Psychological Biases in NBA Predictions

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Abstract

I propose to examine whether psychological biases about recency are present amongst various groups of people when asked to make choices on hypothetical NBA games. The original plan was to determine whether recent actual games in the NBA led to either abnormal amounts of wagers or returns on those wagers, but the data was not available. Although using hypothetical results implies that caution must be exercised when interpreting experimental findings, it can still be helpful to see whether these psychological biases exist. Specifically, I will be examining the nature of these biases across four different groups of people: people with a math and sports background, people with neither a math and sports background, people with a sports background but no mathematical training, and people with math training but no sports background. I attempt to determine the different biases that each of these groups of people displays by examining how they value different pieces of information.
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Literature Review

One common psychological mistakes that people fall into is the “gambler’s fallacy;” This is the idea that, in situations where the probability of the outcome is known, the frequency of an event occurring over a small sample makes it more or less likely for that event to continue occurring in the future. For example, one might believe that when a fair coin lands heads 5 times in a row, the 6th toss is more likely to land on heads. The gambler’s fallacy was first discussed and discovered academically in a 1971 paper by Kahneman and Tversky titled “Belief in the Law of Small Numbers”, where people demonstrated the incorrect belief that outcomes like the flip of a fair coin are dependent on which side the coin landed on in the immediate past. In the context of sports, the “gambler’s fallacy” would present itself in the form of people deciding to wager on certain teams that had been on losing streaks. One concept that goes hand in hand with the gambler’s fallacy is the recency bias. While some might see a coin flip heads five times in a row and think that the next one will be tails, other might think that heads are “hot” and think that heads will come again. In terms of my analysis for this experiment, I will focus on the recency bias as it shows a similar line of thinking as the “gambler’s fallacy” but is more applicable to this experiment.
In the 2012 paper “Behavioral Biases, Order Imbalance, and Expected Returns: Evidence from the NFL Betting Markets,” University of Chicago grad students Shrihari Santosh and Yuan Hou looked to determine whether the recency bias phenomenon did exist in the NFL markets. One of their conclusions was that NFL teams that had lost their 4 previous games were bet on 9% less often, and bets on those teams yielded a 15% excessive return. The results of Santosh and Hou’s work imply two different things. First, people were more likely to choose against a team that had been performing poorly, which is an example of the recency bias. Second, it implies that there is an inefficiency in the market, as those bets placed on teams that had been losing recently performed above the expected return.

My original plan for this experiment was to build off this conclusion by Santosh and Hou by applying similar analysis to the NBA. Applying this analysis to the NBA can be even more fruitful because there are so many more games played, and thus more data, each season. However, the data necessary for an NBA analysis could not be obtained in a useful time frame, so instead I propose to look more at the existence of psychological biases and the nature of these biases rather than whether they open up profitable situations in the sports betting market. Though having data from actual NBA games would be more helpful in determining the profitability of different strategies, having subjects make choices based on hypothetical data gives us insight that one cannot obtain based on actualized betting data. Using hypothetical games allows us to separate subjects into groups based on their mathematics and sports backgrounds and test for differences between these groups, giving us a better idea of the existence and nature of the psychological biases at play.
Methodology

Objective:

The objective of this study is to test for both the existence and nature of psychological biases such as the recency bias and the gambler’s fallacy. Furthermore, this study aims to examine how these biases manifest themselves within the different relevant groups, which in this study are people with solid mathematical backgrounds, people who follow sports, and those who neither follow sports or have significant mathematical training.

Data Set:

A hypothetical 10 game schedule was created for 10 different NBA teams, with scores for those games being taken from the month of March in the NBA, so that the hypothetical scores could mirror actual NBA scores. Each NBA team was given a record and a winning streak, and then certain teams were pitted against each other based on those records and streaks. For example, teams on long winning streaks were pitted against similarly hot teams, extremely cold teams, and teams somewhere in the middle. By creating these matchups, we could see how each participant valued things like recent performance in their choices for these hypothetical games.

Every team in the hypothetical standings had a counterpart with the same record but a different streak. For example, the top two teams in the standings were both 9-1 but one had a long winning streak while the other ended the sample with a loss. Here is a segment of the data set that participants were given:
These are the two best teams in the hypothetical survey. The teams played a 10 game schedule but I only included the last four games for aesthetic, fitting purposes. Clearly, the Warriors end on a huge winning streak while the 76ers ended their season with a loss. By creating these teams with similar records but different winning or losing streaks, the data has built in natural comparisons to ask participants about. If the Warriors played the 76ers as small favorites (which they do in the survey), a participant picking the 76ers, for example, would indicate an indifference towards recent performance. By structuring the data set in this way, I hope to get a better idea of the psychological biases at play for each group of people being analyzed.

**Survey:**

Participants were recruited for the survey by asking friends to participate, and then filtered into the relevant groups by several background questions. They were asked how many math classes, specifically in the area of probability and statistics, they had taken, as well as how closely they follow the NBA. Because the aim of the experiment was to identify how different groups of people value different trends, I incorporated a spread into the hypothetical matchups to emphasize the importance of the recent trends of each team rather than their overall record. Had there been no spreads, I would expect participants to just choose whichever team had the better record by default rather than looking at their recent performances and their streaks over the 10
game sample. In the introduction to the survey that I gave participants, I emphasized that the purpose of the spread was to create indifference between the two choices based on skill level, forcing participants to make their choice based on other pieces of data like win streak. However, I made sure to take into account the fact that many would not fully grasp the concept when making my hypotheses, analyzing results, and ultimately making my conclusions. In terms of the survey itself, I made sure that each team was matched up against its two “counterpart” teams, meaning that every team was pitted against the other team with the same record and the other team with the same streak. For example, the Golden State Warriors were 9-1 and ended the hypothetical season on a 9 game winning streak. Their two counterpart teams would be the Philadelphia 76ers, who finished with the same 9-1 record, and the Cleveland Cavaliers, who finished the hypothetical season losing 9 games in a row, which is the same streak, only negative. I made sure that these counterpart matchups were included for every team to create the direct hypothetical games that would give relevant information about the participants’ biases. If I were to just create matchups were teams on 1 game winning streaks played teams on 3 game winning streaks, the results would not be as telling because those teams aren’t natural, direct comparisons. So, the deliberate choices for which games I asked about are perhaps the most important part of the experiment’s methodology.

**Hypotheses:**

I have various hypotheses for each group and aspect of the survey. The first group I will consider is the group of people that have neither a statistical background nor a sports background. This group of people is likely going to be similar to the group of people that Kahneman and Tversky wrote about in their article on the “law of small numbers.” This group of
people will be more susceptible to problems like the gambler’s fallacy and recency bias because of their lack of training. As such my formal hypothesis is as follows:

**Hypothesis:** The group of people with no statistical training or sports background will exhibit a strong recency bias by picking very hot teams (and picking against very cold teams) an excessive amount of the time.

The next group I will analyze is the group of people that have heavy statistical training (4 or more classes) and a strong NBA fandom (2-3 times a week or more). People with a strong statistical background, who have been trained not to let recent outcomes dictate what they think will happen in the future, should not show as strong a bias for teams that have been on streaks. In addition, people who are avid sports fans are more likely to understand the concept of the spread, and the subsequent indifference that one should have when choosing a certain side of a spread. Though I clearly explained in the survey that the spread is meant to equalize the two teams (thus implying indifference), people who are new to the concept might not understand it well and thus just choose the team with the better record. However, a sports fan who will understand the spread knows he should tend towards indifference in the survey. My formal hypothesis for this group is as follows:

**Hypothesis:** The group of people who have math training and sports background will exhibit a pattern of indifference in their choices, leading to close to 50/50 splits for all types of matchups, because they are not as susceptible to the recency bias.

The next two groups serve as a type of middle ground. The group of people that has the statistical training might know not to overestimate the value of streaks but they also might not have an excellent grasp on the concept of the spread. On the other hand, sports fans who are
more likely to understand the spreads but maybe not as knowledgeable about probability and
statistics will exhibit some tendencies of the believers in the “law of small numbers.” My
hypothesis for these two groups is the same, though I will analyze each group separately in the
results section. It is as follows:

**Hypothesis:** The group for people with either a strong sports background or a strong math
background (but not both), will exhibit a slight recency bias in terms of slightly favoring very hot
teams (or not favoring very cold teams), but that bias will not be as pronounced as the initial
group of people with neither a sports background or a statistical background.

In terms of quantitative hypotheses, I would roughly guess that the non sports/non math
group will choose the streaky team 80% of the time. I would guess the sports/math group would
show relative indifference, so I expect them to be close to 50% in their choices. For the middle
two groups, I hypothesize that they will choose the streaky team roughly 60% of the time.

**Results:**

In order to analyze the data, I categorized the teams as very hot, very cold, hot, or cold. A
team on a 5 game winning streak was considered “very hot” while a team on a 5 game losing
streak was “very cold.” Teams with streaks less than 5 were considered either hot or cold
depending on whether they were on a winning streak or losing streak. This categorization of the
teams allows for better analysis of what effect the streak specifically had on the participants’
choices in the hypothetical matchups.
The first group I will discuss is the group of people with no math background and no sports background. As I mentioned in my hypothesis section, there were 14 people who fit into this group, meaning that they had taken either 0 or 1 probability and statistics courses and they follow the NBA at a maximum of 1 time per month. The hypothesis I chose to test was that this group of people would be exhibit their recency bias and belief in the “law of small numbers” by using a team’s streak to mostly inform their decision. Here are the results in table form:

<table>
<thead>
<tr>
<th>No math/no sports</th>
<th>Very Cold Teams</th>
<th>Cold Teams</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Hot Teams</td>
<td>47/70(67.14%)</td>
<td>25/42(59.5%)</td>
</tr>
<tr>
<td>Hot Teams</td>
<td>19/28(67.86%)</td>
<td>17/28(60.7%)</td>
</tr>
</tbody>
</table>

So, there is a consistent trend of the hot teams being chosen more often than the cold teams. When very hot teams were pitted against very cold teams, they were chosen 7.64% more often than when they were pitted against cold teams. This suggests that the teams with the longer losing streaks (i.e. teams with worse recent performance) were picked at a lesser frequency than teams on shorter streaks. This suggests that, when comparing very hot teams to very cold teams and cold teams, that the participants in this group did value recent performance. The same effect is seen when choosing between hot teams and then very cold and cold teams, where very cold teams were picked 7.16% less frequently. Overall, these numbers are in line with my general hypothesis that people in this group would overvalue streaks in their choices. However, it is interesting that, even though the cold teams outperformed the very cold teams, the very hot teams did not outperform the hot teams in the same fashion. This would suggest that, even
though there are clear signs of recency bias in the data for the cold teams, there is no overarching recency bias seen in the sample for this group. So, for this group, the results indicate the presence of a recency bias but not a definitive overarching belief in the idea that recent performance was the only deciding factor for this group. There are a few caveats that must be considered when analyzing the data. First, as I mentioned in my methodology section, the sample size is not ideal because there were only 2 survey questions that pitted hot teams against cold teams and hot teams against very cold teams. Of course, a survey with many more questions wasn’t possible without risking the participants losing attention, so this is unavoidable, but it is something that must be considered.

The next group that I will discuss is group of people that follow sports often and have a strong statistical background. This group consist of people that follow the NBA either 2-3 times per week or daily as well as people that have taken 4 or more probability and statistics courses. There were 18 people that fell into this group, 12 of which who took 5 statistics classes while following the NBA daily and 6 of which who took 5 statistics classes and follow the NBA 2 or 3 times a week. The hypothesis that I tested for this group was that participants’ would exhibit more indifference towards a team’s recent performance. I expected there to be a 50/50 split on most games, even if it were between a very hot team and a cold team, or even the cold teams to outperform the hot teams on occasion. The results for this group are displayed in this table:

<table>
<thead>
<tr>
<th>Sports/Math</th>
<th>Very Cold Teams</th>
<th>Cold Teams</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Hot</td>
<td>49/89(55.6%)</td>
<td>26/53(49.05%)</td>
</tr>
<tr>
<td>Hot</td>
<td>19/36(52.78%)</td>
<td>18/35(51.42%)</td>
</tr>
</tbody>
</table>
There is a small discrepancy in the data for this group because multiple participants neglected to answer a question on the survey. This resulted in, for example, 35 data points for hot versus cold teams instead of the 36 that should be expected for a group of 18 participants. Rather than scrap the incomplete surveys, I chose to use these surveys because participants were already at a premium and only a single question was missing for each incomplete survey. These results again partially confirm my hypothesis for each group. In the no sports/no math group, hot teams were picked over cold teams at a minimum rate of 59.5%. For this group, even the very hot teams were preferred over the very cold teams only 55.6% of the time. There is still a small recency bias displayed by this group in the sense that very hot teams were chosen 6.55% more often against very cold teams than they were against regular cold teams. However, hot teams were chosen against very cold teams only 1.36% more often than they were picked against cold teams. The differences in performance between the streaky teams and the more neutral teams are still present, but they are much less pronounced for this group. However, in the case of this group, where there is clear indifference, the slight preference (or non-preference, in this case) for the cold team versus the very cold team might not be significant. If the group were truly indifferent, it is unlikely that each question would be answered evenly for each team. For example, if a coin were flipped 36 times, it is extremely statistically unlikely that it lands on heads 18 times and tails 18 times. So, the fact that the very hot teams did slightly better against the very cold teams than the cold teams might not necessarily be an example of a slight recency bias but rather a fluke. It might have been equally likely that very hot teams were picked 45% of the time against very cold teams rather than 55%. On the whole, the proximity of the participants’ choices to 50% regardless of streak affirm my hypothesis to this group to some extent.
The next group I will discuss is the group of people who have advanced statistical training but no sports background. There were only 9 people who took the survey that fell into this group, which had the requirements of taking 4 or more statistics courses and following the NBA less often than once a month. My hypothesis for this group was that the members’ statistical background would deter them from depending solely on a team’s recent performance as their reason for choosing a certain team. Below is a table of the results for the group of 9 participants that had been extensively trained statistically but did not follow sports.

<table>
<thead>
<tr>
<th>Math/No Sports</th>
<th>Very Cold Teams</th>
<th>Cold Teams</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Hot Teams</td>
<td>26/45(57.78%)</td>
<td>19/27(70.37%)</td>
</tr>
<tr>
<td>Hot Teams</td>
<td>8/18(44.4%)</td>
<td>10/18(55.5%)</td>
</tr>
</tbody>
</table>

A couple contradicting conclusions can be drawn from these results. First, very hot teams strongly outperformed hot teams, as they were chosen at least 10% more often than hot teams versus both very cold teams and cold teams. This would suggest that there is a strong recency bias present among this group as the teams that had performing extremely well recently were picked far more often. However, cold teams drastically underperformed the very cold teams, which contradicts the idea that this group had a strong recency bias. Furthermore, comparing these results to the original group of people who had no sports and no math background can give us a better idea of how specifically a math background affected the participants’ tendencies. The math savvy participants in this group picked the very hot team significantly less often, 9.36% of the time, than the group that did not have a math background or sports tendencies. This piece of
information would suggest that my hypothesis that this group would be closer to indifference is accurate in the case of very hot teams against very cold teams. Furthermore, the math savvy participants in this group chose the hot team only 44% of the time versus the very cold teams, which is the exact opposite of what one would expect from a hot versus very cold matchup. The no sports, no math group picked the hot team 67.86% of the time versus the very cold teams, which is a massive difference. Again, this suggests that the members of the math, no sports group exhibit far less emphasis on recent performance, which is in line with my hypothesis. However, the math savvy group chose the very hot team a whopping 70.37% of the time, which is higher than any other frequency in the survey. The no math, no sports group chose the hot teams only 59.5% of the time, which of course is significantly less than 70.37%. This comparison shows that there is not necessarily a straightforward relationship between statistical training and recency bias. Overall, there are certainly pieces of data that support my original hypothesis that this group trends towards indifference, but unfortunately, they are not conclusive.

One important caveat when considering this group is the small sample size. As I mentioned earlier, only 9 of the participants in the survey fell into this category, compared to 13 and 18 in the previous two groups. At the start of the experiment, my goal was to reach 15 participants for each group that I wanted to analyze. Though I worked hard to find as many participants from many different backgrounds, the people who were willing to participate in the survey were simply not people who were statistically trained but not sports fans. The small sample size of this group (and every group I analyze, for that matter) means that the data is more susceptible to a fluke such as a subject choosing their favorite team instead of being impartial. However, even
though the analysis for the third group would be better if it had a bigger sample size, it still leads to some of the interesting findings that I discussed earlier.

The last group that I want to analyze is the group of people that were sports fan but did not necessarily have any statistical training. There were 16 participants in this group, most of which being people that followed the NBA daily but had taken zero math courses. My hypothesis for this group was similar to my hypothesis for the third group (math, no sports) in that I thought there would a general pattern of indifference relative to the group of people that did not have a statistical or sports background but still some signs of a recency bias. The results for this group are displayed in the table below:

<table>
<thead>
<tr>
<th>Sports, No Math</th>
<th>Very Cold Teams</th>
<th>Cold Teams</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Hot Teams</td>
<td>36/64 (56.25%)</td>
<td>29/48 (60.4%)</td>
</tr>
<tr>
<td>Hot Teams</td>
<td>22/32 (68.75%)</td>
<td>19/32 (59.38%)</td>
</tr>
</tbody>
</table>

Again, the results for this group are a mixed bag when evaluating my hypothesis. When playing against very hot teams, cold teams actually performed better than the very cold teams. Furthermore, hot teams were chosen against very cold teams 68.75% of the time, 12.5% more often than very hot teams were chosen against that same set of very cold opponents. I predicted that there would be a slight recency bias, but the fact that cold teams outperformed very cold teams and hot teams outperformed very hot teams contradicts that prediction. At the same time, I expected that the sports’ fans knowledge of the spread might lead to some general indifference, but that is not reflected in the results. The hot and very hot teams were all picked over 55% of the time, and the hot teams were preferred to the very cold teams over 68% of the time, which
was one of the strong preferences of the whole experiment. Comparing these results to the original non-sports, non-math group allows us to better determine exactly how being a sports fan affected one’s answers in the survey. While I expected there to be less recency bias and more indifference because of the sports fans’ perceived knowledge of the spread, the results did not bear this out. When very hot teams played very cold teams, the non-sports, non-math group chose the very hot teams 67.86% of the time, compared to only 56.25% for the sports fans who weren’t trained in math. In isolation, this piece of data backs up my hypothesis because it suggests that the non-sports fans exhibited a strong recency bias while the sports fans did not. However, in all other possible comparisons for hot teams versus cold teams, the results for the two groups were extremely similar, which of course is not what I anticipated at all. Based on these results, it is impossible to make a conclusion about the existence of a recency bias for the sports fans only group. One important caveat to make for this section is the difference between being a sports fan and understanding how the spread works. My hypothesis for this group was based on the assumption that being a sports fan made it more likely that one would understand the spread. While I am sure that assumption is true, it is hard to quantify just how likely it is and how many of the 16 person sample I had for this group did understand the concept of the spread. Furthermore, just because a sports fan understands the spread(and thus knows to be indifferent) doesn’t mean they will necessarily demonstrate indifference by choosing the hot and cold teams half the time. They might be more inclined to just pick whatever team they like better because they know it theoretically does not matter because of the spread. However, there are not many people that are both familiar with how spreads work and willing to talk about that knowledge, so assumptions had to be made for the purposes of the experiment.
Another way to analyze the results of the experiment are to look at each comparison (i.e. very hot teams vs. very cold teams) rather than looking at the results for each group.

<table>
<thead>
<tr>
<th>Very Hot vs. Very Cold</th>
<th>Math Background</th>
<th>No Math</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sports Background</td>
<td>49/89 (55.6%)</td>
<td>36/64 (68.75%)</td>
</tr>
<tr>
<td>No Sports</td>
<td>26/45 (57.78%)</td>
<td>47/70 (67.14%)</td>
</tr>
</tbody>
</table>

In terms of using this way of visualizing the data to evaluate my hypotheses, this chart just reinforces my previous analysis. Like I expected, the group of people with a sports and math background were the most indifferent towards the very hot teams, while the group of people with no sports or math background exhibited a strong bias towards the very hot teams. However, the data for the other two groups does not back up what I hypothesized about them, as the sports background group with no math background exhibited a strong recency bias while the group of people with the math background that don’t follow sports did not.

The next comparison to look at is the matchup of very hot teams vs. cold teams. The chart is below:

<table>
<thead>
<tr>
<th>Very Hot vs. Cold</th>
<th>Math Background</th>
<th>No Math</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sports Background</td>
<td>26/53 (49.05%)</td>
<td>29/48 (60.4%)</td>
</tr>
<tr>
<td>No Sports</td>
<td>19/27 (70.3%)</td>
<td>17/28 (60.7%)</td>
</tr>
</tbody>
</table>

Looking at the matchups of very hot versus cold teams affirms my previous analysis of the various groups. The no math, no sports group chose the very hot team over 11% more often than
the math, sports group, which was mostly indifferent, as I had hypothesized. However, the no sports, math group chose the very hot team 70.3% of the time, which was significantly more often than the no math, no sports group, which I did not expect. So, this chart fits in with my some of my initial beliefs, but the surprising frequency with which the no sports, math group chose the hot team make it difficult to confirm my hypothesis for that group.

The next matchup to look at would be the match up of hot teams versus very cold teams. A table of those results is displayed below:

<table>
<thead>
<tr>
<th>Hot vs. Very Cold</th>
<th>Math Background</th>
<th>No Math</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sports Background</td>
<td>19/36(52.78%)</td>
<td>22/32(68.75%)</td>
</tr>
<tr>
<td>No Sports</td>
<td>8/18(44.4%)</td>
<td>19/28(67.86%)</td>
</tr>
</tbody>
</table>

Again, the group with no math or sports background behaves as expected, choosing the hot team 67.86% of the time compared to only 52.78% by the group with sports and math background.

This piece of data backs up my hypotheses for these two groups. However, the other two groups are again problematic. While I expected a slight recency bias out of the group with a sports background but no math training, that group chose the hot team a high 68.75% of the time, which was even more frequently than the no sports, no math group. So, this table reiterates the idea that my hypotheses for the “extreme” groups ended up being pretty accurate while the middle two groups did not follow a discernable pattern in their choices and biases.

Lastly, the results of the last comparison, hot teams vs. cold teams, are displayed below:

<table>
<thead>
<tr>
<th>Hot Vs. Cold</th>
<th>Math Background</th>
<th>No Math</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sports Background</td>
<td>18/35(51.42%)</td>
<td>19/32(59.38%)</td>
</tr>
</tbody>
</table>
This matchup was perhaps the least informative of all the matchups, which makes sense because it was the matchup where no team was on a prolonged winning or losing streak. It also is the matchup that is most in line with my hypotheses: the sports/math group showed relative indifference towards hot teams, while the middle two groups (no sports/math and math/no sports) both showed slighter recency biases than the no math no sports group. However, this group also had a smaller sample than some of the other groups, as only two questions on the survey pitted hot teams against cold teams. In the context of all the other results, especially the group-by-group analysis, it is hard to conclude that my hypotheses were all correct based on the above table.

**Conclusion:**

I began this experiment with the prediction that people with who were not sports fans and did not have statistical training would show signs of the belief in the “law of small numbers,” first posited by Kahneman and Tversky, meaning they would place a very heavy emphasis on a team’s recent performance when making predictions. The results of the experiment, for the most part, ended up confirming that prediction. Likewise, I believed that the group of people that both followed sports closely and had a strong statistical training would “correctly” exhibit a pattern of indifference in their choices because their backgrounds make them more likely to understand that, when the spread is introduced, the choices are equally correct in any given matchup. Again,
the results of the experiment seemed to confirm this expectation. However, when analyzing the results of people who were either sports fans with no math background or non-sports fans with a strong math background, the results of the experiment got murky. Ideally, I would have expected both of these groups of people to be in between the first two groups in the experiment by exhibiting a slighter recency bias and more indifference. The results for these two groups did not match up with what I expected, as there were instances of a strong recency bias and little evidence of general indifference. Given those results, it is impossible to unequivocally conclude that either a sports background or a statistical background is sufficient to be free of the pitfalls of the “law of small numbers.” However, because of the positive results of the initial two groups, I think my general ideas for this experiment were correct. One possible extension of the experiment would be to focus on degrees of statistical background and sports fandom to exactly pinpoint the effect that each of these characteristics has on one’s predictions. This was one of my goals when I started the experiment but my methodology ended up not being sound enough to make any progress. I attempted to identify people of a moderate statistical or sports background (as opposed to the extremes that I ended up using) by including choices that reflected a medium amount of sports or math knowledge. However, the problem I found with this is that I did not feel comfortable making the assumption that statistical knowledge was linearly correlated with the number of statistical classes one had taken. For example, because the statistical concepts in this experiment, like recency bias and the law of averages, are relatively simple, I determined that a person who had taken 3 statistics courses might not be any less knowledgeable about the concepts in this experiment than someone who had taken 5 or more. As a result, the only assumptions I felt comfortable making for the purposes of this experiment were that people with
zero or one statistics classes would be less knowledgeable about statistics than people who had taken several courses in the area. So, a possible extension of this experiment would be to distribute a survey that began with several statistics questions of varying degrees to get a better idea of one’s statistical background, and then have them choose between the NBA teams. However, in terms of feasibility, that might be problematic due to the amount of time needed for participants to complete such a survey. There were a couple big limitations of my experiment. First, as I have discussed before, a bigger sample size would have led to better results. Though reaching out to hundreds of people, only 85 people took my survey. Of those 85, only 57 met the qualifications to be in one of the four groups I used for analysis. However, because the survey had 15 questions, there were 855 data points in total, so it’s not like the sample was tiny. The biggest limitation for the experiment was simply time. In my introduction, I tried to explain the concept of the spread succinctly in a few sentences. Ideally, I would have been able to give them a better idea of how the spread worked by getting them all together and speaking to them in person and then answering questions. However, the participants simply did not have time to do this as people are typically extremely busy and putting aside a couple hours to help me for my thesis was too much to ask. I adjusted my hypotheses to reflect the expected confusion about the spread, but still, the experiment would have been better if I had more time to explain more in depth what concepts were in play. Furthermore, there was a potentially overwhelming amount of data for the participants to take in and analyze in a short amount of time. If I were taking the survey as a participant, properly analyzing the data and making my predictions would have taken me roughly 30 minutes to an hour, which is simply a huge amount of time to ask somewhat to commit for an experiment like this. At the same time, I had to make a tradeoff because I needed
to collect as much data as I could. If I made the survey shorter or decreased the amount of teams and games that hypothetically took place, I would have significantly less data. For some of the matchups, like hot teams versus cold teams and hot teams versus very cold teams, I only had two games worth of data (per participant). But again, I couldn’t add any more games or questions to the survey because of the aforementioned time constraints and the risk of having the participants completely tune out and choose randomly. Unfortunately, time constraints are always going to be a problem as long as the experiment relies on participants volunteering to collect data. I strongly suspect that my experiment would have more conclusive or informative results had the participants taken more time for their answers, but that is simply an unreasonable expectation for this experiment in my experience.

References:
