H. wrote the paper. All authors approved the final manuscript.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information is available for this paper at https://doi.org/10.1038/s41562-018-0460-y.

Reprints and permissions information is available at www.nature.com/reprints.

Correspondence and requests for materials should be addressed to S.M.

nature research

Corresponding author(s): Satyam Mukherjee

Reporting Summary

Nature Research wishes to improve the reproducibility of the work that we publish. This form provides structure for consistency and transparency in reporting. For further information on Nature Research policies, see Authors & Referees and the Editorial Policy Checklist.

Statistical parameters

When statistical analyses are reported, confirm that the following items are present in the relevant location (e.g. figure legend, table legend, main text, or Methods section).

n/a	Confirmed	
☐	☒	The exact sample size (*n*) for each experimental group/condition, given as a discrete number and unit of measurement
☐	☒	An indication of whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
☐	☒	The statistical test(s) used AND whether they are one- or two-sided *Only common tests should be described solely by name; describe more complex techniques in the Methods section.*
☐	☒	A description of all covariates tested
☐	☒	A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons
☐	☒	A full description of the statistics including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals)
☐	☒	For null hypothesis testing, the test statistic (e.g. *F*, *t*, *r*) with confidence intervals, effect sizes, degrees of freedom and *P* value noted *Give P values as exact values whenever suitable.*
☒	☐	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☒	☐	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☒	☐	Estimates of effect sizes (e.g. Cohen's *d*, Pearson's *r*), indicating how they were calculated
☒	☐	Clearly defined error bars *State explicitly what error bars represent (e.g. SD, SE, CI)*

Our web collection on statistics for biologists may be useful.

Software and code

Policy information about availability of computer code

Data collection	Match-level data and profiles of players were directly downloaded from ESPN website. Data for Indian Premier League were accessed from Cricinfo website.
Data analysis	The variables in the model were created in Python2.7. The regression and distribution plots were done in Stata14

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors/reviewers upon request. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Research guidelines for submitting code & software for further information.

Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A list of figures that have associated raw data
- A description of any restrictions on data availability

Data used in the study are available in GitHub https://github.com/smukherjee0305/Skills_Shared_Success_Sports.

Field-specific reporting

Please select the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☒ Behavioural & social sciences ☐ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/authors/policies/ReportingSummary-flat.pdf

Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	This is a quantitative study demonstrating how prior shared success between team members significantly improve the team's odds of winning in all sports, based on existing sports data.
Research sample	Our study consists of comprehensive database of matches in NBA, EPL, IPL, MLB, and Dota2. We downloaded data of 15382 matches and 1800 players between NBA season 2002-3003 and season 2013-2014. For EPL we downloaded score information for 5104 matches and profiles of 2988 soccer players (season 2005-2006 through 2013-2014). In MLB we gathered data of 29160 matches and 4001 players, played between 2002 and 2013. For Dota2, our dataset includes the game log of all Dota2 matches in 2011. For cricket we downloaded data for 404 matches played during IPL 2008 and IPL 2013. We also downloaded data for International and country-level 5123 T20 matches played between 2006 and 2013. Overall we gather data of 220 players who played T20 matches between 2006 and 2013.
Sampling strategy	We construct players' skill and prior shared success based on game statistics between season 2002-2003 and 2012-2013 (in NBA), between season 2005-2006 and 2012-2013 (in EPL), and years 2002-2012 (MLB) and years 2008-2012 (IPL). To ensue reliable statistical estimates, we get the data of prior shared success within the last 10 years, resulting in analysis for the season 2013-2014 for NBA and EPL, and year 2013 for IPL and MLB. For Dota2, the game started in November 2011. Therefore, we used the matches in the first week of December 2011 to construct the measures and used the second week of December to test the models. Number of observations for NBA 2013-2014, EPL 2013-2014, IPL 2013, MLB 2013, and Dota2 are 1315, 380, 74, 2422, and 4357 games respectively.
Data collection	NBA data was directly downloaded from http://www.espn.com/nba/ and https://www.basketball-reference.com/players/ (for box plus/minus information). Soccer data were downloaded from http://www.espn.in/football/league/_/name/eng.1/; baseball data: http://www.espn.com/mlb/; IPL data: http://www.espncricinfo.com/indian-premier-league-2013/engine/series/586733.html; The Dota2 data set was retrieved from Steam and Dota2 using their Web APIs: - Steam web api. https://developer.valvesoftware.com/wiki/Steam_Web_API - Dota2 web api. https://wiki.teamfortress.com/wiki/WebAPI#Dota_2 It was retrieved in XML and was afterwards migrated to a local PostgreSQL data base. The data set was made public by the community of Dota2 players, and contains the match history as well as details of the matches that were played in the year 2011. Our work is not a randomized experiment.
Timing	Downloading of sports data started on Fall 2014 and completed on Spring 2015. Dota2 data were accessed on December 2012
Data exclusions	2 games in IPL 2013 didn't yield outcome and are not included, yielding 74 observations. In MLB season 2013, there are 2430 matches, 8 matches didn't have any data information from the ESPN MLB web-page, resulting in 2422 observations.
Non-participation	There are no participants in this study.
Randomization	Our work is data driven, not a random experiment

Reporting for specific materials, systems and methods

Materials & experimental systems

n/a	Involved in the study
☒	☐ Unique biological materials
☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology
☒	☐ Animals and other organisms
☒	☐ Human research participants

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging