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Competition and Risk-Taking

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Competition and risk-taking*

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Abstract

In many situations, agents take risks by choosing an action that increases their performance immediately, but that potentially leads to a large loss. The current paper studies how such risk-taking behavior depends on the level of competition that the agents face. We study a tournament model and we find that more intense competition, measured by the number of competitors as well as their relative standing, induces agents to take higher risks. We use a rich panel data set on professional biathlon competitions as well as survey data from professional biathletes to confirm the model predictions. Finally, we discuss implications for organizational decision-making.

JEL Codes: *M51, M52, Z22*

Keywords: *Risk-taking, competition, tournament, incentives, biathlon*

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1. Introduction

Consider an associate at a prestigious law firm whose goal is to become partner. To outshine the coworkers, the associate regularly works 80 to 100 hours a week. On the evening of a particularly stressful day, the associate accidentally sends an e-mail to the wrong client, thereby revealing sensitive information about another client. The associate apologizes to the firm whose information was disclosed, but the law firm loses this client anyhow. As a result, the associate's striving for partnership suffers a significant setback.[1]

As a second example, consider a young researcher who is not yet tenured. The researcher has gathered experimental data to test an innovative hypothesis. The statistical tests point in the correct direction, but the results are not quite significant. The researcher is convinced that some of the subjects did not fully understand the experiment and decides to drop these "outliers". In consequence, the results become significant and the researcher publishes the study in a high-quality journal, thereby improving the chance to get tenure.[2]

As a third example, consider the manager of a publicly financed hospital. The manager is informed that several of the hospitals in the county will be closed and that this decision will depend on the hospitals' financial health. The manager advises the medical directors to talk patients into expensive treatments and to admit as many patients as possible. During one unnecessary surgery complications occur, and the patient sues the hospital afterwards for damages. The case is settled, but the hospital pays a large sum in compensation to the patient and it is more likely to be closed as a result.[3]

Although these examples describe very different decision problems, they have several

[1]There is a lot of evidence that people are more likely to make mistakes when working long hours. Related to the example, 52% (43%) of the respondents to a recent survey by Tessian say that they are more likely to make mistakes with serious cybersecurity implications if they are stressed (tired) (Bishop 2022). DeVaro (2022) presents additional examples of long working hours leading to grave errors.

[2]There are several high-profile cases in which researchers were caught falsifying data and making up studies. Moreover, about one in 12 of the PhD students recruited for a recent study admit that they would publish fraudulent results if it helped them to get ahead in academia (van de Schoot et al. 2021).

[3]A study by the SOCIUM research center of the University of Bremen conducted interviews with around sixty doctors and hospital directors. The study finds evidence that the economization of hospitals in Germany and the associated financial incentives as well as economic pressure of doctors may endanger patients' health by talking them into expensive and unnecessary treatments (Knight 2017).

important commonalities. In all of the examples, the decision-makers find themselves in some type of competition against other agents. The decision-makers can take an action that increases their performance immediately (working long hours, manipulating data, recommending unnecessary treatments), but that comes at the risk of a potentially large loss to their performance (due to a mistake, being caught, or complications). Comparable decision problems are prevalent in practice, and the goal of our paper is to study such type of risk-taking. More specifically, we aim to investigate how this type of risk-taking is affected by the intensity of competition.

Our study comprises a theoretical and an empirical part. The theoretical part follows the seminal work of Lazear and Rosen (1981) and it models the competition among the agents as a rank-order tournament. There are several agents competing against each other, and the best-performing one receives a prize.[4] The agents are heterogeneous in that they start the tournament from different positions. They decide about the speed with which they perform their tasks, and they possibly make mistakes, reducing their performance. Quicker speed leads to a larger maximum performance, but also to more mistakes on average and can thus be understood as a riskier strategy.[5] We model the intensity of competition both by the proximity in the starting positions and the number of competing agents.

The model's main finding is that agents take more risks when the intensity of competition becomes higher, that is, when they are located close to each other and when the number of competitors is large. Intuitively, when agents act excessively restrained in such situations, they have almost no chance of winning the tournament. Thus, they are willing to take more risks and they decide to work at a faster pace. An immediate consequence is that agents make more mistakes on average when the level of competition is high.

The paper's empirical part uses data from professional biathlon competitions to verify

[4]Depending on the specific application of our model, "agents" could be employees, researchers, managers, and so on.

[5]While we refer to the choice variable as task speed in our model (which is closely related to the long working hours in the first of the three introductory examples), alternative interpretations such as those from the other examples are possible as well.

the model's main predictions.[6] Biathlon is a winter sport that combines cross-country skiing and rifle-shooting. The total skiing distance is divided into multiple laps, and at the end of each lap (except for the last one), athletes enter the shooting range to shoot at five targets. Missed shots result in a penalty. Depending on the discipline, the penalty is given by either an additional distance athletes have to ski before entering the next lap, or by time added to their total course time. In the disciplines that we focus on in our study, which are Mass Start and Pursuit, all athletes are on the course at the same time, and the final ranking is determined by the order of finishing the course. Accordingly, athletes are informed about their intermediate rank and the distance to their competitors throughout the race. In both disciplines, athletes have to complete five laps and thus four shooting bouts. As a measure of risk-taking, we use the time that the athletes require to complete the last course section of the fourth round. The argument is that rifle shooting is a precision task that requires the athlete to be calm and concentrated. A higher intensity in skiing right before the shooting is physiologically demanding and therefore leads to worse shooting accuracy. We are able to verify this argument empirically by showing that faster skiing increases the average number of missed shots in the following shooting bout.[7]

Consistent with our theoretical model, we use different measures for the intensity of competition. First, we use the number of athletes who are located within a short time interval in front of and behind the athlete at the start of the last course section of the fourth round. Second, we use the distance (in seconds) between athletes and the next competitors in front of and behind them. Our empirical analysis supports the results of our model. For both of our competition measures, we find that higher intensity of competition is associated with a faster skiing time in the last section of the fourth round, that is, with more risky

[6]Data from biathlon have been used in other recent research in management and economics. See, e.g., Harb-Wu and Krumer (2019) on performance under pressure, and Krumer (2021) on discouragement when lagging behind.

[7]Because of the observed relationship between the skiing speed (i.e., task speed) and the number of missed shots (i.e., mistakes), we feel that biathlon data are particularly suited to verify the model's predictions. More generally, Kahn (2000) and Bar-Eli et al. (2020) highlight the benefits of using professional sports data to test predictions in the context of labor-market research.

behavior.

We conduct several robustness checks. Among other things, we issued a survey among the biathletes to elicit their risk preferences. We find that more risk-loving biathletes generally take higher risks, thus substantiating the validity of our measure of risk-taking. We further observe that controlling for risk preferences does not have an impact on our main empirical results. Accordingly, we can rule out heterogeneities in risk preferences as a potential explanation for our findings.

Baron and Kreps (1999, p. 27) provide a general classification of jobs according to the risk that managers wish their employees to take. The three classes of jobs are denoted as "guardians", "stars", and "foot soldiers". In a guardian job, bad performance is disastrous from the firm's point of view, whereas good performance is only slightly better than average performance. Hence, in a guardian job, managers want their employees to be careful at all times and to refrain from taking unnecessary risks. A star job is the exact opposite in that bad performance is not too problematic for the firm, but good performance is extremely valuable. In these jobs, managers want to induce their employees to take risks, since the upsides to great performance are much more important than the downsides to poor performance. Finally, a foot soldier job is in-between these two extremes, meaning that both good and bad performances have moderate effects on the firms' profit.

Regardless of the exact level of risk that is desirable from the firm's point of view, a conflict of interest between managers and their employees is conceivable when employees have an incentive to take levels of risk that are different from those preferred by the managers. Our study allows us to understand when such a conflict of interest arises, and how to potentially address it. We find that employees take large risks when they face strong competition within their firm. An implication is that managers that desire their employees to refrain from any unnecessary risk should ensure that employees are by no means inclined to compete against their fellow employees. Not only does this mean that the managers should not award bonuses or promotions based on relative performance, but also that any information about the employees' relative performance should be withheld even if it is of no direct consequence for employee remuneration (Sheremeta 2010, Blanes i Vidal and Nossol 2011). Furthermore, if managers are unable to eliminate all incentives to take risks, they need to ensure that these incentives are not very salient (Englmaier et al. 2017). On the contrary, managers that desire their employees to take risks should make use of instruments to foster competition among the employees.

The paper is structured as follows. The next section discusses related literature, while Section 3 presents the theoretical model. Section 4 contains the empirical investigation, and Section 5 provides robustness checks for our results. Section 6 discusses implications for organizational decision-making and concludes.

2. Related literature

Our paper contributes to the theoretical literature on risk-taking in tournaments. Hvide (2002) and Nieken and Sliwka (2010) study risk-taking behavior in tournaments with two homogeneous contestants. Taylor (2003), Kräkel and Sliwka (2004), and Kräkel (2008) extend the analysis by allowing the two contestants to be heterogeneous, while Gilpatric (2009) considers more than two homogeneous contestants. To our knowledge, our model is the first to study risk-taking in a tournament with more than two heterogeneous contestants.[8] While such a model becomes quickly intractable, we impose distributional assumptions that allow us to solve the model and investigate how the intensity of competition, as measured by the number of contestants and the degree of heterogeneity, affects risk-taking behavior.

Our paper further contributes to the empirical literature by analyzing the impact of competition on risk-taking. The existing work has focused on the financial industry and on sports. An observation from the financial industry is that the inflow into a fund tends to be a convex function of the fund's return relative to other funds. As a consequence, managers whose funds are underperforming have an incentive to invest in more risky assets (e.g., Brown

[8] More precisely, we consider a model with $n \geq 2$ contestants on two starting positions.

et al. 1996, Chevalier and Ellison 1997, and Kirchler et al. 2018). While the literature is able to explain risk-taking behavior resulting from performance differences relative to a single benchmark (the average market return), our paper focuses on the effects of the intensity of competition among individual agents on their risk-taking behavior.

Studies using data from sports competitions mirror the results from the financial literature and show that athletes who are trailing during the tournament tend to deviate to riskier strategies (e.g., Grund and Gürtler 2005, Genakos and Pagliero 2012, Grund et al. 2013, and Feess et al. 2016). We also control for athletes' (intermediate) ranks in our analysis; however, the focus of our paper is on the relation between the intensity of competition and risk-taking behavior. In contrast to the existing literature, we are able directly to measure competition in two different ways by using the number of competitors surrounding the athlete, as well as their respective distances. Another important finding in the literature is the existence of gender differences, with female athletes taking fewer risks than male athletes (e.g., Böheim and Lackner 2015, Feess et al. 2016, and Böheim et al. 2016). While our data set also covers both female and male athletes, we do not find any significant gender effects on risk-taking. As our results are driven by strategic decisions, this is in line with the findings of Bandiera et al. (2021), who show, by aggregating existing literature, that gender differences in response to incentives are close to zero.

Moreover, since we have detailed data on athletes' risk-taking decisions as well as their risk preferences, we are able to verify our risk measure empirically and to exclude heterogeneities in risk preferences as a potential explanation for our findings.

Finally, since in both our theoretical model and the empirical investigation, higher risks result from the decision to work at a faster pace and to make more mistakes as a result, our paper is also related to the literature on the quantity-quality tradeoff. The famous paper by Kerr (1975) contains real-world examples illustrating this tradeoff, and a recent empirical investigation is provided by Hong et al. (2018).[9] We confirm that such a tradeoff exists in

[9]The quantity-quality tradeoff can be understood as a special case of the multitasking problem. This problem has been studied, among others, by Feltham and Xie (1994) and Baker (2002).

biathlon and that the athletes who ski relatively fast right before the final shooting bout tend to make more mistakes. We use this finding in the construction of our measure of risk-taking.

3. Model

3.1. Model description

We consider a tournament model with $n \geq 2$ agents who compete for a single prize $v > 0$. The performance y_i of agent $i \in \{1, ..., n\}$ is given by $y_i = p_i + s_i + \varepsilon_i$, where p_i denotes the agent's actual position in the contest (and/or skill), s_i is the speed with which tasks are performed, and ε_i denotes a random variable capturing mistakes the agent possibly makes.[10] When agents make mistakes, their output is reduced, meaning that the realizations of ε_i are non-positive. Furthermore, mistakes are more likely when working faster. A relatively simple and tractable way to capture this is to assume that the ε_i are distributed according to the reflected exponential distribution, with density $f_{\varepsilon_i}(x) = \lambda(s_i)\exp(\lambda(s_i)x)$ and distribution function $F_{\varepsilon_i}(x) = \exp(\lambda(s_i)x)$ for $x \leq 0$, where λ is a continuously differentiable, strictly decreasing, and positive function. The assumption $\lambda' < 0$ furthermore ensures that the mean $\mu_{\varepsilon_i} = -1/\lambda(s_i)$ is decreasing in s_i, which implies that working faster leads to more mistakes on average.

Moreover, we assume that the agents' average output does not depend on the individual working speed, that is, the higher output due to the higher speed with which the tasks are performed, and the additional mistakes offset each other on average. Formally, this means that $\frac{d}{ds_i}\left(s_i - \frac{1}{\lambda(s_i)}\right) = 0$, or, equivalently, $\lambda'(s_i) = -\left(\lambda(s_i)\right)^2$ for all s_i.[11] Agents have a

[10] In our analysis, we disregard actions that affect the performance of other agents, such as sabotage. For studies of sabotage in tournaments, see, e.g., Lazear (1989) and Carpenter et al. (2010). Gürtler and Chowdhury (2015) provide a survey of the literature.

[11] Note that the differential equation $\lambda'(s_i) = -\left(\lambda(s_i)\right)^2$ is solved by $\lambda(s_i) = 1/(c_\lambda + s_i)$, where $c_\lambda \in \mathbb{R}$. Then, λ is well-defined for all $s_i \neq -c_\lambda$. Hence, in the following, we restrict the domain of λ, and therefore the set of work speeds the agents choose to $s_i > -c_\lambda$. Furthermore, we assume parameters to be such that $\bar{s} > -c_\lambda$.

preferred speed $\bar{s}$ at which they wish to perform their tasks. A deviation from that speed to another level (in either direction) leads to costs $kc(s_i - \bar{s})$, where $k > 0$ is a parameter, the function c is twice continuously differentiable and satisfies $c'(s_i - \bar{s}) > 0$ if and only if $s_i > \bar{s}$, and c'' is bounded from below by a positive number. Together the assumptions from this paragraph imply that $\bar{s}$ represents the efficient work pace, since other levels of s_i yield the same expected output, but higher cost.[12] Additionally, the assumptions ensure that the agents' choice of the working speed is (purely) a choice of risk. Since the deterministic gain on their performance through the increased speed is in expectation offset by the negative effect of probabilistic mistakes, a larger speed leaves the mean unchanged, but spreads the distribution of the overall performance, that is, it corresponds to a riskier strategy.

Agents are heterogeneous with regard to their actual position in the tournament. In particular, $n_t \geq 1$ of the agents are trailing behind at position p_t, whereas the remaining $n_l = n - n_t \geq 1$ agents are leading at position $p_l > p_t$. The agent with the relatively largest output wins the prize. Agents choose their speed s_i so as to maximize their expected payoff.

3.2. Equilibrium characterization and comparative statics results

Denoting agent i's winning probability when choosing working speed s_i by $P_i(s_i)$, the expected payoff U_i, as a function of the work pace s_i, is given by

$$U_i(s_i) = vP_i(s_i) - kc(s_i - \bar{s}). \tag{1}$$

Agent i wins the tournament only if $y_j < y_i$, or, equivalently, $\varepsilon_j < p_i - p_j + s_i - s_j + \varepsilon_i$, for all $j \neq i$. Hence, the winning probability P_i is given by

$$P_i(s_i) = \int \Pi_{j \neq i} F_{\varepsilon_j}(p_i - p_j + s_i - s_j + x) f_{\varepsilon_i}(x) dx. \tag{2}$$

[12] We believe that a model in which deviations from $\bar{s}$ yield no direct cost, but lower expected output, would lead to implications very similar to ours. We opt for the current modeling approach for tractability reasons. A similar modeling approach, where changes in risk lead to cost, but do not affect the expected output, is adopted by Gilpatric (2009).

As it is standard in the literature, we follow a first-order approach and determine the equilibrium by the first-order conditions to the agents' maximization problems. Thus, we assume that k is sufficiently large such that the objective functions are quasiconcave and the first-order approach is valid.

Defining the difference in positions by $\Delta p := p_l - p_t$ and simplifying notation by setting $\lambda_i = \lambda(s_i)$, $\lambda_t^* = \lambda(s_t^*)$ and $\lambda_l^* = \lambda(s_l^*)$, the following Proposition 1 characterizes the agents' equilibrium behavior.

Proposition 1. *If k is sufficiently large, there exists an equilibrium in which all trailing agents at position p_t choose the work pace s_t^*, and all leading agents at p_l choose s_l^*, where s_t^* and s_l^* are jointly determined by*

$$v \exp\left(n_l \lambda_l^* (s_t^* - s_l^* - \Delta p)\right) \lambda_t^* \left(\frac{(n_t - 1)\lambda_t^* + n_l \lambda_l^*}{n_t \lambda_t^* + n_l \lambda_l^*} \right)^2 - kc'(s_t^* - \bar{s}) = 0 \tag{3}$$

and

$$\begin{aligned} &- v \frac{\exp(n_l \lambda_l^* (s_t^* - s_l^* - \Delta p))}{n_t \lambda_t^* + n_l \lambda_l^*} (\lambda_l^*)^2 \left(\frac{n_t \lambda_t^* + (n_l - 1)\lambda_l^*}{n_t \lambda_t^* + n_l \lambda_l^*} + \lambda_l^* (s_t^* - s_l^* - \Delta p) + 1 \right) \\ &+ v \frac{\exp(n_l \lambda_l^* (s_t^* - s_l^* - \Delta p))}{n_l} \lambda_l^* \left(\frac{2n_l - 1}{n_l} + \lambda_l^* (s_t^* - s_l^* - \Delta p) \right) + v \left(\frac{n_l - 1}{n_l} \right)^2 \lambda_l^* \\ &- kc'(s_l^* - \bar{s}) = 0. \end{aligned} \tag{4}$$

In this equilibrium, it holds that $s_t^* > \bar{s}$, while it is not clear whether $s_l^* > \bar{s}$.

In equilibrium, agents choose their work pace such that the gain from marginally working faster, that is, the marginal winning probability times the prize, equals the marginal cost. For the trailing agents at position p_t, this implies that they decide to work faster than they would do in the absence of tournament incentives and that, in consequence, they make more mistakes. Intuitively, the trailing agents have a lot to gain by working faster, but not much to lose in case they make a lot of mistakes. The situation is different for the leading agents at position p_l. For them, it is unclear whether they work faster or slower than in the absence of tournament incentives. The leading agents might have a decent chance to win the tournament if they manage to avoid too many mistakes, and then it could be optimal to be rather careful and to work at a slower pace.

Next, we investigate how the equilibrium choices of working speeds s_t^* and s_l^* depend on the difference in starting positions Δp and on the number of competitors n_t and n_l in each of the two positions. In general, a change in one of the parameters has a direct and an indirect effect on the equilibrium work pace. The parameter change affects an agent's optimal work pace directly by affecting the marginal gain from working faster. The indirect effect arises, since the change in the parameter also affects the work pace of the agents in the other position, and this also has an impact on the own incentive to work fast. In line with our earlier assumptions, we assume that the cost function is sufficiently convex. In this case, the direct effects always prevail, which enables us to investigate the impact of parameter changes on the equilibrium work paces s_t^* and s_l^*.

Proposition 2. *If k is sufficiently large, the trailing agents work slower when the difference in initial positions becomes larger, that is, it holds that $\frac{\partial s_t^*}{\partial \Delta p} < 0$. Furthermore, they work faster the more competitors are at the trailing position, that is, it holds that $\frac{\partial s_t^*}{\partial n_t} > 0$. If, in addition, Δp is sufficiently low, similar results also hold true for the leading agents, that is, it holds that $\frac{\partial s_l^*}{\partial \Delta p} < 0$ and $\frac{\partial s_l^*}{\partial n_l} > 0$. Furthermore, if Δp is sufficiently low, all agents increase their working speed the more competitors they face on the other positions, that is, it holds that $\frac{\partial s_t^*}{\partial n_l} > 0$ as well as $\frac{\partial s_l^*}{\partial n_t} > 0$.*

The proposition states that the agents tend to work relatively fast if the level of competition is large in the sense that all agents are located close to each other, that is, when Δp is small, and there are many agents at the two positions, that is, when n_t and n_l are large. Intuitively, if agents act excessively restrained in such a situation, they have almost no chance to win the tournament. Thus, they are willing to take more risks, and they decide to work at a faster pace. An immediate consequence is that agents make more mistakes on average when the level of competition is high.

4. Empirical analysis

In our empirical analyses, we use race data from professional biathlon competitions. Before we describe the data set in more detail in the following section, we briefly introduce the sport and explain why it yields an ideal test bed for our model predictions.

4.1. Biathlon competitions

Professional biathlon is an individual sport that combines cross-country skiing and rifle shooting in the following way: A given distance - the precise number of kilometers depends on discipline and gender - has to be completed on the skiing course from start to finish. The total distance is divided into three or five laps. At the end of each lap, except for the last one, the athletes enter the shooting range, in which they shoot on five targets. Every missed shot results in a penalty that is defined as additional skiing distance in a separate penalty loop, or penalty time added to the athletes' total race time. Hence, the athletes' success in a biathlon competition depends both on their skiing performance as well as on their shooting performance throughout the race. In particular, a good result requires the ability to perform well in the precision task of rifle shooting between the physically intense cross-country skiing intervals on the course.[13] At the end of the competition, the athletes' final ranks are determined by the relative total time, that is, the fastest athlete wins the race, the second-fastest athlete is runner-up, and so on.[14] Rewards are allocated according to the final rank.

In our analyses, we mainly restrict attention to the disciplines *Pursuit* and *Mass Start*, since these are the only individual biathlon competitions in which all athletes are on the course simultaneously and the final ranking is determined by the order in which athletes cross the finish line, that is, the athlete reaching the finish first receives the first prize, the

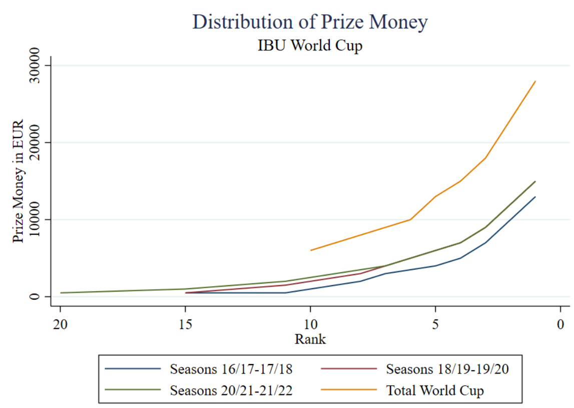
[13] The overall performance in biathlon competitions is therefore comparable to agents' output in our model. Here, the speed with which tasks are performed is represented by the athletes' skiing speed, while the number of mistakes is represented by the number of missed shots in biathlon races.

[14] In a biathlon competition, the clock never stops; that is, the total time is measured from the start of the race until the athlete crosses the finish line. In particular, this includes the time on the skiing course, the time in the shooting range, and the penalty.

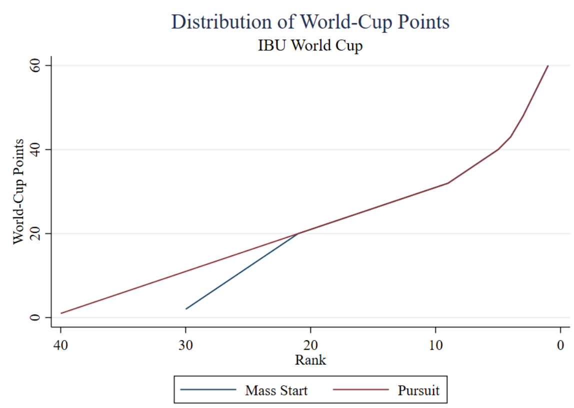
next athlete receives the second prize, and so on. Therefore, it is reasonable to assume that athletes are informed at all times during the race about their relative intermediate position and, in particular, of other competitors who are close to their own position.[15]

In this paper, we consider data from the IBU World Cup, organized by the International Biathlon Union (IBU). The World Cup is a competition in which athletes compete in a number of races in one season. While for every race there are direct incentives in form of prize money that is distributed according to the final rank in the specific race, the result also counts toward a total World-Cup score for the whole season. At the end of the season, the athlete with the highest total sum of World-Cup points is the winner of that season's World-Cup.[16]

Figure 1: Reward structure in biathlon competitions



(a) Prize money



(b) World-Cup Points

Figure 1 displays the incentive structure more closely. The distribution of prize money for each individual race has been equal for Mass Start and Pursuit since the season 2016/17,

[15]This will be an important assumption in our main analyses. In the other individual disciplines *Sprint* and *Individual*, the race starts at a different time for every athlete. The final rank is then determined according to the relative time it took the athletes to complete the course, including penalty times for missed shots. Therefore, in these disciplines, during the race, athletes only have information about their competitors' split times who started the race before them (if they have not been overtaken until then) and, thus, they have no information about their intermediate rank relative to all other athletes, as it is the case in Pursuit and Mass Start.

[16]In addition to the overall World-Cup ranking that includes all races there are rankings for each of the disciplines. Since the overall World Cup is the most prestigious ranking and captures the athletes' performance in all disciplines, we restrict attention to the overall World-Cup standings.

but differed between the years. In Panel 1a, the prize money is plotted on the athletes' final rank in a race. Panel 1a also includes the distribution of prize money for the final standing in the World Cup, that is, the rank of the accumulated points across all races throughout a season. We show only one graph for this competition, since the amount of prize money has not changed over the seasons.

Note that, in all seasons, only the first 20 athletes in each race received any prize money, while the remaining 10 (in Mass Start races) or 40 (in Pursuit races) athletes do not receive any prize money. For the World Cup, only the best 10 athletes get rewarded. All prize structures are highly convex with regard to the final rank.

In Panel 1b, we plot the distribution of World-Cup Points that are rewarded in Mass Start and Pursuit races. While in Mass Start races all qualified athletes who finish the race receive some points, in Pursuit races only the best 40 athletes are rewarded.[17]

4.2. Data

Our data set consists of all IBU World Cup races in the disciplines Pursuit and Mass Start between the seasons 2016/17 and 2021/22.[18] While the two disciplines we consider in this paper, Mass Start and Pursuit, are almost identical regarding the general structure of the race, the important difference is the schedule according to which athletes begin the race. As the name suggests, in Mass-Start races all 30 biathletes start the race together at the same time and enter the course simultaneously. In Pursuit races, the athletes' starting time is determined by the results of the previous race, that is, the winner of the previous Sprint/Individual competition starts first, the runner-up enters the course next, and so on. The time between athletes' starting time equals the difference in the finishing time in the previous race. As in Mass-Start races, however, the final ranking of the Pursuit race is determined by the order in which the biathletes cross the finish line. Since by this rule

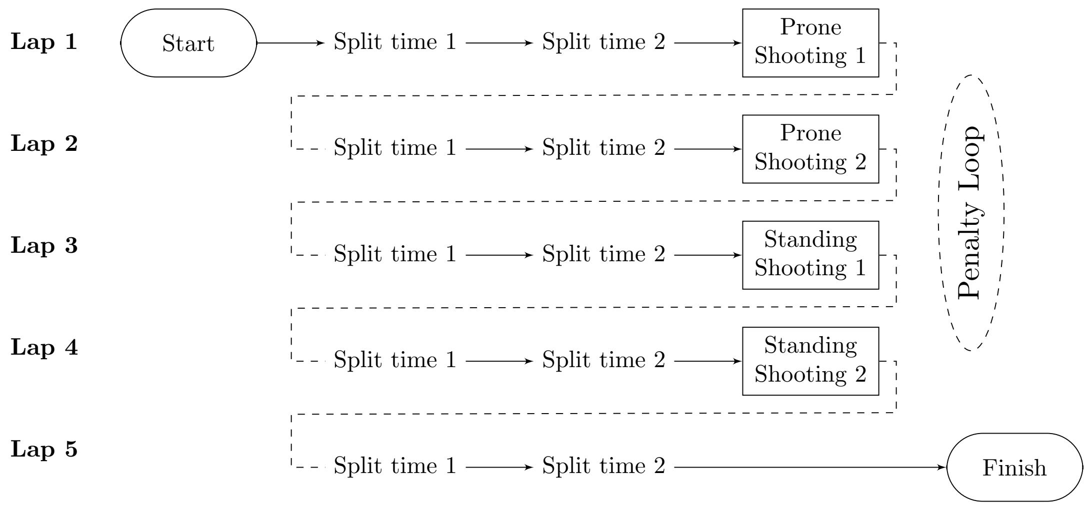
[17]Since in Pursuit races the worst 20 athletes do not receive any reward, we exclude these (intermediate) ranks in the main analyses, since these athletes do not have strong individual incentives to perform well. We elaborate more on this in the corresponding sections.

[18]All data were downloaded from realbiathlon.com on 28 March 2022.

athletes head into the race with a predetermined handicap, we control for the difference at the start in all of the analyses.

To illustrate the race structure, and in particular the split times we use for our analysis, Figure 2 shows the sequence of tasks athletes have to perform during a race.

Figure 2: Illustration of race structure in a biathlon competition



Right with the start of the race, the athletes enter the first skiing lap on the course. After the first lap of skiing, all competitors arrive at the shooting range and have to shoot at five targets. For every miss of those five shots, athletes have to ski one penalty loop, which makes an additional skiing distance of 150 meters per missed shot, before entering the second skiing lap. An athlete who hits all five targets enters the regular skiing course immediately after the shooting bout. In each race, there are four shooting bouts in total. The first and second round are shot in prone position (lying on a mat in the shooting range), while the third and fourth round are taken in standing position. Targets are larger in the latter position. After the fourth shooting bout, the athletes have to ski the regular lap one last time before reaching the finish line.

The number of split times that are taken in each lap differs between event locations. While we have data on the athletes' total net times right before and after the shooting bouts, there are also split times during the skiing lap. Since the time is taken at least twice between the shooting bouts in all races, we always consider the last two split times during the lap and label them as *Split time 1* and *Split time 2* in the order they are taken.

In the main analyses, we will refer to the skiing distance from Split time 1 and Split time 2 until the end of the skiing lap as *last half* and *last quarter*, respectively. This is not accurate in the sense that the last half (quarter) covers exactly the second half (fourth quarter) of the course, but it simplifies the terminology.[19]

Our data set consists of 130 races between the seasons 2016/17 and 2021/22, including 50 Mass Start races (equal number of races by gender), each with 30 participants and 80 Pursuit races (equal number of races by gender), each with 60 competitors. In order to interpret the estimated coefficients in our empirical analyses, in Table 1 we report the summary statistics of the variables that are most important to our analyses, that is, the individual-level race data in the last two laps, separated by gender and discipline from the *IBU World Championships 2017* in Hochfilzen. All split times are measured in seconds.

The variable *Ski time lap 4* describes the time the athletes need to complete the skiing course in the fourth lap. The next variables, *Ski time last half lap 4* and *Ski time last quarter lap 4*, are given by the skiing times in the last half/quarter of the skiing course, as explained in the discussion of Figure 2. The number of missed shots in the final shooting bout is given by the variable *Missed shots bout 4*, with the corresponding penalty time *Penalty time lap 4*. Finally, the table includes the ski time in the last lap and the total race time.

Additionally, in cooperation with the International Biathlon Union (IBU), we issued a

[19]Since the terrain as well as the distance between the split times differ between event locations, for all analyses we normalize all skiing times on the race level by subtracting its mean and dividing by the standard deviation. Normalizing on the level of gender and discipline instead, which is necessary since the total race distance differs between those does not qualitatively change our results.

Table 1: Race data from the IBU World Championships 2017 – Mean (standard deviation)

	MS Male	MS Female	PU Male	PU Female
Ski time lap 4	398.9	368.3	327.4	287.9
	(8.862)	(11.73)	(7.380)	(7.008)
Ski time last half lap 4	172.3	201.0	176.6	121.8
	(5.046)	(6.423)	(4.350)	(3.173)
Ski time last quarter lap 4	101.2	124.9	111.8	47.11
	(2.855)	(3.443)	(2.732)	(1.015)
Missed shots bout 4	0.633	0.567	0.842	0.672
	(0.765)	(1.073)	(0.727)	(0.758)
Penalty time lap 4	18.19	18.43	22.63	21.23
	(16.22)	(24.71)	(15.06)	(17.78)
Ski time lap 5	390.4	362.7	318.9	282.4
	(14.79)	(15.39)	(12.76)	(9.662)
Total race time	2213.6	2109.5	1970.7	1819.7
	(49.63)	(79.67)	(84.69)	(78.40)

survey among professional biathletes to elicit their risk preferences.[20] We measured risk preferences qualitatively based on the method of Dohmen et al. (2011). We asked two questions measuring risk preferences in general and six questions measuring context-specific risk preferences. Two of these six questions specifically asked for athletes' risk preferences in a biathlon race. All questions are answered on a scale from zero to ten, with lower numbers indicating greater aversion to risk. Summary statistics of all survey items, split by gender, can be found in Table 2. Detailed statistics, a full list of all questions as well as a discussion

[20] The survey was preregistered on the OSF Registries portal of the Center for Open Science (Registration DOI: (textf10.17605/OSF:.IO/7K5HS/). Potential survey participants included all athletes who appeared as observations in our main analysis sample in Section 4. From these 426 potential participants, we reached out to a total of 341 athletes. Of these, the IBU contacted 246 athletes who were mainly active in the season 2021/22 via e-mail. For the remaining athletes who were not contacted by the IBU, we searched for publicly available contact addresses. We managed to reach out to 95 additional athletes via social media (LinkedIn and Instagram) or via publicly available e-mail adresses. The online survey was open from 19 April to 31 May 2022. Overall, we received 111 valid survey responses, which corresponds to an overall response rate of approximately 0.326. 102 of those responses stem from the IBU outreach, corresponding to an IBU-specific response rate of 0.439. The remaining responses stem from the social-media outreach, corresponding to a social media-specific response rate of 0.084. For each valid answer, each athlete received a compensation payment of 50 Euros.

Table 2: Summary statistics of survey data

	Female Survey Participants					*Male Survey Participants*				
	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N
General										
General risk	5.6	2.2	1	10	36	6.1	2.0	3	10	37
Context										
Biathlon risk	5.8	2.1	2	9	36	6.6	1.8	2	10	37
Health risk	3.0	2.6	0	8	36	3.9	2.1	0	10	37
Finance risk	4.1	2.5	0	10	36	5.2	2.4	0	10	37
Leisure risk	5.5	2.5	1	9	36	5.4	1.8	0	10	37
Career risk	5.3	2.3	0	9	36	5.5	1.7	2	8	37

Notes: In this Table, we only show the summary statistics of the answers of those athletes whose data are used in our empirical analyses. This corresponds to the first 40 athletes at the point in time when the last course section of the fourth lap starts. 73 out of the total of 111 athletes who took part in the survey were among those 40 during our observation period at least once.

related to potential selection biases of survey participation can be found in Section 7.7 of the Appendix. The data allow us to conduct robustness checks as well as heterogeneity analyses of our main results, which will be presented in Section 5.

4.3. Risk measure

As outlined in the introduction, we associate an increase in the skiing speed towards the end of a lap compared to the otherwise optimal choice of speed as a deviation from standard behavior towards a more risky strategy. The argument to support this claim is as follows.

From an intuitive viewpoint, it seems reasonable to expect a tradeoff between the performance in the two tasks in a biathlon race: While cross-country skiing is a physiologically demanding sport, rifle shooting is a precision task that requires the athlete to be calm and concentrated. A higher intensity in skiing therefore leads to worse shooting accuracy.[21] We will verify this claim empirically later in the section; for now, we assume that the described tradeoff between the two tasks indeed exists. Then, since only the overall performance is rewarded in biathlon competitions, we can assume that every athlete has an individual-specific optimal strategy of physiological intensity in skiing to maximize the overall performance. This assumption is reasonable, since our data set comprises only competitions of highly-trained athletes who are the world's best in their sport.

Suppose now that an athlete deviates from the optimal behavior and increases the skiing speed towards the end of a lap. The faster skiing enhances the overall performance, but also comes with the higher risk of missing the target in the upcoming shooting bout. Since every missed shot results in a penalty, which again reduces the overall performance, the initial deviation from the optimal behavior to an increase in skiing speed leads to potentially better (in case the athlete does not receive an additional penalty) or worse (in case of an additional penalty) overall performance. This mirrors the assumptions imposed in our model that the gain in performance through a deviation from the optimal speed with which tasks are performed leads to an increase in the probability of making costly mistakes. Thus, increasing the skiing speed results in a more dispersed overall performance, that is, it is a riskier strategy.

Next, we show empirically that the previous claim holds true and that there indeed exists a tradeoff between skiing and shooting performance. More precisely, we show that a faster skiing time in the last section of the fourth lap corresponds to a larger number of missed

[21]This tradeoff is known in the sports-science literature investigating the determinants of shooting performance in biathlon. See Hoffman et al. (1992) or Laaksonen et al. (2018) for an overview. It should be noted that the effect is highly recognized in standing shootings (bout 3 and 4). In contrast, for prone shootings (bout 1 and 2) the evidence is mixed and ambiguous. The reason is that stance as well as shooting at the right point in time of the cardiac cycle are the most relevant determinants of shooting performance. Both are harder to control in a standing position and thus more affected by exerting higher physical efforts shortly before. Harb-Wu and Krumer (2019) do not find a statistically significant effect of skiing time on shooting performance. There are two reasons why their results differ from ours. First, they focus on the first shooting bout, which is prone and not standing as in our analysis. Second, they analyze the impact of total skiing time, while we only focus on the skiing time of the last course section before the shooting bout is entered.

shots.[22]

Since we want to regress the number of missed shots in a shooting bout on the skiing time and potential confounders, we face a similar estimation problem to Harb-Wu and Krumer (2019) in their analysis of biathletes' shooting performance in front of a supporting audience. Thus, we rely on similar estimation methods. We estimate the following equation.[23]

$$ms_{ist} = \alpha + \beta \cdot split_{ist} + \gamma \cdot \mathbf{x}_{ist} + \mu_{is} + \phi_t + \epsilon_{ist}. \tag{5}$$

The dependent variable ms_{ist} on the left-hand side denotes the number of missed shots of athlete i, in season s and race t, at the shooting bout of lap 4. Our regressor of interest, $split_{ist}$, describes the net skiing time in the last course section (last quarter) of the fourth lap. As illustrated in Figure 2, this is the time between the last split time, *Split time 2*, and the time the athlete arrives at the shooting range. We furthermore add control variables $\mathbf{x}_{ist}$ as well as fixed effects on athlete-season-level and race-level with μ_{is} and ϕ_t, respectively, to the right-hand side of equation (5).

Since the dependent variable, the number of missed shots in the fourth shooting bout, is a count variable with integer values between zero and five, we estimate equation (5) using a Poisson model. More specifically, due to overdispersion and inflated zeros, we rely on the Poisson Pseudo Maximum Likelihood estimator.[24] Table 3 shows the estimated coefficients.[25]

[22]Since in the considered disciplines the athletes have to pass four shooting bouts, we could in principle use any of the first four laps. It seems reasonable to us, though, that particularly the last shooting bout and therefore the lap before the last shooting is subject to strategic decisions by the athletes. Deviations from trained behavior in the first three laps might rather be driven by unobservable confounders and are therefore omitted in our analysis. The main analyses in the next sections also focus on the fourth lap of every race.

[23]Since unobserved heterogeneity is likely to be correlated with regressors, we rely on a fixed-effects model.

[24]We implement the estimation in Stata using the *ppmlhdfe* command of the *ppml* package; see Correia et al. (2020).

[25]As a robustness check regarding the choice of the course section, we repeated the estimation with the second half of the lap. The results can be found in Table A.8 in Appendix 7.2.1 and yield qualitatively similar results.

Table 3: Tradeoff between skiing performance and shooting accuracy

	Total number of missed shots			
	(1)	(2)	(3)	(4)
Ski time last quarter	-0.074***	-0.061***	-0.063***	-0.062***
	(0.014)	(0.016)	(0.017)	(0.017)
Time first shot bout 4				0.018***
				(0.004)
N	5501	5501	5501	5501
Race FE	Yes	Yes	Yes	Yes
Athlete season FE	Yes	Yes	Yes	Yes
Difference at start	Yes	Yes	Yes	Yes
Intermediate rank	No	Yes	Yes	Yes
Previous ski times lap 1-3	No	Yes	Yes	Yes
Sum of previous missed shots	No	Yes	Yes	Yes
Previous ski time lap 4	No	No	Yes	Yes

Notes: The table shows the tradeoff between skiing performance and shooting accuracy. The estimates are obtained using a Poisson Pseudo Maximum Likelihood estimator. The dependent variable is the total number of missed shots in the last shooting bout. The skiing times are normalized and thus need to be interpreted in terms of standard deviations. The richest specification includes race and athlete season fixed effects, as well as controls for past skiing performance, shooting performance, and for the intermediate rank. Standard errors are clustered on race level in parentheses.
$^{*} < 0.1$, $^{**} < 0.05$, $^{***} < 0.01$

From specifications (1) to (4), we add further control variables that could confound the effect of interest. The estimated equation in the first Column only includes the ski time in the last course section, the fixed effects, as well as the difference in starting time in Pursuit races. In Column (2), we add the intermediate rank and the absolute values of previous skiing and shooting performance in the race until the end of the third lap, in order to proxy the daily form in the specific race.[26] The third specification additionally includes the skiing time in the fourth lap until the last course section to control for the physiological intensity that could confound the strategic choice on the skiing speed in the last course section. In the final specification in Column (4), we add the variable *Time first shot bout 4*. The value

[26]The intermediate rank is the relative position of an athlete at the point in the race at which the measurement of the considered skiing time starts, that is, the leading athlete is on rank 1, the following athlete is on rank 2, and so on. In this context, this refers to *Split time 2* in Figure 2. We include the intermediate rank, as it can be expected to influence the athletes' incentives in a race (see, e.g., Genakos and Pagliero 2012).

of this variable is the time the athlete needs between arriving at the shooting range and taking the first shot. As one can see, the corresponding estimated coefficient is positive and statistically significant. This is reasonable as there is evidence for a positive correlation between the required preparation time and the probability for failure in precision tasks such as rifle shooting.[27] The estimated coefficient of interest remains at a similar size and is statistically significant across all specifications.

Since the interpretation of the size of estimated coefficients in a Poisson model is rather inconvenient, we report in Table 4 the corresponding incidence ratios.

Table 4: Tradeoff between skiing performance and shooting accuracy (incidence ratios)

	Total number of missed shots			
	(1)	(2)	(3)	(4)
Ski time last quarter	0.929***	0.940***	0.939***	0.940***
	(0.013)	(0.015)	(0.016)	(0.016)
Time first shot bout 4				1.018***
				(0.004)
N	5501	5501	5501	5501
Race FE	Yes	Yes	Yes	Yes
Athlete Season FE	Yes	Yes	Yes	Yes
Difference at start	Yes	Yes	Yes	Yes
Intermediate Rank	No	Yes	Yes	Yes
Previous ski times lap 1-3	No	Yes	Yes	Yes
Sum of previous missed shots	No	Yes	Yes	Yes
Previous ski time lap 4	No	No	Yes	Yes

Notes: The table shows the tradeoff between skiing performance and shooting accuracy. The estimates are obtained using a Poisson Pseudo Maximum Likelihood estimator. The dependent variable is the total number of missed shots in the last shooting bout. The skiing times are normalized and thus need to be interpreted in terms of standard deviations. The table shows the exponential of the estimated coefficents and thus the factor by which the average of the dependent variable changes upon an increase of the regressor by one standard deviation. The richest specification includes race and athlete season fixed effects, as well as controls for past skiing performance, shooting performance, and for the intermediate rank. Standard errors are clustered on race level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

The interpretation of the coefficients is as follows. Consider the estimated coefficient in

[27] The explanation is that shooting is a precision task in which athletes recall a trained automatism. In such tasks, it is common that a faster execution is associated with better performance. See Strittmatter et al. (2022).

the fourth Column of Table 4. The point estimate of 0.94 for the coefficient for *Ski time last quarter* means that a decrease in skiing time on the last quarter of the fourth lap by one standard deviation yields a 6% decrease in shooting accuracy. This means that, taking the example of the data from the IBU World Championships in male Mass Start races shown in the first Column of Table 1, skiing about 2.8 % faster (2.855 seconds) results in an increase in the average number (for a mean of 0.633) of missed shots of 6% in the final shooting bout.

This tradeoff between skiing performance on the course and potential missed shots at the shooting bout mirrors the distributional assumptions in our model, in which a higher working pace, deterministically enhancing the overall performance, comes at the cost of an increase in the probability of making mistakes, potentially reducing the overall performance. Therefore, the analyses on the effect of competition on risk-taking behavior in biathlon competitions serve as well-suited tests of our model predictions.

4.4. Effect of competition

In this section, we analyze the effect of an increase in competition on the athletes' skiing speed. As we have argued in Section 4.3, we interpret a deviation to a faster (slower) skiing speed in the last course section of the fourth lap as the choice of a more (less) risky strategy. In the following subsections, we empirically confirm the model predictions of Proposition 2 regarding the effects of competition, namely the number of competitors who are close to an athlete, as well as the distance to the next competitors, on athletes' decisions to increase the skiing speed in the relevant section of the fourth lap.

4.4.1. Effect of the number of competitors on risk-taking

First, we consider the effect on risk-taking of the number of competitors who are in close distance to an athlete, that is, we estimate a fixed-effects model of the following form.

$$split_{ist} = \alpha + \beta \cdot \mathbf{comp}_{ist} + \gamma \cdot \mathbf{x}_{ist} + \mu_{is} + \phi_t + \epsilon_{ist}. \tag{6}$$

Here, the dependent variable $split_{ist}$ denotes the skiing time of athlete i in race t of season s for the last quarter of the fourth lap. The variables of interest on the right-hand side are summarized in the vector $\mathbf{comp}_{ist}$, which denotes the level of competition for athlete i. The vector $\mathbf{x}_{ist}$ contains additional control variables, such as the intermediate rank and previous performances, while the variables μ_{is} and ϕ_t again denote athlete-season and race fixed effects, respectively.

In this subsection, we measure the level of competition by the number of competitors who are close to an athlete. More precisely, the variable vector of interest in the estimated equation (6) is set to

$$\mathbf{comp}_{ist} = (nb\ front_{ist}, nb\ front^2_{ist}, nb\ behind_{ist}, nb\ behind^2_{ist}), \tag{7}$$

where $nb\ front_{ist}$ and $nb\ behind_{ist}$ are defined as the number of competitors who are, at the last split time before the fourth shooting bout, within an interval of five seconds in front of or behind the respective athlete.[28]

While the choice of five seconds for the length of the interval seems arbitrary, a sufficiently small length ensures two assumptions to hold. First, an athlete views contestants within that distance at the intermediate point in the race as direct competitors who are at a comparable intermediate standing and can be overtaken or are able to overtake the athlete. Hence, the variable $\mathbf{comp}_{ist}$ captures the incentive regarding the number of ranks an athlete could improve or lose. Second, if the length of the interval is sufficiently small, it seems reasonable that, conditional on the control variables which include the complete past race performance as well as fixed effects to account for unobserved heterogeneity, the number of athletes in

[28]In Appendix 7.4, we also consider a specification in which we set the vector $\mathbf{comp}_{ist}$ to the potential prize money an athlete can gain or lose by overtaking or being overtaken by all athletes close in front of or behind the athlete, respectively. The results show that the higher the potential gain/loss is in terms of potential prize money, the more risk the athletes are willing to take. Moreover, we expect the effect to be non-linear, as an increase in the skiing speed, the left-hand side, is limited by the physiological ability to intensify even further the effort during a highly demanding professional race. However, as a robustness check we also present estimates of a specification using only linear terms in Figure A.3, which yields qualitatively the same results.

that interval is exogenous.[29]

As we have discussed in the model, we would expect that not only the number of competitors who are close to an athlete influences strategic behavior, but also the distance to the competitors. Rather than including the effect of the distance in this part of the paper, we separate the analyses of these two dimensions of competition; subsection 4.4.2 analyzes the effect of the distance to an athlete's competitors on risk-taking decisions.[30]

Table 5 presents the estimation results.

[29]To ensure that our results are not driven by the specific choice of the interval, we re-estimated the model for lengths of $1, 2, ..., 10$ seconds, and we obtain very similar results. In Appendix 7.3, we plot in Figure A.3 the estimated coefficients for all integers between 1 and 10 seconds. Additionally, we also considered the skiing time in the last half of the fourth lap as the dependent variable instead, which leads qualitatively to the same results. Detailed regression results are presented in Table A.10.

[30]One might wonder, though, whether the distance to the competitors is an omitted confounder for the effect of the number of close competitors. To address this concern, observe that the length of the interval is sufficiently small such that an athlete can be expected to be able to overtake (be overtaken by) any athlete within this short distance in front (behind). Furthermore, including the distance to the next athlete in front and behind in the regressions does not qualitatively change the point estimates for the coefficients of the number of close competitors.

Table 5: Effect of competition on skiing speed

	Ski time last quarter			
	(1)	(2)	(3)	(4)
Nb front	-0.270***	-0.284***	-0.279***	-0.224***
	(0.023)	(0.020)	(0.018)	(0.019)
Nb front^2	0.029***	0.028***	0.029***	0.024***
	(0.004)	(0.004)	(0.003)	(0.003)
Nb behind	-0.112***	-0.101***	-0.069***	-0.057***
	(0.024)	(0.022)	(0.021)	(0.020)
Nb behind^2	0.011**	0.010*	0.005	0.004
	(0.006)	(0.005)	(0.005)	(0.005)
N	4326	4326	4326	4326
Race FE	Yes	Yes	Yes	Yes
Athlete Season FE	Yes	Yes	Yes	Yes
Difference at start	Yes	Yes	Yes	Yes
Intermediate Rank	No	Yes	Yes	Yes
Previous ski times lap 1-3	No	No	Yes	Yes
Sum of previous missed shots	No	No	Yes	Yes
Previous ski time lap 4	No	No	No	Yes

Notes: The table shows the effect of increased competition measured by the number of competitors close in front and behind on skiing time of the last quarter of the fourth lap. The dependent variable is normalized on race level; thus, marginal effects need to be interpreted in standard deviations. The richest specification includes race and athlete season fixed effects, as well as controls for past skiing performance, shooting performance, and for the intermediate rank. Standard errors are clustered on race level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

From specifications (1) to (4) in Table 5, we increase the number of control variables that could possibly confound the effect of interest. While the specification in Column (1) only includes the fixed effects as well as the difference in starting time in Pursuit races as control variables, we add the intermediate rank in the second Column. In the third specification, we also control for the athletes' form on the day by including the net ski times in the previous laps, as well as the total number of missed shots in the first three laps. Since the dependent variable is the ski time in the last course section, the *last quarter*, the effect of interest could also be confounded by athletes' decisions on skiing intensity earlier in the same lap. To control for that, we also include the ski time in the fourth lap until the last course section. Therefore, the estimated specification in Column (4) includes all available data on skiing and shooting performance until the dependent variable is measured.

We can see across all specifications, (1) to (4), that estimated coefficients for the number of competitors close to an athlete are statistically significant, indicating that there exists an effect of the intensity of competition on the athletes' risk-taking decisions. Taking the richest specification in Column (4), the point estimates can be interpreted as follows: If an athlete has one competitor close in front within a range of five seconds, the athlete on average skis about 0.2 standard deviations faster, compared to when there is no competitor close in front (as the sum of the corresponding linear and quadratic term is -0.2).

Furthermore, it is worth emphasizing that the effect is much more pronounced if athletes face competition in front of them rather than behind. As can be seen from Column (4), the point estimate for the linear effect of the number of competitors in front is more than three times as large as the corresponding point estimate for the competitors behind an athlete, in absolute value. One might conjecture that athletes are generally more aware of competitors who are close in front rather than of those who are close behind such that the strategic reaction to increase the skiing speed is more pronounced for the number of competitors close in front.

To conclude, the estimation results in Table 5 yield robust evidence that a higher intensity of competition leads to a faster skiing time. Since we are using a rich panel data set, we have the opportunity to control for many sources of observed and unobserved heterogeneity. Given the assumptions regarding our measure of competition, as discussed above, we are relatively confident that the observed effect represents a causal relationship.[31] This confirms the corresponding prediction from our model in Proposition 2.

[31] A potential concern regarding our results is that they are driven by "grouping behavior", that is, that athletes ski faster because they are surrounded by competitors, rather than strategic decisions on risk-taking behavior. We address this concern in Section 5.

4.4.2. Effect of distance on risk-taking

In this section, we consider the effect of the athletes' distance to other competitors on risk-taking behavior, and again confirm the model predictions regarding this second dimension of competition.

To tackle this question, we reshape the data into a network format. In the previous analyses, one observation corresponds to an athlete i in race t in season s. Now, one observation corresponds to an athlete/co-athlete tuple.[32] This data structure allows us to identify exactly how the distance between athletes affects their skiing speed.[33]

We are again interested in estimating equation (6). However, the competition vector now includes variables measuring the distance between athletes. Specifically,

$$\begin{aligned}\beta \cdot \mathbf{comp}^j_{ist} = {} & \beta_1 \, |\Delta time^j_{ist}| + \beta_2 \, \mathbb{1}_{\Delta time^j_{ist}<0} + \beta_3 \, \mathbb{1}_{\Delta time^j_{ist}<0} \times |\Delta time^j_{ist}| \\ & + \sum_{k=2}^{n} \beta_{4k} \mathbb{1}_{\Delta rank^j_{ist}=k} + \sum_{k=2}^{n} \beta_{5k} \mathbb{1}_{\Delta rank^j_{ist}=k} \times |\Delta time^j_{ist}| \\ & + \sum_{k=2}^{n} \beta_{6k} \mathbb{1}_{\Delta rank^j_{ist}=k} \times |\Delta time^j_{ist}| \times \mathbb{1}_{\Delta time^j_{ist}<0}.\end{aligned}$$

Here $\Delta time^j_{ist} := net\_time_{ist} - net\_time_{jst}$ measures the distance of athlete i to athlete j in time, with the variable net_time_{ist} denoting the cumulative skiing time of athlete i until the point in time the last course section starts. The variable $\mathbb{1}_{\Delta time^j_{ist}<0}$ is an indicator equal to one in case athlete j is behind athlete i. The third component is an interaction of the latter two. The regressor $\mathbb{1}_{\Delta rank^j_{ist}=k}$ denotes an indicator which is equal to one in case the distance of athlete i to athlete j in absolute ranks is equal to k at the beginning of the last course section. For instance, $\mathbb{1}_{\Delta rank^j_{ist}=2}$ is equal to one in case athlete j is two ranks apart from athlete i, either in front or behind.

Thus, $-(\beta_1 + \beta_{5k})$ measures the marginal effect on skiing time when athlete j is located

[32] Let R be the set of all athletes i in race t. Now our sample consists of all athlete/co-athlete tuples $(i, j) \in R \times R$ with $j \neq i$.

[33] Network data structures are, for instance, used in the education economics literature. See Isphording and Zölitz (2020).

in front of athlete i, comes one second closer, and is at a distance of k ranks. On the other hand, $-(\beta_1 + \beta_3 + \beta_{5k} + \beta_{6k})$ measures the marginal effect on skiing time when athlete j is located behind athlete i, comes one second closer and is at a distance of k ranks.[34]

We restrict our sample to athlete/co-athlete tuples with $|\Delta time_{ist}^{j}| < 30$; that is, we consider only tuples who are up to 30 seconds apart from each other. Moreover, we only consider athlete/co-athlete tuples who are five ranks away from each other.[35]

[34]Thus, our specification reflects the possibility that marginal effects of distance of athlete j to i are heterogeneous with regard to the distance in ranks.

[35]We therefore assume that only the five closest athletes within a distance of 30 seconds play a role in explaining athlete i's skiing time on the last course section, and we consider only the corresponding subset of athlete/co-athlete tuples. While we believe that this is a reasonable assumption, our results are robust with regard to other sample selections.

Table 6: Effect of competition measured by absolute distance on skiing speed

	Ski time last quarter			
	(1)	(2)	(3)	(4)
Distance ($\hat{\beta}_1$)	0.015***	0.014***	0.009***	0.018***
	(0.002)	(0.001)	(0.001)	(0.002)
Behind × Distance ($\hat{\beta}_3$)	-0.013***	-0.013***	-0.007***	-0.011***
	(0.002)	(0.002)	(0.001)	(0.002)
2 ranks away × Distance ($\hat{\beta}_{52}$)				-0.003*
				(0.002)
2 ranks away × Behind × Distance ($\hat{\beta}_{62}$)				-0.004*
				(0.002)
3 ranks away × Distance ($\hat{\beta}_{53}$)				-0.006***
				(0.002)
3 ranks away × Behind × Distance ($\hat{\beta}_{63}$)				-0.006***
				(0.002)
4 ranks away × Distance ($\hat{\beta}_{54}$)				-0.008***
				(0.002)
4 ranks away × Behind × Distance ($\hat{\beta}_{64}$)				-0.008***
				(0.002)
5 ranks away × Distance ($\hat{\beta}_{55}$)				-0.009***
				(0.002)
5 ranks away × Behind × Distance ($\hat{\beta}_{65}$)				-0.009***
				(0.003)
N	28147	28147	28147	28147
Race FE	No	Yes	Yes	Yes
Athlete Season FE	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes

Notes: The table shows the estimates regarding the effect of competition measured by the absolute distance in time to a competitor in front of/behind on skiing time of the last quarter of the fourth lap. Column (4) additionally includes interactions of the absolute distance of a competitor with the respective distance in ranks. Additional controls account for past skiing performance, shooting performance, intermediate rank, and the distance in World-Cup points pre-race to the respective competitor. The specifications from Columns (2) to (4) account for race and athlete season fixed effects. Standard errors are clustered on race level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

The results can be found in Table 6. Columns (1) to (3) do not account for heterogeneities with regard to the distance in rank, and thus the point estimates need to be interpreted as average marginal effect of competitors in front of or behind within a 30-second interval. As

$-\hat{\beta}_1 < 0$ for all three specifications, we see that the closer a competitor is in front, the faster the athlete skis in the last course section. The marginal effect of a competitor behind coming closer is given by $-(\hat{\beta}_1 + \hat{\beta}_3)$. The average effect of a competitor behind coming closer is much smaller and close to zero.

Column (4), in contrast, accounts for heterogeneous effects and additionally shows the estimates of all interaction terms of the distance measures and the distance rank dummies. The base line estimates, $-\hat{\beta}_1 = -0.018$ and $-(\hat{\beta}_1 + \hat{\beta}_3) = -(0.018 - 0.011) = -0.007$, now show the average change in skiing time when the first competitor in front of or behind comes closer. More precisely, the point estimates of specification (4) can be interpreted as follows: If the first competitor in front is one second closer, the athlete reduces the skiing time in the last course section by 0.018 standard deviations.

The estimated coefficients of the interaction terms $\hat{\beta}_{5k}$ and $\hat{\beta}_{6k}$ with $k \in \{2, 3, 4, 5\}$ are all negative and increasing in absolute values by rank. This implies that the marginal effect of reduced distance of an athlete to the competitor decreases in absolute values the further away the competitor is (in terms of ranks). The interaction effects show that, for athletes who are located more than two ranks behind, the marginal effect of coming closer is almost zero. For athletes located close in front, the effect becomes very small, but is still positive and statistically significant up to a distance of five ranks.

Overall, we conclude that there is a robust correlation between the distance to a competitor and risk-taking decisions, and thus the results support Proposition 2. We find that the closer an athlete is either in front of or behind a competitor, the shorter the respective skiing time of the athlete is in the last course section of the fourth lap, and therefore the athlete takes higher risks. Moreover, the effect is smaller in magnitude for competitors located close behind, compared to those located close in front. Finally, the effect is heterogeneous with regard to the distance in ranks, as the closer the athletes are in terms of rank, the larger the marginal effect is in absolute values.

5. Robustness

This section has three objectives. First, we would like to confirm the claim that strategic decisions are more important towards the end of the race, thereby substantiating our assumption to focus on the fourth lap. Second, we want to show that it is unlikely that the observed effect can be accounted for by grouping behavior. By grouping behavior we mean that athletes ski faster, simply because they are surrounded by competitors rather than as a response to a strategic decision. One can think of slipstream or a motivational push caused by observing other athletes. Third, we use our survey data to analyze whether the results of Section 4.4 are robust or heterogeneous with regard to the athletes' risk preferences.

We present the main findings of these robustness checks here, but relegate detailed analyses to the Appendix. In Section 7.5 of the Appendix, we show the results of a dynamic panel-data estimation in the style of Arellano and Bond (1991) and Anderson and Hsiao (1982). This approach allows us to pool data from all four laps and to identify, by using within-race variation, heterogeneities regarding risk-taking behavior across laps. More precisely, we re-estimate equation (6) including interaction terms of the competition measures and lap dummies. The results can be found in Table A.12. They show that the marginal effect of increased competition on skiing speed in the last course section is larger in magnitude in the fourth lap compared to the third lap. This finding provides evidence that strategic decisions are more important towards the end of the race compared to earlier points of the race.[36] Moreover, existing heterogeneities make it very unlikely that the observed effect is due to grouping behavior. For instance, if slipstream is responsible for the observed effect, one would not expect differences in magnitude across laps.

[36] This claim is further supported by two other arguments. First, the closer athletes are to the finish line, the more informative is their intermediate position in the race, that is, their intermediate rank as well as the number of close competitors and the distance to other athletes. Second, we argue that strategic behavior is a deviation from otherwise optimal behavior, the optimal trained skiing intensity given the tradeoff between skiing speed and shooting accuracy. Summary statistics, which are available upon request, show that the standard deviation of *all* skiing time variables *Ski time lap*, *Ski time last half* and *Ski time last quarter* increases over *all* laps. This clearly indicates that the differences between individual skiing performances increase during the race, as athletes get more tired and strategic decisions become more important.

In Section 7.6 of the Appendix, we present a placebo test by using data from a different discipline, namely *Sprint*. In sprint races, athletes do not start the race simultaneously, but instead staggered, with a distance of 30 seconds. Moreover, the final performance is determined relatively after all athletes finished the race. In contrast to mass start and pursuit races, athletes ski a total of three laps and enter the shooting bout twice. In case of a missed shot, the penalty lap amounts to 150 meters as well. The monetary incentives and incentives with regard to World-Cup points are the same as for Mass Start and Pursuit races. Due to the staggered start, data from sprint races cannot be used to analyze the effects of competition on risk-taking. However, athletes encounter other athletes on the course who may not be in direct competition to them. This allows us to provide suggestive evidence that the estimated effect is not due to grouping behavior.

In Table A.13 of the Appendix, we present results of regressions using the same competition vector as in (7); however, the number of athletes in front of and behind only include the athletes who are in sight. More precisely, we determine the number of competitors who are close in front (behind) by counting the number of competitors who pass the start of the last course section up to five seconds before (after) the respective athlete. These athletes can be close to each other for two reasons. On the one hand, athletes encounter competitors who started shortly before or after them; on the other, these can also be athletes who are one lap ahead or behind them.

The results show no statistically significant effect on more athletes in sight behind or in front. This result again provides evidence against the concern that our results are driven by grouping behavior.

Table 7: Effect of risk preferences on skiing speed

	Ski time last quarter			
	(1)	(2)	(3)	(4)
General risk	-0.861**			
	(0.417)			
Biathlon race risk		-0.436**		
		(0.212)		
Health risk			-0.426**	
			(0.210)	
Career risk				-0.423**
				(0.211)
Nb front	-0.139***	-0.173***	-0.117***	-0.151***
	(0.044)	(0.045)	(0.023)	(0.046)
Nb behind	-0.019	-0.017	-0.023	0.004
	(0.043)	(0.049)	(0.026)	(0.041)
Nb front×General risk	0.003			
	(0.007)			
Nb behind×General risk	-0.001			
	(0.006)			
Nb front×Biathlon race risk		0.008		
		(0.007)		
Nb behind×Biathlon race risk		-0.001		
		(0.007)		
Nb front×Health risk			-0.002	
			(0.006)	
Nb behind×Health risk			0.000	
			(0.006)	
Nb front×Career risk				0.005
				(0.007)
Nb behind×Career risk				-0.005
				(0.007)
N	1336	1336	1336	1336
Race FE	Yes	Yes	Yes	Yes
Athlete Season FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: The table shows the effect of general and context-specific risk preferences and increased competition measured by the number of competitors close in front and behind on skiing time of the last quarter of the fourth lap. Moreover, the table shows interaction terms of our competition measures and risk measures. The dependent variable is normalized on race level; thus, marginal effects need to be interpreted in standard deviations. All specifications include race and athlete season fixed effects, as well as controls for past skiing performance, shooting performance, and for the intermediate rank. Standard errors are clustered on race level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

In our model, increased risk-taking as a result of increased competition is due to strategic behavior by the agents. An important question is whether our empirical results are influenced or partially confounded by risk preferences of the athletes. Our survey data allow us to answer two kinds of questions. First, they allow us to check whether our main empirical results of Section 4.4 are robust to controlling for individual risk preferences, thus substantiating our claim that the observed patterns are due to strategic behavior. Second, we are able to check whether the effect of increased competition on risk-taking is heterogeneous with regard to the athletes' risk preferences.

We approach both questions by re-estimating equation (6) and including risk preferences of the athletes as additional control variables. Moreover, we interact the risk variables with the variables measuring competition. The results can be found in Table 7.[37]

First, we observe that more risk-loving athletes generally ski faster in the last course section of the fourth lap. This holds for our general risk measure and all context-specific risk measures, thus validating our measure of risk-taking. Second, we observe that our competition effect is robust with regard to the inclusion of risk preferences as control variables. The coefficient of an increased number of athletes close in front is negative and statistically significant. Once we control for risk preferences in biathlon races, the estimate jumps about one third in magnitude (see Column (2) compared to (1) or (4)). Third, we see that none of the competition and risk-interaction effects is significantly different from zero. This provides evidence that there exist no heterogeneities in the effect of increased competition on risk-taking with regard to risk preferences. The observation that the estimates of all risk measures are negative and statistically significant suggests that risk-loving athletes already take a rather high level of risk, irrespectively of the level of competition.

[37]A discussion regarding the representativeness of our survey sample can be found in the Appendix in Section 7.7. While the relatively weaker athletes were more likely to take the survey, we see no obvious reason why the results should not be generalizable with regard to the whole sample. Moreover, we ran regressions classifying the risk preferences categorically and restricted to reliable answers. Following the approach of Gillen et al. (2019), we asked the general as well as the biathlon-related risk question a second time with a slightly different wording. A completely consistent answer would yield a zero difference of both questions. An analysis including observations up to a difference of one yields qualitatively similar results and is available upon request.

6. Conclusion and implications

We have studied how the intensity of competition among agents affects their risk-taking behavior. We started by developing a theoretical model, in which we found that greater competition, measured either by the closeness of competing agents or their number, induces agents to take larger risks. We went on by testing the model's predictions using data from professional biathlon, as well as survey data from professional biathletes. We found support for all the theoretical results. We believe that biathlon data are particularly suited for the study of our research question. First, the data allowed us to construct and validate precise measures of risk-taking and the intensity of competition. Second, the specific type of risk that we considered in biathlon competitions – the risk of making more mistakes when working faster – is relevant in many different industries, and we are thus confident that our results are widely transferable beyond biathlon.

Competition is often used by firms as a strategic instrument to motivate employees, but it may also occur naturally without any additional managerial actions. Thus, the results of our paper are highly relevant for organizational decision-making. Our analysis highlights that competition – besides its well-known positive consequences – potentially harms firms, as it may provide incentives to take undesirably high risks that can result in detrimental outcomes for the firm.

The implications of our paper's findings for organizational decisions depend on the type of job the employees are performing. As mentioned in the introduction, Baron and Kreps (1999) classify jobs as guardian jobs, star jobs, or foot soldier jobs. In a guardian job, firms want their employees to be careful at all times and to refrain from taking unnecessary risks. Accordingly, employees should not feel any desire to compete against their peers. Not only does this mean that firms should not reward employees based on their performance relative to other employees, but also that any information about relative employee performance should be withheld. The reason is that the availability of information regarding relative employee performance may already be enough to incentivize employees even if monetary rewards are not tied to performance (e.g., Sheremeta 2010 and Blanes i Vidal and Nossol 2011). Furthermore, if firms are unable to eliminate all incentives to take risks, they should make sure that these incentives are not very salient (Englmaier et al. 2017).

The implications are different when employees perform star jobs. In these jobs, firms want to induce their employees to take risks, since the upsides to great performance are much more important than the downsides to poor performance. Applying the findings from our study, this means that employees should be encouraged to compete against each other and that firms should let their employees know that competition is intense. More specifically, to induce risk-taking, firms should make sure that the competition includes many employees and that these employees are comparable in their capabilities. Furthermore, firms should hide intermediate performance information from their employees, so that they believe the competition to be close at all times.

Finally, in foot-soldier jobs, firms either do not care about the level of risk that employees choose, or they find intermediate risk levels desirable. In both cases, optimal decisions are likely to be between those we described as optimal for guardian and star jobs.

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7. Appendix

7.1. Omitted proofs

Proof of Proposition 1. Consider an agent i at position p_t and suppose that the $n_t - 1$ other agents at position p_t choose s_t^* and the n_l agents at position p_l choose s_l^*.[38] Furthermore, let $p_l + s_l^* \geq p_t + s_t^*$.[39] Define $\lambda_i = \lambda(s_i)$, $\lambda_t^* = \lambda(s_t^*)$, and $\lambda_l^* = \lambda(s_l^*)$.

First, suppose that $s_i \leq s_t^*$.

Then, the winning probability $P_i(s_i)$ is given by

$$
\begin{aligned}
P_i(s_i) &= \int \Pi_{j\neq i} F_{\varepsilon_j}\left(p_i - p_j + s_i - s_j + x\right) f_{\varepsilon_i}(x)dx \\
&= \int_{-\infty}^{0} \left(\exp\left(\lambda_t^*(s_i - s_t^* + x)\right)\right)^{n_t-1} \left(\exp\left(\lambda_l^*\left(p_t - p_l + s_i - s_l^* + x\right)\right)\right)^{n_l} \lambda_i \exp\left(\lambda_i x\right) dx \\
&= \int_{-\infty}^{0} \exp\left(\left(n_t - 1\right)\lambda_t^*(s_i - s_t^* + x)\right) \exp\left(n_l\lambda_l^*\left(p_t - p_l + s_i - s_l^* + x\right)\right) \lambda_i \exp\left(\lambda_i x\right) dx \\
&= \lambda_i \exp\left(\left(n_t - 1\right)\lambda_t^*\left(s_i - s_t^*\right) + n_l\lambda_l^*\left(p_t - p_l + s_i - s_l^*\right)\right) \\
&\qquad \cdot \int_{-\infty}^{0} \exp\left(\left(\left(n_t - 1\right)\lambda_t^* + n_l\lambda_l^* + \lambda_i\right) x\right) dx \\
&= \lambda_i \exp\left(\left(n_t - 1\right)\lambda_t^*\left(s_i - s_t^*\right) + n_l\lambda_l^*\left(p_t - p_l + s_i - s_l^*\right)\right) \\
&\qquad \cdot \lim_{u\to\infty} \left(\frac{\exp\left(\left(\left(n_t - 1\right)\lambda_t^* + n_l\lambda_l^* + \lambda_i\right) x\right)}{\left(n_t - 1\right)\lambda_t^* + n_2\lambda_l^* + \lambda_i}\right)_{-u}^{0} \\
&= \lambda_i \exp\left(\left(n_t - 1\right)\lambda_t^*\left(s_i - s_t^*\right) + n_l\lambda_l^*\left(p_t - p_l + s_i - s_l^*\right)\right) \left(\frac{1}{\left(n_t - 1\right)\lambda_t^* + n_l\lambda_l^* + \lambda_i}\right) \\
&\qquad - \lambda_i \exp\left(\left(n_t - 1\right)\lambda_t^*\left(s_i - s_t^*\right) + n_l\lambda_l^*\left(p_t - p_l + s_i - s_l^*\right)\right) \\
&\qquad \cdot \lim_{u\to\infty} \left(\frac{\exp\left(-\left(\left(n_t - 1\right)\lambda_t^* + n_l\lambda_l^* + \lambda_i\right) u\right)}{\left(n_t - 1\right)\lambda_t^* + n_l\lambda_l^* + \lambda_i}\right) \\
&= \frac{\lambda_i}{\left(n_t - 1\right)\lambda_t^* + n_l\lambda_l^* + \lambda_i} \exp\left(\left(n_t - 1\right)\lambda_t^*\left(s_i - s_t^*\right) + n_l\lambda_l^*\left(p_t - p_l + s_i - s_l^*\right)\right).
\end{aligned}
$$

[38] By assumption, we have $n_t \geq 1$, that is, there is at least one agent at position p_t, and therefore it holds that $n_t - 1 \geq 0$.

[39] Note that, if the parameter $k > 0$ is sufficiently large, in any equilibrium it must hold that $p_l + s_l^* \geq p_t + s_t^*$. As the cost function is identical for all agents with a minimum at $\bar{s}$, the equilibrium choices s_t^* and s_l^* are arbitrarily close to $\bar{s}$ if k is sufficiently large. Since $p_t < p_l$, this ensures that there is no equilibrium in which $p_t + s_t^* > p_l + s_l^*$.

Hence, agent i's payoff becomes

$$U_i(s_i) = v\frac{\lambda_i}{(n_t-1)\,\lambda_t^* + n_l\lambda_l^* + \lambda_i}\exp\left((n_t-1)\lambda_t^*(s_i - s_t^*) + n_l\lambda_l^*(p_t - p_l + s_i - s_l^*)\right)$$
$$- kc(s_i - \bar{s}).$$

The first-order condition is

$$\begin{aligned}\frac{\partial U_i\left(s_i\right)}{\partial s_i} = {} & v\frac{\lambda_i'\left(\left(n_t-1\right)\lambda_t^* + n_l\lambda_l^* + \lambda_i\right) - \lambda_i\lambda_i'}{\left(\left(n_t-1\right)\lambda_t^* + n_l\lambda_l^* + \lambda_i\right)^2} \\ & \cdot\exp\left((n_t-1)\lambda_t^*(s_i - s_t^*) + n_l\lambda_l^*(p_t - p_l + s_i - s_l^*)\right) \\ & + v\frac{\lambda_i}{\left(n_t-1\right)\lambda_t^* + n_l\lambda_l^* + \lambda_i} \\ & \cdot\exp\left(\left(n_t-1\right)\lambda_t^*\left(s_i - s_t^*\right) + n_l\lambda_l^*\left(p_t - p_l + s_i - s_l^*\right)\right)\left(\left(n_t-1\right)\lambda_t^* + n_l\lambda_l^*\right) \\ & - kc'(s_i - \bar{s}) \\ = {} & 0,\end{aligned}$$

which can be rewritten as

$$\begin{aligned}& v\exp\left(\left(n_t-1\right)\lambda_t^*\left(s_i - s_t^*\right) + n_l\lambda_l^*\left(p_t - p_l + s_i - s_l^*\right)\right)\frac{\left(n_t-1\right)\lambda_t^* + n_l\lambda_l^*}{\left(n_t-1\right)\lambda_t^* + n_l\lambda_l^* + \lambda_i} \\ & \cdot\left(\frac{\lambda_i'}{\left(n_t-1\right)\lambda_t^* + n_l\lambda_l^* + \lambda_i} + \lambda_i\right) - kc'\left(s_i - \bar{s}\right) = 0.\end{aligned}$$

In equilibrium, $s_i = s_t^*$ and $\lambda_i = \lambda_t^*$, and the condition simplifies to

$$v\exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right)\frac{(n_t-1)\lambda_t^* + n_l\lambda_l^*}{n_t\lambda_t^* + n_l\lambda_l^*}\left(\frac{\lambda_t^{*\prime}}{n_t\lambda_t^* + n_l\lambda_l^*} + \lambda_t^*\right) - kc'(s_t^* - \bar{s}) = 0.$$

Substituting $-(\lambda_t^*)^2$ for $\lambda_t^{*\prime}$, we obtain

$$\begin{aligned}& v\exp\left(n_l\lambda_l^*\left(p_t - p_l + s_t^* - s_l^*\right)\right)\frac{\left(n_t-1\right)\lambda_t^* + n_l\lambda_l^*}{n_t\lambda_t^* + n_l\lambda_l^*}\left(-\frac{\left(\lambda_t^*\right)^2}{n_t\lambda_t^* + n_l\lambda_l^*} + \lambda_t^*\right) \\ & - kc'\left(s_t^* - \bar{s}\right) = 0,\end{aligned}$$

which is equivalent to

$$v \exp\left(n_l \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right)\right) \lambda_t^* \left(\frac{\left(n_t - 1\right) \lambda_t^* + n_l \lambda_l^*}{n_t \lambda_t^* + n_l \lambda_l^*}\right)^2 - kc'(s_t^* - \bar{s}) = 0. \tag{8}$$

Suppose now that $s_i \geq s_t^*$ and $p_t + s_i \leq p_l + s_l^*$. Then, the winning probability $P_i(s_i)$ is given by

$$
\begin{aligned}
P_i(s_i) &= \int \Pi_{j \neq i} F_{\varepsilon_j} \left(p_i - p_j + s_i - s_j + x\right) f_{\varepsilon_i}(x) dx \\
&= \int_{-\infty}^{s_t^* - s_i} \left(\exp\left(\lambda_t^*(s_i - s_t^* + x)\right)\right)^{n_t - 1} \left(\exp\left(\lambda_l^* \left(p_t - p_l + s_i - s_l^* + x\right)\right)\right)^{n_l} \lambda_i \exp\left(\lambda_i x\right) dx \\
&\quad + \int_{s_t^* - s_i}^{0} \left(\exp\left(\lambda_l^* \left(p_t - p_l + s_i - s_l^* + x\right)\right)\right)^{n_l} \lambda_i \exp\left(\lambda_i x\right) dx \\
&= \int_{-\infty}^{s_t^* - s_i} \exp\left(\left(n_t - 1\right) \lambda_t^*(s_i - s_t^* + x)\right) \exp\left(n_l \lambda_l^* \left(p_t - p_l + s_i - s_l^* + x\right)\right) \lambda_i \exp\left(\lambda_i x\right) dx \\
&\quad + \int_{s_t^* - s_i}^{0} \exp\left(n_l \lambda_l^* \left(p_t - p_l + s_i - s_l^* + x\right)\right) \lambda_i \exp\left(\lambda_i x\right) dx \\
&= \lambda_i \exp\left(\left(n_t - 1\right) \lambda_t^* \left(s_i - s_t^*\right) + n_l \lambda_l^* \left(p_t - p_l + s_i - s_l^*\right)\right) \\
&\quad \cdot \int_{-\infty}^{s_t^* - s_i} \exp\left(\left(\left(n_t - 1\right) \lambda_t^* + n_l \lambda_l^* + \lambda_i\right) x\right) dx \\
&\quad + \lambda_i \exp\left(n_l \lambda_l^* \left(p_t - p_l + s_i - s_l^*\right)\right) \cdot \int_{s_t^* - s_i}^{0} \exp\left(\left(n_l \lambda_l^* + \lambda_i\right) x\right) dx \\
&= \lambda_i \exp\left(\left(n_t - 1\right) \lambda_t^* \left(s_i - s_t^*\right) + n_l \lambda_l^* \left(p_t - p_l + s_i - s_l^*\right)\right) \\
&\quad \cdot \lim_{u \to \infty} \left(\frac{\exp\left(\left(\left(n_t - 1\right) \lambda_t^* + n_l \lambda_l^* + \lambda_i\right) x\right)}{\left(n_t - 1\right) \lambda_t^* + n_l \lambda_l^* + \lambda_i} \right)_{-u}^{s_t^* - s_i} \\
&\quad + \lambda_i \exp\left(n_l \lambda_l^* \left(p_t - p_l + s_i - s_l^*\right)\right) \\
&\quad \cdot \left(\frac{\exp\left(\left(n_l \lambda_l^* + \lambda_i\right) x\right)}{n_l \lambda_l^* + \lambda_i} \right)_{s_t^* - s_i}^{0}.
\end{aligned}
$$

This reduces to

$$
\begin{aligned}
P_i(s_i) &= \lambda_i \exp\left(\left(n_t - 1\right)\lambda_t^*\left(s_i - s_t^*\right) + n_l\lambda_l^*\left(p_t - p_l + s_i - s_l^*\right)\right) \\
&\quad \cdot \left(\frac{\exp\left(\left(\left(n_t - 1\right)\lambda_t^* + n_l\lambda_l^* + \lambda_i\right)\left(s_t^* - s_i\right)\right)}{\left(n_t - 1\right)\lambda_t^* + n_l\lambda_l^* + \lambda_i}\right) \\
&\quad + \lambda_i \exp\left(n_l\lambda_l^*\left(p_t - p_l + s_i - s_l^*\right)\right) \\
&\quad \cdot \left(\frac{1 - \exp\left(\left(n_l\lambda_l^* + \lambda_i\right)\left(s_t^* - s_i\right)\right)}{n_l\lambda_l^* + \lambda_i}\right) \\
&= \frac{\lambda_i}{\left(n_t - 1\right)\lambda_t^* + n_l\lambda_l^* + \lambda_i} \exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*) + \lambda_i(s_t^* - s_i)\right) \\
&\quad + \frac{\lambda_i}{n_l\lambda_l^* + \lambda_i} \exp\left(n_l\lambda_l^*\left(p_t - p_l + s_i - s_l^*\right)\right) \\
&\quad - \frac{\lambda_i}{n_l\lambda_l^* + \lambda_i} \exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*) + \lambda_i(s_t^* - s_i)\right) \\
&= \left(\frac{1}{\left(n_t - 1\right)\lambda_t^* + n_l\lambda_l^* + \lambda_i} - \frac{1}{n_l\lambda_l^* + \lambda_i}\right)\lambda_i \exp(\lambda_i(s_t^* - s_i)) \\
&\quad \cdot \exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
&\quad + \frac{\lambda_i}{n_l\lambda_l^* + \lambda_i} \exp\left(n_l\lambda_l^*\left(p_t - p_l + s_i - s_l^*\right)\right).
\end{aligned}
$$

Hence, agent i's payoff is given by

$$
\begin{aligned}
U_i(s_i) = v &\left(\frac{1}{\left(n_t - 1\right)\lambda_t^* + n_l\lambda_l^* + \lambda_i} - \frac{1}{n_l\lambda_l^* + \lambda_i}\right)\lambda_i \exp(\lambda_i(s_t^* - s_i)) \\
&\cdot \exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
&+ v\frac{\lambda_i}{n_l\lambda_l^* + \lambda_i} \exp\left(n_l\lambda_l^*\left(p_t - p_l + s_i - s_l^*\right)\right) \\
&- kc(s_i - \bar{s}).
\end{aligned}
$$

The first-order condition is

$$
\begin{aligned}
\frac{\partial U_i\left(s_i\right)}{\partial s_i} = v[& \left(\frac{-\lambda_i'}{\left((n_t-1)\lambda_t^* + n_l\lambda_l^* + \lambda_i\right)^2} + \frac{\lambda_i'}{(n_l\lambda_l^* + \lambda_i)^2}\right)\lambda_i \exp(\lambda_i(s_t^* - s_i)) \\
& + \left(\frac{1}{\left(n_t-1\right)\lambda_t^* + n_l\lambda_l^* + \lambda_i} - \frac{1}{n_l\lambda_l^* + \lambda_i}\right) \\
& \cdot \left(\lambda_i' \exp(\lambda_i(s_t^* - s_i)) + \lambda_i(\lambda_i'(s_t^* - s_i) - \lambda_i)\exp(\lambda_i(s_t^* - s_i))\right)] \\
& \cdot \exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
& + v\frac{\lambda_i'(n_l\lambda_l^* + \lambda_i) - \lambda_i\lambda_i'}{(n_l\lambda_l^* + \lambda_i)^2}\exp\left(n_l\lambda_l^*(p_t - p_l + s_i - s_l^*)\right) \\
& + v\frac{\lambda_i}{n_l\lambda_l^* + \lambda_i} n_l\lambda_l^* \exp\left(n_l\lambda_l^*(p_t - p_l + s_i - s_l^*)\right) \\
& - kc'(s_i - \bar{s}) \\
= 0. &
\end{aligned}
$$

In equilibrium, $s_i = s_t^*$ and $\lambda_i = \lambda_t^*$, and the condition simplifies to

$$
\begin{aligned}
v[& \left(\frac{-\lambda_t^{*\prime}}{\left(n_t\lambda_t^* + n_l\lambda_l^*\right)^2} + \frac{\lambda_t^{*\prime}}{(n_l\lambda_l^* + \lambda_t^*)^2}\right)\lambda_t^* \\
& + \left(\frac{1}{n_t\lambda_t^* + n_l\lambda_l^*} - \frac{1}{n_l\lambda_l^* + \lambda_t^*}\right) \\
& \cdot \left(\lambda_t^{*\prime} - (\lambda_t^*)^2\right)] \\
& \cdot \exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
& + v\frac{\lambda_t^{*\prime}(n_l\lambda_l^* + \lambda_t^*) - \lambda_t^*\lambda_t^{*\prime}}{(n_l\lambda_l^* + \lambda_t^*)^2}\exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
& + v\frac{\lambda_t^*}{n_l\lambda_l^* + \lambda_t^*} n_l\lambda_l^* \exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
& - kc'(s_t^* - \bar{s}) \\
= 0. &
\end{aligned}
$$

Substituting $-(\lambda_t^*)^2$ for $\lambda_t^{*\prime}$, we obtain

$$
\begin{aligned}
0 = {} & v\left[\left(\frac{(\lambda_t^*)^2}{\left(n_t\lambda_t^* + n_l\lambda_l^*\right)^2} + \frac{-(\lambda_t^*)^2}{(n_l\lambda_l^* + \lambda_t^*)^2}\right)\lambda_t^* + \left(\frac{1}{n_t\lambda_t^* + n_l\lambda_l^*} - \frac{1}{n_l\lambda_l^* + \lambda_t^*}\right)\left(-(\lambda_t^*)^2 - (\lambda_t^*)^2\right)\right] \\
& \cdot \exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
& + v\frac{-(\lambda_t^*)^2 n_l\lambda_l^*}{(n_l\lambda_l^* + \lambda_t^*)^2}\exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
& + v\frac{\lambda_t^*}{n_l\lambda_l^* + \lambda_t^*} n_l\lambda_l^* \exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
& - kc'(s_t^* - \bar{s}) \\
= {} & v\lambda_t^*\left[\left(\frac{(\lambda_t^*)^2}{\left(n_t\lambda_t^* + n_l\lambda_l^*\right)^2} + \frac{-(\lambda_t^*)^2}{(n_l\lambda_l^* + \lambda_t^*)^2}\right) - \left(\frac{2\lambda_t^*}{n_t\lambda_t^* + n_l\lambda_l^*} - \frac{2\lambda_t^*}{n_l\lambda_l^* + \lambda_t^*}\right)\right] \\
& \cdot \exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
& + v\lambda_t^*\left[\frac{-\lambda_t^* n_l\lambda_l^*}{(n_l\lambda_l^* + \lambda_t^*)^2} + \frac{n_l\lambda_l^*}{n_l\lambda_l^* + \lambda_t^*}\right]\exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
& - kc'(s_t^* - \bar{s}) \\
= {} & v\lambda_t^*\left[\left(\frac{(\lambda_t^*)^2 - 2\lambda_t^*(n_t\lambda_t^* + n_l\lambda_l^*)}{\left(n_t\lambda_t^* + n_l\lambda_l^*\right)^2} + \frac{-(\lambda_t^*)^2 + 2\lambda_t^*(n_l\lambda_l^* + \lambda_t^*)}{(n_l\lambda_l^* + \lambda_t^*)^2}\right)\right]\exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
& + v\lambda_t^*\left[\frac{-\lambda_t^* n_l\lambda_l^* + n_l\lambda_l^*(n_l\lambda_l^* + \lambda_t^*)}{(n_l\lambda_l^* + \lambda_t^*)^2}\right]\exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
& - kc'(s_t^* - \bar{s}) \\
= {} & v\lambda_t^*\left[\left(\frac{(\lambda_t^*)^2 - 2\lambda_t^*(n_t\lambda_t^* + n_l\lambda_l^*)}{\left(n_t\lambda_t^* + n_l\lambda_l^*\right)^2} + \frac{(\lambda_t^*)^2 + 2\lambda_t^* n_l\lambda_l^*}{(n_l\lambda_l^* + \lambda_t^*)^2}\right)\right]\exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
& + v\lambda_t^*\left[\frac{(n_l\lambda_l^*)^2}{(n_l\lambda_l^* + \lambda_t^*)^2}\right]\exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
& - kc'(s_t^* - \bar{s}) \\
= {} & v\lambda_t^*\left[\frac{(\lambda_t^*)^2 - 2\lambda_t^*(n_t\lambda_t^* + n_l\lambda_l^*)}{\left(n_t\lambda_t^* + n_l\lambda_l^*\right)^2} + 1\right]\exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
& - kc'(s_t^* - \bar{s}) \\
= {} & v\lambda_t^*\left[\frac{(\lambda_t^*)^2 - 2\lambda_t^*(n_t\lambda_t^* + n_l\lambda_l^*) + \left(n_t\lambda_t^* + n_l\lambda_l^*\right)^2}{\left(n_t\lambda_t^* + n_l\lambda_l^*\right)^2}\right]\exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
& - kc'(s_t^* - \bar{s}).
\end{aligned}
$$

This is equivalent to

$$v \exp\left(n_l \lambda_l^* (s_t^* - s_l^* - \Delta p)\right) \lambda_t^* \left(\frac{(n_t - 1)\lambda_t^* + n_l \lambda_l^*}{n_t \lambda_t^* + n_l \lambda_l^*} \right)^2 - kc'(s_t^* - \bar{s}) = 0, \tag{9}$$

which is identical to condition (8). Equation (3) follows.

Clearly,

$$v \exp\left(n_l \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right)\right) \lambda_t^* \left(\frac{\left(n_t - 1\right) \lambda_t^* + n_l \lambda_l^*}{n_t \lambda_t^* + n_l \lambda_l^*} \right)^2 > 0.$$

Hence, we obtain $s_t^* > \bar{s}$.

Next, consider the leading agents. Consider agent i at position p_l and suppose that the n_t agents at position p_t choose s_t^* and the $n_l - 1$ agents at position p_l choose s_l^*.[40] **Furthermore, suppose that** $p_t + s_t^* \leq p_l + s_i \leq p_l + s_l^*$**.**[41]

Then, the agent's winning probability $P_i(s_i)$ is given by

$$
\begin{aligned}
P_i(s_i) &= \int \Pi_{j \neq i} F_{\varepsilon_j}(p_i - p_j + s_i - s_j + x) f_{\varepsilon_i}(x) dx \\
&= \int_{-\infty}^{p_t - p_l + s_t^* - s_i} \left(\exp(\lambda_t^*(p_l - p_t + s_i - s_t^* + x))\right)^{n_t} \\
&\quad \cdot \left(\exp(\lambda_l^*(s_i - s_l^* + x))\right)^{n_l - 1} \lambda_i \exp(\lambda_i x) dx \\
&\quad + \int_{p_t - p_l + s_t^* - s_i}^{0} \left(\exp\left(\lambda_l^*\left(s_i - s_l^* + x\right)\right)\right)^{n_l - 1} \lambda_i \exp\left(\lambda_i x\right) dx \\
&= \int_{-\infty}^{p_t - p_l + s_t^* - s_i} \left(\exp\left(n_t \lambda_t^*\left(p_l - p_t + s_i - s_t^* + x\right)\right)\right) \\
&\quad \cdot \left(\exp\left(\left(n_l - 1\right) \lambda_l^*\left(s_i - s_l^* + x\right)\right)\right) \lambda_i \exp\left(\lambda_i x\right) dx \\
&\quad + \int_{p_t - p_l + s_t^* - s_i}^{0} \exp\left(\left(n_l - 1\right) \lambda_l^*\left(s_i - s_l^* + x\right)\right) \lambda_i \exp\left(\lambda_i x\right) dx \\
&= \lambda_i \exp\left(n_t \lambda_t^*\left(p_l - p_t + s_i - s_t^*\right) + \left(n_l - 1\right) \lambda_l^*\left(s_i - s_l^*\right)\right) \\
&\quad \cdot \int_{-\infty}^{p_t - p_l + s_t^* - s_i} \exp\left(\left(n_t \lambda_t^* + (n_l - 1)\lambda_l^* + \lambda_i\right) x\right) dx \\
&\quad + \lambda_i \exp\left(\left(n_l - 1\right) \lambda_l^*\left(s_i - s_l^*\right)\right) \int_{p_t - p_l + s_t^* - s_i}^{0} \exp\left(\left(\left(n_l - 1\right) \lambda_l^* + \lambda_i\right) x\right) dx \\
&= \lambda_i \exp\left(n_t \lambda_t^*(p_l - p_t + s_i - s_t^*) + (n_l - 1)\lambda_l^*(s_i - s_l^*)\right) \\
&\quad \cdot \lim_{u \to \infty} \left(\frac{\exp\left(\left(n_t \lambda_t^* + (n_l - 1)\lambda_l^* + \lambda_i\right) x\right)}{n_t \lambda_t^* + (n_l - 1)\lambda_l^* + \lambda_i} \right)_{-u}^{p_t - p_l + s_t^* - s_i} \\
&\quad + \lambda_i \exp\left(\left(n_l - 1\right) \lambda_l^*\left(s_i - s_l^*\right)\right) \left(\frac{\exp\left(\left(\left(n_l - 1\right) \lambda_l^* + \lambda_i\right) x\right)}{(n_l - 1)\lambda_l^* + \lambda_i} \right)_{p_t - p_l + s_t^* - s_i}^{0},
\end{aligned}
$$

[40] Analogously to the argument above for the trailing agents, by assumption we have $n_l - 1 \geq 0$.

[41] Note that, similar to the argumentation above, if the parameter $k > 0$ is sufficiently large, any deviations $s_i < s_l^*$ that are small enough such that $p_t + s_t^* > p_l + s_i$ cannot be profitable. As the cost function is identical for all agents with a minimum at $\bar{s}$, the equilibrium choices s_t^* and s_l^* are arbitrarily close to $\bar{s}$ if k is sufficiently large. At the same time, deviations s_i far from $\bar{s}$ become arbitrarily costly if k is sufficiently large. Hence, since $p_t < p_l$, this ensures that, for equilibrium characterization, it is sufficient to consider the case in which $p_t + s_t^* \leq p_l + s_i$.

which reduces to

$$
\begin{aligned}
&= \lambda_i \exp\left(n_t \lambda_t^* \left(p_l - p_t + s_i - s_t^*\right) + \left(n_l - 1\right) \lambda_l^* \left(s_i - s_l^*\right)\right) \\
&\quad \cdot \left(\frac{\exp\left(\left(n_t \lambda_t^* + \left(n_l - 1\right) \lambda_l^* + \lambda_i\right) \left(p_t - p_l + s_t^* - s_i\right)\right)}{n_t \lambda_t^* + \left(n_l - 1\right) \lambda_l^* + \lambda_i} \right) \\
&\quad + \lambda_i \exp\left(\left(n_l - 1\right) \lambda_l^* \left(s_i - s_l^*\right)\right) \left(\frac{1}{\left(n_l - 1\right) \lambda_l^* + \lambda_i} \right) \\
&\quad - \lambda_i \exp\left(\left(n_l - 1\right) \lambda_l^* \left(s_i - s_l^*\right)\right) \left(\frac{\exp\left(\left(\left(n_l - 1\right) \lambda_l^* + \lambda_i\right) \left(p_t - p_l + s_t^* - s_i\right)\right)}{\left(n_l - 1\right) \lambda_l^* + \lambda_i} \right) \\
&= \frac{\lambda_i}{n_t \lambda_t^* + \left(n_l - 1\right) \lambda_l^* + \lambda_i} \exp\left(\left(n_l - 1\right) \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right) + \lambda_i \left(p_t - p_l + s_t^* - s_i\right)\right) \\
&\quad + \frac{\lambda_i}{\left(n_l - 1\right) \lambda_l^* + \lambda_i} \left(\exp\left(\left(n_l - 1\right) \lambda_l^* \left(s_i - s_l^*\right)\right)\right. \\
&\quad \left. - \exp\left(\left(n_l - 1\right) \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right) + \lambda_i \left(p_t - p_l + s_t^* - s_i\right)\right)\right).
\end{aligned}
$$

Hence, agent i's payoff becomes

$$
\begin{aligned}
U_i(s_i) = v &\frac{\lambda_i}{n_t \lambda_t^* + \left(n_l - 1\right) \lambda_l^* + \lambda_i} \exp\left(\left(n_l - 1\right) \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right)\right. \\
&\left. + \lambda_i (p_t - p_l + s_t^* - s_i)\right) + v \frac{\lambda_i}{(n_l - 1) \lambda_l^* + \lambda_i} \\
&\cdot \left(\exp\left((n_l - 1) \lambda_l^* (s_i - s_l^*)\right) - \exp\left((n_l - 1) \lambda_l^* (p_t - p_l + s_t^* - s_l^*)\right.\right. \\
&\left.\left. + \lambda_i \left(p_t - p_l + s_t^* - s_i\right)\right)\right) - kc\left(s_i - \bar{s}\right).
\end{aligned}
$$

The first-order condition is

$$
\begin{aligned}
\frac{\partial U_i(s_i)}{\partial s_i} = {} & v\frac{\lambda_i'(n_t\lambda_t^* + (n_l-1)\lambda_l^* + \lambda_i) - \lambda_i\lambda_i'}{(n_t\lambda_t^* + (n_l-1)\lambda_l^* + \lambda_i)^2} \\
& \cdot \exp\left((n_l-1)\lambda_l^*(p_t - p_l + s_t^* - s_l^*) + \lambda_i(p_t - p_l + s_t^* - s_i)\right) \\
& + v\frac{\lambda_i}{n_t\lambda_t^* + (n_l-1)\lambda_l^* + \lambda_i} \\
& \cdot \exp\left((n_l-1)\,\lambda_l^*\,(p_t - p_l + s_t^* - s_l^*) + \lambda_i\,(p_t - p_l + s_t^* - s_i)\right) \\
& \cdot \left(\lambda_i'\,(p_t - p_l + s_t^* - s_i) - \lambda_i\right) \\
& + v\frac{\lambda_i'\left((n_l-1)\,\lambda_l^* + \lambda_i\right) - \lambda_i\lambda_i'}{((n_l-1)\lambda_l^* + \lambda_i)^2} \\
& \cdot (\exp((n_l-1)\lambda_l^*(s_i - s_l^*)) - \exp((n_l-1) \\
& \cdot \lambda_l^*(p_t - p_l + s_t^* - s_l^*) + \lambda_i(p_t - p_l + s_t^* - s_i))) \\
& + v\frac{\lambda_i}{(n_l-1)\lambda_l^* + \lambda_i}\exp((n_l-1)\lambda_l^*(s_i - s_l^*))(n_l-1)\lambda_l^* \\
& - v\frac{\lambda_i}{(n_l-1)\lambda_l^* + \lambda_i}\exp((n_l-1)\lambda_l^*(p_t - p_l + s_t^* - s_l^*) \\
& + \lambda_i(p_t - p_l + s_t^* - s_i)) \\
& \cdot (\lambda_i'(p_t - p_l + s_t^* - s_i) - \lambda_i) \\
& - kc'(s_i - \bar{s}) = 0,
\end{aligned}
$$

which can be rewritten as

$$
\begin{aligned}
& v \frac{\lambda_i' \left(n_t \lambda_t^* + \left(n_l - 1\right) \lambda_l^*\right)}{\left(n_t \lambda_t^* + \left(n_l - 1\right) \lambda_l^* + \lambda_i\right)^2} \exp\left(\left(n_l - 1\right) \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right) + \lambda_i \left(p_t - p_l + s_t^* - s_i\right)\right) \\
& + v \frac{\lambda_i}{n_t \lambda_t^* + \left(n_l - 1\right) \lambda_l^* + \lambda_i} \\
& \cdot \exp\left(\left(n_l - 1\right) \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right) + \lambda_i \left(p_t - p_l + s_t^* - s_i\right)\right) \left(\lambda_i' \left(p_t - p_l + s_t^* - s_i\right) - \lambda_i\right) \\
& + v \frac{\lambda_i' \left(\left(n_l - 1\right) \lambda_l^*\right)}{\left(\left(n_l - 1\right) \lambda_l^* + \lambda_i\right)^2} \\
& \cdot \left(\exp\left(\left(n_l - 1\right) \lambda_l^* \left(s_i - s_l^*\right)\right) - \exp\left(\left(n_l - 1\right) \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right) + \lambda_i \left(p_t - p_l + s_t^* - s_i\right)\right)\right) \\
& + v \frac{\lambda_i}{\left(n_l - 1\right) \lambda_l^* + \lambda_i} \exp\left(\left(n_l - 1\right) \lambda_l^* \left(s_i - s_l^*\right)\right) \left(n_l - 1\right) \lambda_l^* \\
& - v \frac{\lambda_i}{\left(n_l - 1\right) \lambda_l^* + \lambda_i} \exp\left(\left(n_l - 1\right) \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right) + \lambda_i \left(p_t - p_l + s_t^* - s_i\right)\right) \\
& \cdot \left(\lambda_i' \left(p_t - p_l + s_t^* - s_i\right) - \lambda_i\right) \\
& - k c'(s_i - \bar{s}) = 0.
\end{aligned}
$$

In equilibrium, $s_i = s_l^*$ and $\lambda_i = \lambda_l^*$, and the condition simplifies to

$$
\begin{aligned}
& v \frac{\lambda_l^{*\prime} \left(n_t \lambda_t^* + \left(n_l - 1\right) \lambda_l^*\right)}{\left(n_t \lambda_t^* + n_l \lambda_l^*\right)^2} \exp\left(n_l \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right)\right) \\
& + v \frac{\lambda_l^*}{n_t \lambda_t^* + n_l \lambda_l^*} \exp\left(n_l \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right)\right) \left(\lambda_l^{*\prime} \left(p_t - p_l + s_t^* - s_l^*\right) - \lambda_l^*\right) \\
& + v \frac{\lambda_l^{*\prime} \left(\left(n_l - 1\right) \lambda_l^*\right)}{\left(n_l \lambda_l^*\right)^2} \left(1 - \exp\left(n_l \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right)\right)\right) \\
& + v \frac{1}{n_l} \left((n_l - 1)\lambda_l^* - \exp\left(n_l \lambda_l^* (p_t - p_l + s_t^* - s_l^*)\right) \left(\lambda_l^{*\prime} (p_t - p_l + s_t^* - s_l^*) - \lambda_l^*\right)\right) \\
& - k c'(s_l^* - \bar{s}) = 0,
\end{aligned}
$$

which can be further rewritten as

$$
\begin{aligned}
& v \frac{\exp\left(n_l \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right)\right)}{n_t \lambda_t^* + n_l \lambda_l^*} \\
& \cdot \left(\frac{\lambda_l^{*\prime} \left(n_t \lambda_t^* + \left(n_l - 1\right) \lambda_l^*\right)}{n_t \lambda_t^* + n_l \lambda_l^*} + \lambda_l^* \left(\lambda_l^{*\prime} \left(p_t - p_l + s_t^* - s_l^*\right) - \lambda_l^*\right) \right) \\
& - v \frac{\exp\left(n_l \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right)\right)}{n_l} \left(\frac{\lambda_l^{*\prime} \left(n_l - 1\right)}{n_l \lambda_l^*} + \lambda_l^{*\prime} \left(p_t - p_l + s_t^* - s_l^*\right) - \lambda_l^* \right) \\
& + v \frac{n_l - 1}{n_l} \left(\frac{\lambda_l^{*\prime}}{n_l \lambda_l^*} + \lambda_l^* \right) - kc'(s_l^* - \bar{s}) = 0.
\end{aligned}
$$

Substituting $-(\lambda_l^*)^2$ for $\lambda_l^{*\prime}$, we obtain

$$
\begin{aligned}
& - v \frac{\exp\left(n_l \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right)\right)}{n_t \lambda_t^* + n_l \lambda_l^*} \left(\lambda_l^*\right)^2 \left(\frac{n_t \lambda_t^* + \left(n_l - 1\right) \lambda_l^*}{n_t \lambda_t^* + n_l \lambda_l^*} + \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right) + 1 \right) \\
& + v \frac{\exp\left(n_l \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right)\right)}{n_l} \lambda_l^* \left(\frac{2n_l - 1}{n_l} + \lambda_l^* \left(p_t - p_l + s_t^* - s_l^*\right) \right) \\
& + v \left(\frac{n_l - 1}{n_l} \right)^2 \lambda_l^* - kc'(s_l^* - \bar{s}) = 0.
\end{aligned} \tag{10}
$$

Now, suppose that $s_i \geq s_l^*$ and $p_t + s_t^* \leq p_l + s_l^*$. Then, the agent's winning probability $P_i(s_i)$ is given by

$$
\begin{aligned}
&P_i(s_i) \\
&= \int \Pi_{j\neq i} F_{\varepsilon_j}(p_i - p_j + s_i - s_j + x) f_{\varepsilon_i}(x) dx \\
&= \int_{-\infty}^{p_t - p_l + s_t^* - s_i} \left(\exp(\lambda_t^*(p_l - p_t + s_i - s_t^* + x))\right)^{n_t} \left(\exp(\lambda_l^*(s_i - s_l^* + x))\right)^{n_l - 1} \lambda_i \exp(\lambda_i x) dx \\
&\quad + \int_{p_t - p_l + s_t^* - s_i}^{s_l^* - s_i} \left(\exp\left(\lambda_l^*\left(s_i - s_l^* + x\right)\right)\right)^{n_l - 1} \lambda_i \exp\left(\lambda_i x\right) dx \\
&\quad + \int_{s_l^* - s_i}^{0} \lambda_i \exp(\lambda_i x) dx \\
&= \int_{-\infty}^{p_t - p_l + s_t^* - s_i} \exp(n_t \lambda_t^*(p_l - p_t + s_i - s_t^* + x)) \exp\left(\left(n_l - 1\right) \lambda_l^* \left(s_i - s_l^* + x\right)\right) \lambda_i \exp\left(\lambda_i x\right) dx \\
&\quad + \int_{p_t - p_l + s_t^* - s_i}^{s_l^* - s_i} \exp\left(\left(n_l - 1\right) \lambda_l^* \left(s_i - s_l^* + x\right)\right) \lambda_i \exp\left(\lambda_i x\right) dx \\
&\quad + \int_{s_l^* - s_i}^{0} \lambda_i \exp(\lambda_i x) dx \\
&= \lambda_i \exp\left(n_t \lambda_t^* \left(p_l - p_t + s_i - s_t^*\right) + \left(n_l - 1\right) \lambda_l^*(s_i - s_l^*)\right) \\
&\quad \cdot \int_{-\infty}^{p_t - p_l + s_t^* - s_i} \exp\left((n_t \lambda_t^* + (n_l - 1)\lambda_l^* + \lambda_i) x\right) dx \\
&\quad + \lambda_i \exp\left((n_l - 1)\lambda_l^*(s_i - s_l^*)\right) \int_{p_t - p_l + s_t^* - s_i}^{s_l^* - s_i} \exp\left(\left(\left(n_l - 1\right) \lambda_l^* + \lambda_i\right) x\right) dx \\
&\quad + \lambda_i \int_{s_l^* - s_i}^{0} \exp(\lambda_i x) dx \\
&= \lambda_i \exp\left(n_t \lambda_t^*(p_l - p_t + s_i - s_t^*) + (n_l - 1)\lambda_l^*(s_i - s_l^*)\right) \\
&\quad \cdot \lim_{u \to \infty} \left(\frac{\exp\left((n_t \lambda_t^* + (n_l - 1)\lambda_l^* + \lambda_i) x\right)}{n_t \lambda_t^* + (n_l - 1)\lambda_l^* + \lambda_i} \right)_{-u}^{p_t - p_l + s_t^* - s_i} \\
&\quad + \lambda_i \exp\left(\left(n_l - 1\right) \lambda_l^* \left(s_i - s_l^*\right)\right) \left(\frac{\exp\left(\left(\left(n_l - 1\right) \lambda_l^* + \lambda_i\right) x\right)}{(n_l - 1)\lambda_l^* + \lambda_i} \right)_{p_t - p_l + s_t^* - s_i}^{s_l^* - s_i} \\
&\quad + \lambda_i \left(\frac{\exp(\lambda_i x)}{\lambda_i} \right)_{s_l^* - s_i}^{0},
\end{aligned}
$$

which reduces to

$$
\begin{aligned}
&\lambda_i \exp\left(n_t\lambda_t^*\left(p_l - p_t + s_i - s_t^*\right) + \left(n_l - 1\right)\lambda_l^*\left(s_i - s_l^*\right)\right) \\
&\quad \cdot \left(\frac{\exp\left(\left(n_t\lambda_t^* + \left(n_l - 1\right)\lambda_l^* + \lambda_i\right)\left(p_t - p_l + s_t^* - s_i\right)\right)}{n_t\lambda_t^* + \left(n_l - 1\right)\lambda_l^* + \lambda_i}\right) \\
&\quad + \lambda_i \exp\left(\left(n_l - 1\right)\lambda_l^*(s_i - s_l^*)\right) \\
&\quad \cdot \left(\frac{\exp(((n_l-1)\lambda_l^* + \lambda_i)(s_l^* - s_i))}{\left(n_l - 1\right)\lambda_l^* + \lambda_i} - \frac{\exp\left(\left(\left(n_l - 1\right)\lambda_l^* + \lambda_i\right)\left(p_t - p_l + s_t^* - s_i\right)\right)}{\left(n_l - 1\right)\lambda_l^* + \lambda_i}\right) \\
&\quad + \lambda_i\left(\frac{1}{\lambda_i} - \frac{\exp(\lambda_i(s_l^* - s_i))}{\lambda_i}\right) \\
&= \lambda_i \frac{\exp\left((n_l-1)\lambda_l^*(p_t - p_l + s_t^* - s_l^*) + \lambda_i(p_t - p_l + s_t^* - s_i)\right)}{n_t\lambda_t^* + \left(n_l - 1\right)\lambda_l^* + \lambda_i} \\
&\quad + \lambda_i \frac{\exp(\lambda_i(s_l^* - s_i))}{(n_l-1)\lambda_l^* + \lambda_i} \\
&\quad - \lambda_i \frac{\exp\left((n_l-1)\lambda_l^*(p_t - p_l + s_t^* - s_l^*) + \lambda_i(p_t - p_l + s_t^* - s_i)\right)}{(n_l-1)\lambda_l^* + \lambda_i} \\
&\quad + 1 - \exp(\lambda_i(s_l^* - s_i)).
\end{aligned}
$$

Hence, agent i's payoff becomes

$$
\begin{aligned}
U_i(s_i) = v\lambda_i &\frac{\exp\left((n_l-1)\lambda_l^*(p_t - p_l + s_t^* - s_l^*) + \lambda_i(p_t - p_l + s_t^* - s_i)\right)}{n_t\lambda_t^* + \left(n_l - 1\right)\lambda_l^* + \lambda_i} \\
&+ v\lambda_i \frac{\exp(\lambda_i(s_l^* - s_i))}{(n_l-1)\lambda_l^* + \lambda_i} \\
&- v\lambda_i \frac{\exp\left((n_l-1)\lambda_l^*(p_t - p_l + s_t^* - s_l^*) + \lambda_i(p_t - p_l + s_t^* - s_i)\right)}{(n_l-1)\lambda_l^* + \lambda_i} \\
&+ v(1 - \exp(\lambda_i(s_l^* - s_i))) \\
&- kc(s_i - \bar{s}).
\end{aligned}
$$

The first-order condition is

$$
\begin{aligned}
&\frac{\partial U_i(s_i)}{\partial s_i}\\
&= v\lambda_i' \frac{\exp\left((n_l-1)\lambda_l^*(p_t-p_l+s_t^*-s_l^*)+\lambda_i(p_t-p_l+s_t^*-s_i)\right)}{n_t\lambda_t^*+(n_l-1)\lambda_l^*+\lambda_i}\\
&\quad + v\lambda_i[\frac{(n_t\lambda_t^*+(n_l-1)\lambda_l^*+\lambda_i)\left(\lambda_i'(p_t-p_l+s_t^*-s_i)-\lambda_i\right)}{(n_t\lambda_t^*+(n_l-1)\lambda_l^*+\lambda_i)^2}\\
&\quad \cdot \exp((n_l-1)\lambda_l^*(p_t-p_l+s_t^*-s_l^*)+\lambda_i(p_t-p_l+s_t^*-s_i))\\
&\quad - \frac{\lambda_i' \exp((n_l-1)\lambda_l^*(p_t-p_l+s_t^*-s_l^*)+\lambda_i(p_t-p_l+s_t^*-s_i))}{(n_t\lambda_t^*+(n_l-1)\lambda_l^*+\lambda_i)^2}]\\
&\quad + v\lambda_i' \frac{\exp(\lambda_i(s_l^*-s_i))}{(n_l-1)\lambda_l^*+\lambda_i}\\
&\quad + v\lambda_i\left[\frac{((n_l-1)\lambda_l^*+\lambda_i)(\lambda_i'(s_l^*-s_i)-\lambda_i)\exp(\lambda_i(s_l^*-s_i))-\lambda_i'\exp(\lambda_i(s_l^*-s_i)))}{((n_l-1)\lambda_l^*+\lambda_i)^2}\right]\\
&\quad - v\lambda_i' \frac{\exp\left((n_l-1)\lambda_l^*(p_t-p_l+s_t^*-s_l^*)+\lambda_i(p_t-p_l+s_t^*-s_i)\right)}{(n_l-1)\lambda_l^*+\lambda_i}\\
&\quad - v\lambda_i[\frac{((n_l-1)\lambda_l^*+\lambda_i)(\lambda_i'(p_t-p_l+s_t^*-s_i)-\lambda_i)}{((n_l-1)\lambda_l^*+\lambda_i)^2}\\
&\quad \cdot \exp\left((n_l-1)\lambda_l^*(p_t-p_l+s_t^*-s_l^*)+\lambda_i(p_t-p_l+s_t^*-s_i)\right)\\
&\quad - \frac{\lambda_i' \exp\left((n_l-1)\lambda_l^*(p_t-p_l+s_t^*-s_l^*)+\lambda_i(p_t-p_l+s_t^*-s_i)\right)}{((n_l-1)\lambda_l^*+\lambda_i)^2}]\\
&\quad - v(\lambda_i'(s_l^*-s_i)-\lambda_i)\exp(\lambda_i(s_l^*-s_i))\\
&\quad - kc'(s_i-\bar{s})\\
&= 0.
\end{aligned}
$$

In equilibrium, $s_i = s_l^*$ and $\lambda_i = \lambda_l^*$, and the condition simplifies to

$$\begin{aligned}
& v(\lambda_l^*)' \frac{\exp(n_l \lambda_l^*(p_t - p_l + s_t^* - s_l^*))}{n_t\lambda_t^* + n_l\lambda_l^*} \\
& \quad + v\lambda_l^* [\frac{(n_t\lambda_t^* + n_l\lambda_l^*)\left((\lambda_l^*)'(p_t - p_l + s_t^* - s_l^*) - \lambda_l^*\right)}{(n_t\lambda_t^* + n_l\lambda_l^*)^2} \\
& \quad \cdot \exp(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)) \\
& \quad - \frac{(\lambda_l^*)' \exp(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*))}{(n_t\lambda_t^* + n_l\lambda_l^*)^2}] \\
& \quad + v(\lambda_l^*)' \frac{1}{n_l\lambda_l^*} \\
& \quad + v\lambda_l^* \left[\frac{(n_l\lambda_l^*)(-\lambda_l^*) - (\lambda_l^*)'}{(n_l\lambda_l^*)^2}\right] \\
& \quad - v(\lambda_l^*)' \frac{\exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right)}{n_l\lambda_l^*} \\
& \quad - v\lambda_l^* [\frac{n_l\lambda_l^*((\lambda_l^*)'(p_t - p_l + s_t^* - s_l^*) - \lambda_l^*)}{(n_l\lambda_l^*)^2} \\
& \quad \cdot \exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right) \\
& \quad - \frac{(\lambda_l^*)' \exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right)}{(n_l\lambda_l^*)^2}] \\
& \quad + v\lambda_l^* \\
& \quad - kc'(s_l^* - \bar{s}) \\
& = 0.
\end{aligned}$$

Substituting $-(\lambda_l^*)^2$ for $\lambda_l^{*\prime}$, we obtain

$$\begin{aligned}
& - v\frac{\exp(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*))}{n_t\lambda_t^* + n_l\lambda_l^*}(\lambda_l^*)^2 \left[\frac{(n_t\lambda_t^* + n_l\lambda_l^*)\left(\lambda_l^*(p_t - p_l + s_t^* - s_l^*) + 1\right) - \lambda_l^*}{n_t\lambda_t^* + n_l\lambda_l^*} + 1\right] \\
& \quad + v\frac{\exp\left(n_l\lambda_l^*(p_t - p_l + s_t^* - s_l^*)\right)}{n_l}\lambda_l^* \left[1 + \frac{n_l\lambda_l^*((\lambda_l^*)^2(p_t - p_l + s_t^* - s_l^*) + \lambda_l^*) - (\lambda_l^*)^2}{n_l(\lambda_l^*)^2}\right] \\
& \quad - v(\lambda_l^*)^2\frac{1}{n_l\lambda_l^*} + v\lambda_l^*\frac{-n_l(\lambda_l^*)^2 + (\lambda_l^*)^2}{(n_l\lambda_l^*)^2} + v\lambda_l^* \\
& \quad - kc'(s_l^* - \bar{s}) \\
& = 0,
\end{aligned}$$

which is equivalent to

$$
\begin{aligned}
&-v\frac{\exp\left(n_l\lambda_l^*\left(p_t-p_l+s_t^*-s_l^*\right)\right)}{n_t\lambda_t^*+n_l\lambda_l^*}\left(\lambda_l^*\right)^2\left(\frac{n_t\lambda_t^*+\left(n_l-1\right)\lambda_l^*}{n_t\lambda_t^*+n_l\lambda_l^*}+\lambda_l^*\left(p_t-p_l+s_t^*-s_l^*\right)+1\right)\\
&+v\frac{\exp\left(n_l\lambda_l^*\left(p_t-p_l+s_t^*-s_l^*\right)\right)}{n_l}\lambda_l^*\left(\frac{2n_l-1}{n_l}+\lambda_l^*\left(p_t-p_l+s_t^*-s_l^*\right)\right)\\
&+v\left(\frac{n_l-1}{n_l}\right)^2\lambda_l^*-kc'(s_l^*-\bar{s})=0.
\end{aligned}
\tag{11}
$$

This is identical to equation (10). The first three terms have different signs. Thus, in general, it is unclear whether or not $s_l^*>\bar{s}$.

□

Proof of Proposition 2. As shown in Proposition 1, the equilibrium is characterized by the first-order conditions in equations (3) and (4). To simplify notation, in the following we denote the left-hand side of these equations by H_1 and H_2, respectively. Hence, equations (3) and (4) are fulfilled, if and only if the function $H=(H_1,H_2):\mathbb{R}^2\to\mathbb{R}^2$, defined by $(s_t^*,s_l^*)\mapsto(H_1(s_t^*,s_l^*),H_2(s_t^*,s_l^*))$, vanishes, that is, if $H(s_t^*,s_l^*)=0$. The Jacobian determinant of H is given by

$$
|J|=\begin{vmatrix}\frac{\partial H_1}{\partial s_t^*} & \frac{\partial H_1}{\partial s_l^*}\\ \frac{\partial H_2}{\partial s_t^*} & \frac{\partial H_2}{\partial s_l^*}\end{vmatrix}=\frac{\partial H_1}{\partial s_t^*}\frac{\partial H_2}{\partial s_l^*}-\frac{\partial H_2}{\partial s_t^*}\frac{\partial H_1}{\partial s_l^*}.
$$

Notice that only the first product depends on the cost function, the second one does not. We assume that k is sufficiently large such that $\frac{\partial H_1}{\partial s_t^*}<0$, $\frac{\partial H_2}{\partial s_l^*}<0$, and $|J|>0$. By the implicit function theorem,[42] we have

$$
\frac{\partial s_t^*}{\partial\Delta p}=\frac{1}{|J|}\begin{vmatrix}-\frac{\partial H_1}{\partial\Delta p} & \frac{\partial H_1}{\partial s_l^*}\\ -\frac{\partial H_2}{\partial\Delta p} & \frac{\partial H_2}{\partial s_l^*}\end{vmatrix},
$$

[42] See equation 8.29 and the discussion in Chiang and Wainwright (2005).

where

$$\begin{vmatrix} -\frac{\partial H_1}{\partial \Delta p} & \frac{\partial H_1}{\partial s_l^*} \\ -\frac{\partial H_2}{\partial \Delta p} & \frac{\partial H_2}{\partial s_l^*} \end{vmatrix} = -\frac{\partial H_1}{\partial \Delta p}\frac{\partial H_2}{\partial s_l^*} + \frac{\partial H_2}{\partial \Delta p}\frac{\partial H_1}{\partial s_l^*}.$$

Again, $\frac{\partial H_2}{\partial \Delta p}\frac{\partial H_1}{\partial s_l^*}$ does not depend on the cost function. Therefore, whenever k is sufficiently large, we have $sgn\left(\frac{\partial s_t^*}{\partial \Delta p}\right) = sgn\left(\frac{\partial H_1}{\partial \Delta p}\right)$. We observe

$$\frac{\partial H_1}{\partial \Delta p} = -n_l \lambda_l^* v \exp\left(n_l \lambda_l^* \left(s_t^* - s_l^* - \Delta p\right)\right) \lambda_t^* \left(\frac{\left(n_t - 1\right)\lambda_t^* + n_l \lambda_l^*}{n_t \lambda_t^* + n_l \lambda_l^*}\right)^2 < 0.$$

Furthermore,

$$\frac{\partial s_t^*}{\partial n_l} = \frac{1}{|J|}\begin{vmatrix} -\frac{\partial H_1}{\partial n_l} & \frac{\partial H_1}{\partial s_l^*} \\ -\frac{\partial H_2}{\partial n_l} & \frac{\partial H_2}{\partial s_l^*} \end{vmatrix},$$

where

$$\begin{vmatrix} -\frac{\partial H_1}{\partial n_l} & \frac{\partial H_1}{\partial s_l^*} \\ -\frac{\partial H_2}{\partial n_l} & \frac{\partial H_2}{\partial s_l^*} \end{vmatrix} = -\frac{\partial H_1}{\partial n_l}\frac{\partial H_2}{\partial s_l^*} + \frac{\partial H_2}{\partial n_l}\frac{\partial H_1}{\partial s_l^*}.$$

If k is sufficiently large, we have $sgn\left(\frac{\partial s_t^*}{\partial n_l}\right) = sgn\left(\frac{\partial H_1}{\partial n_l}\right)$, where

$$\begin{aligned}\frac{\partial H_1}{\partial n_l} &= -v\lambda_t^* \exp\left(n_l \lambda_l^* \left(s_t^* - s_l^* - \Delta p\right)\right) \lambda_l^* (\Delta p + s_l^* - s_t^*) \left(\frac{\left(n_t - 1\right)\lambda_t^* + n_l \lambda_l^*}{n_t \lambda_t^* + n_l \lambda_l^*}\right)^2 \\ &\quad + v\lambda_t^* \exp\left(n_l \lambda_l^* \left(s_t^* - s_l^* - \Delta p\right)\right) 2 \left(\frac{\left(n_t - 1\right)\lambda_t^* + n_l \lambda_l^*}{n_t \lambda_t^* + n_l \lambda_l^*}\right) \frac{\lambda_t^* \lambda_l^*}{\left(n_t \lambda_t^* + n_l \lambda_l^*\right)^2}.\end{aligned}$$

If Δp is sufficiently small and k is sufficiently large, the term $|\Delta p + s_l^* - s_t^*|$ is small as well (as argued before, if k is large, s_t^* and s_l^* are close to $\bar{s}$ and therefore $|s_t^* - s_l^*|$ is sufficiently small), in which case $\frac{\partial H_1}{\partial n_l} > 0$.

Furthermore,

$$\frac{\partial s_t^*}{\partial n_t} = \frac{1}{|J|}\begin{vmatrix} -\frac{\partial H_1}{\partial n_t} & \frac{\partial H_1}{\partial s_l^*} \\ -\frac{\partial H_2}{\partial n_t} & \frac{\partial H_2}{\partial s_l^*} \end{vmatrix},$$

where

$$\begin{vmatrix} -\frac{\partial H_1}{\partial n_t} & \frac{\partial H_1}{\partial s_l^*} \\ -\frac{\partial H_2}{\partial n_t} & \frac{\partial H_2}{\partial s_l^*} \end{vmatrix} = -\frac{\partial H_1}{\partial n_t}\frac{\partial H_2}{\partial s_l^*} + \frac{\partial H_2}{\partial n_t}\frac{\partial H_1}{\partial s_l^*}.$$

If k is sufficiently large, we have $sgn\left(\frac{\partial s_t^*}{\partial n_t}\right) = sgn\left(\frac{\partial H_1}{\partial n_t}\right)$, where

$$\begin{aligned}
\frac{\partial H_1}{\partial n_t} &= v\exp\left(n_l\lambda_l^*(s_t^* - s_l^* - \Delta p)\right)\lambda_t^* \\
&\quad \cdot 2\left(\frac{(n_t-1)\lambda_t^* + n_l\lambda_l^*}{n_t\lambda_t^* + n_l\lambda_l^*}\right)\frac{\lambda_t^*(n_t\lambda_t^* + n_l\lambda_l^*) - \lambda_t^*((n_t-1)\lambda_t^* + n_l\lambda_l^*)}{(n_t\lambda_t^* + n_l\lambda_l^*)^2} \\
&= 2v\exp\left(n_l\lambda_l^*(s_t^* - s_l^* - \Delta p)\right)(\lambda_t^*)^3\frac{(n_t-1)\lambda_t^* + n_l\lambda_l^*}{(n_t\lambda_t^* + n_l\lambda_l^*)^3} \\
&> 0.
\end{aligned}$$

With a similar argumentation as before, if k is sufficiently large, we have $sgn\left(\frac{\partial s_l^*}{\partial \Delta p}\right) = sgn\left(\frac{\partial H_2}{\partial \Delta p}\right)$. We observe

$$\begin{aligned}
\frac{\partial H_2}{\partial \Delta p} &= v\frac{n_l\left(\lambda_l^*\right)^3}{n_t\lambda_t^* + n_l\lambda_l^*}\exp\left(n_l\lambda_l^*\left(s_t^* - s_l^* - \Delta p\right)\right) \\
&\quad \cdot\left(\frac{n_t\lambda_t^* + \left(n_l-1\right)\lambda_l^*}{n_t\lambda_t^* + n_l\lambda_l^*} + \lambda_l^*\left(s_t^* - s_l^* - \Delta p\right) + 1\right) \\
&\quad + v\frac{\left(\lambda_l^*\right)^3}{n_t\lambda_t^* + n_l\lambda_l^*}\exp\left(n_l\lambda_l^*\left(s_t^* - s_l^* - \Delta p\right)\right) \\
&\quad - v\left(\lambda_l^*\right)^2\exp\left(n_l\lambda_l^*\left(s_t^* - s_l^* - \Delta p\right)\right)\left(\frac{2n_l - 1}{n_l} + \lambda_l^*\left(s_t^* - s_l^* - \Delta p\right)\right) \\
&\quad - v\frac{\left(\lambda_l^*\right)^2}{n_l}\exp\left(n_l\lambda_l^*\left(s_t^* - s_l^* - \Delta p\right)\right) \\
&= v\frac{\left(\lambda_l^*\right)^3}{n_t\lambda_t^* + n_l\lambda_l^*}\exp\left(n_l\lambda_l^*\left(s_t^* - s_l^* - \Delta p\right)\right) \\
&\quad \cdot\left(\frac{n_t n_l\lambda_t^* + \left(n_l-1\right)n_l\lambda_l^*}{n_t\lambda_t^* + n_l\lambda_l^*} + n_l\lambda_l^*\left(s_t^* - s_l^* - \Delta p\right) + n_l + 1\right) \\
&\quad - v\left(\lambda_l^*\right)^2\exp\left(n_l\lambda_l^*\left(s_t^* - s_l^* - \Delta p\right)\right)\left(2 + \lambda_l^*\left(s_t^* - s_l^* - \Delta p\right)\right).
\end{aligned}$$

This is negative if and only if

$$
\begin{aligned}
&\frac{n_t n_l \lambda_t^* \lambda_l^* + (n_l - 1)\, n_l \left(\lambda_l^*\right)^2}{n_t \lambda_t^* + n_l \lambda_l^*} + n_l \left(\lambda_l^*\right)^2 \left(s_t^* - s_l^* - \Delta p\right) + \left(n_l + 1\right) \lambda_l^* \\
&\qquad < 2\left(n_t \lambda_t^* + n_l \lambda_l^*\right) + \lambda_l^* \left(n_t \lambda_t^* + n_l \lambda_2^*\right)\left(s_t^* - s_l^* - \Delta p\right) \\
\Leftrightarrow \quad &\frac{n_t n_l \lambda_t^* \lambda_l^* + (n_l - 1)\, n_l \left(\lambda_l^*\right)^2}{n_t \lambda_t^* + n_l \lambda_l^*} < 2 n_t \lambda_t^* + (n_l - 1)\, \lambda_l^* + n_t \lambda_t^* \lambda_l^* \left(s_t^* - s_l^* - \Delta p\right) \\
\Leftrightarrow \quad &\frac{-2\left(n_t \lambda_t^*\right)^2 - n_t \left(2 n_l - 1\right) \lambda_t^* \lambda_l^*}{n_t \lambda_t^* + n_l \lambda_l^*} + n_t \lambda_t^* \lambda_l^* \left(\Delta p + s_l^* - s_t^*\right) < 0.
\end{aligned}
$$

If Δp is sufficiently small, $|\Delta p + s_l^* - s_t^*|$ is small as well, in which case $\frac{\partial H_2}{\partial \Delta p} < 0$.

Again, with a similar argumentation as before, if k is sufficiently large, we have $sgn\left(\frac{\partial s_l^*}{\partial n_t}\right) = sgn\left(\frac{\partial H_2}{\partial n_t}\right)$. We observe

$$
\begin{aligned}
\frac{\partial H_2}{\partial n_t} &= v \left(\lambda_l^*\right)^2 \frac{\exp\left(n_l \lambda_l^* \left(s_t^* - s_l^* - \Delta p\right)\right) \lambda_t^*}{\left(n_t \lambda_t^* + n_l \lambda_l^*\right)^2} \left(\frac{n_t \lambda_t^* + (n_l - 1)\, \lambda_l^*}{n_t \lambda_t^* + n_l \lambda_l^*} + \lambda_l^* \left(s_t^* - s_l^* - \Delta p\right) + 1\right) \\
&- v \left(\lambda_l^*\right)^2 \frac{\exp\left(n_l \lambda_l^* \left(s_t^* - s_l^* - \Delta p\right)\right)}{n_t \lambda_t^* + n_l \lambda_l^*} \left(\frac{\lambda_t^* \lambda_l^*}{\left(n_t \lambda_t^* + n_l \lambda_l^*\right)^2}\right).
\end{aligned}
$$

This is positive if and only if

$$
\begin{aligned}
&\left(n_t \lambda_t^* + n_l \lambda_l^*\right) \left(\frac{n_t \lambda_t^* + (n_l - 1)\, \lambda_l^*}{n_t \lambda_t^* + n_l \lambda_l^*} + \lambda_l^* \left(s_t^* - s_l^* - \Delta p\right) + 1\right) > \lambda_l^* \\
\Leftrightarrow \quad &2 n_t \lambda_t^* + 2\left(n_l - 1\right) \lambda_l^* - \left(n_t \lambda_t^* + n_l \lambda_l^*\right) \lambda_l^* \left(\Delta p + s_l^* - s_t^*\right) > 0.
\end{aligned}
$$

If Δp is sufficiently small, $|\Delta p + s_l^* - s_t^*|$ is small as well, in which case $\frac{\partial H_2}{\partial n_t} > 0$.

Again, with a similar argumentation as before, if k is sufficiently large, we have $sgn\left(\frac{\partial s_l^*}{\partial n_l}\right) = sgn\left(\frac{\partial H_2}{\partial n_l}\right)$.

We observe

$$\begin{aligned}
\frac{\partial H_2}{\partial n_l} &= \\
&- v\frac{(\lambda_l^*(s_t^* - s_l^* - \Delta p))\exp(n_l\lambda_l^*(s_t^* - s_l^* - \Delta p))(n_t\lambda_t^* + n_l\lambda_l^*) - \lambda_l^*\exp(n_l\lambda_l^*(s_t^* - s_l^* - \Delta p))}{(n_t\lambda_t^* + n_l\lambda_l^*)^2} \\
&\quad \cdot (\lambda_l^*)^2\left(\frac{n_t\lambda_t^* + (n_l - 1)\lambda_l^*}{n_t\lambda_t^* + n_l\lambda_l^*} + \lambda_l^*(s_t^* - s_l^* - \Delta p) + 1\right) \\
&\quad - v\frac{\exp(n_l\lambda_l^*(s_t^* - s_l^* - \Delta p))}{n_t\lambda_t^* + n_l\lambda_l^*} \\
&\quad \cdot (\lambda_l^*)^2\frac{\lambda_l^*(n_t\lambda_t^* + n_l\lambda_l^*) - \lambda_l^*(n_t\lambda_t^* + (n_l - 1)\lambda_l^*)}{(n_t\lambda_t^* + n_l\lambda_l^*)^2} \\
&\quad + v\frac{(\lambda_l^*(s_t^* - s_l^* - \Delta p))\exp(n_l\lambda_l^*(s_t^* - s_l^* - \Delta p))n_l - \exp(n_l\lambda_l^*(s_t^* - s_l^* - \Delta p))}{n_l^2} \\
&\quad \cdot \lambda_l^*\left(\frac{2n_l - 1}{n_l} + \lambda_l^*(s_t^* - s_l^* - \Delta p)\right) \\
&\quad + v\frac{\exp(n_l\lambda_l^*(s_t^* - s_l^* - \Delta p))}{n_l} \\
&\quad \cdot \lambda_l^*\frac{2n_l - (2n_l - 1)}{n_l^2} \\
&\quad + 2v\frac{n_l - 1}{n_l}\frac{n_l - (n_l - 1)}{n_l^2}\lambda_l^*,
\end{aligned}$$

which can be rewritten as

$$\begin{aligned}
\frac{\partial H_2}{\partial n_l} &= \\
&- v\frac{(\lambda_l^*(s_t^* - s_l^* - \Delta p))\exp(n_l\lambda_l^*(s_t^* - s_l^* - \Delta p))(n_t\lambda_t^* + n_l\lambda_l^*) - \lambda_l^*\exp(n_l\lambda_l^*(s_t^* - s_l^* - \Delta p))}{(n_t\lambda_t^* + n_l\lambda_l^*)^2} \\
&\quad \cdot (\lambda_l^*)^2\left(\frac{n_t\lambda_t^* + (n_l - 1)\lambda_l^*}{n_t\lambda_t^* + n_l\lambda_l^*} + \lambda_l^*(s_t^* - s_l^* - \Delta p) + 1\right) \\
&\quad - v\frac{\exp(n_l\lambda_l^*(s_t^* - s_l^* - \Delta p))}{n_t\lambda_t^* + n_l\lambda_l^*}\frac{(\lambda_l^*)^4}{(n_t\lambda_t^* + n_l\lambda_l^*)^2} \\
&\quad + v\frac{(\lambda_l^*(s_t^* - s_l^* - \Delta p))\exp(n_l\lambda_l^*(s_t^* - s_l^* - \Delta p))n_l - \exp(n_l\lambda_l^*(s_t^* - s_l^* - \Delta p))}{n_l^2} \\
&\quad \cdot \lambda_l^*\left(\frac{2n_l - 1}{n_l} + \lambda_l^*(s_t^* - s_l^* - \Delta p)\right) \\
&\quad + v\lambda_l^*\frac{\exp(n_l\lambda_l^*(s_t^* - s_l^* - \Delta p))}{n_l^3} \\
&\quad + 2v\lambda_l^*\frac{n_l - 1}{n_l^3}.
\end{aligned}$$

If $\Delta p + s_l^* - s_t^* \to 0$, this is reduced to

$$\begin{aligned}\frac{\partial H_2}{\partial n_l} &= v\lambda_l^* \frac{1}{(n_t\lambda_t^* + n_l\lambda_l^*)^3} (\lambda_l^*)^2 \left(2n_t\lambda_t^* + 2(n_l - 1)\lambda_l^* + \lambda_l^*\right) \\ &\quad - v\lambda_l^* \frac{1}{(n_t\lambda_t^* + n_l\lambda_l^*)^3} (\lambda_l^*)^3 \\ &\quad - v\lambda_l^* \frac{1}{n_l^3}(2n_l - 1) \\ &\quad + v\lambda_l^* \frac{1}{n_l^3} \\ &\quad + 2v\lambda_l^* \frac{n_l - 1}{n_l^3} \\ &= v\lambda_l^* \frac{1}{(n_t\lambda_t^* + n_l\lambda_l^*)^3} (\lambda_l^*)^2 \left(2n_t\lambda_t^* + 2(n_l - 1)\lambda_l^*\right).\end{aligned}$$

If Δp is sufficiently small, $|\Delta p + s_l^* - s_t^*|$ is small as well, in which case $\frac{\partial H_2}{\partial n_l} > 0$. □

7.2. Robustness: Course section

7.2.1. Risk measure

This section contains results showing the robustness of the risk measure with regard to a different course section. While in the main part of the paper we were looking at the *last quarter* of each lap, here we consider the time in the *last half*, the time measured from *Split time 1*, as illustrated in Figure 2, until the end of the lap, as the independent variable of interest. The following Tables A.8 and A.9 show the results of the Pseudo Poisson Maximum Likelihood estimation and the corresponding incidence ratios, respectively.

Table A.8: Tradeoff between skiing performance (last half) and shooting accuracy (PPML estimates)

	Total number of missed shots			
	(1)	(2)	(3)	(4)
Ski time last half	-0.071***	-0.062***	-0.066***	-0.067***
	(0.015)	(0.018)	(0.020)	(0.020)
Time first shot bout 4				0.018***
				(0.004)
N	5501	5501	5501	5501
Race FE	Yes	Yes	Yes	Yes
Athlete Season FE	Yes	Yes	Yes	Yes
Difference at start	Yes	Yes	Yes	Yes
Intermediate Rank	No	Yes	Yes	Yes
Previous ski times lap 1-3	No	Yes	Yes	Yes
Sum of previous missed shots	No	Yes	Yes	Yes
Previous ski time lap 4	No	No	Yes	Yes

Notes: The table shows the tradeoff between skiing performance and shooting accuracy. The estimates are obtained using a Poisson Pseudo Maximum Likelihood estimator. The dependent variable is the total number of missed shots in the last shooting bout. The skiing times are normalized and thus need to be interpreted in terms of standard deviations. The richest specification includes race and athlete season fixed effects, as well as controls for past skiing performance, shooting performance, and for the intermediate rank. Standard errors are clustered on race level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Table A.9: Tradeoff between skiing performance (last half) and shooting accuracy (incidence ratios)

	Total number of missed shots			
	(1)	(2)	(3)	(4)
Ski time last half	0.931***	0.940***	0.937***	0.936***
	(0.014)	(0.017)	(0.019)	(0.019)
Time first shot bout 4				1.018***
				(0.004)
N	5501	5501	5501	5501
Race FE	Yes	Yes	Yes	Yes
Athlete Season FE	Yes	Yes	Yes	Yes
Difference at start	Yes	Yes	Yes	Yes
Intermediate Rank	No	Yes	Yes	Yes
Previous ski times lap 1-3	No	Yes	Yes	Yes
Sum of previous missed shots	No	Yes	Yes	Yes
Previous ski time lap 4	No	No	Yes	Yes

Notes: The table shows the tradeoff between skiing performance and shooting accuracy. The estimates are obtained using a Poisson Pseudo Maximum Likelihood estimator. The dependent variable is the total number of missed shots in the last shooting bout. The skiing times are normalized and thus need to be interpreted in terms of standard deviations. The table shows the exponential of the estimated coefficents and thus the factor by which the average of the dependent variable changes upon an increase of the regressor by one standard deviation. The richest specification includes race and athlete season fixed effects, as well as controls for past skiing performance, shooting performance and for the intermediate rank. Standard errors are clustered on race level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Clearly, we can see that the estimation results in the main part of the paper are robust with regard to changing the considered course section.

7.2.2. Effect of number of close competitors on risk-taking

In this section, we check our main results regarding the effect of the number of competitors who are close to an athlete on risk-taking behavior with regard to the choice of the considered course section. As in section 7.2.1, we re-estimate the specifications from the main part of the paper with the *last half* of the fourth round instead of the *last quarter*. The following Table A.10 shows the estimation results if the dependent variable is the skiing time from *Split time 1* until the shooting bout, i.e., the *last half*.

Table A.10: Effect of competition on skiing speed (last half)

	Ski time last half			
	(1)	(2)	(3)	(4)
Nb front	-0.243***	-0.256***	-0.238***	-0.193***
	(0.022)	(0.021)	(0.018)	(0.017)
Nb front^2	0.025***	0.026***	0.025***	0.023***
	(0.005)	(0.005)	(0.004)	(0.004)
Nb behind	-0.131***	-0.130***	-0.103***	-0.086***
	(0.020)	(0.017)	(0.015)	(0.014)
Nb behind^2	0.015***	0.016***	0.012***	0.008**
	(0.004)	(0.003)	(0.003)	(0.003)
N	4326	4326	4326	4326
Race FE	Yes	Yes	Yes	Yes
Athlete Season FE	Yes	Yes	Yes	Yes
Difference at start	Yes	Yes	Yes	Yes
Intermediate Rank	No	Yes	Yes	Yes
Previous ski times lap 1-3	No	No	Yes	Yes
Sum of previous missed shots	No	No	Yes	Yes
Previous ski time lap 4	No	No	No	Yes

Notes: The table shows the effect of increased competition measured by the number of competitors close in front and behind on skiing time of the last quarter of the fourth lap. The dependent variable is normalized on race level, thus marginal effects need to be interpreted in standard deviations. The richest specification includes race and athlete season fixed effects, as well as controls for past skiing performance, shooting performance and for the intermediate rank. Standard errors are clustered on race level in parentheses.
*< 0.1, **< 0.05, ***< 0.01

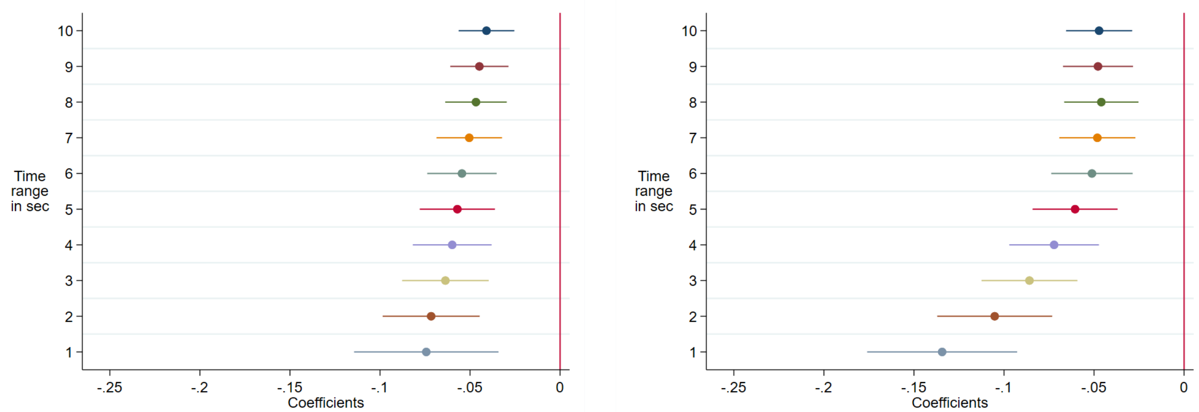
Clearly, estimation results do not change qualitatively compared to the results in the main part of the paper.

7.3. Robustness: Interval length

Next, we check for robustness with regard to a different dimension of choice in our analyses, namely the length of the interval in which we consider other athletes to be direct competitors who can be seen to be at the same intermediate standing. To show that our results are robust to changes in the length of the interval, from here on called the *bandwidth*, we re-estimate the model from Column (4) in Table 5 using only linear terms for the competition variables for different bandwidths. Figure A.3 plots the estimated coefficients on the bandwidth.

Figure A.3: Robustness - Effect of competition on skiing speed (last quarter)

(a) Competitors behind athlete (b) Competitors in front of athlete



Notes: The graph shows the coefficients and the corresponding confidence intervals for the effect of competition on skiing time of the last quarter of the fourth lap estimated by equation (6). Competition is measured by the number of close competitors behind (in front of) the athlete. The coefficients differ with regard to the time range chosen (from 1 to 10 seconds) to count the number of athletes close in front and behind.

7.4. Robustness: Effect of monetary incentives on risk-taking behavior

In this extension, we turn to the effect of monetary incentives on skiing speed, that is, we consider the same specification as in equation (6) in the analysis of the effect of the number of close competitors on risk-taking in Section 4.4, but set

$$\mathbf{comp}_{ist} = (\textit{potential prize in front}_{ist}, \textit{potential prize behind}_{ist}),$$

where the variables $\textit{potential prize in front}_{ist}$ and $\textit{potential prize behind}_{ist}$ are defined as the difference between the amount of prize money the athlete would have received if he or she had been five seconds faster or slower, respectively, and the race had been finished at the considered split time, and the corresponding prize money if the athlete had finished the race at the current rank. More precisely, the value of $\textit{potential prize in front}_{ist}$ is defined as follows: We consider the intermediate rank which determines the prize money the athlete would have received if the race had been over immediately. Then we calculate the hypothetical intermediate rank of the athlete if he or she had been five seconds faster at the split time. This again determines the corresponding prize money and the variable is the difference between the latter and the former. The variable *potential prize behind*$_{ist}$ is defined analogously, by calculating the intermediate rank of the athlete if he or she had been five seconds slower at the split time.[43]

Table A.11: Effect of monetary incentives on skiing speed

	Ski time last quarter		
	(1)	(2)	(3)
Potential prize in front	-0.13421***	-0.10296***	-0.07568***
	(0.01566)	(0.01557)	(0.01524)
Potential prize behind	0.05634***	0.01453	0.01275
	(0.01311)	(0.01348)	(0.01307)
N	4326	4326	4326
Race FE	Yes	Yes	Yes
Athlete Season FE	Yes	Yes	Yes
Difference at start	Yes	Yes	Yes
Previous ski times lap 1-3	No	Yes	Yes
Sum of previous missed shots	No	Yes	Yes
Previous ski time lap 4	No	No	Yes

Notes: The table shows the effect of increased competition measured by hypothetical gain/loss in prize money the athlete would have won if the race had ended at this point in time, and the athlete had been five seconds faster/slower. The dependent variable is normalized on race level; thus, marginal effects need to be interpreted in standard deviations. The richest specification includes race and athlete season fixed effects, as well as controls for past skiing performance, shooting performance, and for the intermediate rank. Standard errors are clustered on race level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

Except for the variable of interest, **comp**, Column (1) in Table A.11 coincides with the first specification shown in Table 5. In the following Columns (2) and (3), except for the intermediate rank, the same control variables are included. Across all specifications, we can see that there is a negative and statistically significant effect of *Potential prize in front* on the skiing time in the last course section. More precisely, the point estimate for this variable in specification (3) can be interpreted as follows: If the potential gain in the prize money the athletes get if they were able to overtake all competitors who are within a five-second interval in front increases by 1.000 EUR, they ski approximately 0.0757 standard deviations faster.[44]

[43]Notice that the value of *potential prize in front*$_{ist}$ is non-negative, while *potential prize in behind*$_{ist}$ is non-positive.

[44]To ease the interpretation, we re-scaled the prize money such that the variable value is in units of 1000 EUR.

The effect of *Potential prize behind*, on the other hand, vanishes completely as soon as we control for the athletes' previous performance in the race. Overall, the estimation results in Table A.11 suggest that there is a robust effect of monetary incentives on the athletes' skiing speed in biathlon competitions.[45]

7.5. Robustness: Dynamic panel data analysis

In this section, we take a methodologically different approach by pooling data from the first four laps and using dynamic panel data methods.[46] In the following, we estimate the following equation:

$$split_{istl} = \beta \cdot \mathbf{comp}_{istl} + \gamma_1 \cdot \mathbf{x}_{istl} + \gamma_2 \cdot \tilde{\mathbf{x}}_{istl} + \mu_{is} + \phi_t + \epsilon_{istl}. \tag{12}$$

The dependent variable $split_{istl}$ denotes the skiing time of athlete i in the last course section of lap l. The vector $\mathbf{x}_{istl}$ accounts for confounding factors and includes the cumulative skiing time, the cumulative missed shots, and the intermediate rank at the point the last course section of lap l starts. The vector $\tilde{\mathbf{x}}_{istl}$ contains lap dummies. The competition vector is defined as in (7), but now additionally includes interactions with the lap dummy of lap four. This allows us to detect heterogeneities in risk-taking across laps. Note that this implies that we include functions of lagged dependent variables as regressors. This approach suffers from endogeneity problems for standard fixed effects estimations.[47] To tackle this problem, we start by first differencing (12) with regard to the lap, which cancels out the fixed effects. Furthermore, we make the following identifying assumptions. First, we assume that the variables in $\mathbf{x}_{istl}$ are predetermined, in the sense that they are not correlated with past shocks, but may be correlated with contemporaneous or future shocks, i.e., ϵ_{istl}, $\epsilon_{ist(l+1)}$, $\epsilon_{ist(l+2)}, \epsilon_{ist(l+3)}$. The vectors $\tilde{\mathbf{x}}_{istl}$ and $\mathbf{comp}_{istl}$ are assumed to be exogenous. To

[45]Moreover, we did a similar analysis using the potential gain (loss) in World Cup points in case the athlete had been five seconds faster (slower). The results are qualitatively similar and available upon request.

[46]A similar approach is used by Genakos and Pagliero (2012).

[47]See Nickell (1981).

put it differently, we assume:

$$\mathbb{E}\left[\epsilon_{istl} \mid \mu_{is}, \phi_t, \tilde{\mathbf{x}}_{istl}, \mathbf{comp}_{istl}, \mathbf{x}_{ist(l-1)}, ..., \mathbf{x}_{ist1}\right] = 0, \qquad l = 2, 3, 4. \tag{13}$$

We would like to illustrate briefly the validity of our identifying assumption by taking a closer look at the first difference of (12), where Δ denotes the first difference of the respective variables.

$$\begin{aligned} \Delta split_{istl} =& \gamma_{11}\Delta\ cst_{istl} + \gamma_{12}\Delta\ cms_{istl} + \gamma_{13}\Delta\ inter\_rank_{istl} \\ &+ \gamma_2\Delta\tilde{\mathbf{x}}_{istl} + \beta\Delta\ \mathbf{comp}_{istl} + \Delta\ \epsilon_{istl} \end{aligned} \tag{14}$$

Here, the variables cst_{istl} and cms_{istl} denote the cumulative skiing time and the cumulative missed shots, respectively, while $inter\_rank_{istl}$ is the intermediate rank of athlete i at the point where the last course section of lap l starts. The variable pre_split_{istl} denotes the skiing time of athlete i in lap l until the point where the last course section of lap l starts. Equation (14) can be rewritten as:

$$\begin{aligned} split_{istl} - split_{ist(l-1)} = \gamma_{11}(split_{ist(l-1)} \ + \ pre\_split_{istl}) + \gamma_{12} ms_{istl} \\ + \gamma_{13}(inter\_rank_{istl} - inter\_rank_{ist(l-1)}) + \gamma_2\Delta\mathbf{x}_{istl} \\ + \beta\Delta\ \mathbf{comp}_{istl} + (\epsilon_{istl} - \epsilon_{ist(l-1)}). \end{aligned}$$

Now, consider the first lags of $\mathbf{x}_{istl}$, which are $cst_{ist(l-1)} = pre\_split_{ist1}$ for $l = 2$ and $cst_{ist(l-1)} = pre\_split_{ist1} + \sum_{k=2}^{l}(split_{ist(k-1)} + pre\_split_{istk})$ for $l = 3, 4$. Moreover, $cms_{ist(l-1)} = 0$ for $l = 2$ and $cms_{ist(l-1)} = \sum_{k=1}^{l-2} ms_{istk}$ for $l = 3, 4$. Recall that $inter\_rank_{ist(l-1)}$ denotes the intermediate rank when the last course section of lap $l - 1$ starts. All these components are determined before $\Delta\epsilon_{istl}$ realizes. This makes assumption (13) valid, which implies that $\mathbb{E}\left[\mathbf{x}_{ist(l-1)}\Delta\epsilon_{istl}\right] = 0$ and $\mathbb{E}\left[\tilde{\mathbf{x}}_{istl}\Delta\epsilon_{istl}\right] = 0$ for $l = 2, 3, 4$ hold.

Thus, we may use the first and further lags of the predetermined variables as instruments for estimating the first difference equation (14). Note that this implies that we need to drop the data from the first two laps. Usually, using only predetermined variables would force us to drop only data from $l = 1$. However, as we want to use cumulative missed shots as a confounder and $cms_{ist1} = 0$ for all i, it is not a relevant instrument for $l = 2$.[48] The first differences of the exogenous variables serve as instruments for themselves. This approach using only one lag as instrument leads to the level IV estimator of Anderson and Hsiao (1982) while using all available moment conditions leads to the more efficient GMM estimator of Arellano and Bond (1991). We present results for two specifications of both estimators in Table A.12.[49]

The first two Columns show the results of the IV estimator of Anderson and Hsiao (1982) and the GMM estimator of Arellano and Bond (1991) for a specification with only linear competition measures. Columns (3) and (4) again show both estimators for a specification also containing squared competition measures. Standard errors are clustered on race level according to Windmeijer (2005).

The results of the four specifications suggest that there indeed exist heterogeneities in risk-taking across laps. The linear interaction of the fourth-lap dummy with the number of athletes close in front is negative and statistically significant across all four specifications. The interaction term of the squared number of athletes close in front and the fourth lap dummy is positive and statistically significant. This shows that the marginal effect on risk-taking in the fourth lap of an additional athlete close in front is more convex as well. We see that the interaction term of the variable counting the number of athletes close behind is negative and statistically significant across all four specifications as well. The squared

[48] Omitting the cumulative missed shots as a confounder and running the regressions from $l = 2$ to $l = 4$ does not change the results. However, we consider it as an important confounder because it determines the number of skied penalty laps and therefore contributes to the tiredness of athletes.

[49] All estimations were conducted in Stata using the *xtabond2* command of Roodman (2009).

interaction is insignificant and close to zero.[50]

In case our results of Section 4.4 could be attributed to grouping behavior, one would expect the effects to be homogeneous across laps. Using this rich panel data set and making use of within race variation, we were able to identify heterogeneous effects on skiing speed upon increased competitions across laps. This let us conclude that observed effects in Section 4.4 rather show risk-taking behavior of the athletes.

[50]The last three lines of additional statistics show results related to the Hansen test going back to Hansen (1982). HDF denotes the degrees of freedom, HT denotes the value of the test statistic, and HP denotes the respective p-value for rejecting the null, i.e., that instruments are exogenous. The results suggest that our approach is valid, because we cannot reject the null for all specifications. Although there exists no specific threshold, p-values from 0.3 to 0.5, according to Kiviet (2020), suggest a valid estimation approach. Thus, specification (1) should be interpreted with some caution.

Table A.12: Heterogeneity analysis of risk-taking across laps

	Ski time last quarter			
	(1)	(2)	(3)	(4)
Nb front	-0.088***	-0.086***	-0.167***	-0.164***
	(0.008)	(0.008)	(0.012)	(0.012)
Nb front^2			0.011***	0.011***
			(0.002)	(0.002)
Nb behind	-0.012*	-0.009	-0.042***	-0.043***
	(0.007)	(0.006)	(0.013)	(0.013)
Nb behind^2			0.004**	0.004***
			(0.002)	(0.002)
4th lap × Nb front	-0.024**	-0.025**	-0.065***	-0.059***
	(0.012)	(0.012)	(0.020)	(0.021)
4th lap × Nb front^2			0.013***	0.012***
			(0.004)	(0.004)
4th lap × Nb behind	-0.041***	-0.045***	-0.046**	-0.049**
	(0.011)	(0.010)	(0.022)	(0.025)
4th lap × Nb behind^2			0.003	0.004
			(0.005)	(0.006)
N	8478	8478	8478	8478
FD IV	Yes	No	Yes	No
FD GMM	No	Yes	No	Yes
Hansen test DF	3	10	3	10
Hansen test statistic	7.280	12.630	1.730	8.320
Hansen test p-value	0.063	0.245	0.631	0.597

Notes: The table shows the effect of increased competition measured by the number of competitors close in front and behind on skiing time of the last quarter of the lap. To detect heterogeneities, the specification also includes interactions of the competition measures with a dummy for the fourth lap. Columns (1) and (3) show FD IV level estimators, while Columns (2) and (4) show FD GMM estimations. HDF denotes the degrees of freedom, HT denotes the value of the test statistic and HP denotes the respective p-value for the test of Hansen (1982). Additional controls account for past skiing and shooting performance, as well as intermediate rank. The dependent variable is normalized on race level; thus, marginal effects need to be interpreted in standard deviations. Standard errors are clustered on race level in parantheses according to Windmeijer (2005).
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

7.6. Robustness: Sprint races

In this section, we use data from a different discipline, namely sprint races. In the following regressions, we use the same competition vector as in (7); however, as described in Section

5, the number of athletes in front and behind only include the athletes who are in sight. The results can be found in Table A.13.

Table A.13: Analysis of sprint races

	Ski time last quarter			
	(1)	(2)	(3)	(4)
Nb front	-0.021	-0.020	-0.014	-0.012
	(0.015)	(0.015)	(0.029)	(0.029)
Nb behind	-0.018	-0.017	0.020	0.020
	(0.013)	(0.013)	(0.032)	(0.031)
Nb front^2			-0.005	-0.005
			(0.018)	(0.018)
Nb behind^2			-0.023	-0.022
			(0.018)	(0.017)
N	7379	7379	7379	7379
Race FE	Yes	Yes	Yes	Yes
Athlete Season FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Bib FE	No	Yes	No	Yes

Notes: The table shows the marginal effect of an increased number of athletes in sight (in front and behind) on the skiing time of the last quarter of the second lap in sprint races only. Columns (1) and (2) use a dummy as regressor which is equal to one in case there is at least one athlete close in front/behind in sight. Columns (3) and (4) show estimations using the absolute number of competitors close in front or behind. All estimations include athlete season as well as race fixed effects. Additional controls account for past skiing and shooting performance, as well as the intermediate rank. The dependent variable is normalized on race level; thus, marginal effects need to be interpreted in standard deviations. Standard errors are clustered on race level in parentheses.
$^{*}< 0.1$, $^{**}< 0.05$, $^{***}< 0.01$

In Columns (1) and (2), we show a specification only including linear terms for the number of athletes in sight. Columns (3) and (4) show quadratic specifications. In contrast to (1) and (3), specifications (2) and (4) also control for bib number fixed effects. The bib number determines the starting order of the athletes.[51]

Across all four specifications, we see no statistically significant effect. If our main results were due to grouping behavior, one would expect to see the same effects in sprint races. However, as this is not the case, this analysis lets us again conclude that the estimated effect

[51]We include block bib number fixed effects by including a dummy for each interval of 10 bib numbers.

of the main part is not due to grouping behavior.

7.7. Robustness: Survey results

This subsection comprises four parts. First, we provide some robustness checks of our regression-based analysis using survey data presented in Section 5. Second, we present a list of all questions contained in the survey. Third, we present distributions as well as further summary statistics of the survey data we collected. Fourth, we conclude this subsection with a discussion of potential selection biases.

7.7.1. List of survey questions

We based our questions on Dohmen et al. (2011) and elicited risk preferences qualitatively. The following list includes all questions of the survey. All risk questions are answered on a scale from zero (risk-averse) to ten (risk-loving). The Figures A.4, A.5, and A.6 show histograms of the survey data.

1. First, we asked for background information, including full name, year of birth, height [in cm], gender, marital status, parental education.

2. How do you rate yourself personally: In general, are you someone who is willing to take risks, or do you try to avoid risks?

3. How do you evaluate your attitude towards risk in a biathlon race (e.g. ski fast and energy-draining at the risk of more errors at the shooting bout or quick shooting during bad weather conditions)?

4. One can evaluate different areas in a different way. How do you evaluate your attitude towards risk regarding the following areas?

   (a) How is it regarding career prospects?

   (b) How is it with your health?

(c) How is it regarding leisure activities?

(d) How is it regarding financial investments?

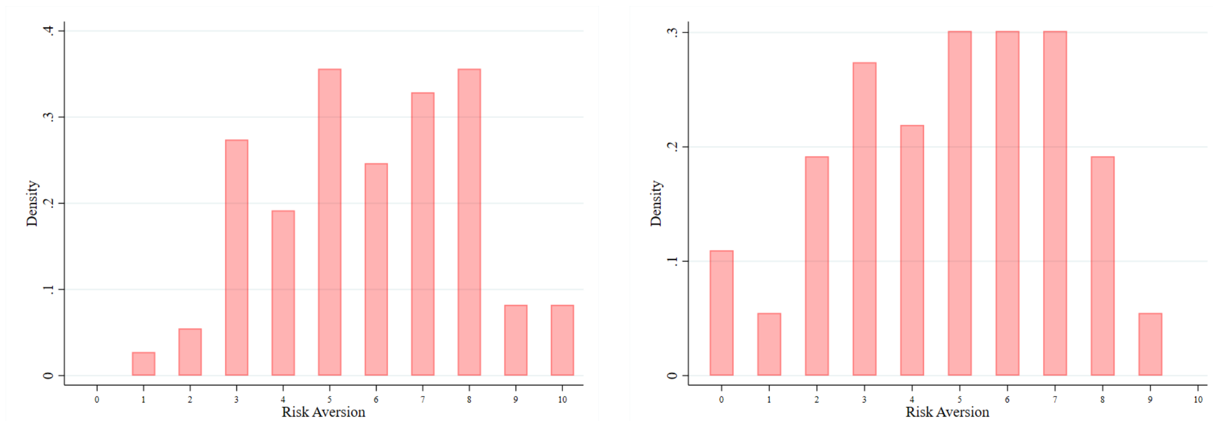
5. How do you rate yourself personally: In general, are you someone who is fully prepared to take risks, or do you prefer safety?

6. How do you evaluate your attitude towards risk avoidance in a biathlon race (e.g. ski slow and energy-saving to increase shooting precisions or taking long breaks between shots during bad weather conditions)?

7.7.2. Distributions and cross correlations of survey items

Figure A.4: General risk questions

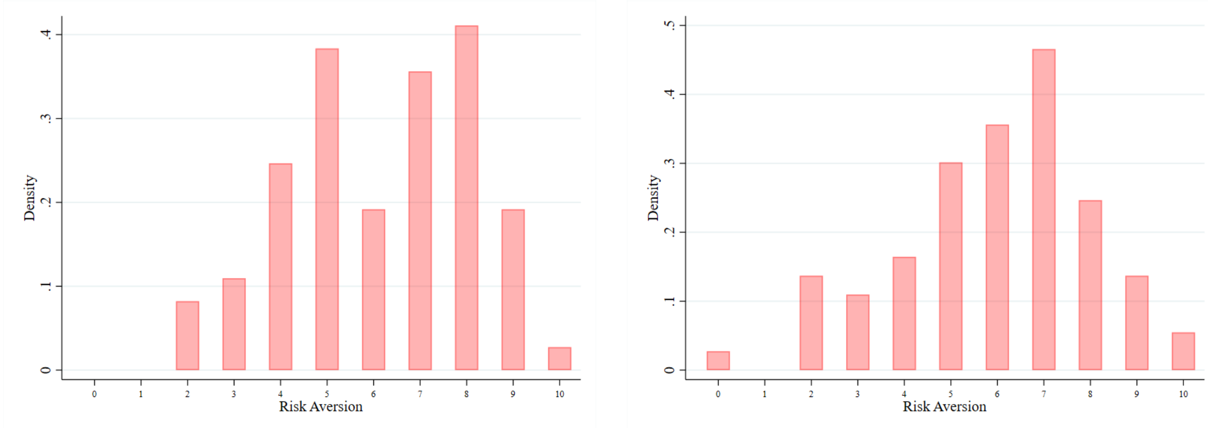
(a) General risk aversion (b) General risk aversion – instrument



Notes: Survey results in sub-figure (A.4a) correspond to the general risk question which asks respondents: *"How do you rate yourself personally: In general, are you someone who is willing to take risks, or do you try to avoid risks?"* The value 0 means *risk-averse* and the value 10 means *risk-loving*. To prevent measurement error, we follow the approach by Gillen et al. (2019) and rephrase the general risk question in part (A.4b) with a slightly different wording: *"How do you rate yourself personally: In general, are you someone who is fully prepared to take risks, or do you prefer safety?"* The value 0 means *prefer safety* and the value 10 means *fully prepared to take risks*.

Figure A.5: Biathlon risk questions

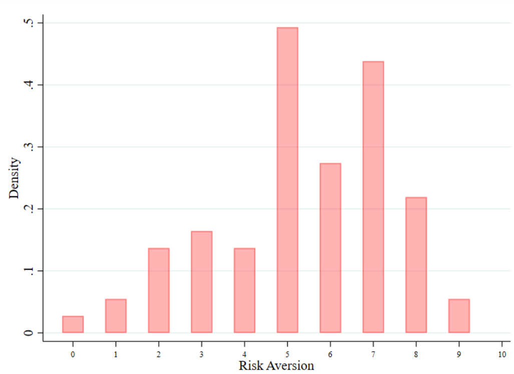
(a) Taking risk in a biathlon race (b) Taking risk in a biathlon race – instrument



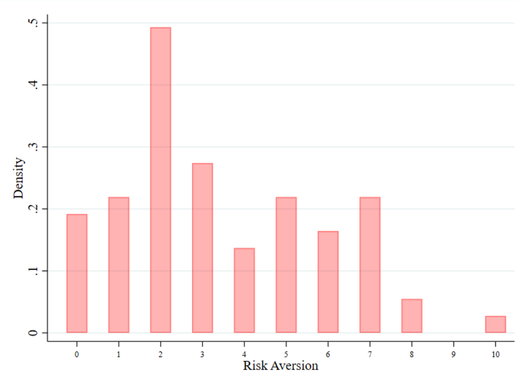
Notes: Survey results in sub-figure (A.5a) correspond to the biathlon risk question which asks respondents: *"How do you evaluate your attitude towards risk in a biathlon race (e.g. ski fast and energy-draining at the risk of more errors at the shooting bout or quick shooting during bad weather conditions)?"* The value 0 means *risk-averse* and the value 10 means *risk-loving*. To prevent measurement error, we follow the approach by Gillen et al. (2019) and rephrase the biathlon risk question in part (A.5a) with a slightly different wording: *"How do you evaluate your attitude towards risk-avoidance in a biathlon race (e.g. ski slow and energy-saving to increase shooting precision or taking long breaks between shots during bad weather conditions)?"* The value 0 means *prefer safety* and the value 10 means *fully prepared to take risks*.

Figure A.6: Context-specific risk questions

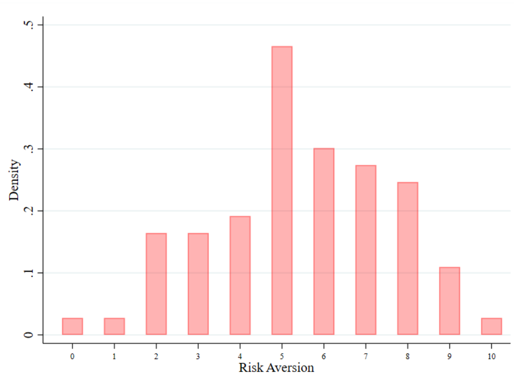
(a) Taking risk in career



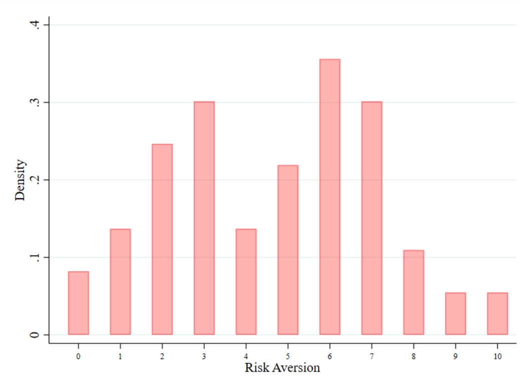
(b) Taking risk in health



(c) Taking risk in leisure



(d) Taking risk in finance



Notes: In the context-specific risk questions, respondents were asked: *"One can evaluate different areas in a different way. How do you evaluate your attitude towards risk regarding the following areas? How is it ... regarding career prospects (A.6a)? ... with your health (A.6b)? ... regarding leisure activities (A.6c)? regarding financial investments (A.6d)?"* The value 0 means *risk averse* and the value 10 means *risk loving*.

Table A.14 shows the cross correlations of all survey items.

Table A.14: Cross correlations survey items

	Cross correlations risk measures						
	General risk	General risk - 2nd	Biathlon risk	Biathlon risk - 2nd	Career risk	Health risk	Finance risk
General risk	1						
General risk - 2nd	0.648	1					
Biathlon risk	0.536	0.473	1				
Biathlon risk - 2nd	0.248	0.402	0.588	1			
Career risk	0.798	0.570	0.513	0.287	1		
Health risk	0.332	0.220	0.229	0.141	0.338	1	
Finance risk	0.588	0.300	0.519	0.177	0.503	0.415	1

Notes: The table shows cross correlations of all survey items.

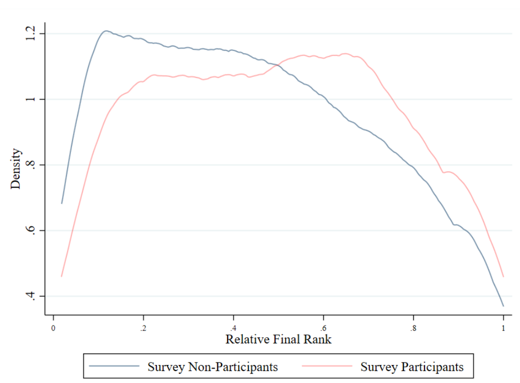
7.7.3. Discussion selection bias

Next, we would like to check whether a selection bias regarding the survey participation exists. First, Figure A.7 shows the comparison of the distributions of the relative final rank (final rank divided by the maximum of final ranks in a race), normalized total course time, total number of missed shots, and normalized skiing time of the last course section of the fourth lap of athletes who participated in the survey and those who did not participate. The plots suggest that athletes participating in the survey have on average a slightly weaker performance than non-participants. This is underlined by the right shift of the distributions of the final rank, as well as the total course time of survey participants, compared to non-participants. This is probably due to the fact that the compensation payment for survey participation of 50 Euros is relatively more attractive for athletes whose performance is below-average.

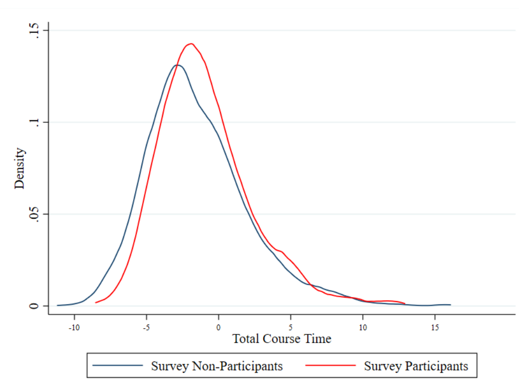
However, we have no reason to assume that this systematically distorts the representativeness of our results in Section 5.

Figure A.7: Performance data: Comparison survey participants to non-participants

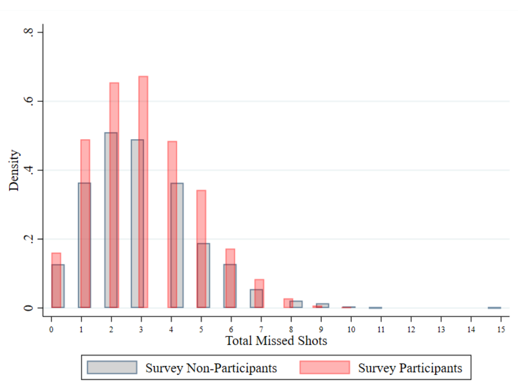
(a) Relative Final Rank



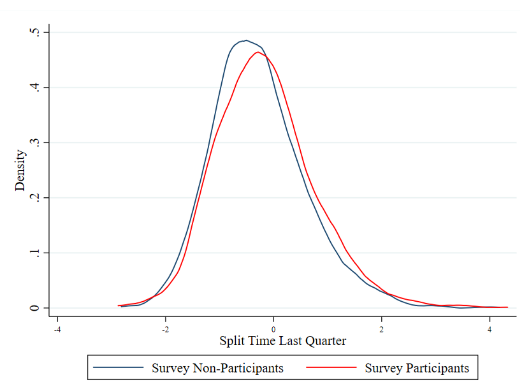
(b) Total Course Time



(c) Total Missed Shots



(d) Split Time Last Quarter



Notes: Figures A.7a, A.7b, and A.7d show kernel density plots of the relative final rank, the total course time, as well as the course time of the last course section of the fourth lap of survey participants and non-participants. Figure A.7c shows a histogram of the total number of missed shots of survey participants and non-participants.