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Abstract

Does information processing affect individual risk-taking behavior? In this paper, we provide 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, resulting in increased risk-taking behavior. For the estimation of causal effects, we exploit the fact that tiny time differences can be attributed to random shocks. We link our findings to prior research in psychology and economics, suggesting that different ways of information processing can explain our results. In contrast to recent studies in the field of behavioral economics, we then argue that high stakes and individual experience can magnify behavioral biases.

Keywords

Risk Taking, Limited Attention, Left-Digit Bias.

JEL Classification

D03, D81, D83, L83.

1 Introduction

Individuals often have to make decisions under uncertainty that involve risk-return trade-offs. While traditional economic models assume perfect information processing and foresight, a large body of research in behavioral economics documents limits to individual cognitive abilities (DellaVigna, 2009). The literature has focused in particular on the question how limited attention affects consumption choices and has provided evidence for a left-digit bias, the empirical regularity that people tend to focus on the leftmost digit of a number and pay only partial attention to other digits (Korvorst and Damian, 2008; Lacetera, Pope and Sydnor, 2012). Despite this empirical evidence, three challenges remain. First, estimating causal effects of a left-digit bias is difficult due to bunching of data. Furthermore, it remains unclear whether limited attention also influences the process of individual decision making with respect to risk taking. Finally, there is an ongoing discussion whether individual experience or high stakes mitigate behavioral biases.[1]

In this paper, we propose a new approach to address these three challenges by estimating the impact of behavioral biases on risk-taking in a setting with professional and experienced athletes in fierce competition. We investigate empirically 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 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 behavioral 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 than if it is large. In the empirical part, we apply a regression discontinuity

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

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 behavior, which increases the probability of not successfully finishing the race by up to 28.5%. Moreover, the standard deviation of race times in the second run increases by about 26.1%. The estimated effect is robust to using different bandwidths and to the inclusion of race-fixed effects. To account for genetic determinants of risk-taking behavior, 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 to the leader after the first run, thus having 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 behavior. 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 behavioral bias does not disappear when restricting the sample to older, more experienced athletes. On the contrary, the adoption of risky behavior is large and significant among athletes aged 25 and older. Furthermore, the left-digit bias is also present in races with particularly high stakes.

In order 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 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.

Our results contribute to a number of studies in psychology and economics. In particular, the observation of a persistent behavioral 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 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. The very high stakes in World Cup competitions cause athletes to exert extreme effort during the race, making them vulnerable to behavioral biases afterwards. The aforementioned placebo tests reveal that it is the very information provided to athletes that shapes their behavior. Neither time differences expressed in minutes nor the time gap to the second or third contestant is correlated with second-run behavior. 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 behavioral 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 behavior. Our findings are closely related to the work by Lacetera, Pope and Sydnor (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 cutoffs. 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 behavioral biases can be amplified by high stakes and individual experience. Third, our results show that limited attention affects risk-taking behavior 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, Hossain and Morgan, 2010). The importance of heuristic thinking appears to be much larger if it can be documented even in settings where information is readily available. Again, we provide a psychological rationale for the persistence of behavioral biases in our setting.

Finally, our findings also contribute to a growing literature on the heterogeneity of risk-taking behavior across individuals. Understanding the determinants of risk preferences is particularly important because the assumptions about individual risk behavior 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, Cronqvist and Siegel, 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 behavior under uncertainty.

The paper proceeds as follows. In Section 2, we illustrate how limited attention can generate discontinuities in risk behavior among professional athletes. Section 3 presents some general information on World Cup alpine skiing and descriptive statistics on our data set. Section 4 provides a description of our econometric approach. In Section 5, we show the main empirical findings, discuss effect heterogeneity, provide a psychological explanation and numerous robustness checks. Finally, Section 6 concludes.

2 Theoretical Considerations

2.1 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 emphasizes 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, O'Donoghue and Vogelsang (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, Schwartzstein and Shleifer, 2008). Chetty, Looney and Kroft (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, Pope and Sydnor (2012) as well as Busse et al. (2013) advance this work by showing that

[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.

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

2.2 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 behavior 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 only two elements: winning the race and not finishing the race, both of which occur with certain probability depending on an athlete's risk choice in the second lap. To illustrate this as simple as possible we assume that the athlete cares only about winning. We normalize the direct utility of a victory to one and the direct utility of finishing behind or not finishing the race at all to zero.

We consider the decision problem of an athlete i who trails the leader $j = 1$ after the first run. Athlete i is endowed with talent ξ_i, incurred a distance d_i in the first run and chooses which level of risk r_i to take in the second run. More talent increases the chance of finishing the race $\phi(\cdot)$, taking more risk decreases it. If she takes more risk r_i, the probability $\phi(r_i)$ to finish the race decreases, $\phi' < 0$. Since we are free to choose the unit of measurement of the risk variable, we may assume that taking risk reduces the distance d_i the racer had after the first run. Hence, the chance to finishing the race is given by $\pi(d_i - r_i - (0 - r_j))$, where 0 denotes, trivially, the distance of the leader $j = 1$ and r_j the risk chosen by the leader to herself. Athlete i takes the risk decision of the leader as given. Distance is negatively related to talent but randomly the distance may be higher or lower than predicted by talent alone, thus $d_i = \delta(\xi_i, \varepsilon)$ with $\delta_\xi < 0$ and $\delta_\varepsilon > 0$, while $E(\varepsilon) = 0$. In Figure A.8 in the Appendix, 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. For our theoretical model we further assume that the marginal winning probability is concave, hence we assume $\pi' < 0$, $\pi'' > 0$ and $\pi''' < 0$ for positive arguments.

These arguments let us write the utility function in the following way (we omit the talent variable ξ in what follows)

$$U(r_i) = \phi(r_i) \times \pi(d_i - r_i). \tag{1}$$

We use this cost-benefit framework to investigate the implications of a particular behavioral bias: the left-digit bias. Drawing on work by Lacetera, Pope and Sydnor (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_i 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 $d \equiv (T_i - T_1)$. This distance can be broken down into two parts. The first part, $d_{i,l}$, indicates the number of tenths of a second in the distance (i.e., the left digit). The second part, $mod(T_i - T_1, 10)$, 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 and a modulo of 9. We can express the *perceived* distance $\hat{d}_i$ as

$$\hat{d}_i = d_{i,l}10 + (1 - \theta) \times mod(T_i - T_1, 10), \tag{2}$$

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

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

[4] Note that the estimated winning probability in Figure A.8 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.

hundredths of a second. As long as d_i is below that threshold, the athlete will perceive a change of $(1-\theta)$ for every one-unit increase in d_i. 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 1 about here —

The biased perception of distances is illustrated by the step function in the lower half of Figure 1. 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 increased probability of winning when taking more risk $-\pi'(d_i - r_i + r_1)$ (holding r_i and r_1 fixed). While the actual probability gain $-\pi'\ (d_i - r_i + r_1)$ is a smooth downward sloping function, the *perceived* probability gain $-\pi'(\hat{d}_i - r_i + r_1)$ is again a step function. The important observation is that to the left of each tenths-of-a-second threshold it holds that $d_i > \hat{d}_i$. And because the winning probability is a negative function of the distance to the leader, it also holds that $-\pi'(d_i - r_i + r_1) < -\pi'(\hat{d}_i - r_i + r_1)$ to the left of each threshold.

While taking the actions of the leader as given, the perceived first order condition of the athlete reads

$$\hat{U}'(r_i) = \phi'(r_i)\pi(d_i - r_i + r_1) - \phi(r_i)\pi'(\hat{d}_i - r_i + r_1) =: 0, \tag{3}$$

which is equal to zero in the optimum. The first term $\phi'(r_i)\pi(d_i - r_i + r_1)$ is the cost of taking additional risk while the second term, $-\phi(r_i)\pi'(\hat{d}_i - r_i + r_1)$, is positive and captures the increased probability to win when the athlete follows a riskier strategy. We assume that the biased distance results in an excessive estimate of the increased chance of winning when taking additional risk while we assume the athlete does not take into account that the actual winning probability is also higher since $\hat{d}_i < d_i$. Hence, the biased distance d_i only appears in the second term of equation (3).[5] Note that the presence of a left-digit bias ($\theta > 0$) causes $\hat{d}_i$ to be smaller than d_i. The following proposition states that a reduced value of $\hat{d}_i$, through the left-digit bias, increases risk taking.

[5]If the athlete takes the perceived higher cost of risk taking into account, the statement in Proposition 1 still holds whenever $\pi(d_i - r_i + r_1)$ is convex enough such that the hazard rate is increasing when you are closer to the leader, i.e., we need π'/π decreasing when $d - r$ grows larger.

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 leads to an increased probability of not finishing the second run.*

Proof. Whenever $\hat{d}_i < d_i$, we have $-\phi(r_i)\pi'(\hat{d}_i - r_i + r_1) > -\phi(r_i)\pi'(d_i - r_i + r_1)$, since $-\pi'(\cdot)$ is a decreasing function. Thus, $\hat{U}'(r_i, \hat{d}_i) > \hat{U}'(r_i, d_i)$. Denote the optimal risk choice by r_i^*. Therefore, $r_i^*(\hat{d}_i) > r_i^*(d_i)$, because $\hat{U}''(r_i^*) < 0$ in the optimum. □

The model also predicts that this effect of a left-digit bias fades away as the distance to the leader becomes larger. Athletes toward the end of the classification have a very low probability of winning and the misperception of the increased probability to win is much lower, as π'' becomes smaller in absolute terms when the distance becomes larger (see Figure 2). This effect makes the change in risk taking smaller as well.

Proposition 2. *The importance of the left-digit bias decreases in the distance to the leader of the opening run.*

Proof. Using the proof of Proposition 1, the difference in perceived and actual winning probabilities equals in first order Taylor approximation, $-\phi(r_i)\pi'(\hat{d}_i - r_i + r_1) - [-\phi(r_i)\pi'(d_i - r_i + r_1)] \approx -\phi(r_i)\pi''(d_i - r_i + r_1)(\hat{d}_i - d_i)$. Since $\pi''' < 0$, $\pi''(d_i - r_i + r_1)$ decreases when the distance d_i rises. Furthermore higher distance d_i is correlated with lower talent ξ_i, this lowers $\phi(r_i)$. Both effects go in the same direction. □

Our model can also be used to infer predictions on the leader's behavior if we extend the winning probability function $\pi(\cdot)$. We assume that $\pi(\cdot)$ becomes eventually concave for negative arguments. In that case, we get an equivalent prediction as in Proposition 1 for the leader after the opening run. Her winning probability equals $\pi(-(d_i - r_i) - r_1)$, where $\pi(\cdot)$ is the same function as above. Assuming the leader suffers from the left-digit bias as well, she perceives the distance of the follower being too low, $\hat{d}_i - d_i$. Using the same argument as in the proof of Proposition 2, the first order condition of the leader reads $\hat{U}'(r_1) = \phi'(r_1)\pi(-(d_i - r_i) - r_1) - \phi(r_i)\pi'(-(\hat{d}_i - r_i) - r_1) =: 0$, the difference in perceived and actual winning probabilities equals in first order Taylor approximation, $-\phi(r_1)\pi'(-\hat{d}_i + r_i - r_1) - [-\phi(r_i)\pi'(-d_i + r_i - r_1] \approx -\phi(r_i)\pi''(-d_i + r_i - r_1)(\hat{d}_i - d_i) > 0$, whenever $\pi'' < 0$.

Finally, when talent (ξ) strongly affects the survival probability (ϕ), the model states that, on average, the probability of finishing the race decreases with the distance after the opening run. Using our data set we can confirm this prediction: athletes with a larger distance to the leader are more likely not to finish the second run. The more important theoretical prediction, however, is that the probability of not finishing the race exhibits an upward jump at the discontinuity points of the $\hat{d}(d)$ function. Testing this prediction is the purpose of Sections 4 and 5.

3 Data

3.1 World Cup Alpine Skiing

The first alpine skiing races were organized 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 behavior. 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 role for individual performance as well.[6] 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.

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

3.2 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 (2013). 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 five percent, and have an average time distance to the leader of 2.02 seconds.

Figure 2 depicts the success of athletes by their rank after the first run.

— Figure 2 about here —

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.

4 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 behavior 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.[7]

— 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

$$S_{i,j} = \begin{cases} 1 & \text{if athlete } i \text{ successfully finished race } j \\ 0 & \text{if athlete } i \text{ did not successfully finish race } j. \end{cases} \tag{4}$$

Based on our considerations in Section 2, 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 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.[8]

[7]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).

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

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 τ, by fitting the linear regression

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

where $D[\mathrm{mod}(T_{i,j} - T_{1,j}, 10) = 9]$ 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, $\mathbf{X}_{i,j}$ captures individual characteristics (i.e., age, experience, prior successes), and $\varepsilon_{i,j}$ is the standard error term which we cluster at the athlete level.[9] 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 (5) 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

[9]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.

polynomial does not affect our estimates.[10]

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.[11] 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 3, 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 shown 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 behavior 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 the precision of the estimation (Frölich, 2007). For a comparison, we report results both with and without using control variables.

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[10] 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). We provide visual fits with different polynomials in Figure 4.

[11] 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).

5 Results

5.1 Main Effects

In our main analysis, we test proposition 1 that predicts that athletes change their behavior 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 percent 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 percent (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.[12]

According to proposition 2, we should observe a left-digit bias to have larger effects among athletes close to the leader of the opening run because the relative over-estimation of the winning probability is higher in this sample. 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.[13]

— Figure 5 about here —

The results in Figure 5 demonstrate that the treatment effect is significant only among athletes in close distance to the victory. Once we drop athletes with low winning probabilities, the treatment effect is no longer significantly different from zero.

5.2 Left-Digit Bias in Tournaments

The setting of World Cup alpine skiing is characterized 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 behavioral 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

[12]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, Cronqvist and Siegel (2010) find that up to one third of the variance in stock market participation and asset allocation can be attributed to genetic factors.

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

to those mental activities which demand it because of their complexity.[14] In our setting of World Cup alpine skiing, the athlete's System 1 is used to recognize 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 behavioral 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 all the time.[15] 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 behavioral biases in the context of large stakes.

High Stakes and Behavioral 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 behavioral 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

[14] 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 recognizes that the person in the picture is angry. It takes no effort to recognize 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.

[15] 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."

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.

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 behavior, we first split our data by the prize money for the winner. In Table 4 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 percent more likely not to finish the second run.

— Table 4 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 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 behavioral 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 Behavioral Biases. — Many behavioral 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 behavioral 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.[16] We investigate this relationship between the left-digit bias and athletes' experience. The median athlete has about 60 World Cup races of experience.[17] 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 behavioral bias does not vanish. In columns 4 and 5 of Table 4 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 behavioral bias in our setting. 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 can actually magnify the bias. Having participated in numerous races renders looking at the classification and time distances into a routine task. Thus experienced athletes tend to rely more on System 1 when dealing with time distances. System 1, however, is prone to making mistakes.

[16] In a subsequent study, List (2011) randomizes 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.

[17] Figure A.6 in the appendix plots the distribution of experience.

Overall, we find that large stakes, competition and experience do not eliminate behavioral biases. First, experience does not improve the functioning of System 1 where the bias occurs. Moreover, experience renders looking at the classification and time distances into a routine task. Thus, athletes tend to rely more on System 1 if they are experienced. This magnifies the left-digit bias. 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, high stakes can magnify—rather than minimize—behavioral biases. They increase pressure and lead to ego-depletion. As a result, professionals do not get it right. Because of their experience, they rely on mechanisms like heuristic thinking that have been shown to lead to inefficient decisions. The presence of high stakes and competition can increase this behavioral bias.

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.

5.3 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 behavior. 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 behavior than athletes in the control group. In a second step, we add athlete-fixed effects to our baseline regression.[18] 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 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).[19] There are good reasons to assume that

[18]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.

[19]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.

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 5 show no evidence of a left-digit bias concerning the time distance to other ranks.

— Table 5 about here —

It seems to be the very information about the distance to the leader that drives risk behavior in the second run. We can refer to our explanations in Section 5.2 to understand this zero result. Each athlete uses System 1 when dealing with the easily observable time distance to 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 behavioral biases such as heuristic thinking.

Information Availability. — We can test whether the availability of information is crucial for the behavioral 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 5 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.

In addition to the time difference to the leader, each athlete is provided with the classification after the opening run. As shown in Figure A.7, this table includes each racer's time. 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 second measure of 54 while the third one's time begins with 55.[20] We can test whether athletes misinterpret time differences because of a left-digit bias with respect to the time (not time difference) of the opening run.

Results shown in Table B.8 of 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. 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.[21] 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 5 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

[20]We provide a detailed description of the different treatment variables in Table B.7 in the Appendix.

[21]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.

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 2, we should find a discontinuity at the 4-5 cutoff. This, however, is not confirmed by the estimation result shown in Table 5.

5.4 Left-Digit Bias and Individual Success

The analysis thus far has shown that the left digit in an athlete's time distance to the leader affects her subsequent risk behavior, measured as the probability of not finishing the race. However, it remains unclear whether the left digit also affects individual race times or the 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 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 6 about here —

To examine the effects of left digits on the set of finishers, we perform five separate tests reported in Table 6. 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 standardized 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 standardization 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 behavior 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.

Effect on the Leader. — There is a second explanation why we find no effect of left digits on the probability of victory. Throughout our analysis, we focus on athletes ranked second or worse after the opening run. In particular, we test whether there is evidence of a left-digit bias in the way they process information. We can also test for heuristic thinking among the leaders of the opening run. In each race, the leader will choose the amount of risk for the second run based on how close her contestants are after the first run. In the presence of a left-digit bias, the leader will perceive a second-ranked athlete with a distance of nine hundredths of a second to be much closer than an athlete with a distance of one tenth of a second. As a result, we expect the leader to 'push it to the limit' if her contestants are *perceived* to be very close. Using the same approach as in our main analysis, we find evidence for a left-digit bias among leaders. If the second-ranked athlete has a low left-digit in her time gap, the leader is about four percentage points more likely not to finish the second run.[22] Given the fact that we can use data on only 792 races, the relatively small sample of 312 observations employed in this exercise causes the effect to be only significant at the ten percent level.

The observation that the leader of a World Cup race also exhibits a left-digit bias can help understand why we do not observe a significant effect on the probability of victory in Table 6.

[22]Technically, we consider the leader to be treated if the athlete ranked second after the opening run has a right digit of 8 or 9 in her distance to the leader. The control group consists of leaders whose second-ranked contestants have a right digit of 0 or 1 in their time distance. We run OLS regressions with and without control variables as we do in our main analysis. The point estimates are given by -0.035 and -0.036 with t-values of -1.66 in both cases.

Consider a situation in which the second-ranked athlete after the opening run trails the leader by, for example, nine hundredths of a second. Both athletes receive the signal about the time difference and underestimate it due to a left-digit bias. The leader does not want to lose the lead while the second-ranked athlete does not want to forfeit the opportunity to win the race. As a result, both choose a risky strategy for the second run. We observe that survival rates drop for both athletes. And since sometimes the leader, sometimes the second does not finish the race, we do not find a significant correlation between the low left-digit of the second and the probability of victory for the athletes not leading after the opening run.

6 Conclusion

This paper investigates the effects of heuristic information processing and left-digit biases on risk-taking behavior 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 thirty percent 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. If anything, these differences are even larger among experienced athletes and in races with large prize money. 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 behavior that is crucial for many economic questions. Limited attention is likely to affect our everyday risk behavior. 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 behavioral 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 behavior under the two regimes can differ substantially. These and other aspects of limited attention are left to future research.

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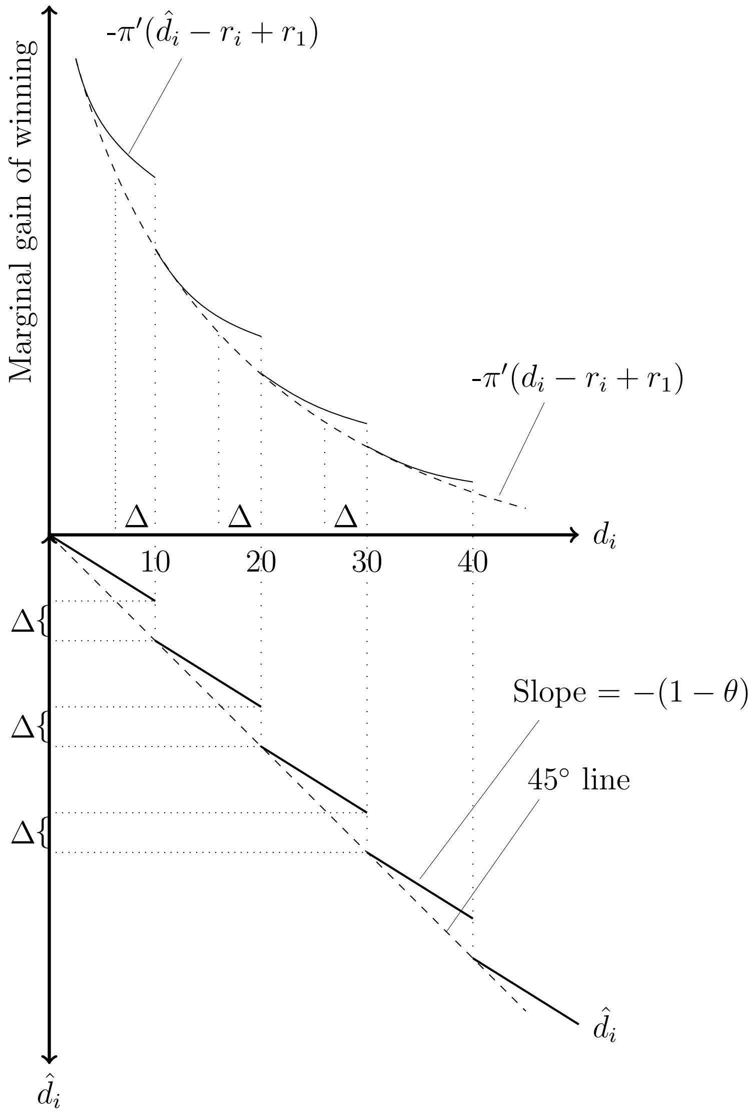
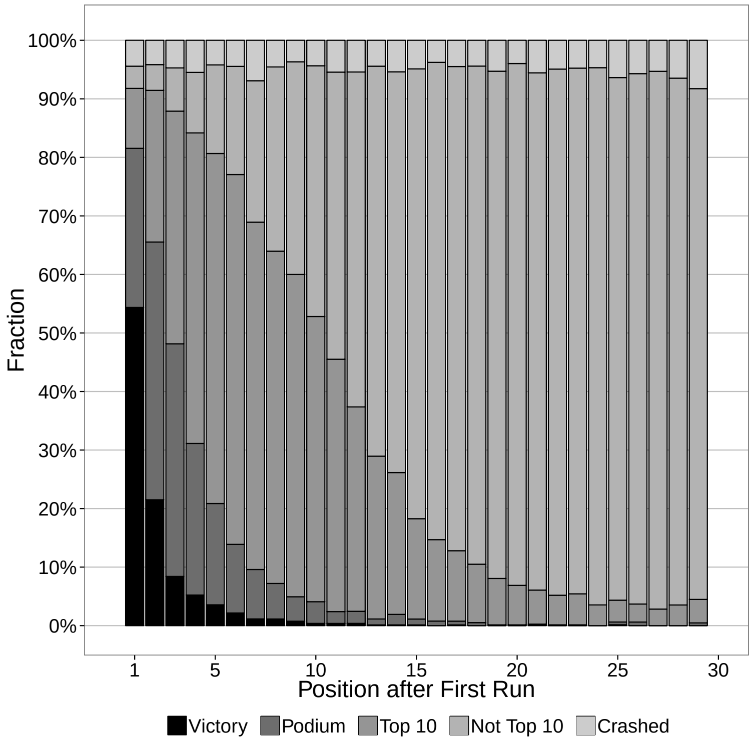
Figures and Tables

Figure 1: Distance, Perceived Distance, and Probability of Survival



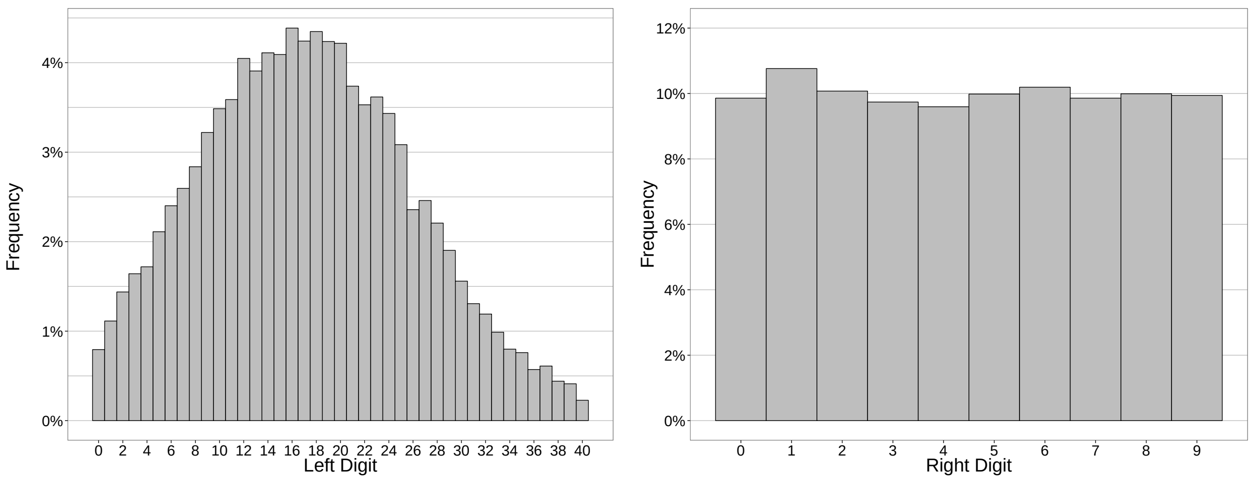
Note: The upper half of the figure illustrates how the discontinuity in the perceived distance $\hat{d}_i$ causes a discontinuity in the marginal gain of winning $-\pi'(\hat{d}_i - r_i + r_1)$. In lower half we show the discontinuities between actual distance d_i and perceived distance $\hat{d}_i$.

Figure 2: Relationship between Final Position and Position after First Run



Note: The figure shows the final race position for every position after the first run. The first bar (black) is the fraction of athletes who won the race. The second bar is the fraction of athletes who finished on the podium (but did not win the race). The third bar is the fraction of athletes who made it into the top ten (but not on the podium). The fourth bar is the fraction of athletes who are outside of the top ten. The fifth bar (light gray) is the fraction of athletes who did not finish the race.

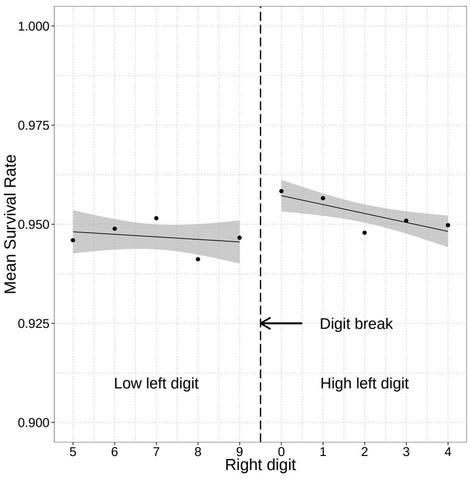
Figure 3: Histogram of of Left- and Right-Digits



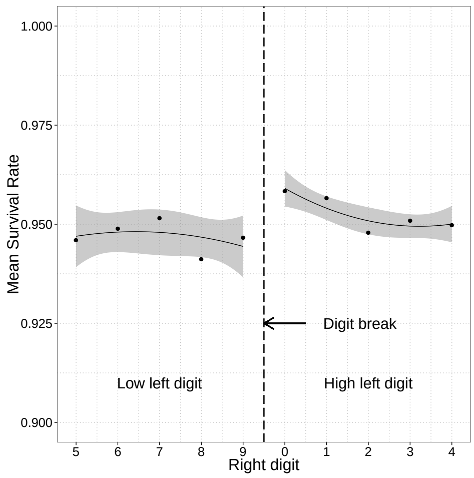
Note: The figure shows two histograms of the time difference to the leader after the first run. Panel (a) depicts the left-digit of a athlete's time difference to the leader of the first run, while panel (b) depicts the right-digit of the time difference to the leader of the first run.

Figure 4: Survival Rate by Right-Digit

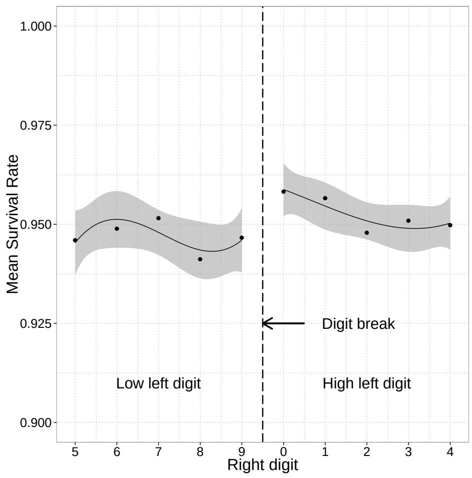
(a) Linear Fit



(b) Quadratic Fit

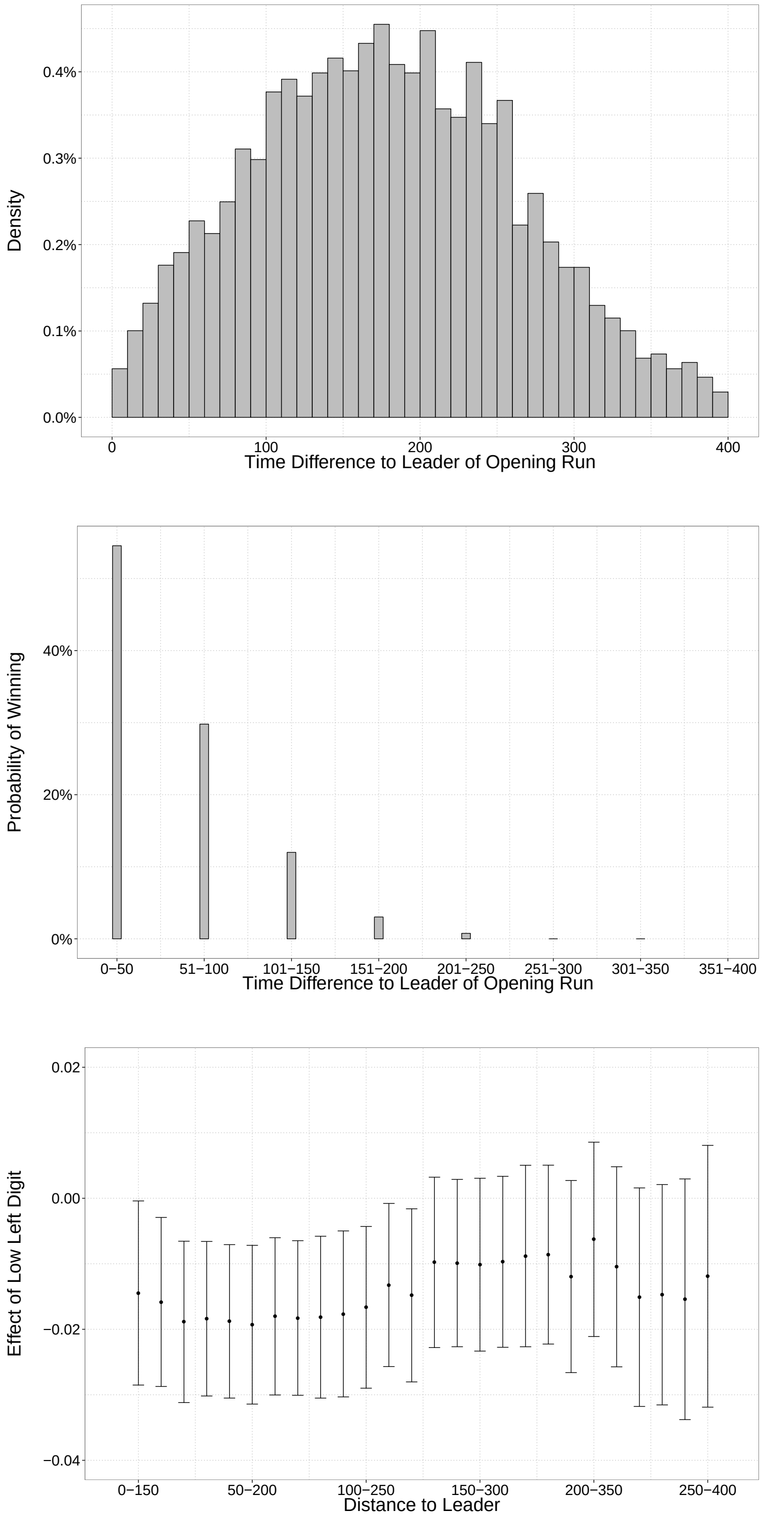


(c) Cubic Fit



Note: The figure plots the average survival rates for every right digit using a linear specification (Panel a), quadratic terms (Panel b), and cubic terms (Panel c). Each average survival rate is separately calculated for the group of individuals with right digits ranging from five to nine and for those with right digits ranging from zero to four. 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. Confidence intervals at the 90 percent level are shown.

Figure 5: Treatment Effect by Distance to Leader



Note: The top figure shows the distribution of time differences to the leader after the opening run. In the middle, we show the probability of victory by an athlete's distance to the leader after the first run. Note that the leaders themselves are included in the first bar. In the lower figure, the estimated treatment effect for samples restricted by the distance to the leader is plotted. Confidence intervals at the 95 percent 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	8,478	0.95	0.22	0	1	13,227
Distance to leader of first run	222.01	536.99	1	8,160	8,478	202.06	481.09	0	8,203	13,227
Position after first run	14.92	7.89	2	30	8,478	14.19	8.42	1	30	13,227
Final Position	13.46	8.05	0	31	8,478	12.88	8.32	0	31	13,227
Age	25.74	3.68	16.89	37.64	8,478	25.83	3.66	15.82	37.65	13,227
Male	0.5	0.5	0	1	8,478	0.51	0.5	0	1	13,227
Experience	36.72	26.49	1	152	8,478	37.3	26.31	1	155	13,227
No. podiums at time of race	7.46	14.47	0	101	8,478	8.14	14.75	0	110	13,227
No. victories at time of race	2.57	6.12	0	58	8,478	2.88	6.25	0	53	13,227

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. 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	26.18	26.20	-0.02	0.84
Male	1.50	1.50	-0.00	0.93
Experience	36.58	36.86	-0.28	0.62
B: Risk Preferences				
Average Survival	0.96	0.96	-0.00	0.33
Survival in Last Race	0.96	0.96	0.00	0.29
C: Overconfidence				
Athlete's No. of Victories	2.57	2.56	0.01	0.94
Athlete's No. of Podiums	7.46	7.46	0.00	0.99
D: Athlete Skill				
Victories in Career	5.71	5.32	0.38	0.20
Podiums in Career	16.14	15.43	0.71	0.22
E: Competition				
Total Podiums in Top 5	73.20	72.90	0.30	0.77
Total Victories in Top 5	27.40	27.19	0.21	0.61
Total Podiums in Top 10	118.73	118.65	0.09	0.95
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

Note: The table shows mean comparisons (t-tests) for all relevant pre-treatment variables. 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 is the indicator for successfully finishing in 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 of athletes who are leading (lagging) by 10 hundredths of a second after the first run. We apply the wide bandwidth for the treatment. Results are qualitatively similar when using the narrow bandwidth.

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***	-0.015***
	(0.004)	(0.004)	(0.005)	(0.005)
Change in Probability of not Surviving	-28.5%	-28.5%	-26.4%	-30.5%
Observations	8,482	8,401	8,401	8,080
R-squared	0.001	0.007	0.149	0.005
B: Narrow Bandwidth				
Low Left-Digit	-0.011*	-0.012*	-0.010	-0.012*
	(0.006)	(0.006)	(0.007)	(0.007)
Change in Probability of not Surviving	-22.4%	-24.4%	-20.3%	-24.4%
Observations	4,141	4,105	4,105	3,953
R-squared	0.006	0.009	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 digit 8 or 9 on the probability of survival. In Panel B, we estimate perform the same regression using the narrow bandwidth. 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 two observations in the estimation sample. 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 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	-0.014***	-0.015***	-0.052**	-0.014**	-0.016***
	(0.004)	(0.005)	(0.022)	(0.006)	(0.005)
Change in Prob. of not Surviving	-28.5%	-30.5%	-105.9%	-28.5%	-32.6%
Observations	8,401	7,374	475	4,716	6,164
R-squared	0.005	0.013	0.046	0.002	0.011
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. 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 ten percent (or less) of the races have been completed. In column (4) we only consider athletes with above-median age (25 years of age), 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 5: 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)	(0.008)
Change in Prob. of not Surviving	-4.1%	0.0%	-2.0%	-8.2%
Observations	3,938	6,907	4,282	4,062
R-squared	0.002	0.001	0.005	0.005
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. 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 ***.

Table 6: Effect on Probability of Winning and Time in Second Run

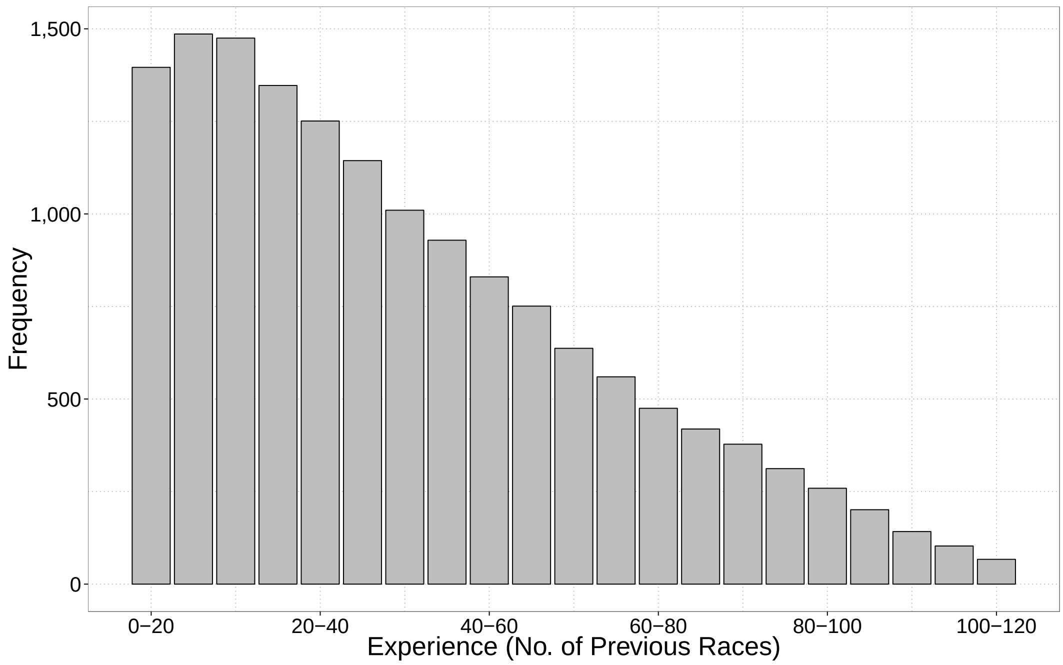
	Mean			Standard Deviation	
	Probability of Winning	Time 2nd Run Measure 1	Time 2nd Run Measure 2	Time 2nd Run Measure 1	Time 2nd Run Measure 2
High Left Digit	0.019	1.017	1.024	0.023	0.022
Low Left Digit	0.015	1.018	1.025	0.029	0.028
Difference	-0.004	0.001	0.001	0.005	0.006
P-value	0.169	0.246	0.264	0.000	0.000

Note: The table shows the results of five different test between treatment and control group. The first three columns report the results of a t-test for equal means for the variables probability of winning the race, time in the second run scaled by the time of the subsequent winner, and time in the second run scaled by the time of the best second run athlete. The fourth and fifth column report the results from a variance-comparison tests for the two time measures, namely individual race time in the second run scaled by the time of the subsequent winner and individual race time in the second run scaled by the time of the best second run athlete.

Appendix

A Additional Figures

Figure A.6: Distribution of Athlete Experience



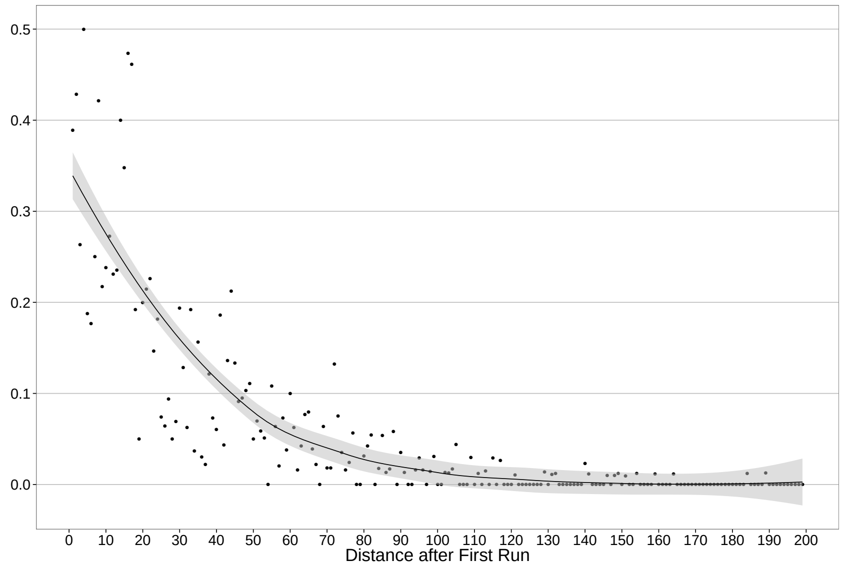
Note: The figure plots the distribution of athlete experience. We count each completed race within the slalom and giant slalom discipline as one experience. The median of the distribution is 17. Across disciplines, the distribution has a similar shape with a median of about 60 races.

Figure A.7: Example of FIS World Cup Results Table

Rank	Bib	FIS Code	Name	Year of Birth	NSA	Time	Diff.	Ski
1	2	491879	SALARICH Joaquim	1994	SPA	55.44		
2	6	481103	ANDRIENKO Aleksander	1990	RUS	56.67	1.23	Rossignol
3	10	30149	SIMARI BIRKNER C.	1980	ARG	56.80	1.36	
4	17	430429	BYDLINSKI Maciej	1988	POL	56.99	1.55	Atomic
5	13	40594	PERAUDO Ross	1992	AUS	57.11	1.67	
6	16	320293	KYUNG Sung-hyun	1990	KOR	57.12	1.68	Salomon
7	21	30266	GASTALDI Sebastiano	1991	ARG	57.24	1.80	Rossignol
7	12	92562	PRISADOV Stefan	1990	BUL	57.24	1.80	Fischer
9	34	221213	RAPOSO Charlie	1996	GBR	57.34	1.90	
10	50	400237	MEINERS Maarten	1992	NED	57.36	1.92	Rossignol

Note: The figure shows an example of how the FIS plots the results of an opening slalom run. The important performance measures for our analysis are shown in column 7 (“Time”) and 8 (“Diff.”).
Source: http://data.fis-ski.com/pdf/2015/AL/0219/2015AL0219RLR1.pdf

Figure A.8: Winning Probability by Distance



Note: The figure shows 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.

B Additional Tables

Table B.7: Generic Results and Treatment Variables

Rank	Name	Time	Distance	Low Left-Digit Narrow BW	Low Left-Digit Wide BW	Same Full Second
1	A	54.91	-	-	-	-
2	B	54.98	0.07	-	-	T
3	C	54.99	0.08	-	T	T
4	D	55.00	0.09	T	T	C
5	E	55.01	0.10	C	C	C
6	F	55.02	0.11	-	C	C

Note: The table shows a generic result after an opening run as well as the three different treatment variables used in the analysis. Being part of the treatment group is denoted by a 'T', while the control group is denoted by 'C'.

Table B.7 shows a generic result for an opening run of a slalom race. All six contestants shown have a very similar performance with athletes B to E trailing the leader by up to 0.11 seconds. The first treatment variable ('Low Left-Digit, Narrow BW') is based on the time distance to the leader. In particular the *right* digit in the time distance determines the treatment status. If the right digit is 9, the athlete is part of the treatment group. In contrast, any athlete with a right digit of 0 is part of the control group. In a similar vein, the second treatment variable ('Low Left-Digit, Wide BW') is defined. The only difference is that the wide bandwidth includes right digits 8 for the treatment and 1 for the control group.

The definition of the third treatment variable is based on each athlete's time (shown in column 3). Any athlete whose time distance to the leader is less than 0.3 seconds is either part of the treatment or control group. To be considered as treated, an athlete must have the same full second count as the leader. In the example above, athletes B and C have a time of 54 seconds plus some hundredths of a second. In contrast, athletes D, E and F have a time that begins with 55. Hence, the former define the treatment and the latter the control group.

Table B.8: Left-Digit Bias in Opening Run Time

	Dependent variable = 1 if athlete finished the race			
	Logit Estimation		OLS Estimation	
	(1)	(2)	(3)	(4)
Same Full Seconds in Opening Run	-0.033*** (0.009)	-0.041*** (0.011)	-0.022 (0.052)	-0.036*** (0.011)
Change in Probability of not Surviving	-67.1%	-83.4%	-44.7%	-73.2%
Observations	691	686	686	684
R-squared	0.006	0.021	0.717	0.024
Controls	-	Yes	Yes	Yes
Fixed Effects	-	-	Race	Athlete

Note: The table shows the results of four separate regressions. We estimate the effect of having the same number of full seconds as the leader of the opening run on survival in the second run. Treated athletes have the same full seconds and trail the leader by less than 0.3 seconds while the control group has a different full second (but still lagging 0.3 seconds at most). Controls include age, experience, and prior successes. Columns 1 and 2 report marginal effects while columns 3-5 show OLS estimates. When applying athlete fixed effects, the sample is reduced to athletes with at least two observations in the estimation sample. 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 ***.