Does Momentum Exist in Competitive Volleyball?

• **Articles**

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Since T. Gilovich, R. Vallone, and A. Tversky published their seminal 1985 paper, "**The Hot Hand in Basketball: On the Misrepresentation of Random Sequences**," there has been considerable study of the question of momentum in sports. The term "momentum" here refers to a condition in which psychological factors cause a player or team to achieve a higher (or lower) than normal performance over a period of time due to a positive correlation between successive outcomes. Put more plainly, sports momentum—if and when it exists—can be summarized as "success breeds success" (or, perhaps, "failure breeds failure"). Gilovich and colleagues referred to it as the "hot hand."

Gilovich's research team studied questions such as whether a basketball player who has made several shots in a row becomes more likely to make the next shot than his or her normal shooting percentage would indicate. Finding no evidence for the existence of momentum, they concluded that basketball shots behave as independent trials.

Basketball, baseball, tennis, and many other sports have been analyzed for momentum, and little statistical evidence has been found, although controversy about the issue continues. The best evidence for momentum has come in sports that involve competition between individuals, rather than teams, and have little variation within the course of play, such as bowling and horseshoes.

Here, we investigate whether momentum exists in volleyball. By some accounts, volleyball is the most popular sport in the world in terms of the number of participants; the Fédération Internationale de Volleyball (FIVB) estimates approximately 800 million people play the game.

There are, of course, many ways in which momentum could manifest itself in volleyball. We focus on whether "runs" of consecutive points by a team give evidence of momentum or whether they are manifestations of the natural variability that appears in the outcomes of chance events. We provide three analyses to help address the question and find the results of all three consistent. The data come from 55 games played in the course of 16 matches during the 2007 NCAA Collegiate Women's Volleyball season between the California State University Northridge team (CSUN) and 15 opponents, most of them members of the Big West Conference (to which CSUN belongs).

Volleyball Basics

To understand the possible propensity and nature of runs in competitive volleyball, we need a basic understanding of fundamental components of the sport in its modern form. A volleyball match consists of either a best-of-three or a best-of-five series of games (also called sets), where each game is played until one team reaches a certain score—typically 25 or 30 points—and is ahead by at least two points. A best of $2n$-1 game match ends as soon as one team wins n games.

There are six players on a side at any given time, each having nominal positions on the court—three in the front row and three in the back. Only players who begin the rally in front-row positions can jump close to the net either to attack the ball (typically with a hard-driven ball known as a "spike") or to block the opposing team's attack. Volleyball uses a system of rotation, so the same players do not always stay in the same positions.

Play begins when a member of one team serves the ball across the net to the opposite team. The action this generates is called a "rally." Whichever team wins the rally earns a point, regardless of which team served. (This rally-scoring system is a departure from the scoring system used many years ago, known as side-out scoring, in which only the serving team could score.) If the team that was serving wins the point, the same player serves again. If the receiving team (the team not serving) wins the point (called a "side-out"), it serves next, at which time rotation comes into play as each player on this team moves clockwise to the next of the six positions. The player who moves to the back-right position (facing the net) becomes the new server.

We can now see the structure of a run in a volleyball game: A run begins when the receiving team wins the point and continues as long as that team serves and wins subsequent rallies. The only exception is if the team that serves to begin the game wins an immediate string of points. A run therefore terminates either when the receiving team wins a rally or when the serving team reaches the score necessary to win the game and is ahead by at least two points.

For this analysis, we will not allow a run to carry over from one game to the next. There are several reasons for this choice: (1) There is a significant time gap between the end of one game and the start of the next; (2) each team is free to start the new game with a rotation completely different from that in which it ended the previous game; (3) it is not uncommon for different players to be inserted into the match at this point. Each of these factors may interfere with the assessment of any momentum that may contribute to runs.

As is the case in basketball, volleyball coaches often stress the importance of limiting the runs achieved by their opponents (i.e., stopping their momentum). Of course, a run could just as easily be engendered by negative momentum, wherein a team's poor performance during the run of points by its opponent may feed upon itself. That volleyball coaches believe in momentum is evidenced by the great majority of time-outs being called when the opposing team has scored a run of several points. In our database, 88 of the 141 time-outs (62%) were called immediately after a run of three or more points by the opponent, and 95% were called after runs of at least two opponent points.

Modeling Volleyball Play

To assess whether runs of points in volleyball games suggest a momentum effect, a probability model must be provided as a point of reference for how runs would behave in the absence of momentum. There is no unique model that perfectly represents the structure of volleyball games; rather, there is a choice between models of varying complexity and accurate representation of the game. The simplest model is a coin-toss model, in which each team is equally likely to win each point. In this model, the lengths of runs are easily seen to be geometric random variables with parameter 1/2; thus the chance any given rally (except for the first of the game) is the start of a run of length k is $(1/2)^{k+1}$. The coin-toss model, however, does not do a good job of representing volleyball.

First, one team is often significantly stronger than the other. A generalization to a biased coin-toss model can account for this by choosing one team and letting the probability that this team will win any point be p. This model, along with the special case $p = 1/2$, represents the points of a volleyball game as a single sequence of independent Bernoulli trials. This sort of model, however, is still not sufficiently complex to model volleyball play well.

Second, in competitions between skilled volleyball teams, the serving team is actually at a significant disadvantage because the receiving team has the first opportunity to attack. Rallies are generally won by a successful attack and only rarely as a result of a serve. In women's collegiate matches, the proportion of times an average team is able to side-out when receiving serve (the side-out percentage) is typically about 60%; thus, the serving team "holds serve" only about 40% of the time. Therefore, the chance a team will win a point depends greatly on whether it is serving or receiving.

A probability model for volleyball that accommodates both the difference in team abilities and the disadvantage of serving can be constructed using only two parameters. Calling the two teams in a match Teams A and B, let p_A be the probability that Team A wins a point when it serves to begin the rally and let p_B be the corresponding probability for Team B. If Team A is somewhat superior to Team B, for example, typical values for these parameters might be something like $p_A = .45$ and $p_B = .35$.

This model is a two-state Markov chain with transition matrix.

	Team A serves next	Team B serves next
Team A serves	p_A	$1–p_A$
Team A serves	$1–p_B$	p_B

We refer to this model as a switching Bernoulli trials (SBT) model, to contrast with the previous simpler models that treat the course of play as being comprised of a single sequence of Bernoulli trials.

The SBT model incorporates team and overall serving effects, but is not flexible enough to account for rotational/player effects. On any volleyball team, some players are more skilled than others at attacking, and some are more capable at back row defense, etc. Players also differ in serving ability. Thus, a team may be stronger in certain rotations than others—when their best attacker is in the front row and their best server is serving, for example.

Normally, each time a team is in a certain rotation within a given game, the team has the same players in the game, or the situation would be even more complicated. Even so, a model that incorporates rotational/player effects requires a combination of 12 Bernoulli trials submodels, as there are six rotations for each team and either team can be serving. This 12-parameter model is unwieldy, and parameter estimation is poor due to the limited sample size for each rotation. Also, the rotation configuration (how each team lines up against the other) often differs from one game to the next, and different players are frequently substituted into the line-up when a new game begins.

Fortunately, our data suggest the rotational/player effect is small. Coaches, in fact, often try to arrange their line-up according to what mathematicians call a "maximin criterion" so their weakest rotation is as strong as possible. This tends to equalize the strengths of their rotations.

One aspect of the game that can potentially make one rotation particularly strong is if a team has a player with a powerful and reliable jump serve. This serve is similar to a spike and can be disruptive to the receiving team's efforts to achieve a side-out. However, women volleyball players rarely have the strength to have a dominating jump serve, and few players used jump serves in the matches analyzed.

Somewhat like Goldilocks, then, we disdain those models that are either "too cold" (simplistic and unrepresentative) or "too hot" (complex and unstable) and choose the SBT model as "just right" for the task at hand—simple enough to estimate parameters well and interpret effects easily, yet representative enough to provide an accurate baseline for how volleyball play should progress if psychological momentum is not present. Note that in the SBT model, point runs will tend to be shorter than in a single Bernoulli trials model because most rallies in a typical match end in a side-out.

Analyzing Volleyball Runs

Working with the SBT model, suppose Team B has just won a point, and let L_A be the length of the subsequent run of points, if any, for Team A. Such a run must begin with a side-out by Team A, after which the number of points in the run is a geometric random variable with parameter p_A. We therefore have $P(L_A \geq l) = (1-p_B)\, p_A^{l-1}$ for l = 1, 2, 3, … . A parallel expression gives the probability distribution of a run of points for Team B. Note that we are ignoring two boundary effects here, namely that the first run of a game need not start with a side-out and that the last run is truncated by the end of the game.

Now suppose we attempt to apply the distribution theory our model generates to an analysis of actual games. The critical information from the match is summarized in a two-by-two table such as Table 1, compiled from a best-of-three-game match between CSUN (Team A) and UCLA (Team B). (UCLA won both games, making the third game unnecessary.)

	Points Won			
		CSUN	UCLA	Total
Serves	CSUN	9	34	43
	UCLA	33	26	59
Total		42	60	

Table 1. Match Summary Data, CSUN vs. UCLA, 09/14/07

What information does this table contain? We can see UCLA earned 34 side-outs when CSUN was serving, and CSUN achieved 33 side-outs when UCLA served. The first serve alternates from game to game, so each team served first once. Neither team won the first point when serving to start the game; therefore, CSUN had N_A = 33 runs of points during the match and UCLA had N_B = 34. (These totals include many runs of just one point.)

The values of the transition probabilities p_A and p_B can be estimated by the sample proportions $\hat{p}_A$ = 9/43 = .209, $\hat{p}_B$ = 26/59 = .441. With this information, we can estimate the number of runs of each length that each team would be expected to achieve in a match with parameters N_A, N_B, $p_A = \hat{p}_A$ and $p_B = \hat{p}_B$. Letting R_l^A and R_l^B be the numbers of runs of at least l points for teams A and B, respectively, we have approximately $E(R_l^A) = N_A(1-\hat{p}_B)\hat{p}_A^{l-1}$ and $E(R_l^B) = N_B(1-\hat{p}_A)\hat{p}_B^{l-1}$ for l = 1, 2, 3… . Slight adjustments are needed to account for the boundary effects.

Compiling the expected numbers of runs for each team in each match in the database by the above formulas (with adjustments) gives the results shown in Table 2 and Figure 1.

Length	Actual	Expected
4	67	69.7
5	35	30.1
6	11	13.2

Table 2. Actual and Expected Numbers of Runs of Each Length ≥ 4, According to the SBT Model

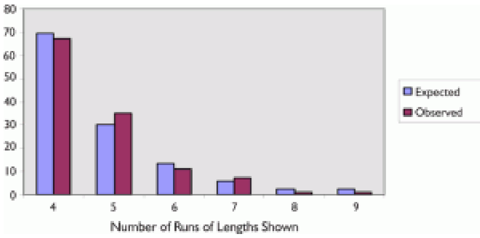

Figure 1. Actual and expected numbers of runs of each length ≥ 4, according to the SBT model

The agreement between the actual numbers of long runs and the values the SBT model predicts is excellent. If momentum had been a significant factor, we would have expected the actual numbers of long runs to generally exceed the predicted numbers, but this is not what we see in Table 2. In fact, the total number of runs of at least four points was fewer than the predicted total. The results shown in Table 2 and Figure 1 are compatible with the hypothesis that the points scored in volleyball games depend on which team is serving, but are otherwise independent.

There is another way to test whether the SBT model will produce run patterns that are consistent with those observed in actual volleyball. Suppose we wish to assess the run patterns observed in a particular game played to 30 points that has the game summary shown in Table 3.

		Points Won	
		Team A	Team B
Serves	Team A	n_A	N_B-n_B
	Team B	N_A-n_A	n_B
Total		N_A	N_B

Table 3. General Game Summary Table

Without loss of generality, assume Team A was the winner, so N_A = max(30, N_B-2). In the SBT model, the a priori probability of any particular sequence of play that results in Table 3 and represents a possible game (one in which Team A does not reach a winning position before all the totals in the game table have been achieved) is . As this value does not depend on the particular

$p_A^{n_A}(1-p_A^{N_B-n_B})p_B^{n_B}(1-p_B^{N_A-n_A})$ ordering of rally outcomes, each allowable configuration that leads to the desired table is equally likely. In principle, then, one could analyze the run patterns of a given game combinatorially by considering all such configurations. For example, if the longest run in a game with a given game summary table consists of six points, one could count the proportion of configurations having the specified game table in which the longest run was six or longer. This would serve as a measure (essentially a *p*-value) of how unusual such a run is.

However, the combinatorial approach is too complex for easy use. An alternative is to use simulation. One simulation option is to use the observed values = $n_A/(n_A+N_B-n_B)$ and = $n_B/(n_B+N_A-n_A)$ as the probabilities teams A and B will win a given point

$\hat{p}_A$ $\hat{p}_B$ when serving and reject any outcome that does not match the game summary table. Any values in (0,1) can be used for these probabilities; however, the simulation runs faster if values are used that are at least close to and .

$\hat{p}_A$ $\hat{p}_B$

Simulating a game many times produces results for a random sample of all possible configurations having the given game summary table. Comparing the run patterns for the sample to those of the actual game provides another approach to assessing the assumption that rally outcomes are independent once serving is accounted for.

To obtain the results shown in Table 4, 100 simulations were enacted for each of the 55 games in the database. The number of runs of each specified length was then divided by 100 to produce an expected number of runs of each length for all games based on the SBT model. Table 4 and Figure 2 compare these values to the actual numbers of runs of each length ≥ 4.

Length	Actual	Simulated
4	67	67.1
5	35	28.9
6	11	12.8
7	7	5.2
8	1	1.9
≥9	1	1.9
Total	**122**	**117.9**

Table 4. Actual and Simulated Expected Numbers of Runs of Each Length ≥ 4, According to the SBT Model

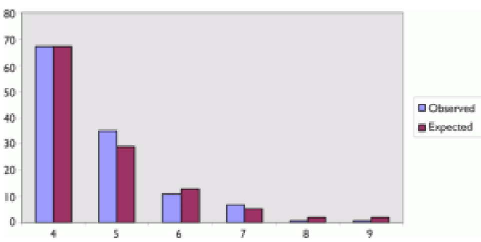

Figure 2. Actual and simulated expected numbers of runs of each length ≥ 4, according to the SBT model

Once again there is outstanding agreement between the actual numbers of runs of various lengths and the values the SBT model predicts. Although the total number of actual runs of at least four points was higher than the average for the simulation, the difference is slight. There is only one case, runs of length five, where the actual number of runs is noticeably greater than the simulated value.

To make sure this case does not give a meaningful indication of a momentum effect, we can make a formal check: Since five-point runs occur rarely, we can approximate the probability distribution of their number as a Poisson random variable with parameter λ equal to the simulated expected number, 28.9. The observed value $X = 35$ then gives a p-value of $P(X \geq 35) = 15\%$. Thus, the excess number of runs of length five observed is not significant and most likely an artifact of chance variation.

We again have solid evidence that the course of play in volleyball is well-described by the rather simple SBT model (at least as far as run frequencies and run lengths are concerned) and—much more important—behaves as if the points scored depend on which team is serving, but are otherwise independent.

There is yet a third way we can evaluate whether volleyball runs show evidence of momentum. If rally outcomes behave according to the SBT model, the chance that one team will win the next point at any time during a run of points by the other team is its (constant) probability of siding-out. Thus, we can look at each such instance during all point runs and compare the proportion of times the run ended on the next rally with the receiving team's side-out percentage.

In the CSUN vs. Santa Barbara match (10/02/07), for example, each team had several runs of at least three points (see Table 5). Consider the CSUN run of seven points: Santa Barbara had five opportunities to terminate the run—after the third, fourth, fifth, sixth, and seventh points. They were successful once, after the seventh point. For the match as a whole, Santa Barbara had 4×1 + 4×2 + 0×3 + 1×4 + 1×4 = 21 opportunities to stop a CSUN run and was successful 4 + 4 + 0 + 1 + 1 = 10 times, for an overall proportion of 10/21 = 48%. This value is somewhat lower than Santa Barbara's 58% side-out percentage for the match.

Run Length:	3	4	5	6	7
CSUN	4	4	0	1	1
Santa Barbara	6	1	3	1	0

Table 5. Numbers of Runs of Lengths ≥ 3, CSUN vs. Santa Barbara, 10/20/07

The reverse computation, for CSUN stopping Santa Barbara runs, is slightly different. Using the same method as before, we would conclude that CSUN stopped a Santa Barbara run 11 out of 21 times. However, two of the Santa Barbara runs were not stopped by CSUN points because each ended with Santa Barbara winning the game; therefore, two opportunities and two successful stops must be subtracted. Thus, CSUN actually stopped a Santa Barbara run 9/19 = 47% of the time, compared with CSUN's 59% side-out percentage for the match.

If our conclusion were to be based on this match alone, we would report that there is some evidence in favor of momentum, given that each team stopped runs less often than their overall side-out percentage. However, using the data from all 32 cases (16 matches x two teams each) in the database tells a different story. To reduce the effects of heterogeneity among matches, Table 6 groups the results into four categories so matches in the same category have similar side-out percentages. Category boundaries were determined so the total numbers of opportunities to stop a run after the third point were similar for each category.

Side-Out %	# Opportunities	# Stops	Stop Proportion	Overall Side-Out %
<=51%	112	58	51.8%	48.2%
(51%,55%]	135	75	55.6%	52.8%
(55%,59%]	114	63	55.3%	57.7%
>59%	128	84	65.6%	65.1%

Table 6. Proportion of Rallies in Which a Run Was Stopped vs. Match Side-Out Percentage

Within each range of match side-out percentages, the stop proportion shown in Table 6 is the proportion of all rallies after the third point of a run in which the run was stopped. Note that these values are close to the overall side-out percentages for each category. Figure 3 shows a comparison.

A chi-square test of conditional independence shows no significant difference between the stop proportions and side-out percentages (p = .81). As with the previous two analyses, this approach also shows the run data to be consistent with the SBT model. All three run analyses support the contention that runs such as those observed in volleyball behave as the natural consequence of play involving rallies whose outcomes are affected only by the abilities of the two teams and which team is serving. No evidence for momentum in collegiate women's volleyball has been found.

Conclusion

Players, coaches, and fans almost invariably focus on the perceived significance of runs in sports, whether they involve consecutive field goals in basketball, hitting streaks in baseball, runs of points in volleyball, or a team winning or losing streak in any sport. It is hard to let go of the impression that when teams or players are successful several times in succession, they are likely to continue to play at a higher-than-normal level, at least in the short run. Yet statistical analyses often fail to support the notion that these patterns are anything more than those that occur naturally in sequences of chance events. Contrary to the strongly held intuition of most observers of athletic contests, outcomes of such events are often compatible with models that do not presume the presence of momentum.

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Further Reading

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