Is there a gender difference in the ability of dealing with failures? Evidence from professional golf tournaments[a]

by

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Abstract

Recent experimental evidence suggests that women in general are more discouraged than men by failures which potentially can explain why women, on average, are less likely than men to reach top-positions in firms. This paper provides the first quasi-experimental evidence from the field on this issue using data from all-female and all-male professional golf tournaments to see if this result can be replicated among competitive men and women. These top-performing men and women are active in an environment with multiple rounds of competition and the institutional set-up of the tournaments makes it possible to causally estimate the effect of the result in one tournament on the performance in the next. The results show that both male and female golfers respond negatively to a failure and that their responses are virtually identical. This finding suggests that women's difficulties in reaching top-positions in firms are caused by external rather than internal barriers.

Keywords: glass ceiling, failure, gender, regression discontinuity design, golf

JEL-codes: J16, J24, L83, C93

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1 Introduction

Women are underrepresented in absolute top-positions in firms and other organizations (see, e.g., Bertrand and Hallock [2001], Wolfers [2006] and Bertrand [2009]). One important explanation for this observation is that women, on average, choose less competition-intensive careers than men. Women are, for example, typically underrepresented in the private sector (see, e.g., Lanfranchi and Narcy [2015]). In experiments it has also been shown that women to a greater extent than men choose piece rate schemes over winner-takes-it-all schemes (see Niederle and Vesterlund [2007] and Dohmen and Falk [2011]).

More puzzling, however, is the observation that there also seems to be a glass ceiling for the women that actually enter highly competitive work environments, i.e. also competitive women struggle to reach top-positions in firms (see, e.g, Albrecht, Björklund and Vroman [2003] and Arulampalam, Booth and Bryan [2007] for evidence of the glass ceiling effect). Discrimination of women is probably one explanation for this phenomenon but it could potentially also be driven by remaining gender differences in competitiveness. Individuals that want to make career progress in competitive environments typically participate in multiple rounds of competitions in which they repeatedly compete for new positions and promotions. Most individuals are bound to experience multiple failures in the initial stages of their careers because they are competing against more experienced competitors and such negative outcomes might be detrimental for the confidence and subsequent performance (see Rosenqvist and Skans [2015] for the importance of previous competitive outcomes on current performance). Having a firm belief in one's ability is arguably important for not becoming too discouraged by failures and since previous evidence indicates that men have higher levels of confidence than women (see, e.g., Lundeberg, Fox and Punćcohaŕ [1994], Barber and Odean [2001] and Niederle and Vesterlund [2011]), women are potentially more vulnerable to failures with respect to the ability of bouncing back. Consistent with this hypothesis recent experimental evidence on university students in the UK suggests that women, on average, respond more negatively than men to failures with respect to subsequent performance which potentially can explain why women, on average, are less likely than men to make substantial career advancements (see Gill and Prowse [2014] for the experimental study).

While the finding in Gill and Prowse (2014) is highly interesting for the understanding of the general behavior of men and women it is only relevant for the glass ceiling phenomenon if it can be replicated among competitive men and women that have actually chosen to enter competition-intensive work environments. Identifying causal effects of successes/failures on subsequent performance for competitive men and women on the regular labor market is however difficult because of the general scarcity of relevant data and because of systematic ability differences between individuals that fail and individuals that succeed. For these reasons researchers have turned to the world of sports. While the performance in the sport setting relate to very particular tasks, it is a setting where highly competitive men and women are active and where performance data often is readily available. As such sports competitions constitute a useful testing ground for theories about the behavior of competitive men and women.[1]

Wozniak (2012) and Jetter and Walker (2015) both use data from all-male and all-female professional tennis tournaments to study how the probability of winning the current game is affected by previous results. Using selection-on-observables strategies to identify the causal effect of previous results on current performance they both find that men and women are more likely to win the current game if they have experienced recent successes and that these effects are very similar in magnitude across the genders. Similarly, Banko, Leeds and Leeds (forthcoming) study if female tennis players are more likely than men to lose in straight sets (the hypothesis being that women find it harder to come back after losing the first set) but do not find any gender differences. Overall, these findings would suggest that the result in Gill and Prowse (2014) about women being particularly sensitive to failures does not hold among competitive men and women and that these men and women instead are equally sensitive to previous competitive outcomes with respect to current performance. A fundamental problem with these observational tennis studies is, however, that they cannot control for the counterfactual development which makes it hard to determine if persistent successes (and failures) are due to causal success/failure effects (i.e. the first success causing the

[1] Data from golf tournaments have, e.g., been used to study predictions of tournament theories (Ehrenberg and Bognanno [1990a and 1990b], Orszag [1994] and Melton and Zorn [2000]), peer effects (Guryan, Kroft and Notowidigdo [2009]) and loss aversion (Pope and Schweitzer [2011]).

next one) or just time-varying ability. In addition the result of a tennis game is affected by the performance of the opponent making it even more difficult to cleanly estimate causal success/failure effects on subsequent performance.

With respect to this issue Rosenqvist and Skans (2015), using data from professional golf tournaments on the male European Tour, made a key contribution by providing quasi-experimental evidence from professional golf tournaments where same-ability players randomly end up in success or failure states. In these tournaments players are separated into success and failure half-way through the tournaments by the so called cut (a qualification threshold). Players close to the cut have performed almost equally well but will arguably perceive their performances differently in terms of success or failure. By comparing the performance of marginally successful players and their marginally unsuccessful “copies” in the next tournament the confounding impact of ability can be purged from the analysis and the causal effect of experiencing a success (relative to a failure) can be identified (i.e. a regression discontinuity [RD] strategy is used for identification). Rosenqvist and Skans (2015) found that male golfers substantially enhance their performance after a success but unfortunately they did not have data to analyze the corresponding behavior of female golfers. In this paper I add data from the PGA Tour (main tour for men in the US) and the LPGA Tour (main tour for women in the US) making it possible to use the same RD strategy to examine potential gender differences in the causal impact of a previous success/failure on current performance.

Thus, in this paper I provide the first quasi-experimental evidence from the field on potential gender differences in the productivity response to previous competitive outcomes among competitive men and women. These top-performing male and female athletes are active in an environment with multiple rounds of competition which resembles the situation for men and women in the corporate sector trying to make career progress.

A preview of the results shows that the current performance of both male and female golfers is negatively affected by a previous failure and that the effects are virtually identical in magnitude. The results suggest that the confidence of top-performing competitive men and women is affected by previous competitive experiences and that this effect has a substantial impact on subsequent performance. However, women show no tendencies of being more sensitive than men to previous outcomes. Thus, if the behavior of these professional male and female athletes is similar to the behavior of competitive men and women in the civil society it seems unlikely that women are unable to reach top-positions in firms because they are worse than men at dealing with failures. Instead it seems likely that women's difficulties in reaching top-positions in firms and other organizations are caused by external barriers, which calls for more research on the structure of these barriers and on ways of penetrating them.

The remainder of this paper is structured as follows. Section 2 gives a detailed description of the data and Section 3 explains and tests the validity of the identification strategy. In Section 4 I present the main results. Section 5 concludes.

2 Data

2.1 General description

In this paper I use data from professional golf tournaments. The data come from the European Tour (males)[2], the PGA Tour (males) and the LPGA Tour (females).[3] The typical tournament in these tours is played over four days (normally Thursday–Sunday) and the players play 18 holes each day. The goal is to use as few strokes as possible to complete the holes. All entrants in a tournament play the first two days and based on the results after two completed days of play a line is drawn in the list of results that separates the 70 best players from the rest of the field. This line is called the *cutline* or the *cut* since players outside top-70 are eliminated from the tournament at this stage.[4] The cut thus specifies the maximum number of strokes that a player is allowed to have to be qualified for the rest of the tournament. If a player satisfies that criterion he or she *makes the cut*. Note that the cut is decided after two days of play which makes it hard to predict for the players while they are playing. It is however highly predictable at the late stages of the second round. Players that make the cut continue the tournament during the weekend and the final result is based on the total number of strokes used after 72 holes. All players that make the cut and finish the tournament receive prize money and

[2] This data was used in Rosenqvist and Skans (2015).

[3] The data from the European Tour has been collected manually from the European Tour website (www.europeantour.com). The data from the PGA Tour has been collected manually from the PGA Tour website (www.pgatour.com) and from https://sports.yahoo.com/. The data from the LPGA Tour has been collected manually from the LPGA Tour website (www.lpga.com) and from https://sports.yahoo.com/. Small parts of the data on the female golfers also come from the following sites: www.golfdata.se, http://www.foxsports.com/ and golfweek.com.

[4] The exact rule varies between the different tours and it has also varied within tours over time. The most common use of the cut is however that players that are tied for the 70:th position or better make the cut.

the exact amount depends on the player's final position. Players that fail to make the cut must leave the tournament empty-handed after two days of play. Since a made cut brings with it money, prestige and ranking points it seems reasonable to assume that players that fail to make the cut experience a failure relative to those players that make the cut. Importantly, at the cut there is only a one-stroke-difference between success and failure making this setting ideal for identifying potential success/failure effects through an RD strategy.

The data is structured in pairs of tournaments played during two consecutive weeks where the first tournament plays the role of a "treatment" tournament and the second the role of an "outcome" tournament. In the first tournament I have data on the value of the cut and the total number of strokes of each player after 36 holes.[5] It is therefore possible to determine if a player made the cut or not, i.e. if he or she is treated. I have access to the same kind of information for the second tournament which is used to measure potential performance effects of making the cut in the first tournament (conditional on ability). The number of strokes after 36 holes is used because all players participate up to that point. It should be noted that not all players in the first tournament participate in the second tournament which means that the outcome is missing for some of the players that participated in the first tournaments. To reduce the potential problem of selective participation in the second tournament I only use results from tournament pairs where the participation rate is at least 60 % in the second tournament.[6]

The dataset further contains information on total prize money for all tournaments and individual player characteristics in the form of experience measures and ability measures.

There are some institutional differences between the male and female golf tours. First, while men always play over four days (unless the weather forces the competition to be shortened) some tournaments on the LPGA Tour only have three days of play. The cut is still after 36 holes but those who make the cut only play 18 additional holes instead of 36. Since this institutional difference has nothing to do with the cut-rule or

[5] For a large share of the data I only have access to results for players within a six-stroke difference from the cut. To create consistency across tournaments this restriction is used throughout the paper though some tournaments contain data on more players in the list of results.

[6] Making the cut is generally associated with a higher probability of participating in the outcome tournament. But conditional on the empirical RD model making the cut has a negative effect on participation (statistically significant for men). This is, however, only a problem if it biases the distribution of the skill of the participating players around the cut. I test this in Section 3.2.

the importance of making the cut it seems unlikely that it should matter for the success/failure effects. Secondly, the average prize money in men's tournaments is much higher than the average prize money in women's tournaments. The average prize money for men in my data is roughly $4,000,000 while the corresponding amount for women is $1,400,000. Essentially, this means that making (or failing to make) the cut has much larger financial consequences for male golfers than for female golfers. Even though the gender difference in prize money is large there is still substantial prize money involved also in women's tournaments suggesting that perceptions of success or failure following a made or missed cut are likely to emerge both for male and female golfers. To make sure that difference in prize money does not interfere with the analysis I do robustness checks in section 4.2 on samples that are comparable in terms of prize money.

2.2 Descriptive statistics

The most widely used sample in the paper contains 189 tournament pairs from the European Tour, 251 from the PGA Tour and 202 from the LPGA Tour. The total number of observations pertaining to the European Tour is 21,912 (16,515 participate in the outcome tournaments). The corresponding numbers for the PGA Tour and the LPGA Tour is 28,988 (19,604 participate in the outcome tournaments) and 21,682 (17,014 participate in the outcome tournaments). The number of unique players in the sample of 16,515 observations with non-missing information on outcomes on the European Tour is 1,020. The corresponding numbers for the PGA Tour and the LPGA Tour is 807 and 673.

Table 1 provides summary statistics for the sample that I use to examine treatment effects, i.e. for observations with non-missing data on the outcome variables. The stats are presented separately for men and women. Two general facts related to the empirical strategy should be highlighted. First, players that are successful in the treatment tournament (i.e. Cut=1) have better results than the unsuccessful players (i.e. Cut=0) in the outcome tournament. The successful players have fewer strokes after two rounds and are more likely to make the cut. This difference in future performance between successful and unsuccessful players is particularly pronounced for women. Second, while the above finding is consistent with a positive impact of a success on future performance a complicating factor is that successful players were better than their unsuccessful counterparts already before the treatment tournament (see stroke average in the previous year). Thus, a simple comparison of mean future outcomes between successful and unsuccessful players is biased by ability differences. This highlights the need for an empirical model that allows us to estimate the impact of making the cut, relative to failing to make it, on future performance conditional on ability. A model that does just that is explained in Section 3.

It should be noted that the female golfers have roughly three years less experience than the males as measured by time as a professional golfer (being a professional golfer means that the golfer can compete for money). This implies that the two samples are not completely comparable. On the other hand, as Hensvik (2014) shows, women in the higher ranks of firms are often less experienced than their male peers making the data in this paper empirically relevant. Nevertheless, in section 4.2 I do robustness checks on samples that are comparable in terms of experience.

Table 1: Descriptive statistics for the used sample

	Males			Females		
	All	Cut=1	Cut=0	All	Cut=1	Cut=0
Treatment tournaments						
Average cut	143.01	143.01	143.00	145.45	145.51	145.38
Normalized strokes	0.19	-2.06	3.01	0.07	-2.18	3.00
…standard deviation	3.00	1.64	1.64	3.05	1.67	1.63
Made the cut	0.56	1.00	0.00	0.56	1.00	0.00
Outcome tournaments						
Average cut	142.75	142.77	142.72	145.61	145.72	145.47
Strokes relative to the cut	0.31	-0.14	0.87	0.05	-0.77	1.12
…standard deviation	4.37	4.31	4.38	4.68	4.49	4.71
Made the cut	0.55	0.59	0.50	0.56	0.63	0.47
Player characteristics						
Years as pro	11.98	12.02	11.93	8.63	8.51	8.80
…standard deviation	6.38	6.29	6.50	5.79	5.59	6.04
…nonmissing	0.98	0.98	0.97	1.00	1.00	1.00
Stroke average in previous year	71.67	71.56	71.81	72.96	72.72	73.28
…standard deviation	1.16	1.09	1.23	1.36	1.29	1.39
…nonmissing	0.88	0.90	0.87	0.93	0.95	0.91
Number of tournaments	440	440	440	202	202	202
Number of clusters (strokes by tournament)	5,229	2,627	2,602	2,404	1,208	1,196
Number of observations	36,119	20,100	16,019	17,014	9,597	7,417

Notes: This table contains statistics on players that participated in outcome tournaments with high participation rates (i.e. where at least 60 % of the players in the treatment tournament also participated in the outcome tournament).

3 Empirical strategy

3.1 Empirical model

The fundamental assumption behind the empirical strategy is that players with results close to the cut ended up on the right or wrong side of it by chance. If so, the ability of the players close to cut should be virtually identical which means that I can estimate the effect of making the cut on future performance conditional on ability, i.e. I can estimate the causal effect of experiencing a relative success on the performance in the next tournament. The validity of this assumption is of course central for this exercise and it will be studied in detail in Section 3.2.

In the ideal RD setting the researcher can compare the mean outcome of the treated and the controls that are infinitely close to the threshold since these individuals have balanced covariates. In practice, however, the number of observations typically goes to zero as we get closer and closer to the threshold forcing the researcher to adopt a wider bandwidth. With a wider bandwidth comes the problem of unbalanced covariates which means that the simple comparison of outcomes must be abandoned in favor of a method that approximates the value precisely at the cutoff for treated and controls respectively. When the variable that determines assignment to treatment (hereafter called *running variable*) is discrete, as in this paper, the bandwidth is by construction too wide for a simple comparison of mean outcomes. Instead I use the relation between the running variable and the outcome variable to approximate the outcome for hypothetical individuals that just marginally are on the success respectively failure side of the threshold (see Lee and Lemieux [2010] for a thorough description of this method). This is done using the regression model specified in Eq. (1):

$$Y_{ic} = \beta_0 + \beta_1 I[Z_{ic} \leq 0] + \beta_2 Z_{ic} + \beta_3 I[Z_{ic} \leq 0] Z_{ic} + \delta_c + u_i \qquad (1)$$

The outcome, denoted Y_{ic}, is a measure of the performance in the second tournament (typically the number of strokes), where the subscript *c* highlights that it is a competition specific outcome. Z_{ic} is the number of strokes after 36 holes in the treatment tournament normalized by the subtraction of the cut in the tournament. Thus, as Z_{ic} crosses zero from the positive side the treatment goes from off to on. Since both Z_{ic} and Y_{ic} constitute measures of ability (the higher the worse) we expect a positive relation between the two. The terms $\beta_2 Z_{ic}$ and $\beta_3 I[Z_{ic} \leq 0]Z_{ic}$ allow this relation to be different on the two sides of the threshold. With the help of the estimated relation between Z_{ic} and Y_{ic} it is possible to predict the values of Y_{ic} as Z_{ic} approach zero from below and above respectively. The difference between these two values measures what happens with the outcome as the treatment is turned on while the running variable is held constant. Thus, the estimate of β_1 approximates the difference in mean outcome for treated and controls that are infinitely close to the threshold (i.e. that have virtually the same ability). δ_c captures competition fixed effects and u_i is an error term.

If players close to the threshold really have the same ability, the estimate of β_1 corresponds to the causal effect of making the cut, relative to failing to make it, on the performance in the outcome tournament. Importantly, β_1 gives the performance difference between marginal winners and marginal losers not between marginal winners and completely unaffected players. Thus, if marginal winners outperform marginal losers this potential difference can be driven both by marginal winners improving their performance (relative to their hypothetical unaffected control state) and by marginal losers decreasing their performance (relative to their hypothetical unaffected control state). The data do not allow me to disentangle these two potential mechanisms.

As in Rosenqvist and Skans (2015) I cluster the standard errors at the strokes by tournament level because of potential joint specification errors for each stroke-group (see Lee and Card [2008] for a discussion of standard errors when performing RD analyses with a discrete running variable).

The main purpose of the paper is to investigate if the value of β_1 is different for men and women and such tests can be done by interacting all variables in Eq. (1) with an indicator for being a woman. By doing so success/failure effects for both men and women can be estimated in a joint regression framework and potential gender differences can be directly examined. Formally I use the statistical model specified in Eq. (2):

$$Y_{ic} = \beta_0 + \beta_1 I[Z_{ic} \leq 0] + \beta_2 Z_{ic} + \beta_3 I[Z_{ic} \leq 0]Z_{ic} + \beta_4 Female_i \quad (2)$$
$$+\beta_5 Female_i I[Z_{ic} \leq 0] + \beta_6 Female_i Z_{ic} + \beta_7 Female_i I[Z_{ic} \leq 0]Z_{ic} + \delta_c + u_i$$

In this model, β_1 corresponds to the causal effect of making the cut, relative to failing to make it, on the performance in the outcome tournament for men while the sum of β_1 and β_5 gives the corresponding effect for women. The difference between the genders is thus given by β_5 which constitutes the main parameter of interest.

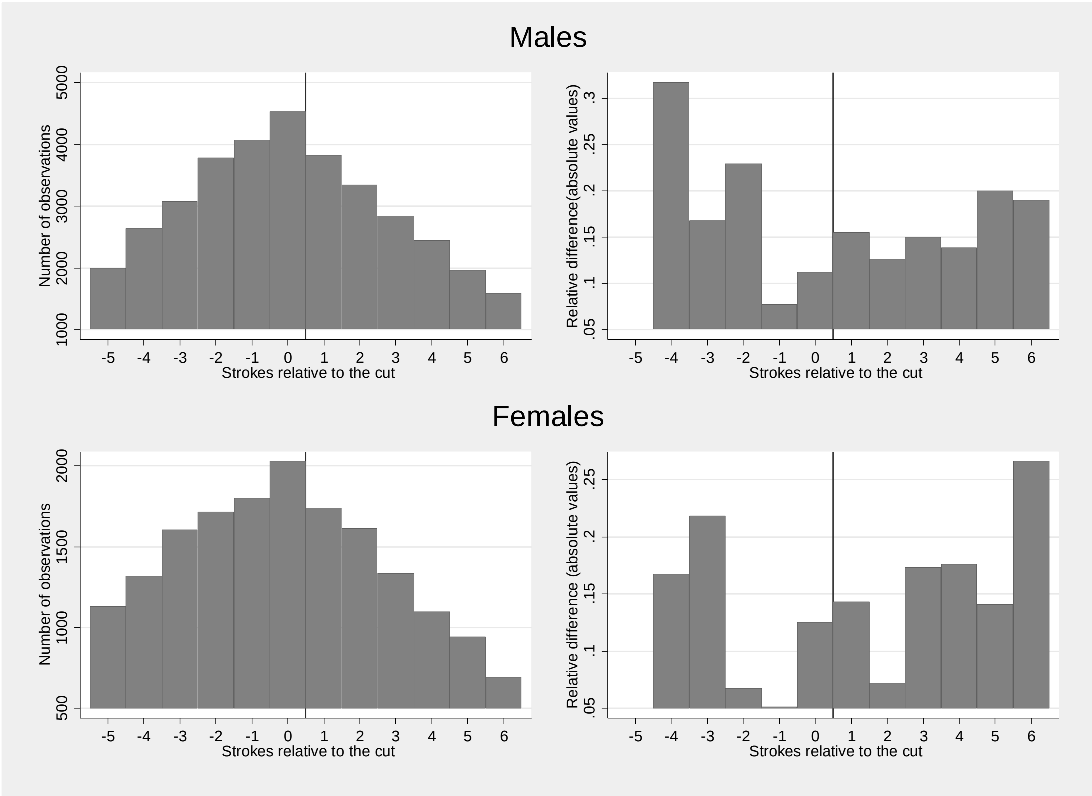
3.2 Validity of the empirical strategy

Two conditions need to be fulfilled in order for the empirical strategy to be valid. First, the ability of players must be continuous in the running variable across the threshold. Second, it is required that the incomplete participation in the outcome tournament does not bias the ability balance at the threshold. Thus, it is not enough that players distribute themselves randomly around the cutoff in the treatment tournament, instead the test of the randomization must be done *conditional on participation in the second tournament*.

To test if players close to the cutline that actually participated in the subsequent outcome tournament ended up on the success respectively failure side of the threshold by random chance rather than by deterministic reasons driven by ability differences I investigate if the number of observations evolves smoothly over the cutoff and if predetermined measures of experience and ability are continuous around the cutoff conditional on the empirical model (i.e. Eq. [1]).

Figure 1 describes the distribution of the running variable for males (top panel) and females (bottom panel) respectively. Positive numbers on the running variable indicate that the players failed to make the cut with 1 stroke, 2 strokes and so on. For both men and women the number of observations reaches its maximum at 0 meaning that the most common result after 36 holes is to have the same number of strokes as the cut stipulates. This is however not an unnatural mass point, rather it is the distribution one would expect to see even if there was no cut and all players were allowed to complete the tournament. Since the cut by definition lies in the middle of the field and since ability arguably is normally distributed variable, it is not surprising to see that most players end up exactly on the cut. A more interesting exercise is instead to see how the relative difference in the number of observations between 0 (made the cut) and 1 (did not make the cut) looks like in comparison with other relative differences. This is shown in the right hand side of Figure 1. The value at e.g. -4 represents the absolute difference in the number of observations between -5 and -4 divided by the number of observations at -5. Thus, the relevant bar for our purposes is the one at 1. As can be seen, the relative difference between 0 and 1 does not in any way stand out in the distribution of relative differences which suggests that neither men nor women can “force” themselves into just barely making the cut.

Figure 1 Distribution of running variable for males and females

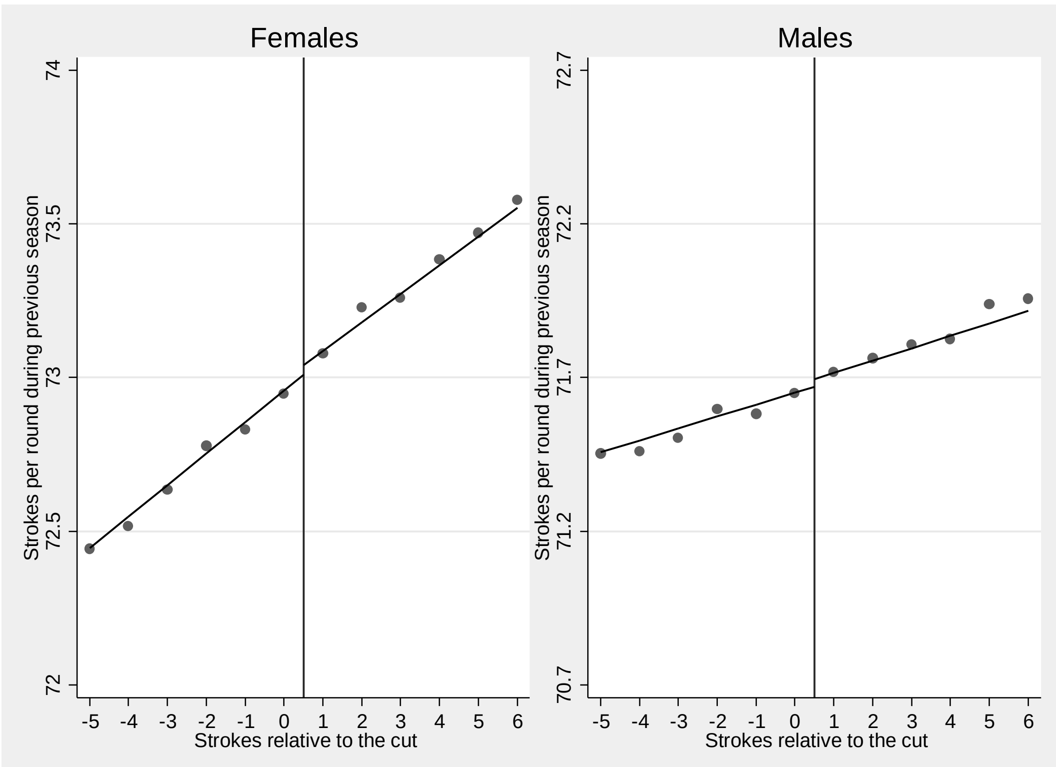


Notes: The histograms for males are based on 36,199 observations. The histograms for females are based on 17,014 observations.

Even if no signs of manipulation at the cutoff can be found by looking at the distribution of the running variable we can still not rule out the possibility that marginal winners and marginal losers are different from each other in a systematic way. In Figure 2 I therefore examine how the predetermined ability of the players evolves over the threshold for women and men. The predetermined ability is measured using the average number of strokes used per round in the season preceding the treatment tournament. This statistic is generally considered a precise measure of a player’s underlying ability and it tends to be stable over years. The last point is clear in Figure 2 since we see that female and male golfers that performed poorly in the treatment tournament (e.g. strokes relative to the cut equal to 5 or 6) also displayed a high stroke average in the previous season. The fact that the data shows a strong positive association between the running variable and the stroke average the previous season suggests that the stroke average the previous season is an accurate measure of the players' ability going in to the treatment tournament.

Reassuringly for the empirical strategy there is no jump in this ability measure at the cutoff meaning that any potential jumps in the outcome variables at the cutoff are not driven by predetermined ability differences. While the overall picture looks the same for women and men the relation between previous and current performance is stronger for women (i.e. the slope is steeper). This means that female golfers exhibit a greater consistency in their performances than men. Simply put, women are more stable than men. While this result lies outside the focus of this paper it is an interesting finding that calls for more research on the consistency in performance of men and women in different contexts.

Figure 2 Strokes per round during the previous season

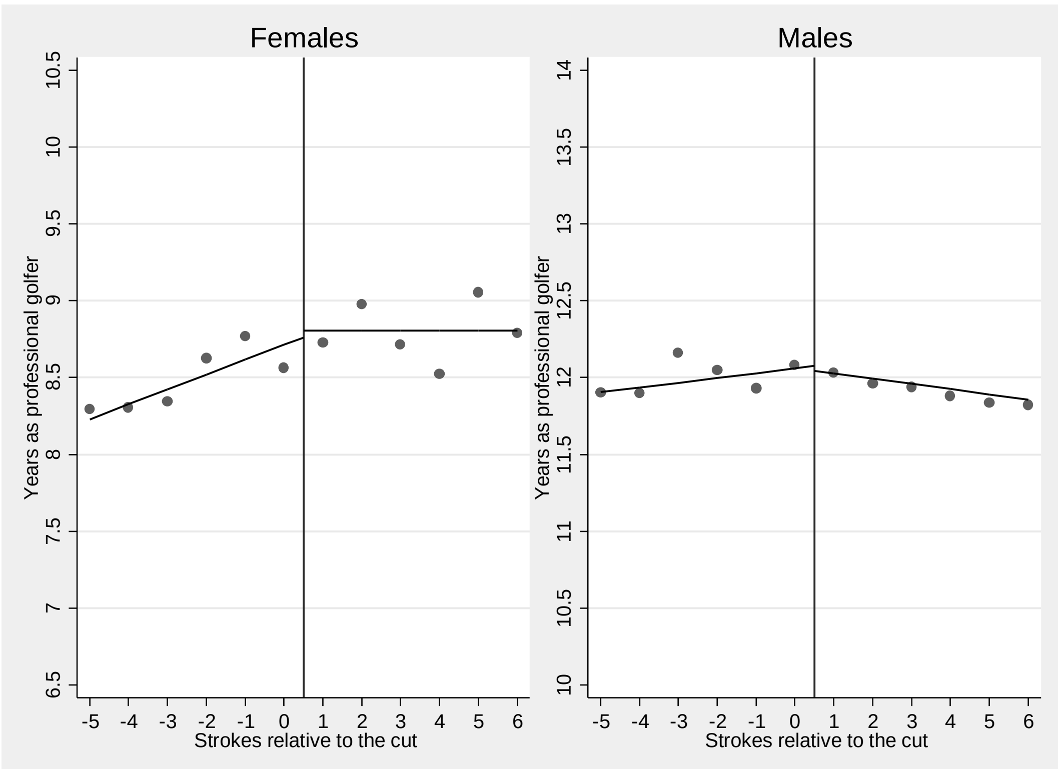


Notes: The figure is based on observations with non-missing data on the relevant characteristic which amounts to 15,878 observations for females and 31,940 observations for males.

Another way of testing if marginal winners and marginal losers are comparable is to examine how the experience of the players evolves over the threshold. If there is a jump at the cutoff such that more experienced players to a greater extent are on the success side it would indicate that the cut is very predictable and that experienced players better can predict the cut and adjust their play so that they just marginally make it. Figure 3 shows, however, that such worries are misplaced since the measure of experience displays smoothness at the cutoff. The specific measure of experience is the number of years as a professional golfer which captures how long the player has been competing for money. The relation between the running variable and experience is unclear. For women, relatively inexperienced players have the best results while inexperienced men display large variation in their results. The picture around the threshold is however similar for the two genders; there is no discontinuity in experience as the running variable crosses the cut.

Overall, these validity checks confirm that the empirical strategy can give a robust identification of success/failure effects on performance.

Figure 3 Years as professional golfer



Notes: The figure is based on observations with non-missing data on the relevant characteristic which amounts to 16,994 observations for females and 35,350 observations for males.

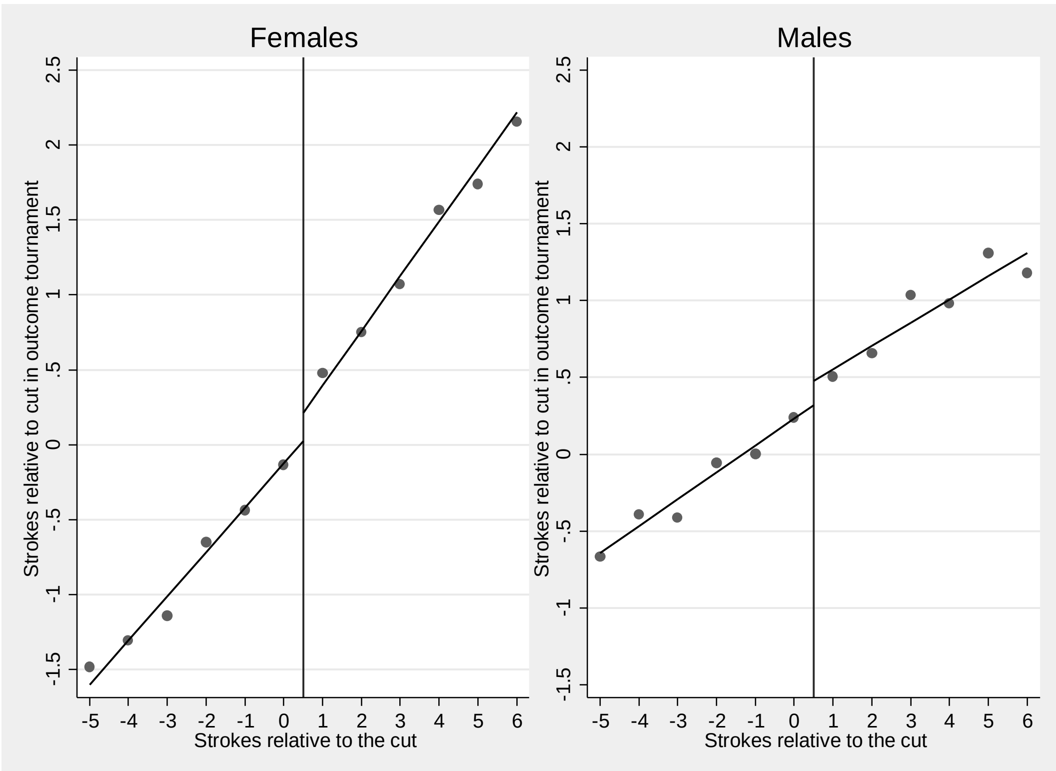
4 Results

4.1 Main results

Figure 4, Figure 5 and Table 2 present the main results, i.e. estimates of the effect of a previous (relative) success on current performance conditional on ability.

Figure 4 shows the number of strokes after two days in the outcome tournament (normalized by the cut in the relevant outcome tournament) on the y-axis and the number of strokes relative to the cut in the treatment tournament on the x-axis. It is clear that a good performance in the treatment tournament (i.e. a low x-value) is associated with a good performance also in the outcome tournament (i.e. a low y-value). Thus, relatively better players persistently perform well whereas relatively worse players persistently perform poorly. The focus of our attention should however be the action at the cutoff where we see that the hypothetical marginal winners (just below 0.5) outperform the hypothetical marginal losers (just above 0.5) for both women and men. The difference at the threshold is virtually identical for the two sexes amounting to roughly 0.16 shots.

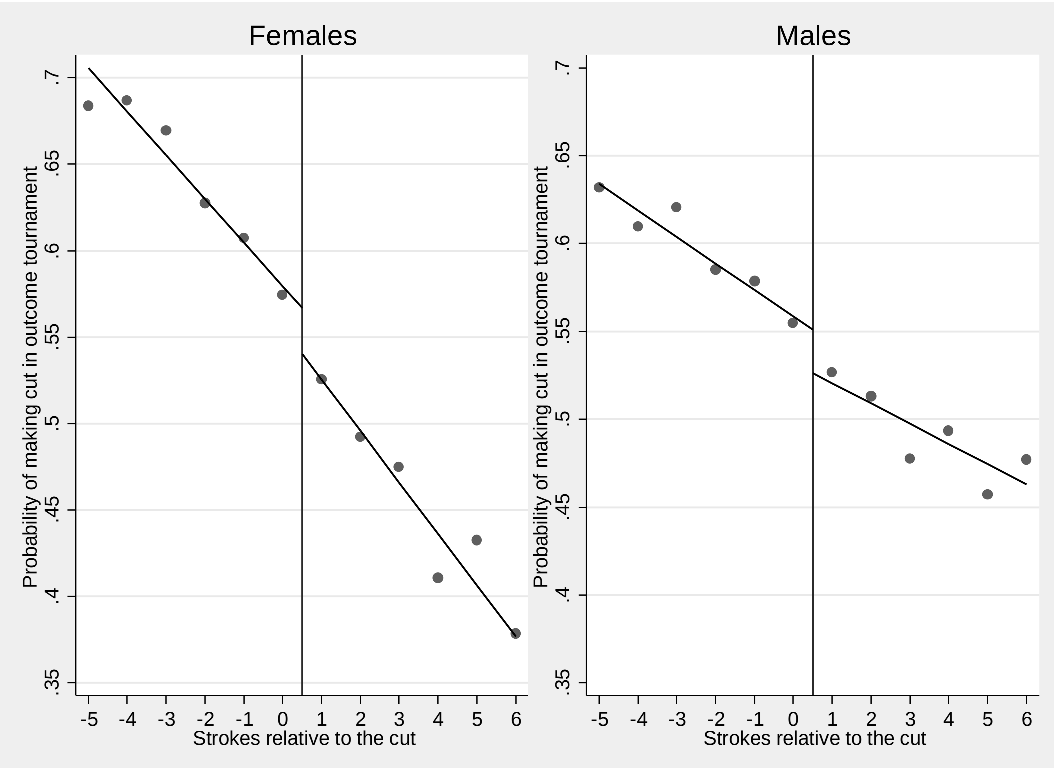
Figure 4 Strokes relative to the cut in the outcome tournament



Notes: The figure is based on observations with non-missing data on the outcome variable which amounts to 17,014 observations for females and 36,119 observations for males.

Figure 5 shows the results when making the cut in the outcome tournament is used as the outcome. Again we see that women and men behave similarly at the cutoff with marginal winners being about 2.5 percentage points more likely to make the cut in the next tournament than marginal losers. Making the cut is of substantial economic importance for the players and so the performance difference at the cutoff that we saw in Figure 4 has quite large real effects.

Figure 5 Probability of making the cut in the outcome tournament



Notes: The figure is based on observations with non-missing data on the outcome variable which amounts to 17,014 observations for females and 36,119 observations for males.

Table 2 contains the formal estimates of the results shown so far as well as tests of the differences between men and women. The estimates in column (1) corresponds to estimates of β_1 when I estimate Eq. (1) using the full sample. In columns (2) and (3) I do the same thing for males and females respectively. The estimates in column (4) corresponds to estimates of β_5 when I estimate Eq. (2) using the full sample. The negative effect on the number of strokes in the outcome tournament is significant on the 5 percent level for the full sample (column [1]) and for males (column [2]). As we saw in Figure 4 women exhibit a similar performance difference at the threshold but due to the smaller sample size the precision is not enough to establish a statistically significant effect (see column [3]). The difference in effect size between men and women is very small (roughly ten times smaller than the baseline effect in column [1]) and statistically insignificant (see column [4]), and it actually goes in the opposite direction of what should be expected if women are more sensitive than men to previous competitive outcomes.

With regard to performance differences between marginal winners and marginal losers measured by the propensity to make the cut in the outcome tournament, which are presented in panel B, we find a statistically significant result also for women (column [3]). Again the difference in effect size between men and women is small and statistically insignificant (see column [4]).

It should of course be noted that the precision allows for large differences between men and women before statistical significance is actualized and if the point estimates of the gender differences would be large but statistically insignificant I would be reluctant to rule out gender differences in the performance response to previous results. But since the point estimates for men and women are virtually identical the precision becomes a minor issue. Thus, overall the results suggest that there are no gender differences in the performance response to previous competitive outcomes.

Table 2. Main results – Marginal winners relative to marginal losers

Column:	(1)	(2)	(3)	(4)
Sample:	All	Males	Females	All
Estimate:	Main	Main	Main	Females-Males
Panel A.				
Outcome:	Strokes after 36 holes in outcome tournament			
Making the cut	-0.1629**	-0.1706**	-0.1558	0.0148
	(0.0673)	(0.0804)	(0.1200)	(0.1444)
Observations	53,133	36,119	17,014	53,133
Mean of dep.	143.8936	143.0593	145.6649	143.8936
Panel B.				
Outcome:	Indicator for making the cut in outcome tournament			
Making the cut	0.0255***	0.0266***	0.0240*	-0.0025
	(0.0079)	(0.0097)	(0.0133)	(0.0164)
Observations	53,133	36,119	17,014	53,133
Mean of dep.	0.5527	0.5487	0.5612	0.5527
Sample window	[-5,6]	[-5,6]	[-5,6]	[-5,6]
Linear RV	Yes	Yes	Yes	Yes
By treatment RV	Yes	Yes	Yes	Yes
Quadratic RV	No	No	No	No
By tournament RV	No	No	No	No
Covariates	No	No	No	No

Notes: Standard errors are clustered on the strokes * tournament level (in parentheses). */**/*** significant at the 10 /5/1 percent level. RV=running variable.

4.2 Robustness checks: model variations and experience and prize money

In Table 3 the results from Table 2 are subjected to a number of robustness checks in the form of model variations. The estimates in all seven columns come from variations of Eq. (2) and they all correspond to estimates of β_5 in that model (i.e. the interaction between making the cut and being a woman).[7] In columns (1–4) the bandwidth is gradually reduced and in column (5) I introduce a quadratic control for the running variable. In column (6) I add covariates (experience and predetermined ability) to the baseline model and specification (7) allows the linear relation between the outcome and the running variable to be specific for each tournament. Overall, the point estimates of the interaction effect are fairly robust to these model variations although they display some sensitivity to the very small bandwidths (see especially column [3]). As we can see in Figures 4 and 5 this is mainly driven by the fact that males with a running variable equal to three display quite extreme results in relation to the general trend. Given that the other estimates are reasonably similar to the ones presented in Table 2 I

[7] Separate results for men and women are presented in Table A1 in the appendix.

interpret the results as suggesting that men and women do indeed respond similarly to previous results with respect to current performance. As Table A1 in the appendix shows making the cut in the treatment tournament, relative to failing to make it, decreases the number of strokes after 36 holes in the outcome tournament by roughly 0.15 strokes for both men and women. Similarly, the probability of making the cut in the outcome tournament increases by about two percentage points for both men and women.

Table 3. Robustness checks – model variations

Column:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Strokes after 36 holes in the outcome tournament							
Making the cut * Female	-0.0229	0.0075	-0.2635	-0.1437	-0.0281	0.0382	0.0102
	(0.1548)	(0.1705)	(0.1978)	(0.2622)	(0.1402)	(0.1382)	(0.1364)
Observations	47,725	40,870	32,638	22,964	53,133	53,133	53,133
Mean of dep.	143.9033	143.8988	143.9144	143.8884	143.8936	143.8936	143.8936
Panel B. Making the cut in the outcome tournament							
Making the cut * Female	0.0019	-0.0119	0.0216	-0.0001	0.0011	-0.0042	0.0003
	(0.0176)	(0.0197)	(0.0229)	(0.0303)	(0.0159)	(0.0161)	(0.0155)
Observations	47,725	40,870	32,638	22,964	53,133	53,133	53,133
Mean of dep.	0.5513	0.5505	0.5470	0.5474	0.5527	0.5527	0.5527
Sample window	[-4,5]	[-3,4]	[-2,3]	[-1,2]	[-5,6]	[-5,6]	[-5,6]
Linear RV	Yes	Yes	Yes	Yes	Yes	Yes	Yes
By treatment RV	Yes	Yes	Yes	Yes	No	Yes	Yes
Quadratic RV	No	No	No	No	Yes	No	No
By tournament RV	No	No	No	No	No	No	Yes
Covariates	No	No	No	No	No	Yes	No

Notes: Standard errors are clustered on the strokes * tournament level (in parentheses). */**/*** significant at the 10 /5/1 percent level. RV=running variable.

As pointed out in section 2 the male and female golfers studied in this paper differ in terms of experience and they are active in environments with different financial conditions. These differences might interfere with the analysis in such a way that I estimate institutional differences instead of gender differences and to examine this potential problem I reestimate the model in Table 4 on samples that are fairly comparable in terms of experience and prize money. Since I have much more observations on male golfers than on female golfers, I make sample restrictions on the male sample to achieve comparability across sexes. I drop all men that have more than 18 years of experience and that participated in tournaments with total prize money of more than $3,300,000. These restrictions leave me with a sample of male golfers that, on average, have an experience of 9.5 years (compared with 8.6 for women) and that participate in tournaments with an average prize sum of $1,800,000 (compared with $1,400,000 for women). Thus, with these restrictions the samples are substantially more similar than before while they still allow me to keep roughly 15,000 observations on male golfers. The results from this exercise, which are presented in Table 4, are similar to the corresponding estimates in Table 2. The success effect for men on the number of strokes goes up somewhat in absolute terms (see column [2] of panel A) while the effect on making the cut instead makes a modest move downwards (see column [2] of panel B). But overall, the results are strikingly robust to these substantial sample restrictions suggesting that the gender differences in experience and prize money do not interfere with the main conclusion that competitive men and women respond similarly to previous results with respect to current performance.

Table 4. Robustness checks – similar experience and prize money across genders

Column:	(1)	(2)	(3)	(4)
Sample:	All	Males	Females	All
Estimate:	Main	Main	Main	Females-Males
Panel A.				
Outcome:	Strokes after 36 holes in outcome tournament			
Making the cut	-0.1837**	-0.2151*	-0.1558	0.0593
	(0.0868)	(0.1241)	(0.1200)	(0.1726)
Observations	32,164	15,150	17,014	32,164
Mean of dep.	144.6088	143.4227	145.6649	144.6088
Panel B.				
Outcome:	Indicator for making the cut in outcome tournament			
Making the cut	0.0230**	0.0220	0.0240*	0.0021
	(0.0099)	(0.0146)	(0.0133)	(0.0197)
Observations	32,164	15,150	17,014	32,164
Mean of dep.	0.5608	0.5605	0.5612	0.5608
Sample window	[-5,6]	[-5,6]	[-5,6]	[-5,6]
Linear RV	Yes	Yes	Yes	Yes
By treatment RV	Yes	Yes	Yes	Yes
Quadratic RV	No	No	No	No
By tournament RV	No	No	No	No
Covariates	No	No	No	No

Notes: Standard errors are clustered on the strokes * tournament level (in parentheses). */**/*** significant at the 10 /5/1 percent level. RV=running variable.

4.3 Additional results: high and low stakes

In Section 4.1 I found that marginal winners, in the treatment tournament, outperform marginal losers with respect to the performance in the outcome tournament. In this section I investigate how sensitive this performance difference is to the magnitude of the initial relative success/failure (i.e. the total prize money in the treatment tournament) and to the stakes in the outcome tournament (i.e. the total prize money in the outcome tournament).[8] The exercises are performed separately for men and women and the sensitivity of the effect sizes to the prize money is then compared. The magnitude of the initial relative success/failure is a binary variable that takes on the value 1 if the total prize money in the treatment tournament was above the median of the prize money in the treatment tournaments within the relevant combination of Tour and season and 0 otherwise. The stakes in the outcome tournament are also coded as a binary variable where 1 indicates that the prize money in the outcome tournament was above the median of the prize money in the outcome tournaments within the relevant combination of Tour and season.

I further group the players in four categories according to the values of the aforementioned two variables (i.e. zero-zero, zero-one, one-one and one-one). Doing so, I can in a simple way investigate how the success/failure effect is affected by the stakes in the outcome tournament holding the magnitude of the initial success/failure constant and vice versa.[9]

My findings are presented in Table 5 where I for ease of presentation only use making the cut in the outcome tournament as the outcome variable. In panel A I focus on players who participated in a treatment tournament with below median prize money. Thus, marginal winners and losers in this sample experienced relatively small successes respectively failures. I then investigate how the performance difference between these players in the outcome tournament is affected by the size of the prize money in the outcome tournament. In panel B I do the corresponding exercise for players that participated in a treatment tournament with above median prize money. In panels C and D I instead keep the prize money in the outcome tournaments fixed and vary the prize money in the treatment tournaments.

Azmat, Calsamiglia and Iriberri (forthcoming) and Gill and Prowse (2014) have previously done similar investigations in other settings. Azmat, Calsamiglia and Iriberri (forthcoming) study potential gender differences in the reaction to changed stakes. They

[8] Note that I only have data on the total prize money in the tournaments, not the prize money for the individual players. Thus, I use variation in prize money between tournaments and not between players within tournaments.
[9] This was also done in Rosenqvist and Skans (2015) using a slightly different empirical approach. They found that the success/failure effect for male golfers on the European Tour was entirely driven by high stakes outcome tournaments.

study Spanish high school students and find that female students have a tendency of choking under pressure, in the sense that the gender gap in test results (to the advantage of females) is smaller in high stakes test than in low stakes test. Intuitively, positive recollections of previous performances should be particularly important in situations where the probability of choking under pressure is relatively high (i.e. high stakes situations). Thus, the effect of making the previous cut on current performance should generally be higher in high stakes outcome tournaments, and if the results in Azmat, Calsamiglia and Iriberri (forthcoming) are relevant also for adult competitive women this pattern should be particularly pronounced for female golfers since they are suggested to be more likely to choke under pressure. This reasoning implies that the estimates in column (2) of panels A and B generally should be higher than the corresponding estimates in column (1) and that the difference in column (3) should be higher for females than for males. The estimates in columns (1–2) of panels A and B are only statistically significant on one occasion (see males in panel B) but the fact that high stakes outcome tournaments always produce greater point estimates than low stakes outcome tournaments strengthens the notion that earlier successes (which are assumed to build confidence) are most valuable in high stakes environments when players are likely to be under pressure. The success/failure effect for women is, however, not more sensitive to the prize money in the outcome tournament than the effect for men; instead, if anything, the estimates suggest that men are more confidence-dependent than women in high stakes situations since they seem to be very sensitive to the outcome of previous performances in exactly those cases. It should however be noted that the gender difference is the effect-sensitivity to the prize money in the outcome tournaments is statistically insignificant in both panel A and panel B (see the difference-in-differences estimates at the bottom of the respective panels).

Gill and Prowse (2014) study male and female university students in a laboratory setting. They find that men react to the size of an initial success/failure in such a way that conditional on losing their subsequent effort is only negatively affected if the loss was big (i.e. if a lot of money was foregone). Conditional on winning, subsequent effort is not affected by the size of the win. For my setting, this would suggest that the performance difference between marginal winners and marginal losers among men should be highest after a treatment tournament with above median prize money. This implies that the estimates for males in column (2) of panels C and D should be higher than the corresponding estimates in column (1). The differences between the estimates are, however, very small and go in opposite directions in panels C and D which suggest that the success/failure effect for male golfers is insensitive to the prize money in the treatment tournament. For women, Gill and Prowse (2014) find that conditional on losing, the subsequent effort is not affected by the size of the loss. Conditional on winning, however, subsequent effort decreases in the prize money. Thus, if the results in Gill and Prowse (2014) hold true in a wider context, the performance difference between marginal winners and marginal losers among female golfers should be at its maximum after a treatment tournament with below median prize money. This implies that the estimates for females in column (1) of panels C and D should be higher than the corresponding estimates in column (2). Looking at the point estimates this is true in both cases although the differences fail to exhibit statistical significance (see column [3]). Still, the rather surprising result from Gill and Prowse (2014) about small previous successes being more beneficial for women’s current performance than large ones is tentatively confirmed by my results, which calls for more research on the potential mechanisms behind this peculiar result. Comparing men and women with respect to the effect-sensitivity to the prize money in the treatment tournaments we see that women, according to the point estimates, are more sensitive (see the difference-in-differences estimates at the bottom of panels C and D). But since the data are cut so thin in this exercise the difference-in-differences estimates are not statistically significant.

Overall, the most important findings from this exercise are that women benefit from relatively small rather than large previous successes and that both men and women (especially men) are particularly dependent on positive recollections of previous performances when competing in high stakes situations.

Table 5. The importance of a previous success in situations with high and low stakes

Column:	(1)	(2)	(3)
Panel A. Prize money in treatment tournament low			
Prize money in outcome:	Low	High	Difference (High-Low)
Males: Making the cut	0.0085	0.0457*	0.0372
	(0.0150)	(0.0255)	(0.0296)
Females: Making the cut	0.0296	0.0474	0.0177
	(0.0202)	(0.0313)	(0.0372)
Difference-in-differences (Females-Males):	-0.0195 (0.0476)		
Panel B. Prize money in treatment tournament high			
Prize money in outcome:	Low	High	Difference (High-Low)
Males: Making the cut	0.0008	0.0526***	0.0518*
	(0.0242)	(0.0178)	(0.0301)
Females: Making the cut	0.0054	0.0100	0.0047
	(0.0320)	(0.0278)	(0.0424)
Difference-in-differences (Females-Males):	-0.0471 (0.0520)		
Panel C. Prize money in outcome tournament low			
Prize money in treatment:	Low	High	Difference (High-Low)
Males: Making the cut	0.0085	0.0008	-0.0077
	(0.0150)	(0.0242)	(0.0285)
Females: Making the cut	0.0296	0.0054	-0.0243
	(0.0202)	(0.0320)	(0.0379)
Difference-in-differences (Females-Males):	-0.0166 (0.0474)		
Panel D. Prize money in outcome tournament high			
Prize money in treatment:	Low	High	Difference (High-Low)
Males: Making the cut	0.0457*	0.0526***	0.0069
	(0.0255)	(0.0178)	(0.0311)
Females: Making the cut	0.0474	0.0100	-0.0373
	(0.0313)	(0.0278)	(0.0419)
Difference-in-differences (Females-Males):	-0.0442 (0.0522)		

Notes: Standard errors are clustered on the strokes * tournament level (in parentheses). */**/*** significant at the 10 /5/1 percent level.

4.4 Additional results: good and bad days

For about 80 % of the observations I have the results on both round 1 and round 2 in the outcome tournament while the remaining observations only have the aggregate score over the two rounds.[10] This makes it possible to investigate if a previous success is more beneficial on relatively good or bad days or if the effect is constant. For each observation with non-missing data I calculate the best day and the worst day and I then examine how a previous success affects the results on the respective days conditional on

[10] The detailed information exists for 100 % of the tournaments on the PGA Tour, about 85 % of the tournaments on the LPGA Tour and about 50 % of the tournaments on the European Tour.

the RD-model.[11] Table 6 shows the results. The pattern of the results suggests that a previous success is particularly important on a relatively bad day when the players are struggling out on the course. The making-the-cut effect is roughly twice as big on a bad day compared to a good day and the effect is only statistically significant on bad days (see column [1]). The same general pattern is apparent both for women and men (columns [2–3]). Arguably, these results strengthen the notion that confidence is the main factor behind the positive success effect since players are more likely to start doubting their ability on relatively bad days. But with a success in fresh memory these negative thoughts might be easier to keep at bay making the recently successful players less likely to post very bad results.

Table 6. The effect of a previous success on good and bad days

Column:	(1)	(2)	(3)	(4)
Sample:	All	Males	Females	All
Estimate:	Main	Main	Main	Females-Males
Panel A.				
Outcome:		Number of strokes on a good day		
Making the cut	-0.0425	-0.0541	-0.0197	0.0344
	(0.0403)	(0.0495)	(0.0685)	(0.0845)
Observations	42,160	27,520	14,640	42,160
Mean of dep.	70.2238	69.8351	70.9546	70.2238
Panel B.				
Outcome:		Number of strokes on a bad day		
Making the cut	-0.0931**	-0.0983*	-0.0833	0.0150
	(0.0442)	(0.0549)	(0.0730)	(0.0914)
Observations	42,160	27,520	14,640	42,160
Mean of dep.	73.3259	72.9582	74.0170	73.3259
Sample window	[-5,6]	[-5,6]	[-5,6]	[-5,6]
Linear RV	Yes	Yes	Yes	Yes
By treatment RV	Yes	Yes	Yes	Yes
Quadratic RV	No	No	No	No
By tournament RV	No	No	No	No
Covariates	No	No	No	No

Notes: Standard errors are clustered on the strokes * tournament level (in parentheses). */**/*** significant at the 10 /5/1 percent level. RV=running variable.

5 Conclusion

In experiments women have been found to decrease their performance following a setback while men appear to be unaffected (see Gill and Prowse [2014]). It has further been suggested that this gender difference in dealing with failures partly might explain

[11] About 10 % of the observations have identical results on the two rounds and consequently their worst day score is identical to their best day score.

the presence of a glass ceiling for women on the labor market, based on the logic that early career failures leave deeper scars on women than on men. This result has, however, not been replicated among men and women that have actually chosen to enter competition-intensive work environments (see Jetter and Walker [2015] and Banko, Leeds and Leeds [forthcoming] that have investigated the behavior of professional male and female tennis players). Instead these studies have found that competitive men and women are equally sensitive to previous results. But the identification in all field studies on this issue so far has relied on selection-on-observables strategies which leaves a remaining uncertainty about the robustness of the results.

In this paper I contribute to the literature by providing quasi-experimental evidence from a field setting very well suited for identifying causal effects of a previous success/failure on current performance. I use data from about 200 all-female and 450 all-male golf tournaments respectively. These tournaments entail a very sharp qualification rule which can be used to study the effect of a previous success, relative to a failure, on current performance holding ability constant (this empirical strategy was previously used in Rosenqvist and Skans [2015] but only for male golfers). Half-way through professional golf tournaments the worst performing half of the players are eliminated from the tournament. The other players continue the tournament and earn at least some prize money in the end. Players that just barely are eliminated (marginal losers) and players that just barely were allowed to complete the tournament and earn prize money (marginal winners) performed almost equally well, but arguably they will experience the performance differently in terms of success or failure. Using an RD design I estimate the performance difference in the tournament the following week between marginal winners and marginal losers.

The analysis reveals two main findings. First, marginal winners generally outperform marginal losers in the subsequent tournament. Marginal winners have roughly 0.16 less shots (significant on the 5 percent level) after 36 holes in the outcome tournament and they are 2.5 percentage points more likely to make the cut (significant on the 1 percent level). This result shows that the finding in Rosenqvist and Skans (2015) about the existence of substantial causal success effects holds true also in a wider setting where women are included. Second, men and women exhibit virtually identical results suggesting that top-performing women can tackle failures just as good as top-performing men. Thus, if the behavior of these professional male and female athletes is similar to the behavior of competitive men and women in the civil society it seems unlikely that women are unable to reach top-positions in firms because they are worse than men at dealing with failures. Instead it seems likely that women’s difficulties in reaching top-positions in firms and other organizations are caused by external barriers, which calls for more research on the structure of these barriers and on ways of penetrating them.

The analysis has also produced four additional results. First, the data suggest that female golfers are more consistent performers than male golfers, i.e. women’s results are very stable over time. To the best of my knowledge, it is the first time that this has been shown and an interesting avenue for future research is to explore how general this apparent gender difference in performance persistence is. Potentially, it could be due to that male golfers choose riskier strategies than female golfers which produces greater variation in the number of strokes. Second, female golfers benefit more from relatively small previous successes than large ones which replicates the finding in Gill and Prowse (2014). Third, both men and women (especially men) are particularly dependent on having had a recent success when competing in high stakes environments. This result strongly suggests that confidence is the main factor behind the success effect both for women and men since confidence arguably is crucially important when players are under intense pressure. Fourth, for both men and women higher confidence (from a previous success) tends to help the players by improving their lowest ability level rather than their highest, effectively reducing between day variance in performance.

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Appendix

Table A1. Robustness checks

Column:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Strokes after 36 holes in the outcome tournament - Males							
Making the cut	-0.1087	-0.1051	-0.0230	-0.1624	-0.1604**	-0.1513*	-0.1647**
	(0.0855)	(0.0940)	(0.1101)	(0.1433)	(0.0775)	(0.0791)	(0.0749)
Observations	32,532	27,938	22,410	15,783	36,119	36,119	36,119
Mean of dep.	143.0738	143.0718	143.0944	143.0561	143.0593	143.0593	143.0593
Panel B. Strokes after 36 holes in the outcome tournament - Females							
Making the cut	-0.1315	-0.0976	-0.2866*	-0.3061	-0.1885	-0.1131	-0.1544
	(0.1291)	(0.1423)	(0.1643)	(0.2197)	(0.1169)	(0.1134)	(0.1140)
Observations	15,193	12,932	10,228	7,181	17,014	17,014	17,014
Mean of dep.	145.6794	145.6854	145.7111	145.7179	145.6649	145.6649	145.6649
Panel C. Making the cut in the outcome tournament - Males							
Making the cut	0.0188*	0.0194*	0.0076	0.0213	0.0248***	0.0248***	0.0268***
	(0.0104)	(0.0116)	(0.0134)	(0.0177)	(0.0093)	(0.0095)	(0.0091)
Observations	32,532	27,938	22,410	15,783	36,119	36,119	36,119
Mean of dep.	0.5471	0.5475	0.5434	0.5452	0.5487	0.5487	0.5487
Panel D. Making the cut in the outcome tournament - Females							
Making the cut	0.0207	0.0075	0.0292	0.0212	0.0260**	0.0206	0.0271**
	(0.0142)	(0.0159)	(0.0186)	(0.0246)	(0.0128)	(0.0130)	(0.0126)
Observations	15,193	12,932	10,228	7,181	17,014	17,014	17,014
Mean of dep.	0.5604	0.5568	0.5548	0.5523	0.5612	0.5612	0.5612
Sample window	[-4,5]	[-3,4]	[-2,3]	[-1,2]	[-5,6]	[-5,6]	[-5,6]
Linear RV	Yes	Yes	Yes	Yes	Yes	Yes	Yes
By treatment RV	Yes	Yes	Yes	Yes	No	Yes	Yes
Quadratic RV	No	No	No	No	Yes	No	No
By tournament RV	No	No	No	No	No	No	Yes
Covariates	No	No	No	No	No	Yes	No

Notes: Standard errors are clustered on the strokes * tournament level (in parentheses). */**/*** significant at the 10 /5/1 percent level. RV=running variable.