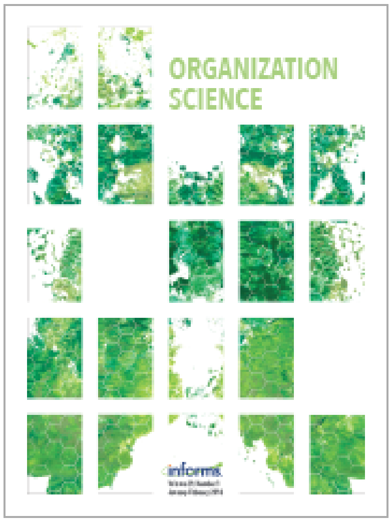

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Competitive Familiarity: Learning to Coordinate by Competing

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Abstract. This paper develops and tests a theory of organizational learning, proposing that prior competitive interaction improves coordination among teammates. We test the theory using millions of experiments in the formation of eSports teams. The results show that exogenously assigned teams of former competitors are highly effective—The marginal returns to prior competitive interaction are even larger than the returns to prior collaborative interaction. The evidence suggests that teammates learn to coordinate by competing, a finding with implications for organizational design and the management of human capital.

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Keywords: competition • collaboration • organization design • team performance • strategic human capital

Introduction

One fruitful extension of the seminal work of Arrow (1962) on learning by doing—the idea that performance improves through repetition—posits that repeated *collaboration* improves coordination among teammates (Hackman et al. 2009, Desai and Madsen 2021). This paper builds on and extends theories of organizational learning, advancing the idea that repeated *competition* might also influence team performance. Repeated competition followed by collaboration, or "competitive familiarity," emerges from a wide range of organizational interactions, for example, when competitors become collaborators in new product development teams, following mergers by firms in the same industry, and when employers poach talent from competitors. Yet, we know little about how current collaborators might benefit from knowledge accumulated via prior competitive interactions.

In this paper, we propose that when competitive behavior is observable, competitive familiarity will tend to improve organizational performance by facilitating learning among teammates. The intensity and salience of competition provides teammates with unique insight into one another's behavior, leading to improved coordination among contemporaneous teammates.

We test the theory using a large and rich panel data set on teams competing in Defense of the Ancients 2 (DOTA2)—a popular high-stakes competitive strategy online game requiring team-based problem solving. Although studies of sports teams have made important contributions to organizational research (Campbell et al. 2014, Hill et al. 2017), eSports offers some additional opportunities for scholars (Waguespack et al. 2018, Clement 2023). Importantly, the context allows one to exploit the exogenous assignment of individuals to teams—That is, in our test sample, team members do not control which team they are assigned to—providing millions of organizational design experiments.

The results show that competitive familiarity causes team performance to improve meaningfully. Indeed, the marginal returns to competitive familiarity are even larger than the returns to prior collaborative experience ("cooperative familiarity"); and the absolute returns to competitive familiarity are increasing in the extent to which teammates have competed in the past. Interestingly, we also show that competitive and cooperative familiarity are complements, suggesting that competitive familiarity provides teammates with unique mutual insight into one another's behavior.

This paper makes two main contributions. First, we develop a novel extension of theories of organizational learning, highlighting the potential benefits of competitive familiarity as a coordination mechanism for team-based production. Efficiently coordinating interdependent actors is at the heart of organizational design (Becker and Murphy 1992, Puranam et al. 2012), and organizational scholars have long studied coordination as one of the central challenges, and opportunities, for organizations (March and Simon 1958, Rawley 2010). This paper proposes a new approach for organizational designers to improve team coordination.

Second, we provide new evidence on team learning, in the context of temporary teams. Temporary teams are increasingly important in modern organizations (Bechky 2006, Akşin et al. 2021), yet we still only partially understand how knowledge is developed and shared within such teams (O'Toole et al. 2023). The results in this paper show that, although both cooperative and competitive familiarity improve the performance of temporary teams, competitive familiarity stimulates incremental coordination benefits. Interestingly, although the benefits of familiarity increase with more competitive (and cooperative) exposure, even teams with relatively low levels of competitive familiarity experience some benefits, suggesting that mutualism develops rapidly from competitive interactions.

Theory

Cooperative and Competitive Interaction

This paper advances the idea that team members learn about each other by collaborating *and* by competing. Our theory of learning by competing builds on and extends research on the consequences of repeated cooperation among teammates (Lewis et al. 2005, Argote et al. 2021). We build on the extant literature by considering how shared experience improves team learning and performance and extend it conceptually and empirically by evaluating the role of competitive familiarity in teams.

Learning by doing has a long and distinguished history in the literature on organizational design (Asher 1956, Lieberman 1987, Hatch and Mowery 1998, Thompson 2010). Although early applications emphasized individual learning effects (Wright 1936), more recent scholarship has called attention to how repeated interaction among teammates enables team learning and coordination (Rapping 1965, Argote and Epple 1990).[1] Repeated interaction provides individuals with the opportunity to observe and react to each other and to develop relationship-specific knowledge, providing "a script for an expected pattern of interaction, derived through generalization from repeated similar interpersonal experiences" (Baldwin 1992, p. 462). To the extent that organizational learning reflects aggregate team learning, learning by doing in teams represents an important mechanism for improving organizational performance. In short, repeated collaboration among teammates engenders cooperative familiarity,[2] characterized by the development of cognitive, social, and organizational systems, based on trust (Edmondson 1999, Jarvenpaa and Leidner 1999) and transactive memory systems—knowledge of who knows what (and who does not know what) in a group (Wegner 1986, Ren and Argote 2011). As a result, cooperative familiarity enables individuals to communicate and coordinate more effectively within a team (Rico et al. 2008, Akşin et al. 2021). Thus, our core assumption, which we subsequently test, is that increasing prior collaboration improves team performance.

The main idea in this paper—that competitive familiarity creates an economically useful resource for organizations—is novel, but the notion that there are different manifestations of learning by doing is not new. For example, organizational scholars have shown that firms learn by exporting (Salomon and Shaver 2005), working together (Kellogg 2011), and by supplying (Alcacer and Oxley 2014), whereas research on the microfoundations of organizational learning has demonstrated how different types of shared experiences might affect team performance including: breadth and depth of experience (Merluzzi and Phillips 2016), recency and novelty of experience (Argote 2013), successful and unsuccessful experience (Wilhelm et al. 2019), and task complexity (Avgerinos et al. 2020).

Competitive familiarity is much less studied than cooperative familiarity, and yet, it is a regular feature of organizational life. Indeed, competitive familiarity arises quite purposefully in some contexts. For example, multinational corporations such as Haier and Tencent rotate employees among competing project teams (Meyer et al. 2017, Murmann and Zhu 2021). Cybersecurity firms and forward-looking chief executive officers (CEOs) often use "red teams" (i.e., contrarian teams) made up of insiders who temporarily act like competitors to pre-emptively identify technological or organizational flaws (Dewar et al. 2019). Samsung encourages zero-sum competition among teams at the early stages of new product development, before combining them for subsequent development (Siegel and Chang 2005), and information technology firms integrate engineers from competing internal technology teams to develop and improve customer solutions (Taylor 2010). Political organizations (Goodwin 2005) and professional sports teams (Fonti et al. 2023) too often field teams of former rivals. Similarly, prize-based engineering tournaments typically involve temporary teams of professionals (i.e., coders, engineers, and developers) who compete to create technical solutions to specific problems while allowing them to become collaborators on future projects (Lakhani et al. 2013, Paik et al. 2020). Although there is extensive research on how repeated collaboration shapes competitive interaction among former teammates (Campbell et al. 2014, Grohsjean et al. 2016, Uribe et al. 2020), there is little on the performance implications of former competitors becoming collaborators on the same team. Yet, as the previous examples suggest, competitive familiarity appears quite ubiquitous. Thus, by studying cooperative familiarity as a potential organizational asset, this paper fills a gap in the literature.

Competitive Familiarity, Trust in Competence, and Team Performance

Prior research on cooperative familiarity often invokes the role of trust in supporting the development of transactive memory systems. For example, in the seminal studies of Wegner (1986) of the interactions between married couples trust in motives, the belief that another will not behave opportunistically is a prerequisite for the emergence of a transactive memory system. Yet, trust in competence—the belief in another's ability to carry out a task effectively—can also be the basis of a trusting relationship (Mayer et al. 1995, Twyman et al. 2008), suggesting a more nuanced role of trust as an antecedent to the formation of transactive memory systems.

Competition, by nature, involves a zero-sum element whereby the gains of one arise at the expense of another. As a result, competitors often behave opportunistically toward one another, suggesting that competition will tend to inhibit the development of trust in motives. However, competitive interaction may enhance trust in competence when competitors are able to reliably learn from one another, for example, by observing one another's actions or the outcomes of one another's actions (Prato and Stark 2023). Throughout the remainder of the paper, we maintain the assumption that competitors have the potential to learn from one another and demonstrate that the assumption holds in our empirical context.

Just as repeated collaboration among teammates leads to mutual understanding, we propose that repeated competitive interaction should also facilitate mutual insight, thereby improving subsequent coordination when competitors become teammates. Cooperative familiarity, arising from shared experience as collaborators on the same team, facilitates the development of transactive memory systems, which enhances coordination by enabling teammates to divide their labors more efficiently (Deming 2017). Competitive familiarity arises from shared experience too, and while the nature of the shared experience may be qualitatively different, it seems reasonable to conclude that competitive familiarity is a candidate for facilitating team learning and the development of mutual insight. Hence, we predict the following.

Hypothesis 1. *Competitive familiarity improves team performance.*

Hypothesis 1 proposes a test of competitive familiarity as a form of learning by doing. It is a crucial first step in showing the existence of competitive familiarity as an important organizational design element. However, if we take the concept of competitive familiarity seriously, we can say more about how it translates experience into mutual learning.

Although the precise nature of the relationship-specific knowledge gained through collaborative versus competitive interaction is, undoubtedly, somewhat context specific, we can put a bit more conceptual structure on how each form of familiarity operates in general. Two types of differences seem germane. First, competitive interactions are more intensive than cooperative interactions (Grohsjean et al. 2016, Luciano et al. 2018). Although acquiescence to another's volition can lubricate cooperation, competition pushes opponents to wrestle over conflicting objectives. As a result, the crucible of competitive interaction forges powerful learning experiences (Tsai et al. 2011). Second, although teammates with the right incentives may heed one another for the sake of cooperation, competitors tend to notice and remember more subtle behaviors that teammates may not (Prato and Stark 2023).

Given the particularly intense and salient nature of competitive interaction, one clear implication is that competitive familiarity should provide teammates with a *unique* perspective on one another's preferences, styles, and idiosyncrasies. In other words, competitive interaction should compel individuals to observe one another differently, allowing former competitors to develop nonredundant knowledge relative to former teammates. Thus, competitive familiarity should generate distinct learning effects compared with cooperative familiarity. Given that cooperative and competitive familiarity should offer nonredundant insights, Hypothesis 2 predicts the following.

Hypothesis 2. *Competitive and cooperative familiarity are complements.*

Our first two hypotheses predict that competitive familiarity will improve team performance by enabling a team to coordinate their efforts more effectively. Thus, to push the theory further, we examine the coordination mechanism explicitly.

Competitive Familiarity and Implicit Coordination

Cooperative familiarity among team members affects team performance via improved coordination (Argote et al. 2021), which may be explicit or implicit (Rico et al. 2008). Explicit coordination relies on team members intentionally using planning and communication to manage their multiple interdependencies (Srikanth and Puranam 2011). Implicit coordination instead "takes place when team members anticipate the actions and needs of their colleagues and task demands and dynamically adjust their own behavior accordingly, without having to communicate directly with each other or plan the activity" (Rico et al. 2008, p. 164).

Applying the implicit/explicit coordination dichotomy to competitive familiarity points directly to a potentially testable mechanism behind our main results. Cooperative familiarity results in improved implicit and explicit coordination, as teams plan, communicate, and harmonize their efforts. By contrast, most forms of communication and planning are absent in the context of competitive interaction: competitors may observe each other as they interact, but do not plan or communicate how to coordinate. Yet, if the nature of competition translates into unique mutual understanding, as proposed in Hypothesis 2, teammates with higher levels of competitive familiarity should be more adept at using observed actions and reactions for efficient implicit coordination. Instead of relying on explicit coordination to guide them, former competitors can dynamically anticipate one another's actions based on prior observed interactions. On the other hand, former teammates will typically have more well-developed explicit communication systems, since they will have experience discussing and planning their interactions. This is not to say that cooperative familiarity cannot improve implicit coordination, or that competitive familiarity will not improve explicit coordination. Rather, the point is that competitive familiarity should be particularly strong at facilitating implicit coordination—coordination without explicit communication, planning, or modularization. Thus, it seems straightforward to propose that competitive familiarity should primarily stimulate a team's implicit coordination ability.

Said another way, to the extent that competitive familiarity helps develop those aspects of a team's transactive memory system that improve implicit coordination and that a transactive memory system is a form of shared social capital among teammates, one should expect competitive familiarity to be particularly effective at improving a team's ability to coordinate implicitly. Thus, we propose the following.

Hypothesis 3. *Competitive familiarity improves implicit coordination.*

Hypothesis 3 advances the idea that by heightening mutual awareness among teammates competitive interaction becomes uniquely valuable for improving implicit coordination. One implication is that competitive familiarity should be more important in contexts where explicit coordination is more difficult, a testable implication we will take directly to the data.

Before turning to the empirical context, at least two caveats are in order. First, there are meaningful boundary conditions to our theory. Even though we expect that our hypotheses should be true generally, we acknowledge that the relative magnitude of the effect of competitive familiarity will vary by institutional setting. For example, in contexts where competitors cannot observe one another's actions (or at least the outcome of their actions), teammates have few interdependencies, or where there is little variation in an individual's potential set of actions, competitive familiarity should be relatively less important, as there is little scope for developing trust in competence, social learning or coordination in such settings. The need for extemporaneous coordination, and therefore the value of competitive familiarity, will also be reduced in contexts where tasks can be substantially decomposed, and interdependencies effectively managed by team members through specialization and a clear division of labor (Baldwin and Clark 2000). However, at least when competitive behavior is observable, the potential action space is large, and tasks are nondecomposable one should expect an economically meaningful competitive familiarity effect.

Second, although we have focused on the positive aspects of competitive familiarity, we acknowledge that competition can cause friction as well. For example, prior research has shown that competitive interaction can evolve into rivalries among contemporaneous *competitors* (Kilduff et al. 2010, Uribe et al. 2020), perhaps suggesting that prior competitive interaction could provoke rivalries among *teammates* as well. Indeed, in a laboratory experiment, Johnson et al. (2006) showed that former competitors tend to keep valuable information proprietary when subsequently working together, negatively affecting team performance, a phenomenon they call "cutthroat cooperation." Their work is consistent with game theoretic simulations showing that the transition from competitive to cooperative reward structures may be psychologically difficult, even when cooperation is in the best interest of group members (Bó 2005). We deal with rivalry and cutthroat competition empirically—our analyses directly account for the extent of prior competition, and any unmeasured cutthroat cooperation associated with past competition would only work against finding support for our hypotheses—but it is only fair to note that prior competition could create some meaningful social costs, even among contemporaneous teammates. Thus, theorizing that competitive familiarity will improve team performance has a meaningful null to overcome (i.e., that prior competition may create social frictions).

Caveats aside, the theory of competitive familiarity developed above builds on and extends the concepts of learning by doing in teams, team familiarity, and implicit coordination. Just as teammates learn to be more productive by working together, we propose that teammates learn to be more productive by competing against one another. Before turning to the empirical tests of the theory we describe the institutional context in more detail.

Institutional Context

Competitive familiarity exists in many teams. However, in most settings team members are not allocated to teams at random, making it difficult to estimate the causal effect of competitive familiarity on team performance. We overcome the problem of endogenous sorting by testing our theory using data on teams that are exogenously assigned, providing millions of experiments in competitive familiarity.

Specifically, we study teams playing a multiplayer online competitive strategy game, DOTA2, a zero-sum game comprised of two five-person teams playing head-to-head. With millions of concurrent players and thousands of professional teams, DOTA2 is one of the most popular eSports games worldwide and one of the most economically important team-based games (Goldman Sachs 2018). The game attracts players from every corner of the world, boasting major tournaments, which routinely sell out arenas with tens of thousands of seats.

All DOTA2 players have a rating—called a "matchmaking rating" (MMR)—associated with their past performance. Although the exact MMR calculation is not published, it is known that MMR is based primarily on how often a player's team wins or loses. If a team wins, everyone on the team gets the same rating boost, and if the team loses, everyone suffers the same rating penalty. Elite players take their ratings very seriously, as the highest rated players are more likely to be invited to tournaments, where they are exposed to many new potential fans and provided the opportunity to win millions of dollars of prize money.

Most DOTA2 matches are "ranked solo player" games, which are organized via a matchmaking algorithm that automatically assigns individual players to teams with the objective of making matches competitive—that is DOTA2 randomizes on expected outcomes, based on players' MMR—providing experimental variation in the assignment of players to teams. Ranked solo player matches are stratified within bands of player ability, such that players always play with and against players of approximately the same ability; and players are randomly assigned from a queue of players who join the gaming platform at approximately the same time. Thus, team assignment is exogenous but not completely random (Dota Team 2013). Although matchmaking is not random in all games, we verify that players were effectively exogenously assigned to teams in the subset of the data that we use. Thus, DOTA2 offers a unique laboratory for studying the effects of competitive familiarity on team performance.

We use tournaments to identify professional players, but exclude tournament matches from our main analyses, as tournament teams are endogenously formed. Instead, our test sample consists almost entirely of ranked solo matches (with some minor exceptions, as discussed in the robustness checks later), comprised, in whole or in part, of professional DOTA2 players. "Team play" matches are excluded from the analyses (about 2% of all ranked matches) because team play allows for endogenous team formation. Unranked matches are also excluded, because players may not be fully engaged in matches that do not affect their ratings. However, we use *all* matches with at least one professional player to properly compute the measures of interest in our regressions.

DOTA2 teams are analogous to temporary teams in other organizational contexts, with well-defined outcomes, operating in a dynamic uncertain environment, where team outcomes are influenced by how effectively teammates coordinate with one another to solve complex problems for economic gain. However, DOTA2 teams do differ in some ways from teams in traditional business organization. For example, DOTA2 matches are faster (typically about one hour) and probably more intense than a more traditional project team experience. Also, competitive behavior is readily observable both during and after a match, as the gaming platform tracks players at a fine level of detail over time with a consistent, unique identifier, creating a rich database on individual players and their interactions. Although the observability of competitive interactions makes DOTA2 an excellent laboratory for testing our theory that competitive familiarity improves team performance, transparency may also increase the returns to competitive familiarity. As a result, we must be cautious in generalizing the precise economic magnitude of the effects in this study to other contexts.

Before turning to the data and empirical tests, some additional institutional details are important to describe. Each of the players on a DOTA2 team controls exactly 1 of the 112 game characters, known as "heroes," who have unique characteristics and abilities. Once an individual is assigned to a team, the player may consult with the team about which hero they want to deploy, as each player's optimal hero choice is contingent on both personal preference and their teammates' hero choices. Although teammates can, and often do, communicate (privately) extensively throughout a match through voice and text, prematch discussions are typically quite brief (i.e., usually less than five minutes) in ranked solo player matches, as social norms dictate that games should start quickly, and most experienced players understand well the broad parameters of how teams should be configured. We use each team's choice of heroes to create control variables, but it is worthwhile to note that, although hero selection is endogenous, hero choice does not bias the results, as cooperative and competitive familiarity are measured based on player histories, not on choices made in the focal match.

The play of the game is fast paced and complex. At the beginning of a match each team has only "human" resources in the form of the heroes selected, and the division of labor within the team is largely determined by hero types. As the game progresses, players accumulate other resources (e.g., money, tools, etc.) that are shared within the team, and the division of labor within the team becomes more nuanced. Although some cooperative interactions, such as resource transfers, are ostensibly dyadic, the optimal relationship between any pair of players, at any given moment, depends heavily on the resources and behaviors of their other teammates, such that implicit coordination among teammates is essential to winning. Competitive interactions can be dyadic or multiplex, with certain hero types more likely to be in direct confrontation with one another; but well performing teams support one another, through resource transfers and other behaviors, even during dyadic competitive interactions.

Based on the nature of DOTA2, it seems a natural setting for studying learning by doing, as players observe and react to both teammates and opponents in such a way that would appear to facilitate learning about others' idiosyncrasies and abilities. Indeed, a former professional player, Su "Super" Peng, told us (through a well-placed intermediary) that competition enabled him to "feel" a competitor's style of play, leading him to understand his opponent at a deep level. Whether Su Peng's anecdotal observation, suggestive of a competitive familiarity effect, can be more systematically proven is the focus of our empirical tests.

Data and Measures

Data

Given the enormous number of DOTA2 matches played, calculating familiarity measures on the full population of players would require extraordinary computational power. As a result, we follow a standard sampling strategy for large networks, whereby we compute complete familiarity measures for all focal players (egos) but allow incomplete measures for nonfocal players (alters) (Smith and Moody 2013). From Dotabuff.com, a publicly available website chronicling every DOTA2 game, we identified 4,272 serious players—those who participated in at least one professional DOTA2 match—as the focal players. Using the DOTA2 WebAPI service, we downloaded data on all the matches played by each focal player, allowing us to track their full careers, from the inception of the game in 2011 through to the end of 2016.[3] Although our sampling strategy does not result in complete familiarity measures for the less serious players, unobserved alter nodes are unlikely to result in any systematic biases in our key measures (Smith et al. 2017).

Professional players are quite active. They average 20.50 games per month (standard deviation = 8.99), with 9.61 unique teammates per month (standard deviation = 42.83) and against 6.50 unique opponents per month (standard deviation = 17.90). The full set of matches with at least one professional player consists of approximately 9.2 million matches with 306,949 unique players. Our main results are estimated on the subset of 6,444,502 ranked public matches with a majority of (i.e., at least three) nonanonymous players per team, though the results are not sensitive to samples with different limits on the number of anonymous players.

To avoid double counting observations, we select one team from each match to include in our regressions, although we also capture and include all the information about their opponents as control variables.[4] An added benefit of randomly selecting one team out of each pair is that we can evaluate whether DOTA2's matchmaking algorithm effectively randomizes teams by comparing the means of the covariates between focal and opponent teams. We find that all the variables are statistically similar across the two samples (Table 1). Thus, we can safely conclude that DOTA2's exogenous assignment process is equivalent to random assignment.

Main Measures

The dependent variable in the empirical tests is *Victory*, an indicator set equal to one if the focal team wins the match and zero otherwise. Using victory to measure the outcome of team efforts follows common practice among scholars studying the organizational performance of traditional sports teams (Smith and Hou 2015, Fonti and Maoret 2016, Stuart 2017) and is particularly germane in our context, as a player's ranking (i.e., their MMR), and hence their status and eligibility for high-profile tournaments, is completely determined by team outcomes.

Competitive Familiarity, the key explanatory variable, is computed as the mean of the sum of the number of times each player has played against each of their teammates in the past. The measure closely parallels *Cooperative familiarity*, which we compute, following previous studies (Reagans et al. 2005), as the mean of the sum of the number of times each player has played on the same team with each of their teammates in the past. We use mean levels of prior interaction to measure familiarity, as opposed to total interaction, to properly account for anonymous players with unknown levels of familiarity. Thus, our two familiarity measures represent the average experience team members have interacting in different ways—playing against or with each other. Both measures are logged in the regressions so that we can interpret the marginal effect of each directly from the coefficient estimates.

Heroes are classified into two types—"carry" or "support"—by the gaming platform, based on two distinct sets of tactics and behaviors usually followed by heroes of those types, which we exploit as a natural way to parsimoniously characterize player experience.[5] Following the prior literature, we control for whether

Table 1. Descriptive Statistics (n = 6,444,502)

Variable	Mean	Standard deviation	Median	Minimum	Maximum
Victory	0.52	0.50	1	0	1
Competitive familiarity	1.92	5.35	0	0	538
Opponent competitive familiarity	2.01	5.53	0	0	508
Cooperative familiarity	28.58	84.99	1.60	0	3,966
Opponent cooperative familiarity	32.36	91.45	1.88	0	3,964
Specialist team	0.08	0.26	0	0	1
Opponent specialist team	0.08	0.27	0	0	1
Generalist team	0.06	0.24	0	0	1
Opponent generalist team	0.06	0.24	0	0	1
Skill overlap	0.53	0.13	0.53	0.02	0.8
Opponent skill overlap	0.52	0.13	0.53	0.02	0.8
Explicit coordination friction	0.17	0.38	0	0	1
Opponent explicit coordination friction	0.17	0.37	0	0	1
Competitive salience	1.56	7.48	0	0	531
Competitive intensity	0.36	0.81	0	0	65

Notes. Measures are properly computed including *all* DOTA2 matches with at least one professional player, including matches where teams are formed endogenously—which explains why cooperative and competitive familiarity are relatively "large"—but the test sample (n = 6,444,502) is comprised only of DOTA2 matches where teams are exogenously assigned (with some minor exceptions, as explained in the text). Familiarity measures are logged before entering the regressions in the tables below.

teams are characterized as specialist teams, generalist teams, or neither, by first defining a player's level of specialization, based on the diversity of their experience—players who typically play either carry or support are "specialists," whereas players who often play both carry and support are "generalists"—and then aggregating the individual measures to the team level (Teodoridis et al. 2019). *Specialist teams* are defined as those where a majority are specialists, whereas *Generalist teams* are those where a majority are generalists. All other teams are neither specialist nor generalist teams.

We control for *Skill overlap*—the degree to which team members' skills are redundant with one another in terms of their functional backgrounds—using each player's history of hero choices, before the focal match, as in prior studies (Choudhury and Haas 2018). We average individual measures across team members to compute skill overlap at the team level.

To rule out the possibility that certain combinations of player types influence the odds of winning (e.g., one carry, four support; two carry, three support; etc.), we also include a set of team configuration indicators. Finally, to control for systematic temporal effects, we also include a full set of indicators that correspond to the year and calendar month in which the match takes place.

To test for the presence of an implicit coordination effect associated with competitive familiarity, as predicted by Hypothesis 3, we exploit a feature of the institutional setting that reduces the ability of players to explicitly coordinate, increasing the importance of implicit coordination. Specifically, we exploit variation in latency and communication ability between teams using likely mismatches between a player's home server and the host server for the focal match.

Host servers—the server clusters on which matches are played—are distributed by the game publisher across the world with three in Europe and two in North America and Asia, respectively. By default, players are assigned to play on a server within their region, which would normally be the closest server to them; however, players can override the default setting. Therefore, we infer that a player's "home server"—the server they usually play on—is the server closest to them, and that they are more likely to speak a common language with others who have the same home server, compared with those with different home servers.

It is, of course possible that a player routinely plays on a server that is not in their region. It is also possible that players on different home servers might speak the same language, and it is even likely that some players with a common home server do not speak the same language. However, as a first approximation, having a common home server would seem to increase the probability of sharing physical proximity and language. The approximation is benign in the sense that any measurement error would only bias the results toward zero.

The host server is the (inferred) home server for all players in 39% of all matches. However, 61% of the matches in our test sample feature at least one player playing on a nonhome server, introducing two types of explicit coordination frictions. First, if playing on a nonhome server increases a player's distance from the host server, it will increase latency—the time it takes for a data packet, such as a player's message or action, to get from one player's device to another. DOTA2 is an extremely fast paced game, so latency is an important institutional feature. Low latency (i.e., less than 50 milliseconds) allows teammates to communicate, observe, and react to one another's actions in "real time," whereas high latency (i.e., more than 100 milliseconds) introduces small, but meaningful, lags between players' messages and actions and their teammates' receipt of and reaction to said messages and actions. DOTA2 players report that playing on a nonhome server routinely add hundreds of milliseconds to the latency they experience.

Second, playing on a nonhome server increases the probability that teammates do not share a common language, introducing additional communication frictions as well. Thus, in matches where one or more players are not playing on their home server, explicit coordination frictions should increase. As a result, teams comprised of players who are all on their home server will be relatively advantaged (i.e., probabilistically), compared with teams where at least one member is playing on a nonhome server. Our assumption is that the main effect of the latency friction will be negative—frictions, after all, should be bad—but, if implicit coordination is a good substitute for explicit coordination, the marginal effect of competitive familiarity should be increasing in explicit coordination frictions.

Although competing on more distant servers increases latency, which is a disadvantage in any given match, players report a willingness to explore outside of their home geography to expose themselves to different gameplay styles and strategies. For example, an experienced player we interviewed noted that she learned by playing in different geographies, saying: "The play style on European servers is very different from the [play style on] North American servers. The European play style focuses more on gaining a mid-game advantage … . Players in the United States seem to prefer a [different] style, where the carry farms for a long time to gain a late game advantage."

We construct our explicit coordination friction measure in three steps. First, we identify the presumed home server for each player in our sample. Next, for each team we construct the indicator variable *Explicit coordination friction*, which is equal to one if at least one team member is playing on a nonhome server and no players on the opponent team are playing on a nonhome server and zero otherwise. *Opponent explicit coordination friction* is constructed in parallel. Approximately 34% of all matches feature such mismatches (17% where the focal team has a server mismatch and the other team does not, and 17% where the opponent team has a server mismatch and the focal team does not).

Finally, to probe the underlying mechanism behind competitive familiarity further, we exploit role differentiation (i.e., carry or support) within the game to characterize past competitive interactions among current teammates. Although DOTA2 is fluid and complex game where all players interact, players usually compete most directly with players of the opposite type, allowing us to exploit role categorization to form a coarse measure of the relative intensity and salience of competition. Symmetric competitive interactions between players of the same type (i.e., carry-carry or support-support) are less intense but more salient, because players have comparable resources and tactical options. Conversely, asymmetric competitive interactions between players of different types (carry-support or support-carry), are more intense, but less salient.

We measure *Competitive salience* by counting the number of times a player competed with their current teammates in prior matches where they were playing the same type, and *Competitive intensity* by counting the number of times that a player competed with their teammates in prior matches where they were playing a different type. Both measures are averaged at the team level and logged in the regressions.[6]

Descriptive Statistics

Table 1 contains descriptive statistics for the key variables used in the regressions. The means of *Competitive* and *Cooperative familiarity* are 1.92 and 28.57, respectively. Therefore, in a representative dyad, team members have played against each other a little more than once on average (i.e., about 10 dyadic interactions in total for the team) and together about 29 times. Given that players are exogenously assigned to teams in our test sample, it may appear surprising at first that players would have such frequent interaction. However, two key factors tend to increase familiarity.

First, players are assigned to teams within individual rating (MMR) bins, so that top players play with and against other top players. Only a tiny fraction of DOTA2 players are professionals, but a significant number of the top players—the players we focus on—are professionals. As a result, professional players play with and against each other far more frequently than would any pair of randomly selected players from the full population. Thus, the focal players in our analyses will tend to interact more often with one other.

Second, although players are exogenously assigned to teams in our test sample, familiarity itself is not random; indeed, our two measures of familiarity are computed using *all* matches played by every professional player, including matches where teams are endogenously determined (e.g., in tournaments). Nonrandom selection into teams in tournament matches explains why the mean of cooperative familiarity is so much larger than the mean of competitive familiarity—it is far more common for team members to play together repeatedly in a tournament, or in multiple tournaments, than it is for them to be assigned to play against any other individual, even among the small set of top players. Nevertheless, the assignment of a particular level of competitive familiarity to any given team is exogenous in the matches we study—no player has any control over who they are playing with or against in ranked matches (with a few exceptions that do not meaningfully influence the results, as we demonstrate below). At the same time, top players are more likely to face one another compared with any other randomly selected player. Thus, it is not surprising that competitive familiarity and opponent competitive familiarity are correlated at 0.74. However, the variance inflation factors for the variables are low (1.48 and 1.63, respectively) in our main specification, suggesting that collinearity is not a statistical issue in our analyses. Moreover, allowing competitive familiarity and opponent competitive familiarity to enter the regressions separately has no meaningful impact on the results. No other variables in our analysis are highly correlated (above 0.40). See Table 2 for the full correlation matrix.

In the main tests, the familiarity measures enter in logs, which facilitates the interpretation of the results as elasticities. We verify the results are not different in terms of sign, significance, and approximate economic magnitude if we standardize the familiarity measures (e.g., to be mean zero and standard deviation one) to explicitly overcome skewness.

Empirical Design

The analyses are conducted at the team-match level. Because the game publisher organizes matches with the goal of making the probability of winning close to 50%, linear probability models will generate unbiased and homoscedastic coefficient estimates (Angrist and Pischke 2009).[7] Thus, we conduct the main empirical tests using Ordinary least-squares (OLS) regressions, although we verify that the results are consistent with limited dependent variable specifications. Our core test of the effect of competitive familiarity on performance is

$$Victory_{jm} = a + B_1(Competitive\ familiarity_{jm}) + B_2(Cooperative\ familiarity_{jm}) + \boldsymbol{X_c B_c} + e_{jm}, \quad (1)$$

for team j, and match m, where c indexes a vector of control variables, as described previously, and e is a mean zero disturbance term. Because players are exogenously assigned to teams in the sample, none of the independent variables in our main regressions are choice variables, and we can interpret the coefficient B_1 as the causal effect of competitive familiarity on the probability of victory.

The theory makes a straightforward prediction—competitive familiarity should improve team performance: Hypothesis 1 predicts $B_1 > 0$. Additionally, because opponent effects should work exactly as focal team effects, but in the opposite direction—opponent teams with high levels of social and competitive familiarity will be particularly effective at defeating the focal team—the theory also suggests that we should see parallel, but opposite signed, effects for a focal team's

Table 2. Correlation Matrix for Key Variables

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	*Victory*																
2	*Competitive Familiarity*	0.01															
3	*Opponent Competitive Familiarity*	−0.03	0.73														
4	*Competitive Salience*	0.01	1.00	0.73													
5	*Opponent Competitive Salience*	−0.03	0.73	1.00	0.72												
6	*Competitive Intensity*	0.01	0.69	0.55	0.63	0.53											
7	*Opponent Competitive Intensity*	−0.03	0.54	0.69	0.52	0.63	0.57										
8	*Cooperative Familiarity*	0.03	0.16	0.11	0.16	0.11	0.16	0.12									
9	*Opponent Cooperative Familiarity*	−0.05	0.11	0.17	0.10	0.17	0.11	0.17	0.04								
10	*Specialist Team*	0.01	0.11	0.11	0.11	0.10	0.13	0.11	0.02	0.00							
11	*Opponent Specialist Team*	−0.01	0.11	0.11	0.10	0.10	0.11	0.12	0.01	0.02	0.06						
12	*Generalist Team*	0.00	0.01	0.01	0.01	0.00	0.03	0.03	0.05	0.00	−0.07	0.00					
13	*Opponent Generalist Team*	0.00	0.01	0.01	0.00	0.01	0.02	0.03	0.00	0.05	0.00	−0.07	0.02				
14	*Skill Overlap*	−0.03	−0.22	−0.18	−0.20	−0.16	−0.34	−0.29	−0.23	0.05	−0.04	−0.07	−0.17	−0.06			
15	*Opponent Skill Overlap*	0.05	−0.18	−0.23	−0.16	−0.21	−0.29	−0.34	0.05	−0.24	−0.07	−0.03	−0.06	−0.17	0.40		
16	*Explicit Coordination Friction*	−0.01	0.01	0.01	0.01	0.01	0.02	0.03	−0.01	0.01	0.00	0.01	0.01	0.01	−0.03	−0.05	
17	*Opponent Explicit Coordination Friction*	0.00	0.02	0.02	0.01	0.02	0.03	0.02	0.01	−0.01	0.01	0.00	0.01	0.01	−0.05	−0.04	−0.21

opponent. Thus, including opponent measures in our econometric analyses both provides additional controls and offers a further empirical test of our theory.

To test Hypothesis 2—which predicts that competitive and cooperative familiarity are complements—we augment Expression (1) by including the interaction terms: *Competitive familiarity* × *Cooperative familiarity* and *Opponent competitive familiarity* × *Opponent cooperative familiarity*. The interaction terms capture the returns to increasing both dimensions of familiarity together. A positive (negative) coefficient on the focal (opponent) team interaction terms would suggest that the two dimensions of familiarity are complements.

To test Hypothesis 3, predicting that cooperative familiarity improves implicit coordination, we introduce *Explicit coordination friction*, *Opponent explicit coordination friction*, and their interactions with *Competitive familiarity* and *Opponent competitive familiarity*, respectively. Because implicit coordination substitutes for explicit coordination—correctly anticipating a teammate's behavior substitutes for hearing a player announce their intentions or seeing a player make a move—impairments to explicit coordination should increase the *marginal* returns to competitive familiarity even while the main effect of impairing explicit coordination should be negative (i.e., it will hamper overall team performance).

Results

Baseline Results

The main results are presented in Table 3. We begin, with column 1, by replicating the results from Ching et al. (2021), who use the same data set to show that cooperative familiarity complements the unique skills specialists bring to a team (see their table 4, column 1).[8] For presentation purposes, all coefficient estimates and standard errors in the regression tables are multiplied by 100, and all familiarity measures enter in logs. Table 3, column 2, includes only competitive familiarity and opponent competitive familiarity, month, and configuration fixed effects, whereas column 3 of Table 3 also includes cooperative familiarity and opponent cooperative familiarity. The estimated relationships are all in

Table 3. Competitive Familiarity and the Probability of Victory

	Dependent variable = *Victory*					
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) Logit	(6) OLS
Competitive familiarity		6.09*	5.33*	5.03*	5.09*	5.02*
		(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Opponent competitive familiarity		−7.09*	−5.98*	−5.62*	−5.69*	−5.63*
		(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Cooperative familiarity	0.87*		1.27*	0.93*	0.92*	0.87*
	(0.02)		(0.01)	(0.01)	(0.01)	(0.01)
Opponent cooperative familiarity	−1.77*		−1.79*	−1.44*	−1.42*	−1.38*
	(0.02)		(0.01)	(0.01)	(0.01)	(0.01)
Specialist team	1.92*			1.45*	1.46*	−6.05*
	(0.08)			(0.08)	(0.07)	(0.44)
Specialist opponent	−2.44*			−1.55*	1.57*	8.00*
	(0.08)			(0.07)	(0.07)	(0.43)
Generalist team	−0.34*			−0.24*	−0.28*	−0.24
	(0.10)			(0.08)	(0.10)	(0.42)
Generalist opponent	0.90*			0.46*	0.70*	−0.49
	(0.10)			(0.08)	(0.10)	(0.42)
Skill overlap	−2.37*			−17.07*	−17.48*	−18.57*
	(0.02)			(0.30)	(0.30)	(0.31)
Opponent skill overlap	2.94*			18.17*	18.39*	19.75*
	(0.02)			(0.30)	(0.30)	(0.31)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Configuration fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Complementary controls	Yes	No	No	No	No	Yes

Notes. N = 6,444,502. For presentation purposes, all coefficients and standard errors are multiplied by 100. To facilitate interpretation, all the familiarity measures are entered in logs. The results are similar in terms of sign, significance, and approximate economic magnitude if we standardize the measures instead (i.e., to deal with skewness in the measures). Specialist and generalist teams are those with at least three specialists or generalists, respectively. Column (1) replicates the key result in Ching et al. (2021). We use mean centered variables for the remainder of Table 3. Marginal effects are reported in (5). In (6), the complementarity controls (from Ching et al. 2021) are as follows: *Specialist Team* × *Cooperative familiarity*, *Generalist Team* × *Cooperative familiarity*, *Specialist Opponent* × *Opponent Cooperative familiarity*, *Generalist opponent* × *Opponent cooperative familiarity*. Robust standard errors are in parentheses.

*Coefficients that are significant at the 5% level (two-sided t test).

the direction expected: Familiarity among members of the focal team increases the odds of winning, whereas familiarity among members of the opponent team decreases it for both competitive and cooperative familiarity. The interpretation of the economic magnitudes—doubling competitive familiarity, from the mean value of competitive familiarity (i.e., 1.92 competitive interactions), leads to a 5.33% increase in the probability of victory, whereas doubling cooperative familiarity, from its mean value (28.58 cooperative interactions), leads to a 1.27% increase in the probability of victory.

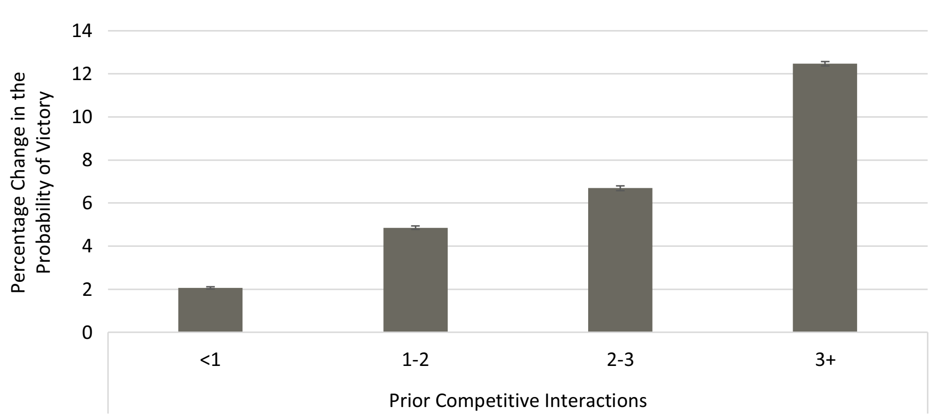
Column 4 of Table 3 includes the additional team controls. The point estimates of the control variables are all in the direction expected. Specialist teams outperform generalist teams, and teams with high skill overlap underperform. The results on competitive and cooperative familiarity remain consistent: doubling competitive familiarity from the mean increases the probability of victory by 5.03%, which is five times the effect of doubling cooperative familiarity from its mean value (0.93%). As expected, opponent effects are approximately of the same magnitude but of the opposite sign. All the familiarity measures are precisely estimated. Column 5 repeats the same regression but with a logit specification, and average marginal effects are reported. The results are consistent with the linear probability model.

Finally, Table 3, column 6, includes all the control variables from column 4 of Table 3 and adds focal and opponent team interactions to control for complementarities between cooperative familiarity, skill overlap, and specialization (Ching et al. 2021). One can see that this specification is somewhat overdetermined, as the point estimates on specialist teams and skill overlap are too large and even of the wrong sign in the case of specialist teams; however, the coefficients on the four competitive and cooperative familiarity regressors are only slightly attenuated. Even in this overly saturated regression, the effect of doubling competitive familiarity is still more than five times larger than the effect of doubling cooperative familiarity. Opponent effects are similar, although the relative marginal effect of opponent competitive familiarity is "only" about four times larger than that of opponent cooperative familiarity.

Taken together, the interpretation of Table 3 is that competition increases the returns to competitive familiarity over and above any social frictions created by past rivalries and by more than increasing cooperative familiarity by the same proportion. Teams of former competitors are powerful teams.

Although competitive familiarity has a substantially larger marginal effect, for a typical team the impact of cooperative familiarity on performance is still larger, in the aggregate, because cooperative familiarity is far more common than competitive familiarity. Using the coefficient estimates from Table 3, column 4, at the mean values of the covariates, cooperative familiarity increases the probability of winning by about 2.92% ($\ln(28.58) \times 0.0087 = 2.92\%$), whereas competitive familiarity increases the probability of winning by about 3.27% ($\ln(1.92) \times 0.0502 = 3.27\%$). We focus on the marginal effects in our interpretation of the relative importance of the two types of familiarity because marginal effects are more managerially relevant, as they tell us how quickly the two forms of familiarity translate into performance effects. However, one might reasonably wonder if the competitive familiarity effect is driven by small changes in the levels of competitive familiarity at

Figure 1. Prior Competitive Interactions Among Teammates and the Probability of Victory



Notes. This figure plots the point estimates, with twice the standard error bars, of a regression of the categorical variable "victory" against a vector of dummy variables that correspond to the average number of competitive interactions among members of the team before the focal match. The vertical axis is the percentage change in the probability of victory, whereas the horizontal axis represents four categories of prior competitive interaction (e.g., less than one prior competitive interaction per person per team, up to more than three interactions per person per team.). For presentation purposes, all coefficients and standard errors are multiplied by 100. The baseline case is a team where members had zero competitive interactions (i.e., they never competed before).

the low end of the competitive familiarity distribution, with the effect disappearing at higher levels of competitive familiarity.

Additional analyses reveal that the learning effects are roughly linear in competitive familiarity for most of the empirical distribution. Figure 1 shows the point estimates of a regression where the probability of victory is estimated against a vector of dummy variables that correspond to the number of average competitive interactions the focal team has had previously. For presentation purposes, the estimates are multiplied by 100. The baseline case is a team with zero competitive interactions. Hence, a team with more than three competitive interactions is on average 9% more likely to win a match than a team without any competitive interactions. As one can see, with each successive increase in competitive familiarity, the probability of winning increases. Thus, we conclude that the large marginal effect of competitive familiarity is consistent across much of the mass of the, admittedly narrow, distribution. Later, we provide additional evidence that the competitive familiarity effect persists over an even wider swath of the distribution.

Complementarity Between Competitive and Cooperative Familiarity

Evaluating Hypothesis 2—that competitive and cooperative familiarity are complements—helps test whether competitive familiarity gives one *unique* insight. The idea is that competitive familiarity is not merely a substitute for cooperative familiarity, because the salience and intensity of competitive interaction offers teammates qualitatively different insights that cannot be as readily obtained through cooperative interaction.

We test for complementarity between competitive and cooperative familiarity by including their interaction in Table 4, column 1. For parsimony, main effects are not tabulated, but we note here that they are consistent in sign, significance, and approximate economic magnitude with the estimates in Table 3. The positive coefficient on the interaction term for focal teams and the negative coefficient for opponent teams suggests that competitive familiarity and cooperative familiarity are indeed complementary. Figure 2 graphically summarizes the relative magnitudes of the main effects of the two kinds of familiarity, and their interaction. Although the main effect of competitive familiarity

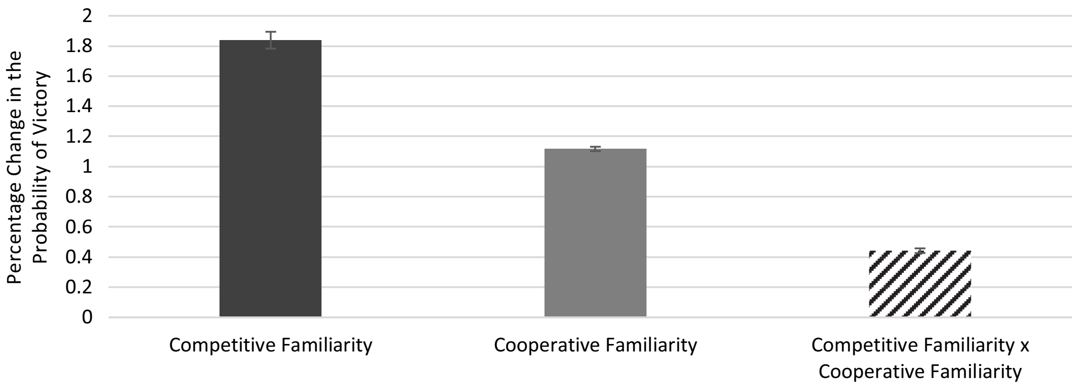
Table 4. Mechanisms

	Dependent variable = *Victory*		
	(1) Complementarity between competitive and cooperative familiarity	(2) Explicit coordination friction and implicit coordination	(3) Salience and intensity of prior competitive interaction
Competitive familiarity × Cooperative familiarity	1.12*		
	(0.01)		
Opponent competitive familiarity × Opponent cooperative familiarity	−1.28*		
	(0.01)		
Competitive familiarity × Explicit coordination friction		0.54*	
		(0.07)	
Opponent competitive familiarity × Opponent explicit coordination friction		−0.63*	
		(0.06)	
Competitive salience			4.59*
			(0.05)
Competitive intensity			2.15*
			(0.09)
Opponent competitive salience			−5.10*
			(0.05)
Opponent competitive intensity			−2.25*
			(0.09)
Main effects	Yes	Yes	Yes
Other interactions	No	Yes	No
Controls	Yes	Yes	Yes

Notes. $N = 6{,}444{,}502$. For presentation purposes, all coefficients and standard errors are multiplied by 100. To facilitate interpretation, all the familiarity measures are entered in logs. Robust standard errors in parentheses. "Main effects" include *Competitive familiarity* and *Opponent competitive familiarity* (in columns 1 and 2), *Cooperative familiarity* and *Opponent cooperative familiarity* (in all columns), *Explicit coordination friction* and *Opponent explicit coordination friction* (in column 2 only). "Other interactions" include *Cooperative familiarity* × *Explicit coordination friction* and *Opponent cooperative familiarity* × *Opponent explicit coordination friction*. "Controls" include all the variables from Table 3, column 4—focal and opponent skill overlap, specialist team, generalist team, configuration fixed effects, month controls, complementarity controls, and an intercept.

*Coefficients that are significant at the 5% level (two-sided *t* test).

Figure 2. Prior Interactions Among Teammates and the Probability of Victory



Notes. This figure plots the coefficients for the focal teams reported in Table 4, column 1, with twice the standard error bars. The vertical axis represents the percentage change in the probability of victory for a team. The figure shows that doubling competitive familiarity, from the mean of competitive familiarity, increases a team's probability of victory by 1.83%. By comparison, doubling cooperative familiarity, from the mean of cooperative familiarity, leads to a 1.11% increase in the probability of victory. Doubling both types of familiarity, from their respective means, increases the probability of victory by an additional 0.44%.

remains more than four times larger than the main effect of cooperative familiarity, the interaction between the two sources of familiarity is approximately equal to the main effect of cooperative familiarity. The result highlights the economic importance of the complementarity between cooperative and competitive familiarity while underscoring the unique power of competitive familiarity. One straightforward implication for managers is that competitive familiarity and cooperative familiarity can be used in concert to help improve team performance.

Implicit Coordination

To test whether implicit coordination is indeed a channel by which competitive familiarity is translated into performance, as proposed by Hypothesis 3, we include the main effect of *Explicit coordination friction* and its interaction with *Competitive familiarity* in Table 4, column 2. The main effect of *Explicit coordination friction* is negative and precisely estimated, as expected: Increasing the probability of experiencing frictions to explicit coordination among teammates hampers team performance (for parsimony we do not tabulate the main effect, but the point estimate is approximately −3%, and it is precisely estimated). More importantly for our theory, the interaction between *Competitive familiarity* and *Explicit coordination friction* is positive and precisely estimated. Competitive familiarity reduces the negative effects of frictions in explicit coordination at a rate of about 0.54% for a doubling of competitive familiarity from the mean. The results are quite similar in terms of sign, significance, and approximate economic magnitude if we also control for the focal team's and opponent team's average cumulative experience in high latency matches.

Extensions and Robustness Tests

To challenge our main results further, we perform a series of extensions and robustness checks. First, we exploit a fine-grained measure of competitive interaction to evaluate the relative importance of the intensity and salience of prior competitive interactions, as a way of probing the underlying mechanism behind competitive familiarity further. Our theory predicts that the salience and intensity of prior competitive interactions leads to improved coordination among teammates, but our main results on competitive familiarity represent the joint effect of these two mechanisms. To try to parse the distinct effects of each, we regress performance on *competitive intensity* and *competitive salience* separately and tabulate the results in Table 4, column 3. The results show that the marginal effect of competitive salience is stronger than the marginal effect of competitive intensity (4.59% versus 2.15%, respectively), suggesting that individuals are better able to coordinate with former competitors with whom they understand well. Even more importantly, the results demonstrate that, at least within the context of DOTA2, both the intensity and salience of prior competitive interactions influence performance meaningfully. Interviews with professional players corroborate the regression results, with several players noting that they pay close attention to both head-to-head competitive interactions (i.e., competitive intensity) and to the actions of competitors who play the same role as themselves (i.e., competitive salience).

Competitive familiarity looks to be relatively rare in our data—on average, in any given match, each dyad contains a pair of players who have played against each other a little less than twice—in part because almost half the matches feature teams where none of the players have ever played against one another.

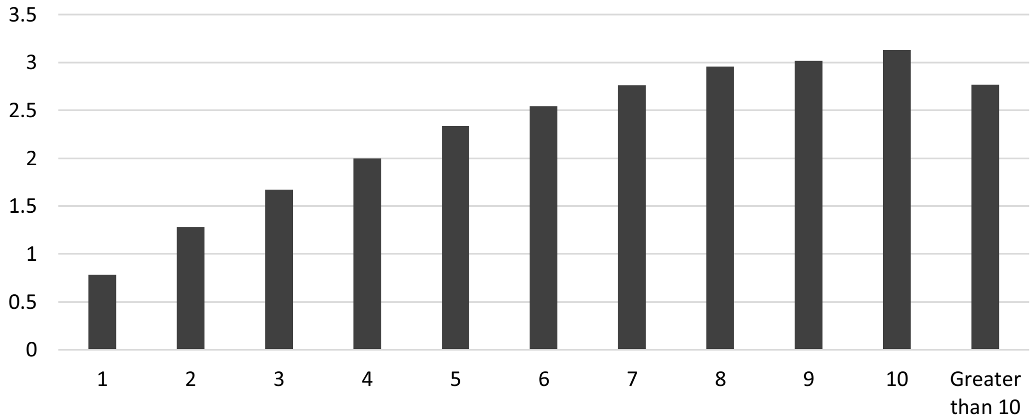
Although O'Toole et al. (2023) demonstrate that transactive memory systems can develop even with limited exposure, and the relative paucity of competitive familiarity should not be a source of bias if players are truly exogenously assigned, we verify that the relationship holds when excluding matches where average competitive familiarity is low (e.g., less than one).

Our main analyses include a small number of games where all five members of a team are not exogenously assigned ("party play"). Running our main specification on matches where party play was explicitly disallowed leads to similar point estimates. The results are also robust to excluding matches where at least one player abandons the match before it is complete and to controlling for aggregate individual experience and total team experience. The results also hold if we replace total experience with (logged) variables, which simultaneously control for (i) the number of matches played against professional players in the past, (ii) the number of matches played with professional players in the past, (iii) the number of matches opponents played against professional players in the past, and (iv) the number of matches opponents played a with professional players in the past, although the cooperative familiarity results are somewhat attenuated. In other robustness checks, winsorizing our key explanatory variables at the 10th and 90th percentile cutoff generates nearly identical results, and the results with mean centered variables are consistent in terms of sign significance and approximate economic magnitude, as are forgetting adjusted estimates, based on dyadic time since the last competitive interaction.

Finally, we are interested in whether the relatively large competitive familiarity effects, compared with cooperative familiarity effects, are persistent across the distributions of familiarity or whether the results are picking up marginal effects at different points in the distributions. Although Figure 1 suggests that learning effects in competitive familiarity are relatively linear initially, common sense suggests that there should be diminishing marginal returns to competitive familiarity eventually. If cooperative familiarity also exhibits diminishing marginal returns, and the average team has meaningfully higher levels of cooperative familiarity, it may appear that the marginal returns to cooperative familiarity are larger simply because we are drawing the bulk of our sample from different parts of the familiarity distributions (i.e., further along the horizontal axis for cooperative familiarity).

To explore whether the relatively large cooperative familiarity effects are persistent, we perform a series of regressions where we limit the values for both social and competitive familiarity to the *same levels*. Figure 3 summarizes the relative difference in the respective point estimates for competitive and cooperative familiarity. The samples are restricted to observations where the average values of competitive and cooperative familiarity are greater than zero. We see that for most levels, the impact of competitive familiarity is more than three times that of cooperative familiarity. Even at low levels (e.g., one and two units) and high levels (e.g., above 10 units) of both types of familiarity, the relative magnitude is larger for competitive familiarity. The fact that the relative economic importance of

Figure 3. Relative Performance Difference of Competitive to Cooperative Familiarity (Vertical Axis) at the Same Level of Competitive and Cooperative Familiarity (Horizontal Axis)



Notes. This figure plots the ratio of the point estimates of competitive familiarity and cooperative familiarity in eleven different regressions where both measures are limited to the same level (i.e., we compare teams with x units of cooperative familiarity against a team with x units of competitive familiarity). The vertical axis captures the ratio of the coefficient estimates (competitive familiarity: cooperative familiarity), while the horizontal axis is the measure limit—the level of both competitive familiarity and cooperative familiarity (i.e., the "x" in the first sentence of the caption). For example, when the measure limit is equal to five, the members of the focal team have collaborated on average five times and have competed five times before the focal match. The regressions are equivalent to the specification in Table 3, column 4, except for the measure limit restriction.

competitive familiarity is persistent across the range of the familiarity distributions lends confidence to our interpretation that competitive familiarity is a powerful managerial lever for improving team performance.

Discussion and Conclusion

The antecedents and consequences of team learning have long been of interest to organizational scholars. We propose that prior competitive interaction among contemporaneous teammates—competitive familiarity—facilitates team learning and improves team coordination and performance. We find causal evidence in support of our theory in the context of eSports, a large and rapidly growing segment of the entertainment industry. Interestingly, the evidence shows that competitive familiarity provides teammates with larger benefits than the oft reported advantages of repeated collaborative interaction. Furthermore, competitive familiarity creates unique mutual benefits in addition to those gained through cooperative familiarity. Our interpretation, supported by supplemental analyses, is that the intensity and salience of competition underlies this complementarity. The results speak to the duality of competitive experience, which is like cooperative experience in the sense that it builds familiarity, yet different in the sense that competition facilitates a different, and perhaps deeper, kind of understanding of others. Indeed, it seems that actions that might go unnoticed or unremembered by collaborators may be strikingly apparent to, and long remembered by, competitors.

Although eSports teams may be interesting in their own right, the results of this research should generalize to other settings as well. For example, insights from eSports teams would seem germane to many temporary teams, distributed teams (Majchrzak et al. 2004), nonhierarchical teams, and online labor platforms (Kretschmer et al. 2022), to name a few of the most direct connections. Of course, conventional sports teams are the closest "traditional" organizational analogue to eSports teams. Yet, even casual observation suggests that many workers experience competitive familiarity in their jobs.

However, it is fair to acknowledge that we have only demonstrated that competitive familiarity is an important lever for improving organizational performance in one context. We have pointed out many parallels between eSports team and teams in traditional organizations, but there are important differences too. For example, feedback loops are faster, and competitors' actions may be more readily observable in DOTA2 compared with many other settings. Therefore, testing the theory in other contexts will be important for further our understanding of competitive familiarity. Another limitation of this research is that we cannot directly observe the conceptual mechanisms at work in the data, but rather must infer such effects using theory, and the pattern of evidence, to show that the performance effect of competitive familiarity is likely due, at least in part, to implicit coordination and transactive memory systems. Developing empirical strategies that more directly observe the pathways through which competitive familiarity operates presents an interesting opportunity for future studies.

Although we do not believe that the positive effect of competitive familiarity on team performance has ever been reported previously, the results do not necessarily contradict the findings of prior research on the performance implications of relational rivalry, which found that rivals could experience social frictions when working together. Rather, our interpretation assumes the prior research is correct, and that social frictions partially offset the implicit coordination benefits of competitive familiarity. Indeed, it seems self-evident that in settings where past rivalry is particularly toxic, and/or where gains from cooperation are relatively unimportant to individual teammates (e.g., when incentives are not well aligned), that competitive familiarity would not be as productive for organizations. Nevertheless, this paper does offer a fundamentally different perspective about the potential upside of teams composed of previous competitors. Whereas evidence of social frictions was previously taken as evidence that teams of former competitors would impose substantial inefficiencies, we show that there can be significant benefits to competitive familiarity.

Besides being of interest to organizational scholars, this research also has implications for managers, particularly senior managers, and human resource managers. For organizations with workers who compete in the normal course of business, this research suggests managers should harvest the benefits of competitive familiarity by facilitating cooperative interactions among members with more competitive experience. For example, a firm could rotate workers so that they were placed on teams with former competitors or provide incentives to encourage workers to find collaborative solutions with those they may perceive as rivals. For organizations without a large reservoir of competitive experience to exploit, but where project teams are common, we suggest human resource managers create meaningful competitions as an opportunity for workers to learn about one another. For example, a consulting firm could benefit from holding case competitions to encourage consultants to better understand one another's abilities.

Organizational learning is a key driver of competitive advantage. This paper advances and tests the idea that teams will be more effective when teammates have competed against one another in the past. After analyzing millions of experiments where team members were exogenously assigned to teams, the results show that increasing competitive familiarity causes team performance to improve. Interestingly, the benefits of competitive familiarity are even larger than the well-known benefits of cooperative familiarity across a wide range of different specifications. Moreover, the two forms of familiarity are complements, suggesting that competitive familiarity provides uniquely useful information to teammates. Although the implications of prior collaboration on team performance have attracted far more attention than prior competition, it appears that competitive familiarity can be a powerful organizational design lever for improving team performance.

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Endnotes

[1] The distinction between team and individual learning effects is important because the nature of learning differs by level. When individuals improve their performance by repeating a given task they enjoy task-specific learning (Gibbons and Waldman 2004, Ferguson and Hasan 2013). Learning becomes social when shared experience influences performance, for example, when a group of individuals must coordinate to perform a set of tasks efficiently.

[2] For clarity, throughout this paper, we refer to prior cooperative interaction between teammates as "cooperative familiarity," which clearly connects the term to the concept of "team familiarity" discussed in the existing literature (Huckman and Staats 2011) while distinguishing it from our key concept of "competitive familiarity."

[3] DOTA2 provides a WebAPI where developers can retrieve complete match history and details. Some players hide their identity from the public before the start of any match. However, serious players are unlikely to play games anonymously, as they monetize their play by encouraging fans to follow their matches.

[4] In our analyses, the team that moves first is the focal team and the second mover is the opponent team. The team that moves first does have a small, but meaningful, advantage, as evidenced by the 52% victory rate for focal teams (Table 1), but because the 10 players are randomly allocated to teams within a match, the interpretation of the results are not affected by which team we choose as the focal team.

[5] Support players tend to be more defensive players who develop resources over the full game, whereas carry players tend to be attackers who consume resources in short bursts toward the end of the game.

[6] The measures are complete nonoverlapping subsets of competitive familiarity: The sum of *Competitive salience* and *Competitive intensity* is equal to *Competitive familiarity*.

[7] All the predicted values of our ordinary least squares regressions fall within the 0%–100% range. The minimum predicted probability of victory was 30%, whereas the maximum was 71%.

[8] Ching et al. (2021) use the term "social familiarity" to refer to what we call "cooperative familiarity" and "functional familiarity" to refer to what we call "skill overlap."

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