Teamwork in Contests*

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July 4, 2024

Abstract

We study self-organized teams in dynamic contests. Using data from Kaggle, we document that teams outperform solo players, but few players choose to form teams. Every new team alters the composition of players, discouraging less productive solo players to make submissions. We estimate the structural parameters of a dynamic contest model, including the team formation and submission costs. We find that team formation incentives diminish with the number of teams, as do the incentives to make submissions. We empirically evaluate the productivity—discouragement tradeoff caused by teamwork and discuss implications for contest design, including facilitating teamwork and hosting open competitions.

Keywords: Contests, teamwork, collaboration, contest design, dynamic games

*Acknowledgements: We thank workshop and conference participants at the Banff Innovation, Productivity and Growth Conference, Econometric Society Winter Meeting (University of Nottingham), Pontificia Universidad Católica de Chile, Universidad Nacional Andrés Bello, University of British Columbia (Sauder School of Business), and University of South Carolina for helpful comments and suggestions. Guillermo Marshall is supported in part by funding from the Social Sciences and Humanities Research Council of Canada.

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1 Introduction

Over the last decade, contests sponsored by firms and government agencies have attracted thousands of participants competing for large monetary prizes. Designers of these contests faces many choices, such as the structure of prizes, the length of the contest, and what information to display on a leaderboard, among others. However, one aspect that deserves more attention is the organization of players into self-organized teams. Although the formation of a team may improve the performance of its members, it may also discourage other players during the competition: it increases the share of high-performing competitors.

To explore this tradeoff, we empirically investigate team formation in dynamic contests and derive practical implications for contest design. Specifically, our framework allows us to shed light on questions such as: Do self-organized teams perform better than solo players? Why and when do self-organized teams form in a dynamic contest? What are the equilibrium effects of team formation on other competitors' incentives to make submissions and form teams? From the perspective of a contest designer, what conditions make teamwork desirable? These insights inform the design and management of contests.

Our contribution is to address these questions by combining policy evaluation techniques with a novel structural model of team formation in dynamic contests. We present three key findings. First, we document that, on average, self-organized teams outperform solo players. Second, we introduce a novel structural model of team formation. In the model, players compare the marginal benefit of teamwork (which evolves with the state of the competition) against the cost of team formation. The type of competitor (team or solo player) and the state of the competition impact players' incentives to make submissions and form teams. Third, we use our structural estimates to explore team formation incentives, equilibrium effects of teamwork, and implications for contest design, including the impact of reducing the cost of team formation and limiting entry.

Our empirical setting is Kaggle, the largest platform for online data science competitions, where players create algorithms to predict outcomes based on covariates.[1] Our sample includes 131 featured competitions offering at least $5,000 in prizes, typically lasting several months and attracting thousands of participants who can make multiple submissions.[2] Kaggle competitions provide an ideal setting to investigate the effect of teamwork on performance. First, they offer detailed information about the timing and performance of every submission in a competition, the identity of the player making each submission, the timing of team formation, and the composition of each team. This allow us to reconstruct the real-time public leaderboard and the composition of competitors (teams or solo players) throughout each competition. Second, players must make at least one submission before forming a team, enabling us to compare individual performance before and after team formation.

Our first contribution is to investigate the benefits of teamwork for members of self-organized teams in dynamic contests, which remains unexplored. Using a differences-in-differences design, we exploit the timing of team formation to compare the performance of players who form a team with those who work solo (and never form a team) before and after the team forms. In the estimation, we use the full sample and a subsample that matches a team with a similar solo player on observable covariates up to the point of team formation.

Our estimates show that, after team formation, self-organized teams score 0.048 to 0.06 standard deviations higher than solo players, comparable to the gap between 1st and 40th place. Teams perform similarly to solo players before formation, but significantly better immediately after, with gains persisting long-term. Moreover, these performance gains persist over time and positively impact final standings, although not for every team.

We use a similar research design to study whether self-organized teams submit more sub-

[1] www.kaggle.com. For instance, the ride-sharing company Lyft is hosting a competition where participants need to predict the movement of traffic agents around an autonomous vehicle.

[2] Featured competitions are "full-scale machine learning challenges which pose difficult, generally commercially-purposed prediction problems."

missions than solo players. We find that players in self-organized teams do not send more submissions than solo players. These findings indicate that teams and solo players are not the same "type" of competitors. On average, teams produce higher-quality submissions and do not increase the quantity of submissions relative to solo player.

Armed with the finding that players can improve their "type" by forming self-organized teams, our second contribution is to introduce a novel structural model of team formation in dynamic contests. In our model, players get random opportunities to form teams or make submissions. Players form teams to become more productive but are discourage by prize sharing (in the event of winning) and team formation costs. Players also decide whether to make submissions by paying a submission cost. Teams and solo players have different probabilities of becoming the competition leader after making a submission. These probabilities decrease for both types of competitors as the maximum score increases, reflecting that progress is easier at the beginning of the competition and becomes increasingly harder.

We estimate the model's primitives, including the distribution of team formation and submission costs. The (unconditional) average cost of forming a team across all contests in our data is 40 percent of the contest's prize. While these costs are heterogeneous across players, most players find it too costly to form a team, even knowing their performance will improve.

Next, we explore incentives to form teams and the dynamic equilibrium effects of teamwork. First, we study the probability of forming a team. We find that all else equal, players are *discouraged* from forming teams when they compete against more teams. This is intuitive because the benefit of forming a team is to improve the chances of winning the competition. As players compete against more teams (which are "higher types"), this benefit decreases, so players' incentives to form teams fall. We also find that all else is equal, the marginal benefit of forming a team falls with time. This occurs because players have fewer chances to seize the benefits of teamwork when there is less time remaining in the competition.

We then use our structural model's estimates to study the impact of teamwork on the number of submissions. As the number of teams increases, all else equal, the probability of submitting falls. This result supports the idea that players experience *discouragement* when facing stronger opponents (see, e.g., Brown, 2011). When fixing all other state variables, players have stronger incentives to submit when they are closer to the end of the competition. Intuitively, as time runs out, players anticipate that whoever gets to lead the competition at the current time will likely win.

Our third contribution is to shed light on whether a contest designer should facilitate teamwork by making team formation less costly.[3] On the one hand, more teams will form if it is cheaper to do so, which generates high-scoring submissions as teamwork improves performance relative to working solo. On the other hand, the more teams, the lower a player's incentive to form a team or make a submission. To empirically compare these countervailing forces, we simulate contests with lower team formation costs. In the equilibria of these contests we find more teams, fewer submissions, and higher the maximum scores. In other words, the benefit of facilitating teamwork outweighs the cost. As a corollary, forbidding team formation is detrimental for a contest designer seeking to procure a submission with a high score. However, teamwork may be detrimental for a content designer who cares about the number of submissions (e.g., to procure diverse solutions).

Lastly, we use our structural model's estimates to investigate the impact of competitive pressure on team formation. All the competitions in our data are open to anyone who wishes to participate. However, some competitions (even in Kaggle) restrict the number of participants. We find that the absolute number of teams increases with the number of players, but the relative number of teams decreases. That is, for every additional player added to the contest, fewer than one team forms. Additionally, as the number of teams grows, the number

[3] In practice, a contest designer could facilitate team formation by allowing players to communicate, providing easy access to other players' profiles (e.g., history of achievements), or incorporating online-collaboration tools. Any of these initiatives would likely reduce the cost of forming teams.

of submissions and the maximum score also rise, even though the individual incentives to make submissions fall. These results suggest that contest designers should strive to attract as many players as possible.

Our results suggest that some contest sponsors may need to consider the potential benefits of facilitating teamwork. This is a low-cost intervention that can enhance the value of contests.

Related Literature. Our paper broadly relates to the recent literature on dynamic contests design, including Bhattacharya (2021), Lemus and Marshall (2021), Lemus and Marshall (2024), Benkert and Letina (2020), and Gross (2017), among others. We show that allowing self-organized teams improves performance in contests, which contributes to the broader literature on teamwork and performance (see, e.g., Hamilton et al., 2003; Jones, 2009; Ahmadpoor and Jones, 2019).

Members of self-organized teams can benefit from exploiting their comparative advantages (Büyükboyacı and Robbett, 2017; Büyükboyaci and Robbett, 2019), knowledge diversity (LiCalzi and Surucu, 2012), or avoiding biases, cognitive limitations, and social considerations (see, e.g., Cooper and Kagel, 2005; Sutter et al., 2013; Müller and Tan, 2013; Feri et al., 2010). Girotra et al. (2010) find that teams perform better when members first work independently. In our setting, players must work independently before teaming up. Although we do not observe internal team dynamics, our Online Appendix documents that team members generally have comparable performance histories.

Regarding team size, we find that two- and three-member teams represent 84 percent of all teams, and larger teams do not necessarily perform better. Wu et al. (2019) uses academic papers, patents, and software products to show that smaller teams produce more disruptive research, whereas larger teams expand on the existing knowledge. Ahmadpoor and Jones (2019) find that teamwork has a greater impact than solo work. Azoulay et al. (2010) and Jaravel et al. (2018) show that the premature death of high-skilled team members worsens the future performance of the remaining team members.

Some articles have also provided descriptive evidence of teamwork in Kaggle competitions. For example, Wang et al. (2019) discuss repeated participation in Kaggle competitions. Dissanayake et al. (2019) find that team members with similar characteristics are common, but diverse teams perform better. Dissanayake et al. (2015) also note that less diverse teams can perform better when most members are highly skilled. None of these papers structurally estimate a dynamic model of team formation.

2 Background and Data

2.1 Kaggle Competitions

Kaggle is an online platform that hosts data science competitions. Participants use data from a contest's sponsor to build algorithms to predict some variables of interest. For example, Google Cloud sponsored a competition to assign labels to videos.[4]

Participants in a Kaggle competition have access to two datasets. The first one, the *training* dataset, includes both an outcome variable and covariates, and the participants use it to build and train their algorithms. The second one, the *test* dataset, includes covariates only. Competitors have to submit outcome-variable predictions for each observation in the test dataset. The test dataset is split into two subsets for out-of-sample performance evaluation without revealing which subset an observation belongs to. A submission's performance on the first subset, the *public* score, is instantly posted on a public leaderboard, whereas its performance on the second subset, the *private* score, is made public at the end of the competition only and is used to determine the winner.[5] Public and private scores are highly

[4]https://www.kaggle.com/competitions/youtube8m

[5]The evaluation criterion for the out-of-sample performance of a submission varies across contests. Examples of evaluation criteria include the root mean squared error or R^2.

correlated (the correlation is 0.99 in our sample), so public scores are informative but noisy performance signals.

Competitors can make multiple submissions throughout the competition, subject to a cap on daily submissions. They are also free to form teams subject to four restrictions. First, a player must have made at least one submission before forming a team. Second, the cumulative number of submissions by all team members before the date of team formation cannot exceed the maximum number of allowed submissions per day times the number of days the competition has been running. Third, teams must form before a competition-specific deadline. Fourth, teams cannot disband.

2.2 Data and Descriptive Evidence

We use publicly available information on 131 Kaggle competitions awarding a monetary prize of at least \$5,000.[6] An observation in our dataset is a submission in a contest. We observe each submission's timestamp, an identifier for the player (or team) who made it, and its public and private scores. We also observe team formation dates. These data allow us to track the competitors' composition (solo players or teams) and performance throughout the competition.

Table 1 reports competition-level summary statistics. The table shows that the competitions in our sample offer, on average, a monetary prize of \$54,699 (USD), with some competitions offering as much as \$1,200,000. The competitions attract thousands of participants who make multiple submissions: On average, 1,781 players made at least one submission, and the competitions received 27,922 submissions. Although in all our competitions players can self-organize into teams, most choose to participate as solo players: over 90 percent of competitors are solo players.

[6] https://www.kaggle.com/kaggle/meta-kaggle

[Insert Table 1 about here]

Table 2 presents the distribution of team size across competitions. Panel A includes the full sample of competitors and shows that 90.18 percent are solo players and 5.55 are two-member teams. Panel B restricts attention to competitors that finish in the top 40 and shows that only 66.74 percent are solo players, whereas 15.19 percent are two-member teams. This evidence shows that teamwork is more prevalent when we look at competitors that rank at the top of the leaderboard.

Figure 1 shows the share of competitors across contests by ranking at the end of the competition. The figure reveals that competitors ranked higher are likelier to be teams. For instance, a team won about 60 percent of the competitions, whereas in only about 20 percent of the competitions, a team placed 40th. Thus, top competitors are far more likely to be teams than solo players.

[Insert Table 2 about here] [Insert Figure 1 about here]

All this evidence suggests that self-organized teams perform better than solo players, but relatively few teams form. To understand the mechanisms behind these facts, we first measure the gains from participating in a team, and then we measure how costly it is to form a team. In Sections 3 and 4, we explore whether there is a positive relationship between teamwork and performance. In Section 5, we propose and estimate a model to uncover the cost of team formation. In Sections 6 and 7, we investigate the players' dynamic incentives to form teams and use our findings to discuss implications for contest design.

3 Empirical Strategy

To measure the performance of self-organized teams, we compare the performance of team members and solo players before and after a team forms. An advantage of Kaggle's data is that players must submit at least one submission before forming a team.[7] Thus, we can track a player's performance before and after a team forms.

Our main estimating equation is

$$y_{i,j,c,t} = \beta \cdot 1\{\text{post team formation}\}_{i,j,c,t} + h(\mathbf{x}_{i,j,c,t}, \delta) + \mu_{j,c} + \lambda_{c,t} + \varepsilon_{i,j,c,t}, \tag{1}$$

where $y_{i,j,c,t}$ is an outcome variable (e.g., a submission's score) by competitor j (a unique solo player or team) in competition c at time t, $1\{\text{post team formation}\}_{i,j,c,t}$ is an indicator that takes the value one if competitor j is a team at time t, $\mathbf{x}_{i,j,c,t}$ is a vector of time-varying competitor-level state variables, such as the competitor's distance to the competition leader at time t.[8] The term $h(\cdot, \delta)$ is a quadratic function of the state variables, $\mu_{j,c}$ are competitor–competition fixed effects, $\lambda_{c,t}$ are competition–time fixed effects, and $\varepsilon_{i,j,c,t}$ is an error term clustered at the competitor level.[9]

We also estimate a version of Equation 1 that allows for time-varying effects,

$$y_{i,j,c,t} = \sum_{\tau=-6}^{6} \beta_\tau \cdot 1\{\tau \text{ weeks before/after team formation}\}_{i,j,c,t} + h(\mathbf{x}_{i,j,c,t}, \delta) + \mu_{j,c} + \lambda_{c,t} + \varepsilon_{i,j,c,t}, \tag{2}$$

where $\beta_{-\tau}$ and β_τ, for $\tau = 1, ..., 6$ capture, respectively, the performance of a competitor τ weeks before and τ weeks after the team forms.[10]

[7] In our sample, on average, players submit 19 submissions before forming a team.

[8] We define 'distance' as the difference between the competitor's score at time t and the maximum score.

[9] In our analysis, all the submissions of all members of team j have the same competitor identifier, even those that are submitted before the team forms. The $\mu_{j,c}$ fixed effects then do not "change" for the individuals who form a team after team formation occurs. The effect of team formation will be captured by the coefficient β that multiplies the indicator for team formation.

[10] β_{-1} is normalized to zero. β_0 captures the effect of teamwork at the week of the team formation.

The coefficient β in Equation 1 captures the performance of self-organized teams *relative* to solo players, and the coefficients β_τ from Equation 2 capture this effect over time. In making this comparison, we note that if teamwork creates performance gains, solo players (untreated individuals) may become discouraged from facing stronger opponents. This means untreated players may be indirectly affected by teamwork. We note, however, that this discouragement will only exist if teamwork improves the performance of teams, implying that a positive and significant β coefficient should reflect some degree of performance gains from teamwork, even if solo players are discouraged, making the empirical exercise informative about the impacts of teamwork.

Estimation Methods. We employ two estimation methods. The first one uses the full sample of solo players and two-member teams.[11] This method amounts to a differences-in-differences design where we control for observable variables and fixed effects.

The second estimation method is like the first but uses matching to alleviate the concern that team members (treated units) and solo players (control units) differ in observable characteristics. We have 6,064 teams matched with solo players of similar characteristics at the time of the team formation. Specifically, for every team, we find a solo player with the similar number of submissions and maximum score at the time of the team formation. Table A.1 in the Online Appendix presents a balance analysis for our matching procedure.[12]

Lastly, we note that the coefficient β in Equation 1 (respectively, β_τ in Equation 2) measures the performance of self-organized teams relative to solo players, which is the comparison we focus on this paper. These coefficients do not necessarily measure the causal impact of teamwork in general, precisely because players *self-select* into teams in our setting. It is plausible that players choose to form teams when they privately observe their potential gains from teamwork. Appendix C provides an additional estimation method to control for

[11]We exclude larger teams to avoid issues related to multiple treatments during the competition (i.e., competitors that change types multiple times).

[12]Figure A.1 presents a balance analysis for variables that were untargeted in the matching procedure.

selection using a two-step, Heckman-style selection bias correction (Heckman, 1979) similar to the one used by Lee (1978). The evidence in Appendix C suggests a possible causal effect of teamwork on performance. That is, even if teams were not self-organized, teamwork could enhance performance.

4 The Impact of Teamwork on Performance

4.1 Scores

We begin by measuring the impact of teamwork on scores. To facilitate comparison across competitions, we standardize the scores at the competition level (i.e., mean 0 and standard deviation 1) and transform them so that higher scores indicate better performance.[13]

[Insert Table 3 about here]

Table 3 presents estimates for Equation 1 using the public score as the dependent variable, y.[14] The estimates show that, on average, self-organized teams perform better than solo players. Specifically, on average, team scores are 0.06 and 0.048 standard deviations higher than solo players' scores in the full and matched samples. How large are these magnitudes? The median score difference between the contest winner and the player who finishes in the 40th position is about 0.05, suggesting that teams perform substantially better than solo players.

Figure 2 presents our estimates for Equation 2. We compare the weekly performance of teams and solo players from six weeks before the team formation until six weeks after. We use the full sample of solo players and two-member teams in the first column; we restrict the analysis

[13] Lower or higher scores can be "better," depending on the contest's evaluation metric. For instance, when the metric is RSME, lower scores are better, whereas higher scores are better for the metric R^2.

[14] We present results using the private score in the Online Appendix.

to the matched sample in column 2. Figure 2 shows that, before the actual team formation, scores of players who form teams and solo players (who never form a team) are statistically indistinguishable. After the team formation, team members perform significantly better than solo players. Performance improvement manifests immediately after the team forms and plateaus around three weeks after formation.

[Insert Figure 2 about here]

4.2 Number of submissions

To study the impact of teamwork on the number of submissions, we estimate a version of Equation 1 where the dependent variable, y, corresponds to the number of submissions by each competitor in every week of the competition. In the analysis, an observation is a competitor–week–competition combination.

The first column of Table 4 presents the estimates for Equation 1, using the number of submissions as the endogenous variable for the full sample of competitors. The estimate shows that, on average, teams send 1.626 fewer submissions than solo players. The second column presents estimates for Equation 1 using the subsample of all the teams and their respective solo-player match. The estimates for the matched sample are similar, although the magnitude of the effect is just 0.964 fewer submissions on average.

4.3 Heterogeneity Analysis

We investigate how the ranking and number of submissions compare for teams and solo players at the end of the competition. Figure 3 shows the distribution of the difference between these variables at the end of the competition for both teams and matched solo players. The figure shows the heterogeneous benefits of teamwork, with many negative values, highlighting teamwork's uncertain returns. Panel A shows the distribution of ranking difference; despite the heterogeneous effect, on average, teams rank 40 positions ahead of their matched solo players. Panel B shows that treated teams, on average, decrease their number of submissions by 153 percent. These results suggest that, on average, teamwork decreases the volume of submissions but increases the quality of submissions.

[Insert Table 4 about here] [Insert Figure 3 about here]

Figure A.2, in the Online Appendix, shows the distribution of the time of team formation. It is roughly uniform right before the team-formation deadline (which varies across competitions), with a spike in team formation right at the deadline. Table A.2 shows that teams that form later send more submissions relative to solo players. However, the time of team formation has no impact on final rankings.

As a robustness check, we also explore whether team performance is heterogeneous across different types of contests. Table A.3, in the Online Appendix, shows that the performance gains of teamwork are not statistically different in different types of contests (e.g., contests where players must analyze image data, contests with larger rewards, or contests with larger datasets).

4.4 Implications for Contest Design

The implications of these results for contest design depend on the competition sponsor's preferences. Allowing teamwork has the potential to deliver better results because teams perform better than solo players. On the other hand, teams send fewer submissions than solo players, which can reduce the diversity of approaches.[15]

The ideal experiment to determine the impact of allowing self-organized teams on outcomes

[15] Our model abstracts away from diversity, as we do not explicitly model approaches.

would need to compare two identical contests, except for one allowing teamwork and the other banning it. Our data does not permit such comparison for two reasons. First, all the contests in our data allow players to form teams. Second, each contest is 'unique,' i.e., the problem, the reward, and the competition dates are uniquely defined for each contest.

In the next section, we develop a structural model to explore the dynamic incentives to form teams. The model will help us answer questions related to contest design, including the impact of banning teamwork on contest outcomes.

5 Equilibrium Effects of Teamwork

In this section, we present a dynamic model of team formation where players consider the following economic trade-offs. On the one hand, team formation increases the likelihood of becoming the competition leader. On the other hand, forming a team is costly, and players must share the prize in the case of winning. Players compare the marginal change in their continuation value from forming a team, minus the cost of team formation, against the value of not forming a team and continuing as solo players.

Players can also make a submission by paying a submission cost. They evaluate the value of potentially becoming the competition leader by making a submission versus its cost. The current competition's maximum score, the time left in the competition, and the composition of competitors (teams versus solo players) impact a player's incentives to form a team and make a submission.

We estimate key structural parameters of our model and use them to shed light on players' equilibrium behavior. In particular, we explore dynamic incentives to make submissions and form teams, answering questions such as: Are players discouraged from making submissions when there are more teams? Are players more likely to team up when they compete against more teams? How do players' incentives to form teams and submit evolve over time?

We then use our estimates to simulate alternative contest designs and study the impact of these designs on contest outcomes.

5.1 Empirical Model

There are N forward-looking players competing in a contest. Time is discrete, $t = 0, ..., T$, and payoffs are undiscounted.[16] Players can make submissions and form teams during the contest. There are two possible types of competitors, $\theta \in \{\text{team}, \text{sp}\}$, where 'team' denotes a 2-member team and 'sp' denotes a solo player.[17] A player's type can transition only from sp to team, i.e., teams cannot disband. At every period, there is a unique competition *leader*, and everyone else is a *follower*. A public leaderboard displays, in real-time, the current maximum score, s, and the leader's identity. At the end of the contest, the leader receives a prize $\pi = 1$, and followers get 0; If a team wins, its members split the prize evenly.[18]

The state space is:

$$\mathcal{S} = \{(s, \ell, n^{\text{team}}, t) : \ s = s_1, s_2, ..., \bar{s}; \ \ell = 0, 1; \ n^{\text{team}} = 0, ..., N/2; \ t = 0, .., T.\},$$

where s is the maximum score, ℓ indicates whether the leader is a solo player ($\ell = 0$) or a team ($\ell = 1$), n^{team} is the number of teams, and t is the competition time. We denote the distribution of types by $n \equiv (n^{\text{sp}}, n^{\text{team}})$, where n^{sp} is the number of solo players. We assume that the total number of players is constant throughout the contest, so $n^{\text{sp}} + 2n^{\text{team}} = N$. Although n^{sp} is determined by n^{team}, for notational convenience we use (s, ℓ, n, t) as the

[16] Payoffs are undiscounted; the average competition duration in our sample is 77 days.

[17] This assumption simplifies the model. Empirically, 62.43 percent of multi-player teams are composed of two members.

[18] We make this assumption based on Kaggle's rules: "If a Team wins a monetary Prize, the Prize money will be allocated in even shares between the eligible Team members, unless the Team unanimously opts for a different Prize split and notifies Kaggle before Prizes are issued."

state. Players publicly observe the state before making decisions. At the beginning of the contest, there are no teams, so the initial state is $(0, 0, (N, 0), 0)$.

A player's type and current position determine one of four possible scenarios: the player is either (1) a solo-player follower, (2) a team-member follower, (3) a team-member leader, or (4) a solo-player leader. The terminal values for each case are, respectively,

$$F^{\text{sp}}_{s,\ell,n,T} = F^{\text{team}}_{s,\ell,n,T} = 0, \quad L^{\text{team}}_{s,\ell,n,T} = \frac{\pi}{2}, \quad \text{and} \quad L^{\text{sp}}_{s,\ell,n,T} = \pi. \tag{3}$$

Two independent and mutually exclusive events can occur for $t < T$.[19] In the first event, which occurs with probability λ_1, a randomly selected player decides whether to make a submission, after observing the cost of making a submission, c^{sub}, which is a draw from the distribution K^{sub}.[20] A submission from a player of type θ increases the current maximum score, s, with probability $q^{\theta}(s)$, and it does not increase it with probability $1 - q^{\theta}(s)$. The function $q^{\theta}(\cdot)$ is decreasing (i.e., the higher s, the harder to increase s). Thus, the direct benefit of teamwork is to transition from type 'sp' to the more productive type 'team,' reflected in $q^{\text{sp}}(s) < q^{\text{team}}(s)$ for all s.

In the second event, which occurs with probability λ_2, one of the solo-players followers can form a team; a solo player leading the competition is assumed to never form a team.[21] A solo-player follower choosing to form a team can always do so provided that $n^{\text{sp}} \geq 2$ (i.e., at least two solo players are available). The direct cost of forming a team is c^{team}, a random draw from the distribution K^{team}. We assume that only the player proposing to form a team bears

[19] The assumption that no more than one decision can take place at time t is reasonable given that each time period is short (in our empirical application, for most contests, a period is 9 hours). Our model can be viewed as an approximation to a continuous time model where the probability of more than one decision at any instant of time is approximately zero (see, e.g., Lemus and Marshall (2021)). Because this assumption can lead to equilibrium uniqueness, essentially because each player solves a single-agent problem when making their decisions, other papers have made similar modeling choices (see, e.g., Igami (2017) and Igami and Uetake (2020)).

[20] We assume this distribution is type-independent to avoid identification issues since we added heterogeneity in the probability of success.

[21] We make this assumption to simplify the model. Empirically, only 1.63 percent of teams form by a solo player leading a competition.

this cost.[22] Given that incentives are symmetric for every solo-player follower, whenever one of them benefits from transitioning from 'sp' to 'team,' including paying the team-formation cost, any other solo-player follower who does not need to pay the team-formation cost also benefits from transitioning from solo-player to team.

Solo Player, Follower. A solo-player follower's value at state $(s, \ell, n = (n^{\text{sp}}, n^{\text{team}}), t)$ is

$$\begin{aligned} F^{\text{sp}}_{s,\ell,n,t} &= \frac{\lambda_1}{N} E_{c^{\text{sub}}}\left[\max\{q^{\text{sp}}(s) L^{\text{sp}}_{s',0,n,t'} + (1 - q^{\text{sp}}(s)) F^{\text{sp}}_{s,\ell,n,t'} - c^{\text{sub}}, F^{\text{sp}}_{s,\ell,n,t'}\}\right] + \\ &\frac{\lambda_2}{N} E_{c^{\text{team}}}\left[\max\{F^{\text{team}}_{s,\ell,(n^{\text{sp}}-2,n^{\text{team}}+1),t'} - c^{\text{team}}, F^{\text{sp}}_{s,\ell,n,t'}\}\right] + E[V^{\text{sp, F}}_{s',\ell',n',t'} | (s, \ell, n, t)]. \end{aligned} \tag{4}$$

This expression consists of three distinct terms, each with a specific interpretation. The first term, multiplied by λ_1/N, represents the payoff of the follower solo player when they can make a submission. The second term, multiplied by λ_2/N, denotes the follower solo player's payoff when they can form a team. The final term, $E[V^{\text{sp, F}}_{s',\ell',n',t'} | (s, \ell, n, t)]$, represents the continuation payoff for the follower solo player when one of their rivals takes an action or when no player can take an action in the current period. We now explain each one of these terms in more detail.

In the first term, with probability $\frac{\lambda_1}{N}$, a solo-player follower can choose to make a submission, in which case, after paying the cost c^{sub}, the player becomes the leader with probability $q^{\text{sp}}(s)$, receiving a continuation payoff of $L^{\text{sp}}_{s',0,n,t'}$. With probability $1 - q^{\text{sp}}(s)$, the player fails to become the leader, receiving $F^{\text{sp}}_{s,\ell,n,t'}$, which equals the payoff of not making a submission.

Conditional on having the opportunity to make a submission, the probability that a solo-player follower makes a submission is

$$p^{\text{sp,F}}_{s,\ell,n,t} = \Pr(c^{\text{sub}} < q^{\text{sp}}(s)(L^{\text{sp}}_{s',0,n,t'} - F^{\text{sp}}_{s,\ell,n,t'})). \tag{5}$$

[22] The assumption that team formation is costly is motivated by our discussions with Kaggle users, who suggested that searching and screening potential team members is costly. See Online Appendix B for details.

The solo player compares the marginal benefit and cost of making a submission; see the comparison inside the first maximum operator in (4). The marginal benefit is given by $q^{\text{sp}}(s)(L^{\text{sp}}_{s',0,n,t'} - F^{\text{sp}}_{s,\ell,n,t'})$, reflecting that with probability $q^{\text{sp}}(s)$ the player becomes the leader and the maximum score increases, thus receiving $L^{\text{sp}}_{s',0,n,t'}$ instead of $F^{\text{sp}}_{s,\ell,n,t'}$. The marginal cost is simply c^{sub}.

Next, with probability $\frac{\lambda_2}{N}$, a solo-player follower can choose to form a team with another solo-player follower, after paying the cost c^{team}. If the team forms, the composition of types in the contest changes: it transitions from $n = (n^{\text{sp}}, n^{\text{team}})$ to $n' = (n^{\text{sp}} - 2, n^{\text{team}} + 1)$, and the team members receive the continuation value $F^{\text{team}}_{s,\ell,(n^{\text{sp}}-2,n^{\text{team}}+1),t'}$. If, instead of forming a team, the solo-player decides to continue working solo, the player receives $F^{\text{sp}}_{s,\ell,n,t'}$.

Conditional on having the opportunity to form a team, the probability that a solo-player follower forms a team is

$$p^{\text{team forms}}_{s,\ell,n,t} = \Pr(c < F^{\text{team}}_{s,\ell,(n^{\text{sp}}-2,n^{\text{team}}+1),t'} - F^{\text{sp}}_{s,\ell,n,t'}). \tag{6}$$

A solo-player compares the marginal benefit and the marginal cost of forming a team; see the comparison inside the second maximum operator in (4). The marginal benefit of transition from type 'sp' to type 'team' corresponds to receiving the continuation value of a team follower instead of that of a solo-player follower, taking into account that forming a team also changes the composition of types in the competition, i.e, $F^{\text{team}}_{s,\ell,(n^{\text{sp}}-2,n^{\text{team}}+1),t'} - F^{\text{sp}}_{s,\ell,n,t'}$. The marginal cost is simply c^{team}. An implicit cost of team formation, captured in the continuation values, is that team members must split the prize in the event of winning the competition.

Lastly, the term $E[V^{\text{sp, F}}_{s',\ell',n',t'}|(s,\ell,n,t)]$ captures the impact of the actions of other players on a solo-player follower's continuation payoff. This includes cases where nobody can choose to make a submission or form teams, as well as cases where rivals can make submissions or form teams. For the sake of exposition, we derive this expression in the Online Appendix.

Other Players. There are three other cases: a team-member follower, a team-member leader, and a solo-player leader. In these cases, teams do not form because the competitors either are already a team or leading the competition (we ruled out solo-player leaders forming teams by assumption, see footnote 21). Nevertheless, in all these situations the competitors can choose to make submissions, and their interim payoffs change as the state variables evolve.

The derivation of the value functions for these other cases parallels the logic used for a solo-player follower. To avoid redundancy, we direct readers to the Online Appendix for detailed descriptions of these equations.

Equilibrium. The solution concept we use is Markov perfect equilibrium. We solve the game by backward induction, using the terminal values in equation (3) and working backward to fully solve the model.

5.2 Estimation and Model Fit

We estimate the model using a full-solution method. To compute the equilibrium of the game, we exploit that the state variables are directional—the maximum score, the number of teams, and time cannot decrease—and they are capped, $s \in [s_1, \bar{s}]$, $n^{\text{team}} \in [0, N]$, $\ell \in \{0, 1\}$, and $t \in \{1, \dots, T\}$. This allows us to compute the equilibrium by backward induction.

We set $T = 360$ for estimation. Each time period lasts for about 5 hours in a competition that lasts 77 days, which is the average duration of a competition in our sample.

The full set of primitives for a given contest include i) the probability that an active player can play, λ_1; ii) the probability that an active solo player can form a team, λ_2; ii) the number of periods, T; iv) the functions $q^{\text{team}}(s)$ and $q^{\text{sp}}(s)$, which indicate the probability of advancing the maximum score given that the current maximum score is s for a team and a solo player, respectively; v) the distribution of team-formation and submission costs with support in $[0, 1]$, $K^{\text{team}}(c; \sigma) = c^{\sigma^{\text{team}}}$ and $K^{\text{subs}}(c; \sigma) = c^{\sigma^{\text{subs}}}$, respectively, where σ^{team} and σ^{subs} are positive numbers that can vary across contests.

We use a two-step procedure to estimate the primitives of each contest. In the first step, we estimate iv) without using the full structure of the model, given values of λ_1, λ_2, and T.[23] In the second step, we use the estimates of these primitives to estimate the cost distributions in v) using a generalized method of moments (GMM) estimator.

We specify the functions $q^\theta(s)$, where $\theta \in \{\text{team, sp}\}$ as

$$q^\theta(s) = \frac{\exp\{\beta_0^\theta + \beta_1 s\}}{1 + \exp\{\beta_0^\theta + \beta_1 s\}}.$$

We estimate β_0^θ and β_1 by maximum-likelihood using data on whether each submission increased the maximum score at the time of each submission, s. We allow β_0^θ to vary across contests but we constraint β_1 to be the same across competition. We pool the data from all competitions to gain power in estimating β_1 because in some competitions changes in the maximum score are infrequent.

In the second step, we estimate the parameters σ^{team} and σ^{subs} of the team formation and submission cost distributions, respectively. All else equal, higher submission and team formation costs will decrease the equilibrium number of submissions and teams. We identify the parameters of the cost distributions by matching the data and model predictions. Specifically, we use a GMM estimator for $\sigma \equiv (\sigma^{\text{team}}, \sigma^{\text{subs}})$ that minimizes the percentage difference between the number of teams and submissions observed in the data and those predicted by

[23]We do not estimate λ_1 and λ_2 due to their interaction with the submission and team formation costs, which creates an identification problem when predicting the equilibrium number of submissions or teams. Roughly, an increase in λ_1 (more submission opportunities) can be counteracted by a decrease in average submission cost, posing an identification problem. The same applies to λ_2 and team formation cost. We set $\lambda_1 = 0.25$ and $\lambda_2 = 0.75$, along with $T = 360$, to rationalize the data.

the model. The objective function is given by:

$$f_k(\sigma) = \left(\frac{\text{teams}_k^{data} - \text{teams}_k^{model}(\sigma)}{\text{teams}_k^{data}}\right)^2 + \left(\frac{\text{submissions}_k^{data} - \text{submissions}_k^{model}(\sigma)}{\text{submissions}_k^{data}}\right)^2.$$

We present asymptotic standard errors.

We use the full-solution method to compute $f_k(\sigma)$ for a given value of σ. That is, for a given σ, we compute the equilibrium of the game using backward induction to obtain the matrices of conditional-choice probabilities (CCPs) governing the decisions to form teams $\mathbf{p}^{\text{team}}$ and make submissions, $\mathbf{p}^{\text{subs},\theta,\text{leader}}$ and $\mathbf{p}^{\text{subs},\theta,\text{follower}}$. The dimension of these matrices is $S \times N/2 \times T \times 2$, where S is the size of the set of possible scores, N is the maximum number of teams, T is the maximum number of periods, and 2 are the two possible types of the leader (team or solo player).[24] Using these CCPs, we simulate equilibrium outcomes by simulating the game $ns = 500$ times and averaging equilibrium outcomes across simulations.

Lastly, we restrict the sample to the top 40 players in each contest (measured by the ranking of players at the end of the competition), i.e., $N = 40$. We make this choice for two reasons: First, these players are more likely to form teams. Second, this group of players is less heterogeneous than the entire pool of players, which allows us to abstract away from modeling player heterogeneity. We restrict attention to the 68 contests with at least one team among the top 40 competitors.

[Insert Table 5 about here]

[Insert Figure 4 about here]

Model Estimates and Fit Table 5 shows the model estimates and Figure 4 the fit of the model. Panels A and B of Figure 4 show that the model can replicate well both the number

[24] In the estimation, $S = 20$. In a given contest, the set of scores includes all unique maximum scores in the competition as well as the values $\bar{s} + [0.002 : 0.002 : 0.04]$, where $\bar{s}$ is the highest observed score in the competition, and where the set of scores is constrained to be of size $S = 20$.

of submissions and the number of teams in a contest. Panel C shows that, while the model tends to underestimate the maximum score, especially for those with large maximum scores, the data and model predictions are positively correlated.

Figure A.3 in the Online Appendix shows the distribution of the average cost of forming a team across contests. On average, the mean cost of forming a team is 40 percent of the prize.[25] In addition, team members split the prize in two in case of winning.[26] These facts rationalize the rather puzzling finding that only a few players form teams even though there are performance gains.

6 Dynamic Equilibrium Effects of Teamwork

In this section, we study the dynamic equilibrium effects of teamwork. One of the key economic forces in our framework is the endogenous evolution of the distribution of types. As some competitors become stronger (i.e., two solo players form a team) other competitors can get discouraged. Thus, team formation may worsen overall performance in the contest.

The literature has investigated the impact of player heterogeneity on outcomes for an exogenous distribution of types. For instance, Brown (2011) finds that playing against a highly skilled opponent may reduce effort. Drugov and Ryvkin (2022) show that, in general, this prediction is theoretically ambiguous and provides analytical conditions that guarantee that player heterogeneity causes discouragement. We expand this literature by empirically investigating the extent of discouragement in a setting where players' dynamic decisions to form

[25] Figure A.3 in the Online Appendix also shows that the average expected cost of forming a team across contests is about \$14,000. However, the average expected cost of forming a team, conditional on a player choosing to form a team, is about \$27. The difference between these expected values shows that an unusually low-cost draw is needed for a team to form.

[26] Among team members, while the monetary prize is split in two, it is possible that non-monetary rewards of winning a competition are not. If $L^{\text{team}}_{s,\ell,n,T} = \alpha\pi > 0.5\pi$, and we use $L^{\text{team}}_{s,\ell,n,T} = 0.5\pi$ for estimation, our estimates of the cost distribution would be biased downwards. We abstract away from non-monetary rewards in our model.

teams determine the distribution of types.

Figure 5 presents four exercises that offer insights into the dynamic equilibrium effects of team formation. Panels A and B explore the incentives to form teams, whereas Panels C and D explore the incentives to make submissions. Panel A fixes the score, time, and type of leader but varies the number of teams. The figure shows that the probability that solo-follower players form teams decreases as they currently compete against more teams (downward sloping lines). Moreover, this probability is lower when the current maximum score is higher (dashed line below solid line). The intuition is straightforward. First, as the number of teams increases, the return from teamwork diminishes because teams are stronger competitors. Second, as the maximum score increases, the return from teamwork diminishes because it is harder to become the competition leader, even for teams.

Panel B fixes the score, number of teams, and type of leader but varies the competition time. The marginal benefit of forming a team falls as time goes on because players have fewer chances to exploit the benefits of teamwork.[27] It also falls as the maximum score increases because it is harder to become the competition leader.

Panel C fixes the score, time, and type of leader but varies the number of teams. The figure shows that a player is less likely to make a submission when the number of teams or the current maximum score increases. These results show that players experience *discouragement* when facing more "higher ability" types (teams) or the current maximum score is higher. Figure A.4 in the Online Appendix shows that solo-player followers are more discouraged than team followers from making a submission when there are more teams.

Panel D fixes the score, number of teams, and type of leader but varies the competition time. Close to the end of the competition, players' incentives to make submissions increase because as time runs out, they anticipate less "future competition," i.e., whoever takes the competition's lead will likely win.

[27] Recall that, in our model, competitors have stochastic chances of making submissions.

[Insert Figure 5 about here]

The economic mechanisms described in Figure 5 can be affected by additional forces, which we do not model. For instance, players can procrastinate when deciding to form a team. Also, not every player begins working on the contest at time 0; they enter over time. In addition, players may use the information on the leaderboard to learn about their potential partners and signal their quality (see Section 8 for more on this point). These additional forces push players to *delay* team formation.

We also note that we are not incorporating two institutional details on team formation. The first is that players must make at least one submission before forming a team, and the second is that the team must form before a certain deadline.

Next, we use our structural model's estimates to derive implications for contest design.

7 Contest Design Implications

7.1 Allowing Team Formation

Most, but not all, Kaggle competitions allow teamwork. Why would an online contest platform, such as Kaggle, allow teamwork? As previously discussed in Sections 4 and 6, teamwork creates a tradeoff. On the one hand, players working in teams can improve their performance. On the other hand, they can discourage other players. Hence, an evaluation of the impact of teamwork must compare the benefit of having higher-performing players in the competition against the cost of fewer submissions.

Figure 6 shows that allowing teamwork can have heterogeneous effects across contests on the number of submissions and maximum score. Panel A shows that submissions almost always decrease when teamwork is allowed. Panel B shows that the maximum score decreases for about 15 percent of the competitions, but it increases on average. We find that in 7 out of 68 contests, teamwork reduces both the number of submissions and the maximum score, so banning teamwork would be appropriate in these cases. Also, in 7 out of 68 contests, teamwork increases both the number of submissions and the maximum score, so allowing teamwork is appropriate. However, in 54 out of 68 contents, the contest designer faces a tradeoff: allowing teamwork reduces the number of submissions but increases the maximum score.[28]

[Insert Figure 6 about here]

7.2 Open Contests versus Restricted Entry

Does greater competitive pressure encourage teamwork? To answer this question, we change the number of players in a contest and recompute the equilibrium. Since the opportunities to make submissions (or form teams) are stochastic, in the counterfactual equilibria we keep the opportunities to play constant by adjusting the length of the contest, i.e., $\frac{\lambda_1 T}{N} = \frac{\lambda_1 T'}{N'}$.

Figure 7 presents the results of these counterfactual simulations. Panel A shows that more players in a contest encourages teamwork. Forming a team is one way to "escape" the competition by becoming a higher type. Thus, all else equal, the marginal return of teamwork increases with the number of competitors. Panel B shows the percentage change in the *share* of teams, that is, $\frac{\text{number of teams}(N)}{N}$. The figure shows that this ratio decreases with N, meaning that the numerator grows at a slower rate than the denominator. In other words, adding one player increases the number of teams by less than one.

Panel C shows that the total number of submissions increases with the number of players. Part of this effect is mechanical because there are more players in the competition. However,

[28] Boudreau and Lakhani (2011) findings suggest that there may be gains from letting players self-select into contests that ban or permit teamwork.

more players potentially create more discouragement. Panel D shows precisely this effect: the number of submissions per player decreases with the number of players in the contest. That is, players experience discouragement from facing more competitors.

More players diminish individual incentives to form teams and make submissions. However, there are more players in the contest, which can make up for lower individual incentives. Figure 7, Panel E, shows that this is indeed the case: the maximum score increases with the number of players.

[Insert Figure 7 about here]

These results indicate that more players at the outset increase the maximum score, even after considering the equilibrium effects of more players on the number of submissions and team formation. Therefore, "open contests" (unrestricted entry) procure higher scores than contests restricting entry to a limited number of players.[29]

7.3 Reducing the Cost of Team Formation

A binary choice of allowing or banning teamwork may be suboptimal. An intermediate cost of team formation might achieve the best outcome. More teams form when team formation is cheaper, increasing the likelihood of high-scoring submissions. However, some players may experience discouragement from facing stronger rivals.

We explore whether a contest platform benefits from *facilitating* team formation. For instance, allowing players to communicate, access other players' profiles, or incorporate online collaboration tools may reduce the cost of team formation, facilitating the organization of teams.

[29] Some Kaggle competitions restrict entry; see, e.g.,
https://www.kaggle.com/competitions/cervical-cancer-screening

Figure 8 presents simulated outcomes for contests with varying team-formation costs. Panel A shows that making team formation less costly increases the number of teams, which is a direct effect. Panel B shows that the lower the cost of team formation, the lower the number of submissions, which is an indirect effect driven by discouragement. Panel C shows that, even though the number of submissions decreases, the maximum score *increases*. In other words, the performance improvement we identify in Section 4 more than compensates for the negative impact of more teams on the number of submissions. These results highlight the importance of reducing team-formation costs to improve contest outcomes.[30]

[Insert Figure 8 about here]

8 Conclusion

We present evidence suggesting that, on average, self-organized teams perform significantly better than solo players. Teams' performance gains do not come from more quantity but from higher quality submissions. However, our data reveals that only a few players select to organize themselves into teams, which suggests potentially substantial costs associated with teamwork (splitting the prize in the event of winning and paying a team-formation cost).

Motivated by these results, we build and estimate a structural model to shed light on the players' dynamic incentives to form teams during a contest. Our estimates show that forming a team is quite costly: the average cost equals 40 percent of the contest prize. This high cost explains why collaboration is relatively scarce in our sample of Kaggle contests (around 10 percent of the competitors are teams).

Using our estimates, we explore dynamic incentives to form teams and to make submissions. Team formation discourages other competing players from forming teams and making

[30] Boudreau et al. (2017) presents evidence suggesting that reducing matching frictions among scientists can improve outcomes.

submissions. We then investigate alternative contest designs. Lowering the cost of team formation increases a contest's maximum score. This result arises from two opposing effects of teamwork: more "high type" players emerge, but players are discouraged from submitting and forming teams. We find that the former effect outweighs the latter, improving overall performance. Our analysis suggests contest designers should allow and facilitate self-organized team formation to benefit from these dynamics.

We also use our estimates to investigate how the number of players affects our results. We show that more players discourages players to both form a team and make submissions. However, the fact that there are more players makes up for this discouragement, leading to higher maximum scores. This suggests that contest designers should consider "open contests" rather than limiting the number of players.

Our model simplifies dynamic team formation for tractability. For instance, we only model the competition as one where there is one "leader," and all the other competitors are "followers." A more flexible model would allow for many positions in the leaderboard and incorporate asymmetric incentives to form teams with players in different positions on the leaderboard. We leave these and other open questions for future research.

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Table 1: Competition-level summary statistics

	Mean (1)	St. Dev. (2)	Min (3)	Max (4)
Number of submissions	27,922	33,376	627	159,810
Number of players	1,781	1,928	57	11,111
Number of competitors	1,676	1,818	55	10,450
Percentage of solo players	90.18	5.15	71.60	98.42
Reward quantity (USD)	54,699	136,093	5,000	1,200,000

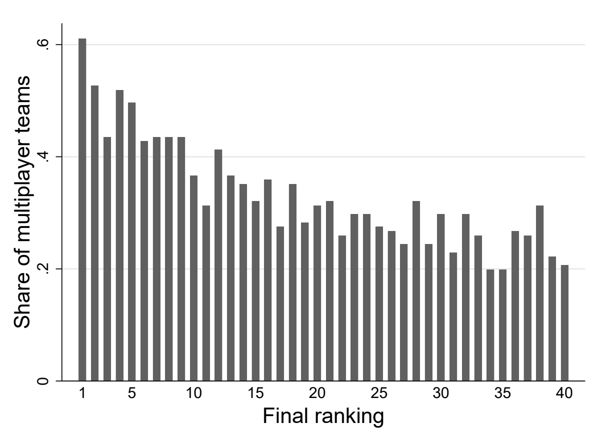
Notes: The table reports summary statistics for 131 competitions. A competitor can be a solo player or a multi-player team.

Table 2: Percentage of competitors of different types across competitions

Number of members	Mean	St. Dev.	Min	Max
Panel A: All competitors				
1	90.18	5.15	71.60	98.43
2	5.55	2.30	0.99	12.29
3 or more	4.15	3.28	0.00	17.84
Panel B: Top 40 competitors				
1	66.74	15.62	22.50	100.00
2	15.19	6.66	0.00	35.00
3 or more	18.07	14.02	0.00	70.00

Notes: The table reports summary statistics for 131 competitions. Panel B considers only teams that finished the competition within the first 40 positions.

Figure 1: Share of multiplayer teams by final ranking



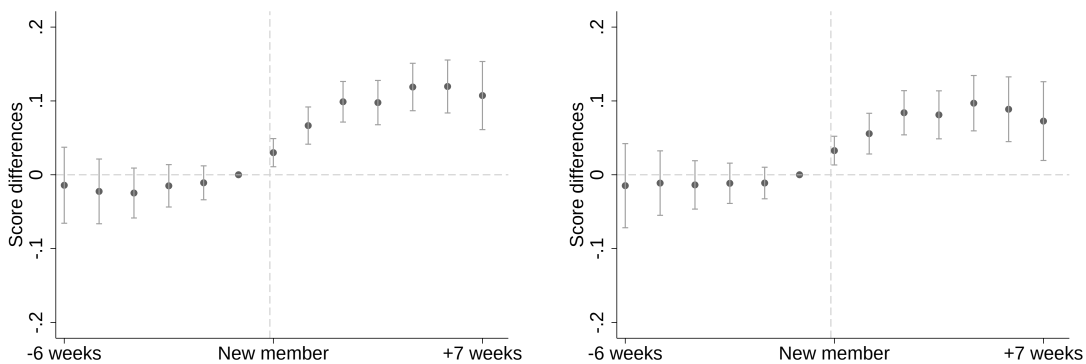
Notes: An observation is a team that finished a competition in the top 40 positions of the final ranking.

Table 3: The impact of collaboration on scores: Team-level estimates

	Score	
	Full sample	Matched sample
Team	0.060***	0.048***
	(0.009)	(0.010)
Observations	3,189,817	432,121
R^2	0.439	0.393

Notes: Standard errors clustered at the team-level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. An observation is a submission. All specifications include competitor–competition fixed effects, competition–day fixed effects, and a second-degree polynomial of competitor-level state variables, including the time t, the total number of submissions by all competitors up until t, the total number of submissions by the competitor submitting up until t, and the submitting competitor's distance to the leader at t. The sample is restricted to include submissions by treated teams that took place six weeks before or after the week in which the team changed its team size.

Figure 2: The impact of teamwork on scores: competitor-level estimates



1) Full sample

2) Matched sample

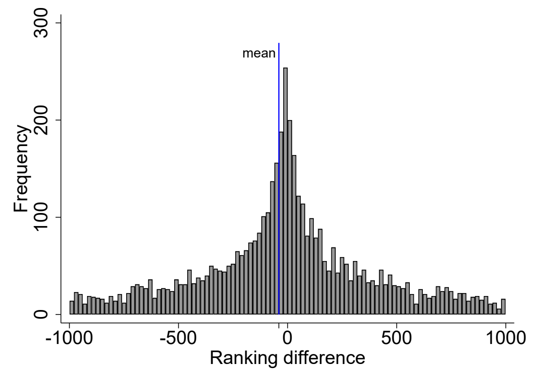
Notes: Standard errors are clustered at the competitor level. The figures show the point estimate of β_τ and the 95-percent confidence intervals around the estimate. An observation is a submission. All specifications include the same sample restrictions and sets of fixed effects and controls as the ones described in Table 3.

Table 4: The impact of collaboration on the number of submissions: Team-level estimates

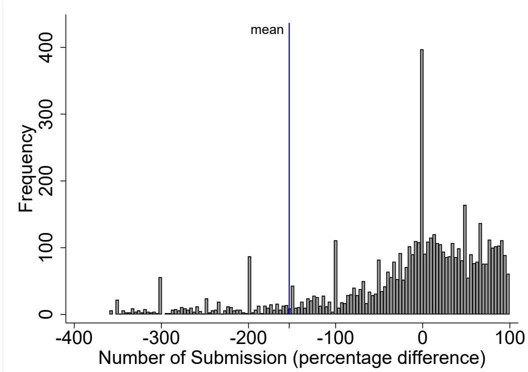
	Number of submissions	
	Full sample	Matched sample
Teams	-1.626***	-0.964***
	(0.162)	(0.149)
Observations	1,282,028	96,452
R^2	0.657	0.557

Notes: Standard errors clustered at the team-level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. An observation is a competition–competitor–week combination. All specifications include competitor fixed effects and competition–week fixed effects. The sample is restricted to include submissions that took place in the first twelve weeks of a competition.

Figure 3: The impact of teamwork on final outcomes: Matching estimates



A) Ranking



B) Number of submissions

Notes: An observation is the difference in an outcome of interest between a team its matched solo player.

Table 5: Empirical model estimates

Panel A: Common parameters across contests

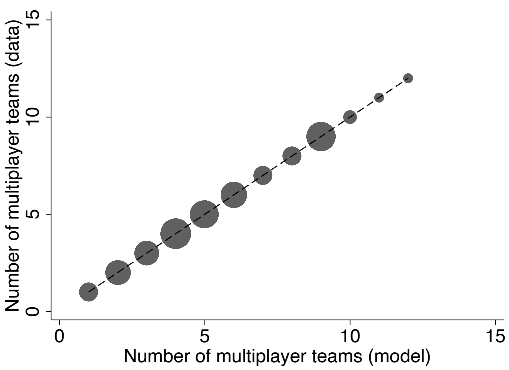
	Estimate	SE
β_1 (q function)	-1.4642	0.0348
$\beta_0^{teams} - \beta_0^{sp}$ (q function)	1.3307	0.0354

Panel B: Contest-specific parameters (partial list of contests)

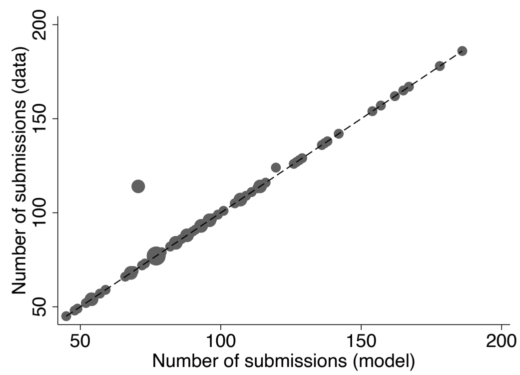
	σ^{team}	SE	σ^{sub}	SE	β_0 (q)	SE	N
TGS Salt Identification Challenge	0.7372	0.0340	0.2990	0.0010	-2.5714	0.2513	54
Quick, Draw! Doodle Recognition Challenge	0.9881	0.0413	0.0424	0.0079	-0.7119	0.2063	77
RSNA Pneumonia Detection Challenge	0.9760	0.0821	0.0997	0.0070	-1.6698	0.2639	107
Human Protein Atlas Image Classification	0.9338	0.0757	0.1820	0.0023	-4.9669	0.2199	90
Traveling Santa 2018 - Prime Paths	0.8174	0.0308	0.1944	0.0036	-2.9767	0.1894	96
Google Cloud & NCAA ML Competition 2019-Mens	0.7624	0.0349	0.0886	0.0063	-0.7583	0.2883	59
Instant Gratification	0.8281	0.0378	0.1649	0.0026	-3.2192	0.2795	108
Predicting Molecular Properties	0.9808	0.0641	0.0781	0.0288	-2.2559	0.2445	138
SIIM-ACR Pneumothorax Segmentation	0.5469	0.0432	0.1763	0.0001	-2.6569	0.2443	96
Lyft 3D Object Detection for Autonomous Vehicles	0.9163	0.0317	0.3689	0.0021	-2.8153	0.2414	48

Notes: SE stands for asymptotic standard errors. See Table A.4 in the Online Appendix for the estimates of the full list of contests.

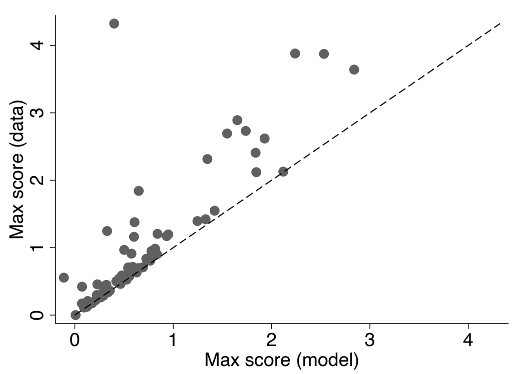
Figure 4: Model fit, by equilibrium outcome



A) Number of teams



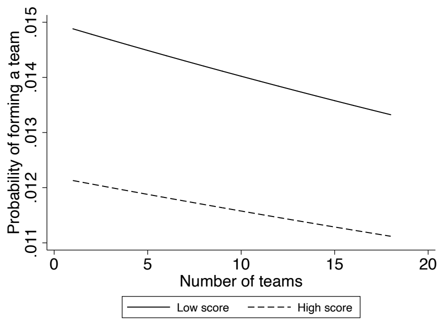
B) Number of submissions



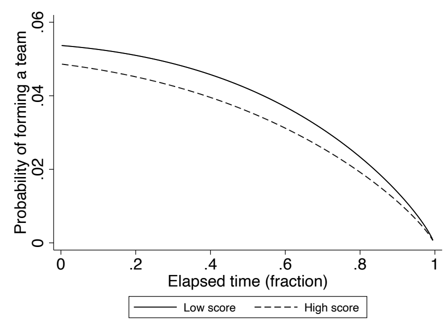
C) Maximum score

Notes: The figures plot equilibrium outcomes in the data against those predicted by the model estimates. Model predictions are computed via simulation. Specifically, we simulate the game $ns = 500$ times and compute the average for each equilibrium outcome across simulations. Bigger dots reflect more observations.

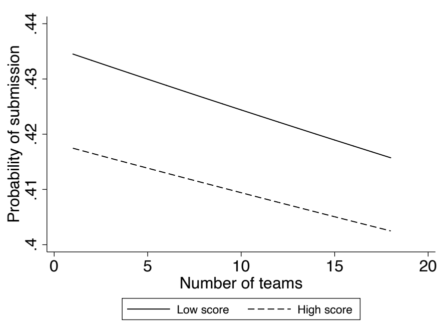
Figure 5: Properties of conditional choice probabilities



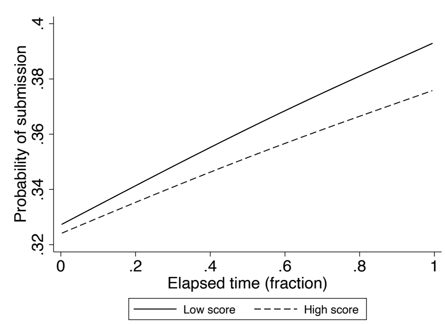
A) Probability of team formation as a function of number of teams



B) Probability of team formation as a function of time



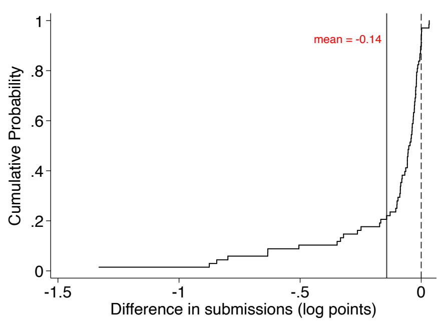
C) Probability of a submission as a function of number of teams



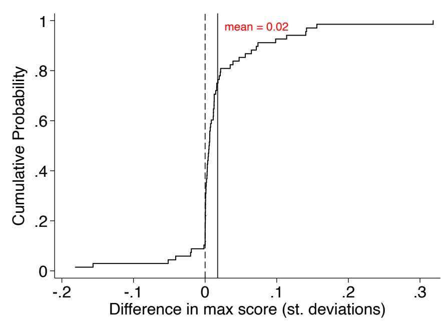
D) Probability of a submission as a function of time

Notes: The figures plot equilibrium conditional choice probabilities computed using model estimates for one contest: the "Don't Get Kicked!" (Predict if a car purchased at auction is a lemon) contest. In Panels A and C, time is fixed at $t = 320$, the leader is a follower $\ell = 0$, and the score is either the second (low) or tenth (high) value of the score grid. Panel C plots the probability of a submission for a follower team. In Panels B and D, the number of teams is fixed at zero, the leader is a follower $\ell = 0$, and the score is either the second (low) or tenth (high) value of the score grid. Panel D plots the probability of a submission for a follower solo player.

Figure 6: Equilibrium impact of allowing teamwork on contest outcomes (teamwork vs no teamwork)



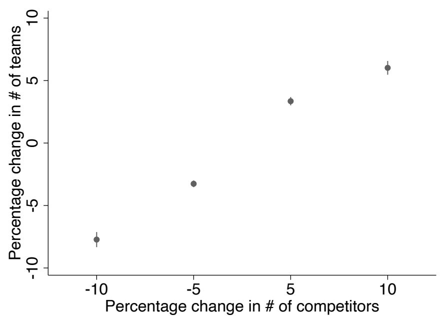
A) Number of submissions



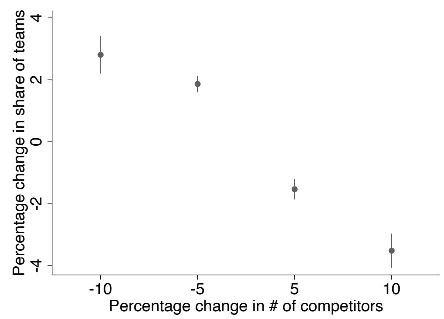
B) Maximum score

Notes: The figures plot a comparison of equilibrium outcomes when allowing teamwork versus when teamwork is banned. An observation is a contest.

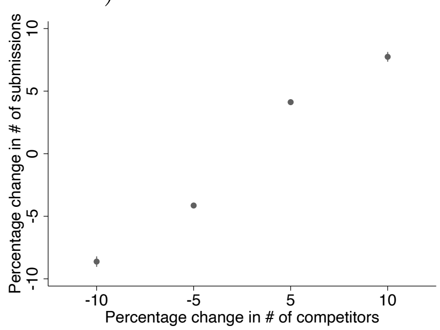
Figure 7: Equilibrium outcomes with increased competition levels



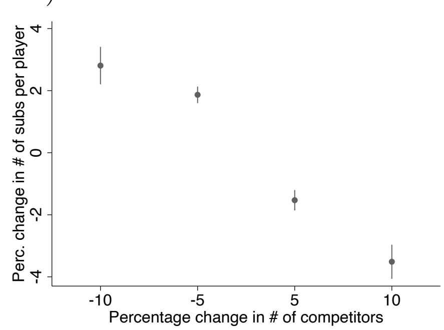
A) Number of teams



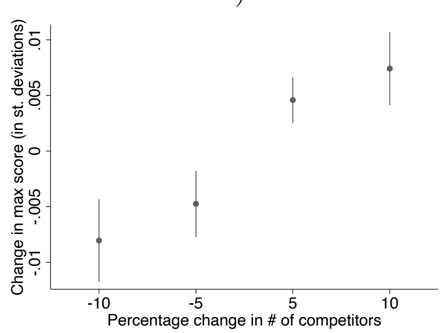
B) Fraction of team members



C) Number of submissions



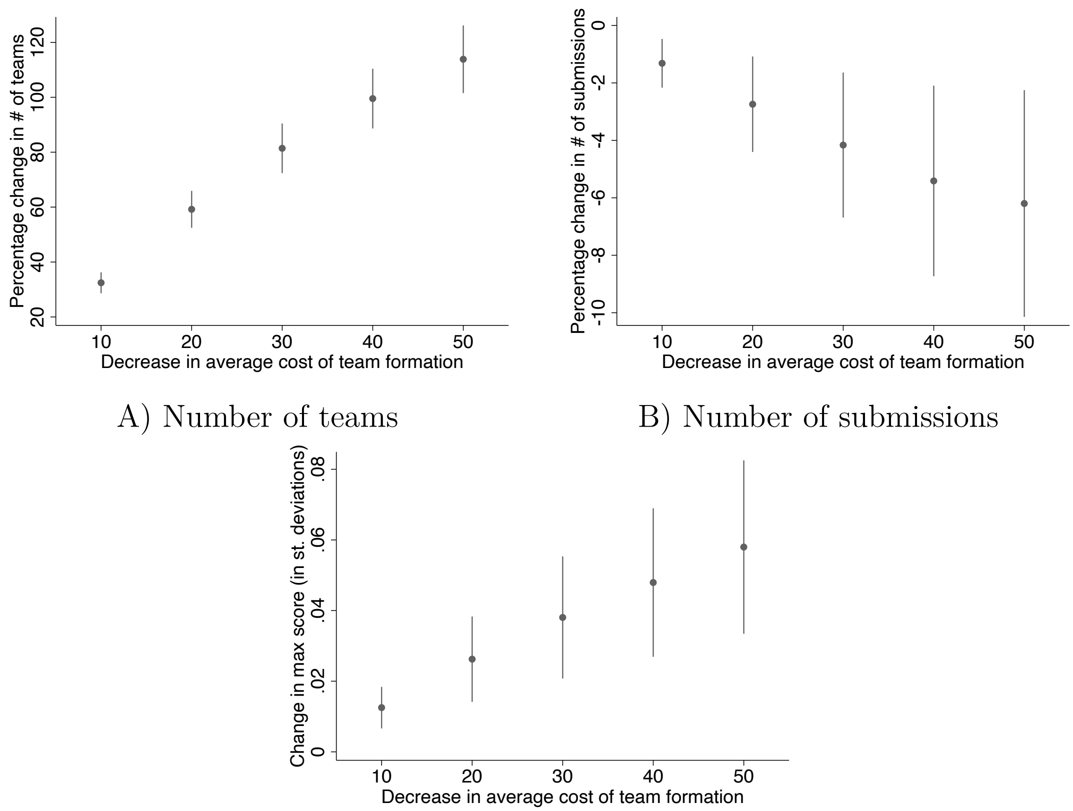
D) Number of submissions per player



E) Maximum score

Notes: The figures plot equilibrium outcomes predicted by the model estimates (as well as 95 percent confidence bands) when the expected contest length increases by X percent in each contest ($X \in \{10, 20, 30, 40, 50\}$). Model predictions are computed via simulation. Specifically, we simulate the game $ns = 500$ times and compute the average for each equilibrium outcome across simulations.

Figure 8: Equilibrium outcomes with reduced costs of team formation



A) Number of teams

B) Number of submissions

C) Maximum score

Notes: The figures plot equilibrium outcomes predicted by the model estimates (as well as 95 percent confidence bands) when the expected cost of forming a team decreases by X percent in each contest ($X \in \{10, 20, 30, 40, 50\}$). Model predictions are computed via simulation. Specifically, we simulate the game $ns = 500$ times and compute the average for each equilibrium outcome across simulations.

Online Appendix

Teamwork in Contests

by Jorge Lemus and Guillermo Marshall

Supplemental Material – Intended for Online Publication

A Appendix: Value Functions Derivations

In this section, we derive the value functions for the remaining cases in the structural model.

Solo Player, Follower (Continuation).

The expected continuation value of a solo player follower when other players can make a submission or form a team, or no other player has such an opportunity, is given by

$$\begin{aligned} E[V^{\text{sp,F}}_{s',\ell',n',t'}|(s,\ell,n,t)] &= \psi(n)F^{\text{sp}}_{s,\ell,n,t'} + \frac{2n^{\text{team}}\lambda_1}{N}F^{\text{sp,rival team}}_{s,\ell,n,t} + \frac{(n^{\text{sp}}-1)\lambda_1}{N}F^{\text{sp,rival sp}}_{s,\ell,n,t} \\ &\quad + \frac{(n^{\text{sp}}-1)\lambda_2}{N}F^{\text{sp, team forms}}_{s,\ell,n,t}. \end{aligned} \tag{7}$$

The probability that nobody can make a submission or form a team is

$$\psi(n) = 1 - \lambda_1 - \lambda_2 + \lambda_2\frac{2n^{\text{team}}}{N}, \tag{8}$$

which is the complementary probability that someone can make a submission or form a team.

The continuation value for a follower-solo player, when a rival team can make a submission is given by

$$\begin{aligned} F^{\text{sp,rival team}}_{s,\ell,n,t} &= \frac{\ell}{n^{\text{team}}}\left[p^{\text{team, L}}_{s,1,n,t}(q^{\text{team}}(s)F^{\text{sp}}_{s',1,n,t'} + (1-q^{\text{team}}(s))F^{\text{sp}}_{s,1,n,t'}) + (1-p^{\text{team, L}}_{s,1,n,t})F^{\text{sp}}_{s,1,n,t'}\right] \\ &\quad + \frac{n^{\text{team}}-\ell}{n^{\text{team}}}\left[p^{\text{team,F}}_{s,\ell,n,t}(q^{\text{team}}(s)F^{\text{sp}}_{s',1,n,t'} + (1-q^{\text{team}}(s))F^{\text{sp}}_{s,\ell,n,t'}) + (1-p^{\text{team,F}}_{s,\ell,n,t})F^{\text{sp}}_{s,\ell,n,t'}\right]. \end{aligned} \tag{9}$$

This event happens with probability $2n^{\text{team}}\lambda_1/N$—note that an individual team can make a submission with probability $2\lambda_1/N$, so that team formation does not change the opportunities for an individual player to make a submission whether part of a team or not. Given that the competition leader and the followers do not have the same incentives to make a submission, we distinguish the cases in which the rival team is the leader or a follower. Conditional that a team is chosen, the competition leader is chosen to make a submission with probability ℓ/n^{team}. In all these cases, a follower-solo player will continue as a follower-solo player, but the score can increase, and a team can become (or remain if $\ell = 1$) the competition leader.

Similarly, the continuation value for a follower-solo player, when another follower-solo player can make a submission is given by

$$F^{\text{sp,rival sp}}_{s,\ell,n,t} = \frac{1-\ell}{n^{\text{sp}}-1}\left[p^{\text{sp,L}}_{s,0,n,t}(q^{\text{sp}}(s)F^{\text{sp}}_{s',0,n,t'} + (1-q^{\text{sp}}(s))F^{\text{sp}}_{s,0,n,t'}) + (1-p^{\text{sp,L}}_{s,0,n,t})F^{\text{sp}}_{s,0,n,t'}\right]$$
$$+\frac{n^{\text{sp}}-1-(1-\ell)}{n^{\text{sp}}-1}\left[p^{\text{sp,F}}_{s,\ell,n,t}(q^{\text{sp}}(s)F^{\text{sp}}_{s',0,n,t'} + (1-q^{\text{sp}}(s))F^{\text{sp}}_{s,\ell,n,t'}) + (1-p^{\text{sp,F}}_{s,\ell,n,t})F^{\text{sp}}_{s,\ell,n,t'}\right], \tag{10}$$

which is an event event that happens with probability $(n^{\text{sp}}-1)\lambda_1/N$.

The probabilities of making a submission by player who is a follower-solo, leader-solo, follower-team, or leader-team, are given, respectively, by

$$p^{\text{sp,F}}_{s,\ell,n,t} = \Pr(c^{\text{sub}} < q^{\text{sp}}(s)(L^{\text{sp}}_{s',0,n,t'} - F^{\text{sp}}_{s,\ell,n,t'})), \tag{11}$$
$$p^{\text{sp,L}}_{s,0,n,t} = \Pr(c^{\text{sub}} < q^{\text{sp}}(s)(L^{\text{sp}}_{s',0,n,t'} - L^{\text{sp}}_{s,0,n,t'})), \tag{12}$$
$$p^{\text{team,F}}_{s,\ell,n,t} = \Pr(c^{\text{sub}} < q^{\text{team}}(s)(L^{\text{team}}_{s',1,n,t'} - F^{\text{team}}_{s,\ell,n,t'})), \tag{13}$$
$$p^{\text{team, L}}_{s,1,n,t} = \Pr(c^{\text{sub}} < q^{\text{team}}(s)(L^{\text{team}}_{s',1,n,t'} - L^{\text{team}}_{s,1,n,t'})). \tag{14}$$

Lastly, the value of a solo-follower player (i) when another solo-follower player (j) can form a team is

$$F^{\text{sp, team forms}}_{s,\ell,n,t} = \left((1-p^{\text{team forms}}_{s,\ell,n,t})\frac{n^{\text{sp}}-2+\ell}{n^{\text{sp}}-1} + \frac{1-\ell}{n^{\text{sp}}-1}\right)F^{\text{sp}}_{s,\ell,n,t'} +$$
$$+\frac{(n^{\text{sp}}-2+\ell)p^{\text{team forms}}_{s,\ell,n,t}}{n^{\text{sp}}-1}\left(\frac{1}{n^{\text{sp}}-2+\ell}F^{\text{team}}_{s,\ell,(n^{\text{sp}}-2,n^{\text{team}}+1),t'} + \frac{n^{\text{sp}}-3+\ell}{n^{\text{sp}}-2+\ell}F^{\text{sp}}_{s,\ell,(n^{\text{sp}}-2,n^{\text{team}}+1),t'}\right), \tag{15}$$

which is an event that happens with probability $(n^{\text{sp}}-1)\lambda_2/N$. Player j chooses not to form a team with probability $1-p^{\text{team forms}}_{s,\ell,n,t}$, in which case player i receives $F^{\text{sp}}_{s,\ell,n,t'}$, and where $p^{\text{team forms}}_{s,\ell,n}$ is an equilibrium object that we derived above. With probability $p^{\text{team forms}}_{s,\ell,n,t}$, player j chooses to form a team with one of the $n^{\text{sp}}-1-(1-\ell)$ solo players. Player j picks player i with probability $1/(n^{\text{sp}}-1-(1-\ell))$ (i.e., every available solo player is chosen with equal probability), and player i receives $F^{\text{team}}_{s,\ell,(n^{\text{sp}}-2,n^{\text{team}}+1),t'}$. With probability $(n^{\text{sp}}-2-(1-\ell))/(n^{\text{sp}}-1-(1-\ell))$, player j forms a team with a solo player other than player i. In this case, player i continues being a follower solo player, although the composition of rival players has changed: there is one more team and two fewer solo players.

Team, Leader. The interim value of a player that is a member of the team leading the competition (denoted team i) is

$$L^{\text{team}}_{s,1,n,t} = \frac{2\lambda_1}{N}E_{c^{\text{sub}}}\left[\max\{q^{\text{team}}(s)L^{\text{team}}_{s',1,n,t'} + (1-q^{\text{team}}(s))L^{\text{team}}_{s,1,n} - c^{\text{sub}}, L^{\text{team}}_{s,1,n,t'}\}\right] + E[V^{\text{team, L}}_{s',\ell',n',t'}|(s,1,n,t)].$$

where

$$E[V^{\text{team, L}}_{s',\ell',n',t'}|(s,\ell,n,t)] = \psi(n)L^{\text{team}}_{s,1,n,t'} + \frac{2(n^{\text{team}}-1)}{N}\lambda_1 L^{\text{team,rival team}}_{s,1,n,t}$$
$$\frac{n^{\text{sp}}}{N}\lambda_1 L^{\text{team,rival sp}}_{s,1,n,t} + \frac{n^{\text{sp}}}{N}\lambda_2 L^{\text{team, team forms}}_{s,1,n,t} \quad (16)$$

Here, $\ell = 1$, since the current competition leader is a team player. In this expression, with probability $2\lambda_1/N$ one of the team members has the opportunity to make a submission, and it does when the expected continuation payoff from making the submission is larger than the continuation payoff of not making it.

With probability $\psi(n)$, none of the players can make a submission or form teams, so the team leading the competition continues to do so and receives $L^{\text{team}}_{s,1,n,t'}$. With probability $\frac{2(n^{\text{team}}-1)}{N}\lambda_1$, one of the players in a rival team is selected to make a submission, and each member of the team leading the competition receives $L^{\text{team,rival team}}_{s,1,n,t}$. With probability $\frac{n^{\text{sp}}}{N}\lambda_1$, one of the solo players is selected to make a submission, and each member of the team leading the competition receives $L^{\text{team,rival sp}}_{s,1,n,t}$. Lastly, with probability $\frac{n^{\text{sp}}}{N}\lambda_2$, one of the solo players can choose to form a team, and each member of the team leading the competition receives $L^{\text{team, team forms}}_{s,1,n}$. The expressions for these values are given by

$$\begin{aligned}
L^{\text{team,rival team}}_{s,1,n,t} &= p^{\text{team,F}}_{s,1,n,t}(q^{\text{team}}(s)F^{\text{team}}_{s',1,n,t'} + (1-q^{\text{team}}(s))L^{\text{team}}_{s,1,n,t'}) + (1-p^{\text{team,F}}_{s,1,n,t})L^{\text{team}}_{s,1,n,t'}),\\
L^{\text{team,rival sp}}_{s,1,n,t} &= p^{\text{sp,F}}_{s,1,n,t}(q^{\text{sp}}(s)F^{\text{team}}_{s',0,n,t'} + (1-q^{\text{sp}}(s))L^{\text{team}}_{s,1,n,t'}) + (1-p^{\text{sp,F}}_{s,1,n,t})L^{\text{team}}_{s,1,n,t'},\\
L^{\text{team, team forms}}_{s,1,n,t} &= p^{\text{team forms}}_{s,1,n,t}L^{\text{team}}_{s,1,(n^{\text{sp}}-2,n^{\text{team}}+1),t'} + (1-p^{\text{team forms}}_{s,1,n,t})L^{\text{team}}_{s,1,n,t'},
\end{aligned}$$

In $L^{\text{team, team forms}}_{s,1,n}$, the composition of teams and solo players changes: there will be one more team and two fewer solo players. The last term, $(1-p^{\text{team forms}}_{s,1,n,t})L^{\text{team}}_{s,1,n}$, corresponds to the case where a solo player can form a team but chooses not to do so. In these expressions, whenever a player makes a submission, the player becomes the leader of the competition with probability $q^{\text{team}}(s)$ if the player is in a team, and with probability $q^{\text{sp}}(s)$ if the player is a solo player.

Following a similar logic, below we derive the value of a team follower and a solo-player leader.

Team, Follower. The interim value of a follower team is

$$F^{\text{team}}_{s,\ell,n,t} = \frac{2\lambda_1}{N}E_{c^{\text{sub}}}\left[\max\{q^{\text{team}}(s)L^{\text{team}}_{s',1,n,t'} + (1-q^{\text{team}}(s))F^{\text{team}}_{s,\ell,n,t'} - c^{\text{sub}}, F^{\text{team}}_{s,\ell,n,t'}\}\right] + E[V^{\text{team, F}}_{s',\ell',n',t'}|(s,\ell,n,t)].$$

where

$$E[V^{\text{team, F}}_{s',\ell',n',t'}|(s,\ell,n,t)] = \psi(n)F^{\text{team}}_{s,\ell,n,t'} + \frac{2(n^{\text{team}}-1)}{N}\lambda_1 F^{\text{team,rival team}}_{s,\ell,n,t} + \frac{n^{\text{sp}}}{N}\lambda_1 F^{\text{team,rival sp}}_{s,\ell,n,t} + \frac{n^{\text{sp}}}{N}\lambda_2 F^{\text{team, team forms}}_{s,\ell,n,t}$$

We define $F^{\text{team,rival team}}_{s,\ell,n,t} = 0$ if $n^{\text{team}} = 0, 1$. For $n^{\text{team}} = 2, ..., N/2$, we define

$$\begin{aligned}
F^{\text{team,rival team}}_{s,\ell,n,t} &= \frac{\ell}{n^{\text{team}}-1}\left[p^{\text{team, L}}_{s,1,n,t}(q^{\text{team}}(s)F^{\text{team}}_{s',1,n,t'} + (1-q^{\text{team}}(s))F^{\text{team}}_{s,1,n,t'}) + (1-p^{\text{team, L}}_{s,1,n,t})F^{\text{team}}_{s,1,n,t'}\right] \\
&+ \frac{n^{\text{team}}-1-\ell}{n^{\text{team}}-1}\left[p^{\text{team,F}}_{s,\ell,n,t}(q^{\text{team}}(s)F^{\text{team}}_{s',1,n,t'} + (1-q^{\text{team}}(s))F^{\text{team}}_{s,\ell,n,t'}) + (1-p^{\text{team,F}}_{s,\ell,n,t})F^{\text{team}}_{s,\ell,n,t'}\right]. \\
F^{\text{team,rival sp}}_{s,\ell,n,t} &= \frac{1-\ell}{n^{\text{sp}}}\left[p^{\text{sp,L}}_{s,0,n,t}(q^{\text{sp}}(s)F^{\text{team}}_{s',0,n,t'} + (1-q^{\text{sp}}(s))F^{\text{team}}_{s,0,n,t'}) + (1-p^{\text{sp,L}}_{s,0,n,t})F^{\text{team}}_{s,0,n,t'}\right] \\
&+ \frac{n^{\text{sp}}-1+\ell}{n^{\text{sp}}}\left[p^{\text{sp,F}}_{s,\ell,n,t}(q^{\text{sp}}(s)F^{\text{team}}_{s',0,n,t'} + (1-q^{\text{sp}}(s))F^{\text{team}}_{s,\ell,n,t'}) + (1-p^{\text{sp,F}}_{s,\ell,n,t})F^{\text{team}}_{s,\ell,n,t'}\right], \\
F^{\text{team, team forms}}_{s,\ell,n,t} &= p^{\text{team forms}}_{s,\ell,n,t} F^{\text{team}}_{s,\ell,(n^{\text{sp}}-2,n^{\text{team}}+1),t'} + (1-p^{\text{team forms}}_{s,\ell,n,t})F^{\text{team}}_{s,\ell,n,t'},
\end{aligned}$$

In these expressions we distinguish whether the team or solo-player that can form a team is leading the competition or not, which is indexed by the variable $\ell \in \{0,1\}$.

Solo Player, Leader. The interim value of a solo player who leads the competition is

$$L^{\text{sp}}_{s,0,n,t} = \frac{\lambda_1}{N}E_{c^{\text{sub}}}\left[\max\{q^{\text{sp}}(s)L^{\text{sp}}_{s',0,n,t'} + (1-q^{\text{sp}}(s))L^{\text{sp}}_{s,0,n,t'} - c^{\text{sub}}, L^{\text{sp}}_{s,0,n,t'}\}\right] + E[V^{\text{sp, L}}_{s',\ell',n',t'}|(s,0,n,t)].$$

where

$$E[V^{\text{sp, L}}_{s',\ell',n',t'}|(s,0,n,t)] = \left(\psi(n)+\frac{\lambda_2}{N}\right)L^{\text{sp}}_{s,0,n,t'} + \frac{2n^{\text{team}}}{N}\lambda_1 L^{\text{sp,rival team}}_{s,0,n,t} + \frac{(n^{\text{sp}}-1)}{N}\lambda_1 L^{\text{sp,rival sp}}_{s,0,n,t} + \frac{(n^{\text{sp}}-1)}{N}\lambda_2 L^{\text{sp, team forms}}_{s,0,n,t}$$

Here, $\ell = 0$, since the current competition leader is a solo player. When the contest does not end, the expressions for these values are given by

$$\begin{aligned}
L^{\text{sp,rival team}}_{s,0,n,t} &= p^{\text{team,F}}_{s,0,n,t}(q^{\text{team}}(s)F^{\text{sp}}_{s',1,n,t'} + (1-q^{\text{team}}(s))L^{\text{sp}}_{s,0,n,t'}) + (1-p^{\text{team,F}}_{s,0,n,t})L^{\text{sp}}_{s,0,n,t'}, \\
L^{\text{sp,rival sp}}_{s,0,n,t} &= p^{\text{sp,F}}_{s,0,n,t}(q^{\text{sp}}(s)F^{\text{sp}}_{s',0,n,t'} + (1-q^{\text{sp}}(s))L^{\text{sp}}_{s,0,n,t'}) + (1-p^{\text{sp,F}}_{s,0,n,t})L^{\text{sp}}_{s,0,n,t'}, \\
L^{\text{sp, team forms}}_{s,0,n,t} &= p^{\text{team forms}}_{s,0,n,t}L^{\text{sp}}_{s,0,(n^{\text{sp}}-2,n^{\text{team}}+1),t'} + (1-p^{\text{team forms}}_{s,0,n,t})L^{\text{sp}}_{s,0,n,t'}.
\end{aligned}$$

B Discussion and Additional Results

In our data, only around 10 percent of the competitors are teams, even though teams, on average, outperform solo players. Several factors may explain the scarcity of teams, such as matching frictions (e.g., language barriers), moral hazard concerns, credit allocation, or asymmetric information about a potential partner, a player's ability, commitment to work, or preference over methodologies.

To better understand some of these issues, we present complementary evidence, which we do not incorporate into our model but leave open for future work. First, Figure A.5 in the Online Appendix documents evidence suggesting assortative matching: teams are more likely to form among similarly-ranked players, and the effect is stronger for players in top positions. Forming a team with a "similar" player may alleviate asymmetric-information concerns (ability) and balance the "power dynamics" inside the team. Figure A.6 in the Online Appendix shows similar assortative-matching patterns in past competitions and contributions to the community (e.g., code sharing and message posting on public forums).

We also present evidence indicating players' actions to gather information about potential partners. First, Figure A.2 shows that a significant fraction of teams form right at the team-formation deadline. This suggests that some players form teams only after gathering as much information as possible from potential teammates. Related to this point, we use that scores on the leaderboard are only a noisy performance signal (see the discussion in Section 2.1). We find evidence suggesting that the noise in the leaderboard makes screening costlier. Specifically, we exploit variation in the precision of the public score as a signal of the private score across contests to measure the impact of asymmetric information on team formation. Table A.5 in the Online Appendix shows that both the number of submissions before team formation and the time of the merger decrease with the precision of the information in the leaderboard. We interpret this finding as indicating the informativeness of more precise signals. When information is more precise, fewer signals are needed to form a more precise posterior belief about the type of a potential teammate, which leads to earlier team formation.

This complementary evidence suggests the positive value of facilitating the formation of self-organized teams in dynamic contests.[31] First, a public leaderboard is vital since it allows players to learn about the performance of prospective partners in the current competition. Second, the leaderboard should be as informative as possible.[32] Third, information about

[31] Blasco et al. (2013) shows that self-organized teams perform better than randomly-formed teams.

[32] The contest designer needs to consider overfitting concerns with a perfectly informative leaderboard.

past performance should be as informative as possible.[33] Fourth, the contest sponsor should provide opportunities to signal skills beyond performance in the current competition. On Kaggle, for example, competitors can develop and share code to analyze a dataset even if they do not participate in a competition. Fifth, the contest sponsor should facilitate the enforcement of prize splits among team members.[34]

[33]Kaggle allocates "medals" based on performance.

[34]In some competitions, it is up to the winning team to reallocate the prize money among its members. In others, the platform allocates the prize in even shares between the team members unless the team requests an alternative prize distribution. See, e.g., some competitions hosted in the platform DrivenData.org.

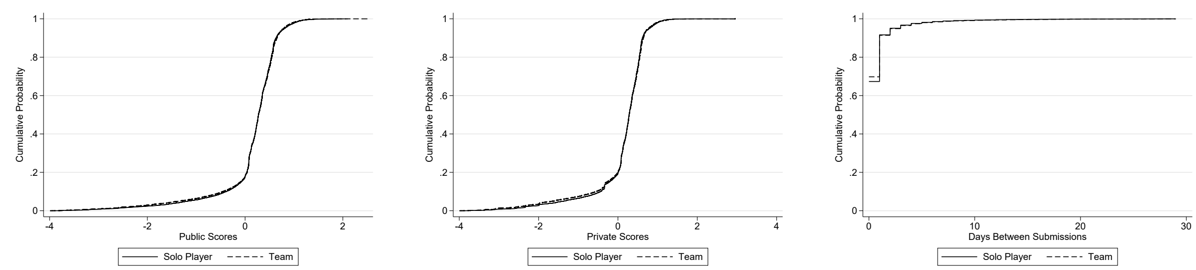
C Additional Tables and Figures

Table A.1: Balance table: pre-merger covariates across treated and non-treated (matched) teams

	Number of submissions up to time of merger	Distance to max score on public leaderboard at time of merger
	(1)	(2)
Non-treated teams	18.93	2.050
Treated teams	19.08	2.051
p-value	0.818	0.993

Notes: Treated teams are teams who welcomed a new member during the competition, non-treated teams are teams who did not change their team size during the competition. The last row of the table reports the p-value of a differences-in-mean test.

Figure A.1: Balance of untargeted variables: pre-merger covariates across treated and non-treated (matched) teams



Public Scores | Private Scores | Days Between Submissions

Notes: An observation is the outcome of a submission (public score, private score, or days between submission) for a team or its matched solo player in a competition. We only consider submissions before the team formation for each team/solo-player match.

Table A.2: The impact of team-formation time on final outcomes

	Number of submissions	Ranking
Team Formation time	2.481***	7.717
	(0.353)	(53.172)
Observations	5687	5394
R^2	0.023	0.009

Notes: An observation is a team in the matched sample. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All specifications include competition fixed effects. The outcome variable corresponds to the difference (in number of submission or ranking) between teams and solo players.

Table A.3: The impact of collaboration on scores: Team-level estimates, heterogeneity analysis with respect to contest characteristics

	(1)	(2)	(3)	(4)	(5)
Teamwork	0.060***	0.058***	0.059***	0.018	0.055***
	(0.009)	(0.011)	(0.012)	(0.018)	(0.010)
Teamwork * Image data		0.010			
		(0.020)			
Teamwork * Large reward			0.003		
			(0.017)		
Teamwork * Post 2015				0.054**	
				(0.021)	
Teamwork* Large dataset					0.038
					(0.024)
Observations	3189817	3189817	3189817	3189817	3189817
R^2	0.439	0.439	0.439	0.439	0.439

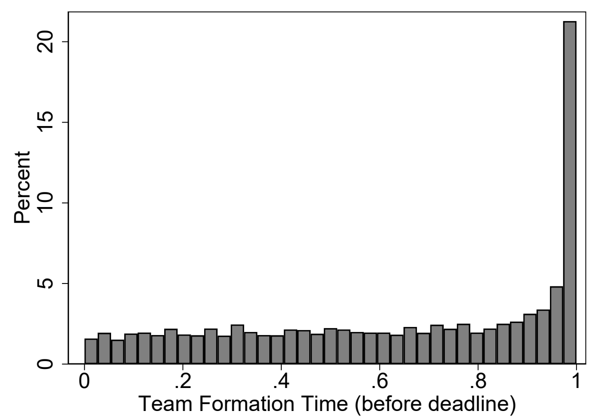
Notes: Standard errors clustered at the team-level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. An observation is a submission made by a team in a competition. All specifications include team fixed effects, competition–day fixed effects, and a second-degree polynomial of variables: total number of submissions by all teams up until the submission time, total number of submissions by the team making the submission up until the submission time, total number of submissions by the member of the team making the submission up until the submission time, the submitting team's distance to the maximum score on the public leaderboard at the submission time, and the fraction of contest time that had elapsed at the submission time. The sample is restricted to include submissions by treated teams that took place six weeks before or after the week in which the team changed its team size, and it also restricts attention to teams with one or two members. Image data is an indicator for whether the contest requires use of video or image data; large reward is an indicator for contests with above average reward quantity; post 2015 is an indicator for contests taking place after 2015 (when the platform incorporated new features that facilitated communication among players, e.g., notebooks); and large dataset is an indicator for whether the dataset has an above average size (in GBs).

Table A.4: Empirical model estimates: Contest-specific parameters

	σ^{team}	SE	σ^{sub}	SE	β_0 (q)	SE	N
Wikipedias Participation Challenge	0.7372	0.0340	0.2990	0.0010	-2.5714	0.2513	54
Allstate Claim Prediction Challenge	0.9881	0.0413	0.0424	0.0079	-0.7119	0.2063	77
dunnhumbys Shopper Challenge	0.9760	0.0821	0.0997	0.0070	-1.6698	0.2639	107
Give Me Some Credit	0.9338	0.0757	0.1820	0.0023	-4.9669	0.2199	90
Dont Get Kicked!	0.8174	0.0308	0.1944	0.0036	-2.9767	0.1894	96
CHALEARN Gesture Challenge	0.7624	0.0349	0.0886	0.0063	-0.7583	0.2883	59
What Do You Know?	0.8281	0.0378	0.1649	0.0026	-3.2192	0.2795	108
Photo Quality Prediction	0.9808	0.0641	0.0781	0.0288	-2.2559	0.2445	138
The Hewlett Foundation: Automated Essay Scoring	0.5469	0.0432	0.1763	0.0001	-2.6569	0.2443	96
KDD Cup 2012, Track 2	0.9163	0.0317	0.3689	0.0021	-2.8153	0.2414	48
Predicting a Biological Response	0.7063	0.0254	0.2117	0.0049	-4.5030	0.2054	86
Online Product Sales	0.8425	0.0533	0.1153	0.0019	-3.4666	0.2399	136
Belkin Energy Disaggregation Competition	1.1112	0.0516	0.0001	1.2204	-1.5078	0.1687	114
Merck Molecular Activity Challenge	1.1375	0.0316	0.0725	0.0086	-2.1444	0.2094	111
Predict Closed Questions on Stack Overflow	0.6024	0.0207	0.2244	0.0034	-3.1526	0.2536	73
Job Salary Prediction	0.5186	0.0316	0.2160	0.0004	-4.2832	0.2913	84
The Marinexplore and Cornell University Whale Detection Challenge	0.6046	0.0188	0.1457	0.0021	-2.8478	0.2377	115
KDD Cup 2013 - Author-Paper Identification Challenge (Track 1)	0.7600	0.0233	0.2404	0.0031	-3.3397	0.1989	79
KDD Cup 2013 - Author Disambiguation Challenge (Track 2)	0.9399	0.0523	0.3025	0.0057	-2.4060	0.1752	57
Packing Santas Sleigh	0.7832	0.1022	0.0012	0.1024	-2.7145	0.2091	124
Higgs Boson Machine Learning Challenge	0.5912	0.0267	0.1865	0.0041	-4.4360	0.1970	93
Liberty Mutual Group - Fire Peril Loss Cost	0.6569	0.0078	0.0832	0.0011	-3.4253	0.2057	165
Helping Santas Helpers	0.4613	0.0383	0.0127	0.0042	-1.4426	0.1547	82
March Machine Learning Mania 2015	0.7870	0.0197	0.3382	0.0018	-3.2821	0.3727	54
Otto Group Product Classification Challenge	0.4291	0.0422	0.0580	0.0025	-5.3629	0.1854	186
ICDM 2015: Drawbridge Cross-Device Connections	0.7009	0.0329	0.0026	0.0117	-1.2911	0.2068	113
Caterpillar Tube Pricing	0.4549	0.0323	0.1307	0.0014	-4.9156	0.1811	126
Liberty Mutual Group: Property Inspection Prediction	0.4527	0.0367	0.0931	0.0011	-4.6258	0.1701	154
Springleaf Marketing Response	0.4481	0.0290	0.1266	0.0001	-4.4269	0.1761	129
Truly Native?	0.5014	0.0186	0.0824	0.0028	-3.1990	0.2677	157
The Allen AI Science Challenge	0.6239	0.0098	0.2061	0.0091	-1.3670	0.4264	94
Santas Stolen Sleigh	0.5105	0.0104	0.0608	0.0041	-2.6891	0.1333	92
Second Annual Data Science Bowl	0.6444	0.0201	0.2063	0.0078	-3.5449	0.4561	88
BNP Paribas Cardif Claims Management	0.9404	0.0853	0.1681	0.0008	-5.6184	0.1826	97
Home Depot Product Search Relevance	0.6244	0.0080	0.1326	0.0020	-4.1634	0.1618	128
Santander Customer Satisfaction	0.6742	0.0315	0.1935	0.0049	-4.9469	0.1476	85
Expedia Hotel Recommendations	0.7309	0.0250	0.0704	0.0038	-3.9245	0.1934	178
Ultrasound Nerve Segmentation	0.7001	0.0178	0.1959	0.0032	-3.6111	0.2230	93
Draper Satellite Image Chronology	1.0776	0.0028	0.2040	0.0028	-2.3338	0.3217	88
Predicting Red Hat Business Value	0.7244	0.0347	0.0816	0.0026	-4.0519	0.1522	167
TalkingData Mobile User Demographics	0.5304	0.0398	0.1297	0.0029	-4.4402	0.1562	127
Outbrain Click Prediction	0.8250	0.0323	0.1861	0.0014	-2.7646	0.1993	99
The Nature Conservancy Fisheries Monitoring	0.4331	0.0234	0.2576	0.0004	-4.1177	0.3615	69
Dstl Satellite Imagery Feature Detection	0.7837	0.3830	0.0030	0.2987	-0.4366	0.1655	109
Intel & MobileODT Cervical Cancer Screening	0.3207	0.0111	0.2771	0.0001	-5.1303	0.7199	53
Cdiscounts Image Classification Challenge	1.1205	0.0302	0.1663	0.0100	-2.1434	0.1914	101
Recruit Restaurant Visitor Forecasting	0.5957	0.0104	0.1939	0.0036	-5.6364	0.1947	84
Statoil/C-CORE Iceberg Classifier Challenge	0.7204	0.0320	0.1438	0.0007	-5.3231	0.1809	114
TrackML Particle Tracking Challenge	0.6868	0.0182	0.0191	0.0171	-2.2821	0.1852	142
Santa Gift Matching Challenge	0.5233	0.0211	0.2443	0.0012	-3.8311	0.2483	77
Google Cloud & NCAA ML Competition 2018-Mens	0.6232	0.0235	0.3723	0.0097	-3.8825	0.3944	45
Google Cloud & NCAA ML Competition 2018-Womens	0.9736	0.0440	0.3123	0.0060	-4.5706	0.7181	52
Google AI Open Images - Object Detection Track	0.7578	0.0355	0.1633	0.0049	-1.5454	0.2206	77
Google AI Open Images - Visual Relationship Track	1.3398	0.0805	0.1764	0.0018	-0.2932	0.3390	107
Airbus Ship Detection Challenge	0.4881	0.0484	0.0840	0.0011	-3.6866	0.2069	162
Peking University/Baidu - Autonomous Driving	0.7695	0.0042	0.2370	0.0158	-2.3647	0.2467	77
TGS Salt Identification Challenge	0.3730	0.0013	0.1176	0.0024	-4.6314	0.1716	137
Quick, Draw! Doodle Recognition Challenge	0.5509	0.0041	0.1592	0.0003	-4.2359	0.1963	116
RSNA Pneumonia Detection Challenge	0.7321	0.0258	0.2913	0.0045	-0.7809	0.4059	66
Human Protein Atlas Image Classification	0.9893	0.0378	0.2128	0.0034	-3.4999	0.1610	91
Traveling Santa 2018 - Prime Paths	0.6300	0.0178	0.2540	0.0042	-3.6389	0.1453	72
Google Cloud & NCAA ML Competition 2019-Mens	0.8570	0.0375	0.3449	0.0062	-4.1496	0.3301	49
Instant Gratification	0.4420	0.0064	0.1786	0.0027	-5.3475	0.1730	105
Predicting Molecular Properties	0.5432	0.0024	0.2743	0.0022	-4.7078	0.1700	68
SIIM-ACR Pneumothorax Segmentation	0.7157	0.0215	0.2234	0.0051	-3.8427	0.3802	83
APTOS 2019 Blindness Detection	0.2581	0.0129	0.1735	0.0021	-5.7479	0.2105	87
Lyft 3D Object Detection for Autonomous Vehicles	0.6575	0.0255	0.1940	0.0195	-1.0558	0.2075	67
Santas Workshop Tour 2019	0.3915	0.0285	0.2427	0.0001	-5.2369	0.2673	68

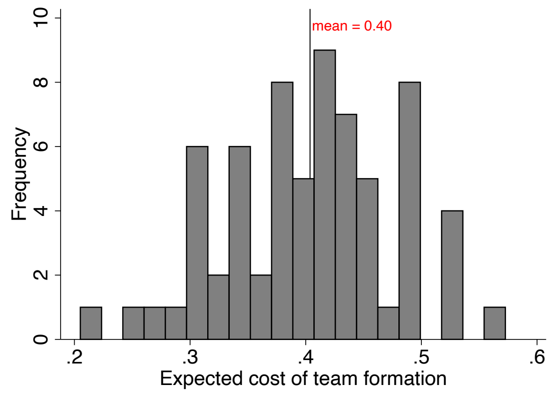
Notes: SE stands for asymptotic standard errors. Numbers smaller than 1e-4 are rounded up to that value.

Figure A.2: Distribution of Timing of Team Formation

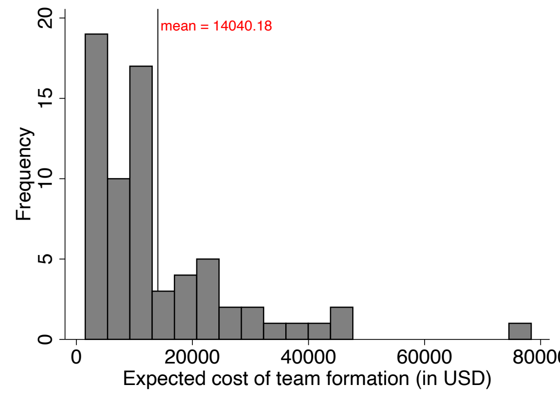


Notes: An observation is a team. The time is measured relative to the team-formation deadline for each competition. There is spike of team formation exactly at this deadline.

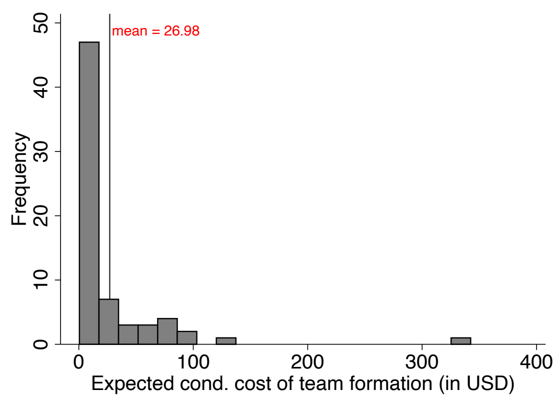
Figure A.3: Average cost of team formation.



A) Expected cost (normalized by prize amount)



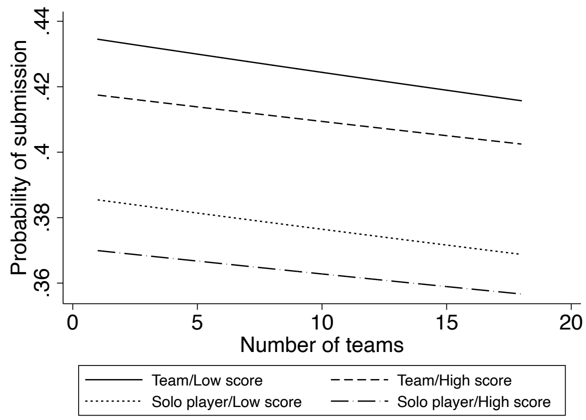
B) Expected cost (in USD)



C) Expected conditional cost (in USD)

Note: An observation is contest. Panel A: “Expected cost” is the unconditional expected cost of team formation (i.e., given the distribution of costs we use in our model, the average cost is given by $\sigma/(1+\sigma)$). Panel B: “Expected cost (in USD).” The model normalizes the value of the prize pool to 1, so to express costs in USD we have to scale the costs up by the size of the prize. Panel C: “Expected conditional cost of team formation (in USD)” is the expected cost conditional on choosing to form a team. Computing this moment is computationally intensive. A middle-ground result is an approximation at time 0: Initially, players are symmetric, the gains from forming a team are bounded by $B = (q^{team}(s_0) - q^{sp}(s_0)) \cdot \text{Prize}/(\text{number of players})$, where $q^j(s_0)$ is the probability of surpassing the maximum score evaluated at the initial score for a player of type j. Thus, we can compute the conditional mean at time zero explicitly: $E[c|c < B] = B \cdot \sigma/(\sigma+1)$. We report this value for every contest.

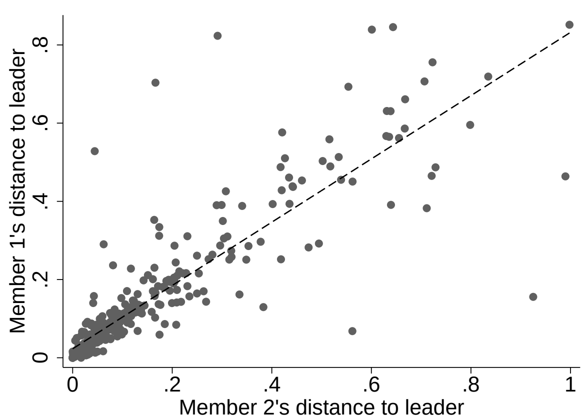
Figure A.4: Properties of conditional choice probabilities



Probability of a submission by a follower as a function of number of teams, by player type

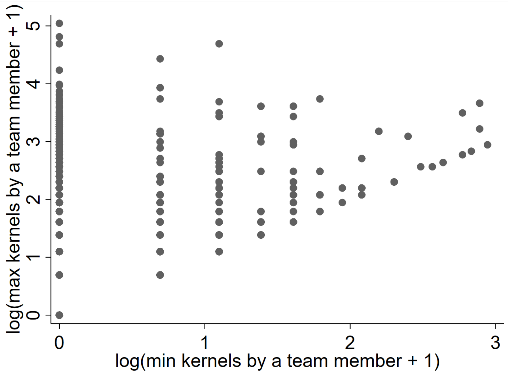
Notes: The figure plots equilibrium conditional choice probabilities computed using model estimates for one particular contest: the "Don't Get Kicked!" (Predict if a car purchased at auction is a lemon) contest. In Panels A and C, time is fixed at $t = 320$, the leader is a follower $\ell = 0$, and the score is either the second (low) or tenth (high) value of the score grid.

Figure A.5: Team member heterogeneity at the time of the merger

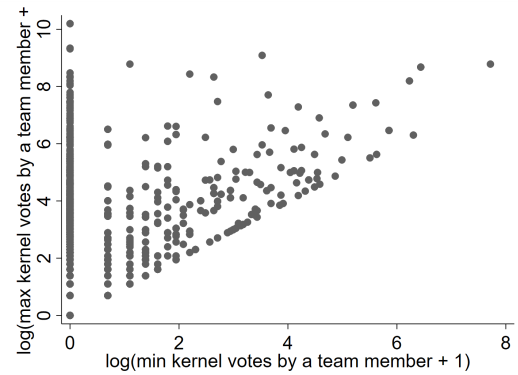


Notes: The figure plots the distance of each team member to the leader at the moment of forming a team. These figures restrict attention to teams in which both members had submitted at least 5 submissions prior to the merger.

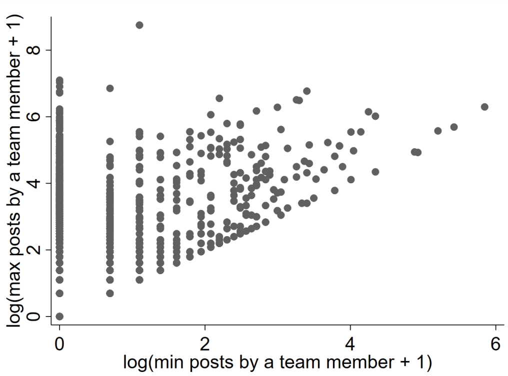
Figure A.6: Are players matching up with players who have similar observed outcomes?



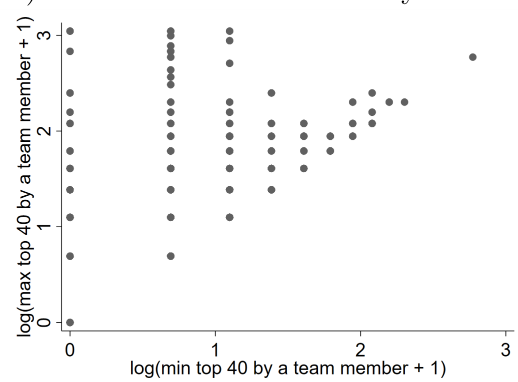
A) Number of kernels uploaded in the past



B) Number of votes earned by kernels



C) Number of past messages on the discussion board



D) Number of past participations in the top 40

Notes: An observation is a multiplayer team. Panel A plots the number of kernels (also known as notebooks) posted by the team members in the past. Kernels are code that players can post so that any user can make use of it. Panel B plots the number of votes earned by the kernels posted by the different team members. Panel C plots the number of discussion board messages posted by the team members in the past. Panel D plots the number of past participations where the team members finished in the top 30 positions.

Table A.5: The impact of performance feedback noise on team formation outcomes: Player-level estimates

	Number of submissions prior to team formation (in logs)	Time of team formation (in logs)
	(1)	(2)
Feedback precision (in St. Dev.)	-0.037**	-0.062***
	(0.016)	(0.018)
Observations	4,410	4,410
R^2	0.201	0.043

Notes: Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. An observation is a competition–player combination over the sample of team players. "Feedback precision" is a measure in [0,100] readily available in the data. When it is 100, the public and private scores take the same value; when it is 0, the public score is uncorrelated with the private score (see Section 2). We standardize it to simplify the interpretation of our results (the mean and standard deviation before standardizing are 31.6 and 23.4, respectively). All specifications include contest-level controls (i.e., total reward quantity, number of prizes, maximum daily submissions, contest length, dataset size, image data indicator) and player-level controls (i.e., public score of first submission, number of past competitions). Column 1 further controls for the time of the team's formation, where time is the fraction of the contest time elapsed at the time of team formation.

D Kaggle Users Interviews

To complement our analysis, we informally interview some Kaggle participants with teamwork experience to inquire about team formation, asking them: "How concerned are you that your teammate will not be a good match?" We reproduce verbatim answers below, which align with our findings on screening potential teammates.

> "In general, teamwork on kaggle works the following way: At the beginning of the competition everybody participates alone. A few weeks before the end of the competition, you look for somebody close to you on a leaderboard and team up with them. You share your solutions, discuss all the ideas, and decide what to do next. Sometimes everybody brainstorms and works on the new ideas together, sometimes everybody continues to improve their solutions, and then combine them."

> "I just want to team up with someone smart who I'll enjoy collaborating with. If they've done well in other competitions, that's good enough. If they are doing well in the same competition, it could be do to noise."

> "I would team up with a person only if I am very sure that I will learn something from that person. I would check that person LinkedIn profile and would also have conversations with that person over call before teaming up. LinkedIn and their previous kaggle work can serve as good indicator. Also during the call, I ask them what have they done so far in the competition. I decide based on the answers which they give to this question"

> "previous experience at kaggle, posts in the current competition, and the current results. Also it is very important if I already participated in another competition with the person. So I know the capabilities of the person, and how hard he/she can work."

E Dealing with Selection in Team Formation

In the main text, we seek to measure the performance of self-organized teams relative to solo players. We find a significant performance increase after the team has formed, relative to the performance of solo players. While the focus of our paper is the impact of self-organized teams on contest outcomes, one may ask whether teamwork in general, not only when teams are self-organized, has a causal impact on performance.

To causally identify the impact of teamwork on scores, treatment assignment must be unconfounded. That is, the probability that a solo player forms a team may depend on player-level state variables ($\mathbf{x}_{i,j,c,t}$), and the player's ability to produce high scores (captured in the player-level fixed effects), but not on the potential outcomes (Imbens and Rubin, 2015). Under this assumption, β can be identified by comparing the observed scores of treated and non-treated teams that have similar state variables.

Unconfoundedness accommodates the cases in which a player's decision to form a team can be explained based on observable state variables (e.g., their position in the leaderboard) or performance-unrelated unobservables (e.g., the size of their social network). This assumption, however, does not accommodate the case in which performance-related unobservables in the error term affect the decision to form a team. For example, a violation of the unconfoundedness assumption would occur if players had perfect foresight about the gains of teamwork, and these gains are heterogeneous across players. In this case, team formation would only occur among players expecting sufficiently large gains, and these gains would at least in part appear in the error term. This is likely to be the case with self-organized teams.

To deal with selection, we implement a two-step, Heckman-style selection bias correction (Heckman, 1979) similar to the one used by Lee (1978). In the first step, we estimate a player-level probit model for the probability of forming a team at time t given a rich set of state variables and an indicator for whether the player is eligible to form a team.[35] Players are eligible to form a team if they join the competition before a preset deadline to form teams. This establishes the relevance of the instrument.

Is the instrument valid? Players must join the competition to download the data and learn about the rules of the competition (one of which is the deadline to form teams). Lemus and Marshall (2021) document that the distribution of entry times of players is roughly uniform throughout a contest, suggesting that players learn about a competition at different times

[35] Specifically, for every contest, we estimate $\Pr(\text{formed team}_{i,j,c,t} = 1) = \Phi(\alpha + 1\{\text{elegible}\}_{i,j,c,t}\beta + h(\mathbf{x}_{i,j,c,t}, \delta))$, where i is a player; the notation is the same as in Equation 1.

and likely join for reasons that are unrelated to the potential benefits of team formation.

Although we acknowledge that entering the competition earlier can have an impact on the performance of a player, we control for measures of the player's progress in the contest (e.g., number of submissions up to time t or distance to the leader at time t). We thus believe that among similar players that entered at similar times (with controls for progress), the eligibility indicator is a plausibly exogenous shifter of the probability of forming a team.

We use the probit estimates to compute the Mills ratio for every player–time combination, which captures the expected value of unobservables governing the decision to form a team (conditional on treatment). We then incorporate the Mills ratio estimates in a version of Equation 1. This approach has the benefit of relaxing the requirement of the treatment indicator being uncorrelated with performance-related unobservables (i.e., it relaxes the unconfoundness assumption).

Table A.6 presents the results of a correction along the lines of Lee (1978), which relaxes the unconfoundness assumption. Columns 1 and 2 replicate Table 3 with two differences. The first one is that we replace the competitor-level fixed effects with player-level fixed effects, as the Mills ratio estimates are constructed at the individual level. The second difference is that we restrict the sample to those players for which we can compute the Mills ratio (column 2). Columns 1 and 2 show that the gains of teamwork are smaller than those in Table 3, possibly because the player-level fixed effects are more flexible and can absorb any changes in the composition of submission authorship caused by teamwork. Column 3 shows the point estimates after we implement the selection correction, which has a minor effect on the point estimate (point estimates are within one standard error of each other). The impact of teamwork on scores remains economically relevant after we correct for selection.

Table A.6: The impact of collaboration on scores: Player-level estimates

	Score		
	(1)	(2)	(3)
Teamwork	0.042***	0.035***	0.044***
	(0.008)	(0.008)	(0.009)
Mills ratio			0.376**
			(0.161)
Observations	3,109,136	2,790,553	2,790,553
R^2	0.371	0.394	0.395

Notes: Standard errors clustered at the team-level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. An observation is a submission made by a player in a competition.

One might assume that teams would form early to maximize the benefits of collaboration if they anticipate significant advantages. However, we do not find evidence to support this assumption. Table A.2 in the Online Appendix shows that the impact of teamwork on performance is unaffected by the timing of the team formation. Moreover, on average, players who form teams have sent 19 submissions before the team forms.

These pieces of evidence combined point towards a plausible *causal* relationship between teamwork and productivity.