# Do Professionals Get It Right?
# Limited Attention and Risk-Taking Behaviour

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**Abstract**

Does information processing affect individual risk-taking behaviour? This paper provides evidence that professional athletes suffer from a left-digit bias when dealing with signals about differences in performance. Using data from the highly competitive field of World Cup alpine skiing for the period of 1992–2014, we show that athletes misinterpret actual differences in race times by focusing on the leftmost digit, which results in increased risk-taking behaviour. For the estimation of causal effects, we exploit the fact that tiny time differences can be attributed to random shocks. We find no evidence that high-stakes situations or individual experience reduces left-digit bias.

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*Keywords: Risk Taking, Limited Attention, Left-Digit Bias*

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Individuals often have to make decisions under uncertainty that involve risk-return trade-offs. Although traditional economic models assume perfect information processing and foresight, a large body of research in behavioural economics has documented the limits of individuals' cognitive abilities (DellaVigna, 2009). The literature has focused in particular on the question of how limited attention affects consumption choices and has provided evidence for a left-digit bias, the empirical regularity of people's tendency to focus on the leftmost digit of a number and pay only partial attention to other digits (Korvorst and Damian, 2008; Lacetera *et al.*, 2012).

Despite this empirical evidence, three challenges remain. First, estimating the causal effects of the left-digit bias is difficult due to bunching of data. Second, it remains unclear whether limited attention also influences the process of individual decision making with respect to risk taking. Finally, there is an on-going discussion about whether individual experience or high stakes situations mitigate behavioural biases.[1]

In this paper, we propose a new approach to addressing these three challenges, namely, by estimating the impact of behavioural biases on risk-taking in a setting involving professional and experienced athletes engaged in fierce competition. We investigate the presence of a left-digit bias by using detailed data on 1,865 athletes in World Cup alpine skiing over the period of 1992–2014. Our empirical analysis exploits the fact that slalom and giant slalom races consist of two separate runs. After the opening run, each athlete obtains information about her own time as well as her distance in relation to the current leader. We explore whether athletes exhibit a left-digit bias when processing this time difference to the leader. In particular, we test whether the use of heuristic thinking affects the way athletes choose their risk strategy in the second run. In the presence of a left-digit bias, our theoretical model shows that athletes misinterpret distances such as nine hundredths of a second to be significantly smaller than, for example, ten hundredths of a second. This behavioural bias in turn leads to the adoption of a more risky strategy because achieving the great success (i.e., winning the race) appears to be more likely if the gap to the current leader is small rather than large. In our empirical analysis,

[1]The presence of behavioural biases in the context of experience, competition and high stake situations has been subject to widespread scepticism (List, 2003; Feng and Seasholes, 2005; Levitt and List, 2008; Pope and Schweitzer, 2011).

we apply a regression discontinuity design for the estimation of causal effects by exploiting the fact that the allocation of right digits in athletes' time distance to the leader can be regarded as quasi-random.

Our empirical findings suggest that professional athletes exhibit a substantial left-digit bias. Individuals with an opening-run time difference to the leader just below a tenths-of-a-second threshold are significantly more likely to adopt a risky behaviour, which increases the probability of not successfully finishing the race by up to 28.0%. Moreover, the standard deviation of race times in the second run increases by approximately 26.1%. The estimated effect is robust when using different bandwidths and including race-fixed effects. To account for genetic determinants of risk-taking behaviour, we add athlete-fixed effects to our baseline specification and obtain very similar estimates. As expected, we find the effect to be present only among athletes close enough to the leader after the first run to have a plausible chance of winning the race. In a placebo test, we construct left-digit breaks based on time differences expressed in minutes, a figure that is not shown to athletes, and find no relationship with second-run behaviour. These results are consistent with our theoretical prediction that athletes receive a signal about their time distance to the leader and pay only limited attention to right digits. In contrast to previous evidence by List (2003), as well as Gardner and Steinberg (2005), we find that the behavioural bias does not disappear when restricting the sample to older, more experienced athletes. Furthermore, the left-digit bias is also present in races with particularly high stakes.

To examine the sensitivity of our empirical findings, we conduct a series of robustness checks. First, we document that there is no difference in predetermined covariates between the treatment and control group. Second, we test alternative digit breaks, finding that all other cutoffs such as 0-1, 2-3, or 6-7, exhibit no discontinuity in survival rates. In our third robustness test, we calculate time distances to the second- and third-ranked athlete. Because these differences are not shown to athletes, they can be used as placebo treatments. All estimates on placebo treatments are very close to zero, thus increasing our confidence that the main findings are in fact driven by limited attention. We also explore whether the effect of the left-digit bias is driven by nervousness and provide evidence that the bias is also present among athletes with arguably low levels of nervousness.

Our results contribute to a number of studies in psychology and economics. In particular, the observation of a persistent behavioural bias in the context of large stakes and highly experienced professionals appears puzzling (Levitt and List, 2007, 2008). We argue that our results can be explained by different ways of thinking (Stanovich and West, 2000; Kahneman, 2011), including the concept of ego-depletion. Baumeister *et al.* (1998) argue that 'all variants of voluntary effort—cognitive, emotional, or physical—draw at least partly on a shared pool of mental energy'. If individuals exert a large amount of physical or mental effort on one particular task, they are less likely to pay full attention to or exert full effort on a subsequent task. The very high stakes in World Cup competitions cause athletes to exert extreme effort during the race, thus making them vulnerable to behavioural biases afterwards. The aforementioned placebo tests reveal that it is the very information provided to athletes that shapes their behaviour. Neither time differences expressed in minutes or the time gap to the second or third contestant is correlated with second-run behaviour. Athletes that are physically exhausted after the opening run appear to use heuristics when processing information about performance differences. Hence, the left-digit bias is present only with respect to information that is readily available.

Our study makes several contributions to the literature on limited attention and risk-taking. In the field of behavioural economics, several studies have investigated how individuals deal with signals and information. We link this research to the literature on the determinants of risk preferences. In particular, we provide evidence that heuristic information processing affects not only consumption choices but also risk-taking behaviour. Our findings are closely related to the work by Lacetera *et al.* (2012), who find that the left-digit bias is present in product markets. A notable advantage of our research design is the smoothness of the assignment variable—the distance to the leader—at the respective cutoff. It allows us to avoid the problem of clustered observations. We can also rule out any kind of manipulation, which is more likely to occur in product markets. Second, our findings suggest that even professional and experienced actors appear to suffer from limited attention. This complements previous research by Busse *et al.* (2013) who document that professional dealers in the wholesale market for cars anticipate that final customers in the retail market will focus on the left digit of the odometer. In contrast, we provide a psychological explanation for why behavioural biases can exist despite high stakes and individual experience. Third, our results show that limited attention affects risk-taking behaviour even though all relevant information is easily observable. Much of the literature on limited attention has focused on settings in which, to some extent, information is shrouded (Brown *et al.*, 2010). The importance of heuristic thinking appears to be much greater if it can even be documented in settings where information is readily available. Again, we provide a psychological rationale for the persistence of behavioural biases in our setting.

Finally, our findings also contribute to a growing literature on the heterogeneity of risk-taking behaviour across individuals. Understanding the determinants of risk preferences is particularly important because the assumptions about individual risk behaviour are key to economic models.[2] A large body of literature has investigated the various determinants of risk preferences and found both genetics (Cesarini *et al.*, 2009; Barnea *et al.*, 2010) and personal experiences (Malmendier and Nagel, 2011; Dohmen *et al.*, 2012; Booth and Nolen, 2012) to be relevant. We find that irrespective of an individual's genetics and experience, the way of processing information also shapes behaviour under uncertainty.

The paper proceeds as follows. In Section 1, we illustrate how limited attention can generate discontinuities in risk behaviour among professional athletes. Section 2 presents some general information on World Cup alpine skiing and descriptive statistics on our data set. Section 3 provides a description of our econometric approach. In Section 4, we show the main empirical findings, discuss effect heterogeneity, provide a psychological explanation and numerous robustness checks. Finally, Section 5 concludes.

## 1 Theoretical Considerations

### *1.1 Left-Digit Bias*

Following the seminal paper by Simon (1955), a large body of literature has examined imperfect individual information processing. Tversky and Kahneman (1974) point out that people tend to rely on specific heuristic principles that reduce the complexity of difficult tasks. These

[2]Recent press coverage emphasises the increased attention paid to the heterogeneity of risk preferences across individuals. See, for instance, the article 'Risk off', in the *The Economist*, January 25, 2014.

heuristics may be useful in many occasions but they can also lead to severe biases that have been documented in various fields of economics. Conlin *et al.* (2007) find that individuals' decisions are excessively influenced by current weather conditions. Gabaix and Laibson (2006) show how shrouding may occur in an economy if at least some customers are myopic. An extension of their framework provides an explanation for thinking in categories, shedding light on the causes of uninformative advertising (Mullainathan *et al.*, 2008). Chetty *et al.* (2009) show that people have a lower demand for products if those are tagged including commodity taxes than if taxes are not included in posted prices. These findings suggest that the salience of taxes plays an important role for individual tax responses.[3] Further research by Ashton (2013), however, indicates that a left-digit bias is the main channel through which tax salience affects consumer decisions.

There is also empirical evidence on the question for which types of goods and transactions people tend to use heuristics. Köszegi and Szeidl (2013) document that individuals tend to focus more on attributes in which disparities are large. In professional skiing, as in many other fields of sport, differences in performance can be very small. Yet focusing on left digits can subjectively generate a sharp distinction between time differences that are in fact very similar. Thus, left-digits may serve as a reference point as described in Köszegi and Rabin (2006) as well as Gill and Prowse (2012).

The recent literature has paid particular attention to a heuristic technique known as the left-digit bias. Basu (1997) examines the prevalence of 99-cent pricing and argues that it can be explained in a model of full rationality. Schindler and Kirby (1997) examine pricing strategies using advertisements data from newspapers and present evidence that the over-representation of 9 endings is due to reference points that are linked to the decimal system. Anderson and Simester (2003) conduct three experiments that randomly vary the ending digits of prices and find that a price of $9 yields significantly higher demand than slightly lower or higher prices, particularly when products are unfamiliar and customers pay limited information. Lacetera *et al.* (2012) as well as Busse *et al.* (2013) advance this work by showing that information-

[3]This evidence is consistent with the results of Finkelstein (2009), suggesting that the introduction of an electronic collection system for highways increases total tolls because driving becomes less elastic with respect to the toll.

processing heuristics matter even in markets with large stakes and easily observed information. In addition to this, Backus *et al.* (2015) provide evidence that round numbers can be used as signals in economic negotiations.

### *1.2 Model*

We discuss the implications of a left-digit bias in World Cup alpine skiing by means of a simple theoretical model. Following the seminal work by Atkinson (1957), risk-taking behaviour is affected by both the motive to achieve and the motive to avoid failure. This is particularly relevant in the context of World Cup alpine skiing in which athletes have to choose very carefully the level of risk they are willing to take. Even small mistakes can lead to errors that cause a substantial loss of time, reducing the probability of being successful.

For simplicity, we assume that the utility of an athlete is comprised of three elements only, winning, not-winning but finishing, and not finishing the race at all. The athlete's risk choice impacts both the variance of time if finishing the race, and the probability to finish the race. We normalise the direct utility of a victory to $U_W$, the direct utility of finishing behind to $U_L < U_W$, the utility of not finishing the race at all to zero.

We consider the decision problem of an athlete $i$ who trails the leader after the first run. Athlete $i$ is endowed with talent $\xi_i$, incurred a distance $d_i$ in the first run and chooses which level of risk $r_i$ to take in the second run. Distance is negatively related to talent but randomly—due to weather and wind conditions—the distance may be higher or lower than predicted by talent alone, thus $d_i = \delta(\xi_i, \varepsilon_i)$ with $\delta_\xi < 0$ and $\delta_\varepsilon > 0$, while $E(\varepsilon_i) = 0$.

Athlete $i$ takes the risk decision of the leader as given. More talent increases the chance of finishing the race $\phi(\cdot)$. Taking more risk decreases the probability of finishing ($\phi' < 0$) but increases the variance of the race time in the second run. We omit the index $i$ in what follows as long as this causes no confusion. Given the race is finished, the chance to win the race is given by $\pi(d + rz)$ where $z$ is a normally distributed random variable. We are free to choose the unit of measurement concerning risk, hence we assume $z$ has unit variance. We assume that a larger distance after the first run reduces the probability to win. If the outcome of risk-taking is success (i.e., a low time in the second run) the realization of $z$ is negative and the winning probability higher. Furthermore, we assume that the marginal winning probability shall be concave. Thus, the derivatives alternate in signs, hence $\pi' < 0$, $\pi'' > 0$, and $\pi''' < 0$ for positive arguments. This is also true in our data, as shown in Figure A1 in the Appendix.

For our theoretical exposition, we make a slightly stronger assumption and we impose that $\pi(\cdot)$ is convex enough such that $\pi'/\pi > \pi'''/\pi''$. This condition holds, for example, for the Pareto distribution.

— Figure 1 about here —

In Figure 1, the probability to win given the distance $d$ in the first run is calculated and the path of $\pi(\cdot)$ is estimated non-parametrically.[4] We see that the winning probability follows a decreasing but convex path as a function of distance $d$.[5] Omitting the talent variable $\xi$ in what follows, these arguments let us write the utility function in the following way:

$$U(r) = E\left[\phi(r) \times \left(\pi(d + rz)U_W + \left(1 - \pi(d + rz)\right) U_L\right)\right]. \tag{1}$$

We use this cost-benefit framework to investigate the implications of a particular behavioural bias: the left-digit bias. Drawing on work by Lacetera *et al.* (2012) we can incorporate limited attention to performance differences. Athletes in the model are assumed to pay full attention to the left digit (i.e., the more visible component) of the time distance to the leader but only partial attention to the right digit. Let $T$ be the time of the athlete in the first run, expressed in hundredths of a second. Then we can define her distance to the leader as $d \equiv (T - T_1)$. This distance can be broken down into two parts. The first part, $d_l$, indicates the number of tenths of a second in the distance (i.e., the left digit). The second part, $mod(T - T_1, 10)$, is the modulo of the distance to the leader with respect to ten (i.e., the right digit). The modulo finds the remainder of the division of the time distance by ten, that is the number of single hundredths of a second. For example, a distance of 39 hundredths of a second yields 3 tenths of a second

[4]Note that the estimated winning probability in Figure 1 measures the winning probability as a function of distance $d$. However, risk changes along the distance, hence the estimated winning probability is not exactly identical to the theoretical $\pi(d - r)$ curve.

[5]Similar patterns of success by time distance to the leader can be shown for a finish in the top 3 and top 5, as shown by Figure A2 in the Appendix.

and a modulo of 9. We can express the *perceived* distance $\hat{d}$ as

$$\hat{d} = d_l 10 + (1-\theta) \times mod(T - T_1, 10), \tag{2}$$

where $\theta \in [0,1]$ is the inattention parameter. Note that $mod(T - T_1, 10) \in \{0, 1, 2, ..., 9\}$ while $d_l \in \mathbb{N}$. For example, a time distance of 119 hundredths of a second would be perceived as $\hat{d} = 11 \times 10 + (1-\theta) \times 9 = 110 + (1-\theta) \times 9$.

This approach generates discontinuities at distinct cutoffs. In particular, at each tenths-of-a-second threshold, the perceived distance jumps. Consider, for example, a distance of 20 hundredths of a second. As long as $d$ is below that threshold, the athlete will perceive a change of $(1-\theta)$ for every one-unit increase in $d$. However, when crossing the cutoff from 19 to 20, the perceived increase will be $1 + \theta \times 9$. With a maximum bias ($\theta = 1$) the perceived increase is 10, while in the absence of any bias ($\theta = 0$) it is 1.

— Figure 2 about here —

The biased perception of distances is illustrated by the step function in the lower half of Figure 2. The absolute discontinuity is the same at each threshold and given by $\Delta = 10 \times \theta$. In the upper half we see the implications of this discontinuity for the perceived chance of winning as a function of distance. While the *actual* change of the winning probability $-\pi'\ (d + rz)$ is a smooth downward sloping function, the *perceived* change of the winning probability $-\pi'(\hat{d} + rz)$ is again a step function. The important observation is that to the left of each tenths-of-a-second threshold it holds that $d > \hat{d}$. And because the winning probability is a negative function of the distance to the leader, it also holds that $-\pi'(d+rz) < -\pi'(\hat{d}+rz)$ to the left of each threshold.

Let us study the optimal risk decision of the athlete. While taking the actions of the leader as given, the perceived first order condition of the athlete reads

$$\hat{U}'(r) = \phi'(r) E\left[\pi(\hat{d} + rz)U_W + \left(1 - \pi(\hat{d} + rz)\right) U_L\right] + \phi(r) E\left[\pi'(\hat{d} + rz) z\left(U_W - U_L\right)\right] =: 0 \tag{3}$$

which is equal to zero in the optimum.

The negative first term $\phi'(r) E\left[\pi(\hat{d} + rz)U_W + \left(1 - \pi(\hat{d} + rz)\right) U_L\right]$ denotes the marginal cost of taking additional risk, it equals the product of increased probability of non-finishing times the expected utility of finishing. The positive second term $\phi(r)E\left[\pi'(\hat{d}+rz)z\,(U_W-U_L)\right]$ captures the benefit of risk taking which is the product of the increased probability to win times the utility gain of $U_W - U$. Note that the presence of a left-digit bias ($\theta > 0$) causes $\hat{d}$ to be smaller than $d$. The following proposition states that a reduced value of $\hat{d}$, through the left-digit bias, increases risk taking and lowers the probability to finish the race.

PROPOSITION 1 *The presence of a left-digit bias leads athletes to overestimate their winning probability and to choose a higher risk level. This decision (i) increases the probability of not finishing the second run, (ii) raises the variance of race time in the second run, (iii) leaves the average race time, given finishing the race, unaffected, and (iv) increases the probability to win, given finishing the race.*

*Proof.* We do a second order Taylor approximation of equation (3). Note that $E[z] = E[z^3] = 0$ and $E[z^2] = 1$. We get

$$\hat{U}'(r) \tilde{=} \phi'(r)\left[\left(\pi(\hat{d}) + \pi''(\hat{d})r^2/2\right)(U_W - U_L) + U_L\right] + \phi(r)\pi''(\hat{d})r\,(U_W - U_L) = 0. \tag{4}$$

We are interested how the derivative changes when the perceived distance changes. We take the derivative to get $\partial\hat{U}'(r)/\partial\hat{d} = \phi'(r)\left(\pi'(\hat{d}) + \pi'''(\hat{d})r^2/2\right)(U_W - U_L) + \phi(r)\pi'''(\hat{d})r\,(U_W - U_L)$. Using equation (4) we may replace $\phi(r)$ and get the following expression

$$\frac{\partial}{\partial\hat{d}}\hat{U}'(r) = \phi'(r)\,(U_W - U_L)\left(\pi'(\hat{d}) - \pi'''(\hat{d})\pi(\hat{d})/\pi''(\hat{d})\right) - \phi'(r)\left(\pi'''(\hat{d})/\pi''(\hat{d})\right)U_L < 0.$$

Since $U_L > 0$ and we assume $\pi'/\pi > \pi'''/\pi''$ and therefore $\pi' > \pi'''\pi/\pi''$, we see that both terms are negative. Thus, whenever $\hat{d} < d$, we have $\hat{U}'(r,\hat{d}) > \hat{U}'(r,d)$. A lower perceived distance reduces the marginal utility of taking risk. Denote the optimal risk choice by $r^*$. Therefore, $r^*(\hat{d}) > r^*(d)$, because $\hat{U}''(r^*) < 0$ in the optimum. Increased risk-taking $r^*(\hat{d})$ directly increases the variance of race time $\left[r^*(\hat{d})\right]^2$ but leaves expected race time unaffected, proving claims (i) to (iii). The increased variance of race time raises the probability to win. The latter equals $E\left[\pi(d+rz)\right] \tilde{=} \pi(d) + \pi''(d)\left[r^*(\hat{d})\right]^2/2$, applying the same Taylor approximation as above, see equation (4). This proves claim (iv). □

The intuition behind Proposition 1 is the following. Taking more risk raises the variance of race time and thereby increases the expected chance of winning, since the probability to win $\pi$ is a convex function of distance. If the distance to the leader is perceived as too small, the perceived gain from risk taking seems higher. This leads to higher risk taking and therefore a lower probability of finishing the race $\phi(r)$ and an increased variance of race time, given the athlete finishes the race.

The model makes an interesting prediction that an athlete with left-digit bias overestimates both the cost and benefit of taking more risk. The lower perceived distance increases the perceived utility of finishing the race $\pi(\hat{d} + rz)U_W + \Big(1 - \pi(\hat{d} + rz)\Big)\, U_L$. This raises the first term in (3), hence the athlete becomes more risk averse when the distance is perceived too low. However, when the probability to win $\pi$ is sufficiently convex (as guaranteed by our assumption $\pi'/\pi > \pi'''/\pi''$ and supported by the data), the benefits of risk taking—the second term in the first order condition (3)—increase more than the costs.

To illustrate the trade-off that athletes face when choosing the risk level for the second run, consider two individuals trailing the leader by nine and ten hundredths of a second, respectively. In the presence of a left-digit bias, the *actual* difference in their time distance to the leader is smaller than the *perceived* difference. The athlete trailing the leader by 0.09 seconds perceives her distance to be significantly smaller. However, the perception of being closer to the victory has two effects: On the one hand, taking *more* risk in the second run appears to be more profitable since winning the race is perceived to be more likely. On the other hand, the athlete wants to take *less* risk in order not to crash and squander the good chance to achieve a high rank behind the winner. We find that the former effect dominates the latter both in our theoretical model and in the empirical analysis. The overestimation of the winning probability thus leads athletes to the left of a tenths-of-a-second cutoff to increased risk-taking in the second run. In Section 4.2 we document empirically that athletes with low left digits indeed have a higher variance of performance, while their average performance is unaffected. While we find supporting evidence for claims (i), (ii), and (iii), claim (iv) on the winning probability is not borne out in the data. Our analysis shows no significant impact of a left-digit bias on the chance of winning, given an athlete finishes the race. We come back to this issue in more detail in

Section 4.2 below.

To conclude this section, we discuss two further aspects of the model. First, the model predicts that the probability of finishing the race decreases with the distance after the opening run if talent ($\xi$) strongly affects the survival probability ($\phi$). The analysis of our data confirms this prediction: athletes with a larger distance to the leader are more likely not to finish the second run.[6] Second, while our model puts forward that athletes rationally behave based on biased information processing, an alternative explanation for the decreased survival probability $\phi$ below the threshold could be nervousness. Feeling closer to the leader could make the athlete more nervous, prompting more mistakes in the second run. In turn, the increased number of mistakes decreases the survival probability and raises the variance of final race times. However, nervousness would also worsen the average race time given the athlete finishes the race. This prediction cannot be observed in the data as we discuss in Section 4.4 in more detail.

## 2 Data

### *2.1 World Cup Alpine Skiing*

The first alpine skiing races were organised in the 1930s, but it was not until 1967 that the *Fédération Internationale de Ski* (FIS) launched the FIS World Cup. During the first couple of years, the disciplines included only slalom, giant slalom, and downhill races. In 1974, combined races were included, while super G was added to the FIS World Cup in 1983. The main interest of our paper is the question how athletes take into account information about their relative distance to the leader. We thus focus only on slalom and giant slalom races because their final standing is calculated by adding up the individual times of two separate runs. The time distance to the leader after the first run indicates how close athletes are to achieving a victory.

Alpine skiing provides a unique real-world setting to examine the effects of left-digit biases on subsequent risk behaviour. All athletes are highly intrinsically motivated, yet the extrinsic motivation—in the form of monetary rewards and international fame—is likely to play a central

[6] While athletes trailing by less than 25 hundredths of a second have a 3.45% probability of not finishing the race, the respective figure is 4.73% for athletes between 26 and 50 hundredths of a second, 5.30% for those trailing between 51 and 75 hundredths of a second, and 5.52% for athletes with a time distance between 76 and 100 hundredths of a second.

role for individual performance as well.[7] Besides the prize money, success in World Cup races can also lead to better sponsorship contracts. Alpine ski races are, particularly in Europe, very popular, which makes competition fierce. Only a few junior athletes make it to the national World Cup team and among them only a small group is very successful.The goal in each race is to slide down a course in the fastest overall time. Each track consists of a series of gates. All of them have to be passed correctly, so that all athletes run the same course.

### *2.2 Data Set and Descriptive Statistics*

We use a panel data set on 995 male and 869 female athletes in all 787 slalom and giant slalom ski races for the period of 1992–2014. The data include information on whether an athlete finished a race, the exact time (in hundredths of a second), the time difference to the winner, as well as gender, age, and discipline of competition. A detailed description of the full data set is provided by Legge and Schmid (2015). The descriptive statistics for all relevant variables are shown in Table 1. In addition to the full sample statistics, we also provide all information based on the sample that only contains observations used for the estimation.

— Table 1 about here —

There are only minor differences between the two samples which is not surprising given the equal distribution of right digits (cf. Figure 3). On average athletes are 25.8 years old, do not finish the race with a probability of 5%, and have an average time distance to the leader of 2.02 seconds.

The numbers indicate that a victory is a likely outcome only for athletes who are in the top fifteen after the first run. While the average winning probability for a top fifteen athlete is 6.65%, it is only 0.03% for athletes outside of the top fifteen after the opening leg. Therefore, we should see only these athletes to respond to a high or low left digit in their time distance to the leader. Figure A3 in the Appendix shows several measures of success of by athletes' rank after the first run.

[7]Following Kahn (2000), we use sports data as an empirical laboratory for the evaluation of individual behaviour. The benefit is that we have exact information on individual performance in a real-world setting with high stakes and competition.

## 3 Econometric Approach

Since World Cup alpine skiing is an outdoor event, external weather and snow conditions vary significantly over the course of a single race and can alter individual race times. However, the mere presence of unstable external conditions does not lead to cancellation and is broadly accepted as a natural source of variation among competitors. Thus, the impact of random wind, weather, and snow conditions is crucial and can even be amplified by the fact that individual race times critically depend on the performance in key sections of the course. An error in these sections, caused by external conditions, not only leads to an immediate time loss but also affects speed, and thus time, in the following sections. We refer to these external conditions as quasi-random noise and argue that it has sufficiently large effects on individual race times in order to randomly affect race times. In our estimation, this random noise is particularly relevant because we test whether athletes adopt a more risky behaviour based on their time distance to the leader in the first run. This distance is affected by random weather shocks, which implies that athletes cannot locate themselves strategically to the left or right of the cutoff (i.e., a tenth-of-a-second threshold). The histogram shown in Figure 3 supports this assumption. There is a smooth distribution of left digits and all possible right digits are almost equally likely.[8]

— Figure 3 about here —

Our data set contains detailed information about whether athletes competed in a race and whether they successfully finished the race or not. We define survival (i.e., finishing the race) of athlete $i$ in any race $j$ as

$$S_{i,j} = \begin{cases} 1 & \text{if athlete } i \text{ successfully finished race } j \\ 0 & \text{if athlete } i \text{ did not successfully finish race } j. \end{cases} \tag{5}$$

Based on our considerations in Section 1, we expect survival rates to be a discontinuous function of the time distance to the leader after the opening run. If athletes are subject to

[8]The fact that all right-digits in our sample are equally likely rules out the possibility of a non-uniform distribution of digits as in collections of many natural numbers (Benford, 1938).

a left-digit bias there should be a negative effect on survival if an athlete randomly achieves a distance with a low left digit. Comparing, for example, two athletes with almost identical distances 9 and 10 hundredths of a second, we suggest that the former should have a lower probability of survival. This is because the athlete with a low left digit underestimates the magnitude of the time distance to the leader.[9]

In order to estimate the effect of interest, we assume that except for the distinct effect of left digits, there is no reason why survival $S_{i,j}$ should be a discontinuous function of the distance to the leader. This is supported by balance tests shown in Table 2. The statistics indicate that athletes close to these cutoffs are not systematically different in their baseline characteristics.

— Table 2 about here —

In our estimation, we apply a regression discontinuity design with two different bandwidths. The narrow bandwidth includes only athletes with a right digit of 0 and those with right digit of 9. Both have almost the same time difference to the leader but the first one has a lower left digit and thus a larger *perceived* chance of being successful. Using this bandwidth, any athlete with a time distance to the leader of 9, 19, 29, etc. hundredths of a second is in the treatment group. For the control group, we take all athletes with a time distance of 10, 20, 30, etc. hundredths of a second. The broader bandwidth compares athletes with a right digit of 8 and 9 with those having a 0 and 1. Under the assumption that in general $S_{i,j}$ should be a continuous function of the distance to the leader, any observed discontinuity in $S_{i,j}$ at tenths-of-a-second cutoff levels is identified as the causal effect of the treatment. Using the narrow bandwidth, we estimate this effect, denoted by $\tau$, by fitting the linear regression

$$S_{i,j} = \alpha + \tau D[\text{mod}(T_{i,j} - T_{1,j}, 10) = 9] + \sum_{k=1}^{5} \gamma_k (T_{i,j} - T_{1,j})^k + \beta T_{i,j} + \mathbf{X}_{i,j}\,\delta + \varepsilon_{i,j} \qquad (6)$$

where $D[\text{mod}(T_{i,j} - T_{1,j}, 10) = 9]$ is an indicator function, taking the value one if the modulo of the distance to the leader with respect to ten is equal to 9, $T_{i,j}$ denotes athlete $i$'s time in the first run, $T_{1,j}$ is the time of the leader of the first run, and $\mathbf{X}_{i,j}$ captures several individual

[9] We provide a detailed description of the treatment variables in the Appendix.

characteristics: age, experience, as well as a prior successes. The standard error term, $\varepsilon_{i,j}$, is clustered at the athlete level.[10] The modulo finds the remainder of the division of the time distance by ten. For example, a distance of 39 hundredths of a second yields a modulo of 9. Note that equation (6) includes a fifth-order polynomial of athlete $i$'s distance to the leader. In our analysis, we use this higher-order polynomial to control for nonlinear fits. However, the particular choice of the polynomial does not affect our estimates.[11]

An important potential bias in our results would arise if athletes with low and high left digits are systematically different with respect to pre-determined covariates. To explore this possibility, we compare the characteristics of treated and non-treated athletes. Balance tests reported in Table 2 show that all tested variables have very similar means and the differences between treatment and control group fall short of conventional levels of statistical significance. In addition, Figure 3 indicates that there is no clustering of observations around the cutoff. While left digits are roughly normally distributed, right digits are evenly distributed.[12] Following McCrary (2008) we argue that athletes cannot influence their location to the left or right of the threshold. For one thing, this is because they have no influence on the leader's race time. In addition, as we argue in Section 2, random weather shocks are sufficiently large to affect each individual race times. Overall the balance tests shown in Table 2 support the assumption that treatment is randomly assigned. Together with the evidence on the smooth distribution of the running variable depicted in Figure 3, we are confident that the main assumptions for identifying causal effects are satisfied.

We add control variables and fixed effects in some specifications to address previous research by Dohmen *et al.* (2011) suggesting that risk-taking behaviour correlates significantly with individual characteristics and decreases, for example, with age. Moreover, the inclusion of covariates may rule out observable and time-fixed non-observable confounders and can improve

[10]We can also cluster standard errors at the race-level and obtain virtually identical results. Note that we do not explicitly control for the presence of superstars in our main regressions. However, we find that —in line with previous research by Brown (2011)— this does not affect our results.

[11]Adding any combination of polynomials up to the order of 15 yields virtually identical results. The fifth-order polynomial is chosen based on significance levels when regressing survival on distance (Lee and Lemieux, 2010).

[12]This feature of our data differs from previous studies using other settings in which the allocation of left digits is not entirely random (cf. Lacetera, Pope and Sydnor, 2012 or Englmaier, Schmoeller and Stowasser, 2013).

the precision of the estimation (Frölich, 2007). For a comparison, we report results both with and without using control variables.

## 4 Results

### *4.1 Main Effects*

In our main analysis, we test Proposition 1 that predicts that athletes change their behaviour based on left digits in their distances to the leader of the first run. Before turning to the econometric estimates, we provide descriptive evidence suggesting that in fact survival rates differ between athletes with low or high left-digits. Figure 4 plots the average probability of finishing the race (henceforth, the probability of survival) by an athlete's right digit in the distance to the leader of the opening run. Each mean survival rate is based on approximately 2,000 observations.

— Figure 4 about here —

We observe that on average about 95 % of athletes successfully finish a race. This probability, however, differs substantially depending on the right-digit in the time distance to the leader. In particular, athletes with a relatively low *left*-digit, i.e. those with a *right*-digit of '8' or '9', exhibit a visibly lower probability of survival.

This simple empirical evidence suggests that athletes may respond to having low or high left digits in their time distance to the leader of the first run. We explore this in more detail by applying the econometric approach outlined in the previous section. Our main estimation results are shown in Table 3.

— Table 3 about here —

Using the full sample and different sets of controls, we find that a low left digit has a significant negative effect on the probability of survival. Applying the wide bandwidth (N=8,482), the results indicate that those athletes with a distance to the leader of 8, 9, 18, 19, 28, 29, etc. hundredths of a second are about 28.5 % (or 1.4 percentage points) more likely not to finish the second run than those with a distance of 10, 11, 20, 21, 30, 31, etc. hundredths of a second.

When we choose the narrow bandwidth (comparing only digits 9 and 0; N=4,141), the effect is similar in magnitude while the significance is reduced due to the smaller sample size. Applying a regression discontinuity design, we exploit the fact that athletes quasi-randomly receive a low or high left-digit in their time distance to the leader. Therefore adding control variables to the regression should not affect our estimates. The observation that point estimates are not sensitive to the specification lends confidence to our results. The estimated effects in columns 2-5 of Table 3 are all very similar to the baseline results, even when adding race- or athlete-fixed effects.[13]

We can show that this discontinuity is present at multiple thresholds. In Figure 5, we plot the average survival rate for various time distances to the leader of the opening run. Each tenth-of-a-second is a threshold.

— Figure 5 about here —

We observe that in total, 16 (or 76%) differences in time window of the first two seconds are negative, 5 (24%) are positive.[14] The average difference in survival between athletes with a high left digit and athletes with a low left digit is 0.012 and thus very similar in magnitude to the main estimates obtained in Table 3. This indicates that the left-digit bias is present at multiple thresholds. In several cases, those athletes with a slightly smaller difference to the leader are more than 50% (or 2.5 percentage points) more likely to crash.[15]

### *4.2 Individual Success and Variance of Performance*

The analysis thus far has shown that the left digit in an athlete's time distance to the leader affects her subsequent risk behaviour, measured as the probability of not finishing the race. However, it remains unclear whether the left digit also affects individual race times or the

[13] The addition of athlete-fixed effects can be motivated by recent research on the determinants of risk preferences. For example, Cesarini *et al.* (2009) as well as Barnea *et al.* (2010) find that up to one third of the variance in stock market participation and asset allocation can be attributed to genetic factors.

[14] We do not show confidence intervals. These are fairly large due to the fact that we only have about 80 observations for each threshold (e.g., combined observations for 8, 9, 10, 11).

[15] Note that we obtain very similar results when using a framework that controls for the time distance to the leader. Figure A4 in the Appendix shows predicted survival rates and differences in survival rates at multiple cutoffs based on a regression of survival on a fifth-order polynomial of the time distance variable and dummies for the left-digit cutoffs. Both levels and differences are virtually identical to the raw descriptive statistics shown in Figure 5.

probability of winning the race. Our previous findings suggest that athletes with a low *perceived* distance to the leader take high risks. A fraction of them does not finish the race. But what happens to those who successfully finish the race? It may be that their increased risk-taking pays off and leads to a better overall time and thus a higher probability of winning the race. However, it is also possible that the higher risk leads to errors that translate into worse final times, a large variance in race times, and a lower probability of winning.

— Table 4 about here —

To examine the effects of left digits on the set of finishers, we perform five separate tests reported in Table 4. The first column compares the winning probability of treatment and control group and shows the results of a test for equality of means. Individuals with a low left digit seem to have a slightly lower probability of winning the race but the difference is not statistically significant. Both the second and third column perform a test for equality of means for two standardised measures of time in the second run. Time measure 1 divides individual race time in the second run by the final second run time of the subsequent winner. Time measure 2 does the standardisation by the final second run race time of the best athlete in the second run. Both measures are comparable in magnitude in treatment and control group and not statistically significant. These findings suggest that athletes taking more risk due to a left-digit bias are not more successful in the second run in case they do finish the race.

In order to explain this result we test whether increased risk-taking affects the variance of race times in the second run. Results in columns 4 and 5 indicate that the standard deviation of athletes with a low left digit is between 21.4% and 26.1% higher when compared to athletes with a high left digit. The variance-comparison tests indicate that both differences are significant at the 1% level. This suggests that the increased risk-taking behaviour of athletes with low left digits does not change their *average* time. It does, however, lead to a situation in which some athletes who finish with few errors perform very well and finish with a low final time, while others who make errors finish with a large final time. This increases the tails of the distribution of race times in the second run and thus the respective standard deviation.

Overall, we find empirical evidence for claims (i), (ii), and (iii) of Proposition 1, namely that a low left digit (i) raises the probability of not finishing the second run, (ii) increases the variance of race time, but (iii) leaves the average race time unaffected. However, there is no evidence for claim (iv) that low left digits lead to an increase in the probability to win.[16]

### *4.3 Left-Digit Bias in Tournaments*

The setting of World Cup alpine skiing is characterised by high stakes, fierce competition and experienced athletes. Our main results suggest that in this setting a left-digit bias is present, causing athletes to be more likely not to finish the race. In what follows, we provide a discussion of why large stakes, experience and competition do not eliminate the behavioural bias.

Previous research in psychology distinguishes two fundamentally different ways of thinking, commonly referred to as 'System 1' and 'System 2' (Stanovich and West, 2000; Kahneman, 2011). The former deals automatically and quickly with signals and information. This occurs without effort and with no sense of voluntary control. In contrast, System 2 allocates attention to those mental activities which demand it because of their complexity.[17] In our setting of World Cup alpine skiing, the athlete's System 1 is used to recognise and judge the distance to the leader. This information is easily observable and athletes are familiar with this type of information. If an athlete, however, wants to know the distance to other ranks she has to actively compute that distance. This task is performed by System 2.

A large body of research documents that behavioural biases such as heuristics arise in System 1. Thus, athletes relying on System 1 when dealing with time distances to the leader are prone to error. The automatic way of thinking tends to simplify information. One way of doing this is to concentrate on left-digits in any number. In theory, System 2 could intervene and prevent a left-digit bias. However, using System 2 requires conscious effort. As Kahneman (2011) explains, the common expression of 'paying attention' is apt. Individuals have a limited budget of mental resources. As a result, athletes cannot pay full attention to every information

[16] One explanation for the absence of this result is the fact that the left digit bias seems to be most pronounced for athletes trailing the leader by 70 to 120 hundredths of a second as indicated by Figure 5. Only few of them are able to compensate their substantial time difference to the leader after the first run.

[17] Kahneman (2011) provides a simple illustration for the difference between System 1 and System 2. When an individual sees the image of an angry woman, for example, System 1 immediately recognises that the person in the picture is angry. It takes no effort to recognise the anger and individuals do not control whether or not to see the anger. The same happens with familiar and simple problems to which one has an immediate solution (e.g., 2+2=4). If individuals face, however, a complex problem like '17 x 24', System 2 takes over because solving this problem takes effort, people are usually not familiar with it and do not know the answer without spending time on calculating the solution.

all the time.[18] However, if stakes are sufficiently high athletes should have a strong incentive to pay attention to the information they receive after the opening run. This reasoning has led prior research to question the existence of behavioural biases in the context of large stakes.

**High Stakes and Behavioural Biases**. — We consider a tournament setting with large stakes reflected not only in substantial prize money, but also in lucrative sponsorship contracts. The incentive structure in such a setting has been subject to previous research by Ehrenberg and Bognanno (1990). An important question is whether high stakes—and the concentration thereof among the most successful athletes—yields higher effort levels and reduces behavioural biases.

As the results in Table 3 indicate, we observe a left-digit bias despite the large stakes present in World Cup alpine skiing. One way of explaining this finding is to refer to the concept of *ego-depletion*. Baumeister *et al.* (1998) argue that 'all variants of voluntary effort—cognitive, emotional, or physical—draw at least partly on a shared pool of mental energy'. If individuals exert a lot of physical or mental effort on one particular task, they are less likely to pay full attention to or exert full effort on a subsequent task. This phenomenon is called ego-depletion. If System 2 is exhausted because of some current or prior activity, System 1 takes over. The existence of this process has been demonstrated in numerous experiments. If individuals, for example, had to keep in mind a seven-digit number for one or two minutes they respond differently to various questions or tasks. In particular, while being cognitively busy they are more likely to make superficial judgments (Kahneman, 2011).

In World Cup slalom races, athletes have to exert a lot of effort and pay full attention during the first run of a slalom race. Compared to other disciplines, slalom races are considered the technical events of alpine ski racing. A course consists of more than fifty gates, all of which must be passed correctly at a speed of about 40 km/h. The vertical offset between gates is around 9 meters while the horizontal offset is about 2 meters. After the opening run, athletes' mental resources are depleted and they rely on System 1 to deal with information and signals. Thus when looking at the distance to the leader they suffer from a left-digit bias.

[18] According to Kahneman (2011), 'Constantly questioning our own thinking would be impossibly tedious, and System 2 is much too slow and inefficient to serve as a substitute for System 1 in making routine decisions.'

Large stakes are likely to magnify this bias. Prize money in World Cup alpine skiing is huge. The winner of a single race earns, on average, about $40,000 while the athlete ranked second only receives $23,000. Moreover, ski races attract a large audience of up to one million per race, thus leading to a considerable sponsorship market. These figures indicate that athletes are subject to significant pressure. At the same time, tiny mistakes can have huge effects on performance, thus causing financial implications for individual athletes. Choking under such immense pressure is a well-known phenomenon. In the seminal work by Baumeister (1984), choking is defined as increased pressure which raises the attention to individuals' own process of performance, thus disrupting the automatic nature of the execution. Experimental evidence suggests that a stressful environment is detrimental to the working memory (Beilock and Carr, 2005; Beilock, 2008). In many fields of sports stakes are also large due to the presence of spectators. Dohmen (2008) investigates whether choking can be observed among professionals performing their usual tasks. In the setting of the German Premier football league Dohmen finds professional players to choke more frequently when playing a home match. Higher stakes or the importance of success, however, do not seem to be associated with more choking.

Turning to World Cup skiing, it is worth noting that pressure caused by other (trailing) contestants does not significantly differ between treated and non-treated athletes in our sample. The balance tests in Table 2 show that the number of athletes within a tenths-of-a-second time window after the first run does not differ between treated and non-treated individuals. Both athletes in the control and treatment group face on average one contestant ahead and behind them whose distance is one tenth of a second or less.

In order to investigate the role of pressure on performance and behaviour, we first split our data by the prize money for the winner. In Table 5 we estimate the effect of low left-digits on survival in a sample of races with above-median prize money. The results of column 2 indicate that the left-digit bias is similar in magnitude to our baseline estimate. In high-prize races, athletes with a low left-digit in their distance to the leader are about 30.5% more likely not to finish the second run.

— Table 5 about here —

As a second test for the role of stakes we split our sample into two periods of the season.

Public attention is exceptionally high at the beginning of a new season. Our results in column 3 indicate that the point estimate is also substantially larger for this sample. Moreover, we find similar evidence for races toward the end of the season. When only two races are left, stakes are usually higher since the overall classification is determined, sponsorship contracts are renewed, and athletes for the national team are selected.

Instead of mitigating behavioural biases, high stakes in the setting of World Cup skiing actually do not affect the presence of a left-digit bias. One explanation for this finding could be that high stakes cause mental stress and lead to higher effort level during the first run. This may cause an increased reliance on heuristics when dealing with information like time distances after the opening run.

**Experience and Behavioural Biases**. — Many behavioural biases were first documented in experimental settings. Participants of lab experiments, however, are usually unfamiliar with the tasks they are asked to solve. In contrast, contestants in World Cup tournaments usually have many years of experience. Following two studies by List (2003, 2004), individual experience could render athletes in our setting less likely to suffer from behavioural biases. List (2003) reports experiments in which subjects gained experience over the course of several weeks. Based on his findings he concludes that 'useful cognitive capital builds up slowly, over days or years' (List 2003, p.67). This experience results in a reduction, although not complete elimination, of the endowment effect.[19] In our setting one could also argue that more experienced athletes are less affected by a low left-digit.

We investigate this relationship between the left-digit bias and athletes' experience. The median athlete has about 60 World Cup races of experience.[20] This translates into six or more years of World Cup level experience. Moreover, virtually all athletes in our sample have participated in at least ten races (or one season) when we use them for our estimation. However, despite the large experience the behavioural bias does not vanish. In columns 4 and 5 of Table 5

[19]In a subsequent study, List (2011) randomises market experience and obtains empirical findings that support the premise that market experience successfully eliminates the gap between willingness-to-accept and willingness-to-pay.

[20] Figure A5 in the appendix plots the distribution of experience.

we restrict the sample to athletes with above-median age or experience. In both cases the point estimate for the effect of low left-digits is very similar to our baseline estimate. Even when restricting the sample to athletes with more than 100 World Cup races, we obtain evidence of a large and significant left-digit bias.

This finding raises the question why experience does not eliminate the behavioural bias in our setting. While we cannot directly examine the mechanisms through which experience affects the left-digit bias, we present recent evidence on the causes of behavioural biases that is consistent with our findings. Following Kahneman (2011), 'As you become skilled in a task, its demand for energy diminishes. Studies of the brain have shown that the pattern of activity associated with an action changes as skill increases, with fewer brain regions involved. Talent has similar effects.' In other words, experience and talent make System 2 work more efficiently and quickly. A trained mathematician, for instance, can solve 17 x 24 much quicker than ordinary people. This advantage, however, is mostly limited to System 2. And because the left-digit bias arises in System 1, experience does not mitigate the problem. In contrast, experience could in theory actually magnify the bias. Having participated in numerous races may render looking at the classification and time distances into a routine task. Thus experienced athletes are likely to rely more on System 1 when dealing with time distances. System 1, however, is prone to making mistakes. In the setting of World Cup tournaments, however, all athletes irrespective of their experience are used to deal with information about performance differences. Hence we only find evidence that the left-digit bias does not vanish with experience and no support for the idea that it is either mitigated or magnified among experienced athletes.

Overall, we find that large stakes, competition and experience do not eliminate behavioural biases. First, experience is likely to render looking at the classification scheme into a routine task and thus may increase the use of heuristics. Second, large stakes and competition cause mental stress (i.e., pressure). Together with heavy physical activity during the first run, athletes are likely to rely on System 1 when processing information after the opening run. As a result, professionals do not get it right.

**Learning Effects**. — Given the result that individual experience does not reduce the existence of the left-digit bias, one might ask whether athletes learn from 'mistakes'. Are individuals less prone to error if, in prior races, they did not successfully finish the race after having (potentially) misinterpreted a time distance due to a low left-digit bias? We test this hypothesis by reducing the sample to all those athletes who were in the treatment group and did not finish the race before a given race $j$. Fitting the same regression as in our main estimation of Table 3, we find that the coefficient on the low left-digit is virtually identical in both groups (-0.013). Hence, we conclude that there is no evidence of learning effects. This is not surprising because, unlike in other settings (e.g., Hart, 2005, Malmendier and Nagel, 2011 or Stango and Zinman, 2014), athletes are not aware of the left-digit bias.

### *4.4 Alternative Explanations*

**Differences in Risk Preferences and Race Tracks**. — One immediate concern with our findings could be that athletes in the treatment and control group have systematically different risk preferences. A large body of literature has investigated the determinants of risk preferences. Since we do not observe individuals' preferences, we can only infer them from prior behaviour. In particular, we can compute probabilities of not finishing the race at the individual level. We take these probabilities into account to test whether individual risk preferences affect our results. In a first step, the balance tests in Table 2 indicate that there is no significant difference in observed probabilities of not finishing the race prior to a particular race. Athletes in the treatment group do not show systematically more risky behaviour than athletes in the control group. In a second step, we add athlete-fixed effects to our baseline regression.[21] The estimates in column 4 of Table 3 show that this does not change our results. In contrast, the point estimates are virtually identical to the ones in our main specification. The fact that adding athlete-fixed effects does not alter our findings also rules out the possibility that our estimates suffer from an omitted variable bias (i.e., from not observing skill or talent).

A second concern addresses the differences across race tracks. In World Cup alpine skiing, race tracks differ substantially in terms of length and difficulty. Thus, the optimal level of

[21]Note that a consequence of including athlete-fixed effects is that we can only use observations of those athletes who are observed both as part of the control and the treatment group.

risk chosen by the athletes varies significantly across race tracks. Moreover it is possible, for instance, that in some locations it is more likely for athletes ranked second or third to surpass the leader by means of an exceptional performance in the second run. We take these considerations into account by adding race-fixed effects to our baseline regression. The results are reported in Table 3. In column 3, race-fixed effects are added. This, however, does not alter the finding that low left-digits are correlated with a significantly lower probability of survival in the second run.

**Reference Points**. — Throughout our theoretical considerations we assume that athletes use victory (or better: the distance to the leader) as a natural reference point when making decisions about risk levels in the second slalom run. In a study by Köszegi and Rabin (2006), the authors argue that rational expectations can serve as reference points. Individuals facing reference-dependent choices use their expectations when making decisions. Empirical support for this idea is provided by Abeler *et al.* (2011).[22] There are good reasons to assume that some athletes in a World Cup contest do not expect to achieve a victory but rather aim for a podium or top-5 finish. While we cannot test for individual-specific reference points, we can examine whether athletes using reference points other than victory also suffer from a left-digit bias. This exercise, however, causes a major problem. In order to use, for example, rank 2 or 3 for a podium finish as reference point, athletes have to compute themselves the time distance. This involves the use of System 2 which suggests that we should not observe any significant difference in survival rates. In fact, results shown in Table 6 show no evidence of a left-digit bias concerning the time distance to other ranks.

— Table 6 about here —

It seems to be the very information about the distance to the leader that drives risk behaviour in the second run. We can refer to our explanations in Section 4.3 to understand this zero result. Each athlete uses System 1 when dealing with the easily observable time distance to

[22]In a related study, Gill and Prowse (2012) argue that a rational agent anticipates possible disappointment. In our case, this applies to athletes that are close to the leader after the opening run and want to avoid forfeiting the opportunity to win the race. Similarly, the leader of the opening run is likely to take into account the expected disappointment that would arise if she does not defend the first rank in the second run.

the leader. However, in order to know the distance to the second, she has to compute the time gap herself. This is carried out by System 2 which is not prone to behavioural biases such as heuristic thinking.

**Information Availability**. — We can test whether the availability of information is crucial for the behavioural bias to arise. To do this, we use the fact that time is not measured using the decade system. Since one minute is sixty seconds we can re-calculate all time distances from seconds to minutes. This turns, for example, 19 hundredths of a second into 0.0032 minutes. As before, we then take the modulus of this number rounded to the nearest integer (this is 2 in the example above) and code the treatment status according to athletes' right digit. If limited attention is the source of our findings, we should not observe any discontinuities in the survival function at thresholds using time distances expressed in minutes. In Table 6 we show that the effect is in fact insignificant. This gives us confidence that the time distances actually shown to the athletes (measured in seconds) are the important signal.

Another way to test for the existence of the left-digit bias is to compare athletes around the one-second threshold. Throughout the paper, we assume that athletes pay full attention to the left-most digit in their time distance to the leader. This implies that athletes trailing the leader by 0.90 to 0.99 seconds should have a lower survival rate than those with a distance between 1.00 and 1.09 seconds. Using our data, we find that the former group has a 1.7 percentage points (or 34%) higher probability of not finishing the second run.

In addition to the time difference to the leader, each athlete is provided with the classification after the opening run. As shown in Figure A6 in the appendix, this classification includes each racer's time to finish the first run. We can use this and test whether there is evidence of a left-digit bias in the processing of this information. For example, consider the case in which the leader of the opening run finished with a time of 54.91 seconds, while the second and third have a time of 54.99 and 55.00 seconds, respectively. In this setting, our main specification would consider both second and third as part of the treatment group (their time differences are 0.08 and 0.09 seconds). However, we can also define treatment and control group based on whether athletes share the same integer on the full second count. In the example above, the first two athletes have a full-second of 54 while the third one's time begins with 55.[23] We examine whether athletes misinterpret time differences because of a left-digit bias with respect to the time (not time difference) of the opening run.

Table B2 in the Appendix presents the results. We employ basically the same specification as in our main analysis. However, we replace the treatment variable as described above. The point estimates show that athletes close to the leader (i.e., trailing by less than 0.3 seconds) are significantly more likely not to finish the second run if they share the leader's count of full seconds.[24] This finding is strongly in line with our previous results and suggests that there is a left-digit bias with respect to the time of the opening run as well.[25] The fact that this time is easily observable by athletes underscores the importance of information availability for the existence of a left-digit bias.

**Alternative Digit Breaks**. — A crucial question concerning our estimation strategy is whether the discontinuity in survival rates is a particular phenomenon of the 9-10 cutoff. Typically we compare, for example, athletes with a time distance to the winner of 9 versus 10 hundredths of second. If limited attention explains our findings above, we should not obtain significant results when using other digits for the cutoff. That is, there should be no difference in survival rates when comparing, for example, a distance of 10 versus 11 hundredths of a second. The descriptive data from Figure 4 suggests that there is only a discontinuity when comparing right-digits 8 and 9 with 0 and 1. Moreover, a placebo test in Table 6 confirms that none of the other possible thresholds exhibits the pattern we find at the cutoff when the left-digit changes. In particular, we test whether athletes perform rounding when processing information about time differences. This would imply that athletes perceive a distance with a right-digit of 4 (compared to a right-digit of 5) as significantly smaller. Following the same idea outlined in Section 1, we should find a discontinuity at the 4-5 cutoff. This, however, is not confirmed by

[23]We provide a detailed description of the different treatment variables in Table B1 in the Appendix.

[24]The cutoff of 0.3 seconds refers to the maximum time distance between the leader and trailing athletes. Our choice of 0.3 seconds as a cutoff is not crucial and we obtain very similar results using 0.2 or 0.4 seconds.

[25]Not surprisingly, the variation is very limited if we add race-fixed effects to the estimation. Hence, the coefficient is insignificant in column 3. More important is the observation that even when estimating with athlete-fixed effects, we obtain a significant negative effect.

the estimation result shown in Table 6.

**Distance to Leader**. — Following our theoretical model, we expect the left-digit bias to have a significant effect only among athletes close to the leader of the opening run. These athletes pay attention to their distance to the leader and may over-estimate their winning probability due to inattention to right digits. To test this, we split our sample of athletes based on to their time difference to the leader after the opening run. Each subsample includes athletes in a range of 150 hundredths of a second. We then run separate regressions for every subsample using our main specification.[26]

— Figure 6 about here —

The results in Figure 6 demonstrate that the treatment effect is significant only among athletes in close distance to the victory. Once we reduce the sample to athletes with low winning probabilities, the treatment effect is no longer significantly different from zero.

**Nervousness**. — Our theoretical and empirical analysis has stressed the idea that the left-digit bias we find is a form of rational strategic decision-making mixed with biased information processing. An alternative explanation is that the mis-perceived time distance to the leader of the first run leads to higher nervousness, which then translates into choking under pressure in a competitive environment with high stakes (Dohmen, 2008). To disentangle rational decision-making mixed with biased information processing from nervousness, we explore the left-digit bias for a sample of athletes with low levels of nervousness. As a measure of nervousness, we use an athlete's average improvement in the second run over the career. Athletes who have proven to considerably increase their performance in the second run are very unlikely to suffer from nervousness. Table B3 in the Appendix reports the results of estimating the main specification for athletes in the lowest quartile of our nervousness measure. The estimated changes in the probability of not surviving for athletes with a low left-digit range from -54.0% to -56.0% and are thus even larger than the estimates found for the full sample. The finding that even racers

[26] This rolling regression procedure has the advantage that the point estimates remain relatively stable across subsamples with similar distances to the leader.

with low levels of nervousness exhibit a substantial change in the probability of not finishing the competition helps us understand the main channel of our results. It suggests that athletes do not fully account for the actual time distance to the leader and act rationally based on this mis-perceived distance.

There are two other pieces of evidence that are not consistent with the hypothesis that athletes with a smaller perceived distance are simply nervous and thus finish with a lower probability. First, nervousness should be greatest in the sample of athletes trailing the leader by a very small distance. However, we do not find any particularly large effect among those athletes as documented in Figure 5. Second, nervousness should lead to a worse performance in general. In our context, we would expect athletes with a low left-digit to perform worse in the second run if nervousness is the main channel. Yet the prediction that average performance decreases as a consequence of nervousness induced by the left-digit bias cannot be supported by the data. Athletes to the left and right of a tenth-of-a-second threshold show a very similar average performance in the second run.

## 5 Conclusion

This paper investigates the effects of heuristic information processing and left-digit biases on risk-taking behaviour in a setting of high stakes, competition, and experienced professionals. By applying a regression discontinuity design in a sample of professional World Cup alpine ski athletes, we present new empirical evidence that individuals misinterpret performance differences even in a professional setting. We find that athletes with a low perceived distance after the first run adopt a more risky strategy in the second run. Our estimates suggest that the probability of not finishing the race increases by up to 28% when comparing individuals with lower and higher left-digits (e.g., nine compared to ten hundredths of a second).

Our findings show that limited attention can be present even in a setting of professional athletes who compete for large prizes. Alpine ski athletes are aware of the fact that tiny differences in their distance to the leader after the first run hardly matter for their prospects in the second run. However, when comparing individuals with arguably similar distances, we find large discontinuities in survival rates. Our results are robust to the inclusion of several control variables as well as race- and athlete-fixed effects. In addition, a large set of robustness checks gives us confidence that limited attention is the source of the significant effect of low left-digits on survival.

Our findings have implications beyond alpine skiing because they add to the understanding of the causes of individual risk behaviour that is crucial for many economic questions. Limited attention is likely to affect our everyday risk behaviour. Prior research by Barber and Odean (2008) highlights the role of salience of stocks for attention-driven buyers. Due to a left-digit bias traders may interpret the magnitude of a 0.9% stock market change in a different way than a 1.0% change. This can then have implications for the amount of risk they are willing to take, even in the presence of large stakes. The behavioural bias we document may also have an impact in other areas. Our results suggest that individuals may have a different perception of a 90 kilometers per hour speed limit when compared to a 100 km/h speed limit. As a consequence, risk behaviour under the two regimes can differ substantially. These and other aspects of limited attention are left to future research.

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Additional Supporting Information may be found in the online version of this article:

**Data S1.**

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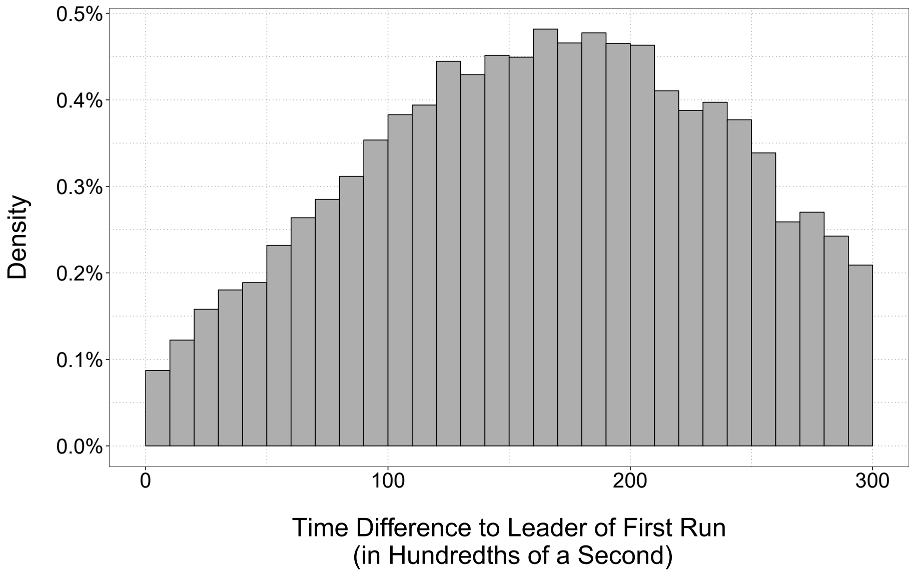
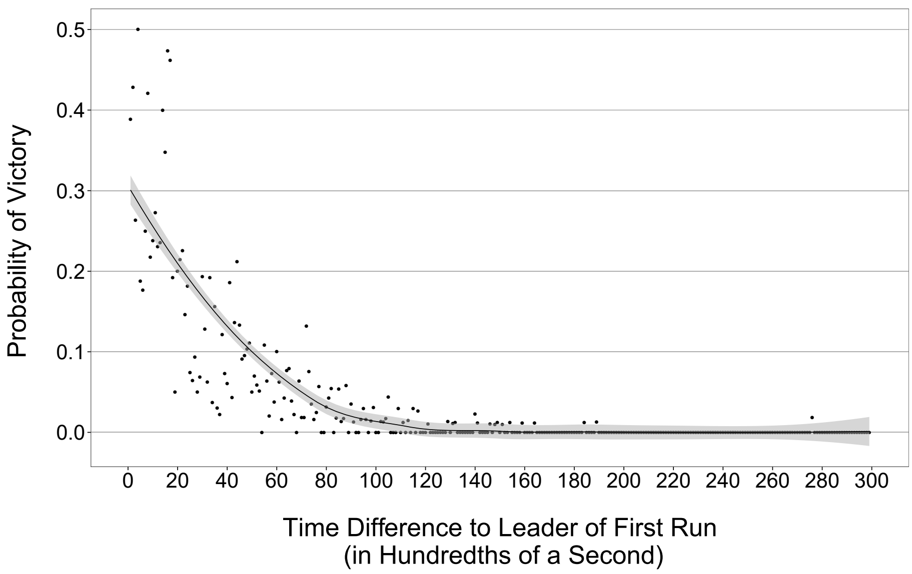
## Figures and Tables

**Figure 1: Distance to the Leader and Winning Probability**

(A) Distribution of Time Differences

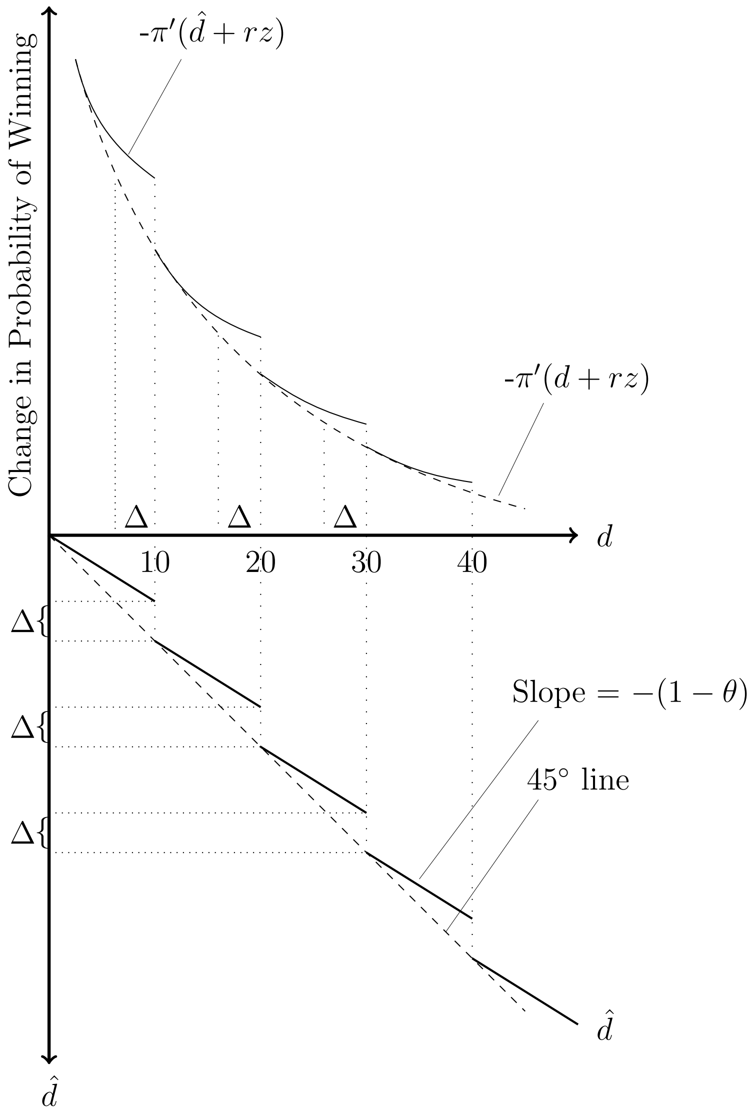



(B) Probability of Victory by Time Difference to the Leader




*Note:* The figure in panel (A) shows the distribution of time differences to the leader after the opening run using the full sample. The figure in panel (B) plots the average probability of winning the race for each hundredth of a second. The solid line is a local linear regression, while the shaded area depicts a 95% confidence interval.

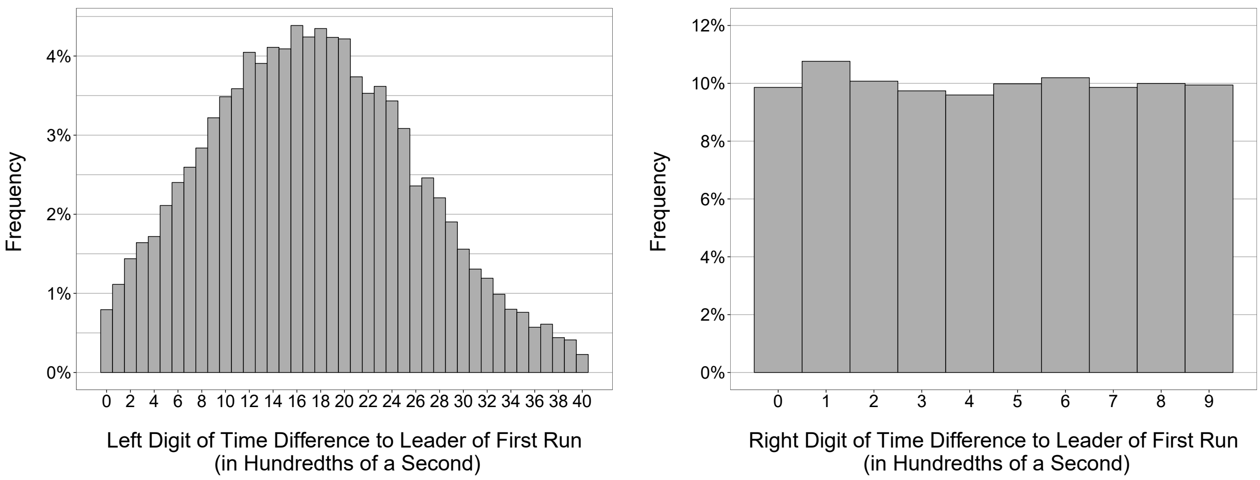
**Figure 2: Perceived Distance and Change in the Probability of Winning**




*Note:* The upper half of the figure illustrates how the discontinuity in the perceived distance $\hat{d}$ causes a discontinuity in the change of the winning probability, $-\pi'(\hat{d}+rz)$, drawn for a realization of $z=0$. In lower half we show the discontinuities between actual distance $d$ (x-axis) and perceived distance $\hat{d}$ (y-axis).

**Figure 3: Distribution of Left- and Right-Digits**

(A) Histogram of Left Digits (B) Histogram of Right Digits



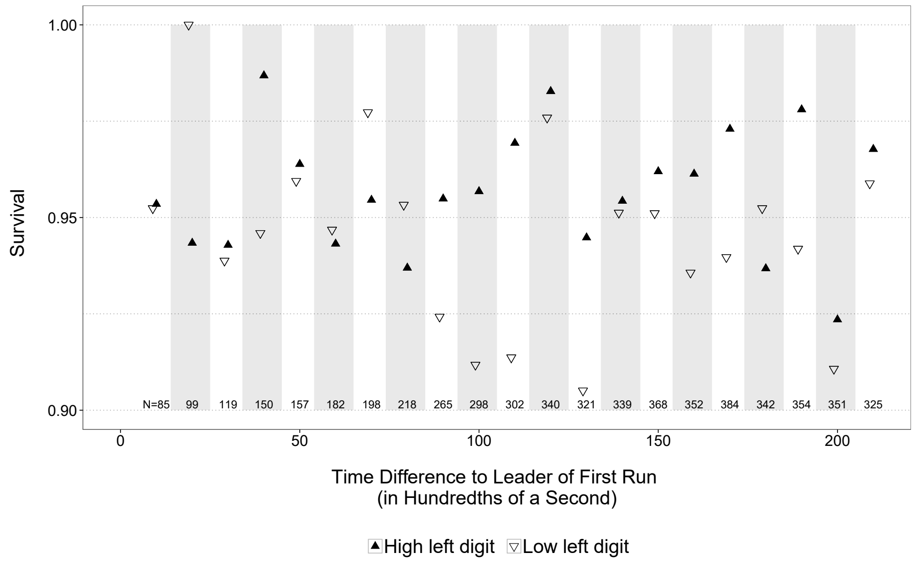

*Note:* The figure shows two histograms of the time difference to the leader after the first run. Panel (A) depicts the left-digit of an athlete's time difference to the leader of the first run, while panel (B) depicts the right-digit of the time difference to the leader of the first run. For example, the time distance of 0.27 seconds can be decomposed into a left digit of 2 and a right digit of 7.

## Figure 4: Survival Rate by Right-Digit

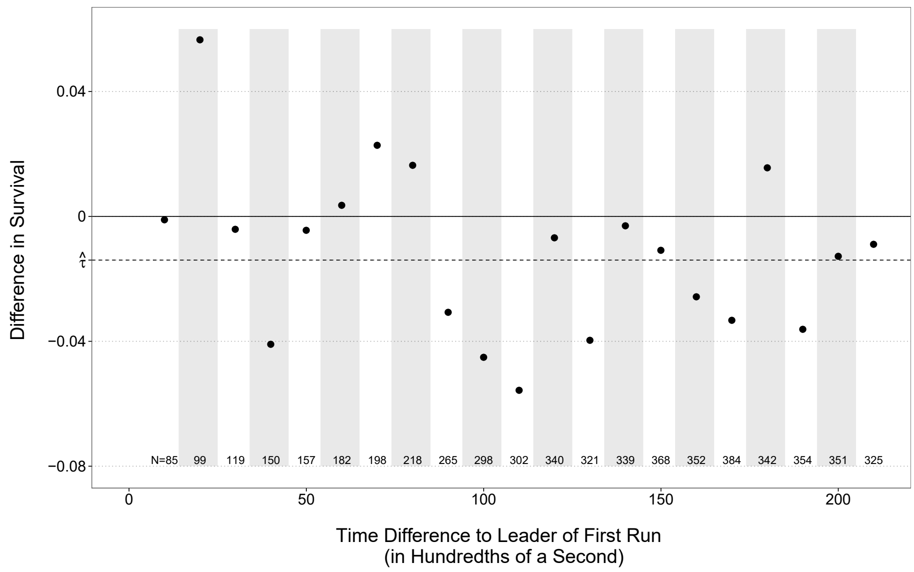

*Note:* The dots in the figure depict the average survival rate for every right digit in the time difference to the leader of the first run. In addition, we show a linear fit for both low and high left digits. Note that we remove all athletes with a distance of 0 to 5 hundredths of a second to avoid that slightly more skilled athletes are to the right of the digit break. The shaded area indicates the 90% confidence interval.

## Figure 5: Discontinuities in Average Survival Rates

(A) Average Survival Rate by Time Difference to the Leader

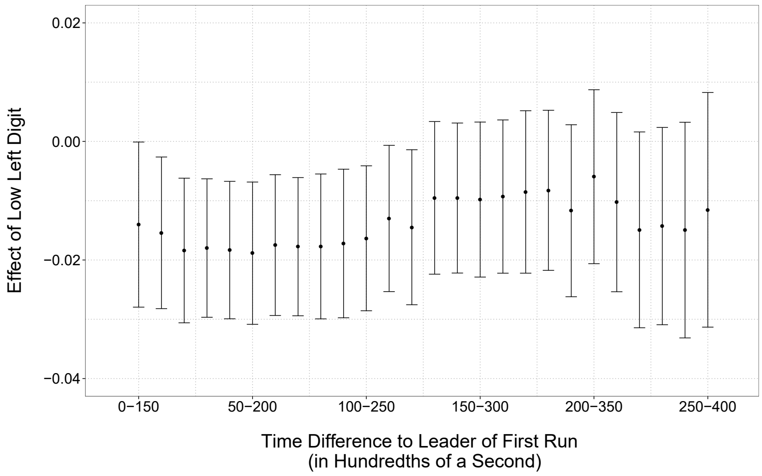



(B) Difference in Average Survival Rate by Time Difference to the Leader




*Note:* The figure in Panel (A) shows the average survival rate for various time distances to the leader of the opening run. The shaded and white bars indicate tenths-of-a-second brackets. For each bracket, we show the average survival rate slightly below (right digits 8 and 9) as well as slightly above (right digits 0 and 1) for each digit break. For example, the first two triangles on the left hand side show the average survival rate of athletes trailing the leader by 8 and 9 hundredths of a second (white triangle) as well as the survival rate for athletes with a difference of 10 and 11 hundredths of a second (black triangle). The figure in Panel (B) shows the difference between the two survival rates for each bracket. The horizontal dashed line depicts the estimated treatment effect, $\hat{\tau} = 0.014$, from our main regression in Table 3. At the bottom of both figures, we show the numbers of observation for each bracket.

# Figure 6: Treatment Effect by Distance to the Leader




*Note:* The figure shows the estimated treatment effect (y-axis) for samples restricted by the distance to the leader (x-axis). The estimation sample includes all athletes with a right digit of 8, 9, 0, and 1 in their time distance to the leader of the first run, expressed in hundredths of a second. Confidence intervals at the 95% level are shown.

## Table 1: Descriptive Statistics

| | Athletes in Estimation Sample | | | | | Athletes in Full Sample | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **SD** | **Min** | **Max** | **N** | **Mean** | **SD** | **Min** | **Max** | **N** |
| Survival | 0.95 | 0.22 | 0 | 1 | 8,482 | 0.95 | 0.22 | 0 | 1 | 13,225 |
| Distance to Leader of First Run | 183.30 | 99.83 | 1 | 2959 | 8,482 | 171.28 | 102.47 | 0 | 1892 | 13,225 |
| Position after First Run | 14.92 | 7.89 | 2 | 30 | 8,482 | 14.19 | 8.43 | 1 | 30 | 13,225 |
| Final Position | 13.47 | 8.04 | 0 | 31 | 8,482 | 12.88 | 8.32 | 0 | 31 | 13,225 |
| Age | 25.79 | 3.72 | 16.89 | 37.64 | 8,482 | 25.88 | 3.7 | 15.82 | 37.65 | 13,225 |
| Male | 0.50 | 0.5 | 0 | 1 | 8,482 | 0.51 | 0.5 | 0 | 1 | 13,225 |
| Experience | 36.70 | 26.49 | 1 | 151 | 8,482 | 37.31 | 26.32 | 1 | 154 | 13,225 |
| No. Podiums at Time of Race | 7.46 | 14.46 | 0 | 101 | 8,482 | 8.14 | 14.73 | 0 | 110 | 13,225 |
| No. Victories at Time of Race | 2.57 | 6.12 | 0 | 58 | 8,482 | 2.87 | 6.24 | 0 | 53 | 13,225 |

*Note:* The table shows descriptive statistics for all relevant variables. Columns (2)–(6) show statistics for the sample used for the main regression analysis with a wide bandwidth. This includes all athletes with a right digit of 8, 9, 0, and 1 in their time distance to the leader of the first run, expressed in hundredths of a second. Columns (7)–(11) show statistics based on the full sample. Experience is measured by the number of races in the discipline of competition (slalom and giant slalom).

## Table 2: Balance Tests

| | Mean Treatment | Mean Control | Difference | p-value |
|---|---|---|---|---|
| *A: Athlete Characteristics* | | | | |
| Age | 26.19 | 26.19 | -0.00 | 0.97 |
| Male | 1.50 | 1.50 | -0.00 | 0.95 |
| Experience | 36.58 | 36.83 | -0.25 | 0.67 |
| *B: Risk Preferences* | | | | |
| Average Survival | 0.96 | 0.96 | -0.00 | 0.29 |
| Survival in Last Race | 0.95 | 0.95 | 0.00 | 0.61 |
| *C: Overconfidence* | | | | |
| Athlete's No. of Victories | 2.58 | 2.56 | 0.02 | 0.89 |
| Athlete's No. of Podiums | 7.47 | 7.44 | 0.03 | 0.92 |
| *D: Athlete Skill* | | | | |
| Victories in Career | 5.68 | 5.30 | 0.38 | 0.20 |
| Podiums in Career | 16.06 | 15.36 | 0.70 | 0.23 |
| *E: Competition* | | | | |
| Total Podiums in Top 5 | 73.21 | 72.83 | 0.38 | 0.70 |
| Total Victories in Top 5 | 27.42 | 27.19 | 0.23 | 0.58 |
| Total Podiums in Top 10 | 118.71 | 118.51 | 0.20 | 0.89 |
| *F: Pressure* | | | | |
| Mass of Athletes Ahead | 1.02 | 1.01 | 0.01 | 0.63 |
| Mass of Athletes Behind | 1.01 | 1.02 | -0.00 | 0.92 |
| FIS World Cup Points | 159.51 | 152.73 | 6.78 | 0.18 |
| First Prize Possible | 0.32 | 0.32 | -0.00 | 0.95 |

*Note:* The table shows mean comparisons (t-tests) for all relevant pre-treatment variables. The sample includes all athletes with a right digit of 8, 9, 0, and 1 in their time distance to the leader of the first run, expressed in hundredths of a second. Age is the exact age in years at the time of the race, experience is measured by the total number of races prior to the race, survival in last race indicates having successfully finished the preceding race, victory and podium measure the total number of an athlete's victories and podiums prior to the race, and mass of athletes ahead (behind) is the total number of athletes who are leading (lagging) by 10 hundredths of a second after the first run.

## Table 3: Effect of Low Left Digits on Survival

| | Dependent variable = 1 if athlete finished the race | | | |
|---|---|---|---|---|
| | Logit Estimation | | OLS Estimation | |
| | (1) | (2) | (3) | (4) |
| *A: Wide Bandwidth* | | | | |
| Low Left-Digit | -0.014*** | -0.014*** | -0.013*** | -0.014*** |
| | (0.004) | (0.004) | (0.005) | (0.005) |
| Change in Probability of not Surviving | -28.0% | -28.0% | -26.0% | -28.0% |
| Observations | 8,482 | 8,482 | 8,482 | 8,182 |
| R-squared | 0.001 | 0.008 | 0.149 | 0.005 |
| *B: Narrow Bandwidth* | | | | |
| Low Left-Digit | -0.011* | -0.012* | -0.010 | -0.011* |
| | (0.006) | (0.006) | (0.007) | (0.007) |
| Change in Probability of not Surviving | -22.0% | -24.0% | -20.0% | -22.0% |
| Observations | 4,141 | 4,141 | 4,141 | 3,821 |
| R-squared | 0.006 | 0.010 | 0.231 | 0.005 |
| Controls | - | Yes | Yes | Yes |
| Fixed Effects | - | - | Race | Athlete |

*Note:* The table shows the results of eight separate regressions. In Panel A, we estimate the effect of a low left digit on the probability of survival using the wide bandwidth. The sample includes all athletes with a right digit of 8, 9, 0, and 1 in their time distance to the leader of the first run, expressed in hundredths of a second. In Panel B, we estimate the same regression using the narrow bandwidth that includes all athletes with a right digit of 9 and 0 in their time distance to the leader of the first run. Thus, in the latter specification, we estimate the effect of digit 9 on the probability of survival. Controls include age, experience, and prior successes. Columns 1 and 2 report marginal effects, while Columns 3-4 show OLS estimates. When applying athlete fixed effects, the sample is reduced to athletes with at least one observation in the treatment and control group. Standard errors (in parentheses) are clustered at the athlete level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

## Table 4: Effect on Average Performance and Variance of Performance

| | Individual Performance | | | Variance of Performance | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Mean Probability of Winning | Mean Time 2nd Run Measure 1 | Mean Time 2nd Run Measure 2 | Std. Dev. Time 2nd Run Measure 1 | Std. Dev. Time 2nd Run Measure 2 |
| High Left-Digit | 0.019 | 1.017 | 1.024 | 0.023 | 0.022 |
| Low Left-Digit | 0.015 | 1.018 | 1.025 | 0.029 | 0.028 |
| Difference | -0.004 | 0.001 | 0.001 | 0.005 | 0.006 |
| P-value | 0.169 | 0.246 | 0.264 | 0.000 | 0.000 |

*Note:* The table shows the results of five different tests between treatment and control group. All samples include athletes with a right digit of 8, 9 (low left digit) as well as 0 and 1 (high left digit) in their time distance to the leader of the first run, expressed in hundredths of a second. Columns (1) to (3) report the results of a t-test for equal means. The variables are the probability of winning the race (Column 1), the time in the second run scaled by the time of the subsequent winner (Column 2), and the time in the second run scaled by the time of the best second run athlete (Column 3). Columns (4) and (5) report the results from a variance-comparison tests for the two time measures.

## Table 5: Effect with High Stakes and Individual Experience

| | Dependent variable equals 1 if athlete finished the race | | | | |
|---|---|---|---|---|---|
| | Baseline | Estimation sample split by | | | |
| | Regression | Prize Money | Early Season | Age | Experience |
| | (1) | (2) | (3) | (4) | (5) |
| Low Left-Digit | -0.013*** | -0.014*** | -0.052** | -0.013** | -0.015*** |
| | (0.004) | (0.005) | (0.022) | (0.006) | (0.005) |
| Change in Prob. of not Surviving | -26.0% | -28.0% | -104.0% | -26.0% | -30.0% |
| Observations | 8,482 | 7,455 | 475 | 4,766 | 6,246 |
| R-squared | 0.015 | 0.018 | 0.054 | 0.003 | 0.013 |
| Controls | Yes | Yes | Yes | Yes | Yes |

*Note:* The table shows the results of five separate logistic regressions. We always estimate the effect of a low left digit on the probability of survival and report marginal effects. All estimation samples include athletes with a right digit of 8, 9, 0, and 1 in their time distance to the leader of the first run, expressed in hundredths of a second. In Column (1) we report the baseline regression from Table 3. In Column (2) we restrict the sample to races with above-median prize money for the winner (>35,000 CHF). In Column (3) we restrict the sample to races at the beginning of the season when 10% (or less) of the races have been completed. In Column (4) we only consider athletes with above-median age (25 years or more), while in Column (5) we restrict the sample to athletes with above-median experience (18 races within discipline). Standard errors (in parentheses) are clustered at the athlete level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

**Table 6: Information Availability and Placebo Tests**

| | Dep. Variable equals 1 if athlete finished the race | | | |
|---|---|---|---|---|
| | Distance 2nd | Time in Min. | Digits 0-1 | Digits 4-5 |
| Low Left-Digit | -0.002 | 0.000 | -0.001 | -0.004 |
| | (0.007) | (0.005) | (0.006) | (0.007) |
| Change in Prob. of not Surviving | -4.0% | 0.0% | -2.0% | -8.0% |
| Observations | 3,970 | 6,907 | 4,313 | 4,095 |
| R-squared | 0.002 | 0.004 | 0.001 | 0.001 |
| Controls | Yes | Yes | Yes | Yes |

*Note:* The table shows the results of four separate OLS regressions. We always estimate the effect of a low left digit on the probability of survival. In Column (1), we use the left-digit of the time difference to the athlete on the second position after the first run. This information is not given to the athletes but has to be computed individually. In Column (2), time distances are converted to minutes. Note that after the conversion a right digit of 9 is impossible. Thus, we compare 8 (treated) versus 0 and 1 (control). Because the converted distances are never shown to athletes, left-digits should not have a significant effect on risk-taking. In Columns (3) and (4), we define treatment as having a right digit of 1 (or 5) versus 0 (or 4). Controls include age, experience, and prior successes. Standard errors (in parentheses) are clustered at the athlete level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.