

Can Losing Lead to Winning?*

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Abstract

Can losing during a competitive task psychologically motivate individuals and teams to exert greater effort and perform better overall? Analysis of over 45,000 collegiate and 18,000 professional basketball games illustrates that being slightly behind at halftime leads to a discontinuous increase in winning percentage. Teams that are losing by a small amount win approximately 2 (NCAA) and 6 (NBA) percentage points more often than expected. In the NBA, this psychological effect is roughly half the size of the proverbial home-team advantage. We present experimental evidence that corroborates the field study and casts doubt on alternative explanations. Our analysis adds to the growing literature that illustrates how non-standard preferences can play a significant role in motivating economic agents.

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Understanding what causes individuals and teams to exert effort is a key focus in economics. Models of labor supply, contract theory, and tournament theory attempt to better understand how wages, bonuses, penalties, and other standard, pecuniary incentives can be used to optimize worker behavior.

Non-standard preferences have also provided insight into how to motivate individuals. For example, reciprocity and fairness led to the fair wage-effort hypothesis (Akerlof and Yellen, 1990), peer effects have been shown to impact worker productivity (Falk and Ichino, 2006; Mas and Moretti, 2009), and there is evidence that altruism or social preferences can also increase employee effort (Hamilton, Nickerson, and Owan, 2003; Bandiera, Barankay, and Rasul, 2005).

In this paper, we explore how another non-standard preference, loss aversion, affects motivation in tournament settings. Loss aversion – the kink in Kahneman and Tversky’s (1979) Prospect Theory value function – predicts that individuals value avoiding losses relative to a reference point more than they value obtaining commensurate gains.¹ While loss aversion is generally applied to realized outcomes, we propose that it may also have a motivational impact on behavior during the realization process of an outcome.² While an individual or team who is losing a competition has not actually lost until the competition is over, one’s performance relative to their opponent during the competition may serve as a salient reference point. Compared to if they were winning (i.e., in the gain domain), one may be willing to exert more effort if they are losing during a competitive task (i.e., in the loss domain). Thus, losing may lead an individual or team to exert greater effort, and win more often.

We test for this psychological effect of losing using both field data from actual competitions and a controlled laboratory experiment. The field study consists of analyzing 18,060 NBA and 45,579 NCAA basketball games. While flexibly controlling for the halftime score difference, we find that teams that are

¹ Loss aversion has been documented in many laboratory (e.g., Thaler, Tversky, Kahneman, and Schwartz, 1997; Gneezy and Potters, 1997) and field settings (see Genesove and Mayer, 2001; Camerer, Babcock, Lowenstein, and Thaler, 1997; Fehr and Goette, 2007; Odean, 1998; Mas, 2008). Heath, Larrick, and Wu (1999) examined how goals may act as reference points.

² Rick and Lowenstein (2008) refer to this increased motivation in the context of cheating as “hypermotivation”. They conjecture that “perceiving oneself as ‘in a hole’ leads to hypermotivation – a visceral state that leads one to take actions that would normally be considered unacceptable”.

losing at halftime win approximately 2 (NCAA) and 6 (NBA) percentage points more often than expected. In fact, over the last 15 years in the NBA where the results are the strongest, teams that are down by 1 point actually win more often (50.4%) than teams that are tied or winning by one at halftime. We show that this finding cannot be explained by discontinuous ability of teams at the discontinuity. Rather, we argue that losing slightly at halftime leads teams to perform better in the second half.

To corroborate these results, we perform a laboratory experiment where participants take part in a competitive task. During a break in the task, they are provided with feedback. We find that individuals who were slightly behind in the task significantly increased their effort after the break relative to the control group (no feedback condition). Importantly, individuals who received feedback that they were slightly ahead in the task did not decrease their effort relative to the control. These laboratory results underscore the field evidence and cast doubt on the possibility that the winning team simply becomes complacent (as opposed to the losing team exerting more effort). The laboratory evidence also helps to generalize our results. They illustrate that coaches or referees are not required to drive the effect and that the findings extend beyond group competition to situations where individuals compete against one another.

Our results contribute to several recent strands of economic literature. First, our analysis adds to the growing literature that provides evidence of non-standard behavior in the field (see Camerer (1998), Camerer, Loewenstein, and Rabin (2003), and DellaVigna (2009) for reviews). Additionally, our findings speak to the debate regarding whether biases can persist in market settings. High-stakes, opportunities to learn, and sorting have all been discussed as explanations for why biases typically found in the laboratory may disappear in market settings (Levitt and List, 2008). For example, in a study of sports card and memorabilia traders, List (2003) found that experienced agents did not exhibit the reference-dependent preferences that inexperienced agents did. Drawing on these findings, List argues that experience and sorting can extinguish bias.

Our findings suggest that even experienced professionals (NBA basketball players) competing for large stakes are prone to exhibit non-standard behavior. In fact, our results are even stronger in the NBA (where the players are more experienced) than in the NCAA. One explanation for this finding is due to selection. While several studies have provided evidence that sorting will attenuate empirical evidence of non-standard preferences (Dana, Weber, and Kuang, 2007 and Lazear, Malmendier, and Weber, 2009), others have argued that, in some cases, market forces may actually amplify non-standard behavior (DellaVigna and Malmendier, 2004 and Malmendier and Szeidl, 2008). For example, because of sorting, it may not be completely surprising that CEOs have been shown to be overconfident (Malmendier and Tate, 2005, 2008). Overconfidence, while a bias, may be an attribute that is associated with the type of person who is willing to work to achieve the level of a CEO. Similarly, it is not overly surprising that NBA basketball players are particularly susceptible to being psychologically motivated by losing given that these are individuals who selected into a job that rewards competitiveness.

Our findings also add to the empirical literature on tournament theory. Several papers have established that tournaments have strong incentive effects (see for example Ehrenberg and Bognanno (1990)). Other recent analyses include work by Eriksson, Poulsen, and Villeval (2008) that examines the impact of feedback on performance under piece rates and tournaments and Bandiera, Barankay, and Rasul (2005) that compares piece rates and tournaments in a field setting. Our findings also relate to work that has shown an impact of non-standard preferences in tournament settings such as the work by Gneezy and Rustichini (2000) that suggests that incentives may crowd out intrinsic motivation.

We organize the paper in the following way: In Section 1, we describe the basketball data and the regression discontinuity design that we use for identification. We report the results from our field study in Section 2. Section 3 describes our experimental design and the results. Section 4 discusses our findings and concludes.

1. Data and Empirical Strategy for Field Study

1.1 Data

The NBA (National Basketball Association) is the professional sporting league for basketball in the United States and Canada.³ It consists of 30 teams that play approximately 82 regular season games each year. Each game consists of four 12-minute quarters, with a 15-minute break for halftime, and an overtime period if the game ends in a tie. The NCAA (National Collegiate Athletic Association) is the collegiate basketball league in the United States. These non-professional teams play approximately 28-30 regular season games each year. Each game consists of two 20-minute halves (no quarters), with a 15-minute break for halftime, and an overtime period if the game ends in a tie.

Our data consist of all NBA games played between the 1993/1994 season and the 2008/2009 season and all NCAA games played between the 1999/2000 season and the 2008/2009 season.⁴ This represents 18,060 unique NBA games and 45,579 unique NCAA games.

These data include information about the date of each game, team identifiers, and an indicator for the home team. Importantly, the data not only indicate the winner of each game, but also contain the score for the home and away team at halftime (NCAA and NBA) and at the 1st and 3rd quarter break (NBA only). Using the dates and team identifiers, we also calculate the season winning percentage for each team.⁵

1.2 Empirical Strategy

Intuition suggests that being ahead in everything from scientific competitions to sports should increase the likelihood of winning. In the case of team sports, for example, basketball, baseball, and football

³ Basketball has served as the domain for several other studies in economics (see, for example, Price and Wolfers (2008), Wolfers (2006), Taylor and Trogdon (2002), and Camerer (1989)).

⁴ The NBA data end on March 1st, 2009 and the NCAA data end on March 22nd, 2009 – both end dates are prior to the completion of the 2008/2009 season.

⁵ For each game, we calculate the home and away teams' season winning percentages *excluding* each game itself. This way, there is no mechanical correlation between a team's winning percentage and probability that the team wins for each line in the data.

teams that are ahead early in the game win over two thirds of the time (Cooper, DeNeve, & Mosteller, 1992) and teams that are further ahead tend to win more (Stern, 1994).

There are at least two reasons why being behind part way through a competition makes it harder to win. Take two students competing to become valedictorian of their class. The student that is behind in the competition will, on average, be less talented.⁶ This person will also be less likely to win because, mechanically, they have to perform that much better than their opponent over the rest of the competition to emerge victorious. Thus, even if two students were of equal quality, we would expect the student that is behind to be less likely to come out on top.

Applying our motivational perspective to the basketball context, we are interested in testing whether a team that is losing at halftime is more likely to win *than expected*. To do this, we fit a model that flexibly controls for the halftime score difference and tests for a discontinuous change in winning probability for teams that are losing at halftime. This approach draws from the identification strategy known as regression discontinuity design (Thistlethwaite & Campbell, 1960). The exact specification that we employ is as follows,

$$Win_i = \alpha + \beta \text{Losing at Halftime}_i + \delta (\text{Score Difference at Halftime})_i + X_i + \varepsilon_i$$

where Win_i is an indicator equal to 1 if the home team won game i .⁷ $\text{Losing at Halftime}_i$ is also an indicator equal to 1 if the home team was losing by 1 or more points at the halftime break.

$(\text{Score Difference at Halftime})_i$ indicates the difference between the home team score and the away team score at halftime. We include this variable linearly in some specifications and a more flexible cubic function of this term in other specifications. X_i is a matrix of control variables for game i such as the winning percentages of the home and away team.

⁶ Consistent with this suggestion, our basketball data shows that the teams that are losing by 1 point at halftime have season winning percentages that are 1.2 percentage points lower on average than teams that are winning by 1 point at halftime.

⁷ All of our analysis focuses on the comparison between the home and away team. In order not to double count all of the data, only 1 team can be chosen from each game to use in the analysis. Rather than choose a team at random (which can result in different figures (See Figure 1 for example) depending on the random selection of teams, we choose the home team as a consistent way to analyze the data. Of course, we could have also compared the away team to the home team and found simply a mirror image of the analysis that we present.

We are interested in the coefficient β from this model, which we argue represents the result from increased effort by the team that finds themselves down at halftime. The key identifying assumption in our empirical strategy is that while all other factors that impact winning are “smooth” through the discontinuity, motivation might change discontinuously as a team finds itself down by 1 point at halftime. We present evidence that this assumption is met in the results section.

This empirical strategy is useful because it allows us to make causal inferences about the effect of being behind at halftime on performance. However, such claims can only be made about points near the discontinuity. As one moves further from the discontinuity, nonlinearity in the halftime score difference variable make such inferences less tenable. Thus, our empirical strategy addresses whether performance increases when losing by a small amount, but cannot speak to whether losing by a large amount at halftime affects subsequent performance.

2. Results of Field Study

2.1 Main Effects

We first examine the relationship between score differential at halftime and winning percentage by simply graphing the raw data. Due to the differences between the NBA and NCAA (points scored per game, games per season, minutes per game, etc.), we perform the analyses separately for these two leagues. Figure 1a and 1b illustrate the percentage of games won by the home team by the score difference at halftime between the home and away team for the NBA and NCAA, respectively.⁸ Not surprisingly, in general, the further teams are ahead, the more likely they are to win. Teams up by six points at halftime, for example, win about 80% of the time. Furthermore, this relationship is quite linear. Every two points better a

⁸ We restrict the sample to games where the score difference at halftime between the two teams is no larger than 10 points. This is convenient for the presentation of the results and eliminates concerns regarding nonlinearities at extreme halftime score difference. It has no impact on the regression discontinuity results.

team is doing relative to its opponent at halftime is associated with an approximately 8 percentage point increase in the probability of winning.

There is a discontinuity, however, around zero. Rather than having a winning percentage that is 8 percentage points less than teams ahead by a point (as the model would predict), home teams that are behind by one point are actually *more* likely than their opponents to win (triumphing in 58.2% relative to 57.1%) in the NBA and only 5.6 percentage points less likely than their opponents to win (59.2% relative to 64.8%) in the NCAA. Thus, in both datasets, teams that are down by a point win more often than expected. The dotted lines in each figure represent a linear fit (linear in a logistic model) of the data while allowing for a discontinuity at 0. These lines enable a graphical illustration of the size of the discontinuity in the data.

To formally test whether the difference in winning percentage is statistically different from expected, we conduct the regression specified in the empirical strategy section. Panels A and B in Table 1 report the results using the NBA and NCAA data, respectively. Columns (1) and (3) control for the halftime score difference linearly while Columns (2) and (4) include a cubic function of the halftime score difference. Columns (1) and (2) include no additional controls and Columns (3) and (4) including the home and away teams' season winning percentages as controls. Looking across specifications, we find that teams that are losing at halftime in the NBA win 5.8 to 8.0 percentage points more often than expected. These numbers are economically large, and also highly significant. The results in the NCAA are smaller, yet continue to be statistically significant for most specifications. We find that in the NCAA, losing at halftime leads to a 2.1 to 2.5 percentage point increase in winning probability.

2.2 Robustness Analysis

To interpret these results as causal, it must be the case that factors affecting winning percentage do not change discontinuously around zero. Analysis of some of the available covariates supports this assumption. Specifically, one test is to see if teams with higher season winning percentages were significantly

more likely to end the first half at a slight deficit. Figure 2 plots the home team winning percentage by halftime score difference. In support of our identification strategy, there is no significant discontinuity that occurs for this covariate in the NBA or the NCAA data. Figure 3 plots the away team winning percentage by halftime score difference. A small discontinuity can be seen in the figure for the NBA data, but it is not significant. Furthermore, it works against our findings (if away teams are slightly better when the home team is losing by one point, we shouldn't find that home teams outperform when down by one). In fact, this discontinuity, while insignificant, explains why the results in Table 1 increase slightly in Panel A when controlling for home and away team winning percentages. Overall, this robustness analysis lends support to our assumption that teams above and below the discontinuity are not significantly different after controlling for the halftime score difference.

Ideally, one would include in the analysis all relevant variables as controls. For example, teams losing by a small amount may be less likely to have key players in foul trouble, have players who excel under pressure in the second half, or be more likely to have the 2nd-half possession arrow. Of course, including all potential variables such as these is infeasible due to data constraints. Our research design, however, is able to overcome these concerns. While it is infeasible to have the complete set of all potential variables in our dataset, there is no reason to expect that any of these variables change discontinuously when the halftime score difference is zero. Like the season winning percentages of the home and away team, these variables should all be changing smoothly across zero. For example, analyzing over 3,000 NCAA basketball games with available play-by-play information on ESPN.com shows no correlation between halftime score difference and 2nd-half possession arrow ($p = .95$). There is also no evidence of a discontinuous change in possession arrow around a halftime score difference of zero. Thus, similar to season winning percentages and possession arrow, other potential variables should all be changing smoothly across zero.

2.3 Ancillary Results

One might worry that our analysis suffers from the fact that the point-difference-at-halftime variable is discrete rather than continuous. We cannot for example, compare teams that were losing by .1 points at halftime. One way to address this concern, however, is to look for other breaks in the action to see whether lumpiness in the score difference variable mechanically leads to discontinuous outcomes.

We test this possibility using quarter-by-quarter scores in the NBA data, looking at the impact of being behind by a small amount at the end of the 1st or 3rd quarter on the outcome of the game. These pauses in the action are short (i.e., one-eighth the length of the halftime break), so being behind during them may be less likely to affect team motivation, but if the results presented in the previous section are driven by lumpiness in the scoring, we should find similar discontinuities at these moments as we do for halftime.

In Table 2, we report the results from an analysis that is analogous to Table 1, but uses the 1st quarter (Panel A) and the 3rd quarter (Panel B) score differences instead of halftime. The coefficients on losing after the 1st and 3rd quarter are all small (less than 2 percentage points across specifications) and never statistically significant. This casts doubt on the possibility that our halftime finding is a simple result of the discreteness of the score difference variable

3. Laboratory Evidence

Using a credible identification strategy, we have shown large and significant effects in a field setting that losing can lead to increased success. This is notable in that it shows that this psychological effect is present in a well-functioning market, with experienced agents, and large stakes.

Of course, as is often the case with field data, it is difficult to rule out all alternative explanations or to fully understand the mechanism underlying the effect. For example, though unlikely, one could argue that teams that are slightly behind win more than expected because referees treat them differently or coaches give motivating speeches at halftime. Additionally, one could argue that while the outcome that we find is

correct, it is not due to losing teams exerting more effort, but rather is the result of winning teams becoming complacent. Parsing out which of these two mechanisms drives the result is useful because it provides insight into how competitive feedback influences net effort overall.

To address these questions, we conducted an experiment that directly tests how competitive feedback influences effort. The results from this experiment underscore our findings from the field and provide clear information regarding the underlying mechanism. Further, the experiment increases the generalizability of our results by showing that losing can lead to additional effort for individuals (rather than just teams) and in situations where coaches and referees are not present.

3.1 Experimental Design

Participants (N= 111) completed a short game as part of a larger series of unrelated experiments for which they were paid \$10. The game involved pressing the ‘a’ and ‘b’ keys on a computer keyboard in succession as quickly as possible. Pressing the combination in the correct order scored a point. The game had two, thirty-second periods divided by a short break. Participants were instructed that they would engage in a short competition with another participant (of the experimenter’s choosing) who had previously completed the game. If the participants scored more points than their opponent over the course of the game, they would receive an additional \$3.

There were three separate conditions: slightly behind, slightly ahead, and control. The only difference between conditions was the information participants received in the break between the two periods. Participants were either informed that they were 1 point behind their opponent (slightly behind), 1 point ahead of their opponent (slightly ahead), or received no feedback and were simply told that the second period was about to begin (control). Due to a large cache of previous participants that had taken part in this competitive button-pushing task, every participant in the experiment had somebody that they could be paired with that had scored either 1 point better or 1 point worse than them after the first period. Thus,

after the first period ended, each participant was quickly randomized into one of three conditions and assigned a competitor accordingly. They then completed the second period of the task and were paid the \$3 if they performed better than the historical score of their assigned competitor.

We examined how competitive feedback influenced effort by taking participants' key presses in the first and second periods and comparing them across conditions.

3.2 Laboratory Results

Figure 3 provides the results from the experiment. First, being slightly behind an opponent led to a significant increase in effort. Participants informed that they were slightly behind their opponents worked harder in the 2nd half of the game, $F(1, 108) = 28.63, p < .001$.⁹ Further, while participants in the other conditions also showed somewhat of an increase in effort (there was an overall increase in effort post-break, $F(1, 108) = 31.71, p < .001$), this was qualified by a Condition x Period interaction, $F(2, 108) = 5.48, p < .005$. Participants that were slightly behind their opponents increased their effort significantly more than participants in any of the other conditions (control: $F(1, 81) = 8.69, p < .005$; slightly ahead: $F(1, 50) = 8.34, p < .01$).

Second, being slightly ahead did not reduce effort. Participants informed that they were slightly ahead of their opponents actually worked *harder* in the 2nd half of the game, though this difference did not reach significance, $F(1, 108) = 2.16, p = .15$. This change in effort was comparable to participants in the control condition, $t(108) = .15, p = .88$, furthering the notion that being slightly ahead did not induce complacency.

The results of this experiment both underscore and help clarify the results from the field study. Being slightly behind drove participants to exert more effort than those that were slightly ahead or received no feedback. Further, while individuals or teams may get complacent when they are far ahead, this study

⁹ We use F-tests to compare all means, unless otherwise noted.

suggests that being slightly ahead does not decrease effort. This result illustrates our main effect in a very controlled setting and rules out several competing hypotheses (i.e., winning team complacency or coaches or referees driving increased effort).

4. Conclusion

We use a combination of field and laboratory evidence to show that teams and individuals that are losing by a small amount during a competitive task win significantly more often than expected relative to teams and individuals that are leading by a small amount. We illustrate that this effect is due to the losing party increasing their level of effort.

Overall, these findings have important implications. Encouraging people to see themselves as behind others, albeit slightly, should increase effort. First, when considering how to motivate students, employees, and others, targeted comparative feedback may help improve performance. Managers trying to encourage employees to work harder, for example, might consider providing feedback about how a person is doing relative to slightly better performer. Second, strategically scheduling breaks should also improve performance. Coaches might want to call time outs when their teams are losing by a little and managers might want to schedule performance meetings when their teams are slightly behind competitors. Encouraging individuals or teams to take stock of their performance when they are slightly behind should help focus them on the deficit, leading to stronger performance, and ultimately, success.

Our results also have implications for the growing literature on tournament theory. Academics have shown particular interest in tournament theory because, under certain sets of assumptions, a tournament pay structure may result in a better incentive mechanism than alternative forms of payment (Lazear and Rosen, 1981). Our results suggest a further potential advantage of tournament theory – that individuals losing by a small amount are psychologically motivated when they reflect on their performance relative to the performance of their competitor.

The results also add to the growing literature demonstrating that individuals are motivated by more than just standard pecuniary incentives. Non-standard preferences can give rise to significant differences in motivation across individuals. Future research should further explore how causing people to focus on situations where they are in a loss domain can increase motivation, and ultimately success.

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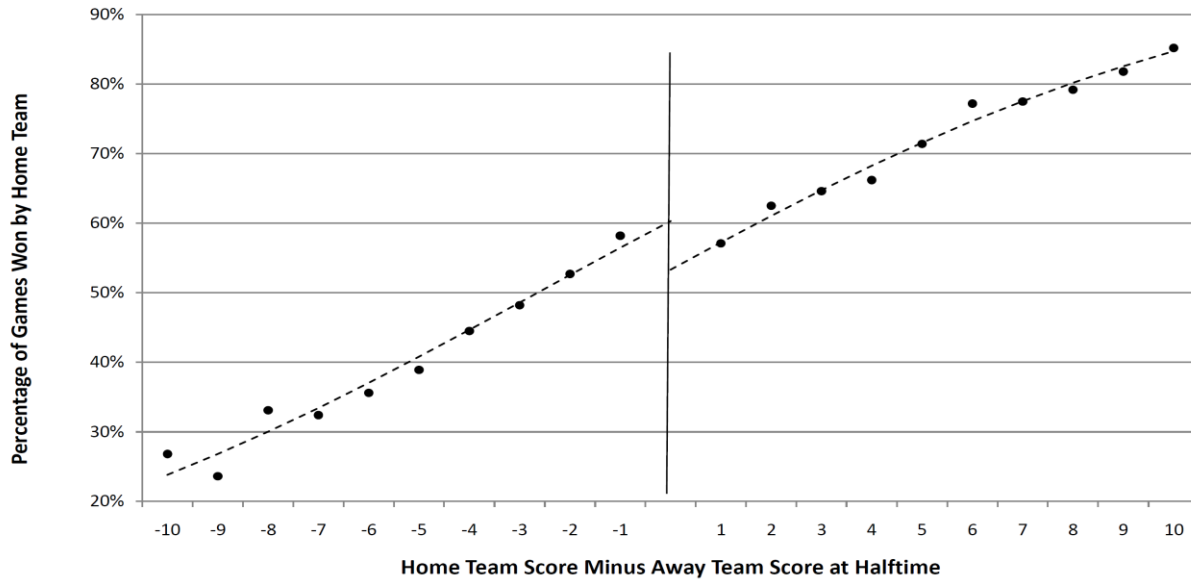
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Figure 1. This figure plots the percentage of games won by the home team by the score difference (home team minus away team) at halftime for NBA (1a) and NCAA (2a) basketball games. The raw data are presented with dots. The dotted line represented a logistic linear fit of score difference on winning, allowing for a discontinuity when a team is behind.

1a. NBA DATA



1b. NCAA DATA

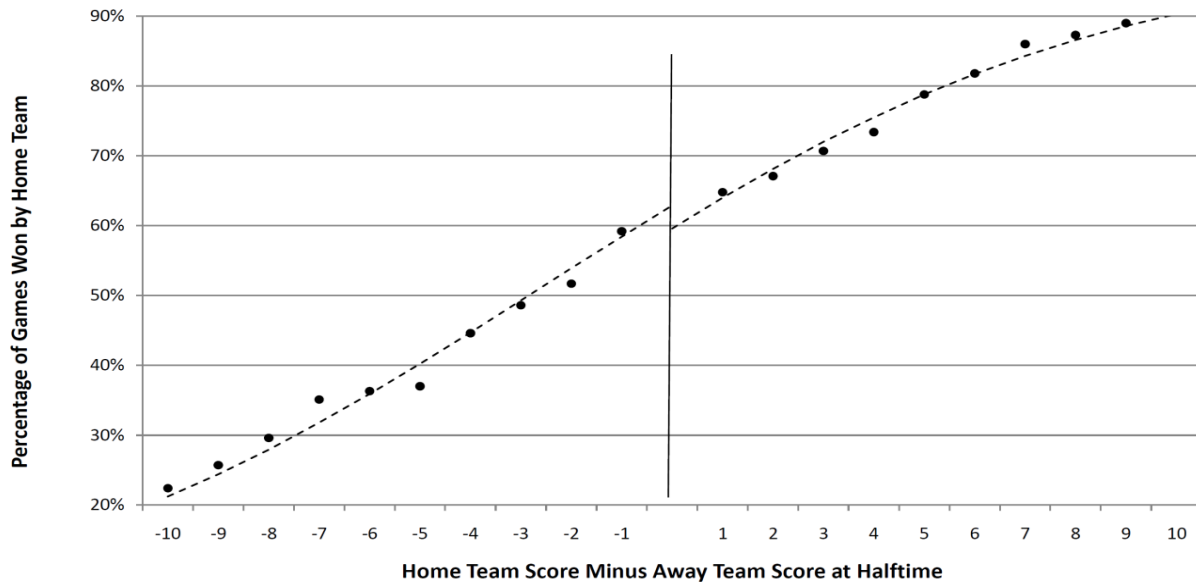
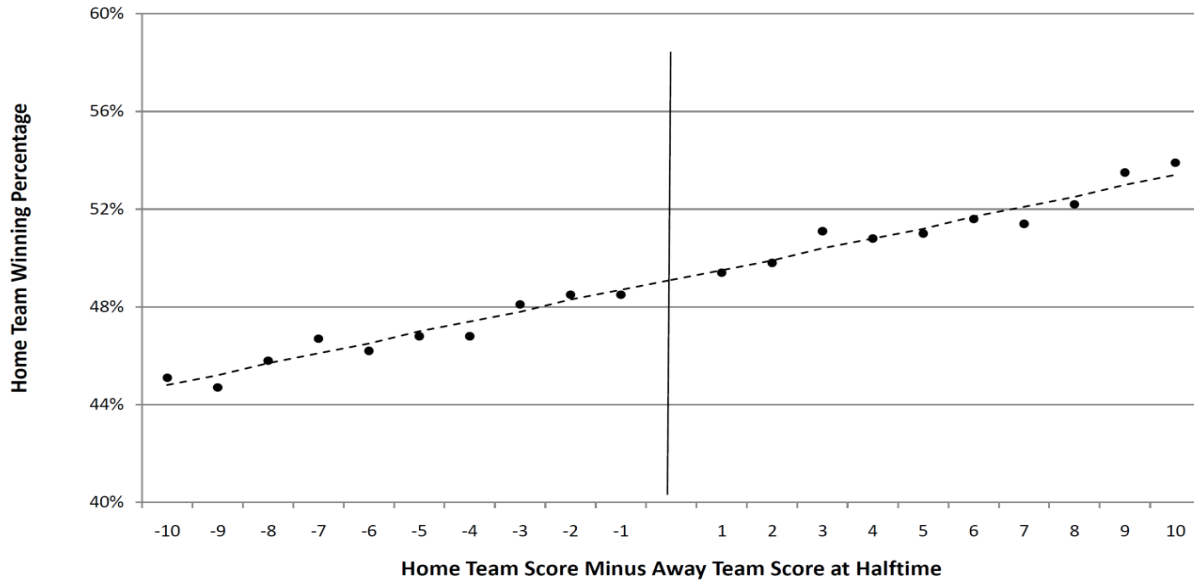


Figure 2. This figure plots the season winning percentage of the home team by the score difference (home team minus away team) at halftime for NBA (1a) and NCAA (2a) basketball games. The raw data are presented with dots. The dotted line represented a logistic linear fit of score difference on season winning percentage, allowing for a discontinuity when a team is behind.

2a. NBA DATA



2b. NCAA DATA

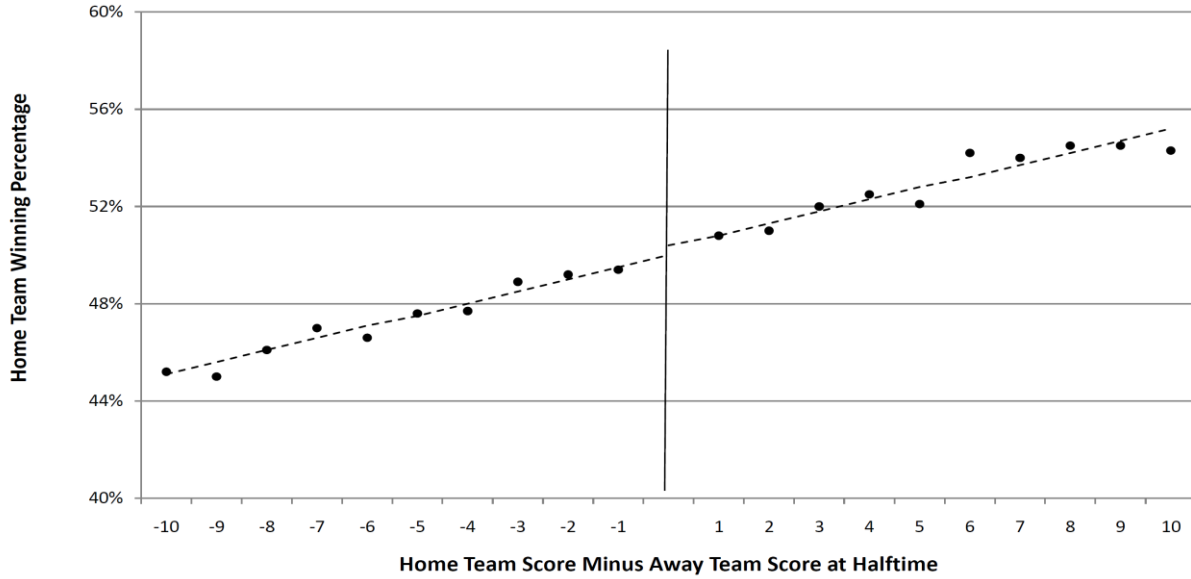
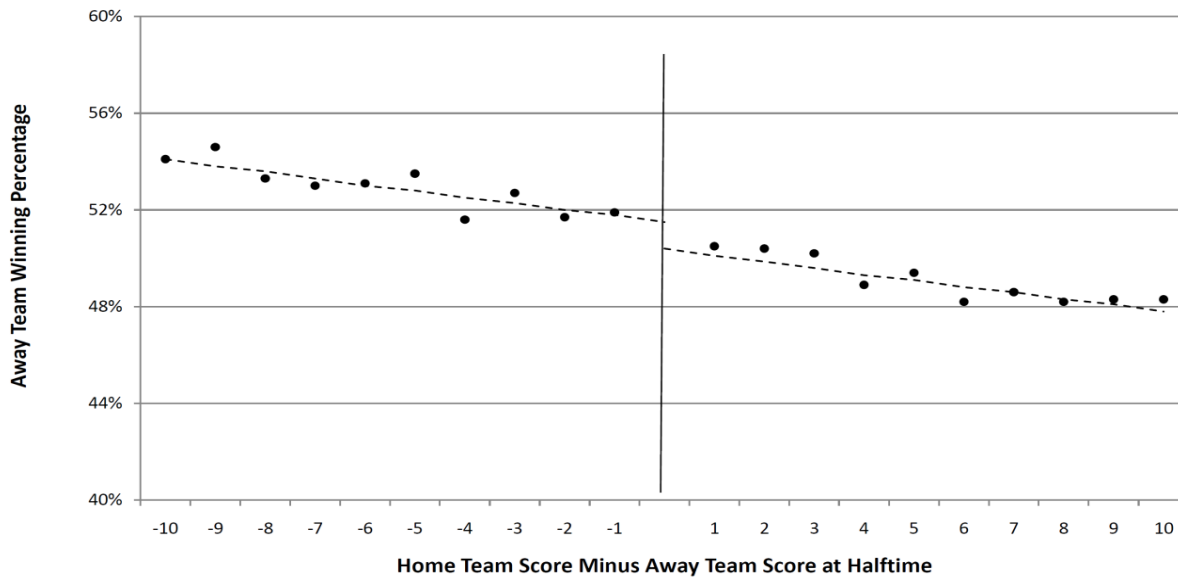


Figure 3. This figure plots the season winning percentage of the away team by the score difference (home team minus away team) at halftime for NBA (1a) and NCAA (2a) basketball games. The raw data are presented with dots. The dotted line represented a logistic linear fit of score difference on season winning percentage, allowing for a discontinuity when a team is behind.

3a. NBA DATA



3b. NCAA DATA

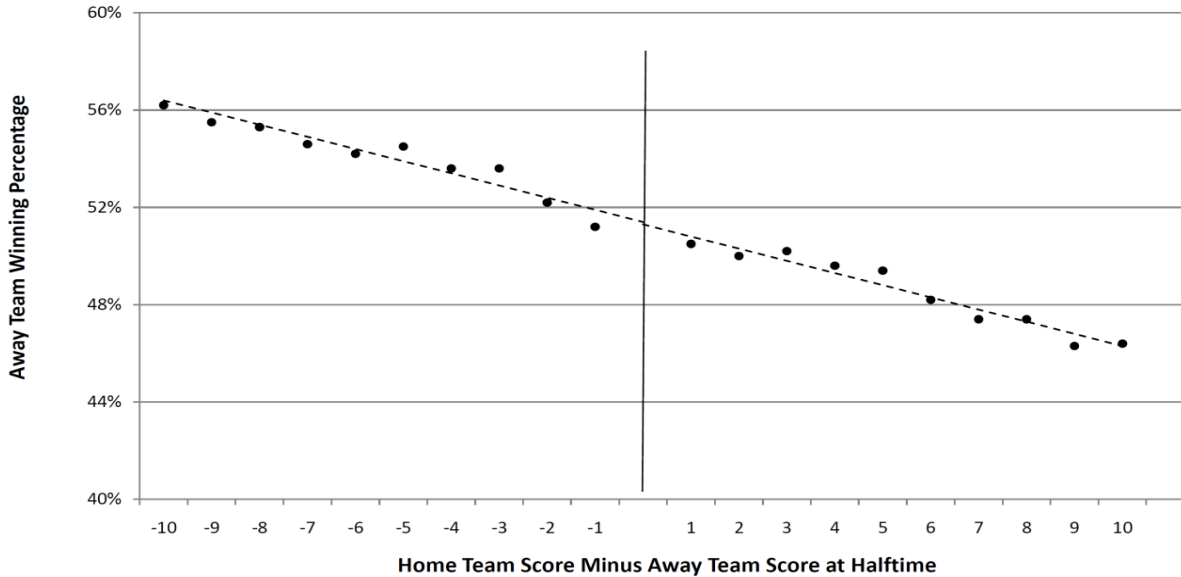


Figure 3. This figure plots effort (the number of button presses) in the first and second period of the experiment described in the paper. The results are presented separately for the three conditions (slightly behind, slightly ahead, and control (no feedback)). Error bars are standard errors of the mean.

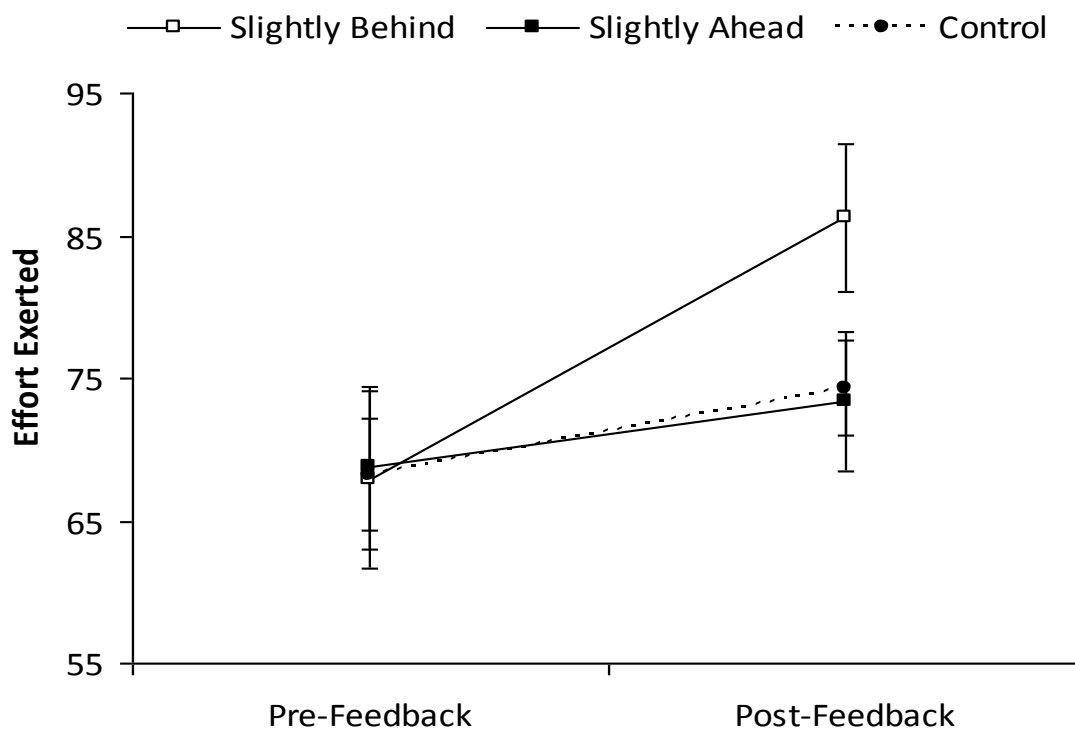


Table 1. The Impact of Losing at Halftime on Winning

Panel A: NBA DATA				
	Dependent Variable: Indicator = 1 if the Home Team Won			
	(1)	(2)	(3)	(4)
Losing at Halftime	.058*** (.015)	.074*** (.021)	.062*** (.015)	.080*** (.020)
Home Team Win. Pct.			.0068*** (.0002)	.0068*** (.0002)
Away Team Win. Pct.			-.0065*** (.0002)	-.0065*** (.0002)
Halftime Score Difference (Linear)	X	X	X	X
Halftime Score Difference (Cubic)		X		X
Pseudo R-squared	.097	.097	.172	.172
Observations	11,968	11,968	11,968	11,968
Panel B: NCAA DATA				
	Dependent Variable: Indicator = 1 if the Home Team Won			
	(1)	(2)	(3)	(4)
Losing at Halftime	.025*** (.010)	.023* (.014)	.025*** (.009)	0.021 (.013)
Home Team Win. Pct.			.0057*** (.0001)	.0057*** (.0001)
Away Team Win. Pct.			-.0055*** (.0001)	-.0055*** (.0001)
Halftime Score Difference (Linear)	X	X	X	X
Halftime Score Difference (Cubic)		X		X
Pseudo R-squared	.143	.144	.207	.208
Observations	29,159	29,159	28,808	28,808

Notes: This table reports marginal-effects coefficients and robust standard errors using a Logit Model. The dependent variable is an indicator that equals one if the home team won. Losing at halftime is an indicator of whether the home team was losing by one or more points. The halftime score difference is the difference between the home team's score and the away team's score at halftime. All NBA (Panel A) and NCAA (Panel B) basketball games are used that contain halftime score differences between -10 and 10 (excluding 0). * significant at 10%; ** significant at 5%; *** significant at 1%

Table 2. The Impact of Losing at 1st and 3rd Quarter Breaks on Winning

Panel A: 3rd Quarter				
	Dependent Variable: Indicator = 1 if the Home Team Won			
	(1)	(2)	(3)	(4)
Losing at 3rd Quarter Break	0.005 (.016)	-0.021 (.024)	0.008 (.016)	-0.019 (.023)
Home Team Win. Pct.			.0048** (.0003)	.0048** (.0003)
Away Team Win. Pct.			-.0051** (.0003)	-.0051** (.0003)
3rd Quarter Score Difference (Linear)	X	X	X	X
3rd Quarter Score Difference (Cubic)		X		X
Pseudo R-squared	.189	.189	.232	.232
Observations	11,968	11,968	11,968	11,968
Panel B: 1st Quarter				
	Dependent Variable: Indicator = 1 if the Home Team Won			
	(1)	(2)	(3)	(4)
Losing at 1st Quarter Break	0.017 (.015)	0.020 (.022)	0.013 (.014)	0.009 (.020)
Home Team Win. Pct.			.0078** (.0002)	.0078** (.0002)
Away Team Win. Pct.			-.0073** (.0002)	-.0073** (.0002)
1st Quarter Score Difference (Linear)	X	X	X	X
1st Quarter Score Difference (Cubic)		X		X
Pseudo R-squared	.062	.062	.162	.162
Observations	11,968	11,968	11,968	11,968

Notes: This table reports marginal-effects coefficients and robust standard errors using a Logit Model. The dependent variable is an indicator that equals one if the home team won the game. Losing at 3rd quarter break and 1st quarter break is an indicator of whether the home team was losing by one or more points at each of these breaks. The 1st and 3rd quarter score difference is the difference between the home team's score and the away team's score at each of those points in the game. All NBA (Panel A) and NCAA (Panel B) basketball games are used that contain halftime score differences between -10 and 10 (excluding 0).

* significant at 10%; ** significant at 5%; *** significant at 1%