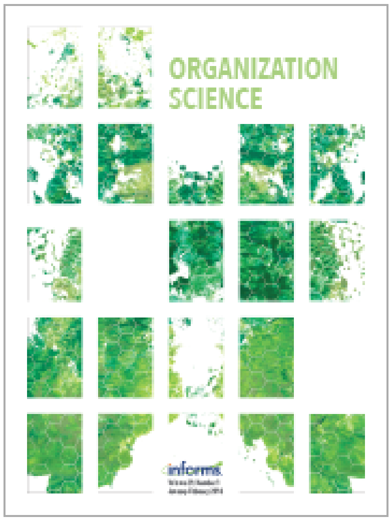

Organization Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

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To cite this article:
Rodolphe Durand; , Henning Piezunka; , Philipp Reineke (2025) Difference in Deference: When Competitors Do Not Give in Despite Having Lost. Organization Science 36(2):940-966. https://doi.org/10.1287/orsc.2023.17474

informs
https://pubsonline.informs.org/journal/orsc

ORGANIZATION SCIENCE
Vol. 36, No. 2, March–April 2025, pp. 940–966
ISSN 1047-7039 (print), ISSN 1526-5455 (online)

Difference in Deference: When Competitors Do Not Give in Despite Having Lost

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Received: March 10, 2023
Revised: February 23, 2024; August 6, 2024
Accepted: August 9, 2024
Published Online in Articles in Advance: November 20, 2024

https://doi.org/10.1287/orsc.2023.17474

Abstract. When a contest is decided, the inferior competitor is supposed to defer to the superior opponent. Yet, sometimes the losing actors refuse to give in. We theorize why and when losing actors do not defer—even when they are supposed to. We hypothesize that when the losing actors categorize their relationship with an opponent as rivalrous beyond the current contest and may obtain some contest-specific gains independent of the focal encounter, they will not defer as much as expected. Unique data from Formula One racing prove strong support. Our findings contribute to research on deference as well as on competition and rivalry. Our study also has broader implications as it helps explain when people do not respect social norms while competing—be it for rewards, for promotions, or in elections.

Keywords: deference • status • competition • rivalry • contest

Introduction

Competition allocates rewards among contenders. Competition is ubiquitous (i.e., anywhere where multiple actors aim for the same goal or resource). In society, competition takes the form of contests: for instance, in sports (e.g., tournaments), politics (elections), and organizational life (e.g., promotions, successions, and nominations). Contests are space and time containers of competition, and contenders (are supposed to) respect the contests' formal and informal rules. One quintessential rule is that contenders defer to a superior opponent when the contest is decided and the opponent's superiority has been established. Therefore, when facing situations that reveal their contextual inferiority, losing competitors are expected to defer to their contextually superior opponent to preserve the rules of the contest and fair play—and more broadly, as a way to respect the broader social order.

Organizations, markets, and social systems would dysfunction profoundly if actors never acknowledged their inferiority and defeat in a given contest. This would hinder the sane beginning of another cycle of fair competition from starting as well as the possibility of future collaboration—instead, nurturing resentment and potentially feeding a spiral of retaliation. Yet, it happens; although defeated in the first round of an election, a candidate may undermine the further electoral process (e.g., by requesting a recount for no good reason). In sport competition, a losing team or athlete may engage in unfair play against its opponent, or an employee passed over for a promotion does not respect and support her newly promoted colleague as she is supposed to. In this study, we examine when a competitor does not defer to an opponent, despite losing a contest. We develop a theory of why proven inferior competitors instead resist the contest rules and social expectations, test it in a specific context, and cautiously reflect on the generalizability of our theory and findings.

In the literature, deference is an essential lubricant of social and market relationships (Coser 1961, Fragale et al. 2012, Jourdan et al. 2017). It characterizes the acts and behaviors that an actor performs to signal a recipient that he or she is "yielding, appeasing, and honoring the recipient's position in the rank order" (Fragale et al. 2012, p. 374). In sociology and organization theory, deference unambiguously expresses and reflects an actor's inferiority to an opponent (Goffman 1956). As a conspicuous characterization of an unequal position in a particular situation (Gould 2003, Faris et al. 2020), deference is enacted by actors who have been proven structurally and even just contextually to be at a disadvantage to an opponent (Henrich and Gil-White 2001, Cattani et al. 2014, Freeland and Hoey 2018). However, prior research on deference envisions deference as a direct and quasi-automatic function of inferiority. Despite the commonality of defeated actors not deferring, prior research on deference falls short in explaining a focal actor's refusal to defer to a superior opponent. In particular, deference theory is hard-pressed to explain differences in deference behavior once status difference between the actor-opponent dyad has been accounted for. In addition, in deference research, superiority can be structural (as across occupations) (Rushing 1962, Jourdan et al. 2017) or specific to a situation or organization (Fragale et al. 2012)—the implications of the nature of an opponent's superiority having not been fully expressed. These questions not only are of theoretical interest but also, are consequential for organizations and society more broadly. Failure to defer to the superior contender as expected could compromise the outcome of the contest, the next round of competition, and the potential for future collaboration between actors.

To account for the not-so-uncommon lack of deference by overpowered competitors, we develop a theory that predicts significant differences in deference—after having controlled for the structural status differences between the actor and the opponent. According to our theory, two characteristics of the actor-opponent confrontation in an actual contest determine deference levels.[1] These are (1) the rivalry between the focal actor and the opponent within and beyond the actual contest (Kilduff et al. 2010, To et al. 2018) and (2) the contest-specific reachable gains independent of the focal interaction.

First, although a contest is a time- and space-delimited container of competition, an actor's categorization of the opponent as a rival hinges on other competitive linkages that bond them. When facing the evidence of their contextual inferiority, an actor may thus continue to perceive the relationship with the (contextually superior) opponent as rivalrous beyond the actual contest (e.g., Bothner et al. 2007, Hallila et al. 2024). Indeed, specific past events may unite the actor and the opponent in a special and adversarial relationship (To et al. 2018). To illustrate, imagine the relationship between two athletes having already competed for the same titles or prizes before the current contest. Absence of antagonistic cues from past contests would probably lead the focal actor who is surpassed by the opponent in the current contest to defer more to the opponent than had there been an accumulation of adversarial cues making the actor-opponent relationship emotionally charged (Kilduff et al. 2010). Hence, we expect that rivalry is positively associated with a lack of contextual deference. This antagonism may spread across domains alien to the current contest. For instance, some chief executive officers compete in areas well outside their company's market performance, such as art collection or charitable causes, which can create out-of-domain rivalry and affect their behavior in professional contexts. Therefore, we also expect that separate domain rivalry induces a contextually proven inferior actor to not defer as expected to the (contextually superior) opponent.

Second, a contender, although being proven inferior locally and temporally, can still pursue contest-specific goals. We can imagine that not deferring as expected sends a signal about the focal actor's determination to some other opponent—possibly more important to the focal actor than the current opponent who the focal actor is facing. In addition, refusal to defer as expected may signal strength, loyalty, or perseverance to partners or allies. Thus, the presence of stakes pertinent to the focal contest but not specifically associated with the focal opponent may alter the extent of an actor's deference. We could expect then that a focal actor will defer less than expected to the contextually superior opponent as an expression sent to another opponent of the focal actor's determination to keep fighting and as the focal actor's concern to benefit an ally.

Methodologically, it is challenging to detect deferential behavior, which is often part of microinteractions that are typically not well documented at a large scale. We have devised a research design that allows us to measure deferential behavior—observing actors literally going out of their way to let other contenders go past them. We examine our hypotheses using a data set on lapping events in the Formula One (F1) car-racing series (Castellucci and Ertug 2010, Aversa et al. 2015, Castellucci and Podolny 2017, Piezunka et al. 2018, Clough and Piezunka 2020). In F1 racing, drivers compete in a series of Grands Prix for the annual title of F1 World Champion. In each Grand Prix, drivers compete on a circular racetrack. If one driver (the "opponent") is clearly doing better than another (the focal driver) over many laps, the opponent—the faster one—will eventually be one lap ahead and thus, come up on the focal driver from behind. In this case, the opponent is not merely "overtaking" the focal actor but "lapping" him; he is about to be more than one lap ahead. As a socially defined container of competition, Grand Prix F1 rules dictate that the focal driver must let the opponent get past him; that is, the contextually inferior driver must defer to the faster one. But, when deferring, the focal driver has discretion regarding how quickly he lets his opponent pass, and it is this discretion that we examine.

For all lappings in all F1 races from 2011 until 2019 (i.e., 7,122 eligible events[2]), we compute, as a measure of deference, how quickly the focal driver grants passage to an opponent. By interfering the least (the most) with the competitive process, the focal actor expresses a more (less) deferential behavior to his faster opponent and so doing, *accepts the rules of the contest and the outcomes of competition more (less)*. Using Heckman two-stage models to estimate the likelihood of being lapped and controlling for status inferiority; other dyad and opponent features; and actor, opponent, and race fixed effects, we find that the variables characterizing (a) the rivalrous nature of the actor-opponent relationship (related to past domain rivalry and to rivalry domains other than the current contest) and (b) the contest-specific stakes significantly reduce the intensity of deference—in proportions that are very material economically.

Keeping in mind the specificities of our setting and the scope conditions that characterize our study and limit the generalizability of its findings (we comment on these in the Discussion section), this paper contributes to three areas of research. First, we complement research on deference (Benjamin and Podolny 1999, Cattani et al. 2014, Jourdan et al. 2017, Freeland and Hoey 2018). Although rules and norms compel an actor to show deference, the idea that there are reasons for the actor to maintain the rivalry with an opponent and to opportunistically snatch some secondary contest-specific gains explains why deference may vanish and lead to abrasive relationships and unnecessary social hostility. Second, we complement research on competition and rivalry. Our study provides evidence that the competition between two actors can become unbounded—they continue to compete even if the contest is decided—and that rivalry in domains extraneous to the focal contest can spill over and affect the opponents' interaction in the focal contest. It relaxes the assumption that actors who are similar and close competitively are the ones who compete particularly fiercely. The paper thus provides a much richer picture of actors' (non-)deferent behavior than does most prior research on deference, competition, and rivalry in isolation. Finally, by highlighting the contextual nature of deference, our research speaks to multiple observable instances of disrespect for institutionalized rules (e.g., recent elections, culture of clashes, or forms of quitting and ghosting in firms) and to research that investigates conformity to social norms. Although the pilots, drivers of F1 cars, who we study know the strict rules that characterize F1 races and that they are scrutinized and filmed second after second, they still do not defer as expected; this nurtures future research related to violation to social norms because most organizational contexts relax both conditions of perfect information about the contest rules and full observability of behaviors.

Theoretical Background

Deference as the Expected Behavior

Rules govern how and when social actors can compete and prevent them from competing when they should not. A fundamental rule consists of signaling an opponent's superiority to mark the ending of a contest. The multiple acts that convey an appreciation of contextual superiority between an actor and a recipient (for instance, presentational and avoidance rituals, such as conspicuously making way for another actor as a mark of one's own respect or the other's superiority) exemplify deference (Goffman 1956). When a nurse lets a doctor recommend a drug (Rushing 1962) or when a market actor extends extra effort to fix quality problems in proportion to its status difference with a high-status partner (Benjamin and Podolny 1999, Castellucci and Ertug 2010), they express deference. Deference is thus an essential behavior that maintains social and economic orders as functional systems rooted in non-conflictual relations that enable actors' interactions (Coser 1961, Gould 2003, Freeland and Hoey 2018). No society or market could function without some actors deferring to others; the alternative would be anarchic violence and chaos (Gould 2003, Piezunka et al. 2018).

It has long been known that deference reflects social position (Goffman 1956). Deference being a conspicuous characterization of a willingness to yield to another's preferences in a particular situation (Gould 2003, Faris et al. 2020) is typically equated with status difference (Henrich and Gil-White 2001, Cattani et al. 2014, Freeland and Hoey 2018).[3] Indeed, at the individual level, deference echoes social and occupational differences (Fragale et al. 2012, Freeland and Hoey 2018); apprentices defer to masters, interns defer to full-timers, and rookies defer to medalists. At the organizational level, lower-status organizations alter their behavior and express more deference to high-status organizations, hoping for positive spillover effects, such as reputation and access to resources (Benjamin and Podolny 1999, Castellucci and Ertug 2010, Jourdan et al. 2017). Therefore, in their contextual encounters, lower-status actors defer to higher-status actors as a function of the status difference between them in an almost mechanical manner (Gould 2003, Podolny 2005).

Yet, the overemphasis on sociological determinants of deference has masked that other factors relate to (non-)deferent behaviors once the status of actors has been accounted for. In collaborative settings, Joshi and Knight (2015) find that beyond task competence traditionally associated with status, social affinity with partners regarding educational level, gender, and ethnicity is another path that reinforces the likelihood for a research team member to defer to another team member. Likewise, in competitive contexts, the relative social position of contenders does not exhaust other dimensions that could explain whether and how a contender would defer to a contextually superior opponent. Notably, deference theory faces significant challenges in explaining variations in deference behavior after accounting for status differences within the actor-opponent dyad. In other words, given two actor-opponent dyads with the same interpersonal status difference, does the defeated actor in one dyad show more (or less) deference to the superior opponent compared with the defeated actor in the other dyad? If so, why? Furthermore, the contextual characteristics around an opponent's superiority in a contest have not been fully explored or articulated in relation to deference. Overall, we investigate the contextual elements that characterize the encounter between two competitors and the losing competitor's behavior as being less deferent than what the social and competition rules would suggest.

Competition, Contests, and Rivalry

Deference marks the ending of a cycle of competition. A competitor acknowledging his defeat opens a new cycle of new competition or other types of social interactions, including collaboration. Indeed, in social systems, competition is an organized selection of contenders, which rewards some merits. As such, competition is one of the most common mechanisms that explains social actors' behavior and social outcomes (Baum and Mezias 1992, Soule and King 2008). Competition is characterized by multiple actors aiming for the same goal, while the environment cannot allow for the copresence of them all (Carroll and Hannan 2000, Durand 2006). As a driving force, competition explains social actors' exit rates from given fields and industries, their strategies (from specialization to deviance), and their appreciation for having won against their opponents (Carroll and Swaminathan 2000, Hahl and Zuckerman 2014, Naumovska and Lavie 2021). The logic of competition suggests that contenders stop exerting efforts against their opponent once the contest is decided and defer to winners so as to let open a new cycle of social interactions. Absent deference to the winner, competition could seem unconcluded and prolong its effects—mostly negative, such as resentment—to future encounters.

Contests are "containers" of competition, bounded, and time and space limited. Contests are common in sports (championships, Olympic games), politics (elections), and organizations and market settings (hiring campaigns, calls for tenders), to name a few. Contests ritualize competition, which needs organization to prevent the anarchic fight of all against all and about everything all the time. As a mechanism to allocate material and symbolic rewards, competition is enacted in actors' behaviors that announce, define, and close contests. Although competition in theory need not be constrained by any principles, it is organized through contests, in which rules and norms more often than not prohibit brute force or ruse (Kreager 2007, Piazza et al. 2024). Therefore, a contest is a time- and space-bounded competition with explicit rules of behavior that allow room for expressing (among other things) respect for adversaries via deference.

Within contests, the intensity of competition varies depending on the competitive relationships between contenders. Kilduff et al. (2010) established the distinction between competition and rivalry. The theory of rivalry posits that rivalrous relationships between competitors extend beyond mere competition for resources or status and are deeply rooted in psychological and social dynamics (Kilduff et al. 2010, To et al. 2018). Rivalry "exists when an actor places greater significance on the outcomes of competition against—or is more 'competitive' toward—certain opponents as compared with others, as a direct result of his or her competitive relationships with these opponents" (Kilduff et al. 2010, p. 945). Rivalry is thus characterized by an intense, ongoing sense of competition that transcends the immediate stakes of a given contest. Porac et al. (1989) document how competitors self-select as rivals to such an extent that they omit the entry of major foreign competitors that disrupt their industry.[4] To et al. (2018, 2020) explain that a rivalrous relationship involves a personal and enduring comparison between actors, which can foster heightened motivation, aggressive behavior, and a profound desire to outperform the rival. Rivalry theory suggests that it can significantly impact an individual's self-concept and identity as rivals often become key reference points against which they measure their own success and worth (Kilduff et al. 2010). As a result, it is likely that a contender's behavior (such as deference) will depend on the intensity of the psychological investment in the interpersonal relationship with the opponent who proves to be superior in a given contest.

Research findings support the notion that rivalry influences behavior in ways distinct from general competition. For instance, studies have shown that rivals are more likely to engage in risk-taking behaviors and exhibit increased effort and persistence compared with nonrival competitors (Kilduff et al. 2010, To et al. 2018). Rivalry can lead to both positive and negative outcomes. On the positive side, it can drive innovation, enhance performance, and create opportunities (To et al. 2020). However, it can also result in negative consequences at both the individual level (such as stress and unethical behavior) (e.g., Pierce et al. 2013) and the structural level (such as reduced opportunities for alliances or career moves) (e.g., Sgourev and Operti 2019). Importantly, research indicates that the intensity of rivalry is not solely dependent on the similarity and proximity of competitors but also dependent on past interactions, the perceived threat posed by the rival, and the emotional investment in the competitive relationship. What needs further clarification is whether rivalry affects contenders' behavior when controlling for the status difference between contenders (i.e., even when the opponents are dissimilar in their social ranks) and after the contest has been decided.

Overall, a closer examination of the antecedents of deference in competitive contexts is in order because disrespect for the rules of a contest may carry the seeds of contestation, potentially leading to a spiral of retaliation, conflict, and eruption of violence. Hence, having accounted for status difference between actors, we develop in the next section a two-pronged theory of contextual deference between a focal contender and the contextually superior opponent in a contest.

Hypotheses

We investigate the two types of reasons why a competitor may not defer when there is a clear situation of the competitor's contextual inferiority to an opponent in a contest: rivalrous relationships and contest-specific stakes. We examine both sources in turn and derive hypotheses.

Rivalry Beyond the Current Contest

As previously exposed, competition is not limited to space- and time-bounded regulated contests; it consists of a succession of contests *and* a set of relationships that informally unite an actor and an opponent beyond the limits of those contests. Such an adversarial relationship between the actor and the opponent characterize rivalry as a special oppositional relationship. Rivalry exacerbates the appreciation of what a contest is about, independent of the objective nature of the potential gain (Thomas et al. 2024). Rivalry exacerbates competition to such an extent that it leads to unethical behaviors (Kilduff et al. 2016, Jansen et al. 2024), excessive motivation (Malhotra 2010, Kilduff 2014), and risk-taking as the focal contenders change emotional and physical states (To et al. 2018). Therefore, an existing rivalry between an actor and the opponent in a given domain and in the specific circumstance of a contest could explain why an evidently inferior contestant will not defer as much as expected to the contextually superior opponent.

Domain rivalry finds its roots in the competition history that ties together two contenders: that is, the succession of contests that make up the two contenders' relationship as rivalrous (Kilduff et al. 2010, 2024; To et al. 2020). Indeed, because contests write a history of oppositional encounters over time (e.g., between champions, party leaders, or firms' managers), contenders develop distinct relationships with their habitual opponents. For instance, Grohsjean et al. (2016) find that hockey players who switch teams play particularly aggressively against their former team to display allegiance to their new one. However, as a reflection of their past solidarity, they play *less* aggressively against a former teammate with whom they had been friends. Grohsjean et al. (2024) illustrate that soccer players that perform on behalf of the same soccer club (e.g., Real Madrid) tend to collaborate less if they face each other as opponents when they perform on behalf of distinct national teams. Likewise, top executives in an industry or politicians are known to develop an interpersonal rivalry as they vie for the same positions at the helm of the largest firms or the top governmental positions, which affects their manifestation of deference vis-à-vis each other depending on circumstances.

Following the theory of rivalry, we expect that the more evidence of a history of equality between contenders there is in past contests, the less likely the contextually inferior actor in a focal contest is to defer to the opponent. As a reflection of multiple hard-fought past battles and the characterization of a special adversarial relationship, a losing contender will commit energy and resources to still qualify as a worthy rival to his contextually superior opponent in the present—and possibly, future—contests (Bothner et al. 2007, Grohsjean et al. 2016, Piezunka et al. 2018). Hence, in a contest where an opponent contextually proves his superiority to a focal actor, the focal actor will not express as much deference as expected if there is evidence that the two contestants have been equal contenders in the same domain, which characterizes their relationship as more rivalrous.

Hypothesis 1a. *The more intense the past domain rivalry between a focal actor and the opponent, the less that the actor will defer should that the opponent prove contextually superior in the current contest.*

In many instances, rivalry extends beyond the contest domain in a special relationship that can still unite an actor and some of the opponents (Sgourev and Operti 2019). Research on rivalry has found that it affects opportunity structures of actors by blocking paths in and beyond a domain's network structure (Sytch and Tatarynowicz 2013, Piezunka et al. 2018). Drawing on these findings, we expand them and reason that rivalry "unites" a focal actor and some of the elected opponents beyond the codified limits of a current contest. For instance, in sports, politics, and management, social actors may compete for art, charity, or sponsorship, domains that are unrelated to the main arenas of their habitual contests. Even if the focal actor is proven to be contextually inferior in the current contest, the focal actor may not defer to the contextually superior opponent because they ascribe great significance to battling against the opponent. The actor considers it worthy of their best efforts to resist the opponent as the two have developed rivalrous relationships in domains beyond that of the current contest. Although rules, norms, and cues would call for the losing actor's deference, separate domain rivalry may entice the actor not to defer so as to preserve the actor's image as a worthy and credible contender in that other competition realm. Substantive deferential behavior would materialize the contextually inferior actor's subjugation and signal a lack of motivation to compete in the current contest *and* the unrelated rivalry domains.

Thus, separate domain rivalry unites a focal actor and some of the opponents in a rivalrous relationship with some bearing in the current contest. Hence, when the focal actor is losing against an opponent with whom the actor competes in unrelated domains, the actor may not defer as much as expected, signaling that they challenge the generalization to broader competition domains the outcome (i.e., the corresponding reward allocation) of the current contest. We, therefore, hypothesize Hypothesis 1b.

Hypothesis 1b. *The more intense the separate domain rivalry between a focal actor and the opponent, the less that the actor will defer should that opponent prove contextually superior in the current contest.*

Contest-Specific Stakes Independent of the Actor-Opponent Interaction

In addition to the rivalrous nature of the actor-opponent relationship beyond the current contest, another situational element can account for why a defeated actor does not defer as much as expected; there may be contest-specific stakes independent of the situated actor-opponent confrontation that the contextually inferior actor may want to reap. The expectation of some achievable gains at the time of the current confrontation can encourage the contextually inferior contender to keep fighting against a contextually superior opponent and to fail to defer as much as expected per the contest rules and social norms.

One reason not to defer as expected in a contest with a contextually superior opponent is that the public signal of deference is mainly directed not to the immediate opponent but to another *key contender who is more important to the focal actor*. Resisting deference can confer gains on the focal actor that deferring too early or ostentatiously would forgo. First, not deferring to the current superior opponent enables the focal actor to maintain his line of behavior and *position against the other key opponent for longer*; hence, not deferring represents a material advantage. Second, deferring to a contextually superior opponent in a contest indicates to the other key opponent that the focal contender is unconditionally giving up. In order to preserve their image with respect to this other key opponent, a focal contender—although manifestly at a disadvantage in the current situation—will nevertheless not defer as diligently as expected. Overall, they will maintain both their material advantage and image as a serious contender in their own eyes and in those of the other key opponent(s) that they focus on.

Another reason not to defer as expected is that the focal actor is not necessarily competing alone. Indeed, a contender's behavior depends on the indirect network structure that characterizes a competition and a contest domain (Sytch and Tatarynowicz 2013). A contest-specific stake may coincide with a focal actor ally's gain or advantage over the direct and contextually superior opponent to whom according to the rules and norms of competition, the focal actor should defer. Not deferring as expected may serve the ally's interests by not facilitating the contextually superior opponent's path of actions. This triadic relationship represents a contest-specific stake and a ground for a focal actor not to defer as expected.

Therefore, the presence of contest-specific stakes (such as competition with a nonfocal but key opponent and concern to benefit an ally) is a distinct reason for a contextually inferior actor in a given contest to nevertheless resist the expected deference so as to keep the contextually superior opponent from entirely benefitting from their relative superiority in the current situation. We, therefore, hypothesize Hypotheses 2a and 2b.

Hypothesis 2a. *The more intense the competition with an opponent other than the focal one, the less a contextually inferior actor will defer to the focal contextually superior opponent in the current contest.*

Hypothesis 2b. *The greater the gains an actor's ally can obtain, the less a contextually inferior actor will defer to a contextually superior opponent in the current contest.*

Data

Context

Testing our theory requires information on the occurrence of deferential behavior in competitive interactions. This is challenging as competitive interactions and deferential behavior are often not well documented. To overcome this challenge, we rely on data from professional sports—a context that scholars have leveraged to gain access to granular data on competitive interactions (Willer et al. 2012, Operti et al. 2020, Fonti et al. 2023, Gaessler and Piezunka 2023, Grohsjean et al. 2024). Specifically, we test our theory in the context of Formula One, an annual car-racing tournament organized by the Fédération Internationale de l'Automobile (FIA), in which drivers compete on racetracks around the world—such as Silverstone (the United Kingdom), Monza (Italy), and Shanghai (China). In our observation period, between 19 and 21 contests—races also called "Grands Prix"—were held per season. All racetracks are circular and range from 3.34 to 7 kilometers. To keep race durations similar, drivers have to complete more laps on shorter courses and fewer laps on longer courses (between 43 and 78 laps in our sample). In each race, drivers gain world championship points that are allocated, via a convex function, according to their finishing positions. The driver with the most points by the end of a season is the F1 World Champion.

F1 is a dynamic multicompetitor tournament (in contrast to dyadic tournaments, such as tennis, with only two competitors per match), but it differs from other multicompetitor tournaments, such as downhill skiing and ice skating, in that all actors compete at the same time. Additionally, teams (or "constructors") employ two pilots who drive technically equivalent cars. In our observation period, between 20 and 24 drivers competed in teams of two for between 10 and 12 constructors per season. Although constructors have some discretion to dictate strategies to their drivers, drivers driving for the same constructor still compete against each other for the world championship. Relative to other studies where rivalry has been studied, our context shares commonalities (intertemporal relationships via repeated contests), clear gain for the winner, and established rules. However, our setting possesses some accentuated characteristics: full observability of contenders' behaviors (as they are filmed), full information about the rules (incentives and penalties, including expectations about deference) by all of the contenders, and a third party arbitrating rules transgressions and conflicts. These characteristics facilitate our measurements and our control for multiple effects (e.g., contest and actor-opponent dyadic characteristics), although at the same time, they may limit the generalizability of our findings (see the Discussion section).

Phenomenon

Within F1, we study the phenomenon of lapping, described above and shown schematically in Figure 1. A race, or "Grand Prix," is a contest in which status differences are manifest. Indeed, if one driver is faster than another, he may eventually catch up from behind, which is called lapping. The defeated driver is then listed as "one lap behind."[5]

Lappings are subject to regulation. When an opponent approaches and the actor does not let him pass, the actor is shown blue flags and is obliged to let him pass "at the earliest opportunity" (FIA 2020a, pp. 12 and 44). Penalties include time penalties that can seriously harm a driver's standing in a race up to the disqualification of the driver in the focal race (FIA 2020b, p. 45). Moreover, not letting a superior opponent pass carries the earning of a bad reputation among fellow drivers, often provoking strong emotional responses, such as obscene gestures and name-calling. However, the actor has some discretion as to whether he lets the opponent pass immediately or resists and delays him. Furthermore, incentives exist to value sportsmanship and deference. Drivers who have not incurred any penalties during an entire season are awarded two additional points, which is the equivalent of the points awarded for a ninth-place finish in 2020 (FIA 2020b, p. 47). In other words, there are substantial incentives in place for drivers to defer, making deference the expected behavior. Our interest, therefore, resides in explaining how diligent a driver is to defer, having been proven inferior by a competitor in a given contest.

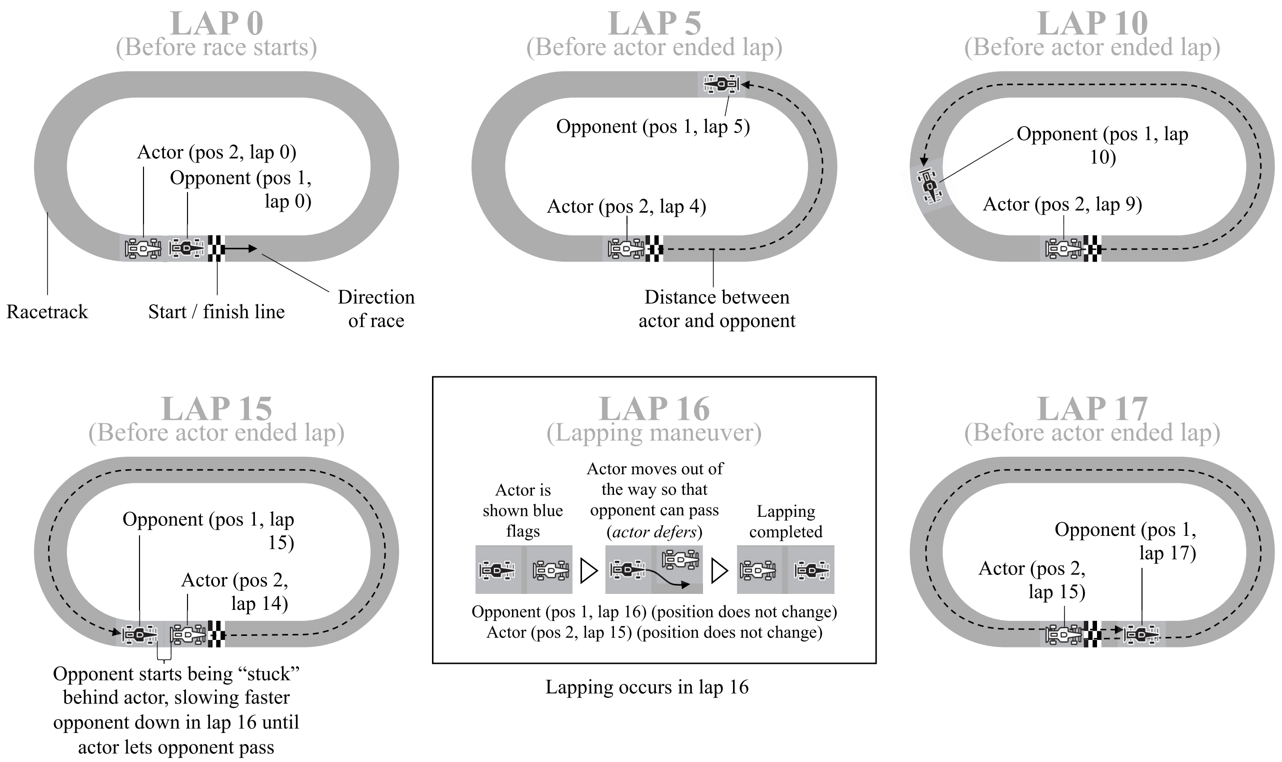
Lapping is thus a threshold event, making an enormous performance differential between an actor and an opponent evident that has been sustained over a sizeable portion of the race. As events, lappings represent a manifestation of competitive superiority and are experienced as such by the actors involved. The head of a Formula one team whose driver had just been lapped commented: "This is an extremely disappointing Sunday and the result is very hard to swallow. To be lapped is very painful for us and our fans" (Velasco 2020). Also, external audiences consider lappings to be a significant moment. The press described the lapping of an otherwise competitive driver as "ignominy" (Medland 2020). At the same time, the drivers who are competitively superior and are lapping other drivers become annoyed when inferior drivers do not move out of their way as it hinders their own progress. The highly accomplished driver Sebastian Vettel commented during the race when another driver did not defer: "It's ridiculous, I mean, it's ridiculous. Honestly. Lost a second. For nothing. For **** sake" (Collantine 2016). Similarly, reigning World Champion at the time Lewis Hamilton commented when a to-be-lapped driver did not defer: "These guys are being crazy" (Fisher 2018). When lapped drivers do not defer, the superior actors even look for ways to enforce the corresponding norm. The following dialogue that took place via the radio during a race exemplifies it. Sebastian Vettel (driver to manager): "Blue flag." Manager: "Copy that, he has blue flag." Vettel: "Yeah, but he doesn't move. Make him move! **** sake." (Collantine 2016)

Sources

The data underlying our analysis are sourced from the appendices that the FIA publishes after each race, including the drivers and their times, positions, and pit stops for each lap. Prior work has leveraged race data to examine actors' behavior (e.g., Bothner et al. 2007, Castellucci and Ertug 2010, Aversa et al. 2015, Marino et al. 2015, Castellucci and Podolny 2017), whereas for the first time to the best of our knowledge, we use lap-by-lap data within single races.

Our longitudinal, highly granular data on every driver's performance in each lap allow us to examine in what round a lapping took place and to what degree it slowed down the opponent. The data set enables the detection of many highly comparable instances (lappings) that permit us to finely study deference behavior. In particular, the detailed, time-stamped data allow us to precisely measure deviations in speed.

Figure 1. Illustration of the Lapping Phenomenon



Notes. The figure illustrates a single lapping maneuver graphically. In this example, the lapping takes place on lap 16, but lapping can occur on any lap after lap 1. Pos, position.

Information on pit stops in each lap allows us to exclude laps with lappings not directly related to race performance or to the behaviors under examination. Furthermore, we report safety-car and red-flagged laps using official FIA data crosschecked with race recordings and live commentaries. When a severe accident or severe weather creates a "hazard on/near/blocking the track," a safety car may be sent onto the track—indicated by flagmen waving yellow flags and holding signs saying "SC"[6]—or the race may be stopped—indicated by red flags—and later restarted. These externalities create large disruptions in lap times, and the laps are, therefore, excluded from our analysis.

Unit of Analysis

Our observation period ranges from the first race in season 2011 until the last race in season 2019, a period for which we have data on 14,550 lappings. Our unit of analysis is the single lapping, each of which is treated as a new observation.[7] We define the actor as the driver at risk of being lapped and opponents as the other drivers who may possibly lap the actor.

Data Cleaning

After cleaning the data, our final, cleaned sample includes 7,436 lappings, in 1,068 of which the focal opponent lapped more than one actor. As we lose additional observations because of lagging, the full model is based on 7,122 lappings. The lappings are conducted in pairs of 51 unique lapping opponents and 60 unique lapped actors (overall, 62 unique drivers) in 951 unique (directed) lapping dyads across 175 unique F1 Grands Prix.

We also create a risk set of all actor-opponent dyads at risk for lapping in a given lap. This set contains all actor-opponent dyads in which the opponent occupies a better race position than the actor at the beginning of the focal lap. In this risk set, we then mark actor-opponent dyad laps in which lappings occur. Our final risk set contains 1,583,317 observations and 1,520,002 valid laps in the full model after lagging.

Measures

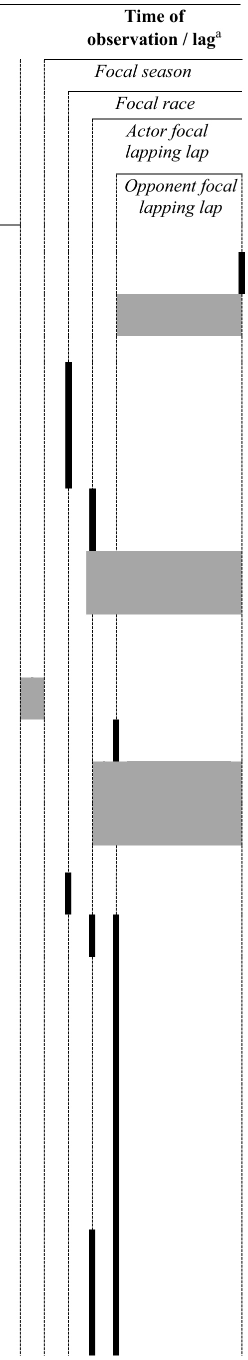
In our analyses, we examine laps in which a *lapping* took place or could have taken place; thus, every observation consists of a single actor-opponent dyad lap, the opponent's race speed in that lap, and covariates.

Figure 2 provides an overview of the variables, their operationalization, and their lags and observation times. We mean centered all independent variables of interest.

Dependent Variable. We measure the focal actor's deference as the speed of his opponent in a lap in which a lapping occurs between that actor and opponent dyad

Figure 2. Variables, Involved Agents, and Data Sources

Var Type	Measure	Predicts: *1st stage*	Predicts: *2nd stage*	Definition	Involved agents	Data source
Dependent variable						
DV 2nd stage	*Opponent speed*		X	Average speed of the opponent in the focal lap.	*Opponent*	*FIA*
DV 1st stage	*Lapping*	X		Binary variable that is 1 if a lapping of actor by opponent occurred in the focal lap.	*Actor, opponent*	*FIA*
Independent variables						
H1a	*Past domain rivalry*		X	Structural equivalence of victories and defeats of actor and opponent in previous races in the focal season.	*Actor, opponent*	*FIA*
H1b	*Separate domain rivalry*		X	Relative search traffic of actor's name minus relative search traffic of opponent's name in Google Trends averaged across the year preceding the focal race.	*Actor, opponent*	*Google Trends API*
H2a	*Nonfocal opponent competition*		X	Logged time difference between actor and closest opponent leading or following actor (negatively coded).	*Actor, opponent, other opponent*	*FIA*
H2b	*Ally's gain*		X	Absolute logged time difference in seconds between the actor's ally and the opponent at the time of the focal lapping (negatively coded).	*Actor, opponent, actor's ally*	*FIA*
Opponent-level control variables						
Control	*Status inferiority*	X	X	Exponential updating based on historical positions in the driver world championship ranking.	*Actor, opponent*	*FIA*
Control	*Race progress*	X	X	Share of race distance completed by the opponent at the beginning of the focal lap.	*Opponent*	*FIA*
Control	*Opponent number of drivers lapped in lap*	X	X	Number of drivers the opponent has lapped in the focal lap (previous lap for 1st stage).	*Opponent*	*FIA*
Control	*Average speed during opponent lap*	X	X	Average speed of all drivers in the lapping lap (previous lap for 1st stage).	*Opponent*	*FIA*
Dyad-level control variables						
Control	*Same team*	X	X	Binary variable that is 1 if actor and opponent drive for the same F1 team.	*Actor, opponent*	*FIA*
Control	*Speed difference*	X	X	Opponent's minus actor's speed in their last-driven laps before the opponent's focal lapping lap.	*Actor, opponent*	*FIA*
Control (traffic)[b]	*# of drivers between opponent and actor leading opponent*	X	X	Drivers who want to lap actor and whom opponent wants to overtake.	*Actor, opponent, other driver(s)*	*FIA*
Control (traffic)[b]	*# of drivers between opponent and actor behind opponent*	X	X	Drivers who want to lap actor and whom opponent wants to lap.	*Actor, opponent, other driver(s)*	*FIA*
Control (traffic)[b]	*# of drivers between opponent and actor behind actor*	X	X	Drivers who want to overtake actor and whom opponent wants to lap.	*Actor, opponent, other driver(s)*	*FIA*
Control (traffic)[b]	*# of drivers between opponent and actor × Distance in focal lap*	X	X	Total number of drivers between actor and opponent × distance between actor and opponent when opponent crosses the finish line at the beginning of the focal lap.	*Actor, opponent, other driver(s)*	*FIA*
Control	*Distance in focal lap*	X		Distance in seconds between actor and opponent when opponent crosses the finish line at the beginning of the focal lap (squared).	*Actor, opponent*	*FIA*
Control	*Position difference*	X		Position difference measured at actor's and opponent's last driven laps before the opponent's focal lapping lap.	*Actor, opponent*	*FIA*



[a]Columns represent the time within a race from earlier (to the left) to later (to the right). In a lap in which an actor is at risk of being lapped, the actor drives in front of the opponent and crosses the start/finish line earlier. Black boxes indicate an observation at a specific point in time. Gray boxes indicates the time frame for observations for which our data do not allow a clear point in time to be determined for when then measure is observed.

[b]Traffic variables encompass the different situations where cars are present between an actor and his focal opponent; this may affect opponent speed, which is our dependent variable (DV) of interest. Note that *Number of drivers between opponent and actor × Distance in focal lap* is the interaction between the total number of cars between the actor and the opponent at the beginning of the focal opponent lap and the distance between the actor and the opponent at the beginning of that lap. A smaller value of this variable (closer to zero) indicates that the opponent is closer to the actor and that there are fewer or no cars between them at the beginning of the focal lap, making lapping more likely.

(i.e., *opponent speed*). If the actor does not defer as diligently as expected, the opponent's speed decreases significantly relative to other opponents' speeds in an average lapping lap. The average speed in our data set across all laps and drivers is 193.19 kilometers per hour (km/h).[8] The fastest single average speed by a driver is

255.01 km/h, and the slowest is 64.33 km/h. The average opponent speed in all laps in which a lapping occurred is 196.70 km/h.

Independent Variables. ***Hypothesis 1a: Past Domain Rivalry.*** To operationalize past domain rivalry, we construct a structural equivalence measure following Piezunka et al. (2018). For this measure, we first construct the square dominance matrix X for all drivers active in the focal season. We then update this matrix for each race with entry x_{ij}, indicating the number of times driver i beat (i.e., had a better finishing rank than) driver j in the focal season up to the focal race. Then, we construct a dyadic structural similarity measure by computing the Euclidian distances between vectors $X_{j\cdot}$ and $X_{i\cdot}$, whereby the resulting measure represents the degree to which the two drivers have beaten and have been beaten by the same competitors. Last, we scale this measure from zero to one by dividing it by the maximum distance observed in a race and subtract the result from one. Smaller values of the final measure (values closer to zero) indicate lower similarity in the competitive space and thus, lower rivalry. Larger values (closer to one) indicate greater similarity in the competitive space and thereby, greater rivalry.[9] We mean centered *Past domain rivalry*.

Hypothesis 1b: Separate Domain Rivalry. This variable measures whether two drivers are rivals in a domain unrelated to the focal contest. Research shows the influence of this kind of anchor on an unrelated contest (Converse and Reinhard 2016, To et al. 2018). In our setting, we capture separate domain rivalry by the degree to which two drivers compete for media attention, which we measure as the difference in search traffic of opponents' and actors' names in Google Trends using data obtained via the Google Trends API (Application Programming Interface—a programmatic way to access Google Trends data) (Vaughan and Romero-Frías 2014). For every term entered, Google Trends returns monthly values from 0 to 100 that represent the term's search traffic relative to the highest search volume of any queried term at any point in the query period. We query values for each actor-opponent pair, average the values per driver for the rolling year preceding the focal race, and calculate the difference. Finally, we take the absolute value of the resulting difference value and code it negatively so that larger values (less negative and closer to zero before mean centering) indicate greater rivalry.

Hypothesis 2a: Nonfocal Opponent Competition. This variable captures whether the focal actor actively competes with a driver other than the focal opponent while being lapped by the focal opponent. If at the time of the focal lapping, the actor and a nonfocal opponent are close and are competing for the same position in the race's rank order, the actor has to let himself be lapped while simultaneously attempting either to keep close to and overtake the other opponent (if that opponent is ahead of him) or to stay ahead of the other opponent (if that opponent is behind him). To measure this effect, we compute a variable that measures the absolute time difference in seconds between the focal actor and his closest opponent on the focal lap—either the driver directly ahead of the actor or the driver directly behind, whoever is closer. Because we expect the effect of nonfocal opponent competition to diminish at greater distances, we log this variable after adding one. Then, we negatively code it so that larger values indicate greater competition. For example, if on the focal lap, the actor was in position 11, the driver in position 10 was two seconds ahead, and the driver in position 12 was three seconds behind, *nonfocal opponent competition* would equal $-\log(2+1)$. If instead, the driver in position 12 was 1.5 seconds behind, *nonfocal opponent competition* would equal $-\log(1.5+1)$.

Our qualitative evidence provides credence to the measure and the theoretical argument. The lapped Formula One driver Romain Grosjean commented on his failure to defer: "I'm sorry if I blocked anyone, it was not my intention. I believe I did my best. I was fighting with Sergey, who was doing a little bit of go-kart racing out there. I couldn't really slow down. Pierre [Gasly] was on my gearbox and Sergey was on my front wing. I passed him, then as soon as I passed him, I let Lewis by" (Formula1.com 2018). On another occasion, he stated: "The blue flag in Singapore, why did I get two penalty points and five-second penalty? Okay, I blocked Lewis and I apologised. I was in my fight as well. By the time I was in front of the Williams, the Williams didn't let the other car by either so I couldn't move straight away" (Rencken and Collantine 2018).

Hypothesis 2b: Ally's Gain. This variable measures whether the focal actor's constructor teammate—his "ally"—is competing with the focal opponent—that is, being crowded by him (Bothner et al. 2007). We operationalize competition between the actor's ally and the opponent as the absolute distance in seconds between them. We add one to the variable; then, we log and negatively code it so that higher values indicate that the actor's ally and the opponent are closer together, increasing the ally's potential gain. If the ally has dropped out of the race, we set this variable to the minimum (most negative) observed value in the focal race. A higher value (closer to zero before mean centering) indicates competition between the actor and the opponent to the indirect benefit of the actor's ally, the stake being the points garnered by the ally (and thus, the team) at the end of the race. For example, this variable would be $-\log(10+1)$ if the actor's ally is either 10 seconds ahead of or behind the actor's opponent.

Opponent Control Variables. Some controls that do not involve the actor but rather, his lapping opponent nevertheless help explain the opponent's speed when lapping the actor. We list them here (see Figure 2).

Opponent Laps Since Last Pit Stop (and Opponent Laps Since Last Pit Stop Squared). This is the number of laps that have passed since the opponent had his last pit stop. We control for this because a driver's speed and his ability to lap and overtake other drivers depend on—among other things—the state of his tires; a frequent reason for pit stops is to replace the tires. We also control for the square of this variable to control for the curvilinear performance profile of new tires. New tires tend to be faster than old tires, but warmer tires tend to be faster than cold tires. Directly after a pit stop, the new tires are cold and have little grip. Therefore, drivers have to take curves more slowly and cannot accelerate as quickly on straights. Once the tires get warmer, speeds increase. However, at some point, the tires' profile degrades, prompting the driver to slow down again. Under normal race conditions, every driver takes one to three pit stops.

Race Progress. This variable operationalizes the opponent's progress at the time of the lapping as the number of laps that he has completed up until the focal lap divided by the number of laps in the race. This is significant because as fuel is burned during the race, the cars become lighter and faster.[10]

Opponent Number of Drivers Lapped in Lap. This counts the drivers who the opponent has lapped on the focal lap. Because lappings are analyzed on a per-lapping level, in rare cases multiple lappings occur for a single opponent in one lap, each of which can lower his race speed.

Average Speed During Opponent Lap. This is the average speed of all drivers during the last lap that the focal opponent drove. It controls for special circumstances, such as accidents and bad weather, that slow down the entire set of drivers and thereby, may prevent lappings.

Dyad-Level Control Variables. Because our unit of analysis is an actor-opponent dyad, we need to control for factors, listed below (see Figure 2 as well), that can affect an actor's deceleration when his opponent is about to bypass him.

Status Inferiority. We control for status inferiority, the traditional antecedent of deference. Because status characterizes the accumulated perception of superiority of an actor relative to others, we computed measures that use exponential updating based on drivers' historical positions in the driver world championship ranking. Using this approach, the status measure for each driver is determined recursively using the following formula:

$$f(P) = u \times p_{t-1}(u-1) \times f(P = [p_{t-2}, p_{t-3}, \ldots, p_{n-1}, p_n]),$$

with P being the vector of performance scores p_i, t being the focal period/season, n being the total number of past periods/seasons for driver i, and u being an updating factor that determines how fast past values decay (i.e., how strongly past vectors factor into current status inferiority scores). We use an updating factor of $(1-0.5^{\frac{1}{4}})$, meaning that the half-life of an observation—the number of seasons required for the weight of a season driver word championship ranking to be reduced by half—is four seasons. We also tested a factor of $(1-0.5^{\frac{1}{2}})$ with a half-life of two seasons. Then, we take the difference of scores of the actor minus the opponent such that higher (positive) values of this variable indicate superior performance of the opponent and lower (negative) values indicate superior performance of the actor. All variables are calculated based on the past season(s), so no information of the focal season is used. Because of this, using this variable would have resulted in the deletion of all observations of drivers completing their first season, which would have reduced our analyses' power and may have biased results. Therefore, we impute status inferiority on the constructor level for drivers' first seasons. As such, missing past driver rank variables (before taking the difference) are replaced by the running five-season average of the average world championship rank across the focal driver's constructors' drivers. If this variable is also missing (because it is the focal constructor's first season), the variable is imputed across the entire field. In that case, the driver rank is replaced by the average driver rank in the prior season. Note that we also tested several versions of three alternative measures with qualitatively equivalent results (one based on the actor's power centrality, one using ranks in the championship, and one based on the actors' lapping history).[11]

Same Team. This binary variable equals one if the opponent and the focal actor drive for the same team. Being the ally of an opponent attempting a lapping may positively affect the tendency to defer.

Speed Difference. This is the speed of the opponent minus the speed of the actor in their laps before the lapping lap. This variable controls for the fact that lappings may slow down opponents in a dyad with higher speed differential in a lapping lap more than opponents in a dyad with lower speed differential. Dyads with a greater speed differential before the lapping may exhibit a greater reduction in speed during lapping because of that higher baseline, regardless of deference.

Traffic Variables. The focal opponent may be hindered in lapping by different types of traffic caused by other drivers between him and the focal actor. In any lap, the presence of traffic makes a lapping less likely. In lapping laps, traffic reduces opponent speed because the opponent has to pass other drivers who generate traffic before being able to lap the focal opponent. However, different other drivers generating traffic may be in different competitive relationships with the focal actor and the opponent, which may prompt them to behave in ways that are more or less obstructive. Drivers may want to lap the focal actor and may want to overtake the focal actor. They may be drivers whom the opponent wants to overtake or lap. We control for all possible types of traffic that arise from these constellations (see Figure 2).

Estimation Procedure

To alleviate concerns of selection into treatment, we use a Heckman two-stage selection model (Heckman 1979). This model predicts the probability of being lapped in a first-stage model and then predicts the hypothesized effects in a second-stage model while correcting for lapping selection effects. As our risk set of potential and observed lappings has a very large number of observations, we chose the two-step Heckman method for our estimation.[12] Because our data structure is nested, we compute two-way clustered standard errors on the levels of the actor and the opponent using 4,000 bootstrap samples.

Heckman models rely on the assumption that the first-stage equation includes variables that are not part of the second-stage equation (Certo et al. 2016). First, to correct for the propensity for lapping in a specific driver dyad during a specific lap, we include those second-stage controls that significantly predict a lapping between a given actor-opponent dyad.[13] Second, we use two additional variables that predict lappings (the first-stage dependent variable, equal to one if lapping occurred) but not the speed at lapping (the second-stage dependent variable). These two variables are as follows.

Distance in Focal Lap. This is how close (in seconds) the opponent is to the actor at the beginning of the lap during which the lapping took place. Lappings require the opponent to be within "striking distance." That is, the opponent must be close enough to the actor to be able to conduct a lapping on the focal lap. Therefore, this variable strongly accounts for selection effects of the lap in which a lapping involving a given driver dyad can take place.

Position Difference. This is the difference in race position between the actor and the opponent at the beginning of the focal lap. A larger absolute difference makes lapping more likely.

As a robustness check, we also estimate a linear regression with fixed effects and clustered standard errors.[14]

Fixed Effects

We use actor and opponent fixed effects because drivers differ in both talent and personality. We use race fixed effects to account for race-specific environmental conditions (such as rain), time-varying aggregate driver characteristics (such as the average race experience of drivers in the race), characteristics of the field of racers (such as the number of drivers), and special properties of the track (such as whether it is a fast track like Monza (the average speed in the sample is 234.01 km/h) or a slow track like Monaco (the average speed in the sample is 147.67 km/h)). Race fixed effects also account for the average time that it takes to complete a lapping lap on a given track in a given race. This is important because on a longer track, on which it takes longer to complete one lap, a lapping might constitute a stronger defeat than it would on a shorter (faster) track.

Results

We outline the descriptive statistics in Table 1. As can be expected, some correlations are high: namely, those between the variables and their squared versions and the interacted variables. There are also high correlations between dyadic distance variables and variables that measure whether there are cars between the actor and the opponent. This makes sense because the closer two cars are, the less chance there is for other cars to be between them. Pit stops are related to race progress because the longer a race lasts, the more likely pit stops become. All in all, correlations between variables are as expected. We calculated variance inflation factors (VIFs) for a linear regression version of the second-stage model without fixed effects. All independent variables have VIF scores less than 1.4, and all control variables have scores less than 10. When calculating VIF with fixed effects, one control variable—*average speed during opponent lap*—had a VIF greater than 10 because of the presence of race fixed effects. We tested whether its absence reduced the VIF (which it did) and whether it altered the structure of our results (which it did not). We, therefore, kept it in the reported models as it is both theoretically important and empirically significant.

Table 2 reports the results of the dyadic linear regression analysis of single lappings (the second stage of our model; the first stage can be found in Appendix A). Model 1 in Table 2 contains all controls. As expected,

Table 1. Descriptive Statistics and Correlation Matrix

	Variable	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1)	*Lapping*	0.005	0.068																			
(2)	*Opponent speed*	194.126	21.380	0.008																		
(3)	*Past domain rivalry*	0.516	0.190	−0.049	−0.015																	
(4)	*Separate domain rivalry*	−13.332	9.422	−0.018	−0.039	0.246																
(5)	*Nonfocal opponent competition*	−5.754	24.736	−0.035	−0.008	0.032	−0.011															
(6)	*Ally's gain*	−21.916	18.300	−0.006	0.008	0.199	0.056	0.054														
(7)	*Opponent laps since last pit stop*	12.195	9.379	0.015	0.031	0.050	−0.003	−0.018	−0.028													
(8)	*Opponent laps since last pit stop squared*	236.684	364.978	0.011	−0.025	0.041	−0.013	−0.016	−0.017	0.923												
(9)	*Opponent race progress*	0.463	0.283	0.052	0.145	0.001	−0.000	−0.084	−0.147	0.481	0.414											
(10)	*Opponent no. of drivers lapped in lap*	0.064	0.266	0.282	0.032	−0.059	−0.048	−0.014	−0.022	0.053	0.039	0.173										
(11)	*Average speed during opponent lap*	94.469	12.369	−0.015	−0.138	−0.033	0.015	−0.004	−0.104	−0.273	−0.262	−0.101	−0.053									
(12)	*Same team*	0.049	0.217	−0.014	−0.003	0.186	0.042	0.005	0.264	0.017	0.014	0.003	−0.013	−0.005								
(13)	*Speed difference*	3.943	10.235	0.017	0.038	−0.095	−0.038	−0.050	−0.001	−0.030	−0.049	−0.079	−0.001	0.028	−0.031							
(14)	*Status inferiority*	3.993	7.406	0.034	0.015	−0.386	−0.204	−0.021	−0.130	−0.048	−0.038	0.018	0.055	0.018	−0.101	0.061						
(15)	*Number of drivers between opponent and actor leading opponent*	5.527	4.594	−0.078	−0.082	0.297	0.196	−0.005	0.175	−0.138	−0.115	−0.168	−0.146	0.052	0.080	−0.058	−0.245					
(16)	*Number of drivers between opponent and actor behind opponent*	0.584	2.235	−0.017	0.019	−0.240	−0.094	−0.133	−0.046	0.083	0.075	0.199	0.113	−0.070	−0.055	0.092	0.157	−0.138				
(17)	*Number of drivers between opponent and actor behind actor*	5.544	4.745	−0.081	−0.006	0.199	−0.000	0.164	0.131	−0.076	−0.075	−0.168	0.002	0.066	0.093	−0.102	−0.132	−0.182	−0.196			
(18)	*Number of drivers between opponent and actor × Distance*	−847.870	572.077	0.103	0.082	−0.280	−0.117	−0.077	−0.238	0.176	0.156	0.228	0.087	−0.261	−0.118	0.065	0.210	−0.448	−0.122	−0.463		
(19)	*Distance in focal lap*	−65.937	27.003	0.165	0.073	−0.205	−0.097	−0.092	−0.192	0.203	0.183	0.278	0.145	−0.404	−0.088	0.009	0.151	−0.304	−0.069	−0.328	0.865	
(20)	*Position difference*	6.744	4.798	0.067	−0.012	−0.466	−0.182	−0.075	−0.199	−0.022	−0.025	−0.053	0.065	0.016	−0.161	0.177	0.352	−0.497	0.365	−0.524	0.537	0.325

Notes. Correlations for $N = 1{,}583{,}317$. SD, standard deviation.

we find that greater *status inferiority* reduces the time that it takes the opponent to complete lapping; thereby, the focal actor is more deferent to a higher-status opponent (we observe an increase in *opponent speed*). Consistent with expectations, an opponent's *race progress* increases *opponent speed*, whereas other dyad controls (traffic-related variables and *same team*) and opponent controls (former drivers lapped by the opponent and *average speed during opponent lap*) reduce *opponent speed*. As expected, *opponent laps since last pit stop* has a curvilinear effect, likely resulting from the changing condition of the car's tires.

In Models 2–5 in Table 2, we separately add the independent variables, and then, in Model 6, we add then all together. Hypotheses 1a and 1b predict that actors exposed to past domain and separate domain rivalry with the focal opponent will defer less willingly. The coefficient for *past domain rivalry* is negative and significant in Model 2 ($\beta = -1.852$; $p < 0.001$) and Model 6 ($\beta = -1.643$; $p < 0.001$) in Table 2. The coefficients for *separate domain rivalry* in Model 3 ($\beta = -0.027$; $p < 0.001$) and Model 6 ($\beta = -0.021$; $p < 0.001$) in Table 2 are negative and significant. Overall, results strongly support Hypotheses 1a and 1b.

Hypotheses 2a and 2b predict that actors with context-specific stakes may defer less willingly, ceteris paribus. The coefficient for *nonfocal opponent competition* is negative and significant in Model 4 ($\beta = -0.089$; $p < 0.001$) and Model 6 ($\beta = -0.074$; $p < 0.01$) in Table 2, as is that for *ally's gain* in Model 5 ($\beta = -0.106$; $p < 0.001$) and Model 6 ($\beta = -0.073$; $p < 0.05$) in Table 2. Overall, results support Hypotheses 2a and 2b.

Table 3 compares the effect sizes of the four main effects, which with a one-standard-deviation change in the predictor variable, range from a −0.317-km/h change in *opponent speed* to a −0.046-km/h change.

Economic Significance of Results

F1 rules incentivize deference to support competition. As discussed earlier, competition allocates rewards to winners, and in F1 contests, these include points, titles, and economic gains. We aimed to estimate the economic gains or losses represented by a lack of deference. Beyond predicting seconds lost during lapping, we investigated whether the speed differences (Table 3) translate into financial impacts on drivers and teams. To proxy these impacts, we collected driver salary data from the beginning of the 2019 season (Racing Elite 2019) and constructor/team valuations and revenues from the end of the 2019 season (Smith 2019). By associating the 2019 start-of-season driver salaries (via simple linear regression) with average driver position outcomes in the 2018 season and associating the 2019 end-of-season constructor valuations and revenues with the 2019 season average constructor driver position outcomes, we can estimate

Table 2. Heckman Two-Step Regression, Second-Stage Ordinary Least Squares Equation Predicting Opponent Speed

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Independent variables						
Past domain rivalry		−1.852***				−1.643***
		(0.000)				(0.000)
Separate domain rivalry			−0.027***			−0.021***
			(0.000)			(0.000)
Nonfocal opponent competition				−0.089***		−0.074**
				(0.001)		(0.008)
Ally's gain					−0.106**	−0.073*
					(0.002)	(0.044)
Opponent controls						
Opponent no. of drivers lapped in lap	−0.313***	−0.268***	−0.323***	−0.262***	−0.286***	−0.218**
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.004)
Opponent laps since last pit stop	−0.133***	−0.130***	−0.132***	−0.131***	−0.132***	−0.129***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Opponent laps since last pit stop squared	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Opponent race progress	2.727***	2.829***	2.733***	2.703***	2.680***	2.763***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average speed during opponent lap	−1.454***	−1.461***	−1.456***	−1.452***	−1.453***	−1.460***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dyad controls						
Same team	−1.401+	−1.410+	−1.387+	−1.413+	−1.096	−1.232
	(0.061)	(0.083)	(0.056)	(0.059)	(0.135)	(0.117)
Speed difference	0.005+	0.003	0.004	0.004	0.005	0.001
	(0.094)	(0.344)	(0.151)	(0.157)	(0.129)	(0.638)
Status inferiority	0.044**	0.027+	0.030*	0.045**	0.044**	0.018
	(0.004)	(0.078)	(0.036)	(0.003)	(0.005)	(0.236)
Number of drivers between opponent and actor leading opponent	−0.630***	−0.615***	−0.631***	−0.630***	−0.628***	−0.613***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of drivers between opponent and actor behind opponent	−0.101	−0.190*	−0.115	−0.146	−0.115	−0.241**
	(0.260)	(0.044)	(0.190)	(0.101)	(0.212)	(0.010)
Number of drivers between opponent and actor behind actor	−0.608***	−0.619***	−0.607***	−0.553***	−0.591***	−0.557***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of drivers between opponent and actor × Distance	−0.042***	−0.044***	−0.043***	−0.042***	−0.042***	−0.044***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	342.778***	335.433***	342.500***	342.337***	342.587***	334.878***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Race fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Actor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Opponent fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes. $N = 1{,}583{,}317$ in the first stage; $N = 7{,}436$ in the second stage. Standard errors are two-way clustered on the level of the actor and the opponent. Standard errors were computed using bootstrap sampling based on between 4,000 and 4,500 samples.
$^{+}p = 0.1$; $^{***}p = 0.001$; $^{**}p = 0.01$; $^{*}p = 0.05$.

the value (cost) to a driver and his constructor of gaining (losing) a single position in a race.

In our data, drivers holding consecutive positions in the final lap were, on average, 8.55 seconds apart. To recoup that difference and gain a position, a driver would have needed to be only 0.28 km/h per lap faster or 16.44 km/h faster in any single lap. An increase of one position in the overall 2018 Grand Prix driver position average was associated with an increase of \$3,049,513 in driver base salary ($p < 0.01$; not including additional performance bonuses) in the beginning of the 2019 season. A decrease of one position was associated with an increase of the log odds of the driver being fired by his constructor at the end of the season by 0.56 ($p < 0.1$). Similarly, an increase of one position in the overall constructor world championship ranking in

Table 3. Main Effect Sizes of Independent Variables (from the Coefficients in Model 6)

Variable	1-Unit change …	1% Change …	1-Standard-deviation change …
	… in predictor variable is associated with an opponent speed (km/h) change of		
Hypothesis 1a: *Past domain rivalry*	−1.643		−0.317
Hypothesis 1b: *Separate domain rivalry*	−0.021		−0.210
Hypothesis 2a: *Nonfocal opponent competition*		−0.0007	−0.102[a]
Hypothesis 2b: *Ally's gain*		−0.0007	−0.046[a]

[a]These values are from the absolute value of the mean of the unlogged, uncentered variable.

2019 was associated with an increase of $78,040,000 ($p < 0.01$) in team valuation and of $27,290,000 ($p < 0.01$) in team revenues at the end of the 2019 season. Given the fact that position averages in one season result from aggregating the results of 21 races and that a team consists of two drivers, gaining a position in a single race can be associated with a $145,214 driver base salary increase, a constructor valuation increase of $1.86 million, and a constructor revenue increase of $650,000.

As reported in Table 4, a speed increase of 1 km/h in a single lap in a single F1 race can, therefore, be associated with an $8,833 increase in driver base salary, a $113,028 increase in team valuation, and a $39,523 increase in team revenues (2019 season). Although these calculations are simplified (as they assume the linearity of the underlying mechanisms and only show general tendencies), the empirical effects estimated in Table 3 associated with a refusal to defer as much as expected can add up to differences of several kilometers per hour per lapping maneuver. As a result, the adversarial relationships beyond the current contest as well as the contest-specific stakes independent of the actor-opponent confrontation, which all lead to deferring less than expected, can be reasonably assumed to have highly economically significant effects—which amount to several million U.S. dollars per season in Formula One alone.

Robustness Tests

We conducted several tests to ensure the robustness of our results. First, we controlled for competitiveness using the Kilduff et al. (2010) measures. We also tested different versions of our past domain rivalry measure (see footnote 9). Additionally, we tested various versions of status (see footnote 11) and its interactions with our independent variables. These tests showed an interaction between nonfocal opponent competition and status inferiority. Finally, we coded binary variables to indicate triad constellations of drivers in the beginning of the focal lopping lap. This allowed us to construct counterfactuals that when controlling for traffic, helped disentangle traffic from nonfocal opponent competition. All robustness checks confirmed our main results. Please find details on the most important of our robustness checks included in Appendix B.

Discussion

Although deference has been shown to be a lubricant of social and market relationships, actors sometimes contravene expectations and do not defer. To illuminate these cases, we examine why contest-inferior actors sometimes do not defer as expected to their superior opponent. We acknowledge that the stakes of a contest cannot be reduced to the accumulated social and structural differences between the two focal contestants. Hence, controlling for status differences between a focal actor and the opponent, we investigate the effects on deference of their adversarial relationships beyond the current contest and the existence of stakes for the focal actor within the contest but unrelated to the focal encounter.

Scope Conditions and Limitations

We envisage F1 as an accentuated version of contests in organizations, whereby contest rules are known ex ante by all contenders, the observability of all of their behaviors is maximum, and the incentives to act according to the formal and informal rules are explicit. This said, we must stress that this paper has boundary conditions

Table 4. Economic Significance of Results

	Driver base salary increase, $	Team valuation increase, $	Team revenue increase, $
Speed increase of 1 km/h in a single lap	8,833	113,028	39,523

Notes. Our results support our theorizing that the coefficients suggest only modest speed differences. However, the speed differences associated with deference in lapping in F1 racing (see Table 3) have substantial financial impacts on drivers and teams. To proxy these impacts, we collected driver salary data from the beginning of the 2019 season (Racing Elite 2019) and constructor/team valuations and revenues from the end of the 2019 season (Smith 2019). By associating the 2019 start-of-season driver salaries (via simple linear regression) with average driver position outcomes in the 2018 season and associating the 2019 end-of-season constructor valuations and revenues with the 2019 season average constructor driver position outcomes, we can estimate the value (cost) of a 1-km/h speed increase (decrease) in a single lap for a driver and his constructor (detailed analysis is available from the authors).

and limitations that may constrain the generalizability of its findings to organizational settings.

First, as for any sport contest, Formula One's participants and organizing principles are specific; for instance, two pilots from the same team compete, and there is an explicit code of conduct that details the tangible rewards and penalties associated with visible behaviors during contests as well as the presence of a referee (Bothner et al. 2007, Grohsjean et al. 2016, Hallila et al. 2024). Contests within organizations—jockeying for a promotion or a succession or access to special resources or budgets—obey idiosyncratic rules and principles (e.g., job listings, hiring and promotion procedures) that differ from sports' ones and do not detail as explicitly rewards and penalties. It is difficult to strongly argue whether with less clear principles and explicit rules, lack of deference would be more or less observed in organizational contests than in the kind of contest that we studied, which complicates the generalizability of our findings. Second, in our setting, not only are the rules known by everybody, but the observability of rivals and competitors and of their second-by-second behavior is almost perfect. This characteristic makes our results conservative; indeed, observing effects while (1) actors know the contest rules and (2) their acts are visible and trackable suggests that in absence of (1) explicit rules and (2) lower observability of actors' behavior, lack of deference by inferior actors in organizational contexts should be more present (although less observable). Third, our hypothesis development concerns actors and opponents. Although this formulation aims at embracing both individuals and organizations, we observed individuals' (pilots) behavior. Hence, the characterization of organizational behavior (firm-to-firm rivalry, firms' stakes) should not be considered as the frictionless extension of what individual actors (pilots or managers) experience and do. Therefore, we refrain from making a direct transposition of our findings to firm-to-firm competition and advocate for a meticulous examination of the conditions that could make a firm characterize another as a rival (e.g., Mawdsley et al. 2023) or as deferring (see Jourdan et al. 2017 for an organization-level analysis of strategic deference).

Further limitations are worth mentioning. First, the competitors are all male. Research has examined whether and how women differ in the way that they compete, with significant influence of how rivalry and deference manifest themselves, in particular in situations where women confront men in a contest (Gneezy et al. 2003, Han et al. 2017, Saccardo et al. 2018, De Sousa and Hollard 2023). Second, we study a within-occupation domain (i.e., manifestation of deference between pilots). As noted earlier, deference occurs across occupations as well (i.e., nurses to doctors or within an organization's sales directors versus corporate finance officers). Although the source and the nature of rivalry may differ, we reason that the underlying logic of our model should resist, but we note that our findings still need replication in crossoccupational settings. Third, studies using sport contexts investigated the individual-team effects on players' behavior (Hallila et al. 2024 on MotoGP (Grand Prix motorcycle racing), Sgourev and Operti 2019 on horse racing (Palio di Siena), and Grohsjean et al. 2016 on hockey). A characteristic of our study is that we focus on a focal actor's relationship with an opponent and ensuing behavior, controlling for team effects but without integrating the potential rivalry across teams and the history of pilots' team memberships. Fourth, our operationalization of variables is meant to express our constructs, whereas our Heckman models, although redressing the likelihood of being lapped, remain correlational. We expect that other methodologies (especially experiments and big data with exogenous shocks) can provide finer-grained operationalization and micro-level tests of our concepts and theory. Fifth, although we accounted for determinants outside the main contest (e.g., separate domain rivalry) and events before the main contest, there is much room left for research on intertemporal choices to defer or not.

Overall, despite its advantages, some specificities of the empirical test of our theory impose caution as to how far we can generalize our findings. Despite these caveats, our empirical study of F1 racing and lapping behavior supports the theory and sheds light on the magnitude and economic importance of the effects, thus contributing to the research on deference, competition, rivalry, and conformity to social norms.

Research on Deference. We extend the research on deference by evidencing factors that explain its contextual manifestation. The traditional view on deference underscores its essential role in social and market interactions and characterizes it as stemming from status differentials (Goffman 1956, Rushing 1962, Benjamin and Podolny 1999, Gould 2003, Castellucci and Ertug 2010, Cattani et al. 2014). Lower-status actors defer to higher-status actors as a function of the status difference between them in an almost mechanical manner (Gould 2003, Podolny 2005). Without a clear social hierarchy, actors are unwilling to defer, and conflict results (Gould 2003, Piezunka et al. 2018). For instance, Faris et al. (2020) find evidence that competition for the same social positions spawns violence among middle schoolers. At the organizational level, lower-status organizations alter their behavior and express more deference to high-status organizations, hoping for positive spillover effects, such as reputation and access to resources (Benjamin and Podolny 1999, Lynn et al. 2009, Castellucci and Ertug 2010, Cattani et al. 2014). For instance, Jourdan et al. (2017)

documented how, in France, minority-logic organizations (private funds) that financed cultural products (movies) had to defer to dominant-logic producers (public funds promoting cinema as an art) to increase their centrality in the production network and have access to promising projects. Therefore, deference has been considered a predictable response to status difference.

Although recent work adopts a more dynamic perspective on status (Askin and Bothner 2016) and introduces more agency into the way that individuals (Fragale et al. 2012, Freeland and Hoey 2018) and organizations (e.g., Han et al. 2017, Jourdan et al. 2017) deal with deference, they tend to ignore complementary factors that, we find, are related to the manifestation of deference. In our theory and models, we account for status difference and find that rivalry (from the same and distinct domains) significantly reduces a proven inferior actor to manifest deference to their superior contender in a given contest. We also find evidence that unrelated to the focal situation in which a superior opponent interacts with an actor who should manifest deference, some contest-specific gains may delay or contradict the actor's willingness to defer. An actor competing with an opponent other than the focal one may accrue benefits by not signaling deference to that focal opponent. Likewise, not deferring may generate gains for a focal actors' allies. A supplemental contribution of this paper is the comparison of the magnitude of the found effects; see Table 3 (from higher to lower: same domain rivalry, distinct domain rivalry, other opponent, and ally gains.)

Hence, we answer a question left largely unanswered in the deference literature. Given two actor-opponent dyads with the same interpersonal status difference, does the defeated actor in one dyad show more (or less) deference to their superior opponent compared with the defeated actor in the other dyad? We find that both rivalrous relationships and contest-specific gains reduce the manifestation of the expected deference above and beyond what status differential accounts for. Thus, we contribute to a view where the intensity of deference is situational, varying with (a) how antagonistic an actor perceives the relationship with an opponent beyond the context of a given contest—in the same or separate domains of rivalry—and (b) the contest-specific gains that may be accrue from not deferring as expected.

Drawing on this study, future research on deference can expand in at least two directions. First, we need to better understand (a) the consequences of a lack of deference for the actor-opponent dyad and (b) how audiences react to it. With respect to the former, how differently may the opponent and the focal actor behave in a future encounter in the same competition domain or in one in a different competition domain? With respect to audience reaction, under which conditions might some groupings (fan clubs, followers, partisans) diffuse a culture of disrespect, disputing the rules of the contest and favoring the norms and behaviors of unbridled competition and social antagonism?

Second, a better examination of the cognitive determinants of deference is in order. Indeed, deference involves loss of recognition for the actor because it is not merely a private concession but a public recognition of one's own inferiority. Despite an empirical approach that enabled us to construct a fine-grained measure of deference (time gained or lost by the superior actor) (see Table 3), we cannot elaborate the conditions that influence how an actor weighs the costs and benefits of their behavior. We highlighted the gains of deferring less than expected (to keep up with a rival and snatch contest-specific gains) but cannot, with our design, determine which conditions are cognitively more salient or whether additional conditions would inflame or stifle these cognitive determinants. Future research is in order to further contextualize—beyond the context of sports—the social conditioning of our main effects.

Research on Competition and Rivalry. Competition is one of the most common mechanisms underlying social actors' behavior and social outcomes (Baum and Mezias 1992, Durand 2006, Soule and King 2008). Yet, ubiquitous a notion as it is in social and organizational studies, competition needs specification to be truly explanatory of behavior. Indeed, the degree of competition between actors varies over time and space (Gould 2003). Moreover, depending on network structures and the induced perceptions of rivalry, the same actors compete differently against each other (Porac et al. 1989, Cattani et al. 2014, Piezunka et al. 2018, Kilduff et al. 2024, Thatchenkery and Piezunka 2025). Competitors are thus neither all equal nor equally competitive all of the time (To et al. 2020, Mawdsley et al. 2023). Our paper distinguishes the temporarily and locally bounded instances—that is, contests—from the rivalry relationships and the stakes that imperceptibly unite actor and opponents.

Contests are time- and space-bounded spaces where competition takes place. However, contenders may be dyadically connected through a specially charged relationship (Kilduff et al. 2010, To et al. 2020) and through structural equivalence in networks (Kilduff et al. 2024). This rivalry affects their behavior when the two actors interact. As such, although scholars tended to assume that competition is the base state of actors' relationships in a social or economic space (Bothner et al. 2012, Grohsjean et al. 2016), the distinction with contest and rivalry contributes to a fine-grained explanation of contenders' expression of socially expected behavior. Although prior works on rivalry focused on unethical behavior (e.g., Kilduff et al. 2010), we extend to deference its influence—after accounting for status differences between social actors and in a highly scrutinized context. Our findings demonstrate that rivalry within and across domains does affect a focal actor's deferent behavior, even when status difference is large and the victory is clear. This suggests that competition exists independently of specific contests, precedes them, and extends across various (un-)related contestable arenas. Consequently, this paper offers a more comprehensive understanding of actors' deferent and nondeferent behaviors than most previous studies that have examined deference and rivalry in isolation.

Although keeping in mind the boundary conditions of our study (exposed above), the rivalry of the actor-opponent relationship and the contest-specific stakes are factors generic enough to be distinguished and integrated in future studies. Future research should measure an actor's behavior both within a space- and time-bounded contest *and* beyond it to capture the whole set of factors that explain the situated manifestation of respect or antagonism. Because competition is a selective force that is socially ritualized in contests, it deserves not to be an unexplored underlying assumption factored into observable behaviors. We need to get a better grasp at its variable strength before, during, and after contests and to include in studies on competitive behavior the factors that capture the social structure (controlling for status inferiority), the special relationship that ties every actor to some special opponents (rivals), and the indirect stakes that are contest specific. These determinants need to be included more in future studies and investigated both more dynamically and in greater detail.

Research on Conformity. As in Coleman's bathtub metaphor, our research explains microprocesses that inform and influence higher-level phenomena, such as conformity or deviance to rules and norms (Durand and Kremp 2016, Piazza et al. 2024). By highlighting the contextual nature of deference and the spilling over of rivalrous relationships, we reveal the countervailing forces that facilitate or hamper the conformity to a social norm—here, deference—that is essential to social and market exchange. Actors' acceptance of their position, role, and functions depends greatly on situational cues and on their own representation of their agency in relation to the given situation (contest) and beyond (past domain and separate domain rivalry). This paper documents the influence of rivalry and contest-specific stakes on the nonobservance of an expected behavior—deference—despite the scrutiny that characterizes the contest we studied (each actor's behavior being constantly monitored).

Although some structural explanations contribute to explain conformity behavior (see the long-known influence of status inferiority on deference or the influence of isomorphism), our findings show remarkable and economically significant variance in the manifestation of the expected behavior by contextually inferior pilots. This paper is thus an invitation not to take for granted observed conformity behaviors (at the market, population, or organizational level) generally viewed as passive assimilation of a social order. Viewing conformity to social norms (e.g., deference) as mere proof of macrotheories (such as social structuration, neoinstitutionalism, or organizational ecology) ignores the broader and more complex dynamics that as we find in a specific context, explain such behavior at the personal and interpersonal levels. As new "big data" and the artificial intelligence-based methods with which to analyze it become available, the dream of thoroughly and simultaneously accounting for both macro- and microprocesses may be approaching practical feasibility. Such studies will be essential in explaining appeasing or escalating behavior related to competition and to conflictive interests between two actors and—beyond that—between followers and communities supporting either opponent.

As rivalrous relationships (e.g., "clashes" and "battles") and self-serving behaviors make the headlines, the study of why and when actors do not defer is of importance. Deference is an essential component of sociability. It is how the multiple contests of our social, political, economic, and professional lives are ended. Although rules and norms call for deference, the idea that there are reasons for an actor to maintain the rival nature of their singular linkages with an opponent and to opportunistically snatch secondary contest-specific gains explains why deference may vanish, leading to abrasive relationships and unnecessary social hostility. In the presence of conditions, such as past domain rivalry, separate domain rivalry, nonfocal opponent competition, and ally's gain, that supersede those of status difference, deference and other marks of respect fade away, increasing the adversarial nature of social relationships. Groups of supporters and collectives may then antagonize other individuals or groups, adding to the chauvinism and polarization that can destroy the social fabric.

We see our paper as a steppingstone to better predicting offline and online deviance, group polarization, and likely bursts of violence. It is a call for an even better integration of micro- and macro-level work to help elucidate why and how deference and respect as well as contentiousness and aggressivity may diffuse or dissipate in social milieus. We hope to have paved the way for such future investigation of deference and other behaviors in competitive contexts.

Appendix A. Heckman Two-Step Regression, First-Stage Selection Equation Predicting Lapping

Table A.1. Heckman Two-Step Regression, First-Stage Selection Equation Predicting Lapping

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Opponent controls						
Opponent race progress	0.066	0.119^{+}	0.066	0.066	0.057	0.111^{+}
	(0.283)	(0.060)	(0.283)	(0.283)	(0.336)	(0.080)
Average speed during opponent lap	0.019***	0.019***	0.019***	0.019***	0.019***	0.019***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dyad controls						
Same team	−0.421*	−0.429*	−0.421*	−0.421*	−0.419*	−0.428*
	(0.015)	(0.022)	(0.015)	(0.015)	(0.015)	(0.019)
Speed difference	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Status inferiority	0.015***	0.014***	0.015***	0.015***	0.015***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of drivers between opponent and actor leading opponent	−0.031***	−0.030***	−0.031***	−0.031***	−0.031***	−0.031***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of drivers between opponent and actor behind opponent	0.303***	0.300***	0.303***	0.303***	0.305***	0.303***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of drivers between opponent and actor behind actor	−0.629***	−0.613***	−0.629***	−0.629***	−0.627***	−0.612***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of drivers between opponent and actor × Distance	−0.012***	−0.012***	−0.012***	−0.012***	−0.012***	−0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distance in focal lap[a]	0.498***	0.499***	0.498***	0.498***	0.499***	0.500***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Position difference[a]	0.025***	0.028***	0.025***	0.025***	0.024***	0.028***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	−0.988***	−1.052***	−0.988***	−0.988***	−0.985***	−1.050***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mills ratio lambda	0.208**	0.189*	0.204**	0.195*	0.200*	0.169*
	−0.008	−0.013	−0.009	−0.013	−0.01	−0.026

Note. $N = 1{,}583{,}317$.

[a]*Distance in focal lap* is an appropriate instrument because lappings require the opponent to be within "striking distance." That is, the opponent must be close enough to the actor to be able to conduct a lapping on the focal lap. Given that a lapping occurs on a focal lap, the distance between the actor and the opponent is no longer strongly predictive of lappings because it then only roughly indicates where on the lap the lapping takes place. The impact of the exact lapping location on the opponent speed is then dependent on the layout of the particular racetrack. *Position difference* is indicative of performance difference, making it more likely for lappings to occur. Given that a lapping occurs, position difference does not strongly affect the degree to which the opponent is obstructed anymore. We conduct a likelihood ratio test of the model containing *Distance in focal lap* and *Position difference* in its selection equation versus one that does not them. The test shows that the just-identified model is nested in the overidentified model, indicating that the included instruments are exogenous. We do not include the number of opponent drivers lapped on the focal lap in the first-stage equation because this variable would almost perfectly predict lappings and would not have temporal precedence. We do not control for *Opponent laps since pit stops* and *Laps since pit stops squared* because these variables are not predictive of lapping in the first stage. The pit stop variables control for the curvilinear performance profile of the opponent's tires affecting his ability to lap the actor more or less quickly. However, the performance profile does not affect the likelihood of a lapping involving a specific actor-opponent dyad. We ran models with and without the pitstop variables with qualitatively equivalent results. Overall, results are largely as expected; in particular, distance and position difference between the actor and the opponent positively predict the likelihood of a lapping.

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

Appendix B. Robustness Tests

We conducted several tests to validate the robustness of our results.

First, we controlled for competitiveness using the Kilduff et al. (2010) measures: "All-time competitiveness index," "Recent competitiveness index," and "Recent margin of victory" at both driver and constructor levels. Our results remained consistent with these controls. See Appendix B.3 for the full results.

Second, we controlled for different versions of status. We measured status as the difference in average driver world championship rank over the last five seasons (or available scores up to the last five seasons). Lower rankings indicate better performance. We calculated the difference between the actor's and opponent's scores, with higher values indicating superior opponent performance. We also used exponential updating based on historical positions and points (see the main analysis for a detailed description). Our main results were consistent regardless of the control variable used. See Appendix B.2 for the full results. We also tested interactions between independent variables and status inferiority. These tests showed an interaction between nonfocal opponent competition and status inferiority.

Third, we examined the impact of "dyad power" by splitting past domain rivalry into two variables: joint centrality (the sum of both parties' centralities) and centrality asymmetry (the difference between the parties' centralities). To measure these variables, we constructed the same dominance network underlying our past domain rivalry variable, but we conceptualized past domain rivalry/centrality asymmetry as the driver's centrality difference in this network and overall joint centrality/dyad power as the driver's sum of centralities. We found that higher opponent centrality relative to the actor led to slower lapping and that overall dyad centrality also led to slower lapping. However, these effects were insignificant when entered in partial models by themselves. See Appendix B.1 for the full results.

Fourth, we coded binary variables to indicate the triad constellation of drivers at the beginning of the focal lapping lap. This allowed us to construct counterfactuals that when controlling for traffic, helped disentangle traffic from nonfocal opponent competition. These tests supported our results and confirmed that traffic impacts our findings (as such, we add a traffic control).

Overall, our results were robust across all tests.

B.1. Robustness Tests Related to Past Domain Rivalry

We test an alternative version of the past domain rivalry variable, namely the power centrality of the opponent minus the power centrality of the actor in the directed race dominance network.

For this robustness test, we split past domain rivalry into two separate variables to test for more differentiated effects of joint centrality (i.e., the sum of the centralities of both parties) and centrality asymmetry (i.e., the difference of the centrality of both parties). To do so, we constructed the same dominance network that we construct for our past domain rivalry variable, but we conceptualized past domain rivalry/centrality asymmetry as the driver's centrality difference in this network and overall joint centrality/dyad power as the driver's sum of centralities.

The exact specifications of the variables are as follows.

Past domain rivalry (Power Centrality Diff). Opponents minus the actor's power centrality in the per-race dominance

Table B.1. Second-Stage Ordinary Least Squares Equation Predicting the Opponent Speed with Different Past Domain Rivalry Measures (Power Centrality)

	Model 1	Model 2	Model 3
Independent variables			
Past domain rivalry (Power Centrality Difference)	0.012		0.155*
	(0.589)		(0.013)
Dyad power (Power Centrality Sum)		−0.009	−0.157*
		(0.697)	(0.014)
Separate domain rivalry	−0.027***	−0.027***	−0.027***
	(0.000)	(0.000)	(0.000)
Nonfocal opponent competition	−0.080**	−0.080**	−0.083**
	(0.004)	(0.004)	(0.003)
Ally's gain	−0.072*	−0.072*	−0.077*
	(0.021)	(0.022)	(0.014)
Constant	335.298***	335.235***	335.340***
	(0.000)	(0.000)	(0.000)
Mills ratio lambda	0.170**	0.171**	0.168**
	(0.003)	(0.003)	(0.003)
Standard controls	Included	Included	Included
Race fixed effects	Yes	Yes	Yes
Actor fixed effects	Yes	Yes	Yes
Opponent fixed effects	Yes	Yes	Yes

Notes. $N = 1{,}583{,}317$. Exact p-values are in parentheses.
$^{*}p = 0.05$; $^{**}p = 0.01$; $^{***}p = 0.001$.

network built within the focal season. A higher value of this variable indicates that the opponent has greater power centrality than the actor.

Dyad power (Power Centrality Sum). Opponents plus the actor's power centrality in the per-race dominance network built within the focal season. A higher value of this variable indicates that the opponent and the actor have a larger joint power centrality/have more power in total.

Indeed, we find a differentiated effect in the expected direction. A higher opponent centrality relative to the actor leads to slower lapping. Overall centrality of the dyad leads to slower lappings. By themselves, however, the effects are insignificant, pointing toward the suitability of a combined variable.

B.2. Robustness Tests Related to Status

We conducted several robustness tests for our status measure, which is a key control. First, we computed measures that conceptualize status as the difference in average driver world championship rank across the last five seasons (or across however many scores up to the last five scores are available). Driver world championship rankings are performance scores where lower rankings (closer to first place) indicate better performance. We then take the difference of scores of the actor minus the opponent such that higher (positive) values of this variable indicate superior performance of the opponent and lower (negative) values indicate superior performance of the actor.

We also computed measures that use exponential updating based on historical positions in the driver world championship ranking and driver world championship points. Using this approach, the status measure for each driver is determined recursively using the following formula:

$$f(P) = u \times p_{t-1} + (u-1) \times f(P = [p_{t-2}, p_{t-3}, \ldots, p_{n-1}, p_n]).$$

P is the vector of performance scores, t is the focal period/season, n is the total number of past periods/seasons for driver i, and u is an updating factor that determines how fast past values decay/how strongly past vectors factor into current status inferiority scores. The update factor u determines how strongly recent values are taken into account. An update factor of 0.5 means that the value of the last season $t-1$ is taken into account by 50% (1/2), $t-2$ is taken into account by $^1/_4$, $t-3$ is taken into account by 1/8, and so on. We tested updating factors of $(1-0.5^{\frac{1}{4}})$ and $(1-0.5^{\frac{1}{2}})$, meaning that the half-life of an observation/the

Table B.2. Second-Stage Ordinary Least Squares Equation Predicting Opponent Speed with Different Status Controls (World Championship (WC) Rank and Points Exponential Updating)

	Model 1	Model 2	Model 3	Model 4	Model 5
Independent variables					
Past domain rivalry	−1.580***	−1.598***	−1.617***	−1.609***	−1.603***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Separate domain rivalry	−0.021***	−0.021***	−0.022***	−0.021***	−0.021***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nonfocal opponent competition	−0.082**	−0.083**	−0.081**	−0.081**	−0.081**
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Ally's gain	−0.074*	−0.073*	−0.073*	−0.073*	−0.073*
	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)
Additional controls					
Status inferiority (WC rank difference exponential updating seasons 0.5 factor)	0.012 (0.141)				
Status inferiority (WC rank difference exponential updating seasons 0.25 factor)		0.014 (0.148)			
Status inferiority (WC point difference all time)			0.000 (0.299)		
Status inferiority (WC point difference exponential updating seasons 0.5 factor)				0.000 (0.127)	
Status inferiority (WC point difference exponential updating seasons 0.25 factor)					0.000 (0.102)
Constant	335.089***	335.107***	334.948***	334.887***	334.871***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mills ratio lambda	−0.146***	−0.148***	−0.152***	−0.151***	−0.151***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Standard controls	Included	Included	Included	Included	Included
Race fixed effects	Yes	Yes	Yes	Yes	Yes
Actor fixed effects	Yes	Yes	Yes	Yes	Yes
Opponent fixed effects	Yes	Yes	Yes	Yes	Yes

Notes. N = 1,583,317. Exact p-values are in parentheses.
*p = 0.05; **p = 0.01; ***p = 0.001.

Table B.3. Second-Stage Ordinary Least Squares Equation Predicting Opponent Speed with Different Status Controls (World Championship (WC) Rank Averages)

	Model 1	Model 2	Model 3
Independent variables			
Past domain rivalry	−1.627***	−1.480***	−1.613***
	(0.000)	(0.000)	(0.000)
Separate domain rivalry	−0.020***	−0.018***	−0.022***
	(0.000)	(0.000)	(0.000)
Nonfocal opponent competition	−0.080**	−0.082**	−0.082**
	(0.004)	(0.003)	(0.003)
Ally's gain	−0.076*	−0.075*	−0.073*
	(0.014)	(0.015)	(0.018)
Additional controls			
Status inferiority (WC rank difference average across 100 races)	0.026*		
	(0.013)		
Status inferiority (WC rank difference average across 50 races)		0.037***	
		(0.000)	
Status inferiority (WC rank difference average across 5 seasons)			0.004
			(0.630)
Constant	334.476***	334.441***	335.080***
	(0.000)	(0.000)	(0.000)
Mills ratio lambda	−0.142**	−0.137**	−0.150***
	(0.001)	(0.002)	(0.001)
Standard controls	Included	Included	Included
Race fixed effects	Yes	Yes	Yes
Actor fixed effects	Yes	Yes	Yes
Opponent fixed effects	Yes	Yes	Yes

Notes. $N = 1{,}583{,}317$. Exact p-values are in parentheses.
$^*p = 0.05$; $^{**}p = 0.01$; $^{***}p = 0.001$.

Table B.4. Second-Stage Ordinary Least Squares Equation Predicting Opponent Speed with Different Status Controls (Lapping-Based Measures)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Independent variables						
Past domain rivalry	−1.305***	−1.168***	−1.309***	−1.171***	−1.307***	−1.167***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Separate domain rivalry	−0.021***	−0.022***	−0.021***	−0.022***	−0.021***	−0.022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nonfocal opponent competition	−0.081**	−0.084**	−0.082**	−0.085**	−0.082**	−0.084**
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Ally's gain	−0.067*	−0.070*	−0.067*	−0.070*	−0.067*	−0.070*
	(0.030)	(0.023)	(0.031)	(0.024)	(0.031)	(0.023)
Additional controls						
Status inferiority (log)	0.246***		0.244***			
	(0.000)		(0.000)			
Status inferiority (count)		0.065***		0.064***		
		(0.000)		(0.000)		
Status superiority (log)			−0.316			
			(0.392)			
Status superiority (count)				−0.172		
				(0.388)		
Status inferiority superiority difference (log)					0.245***	
					(0.000)	

Table B.4. (Continued)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Status inferiority superiority difference (count)						0.065*** (0.000)
Constant	334.108*** (0.000)	334.466*** (0.000)	334.132*** (0.000)	334.480*** (0.000)	334.123*** (0.000)	334.468*** (0.000)
Mills ratio lambda	−0.119** (0.008)	−0.129** (0.004)	−0.118** (0.008)	−0.128** (0.004)	−0.118** (0.008)	−0.128** (0.004)
Standard controls	Included	Included	Included	Included	Included	Included
Race fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Actor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Opponent fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes. $N = 1{,}583{,}317$. Exact p-values are in parentheses.
$^{*}p = 0.05$; $^{**}p = 0.01$; $^{***}p = 0.001$.

number of seasons required for the weight of a season driver world championship ranking to be reduced by half is four seasons and two seasons, respectively. Because this measure is based on the same difference in world championship rank between the actor and the opponent, this variable can be interpreted in the same way as the average world championship rank measure. As such, significant positive coefficients in the second-stage equation

Table B.5. Second-Stage OLS Equation Predicting Opponent Speed with Competitiveness Controls

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Independent variables							
Past domain rivalry	−1.643*** (0.000)	−1.578*** (0.000)	−1.380*** (0.000)	−1.075*** (0.000)	−1.807*** (0.000)	−1.821*** (0.000)	−1.191*** (0.000)
Separate domain rivalry	−0.021*** (0.000)	−0.021*** (0.000)	−0.021*** (0.000)	−0.017*** (0.000)	−0.021*** (0.000)	−0.021*** (0.000)	−0.018*** (0.000)
Nonfocal opponent competition	−0.074** (0.008)	−0.072** (0.010)	−0.072** (0.010)	−0.062* (0.025)	−0.072** (0.009)	−0.072** (0.009)	−0.073** (0.009)
Ally's gain	−0.073* (0.019)	−0.074* (0.017)	−0.074* (0.017)	−0.077* (0.013)	−0.077* (0.013)	−0.077* (0.013)	−0.081** (0.009)
Additional controls							
Constructor competitiveness (all time)		−0.722** (0.004)					
Constructor competitiveness (60 races)			−1.459*** (0.000)				
Constructor margin of victory (60 races)				0.116*** (0.000)			
Driver competitiveness (all time)					0.221 (0.298)		
Driver competitiveness (60 races)						0.252 (0.238)	
Driver margin of victory (60 races)							0.082*** (0.000)
Constant	334.878*** (0.000)	335.297*** (0.000)	335.188*** (0.000)	334.504*** (0.000)	334.521*** (0.000)	334.516*** (0.000)	333.720*** (0.000)
Mills ratio lambda	0.169** (0.003)	0.186** (0.001)	0.191*** (0.001)	0.204*** (0.000)	0.153** (0.007)	0.155** (0.007)	0.175** (0.002)
Standard controls	Included	Included	Included	Included	Included	Included	Included
Race fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Actor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Opponent fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. $N = 1{,}583{,}317$. Exact p-values are in parentheses.
$^{*}p = 0.05$; $^{**}p = 0.01$; $^{***}p = 0.001$.

for these variables indicate that greater status superiority of the opponent over the actor increases lapping speed/ deference as expected.

All variables are calculated based on the past seasons, so no information of the focal season is used in any of the variables. Because of this, using this variable would have resulted in the deletion of all observations of drivers completing their first season, which would have reduced our analyses' power and may have biased results. For a driver's first season, we computed variables on the constructor level. As such, the driver's missing rank variable (before taking the difference) is replaced by the running five-season average of the average world championship rank across the focal driver's constructors' drivers. If this variable is also missing (because it is the focal team's first season), the variable is computed across the entire field. In that case, the driver rank is replaced by the average driver rank in the prior season.

We tested various variables that conceptualize status as the exponential updating version of performance that more strongly takes past performance into account. Interestingly, the variables are significant in the partial models (see the main analysis in the article) but not in the full models, suggesting that taken together, the rivalry and stake factors appear to overshadow the main association between status and deference. We also computed versions of the variables where we conducted exponential updating on a per-race and not per-season basis that takes more recent results more strongly into account (not reported here). Our main results remain qualitatively equivalent regardless of the type of control variable we use. In the main analysis, we choose the control that captures longer-term status effects because they were most in line with the definition of status.

We also computed tested status variables that conceptualize status by past performance more directly. First, we use the actor minus the opponent difference in driver world championship rank over the past 50 and 100 races and the past five seasons at the beginning of the focal race (because smaller ranks are better, a higher value of this variable indicates the opponent's superior world championship rank).

Finally, we conceptualized a third set of variables that conceptualized status by the number of lappings of a focal actor by his opponent from the beginning of the focal season to the focal lap. We logged this count (after adding one) to account for a diminishing effect of multiple lappings over time but also tested an unlogged version. Additionally, we created a status superiority measure, measuring lappings of the focal opponent by the actor that we entered separately. Lastly, we tested a combined measure where we subtracted status superiority from status inferiority, again testing both logged and unlogged versions.

Tables B.2–B.4 contain the three sets of additional models. Our results hold across all tests.

B.3. Addition of Controls Related to Competitiveness

We conducted a test of the robustness of our results to the competitiveness dimensions. For this robustness test, we coded versions of the Kilduff et al. (2010) measures for "All-time competitiveness index," "Recent competitiveness index," and "Recent margin of victory" in data (both on a driver level (competitiveness of drivers) and on a constructor level (competitiveness of constructors)).

B.3.1. Driver-Level Variables.

1. *Driver competitiveness (all time)*. The share of all past races where the actor and the opponent jointly competed and the weaker driver of the two had a better finishing rank. For example, if of 10 races where the actor and the opponent competed, the opponent finished before the actor in 8 races, this variable would be 0.2. If the actor had finished before the opponent in six races, this variable would be 0.4. As such, a higher variable (closer to 0.5) indicates greater competition.

2. *Driver competitiveness (60 races)*. This is the same as *Driver competitiveness (all time)*, but only the past 60 races (approximately the past three seasons/years) in which the actor and the opponent both competed are considered.

3. *Driver margin of victory (60 races)*. The running mean of the absolute difference between the actor's finish rank and the opponent's finish rank for the past 60 races (approximately the past three seasons/years). As such, a higher value of this variable indicates lower competition.

B.3.2. Constructor-Level Variables. These variables are constructed in the same fashion as driver variables, but as the underlying data, average team-level finishing ranks of the actor's and the opponent's constructors are used.

1. *Constructor competitiveness (all time)*. The share of all past races where at least one driver of the actor's and the opponent's constructors jointly competed and the stronger constructor of the two had a better finishing rank. As such, a higher variable (closer to 0.5) indicates greater competition.

2. *Constructor competitiveness (60 races)*. This is the same as *Constructor competitiveness (all time)*, but only the past 60 races (approximately the past three seasons/years) in which the actor and the opponent both competed are considered.

3. *Constructor margin of victory (60 races)*. The running mean of the absolute difference between the actor's and the opponent's constructor (average driver) finish rank for the past 60 (approximately the past three seasons/years) races. As such, a higher value of this variable indicates lower competition.

Including these competitiveness controls produces qualitatively equivalent results. When these variables are significant, it is in the expected directions (negative for competitiveness and positive for the margin of victory variables).

Endnotes

[1] Although our empirical context concerns only male contenders, we generally use "they" and "their" as the neutral pronoun to avoid gender-specific characterizations. However, when referring to our empirical context, we use "he" and "his" because only men drove Formula One cars during our observation period.

[2] The lappings are conducted in pairs of 51 unique lapping opponents and 60 unique lapped actors (overall, 62 unique drivers) in 951 unique (directed) lapping dyads across 175 unique F1 Grands Prix.

[3] Status characterizes the accumulated perceptions of superiority of an actor relative to others that provide this actor with symbolic and material advantages (Berger et al 1998, Podolny 2005).

[4] In strategy, Mawdsley et al (2023, p. 1256) define rivals as "those competitors that a firm considers as worthy of greater strategic attention and with which service substitutability is the highest."

[5] Lappings occur because one driver and his car are superior to another, but they can also occur because of accidents, severe weather, or a driver making a pit stop to change tires. We exclude the latter events from our cases.

[6] The safety car is much slower than an F1 car, and drivers are not allowed to overtake it or each other until the safety-car phase ends. Thus, in safety-car laps, the drivers draw closer to each other. Once the debris caused by the accident has been removed or the weather improves and the race can continue safely, the safety car leaves the track.

[7] Note that we account econometrically for the rare events in which (a) an opponent lapped multiple actors in a lap and (b) a focal actor is lapped by multiple opponents.

[8] The source data contain lap timings in seconds. For ease of interpretation, we convert this measure (by which more seconds signal lower deference) into average race speeds (so that a higher speed signals greater deference) by dividing the length of the focal racetrack by the observed lap time (in seconds) for each lapping and multiplying the result by 3,600. The result is average race speed in kilometers per hour.

[9] We test an alternative version of this variable. For this test, we computed the power centrality of the opponent minus the power centrality of the actor in the directed race dominance network. To estimate this variable, we first construct a square dominance matrix $\boldsymbol{X}$, wherein each entry x_{ij} details the victories of driver i over driver j in all prior races of the focal season. This matrix represents a directed network of dominance relationships, with x_{ij} representing a directed tie between i and j with weight x_{ij}. In this matrix, we calculate the Bonacich power centralities for each possible driver combination i and j. We set the decay rate to one. Then, we subtract the power centrality of the actor from that of the opponent. If the resulting value is positive, this indicates that the opponent occupies a better, more central, more powerful position in the season-race-level dominance matrix at the beginning of the focal race. We also test a version where we add both the power centrality sum and difference simultaneously (see the appendix for detailed results).

[10] In seasons before 2010, F1 cars were allowed to refuel during pit stops. However, refueling was banned at the end of the 2009 season to increase safety. Thus, in our data, this variable controls for the fact that speeds tend to increase monotonically during the race.

[11] First, we use the actor minus opponent difference in driver world championship rank over the past 50 and 100 races at the beginning of the focal race (because smaller ranks are better, a higher value of this variable indicates the opponent's superior world championship rank). Second, we test versions of world championship rank and world championship point-based measures that apply exponential decay to weight more recent data more strongly. Third, we count the lappings of a focal actor by his opponent from the beginning of the focal season to the focal lap. We logged this count (after adding one) to account for a diminishing effect of multiple lappings over time but also tested an unlogged version. Additionally, we created a status superiority measure, measuring lappings of the focal opponent by the actor that we entered separately. Lastly, we tested a combined measure where we subtracted status superiority from status inferiority, again testing both logged and unlogged versions. Results are qualitatively equivalent across all tests.

[12] Heckman models can be estimated using a maximum likelihood estimator (MLE) method as well as a two-step estimator. The MLE method is more efficient and less noisy if multivariate normality of the error terms is given. However, it imposes the extra assumption that the error terms are independent of (x, z) and has a normal distribution, whereas the two-step estimator method only assumes univariate normality of the marginal distribution (Wooldridge 2002, p. 632). As a result, the two-step estimator method is expected to be more robust, and it may be preferred for exploring large data sets.

[13] We tested whether adding additional variables that do not predict lapping in the first stage (the independent variables and the number of laps since pitstop (and the number of laps since pitstop squared)) alter second-stage results, which they did not. Therefore, we exclude those from the first equation (see Figure 2).

[14] Note that one-way clustering, two-way clustering, and three-way clustering of standard errors on the level of the opponent, the actor, and the race yield qualitatively equivalent results. However, three-way clustering resulted in variance-covariance matrices with negative eigenvalues for some models. We, therefore, report models (Table 2) with two-way clustering on the opponent and the actor.

References

Askin N, Bothner MS (2016) Status-aspirational pricing: The "Chivas Regal" strategy in US higher education, 2006–2012. *Admin. Sci. Quart.* 61(2):217–253.

Aversa P, Furnari S, Haefliger S (2015) Business model configurations and performance: A qualitative comparative analysis in Formula One racing, 2005–2013. *Indust. Corporate Change* 24(3):655–676.

Baum JAC, Mezias SJ (1992) Localized competition and organizational failure in the Manhattan hotel industry, 1898–1990. *Admin. Sci. Quart.* 37(4):580–604.

Benjamin BA, Podolny JM (1999) Status, quality, and social order in the California wine industry. *Admin. Sci. Quart.* 44(3):563–589.

Berger J, Ridgeway CL, Fisek MH, Norman RZ (1998) The legitimation and delegitimation of power and prestige orders. *Amer. Sociol. Rev.* 63(3):379–405.

Bothner MS, Kang JH, Stuart TE (2007) Competitive crowding and risk taking in a tournament: Evidence from NASCAR racing. *Admin. Sci. Quart.* 52(2):208–247.

Bothner MS, Kim YK, Smith EB (2012) How does status affect performance? Status as an asset vs. status as a liability in the PGA and NASCAR. *Organ. Sci.* 23(2):416–433.

Carroll GR, Hannan MT (2000) Why corporate demography matters: Policy implications of organizational diversity. *Calif. Management Rev.* 42(3):148–163.

Carroll GR, Swaminathan A (2000) Why the microbrewery movement? Organizational dynamics of resource partitioning in the US brewing industry. *Amer. J. Sociol.* 106(3):715–762.

Castellucci F, Ertug G (2010) What's in it for them? Advantages of higher-status partners in exchange relationships. *Acad. Management J.* 53(1):149–166.

Castellucci F, Podolny JM (2017) The dynamics of position, capability, and market competition. *Indust. Corporate Change* 26(1):21–39.

Cattani G, Ferriani S, Allison PD (2014) Insiders, outsiders, and the struggle for consecration in cultural fields: A core-periphery perspective. *Amer. Sociol. Rev.* 79(2):258–281.

Certo ST, Busenbark JR, Woo HS, Semadeni M (2016) Sample selection bias and Heckman models in strategic management research. *Strategic Management J.* 37(13):2639–2657.

Clough DR, Piezunka H (2020) Tie dissolution in market networks: A theory of vicarious performance feedback. *Admin. Sci. Quart.* 65(4):972–1017.

Collantine K (2016) 2016 Japanese Grand Prix team radio transcript. *Racefans* (October 17), https://www.racefans.net/2016/10/17/2016-japanese-grand-prix-team-radio-transcript/.

Converse BA, Reinhard DA (2016) On rivalry and goal pursuit: Shared competitive history, legacy concerns, and strategy selection. *J. Personality Soc. Psych.* 110(2):191–213.

Coser LA (1961) The termination of conflict. *J. Conflict Resolution* 5(4):347–353.

De Sousa J, Hollard G (2023) From micro to macro gender differences: Evidence from field tournaments. *Management Sci.* 69(6): 3358–3399.

Durand R (2006) *Organizational Evolution and Strategic Management* (Sage Publishers, London).

Durand R, Kremp PA (2016) Classical deviation: Organizational and individual status as antecedents of conformity. *Acad. Management J.* 59(1):65–89.

Faris R, Felmlee D, McMillan C (2020) With friends like these: Aggression from amity and equivalence. *Amer. J. Sociol.* 126(3): 673–713.

FIA (2020a) Appendix H to the International Sporting Code. *FIA* (October 3), https://www.fia.com/sites/default/files/appendix_h_2020_published_10_03_2020.pdf.

FIA (2020b) Appendix L to the International Sporting Code. *FIA* (June 20), https://www.fia.com/sites/default/files/appendix_l_2020_publie_le_20_juin_2020.pdf.

Fisher B (2018) F1: Lewis Hamilton wins the Singapore Grand Prix—As it happened. *Guardian* (September 16), https://www.theguardian.com/sport/live/2018/sep/16/f1-singapore-grand-prix-live.

Fonti F, Ross J-M, Aversa P (2023) Using sports data to advance management research: A review and a guide for future studies. *J. Management* 49(1):325–362.

Formula1.com (2018) Grosjean closer to race ban after Singapore blue-flag penalty. (September 17), https://www.formula1.com/en/latest/article/grosjean-closer-to-race-ban-after-singapore-blue-flag-penalty.6k8oYb6W76UuYkuG468sAS.

Fragale AR, Sumanth JJ, Tiedens LZ, Northcraft GB (2012) Appeasing equals: Lateral deference in organizational communication. *Admin. Sci. Quart.* 57(3):373–406.

Freeland RE, Hoey J (2018) The structure of deference: Modeling occupational status using affect control theory. *Amer. Sociol. Rev.* 83(2):243–277.

Gaessler F, Piezunka H (2023) Training with AI: Evidence from chess computers. *Strategic Management J.* 44(11):2724–2750.

Gneezy U, Niederle M, Rustichini A (2003) Performance in competitive environments: Gender differences. *Quart. J. Econom.* 118(3): 1049–1074.

Goffman E (1956) The nature of deference and demeanor. *Amer. Anthropologist* 58(3):473–502.

Gould RV (2003) *Collision of Wills: How Ambiguity About Social Rank Breeds Conflict* (University of Chicago Press, Chicago).

Grohsjean T, Piezunka H, Mickeler M (2024) When colleagues compete outside the firm. *Strategic Management J.* Forthcoming.

Grohsjean T, Kober P, Zucchini L (2016) Coming back to Edmonton: Competing with former employers and colleagues. *Acad. Management J.* 59(2):394–413.

Hahl O, Zuckerman EW (2014) The denigration of heroes? How the status attainment process shapes attributions of considerateness and authenticity. *Amer. J. Sociol.* 120(2):504–554.

Hallila P, Frankort HT, Aversa P (2024) Revving up or backing down? Cross-level effects of firm-level tournaments on employees' competitive actions. *Acad. Management J.*, ePub ahead of print January 18, https://doi.org/10.5465/amj.2022.0946.

Han JY, Shipilov AV, Greve HR (2017) Unequal bedfellows: Gender role-based deference in multiplex ties between Korean business groups. *Acad. Management J.* 60(4):1531–1553.

Heckman JJ (1979) Sample selection bias as a specification error. *Econometrica* 47(1):153–161.

Henrich J, Gil-White FJ (2001) The evolution of prestige: Freely conferred deference as a mechanism for enhancing the benefits of cultural transmission. *Evolution Human Behav.* 22(3):165–196.

Jansen M, Pierce L, Snyder J, Nguyen H (2024) Product sales incentive spillovers to the lending market: Evidence from subprime auto loan defaults. *Management Sci.* 70(8):5463–5480.

Joshi A, Knight AP (2015) Who defers to whom and why? Dual pathways linking demographic differences and dyadic deference to team effectiveness. *Acad. Management J.* 58(1):59–84.

Jourdan J, Durand R, Thornton PH (2017) The price of admission: Organizational deference as strategic behavior. *Amer. J. Sociol.* 123(1):232–275.

Kilduff GJ (2014) Driven to win: Rivalry, motivation, and performance. *Social Psych. Personality Sci.* 5(8):944–952.

Kilduff GJ, Elfenbein HA, Staw BM (2010) The psychology of rivalry: A relationally dependent analysis of competition. *Acad. Management J.* 53(5):943–969.

Kilduff GJ, Galinsky AD, Gallo E, Reade JJ (2016) Whatever it takes to win: Rivalry increases unethical behavior. *Acad. Management J.* 59(5):1508–1534.

Kilduff M, Wang K, Lee SY, Tsai W, Chuang YT, Tsai FS (2024) Hiding and seeking knowledge-providing ties from rivals: A strategic perspective on network perceptions. *Acad. Management J.*, ePub ahead of print January 4, https://doi.org/10.5465/amj.2022.0091.

Kreager DA (2007) Unnecessary roughness? School sports, peer networks, and male adolescent violence. *Amer. J. Sociol.* 72(5):705–724.

Lynn FB, Podolny JM, Tao L (2009) A sociological (de)construction of the relationship between status and quality. *Amer. J. Sociol.* 115(3):755–804.

Malhotra D (2010) The desire to win: The effects of competitive arousal on motivation and behavior. *Organ. Behav. Human Decision Processes* 111(2):139–146.

Marino A, Aversa P, Mesquita L, Anand J (2015) Driving performance via exploration in changing environments: Evidence from Formula One racing. *Organ. Sci.* 26(4):1079–1100.

Mawdsley JK, Paolella L, Durand R (2023) A rivalry-based theory of gender diversity. *Strategic Management J.* 44(5):1254–1291.

Medland C (2020) 2020 Turkish Grand Prix report: Hamilton's sensational win clinches 7th F1 title. *Motorsport* (November 15), https://www.motorsportmagazine.com/articles/single-seaters/f1/2020-turkish-grand-prix-report-sensational-hamilton-victory-to-clinch-7th-title.

Naumovska I, Lavie D (2021) When an industry peer is accused of financial misconduct: Stigma vs. competition effects on non-accused firms. *Admin. Sci. Quart.* 66(4):1130–1172.

Operti E, Lampronti SY, Sgourev SV (2020) Hold your horses: Temporal multiplexity and conflict moderation in the Palio di Siena (1743–2010). *Organ. Sci.* 31(1):85–102.

Piazza A, Bergemann P, Helms W (2024) Getting away with it (or not): The social control of organizational deviance. *Acad. Management J.* 49(2):249–272.

Pierce JR, Kilduff GJ, Galinsky AD, Sivanathan N (2013) From glue to gasoline: How competition turns perspective takers unethical. *Psych. Sci.* 24(10):1986–1994.

Piezunka H, Lee W, Haynes R, Bothner MS (2018) Escalation of competition into conflict in competitive networks of Formula One drivers. *Proc. Natl. Acad. Sci. USA* 115(15):E3361–E3367.

Podolny JM (2005) *Status Signals: A Sociological Study of Market Competition* (Princeton University Press, Princeton, NJ).

Porac JF, Thomas H, Baden-Fuller C (1989) Industries as cognitive communities: The case of Scottish knitwear manufacturers. *J. Management Stud.* 26:397–416.

Racing Elite (2019) REVEALED: 2019 F1 driver salaries—Who is the richest F1 driver? Accessed March 4, 2023, https://racing-elite.com/2019/01/19/revealed-2019-f1-driver-salaries-who-is-the-richest-f1-driver/.

Rencken D, Collantine K (2018) Grosjean accepts some of his penalty points are deserved. (November 5), https://www.racefans.net/2018/11/05/grosjean-admits-some-of-his-penalty-points-are-deserved/.

Rushing WA (1962) Social influence and the social-psychological function of deference: A study of psychiatric nursing. *Soc. Forces* 41(2):142–148.

Saccardo S, Pietrasz A, Gneezy U (2018) On the size of the gender difference in competitiveness. *Management Sci.* 64(4):1541–1554.

Sgourev SV, Operti E (2019) From Montagues to Capulets: Analyzing the systemic nature of rivalry in career mobility. *Acad. Management J.* 62(5):1333–1357.

Smith C (2019) Formula One's most valuable teams. *Forbes* (November 26), https://www.forbes.com/sites/chrissmith/2019/11/26/formula-one-team-values-ferrari-mercedes/#248315e1ddb5.

Soule SA, King BG (2008) Competition and resource partitioning in three social movement industries. *Amer. J. Sociol.* 113(6):1568–1610.

Sytch M, Tatarynowicz A (2013) Friends and foes: The dynamics of dual social structures. *Acad. Management J.* 57(2):585–613.

Thatchenkery S, Piezunka H (2025) Competition in collaboration: The problem of (mis) aligned perception. *Admin. Sci. Quart.* Forthcoming.

Thomas A, Piezunka H, Dahlander L (2024) Outshining your rival: Interpersonal rivalry and its effects on organizational contributions. The Wharton School Research paper, University of Pennsylvania, Philadelphia.

To C, Kilduff GJ, Rosikiewicz BL (2020) When interpersonal competition helps and when it harms: An integration via challenge and threat. *Acad. Management Ann.* 14(2):908–934.

To C, Kilduff GJ, Ordoñez L, Schweitzer ME (2018) Going for it on fourth down: Rivalry increases risk taking, physiological arousal, and promotion focus. *Acad. Management J.* 61(4):1281–1306.

Vaughan L, Romero-Frías E (2014) Web search volume as a predictor of academic fame: An exploration of Google trends. *J. Assoc. Inform. Sci. Tech.* 65(4):707–720.

Velasco P (2020) Binotto: To be lapped is very painful for us and our fans. *GP Today* (July 19), http://www.gptoday.com/full_story/view/726805/BinottoTo_be_lapped_is_very_painful_for_us_and_our_fans/.

Willer R, Sharkey A, Frey S (2012) Reciprocity on the hardwood: Passing patterns among professional basketball players. *PLoS One* 7(12):e49807.

Wooldridge JM (2002) *Econometric Analysis of Cross Section and Panel Data* (MIT Press, London).

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