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Abstract

Rankings have become increasingly important over the past decades and impose a sharp distinction between success and failure. In this paper we examine the effects of ranking positions and great successes on individual performance by using a rich set of data on World Cup alpine ski races for the period of 1992-2013. We apply a regression discontinuity design and exploit close races as a source of quasi-randomized treatment. Our results suggest substantial short-run effects of podium finishes on performance, especially for racers in the middle of the skill distribution. However, the effects are short-lived and mostly driven by individuals who miss prestigious ranks by a tiny margin. We identify media attention as the key channel for performance effects and provide empirical evidence for an increasing media bias in favor of top-ranked competitors in the last two decades. These findings highlight a serious drawback of rankings.

Keywords

Performance, Success, Rankings, Media Attention, Skiing.

JEL Classification

D03, L83, M50.

1 Introduction

"Success is not final, failure is not fatal."

— Don Shula

Striving for success is a key driver of human behavior and a major source of economic activity. Typically, differences in performance explain who is successful and wins prizes, achieves goals, or reaches high positions in a ranking. Yet it is unclear whether there exists a feedback mechanism and success itself has an impact on subsequent performance. Recently, numerous studies have demonstrated the importance of one-time successes with respect to long-term career achievements. First-job experience has been found to be important for managers' career paths (Cox and Harquail, 1991; Oyer, 2008), salary increases (Topel and Ward, 1992; Kahn, 2010), as well as sport athletes' prospects to get a contract as a professional (Rosen and Sanderson, 2001). It is also correlated with policy preferences (Giuliano and Spilimbergo, 2013) and economists' research productivity (Ginther and Kahn, 2004; Oyer, 2006; Hilmer and Hilmer, 2007).

When estimating the effect of great successes, however, previous research has suffered from a major identification problem. Success and ranking positions are not randomly assigned. Being successful is mostly the result of superior skills and effort. Therefore, the effect of great successes on individual performance is difficult to disentangle from the effect of higher skills and effort as they usually come hand in hand. Thus, it remains unclear whether there is indeed a causal effect of a one-time success on subsequent performance. Consider, for example, a university graduate who is selected for a high-profile job when she enters the labor market. If she follows a successful career afterwards, both the good initial placement as well as the high subsequent performance might be the result of unobserved individual characteristics. Several studies make use of instruments, such as graduation in a recession, to address this identification problem (Oyer, 2006; Kahn, 2010; Oreopoulos, von Wachter and Heisz, 2012). The underlying assumption, however, that the treatment—the state of the economy at the time when individuals enter the labor market—is assigned randomly seems to be questionable (Beffy, Fougère and Maurel, 2012; Hagedorn and Manovskii, 2013; Bianchi, 2013).

In this paper, we propose a novel empirical strategy to examine the impact of both one-time great successes and ranking positions at the individual level. We examine risk behavior and performance in the highly competitive field of World Cup alpine skiing and use close races as a quasi-random assignment of relative positions and success. In such races it is often a tiny margin—a few hundredths of a second—that determines whether a racer finishes first or second, third or fourth, or even sixth or tenth. Assuming small time differences to be random, we are able to test whether relative positions and one-time successes have an effect on racers' subsequent performance in the short and long run. In contrast to many other sports, skiing has the advantage that there is no direct interaction among racers and that small time differences resulting from random shocks, like wind and snow conditions, can manipulate ranking positions. Therefore, luck is more prevalent in skiing than in other sports such as, for example, golf (Connolly and Rendleman, 2008). Close races thus provide a natural experiment to estimate the effects of one-time successes and ranking positions using a regression discontinuity design (RD). The setting satisfies the key identification assumption: a smooth distribution of the assignment variable—the distance to a victory or podium finish—around the threshold. Moreover, manipulation is unlikely because every racer wants to be as fast as possible and does not know the cutoff in advance.

We use data on 2,755 athletes in all World Cup ski races for the period of 1992–2013 to estimate the impact of relative ranking positions and one-time great successes. Our analysis takes into account risk behavior, measured as the probability of finishing subsequent races, as well as the change in absolute and relative performance. In the first step, we find that both a podium finish and a victory have no significant effect on the probability of finishing the next race. This rejects the hypothesis that racers adopt a more risky strategy in case of being successful. Furthermore, it allows us to estimate the effect on performance without taking into account stratification problems due to attrition.

In our main analysis, we estimate the effect of one-time successes on subsequent performance. The results suggest a substantial treatment effect of achieving a podium finish in the short term, especially for racers in the middle of the skill distribution. Compared to the control group—those racers who just missed the podium—we estimate that achieving a podium finish in a close race improves performance in the next race by about 6–8 percent or 1–2 ranking positions. These findings are similar to other studies on the effects of one-time successes in the labor market (Altonji, Kahn and Speer, 2013). We document, however, that the effect is largely driven by a substantial drop in the performance of racers who miss the podium by a tiny margin. Also, the results show that the effect is short-lived and subsides after the first subsequent race. We investigate the potential explanations of the effect, focusing in particular on equipment change and media attention. While we find no change of equipment, our findings suggest that racers who finish on the podium are mentioned 88.2% percent more often in the newspapers after a close race. Since media attention is crucial for sponsorship contracts, being among the top-3 finishers is of high importance. Our analysis demonstrates that the gap between successful and unsuccessful racers in both subsequent performance and media attention has increased substantially in the past two decades. We conduct a series of robustness checks to assess the validity of our findings. First, all of the point estimates are not sensitive to using different bandwidths. Second, we show that there are no systematic differences between those who achieve a podium finish in a close race and those who just miss them. This implies that treatment is indeed assigned in a quasi-random manner. Third, we also apply additional checks by estimating models using placebo outcomes. Furthermore, we show that the documented performance effects are specific to the podium versus non-podium cutoff and not just an effect of a higher ranking position in general.

Our paper provides several novelties. First, there is little causal evidence on the question whether relative positions and great successes affect subsequent performance. Our study proposes a new methodological approach to explore these effects by using quasi-random successes. Second, to our knowledge, this paper is the first to provide evidence on the increasing importance of rankings. In an information-rich economy, media attention is a scarce resource (Falkinger, 2007, 2008). With increasing importance of sponsorship contracts in professional sports, being on the podium is crucial as it leads to substantially higher media attention. Finally, previous research has largely neglected the potential drawbacks of rankings.[1] Our empirical findings, however, suggest a substantial decrease in performance of those racers who miss prestigious ranking positions. From a policy perspective, this implies that one has to bear in mind that rankings may have negative consequences at the individual level even if their overall effect is positive (Azmat and Iriberri, 2010; Tran and Zeckhauser, 2012; Kuhnen and Tymula, 2012). These implications extend to a variety of areas because rankings are widely used when evaluating students' and workers' performances. Understanding the consequences of rankings on performance and risk behavior is crucial for optimizing organizations with heterogeneous individuals.

The paper proceeds as follows. Section 2 explains the concept of quasi-random successes and discusses their expected effects. Based on this, we describe our identification strategy. Section 3 presents general information on World Cup alpine skiing as well as descriptive statistics on our dataset. Section 4 provides the econometric findings, several robustness checks, and our interpretation of the results. Section 5 concludes.

2 Quasi-Random Successes, Behavior, and Performance

Previous research has shown that one-time successes have large short- and long-term performance consequences. This section surveys the relevant literature and provides information on the use of close races as an external source of variation in success. We then describe our econometric framework.

2.1 Literature Review

Success changes the way individuals think about themselves, their potential, and their targets. Most of the previous literature has described success as a signal that can influence future effort and motivation. In particular, it has been stressed that success increases self-confidence, leads to more ambitious goal setting, changes the self-image, and leads to more external support. Furthermore, several scholars have argued that success may contain an

[1] There is, however, a recent literature on the negative effects of information provision. Mas (2006) as well Card et al. (2012) document that knowledge about one's own relative position in a ranking (e.g. of incomes) may have a negative impact on individual performance.

addictive component.

A large body of literature has pointed out the benefits from a positive self-image that comes from being successful (Kahneman, Wakker and Sarin, 1997; Klaassen and Magnus, 2001; Santos-Pinto and Sobel, 2005; Santos-Pinto, 2008, 2010). Specifically, success may affect a subject's self-view and thus cause more ambitious goal setting behavior. Rachlin (2000) describes that successful self-regulation crucially depends on individuals' ability to learn about themselves coupled with the ability to keep track of their own action.[2] In this sense, individuals have been found to regard each decision as a possible precedent for future ones (Bénabou and Tirole, 2002, 2004). This way of thinking in sequences of choices might explain why a single great success can change future behavior. With each new evaluation (or ski race, as in our case) individuals learn more about their abilities, and consequently make choices in order to achieve or preserve favorable self-conceptions.[3] From an empirical standpoint, however, it remains unclear to what extent individuals actually adjust their goals. Camerer et al. (1997) and Farber (2005) have analyzed New York cab drivers' goal setting behavior and provide no conclusive evidence concerning the question whether car drivers set a fixed daily income target or adjust their labor supply according to past outcomes.

Our analysis also builds upon previous research on the effects of rankings and relative positions on performance. Early research in psychology has found relative positions to matter for individual well-being. The 'big fish in a small pond'-effect is based upon this concept and states that individuals' self-perception negatively depends on their peers' ability (Marsh and Parker, 1984). Subsequent studies have documented that the knowledge of relative positions also affects individual performance. Azmat and Iriberri (2010) find positive effects on performance when providing students with information on their relative rank. Tran and Zeckhauser (2012) show that Vietnamese students who receive information about their relative rank in an English course perform better than those who were not informed. Moreover, Kuhnen and Tymula (2012) show that the mere announcement of a relative ranking scheme has an effect

[2]Keeping track of one's own actions plays a key role in the context of skiing since athletes in general are usually better informed about their past (relative) performance than ordinary workers due to the extensive use of rankings and statistics in this field.

[3]As Bénabou and Tirole (2004) point out, this idea is prevalent in psychology and also well supported empirically. See for example experiments by Kirby and Guastello (2001) or Quattrone and Tversky (1984).

on workers' performance in solving math tasks. While these studies only consider the overall effect of rankings, our study focuses on the effect of rankings at the individual level.

Success also has a flip side because it is assigned to only a few individuals, while the others are not successful. The experimental literature in psychology has found that non-success can have detrimental effects on performance (Shrauger and Rosenberg, 1970; Dutton and Brown, 1997). The concept of "counterfactual thinking" offers a central explanation for these empirical findings and argues that people compare actual outcomes to what might have been. In a seminal study, Medvec, Madey and Gilovich (1995) show that Olympic bronze medalists tend to be happier than those who won silver. In this example, the most likely counterfactual outcome for the silver medalist is winning the gold medal, whereas for the bronze medalist it is being fourth and thus finishing the competition without a medal.

More recently, economists have turned their interest toward the consequences of non-success. The negative impact of disappointment on individual effort has been documented in a study by Mas (2006) using a sample of New Jersey police officers. In a similar vein, Card et al. (2012) report that informing people about their relative income leads to negative job satisfaction and higher search effort among workers who earn a below-median income—those individuals who are relatively less successful.[4]

2.2 Quasi-Random Successes in Alpine Skiing

In contrast to other fields of sport, World Cup alpine skiing offers a unique feature that allows us to determine 'quasi-random successes'. We illustrate this by a simple thought experiment. Assume there are only three variables that determine racer i's final race time, $T_{i,j}$, in a given race j: the time-invariant skill of racer i, denoted by θ_i, her training or fitness level, denoted by $\lambda_{i,j}$, and a noise parameter $n_{i,j}$ that captures all kinds of random shocks such as weather or snow conditions that can be heterogeneous or homogeneous across racers. This setting allows us to write the time of racer i in race j as a function of a her skill and training levels

[4]In many fields, the pros and cons of transparency (i.e. providing more public information) are debated: see Jin and Leslie (2003) for the effects on product quality, Dranove et al. (2003) and Pope (2009) for health care or Gavazza and Lizzeri (2007) for transparency in bureaucracies. Bouton and Kirchsteiger (2012) provide a theoretical discussion. The study by Morris and Shin (2002) also documents negative effects of information provision. They describe public information as a double-edged instrument which, on the one hand, conveys information, but also serves as focal points for the beliefs of a group as a whole.

as well as some random noise:

$$T_{i,j} := f(\theta_i, \lambda_{i,j}, n_{ij}). \tag{1}$$

Moreover, her position, $P_{i,j}$, is a function of her own time as well as her competitors' times:

$$P_{i,j} := g(T_{i,j}, T_{s,j}) = g(\theta_i, \lambda_{i,j}, n_{i,j}, \theta_s, \lambda_{s,j}, n_{s,j}) \qquad \forall s \neq i \tag{2}$$

By means of this equation, we can illustrate why quasi-random successes are possible. Usually, skill differences explain most of the variation in ranking positions. This does not, however, imply that ranking positions are entirely driven by skill levels. Figure 1 depicts a histogram of winners' and third-ranked racers' ranking positions in the previous race. The fact that 40.3% of current winners and 22.6% of current third-ranked racers achieved a podium in their past race documents positive serial correlation of our success measures. Yet the spread of the distribution reveals substantial variation in ranking positions. This challenges the idea that skill differences entirely determine ranking positions. In particular, if two racers have almost identical skill and training levels, random fluctuations in the noise term become critical. As we will show below, variations in $n_{i,j}$ can reduce racer i's race time sufficiently to overcome skill and training deficits. In this way, a less skilled racer can be lucky and draw a very low $n_{i,j}$ which enables her to achieve a better race time than a more skilled competitor.

For our estimation, the key identifying assumption is that this noise has sufficiently large effects on individual race times in order to randomly assign relative ranking positions in close races. In skiing, the individual noise term, $n_{i,j}$, comprises several components. First, alpine skiing is an outdoor event and thus wind and weather conditions vary significantly over the course of a single race. Most notably changes in snow, wind, and sight alter individual prospects of success and can also lead to cancellation if race conditions are considered to be a serious risk for the racers.[5] Yet, the mere presence of unstable external conditions does not lead to cancellation and is broadly accepted as a natural source of variation among competitors. The impact of random wind, weather, and snow conditions is amplified by the

[5] The following article about the performance of U.S. racer Bode Miller in 2009 illustrates the impact of wind. "Miller, a two-time overall World Cup winner, finished ninth Saturday as the Saslong downhill in Val Gardena, Italy, marked its 40th year. His performance was affected by a strong headwind that whipped up just as he and the other top contenders took the course." New York Times, 20. December 2009.

fact that individual race times critically depend on the performance in key sections of the course. An error in these sections not only leads to an immediate time loss but also affects speed, and thus time, in the following sections. In the Vancouver 2010 Olympics downhill race, for example, the Swiss racer Didier Cuche lost 0.30 seconds and fell back from second to sixth rank because of a minor mistake in the last ten seconds of the race.

Since our dataset covers twenty-two years of World Cup alpine ski races, we can provide empirical support for the presence of quasi-random successes. In 352 races, the time difference which determined whether or not a racer achieved a podium finish was less than five hundredths of a second. This tiny difference is much less than the *individual* variation in race times which can be estimated in different ways.[6] It may seem most appealing to use training data as a proxy for individual time variation. However, in training sessions racers usually follow a more risky strategy in key sections to find the optimal behavior. Moreover, they often do not finish the race track in the fastest possible way since they want to reduce the risk of crashing. Thus, we are forced to rely on other proxies for the individual variation in race times.

Our data include information on both the *average* time differences between two ranks as well as the individual variation of race times *per racer*. The average time distance between podium and fourth rank, for example, is 0.21 seconds. To assess the magnitude of this, we construct measures for the individual variation. Using the full sample, the average distance to the podium (across all races and racers) is 1.83 seconds. However, only the best racers compete for a World Cup podium finish and their individual variation in race times is considerably smaller. Thus we restrict the sample to all racers with at least one second-place finish in their careers and at least four race times at a given place. Using this restricted sample, the average distance to the podium (at a given race track) is 1.06 seconds. This is more than five times larger than the average time difference that determines the treatment. The numbers indicate that assignment to treatment often occurs according to time differences that are much smaller than individual time variation.

We can also support our identifying assumption by comparing the distributions of indi-

[6]By 'individual variation' we denote the counterfactual situation where the same racer slide down the same race track several times so that we can compute her variation in race times.

vidual and treatment-relevant time differences depicted in Figure 2. The first distribution (dotted line) captures the distances to the respective cutoffs which determine treatment, i.e. podium and victory. The second distribution (dashed line) shows the differences within winners and third-rank finishers, respectively. To compute this, we take the absolute difference between two race times: the time in the race when a racer finished on the podium or won a particular race and the next consecutive race time she achieved on the same course. Note that Figure 2 also depicts vertical lines for both the smallest and largest bandwidths we use for our estimation: 5 and 25 hundredths of a second. Even the larger one is fairly small compared to the time distances that assign the treatment.

This empirical evidence emphasizes the importance of race specific noise and supports our identifying assumption that a worsening of weather conditions or a small error can alter race times sufficiently to assign final ranking positions in a quasi-random manner. Alpine skiing thus provides a quasi-experimental setting with high stakes and fierce competition where, in close races, success is quasi-randomly assigned.

2.3 Econometric Framework

Success in Alpine Skiing can be divided into small and large prizes. The small prizes concern results of single races, while the large prize is based on the final ranking in a specific discipline and over all disciplines. There are two reasons why our analysis focuses on the small prizes. First, our source of randomness is present in single races and likely to even out over the whole season. This complicates the use of close races in the competition for the large prize. Second, we count on a limited amount of observations for the large prize because there are only 12 large prizes per season.[7] Single races reward mainly podium racers, and more specifically the winner of a race. This is reflected prize money and in substantially larger media attention. We mainly use podium finishes as a success treatment. In comparison with World Cup victories, this has a couple of advantages. On the one hand, we can draw on more observations, especially when using the smallest bandwidth. Furthermore, using RD for the effect of a quasi-random victory implies that almost all observations in the control group

[7]There is one large overall prize and five discipline-specific large prizes for both men and women.

finished on the podium and are therefore treated with success, although the treatment dose is lower. Thus, when using a victory as treatment, we only estimate the additional effect compared to a podium finish.

In a first step we examine whether quasi-random successes have an impact on subsequent risk behavior. The result for this outcome is important in itself but also has major implications for the estimation of the effect on performance, as we explain below. The role of risky behavior in tournaments has been examined in various studies, yet the evidence is not conclusive.[8] In our estimation, we test whether racers adopt a more risky strategy. Our data set contains detailed information about whether racers competed in a race and successfully finished.[9] We define survival in the subsequent race $j+1$ as

$$s_{i,j+1} = \begin{cases} 1 & \text{if successfully finished the race} \\ 0 & \text{if not successfully finished the race.} \end{cases} \tag{3}$$

Table B.7 in the appendix provide the estimates of the regression of survival in the next race on a quasi-random podium finish. All specifications include controls for competition and racer characteristics such as previous podiums and victories as well as experience and age. We use three bandwidths—5, 15, and 25 hundredths of a second—to check the robustness of our results. In all estimations of podium finishes on survival, we find no significant effect, irrespective of the bandwidth. These results support the view that one-time successes do not alter the probability of crashing in the subsequent races.[10]

This finding allows us to estimate the effect on performance without taking into account attrition bias by using a principal stratification framework (Frangakis and Rubin, 2002).

[8] In the context of our study, it is likely that racers change their behavior and perception of risk after quasi-random successes. Racers may misinterpret one-time quasi-random victories as signals of high ability. As a consequence, they might act too ambitiously in subsequent races, leading to an increase in the probability of crashes. Hoelzl and Rustichini (2005), for example, find in an experiment that overconfidence becomes important when monetary payments are at stake. Alternatively, individuals may feel the pressure to be very successful again—for reasons of external expectations or addiction to success—which could lead to sub-optimal behavior in the following races.

[9] Note that we only analyze racers who actually competed in the race following treatment.

[10] It may be that a more risky racing behavior does not lead to a crash but to significant time loss. Therefore, we estimate the effect of a one-time success on the variance of race times in the next three races as a alternative measure of risk behavior. The results are reported in columns 4 and 5 of Table B.7 in the appendix and suggest that the point estimates are close to zero and far from significant. Overall, these findings strengthen our confidence that success does not alter risk behavior.

Consider, for example, the case in which a one-time success had a negative effect on the survival probability. This would indicate increasing risk-taking among successful (i.e. treated) racers. In this case, we would only observe race times of treated racers in those subsequent races that they actually finished without crashing. Under the assumption of a standard risk-return trade-off, our estimates of the treatment effect would be biased upwards. In other words, we would misinterpret observed differences resulting from a selective sample as being the effect of the treatment (see appendix A.1 for further details).

2.3.1 Performance Measures

A priori, the most appealing variable for performance measurement is the ranking position in subsequent races. However, using this relative measure may cause a violation of the stable unit treatment value assumption (SUTVA). This assumption is crucial for the estimation of causal effects (Angrist, Imbens and Rubin, 1996) because it allows us to write the individual potential outcome as a function of the individual treatment status and not as function of the treatment status of all racers. Yet the assignment of treatment in any race j to one racer might affect the relative performance outcomes of *other racers* in the subsequent race (see appendix A.2 for further details). For this reason, we confine our empirical analysis to the use of absolute race times as performance measure. In particular, we use the change in the absolute time of racer i before and after race j:

$$\Delta T_{i,j} = (T_{i,j-1} - T_{i,j+1})/T_{i,j-1}. \tag{4}$$

The transformation from levels to changes removes a substantial amount of serial correlation in individual performance.[11] As a benchmark race time we use the racer's result in race $j-1$ because, by definition, there will be little difference in times for race j if we focus on close races. Regarding the time horizon for the treatment effect, we primarily focus on the short-term change in performance but also estimate the effect on races $j+2$ and $j+3$.

A simple regression of future performance on current success is likely to yield biased coefficients because success is not randomly assigned. As outlined above, both success and

[11] Note that when using changes instead of levels in our estimation, we still control for the number of races, podium finishes, and victories in a racer's career.

future performance are largely driven by talent which is not observable. Thus we rely on a regression discontinuity design which requires only mild assumptions for the estimation of causal effects.[12] Randomized variation around some threshold results from agent's inability to precisely control the assignment variable near the cutoff (Lee, 2008). In alpine skiing, racers cannot strategically manipulate their race time and usually do not know the cutoff in advance. Yet, distinctive cutoff times determine which racer wins the race or who achieves a podium finish. Therefore, it seems very appealing to use an RD design to estimate the effect of success on subsequent performance because the treatment assignment close to the threshold is arguably randomized.

In any World Cup ski race j, racer i achieves a podium finish if her race time, $T_{i,j}$, is superior to a cutoff time c_j which is determined by her competitors. This setting generates a *sharp* discontinuity in the treatment (i.e. achieving the podium) as a function of race times. We denote the treatment status by the dummy variable $D_{i,j} \in \{0, 1\}$ such that $D_{i,j} = 1$ if $T_{i,j} \leq c_j$ and $D = 0$ if $T_{i,j} > c_j$. More precisely, we define those racers above (below) the cutoff as treated (non-treated). This may include racers ranked fourth or fifth if their race times are within the bandwidth. Table 1 shows the number of those racers —including their ranking position— around the cutoff when using different bandwidths.

We estimate the effect of racer i's relative position in race j, $P_{i,j}$, on her performance in the subsequent races. The outcomes ($Y_{i,j}$) can be written as functions of four variables: the race time $T_{i,j}$, her relative position $P_{i,j}$ determining the treatment status, her own characteristics summarized as $\mathbf{X}_{i,j}$, as well as her competitors' characteristics $\mathbf{Z}_{i,j}$:

$$Y_{i,j} = h(T_{i,j}, P_{i,j}, \mathbf{X}_{i,j}, \mathbf{Z}_{i,j}) \tag{5}$$

where the vector $\mathbf{X}$ contains racer i's age, age squared, gender, as well as the number of her victories, podium finishes and races in the past. The vector $\mathbf{Z}$ comprises the total number of victories and podium finishes among competitors in the top 5 and top 10.

For the estimation, we assume that, except for the treatment, there is no reason why subsequent performance $Y_{i,j}$ should be a discontinuous function of the race time. We will

[12]Details are explained in Appendix A.3.

test this assumption using a large set of balance tests in the empirical section. If this assumption holds, a discontinuity in $Y_{i,j}$ at the cutoff level c_j is identified as the causal effect of the treatment. We estimate the treatment effect τ by fitting the linear regression

$$Y_{i,j} = D_{i,j}\tau + (T_{i,j} - c_j)\beta + D_{i,j}(T_{i,j} - c_j)\phi + \mathbf{X}_{i,j}\,\gamma + \mathbf{Z}_{i,j}\,\delta + \varepsilon_{i,j} \tag{6}$$

where ϕ allows for different slopes to the left and right of the cutoff and $\varepsilon_{i,j}$ is the standard error term which we cluster at the racer level. We include squared and cubic terms of $(T_{i,j}-c_j)$ and $D_{i,j}(T_{i,j} - c_j)$ when using larger bandwidths to allow for a nonlinear relationship.[13]

Using RD allows for the estimation of causal (heterogeneous) treatment effects which can be interpreted as a 'weighted' average treatment effect (Lee and Lemieux, 2010). Our descriptive statistics show that individuals have imprecise control over the assignment variable $T_{i,j}$ (i.e. their race time) due to random noise $n_{i,j}$. For small bandwidths around the cutoff c_j, we argue that all observed ($\mathbf{X}$) and unobserved ($\mathbf{U}$) predetermined characteristics of racer i have identical distributions on both sides of the threshold. In this case, treatment is assigned randomly. Following Lee and Lemieux (2010), we derive the treatment effect as

$$\begin{aligned} &\lim_{\varepsilon\downarrow 0} E[Y_{i,j}|T_{i,j} = c_j + \varepsilon] - \lim_{\varepsilon\uparrow 0} E[Y_{i,j}|T_{i,j} = c_j + \varepsilon] \\ &= \sum_{x,u} \tau(x,u) Pr[\mathbf{X} = x, \mathbf{U} = u | T_{i,j} = c_j] \\ &= \sum_{x,u} \tau(x,u) \tfrac{f(c_j|\,\mathbf{X}=x,\mathbf{U}=u)}{f(c_j)} * Pr[\mathbf{X} = x, U = u | T_{i,j} = c_j] \end{aligned} \tag{7}$$

where $Y_{i,j}$ denotes the outcome variable. The discontinuity in treatment could be interpreted as an average treatment effect for the entire population if it was not for the term $f(c_j|\,\mathbf{X} = x, \mathbf{U} = u)/f(c_j)$. This ratio, however, implies that we estimate instead a *weighted* average treatment effect. The weights are proportional to the ex ante likelihood that a racer's characteristics $\mathbf{X}$ are close to the cutoff. In alpine skiing, we argue that noise is sufficiently important to interpret the RD gap as applying to a larger set than just the top racers.

Throughout our estimations we restrict the sample to races within season and discipline.

[13] The seminal work by Hahn, Todd and van der Klaauw (2001) suggest to use local linear regression in an RD setting. One problem with this approach, however, is that data far away from the cutoff might be used to predict the value of $Y_{i,j}$ at the cutoff. Thus, we only use squared and cubic terms of $(T_{i,j} - c_j)$ for larger bandwidths.

This is necessary because times vary substantially across disciplines (see Figure B.9 in the appendix) and seasons are separated by more than half a year.[14] The inclusion of control variables should not be necessary if treatment is fully randomized. Balance tests shown in Table 2 largely support the assumption that treatment has been randomly assigned close to the threshold. However, when increasing the bandwidth the assumption of randomization becomes obviously questionable. At some point, those on the podium have significantly more prior victories and podium finishes. The inclusion of covariates rules out observable confounders and also improves the precision of the estimation (Froelich, 2007). Following the work by Lee and Lemieux (2010), we implicitly control for the lagged value of the dependent variable by using the change in race times. This also lowers the variance in the RD estimator.

We test the robustness of our estimates with respect to changing the bandwidth. Based on the distribution of race time differences plotted in Figure 2, we choose three different bandwidths for our estimation: five, fifteen, and twenty-five hundredths of a second. As discussed earlier, these bandwidths are much smaller than the individual variation in race times. They are also substantially smaller than the optimal bandwidth suggested by Imbens and Kalyanaraman (2012).

3 Data

Following Kahn (2000), we use sports data as an empirical laboratory for the evaluation of how success affects subsequent performance. The benefit is that we have exact information on individual performance as well as complete career paths.[15]

3.1 World Cup Alpine Ski Racing

The origins of alpine skiing competitions go back to the 1930s when ski clubs, most prominently in Switzerland, Austria, and Germany, decided to organize races. However, these first attempts were individual events and most participants used to be from the host country, with

[14]Typically, the last race of a season is in March, while the first race of the new season takes place in October.

[15]Klaassen and Magnus (2009) discuss the usefulness of sports data to examine behavioral questions.

only few racers coming from abroad. In 1967 the *Fédération Internationale de Ski* (FIS) decided to bring these separate events together and launched the FIS World Cup. During the first years, it included only three disciplines: slalom, giant slalom, and downhill races. It was in 1974 when combined races were included, while super G was added to the FIS World Cup in 1983.

Alpine skiing provides a unique real-world setting to examine the effects of a one-time success on subsequent performance and behavior. Ski 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. Alpine ski competitions enjoy great popularity, particularly in Europe. The downhill race in Wengen (Switzerland), for instance, counts on a TV audience of over one million viewers in Switzerland (1/8 of the country's population) for each of the races between 2007 and 2012 (Ski World Cup Wengen, 2012). A similar appeal comes from the downhill and slalom races in Kitzbühl, each of which is watched by more than 1.3 million Austrians.

The prize money of all ten top athletes in the season of 2012/2013 sums up to $4.4 million for men and $4.2 million for women (FIS 2013). However, the distribution of income in prize money is highly skewed. The highest income among male racers was $589,009 and among females it was $771,289. Number ten of the prize money ranking earned only $109,010 and $126,858, respectively.[16] A considerable fraction of 76% of male and 80% of female racers earned less than $50,000.[17]

The goal of alpine skiing is to slide down a race course in the fastest overall time. Each course consists of a series of gates. All of them have to be passed correctly, so that all racers run the same course. The five disciplines differ in terms of the vertical and horizontal distance between the gates as well as the horizontal distance between start and finish. The differences can be illustrated by the traditional race in Wengen, Switzerland (see Fgure B.8 in the appendix). While the slalom has a total of about 130 gates on a horizontal distance of

[16] Note that these prizes are large enough to incentivize racers to exert high effort but not too large to cause one-time winners to reduce their subsequent efforts.

[17] Besides the prize money, success in World Cup races can also lead to better sponsorship contracts. While there is no reliable data on sponsorship incomes, insiders estimate that in the case of top athletes, this source of income makes up three to four times the amount of prize money.

1,200 meters (in the total of two runs), the 50 gates on the downhill course are distributed over more than 4,000 meters. Furthermore, the downhill race descends more than 1,000m from start to finish, in contrast about 400m for the slalom race. Differences in gate distances and descending gradients translate into differences in speed. The average speed of a downhill racer is about 100 km/h, while a slalom athlete usually achieves about 40 km/h.

3.2 Dataset and Descriptive Statistics

We use a panel data set on 1,501 male and 1,254 female athletes in all World Cup ski races for the period of 1992-2013. The data include information on whether a racer finished the race, the exact result (in hundredths of a second), the time difference to the winner, as well as gender, age, and discipline of competition.[18] The panel structure allows us to measure each racer's performance in the races after a certain relative position is achieved. In total, our data set contains 87,612 observation. The unit of observation is a racer in a certain race. The benefit of observing a long time span of more than twenty years is that it enables us to observe entire career paths of individuals.

Table 3 reports descriptive statistics for all racers and the subsamples of top-15, top-3 and winning racers for the period of 1992–2013.[19] The share of racers on the podium is less than 10% of the total number of observations. Observations for the assignment variable are more numerous than observations for past and future performance because we only use outcomes within season and discipline. Furthermore, we cannot use observations at the beginning (end of the season) because we would lack past (current) performance. Taken together, these account for around a fourth of the total observations.

Overall, 65% of those racers who compete in a given race finish the race and get a positive race time. This number is much higher for podium finishers and winners. Comparing the time of two consecutive races, the average change in time is almost zero with a relatively high standard deviation (0.17). These figures indicate that skiers take high risks and support

[18]Race times are actually measured more precisely than stated in official reports. For any time in hundredths of a second, the measurement was accurate at the millisecond level.

[19]Note that we shrink our sample to the years 1992-2013 since for this period there were no rule changes with implications for our estimation.

the use of changes in performance for our estimation. We also report the level of future performance in Table 3. The mean time in the next race is 109 seconds. On average, racers in the top-15 have a distance of 0.64 seconds to the podium and 1.34 seconds to the winners.

Competition in alpine skiing is fierce. Only few junior racers make it to the World Cup team and, among them, only a small group is successful. From our total sample of 1,501 male and 1,254 female athletes, only 110 men (7.33%) and 95 women (7.6%) ever won a race during their entire career. A large fraction of the group of winners—39.5% (41.0%) of all men (women)—only won a single race. The fraction of racers with at least one podium finish is 14.2% (14.7%) for the sample of men (women). From the sample of men (women) 18.25% (27.7%) were at least classified once in the top five and 25.8% (19.0%) were ranked in the top ten.

Figure B.10 in the appendix presents a histogram of the distribution of different career achievement measures while discarding the zero entries. The graphs are qualitatively similar for all measures and indicate that career success is positively skewed. This suggests that only few competitors are very successful over a lifespan which is in line with empirical evidence concerning the presence of superstars in music, entertainment, and academia (Rosen, 1981; Hamlen, 1991).[20] Figure B.11 in the appendix depicts different achievement measures as well as the total number of races over time. The average number of races has changed only slightly from 34.8 (35.3) during the 1990s to 36.3 (34.1) during the 2000s for men (women). The average number of racers who could win at least one race during an entire season decreased from 18.0 to 16.25 (18.1 to 14.2) for men (women). This means that the average number of victories per winning racer has not changed considerably.[21] Overall, the figures indicate that competition has been fairly constant during our sample period.

[20] The most successful athletes in the history of alpine skiing are Ingemar Stenmark (Sweden, 1973–1989) with 86 victories and Annamarie Moser-Proell (Austria, 1969–1980) with 62 victories.

[21] The number of victories per winner in the men's competition is 1.95 in the 1990s and 2.0 in the 2000s. For women we observe a slight increase from 2.1 to 2.4 races per winner indicating that competition has increased over time.

4 Empirical Results

This sections presents our empirical estimates for the effect of quasi-random successes on subsequent performance. As discussed in section 2.3, there is no significant effect on the probability of finishing the next race. This allows us to estimate the effects on performance without taking into account principal stratification. We will restrict our sample to close races in which success is randomly assigned. This excludes, however, most combined competitions.[22] These races typically exhibit larger time differences and a higher variance over time. This is mainly because combined races tend to be longer and have a smaller group of starters, which makes competition less fierce. Furthermore, there are only about five combined races per year as opposed to the other disciplines with about eleven.

4.1 Main Results

In our main analysis we explore the effect of being successful on performance in the short- and long-term. Moreover, we decompose the effects of success and non-success and discuss effect heterogeneity.

The Short-Term Effect

We begin our empirical analysis by examining the main question of interest, namely how a quasi-random podium finish affects performance in the subsequent race. Table 4 reports the results of estimating equation (6) using both RD and ordinary least squares (OLS). Using the full sample, the OLS estimates show no effect of a podium finish on subsequent performance. This is not surprising given the fact that the control group includes all racers ranked fourth or worse, up to rank 89. This set of racer is very different in terms of skills when compared to podium finishers and has more potential for performance improvement. When restricting the sample to racers in the top 5, we find a significant and positive effect on performance in the subsequent race.

[22]During a long period of our sample, namely from 1992 to 2005, combined races were not a separate race discipline because the final time was calculated by adding the final times achieved in downhill and slalom races at the place of the event. More recently, however, some of the combined races were replaced by a so called super-combined race with separate downhill and slalom runs.

However, as outlined above, we cannot disentangle success and superior skill if we do not focus on close races. To account for this, we estimate our equation of interest using RD. The results in Table 4 show that a quasi-random podium finish has a significant and substantial positive effect on the performance in the next race. The point estimates suggest an improvement of 6.5 to about 8 percent which is very similar across all bandwidths. This significant treatment effect, however, leaves open the question whether podium finishers improve their performance or whether non-podium finishers suffer from a loss in subsequent performance. To explore this, we separate the effects of success and non-success. We plot the performance changes around the cutoff in Figure 4. The graph indicates no performance improvement in the sample of racers who just make it to the podium. On the contrary, the treatment effect of a podium finish appears to be driven by a substantial drop in performance of racers who miss the podium by a tiny margin.

Effect Heterogeneity

We explore whether success has heterogeneous short-term effects by analyzing different subsets of racers. Intuitively, we expect superstars to respond less to a one-time success than other racers. To explore this in detail, we split the sample into three different skill groups. Since skill is not directly observable we separate racers based on their current World Cup point scores: (1) high-skilled racers who are among the top four in the ranking for the big prize, (2) medium-skilled racers who are ranked fifth to fifteenth in the overall ranking, and (3) low-skilled racers who are classified below.[23] Using the split samples and estimating equation (6), we get the results shown in Table 5. We find that racers in the middle of the skill distribution respond strongest to a podium finish, while the effect on superstars and low-skill racers is not significant.

We also examine whether treatment effects differ between men and women. When restricting the sample to female racers, the point estimate increases to 8–9 percent. This finding is consistent with evidence from previous research showing that womens' performance tends to

[23]For each race, points are awarded to the top 30 competitors: 100 points to the winner, 80 to the second, 60 to the third, 50 to the fourth, winding down to 1 point for 30th place. The racer with the most points at the end of the season in mid-March wins the World Cup. In addition, sub-prizes are awarded in each individual race discipline. Details can be found in the Official Rules for the FIS Alpine Ski World Cup.

respond stronger to success and non-success in highly competitive settings (Gneezy, Niederle and Rustichini, 2003).

The Long-Term Effect

Several previous studies have documented a long-term effect of one-time big successes. Yet it may be possible to erroneously interpret observed differences in subsequent performance—actually stemming from skill differences—as a consequence of current success. This concern particularly arises in the long run. Our setting, however, allows us to examine the long term consequences of *quasi-randomized* successes. We reestimate equation (6) using time changes in the second and third race relative to the time in the last race as dependent variable. The results in Figure 5 indicate that the treatment effect subsides after the first race. The point estimates clearly decrease after the first race following the treatment.[24] One reason for this decline in the effect of success is the fact that there is a new allocation of success after the first subsequent race. Our results suggest that racers incorporate only information about their position in the previous race. Another important aspect to note is the fact that two World Cup alpine ski races are, on average, fifteen days apart and thus the second race after treatment takes place already a month after the success.

4.2 The Role of Rankings and Media Attention

In the analysis so far we have examined the effect of quasi-random podium finishes on subsequent performance. A natural question following these results is whether the treatment effect is specific to a podium finish or just the effect of a higher position in the ranking. In this context, we also address the question whether a quasi-random victory causes an additional performance effect to the podium finish. To explore this, we use each rank as a separate treatment dummy in equation (6). Figure 6 shows the point estimates for the smallest and largest bandwidths and for all ranking positions from one to twelve. Irrespective of the bandwidth we observe that only the treatment 'rank 3' has a significant impact on subsequent

[24] Not surprisingly, the confidence intervals of the treatment effect increase as a consequences of the decreasing number of observations for future races.

performance.[25] This strengthens our confidence that our main results indeed stem from the very success of a podium finish.[26]

These findings underscore the importance of finishing on the podium but do not answer the question what mechanism drives the difference between third and fourth. A first explanation is that racers on the podium receive additional support from the coaching staff or get access to better equipment. Yet, team hierarchies and equipment suppliers only change between and not within seasons. The fraction of racers who change their equipment within a season is 0.20% for changes of skis, 0.18% for changes of bindings, and 0.15% for changes of boots.

An second explanation for the importance of the podium versus non-podium cutoff is the discontinuity in media attention. In an information-rich world, consumers with limited attention tend to focus on the most important information from a given field of interest (Falkinger, 2007, 2008). This is anticipated by the media and leads to a situation where media outlets narrow the focus of their reports. In sports in general, and in alpine skiing in specific, the podium creates a natural spotlight for newspaper articles and television news. As sponsoring contracts constitute a central source of income for most racers, media attention is particularly important because it creates access to better sponsorship deals.[27]

From an econometric point of view, a major identification problem complicates the estimation of the impact of success on subsequent media attention. Those who are successful in World Cup alpine ski races are typically well known and have been successful in the past. Thus, it is usually the most-skilled racers (i.e. superstars) who finish on the podium and get media coverage. To overcome this identification problem, we again focus on close races in which success is randomly assigned.

We examine the effect of being successful on media attention based on data of more than 200 newspaper titles. The collection contains German-, French-, Italian-, and English-

[25] Note that we always include all racers with lower ranking positions and within the respective bandwidth in the control group.

[26] When estimating the effect of a quasi-random victory both the OLS and the RD point estimates are very close to zero. This is not surprising in light of the fact that most racers in the control group of the victory estimation are treated with a podium finish.

[27] As mentioned above, this source of income amounts to up to four times more than the sum of prize money in the case of the most successful racers.

speaking newspapers.[28] We estimate a version of equation (6) and replace the outcome variable by the total number of articles that mention racer i. We use the number of articles on the day after the race as a measure of media attention because most newspapers report on World Cup ski races the day after.[29]

We find that finishing on the podium in a close race increases racer i's media attention by about four articles. This constitutes an increase of 88.17% when compared to a racer in the control group who is mentioned in 4.86 articles on the day after the race. To assess whether our treatment effect on performance varies as a function of media attention, we use variation in media focus over time. We do so by running rolling regressions over 10-, 15-, and 20-year periods. Irrespective of the interval and bandwidth, our results indicate that the effect of a quasi-random success has increased in the past twenty years. Panel (a) of Figure 7 shows the point estimate for the effect on media attention. We observe that the effect has increased substantially over the past two decades. A similar result is documented in panel (b) which uses the change in performance as dependent variable. Again the treatment effect increases substantially over time. This finding is in line with our argument that media attention is the key channel for the performance effect.

4.3 Robustness Tests

In order to assess the validity and sensitivity of our research design, we perform a number of robustness checks. This comprises a discussion of the key identifying assumptions, the econometric specification, placebo regressions, and alternative explanations for the treatment effect.

Robustness of Main Results

An important potential source of bias in our results could arise if treated and non-treated racers are systematically different with respect to pre-determined covariates. If finishing

[28]Our collection includes all major Swiss print and online titles. It is based on the web search machine Swissdox. The full list of newspapers is available upon request.

[29]For robustness checks we also take the week and month after the race. After one week, the difference is still 5.97 articles which equals a 30% increase when compared to the control group. After a month the difference is not significant anymore.

on the podium in a close race is driven by skills instead of luck, our RD approach would not allow us to assess the effects of quasi-random successes. To address this concern, we compare the characteristics of treated and non-treated racers. Table 2 provides balance tests for a wide range of covariates. Most important are the comparisons with respect to past achievement. These achievements may proxy skill differences across racers. We find that there are no significant differences with respect to the total number of prior victories and podium finishes. This indicates that those who make it to the podium are not systematically more skilled. Moreover, there is no evidence that they are more experienced or older. We can also rule out the concern that the location or starting position (bib number) influence our estimates. It is, however, important to note that treated and non-treated racers obviously become systematically different if we extend the bandwidth. In the last column of Table 2 we show this with a bandwidth of 25 hundreds of a second. To ensure that our estimates are unbiased even with the largest bandwidth we use control variables for prior achievements. Overall, however, Table 2 indicates that success is randomly assigned if we focus on very small time differences. This strengthens our key identifying assumption.

When applying a regression discontinuity design, we exploit the fact that treatment is randomly assigned in the vicinity of the cutoff. Thus, for the smaller bandwidths, it is not necessary to use control variables in the estimation. There are, however, a number of advantages of using them. First, they improve the efficiency of the estimation (Froelich, 2007). Second, we do not observe skill or effort levels but can only examine whether proxies for skill are balanced around the cutoff. Finally, as shown above, the assumption of randomness might be limited when using the larger bandwidths. We derive confidence in our findings from two results. For one thing, our estimates in Table 4 indicate that the results are robust to using different bandwidths. Moreover, Figure 4 plots the discontinuity without controls. Again, the estimated difference in the performance change of treated and non-treated is of the same magnitude as in the RD estimation in which we use controls.

Another potential source of bias might arise from the fact that ski racers may adjust the level of risk depending on their treatment status. For example, it may be that the probability of crashing and not achieving a race time is positively affected by missing the podium in a close race. As discussed in section 2.3, we can rule out the effect of quasi-random successes on risk-taking behavior. Irrespective of the bandwidth or sample of racers we find no evidence for a significant impact on the probability of crashing and no evidence on an increase in time variation. Thus we can estimate performance effects without taking into account principal stratification.

A final econometric robustness check concerns the use of placebo outcome regressions. In Table 6 we use pre-treatment performance as dependent variable. In particular, we plug in $[(T_{i,j} - T_{i,j-1})/T_{i,j}]$ for $Y_{i,j}$ in equation (6). The results show, as expected, that there is no effect of success on pre-treatment performance. We perform the same robustness test for pre-treatment media attention and find an effect of 0.33 that is far from significant (p-value: 0.69).

Alternative Channels and Bias in Media Attention

One concern regarding the importance of media attention as a source of the treatment effect might be that racers who finish on the podium in a close race may benefit from additional outside support. The relative importance of this channel, however, seems to be quite low. First and foremost, we only find a significant treatment effect in the short run. Moreover, racers' outside support is rather sticky. The empirical quantification of equipment changes during the season supports this conjecture. Only very few racers change their equipment technology during the season. Furthermore, contracts and team hierarchies are typically determined between seasons. Since all our estimations are within season, outside support is very unlikely to be the primary explanation for the significant effect of podium finishes.

Another potential concern arises when examining the effect of success on media attention. For two reasons our estimates could be biased upward. First, the total number of newspapers and articles on World Cup skiing might have increased in the past decades. Second, data is not available for all newspapers from the early 1990s onward. Thus the increasing gap between those racers who finish on the podium and those who do not might be a spurious effect, driven by the overall increase in articles. We rule out this potential bias by restricting the set of newspapers to the largest Swiss newspaper *Blick*. Again we estimate equation (6) using the number of articles published the day after the race as outcome variable. Rolling regressions with only the number of articles that appeared in the *Blick* yields a very similar graph as in panel (a) of Figure 7. Again, there is a clear upward trend indicating an increased focus of newspapers on the top-3 finishers.

4.4 Interpretation of Findings

Our results suggest that a quasi-random success affects racers' subsequent performance. However, long term performance is not affected by a podium finish in a close race. This result contrasts previous empirical studies who find persistent effects of success. The decomposition of the observed difference in performance shows that the drop in performance of non-successful racers explains most of the treatment effect. Since there is no immediate change of the racer's technology we argue that psychological factors are the main mechanism driving our results.

In particular, our findings suggest that counterfactual thinking, the impact of "what might have been", not only influences emotional reactions (Medvec, Madey and Gilovich, 1995) but also affects future performance. Our data on alpine skiing include highly ambitious individuals who are able to interpret the difference to success in a rational way and put it into perspective against the pure signal of success/non-success. As a consequence, the relationship between success and performance may be even more pronounced in other settings where the closeness to success is less obvious.

Our empirical analysis further reveals that the effect of success is only present for racers in the middle of the skill distribution. This finding adds to previous evidence that high-skilled workers recover more quickly from graduating in a recession than medium-skilled workers (Oreopoulos, von Wachter and Heisz, 2012). The differential effects may result from the fact that high-skilled individuals in alpine skiing are aware of their ability and know that they will get another chance to show their potential in future races. This might be different for middle-skill racers who know that their chances for success in the next races are limited. Thus, missing the podium in a close race might be seen as a squandered opportunity. When applying this finding to the labor market in general, one has to bear in mind a key difference:

there is a higher persistence in outcomes in the labor market than in alpine skiing. As a result, the chances for a reversal of performance are much more limited. Thus our estimated effects on medium-skilled racers who have less opportunity to make up for the missed success (i.e. podium finish) are of particular relevance with respect to the labor market.

A novel finding of our analysis is that the impact of success vanishes after the first race following the treatment. This suggests that individuals incorporate only very recent signals about being successful or not. The lack of long-term effects might be a consequence of a central feature of alpine skiing where each competition is in principle independent from previous races. An important direction for future research is to explore whether the long-term results generalize to a setting with more inertia in success and ranking positions. This is of particular relevance for both academic and policy discussions because it may lead to important implications for the optimal design of tournament schemes.

The main effect of our analysis, the impact of success on subsequent performance, could arise from different channels. We explore these channels and argue that a changes in equipment and outside support seem unlikely to drive our findings. In contrast, our analysis of media data shows that the effect of success on performance exhibits a positive time trend which matches the positive trend in the gap in media attention for podium and non-podium racers. This finding is consistent with theoretical studies on markets for attention (Falkinger, 2007, 2008). In an information-rich world, media have to concentrate information and sport athletes compete for the scarce resource of media attention. Since ski racers draw a large share of their earnings from sponsorship contracts, being among the top-3 is of particular importance to get higher media attention which translates into better sponsorship deals.

5 Conclusion

This paper investigates how quasi-random successes affect subsequent risk behavior and performance. While previous research has emphasized the importance of great successes, it is difficult to separate the effect of success from unobserved skills and effort. By applying a regression discontinuity design for quasi-randomized positions in a sample of World Cup alpine ski racers, we present novel evidence that even small changes in the relative position can affect future performance. Results suggest that missing the podium by a tiny margin has a substantial negative effect on subsequent race times. Our analysis of data on more than 200 newspapers suggests that rankings affect performance through creating a discontinuity in media attention for successful and unsuccessful racers. The impact of success on performance has been enhanced by an increasing gap in media attention between third and fourth in the past two decades. The absence of a long-term effect suggests that in a setting of repeated games the importance of rankings is limited to the very immediate future.

Understanding the economic consequences of success and rankings is important because it extends beyond alpine skiing. It is likely that success and changes in relative positions also affect performance in fields such as education and private business. For example, imagine a student who is moved to another class and finds herself in a new relative skill distribution. If relative positions play a role, the new environment has an effect on her absolute performance. The same argument is likely to hold for workers who change their employer as well as for sport athletes who compete with different sets of rivals.[30] In all these cases, the introduction of a ranking makes differences in performance visible, which is considered as a method to enhance effort (Lazear and Rosen, 1981; Palomino and Prat, 2003; Marino and Zabojnik, 2004; Coffey and Maloney, 2010). Recent empirical studies, however, tend to focus only on the positive effects of rankings among workers and students (Azmat and Iriberri, 2010; Kuhnen and Tymula, 2012; Tran and Zeckhauser, 2012). In contrast to these studies, we explore a setting in which success and ranking positions are quasi-randomized. This allows us to identify the causal effect of rankings at the individual level. The results we obtain document novel empirical evidence for potential drawbacks of rankings. Those individuals who miss prestigious ranks seem to be disappointed and subsequently perform worse. This adds to previous research on the role of knowledge about relative payment and performance schemes in the workplace (Mas, 2006; Card et al., 2012). Especially if individuals are exposed to widespread public attention, the negative effects of non-success indicate that the benefits of rankings may be more limited than suggested by previous theoretical and empirical research.

[30]This line of reasoning is related to the 'big fish in a small pond'-literature (Marsh and Parker, 1984).

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Tables and Figures

Table 1: Number Individuals Within Bandwidth, by Ranking Position

	Bandwidth		
	5	15	25
#1	6	21	63
#2	22	121	257
#3	159	386	539
#4	160	397	533
#5	33	172	319
#6	7	55	179
#7	1	23	86
#8	.	3	38
#9	.	2	21
#10	.	.	5
#11	.	.	2

Note: The table shows how many individuals of each rank are within a given bandwidth when using a podium finish as treatment. Bandwidths are 5, 15, and 25 hundredths of a second, respectively. Those ranked 1–3 are in the treatment group while all other racers are in the control group.

Table 2: Balance of Covariates for Full Sample

	Bandwidth 5	Bandwidth 15	Bandwidth 25
Racer's gender	0.02	-0.00	-0.01
	(0.04)	(0.02)	(0.02)
Racer's number of victories	-1.42	0.03	0.73**
	(0.92)	(0.34)	(0.32)
Racer's number of podiums	-2.81	0.16	1.74**
	(2.14)	(0.84)	(0.78)
Racer's number of races	-8.96	-2.87	0.91
	(7.08)	(3.88)	(3.48)
Racer's age	-0.41	-0.33	-0.13
	(0.28)	(0.17)	(0.14)
# podiums among top 5	-0.32	0.80	-0.80
	(5.20)	(2.74)	(2.04)
# victories among top 5	0.30	0.58	-0.19
	(2.24)	(1.14)	(0.85)
# podiums among top 10	-3.32	-0.53	-1.16
	(7.46)	(3.95)	(3.10)
Home dummy	-0.01	0.01	-0.00
	(0.03)	(0.02)	(0.01)
Length of next race	-0.02	-0.00	-0.01
	(0.04)	(0.02)	(0.01)
Bib change	-0.24	-0.10	-0.09
	(0.16)	(0.08)	(0.07)

Note: The table shows a linear regression of various pre-determined covariates on the treatment dummy for podium. Bandwidths are 5, 15, and 25 hundredths of a second, respectively. Standard errors (in parentheses) are clustered at the racer level. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

Table 3: Descriptive Statistics

Category	Variable	Mean	Std. Dev.	Min.	Max.	N
(A) All racers						
Outcomes	Finished next race	0.65	0.48	0	1	62,182
	Change in time	-0.02	0.17	-1	0.57	24,993
	Time in next race	10,925.44	2,445.27	5,307	21,492	40,223
Treatment	Victory	0.02	0.13	0	1	87,612
	Podium	0.05	0.22	0	1	87,612
Assignment	Distance to winner	248.77	203.25	0	19,903	52,890
	Distance to podium	183.23	197.26	-397	19,848	52,890
Career achievements	# victories at time of race	1.7	5.17	0	59	87,612
	# podiums at time of race	4.93	12.19	0	110	87,612
(B) Top 15 Racers						
Outcomes	Finished next race	0.82	0.39	0	1	18,048
	Change in time	-0.01	0.17	-1	0.56	10,535
	Time in next race	11,039.49	2,495.45	5,307	21,492	14,713
Treatment	Victory	0.07	0.25	0	1	21,584
	Podium	0.2	0.4	0	1	21,584
Assignment	Distance to winner	136.21	95.47	0	1,445	21,570
	Distance to podium	65.12	77.59	-397	1,385	21,584
Career achievements	# victories at time of race	3.93	7.55	0	58	21,584
	# podiums at time of race	10.98	17.1	0	109	21,584
(C) Racers on podium						
Outcomes	Finished next race	0.86	0.35	0	1	3,693
	Change in time	-0.01	0.16	-0.91	0.56	2,391
	Time in next race	11,013.25	2,496.35	5,307	17,717	3,167
Treatment	Victory	0.34	0.47	0	1	4,337
	Podium	1	0	1	1	4,337
Assignment	Distance to winner	38.79	49.32	0	397	4,335
	Distance to podium	-32.4	45.22	-397	0	4,337
Career achievements	# victories at time of race	6.99	9.54	0	58	4,337
	# podiums at time of race	18.03	20.49	0	109	4,337
(D) Winners						
Outcomes	Finished next race	0.87	0.34	0	1	1,241
	Change in time	-0.01	0.17	-0.9	0.56	830
	Time in next race	10,984.11	2,497.71	5,331	17,599	1,077
Treatment	Victory	1	0	1	1	1,453
	Podium	1	0	1	1	1,453
Assignment	Distance to winner	0	0	0	0	1,453
	Distance to podium	-70.40	53.08	-397	0	1,453
Career achievements	# victories at time of race	8.85	10.81	0	58	1,453
	# podiums at time of race	21.69	22.18	0	109	1,453

Note: The table presents descriptive statistics for outcome variables, assignment variables, and measures of performance. Standard errors are clustered at the racer level. The numbers of observations are explained as follows: In total we have 87,612 observations of which 52,890 racers finished 'today's race'. For the subsequent races we have 54,194 participants of which 76% (= 40,223) finished successfully. For the change in time, we can use only those with a time in the previous as well as the subsequent race. The low average 'time in next race' in part (A) for all racers is the result of compositional effects: there are more finished racers in shorter races.

Table 4: Effect of Podium Finish on Performance in Next Race

	Treatment Effect	# Observations
Bandwidth 5	0.080** (0.037)	383
Bandwidth 15	0.065* (0.035)	1,162
Bandwidth 25	0.065* (0.038)	2,019
OLS	0.008 (0.005)	12,857
OLS (top 5)	0.016** (0.008)	3,773

Note: The table shows linear regression results using the change in performance —as defined in equation (5)— as dependent variable. Bandwidths are 5, 15, and 25 hundredths of a second, respectively. We control for survival in the last race. For bandwidths 15 and 25 we use squared and cubic terms of the running variable $(T_{i,j} - c_j)$. The second OLS estimation is limited to racers who finished in the top 5. Standard errors (in parentheses) are clustered at the racer level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table 5: Effect of Podium Finish by Skill Level

	High-Skilled		Medium-Skilled		Low-Skilled	
	Estimate	N	Estimate	N	Estimate	N
Bandwidth 5	0.024 (0.064)	138	0.154** (0.071)	157	0.001 (0.071)	83
Bandwidth 15	-0.011 (0.052)	402	0.148** (0.064)	497	0.052 (0.067)	249
Bandwidth 25	0.018 (0.055)	669	0.147** (0.064)	850	0.022 (0.067)	471

Note: The table shows the regression results for the change in performance. We use a podium finish as treatment and separate the sample of racers by skill level. The high-skilled racers are the top four racers of a discipline, while the middle-skilled racers are those on position five to 14, and the low-skilled are position 15 and below. Standard errors (in parentheses) are clustered at the racer level Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

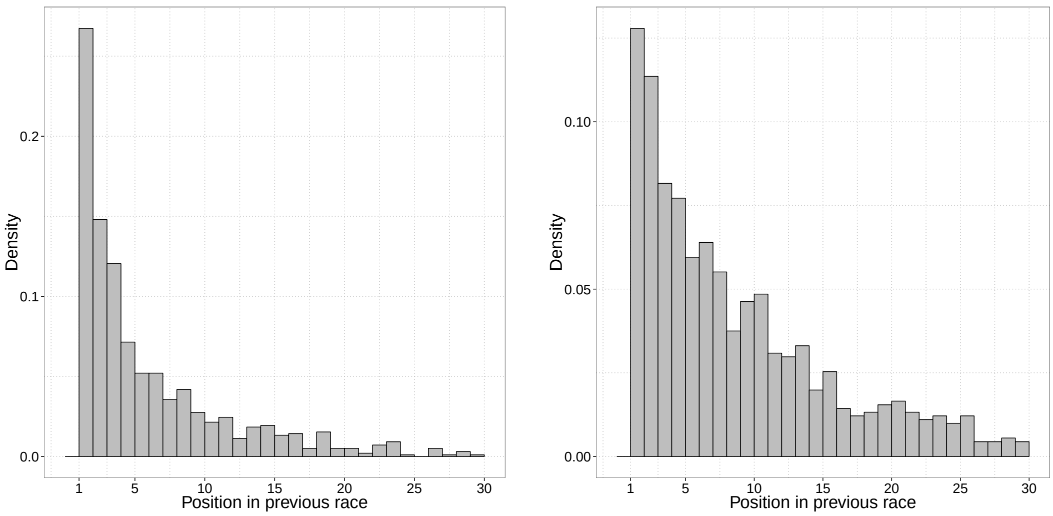
Table 6: RD Placebo Outcome: Effect on Previous Race

	Podium	Victory
Bandwidth 5	0.015	0.004
	(0.032)	(0.033)
N	291	117
Bandwidth 15	0.016	0.000
	(0.031)	(0.033)
N	861	302
Bandwidth 30	0.000	-0.004
	(0.023)	(0.041)
N	1,477	523

Note: The table shows linear regression results using performance, defined in equation (5), as dependent variable. Bandwidths are 5, 15, and 25 hundredths of a second, respectively. We use $T_{i,j}$ as covariate for the estimation with the smallest bandwidth (.05 sec). For larger bandwidths we use squared and cubic terms of $T_{i,j}$. Standard errors (in parentheses) are clustered at the racer level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Figure 1: Previous Positions of Winners and Third-Ranked Racers

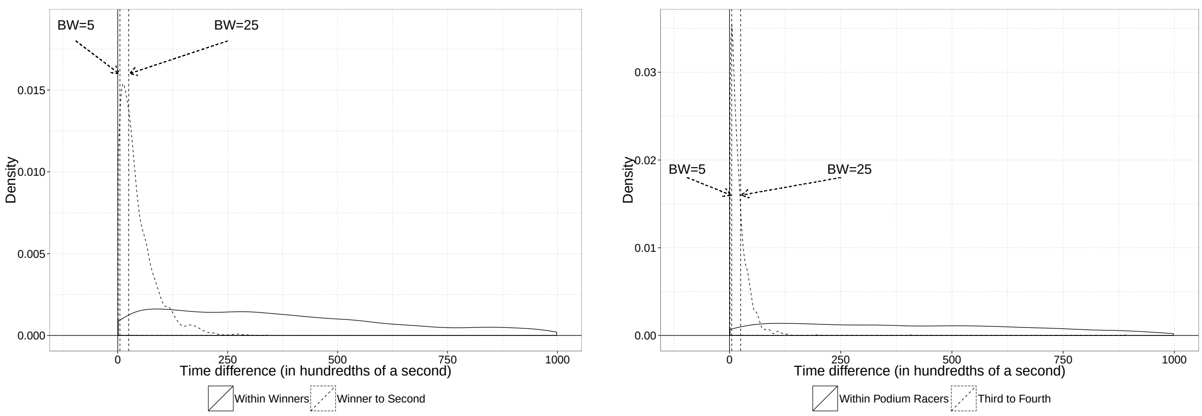
(a) Winner **(b) Third Rank**



Note: The histogram shows the ranking positions in the previous race of winners and third-ranked racers in the current race.

Figure 2: Time Differences and Bandwidth Choice

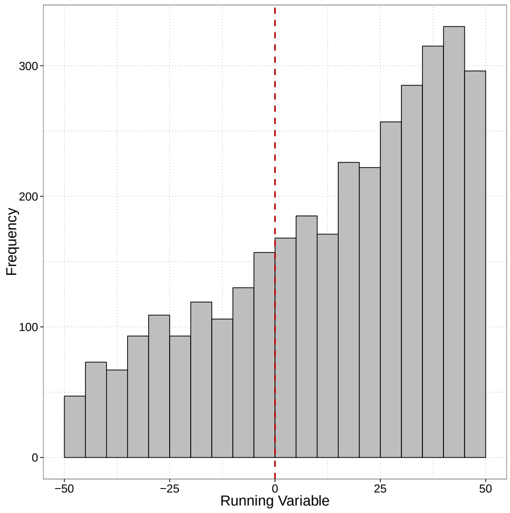
(a) Winner **(b) Third Rank**



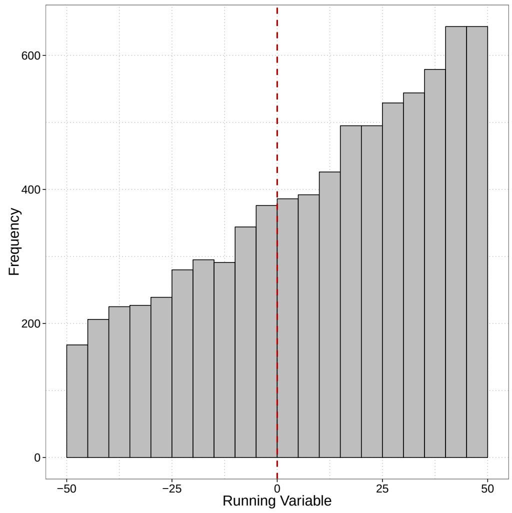
Note: The figure shows the densities of the distance between winners and seconds (panel (a)) as well as third and fourth finishers (panel (b)). In addition, we plot the time difference for winners with respect to their next race at the same race track ('within winners'). We do the same for podium finishers ('within third place racers'). The vertical lines indicate the smallest and largest bandwidths we use in the estimation: 5 and 25 hundredths of a second.

Figure 3: Observations around the Cutoff

(a) Winner

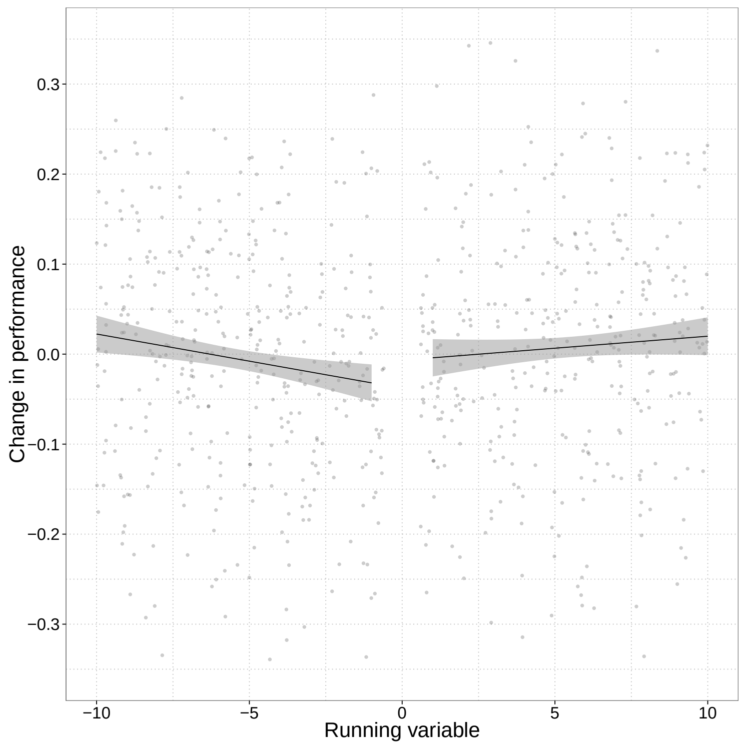


(b) Third Rank



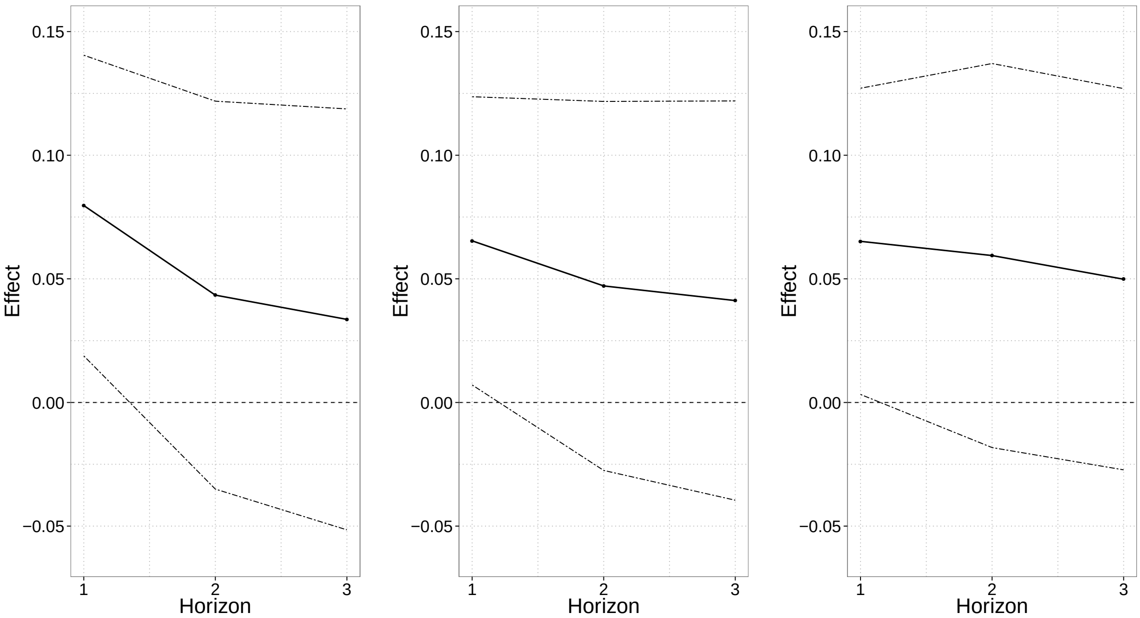
Note: The histogram shows the density of race times around the cutoff. In line with McCrary (2008), this indicates that there is no manipulation around the respective cutoffs. In panel (a) we plot the distance to rank 2 (from left-hand side) and 1 (from right-hand side), respectively. For the distance to the podium in panel (b), we plot the distance to rank 4 and 3, respectively.

Figure 4: Regression Discontinuity – Effect of Podium on Time



Note: The figure plots the change in absolute performance ($\Delta T_{i,j} = (T_{i,j-1} - T_{i,j+1})/T_{i,j-1}$) against the distance to the podium in race j. The shaded areas denote 90% confidence intervals. For individuals who miss the podium we use the distance to the third (negative values) as the running variable on the horizontal axis. In contrast, for racers on the podium we use the distance to the fourth (positive values) as the running variable.

Figure 5: Long Term Effects of a Podium Finish

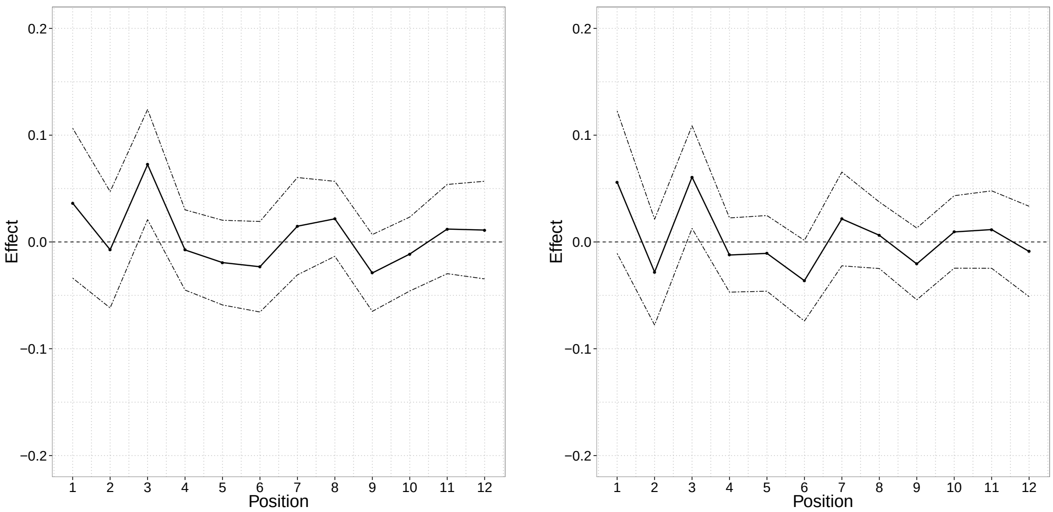


(a) Bandwidth 5 **(b) Bandwidth 15** **(c) Bandwidth 25**

Note: The figure shows the RD point estimates for the effect of a podium finish on the change in performance. The time horizons indicate races $j + 1$, $j + 2$, and $j + 3$. Confidence intervals are at 90% level. Bandwidths vary from 5 to 25 hundreds of a second. Number of observations are 383, 1'162, and 2'019 for horizon 1; 264, 822, and 1'418 for horizon 2; 200, 648, and 1'108 for horizon 3.

Figure 6: Effect of a Higher Ranking Position on Performance

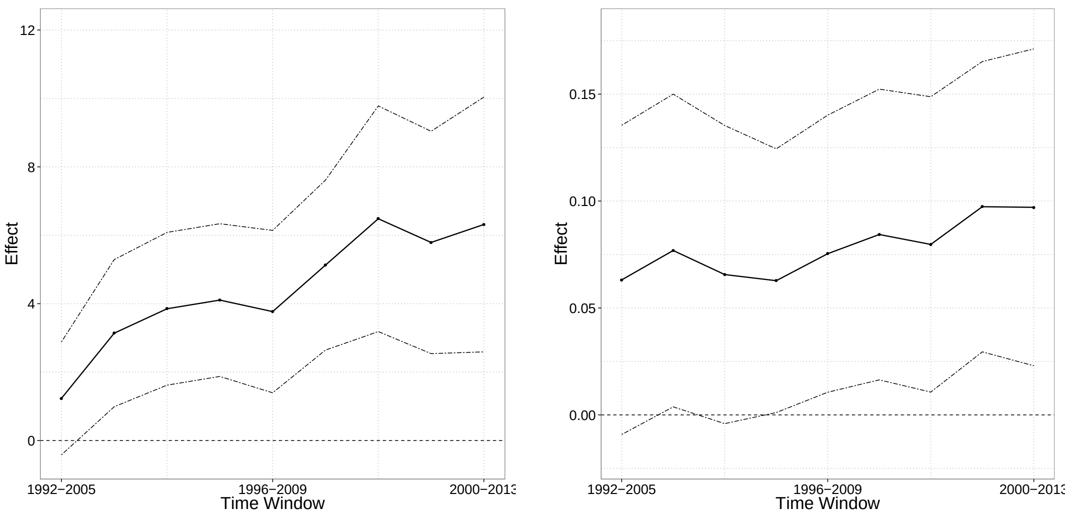
(a) Bandwidth 5 **(b) Bandwidth 25**



Note: The figure plots the RD point estimates for the effect of position 1–12, respectively. The outcome variable in each regression is the change in performance. Confidence intervals are at the 90% level.

Figure 7: Effect of Podium Finish: Rolling Regressions

(a) Effect on Media Attention **(b) Effect on Performance**



Note: The figure plots the RD point estimates for the effect of a podium finish on media attention on the day after treatment (Panel (a)) and on the change in performance in the subsequent race (Panel (b)) . For each regression we use a different time period, starting from 1992–2005 and ending in 2000–2013. Confidence intervals are at the 90% level and the bandwidth is five hundreds of a second. The number of observations for both panels is 226, 242, 250, 266, 270, 275, 269, 287, and 283, respectively.

Appendix

A Econometrics

A.1 Survival and Attrition

One problem that may arise when estimating the effect of a ranking position on future performance is that racers differ with respect to their probability of survival, i.e. not crashing. If this probability is related to success our estimates for performance would be biased. It could be, for example, that racers who are very successful once adopt a riskier behavior in subsequent races in order to be successful again.

Following Frangakis and Rubin (2002), we denote racers with a constant low (high) probability of survival by DD (LL). While the survival probability of this set of racers is unaffected by the treatment, other racers adjust their behavior when being treated, in other words after a quasi-random success. The racers in subset LD adopt a more risky strategy after treatment while those in subset DL follow a low-risk strategy in case they achieve a quasi-random success. In the regression of the probability of survival ($s_{i,j+1}$) on treatment $D_{i,j}$ and controls for a racer's own characteristics $\mathbf{X}_{i,j}$ and competitors' characteristics $\mathbf{Z}_{i,j}$

$$s_{i,j+1} = D_{i,j}\tau + \mathbf{X}_{i,j}\,\gamma + \mathbf{Z}_{i,j}\,\delta + \varepsilon_{i,j} \tag{8}$$

we should expect $\tau = 0$ for the two types with constant behavior (DD and LL). For types DL we expect $\tau < 0$ and for types LD we should see an increase in the probability of survival. Thus we have two problems if the coefficient τ is significantly negative: First, our estimates with respect to subsequent performance would be biased upwards because we would only observe treated racers in case they are successful in subsequent races. Second, the overall gain from imposing a ranking will be reduced and perhaps negative if one-time successes lead to a strong increase in risky-behavior.[31]

A.2 Relative Performance Measures and SUTVA

The Stable Unit Treatment Value Assumption is fundamental to most estimators used in the program evaluation literature. It allows to write the treatment status of individual i only dependent on her assignment, and the outcome of individual i only dependent on her assignment and treatment status. More formally, SUTVA is defined as follows (according to Angrist, Imbens and Rubin (1996, 446))

(a) If $Z_i = Z_i'$, then $D(\mathbf{Z}) = D(\mathbf{Z}')$

(b) If $Z_i = Z_i'$, then $Y_i(\mathbf{D}, \mathbf{Z}) = Y_i(\mathbf{D}', \mathbf{Z}')$

This allows us to write $D_i(\mathbf{Z}) = D_i(Z_i)$ and $Y_i(\mathbf{D}, \mathbf{Z}) = Y_i(D_i, Z_i)$.

Applying this assumption to our paper, let us define the vector of final times $\mathbf{T}$ in race j as well as vectors of assignments (to the podium) ($\mathbf{Z}$) and treatments ($\mathbf{D}$):

$$\mathbf{T} = \begin{pmatrix} t_1 \\ t_2 \\ t_3 \\ \vdots \\ t_N \end{pmatrix} \qquad \mathbf{Z} = \begin{pmatrix} z_1 \\ z_2 \\ z_3 \\ \vdots \\ z_N \end{pmatrix} \qquad \mathbf{D} = \begin{pmatrix} d_1 \\ d_2 \\ d_3 \\ \vdots \\ d_N \end{pmatrix} \tag{9}$$

We assume that there is a positive probability of a crash. We model survival as

$$S_i = \begin{cases} 1 \text{ if } S_i^* > 0 \\ 0 \text{ if } S_i^* \leq 0 \end{cases} \tag{10}$$

with

$$S_i^* = \theta_i a_1 + \mu_j + \varepsilon_i \tag{11}$$

[31] This finding would be in line with the above-mentioned research on addiction to success.

where S_i^* is a latent variable, θ_i is a racer's skill, $a_1 > 0$ is a coefficient, μ_j is a race fixed effect, ε_i is an unobserved component. With $a_2 < 0$ being some coefficient, the final time can be written as

$$T_i = \begin{cases} \text{NA} & \text{if } S_i = 0 \\ \theta_i a_2 + \delta_j + v_i & \text{if } S_i = 1 \end{cases} \tag{12}$$

We consider a specific race with three top racers under two circumstances. First, conditions are equal for all racers. Second, the three top racers ($i \in \{1, 2, 3\}$) suffer from bad weather conditions, which makes it impossible for them to attain a place on the podium.

$$\mathbf{Z} = \mathbf{D} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 1 \\ 1 \end{pmatrix} \qquad \mathbf{Z}' = \mathbf{D}' = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \end{pmatrix} \tag{13}$$

In this case, it is obvious that the assignment status of individuals 4–6 depends upon the assignment of the three top racers. However, since $D_i = Z_i$, the individual treatment status D_i can still be written as a function of the assignment Z_i.

Turning to the implication (b) of SUTVA, we first note that our outcome can be written purely as a function of the assignment, i.e. $Y_i(\mathbf{Z}, \mathbf{D}) = Y_i(\mathbf{Z})$. This comes from the fuzzy design where $\mathbf{Z} = \mathbf{D}$.

Any measure of relative performance —such as the position— depends on a racer's own time as well as the competitors' times: $P_{i,j} = g(T_{i,j}, T_{s,j}) = g(\theta_i, \lambda_{i,j}, n_{i,j}, \theta_s, \lambda_{s,j}, n_{s,j}) \quad \forall s \neq i$. The winner's time is often the benchmark and can be written as

$$T_{\text{win},j} = \min_{i \in S}(T_{i,j}) \tag{14}$$

where S indicates the set of survivors. For the sake of illustration, we specify equation (12) for survivors as

$$T_{i,j} = \theta_i a_2 + \delta_j + \text{Exp}_i a_3 + \text{Exp}_i^2 a_4 + \tau_i a_5 + u_i \tag{15}$$

where Exp_i is experience and treatment τ_i equals one if racer i won the last race and zero otherwise. Imagine that the winner in a given race j is determined by a tiny time difference between racer 1 and 4. Assume both racers to have the same skill level θ_i, but while racer 1 is a rookie, racer 4 is an experienced and successful racer. Racer i's relevant outcome $Y_i = P_{i,j+1}$ in the next race depends on the performance of the best racer in that race. So if racer 4 wins today and $a_5 \neq 0$, $T_{\text{win},j+1}$ is likely to be lower than if racer 2 wins (because racer 4 is more experienced and experience positively affects performance).

Therefore, the outcome of racer i in race $j+1$ is likely to depend on the assignment of the winner (note that treatment and assignment are henceforth defined for the victory treatment and not the podium treatment as above)

$$\mathbf{Z} = \mathbf{D} = \begin{pmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \qquad \mathbf{Z}' = \mathbf{D}' = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{pmatrix} \qquad \text{and} \qquad Y_i(\mathbf{Z}) \neq Y_i(\mathbf{Z}')$$

which violates definition (b) of SUTVA.

This problem arises to different extents with all kinds of relative performance measures. Thus we limit our analysis to using absolute race times as outcome variable for performance.

A.3 Identifying Assumptions

In order to estimate causal effects in a regression discontinuity design, four assumption have to be satisfied. First, the treatment must be determined exclusively by the assignment variable. This is obviously true in our case since an individual's race time determines the position (i.e. treatment). Second, there has to be a discontinuity in the level of treatment at the cutoff. Again, this is straightforward in our case since only three racers make it to the podium. Third, we must exclude the possibility of manipulation around the cutoff (McCrary, 2008). Since all racers want to be as fast as possible and do not know about the threshold when racing, manipulation is not an issue. Also the density of observations is smooth around the cutoff, as shown by figure 3. Finally, there must not be any discontinuities in the distributions of other variables at the cutoff (Hahn, Todd and van der Klaauw, 2001; Imbens and Lemieux, 2008). We provide evidence for this by means of the balance tests in Table 2.

According to Heckman, LaLonde and Smith (1999), RD estimators are a special case of selection on observables. The first crucial assumption for the estimation is that treatment is randomly assigned. Using an valid RD design, this assumption is trivially satisfied around the cutoff. However, the second key assumption, overlap, is clearly violated. Thus we have to impose the assumption of continuity of all other factors to compensate for the failure of the overlap condition. This is done by providing balance tests that are reported in Table 2.

B Additional Tables and Figures (Not for Publication)

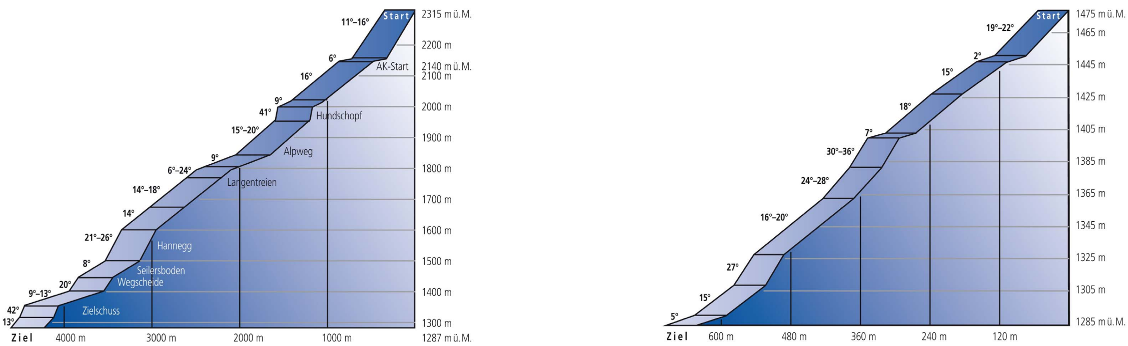
Table B.7: Effect of Podium Finish on Risk Behavior

	Effect on Survival	N	Effect on Variance	N
Bandwidth 5	0.017 (0.069)	521	-0.022 (0.016)	308
Bandwidth 15	-0.014 (0.062)	1,559	-0.006 (0.015)	974
Bandwidth 25	0.021 (0.067)	2,674	-0.009 (0.015)	1,690
OLS	0.007 (0.010)	19,122	0.001 (0.002)	10,800
OLS (top 5)	0.021 (0.014)	5,051	-0.001 (0.003)	3,200

Note: The table shows the results of linear regressions using finishing the next race as dependent variables. Bandwidths are 5, 15, and 25 hundredths of a second, respectively. We control for survival in the last race. For bandwidths 15 and 25 we use squared and cubic terms of the running variable $(T_{i,j} - c_j)$. The second OLS estimation is limited to racers who finished in the top 5. Standard errors are clustered at the racer level and shown in parentheses. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

Figure B.8: Profile of Downhill and Slalom Race

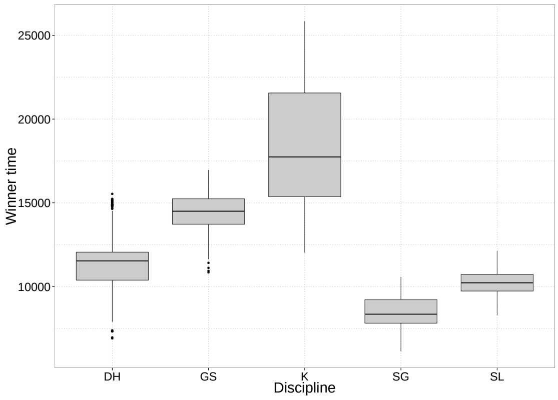
(a) Downhill (b) Slalom



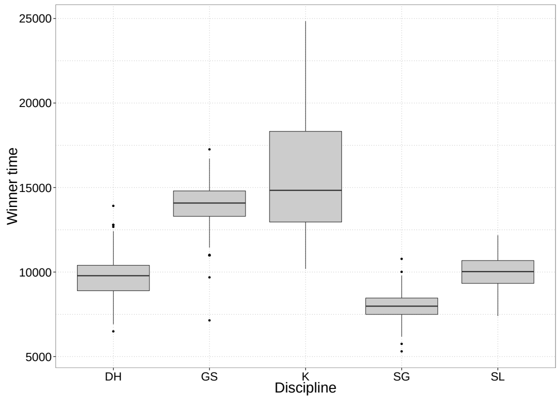
Note: The figure shows an illustration of the profiles of downhill and slalom race in Wengen. Source: www.lauberhorn.ch

Figure B.9: Winner Times in Different Disciplines

(a) Men



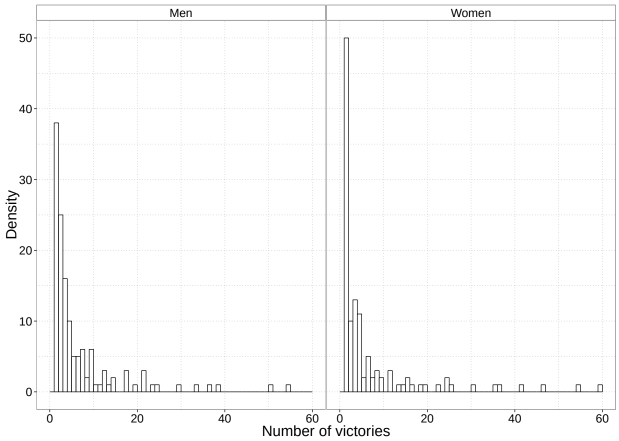
(b) Women



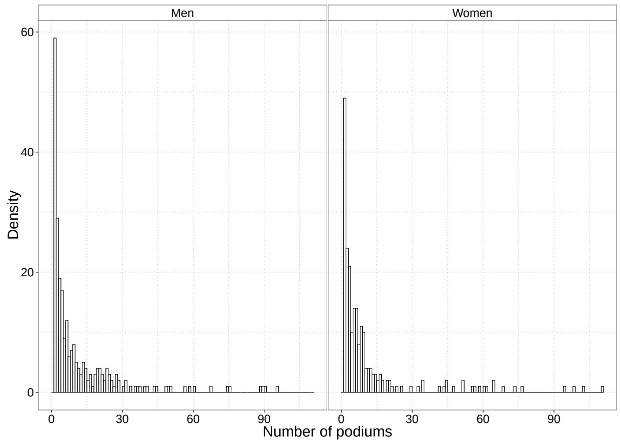
Note: The figure shows a boxplot of winner times (in hundredths of a second) for each category downhill (DH), giant slalom (GS), comined race (K), super giant slalom (SG), and slalom (SL). Note that 25,000 hundredths of a second (or centiseconds) equal 4 min 10 sec, while 15,000 centiseconds equal 2 min 30 sec, and 10,000 centiseconds equal 1 min 40 sec, respectively.

Figure B.10: Distribution of Career Achievements

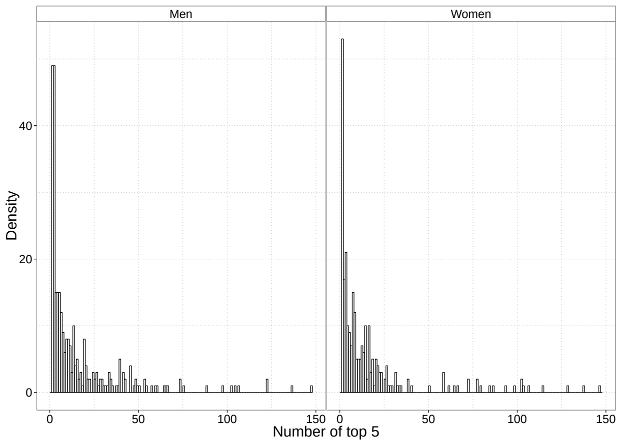
(a) Victories



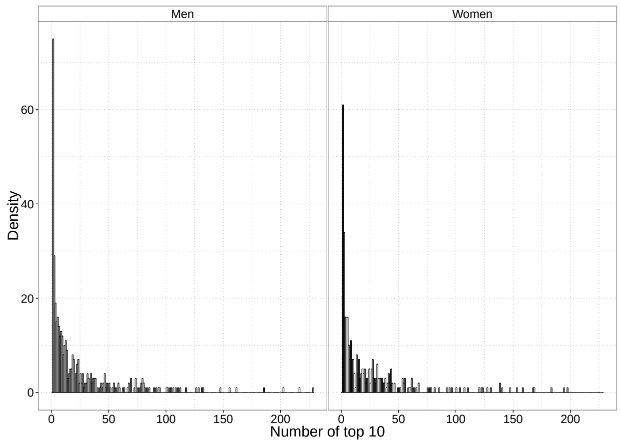
(b) Podium Finishes



(c) Top Five Classifications



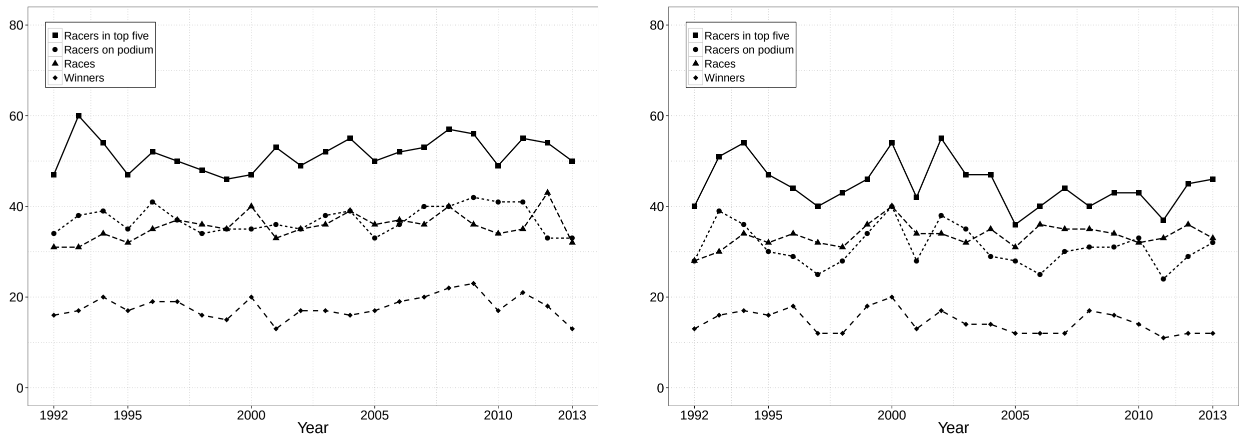
(d) Top Ten Classifications



Note: The histogram shows the total number of victories, total number of podiums, total number of top give classifications, and total number of top ten classifications during a racer's active career. Note that we discard zero entries for illustration purposes. The number of racers who had never won a racer during their career is 1,387 (1,161) for men (women). The number of racers without podium is 1,298 (1,076) for men (women). For top five and top ten classifications the numbers are 1,241 (1,022) and 1,133 (905) for men (women).

Figure B.11: Composition of the Starting Grid per Season

(a) Men **(b)** Women



Note: The figure depicts the number of racers with at least one victory in a given year (dotdashed line). Furthermore, it also shows the number of races per season (dotted line) as well as the number of racers on the podium (dashed line), and in the top five (solid line). The sample period is 1992–2013.