Psychology

Momentum and Elite Performance

Seppo E. Iso-Ahola* and Charles O. Dotson

Department of Kinesiology, University of Maryland, College Park, MD, USA

A new theory proposes that initial success increases the likelihood of subsequent success by creating three types of momentum effects: frequency, intensity and duration. Using a large data set (11,015 tournament results from four consecutive PGA Tour seasons), the present study is the first to examine these three effects and the relationship between momentum and elite performance. Results showed that performance successes measured with four outcome variables (making a "cut", top 30, 20, 10 finishes) not only occurred in sequence, rather than randomly, but that higher-ranked players were able to put together more frequent and more lasting strings of successful performances. They also bounced back faster as indicated by shorter durations of missed cuts, top 30, 20 and 10 performances. The data suggest that better players are in part better because they create more occurrences of momentum and ride them longer. When these momentum influences were removed from regressions analysis, eta squares were reduced to trivial effect sizes, thereby demonstrating the powerful effect of momentum and simultaneously ruling out any meaningful role for randomness. As a whole, the results support the theory and suggest that momentum is a force that explains elite performance and the way in which better players consistently achieve better results than lower-ranked competitors. Although the analyses were based on overt indicators of behavioral momentum, it is noted that the causes and effects of momentum are psychological. Momentum affects and is affected by conscious and nonconscious cognitions and thoughts.

Momentum | hot hand | elite performance | success-failure

In all fields of human endeavor, great careers are built on repeated success. "One- trick-pony" or "flash-in-the-pan" performances do not make a successful career. Those who rise to the top of their profession rack up repeated successes, whereas "also rans" fail to capitalize on initial success. What, then, explains repeated success? That is, does success breed success, and if so, how?

The basic tenet of momentum theory is that a dependency structure between consecutive successes exists such that previous performance significantly affects subsequent performance. The first empirical validation of this proposition, reported by Iso-Ahola and Mobily (1) in a statewide racquetball study, showed that winning the first game was a strong predictor (phi = .73) of the match's winner. Subsequent research over 30 years has tested this basic tenet in a wide variety of performance contexts (2), from sports (3-5) to motor performance (6) to financial investing (7-8). The general conclusion from this body of evidence is that success indeed breeds success and that momentum is a "temporary and occasional yet powerful phenomenon that can be flushed out by tight methodologies and statistical analyses" (9, p. 22), especially when the frequency of the phenomenon is taken into account (10). According to a recently developed theory of psychological momentum (9), initial success is critical for momentum building and has three momentum effects: an individual or team that has more occurrences of momentum during the entire contest is more likely to win or be successful (frequency effect); momentums of higher intensity increase the likelihood of final success or winning (intensity effect); and the performer whose momentums last longer is more likely to win or be successful (duration effect).The purpose of this present, first of its kind, "unobtrusive" study was to test the basic tenet of the theory and examine the way it is manifested in these three forms of behavioral momentum .

Competitive sports provide good settings for testing momentum effects. The belief in momentum's influence is strong as over 90% of sports fans (11) and coaches (4) believe that performance success is critically determined by momentum. More so, players themselves believe in the power of momentum as a single successful shot is sufficient to considerably elevate NBA players' likelihood of taking the next *team* shot (12), reflecting their tendency to change their behavior and "overgeneralize" from one successful performance to future actions (13). The PGA Tour is another elite performance setting and a good field laboratory where momentum can empirically be examined and tested. Theoretically, there are numerous opportunities for players to create and take advantage of momentum's frequency, intensity and duration effects facilitated by initial success—whether between or within tournaments.

On Tour, professional golfers' performance indicators are tracked throughout the year. These recordings provide extensive data from "driving" to "putting" during each tournament round. Our focus in this investigation was on individual performance results from tournament to tournament over four years of competition. More specifically, we focused on four key outcome measures: cuts made, top 30, 20, and 10 achievements. Momentum is manifested if players get on a roll and make "runs" of several cuts, top 30, 20, and 10 performances in a row. Of theoretical interest are frequency and duration effects, that is, the frequency and length of runs. The intensity effect, in turn, is particularly reflected in successful top 10, 20 and 30 runs. When a player is able to achieve a top 10, 20, or 30 result during a given week, such a performance comprises a high impact or "intensity" success and thus might be likened to a ferocious dunk in basketball, a home run in baseball, or a quick striking touchdown in football. According to the theory, it creates a high-intensity momentum and therefore leads to subsequent top performances in ensuing weeks. Naturally, a top 10 achievement has a higher intensity than top 30 or top 20 achievements.

Overall, the study sought to answer the question of whether success breeds success. To this end, the first sub-question was: How many cuts do players make on average and do they occur in sequence? The second question addressed: How many top 10, 20, and 30 performances are achieved on average and do they occur in sequence? Finally, we asked: is the play of better players characterized by greater momentum in the form of more frequent sequential runs and more lasting runs than that of lower ranked players? To answer the last question, players were divided into

Conflict of interest: No conflicts declared.

* Corresponding Author: Seppo E. Iso-Ahola. 22351 SPH Building, College Park, MD 20742, USA. Email: isoahol@umd.edu

five groups based upon the current year's money list: Top 25 players, 26-50, 51-75, 76- 100, and 101-125. This money ranking is widely accepted as a valid indicator of the level at which a player performs. However, it should be noted that all of these 125 players are elite competitors, in that any single player is capable of winning a tournament during a given week. Nevertheless, among the rankings, the higher ranked players are regarded as *consistently* better performers. An interesting theoretical question is whether these higher ranked players have achieved their status by experiencing more frequent and more lasting occurrences of momentum. Such momentum effects would translate into higher earnings and placements on the money list. As such, the result would also provide support for the theory.

METHOD

Data Source

Data for the study were obtained from the PGA Tour's ShotLinks System. This system essentially consists of a database of detailed shot and scoring performances of each player competing in PGA Tour tournaments. Access to the ShotLinks data was provided following the acceptance of a formal proposal to the ShotLink Intelligence Program (SLIP). ShotLinks data are available in various formats, created to meet a variety of needs. For the present study, we were interested in outcome measures describing PGA Tour players' performances for rounds completed during the course of a season of play. Because the United States Golf Association had imposed new rules regarding allowable dimensions of iron "grooves" effective starting with the 2010 golfing season, we elected to recover performance data for the 2010 to 2013 PGA tournament schedule. Thus, our start date for data recovery was the earliest year (2010) for which PGA Tour tournament competition was under a common set of playing conditions. We stopped data collection at the latest year (2013) for which a full year of data were available. Consequently, the sample size consisted of all the available data from four years (2010-2013) of PGA Tour competition, excluding some non-traditional tournaments (e.g., World Match play), as explained below.

About 144 players participate in a typical tournament of the PGA Tour. Multiplied by 45 (the typical schedule of 45 tournaments per year) times four years, approximately 25,000 player tournament outcomes were available for recovery from the ShotLinks database. All ShotLinks databases are available in text delimited format, easily dropped into spreadsheet based programs (e.g., Excel). Using an Excel spreadsheet, data editing, screening and variable designations were completed. Because the purpose of the study was to investigate the validity the behavioral dimension of momentum theory as characterized by the frequency, duration and intensity effects on golf performance, it was necessary to recover performance data for players competing frequently with few skipped tournaments throughout each season of PGA Tour events. Since the top 125 ranked players are fully exempt to enter any event on the PGA Tour schedule for each season, and, as such, participate in far more events than partial-or nonexempt players, we elected to include only the fully exempt players in the data analysis. Thus, the inference space to which the results of the study may apply is the collective group of the highest ranking professional golfers in the world.

Professional golfers eligible to compete on the PGA Tour are likened to independent contractors. As such these players are free to set their own tournament schedule. During a typical year, the top 125 ranked players elect to participate in slightly over half of the yearly tour events (about 23 out of the total 45). Thus, during a typical weekly tournament, the field of 144 participants includes, in addition to fully exempt players electing to play that week, a few partially exempt and non-exempt status players, as well as players receiving tournament sponsor invitations. In general, these fill-in players compete in far fewer tournaments than fully exempt players and instead, are more likely to compete in tournaments organized by the Web.com Tour, regionally sanctioned tours, or foreign tours. The latter types of tournaments are considered to be the minor league of professional golf when compared to the PGA Tour. Thus, these types of players were excluded from further analysis due to large gaps in their week-to-week play or their infrequent play not allowing direct comparisons with those performing at the highest level of competition. Among the fully exempt players, the vast majority rarely skip more than two weeks between tournaments. Because the top 125 ranked players are fully exempt for only one season and must maintain that status or be replaced with new players meeting full exempt criteria, these rankings were adjusted accordingly for each of the four tournament years' data.

A few tournaments each year were excluded from the data set. These included tournaments played in the match play format (e.g., World Match Play Championship) not permitting stroke play comparisons; five-round events (e.g., Humana Challenge) with different cut procedures than the standard four day PGA tournament format; and all weekly tournaments played opposite World Golf Championship events in which the level of competitive play is inferior to a typical PGA Tour event.

Variables

Data were generated on a per year basis for each of that year's top 125 ranked players. Variables recovered for each player included cuts made, top 10, top 20 and top 30 performances for each tournament in which a given player competed. Data for players entering a tournament but failing to finish due to withdrawal, disqualification, or injury were excluded from that week's dataset. For each type of outcome variable (e.g., cuts made) eight representations per year were created for each of the 125 players: total number of successful cuts, total number of unsuccessful cuts, total number of runs of successful and unsuccessful cuts combined, total number of runs of successful cuts, total number of runs of unsuccessful cuts, average length of runs of successful cuts, average length of runs of unsuccessful cuts, and longest run of successful cuts.

Player Groupings

Using the criteria described above, 11,015 of the original 25,000 player tournament outcomes were retained for inclusion in the study's data analysis. Thus, for each of the 32 created variables, a total of 500 player outcomes was created.

On a per year basis, players were grouped into one of five Quintile groups based on money rankings for that year (Q1 1-25, Q2 26-50, Q3 51-75, Q4 76-100, Q5 101-125). With this quintile grouping of 125 players per year for four years, a total of 500 player outcomes for each of 32 variables was available for analysis. Based on the money earned, the five groups were shown to be highly significantly different using one-way ANOVA ($p < 0.000$) with a very strong group separation Eta square factor of 0.81. Initially, statistical analyses were conducted retaining year as a classification variable. However, no main or interaction effects with other grouping variables were found for the factor "year of play" included in the study. Thus, the quintile groupings summed across the four years were employed for all statistical analyses giving a total sample of 500 subject outcomes (100 per quintile group).

Data Analysis

Transition Analysis: Pearson Chi Square (χ^2) for a two-by-two contingency table of tournament (i) and tournament (i+1) summed across a full season of PGA tournaments was determined to assess the independence of performance during tournament (i) and tournament (i+1). Effect sizes were determined by the phi procedure.

Differences Among Quintile Groups: Mean differences among each of the 32 internal measures of momentum were determined by parametric analysis of variance. Levene's Test of equality of error variances was employed to assess presence of homogenous group variances. When the Levene Test was significant, the confidence intervals (Tables 1-4) for individual group means were calculated employing each group's individual standard error rather than the pooled standard error. Test of equality among the Quintile groups was accomplished by F test for the main effect of a one-way ANOVA at $p<0.05$. In other words, differences among quintile groups for a given momentum variable were inferred when the omnibus F was significant at $p<0.05$. Differences between adjacent Quintile groups following a significant main effect by the F test were probed from the a priori selected orthogonal set of Helmert Contrasts and adjusted sequentially upon an observed significant individual contrast. This process was guided by the a priori assumption that Quintile groups monotonically follow a hierarchy. Effect sizes were determined by Eta Square procedure. With statistical power set at 0.95, we determined that the omnibus F detects among quintile group variances as small as eta squares of 0.035, and validated our decision to include the four years (2010-2013) of PGA Tour performance data to detect non-trivial effects among quintile player groups for the momentum variables. In this way, we were also able to demonstrate sensitivity analysis for our four-year PGA Tour data set. To promote readability and brevity, only p-values and Eta Squares are reported in the text while the relevant F values and degrees of freedom can be obtained from the authors.

All statistical analyses were completed employing IBM® SPSS® Statistics 21.

RESULTS

Does making "cuts" occur in sequence—more so for better players?

On average, the top 125 players participated in 23 tournaments each year and made an average of 15.9 cuts or 68.6% of the tournaments entered. These successful cuts were achieved within an average sequence of 9.8 runs per year. To answer the general question about success breeding success, we conducted Transition Analysis based on 11,015 tournament results from the 2010-2013 PGA Tour seasons. When considering all players across these four seasons, a significant ($p<0.000$, $\eta^2 = 0.07$) transition from tournament to tournament was observed for making the cut, showing that overall, 6.8% more cuts were made in the next tournament after successfully making the previous tournament's cut. This was particularly pronounced for Quintile 1 players (25 best ranked) ($p<0.001$, $\eta^2 = 0.08$) as they made 7.6% more cuts in the tournament following the preceding tournament's successful performance; the next highest percentage was among Q4 players at 4.4%. Transition Analysis for top 10, 20 and 30 placements from tournament to tournament mirrored those for the "cut" variable. That is, among those who initially achieved top 10, 20 and 30 finishes, more similar performances were observed in the following tournament: 5.9%, 8.3%, and 9.9% respectively (all $p<0.000$, η^2's = 0.06, 0.08, 0.10).

Table 1. Means, confidence intervals, p values and eta squares for Sequential Contrasts for "making cuts"

Measure		Quintile Group Means					Sequential Contrasts				
Number of successful cuts out of total events entered		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ34	Q3vsQ4	Q4vsQ5	
		17.49	16.74	16.00	15.22	13.86	0.104	0.005	0.091	0.003	Ï
	ä	(16.84-18.14)	(16.09-17.39)	(15.35-16.65)	(14.57-15.87)	(13.21-14.51)	0.005	0.014	0.005	0.015	Ÿ
Number of runs of successful and unsuccessful cuts		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ345	Q3vsQ45	Q4vsQ5	
		6.44	9.44	10.83	11.23	11.26	0.000	0.000	0.285	0.947	
		(5.81-7.07)	(8.81-10.07)	(10.20-11.46)	(10.60-11.86)	(10.63-11.89)	0.068	0.031	0.002	0.000	
The single longest run of successful cuts		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ3	Q3vsQ45	Q4vsQ5	
		9.51	7.34	6.08	5.65	4.94	0.000	0.001	0.017	0.060	
		(9.44-9.58)	(7.28-7.40)	(6.04-6.12)	(5.61-5.69)	(4.90-4.98)	0.049	0.017	0.009	0.005	
Number of runs of successful cuts		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ345	Q3vsQ45	Q4vsQ5	
		3.58	4.98	5.40	5.42	5.33	0.000	0.028	0.897	0.688	
		(3.27-3.89)	(4.67-5.29)	(5.09-5.71)	(5.11-5.73)	(5.02-5.64)	0.066	0.008	0.000	0.000	
Average length of a run of successful cuts		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ345	Q3vsQ45	Q4vsQ5	
		6.13	3.83	3.19	2.83	2.55	0.000	0.001	0.091	0.413	
		(6.05-6.22)	(3.78-3.88)	(3.16-3.22)	(2.81-2.86)	(2.53-2.57)	0.072	0.019	0.004	0.001	
Number of unsuccessful cuts out of total events entered		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ3	Q3vsQ45	Q4vsQ5	
		3.68	6.16	7.95	8.83	9.22	0.000	0.000	0.005	0.375	
		(3.63-3.73)	(6.10-6.22)	(7.89-8.01)	(8.77-8.89)	(9.15-9.29)	0.045	0.023	0.011	0.001	
Number of runs of unsuccessful cuts		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ345	Q3vsQ45	Q4vsQ5	
		2.86	4.46	5.43	5.81	5.93	0.000	0.000	0.055	0.649	
		(2.49-3.23)	(4.09-4.83)	(5.06-5.80)	(5.44-6.18)	(5.56-6.30)	0.054	0.050	0.005	0.000	
Average length of a run of unsuccessful cuts		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ345	Q3vsQ45	Q4vsQ5	
		1.17	1.33	1.50	1.56	1.59	0.022	0.000	0.195	0.712	
		(1.07-1.27)	(1.23-1.43)	(1.40-1.60)	(1.46-1.66)	(1.49-1.69)	0.010	0.025	0.003	0.000	

ä = 95% Confidence Interval; Ï = Contrast p-value, Value double underlined significant beyond 0.05; Ÿ = Contrast Eta Square

Qi=Quintile group i; Qij=Combined Quintile groups i and j

Quintile groups with common double underline are considered equal with p > 0.05

Sequential Contrasts; Contrasts applied from right to left pre-planned for Orthogonal Helmert basis, with a significant contrast informing basis for the next left most contrast

Quintile 1 and 2 players averaged making 17.5 and 16.7 cuts per year (Table 1), respectively, with both differing significantly ($p<0.000$, $\eta^2 = 0.04$) from the remaining three groups but not from one another ($p<0.104$, $\eta^2 = 0.01$), as indicated by Sequential Contrast analysis. The top two groups achieved their higher number of cuts made with significantly fewer runs ($p<0.000$, η^2's = 0.25, 0.03) than did the remaining subgroups, with Quintile 1 requiring an even smaller number of total runs (6.4) of successful and unsuccessful cuts than Q2 players (9.4), $p<0.000$, $\eta^2 = 0.07$), indicating fewer but longer runs.

We also looked at players' average run length of successful cuts (ANOVA $p<0.000$, $\eta^2 = 0.23$) and a special case of their longest run of successful cuts (ANOVA $p<0.000$, $\eta^2 = 0.27$). As for the former, Quintile 1 players' average run length of successful cuts was 6.1, which was almost double that of the next highest average run length of 3.8 for Q2 (Table 1), with the difference being highly significant ($p<0.000$, $\eta^2 =0.07$). Quintile 2 in turn exhibited a significantly ($p<0.001$, $\eta^2 = 0.02$) longer average run of successful cuts than the remaining three groups. As for the longest run, Quintile 1 players' longest run of successful cuts was 9.5 which differed significantly ($p<0.000$, $\eta^2 = 0.05$) from that of Q2 (7.3). Quintile 2's longest run of successful cuts also differed significantly ($p<0.001$, $\eta^2 = 0.02$) from Q3 (6.1), which in turn was significantly ($p<0.017$, $\eta^2 = 0.01$) different from the two lowest money ranked groups Q4 (5.6) and Q5 (4.9). As a point of reference, Quintile 1 players' longest run of successful cuts accounted for more than 50% of their total cuts made per year (54.8%), whereas the remaining groups' typical longest run of successful cuts accounted for less than half of their total seasonal cuts. Finally, for the average length of runs of unsuccessful cuts (ANOVA $p<0.000$, $\eta^2 = 0.09$), when Quintile 1 players missed a cut, their run duration of misses (1.17) was significantly ($p<0.022$, $\eta^2 = 0.01$) shorter than the average run duration of missed cuts for Q2 (1.33), which in turn was significantly ($p<0.000$, $\eta^2 = 0.03$) shorter than that of Q3 (1.5), Q4 (1.56), and Q5 (1.59).

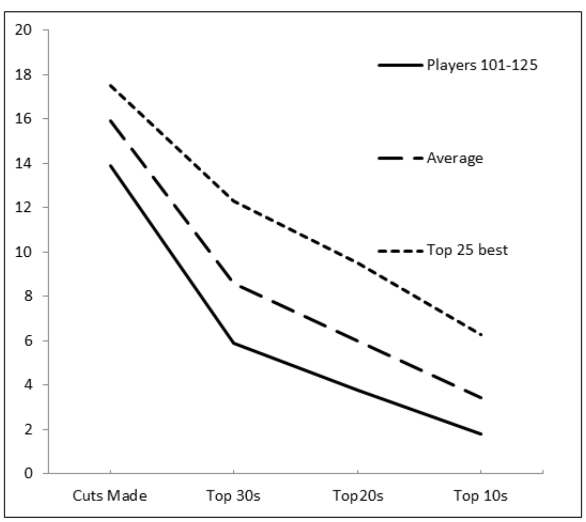

Figure 1. Number of achievements as a function of player ranking.

How many "cuts", top 30, 20, and 10 performances?

As expected, the number of "cuts made", top 30, 20 and 10 achievements progressively decreased from "cuts" to top 10s (Figure 1). On average, players made 15.9 cuts, 8.6 top 30s, 6.1 top 20s, and 3.5 top 10s. Comparing the subgroups, the best players (Quintile 1) averaged about one top 10 finish in every three tournaments, while Quintile groups 2-5 progressively achieved fewer top 10 performances: about one in six among Q2 players, one in eight in Q3, one in 11 in Q4, and one in 13 in Q5. For each top 10-20-30 achievement among the groups, ANOVAs ($p<0.000$, η^2's = 0.58, 0.49, 0.45 respectively) followed by Sequential Contrast analysis revealed all five groups to be pair-wise significantly different (top 10 $p<0.02$, η^2's = 0.01-0.15; top 20 $p<0.003$, η^2's = 0.01-0.09; top 30 $p<0.006$, η^2's = 0.01-0.08). While these results are interesting in their own right, they also validate the present system to rank players and grouping them into five quintiles as we have done for our analyses. In an experimental sense, this is equivalent to "manipulation checks".

Do top 30 performances occur in sequence—more so for better players?

Also as expected, successful top 30 finishes exhibited a pair-wise significant ($p<0.006$, η^2's = 0.08, 0.02, 0.01, 0.01) linear decrease from Quintile 1 players (12.4) to Q5 players (5.9) (see Table 2). The reverse was also true as failures to achieve top 30 outcomes progressively and significantly ($p<0.018$, η^2's= 0.08, 0.02, 0.01) increased from Q1 (8.8) to a plateau among Q4 (16.9) and Q5 (17.2) players.

First, when separating runs of top 30 successes from those of failures, a logical and expected pattern was found. Monotonically across the subgroups (Table 2), more runs of successes were created by the higher ranked than the lower ranked groups ($p<0.000$, $\eta^2 = 0.09$), with Q5 players standing significantly ($p<0.001$, $\eta^2 = 0.03$) apart from other groups; Q1-4 clustered into two distinct groupings with Q1 and Q2 exhibiting a significantly greater number of successful runs than Q3 and Q4 ($p<0.002$, $\eta^2 = 0.02$). Second, when looking at runs of the top 30 failures, the overall effect was significant (ANOVA $p<0.002$, $\eta^2 = 0.03$) with Q1 (4.9) exhibiting a significantly smaller number of runs of top 30 failures compared to the lower money ranked groups ($p<0.000$, $\eta^2=0.03$). Third, the average duration of runs of successes (ANOVA $p<0.000$, $\eta^2 = 0.29$) and failures (ANOVA $p<0.000$, $\eta^2 = 0.18$) significantly separated the five groups. Q1 players' average duration of successful top 30 runs (2.6) was 54.1% longer than the next highest ranked groupings of Q2 and Q3 players ($p<0.000$, $\eta^2 = 0.17$), who in turn averaged 18.7% longer successful runs ($p<0.000$, $\eta^2 = 0.02$) than did the combined Q4 and Q5 groups. In reverse, Q1 players' average run of top 30 failures (1.8) was 27% shorter ($p<0.001$, $\eta^2 = 0.02$) than Q2 (2.5). The Q2 group then averaged a significant 24.6% shorter run of top 30 failures ($p<0.003$, $\eta^2 = 0.02$) than the next shortest run of top 30 failures by Q3 players (3.1), who in turn averaged significantly shorter runs of failures by 13.2% ($p<0.018$, $\eta^2 = 0.01$) than the lowest ranked Q4 and Q5 groups. Finally, an overall significant (ANOVA $p<0.000$, $\eta^2 = 0.37$) effect for the longest run of top 30 successes indicated that the Q1 group, at an average longest run of 4.9, was a significant 1.5 times longer in duration ($p<0.000$, $\eta^2 = 0.10$) than the next closest Q2 group (3.2). The latter group differed significantly from the Q3 group ($p<0.042$, $\eta^2 = 0.01$), which in turn had a significantly larger single longest run of top 30 successes ($p<0.000$, $\eta^2 = 0.02$) than the combined Q4 (2.3) and Q5 (2.0) groups.

Taken together, these results show clearly that top 30 performances occur in sequence and more so for the higher-ranked players. As such, the findings are consistent with the theoretical predictions. It is worth noting that while the traditional significance tests showed differences among the 5 groups on all variables, eta square analysis further clarified these significant differences with the eta square values reflecting strong separation between and among the groups on the momentum-related variables (i.e., numbers, runs and durations of top 30 successes and failures).

Table 2. Means, confidence intervals, p values and eta squares for Sequential Contrasts for top 30 finishes

Measure		Means					Sequential Contrasts				
Number of successful Top 30s out of total events entered		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ3	Q3vsQ4	Q4vsQ5	
		12.35	9.45	8.08	7.12	5.92	0.000	0.000	0.006	0.001	Ï
	ä	(12.30-12.40)	(9.39-9.51)	(8.03-8.13)	(7.08-7.16)	(5.88-5.96)	0.077	0.017	0.008	0.013	Ÿ
Number of runs of successful and unsuccessful Top 30s		Q1	Q2	Q3	Q4	Q5	Q1vsQ234	Q2vsQ34	Q3vsQ4	Q4vsQ5	
		10.08	10.94	10.45	10.50	9.21	0.116	0.210	0.907	0.003	
		(9.48-10.68)	(10.34-11.54)	(9.85-11.05)	(9.90-11.10)	(8.61-9.81)	0.005	0.003	0.000	0.018	
The single longest run of successful Top 30s		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ3	Q3vsQ45	Q4vsQ5	
		4.94	3.23	2.84	2.32	2.04	0.000	0.042	0.000	0.143	
		(4.90-4.98)	(3.21-3.25)	(2.82-2.86)	(2.30-2.34)	(2.02-2.06)	0.103	0.005	0.020	0.003	
Number of runs of successful Top 30s		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ34	Q3vsQ4	Q4vsQ5	
		5.22	5.32	4.86	4.69	3.96	0.658	0.005	0.451	0.001	
		(4.90-5.54)	(5.00-5.64)	(4.54-5.18)	(4.37-5.01)	(3.64-4.28)	0.000	0.014	0.001	0.019	
Average length of a run of successful Top 30s		Q1	Q2	Q3	Q4	Q5	Q1vsQ23	Q2vsQ3	Q3vsQ45	Q4vsQ5	
		2.59	1.75	1.62	1.41	1.42	0.000	0.172	0.018	0.896	
		(2.56-2.61)	(1.74-1.76)	(1.61-1.63)	(1.40-1.42)	(1.41-1.44)	0.166	0.003	0.008	0.000	
Number of unsuccessful Top 30s out of total events entered		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ3	Q3vsQ45	Q4vsQ5	
		8.82	13.45	15.87	16.93	17.16	0.000	0.000	0.018	0.688	
		(8.02-9.62)	(12.65-14.25)	(15.07-16.67)	(16.13-17.73)	(16.36-17.96)	0.083	0.023	0.007	0.000	
Number of runs of unsuccessful Top 30s		Q1	Q2	Q3	Q4	Q5	Q1vsQ234	Q2vsQ34	Q3vsQ4	Q4vsQ5	
		4.86	5.62	5.59	5.81	5.25	0.000	0.720	0.788	0.030	
		(4.06-5.66)	(4.82-6.42)	(4.79-6.39)	(5.01-6.61)	(4.45-6.05)	0.029	0.000	0.000	0.009	
Average length of a run of unsuccessful Top 30s		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ3	Q3vsQ45	Q4vsQ5	
		1.84	2.52	3.14	3.37	3.74	0.001	0.003	0.018	0.071	
		(1.82-1.85)	(2.50-2.54)	(3.11-3.17)	(3.34-3.40)	(3.70-3.78)	0.019	0.015	0.009	0.005	

ä = 95% Confidence Interval; Ï = Contrast p-value, Value double underlined significant beyond 0.05; Ÿ = Contrast Eta Square
Qi=Quintile group i; Qij=Combined Quintile groups i and j
Quintile groups with common double underline are considered equal with p > 0.05
Sequential Contrasts; Contrasts applied from right to left pre-planned for Orthogonal Helmert basis,
with a significant contrast informing basis for the next left most contrast

Table 3. Means, confidence intervals, p values and eta squares for Sequential Contrasts for top 20 finishes

Measure		Means					Sequential Contrasts				
Number of successful Top 20s out of total events entered		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ3	Q3vsQ4	Q4vsQ5	
		9.45	6.77	5.64	4.64	3.78	0.000	0.000	0.000	0.003	Ï
	ä	(9.40-9.50)	(6.72-6.82)	(5.60-5.68)	(4.61-4.67)	3.75-3.81)	0.091	0.016	0.013	0.009	Ÿ
Number of runs of successful and unsuccessful Top 20s		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ34	Q3vsQ4	Q4vsQ5	
		10.48	9.59	8.66	8.23	6.82	0.018	0.000	0.252	0.000	
		(10.42-10.54)	(9.53-9.65)	(8.61-8.71)	(8.18-8.28)	(6.78-6.86)	0.009	0.021	0.002	0.023	
The single longest run of successful Top 20s		Q1	Q2	Q3	Q4	Q5	Q1vsQ23	Q2vsQ3	Q3vsQ45	Q4vsQ5	
		2.99	2.19	1.94	1.52	1.37	0.000	0.061	0.000	0.261	
		(2.97-3.01)	(2.17-2.21)	(1.92-1.96)	(1.51-1.53)	(1.36-1.38)	0.094	0.005	0.027	0.002	
Number of runs of successful Top 20s		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ34	Q3vsQ4	Q4vsQ5	
		5.29	4.53	3.87	3.50	2.82	0.000	0.000	0.062	0.001	
		(5.01-5.57)	(4.25-4.81)	(3.59-4.15)	(3.22-3.78)	(2.54-3.10)	0.022	0.036	0.005	0.017	
Average length of a run of successful Top 20s		Q1	Q2	Q3	Q4	Q5	Q1vsQ23	Q2vsQ3	Q3vsQ45	Q4vsQ5	
		1.86	1.46	1.37	1.20	1.24	0.000	0.212	0.016	0.499	
		(1.84-1.87)	(1.45-1.47)	(1.36-1.38)	(1.19-1.20)	(1.23-1.25)	0.086	0.003	0.010	0.001	
Number of unsuccessful Top 20s out of total events entered		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ3	Q3vsQ45	Q4vsQ5	
		11.72	16.13	18.31	19.41	19.30	0.000	0.000	0.042	0.853	
		(10.89-12.55)	(15.30-16.96)	(17.48-19.14)	(18.58-20.24)	(18.47-20.13)	0.076	0.018	0.006	0.000	
Number of runs of unsuccessful Top 20s		Q1	Q2	Q3	Q4	Q5	Q1vsQ234	Q2vsQ34	Q3vsQ4	Q4vsQ5	
		5.19	5.06	4.79	4.73	4.00	0.072	0.123	0.789	0.001	
		(4.88-5.50)	(4.75-5.37)	(4.48-5.10)	(4.42-5.04)	(3.69-4.31)	0.006	0.005	0.000	0.020	
Average length of a run of unsuccessful Top 20s		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ34	Q3vsQ4	Q4vsQ5	
		2.38	3.52	4.29	4.57	5.64	0.000	0.000	0.337	0.000	
		(2.36-2.40)	(3.49-3.55)	(4.25-4.33)	(4.54-4.60)	(5.58-5.70)	0.025	0.021	0.001	0.022	

ä = 95% Confidence Interval; Ï = Contrast p-value, Value double underlined significant beyond 0.05; Ÿ = Contrast Eta Square
Qi=Quintile group i; Qij=Combined Quintile groups i and j
Quintile groups with common double underline are considered equal with p > 0.05
Sequential Contrasts; Contrasts applied from right to left pre-planned for Orthogonal Helmert basis,
with a significant contrast informing basis for the next left most contrast

Do top 20 performances occur in sequence—more so for better players?

Table 3 presents the results for top 20 performances. Regarding the number of top 20 finishes, the highest-ranked group achieved 2.5 times more of them (9.5) than the lowest-ranked group Q5 (3.8), with the number decreasing linearly and pair-wise significantly from Q1 to Q5 (ANOVA p<0.000, $\eta^2 = 0.49$). The best players (Q1) achieved these top 20 finishes in about 45% of the tournaments entered, whereas Q5 players did so only in 16% of the tournaments entered. With the exception of the number of unsuccessful top 20 runs, regardless of the internal representation of top 20 successes/failures, the Q1 group achieved significantly better Top 20 comparisons than any lower ranked group (range of Sequential Contrast p's = 0.018-0.000, η^2 range = 0.01-0.09). Among four of the eight measured characterizations of Top 20 performances, the Q1 players exhibited moderate etas squares (0.076-0.094) in comparison to the next highest ranked group, indicative of a powerful separation as a result of momentum. Because of the large differences between the five groups in the number of top 20 finishes, the higher-ranked players exhibited a significantly greater number of successful runs (ANOVA p<0.000, $\eta^2 = 0.27$) and a smaller number of unsuccessful runs (ANOVA p<0.000, $\eta^2 = 0.06$) than the lower-ranked players. For example, the number of runs of top 20 finishes was significantly (p<0.000, $\eta^2 = 0.02$) greater in Q1 (5.3) than Q2 (4.5) players who in turn had a significantly (p<0.000, $\eta^2 = 0.04$) greater number of these runs than Q3 (3.9) and Q4 (3.5) combined, and the combined Q3 and Q4, in turn, had more (p<0.000, $\eta^2 = 0.04$) of them than Q5 (2.8) players. On the other hand, top players bounced back more quickly to top 20 performances by exhibiting shorter average runs of top 20 failures (ANOVA p<0.000, $\eta^2 = 0.22$) (2.4 for Q1 compared to 5.6 for Q5). Finally, the single longest run of top 20 successes decreased linearly and significantly (ANOVA p<0.000, $\eta^2 = 0.27$) from the highest-ranked players (3.0) to the lowest (1.4), which mirrors other comparisons reported above.

This latter comparison is worthy of emphasis. Note that the lowest ranked players, Q5, do experience the intensity effect afforded from top 20 successes. While they achieved almost four (3.8) of such successes per year, they rarely strung any two of them together (the average longest run of 1.4). Thus, although top 20 achievements unquestionably contributed to these players' experiencing the intensity of momentum, failure to extend or combine this short-lived intensity effect with the concomitant duration component of momentum through back-to-back top 20s mitigates the success-breed-success effect for these (Q 5) players. This becomes particularly evident when we juxtapose the Q5 players' momentum profile with the intensity-duration profile of Q1 players. These highest-ranked performers achieved almost three times as many top 20s per season as Q5 athletes (9.5 vs. 3.8), and importantly, did so by successfully stringing about three top 20s in a row once a year and typically achieved back-to-back top 20s. All of this demonstrates that the combination force of a high impact top 20 result (intensity effect) integrated with typical consecutive successes (duration effect) separates Q1 performers from lower ranked players.

Overall, then, the data strongly support the theory that success breeds success via sequential runs or occurrences of momentum, and more so for higher-ranked players. The more that frequent successes are bunched together, the greater are the results (a higher performer ranking). While failure is inevitable, players who can quickly bounce back by starting new runs of successes ultimately produce more and better outcomes, as indicated by higher frequencies of top 20 finishes and more of them in a row by Q1 players. Eta square values, again, demonstrate strong separation among the groups and indicate that higher-ranked players have more frequent and more lasting momentums of top 20 performances, as well as shorter runs of top 20 misses.

Table 4. Means, confidence intervals, p values and eta squares for Sequential Contrasts for top 10 finishes

Measure		Means					Sequential Contrasts				
Number of successful Top 10s out of total events entered		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ3	Q3vsQ4	Q4vsQ5	
		6.33	3.79	3.17	2.24	1.78	0.000	0.001	0.000	0.017	Ï
	ä	(6.29-6.37)	(3.76-3.82)	(3.15-3.19)	(2.22-2.26)	(1.76-1.80)	0.148	0.009	0.020	0.005	Ÿ
Number of runs of successful and unsuccessful Top 10s		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ3	Q3vsQ4	Q4vsQ5	
		9.00	6.91	6.13	4.96	4.20	0.000	0.007	0.000	0.008	
		(8.95-9.05)	(6.87-6.95)	(6.09-6.17)	(4.93-4.99)	(4.17-4.23)	0.064	0.009	0.020	0.008	
The single longest run of successful Top 10s		Q1	Q2	Q3	Q4	Q5	Q1vsQ23	Q2vsQ3	Q3vsQ45	Q4vsQ5	
		2.31	1.54	1.44	1.16	1.03	0.000	0.291	0.000	0.170	
		(2.29-2.33)	(1.53-1.55)	(1.43-1.45)	(1.15-1.17)	(1.02-1.04)	0.140	0.002	0.025	0.003	
Number of runs of successful Top 10s		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ3	Q3vsQ45	Q4vsQ5	
		4.32	3.00	2.48	1.85	1.59	0.000	0.000	0.000	0.080	
		(4.29-4.35)	(2.98-3.02)	(2.46-2.50)	(1.83-1.87)	(1.57-1.61)	0.086	0.013	0.038	0.003	
Average length of a run of successful Top 10s		Q1	Q2	Q3	Q4	Q5	Q1vsQ23	Q2vsQ3	Q3vsQ45	Q4vsQ5	
		1.48	1.20	1.19	1.00	0.97	0.000	0.843	0.000	0.593	
		(1.47-1.49)	(1.20-1.21)	(1.19-1.20)	(0.99-1.00)	(0.96-0.98)	0.065	0.000	0.036	0.000	
Number of unsuccessful Top 10s out of total events entered		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ3	Q3vsQ45	Q4vsQ5	
		14.84	19.11	20.78	21.81	21.30	0.000	0.006	0.136	0.395	
		(14.01-15.67)	(18.28-19.94)	(19.95-21.61)	(20.98-22.64)	(20.47-22.13)	0.075	0.012	0.003	0.001	
Number of runs of unsuccessful Top 10s		Q1	Q2	Q3	Q4	Q5	Q1vsQ23	Q2vsQ3	Q3vsQ4	Q4vsQ5	
		4.68	3.91	3.65	3.11	2.61	0.000	0.15	0.00	0.01	
		(4.65-4.71)	(3.88-3.94)	(3.62-3.68)	(3.09-3.13)	((2.59-2.63)	0.051	0.00	0.01	0.01	
Average length of a run of unsuccessful Top 10s		Q1	Q2	Q3	Q4	Q5	Q1vsQ2	Q2vsQ3	Q3vsQ4	Q4vsQ5	
		3.44	5.48	6.45	7.98	9.38	0.000	0.024	0.000	0.001	
		(3.41-3.47)	(5.44-5.53)	(6.40-6.50)	(7.92-8.04)	(9.29-9.48)	0.032	0.007	0.018	0.015	

ä = 95% Confidence Interval; Ï = Contrast p-value, Value double underlined significant beyond 0.05; Ÿ = Contrast Eta Square

Qi=Quintile group i; Qij=Combined Quintile groups i and j

Quintile groups with common double underline are considered equal with p > 0.05

Sequential Contrasts; Contrasts applied from right to left pre-planned for Orthogonal Helmert basis, with a significant contrast informing basis for the next left most contrast

Do top 10 performances occur in sequence-more so for better players?

Table 4 presents the results pertaining to top 10 performances. With few exceptions, the patterns of differences in top 10 finishes are similar to top 20 and 30 performances. In fact, the results show that all eight internal representations of top 10 successes and failures strongly favor the highest-ranked Q1 players (Sequential Contrast p's<0.000, η^2 range = 0.03-0.15) over the next highest ranked quintile group(s). As can be seen, the higher-ranked players had significantly (ANOVA p<0.000, η^2 = 0.58) more top 10s than the other groups, linearly decreasing from Q1 to Q5 players, with Q1 players achieving 3.6 times more top 10 performances per season than Q5 players. As for "runs" of top 10s, Q1 players exhibited the largest number of runs of successes (ANOVA p<0.000, η^2 = 0.46), with Q1 being significantly (p<0.000, η^2 range = 0.09-0.34) different from each of the lower ranked quintile groups. The higher-ranked players had more total runs of top 10s (ANOVA p<0.000, η^2 = 0.41). Their average run length of successes (ANOVA p<0.000, η^2 = 0.21) and longest run of top 10 successes (ANOVA p<0.000, η^2 = 0.31) were greater in duration, and their average run length of top 10 failures (ANOVA p<0.000, η^2 = 0.32) shorter, than those of the lower-ranked players.

Taken together, these results are consistent with the top 20 and 30 performances and as such, replicate the earlier patterns and therefore lend further credence to the theory. Obviously, there are fewer top 10s than top 20s and fewer top 20s than top 30s, but what is striking is the similarity of patterns among the player groups in these three performance categories. Top 10 performances occur in sequence and more so for higher-ranked players. Clearly, the higher-ranked players not only have more of these top performances but they get on longer runs of successes and shorter runs of failures than the lower-ranked players. Eta square values are particularly noteworthy as they reflect a very strong separation among the groups on all top 10 performance outcome variables.

Successful performances—momentum vs. random?

Among these elite Tour players, what separates more successful from less successful performances? The answer is clear: from Q1 to Q5 players, each quintile group makes significantly more cuts and achieves significantly more top 30, 20, and 10 finishes than the next lower ranked group of players. Importantly, as the intensity of the tournament outcome increases (from cuts made to top 10s), the degree of separation from the lower ranked players strongly increases, as indicated by the eta square effect sizes (Figure 2). It is noteworthy how the best 25 players (Q1 group) separate themselves from others as the achievement level increases (i.e., the greatest separation in the top 10 finishes).

Examining the annual money earned in the season-long PGA tournament competition (and player ranking) as a function of the four performance achievements, results showed that, taken together, cuts made and top 30-20-10 achievements explained 67.1 % of variance in the annual earnings. This explained variance was consistent across the four years (2010-2013) of the Tour performance data analyzed. Thus, it is clear that performance at the highest level requires multiple top achievements annually. But an important question is: Do PGA Tour players achieve these successful outcomes in a random fashion (i.e., one success here and there) or do they result from the systematic influence of momentum?

To answer this question, we computed the number of runs of successes (the frequency effect) and the average run length of successes (the duration effect) for cuts made and top 30-20-10 achievements. Results revealed that players who had more successful runs and whose average run length was greater clearly separated themselves from others, as indicated by the eta square effect sizes. Figure 3 demonstrates this effect for the number of runs of successes, and Figure 4 shows a similar effect for the average run length. The influence of momentum became even more evident when we regressed the number of successful runs and their duration on cuts made and top 30-20-10 season-long achievements. These two predictors (frequency and duration) strongly explained differences in performance outcomes: The number of successful runs and their length explained 91.5% of top 10, 87.1% of top 20, 84.9% of top 30 achievements and 55.5% of the season-long cuts made. Another way to see this influence of momentum is to remove the number of successful runs and their length from regression analysis and then compute the adjusted eta squares. When this was done, eta squares were reduced to trivial effect sizes: Top 10 to 0.016 (from 0.58), top 20 to 0.015 (from 0.49), top 30 to 0.009 (from 0.44), and cuts made to 0.007 (from 0.13). In short, these results powerfully demonstrate the influence of momentum on performance achievements on the PGA Tour and simultaneously rule out any meaningful role for randomness.

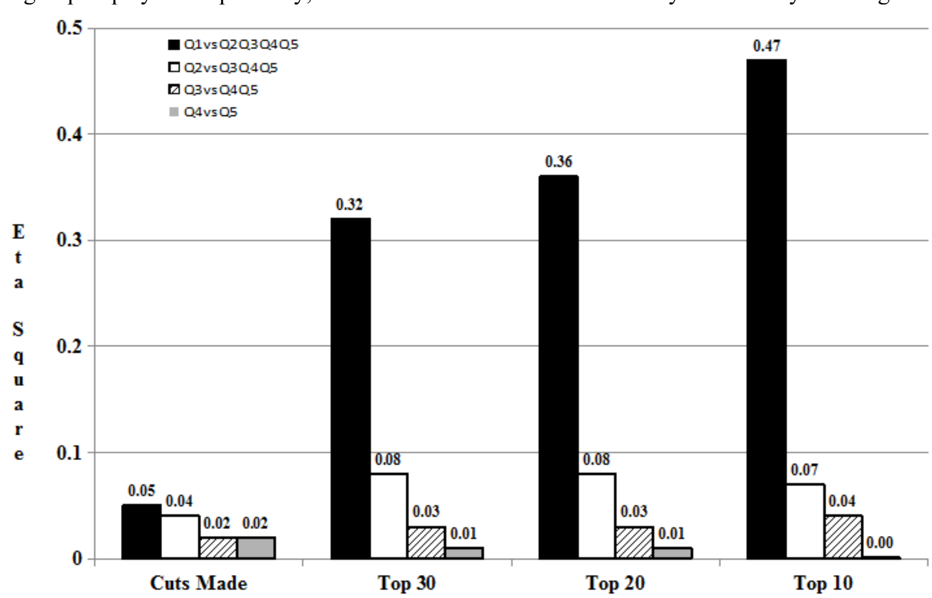

Figure 2. Degrees Separation From Lower Ranked Players, Number of Outcomes

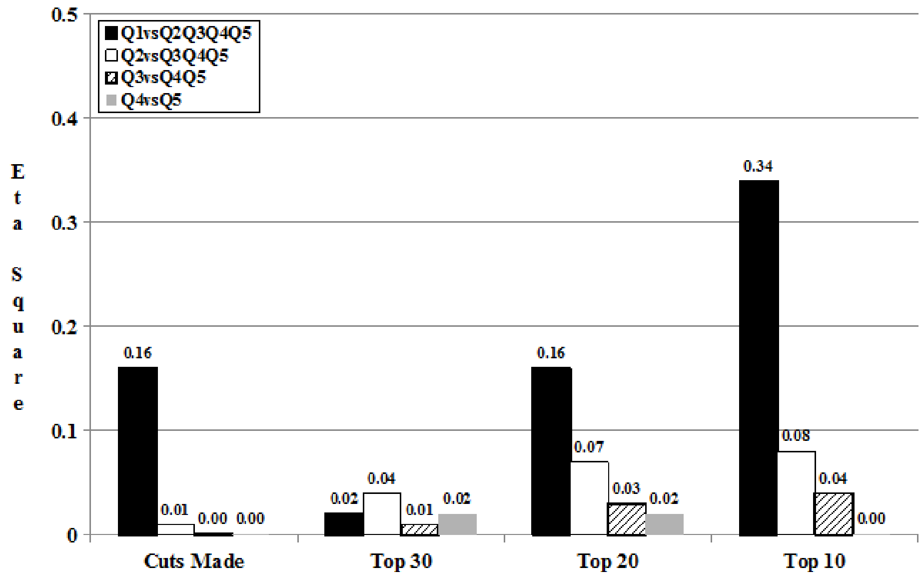

Figure 3. Degrees Separation From Lower Ranked Players, Runs of Successes

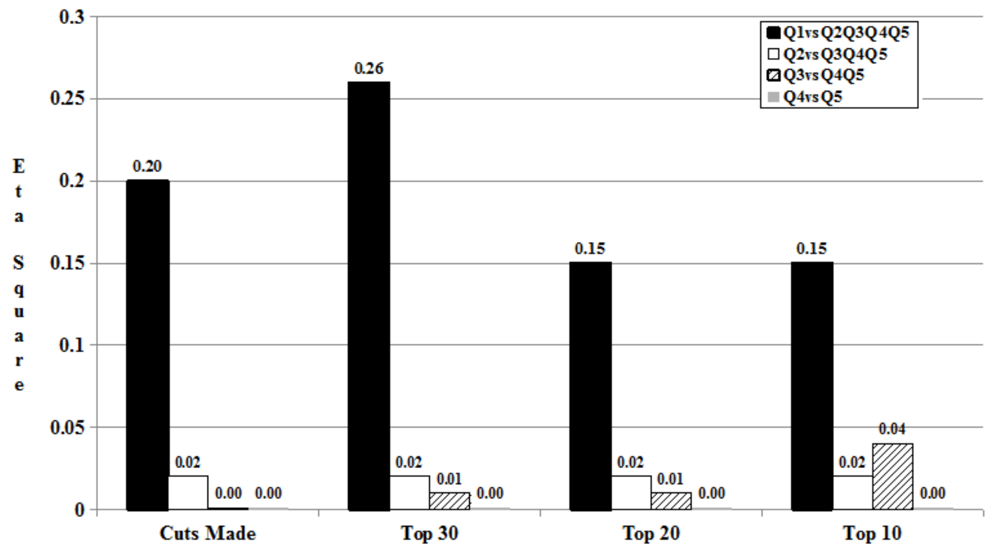

Figure 4. Degrees Separation From Lower Ranked Players, Average Run Length

Table 5. Summary of ETA Squares

Variable	Success Outcomes: Number	Success Outcomes: Runs	Success Outcomes: Average Length	Failure Outcomes: Number	Failure Outcomes: Runs	Failure Outcomes: Average Length	Runs: Total	Longest Run
Cuts	.130	.165	.225	.303	.275	.089	.252	.268
Top 30	.445	.085	.286	.372	.033	.180	.036	.366
Top 20	.491	.271	.181	.322	.064	.224	.182	.272
Top 10	.583	.464	.207	.265	.236	.316	.407	.311
Average	.412	.246	.225	.316	.152	.202	.219	.304
		.294			.223			

Table 5 summarizes eta squares for the four performance variables (cuts, top 30, 20, and 10) for both outcomes (success and failure) in terms of their number, runs and average length. Several observations can be made. First, as noted, eta squares reflect moderate to strong separation among the quintile groups on all variables. Second, the strongest eta square measures were observed in the numbers of top 10 and 20 successes achieved. These high “intensity” successes, strongly separating the quintile groups, speak clearly for the importance of the momentum intensity effect. In this respect, it is worth noting the progressive increase of eta square values from “cuts” to top 10. A similar increase can also be seen in the frequency of successful runs from "cuts" to top 10, further emphasizing the intensity effect. On the other hand, the average length of successful runs of top 30 and cuts made separate the groups somewhat better than duration of top 10 and 20 successes. Third, when comparing success and failure outcomes overall, momentum measures for success variables showed a larger average eta square value, thus reflecting success-related momentum's greater ability to separate the player groups. Finally, the observed eta squares for total runs (sum of success and failure runs) and the longest run of success demonstrate these variables' strong ability to distinguish the player groups.

DISCUSSION

The basic tenet of the momentum theory is that success breeds success, and this occurs because performers get on a roll of consecutive successes by building momentum from the initial success (9). Thus, momentum becomes "a principle vehicle of performance for goal achievement and future success" (14). The present study tested this tenet by employing a large data set (11,015 tournament results from four competitive seasons) involving elite performers, the 125 best professional golfers of the PGA Tour. More specifically, the study focused on analyzing four outcome variables ("cuts" made, top 30, 20 and 10 performances) and answering the question whether these achievements occur in sequence, not randomly, as well as whether such momentum performances are more likely for higher-ranked than lower-ranked players. The theory posits that initial success creates three types of momentum effects: frequency, intensity, and duration (9). In other words, the likelihood of subsequent success is increased by more frequent, higher-intensity and lasting occurrences of momentum resulting from initial success.

Overall, the data supported the behavioral aspect of the theory and describe what momentum looks like in elite athletes' performance in general and how better players consistently achieve better results than those who are on the lower rungs of the player-ranking list. Higher-ranked performers were not only able to put together more frequent and more lasting strings of successful performances, but also bounced back more quickly from failures as indicated by shorter durations of missed cuts, top 30, 20 , and 10 performances. How can these findings be explained?

Given the psychological underpinnings of causes and effects of momentum (9, 14-17), the observed performance patterns suggest that the best of the best focus on making successful performances happen and seeing them as occurrences of momentum (e.g., a couple of "birdies" or difficult "par" saves in a row), rather than viewing them as avoidance of disasters. Such a mental approach enables these top performers to take their mind away from skill failure to the possibility of continued success. In this scenario, focusing on seeking and grabbing momentum is an antidote to or a psychological strategy against "choking". Performers, however, can make mistakes in perceiving momentum where there is none and not perceiving momentum where is one. Thus, "how to become better at accurately detecting momentum and profitably capitalizing on it in various domains of human performance remains to be investigated in the future" (9, p. 31).

Success among these elite performers gets increasingly better (more meaningful), but also more difficult, when moving from making a cut to achievement of a top 10 outcome (see Figure 1). Mathematically, making cuts is easier than achieving top 10 finishes, but does momentum (i.e., sequential runs of success) play a similar role at all levels of success? If it does, even in top 10 achievements, such evidence would provide strong support for the existence and influence of momentum on subsequent success. The results showed that there was a significant transition or transfer effect from tournament to tournament for making a cut (6.8% more cuts in the following tournament), achieving top 30s (9.9% more), top 20s (8.3% more), and top 10s (5.8% more). The effect was also stronger for higher-ranked players in all four categories of achievement. When looking at these categories more specifically, better players not only made more cuts and had the highest percentage of runs of successful cuts out of the total runs ("frequency effect"), but exhibited a longer average run of successful cuts and had the longest run of successful cuts ("duration effect"). Clearly, better performers get on longer runs of making cuts than lower-ranked players, giving them more frequent opportunities for higher achievements.

Results for top 30, 20 and 10 performances mirrored those for making cuts. Differences among player groups, again, were notable and even striking. For example, the highest-ranked group (best 25 players) had 12.4 top 30s, 9.5 top 20s and 6.3 top 10s, whereas the lowest-ranked group's respective numbers were 5.9, 3.8, and 1.8. Why such large differences and why are better players better? The data clearly point to the influence of momentum. Top 30, 20 and 10 performances not only occurred in sequence in general and not randomly, but more so for higher-ranked players. In short, better players have a greater number of top performances and more runs of them, and their runs of successes last longer and runs of failures are shorter. The intensity effect clearly was evident in top 10 achievements, in the number and duration of them. These findings are congruent with the predictions for the frequency, intensity and duration effects derived from the psychological momentum theory (9).

It is clear from the findings that success on the PGA Tour is not a matter of randomness, one successful performance achieved randomly now and then. Instead, performance achievements are due to the systematic and direct influence of momentum. When the indicators of momentum (frequency and duration) were removed from relevant statistical analyses, eta squares (variance explained) were reduced to trivial effect sizes. In reverse, when they were included in the analyses, they explained between 85-91% of variance in top 30-20-10 achievements. As a whole, these results not only provide strong evidence for the momentum influence in elite performance but also, for the way in which momentum has its effects on performance.

Our findings are consistent with recent studies that have generally confirmed the momentum effects on human performance (e.g., 4-6, 10, 16-17). A growing body of evidence obtained from well-designed studies with large data sets provides increasing support for Jackson and Mosurski's (3) conclusion that "the idea of independence must be abandoned". Our findings, however, go beyond such general conclusions by specifying empirically for the first time the way in which momentum has positive effects on later success. When performers have more frequent and more lasting occurrences of momentum, their chances of future success are elevated significantly. High-intensity momentums resulting from top achievements (top 10 finishes in particular) are likely to further enhance the frequency and duration effects. Future research should explore interactive effects of intensity, frequency and duration in efforts to determine the best combination of the three effects for predicting success.

Regardless of the consistent and theory-supportive findings, we acknowledge the shortcomings of the non-experimental method and its limits on causal conclusions. Although unobtrusive studies are weaker in internal validity, they are stronger in external validity and therefore respond to recent calls for researchers to step outside of artificial laboratory settings to study actual behaviors rather than finger-press movements on computer screens (18). The strength of the study derives from a large longitudinal data set and consistent patterns of results for all the measured variables.

Although we have focused on overt "behavioral momentum" (16-17), it should be noted that momentum does not occur in a psychological vacuum. Behavioral and psychological momentums are inextricably interwoven (15). It is well established (for a review of research, see 9) that both in competitive and non-competitive situations, performers' sense of confidence and competence are greatly affected by initial and continuing successful performances, as are their attributions for success. These perceptions in turn translate into an altered (increased) sense of probability of success and thus give rise to momentum (14). Momentum then increases confidence at both conscious and nonconscious levels, making performers increase their effort. In the words of Sidney Crosby, one of the best pro hockey players today: "When the puck's going in for you, you feel confident shooting from different areas…when it goes in, it's more instinctive for you to try it again". Justin Thomas won the first tournament of the 2017 PGA Tour and said afterwards: "The way that I won is going to give me a lot of momentum and a lot of confidence when I get in that position again". He went on to win the very next (second) tournament of the season, and by an unusually large margin.

It is clear, then, that these perceptions, although borne out of overt behavioral outcomes, immediately make momentum a psychological phenomenon, and performers strive to capitalize on it. In short, momentum is always a psychological phenomenon because performers are humans who possess dynamic cognitions and emotions. Whether momentum-related beliefs and perceptions are more conscious in slow-paced activities (e.g., golf) and more nonconscious in fast-paced sports (e.g., ice hockey) remains to be determined.

In conclusion, our findings are important in not only demonstrating the existence of momentum and the characteristics of momentum effects (frequency, intensity, duration) but also, in enhancing a general understanding of the performance-success relationship. To state that success is a matter of better performance is simplistic and superficial because it does not consider what has happened *within* a better performance, why it has become possible. As our findings indicate, better performances result from frequent, lasting and high-intensity occurrences of momentum. Better performers may be said to maximize these characteristics of positive momentum and minimize those of negative momentum. That is, they create more occurrences of positive momentum and make them last longer, as well make negative momentum (runs of unsuccessful performances) shorter. The net result is better performances that are repeatable and predictable when performers learn to capitalize on momentum characteristics and effects. In this way, momentum becomes a key to continued success (14).

Acknowledgements

The statistical results reported in this paper are based on the PGA Tour's ShotLink Mapping data. The Tour granted the authors license to use the ShotLink data solely to create scholarly work. The Tour is not responsible for any conclusions or statements included in this report. The authors thank Walid Briki and Roger Mannell for their helpful comments and suggestions.

1. Iso-Ahola, S., and Mobily, K. 1980. Psychological momentum: A phenomenon and empirical (unobtrusive) validation of its influence in sport competition. *Psychol Rep* 46: 391-401.
2. Oskarsson, A., Van Boven, L., McClelland, G., and Hastie, R. 2009. What's next? Judging sequences of binary events. *Psychol Bull* 135: 262-285.
3. Jackson, D., and Mosurski, K. 1997. Heavy defeats in tennis: Psychological momentum or random effects? *Chance* 10: 27-34.
4. Raab, M., Gula, B., and Gigerenzer, G. 2012. The hot hand exists in volleyball and is used for allocation decisions. *J Exp Psychol*: *Applied* 18: 81-94.
5. Yaari, G., and Davids, G. 2012. "Hot hand" on strike: Bowling data indicates correlation to recent past results, not causality. PLoS ONE 7: e30112.
6. Briki, W., Den Hartigh, R., Markman, K., Micallef, J., and Gernigon, C. 2013. How Psychological momentum changes in athletes during a sport competition. *Psychol Sport Exerc* 14: 389-396.
7. Hendricks, D., Patel, J., and Zeckhauser, R. 1993. Hot hand in mutual funds: Short-run persistence of relative performance, 1974-1988. *J Fin* 48: 93-130.
8. Jegadeesh, N., and Titman, S. 1993. Report to buy winners and selling losers: Implications for stock market efficiency. *J Fin* 48: 65-91.
9. Iso-Ahola, S., and Dotson, C. 2014. Psychological momentum: Why success breeds success. *Rev Gen Psychol* 18: 19-33.
10. Arkes, J. 2013. Misses in "hot hand" research. *J Sports Econ* 14: 401-410.
11. Markman, K., and Guenther, C. 2007. Psychological momentum: Intuitive physics and naïve beliefs. *Pers Soc Psychol Bull* 33: 800-812.
12. Attali, Y. 2013. Perceived hotness affects behavior of basketball players and coaches. *Psychol Sci* 24: 1151-1156.
13. Neiman, T., and Loewenstein, Y. 2011. Reinforcement learning in professional basketball players. *Nature Comm* 2: 1-7.
14. Iso-Ahola, S. G., and Dotson, C. O. 2016. Psychological momentum – A key to continued success. *Front Psychol* 7: 1328 (1-7).
15. Briki, W. 2017. Rethinking the relationship between momentum and sport performance: Toward an integrative perspective. *Psychol Sport Exerc* In press.
16. Hubbard, T. 2015a. The varieties of momentum-like experience. *Psychol Bull* 141: 1081-1119.
17. Hubbard, T. 2015b. Forms of momentum across time: Behavioral and psychological. *J Mind Beh* 36: 47-82.
18. Baumeister, R., Vohs, K., and Funder, D. 2007. Psychology as the science of self-reform and finger movement: Whatever happened to actual behavior? *Persp Psychol Sci* 2: 396-403.