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Don’t Put All Your Legs in One Basket: Theory and Evidence on Coopetition in Road Cycling

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Theory and Evidence on Coopetition in Road Cycling

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Abstract

Road cycling races, although won by individual riders, are a competition of teams. Riding behind other riders significantly reduces the energy required to hold a given speed. These races thus provide free-riding incentives. We introduce a game-theoretic framework of this strategic setup to analyze a team's winning probability in various race situations and to examine group characteristics facilitating coordination. We complement our theoretical results with an empirical analysis using data from more than 40 seasons of professional road cycling races. Our model suggests that asymmetry in rider strength or team strength within a group is favorable for group coordination. Also, adding teammates to competing groups is beneficial because it leads to strategic benefits, increasing the free-riding opportunities in both groups. We find empirical evidence that a teammate in a group behind has a positive impact on win probability, indicating that such an effect indeed exists.

JEL codes: D74,Z20,C79

Keywords: Coopetition; Free-riding; Diversification; Coordination; Sports Economics

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1 Introduction

Road cycling is an endurance sport so strategically rich, it is sometimes even referred to as *chess on wheels*. This is the consequence of the interplay of a) the possibility of free-riding and b) the fact that while individual riders win races, those riders are organized in teams. Free-riding incentives exist because riding behind other riders, a practice referred to as *drafting* or *slipstreaming*, significantly reduces required energy to hold a given speed (up to 40 per cent, see for example Dilger & Geyer (2009)). Consequently, cycling races naturally feature the formation of groups[1] on the road. Individual riders find it challenging to break away from a group, and a well-coordinated large group can either distance itself from or catch up with a smaller group, provided proper coordination (with members taking turns at the front) is maintained. The riders therefore face a *coopetition*-problem: Riders have an interest to cooperate within their group early in the race, but will eventually compete against their group members at some later point.

The coopetition problem has seen considerable attention (introduced by Brandenburger & Nalebuff (2011), for a review see Gernsheimer et al. (2021)) and has also been addressed specifically for effort allocation in simultaneous inter- and intra-group competition (see Münster (2007)). What distinguishes the coopetition dynamics in cycling is that the individual riders are organized in teams, adding layers of strategic complexity. Each racing team comprises several riders with varying individual capabilities. Riders are connected to their team manager in a car following the race via radio at all times, making each team act as a strategic unit. This adds an interesting component to the coopetition dynamics: Heterogeneity among competitors exists along two dimensions, in that competitive advantage can be attained by being stronger, or having more (stronger) teammates available to control the race situation. It is also unclear how teammates are best used strategically! "Using" a teammate to catch a group benefits all members of that group irrespective of their team. One of the interesting questions we can answer with our model is the marginal utility of adding a teammate to a riders group or, alternatively, to a competing group, where the teammate constitutes an exogenous threat.

To our knowledge, this paper is the first to model this strategic setup as a normal-form game. This enables us to make a twofold contribution: Firstly, we provide new results on the dynamics shaping the outcomes of high-stakes professional road cycling races.[2] Secondly, we offer fundamental

[1] We define teams as a set of riders that belong to the same team and groups as a set of riders that rides within a short distance at a respective point in time. Groups might thus consist of riders from various teams.

[2] The sport has evolved into a more tactically sophisticated realm since the media outcry following the release of the Netflix documentary "The Least Expected Day", which exposed the tactical shortcomings of certain cycling

theoretical insights into the interaction between free-riding and diversification in the context of competing public goods: The benefit reaped by diversifying between bets on mutually exclusive events exceeds mere reduction of outcome uncertainty when the process determining the outcome requires ongoing effort from the involved parties.

An exhaustive equilibrium analysis of a multi-hour bike race certainly exceeds the scope of a game-theoretic examination. Instead, we address one specific question teams face in the final part of a race: What value (in terms of win-probability) does a team gain by adding another rider to either the leading or chasing group? To shed light on this, we explore a related question: What group dynamics indicate effective coordination, enabling groups to either maintain distance from or close the gap with other groups? We model the situations of interest as one-shot positioning games with win probabilities as payoffs, featuring players (the teams) with multi-dimensional action spaces (one action per rider), representing pacing strategies of the riders. We assume each rider has an exogenously assigned level of energy at their disposal for the entirety of the race and is fully controlled by his team. The setup of the race is captured by tracking the positions and energy levels of each individual rider. A rider's actions in the game cost a certain amount of energy, and a team's win probability in the sprint is proportional to the remaining energy of their strongest rider in the first group of the race.[3]

Although our modeled one-period simultaneous-move games may appear limiting, road cycling races often hinge on split-second decisions[4] at pivotal race segments familiar to all riders.[5] These critical junctures may occur just before the final sprint or earlier, such as at the conclusion of the race's final climb, after which the formed groups proceed to the sprint. Notably, cycling teams strategically compose their line-ups based on race course profiles[6] and brief their riders before a race on optimal behavior in possible scenarios that may arise at these critical moments beforehand (Croxton (2023)), justifying our approach of focusing on one period only.

We document the following theoretical findings: In order for a group to *coordinate* well, there needs to be consensus about who is required to exert the most effort by riding at the front. One thing that leads to such consensus in the final phase of the race is what we will call *asymmetry* in

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teams.

[3]We will discuss why we choose to have one designated sprinter per team in Section 2.

[4]The benefit of following a decisive attack only exists when the decision to follow is made simultaneously with the other rider's decision to attack.

[5]The most famous example is the almost 300km long one-day race Milan-San Remo, which is notoriously boring until riders try to break away at the steep section of the Poggio, the six-minute long final climb of the race starting only 10km from the finish.

[6]Refer to Appendix C for a case study of how Team Alpecin-Deceuninck used Mathieu van der Poel and Jasper Philipsen in order to maximize free-riding in the 2024 classics season.

a group. Individual capacity disparities, particularly when one rider stands out as the strongest, naturally designate him to lead the group. Similarly, team strength imbalances can dictate group dynamics. If one team has several riders in a group, they can afford to sacrifice riders with minimal costs, given that only their strongest rider is expected to compete in the sprint, prompting the group to demand that team to take the lead. From a team's standpoint, this finding underscores the strategic advantage of having riders spread across competing groups over concentrating them in a single group, surpassing mere diversification. If indeed a team has riders in several groups, each of there riders benefits from their teammate serving as an outside option, reducing the respective stakes in the success in the inter-group competition and thus enhancing free-riding opportunities in that group. This effect stands out even more because placing several riders in one group may prove detrimental to a team. For instance, if Team A dominates a group with multiple riders while other teams have individually stronger but only one rider, there is consensus on Team A bearing the burden of leading the group. Although this may lead to successful coordination within the group, all group members, not just Team A's, reap the benefits. Conversely, if Team A had only one rider, the burden would shift to the strongest rider of the group, aligning with Team A's strategic interests of saving comparably more energy than the in-group opponents.

Our theoretical analysis is complemented by empirical findings supporting our propositions. We use results data from real, high-stakes professional cycling races, which we collected from ProCyclingStats.com, one of the largest online databases for cycling data. The dataset consists of stage results from over 40 seasons of the three Grand Tours (three-week stage races) and eight one-week stage races, as well as final results from eight one-day races in the same seasons. We identify races that were decided between small groups of riders and run fixed-effects regressions to discern the characteristics associated with finishing in the front group and winning the race, respectively. Examining the properties of groups that finish together reveals intriguing insights. Despite the considerable benefits of riding in a group, it is remarkable that many cycling races are won by a single rider with a significant gap over a chasing group. By comparing groups that finish together in a sprint with those trailing behind a solo winner or scattered groups in close proximity at the finish, we gain insights into the group dynamics that foster coordination. Consistent with our hypotheses, our analysis indicates that a group is more likely to stay together when comprised of multiple riders from the same team, indicating that asymmetry in the number of teammates positively affects coordination. Furthermore, our empirical examination of win frequencies aligns with our theoretical expectations. Notably, we find that having a teammate in the first[7] or particularly in the second group increases the win probability of a rider in the first group, highlighting the beneficial impact of teammates within the same group and especially of teammates in the group behind. This latter effect is in line with our theoretical predictions, remarkably robust, and somewhat surprising.

While our model is specific to road cycling, our insights and methods translate to other dynamic coopetition problems which allow for free-riding and strategic division of effort. To illustrate our main finding, the strategic benefit from diversification, in a setting other than cycling races, consider, for instance, the following setup: Two PhD students are about to enter the job market while jointly working on a research project and applying for the same faculty position. Imagine that student A has diversified and is part of a second project with some other co-workers, while student B solely relies on the joint project to demonstrate his skills. Our model then predicts that student A does not simply benefit from diversification itself[8] but also has a strategic benefit from starting a second project: By creating an outside option, student A is forcing student B to take the lead and allowing herself to benefit from an increased free-riding opportunity. Similar considerations hold in other situations like patent races, competition for research grants, political competition[9] or financing of startups.[10]

We proceed by discussing the literature on contests, coordination problems, and sports economics. Section 2 introduces our theoretical model, while Section 3 illustrates the main principles by guiding through simple examples. Subsequently, Section 4 translates these principles into more general theoretical results. Sections 5 and 6 are dedicated to developing and executing an empirical strategy to provide evidence for our theoretical results. Finally, Section 7 concludes.

1.1 Related Literature

We contribute to several strands of literature.

Firstly, we contribute to the literature on cooperation and social dilemmas (for a survey, see Gorman (2014)). Specifically, we add empirical evidence on equilibrium selection in coordination

[7]It is also important to realize that teammates within groups serve more complicated roles than can be expressed within our model: They might help each other out with supplies if one of them runs out or simply provide psychological relief.

[8]Diversification often comes with a decreased risk of total failure or loss and an increased chance of (any) success. It is especially beneficial to risk-averse subjects.

[9]Here, we think about a coopetition problem where different parties must work together in a coalition (where free-riding is possible) and at the same time cooperate in order to win against a competing group, the opposition. Here, diversification, in the sense of "flirting" with the opposition, might also lead to strategic benefits in the coalition.

[10]Having teammates that can be placed in competing groups is analogous to placing effort or money in competing projects.

games with heterogeneous players. Closest to us is Brouwer & Potters (2019) who model the coordination problem within the front group of a cycling race as a threshold public goods game, but refraining from explicitly modelling the strategies of individual teams. Gavrilets (2015) offers a comprehensive review about the collective action literature with heterogeneity, notably showing that the largest contributors towards production of collective goods (on our case offering slipstream to other group members) are typically group members with the highest stake in the game (in our case the strongest team according to some definition of strength). Also related are Attanasi et al. (2016) and Heinz & Schumacher (2017), who investigate predictors of efficient coordination of subjects on group-beneficial outcomes when free-riding is possible.

Secondly, we add to the theoretical and empirical literature on contest theory. Substantial theoretical research has been conducted on the theory of contests (refer to Corchón & Serena (2016) for an overview). Münster (2007) offers insights into how players allocate energy in situations involving simultaneous inter- and intra-group competition, which resembles the situations we research, bar for the fact his model does not allow for individuals to be part of teams that may span across groups. For experimental results, refer to Dechenaux et al. (2015) for a survey. Similar to Brouwer & Potters (2019), we use cycling races as an instance of a contest in the field that provide valuable data for empirical analysis. Despite our model's alignment with contest dynamics, it deviates from the standard contest framework due to the complexity of the strategic setup of a road cycling race. To our knowledge, we are the first to explore contests involving groups where participants can simultaneously engage in multiple groups.

Thirdly, by using data from professional road cycling, we add to the literature which uses sports data to gain economic insights. This has a long-standing tradition, as it provides a natural framework of competition in a strictly regulated environment while at the same time stakes for all agents are very high (Bar-Eli et al. (2020)). Szymanski (2003) and Balafoutas et al. (2019) offer extensive overviews. Game-theoretic analysis has two roles in sports economics: On the one hand, it helps understand the impact of rules on incentive structures of the players (see e.g. Malueg & Yates (2010) and Krumer & Lechner (2017)). On the other hand, choices athletes make help understand and verify equilibrium concepts and behavioral biases. This kind of analysis has been applied famously in tennis (Walker & Wooders (2001)) and football (Palacios-Huerta (2003),), but many sports offer opportunities to understand economic concepts empirically. For instance, Gürtler et al. (2023) use data from biathlon races to to understand the impact of competition on risk-taking and Neugart & Richiardi (2013) investigate free-riding in dynamic choices within a team in swimming. Cycling, too, has received some special attention in the economics and management literature because of its strategic complexity, as is expanded upon in Mignot (2016).

2 Model

We model situations of interest (the decisive part of a bike race) as a one-shot simultaneous-move game with n players (the teams or team managers). Each player i (she) controls a group of k_i agents (the riders). Rider j of team i is characterized by two non-negative integers: Energy $e^0_{i,j}$ and position $p^0_{i,j}$. The position vector p^0 encodes the riders' relative distances. We call all riders with the same position integer a *group* and all riders with the maximal position integer *the breakaway*. The energy vector characterizes the riders' remaining energy budget. Actions in the game cost a certain amount of energy, and a team's win probability in the sprint is proportional to the remaining energy of their strongest rider in the breakaway, where we call a rider *stronger* than another if they have a higher energy parameter.

Position updating is not straightforward, as it depends on all actions taken in the respective rider's group (see below), but position differences can be interpreted as energy differences required to close the respective gap between riders in absence of free-riding.

2.1 Actions and Strategies

Each rider can perform up to 4 different actions, which have different costs:

Table 1: Actions

Action	Energy Cost	Position Impact	
Rest	0	+0 or +1	Follow pace of the group
Pace	1	+1	Set a steady pace for the group
Mark	1	+0 or +1 or +2	Follow if attacks happen, otherwise follow pace of the group
Attack	2	+2	Attack away from the group

e^0 restricts the action that team i can choose for its rider j, that is,

$$A^0_{i,j} = \begin{cases} \{R, P, M, A\} & \text{if } e^0_{i,j} \geq 2 \\ \{R, P, M\} & \text{if } e^0_{i,j} = 1 \\ \{R\} & \text{if } e^0_{i,j} = 0. \end{cases}$$

By playing *Attack* (A), riders try to break away from the other group members, so to split up the group. This can be visualized as a small sprint that riders do. On the other side of the spectrum, the cheapest action is *Rest* (R), which symbolizes riding in the middle or back of a group. Riders choosing this action save energy, but might still be able to profit from another rider in the group playing *Pace* (P). They will be left behind by attackers. Choosing *Mark* (M) means being vigilant to another player attacking: A rider playing M pays an energy cost of 1 to watch out for attacks and thereby making sure that one will not be overtaken by any other rider (neither by riders of the same group nor by riders of a group following behind). If another rider of the group does actually play A, the rider playing M will keep up with that rider, but pay less of an energy cost than the attacker. If no-one attacks, the rider playing M rides along at the pace of the group at a higher price than required. In this sense, M's cost is fixed and the positional consequence is uncertain ex-ante. Choosing P instead results in the respective rider dragging the group behind while not following attacks, but mitigating the resulting gap, should an attack occur.[11]

It might be counterintuitive that P and M are always equally costly, even though M could result in either a sprint or riding slowly. We choose these energy costs for simplicity of the model. Our results are not qualitatively altered by conditioning the energy cost of M on whether there actually is an attack or not, as long as M is always more costly than R and less costly than A. Also, intuitively, M is indeed costly even if no attack occurs, because it requires a rider to be in the front of the group (facing wind) and to focus. For a rigorous formulation of the updating rule, see Appendix.

A team's strategy consists of one action per rider. We denote the strategies as a vector of actions and order this vector by position and, if several riders are at the same position, by effort. For example, the first entry is always the rider of the team closest to the front of the race and if there are two riders of a team in the same group, the first entry refers to the rider with more energy left.

2.2 Payoff Function

After the game, riders have updated positions and energies encoded in vectors e^1 and p^1. We model the sprint for the victory as a Tullock contest with each team's strongest rider in the front group (with maximum position) with remaining energy as effort levels. This means that each

[11] This can often be seen in cycling races if a favorite has a strong team in the mountains. This team will then be collectively at the front of the peloton, setting a high pace in order to discourage attacks.

team's strongest rider in the first group sprints for the win using all remaining energy, and the win probability for that respective sprinter is proportional to the fraction of the sum of energy levels of all sprinters. If no member of the front group has any energy left, each team (not rider!) wins with equal probability. Formally, this is represented by the following payoff function:

Team i's utility coincides with its winning probability and is assumed to be given by

$$u_i = \begin{cases} \frac{\max_{j \in B_i} e^1_{i,j}}{\sum_{k=1}^n \max_{j \in B_k} e^1_{k,j}} & \text{if } \sum_{k=1}^n \max_{j \in B_k} e^1_{k,j} \neq 0 \\ \frac{1}{|\{k \mid B_k \neq \emptyset\}|} & \text{if } \sum_{k=1}^n \max_{j \in B_k} e^1_{k,j} = 0, \end{cases}$$

where $B_i = \{1 \leq j \leq k_i \mid p^1_{i,j} = \max_{(i',j')} p^1_{i',j'}\}$ denotes team i's riders in the front group after positions and energy levels are updated based on the teams' actions.

Teams indirectly determine their contest effort by selecting their riders' actions within the game. Notably, riders from the same team do not sprint against each other under any circumstances. While this might initially seem counter-intuitive, cycling teams typically designate a sprinter while the other riders support their strongest teammate. Our definition of the sprint takes into account that any numerical advantage should have already been utilized earlier, rather than conferring an advantage in the final push to the line. We assume payoffs are structured such that higher remaining energy levels enhance an individual's win probability, rather than explicitly modeling individual sprint capability. This approach is sensible because we explicitly choose to investigate sprints from small groups. Such races are extremely attritional for the members of this group, which may impact individual sprint capabilities severely. Also, if a small group of riders arrive at the finish together, they are likely of very similar rider characteristics (otherwise they would not have selected into the leading group), which makes individual fatigue a potentially pivotal factor in the sprint to the finish line (instead of some sprint capability score independent of e_j).

3 Illustration of Main Principles

In this section, we use our model to shed light on the strategic intricacies of situations that are frequently observed in real races. In the first two subsections, we informally use examples to illustrate our findings, before we move on to show a general result on the cooperation behavior of one group chasing another.

In the following, we adopt specific conventions. Capitalized verbs refer to the actions by their full names (Attack, Pace, Mark, Rest). We refer to the actions Rest and Mark as *successful free-riding* if they result in a maximally feasible position increase (+1 for R, +2 for M). Subsequently, we illustrate how teams can effectively utilize having multiple riders at the front of the race. We present scenarios as one-shot normal form games in the following subsections, identifying trembling hand perfect equilibria (THPE) using risk dominance[12] as a selection criterion in cases of equilibrium multiplicity. Trembling hand perfection rules out Nash equilibria that are not robust to small mistakes, as is to be expected in cycling races. Risk dominance is an empirically proven selection criterion for equilibria in coordination games.[13]

This analysis is essentially divided into two parts. Firstly, we show that a group collectively profits from one team having several riders in a group. Counterintuitively, however, this may hurt the team with several riders in the sense that they would prefer the outcome of the situation in which they had only one rider in the group. Given the nature of our model as a simultaneous one-shot game, they can not change this any more at that point. We will later empirically investigate whether teams end up in such an unfavorable situation. Secondly, we show that having riders in two competing groups (one group trying to stay ahead, the other trying to catch up) presents a favorable scenario for a team. In this setup, both riders are likely to free-ride successfully because their respective teammates pose an external threat to everyone in the group except them.

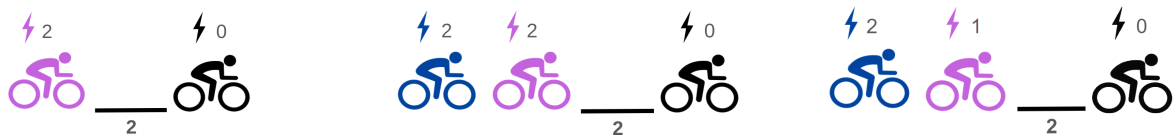
3.1 Teammates in a Group: How to Coordinate a Chase

The possibility of drafting makes coordinating intra-group competition in a homogeneous group a chicken game: Everyone desires someone to chase (or pace), but no one wants to assume the role of the designated chaser (or pacer). To illustrate this, consider the following scenario: One rider has invested all his energy earlier in the race to break away and is now 2 energy units ahead of a chasing group. They can no longer play anything but R, whereas the chasing group needs a positional increase of 2 in order to retain any chance of winning. Varying the composition of the chasing group affects the qualitative equilibrium outcome.

[12] Schmidt et al. (2003) show that changes in risk dominance, unlike changes in payoff dominance, significantly affect play of experimental subjects in symmetric two-player games.

[13] See Selten (1975) for trembling hand perfection and Harsanyi & Selten (1988) for risk dominance. Note that payoff-dominance is not applicable in our situations.

Figure 1: Coordinating a Chase (A)



Situation 1.a Situation 1.b Situation 1.c

A single chaser with remaining energy of at least 2 (as depicted in Situation 1.a) will always catch up by playing A, as this is clearly the dominant strategy in this case. In a situation like 1.c, where there's an additional chaser unable to catch up independently, the blue rider will still opt to Attack, while the pink rider benefits from Marking, resulting in a win probability of 1/3 for all three teams. Situation 1.b presents a more intricate scenario, which can be rigorously analyzed by a game matrix like in Table 2 below. The corresponding game matrices of all the other situations we discuss in the underlying section are presented in Table 8 in the Appendix. The unique THPE of the game in Situation 1.b is highlighted by the red box (omitted strategies are strictly dominated in this instance):

Table 2: Situation 1.b - Payoff Matrix

		Pink Team	
		M	A
Blue Team	M	$\boxed{0,0}$	1,0
	A	0,1	$\frac{1}{3}$,$\frac{1}{3}$

If there are two equally strong competing chasers, both with a remaining energy of 2, the solo escapist will win for sure in equilibrium, because the homogeneous chasing group struggles to coordinate on who takes the lead in increasing the group's position. This is an example of *coordination failure* in the following sense: We refer to a situation as a *coordination problem* if several group members want the group's position vector to increase, but prefer if a rider of another team takes the lead. By taking the lead, we mean that a rider plays Attack (or Pace, depending on the desired position increase). We call a set of actions of group members in a coordination problem a coordination failure if no rider takes the lead. Hence a coordination problem boils down to group members *coordinating* on one rider taking the lead. Note the difference to Situation 1.c, where there are two competing chasers with different remaining energy levels and only one of them is strong enough to close the gap ($e_{i,j} \geq 2$). In such scenario, the stronger rider will close the gap in equilibrium. Consequently, the pink rider profits from being weaker than his blue opponent (as observed in Situation 1.c compared to 1.b), based on the following pattern.

Pattern 1. *If equally strong riders compete, coordination failure may occur.*

Now consider two situations where the chasing group is asymmetric and several riders have enough energy to take the lead, like in the Situations 2.a and 2.b below:

Figure 2: Coordinating a Chase (B)

Situation 2.a

Situation 2.b

Note that, in Situation 2.b, the blue team needs to specify two actions for each strategy, one for each rider, with the aforementioned convention that the stronger rider's action is always specified first. We again omit weakly dominated strategies. Note that, if two members of the same team are part of the same group, some of their strategies are weakly dominated by construction - for example, both members of the same team in the same group should never simultaneously choose A, as this is dominated by the weaker member opting for A, while the stronger one selects M (again, refer to the Appendix for the corresponding payoff matrices).

In Situation 2.a, the higher energy level of the pink rider leads to the chasing group coordinating on this rider taking the lead. This coordination succeeds because the pink rider anticipates that the blue rider will refrain from Attacking, so they have to put up with the blue rider free-riding.

In Situation 2.b, a teammate of the blue rider is added to the chasing group. It now consists of one rider of one team and two riders with energy 2 from a competing team. In this scenario, one of the riders from the team with multiple members in the group will Attack and thus allows the rider from the other team to free-ride. The comparison of Situations 2.a and 2.b with Situation 1.b establishes Pattern 2:

Pattern 2. *Asymmetry in number of team members or rider's strength helps solve coordination problems of groups of riders.*

The mechanism behind this pattern deserves some attention. In order to solve the coordination problem of the group, consensus on who needs to Attack is required. This consensus is established if all riders are aware that one rider has either the most energy or a helper.[14]

Comparing Situations 2.a with 2.b reveals another interesting pattern. If the group's strongest rider is not part of the team with multiple group members, this team would prefer to have only their strongest rider in the group. In other words, the win probability for the blue team is higher in Situation 2.a than in Situation 2.b (refer to Section 4 for the general formulation), leading to Pattern 3:

Pattern 3. *If a team does not have the strongest rider in a group, it is disadvantageous for this team to add a helper to the group.*

This is somewhat surprising: A team might be better off having only one rider within a group than having two. If in an actual race situation, this means that if a team has the opportunity to place a teammate into the group of their strongest rider (for instance by having a teammate catch up from a group behind or drop back from a group in front), they might not always want to do so.

3.2 Teammates Across Groups Create Free-Riding Opportunities

After we have shown that it is not unambiguously good to have more riders in the same group for a team, we will now turn to illustrating why it is never a bad thing to have several riders across groups. For this, consider the following two situations:

Figure 3: Teammates across Groups (A)

Situation 3.a

Situation 3.b

In Situation 3.a, when two riders from opposing teams are not contending with a rival group, it's evident that both have an expected probability of 1/2 of winning the race before competing in the final period. Situation 3.b adds a strong rider from the blue team as (part of) a chasing group to the scenario.[15]

[14] In actual races, consensus is likely to also be affected by other things like, for instance, beliefs about riders' strengths or riders' ambitions.

[15] The corresponding payoff matrices are again presented in the Appendix. In Situation 3.b, it suffices to examine the strategic interaction between the two riders in the front group, as the rider in the chasing group will end up Attacking.

The addition of the chaser strictly improves the winning chances of the blue team. Instead of winning with equal probability (Situation 3.a), the blue chaser *forces* (in equilibrium) the pink rider to Attack and thereby allows the blue rider of the front group to benefit from free-riding, leading to a winning probability of 2/3 for the blue team. What's particularly intriguing is that the chaser never wins in equilibrium; rather, it's his mere presence that influences the outcomes. We observe that adding a teammate to a group behind the front group can yield a positive impact on the win probability of the respective rider within the front group.

Figure 4: Teammates across Groups (B)

Situation 4.a

Situation 4.b

Let's now examine a similar scenario where there is a teammate up front instead of a teammate behind. We compare Situation 4.a, where there's no teammate up front but instead a teammate within the group, with Situation 4.b. In the latter case, a rider of a chasing group has a teammate riding solo up front; we refer to such a rider as a *Satellite* (for the corresponding payoff matrices again see Table 8 in the Appendix).

When having a rider up front, the blue team will instruct the Satellite to play Pace in order to remain ahead of the chasers. This amplifies the energy advantage of the blue rider in Group 2, as it allows him to conserve energy by drafting behind the pink rider who is now forced to Attack if they want to catch up with the Satellite. In this extreme scenario, the blue team wins with certainty. This implies that regardless of the variable energy level x in Situation 4.a, where the pink team's expected equilibrium payoff is positive,[16] the blue team would always prefer Situation 4.b, emphasizing the advantage of initiating a solo breakaway early in the race.

Comparing Situation 3.a with 3.b and 4.a with 4.b illustrates how the blue team *strategically* benefits from having two riders across two groups, leading to the following pattern:

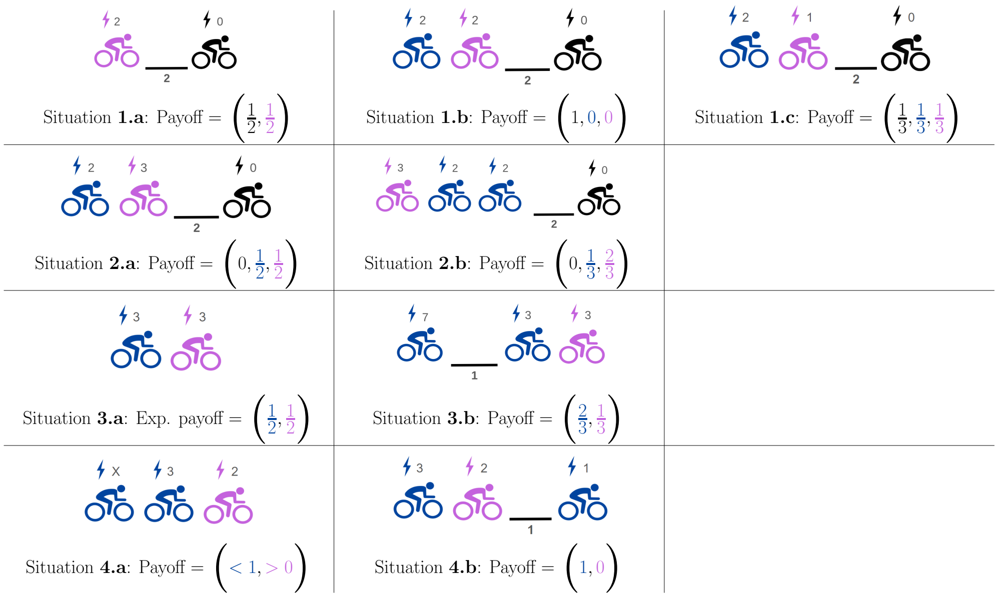
Pattern 4. *Having riders in different groups leads to a strategic advantage for a team in the coordination dynamics in all of the respective groups.*

[16] In Situation 4.a, the blue team mixes between $R|M$ and $M|A$ (the action of the stronger rider is mentioned first) while the pink team mixes between R and M. The resulting expected equilibrium payoff is positive for the pink team. As a consequence, the blue team prefers Situation 4.b over 4.a for all x.

Pattern 4 embodies the central finding of our paper: *the strategic benefit from diversification.* In the above situations, diversification refers to a team placing their riders into more than one group. This strategy enables teams to leverage free-riding opportunities within these groups. The presence of teammates in other groups lowers the pressure to take the lead, as teammates serve as credible outside options.

To recap all the scenarios we have discussed above, consider the following table:

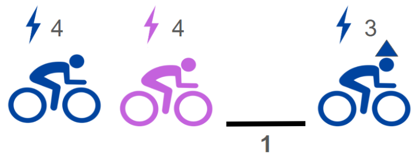
Table 3: Summary of possible setups in the last period



Comparing Situation 1.a, 1.b, and Situation 1.c illustrates how symmetric groups struggle to coordinate, as indicated by Pattern 1. In Situation 2.a and 2.b, we observe two different pathways through which breaking the symmetry leads to successful coordination of the group, denoted by Pattern 2. Comparing Situations 2.a and 2.b also illustrates Pattern 3: it might be disadvantageous to have a helper in a group. Situation 3 and 4 illustrate the strategic benefits of having riders in several groups. A team's weaker rider in the front of the race profits from the threat generated by having a strong teammate chasing. A similar effect can also help the chasing rider if they have an opponent to free-ride on within his group. Overall, this analysis underscores the strategic preference for teams to deploy riders across various groups rather than placing them within the same group, leading to the title of the underlying paper: *The strategic benefit of sending your friends away.*

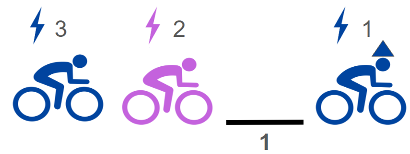
We will now show, rather informally, how this principle can influence decision-making earlier in the race. Imagine the teams play two periods of the positioning game instead of one, with the setup in the penultimate period as depicted in Situation 5.a. Depending on the riders' actions, we might observe the emergence of either Situation 5.b or 5.c from the starting point of 5.a.

Figure 5: A hypothetical penultimate Period



Situation 5.a: Chasers play (M, A)

Situation 5.b: After Satellite (with hat) played Pace



Situation 5.c: After Satellite (with hat) played Attack

It is important to recognize that the pink team in Situation 5.a faces pressure to play Attack (formally, they would opt for this in each subgame-perfect equilibrium) to avoid the Satellite's certain win up front. The blue chasing rider will then play Mark. With this in mind, the blue team has two options for their Satellite rider: either allow the chasing group to catch up so that the Satellite can assist his teammate within the group (Situation 5.b), or maintain the Satellite's lead (Situation 5.c).[17]

Situation 5.c mirrors Situation 4.b, guaranteeing a definite win for the blue team. In contrast, Situation 5.b introduces a possibility, however small, of the pink team winning. This underscores the blue team's preference for their Satellite rider to maintain his distance from the chasing group, highlighting the strategic advantage of strategically distributing riders among various groups and maintaining this arrangement for as long as feasible.

4 General Theoretical Results

In this subsection, we address the dynamics of group coordination and the related problem of successful free-riding within our model in more generality. The following two propositions specifically imply Pattern 1 to Pattern 4 as stated in the previous section. We provide easy-to-understand versions of our propositions in this section. For formal versions and proofs, we refer to the Appendix.

The following proposition formalizes Pattern 1, 2, and 3.

[17] The corresponding actions of the Satellite rider are Pace, in order to fall back into his teammate's group (Situation 5.b), and Attack, in order to stay up front (Situation 5.c).

Proposition 1. *Consider a set of teams represented in a group. Without loss of generality, we focus on teams that each prefer their strongest rider to Attack over no member of the group to Attack. In other words, we focus on teams that play a coordination game amongst each other on who has to use some rider to Attack and who may free-ride.*[18] *Then in any THPE of the resulting coordination game of these teams, the following statements are true for the riders represented in that set:*

If at least one team has two riders with at least two energy units remaining, then

(a) One rider with at least two energy units Attacks, and all other riders successfully free-ride (Mark).

If no rider has a teammate with at least two energy units remaining,[19] *there are several equilibria, which satisfy:*

(b) Each mixed equilibrium has a positive probability of coordination failure.

(c) In the risk-dominant equilibrium,[20] *the strongest rider attacks.*

Proof. See Appendix. □

The rationale behind Proposition 1 is straightforward. In a race scenario involving multiple groups, each group comprising riders who prefer to maintain a high pace faces a coordination challenge: Who will take the lead and endure the wind resistance to allow others to draft behind? Among these riders benefiting from maintaining speed, there exists a hierarchy determining who must undertake this costly task. If a team possesses multiple riders capable of playing Attack, other teams can insist that they sacrifice one of their weaker riders for this purpose. Our proposition demonstrates that each team with such a rider will indeed Attack, thereby eliminating the possibility of coordination failure. If no team enjoys this privileged situation, any scenario where exactly one rider bridges the gap represents a pure Nash equilibrium. While scenario (b) illustrates the potential for coordination failure in equilibrium, scenario (c) indicates that, in the risk-dominant equilibrium, the rider with the most remaining energy will be compelled to close the gap. This finding heavily relies on the assumption of perfect information. In actual race situations, one can often observe riders feign weakness for this very reason.

Proposition 1 offers a formal framework to elucidate the phenomena outlined in Patterns 1 through 3. (b) specifies Pattern 1, while (a) and (c) explain the mechanisms driving Pattern 2 and Pattern 3. When certain riders possess teammates or are stronger than the other group members,

[18] There may be teams that could free-ride but could not afford to have their strongest rider attack, which makes them exempt from any strategic considerations.

[19] Then the teams play a coordination game on whose *strongest* rider has to Attack and who may free-ride. We can assume w.l.o.g. that each team has their strongest rider as the only rider, which means that each team only has A and M as undominated strategies.

[20] See Harsanyi & Selten (1988).

their teams bear the responsibility of pushing the group along by Attacking, thereby solving the group's coordination problem.

To gain further insight into Pattern 4, we require another proposition. This pattern specifically refers to scenarios where one team has multiple riders spread across different groups (which may or may not occur within the framework of Proposition 1). As explained in Section 3.2, the value of teammates in competing groups is created by those teammates constituting a credible outside option and thereby facilitating opportunities for free-riding.

Proposition 2. *Placing a rider's teammate into a different group weakly increases the respective rider's probability of successful free-riding in each THPE.*

Proof. See Appendix. □

This clearly implies Pattern 4 because a positive probability of successful free-riding is a desirable property.

5 Data and Empirical Strategy

We proceed by examining empirical evidence supporting our stylized Patterns 1 - 4, drawing on data from actual professional road cycling races. We exclusively consider individual stages of multi-day stage races in the main text of the paper but demonstrate in the Appendix that our results are qualitatively similar if using data from one day races within the same time period. We introduce and empirically assess hypotheses derived from our theoretical results on the coordination of groups and the strategic advantages of having teammates - in terms of increasing the probability of being at the front of the race and winning, respectively. To this end, we use data on the top 15 finishers of highest-level road cycling races since 1981. We observe the names of these riders, their teams, and the respective riders' gaps (in seconds) to the winning rider.

In order to find evidence for our theoretically derived stylized patterns, we would ideally need a dataset containing the individual energy levels of all riders in the front groups at the decisive moment of a road cycling race. Clearly, this is not feasible. Firstly, not even the riders in the race are aware of the energy levels of their competitors. We try to circumvent this difficulty by only differentiating between riders that are commonly believed to have high energy levels remaining and those that don't, using the same proxy that the riders in the race are likely to use: The past success of individual riders. Specifically, we indicate riders that were amongst the most successful riders of the last season as *Stars*. Secondly, the process of grouping riders is essential. We employ a five-second threshold to determine group composition; if the time gap between two consecutive riders at the finish is below 5 seconds, they are considered part of the same group. Thirdly, there is no extensive database of in-race statistics such as group compositions and gaps between groups, which means that we do not have information about the setup at the front of the race at the decisive moments.

Our theoretical framework offers insights into riders' behavior in the final stages of a race, yet the only large and available dataset consists of race results. Thus, we make use of this dataset to analyze the properties of *successful* riders in specific race situations, about which our stylized patterns make specific claims. These claims are stated in the empirical hypotheses below, mainly addressing the following two key aspects.

We aim to understand which group characteristics facilitate coordination, as outlined in Pattern 1 and Pattern 2. Successful coordination entails group members fulfilling their roles harmoniously, leading to enhanced group cohesion. To investigate this, we contrast groups of riders finishing together with batches of riders finishing in close proximity to one another, examining the differences in riders' characteristics between these two situations.

Additionally, we strive to examine the advantages derived from having a teammate in different groups, as elucidated in Pattern 3 and Pattern 4. To achieve this, we conduct various linear regressions using the race results data. These regressions assess whether a rider's win probability or likelihood of finishing in the leading group is influenced by a teammate's position, such as being in the same group or in the group behind. Our primary theoretical result suggests that having a teammate in a group behind positively impacts a rider's win probability. Although the strategic benefits of extensive free-riding options occur before the finish line, riders with a teammate behind should still be more likely to be observed as victorious at the finish line than riders without a teammate around.

5.1 Race Results Data

We scraped placement and time-gap data from ProCyclingStats.com (`www.procyclingstats.com`). We use results data from 1981 to 2023 on stages of multi-day stage races of the highest division of professional road cycling.[21] We collect all available data of the three grand tours, which all last three weeks: Tour de France, Giro d'Italia, and Vuelta à Espana. Also, we use the results of the

[21]The organization of these races has changed over the years, nowadays they are all part of the UCI World Tour.

seven best-known one-week stage races.[22] As a robustness check, we repeat all our analyses, in the Appendix, for the most famous one-day races with data again ranging from 1981 to 2023.[23] For all of these races, we save the names, teams and time gaps to the winner of the top 15 finishers.

The focus on stage races is motivated by a key characteristic inherent to these events. In nearly every stage of a stage race, the occurrence of an early breakaway is a prevalent phenomenon (see Brouwer & Potters (2019)). This predictable race structure unfolds with remarkable consistency: shortly after the race begins, a group of riders breaks away from the main pack, known as the *peloton*,[24] and gains distance ahead. Subsequently, until the race's final stages, minimal significant action takes place, and the gap between the breakaway and the peloton remains relatively stable. Typically, the peloton possesses the collective strength to reel in the early breakaway, provided they initiate their pursuit early enough.

One-day races are more attritional than stages of stage races and winning them comes with high prize money and reputation. For this reason, the early breakaway almost never wins in one-day races. At the same time, fewer riders finish the race, because time gaps don't matter (as opposed to stage races), which means the groups chasing one another at the end of the race are comparatively small. Still, strategic timing of attacks plays a role in winning these races and a single rider can hold off a group if group members do not cooperate well.[25]

5.2 Data Processing

To conduct our analyses, we initially identified races where the battle for victory unfolded among small clusters of riders. We operationally define a group as comprising riders who finish within a five-second window of one another. In other words, if the time gap between two consecutive riders falls below 5 seconds, they are considered part of the same group. If the time gap between a rider and the one ahead exceeds 5 seconds, the former is deemed to belong to a separate group.[26] Modifying this threshold does not alter the qualitative findings of our analyses (refer to the Appendix for a

[22]These one-week stage races are: Criterium du Dauphiné, Tour de Romandie, Itzulia Basque Country, Tour de Pologne, Tour de Suisse, Paris-Nice, and Tirreno Adriatico.

[23]These one-day races are: Il Lombardia, Tour of Flanders, Paris-Roubaix, Milano-Sanremo, Liège-Bastogne-Liège, Gent-Wevelgem, La Flèche Wallone, and the San Sebástian Classic.

[24]The peloton is cycling lingo and (loosely) defined as the largest group of the most "relevant" riders.

[25]Despite these facts, we can recreate some of our results on stage races on the dataset on one-day races from the same period, as can be seen in the Appendix. It is very important to note that the number of one-day races that feature groups that are large enough to conduct our analyses is quite small, which means that we cannot use our full set of controls on this dataset, which is why we did not include these analyses in the main paper.

[26]We choose this in such a way that the final Tullock contest does not influence group composition: The potential gap created by the final sprint (the Tullock contest) is very unlikely to exceed 5 seconds.

rerun of our analyses with a 1 and 10 second threshold, respectively). We discard all races in which the first two groups both consist of riders of only one team (i.e., there is no intra-group competition) and all races where the last rider of the third group places 15th or worse.[27] This leaves us with 825 stages.[28]

5.3 Individual Rider Data

To control for the strength of individual riders, we use a Star-dummy, based on ProCyclingStats' individual rider scores (PCS-scores) from the season previous to the respective race.[29] A Star is a rider that in the previous season has reached a PCS-score that puts him in the top 20%. These scores are calculated by summing the points earned by a rider across all races they participated in during the respective calendar year. A rider scores points for placing well in races, with more coveted races awarding the top riders more points. We rely on the previous season's PCS-scores to mitigate endogeneity issues.[30]

In many situations, the categorical Star-dummy is sufficiently informative about the pecking order of a group to make a statement about our theoretical predictions, for instance if there is a single rider classified as a Star in a group. Also, we must note that Stars, by definition, are the best finishers of the previous season, even (or especially) when exhausted. This should effectively determine the beliefs of other non-Star group members about that riders energy left.[31]

5.4 Group Characteristics

We define the following variables:

[27] In larger groups, it is hard to justify the game-theoretic formulation of the situation in which every team considers possible strategies of every other team's riders in the group. Also note that we need three complete groups of riders in order to consider teammate-behind-effects of riders that are part of the second group.

[28] We ended up discarding 2892 stages of the 3717 stages we have scraped initially.

[29] PCS-scores are available on ProCyclingStats' website: `https://www.procyclingstats.com/rankings/me/season-individual`.

[30] It is important to note that a rider with more points than another is not necessarily the all-around better rider. This is due to several reasons. Firstly, there is a difference in riding for a stage win or a classification win in a stage race. Secondly, superstar riders pick specific target races for their season, but also participate in so-called tune-up races, where they choose not to compete. Lastly, rider characteristics matter a lot. A great climber stands no chance in a flat sprint, but might still be identified as a Star when looking at generalized rider rankings. Some riders may also accumulate points simply by participating in more races than others. For these reasons, we use a categorical Star-dummy instead of using the raw PCS-score as an ordinal metric of rider strength.

[31] We must note that, given that non-Star group members believe a certain Star rider to win the race even when his "energy battery" is low, forcing the respective Star rider to spend effort is not beneficial anymore. Instead, the non-Star group members might increasingly concentrate on the race against the other non-Star members for second place.

- **Star**: "Star" riders are riders which ranked in the top 20% of the last season's score ranking. Changing the percentile does not lead to qualitative changes in the results (see Appendix).[32]
- **Stronger Rider Around**: Dummy. 1 if a member of the first two groups is a Star and from another team, while the respective rider is not a Star.
- **Stronger Rider in Group**: Dummy. 1 if a rider finishing in the same group is a Star and from another team, while the respective rider is not a Star.
- **Helper**: Dummy. 1 if there is a teammate finishing behind but in the same group.
- **Teammate behind**: Dummy. 1 if at least one rider finishing in the group behind is a teammate.

Summary statistics on these variables can be found in the Appendix. It is noteworthy that Groups 1 and 3 are significantly (on 1% - level, determined by a Wilcoxon-rank-sum test) smaller than Group 2. There is no significant difference between Groups 1 and 3. Stars occur more often in Groups 1 or 2 than in Group 3.[33]

5.5 Hypotheses

Given the aforementioned data, we can translate our stylized patterns from the above section into testable hypotheses. Both Pattern 1 and Pattern 2 propose that groups of riders are more prone to coordination failures when group members exhibit symmetry. Within our theoretical framework, such coordination failures may result in groups fragmenting or being unable to catch up with another leading group. Consequently, the following (testable) hypothesis emerges:

Hypothesis 1. *A winning group arriving together is more likely to be asymmetric.*

To test this, we compare the characteristics of groups of riders finishing together with those of batches of riders finishing in close proximity. If Hypothesis 1 is accurate, we anticipate a higher probability of observing asymmetry, such as the presence of teammates or singled-out Stars, in the former case. This asymmetry fosters consensus among group members regarding their roles, thereby enhancing coordination within the group during the race, and thus leading to an increased likelihood to reach the finish as a group.

Pattern 4 addresses the strategic benefit for a team of having riders placed in different groups. Such diversification helps in the coordination dynamics within each of the groups and theoretically

[32]We have also run the regressions with an "Underdog" dummy, indicating no significant effect on the results. There, "Underdogs" were defined as riders being ranked in the bottom 20% of the last season's score ranking.

[33]All the mentioned differences are significant on the 1% - level, determined by a chi-squared test of proportions.

results in riders being able to save energy for the final sprint (the final Tullock contest in our model). In the results data, we thus expect to observe the following:

Hypothesis 2. *Having a teammate in the group behind positively impacts win probability.*[34]

On the contrary, as per our model, having a teammate within a group could potentially be disadvantageous. This effect hinges significantly on the rider's strength compared to the group members' strength, as outlined in Pattern 3 and in the following hypothesis:

Hypothesis 3. *The effect of having a teammate in the same group positively impacts win probability for the group's strongest rider(s) and negatively impacts win probability for riders that are weaker than other group member(s).*

To test Hypotheses 2 and 3, we conduct fixed-effects regressions using riders' properties on a win-dummy, and similarly on a first-group-dummy.[35] Interpreting the coefficients of these regressions provides comparative-statics insights into win probabilities. Hypothesis 2 predicts a positive impact from the Teammate-behind-dummy, while Hypothesis 3 suggests a negative interaction effect between the Stronger-Rider-in-Group-dummy and the Helper-dummy.

Note that all the hypotheses operate under the assumption that riders who performed well in the previous season (referred to as Stars) are presumed to have larger energy reserves. If this assumption seems circular, it at least does not detract from the interpretation of our results. In our regressions, the Star-dummy variable can also be viewed as a control for publicly available information on race-winning characteristics.

6 Results

We now discuss the results of the empirical analyses outlined in the previous section.

6.1 Comparing Groups

Let's begin by examining the factors that contribute to effective group coordination, particularly in terms of staying together. Nearly half of the races in our dataset (401 out of 825) are categorized as "solo wins".[36] This means that the first and second places are separated by at least 5 seconds.

[34]Note that we cannot measure the impact on win probability of a teammate in front.

[35]The first-group-dummy is a dummy, indicating whether the rider is at the finish part of the winning group.

[36]That is although many solo wins are excluded when we filter out races where both first groups consist of only one team. Hence, the proportion of solo wins (on total wins of "not too large groups") could even be larger.

It's quite perplexing that in so many races, a single rider manages to maintain a lead over pursuing groups. One explanation to this puzzle might be individual strength. One rider might just be so much stronger than the others that they can keep a group at distance, even if the respective group cooperates well.

Another explanation might be the frequent occurrence of coordination failure in the pursuing Group 2 as discussed before. According to our Hypothesis 1, such failures to cooperate should be more likely to occur in symmetric groups. For this, we identify the following two kind of groups: A front group of 3 to 6 riders, versus a Group 2 which loses against a solo rider by at least 10 seconds (see Table 4) of similar size.[37] We then compare the symmetry-characteristics we have available across these groups. If a team comprises more than one rider, we consider it asymmetric in team strength, while the presence of a Star denotes asymmetry in individual strength (see the discussion in Section 5.5). Both factors are expected to enhance coordination and are thus more likely to be observed in groups that finish at the forefront.

We find weak confirmatory evidence for this: At least one Helper is present in 16% of the groups that lose against a solo rider while Stars are present in 53% of the respective groups. In contrast, groups, that do not allow for a solo win, include at least one Helper or one Star with probabilities 24% and 62%, respectively. So asymmetry in pursuing groups indeed seems to make solo wins less likely (though differences are not significant).[38]

Table 4: Asymmetry in losing versus winning groups

	Group losing against solo	Winning Group
Helper is present	16%	24%
Star is present	53%	62%

In the left column of Table 5, we investigate the same issue in a regression framework including additional controls. The regression considers front groups and groups behind a solo as independent draws, with the endogenous variable being a dummy that equals 1 if and only if the group finishes first. The dependent variables are group characteristics, and their estimated coefficients therefore measure the impact of the respective characteristic on the "success probability" of the group, in the

[37]We throw out mountain top finishes as there cooperation failure is most likely not to play a decisive role. Then, both groups end up with an average group size of 3.8 riders. We have 131 groups which come in first and 100 that lose against a solo rider.

[38]Note that the differences between the two kind of groups are not significant (Chi-squared test). Also, an OLS regression, with being in the winning group as the dependent variable, does not allow us to conclude a significant impact of asymmetry (see Table 5).

sense that a positive coefficient indicates that groups that finish together display a higher propensity toward this characteristic than groups that fail to catch a solo. In the right column, the analysis is similar, but the independent draws comprise front groups and sets of riders not finishing as a group (instead of groups behind solos in the case above), with the endogenous variable being a dummy that equals 1 if and only if the former case occurs.

Table 5: Linear Probability Model: Being part of a winning Group (with 3 to 6 riders)

	versus Group behind Solo winner	versus riders not finishing as Group
Intercept	0.519^{***}	0.186^{***}
	(0.140)	(0.051)
Star in Group exists	0.036	-0.020
	(0.075)	(0.045)
Helper in Group exists	0.092	0.179^{***}
	(0.090)	(0.069)
Observations	231	446
R^2	0.024	0.033
Adjusted R^2	-0.007	0.018
F Statistic	0.772 (df=7; 223)	2.16^{**} (df=7; 438)

Note: *p<0.1; **p<0.05; ***p<0.01
The endogenous variables are dummies, indicating whether group finishes first.
We additionally control for the number of teams per group and stage type.

In the left column, we once again do not observe significant results. Nonetheless, the effects suggest the theoretically predicted trend, indicating that the presence of a Star or a Helper tends to increase the likelihood that the respective group did not lose against a solo rider but instead finished together as the first group.

The right column of Table 5 examines how asymmetry properties impact groups' likelihoods of having finished together as a group. We observe that asymmetry in teammates significantly increases the probability that the set of riders where part of a group finishing first, rather than finishing as isolated riders. This indicates that the presence of at least one rider with a teammate enhances group cooperation, thereby increasing the probability of group cohesion and thus supporting Hypothesis 1. Regarding asymmetry in individual strength, we once again rely on the presence of a Star as our best proxy but find no significant effect.

6.2 Impact of Group Characteristics on Win Probabilities

Let us turn to discussing evidence for Hypotheses 2 and 3. We run fixed-effects regressions with two different endogenous variables: A dummy of finishing in the first group (coming close to a win) and a win-dummy.

6.2.1 Who makes the first group?

We test the remaining hypotheses using OLS regressions (logit regressions as robustness checks are in the Appendix). Our dependent variable is a dummy variable, indicating whether the rider in question is part of the first group. The left column of the following table includes all riders finishing in the first two groups; the right column all riders finishing in the first three groups.

Table 6: Linear Probability Model: Finishing in Group 1

	G1 if in G1/G2	G1 if in G1/G2/G3
Intercept	0.485***	0.414***
	(0.070)	(0.063)
Stronger Rider around	-0.185***	-0.165***
	(0.020)	(0.016)
Teammate behind	0.117***	
	(0.023)	
Observations	3834	5240
R^2	0.263	0.213
Adjusted R^2	0.250	0.203
F Statistic	21.3*** (df=63; 3770)	22.6*** (df=62; 5177)

Note: *p<0.1; **p<0.05; ***p<0.01
The endogenous variables are dummies, indicating whether riders are part of Group 1.
We additionally control for year, race, stage type, gap sizes between groups, and group sizes.

We observe that the presence of a stronger rider has a negative impact on the probability of being in the first group. Consequently, being a Star and having no Star present in the first two groups appears to have a positive effect. In addition, conditional on being in one of the first two groups, having a teammate in the group behind has a significantly positive effect.[39] This dummy is not included in the right column because we only look at data on the first three groups for all races.

The effect of a teammate behind is not immediately obvious, as there are several potential

[39] Note that we control for the number of riders in each group in the upcoming analyses. Thus, the larger mean in Group 2 than in Group 1 does not distort our "teammate-behind effect".

mechanisms through which the leading rider could have benefited. The teammate might have been helpful within the same group and then dropped back after his work was completed. Also, a teammate of a rider in Group 1 can cause coordination problems in the group behind because this rider would never cooperate with the others, making it less likely that the pursuing group catches up. Thirdly, having a teammate behind might lead to a strategic benefit to the rider in the front group, facilitating to free-ride and to save effort. However, all these effects ultimately support Hypothesis 2.

6.2.2 Who wins out of the first group?

The Hypotheses 2 and 3 are again checked using OLS regressions (logit regression as robustness checks are in the Appendix), now including only riders that are part of the first group while discarding all races where a solo rider wins.[40] Our dependent variable is a dummy variable specifying whether the rider in question has won the race.

Table 7: Linear Probability Model: Winning the Race from Group 1

Hypothetical teams	NO	NO	YES
Intercept	0.512^{***}	0.508^{***}	0.617^{***}
	(0.151)	(0.151)	(0.113)
Stronger Rider in Group	-0.045	-0.040	-0.031
	(0.030)	(0.029)	(0.032)
Helper	0.080	0.144^{**}	0.254^{***}
	(0.072)	(0.057)	(0.060)
Stronger Rider in Group x Helper	0.167		
	(0.114)		
Teammate behind	0.118^{***}	0.118^{**}	-0.039
	(0.043)	(0.043)	(0.053)
Observations	1303	1303	1152
R^2	0.095	0.093	0.098
Adjusted R^2	0.049	0.048	0.047
F Statistic	2.06^{***} (df=63; 1239)	2.05^{***} (df=62; 1240)	1.91^{***} (df=62; 1089)

Note: *p<0.1; **p<0.05; ***p<0.01
The endogenous variables are dummies, indicating whether riders have won.
We additionally control for year, race, stage type, gap sizes between groups, and group sizes.[41]
In the hypothetical teams treatment we randomly assign teammates.

[40]Winning groups of only one rider must be excluded because then all group members (which is only the solo rider) win the with probability one.

[41]By group size we mean the number of different teams that are part of the respective group. So adding a Helper to a group does not change the group size.

The first two columns indicate a positive impact on the likelihood of winning the race when a teammate is present in either the same group or, particularly, in the group behind. As mentioned earlier, this supports Hypothesis 2.

In the right column of Table 7, we assign teammates randomly[42] in order to check whether some of the discussed effects exist by construction. In particular, Helpers finish by definition after another member of the team. This means that such team member has finished quite well, increasing his win probability by construction. Consequently, the positive effect of having an Helper seems to fully stem from how we defined Helpers in the first place. Also, the interaction term between the Stronger-Rider-in-Group-dummy and the Helper-dummy can thus not be used to confirm or disprove Hypothesis 3. In contrast, the "teammate-behind effect" appears to be driven by an actual in-race (strategic) benefit.

The failure of confirming Hypothesis 3 might also be due to the limitations of our dataset. The above regressions do not necessarily imply that Helpers are not more advantageous to riders with no stronger rider around, such as Star riders. This is because an effective Helper for a Star rider would typically not be part of the winning group at the finish line.[43] Instead, they would exit the winning group after having completed his role.[44] Unfortunately, our results data lacks the capability to capture such Helper dynamics causally.

Despite the dataset's limitations, it is noteworthy that our key finding, the positive "teammate-behind effect", persists across all our analyses. Robustness checks in the Appendix include variations in the definitions of Stars and how groups are defined. Our regression results exhibit resilience to these variations, reinforcing the robustness of our main findings.

7 Conclusion

In this article, we have modeled the strategic considerations that govern interactions of small groups of riders in road cycling races, framing it as a normal form game. We examine the factors that promote coordination within such groups and assess the incremental advantage of incorporating teammates into competing groups to enhance individual team's chances of winning. Our findings shed light on the pivotal role of establishing consensus on who needs to contribute the most to

[42]We assign each rider with equal probability to a number between 1 and 22 (which is the number of teams that typically compete). Riders with the same number are defined as "hypothetical teammates".

[43]Unless they were a Satellite rider being caught just before the finish line. In this particular case, they did not serve as an in-group Helper during the race.

[44]Dropping out of the winning group seems to be more likely for Helpers of Stars as putting all one's eggs into one basket makes much more sense if the team has a Star sprinting for the win.

a public good in resolving the social dilemmas inherent in inter-group competition during cycling races.

Within our model, we unveil a crucial mechanism: In scenarios where groups of riders compete, teams with multiple riders in a single group will always contribute to the inter-group conflict by "sacrificing" their weaker riders first. Conversely, when such an option is unavailable due to the absence of teammates, the onus of leading the inter-group conflict typically falls on the strongest rider, measured by their energy reserves. This mechanism yields several non-trivial implications for a team's utility: Firstly, the presence of a teammate alongside the team's strongest rider may not always confer an advantage, as this teammate is most beneficial to the strongest rider within the group, which could belong to another team. This occurs because the presence of such an helper, regardless of team affiliation, alleviates the pressure on the strongest rider to lead within the group, potentially enabling them to free-ride when they otherwise couldn't.

Secondly, we observe that adding teammates to a competing group consistently proves advantageous. These additional riders serve as an outside threat to all non-teammates within the group, increasing the pressure on these riders to take the lead. If the strongest rider of a group possesses a teammate in a chasing group, the pressure on him to take the lead dissipates because his incentives change, and other teams' beliefs about them as well. Consequently, placing a teammate in a competing group comes with a strategic benefit: It allows for more extensive free-riding. It's worth noting that our theoretical findings hinge on the assumption of perfect information; in a framework of private information, the ability to free-ride would be contingent upon other riders' beliefs regarding the relative remaining strength of members within a given group. We can conclude that having teammates as outside options serves a similar purpose as feigning weakness on race day.

In our empirical analysis, we examine data spanning over four decades of results in major professional stage races and find confirmatory evidence for the stylized patterns elaborated above. Firstly, we find evidence for our theoretical hypothesis that in-group asymmetry solves the coopetition dilemma. The presence of teammates enhances the cohesion of groups, thereby reducing the likelihood of defeat against a solo rider.[45] Furthermore, we establish that having a teammate in the group behind has a positive impact on the likelihood of a rider ending up in the first group of a race and, given that the rider is part of this first group, increases his probability to win the race. Subsequent empirical investigations could utilize rider GPS data or employing increasingly accessible image analysis techniques on TV broadcasts to extract detailed in-race (meta-)data concerning

[45] Note that we cannot establish significance for the latter.

group composition at various points throughout the race, facilitating a more careful analysis of the described dynamics.

Applied to professional cycling, the findings suggest that cycling teams benefit significantly from assembling a strong group of riders for a race, rather than relying solely on a single strong leader. The advantages of having a strong leader can be further enhanced by equipping them with capable supporting helpers who can be placed in front or in chasing groups to facilitate strategic free-riding opportunities for the leader. This tendency can indeed be observed in the professional cycling world, where the practice of lining up multiple leaders has become increasingly prevalent, as evidenced and discussed in the case studies provided in Appendix C.

While our model is tailored to the free-riding dynamics of road cycling races for empirical validation, the core insights extend to other scenarios featuring free-riding and strategic allocation of effort. For instance, these principles can be applied to effort allocation in competing research groups, patent races, political competitions, and startup financing.[46] Any of these scenarios would need careful individual analysis due to the specific incentive structures, but are subject to the same stylized results: If some sort of social dilemma is to be solved, say a public goods game, asymmetric resource-distribution increases the likelihood of a group coordinating by naturally establishing a consensus on the allocation of contributions. For individual actors, being resourceful in one way or another comes at the cost of increased pressure to be that main contributor, whether through personal strength or by having helpers within the same group. However, within a larger context of competing public goods games, this pressure can be alleviated by diversifying resources across multiple competing projects. Remarkably, in this framework, the individual benefits of diversification extend beyond mitigating outcome uncertainty; it also enables the diversifying actor to engage in strategic free-riding by assuming a passive role in each project they are involved in. This strategy allows them to exert lower effort compared to non-diversified actors. Engaging in multiple competing research projects enables free-riding across each endeavor, investing in multiple startups within the same sector provides an excuse to abstain from subsequent investment rounds, and holding stakes in opposing outcomes of political decisions helps evade involvement in contentious debates. Notably, there is limited prior analysis on the strategic advantages of diversification stemming from free-riding options for diversified parties, thus leaving this area very much open to future theoretical and empirical research.

[46] A more comprehensive discussion on this topic is provided in the introduction.

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A Case Study: The Strategic Benefits of Having Multiple Leaders in Road Cycling Races

The tactics employed by cycling teams undergo periodical changes, like in most sports, as teams react to changes other teams make. However, certain aspects of bike races appear to remain constant. Typically, in most races, an early breakaway gets a small advantage early in the day, although there is virtually no chance for that breakaway to outlast the peloton later if one or more teams decide to *control the race*.

Controlling the race means having riders ride at the front of the peloton for most of the day to keep the gap to the breakaway constant, then increase the pace later in the race to outright catch the breakaway. Teams adopt this strategy when they aim to secure the win and are not satisfied with their prospects within the breakaway, such as when they lack representation in that group. In a flat race, most of the controlling comes down to the final kilometers of the race, when the teams that want to catch the breakaway form so-called *leadout trains*, as can be seen in Figure 6a.

Figure 6: Controlling the Race

(a) Controlling a Flat Race

(b) Team Sky's Mountain Train

In the early 2010s, the British cycling team Sky invested considerable amounts of money into the analysis of all aspects of road racing with the sole purpose of winning the Tour de France with a British rider for the first time. Among their tactical innovations was adapting sprint leadouts for mountainous races, leading to the concept of the "Sky Train" or "Mountain Train" (see Figure 6b). This strategy aimed to effectively control mountain stages by organizing a line of strong climbers, with the team captain positioned behind the last helper, at the front of the peloton during long climbs (lasting around thirty to forty minutes). This approach helped stabilize the race by discouraging attacks and maintaining a steady gap to breakaway groups, increasing the likelihood of catching them before the finish line. One of the main results of our paper states that controlling a mountain stage, however, is only helpful, if the hard pace benefits your leader more than the others.

A.1 Who Controls a Race?

Frequently, multiple teams may have motives to take control of the race. However, the practical implementation of this strategy can be disadvantageous for the team conducting it since riders at the front of the peloton can sustain high speeds for only a limited duration before fatigue sets in.

Our strategic analysis focuses on the coordination problem that the teams with an incentive to chase face because of this. Who controls the race? The intuitive answer suggests that the most pressure to do so will be put on the strongest team. Formalizing this is not straightforward, however. Our paper examines the role of strength along two different dimensions: Having more helpers or having a stronger captain. We find that teams with an incentive to chase should use their helpers relatively liberally, but once only team leaders are left, the one most likely to win in a direct sprint will be forced to do the hard work - unless that team has an outside option, i.e. a promising rider in the breakaway! That "unless" is what we want to focus on in the following because it is a factor teams can influence beforehand, e.g. by actively trying to put a rider in the breakaway or even earlier, in the selection of their race roster. As we will expand on now, in many instances, including several leaders with different specialities (for instance breakaway specialists and sprinters)is advantageous for a team. Even having multiple co-leaders of different capabilities in the same speciality can prove useful.

A.2 The Strategic Benefit of Multiple Leaders

One recent example of stellar team strategy in a one-day race was the 2024 edition of "Milano-San Remo". Team Alpecin-Deceuninck nominated two leaders: Breakaway specialist Mathieu van der Poel and sprint specialist Jasper Philipsen. Van der Poel managed to join a small breakaway late in the race, at this point the clear favorite to win the race. Meanwhile, this group was chased by a group containing Philipsen as the fastest sprinter.

If van der Poel were not present in the breakaway, all riders of the chasing group would want Philipsen to ride at the front to catch the breakaway because they most likely would beat all the others in a sprint. Similarly, if Philipsen weren't chasing, van der Poel would be the one pressured to lead the breakaway in order to stay away from the chasing group. However, in reality, with both riders in their respective positions, they both could free-ride within their groups. Why? Van der Poel was indifferent to whether the breakaway was caught because if it was, his teammate Philipsen stood a good chance of winning. Similarly, Philipsen was unconcerned about the breakaway being caught because van der Poel would probably win if it stayed away. One of the events had to happen, of course. Eventually, van der Poel's group did get caught. When that happened, the optimal strageies changed, and Team Alpecin-Deceuninck was prepared! It was now Mathieu van der Poel who immediately started riding at the front. This is due to the fact that Philipsen was now the clear favorite to win the final sprint of the new, larger front group, so they were responsible for making sure that they did not get caught by other groups of riders behind them. Having van der Poel as a helper prevented him from needing to the the riding at the front by himself. Now guess who won the race? A very much rested Jasper Philipsen.

A.3 The Crucial Role of Beliefs

In the 2020 Tour de France, 21-year old Tadej Pogačar made his debut in the biggest stage race in the world with a team of helpers that were completely unable to provide him with assistance in the mountains. However, they were not the main favourite to win the race. That role fell to his compatriot Primož Roglič, who arrived with a team that was perfectly capable of providing him with a mountain train in the decisive stages. In all of these stages, Roglič's team (Jumbo Visma) controlled the race, and every time Pogačar followed their train but never attempted to take the race lead from Roglič. This was until the second last stage[47] of that Tour de France, an individual time trial up a mountain.[48] Only on that day, when team tactics had no impact at all, did it become obvious that Pogačar, not Roglič, was the strongest climber in the race. Roglič had built an advantage of 57 seconds over the previous nineteen race days, but lost close to two minutes on the day. It remains unclear whether Pogačar and his team knew at any point of the race that they had the strongest rider but from how they behaved over the three weeks in July 2020, it is obvious that Jumbo Visma never suspected it.[49] Otherwise, they should not have controlled the mountain stages the way they did.

[47]Since a few decades there is a "gentleman's agreement" among riders for the very last stage that ends in Paris: the general classification is not fought over. Consequently, the penultimate stage is the riders' last chance to attack the leader.

[48]In an individual time trial, the riders do not start all at once but separately in reverse ranking order of the general classification, making free-riding pretty much impossible.

[49]Jumbo Visma's director had stated the day before Stage 20 that they were "95 per cent certain to win the Tour".

Figure 7: How (not) to use your Teammates

(a) Pogačar (in white) behind Jumbo Visma's Mountain Train

(b) Pogačar (in yellow) against Roglič and Vingegaard (both in brown)

A.4 How to Use Multiple Leaders in a Stage Race

We have seen how Alpecin-Deceuninck used two leaders with different skillsets to win Milano-San Remo above. Reading how Roglič lost the Tour de France 2020, you might ask: "If Pogačar was the strongest rider, how could Roglič's team have defeated him anyway?" Our paper provides the answer: by forcing Pogačar to exert himself by chasing down attacks. How this might look in detail became clear two years later, when Pogačar arrived at the Tour de France with a now much stronger team. Ranked as the best rider in the world after his dominant victory in the Tour de France 2021, Pogačar again faced his main rival, Primož Roglič, who now had the support of a co-captain, Danish climber Jonas Vingegaard (who had finished second only to Pogačar the previous year, after Roglič had crashed early in the race). Jumbo Visma designated both Vingegaard and Roglič as equal leaders and utilized their mountain train for both of them.

On stage 11 of that Tour, Jumbo Visma made their bet for the lead on the penultimate mountain of the day, the Col du Galibier. They alternated attacks between Roglič and Vingegaard, prompting Pogačar to close the gap to either attacker repeatedly. After Pogačar caught up, they immediately slowed down, allowing their other leader to follow Pogačar without sprinting all-out every time. That way, they made Pogačar so tired that when they attacked with Vingegaard on the final climb, Pogačar finally cracked and lost several minutes. Vingegaard won the Tour that year, genuinely looking stronger than Pogačar also later in the race. However, Jumbo's strategic brilliance lay in their willingness to sacrifice Vingegaard's ambition for Roglič's. Had Pogačar not followed Roglič on any occasion on the Galibier, the latter might have ridden away to win the Tour instead.

Jumbo Visma have since stuck largely to the multiple-leader strategy and took this to the extreme when they won the Tour of Spain in 2023 with Sepp Kuss, their third-strongest rider. Kuss had been let go in a breakaway in the first of three weeks of racing, gaining a large lead on all other teams' leaders. Jumbo Visma used Vingegaard and Roglič to put the other teams under pressure on all subsequent mountain stages but ended up winning the race with Kuss. Notably, Kuss struggled to follow Vingegaard and Roglič at times, and his odds to win the race before the first stage were a staggering 325:1.

The lessons drawn from these cases and scenarios highlight the value of having multiple leaders when managed strategically. The advantage gained from employing several leaders exceeds the benefits of mere diversification. This strategic benefit arises from a simple principle, which our paper is the first to point out: distributing riders across various groups can create opportunities for free-riding in each of the groups. Consequently, there exists a *Strategic Benefit of Sending Your Friends Away.*

B Theory

B.1 Position Updating

Given actions a and positions p^0, the updated position vector p^1 is constructed as follows:

$$p^1_{i,j} = \begin{cases} p^0_{i,j} + 2 & \text{if } \begin{cases} a^0_{i,j} = A, \text{ or} \\ a^0_{i,j} = M \wedge \exists (i', j') : p^0_{i',j'} = p^0_{i,j} \wedge a^0_{i',j'} = A. \end{cases} \\ p^0_{i,j} + 1 & \text{if } \begin{cases} a^0_{i,j} = P, \text{ or} \\ a^0_{i,j} \in \{R, M\} \wedge \exists (i', j') : p^0_{i',j'} = p^0_{i,j} \wedge a^0_{i',j'} = P, \text{ or} \\ a^0_{i,j} = M \wedge \exists (i', j') : p^0_{i',j'} = p^0_{i,j} - 1 \wedge a^0_{i',j'} = A. \end{cases} \\ p^0_{i,j} & \text{if } a^0_{i,j} \in \{R, M\} \wedge \nexists (i', j') : p^0_{i',j'} = p^0_{i,j} \wedge a^0_{i',j'} = P. \end{cases}$$

B.2 Payoff Matrices

Table 8: Payoff matrices of the discussed situations

Situation **1.a**

		Pink	
		M	A
Black	R	1,0	$\boxed{\frac{1}{2},\frac{1}{2}}$

Situation **1.b**

		Pink	
		M	A
Blue	M	$\boxed{0,0}$	1,0
	A	0,1	$\frac{1}{3},\frac{1}{3}$

Situation **1.c**

		Pink
		M
Blue	M	0,0
	A	$\boxed{\frac{1}{3},\frac{1}{3}}$

Situation **2.a**

		Pink	
		M	A
Blue	M	0,0	$\boxed{\frac{1}{2},\frac{1}{2}}$
	A	0,1	0,1

Situation **2.b**

		Pink	
		M	A
Blue	$M\|M$	0,0	1,0
	$M\|A$	$\boxed{\frac{1}{3},\frac{2}{3}}$	1,0

Situation **3.a**

		Pink		
		R	M	A
Blue	R	$\frac{1}{2},\frac{1}{2}$	$\frac{3}{5},\frac{2}{5}$	0,1
	M	$\frac{2}{5},\frac{3}{5}$	$\frac{1}{2},\frac{1}{2}$	$\frac{2}{3},\frac{1}{3}$
	A	1,0	$\frac{1}{3},\frac{2}{3}$	$\frac{1}{2},\frac{1}{2}$

Situation **3.b**

		Pink		
		P	M	A
Blue	R	$\frac{5}{7},\frac{2}{7}$	$\frac{5}{7},\frac{2}{7}$	0,1
	M	$\frac{5}{7},\frac{2}{7}$	$\frac{5}{7},\frac{2}{7}$	$\boxed{\frac{2}{3},\frac{1}{3}}$
	A	1,0	$\frac{1}{3},\frac{2}{3}$	$\frac{1}{2},\frac{1}{2}$

Situation **4.a**

		Pink	
		R	M
Blue	$R\|M$	$\frac{x}{x+2},\frac{2}{x+2}$	$\frac{x}{x+1},\frac{1}{x+1}$
	$R\|A$	1,0	$\frac{1}{2},\frac{1}{2}$
	$M\|A$	1,0	$\frac{x-1}{x},\frac{1}{x}$

Situation **4.b**

		Pink	
		P	A
Blue	$P\|M$	$\boxed{1,0}$	$\boxed{1,0}$
	$P\|R$	1,0	$\frac{1}{2},\frac{1}{2}$
	$R\|M$	$\frac{2}{3},\frac{1}{3}$	1,0
	$R\|R$	$\frac{3}{4},\frac{1}{4}$	0,1

Note the following:

- In Situation 3.a, there is no Nash-equilibrium in pure strategies. In the THPE both players mix between R, M and A. The equilibrium payoff is $(\frac{1}{2}, \frac{1}{2})$.
- In Situation 4.a, we assume that $x > 3$. For the blue team, the action $M|A$ means that the rider stronger rider (the one with x energy units remaining) plays Mark and the weaker rider Attacks. Again, there is no Nash equilibrium in pure strategies. In the THPE the blue team mixes between $R|M$ and $M|A$ and the pink team mixes between R and M.

B.3 Proof of Proposition 1

In the following, we order e_i^t, p_i^t and s_i w.l.o.g. by magnitude of the components of e_i^t. Note that the game is by construction a coordination game in which each Nash Equilibrium s^* satisfies $s_{i,j} = A$ for some (i, j) and $s_{i',1} = M$ for all $i' \neq i$ (this is then the best response for the designated sprinter of team i').

(a) Let i denote a team with $e_{i,2} \geq 2$. Remember that we assume that each team sometimes prefers $s_{i,1} = A$ over $s_{i,1} = M$ (namely if nobody plays A). It is clear that $s_{i,1} = M$ and $s_{i,2} = A$ leads to a strictly higher payoff for team i than any strategy tuple wit $s_{i,1} = A$, which means that the strategy $s_i = (M|A|...)$ is weakly dominant. Because weakly dominated strategies can never be played in THPE, (a) is true. Given the strategy of team i in (a), A is clearly never a best response to this, which shows that all other riders Mark.

(b) Because the setup is that of a coordination game, for each team, there is a *strict* equilibrium in which one of the riders of this team Attacks (and no other rider Attacks) and a strict equilibrium in which no rider of the team Attacks (and some other rider from another team Attacks), there must be an equilibrium in which each team places a probability strictly between 0 and 1 on Attacking and not Attacking, respectively. Hence, in such a mixed strategy equilibrium, there is a positive probability of no rider Attacking.

(c) W.l.o.g., assume that each team has only one rider and denote $e_i = e_{i,1}$. Let s be the team with the strongest rider and $\bar{e} = \sum_i e_i$. By the Nash-Product theorem in Harsanyi & Selten (1988), we need to show that

$$\forall j \neq s: \left(0 - \frac{e_s - 2}{\bar{e} - 3}\right) \prod_{i \neq s} \left(\frac{e_i - 2}{\bar{e} - 4} - \frac{e_i - 1}{\bar{e} - 3}\right) > \left(0 - \frac{e_j - 2}{\bar{e} - 4}\right) \prod_{i \neq j} \left(\frac{e_i - 2}{\bar{e} - 4} - \frac{e_i - 1}{\bar{e} - 3}\right)$$

See Example 1 for the two player case. Continuing with the general case, dividing by $\prod_{i \neq s,j} \left(\frac{e_i - 2}{\bar{e} - 4} - \frac{e_i - 1}{\bar{e} - 3}\right)$ yields

$$\left(\frac{e_j - 2}{\bar{e} - 4} - \frac{e_j - 1}{\bar{e} - 3}\right) \left(0 - \frac{e_s - 2}{\bar{e} - 3}\right) > \left(0 - \frac{e_j - 2}{\bar{e} - 3}\right) \left(\frac{e_s - 2}{\bar{e} - 4} - \frac{e_S - 1}{\bar{e} - 3}\right)$$

This indeed holds because the inequality boils down to $(e_S - 2)^2 > (e_j - 2)^2$ and because $e_S > e_j$ is true by assumption.

Example 1. *Suppose there are two riders in a group with different levels of energy (strength) and both riders prefer to Attack over no member of the group to Attack. Then, in the risk dominant equilibrium, the stronger rider Attacks.*

Proof. Suppose there are two riders playing a coordination game on who Attacks. The stronger rider (pink) has an energy level of e_S whereas the weaker rider (blue) has one of e_W, with $e_S > e_W$ and $\bar{e} = e_S + e_W$. This corresponds to the following game matrix with the two pure strategy equilibria inside the red boxes.

	A	M
A	$\frac{e_W-2}{\bar{e}-4}, \frac{e_S-2}{\bar{e}-4}$	$\boxed{\frac{e_W-2}{\bar{e}-3}, \frac{e_S-1}{\bar{e}-3}}$
M	$\boxed{\frac{e_W-1}{\bar{e}-3}, \frac{e_S-2}{\bar{e}-3}}$	0,0

Here, the equilibrium where the strong (pink) rider Attacks is the risk dominant one iff the following holds (the product of deviation losses must be highest[50] in the risk dominant equilibrium, see Harsanyi & Selten (1988)):

$$\left(\frac{e_W-2}{\bar{e}-4} - \frac{e_W-1}{\bar{e}-3}\right)\left(0 - \frac{e_S-2}{\bar{e}-3}\right) > \left(0 - \frac{e_W-2}{\bar{e}-3}\right)\left(\frac{e_S-2}{\bar{e}-4} - \frac{e_S-1}{\bar{e}-3}\right)$$

This indeed holds because the inequality boils down to $(e_S-2)^2 > (e_W-2)^2$ and because $e_S > e_W$ is true by assumption. □

B.4 Proof of Proposition 2

Adding a member of team i to a group that previously had no rider of group i creates an outside option in the following way:

- If team i has a rider in the front group and a rider is added to the second group, the win probability for team i in the case of coordination failure in the front group is now (weakly) higher. This means that team i's riders in the front group can play A with lower probability.

[50]We can interpret the product of deviation losses at an equilibrium as a measure of collective reluctancy to deviate from that equilibrium.

- If team i has a rider in the second group and a rider is added to the front group, the win probability for team i in the case of coordination failure in the second group is now (weakly) higher. This means that team i's riders in the second group can play A with lower probability.

Given that team i's riders play A with lower probability, the other teams react (in equilibrium) by playing Attack more often. This further increases the win probability of team i's rider of the initial group (the rider that obtains a new teammate in another group) because they benefit from more extensive free-riding options.

C Empirical Results

C.1 Summary Statistics

Table 9: Summary Statistics Non-Dummies

	Group 1 size	Group 2 size	Group 3 size	Gap between Groups 1 and 2	Gap between Groups 2 and 3
mean	2.18	3.03	2.30	38.7	31.2
std	1.83	2.20	1.93	57.8	65.9
min	1	1	1	5	5
50%	2	2	1	21	14
max	12	12	11	853	1155

Table 10: Mean occurrence of Dummies

	Star	Stronger Rider in group	Helper in group	Teammates behind
Group 1	0.292	0.252	0.048	0.125
Group 2	0.269	0.345	0.065	0.098
Group 3	0.196	0.266	0.053	
Overall	0.253	0.294	0.056	0.113

C.2 Additional Analyses

Hypothetical Teammates

Table 11: Linear Probability Model: Winning the Race from Group 1

Hypothetical teams	NO	YES
Intercept	0.512***	0.618***
	(0.151)	(0.183)
Stronger Rider in Group	-0.045	-0.032
	(0.030)	(0.033)
Helper	0.080	0.247***
	(0.072)	(0.076)
Stronger Rider in Group x Helper	0.167	0.018
	(0.114)	(0.124)
Teammate behind	0.118***	-0.039
	(0.043)	(0.053)
Observations	1303	1152
R^2	0.095	0.098
Adjusted R^2	0.049	0.046
F Statistic	2.06*** (df=63; 1239)	1.88*** (df=63; 1088)

Note: *p<0.1; **p<0.05; ***p<0.01
The endogenous variables are dummies, indicating whether riders have won.
We additionally control for year, race, stage type, gap sizes between groups, and group sizes.
In the hypothetical teams treatment we randomly assign riders to teams.

Robustness of Results: The Definition of Stars

Recall that in each season, we categorize “Star” riders as those who achieved a top 20% score in the previous season. To check the robustness of our results, Stars are defined as riders placed in the top 10% of the previous season, in the following tables. Despite this difference in definition, our regression tables demonstrate that the overall trends in our results remain consistent. One notable change is the significant negative effect of a “Stronger Rider in Group” on win probability. Specifically, being identified as a Star or having no Star present in one’s winning group positively impacts a rider’s chances of winning (see Table 13). However, the majority of effects remain largely unchanged. Especially, the positive influence of having a teammate in the group behind remains significant and maintains its magnitude.

Table 12: Linear Probability Model: Finishing in Group 1 - Fewer Stars

	G1 if in G1/G2	G1 if in G1/G2/G3
Intercept	0.471***	0.398***
	(0.070)	(0.063)
Stronger Rider around	-0.166***	-0.147***
	(0.023)	(0.019)
Teammate behind	0.118***	
	(0.023)	
Observations	3834	5240
R^2	0.256	0.206
Adjusted R^2	0.244	0.196
F Statistic	20.6*** (df=63; 3770)	21.7*** (df=62; 5177)
Note:		*p<0.1; **p<0.05; ***p<0.01

The endogenous variables are dummies, indicating whether riders are part of Group 1.
We additionally control for year, race, stage type, gap sizes between groups, and group sizes.

Table 13: Linear Probability Model: Winning the Race from Group 1 - Fewer Stars

Hypothetical teams	NO	NO	YES
Intercept	0.516***	0.516***	0.599***
	(0.151)	(0.151)	(0.181)
Stronger Rider in Group	-0.067**	-0.061	-0.031
	(0.033)	(0.032)	(0.035)
Helper	0.115	0.149***	0.190***
	(0.071)	(0.057)	(0.054)
Stronger Rider in Group x Helper	0.096		
	(0.119)		
Teammate behind	0.118***	0.119***	0.030
	(0.043)	(0.043)	(0.055)
Observations	1303	1303	1180
R^2	0.095	0.095	0.101
Adjusted R^2	0.049	0.051	0.047
F Statistic	2.07*** (df=63; 1239)	2.09*** (df=62; 1240)	2.03*** (df=62; 1117)
Note:			*p<0.1; **p<0.05; ***p<0.01

The endogenous variables are dummies, indicating whether riders have won.
We additionally control for year, race, stage type, gap sizes between groups, and group sizes.
In the hypothetical teams treatment we randomly assign teammates.

Robustness of Results: The Definition of Groups

In our main analysis we define a rider to be in the same group as the rider in front of him if the gap between the two riders is below 5 seconds (gap threshold). If the gap to the rider in front is 5 or more seconds then the respective rider is defined to be in a new (higher) group. The following tables show how our main regression results depend on how we define groups. In the "larger groups setup" the gap threshold is set to 10 seconds (see Tables 14 and 15). In the "smaller groups setup" the gap threshold is set to 1 second (see Tables 16 and 17).

Table 14: Linear Probability Model: Finishing in Group 1 - Larger Groups

	G1 if in G1/G2	G1 if in G1/G2/G3
Intercept	0.536^{***}	0.419^{***}
	(0.075)	(0.064)
Stronger Rider around	-0.210^{***}	-0.183^{***}
	(0.020)	(0.015)
Teammate behind	0.083^{***}	
	(0.022)	
Observations	3614	5090
R^2	0.276	0.229
Adjusted R^2	0.263	0.219
F Statistic	21.5^{***} (df=63; 3550)	24.0^{***} (df=62; 5027)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The endogenous variables are dummies, indicating whether riders are part of Group 1.
We additionally control for year, race, stage type, gap sizes between groups, and group sizes.

Table 15: Linear Probability Model: Winning the Race from Group 1 - Larger Groups

Hypothetical teams	NO	NO	YES
Intercept	0.457***	0.457***	0.569***
	(0.150)	(0.150)	(0.157)
Stronger Rider in Group	-0.033**	-0.032	-0.024
	(0.030)	(0.029)	(0.032)
Helper	0.091	0.093*	0.167***
	(0.065)	(0.051)	(0.053)
Stronger Rider in Group x Helper	0.005		
	(0.104)		
Teammate behind	0.084**	0.084**	0.002
	(0.041)	(0.041)	(0.056)
Observations	1276	1276	1115
R^2	0.094	0.094	0.095
Adjusted R^2	0.047	0.048	0.042
F Statistic	2.00*** (df=63; 1212)	2.03*** (df=62; 1213)	1.79*** (df=62; 1052)

Note: *p<0.1; **p<0.05; ***p<0.01
The endogenous variables are dummies, indicating whether riders have won.
We additionally control for year, race, stage type, gap sizes between groups, and group sizes.
In the hypothetical teams treatment we randomly assign teammates.

Table 16: Linear Probability Model: Finishing in Group 1 - Smaller Groups

	G1 if in G1/G2	G1 if in G1/G2/G3
Intercept	0.459***	0.383***
	(0.068)	(0.062)
Stronger Rider around	-0.210***	-0.192***
	(0.023)	(0.018)
Teammate behind	0.132***	
	(0.027)	
Observations	3127	4200
R^2	0.270	0.209
Adjusted R^2	0.255	0.197
F Statistic	18.0*** (df=63; 3063)	17.6*** (df=62; 4137)

Note: *p<0.1; **p<0.05; ***p<0.01
The endogenous variables are dummies, indicating whether riders are part of Group 1.
We additionally control for year, race, stage type, gap sizes between groups, and group sizes.

Table 17: Linear Probability Model: Winning the Race from Group 1 - Smaller Groups

Hypothetical teams	NO	NO	YES
Intercept	0.561***	0.560***	0.645***
	(0.137)	(0.137)	(0.154)
Stronger Rider in Group	-0.047	-0.041	-0.028
	(0.034)	(0.033)	(0.037)
Helper	0.077	0.117*	0.135**
	(0.086)	(0.067)	(0.063)
Stronger Rider in Group x Helper	0.097		
	(0.132)		
Teammate behind	0.163***	0.162***	-0.045
	(0.050)	(0.050)	(0.075)
Observations	1079	1079	925
R^2	0.099	0.098	0.091
Adjusted R^2	0.044	0.044	0.026
F Statistic	1.80*** (df=62; 1016)	1.82*** (df=61; 1017)	1.41** (df=61; 863)

Note: *p<0.1; **p<0.05; ***p<0.01
The endogenous variables are dummies, indicating whether riders have won.
We additionally control for year,[51] race, stage type, gap sizes between groups, and group sizes.
In the hypothetical teams treatment we randomly assign teammates.

C.3 Logistic Regressions

Table 18: Logistic Probability Model: Finishing in Group 1

	G1 if in G1/G2	G1 if in G1/G2/G3
Intercept	-0.142	-0.227***
	(0.374)	(0.344)
Stronger Rider around	-1.14***	-1.08***
	(0.122)	(0.106)
Teammate behind	0.624***	
	(0.121)	
Observations	3834	5240
Pseudo R^2	0.228	0.181

Note: *p<0.1; **p<0.05; ***p<0.01
The endogenous variables are dummies, indicating whether riders are part of Group 1.
We additionally control for year, race, stage type, gap sizes between groups, and group sizes.

[51] We exclude the dummy for the year 1988 due to the lack of data for the respective year.

Table 19: Logistic Probability Model: Winning the Race from Group 1

Hypothetical teams	NO	NO	YES
Intercept	0.334	0.313	0.737
	(0.698)	(0.697)	(0.752)
Stronger Rider in Group	-0.193	-0.133	-0.113
	(0.153)	(0.148)	(0.158)
Helper	0.435	0.757^{***}	1.10^{***}
	(0.348)	(0.274)	(0.284)
Stronger Rider in Group x Helper	0.829		
	(0.538)		
Teammate behind	0.829^{***}	0.559^{***}	0.000
	(0.202)	(0.202)	(0.243)
Observations	1303	1303	1129
Pseudo R^2	0.086	0.085	0.080

Note: *p<0.1; **p<0.05; ***p<0.01
The endogenous variables are dummies, indicating whether riders have won.
We additionally control for year, race, stage type, gap sizes between groups, and group sizes.
In the hypothetical teams treatment we randomly assign teammates.

C.4 One-Day Races

Summary Statistics

Table 20: Summary Statistics Non-Dummies

	Group 1 size	Group 2 size	Group 3 size	Gap between Groups 1 and 2	Gap between Groups 2 and 3
mean	2.18	3.48	2.92	50.8	46.5
std	1.58	2.54	2.29	49.4	64.7
min	1	1	1	5	5
50%	2	3	2	28	23
max	10	12	11	219	408

Table 21: Mean occurrence of Dummies

	Star	Stronger Rider in group	Helper in group	Teammates behind
Group 1	0.323	0.288	0.038	0.165
Group 2	0.227	0.454	0.072	0.126
Group 3	0.138	0.325	0.057	
Overall	0.221	0.368	0.059	0.149

Regressions

Table 22: Linear Probability Model: Finishing in Group 1 - One-Day Races

	G1 if in G1/G2	G1 if in G1/G2/G3
Intercept	0.463***	0.315***
	(0.077)	(0.063)
Stronger Rider around	-0.168***	-0.183***
	(0.044)	(0.034)
Teammate behind	0.159***	
	(0.052)	
Observations	593	837
R^2	0.265	0.202
Adjusted R^2	0.249	0.191
F Statistic	16.1*** (df=13; 579)	17.4*** (df=12; 824)

Note: *p<0.1; **p<0.05; ***p<0.01
The endogenous variables are dummies, indicating whether riders are part of Group 1.
We additionally control for race, gap sizes between groups, and group sizes.

Table 23: Linear Probability Model: Winning the Race from Group 1 - One-Day Races

Hypothetical teams	NO	NO	YES
Intercept	0.696***	0.700***	0.690***
	(0.135)	(0.135)	(0.135)
Stronger Rider in Group	-0.227***	-0.220***	-0.221***
	(0.072)	(0.071)	(0.075)
Helper	-0.105	0.165	0.202*
	(0.468)	(0.181)	(0.122)
Stronger Rider in Group x Helper	0.317		
	(0.506)		
Teammate behind	-0.241**	-0.242**	-0.199
	(0.102)	(0.102)	(0.132)
Observations	194	194	178
R^2	0.138	0.137	0.139
Adjusted R^2	0.081	0.084	0.082
F Statistic	2.42*** (df=12; 181)	2.62*** (df=11; 182)	2.43*** (df=11; 166)

Note: *p<0.1; **p<0.05; ***p<0.01
The endogenous variables are dummies, indicating whether riders have won.
We additionally control for race, gap sizes between groups, and group sizes.
In the hypothetical teams treatment we randomly assign teammates.