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When Rivalry Backfires: How Individual Skill and Risk of Status Loss Moderate the Effects of Rivalry on Performance

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Abstract. Existing rivalry research finds that people try harder and perform better when competing against their rivals. However, are there conditions under which rivalry can harm performance? We integrate rivalry theory with regulatory fit theory to propose two moderators of rivalry: individual skill and situational risk for status change. We test our predictions using data from software programming contests involving more than 4.6 million competitive encounters across 16,846 software developers ("coders") to examine the causal effects of rivalry and the conditions under which it may backfire. We find that, on average, coders who are randomly assigned to compete against a field of competitors with whom they share a rivalrous history exhibit higher performance, above and beyond other established drivers of performance in competition. Importantly, however, this positive effect of rivalry is moderated by (1) coders' skill level, such that rivalry is more beneficial for more skilled coders and is harmful for less skilled coders, and (2) coders' risk of experiencing a status change, such that coders who face a possible status loss exhibit decreased performance when competing against rivals. Thus, we extend research on rivalry by revealing the conditions under which it can harm performance, which is vital to understanding its role in organizations.

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Keywords: rivalry • competition • relationships • regulatory fit

Introduction

Rivalry is a subjective relationship between competitors that increases the psychological stakes of their competitions with each other, independent of the objective competitive characteristics of the situation such as incentives (Kilduff et al. 2010, Kilduff 2019). It is common across various competitive environments including the workplace (Kilduff 2014, Xu et al. 2020). Existing research finds that people perform better when competing against their rivals, that is, competitors with whom they share a greater degree of similarity, past repeated competition, and past closely decided head-to-head competition, compared with when they compete against nonrivals (Kilduff et al. 2010, Kilduff 2014, Yip et al. 2018). However, is rivalry always beneficial for performance? Although high-profile examples of rivalry, such as Chris Evert and Martina Navratilova, or Bill Gates and Steve Jobs, may suggest the answer is yes, it is unclear whether the performance boost provided by rivalry may vary across different individuals and situations in the workplace. In this paper, we extend rivalry theory by exploring the conditions under which rivalry between competitors is less beneficial, and perhaps even harmful, to work performance.

To accomplish this, we integrate rivalry theory with regulatory fit theory (Higgins 2005), one of the most influential theories of motivation and performance (Sassenberg and Scholl 2019). Prior work on rivalry has found that it elicits a promotion regulatory focus (To et al. 2018), that is, a focus on achieving ideal outcomes (as opposed to a prevention focus, or a focusing on avoiding losses and maintaining the status quo; Higgins 1997). Further, research on regulatory fit shows that regulatory fit enhances performance, whereas misfit harms performance. Such fit is driven by the extent to which individual and situational factors (e.g., personality, incentives) in a given performance situation elicit the same versus different types and levels of regulatory focus (Higgins 2000). Therefore, the extent to which rivalry boosts performance should depend on the extent to which other individual and situational factors elicit promotion or prevention focus. We leverage this to propose two specific moderators of the effect of rivalry on performance.

First, we examine skill as an important individual-level attribute. Drawing on existing findings (Lanaj et al. 2012), we argue that higher skilled individuals are more likely to be in a promotion-focused state in competitions; thus, when competing against rivals, the greater an individual's skill in a competitive domain, the greater the degree of regulatory fit they will experience (promotion focus from rivalry + promotion focus from high skill = fit). This means that the effect of rivalry on performance will be more positive for higher-skilled individuals. Conversely, lower-skilled individuals who face their rivals will experience lack of regulatory fit, leading to a negative effect of rivalry on performance.

Second, we examine situational risk of status change. Potential status gain elicits promotion focus (Higgins 1997, Higgins et al. 2003) and thus should combine with rivalry to generate regulatory fit. Thus, rivalry should boost the performance of those on the cusp of gaining a meaningful increase in status. However, when individuals face the prospect of status loss, this will elicit a prevention focus (Higgins 1997, Higgins et al. 2003) that is misaligned with the promotion focus elicited by rivalry (prevention focus from potential status loss + promotion focus from rivalry = misfit). Thus, the effect of rivalry on performance will be negative when individuals face status loss.

We test our hypotheses using a large panel data set from a platform where software developers participate in programming contests. This data set has three distinctive features that enable the study of rivalry effects and potential moderators in a systematic way. First, the platform holds contests regularly enough for rivalrous relationships to develop. Second, the platform randomly assigns participants to a temporary competition group for each contest, and this randomization allows for the causal identification of rivalry effects. Third, the data set provides detailed information on each competition and all competing members, from which we can infer individual and situational characteristics, facilitating the investigation of moderators of rivalry. We collect complementary qualitative evidence from a survey to support key assumptions, such as the notion that programmers are aware when they have been assigned to rooms with familiar rivals.

We make several important contributions to the literature. First and foremost, we extend rivalry research. To date, existing research has shown a simple positive main effect of rivalry on performance (albeit with other potential downsides, such as increased unethical behavior; Kilduff et al. 2016). We integrate rivalry theory with regulatory fit theory to explicate individual and situational conditions under which rivalry can harm performance. This provides much-needed insight into the interplay between rivalry and other determinants of motivation and performance, and the contingent effects of rivalry on performance in the workplace. We also make important contributions to rivalry research by (a) examining the effects of rivalry across a "field" of competitors, moving beyond the existing literature's primary focus on dyadic competition, (b) exploring rivalry's performance consequences in cognitive and technical work, thus moving beyond prior research that has focused on performance on more effort-based tasks such as running and simple attention tasks (Kilduff 2014, Yip et al. 2018), and (c) examining an empirical setting that is characterized by random assignment to competitors, thus providing the strongest causal tests yet.[1]

We also make theoretical contributions to several other areas of research. First, by examining how contestants' histories of interaction within a highly structured system of contests can affect their performance, we extend the literature on tournaments and contests which focuses the performance effects of situational aspects such as prize structure (Moldovanu and Sela 2001) and contest size (Boudreau et al. 2011) but tells us little about how relationships between peers affect performance (Connelly et al. 2014).

Second, our results contribute to research on the effects of skill, and risk of status change, on performance. We highlight rivalry as a key factor that can alter the effects of these known drivers of performance. For individual skill, our results show that it is an even more important determinant of performance under conditions of rivalry between competitors. In other words, rivalry increases the strength of the association between skill and performance, thus driving an even bigger performance gap between high and low skilled actors. This extends work on other moderators of the relationship between skill and performance (Boudreau et al. 2016). For risk of status change, we find that, under conditions of rivalry, the prospect of losing something valuable may harm performance (compared with the prospect of gaining something valuable). This extends prior work suggesting effects in the opposite direction: that potential losses motivate greater performance than potential gains (Berger and Pope 2011, Pope and Schweitzer 2011).

Third, by connecting rivalry with regulatory fit and regulatory focus theory (Higgins 1997, 2005), we not only better position rivalry within the constellation of theories of human motivation, but contribute back to regulatory fit theory. We reveal rivalry as another important factor that helps drive regulatory (mis)fit and subsequent performance gains or losses.

Finally, we make an empirical contribution to the study of peer effects. Given the difficulty in causally identifying peer effects, there continue to be concerns about which mechanism drives them. Our empirical approach, which includes random assignment to peer groups, repeated observations (i.e., panel data), and corresponding fixed effects on multiple levels, addresses central identification challenges with peer effects (Manski 1993, Brock and Durlauf 2001, Moffitt 2001, Ioannides 2013, Bramoullé et al. 2020).

Theoretical Background and Hypotheses

Rivalry and Competition

Interpersonal competition is ubiquitous in organizations and is often used to motivate individuals to perform at a higher level, such as in tournaments (see Connelly et al. (2014) for a review of tournament theory and To et al. (2020) for a review of research on interpersonal competition in organizations). Traditionally, within economics, strategy, and organization theory, rivalry and competition have been treated as synonyms (Porter 1980, Yu and Cannella 2007, Katila and Chen 2008, Brown 2011, Uribe et al. 2020) to refer to situations of negative outcome interdependence. Over the past 15 years, however, a body of research has emerged that examines rivalry as a social *relationship* that can exist between pairs of competitors, grounded in their histories of interaction with each other (Kilduff et al. 2010; Kilduff 2014, 2019; Converse and Reinhard 2016; Pike et al. 2018; To et al. 2018; Yip et al. 2018; Operti et al. 2020). The relational and historical nature of rivalry is its key distinguishing feature: rivalry theory argues that any given contest between competitors is situated in the specter of their past competitions, which can affect their motivation, performance, and other behaviors (Kilduff et al. 2010, Converse and Reinhard 2016, Kilduff 2019). By contrast, research on competition and tournaments generally focuses only on objective features of the current competitive situation, such as the number of competitors or prizes (Lazear and Rosen 1981, Connelly et al. 2014, Boudreau et al. 2016, Balietti and Riedl 2021), thus overlooking the role of competitors' histories and relationships.

Specifically, rivalry refers to a relationship between competitors that causes increased psychological stakes of competition, independent of situational competitive factors such as the incentives for victory or the odds of achieving them. Prior research has shown that rivalry is driven by (1) similarity, (2) repeated competition, and (3) closely decided head-to-head contests between competitors (Kilduff et al. 2010, Kilduff 2014). These three aspects are not prerequisites for rivalry and do not have to coincide; rather, they are "factors that tend to lead to its development and increase its intensity" (Kilduff 2019, p. 779).[2] To illustrate the difference between rivalry and competition, consider two employees with prior history of evenly matched performance and/or competition for roles, bonuses, or promotions. They should feel rivalry toward each other, even if the level of objective competition imposed upon them by current incentives has subsided. However, two employees competing for a bonus or promotion without any prior history should feel low levels of rivalry, even if they feel substantial competitive pressure due to high tangible stakes.

Effect of Rivalry on Performance in Workplace Settings

Although intense career-long rivalries between top performers attract the most attention and help to illustrate the phenomenon, rivalry is not restricted to elite or world-famous competitors. It can exist, often at more mild-to-moderate levels, in any competitive environment, and is common in the workplace in particular. Existing research has found that adults from the general U.S. population (Kilduff 2014) and MBA students (Menon et al. 2006) are generally able to name a rival from some domain of their lives. Other work found moderate levels of rivalry between particular pairs of employees at a bank and a chemical company and that this had important effects on behavior (Xu et al. 2020). Furthermore, experiments show that a mild to moderate level of rivalry can form after just a few interactions, even virtually, and that this also affects behavior (Kilduff and Galinsky 2017, Yip et al. 2018).

Two primary outcomes of rivalry observed by prior research are increased task motivation and task performance (Kilduff et al. 2010, Kilduff 2014, Pike et al. 2018, Yip et al. 2018). For example, a study of basketball teams observed that defensive performance, generally thought to be indicative of effort, was greater in games between fiercer rivals (Kilduff et al. 2010). Another found that long-distance runners ran faster in races in which their rivals were also running compared with races in which their rivals were absent (Kilduff 2014). Yet another found that, in an online setting, feelings of rivalry toward one's opponent positively predicted performance on a simple attention task (Yip et al. 2018).

Here, we first seek to replicate the positive main effect of rivalry on performance in a context that differs from those used in prior work in at least two important respects. First, existing investigations of the effects of rivalry on task performance have typically focused on effort-based tasks, often within the domain of athletics. We extend this by examining the link between rivalry and task performance in a highly technical and cognitive task domain. Researchers have become increasingly interested in so-called "knowledge workers," for whom "mental mindsets and intellective abilities are especially relevant to their work" (Reyt and Wiesenfeld 2015, p. 739; see also Barley 1996, Appleyard and Brown 2001, Gargiulo et al. 2009, Von Nordenflycht 2010, Teodoridis et al. 2019, Bechky 2020) and for whom accuracy and problem solving are critical to performance, in addition to effort (Boudreau et al. 2011). We explore whether the performance effects of rivalry observed in physical and/or purely effort-based task domains extend to knowledge work.

Second, rivalry researchers to date have tended to focus on one-on-one competition, which is typical of athletic contests. However, in the workplace, it is common for multiple employees to simultaneously compete for prizes, bonuses, or promotions, such as in sales contests (Chan et al. 2014). In such contexts, individuals may face multiple rivals at the same time: that is, multiple other competitors with whom they have competitive histories that increase the psychological stakes of the contest. Indeed, past research on rivalry shows that actors can, and often do, feel rivalry toward multiple other competitors (Kilduff et al. 2010, Kilduff 2014, Xu et al. 2020).[3] This begs the question: how does simultaneously competing against multiple rivals affect motivation and performance? Given that motivation and effort are the aggregate product of multiple factors (e.g., incentives, job characteristics, etc.; Kanfer et al. 2017), we believe that extra predictive value can be attained by assessing the level of rivalry imposed across the set of competitors that a focal competitor faces.

Thus, by examining the main effect of rivalry on performance within a sample of knowledge workers who compete in randomly assigned groups, we seek to replicate existing rivalry work within a vastly different context. This allows us to (1) test the generalizability of rivalry theory and (2) explore whether an individual may be motivated by the simultaneous presence of multiple rivals.

Baseline Hypothesis. *The greater the level of rivalry that individuals are exposed to, across a set of competitors, the greater their performance.*

Moderators of the Effects of Rivalry on Performance

Thus far, there has been no investigation into possible boundary conditions or moderators of the effects of rivalry on task performance. Although research has acknowledged potential downsides to rivalry such as increased unethical behavior (Kilduff et al. 2016), the current state of the literature suggests that rivalry has a strictly positive effect on task performance. We know from research on competition more generally that it can sometimes harm performance (for a review of that literature, see To et al. (2020)). However, that prior research generally falls into two categories, both of which take a fundamentally different approach from our own. First, there is research that compares competition, that is, a situation where the goals or outcomes of the actors are opposed, such as offering a prize to the top performer, to settings where competition is absent (e.g., cooperation; Deci et al. 1981, Johnson and Johnson 2005). Here, we hold competition constant and examine how varying levels of rivalry between competitors affect their performance. Second, there is work that examines how characteristics of competitions and tournaments influence performance due to their effects on contestants' chances of winning (Terwiesch and Xu 2008, Boudreau et al. 2016, Fang et al. 2020). For example, the presence of a very strong competitor can diminish the motivation of the other competitors, because they perceive their odds of winning as lower (Brown 2011). However, this work takes a fundamentally different approach to the study of competition, focusing on competitors' rational assessments of incentives and odds of success, and does not explore competitors' relationships with each other.

We contribute to the literature by investigating the conditions under which greater rivalry between competitors may lead to *lower performance*, thus extending research on the previously observed positive link between rivalry and performance. Although rivalry may have a positive effect on performance *on average across individuals and situations*, by increasing the desire to win (Kilduff 2014), such average positive effects may have masked conditions under which it can backfire for performance. To direct our investigation into the moderators of rivalry, we integrate rivalry theory with one of the most influential motivational theories of the past 30 years: regulatory fit theory (Higgins 2005), which builds on regulatory focus theory (Higgins 1997).

Regulatory focus theory (Crowe and Higgins 1997, Higgins 1997) proposes that there are two general types of motivational states, characterized by different goals and points of emphasis. A *promotion focus* involves a focus on opportunities, growth, aspirations, and achieving gains, whereas a *prevention focus* emphasizes security, avoiding losses, and maintaining the status quo. Existing research shows that rivalry elicits a promotion focus. In one study, individuals primed with rivalry were more likely to focus on ideal outcomes and approach a task in an eager manner (Converse and Reinhard 2016), and in another, individuals who came face-to-face with a rival competitor reported greater promotion focus directly (To et al. 2018). This occurs because contests between rivals are embedded in a long-running ongoing narrative (Converse and Reinhard 2016, Berendt et al. 2024). Rivals have a history of competing with each other and view new contests as connected to this past history (Berendt et al. 2024) and as related to their long-term legacies (Converse and Reinhard 2016). This contrasts with contests between nonrivals, which are more likely to seen as short-term, one-shot, performance situations. In turn, the longer-term more abstract thinking invoked by rivalry elicits a greater focus on ideal outcomes, that is, a promotion focus (Trope and Liberman 2003, Converse and Reinhard 2016).

Regulatory fit theory connects regulatory focus theory to task performance, arguing that performance is driven by regulatory "fit" across situational factors and individual goals (see Higgins (2005) for a review). This is often studied by examining the fit between individuals' dispositional regulatory focus and a salient situational cue (e.g., task instructions; Freitas et al. 2002), but can also apply to the fit, or lack thereof, across two situational factors. For example, when task instructions and incentives are framed consistently with one another from a regulatory focus standpoint (e.g., they are both promotion focused), persistence and performance increase (Förster et al. 1998, Bianco et al. 2003). However, when they are misaligned, persistence and performance decrease. To illustrate, if, in an experiment, participants were told "DO NOT LOSE" (elicits prevention focus; Lount et al. 2017, p. 87) but were also told they would be paid a bonus if they finished in the top 25% of participants in task performance (elicits promotion focus), this would be a state of misfit.

Thus, regulatory fit theory suggests that the effects of rivalry on performance may be contingent. As a promotion focus-eliciting stimulus, rivalry should increase performance for individuals (1) with dispositionally higher promotion focus and (2) in situations that elicit promotion focus. However, it should be less beneficial, and perhaps even harmful, to the performance of individuals with low promotion focus and/or high prevention focus (due to dispositional and/or situational factors). We leverage this to propose two moderators of the effect of rivalry on task performance: individual skill and situational risk of status change. We select these two moderators because they (1) have theoretical basis as key drivers of regulatory focus, (2) play fundamental roles in competitive and workplace contexts (Magee and Galinsky 2008, To et al. 2020), and (3) are prominent in other theories of motivation and performance (Zajonc 1965, Pettit et al. 2010).

Individual Skill as a Moderator of the Effect of Rivalry on Performance

First, we propose that the effects of rivalry on performance will depend on individuals' skill in the given task domain (overall, compared with the entire "universe" of individuals competing in that task domain). Our basic argument is as follows: First, individuals with higher skill tend to be higher in promotion focus and lower in prevention focus, whereas individuals with lower skill tend to be the opposite. Second, as described above, rivalry is a promotion focus eliciting stimulus. Third, putting these two effects together, this means that higher skilled individuals will experience a state of regulatory fit when they compete against their rivals, whereas lower skilled individuals will experience a state of misfit under conditions of rivalry. Fourth, drawing upon prior findings on regulatory fit and performance, the regulatory fit-state experienced by higher-skilled individuals should positively affect their performance, whereas the misfit-state experienced by lower-skilled individuals should negatively affect their performance.

Supporting the first argument in our theoretical logic, a meta-analysis found that promotion focus is positively associated with individuals' self-efficacy (which can be thought of as self-perceived skill) and self-esteem (which can be thought of as self-perceived worth; Lanaj et al. 2012). Other studies have found a positive association between task performance and promotion focus (Wallace et al. 2009). These findings all suggest that higher skilled individuals, who have typically built self-efficacy and self-esteem via high past performance, will tend to be more promotion focused. This leads us to predict that highly skilled individuals will respond more positively to competition against rivals, as the regulatory state elicited by rivalry (To et al. 2018) will match their dispositional regulatory state (high promotion focus). By contrast, lower-skilled individuals will tend to be less promotion focused and more prevention focused due to lower levels of self-efficacy and self-esteem (McGregor et al. 2007, Bryant 2009, Wallace et al. 2009, Ferris et al. 2011). This will cause them to experience regulatory misfit when competing against their rivals, thus harming their performance (Higgins 2000).

In summary, consistent with our baseline hypothesis and past research linking rivalry to greater quantity of motivation, we expect it to have a baseline positive effect on performance, such that it should boost the performance of individuals of average skill. However, because rivalry also elicits a promotion focus, it will create differing degrees of regulatory fit versus misfit in more versus less skilled individuals. High-skilled individuals will experience rivalry as aligned with the high promotion focus that they bring into the competition, whereas low-skilled individuals will experience it as misaligned with the low promotion focus and higher prevention focus that they bring into the competition. Thus, we expect skill to moderate the effect of rivalry on performance, such that it has a more positive effect on performance the more skilled the individual, and a less positive, and eventually negative, effect on performance the less skilled the individual.[4]

Hypothesis 1. *Individual skill moderates the positive effect of rivalry on task performance, such that the higher the individual's skill, the greater the boost in performance from rivalry, and the lower the individual's skill, the lower the boost in performance from rivalry to the point where rivalry may have a negative association with performance among lower-skilled individuals.*

Risk of Status Change as a Moderator of Rivalry

We propose that the performance effects of rivalry will also depend on a situational factor: whether the individual currently faces the prospect of significant status change depending on the individual's performance in the focal contest. Again, building on the theory of regulatory focus, our basic argument here is as follows. First, facing potential status gain triggers promotion focus, whereas facing potential status loss triggers prevention focus (Förster et al. 2003, Higgins et al. 2003). Second, rivalry elicits promotion focus. Third, putting these two effects together, this means that individuals with a salient opportunity to gain status will experience regulatory fit when competing against rivals, whereas individuals with a salient chance of losing status will experience misfit from rivalry. Fourth, again, regulatory fit will boost performance, whereas misfit will harm it. Thus, the effect of rivalry on performance will be moderated by whether an individual faces potential status gain or status loss (versus no potential status change).

Status is a fundamental human motive (Anderson et al. 2015), and many competitive arenas contain discrete categories or markers of status. These include "Master" titles in chess, thresholds such as a tennis player being in the Association of Tennis Professionals top 100, or a company being in the Fortune 500 (Garcia et al. 2006), selection to esteemed groups such as programs for high potential employees and All-Star teams in professional team sports and tiers in online labor platforms (Boudreau et al. 2016, Maoret et al. 2022). Researchers have found that proximity to meaningful status thresholds increases the magnitude of motivation in competition (Garcia et al. 2006), for example, if a chess player faces an opportunity to gain a Master title based on the performance in the next match. However, the chance to gain a higher-status title, or move up into a higher-status category, will elicit a very different regulatory focus state than the chance of losing one's existing title or status category. The former is a promotion focused situation, highlighting the opportunity for gains, and the latter is prevention focused, highlighting the risk for losses (Förster et al. 2003, Higgins et al. 2003).

Thus, we expect risk of status change to moderate the effect of rivalry on performance. Consistent with our baseline hypothesis, rivalry should have a baseline positive effect on performance for individuals not currently facing the prospect of significant status change, for example, for an individual who is currently in the "middle of the pack" in a given status category. However, for individuals currently facing the prospect of significant status gain, rivalry will reinforce their existing promotion-focused state, creating greater regulatory fit and boosting performance. By contrast, for individuals currently facing the prospect of significant status loss, the promotion focus mindset elicited by rivalry will conflict with their existing prevention focus, leading to regulatory misfit and harming performance. In other words, they will experience a state of goal conflict, as one salient situational factor (potential status loss) will elicit the goal of avoiding mistakes and losses whereas the other (rivalry) will elicit the goal of seizing opportunities and gains, and this conflict will detract from their performance.

Hypothesis 2a (Status Gain). *Potential for significant status change moderates the effect of rivalry on task performance, such that among individuals facing a significant risk of status gain, rivalry has a more positive effect on performance (compared with individuals facing no risk of status change).*

Hypothesis 2b (Status Loss). *Potential for significant status change moderates the effect of rivalry on task performance, such that among individuals facing a significant risk of status loss, rivalry has a more negative effect on performance (compared with individuals facing no risk of status change).*

Empirical Analysis

Empirical Setting

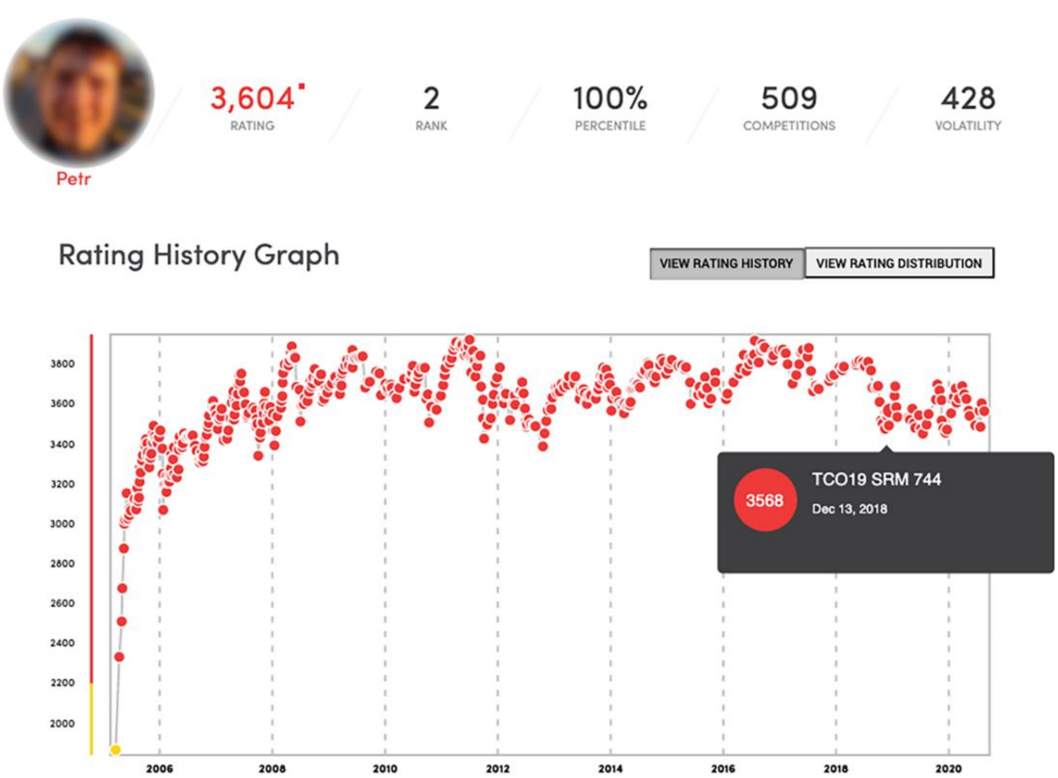
We test our hypotheses using data from Topcoder.com, a leading platform where software developers deliver software solutions to clients through a competitive programming model. Major organizations, including NASA and Fortune 500 companies, have used the platform to connect with a global community of top developers—called coders—to solve complex problems. On the platform, coders connect with each other, compete, and enhance skills across a broad spectrum of technologies and disciplines.

Topcoder hosts contests of different types. We focus on weekly algorithm contests called *single round matches* (SRMs) in which competitors develop software solutions to algorithmic computer science problems. These problems are designed to test coders' ability to analyze and solve computational problems representative of those found in fields like computational biology, machine learning, engineering, and finance. During each contest, coders create solutions for three problems over the course of a 75-minute "coding" phase. Problems are categorized by difficulty as easy, medium, and hard. Coders are awarded points for each problem they solve correctly, based on the difficulty level of the problem and the time elapsed since they first "opened" the problem description. Although coders can communicate before and after the contest, no communication is allowed during the SRM. After the coding phase, there is a 15-minute "challenge" phase. During this phase, coders can view solutions submitted by others in the same competition room and can attempt to invalidate these solutions (i.e., submit test code to expose errors). Coders earn additional points for each successful challenge (+50 points), but unsuccessful challenges result in a penalty (−25 points). After the challenge phase, all solutions are tested by the Topcoder system, and any solutions found to be incorrect receive zero points. SRMs are then discussed in the Topcoder Forum, where participants can engage in postcompetition analysis, discussing both the outcomes and the correct solutions.[5]

A key feature of Topcoder is its skill rating system. This is a public numeric skill rating that reveals each coder's position within the overall skill distribution of developers on the platform. It is modeled after the Elo ranking system used in chess and is important to signal coders' status within the community and market value to potential employers (Lakhani et al. 2010). Throughout the Topcoder platform, coders' screen names are always shown color-coded to indicate their status in the community (red = highest status, followed by yellow, and blue). Coders with a skill rating above 1,200 compete in Division 1 in SRMs, whereas coders with a skill rating below 1,200 compete in Division 2. We leverage this tiered ranking system for our investigation of the effect of status changes. Each coder has a profile page that shows their (a) current skill rating, (b) current rank based on that rating, (c) historical ratings, and (d) geographic location (see Figure 1 for an example).

Our study of rivalry exploits one key feature of Topcoder's SRMs: In each contest, coders are randomly assigned to virtual competition rooms, typically consisting of 15–20 contestants (mean (M) = 18.29; standard deviation (SD) = 1.25). Each competition room can be understood as its own competition, where coders compete for the symbolic recognition—and occasionally financial rewards—of achieving the highest performance in their room (i.e., being crowned the "room winner"; Boudreau et al. 2016). The challenge phase also relies on the competition room structure: only coders within the same room can be challenged during the challenge phase. Crucially, for the purpose of our study, this random room assignment provides exposure to randomly varying levels of rivalry. For example, a coder might be assigned to a room that contains several other coders with whom they share a rivalrous history or to a room filled with unfamiliar coders. This allows us to examine how rivalry affects coder performance and how this varies by coder's skill and risk of status change.

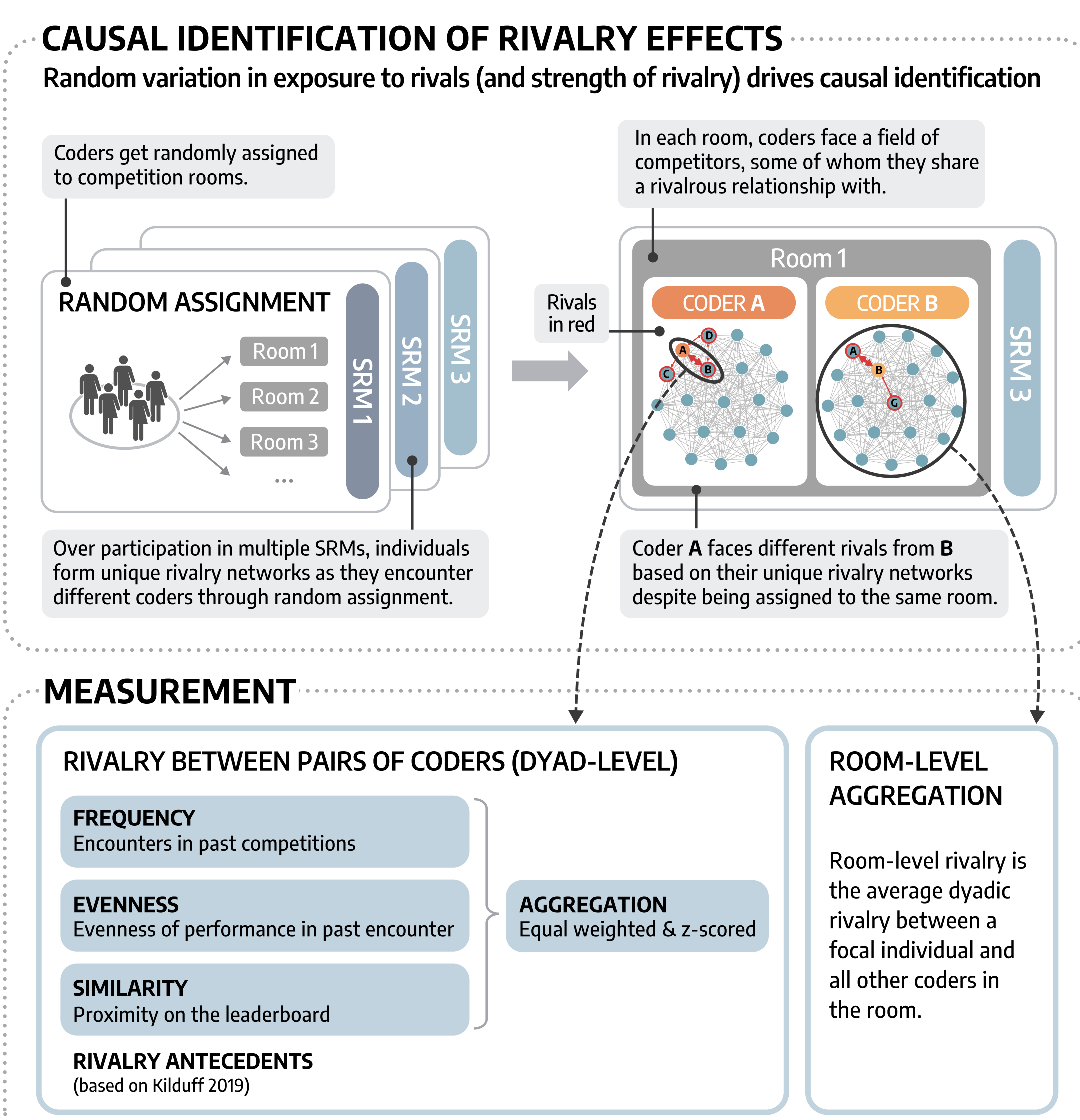
Figure 1. (Color online) Screenshot of Topcoder SRM Subpage of a Leading Competitor



The Topcoder platform and its SRMs have several features relevant to the study of rivalry in organizational research. First, the regular contests foster repeated interactions and social comparisons among coders, facilitating the formation of rivalries (we offer qualitative insights from a survey of coders that corroborates that they pay attention to and recognize who they have been assigned to a room with; Table A10 in the Online Appendix). Second, participants are highly invested, as success on the platform is linked to career opportunities (Lakhani et al. 2010), and many coders prominently feature their Topcoder ranking on their resumes (Boudreau et al. 2012). Third, the complexity of coding tasks—requiring cognitive focus, technical skill, creativity, and effort—offers a realistic approximation of modern knowledge-based tasks, surpassing simpler tasks used in prior rivalry research, such as running (Kilduff 2014) or attention tasks (Yip et al. 2018). Fourth, the random assignment of coders to competition rooms introduces random variation in rivalry that enables us to identify causal effects. Finally, Topcoder provides objective measures of skill and performance, as well as clear status distinctions marked by color-coded rankings.

Our data set covers almost 20 years of data from 2002 to 2019, involving 63,220 coders across 38,522 rooms and 721 contests (SRMs). We focus on contests in Division 1 (267,085 contest performance observations across 16,846 coders) because Division 1 coders, that is, those with skill ratings above 1,200, are the most engaged and regular participants.[6] Furthermore, in our main analyses, we restrict the sample to observations after a coder has spent at least one year on the platform to allow for sufficient time to accumulate a relational history with other coders.[7] Figure 2 provides an overview of the random assignment process and how we construct our rivalry measure.

Figure 2. (Color online) Causal Identification and Measurement of Rivalry Based on Random Room Assignment



Analytical Approach and Estimation Model

Before we describe our measures in detail, we explain the general analytical approach we use to capture the causal effect of competing against a field of (potentially multiple) rivals and potential moderators of this effect (specific details on our measurement will follow thereafter). We measure rivalry at the coder-room level, as an aggregate of all the dyadic rivalry relationships that a focal coder has with the other coders in the room. Although rivalry is a dyadic relationship, the effects of one specific dyadic relationship cannot be isolated in contexts where individuals may face multiple rivals in a contest but produce only one performance outcome. Measuring a field of rivalry in this way is consistent with the peer effects literature on, for example, student achievement, where researchers examine the effect of the entire peer group on a student's achievement (Sacerdote 2001). This is also analogous to workplace competition in which multiple employees compete simultaneously with another (e.g., on a sales floor).

We interact this measure of rivalry with our two moderators of interest: individual skill and situational risk for status change as described below. For an extended discussion how our data and empirical strategy allow us to causally identify peer effects from rivalry see the Online Appendix. Formally, we estimate (via Ordinary Least Squares) an extension of the linear-in-means model for peer effects to a panel data context described in Equation (1) (Hanushek et al. 2003, Bramoullé et al. 2020):

$$\begin{aligned} Y_{i,T^*,r} = {} & \underbrace{\gamma R_{i,T,r}}_{\substack{\text{Rivalry based on}\\ \text{cumulative past encounters}\\ \text{with competitive field}}} + \underbrace{\eta(R_{i,T,r} \times Skill_{i,T,r})}_{\substack{\text{Interaction effect of rivalry}\\ \text{and skill}}} \\ & + \underbrace{\delta(R_{i,T,r} \times StatusChange_{i,T,r})}_{\substack{\text{Interaction effect of rivalry}\\ \text{and risk of status change}}} + \underbrace{\lambda \bar{C}_{i,T,r}}_{\substack{\text{Controls for attributes}\\ \text{of competitive field}}} \\ & + \underbrace{\beta \bar{X}_{i,T,r}}_{\substack{\text{Controls for attributes}\\ \text{of focal coder incl.}\\ \text{skill and risk of status change}}} + \underbrace{\omega_i + \omega_T + \omega_r}_{\substack{\text{Fixed effects for}\\ \text{coder, round, and room}}} + \epsilon_{i,T,r}. \end{aligned} \quad (1)$$

$\boldsymbol{Y}_{i,T*,r}$ refers to the performance of coder $\boldsymbol{i}$ in the contest at time T^*, competition room r,[8] $\bar{\boldsymbol{C}}_{i,T,r}$ is a vector of competitive field attributes separate from rivalry, $\overline{\boldsymbol{X}}_{i,T,r}$ is a vector of individual-level attributes (including the current skill level and the current risk of gaining/losing status), and $R_{i,T,r}$ is aggregate level of rivalry a focal coder i is expose to in room r at time T. We are predominantly interested in estimating the direct effect of the field of rivalry γ and the interaction effects η and δ while controlling for the direct effects of the competitive field λ. We include individual (ϖ_i), room (ϖ_r), and round (ϖ_T) fixed effects, which allow us to account for anything unobserved or unmeasured about individual coders i, the particular room r they have been assigned to and the particular SRM T they are participating in. These fixed effects also account for the fact that observations are not independent of one another, which we also address via clustered standard errors at the coder and room level. The final factor $\varepsilon_{i,T,r}$ is a random error capturing individual, time-varying shocks.

Measures

Dependent Variable: Final Points. Our primary dependent variable is *Final Points*, representing the total number of points a coder scored in a contest (M = 214.5; SD = 236.96).[9] Each SRM includes an easy problem worth up to 250 points, a medium problem worth up to 500 points, and a hard problem worth up to 1,000 points. Points decrease continuously from the moment a coder opens a problem description for the first time until they submit their solution; therefore, faster submissions earn more points. Solutions are automatically tested and are classified as either fully correct or incorrect—no partial credit is awarded. After summing the points from the three problems, we include the points a coder gained or lost through challenges (+50 points per successful challenge and −25 points per unsuccessful challenge).

Independent Variable: Rivalry Score. Our main independent variable is *Rivalry Score*, capturing the level of rivalry a coder is exposed to in a given competition room, based on their history with each of the other coders present. This measure comprises three factors: *Frequency*, *Evenness*, and *Similarity*, which we explain in detail below. The aggregate *Rivalry Score*—which we measure as the average of dyadic rivalry relationships of a coder across all other competitors in the room—lacks a naturally meaningful scale; therefore, we standardize it to have a mean of zero and a standard deviation of one by construction. We calculate this measure for each coder in each room through the following steps (see also Figure 2): 1. compute dyadic rivalry antecedents for each focal-target pair of coders, 2. standardize and aggregate these rivalry antecedents to a dyad-level rivalry measure for each pair of coders (e.g., A's rivalry with B, A's rivalry with C, etc.), and 3. aggregate across dyads to generate a field measure of rivalry for each coder (e.g., A's total rivalry experienced; i.e., coder-room level).

1. **Computing the dyadic rivalry antecedents.** To measure the degree of rivalrous relationship between a pair of coders, we closely follow the approach of prior research (Kilduff 2014). We base our measure on the frequency of past encounters, the evenness of performance in these past encounters, and the past similarity

of coders. We use a one-year time window to create all our rivalry antecedents.[10] This window is long enough to include a substantial number of contests per coder (on average, 38.97 contests) yet short enough to ensure that rivalry reflects relatively recent, salient encounters rather than distant interactions that are unlikely to still influence coders (due to long stretches of inactivity of one or both coders).

Frequency is measured as the number of past encounters between a focal coder and a given competitor over the one-year time window. It captures how often a coder has been randomly assigned to the same room as the competitor. Despite the large pool of potential competitors on Topcoder, repeat encounters are common (see the Online Appendix for descriptive statistics on frequency of encounters). On average, a coder has 3.25 prior encounters with the coders assigned to the same room; thus, rivalry in the Topcoder setting is likely at a moderate rather than intense level.

Evenness is measured as the number of past close encounters between a focal coder and a given competitor during the one-year time window. It is thus a subset of total encounters (i.e., *Frequency*). We define an encounter as "close" if both coders finished within a margin of eight points of each other in total performance, corresponding to the top 10th percentile of closeness in point differences among all coder pairs across the entire data set.[11] The average coder in a given room experienced 0.25 (SD = 0.58) close encounters with other coders in the same room.

Similarity is measured based on coders' relative positions on the published leaderboard in the past. Similarity on the leaderboard fosters social comparison between competitors (Festinger 1954, Garcia et al. 2013), which can breed rivalry over time (Kilduff et al. 2010, Piezunka et al. 2018, Kilduff 2019). Importantly, we examine similarity in *past* leaderboard positions to capture shared history between competitors, while controlling for the competitive effect of *current* similarity (included as one of our measures of peer group characteristics). The rationale is that being listed closely together on the leaderboard over time leads coders to repeatedly see each other's names, and the rivalry fostered by this repeated social comparison may persist even if coders have since diverged in their current ratings. We measure similarity by counting the number of weeks during the one-year time window, up to the focal contest, that two coders have been within ±10 ranks[12] of each other on the leaderboard.[13] The average coder in a given room shared 2.16 (SD = 5.37) weeks of such close proximity on the leaderboard with other coders in the room.

2. **Standardizing and aggregating rivalry antecedents (dyad level)**: We combine the three antecedent measures *Frequency*, *Evenness*, and *Similarity* into an aggregate dyadic rivalry measure for each focal-target coder pair. The aggregation is based on Stouffer z-scores (Stouffer et al. 1949) using the formula specified in Equation (2):

$$R_{i,j,T} = \frac{z\left(\sum_{t=1}^{T} Frequency_{i,j,t}\right) + z\left(\sum_{t=1}^{T} Evenness_{i,j,t}\right) + z\left(\sum_{t=1}^{T} Similarity_{i,j,t}\right)}{\sqrt{3}}. \tag{2}$$

We follow prior work (Kilduff 2014) in taking the simple (equal-weight) average of the three antecedent measures of rivalry. Absent strong theory suggesting a stronger influence of one antecedent over another, using an unweighted average is a principled way of constructing this measure that allows us to keep our analysis focused without making additional, more specific, and speculative assumptions. We conducted additional robustness tests in which we relax the assumption of equal weighting and find that misspecification alone cannot explain our results and our findings are a conservative estimate of the effect of rivalry.[14]

3. **Aggregate to field measure of rivalry (coder-room level):** Because coders can and do experience rivalrous relationships with multiple coders in a room, the observed performance is the result of the effects of all these rivalrous relationships at the same time. To capture the degree of rivalry faced by a coder in a room, we use the average of all the dyadic rivalry measures between the focal coder and the other competitors in that room. The choice to use the average (compared with the sum) has no impact on the findings given the relatively constant room size on Topcoder; however, it has the advantage to account for small differences in the number of competitors per room. We refer to this measure as *Rivalry Score*. Additionally, we provide results for different subsets of coders in a room (top rival, top three rivals, top five rivals) in Table 1.

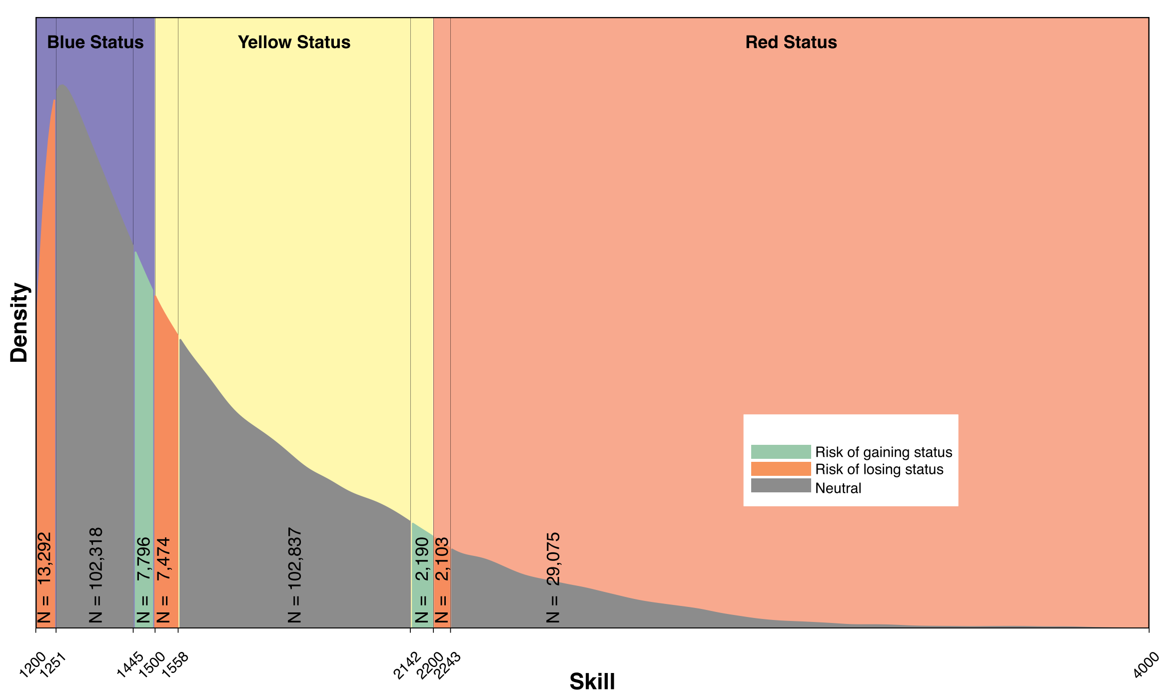
Independent Variable: Skill. All coders on Topcoder have a public numeric skill rating determined by their past performance in SRMs. Topcoder employs an Elo-based system—named after Arpad Elo (Van Der Maas and Wagenmakers 2005)—to capture coders' skill. Elo-based rating systems are widely used (e.g., in chess, American football, and baseball) and have been used in previous studies (Boudreau et al. 2016, Riedl and Woolley 2017). A key feature of this system is that coders gain or lose Elo rating points based on how they perform relative to their expected performance (which is based on their precontest rating). Coders gain more points if they perform better than expected and lose more points if they perform worse than expected. The rating system is zero sum, meaning that points gained by one coder are lost by another. This measure likely reflects a combination of innate abilities and attributes, accumulated learning and task experience, and any recent changes in skill resulting from practice (or lack thereof), age, and health status, among other factors. Importantly, we focus on the effects of coders' own absolute skill within the entire Topcoder platform and not their skill relative to the competitive field within their assigned rooms.

Independent Variable: Risk of Status Change. Topcoder places coders into discrete color-coded status levels, based on their skill rating. For Division 1 (our focus), these include the following: red = 2,200 or above; yellow = 2,199–1,500; blue = 1,499–1,200. These form important status categories and allow us to examine our hypothesized interactions between the potential for status change and with rivalry. To assess whether a focal coder faces a significant risk of losing or gaining status heading into a particular contest we use the following steps: First, within each status level (i.e., red, yellow, or blue), we examined the distribution of all observed changes in rating after SRMs, across the entire data set. Second, we compute the 25th and 75th percentiles in terms of observed rating changes, that is, the top 25% greatest drops and greatest gains, in rating points.[15] Third, if a coder was within that many rating points of a status threshold (and thus had a 25% risk of changing status up or down), they were identified as either having the potential to gain or lose status.[16]

In our analysis, we use a factor variable with three levels (*Neutral*, *Gaining*, and *Losing*) to capture what risk of status change a coder faces. Note that although a coder's skill rating determines their risk of changing status levels, the relationship between skill and status change is discontinuous because status changes occur at specific cutoff points. Only coders whose ratings fall within narrow bands near these cutoffs face a risk of status change. This situation resembles a quasi-experimental setup where coders with very similar skills are "assigned" to different treatments—risk of losing status, gaining status, or no risk—that they cannot control. By comparing coders just above and just below these thresholds, we can observe the effects of status risk (Trochim and Donnelly 2001, Lee and Lemieux 2010). Figure 3 illustrates the distribution of skill and the relationship between skill and risk of status change.

Control Variables. To isolate the effect of rivalry, we include control variables that capture various individual and competition group characteristics that prior research indicates may affect effort and performance in contests (Brown 2011, Boudreau et al. 2016). At the individual level, our primary control variable is the *Number of Prior Contests* a coder has participated in during the relevant window of observation. At the competition group level, we include measures of the

Figure 3. (Color online) Distribution of Skill Across Status Categories Including Boundaries for Classification of Being at Risk for Gaining and Losing Status



Note. Coders are at risk for either gaining (close to upper status boundary) or losing status (close to lower status boundary), along with coders who do not face a meaningful risk of status change (middle).

Table 1. Field Measure of Rivalry

Dependent variable: *Final Points*	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Skill	48.025***	47.705***	47.749***	47.517***	47.269***	47.157***
	(9.152)	(9.148)	(9.161)	(9.162)	(9.167)	(9.168)
Number of Prior Contests	22.147***	21.408***	20.461***	20.374***	20.361***	20.404***
	(1.079)	(1.112)	(1.152)	(1.155)	(1.151)	(1.154)
Peer Mean Skill	58.048	58.507	60.403	58.803	57.078	56.330
	(63.509)	(63.500)	(63.552)	(63.574)	(63.609)	(63.620)
Peer Max Skill	−20.114***	−22.238***	−22.927***	−22.884***	−22.933***	−23.001***
	(5.489)	(5.559)	(5.553)	(5.573)	(5.570)	(5.563)
Number Close Competitors	1.605**	1.401*	1.228*	1.218*	1.218*	1.219*
	(0.593)	(0.592)	(0.593)	(0.594)	(0.594)	(0.594)
Status: Risk Losing	3.565***	3.580***	3.573***	3.572***	3.570***	3.575***
	(1.059)	(1.058)	(1.059)	(1.059)	(1.059)	(1.059)
Status: Risk Winning	−1.933	−1.946	−1.963	−1.966	−1.964	−1.965
	(1.366)	(1.366)	(1.366)	(1.366)	(1.366)	(1.366)
Rivalry w/ Top Rival		2.381***		1.372^+		
		(0.691)		(0.773)		
Rivalry Score			4.320***			
			(0.929)			
Rivalry w/ others than Top Rival				3.460**		
				(1.097)		
Rivalry w/ Top3 Rivals					2.778**	
					(0.881)	
Rivalry w/ others than Top3 Rivals					2.115*	
					(1.010)	
Rivalry w/ Top5 Rivals						3.716***
						(0.943)
Rivalry w/ others than Top5 Rivals						0.974
						(0.936)
Fixed effects						
Coder	Included	Included	Included	Included	Included	Included
Room	Included	Included	Included	Included	Included	Included
Round	Included	Included	Included	Included	Included	Included
No. of observations	209,361	209,361	209,361	209,361	209,361	209,361
Adjusted R^2 (full model)	0.508	0.508	0.508	0.508	0.508	0.508
Likelihood ratio test ($\Delta\chi^2$)						
vs. Model 2			18.493***	20.547***	21.132***	21.059***
vs. Model 3				2.0544	2.6395	2.5666
Variance residual	25,031.511	25,028.704	25,026.493	25,026.248	25,026.178	25,026.187
Variance coder	12,284.309	12,243.396	12,230.613	12,230.974	12,231.086	12,228.161
Variance round	8,686.476	8,621.140	8,514.079	8,497.395	8,489.678	8,496.414
Variance room	4,973.974	4,894.035	5,077.221	4,928.610	4,764.144	4,687.842

Notes. Standard errors are clustered on the coder and room level. All rivalry variables are calculated using a one-year time window. The sample includes only coders with a full one-year history.

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

strength of the competitive field (Boudreau et al. 2011, Brown 2011), including the average skill of peers (*Peer Mean Skill*) and the skill of the most skilled peer (*Peer Max Skill*). Further, based on the social comparison literature, we include a measure for the number of *currently* closely rated competitors (*Number of Close Competitors*; i.e., the number of coders within ±10 ranks to the focal individual on the current leaderboard), which could create social comparison pressure and competitiveness between competitors independent of rivalry (Festinger 1954, Garcia et al. 2013). Thus, we follow Kilduff (2019) in separating current similarity from past similarity in order to more precisely capture the role of past interactions and the preexisting relationship. Like our rivalry measure, these peer group variables are standardized (mean-centered with a standard deviation of one), which allows for direct comparison of coefficients. Note that the size of the competitive field—previously shown to influence competitive performance (Fullerton and McAfee 1999, Moldovanu et al. 2007, Konrad 2009, Boudreau et al. 2011)—is accounted for by the room-level fixed effect. An overview of the descriptive statistics can be found in Table A1 of the Online Appendix.

Results

Main Effect of Rivalry

Table 1 contains the results of models related to our baseline hypothesis. Model 1 is a baseline model without rivalry, in which, as expected, skill is a significant, strong predictor of performance ($\beta = 48.025$; $p < 0.001$). Furthermore, we find that being at risk for losing status significantly increases performance compared with facing no risk of status change ($\beta = 3.565$; $p < 0.001$), consistent with prior research showing that people care more about avoiding status losses than achieving status gains (Bothner et al. 2007; Pettit et al. 2010, 2016; Edelman and Larkin 2015), as well as the more general loss aversion effect that has been shown to motivate greater performance in high-stakes real-world contexts (Berger and Pope 2011, Pope and Schweitzer 2011). Being at risk for gaining status has no significant effect on performance ($\beta = -1.933$; $p = 0.166$). With respect to room-level variables, we see that while the average skill of peers is not a significant predictor of performance, the skill of the strongest competitor has a significant negative effect ($\beta = -20.114$; $p < 0.001$). In line with prior research, this suggests that facing a very strong competitor is demotivating because it reduces the odds of the focal actor finishing first. By contrast, facing a higher number of closely ranked peers has a significant positive effect on performance ($\beta = 1.605$; $p < 0.01$), consistent with the motivational power of social comparison and a level playing field. Lastly, we find a strong positive effect of *Number of Prior Contests* on performance ($\beta = 22.147$; $p < 0.001$), indicating that coders who participate regularly tend to perform better.

In Model 2, we introduce rivalry as it has been measured in prior studies, that is, via the rivalry score a coder has with the single fiercest rival in the room, and find a significant positive effect on performance ($\beta = 2.381$; $p < 0.001$). Then in Model 3, we use the average rivalry score a coder has across the whole field of competitors in the room. We find a significant positive effect ($\beta = 4.320$; $p < 0.001$) and that the model has significantly more explanatory power than Model 2 ($\Delta\chi^2 = 18.493$; $p < 0.001$). That is, in line with our baseline hypothesis, the more rivalry a coder is exposed to, across all of the other coders in their assigned room, the better they perform. A one-standard-deviation increase in rivalry on average leads to 4.32 more final points for the focal coder in a competition. This corresponds to a 21.7% chance of finishing at least one rank higher in the room.

To further explore the potential benefits of the "field" approach to rivalry, we run additional models (Models 4–6) in which we split the field of rivals into different subsets. In Model 4, we include measures for the fiercest rival and an average across the remaining competitors in the room, in Model 5 we include an average measure for the top three rivals and an average across the remaining competitors in the room, and in Model 6 we include an average measure across the top five fiercest rivals and an average across the remaining competitors in the room. These models lend support for the notion that there is additional predictive power from assessing rivalry across a group of rivals but also that, at least in our setting, this effect diminishes the more competitors are considered (i.e., there is no significant effect on performance for rivalry with coders beyond the top five strongest rivals). It is also worth noting that the predictive power of the models splitting up the field into top rivals versus the rest is no stronger than the model that uses the total measure of rivalry. We use the overall field measure in the rest of our analyses.

Moderating Effects

In Table 2, we test our hypotheses regarding the interactions between rivalry and skill and rivalry and risk of status change. We examine the two moderation effects separately in Models 2 and 3 and include them both in Model 4. Both moderation effects individually ($\Delta\chi^2$ Model 2 = 93.606; $p < 0.001$; $\Delta\chi^2$ Model 3 = 43.964; $p < 0.001$) and jointly ($\Delta\chi^2$ Model 4 = 118.36; $p < 0.001$) contribute to a significantly better model fit, so we base our interpretation on the effects of Model 4. In this full model, rivalry still has a significant positive main effect on performance ($\beta = 1.940$, $p < 0.001$), but this is qualified by significant interactions. First, we find a significant positive interaction between *Rivalry* and *Skill* ($\beta = 3.553$; $p < 0.001$), indicating that rivalry benefits performance to a greater level when a coder is highly skilled. To better illustrate this, we plot the effects of rivalry for three skill groups (average skill, −1 standard deviation, +1 standard deviation) in Figure 4(a). Rivalry is beneficial to the performance coders of high (slope = 5.493) and average skill (slope = 1.94) but is detrimental to the performance of lower-skilled coders (slope = −1.612). Facing one standard deviation more rivalry corresponds to a 25.2% increased chance of finishing one place *higher* in the final room standings for higher-skilled coders but an 11.9% increased chance of finishing one place *lower* for lower-skilled coders. Thus, Hypothesis 1 is supported.

Second, although the coefficient is positive, we do not find a significant interaction effect between rivalry and being at risk for gaining status ($\beta = 1.660$; $p = 0.428$). The effect of rivalry on performance thus does not significantly differ for competitors who have the chance of improving in status compared with competitors who do not face meaningful risk of status change. Thus, Hypothesis 2a is not supported.

Third, we find a significant, negative interaction effect between rivalry and being at risk for losing status ($\beta = -6.510$; $p < 0.001$). Thus, rivalry harms the performance of coders who are at risk for losing status compared with coders who do not face the risk of status change. Notably, this effect is bigger than the direct positive effects of being at risk for losing status ($\beta = 2.572$; $p < 0.05$) and rivalry ($\beta = 1.940$; $p < 0.05$),

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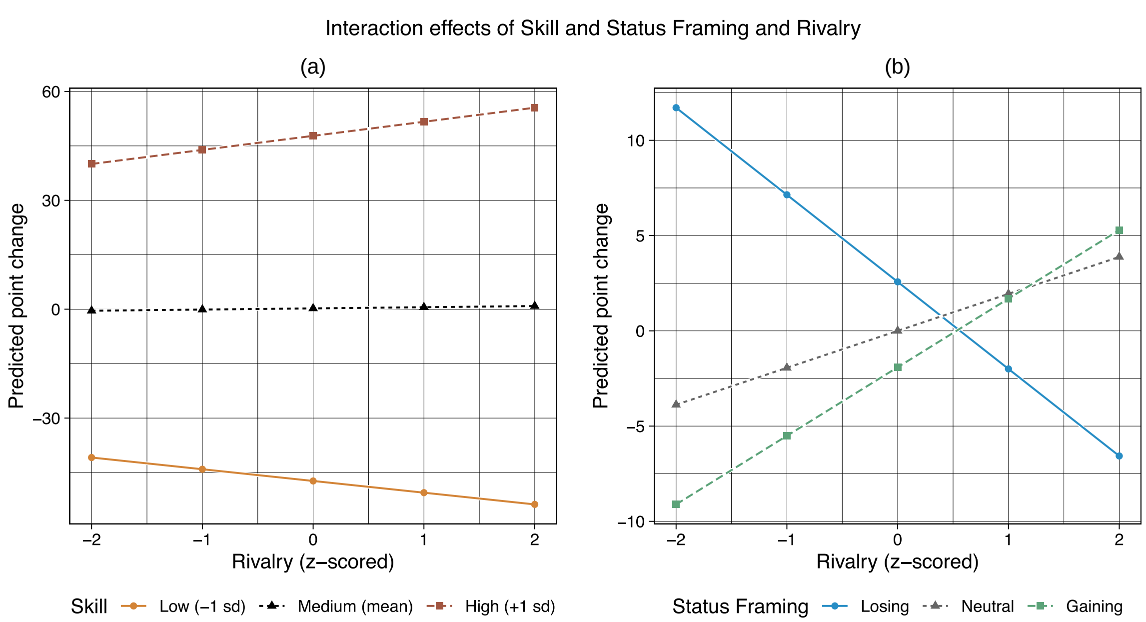
Table 2. Moderation Effects of Skill and Risk of Status Change and Rivalry

Dependent variable: *Final Points*	Model 1	Model 2	Model 3	Model 4
Skill	47.749***	47.430***	47.843***	47.550***
	(9.161)	(9.128)	(9.160)	(9.132)
Number of Prior Contests	20.461***	21.137***	20.538***	21.126***
	(1.152)	(1.140)	(1.149)	(1.139)
Peer Mean Skill	60.403	63.629	60.910	63.751
	(63.552)	(63.364)	(63.543)	(63.382)
Peer Max Skill	−22.927***	−27.435***	−23.196***	−27.194***
	(5.553)	(5.592)	(5.553)	(5.595)
Number Close Competitors	1.228*	0.663	1.138+	0.655
	(0.593)	(0.600)	(0.594)	(0.601)
Status: Risk Losing	3.573***	3.192**	2.697*	2.572*
	(1.059)	(1.061)	(1.106)	(1.106)
Status: Risk Winning	−1.963	−1.805	−2.002	−1.910
	(1.366)	(1.364)	(1.351)	(1.350)
Rivalry Score	4.320***	1.149	5.186***	1.940*
	(0.929)	(0.871)	(0.982)	(0.915)
Skill × *Rivalry Score*		3.885***		3.553***
		(0.720)		(0.726)
Status: Risk Losing × *Rivalry Score*			−8.952***	−6.510***
			(1.630)	(1.630)
Status: Risk Winning × *Rivalry Score*			0.137	1.660
			(1.880)	(1.906)
Fixed effects				
Coder	Included	Included	Included	Included
Room	Included	Included	Included	Included
Round	Included	Included	Included	Included
No. of observations	209,361	209,361	209,361	209,361
Adjusted R^2 (full model)	0.508	0.508	0.508	0.508
Likelihood ratio test ($\Delta\chi^2$) vs. Model 1		93.606***	43.964***	118.36***
Variance residual	25,026.493	25,015.306	25,021.239	25,012.349
Variance coder	12,230.613	12,373.410	12,303.703	12,416.873
Variance round	8,514.079	8,504.554	8,496.038	8,490.428
Variance room	5,077.221	5,148.082	5,112.095	5,173.126

Notes. Standard errors are clustered on the coder and room level. All rivalry variables are calculated using a one-year time window. The sample includes only coders with a full one-year history.
***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $^{+}p < 0.1$.

Figure 4. (Color online) Interaction Effects



Notes. (a) Moderation effect between individual skill and rivalry. (b) Moderation effect between risk of status change and rivalry.

such that the negative effect of rivalry combined potential status loss outweighs the combined positive direct effects of both. Figure 4(b) illustrates these effects. Rivalry has a positive effect on performance for coders who are not close to a status boundary (slope = 1.94) and coders who have the chance to gain status (slope = 3.6). However, there is a strong negative effect for coders who are at risk for losing status (slope = −4.57). Facing one standard deviation more rivalry corresponds to a 22.5% increase in the chance of finishing one place *lower* in the final room standings for a coder who faces significant risk of status loss (versus a 13.2% increased chance of finishing one place *higher* for coders who do not face status risk). Thus, Hypothesis 2b is supported.

Additional Evidence

One limitation of our data set is that we impute rivalry from coders' histories with one another (Kilduff 2014, 2019) rather than measuring it directly. Thus, we sought additional evidence to support our theoretical explanation of the effects that we observe. First, we collected survey data from a subsample of 43 SRM participants (the survey was preregistered; see Table A10 in the Online Appendix for details on recruitment and the full text of the questions we asked and analyses of all preregistered items).[17] A substantial majority of the respondents reported that they (1) pay attention to the other coders in their assigned rooms (86%), (2) have the experience of recognizing other coders in their assigned rooms (92%), (3) experience an increase in energy and/or subjective stakes when they are assigned to a room with familiar others (65%), (4) pay attention to their ratings and the Topcoder leaderboard (90%), and (5) are aware when they face a potential status change (i.e., color change; 79%).

Second, we leverage additional behavioral data from the challenge phase of SRMs to test the notion that the pairs of coders that we identified as stronger rivals were indeed more salient to one another. Specifically, we estimate the probability of a coder choosing to challenge the solution of a particular competitor in their room as a function of the level of dyadic rivalry between them. We control for the skill of both the challenger and target of the challenge, included individual (source and target), round, and room fixed effects, and clustered standard errors on the individual and room level. In the baseline model (Model 1 of Table 3) we find that higher-skilled coders are more likely to challenge other coders ($\beta = 0.326$; $p < 0.001$) and that higher-skilled coders get challenged with lower probability ($\beta = -0.275$; $p < 0.001$). Then, when we add the dyad-level rivalry measure between those coders (Model 2), we find that coders are more likely to challenge those coders with whom they have a higher level of dyadic rivalry ($\beta = 0.015$; $p < 0.001$). This corroborates our survey data and provides further evidence that rivals, as identified by our measures, are more salient to one other and elicit greater levels of competitiveness. Importantly, however, the points gained and/or lost by challenges do not explain the effects of rivalry on performance (see Appendix Table A7, Model 3, in the Online Appendix).

Table 3. Probability That a Coder (Source) Challenges Another Coder (Target)

Dependent variable: *Pr(Challenge)*	Model 1	Model 2
Source Skill	0.326***	0.325***
	(0.008)	(0.008)
Target Skill	−0.275***	−0.280***
	(0.008)	(0.008)
Rivalry Score		0.015***
		(0.003)
Fixed effects		
Source	Included	Included
Target	Included	Included
Room	Included	Included
Round	Included	Included
No. of observations	3,019,035	3,019,035
Deviance	752,608.568	752,578.119
No. of groups: Source	6,415	6,415
No. of groups: Target	12,074	12,074
No. of groups: Room	14,263	14,263
No. of groups: Round	620	620

Notes. Data are on the dyadic level. Rivalry Score is calculated using a one-year time window. Sample only includes coders with a full one-year history
***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $^{+}p < 0.1$.

Robustness Checks

We conduct a range of robustness checks (see Online Appendix). These include (1) tests for potential effects of monetary rewards (Table A3, Model 1) and gender differences (Table A3, Model 2); (2) analyses using alternative operationalizations for rivalry (Table A2; Table A3, Model 3; Table A4 Models 1–4; Table A5; Table A7, Model 1), performance (Table A7 Model 3), skill (Table A3, Model 4), and status risk (Table A6); (3) analyses using different subsamples (Table A4, Models 5–7; Table A7, Model 4); and (4) different model specifications (Table A7 Model 2 and 5; Table A8; Table A9). These findings demonstrate the robustness of our findings. Interestingly, we also find that when monetary prizes are present, the interaction between the risk of gaining status and rivalry has a significant positive effect on performance (Table A3, Model 1), offering some support for Hypothesis 2a.

General Discussion

Leveraging almost 20 years of contests involving experienced computer programmers who were repeatedly and randomly assigned to peer groups in which to compete, we find that coders' prior competitive interaction histories with one another affected their performance, in a manner consistent with the existence of rivalry relationships. Importantly, this positive main effect was qualified by two significant interactions. First, rivalry was more beneficial to more skilled coders but harmed the performance of less skilled coders; second, rivalry interacted negatively with the prospect of status loss. These effects were robust to a variety of different operationalizations and model specifications. We do not find a significant interaction between rivalry and risk of status gain in our main analyses, but this interaction did emerge as significant in analyses of a subset of contests that also provided monetary prizes for winning. Additional data from a survey of Topcoder competitors and dyadic challenge behavior provided further evidence for rivalry as the underlying mechanism behind these effects.

Our paper makes several important theoretical contributions. We substantially extend rivalry theory by integrating it with regulatory fit theory to reveal the conditions under which rivalry benefits versus harms performance. This extends existing work that has revealed positive main effects of rivalry (Kilduff 2014, Yip et al. 2018). Our integration of rivalry theory with regulatory fit theory also suggests additional moderators to rivalry not examined here, namely, any factors that influence regulatory focus (Crowe and Higgins 1997), such as the extent to which tasks, rewards, and incentives are structured or framed as opportunities to be gained versus losses or punishments to be avoided. Furthermore, by identifying risk of status change as moderator of the effects of rivalry, we connect the seemingly related, but to date largely separate, literatures on rivalry and status. In particular, organizational hierarchies can vary in the extent to which they are stable versus mutable (Hays and Bendersky 2015), and our findings suggest that this may be important to understanding the consequences of rivalry. Under conditions of mutable hierarchy, the double-edged sword nature of rivalry may be especially present, as facing potential status loss and gain will be a common experience.

We also contribute to rivalry research in other ways. First, most existing rivalry research has examined one-on-one competition. However, many competitions involve groups of competitors all competing at once, such as salespeople (Chan et al. 2014). By studying the effects of rivalry imposed by a field of competitors, our work better mimics this group competition dynamic and suggests that rivalry can also be thought of in aggregate terms. Further, our analyses provide suggestive evidence that considering rivalry relationships beyond the fiercest rivalry can provide additional predictive power for individual performance. Second, by observing evidence of rivalry effects in this highly technical and cognitive work context, we extend existing work that has focused primarily on rivalry between athletes and performance on effort-based tasks (Kilduff et al. 2010, Kilduff 2014, Converse and Reinhard 2016, Pike et al. 2018, Yip et al. 2018). It is also notable that we observe significant performance effects of rivalry in a context in which all interactions were virtual, and in which rivalries are apt to be fairly mild, rather than intense, due to limitations on repeated competition. Thus, our analyses may represent a conservative test of the effects of rivalry on work performance. Third, our panel analysis method and data set with random assignment to peer groups provided for a precise and controlled test of the causal effects of competitive histories, and by extension, rivalry, in a real-world context involving thousands of competitors across hundreds of contests. This extends prior work that has relied on correlational archival data and laboratory experiments. Lastly, unlike prior research on rivalry (Kilduff et al. 2010), we are able to compare the effects of rivalry in the presence versus absence of financial incentives for winning (Table A3, Model 1, in the Online Appendix). The consistent effects we find suggest that rivalry has a robust effect across different types of contests. Overall, our work provides a more complete picture of the performance effects of rivalry and can help scholars and managers better understand, and potentially manage, rivalry in the workplace.

Beyond these contributions to rivalry research, we also contribute to research on contests. The extensive economics literature on competition in contests following in the tradition of Lazear and Rosen (1981) has relied on an atomistic view to investigate how aspects such as prize structure (Tullock 1980, Lazear and Rosen 1981, Moldovanu and Sela 2001), contest size (Konrad 2009), and skill of competitors (Brown 2011, Boudreau et al. 2016, Riedl et al. 2024) predict outcomes. These analyses tell us little about how the social structure of interactions affects outcomes. We show how the structure of interactions can lead to rivalry networks which interact with individual attributes (skill) and situational factors (risk of status change), thus painting a more complete picture of how actors are likely to behave in contests. We also contribute to this work by adopting a fundamentally different, yet complementary, theoretical perspective on actors' performance in contests. The existing work on contests applies a rational perspective to actors' behavior, exploring their choices about how much effort to exert as driven by their perceived odds of victory and prizes for winning. We complement this by revealing additional factors, rivalry and its interactions with skill and risk of status change, that drive performance independent of the utility capture central to traditional contest models.

Zooming out, to get the complete picture of how a competitor is likely to perform in a contest, three perspectives or theoretical frameworks are needed: contest theory (which emphasizes the odds of winning and the number and size of prizes), social comparison theory (which emphasizes current levels of similarity between competitors), and rivalry theory (which emphasizes history between competitors). Indeed, we find empirical support for all three perspectives. Related to contest theory, we find a robust negative effect of the skill level of the most skilled competitor in a room on a focal coder's performance. This extends existing formal models (Fang et al. 2020), experimental evidence (Flynn and Amanatullah 2012), and evidence from observational data (Brown 2011, Chan et al. 2014) on the performance-harming effects of facing a very strong competitor. Related to social comparison theory, we find a robust positive effect of the number of closely ranked competitors in the room, providing causal evidence of the performance-boosting effects of social comparison with others of similar ability level (Festinger 1954, Garcia et al. 2013) and also highlighting the benefits of level playing fields studied in the contest literature (Konrad 2009, Boudreau et al. 2016). Boudreau et al. (2016) theorize that facing a close competitor (the odds of which are increased in larger competitive fields) will increase performance pressure to "stay ahead." We find direct evidence of this effect using a different modeling approach.

We also contribute to research on the effects of skill and potential for status change on performance. We highlight rivalry as a novel factor that strengthens the link between skill and performance and is thus apt to increase performance differentials between high and low skill competitors. We also reveal that, under conditions of rivalry, facing potential status loss may actually backfire for performance, extending prior research on the motivational benefits of potential loss (Pettit et al. 2010, Berger and Pope 2011, Pope and Schweitzer 2011).

Finally, our study allows us to make important empirical contributions to the peer effects literature. The empirical analysis of peer effects in general has been hampered by both conceptual and data problems (Manski 1993, Brock and Durlauf 2001, Moffitt 2001). In particular, peer composition is often a product of endogenous choices of individuals, that is, individuals have agency over which groups they join and therefore what peer effects they are exposed to (i.e., a sorting problem; Lazear 2000, Ryvkin 2011). By leveraging the repeated random assignment of coders to peer groups, and the resulting panel data structure, we contribute to the applied peer effects literature by presenting evidence of both positive and negative peer effects, and how these peer effects vary across individuals (skill level) and situations (risk of status change), in a setting in which they are especially well identified (Hanushek et al. 2003, Bramoullé et al. 2020). These features of our data and empirical approach also allow us to provide causal evidence for the performance effects of competitors' skill levels, in a field setting. It is rare to have data that satisfy so many aspects examined in the econometrics literature (Hanushek et al. 2003, Bramoullé et al. 2020), the lack of which has in the past contributed to concerns about whether peer effects can be reliably identified in empirical data. The panel data that capture the formation of social networks and behavior over time allow us to identify the existence of social influence effects more accurately by controlling for correlations between social networks, financial stakes, and competition.

Limitations and Future Directions

This work is not without its limitations and also raises a number of important potential directions for future research. First, although the groups of peers with whom coders competed were randomly assigned, thus allowing for causal tests of the performance effects of interaction histories between coders, skill and risk of status change were not manipulated (although risk of status change can be considered quasi-experimental given the discontinuity design; Trochim and Donnelly 2001). Future work might therefore seek to manipulate these factors to provide even more evidence for the moderating effects of skill and risk of status change, although manipulating them in a meaningful way along with rivalry would be a challenge.

Second, as with any empirical project, certain aspects of our empirical setting may be unique and so future work may seek to generalize our findings. In particular, we have noted that the rivalries in this context may tend to be of a milder variety than the intense sports or chief executive officer rivalries that often attract media attention. It is possible that the "field effects" of rivalry that we observe here might be less pronounced in a scenario in which individuals were competing with a truly intense rival; in that case, their motivation to win might be maxed out, and the presence of additional weaker rivals might be less relevant.

Third, in constructing our measure of rivalry, we follow prior work (Kilduff 2014) in taking the simple average of the three main drivers of rivalry. However, it is possible that some antecedents to rivalry may be relatively more important than others. Future research that is able to directly measure feelings of rivalry between competitors (e.g., via self-report) could seek to explore this. Fourth, it would be interesting to explore whether skill and the prospect of status change moderate additional consequences to rivalry beyond performance, such as risk-taking (To et al. 2018), unethical behavior (Kilduff et al. 2016), and social undermining (Xu et al. 2020). Fifth, we focus here on the effects of rivalry on individuals working independently, leaving open the question of how rivalry may affect teams. Research suggests that performance pressure can have both benefits and downsides for teams of knowledge workers, leading to increased task engagement and effort, but also a lack of breath in focus (Gardner 2012). The extent to which interteam, and intrateam, rivalries have similar versus different effects on knowledge work teams is an important direction for future inquiry. Finally, our sample was limited by the fact that it was predominantly male. Although we do not find that gender moderated the effects of rivalry (Table A3, Model 2, in the Online Appendix), future work should examine other more gender-balanced contexts to further investigate any possible gender differences in the effects of rivalry and its interactions with skill and risk of status change.

Practical Implications

Our findings also carry some important practical implications. They suggest that rivalry is relevant to cognitive and technical work and can develop via virtual interaction; thus, rivalry is likely to be present and important across a wide range of organizational contexts. Further, they reveal critical factors that help determine when rivalry is beneficial versus harmful to task performance, helping managers to make better decisions about whether to encourage or discourage rivalry in organizations. Our findings suggest that rivalry, although a potential motivational tool, should be approached with caution. Managers should be especially careful about promoting rivalry between lower-skilled employees or those who are still developing experience and skill at their jobs, or in situations in which employees' status is at risk. The fact that rivalry appears to benefit higher-skilled individuals more than lower-skilled also means that it could cause performance gaps between higher and lower performers to widen, amplifying inequality.

Conclusion

Although famous examples and prior empirical research suggest that rivalry can boost task performance, this may not always be the case. Rather, its effects depend on individual and situational factors. This extends rivalry theory, raises important new questions to inspire future research, and suggests a broad range of practical implications for managers and organizations.

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Endnotes

[1] In fact, to our knowledge this is the first paper that estimates variations of the linear-in-means model with random peer groups and panel data (Bramoullé et al. 2020), allowing us to isolate the causal peer effects of (relational) rivalry, as well as of situational features of the contest (e.g., the strength of the strongest competitor).

[2] For more on how and why these three factors increase rivalry, we refer the reader to Kilduff (2014, 2019), and Kilduff et al. (2010).

[3] Related work on interfirm competition finds that managers form cognitive "reference groups" of multiple other competitors toward whom they direct the most attention (Porac et al. 1995).

[4] We note that Boudreau et al. (2016) also examined skill as a moderator within the same empirical context. However, they explored how skill interacted with the size of the competitive field (i.e., number of competitors) to predict performance, by driving individuals'(-rational) decisions about how much effort to exert as a function of their chance of winning, which is very different from our focus.

[5] See an example here: https://www.topcoder.com/tc?module=Static&d1=match_editorials&d2=srm433.

[6] However, we include encounters from "Division 2" when computing relational histories of encounters (in total, more than 4.6 million dyadic encounters) to capture all prior interactions between coders.

[7] We vary this "loading period" in additional analyses in Table A4 of the Online Appendix.

[8] We adopt the notation that T* describes the state of the world at the conclusion of the contest, whereas T refers to the state of the world before the contest, capturing characteristics that are predetermined before the contest (i.e., the LHS variable is time-lagged relative to the RHS variables).

[9] In Table A7 in the Online Appendix, we provide a robustness test where we use the points from the coding phase only as the dependent variable and find consistent results.

[10] We provide robustness checks using three-month, six-month, three-year, and all-time windows (see Table A4 in the Online Appendix) and find consistent results. We also conduct robustness checks for several of our other measures.

[11] We conduct robustness tests with alternative cutoffs at the 5th, 15th, 20th, and 25th percentiles (see Table A5 in the Online Appendix) and find consistent results.

[12] We test different cutoffs (±5, ±15, ±20, ±25) in our robustness checks (Table A5 in the Online Appendix) and find consistent results.

[13] We use a dichotomous measure of proximity on the leaderboard rather than a continuous rating difference to capture the fact that, when coders view the leaderboard, they see their names surrounded by closely rated competitors. Transforming ratings into ranks also mitigates concerns about nonuniform rating differences across the Topcoder rating distribution; elite coders are generally several hundred rating points apart, whereas coders in the middle of the distribution may be separated by only a few points.

[14] Available upon request.

[15] We find consistent results using alternative thresholds (i.e., 10%, 33%, 25 pts, 50 pts, 100 pts; see Table A6 in the Online Appendix).

[16] Note that red coders cannot move to an even higher status category and therefore cannot face a risk of gaining status.

[17] Preregistration available here: https://osf.io/g9nwc?view_only=061811849ac14b62a9a36f181d3bf9e2.

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