Understanding how status amongst peers affects performance: A golfing natural experiment

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Abstract

This paper investigates how individual's decision making can be affected by their relative standing amongst their nearest observable peers. By taking advantage of the random process used to allocate players to playing partners in golf tournaments I obtain the causal effect of being the best or worst in one's group of peers. Initial results suggest female golfers respond negatively to playing alongside higher ranked peers. Alongside overall performance I also consider as an outcome variable a proxy of risk-taking, the variance of scores across a round, and find that playing alongside better players leads to a reduction in risk-taking.

JEL classification: D83, J44, L83

Keywords: Status competition, peer effects, group dynamics, natural experiment

1 Introduction

In many contexts it seems reasonable to believe that the decisions of economic agents are affected by the group of individuals to which they compare themselves, in particular, effort or performance of an individual in the workplace may be influenced by whether they see themselves as the best or the worst among their observable peers.

In this paper I take advantage of the structure of golf tournaments and the existence of a well-defined ranking of female professional players to test whether being the best, worst or mid-ranking player in a group of observable peers affects players' performance or risk-taking.

Similarly, one might expect the age of an individual relative to other members of a group to affect their behaviour. For example, older members might take a responsibility of being a role model so refrain from behaviours deemed to be undesirable, in the context of golf willingness to take unnecessary risks might be such a behaviour.

Initial results point to a negative effect on performance of being the second or third ranked player in a playing group, which concurs with the one existing study on peer effects in golf which found that raising ability of one's peers had a small negative effect on own performance [**?**]. In contrast to Guryan et al, here the population under study is a female-only group with greater heterogeneity in country of origin. There is existing evidence to suggest that important differences exist in how men and women respond in competitive environments.

Gender differences in attitudes toward competition have been observed in a number of contexts, Sutter and Rützler [2010] found girls as young as 4 were less likely to compete in tournaments than their male peers while Gneezy et al. [2003] in the laboratory observed a deterioration in the performance of female subjects when placed in a competitive environment, while male participants responded positively. However, the deterioration in female performance as a result of competition was much reduced for those subjects competing in female only environments. Booth et al. [2011] report similar results with respect to risk aversion, using a subject pool of students allocated randomly to single-sex or co-educational classes female students were more risk averse than their male counterparts both before and after their course, but the difference was much reduced for those females exposed to a single-sex environment.

Within the golf tournaments considered here the performance of players relative to observable peers has only a marginal impact on financial rewards, thus if the unique objective of players is to maximize their expected return effort and strategy should be independent of the make-up of a player's observable peer group. Any peer effect should result from non-pecuniary rewards or learning effects. There is existing evidence from both laboratory [Azmat and Iriberri, 2010b, Charness et al., 2010] and real world studies [Azmat and Iriberri, 2010a] that non-pecuniary rewards to status within a comparison group can affect behaviour.

A number of theoretical papers have explored how competition for status could lead to differing levels of risk taking at different points of the endowment distributions, and then considered the resulting effects for the distributions of income and wealth [Becker et al., 2005, Hopkins and Kornienko, 2009, Hopkins, 2011]. In all of these examples the authors' assumptions on how status (or rank) enter the utility function are critical in driving the results.[1] An implication of these models is that taking an individual from a group in which he is of high status and placing that same individual in an alternative group in which he is of low status should lead that individual to have observably different attitudes to risk, a hole of a golf course provides players with a choice between risky plays and safe plays so provides an opportunity to test this implication.

Alongside status within a group, I also investigate if relative maturity within a group may have

[1] Becker et al. [2005] assume that consumption and status are complementary while Hopkins [2011] assumes that (in the limit) the marginal utility of status is infinite for the lowest status individual in society.

an impact on decision-making. The idea is to explore if being the most mature member of a group leads a player to take on a different role in the dynamics of the group, the common view would be that more mature individuals tend to be more risk averse, the aim of the analysis here is to observe if this is a genuine age effect or if individuals take less risks because they are the most mature in their group.

The remainder of the paper is organized as follows, section 2 describes the game of golf and the structure of golf tournaments, section 3 details the data sources and the construction of the main explanatory variables, section 4 explains the empirical strategy, section 5 analyses the results and section 6 concludes.

2 The Game of Golf

Within the sport of golf there are variations in the rules of play and the type of competition, but all the data considered here are collected from stroke play tournaments. A round of golf, typically 18 holes, involves trying to get a ball of diameter of at least 42mm and weight of no more than 46 grams into a hole in the ground of diameter of approximately 108mm from varying distances away using a selection of golf clubs to strike the ball. Each of the holes on a course will vary in distance and difficulty with various obstacles placed on the path between the tee (where the ball is first addressed with a club) and the green (an area of specially prepared grass that includes the hole). A golf course is typically designed so that 'par' for the course will be around 72 shots, that is, the number of shots an elite golfer is expected to be able to complete the course in is 72. Holes have their own 'par' score, normally varying from 3 to 5. In stroke play the objective is to complete the round(s) in the lowest possible number of strokes.[2]

Figure 1 provides an example of one of 18 holes of a golf course. The area marked with 1 is the tee, the first shot is taken from this area and the aim is get the ball to the hole, marked with a 10, in the fewest shots possible. The area marked 9 is the green. Between the tee and the green is the fairway (7) and various hazards, water hazards (2 and 6) sand traps or bunkers (5) and trees.

Each hole presents players with choices between safe and risky options. For example faced with a water hazard a player can play safe and aim short of the water or attempt to clear it giving a possible gain of one shot at the risk of dropping in the water and losing two shots.

[2]The par score provided a test for loss aversion amongst professional golfers, [Pope and Schweitzer, 2011] demonstrate that the success rate of golfers when putting for par, to prevent a loss, is considerably higher than when putting for birdie (to win a shot) after controlling for distance to the hole.

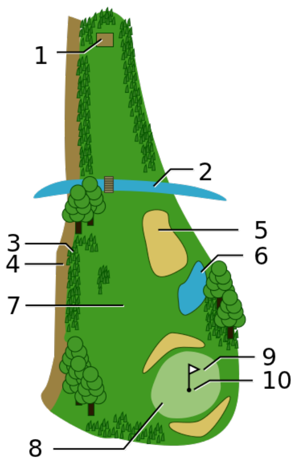

Figure 1: An example of a golf hole

The typical tournament involves 72 holes (4 rounds of 18) and is played over 4 days. In the tournaments included in this study the number of participants varies from 60 up to 150.On the first 2 days all players compete and the first half of the field (plus any ties) with the lowest scores after 36 holes contest the remaining 2 days of the tournament. Prize money is awarded to only those players who ‘make the cut’, those who remain in the tournament on day 3. Due to the change in incentives that may result on the second day as players attempt to position themselves ahead of the cut I restrict attention to the first day’s play.

Players play together in groups of three spread through the day, the groups for the first two days of play are decided and published on the Tuesday before the start of the tournament. Players are paired with the same players on the first two days and alternate between morning and afternoon tee times (if starting their round on Thursday in the morning on the Friday they will start in the afternoon).

The key characteristic of LPGA tournaments that I take advantage is that the playing groups are chosen at random. Players are divided into two groups by the tournament directors, A and B seeds, and players are assigned to play with others from their seed group. Players given an A seeding are typically those with the highest ranking, although may include past major winners or local players of interest. The groups that are drawn from A or B seeds are typically identifiable through the time at which they play, the A seeded players are scheduled to play during the hours in which the tournament is televised. Of the eight tournaments included here seven have approximately 150 players, of which between 60 and 72 are A seeds, the one remaining tournament had a field of 63 players with 15 A seeds. As a result of evidence of non-random sorting of A seeds I mainly focus on the B seeded players. For days 3 and 4 players are placed into groups based on performance on the first days, with the two or three players heading the field starting their rounds last.

3 Data

Performance data for all tournaments and personal information (age and nationality) was collected from the website of the LPGA.[3] Data used to construct the status variables was collected weekly from the Official Women's World Golf Ranking website on the Monday prior to each tournament.[4]

3.1 Constructing the main explanatory variables

The Official Golf World Ranking provides a clear publicly available measure of a player's status. The question of interest here is whether the behaviour of players is affected by being paired with players of higher or lower rank. The main explanatory variables are dummy variables denoting whether a player has the 1st, 2nd or 3rd highest rank in their playing group. Given a player i paired with players j and k the dummy variables were constructed as follows:

$$D_{1i} = \begin{cases} 1 & \text{if } WorldRank_i < \min\{WorldRank_j, WorldRank_k\} \\ 0 & \text{otherwise} \end{cases}$$

$$D_{3i} = \begin{cases} 1 & \text{if } WorldRank_i > \max\{WorldRank_j, WorldRank_k\} \\ 0 & \text{otherwise} \end{cases}$$

$$D_{2i} = 1 - D_{1i} - D_{3i}$$

A small minority of players were unranked, these were mainly rookie year players or amateurs. These were allocated the lowest ranks amongst competitors in the same group.

I construct similar dummy variables to indicate if a player is the oldest, youngest or the mid-aged player of their playing group.

$$D_{yi} = \begin{cases} 1 & \text{if } Age_i < \min\{Age_j, Age_k\} \\ 0 & \text{otherwise} \end{cases}$$

$$D_{oi} = \begin{cases} 1 & \text{if } Age_i > \max\{Age_j, Age_k\} \\ 0 & \text{otherwise} \end{cases}$$

[3] http://www.lpga.com
[4] http://www.rolexrankings.com/en/rankings/

$$D_{mi} = 1 - D_{yi} - D_{oi}$$

4 Empirical Strategy

We have two main questions of interest. Firstly, to what extent is the performance of players, as measured by the number of shots taken to complete 18 holes, affected by the player's status within a group, i.e. does the relative position within a group affect player performance. The second question is whether status in a group affects the strategy of players. It is not possible to observe directly the strategy of each player but each hole includes obstacles which, as described earlier, provides a choice for players between risky and safe strategies. The choice of a player to opt for riskier plays in general should be reflected in a greater variance in scores with respect to par on each hole.

The key to identifying the causal effect of status is the random allocation of players to playing groups. Given that we have random assignment one might assume that estimating an equation of the following form would deliver the causal effect of status positions:

$$O_i = \alpha + \beta_1 D_{2i} + \beta_2 D_{3i} + \delta_{tc} + \epsilon_i \tag{1}$$

where O_i represents the outcome variable of interest and δ_{tc} is a full set of tournament-by-category fixed effects. However, such a regression would ignore that the probability that a player is assigned to each of the three 'treatment' groups is not constant across observations. The highest ranked player in the urn from which groups are selected faces a zero probability of being the second or third highest ranked player in their playing group, while in contrast the lowest ranked player in the urn will be the third ranked player in their group with probability equal to one. Given the likely association between player rank and performance with players' score as the dependant variable we would expect that estimates of β_1 and $beta_2$ are such that $\beta_2 > beta_1 > 0$ since players that are second or third in their group are on average lower ranked than those first in their group so are in general worse players (shoot higher scores).[5]

Since we have an ordered list of the ranking of all players, assuming that players are in fact randomly assigned to groups, it is possible to construct the probability with which each player is assigned to each of the three possible treatments. With n players the probability that a player of rank R is in each of the three treatment groups is given by:

[5]In this context better performance would imply a lower score so a negative coefficient.

$$
\begin{aligned}
Pr(D_1 = 1 \mid R) &= \frac{(n-R)(n-R-1)}{(n-1)(n-2)} \\
Pr(D_2 = 1 \mid R) &= \frac{2(n-R)(R-1)}{(n-1)(n-2)} \\
Pr(D_3 = 1 \mid R) &= \frac{(R-1)(R-2)}{(n-1)(n-2)}.
\end{aligned}
$$

I take advantage of these probabilities in proposing the following empirical specification:

$$O_i = \alpha + \beta_1(D_{2i} - Pr(D_{2i} = 1 \mid R_i)) + \beta_2(D_{3i} - Pr(D_{3i} = 1 \mid R_i)) + \delta_{tc} + \epsilon_i. \tag{2}$$

Ignoring for the moment the tournament and category fixed effects δ_{tc} the parameters in equation 2 have the following interpretation: α is simply the unconditional mean of the outcome variable O, then assuming a player i has probability 1 of being the leading player in their playing group, β_1 then gives the change in the outcome variable O_i that would result if we could place that player in a group in which they were second, likewise β_2 gives the change in O_i that results from placing the player in a group in which they are third ranked.

An alternative specification is the following:

$$O_i = \alpha + \beta_1 D_{2i} + \beta_2 D_{3i} + \beta_3 R_i + \delta_{tc} + \epsilon_i. \tag{3}$$

In the case that the true relationship between R_i and the outcome variable O_i is linear estimating equation 3 would correctly identify the treatment effects of being the second or third ranked player in a group. However, a priori there is no reason to believe that the true relationship will be linear, with the specification of equation 2 I make no such assumption.

A further alternative specification is to semiparametrically estimate the relationship between R_i and O_i. Given the small size of the dataset currently available this is not a viable option, but may become so for subsequent versions of the paper.

5 Results

5.1 Testing for random assignment

A natural test for random assignment regresses the characteristics of a player's playing partners against the player's own characteristics, here I regress the average rank of player i's opponents against player i's own rank R_i, but dividing both by the number of players in the urn from which they were chosen, n. The regression equation used to test for random assignment is the following:

$$\frac{R_j + R_k}{2n} = \alpha + \beta \frac{R_i}{n} + u_i \tag{4}$$

where R_j and R_k are the respective ranks of player i's playing partners in the urn from which player i is chosen. As Guryan et al. (2009) point out, the expectation of abilities of one's playing partners will vary with own ability, considering a field of 60 players, the playing partners of the 1st ranked player are drawn from ranks 2 to 60 while those of the 60th ranked player are drawn from 1 to 59, on average the player ranked 60th will be paired with better players than the player ranked 1st so we should expect β in the above equation to be negative and to vary with the size of the earn. Given random assignment $E(\hat{\beta}) = -\frac{1}{n-1}$, where $\hat{\beta}$ is the OLS estimate of β in equation 4.

A further problem of tests of randomization based on the above regression equation is that the error terms will be correlated across observations and will have non-constant variance, as a result tests of randomization using a test statistic based on a normal distribution will produce a probability of rejection of a true null hypothesis of random assignment distinct from the desired one. However, it is possible to simulate the true distribution of $\hat{\beta}$ for a given urn size n under a null hypothesis of random assignment and compare the observed estimates of β for each of the tournament seed groups to the simulated distribution.

Figure 2 give simulated distributions for urn sizes equal to the number of B seeded players in the tournaments included in the dataset ($n = 48, 72, 78, 84$) with the OLS estimates of β derived from the observed groups in the tournament marked on. Denoting by $\hat{F}_n(\hat{\beta})$ the simulated distributions of $\hat{\beta}$ for an urn of size n the values marked as $\underline{\beta}$ and $\bar{\beta}$ in the figures are defined by $\hat{F}_n(\underline{\beta}) = 0.025$ and $\hat{F}_n(\bar{\beta}) = 0.975$ and provide a 95% confidence interval for acceptance of the null hypothesis of randomized groups.

The estimated β coefficients from equation 4 for the seven tournaments included in the sample all lie within the confidence interval. The same tests of randomization can be completed for any characteristic that can be ordered across players, the procedure outlined above has been repeated using ranking according to age and by alphabetical order and similar results can be observed in charts included in the appendix.

The use of the simulated distribution guarantees the correct probability of a type II error, but this may lead to an unduly large probability of type I error. Consideration of the results from repeating the same analysis using the A seeded players suggests that the test has sufficient power to detect deviations from randomization. Figure 3 shows the simulated distributions of $\hat{\beta}$

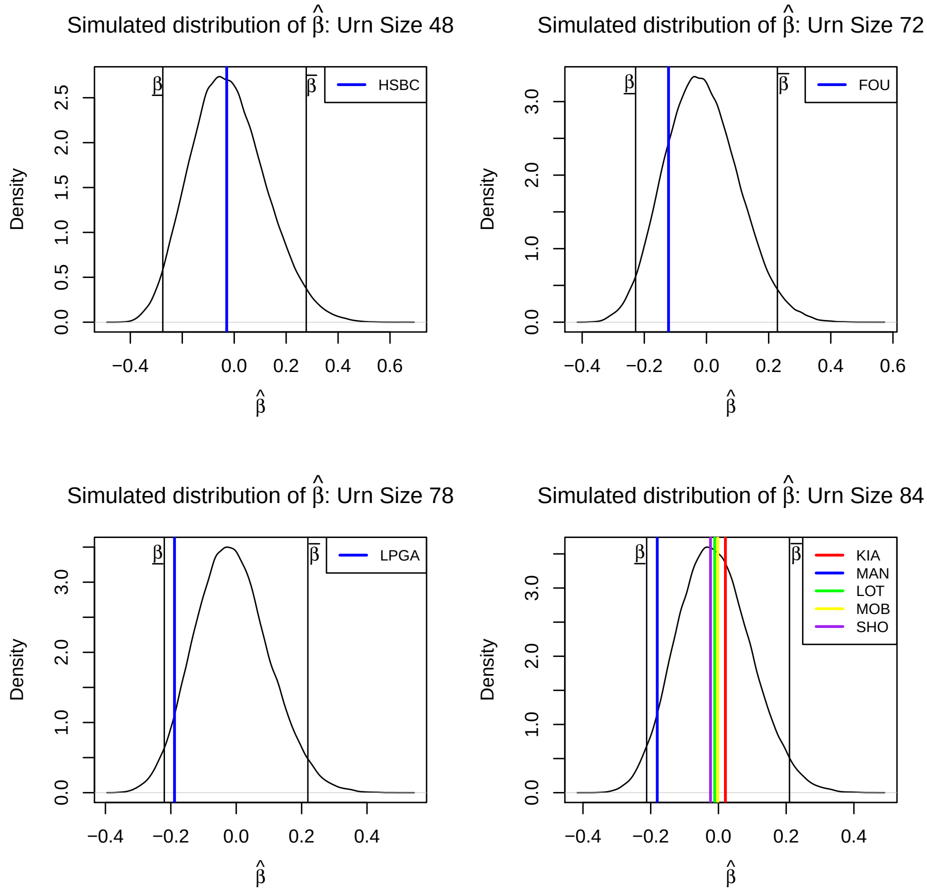

Figure 2: Tests of randomizaton of B seeded players to groups. Distributions of $\hat{\beta}$ under the null hypothesis of randomized groups with players ordered according to their official world rank.

for the urn sizes for the A seeded players, respectively 54, 60 and 72, with the observed $\hat{\beta}$ for six tournaments marked on.[6] In four of the six cases the observed $\hat{\beta}$ lies outside of the 95% confidence interval described, with the evidence suggesting that groups are sorted to put higher ranked players together. This result goes in line with information provided to me by the LPGA that within the A seeds tournament managers and sponsors often select some playing groups to maximise media interest in their event on the first two days of play.

5.2 Peer effects on performance

Given the non-random selection of playing groups within the A seeded players I now restrict attention to players in the urn of B seeded players. Table 1 reports the results from estimating equation 2 with the score after 18 holes as the dependant variable. The table includes results concerning both

[6] A seventh tournament was omitted since the urn consisted only of fifteen players.

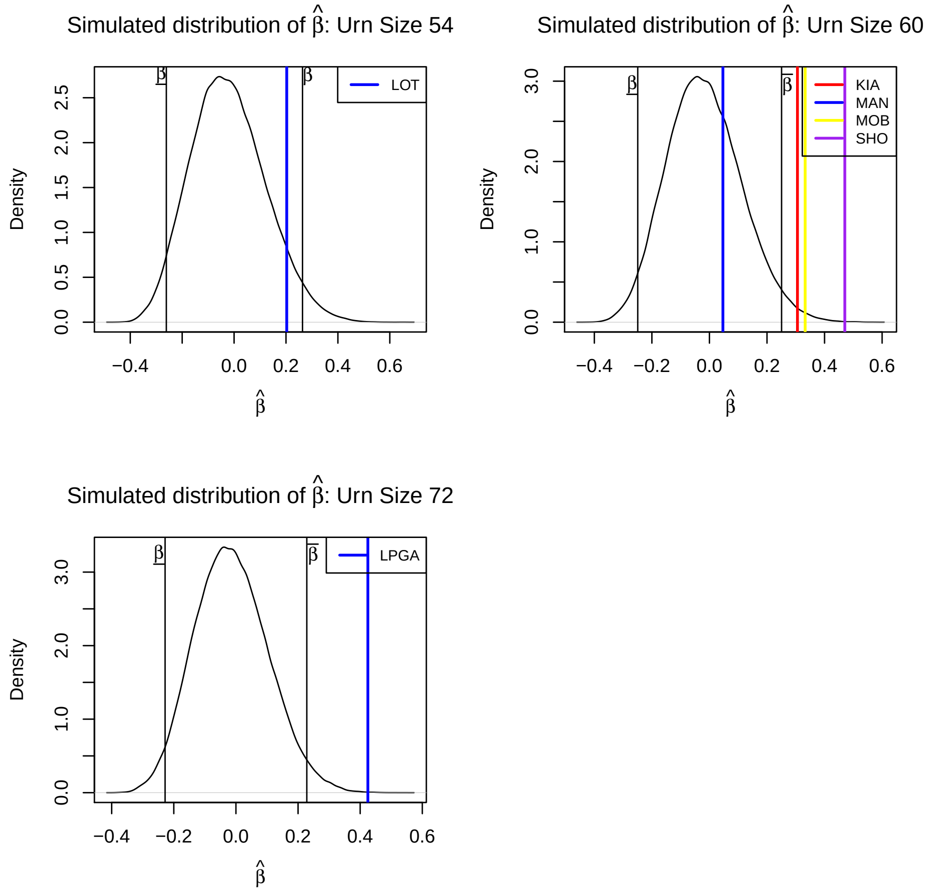

Figure 3: Tests of randomizaton of A seeded players to groups. Distributions of $\hat{\beta}$ under the null hypothesis of randomized groups with players ordered according to their official world rank.

status as measured by world rank and maturity within the playing group. None of the coefficients of interest are significantly different from zero. Nevertheless, point estimates suggest that elite female golfers perform worse when they are placed in a group with higher ranked players. Comparing the penalty for being the worst player in a group (between 0.22 and 0.34) and the coefficient on rank (approximately 2.8) suggests placing a player with stronger competitors is equivalent to moving them 10% further down the distribution of rank. With respect to age, it appears that being the mid-aged player in a group confers an advantage compared to being either the youngest or oldest player in a group. The effect of being the oldest compared to being the youngest varies in sign over the four cases in which it is estimated.

5.3 Peer effects on risk-taking

Table 2 repeats the same regressions as reported in table 1 but with the outcome variable variance of scores across the 18 holes of the round. This variable is intended as a proxy for risk-taking. Status with respect to world ranking within one's playing group has a significant effect (at the 10%

Table 1: The effect of rank on performance

	(1)	(2)	(3)	(4)	(5)	(6)
World Rank in group						
2nd in group	0.107	0.003	-	-	0.064	-0.025
	(0.392)	(0.382)	-	-	(0.395)	(0.384)
3rd in group	0.340	0.253	-	-	0.230	0.216
	(0.476)	(0.463)	-	-	(0.478)	(0.465)
Age Rank in group						
Middle-aged	-	-	-0.377	-0.252	-0.378	-0.262
	-	-	(0.378)	(0.369)	(0.381)	(0.371)
Youngest	-	-	-0.011	0.167	-0.027	0.143
	-	-	(0.461)	(0.449)	(0.464)	(0.452)
Seed group fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	No	Yes	No	Yes
R^2	0.171	0.276	0.173	0.222	0.173	0.222
N	615	615	615	615	615	615

∗ indicates significantly different from zero at 10% level, ** 5% and *** 1%.
Standard errors in parentheses.
Additional controls are rank within urn, age and age-squared.

confidence level) on variance of within round scores in one of four regressions reported in table 2. Playing as the second highest ranked player in the group leads to a reduction in the variance of scores relative to being the highest ranked player in the group. Point estimates suggest that being the lowest ranked player leads to less variance of scores within a round compared to being the highest, but the size of the reduction is approximately a third less than that recorded when the second ranked player. With respect to age a somewhat surprising result is observed. Being assigned to a group in which a player is the oldest of a group is associated with an increase in variance of scores within a round compared to being the youngest or the mid-aged player within a group.

Table 2: The effect of rank on risk-taking

	(1)	(2)	(3)	(4)	(5)	(6)
World Rank in group						
2nd in group	-0.039	-0.042	-	-	-0.043	-0.046*
	(0.027)	(0.027)	-	-	(0.027)	(0.027)
3rd in group	-0.011	-0.013	-	-	-0.012	-0.014
	(0.033)	(0.033)	-	-	(0.033)	(0.033)
Age Rank in group						
Middle-aged	-	-	-0.030	-0.027	-0.035	-0.032
	-	-	(0.026)	(0.026)	(0.027)	(0.027)
Youngest	-	-	-0.033	-0.028	-0.039	-0.034
	-	-	(0.032)	(0.032)	(0.032)	(0.032)
Seed group fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	No	Yes	No	Yes
R^2	0.049	0.058	0.047	0.055	0.052	0.060
N	615	615	615	615	615	615

∗ indicates significantly different from zero at 10% level, ** 5% and *** 1%.
Standard errors in parentheses.
Additional controls include rank in urn, age and age-squared.

5.4 Discussion of results

Combining the results reported in tables 1 and 2 we observe that mid-ranking players in a playing group reduce their risk-taking compared to the case if they were first ranked and face little cost in terms of average performance. However, the lowest ranked in a group reduce their risk-taking to a similar extent but are punished with a worse performance on average. This combination of occurrences might plausibly be explained by the effect of competitive pressures, these are likely to be stronger for those placed with better players. The performance of a player can be considered as the combination of two skills, striking of the ball and shot or strategy selection. Competitive pressures might act negatively on the element of play that is more instinctive, striking the ball, but lead to a more conservative decision with respect to shot selection.

Looking at age, there appears to be a performance penalty for being the eldest in a group and this comes alongside an increase in the variance of hole scores. Playing in a group as the mid-aged player is related to a better average performance with lower variance through the round.

5.5 An alternative measure of status

So far I have considered status of player's to be measured by current world ranking, an alternative is to use career earnings of players. The advantage of this measure is that it implicitly includes the status gains that accrue to players as a result of having won one of the four major tournaments such as the British Open and US Women's Open, but that would be ignored one year after the tournament when using world ranking points to measure status. Major tournaments have much larger prizes than the typical tournaments on the golfing calendar and are the currency on which the great players are compared.[7] However there are disadvantages of using this measure, firstly, it will be slow to adjust to the emergence of a talented young player, Tiger Woods was ranked as world number one long before he became the active player with the highest career earnings. The other main disadvantage is that career earnings data are only comparable for those players that play on the LPGA tour for the majority of the year, there are a number of players that compete predominantly in their home regional tour but participate by invitation in some LPGA events, for some of these career earnings are not available, for the remaining earnings are available but in the currency of their regional tour. A subsequent version of the paper will use this alternative measure to check the robustness of the results using current world ranking as the relevant measure of status.

[7] For example, in men's golf Jack Nicklaus with 18 major winners is widely considered as the greatest player of all time, but Tiger Woods with 14 major wins to date is expected to challenge for the title.

6 Conclusion

This paper has attempted to demonstrate a simple methodology to evaluate how rank, based on any number of characteristics, within a group, may affect the performance of individuals, with the allocation of golf players to playing groups as a motivating example. Additional data points will be added other the coming months which may confirm or refute the relationships suggested by the sample currently available.

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7 Appendix

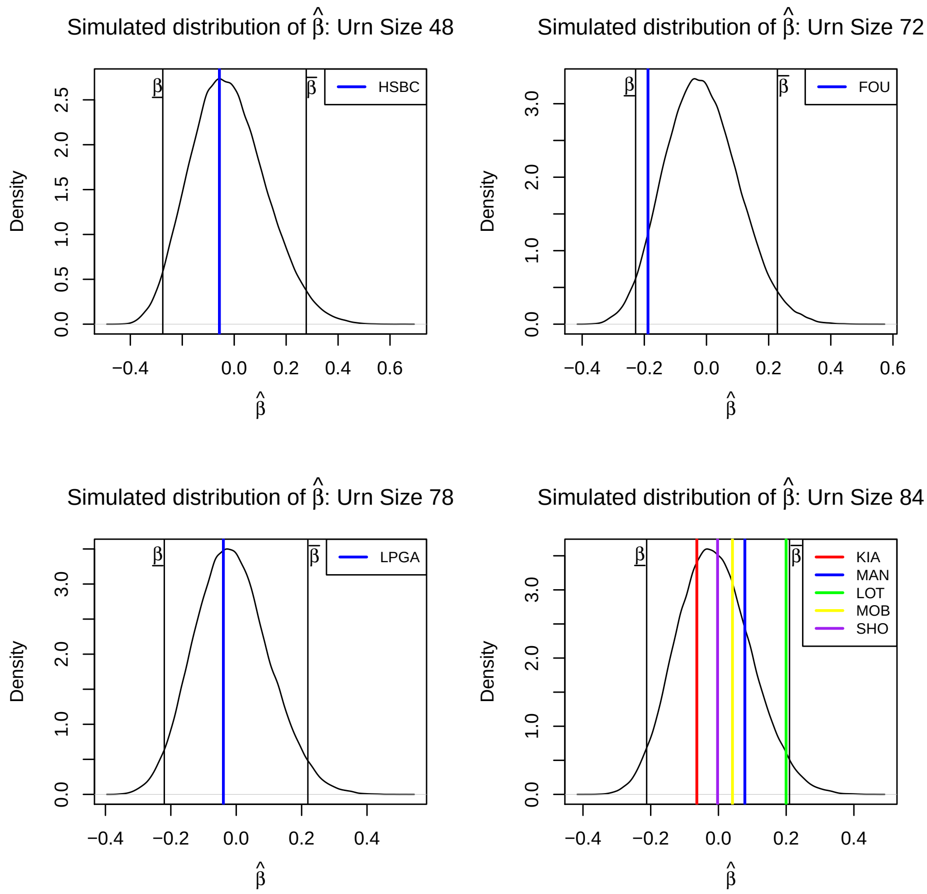

Figure 4: Tests of randomization of B seeded players. Distributions of $\hat{\beta}$ under the null hypothesis of randomized groups with players ordered by age.

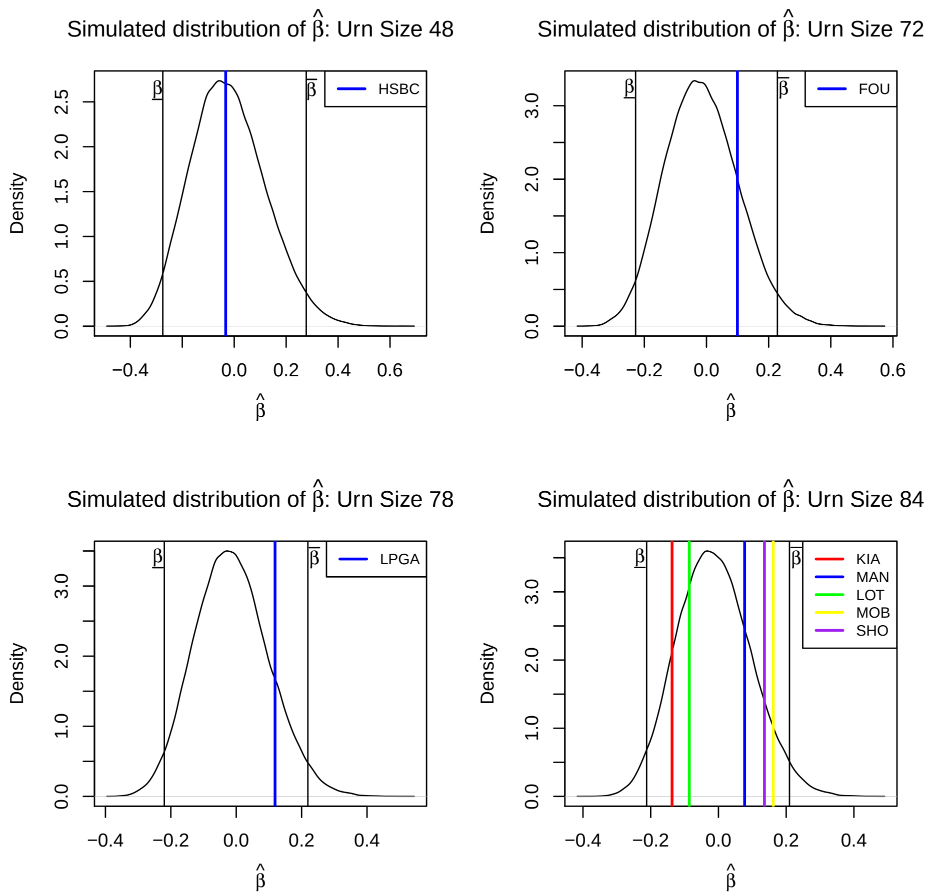

Figure 5: Tests of randomization of B seeded players. Distributions of $\hat{\beta}$ under the null hypothesis of randomized groups with players ranked by alphabetical order.

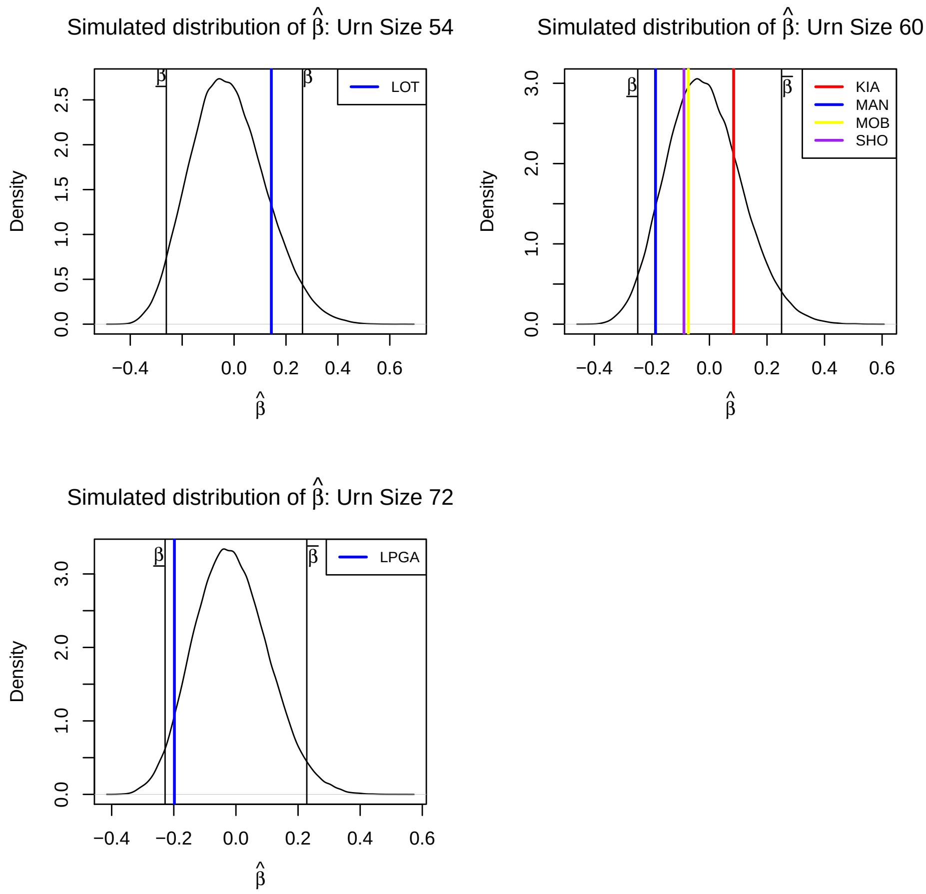

Figure 6: Tests of randomization of A seeded players. Distributions of $\hat{\beta}$ under the null hypothesis of randomized groups with players ordered by age.

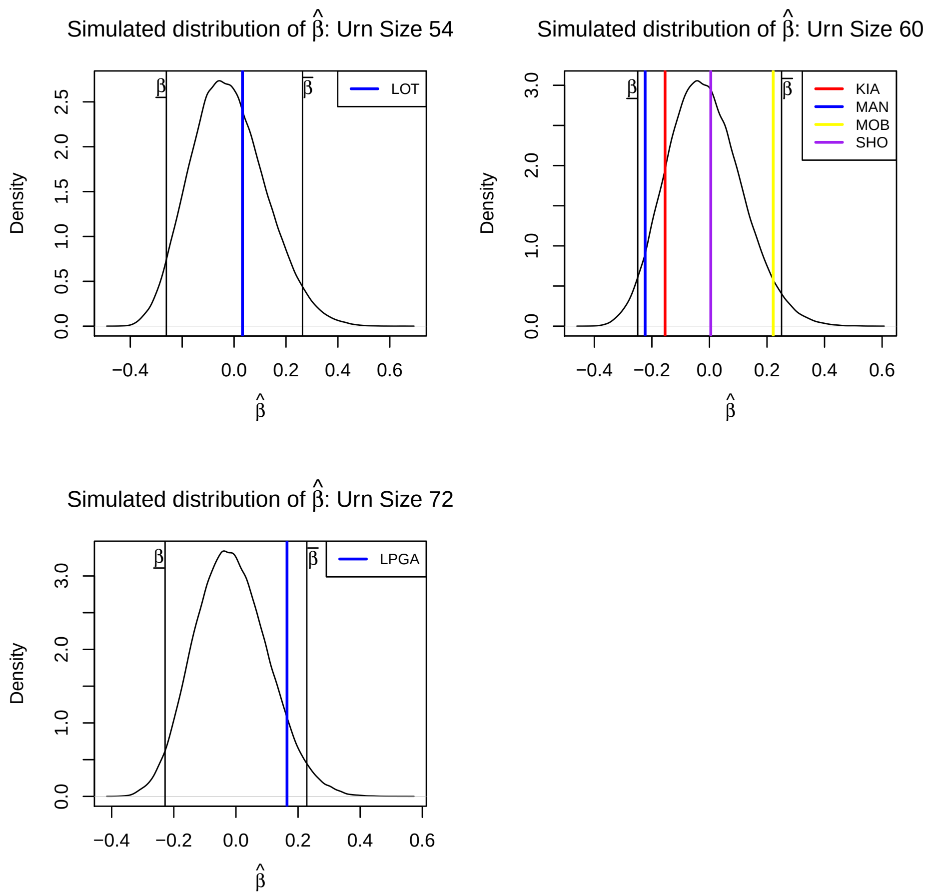

Figure 7: Tests of randomization of A seeded players. Distributions of $\hat{\beta}$ under the null hypothesis of randomized groups with players ordered by alphabetical order.