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Abstract

Individuals, groups, and teams who are behind their opponents in competition tend to be more likely to lose. In contrast, we show that through increasing motivation, being slightly behind can actually increase success. Analysis of more than 18,000 professional basketball games illustrates that being slightly behind at halftime leads to a discontinuous increase in winning percentage. Teams behind by a point at halftime, for example, actually win more often than teams ahead by one, or approximately six percentage points more often than expected. This psychological effect is roughly half the size of the proverbial home-team advantage. Analysis of more than 45,000 collegiate basketball games finds consistent, though smaller, results. Experiments corroborate the field data and generalize their findings, providing direct causal evidence that being slightly behind increases effort and casting doubt on alternative explanations for the results. Taken together, these findings illustrate that losing can sometimes lead to winning.

Keywords
competition, motivation, performance, prospect theory

Disciplines
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Can Losing Lead to Winning?*

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Abstract

Can losing during a competitive task 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. Additional experimental evidence corroborates the field test and casts doubt on alternative explanations.

Following the seminal paper of Lazear and Rosen (1981) on tournament theory, a large literature has emerged exploring the incentive effects of payment schemes that reward relative performance. An important concern with tournament incentives is that players who are losing may get discouraged and reduce their effort levels. A discouragement effect is particularly relevant in dynamic tournaments where interim feedback is provided. For example, students competing to be valedictorian receive feedback during the tournament process. Employees competing for promotion often receive regular performance evaluations, which may cause them to adjust their effort levels.[1] Learning they are behind the competition might lead people to be discouraged and give up.

Despite its importance for tournaments as well as other areas of economics, little empirical evidence exists regarding the impact of losing on behavior. Two notable exceptions include work by Fershtman and Gneezy (2008) showing that direct competition may increase the likelihood that participants give up and quit and work by Muller and Schotter (2007) providing evidence that feedback regarding ability distributions may lead low-ability participants to drop out and exert little to no effort in tournament settings. While quitting seems to occur when players are losing by a large amount, the impact of being behind *by only a small amount* is much less clear. In many real-life tournaments, such as an R&D race, the goal is to maximize the effort of the top contenders. How do teams/players respond when given interim feedback that they are losing by a small amount?

Though one could argue that losing, even by a little, leads players to be discouraged, another possibility based on the psychological literature suggests that being slightly behind might actually lead participants to work harder. 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

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[1] Murphy and Cleveland (1995) find that 74%-89% of business organizations provide a formal performance appraisal to workers.

value obtaining commensurate gains.[2] While loss aversion is often applied to realized outcomes, it may also have a motivational impact on behavior during the realization process of an outcome.[3] 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 beating their opponent (i.e., ahead of their reference point), one may be willing to exert more effort if they are losing during a competitive task (i.e. behind their reference point). Consequently, a player that receives feedback that they are losing by a small amount may significantly increase their overall effort.

In this paper, we provide evidence regarding the impact of losing on performance using both field data from actual competitions and a controlled laboratory experiment. Our field evidence consists of analyzing 18,060 NBA and 45,579 NCAA basketball games. Our data not only provide information regarding the final outcome of each game, but also indicate the score of each team at halftime (interim feedback). Using a regression discontinuity design, we isolate the impact of losing (relative to winning) at the halfway point on subsequent second half performance. We find that teams that are losing at halftime win approximately 2 (NCAA) and 6 (NBA) percentage points more often than expected. In fact, 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. This is in stark contrast to the empirical model, which suggests that – absent a feedback effect – teams that are losing by one point should win 6 percentage points less often than teams that are leading by a point at halftime. The boost in winning percentage due to losing is comparable to a two point difference in score at halftime, or about half the size of the proverbial home-team advantage (Cooper et al. 1992). Applying standard regression discontinuity techniques, we show that this finding is not threatened by differences in observable team attributes around the discontinuity.

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[2] Loss aversion has been documented in many laboratory (e.g., Thaler et al., 1997; Gneezy and Potters, 1997) and field settings (see Genesove and Mayer, 2001; Camerer et al., 1997; Fehr and Goette, 2007; Odean, 1998; Mas, 2008). Heath, Larrick, and Wu (1999) examined how goals may act as reference points.
[3] 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".

In order to corroborate the field results, and rule out competing explanations, we perform a laboratory experiment where participants take part in a competitive task. During a break in the task, they are provided with feedback. Individuals who received feedback that they 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 possible alternative explanations (e.g., winning team complacency or referees driving the result). The laboratory evidence also helps to generalize our results to individual, rather than just team, performance and by illustrating that our findings are not restricted to situations where coaches are present.

Our results contribute to several strands of economic literature. First, they add 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). Our findings are most directly tied to work that has shown that non-standard preferences can cause people to exert greater effort in competitive environments. For example, Akerlof and Yellen (1990) founded the fair wage-effort hypothesis based on the idea that people care about fairness above and beyond standard pecuniary incentives. Similarly, there is evidence that altruism or social preferences can increase employee effort (Hamilton, Nickerson, and Owan, 2003; Bandiera, Barankay, and Rasul, 2005). In addition, Falk and Ichino (2006) and Mas and Moretti (2009) both find evidence that peers can influence effort exertion. Our findings suggest that being slightly behind in a competitive task also has the ability to psychologically motivate individuals to increase their performance levels.

Second, our findings speak to the debate about whether biases 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, however, 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 attributes the effect 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 a psychological motivation driven by losing, given that these are individuals who selected into a job that rewards competitiveness.

Third, our findings 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 laboratory evidence by Eriksson, Poulsen, and Villeval (2008) that examines the impact of feedback on performance under piece rates and tournaments, laboratory evidence by Freeman and Gelber (2009) on the impact of ability information on performance in static games, and field evidence by Bandiera, Barankay, and Rasul (2005) that compares piece rates and tournaments. Several recent theory papers have also discussed the importance of feedback on effort in tournament settings (see, for example, Aoyagi (200X), Lizzeri, Meyer, and Persico (2002), and Ederer (2008). 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 evidence in Section 2. Section 3 describes the experimental design of our laboratory study and delineates its results. Section 4 discusses our findings and concludes.

1. Data and Empirical Strategy for Field Test

1.1 Data

The NBA (National Basketball Association) is the professional sporting league for basketball in the United States and Canada.[4] It consists of 30 teams that play 82 regular season games each year. Each game is made up of four 12-minute quarters, one 15-minute break for halftime, and an overtime period if the game ends in a tie. The NCAA (National Collegiate Athletic Association) is the United States' collegiate basketball league. These non-professional teams play approximately 28-30 regular season games each year, with each game consisting of two 20-minute halves (no quarters), a 15-minute halftime break, 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.[5] 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

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[4] 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)).
[5] 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.

for the home and away team at halftime (NCAA and NBA) and at the 1st and 3rd quarter breaks (NBA only). Using the dates and team identifiers, we also calculate the season winning percentage for each team.[6]

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 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.[7] This person will also be less likely to win because, mechanically, he has to perform that much better than his 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.

In the context of basketball, we are interested in testing whether a team that is losing at halftime wins more often *than expected*. In order to identify the causal effect of losing on subsequent performance, we use a regression discontinuity (RD) design. First introduced by Thistlethwaite and Campbell (1960), RD designs have become a popular identification tool in economics. Recent work has provided a clear understanding of how these models should be estimated (see Imbens and Kalyanaraman (2009), Imbens and Lemieux (2008), and Lee and Lemieux (2009)). RD designs are typically used in situations where the treatment status is determined by whether an observable variable (the forcing variable) is above or below a known threshold. In our analysis, we are interested in the case where teams are "treated" with feedback that

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[6] 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.
[7] 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.

indicates that they are losing. The forcing variable is the score difference at halftime and teams are treated if the forcing variable indicates that the team is losing at the halfway point in the game.

In its most simple form, this model can be estimated as follows,

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

where Win_i is an indicator equal to 1 if the home team won game i.[8] $Losing\ at\ Halftime_i$ is an indicator equal to 1 if the home team was losing by 1 or more points at the halftime break.[9] $(Score\ Difference\ at\ Halftime)_i$ is the forcing variable that indicates the difference between the home team score and the away team score at halftime. While the equation above specifies that the forcing variable enter linearly, we relax this assumption and include a more flexible form in robustness specifications. X_i is a matrix of control variables for game i such as the winning percentages of the home and away team.

We are interested in the coefficient β from this model, which we argue represents the result from increased effort by the teams that finds themselves down at halftime. The key identifying assumption in our empirical strategy is that while motivation might change discontinuously as a team finds itself trailing by one point halfway through the game, all other factors that impact winning change "smoothly" through the discontinuity. An advantage with RD designs is that this assumption can be empirically tested. Specifically, in the results section we present evidence that the observables that we do have in our data (e.g. team winning percentage) do indeed change smoothly through the discontinuity. This lends credibility to the empirical design by suggesting that unobservables above and below the threshold are not causing systematic bias.

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[8] 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.

[9] A question arises in our analysis regarding what to do with teams that are tied at halftime. It is not clear whether being tied is more like losing and thus should be classified as "losing at halftime" or if it is more like winning and should therefore be classified as "winning at halftime". Empirically, in our data, it ends up that tied teams are in the middle (not losing or winning). We do not include the tied teams in our main regression results so that we can accurately contrast the impact of being behind to the impact of being ahead.

In our setting, the forcing variable (score difference at halftime), is discrete. Thus, unlike many RD papers, it is not possible to compare outcomes in very narrow bins right around the discontinuity. As Lee and Lemeiux (2009) point out, the discrete nature of the forcing variable requires that we use regression analysis to estimate the conditional expectation of the outcome variable at the cutoff point by extrapolation.[10] As Lee and Lemieux (2009) note, "in practice, we always extrapolate to some extent, even in the case of a continuous forcing variable. So the fact we must do so in the case of a discrete running variable does not introduce particular complications from an econometric point of view, provided the discrete variable is not too coarsely distributed." Thus, while we extrapolate a small degree in our analysis, it should not bias our results. We also provide some evidence in the results section (using the 1st and 3rd quarter breaks) which suggests that our forcing variable is not too coarsely distributed.

While our identification strategy allows us to make causal inferences about the effect of being behind at halftime on performance, such claims can only be made about points near the discontinuity. As one moves further from the discontinuity, potential 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 Test

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.

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[10] Incidently, the discrete nature of the forcing variable solves the question of what is the optimal bandwidth (an important issue in RD designs). The bandwidth that we use in the paper is set to its narrowest possible value, one point.

Figure 1a and 1b illustrate the percentage of games won by the home team with respect to each halftime score difference in the NBA and NCAA, respectively.[11] Not surprisingly, the further teams are ahead, the more likely they generally are to win. Teams up by six points at halftime, for example, win about 80% of the time. This relationship is approximately linear over the range in our data. Every two points better a team is doing relative to its opponent at halftime is associated with an approximately 6-8 percentage point increase in the probability of winning.

There is a discontinuity, however, around zero. Rather than having a winning percentage that is 6-8 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 zero. 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 than 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.[12] Columns (1) and (2) include no additional controls and Columns (3) and (4) include 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 highly significant. The results in the NCAA are smaller, yet continue to be

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[11] 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 since there are relatively few observations where the halftime score difference was more than 10 point and because it eliminates concerns regarding nonlinearities at extreme halftime score differences. This restriction has no impact on the results that we find – the results are consistent across different choices of windows.

[12] In our analysis, there is a strong reason to assume that the slope of the forcing variable (score difference at halftime) is similar above and below the discontinuity. However, it is not necessary to make this assumption. We have also performed regressions separately above and below the discontinuity and find effects that are virtually identical to those reported.

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 with respect to expectations.

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 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 should not 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. The RD design that we use, 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. Similar to season winning percentages and possession arrow, other potential variables should all be changing smoothly across zero.

2.3 Ancillary Results

As discussed in the empirical strategy section, one potential question regarding our analysis is whether our forcing variable is "too discrete". We cannot, for example, compare teams that were losing by .1 points at halftime to teams that were winning by .1 points. This is likely not an issue in our analysis as a small amount of extrapolation is required in all RD designs. However, one way to potentially address this concern is to look for other breaks in the action to see whether lumpiness in the score difference variable leads mechanically 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 quarters are all small (less than 2 percentage points across specifications) and never statistically significant. This casts further 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), even 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

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completed the game. If the participants scored more points than their respective opponents 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 someone with whom he could be paired who had scored either 1 point better or 1 point worse than him 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. Participants then completed the second period of the task and were paid the $3 if they performed better than the historical score of their assigned competitors.

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, $F(1, 108) = 28.63$, $p < .001$.[13] 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

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[13] We use F-tests to compare all means, unless otherwise noted.

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 test. 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 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 its level of effort.

Our results are consistent with the notion that teams down by one point at halftime are psychologically motivated due to loss aversion. Being in the loss domain can cause teams to get "fired up" and exert greater effort in the second half. This result is consistent with other work that looks at loss aversion in dynamic processes. For example, Camerer et al. (1997) find that taxi drivers exhibit evidence of loss aversion relative to a reference point. Specifically, when the taxi drivers find themselves in the loss

domain (not having yet reached their target earnings for the day), they exert more effort relative to drivers that are in the gain domain. Our findings are similar in that we find evidence of greater effort exertion when players find themselves in the loss domain during the realization of an outcome. Our results are unique, however, in that they extend evidence of loss aversion to situations where one's reference point is a competitor.

Evidence of greater effort exertion due to loss aversion in competitive settings is particularly important for the tournament theory literature. A common worry in tournaments is that being behind can lead to a discouragement effect. Our findings suggest that being behind by a small amount in a tournament actually does the opposite – it motivates. This has important implications for incentive design. Encouraging people to see themselves as behind others, albeit slightly, should increase effort. 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. 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 eventual triumph. Future research may consider further exploring how causing people to focus on situations where they are in a loss domain can increase motivation, and ultimately success.

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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.
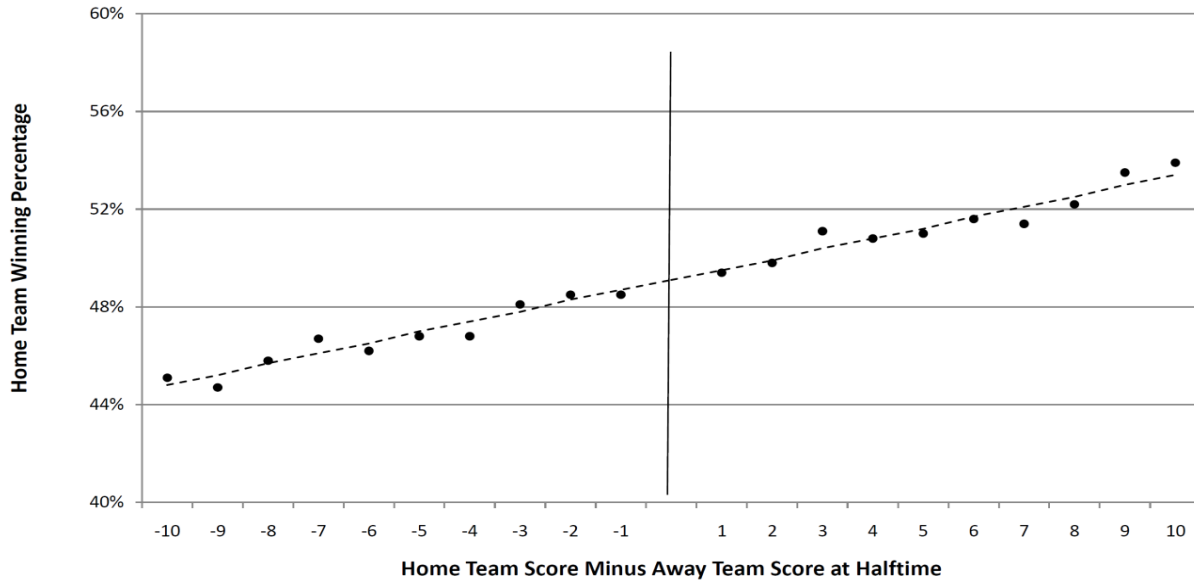
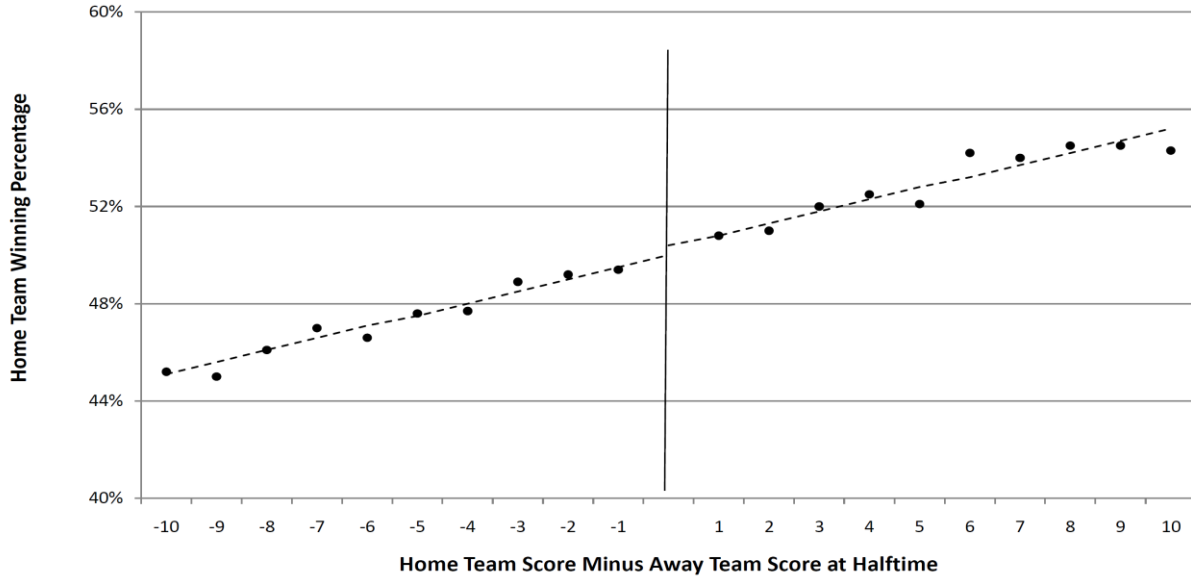**1a. NBA DATA**
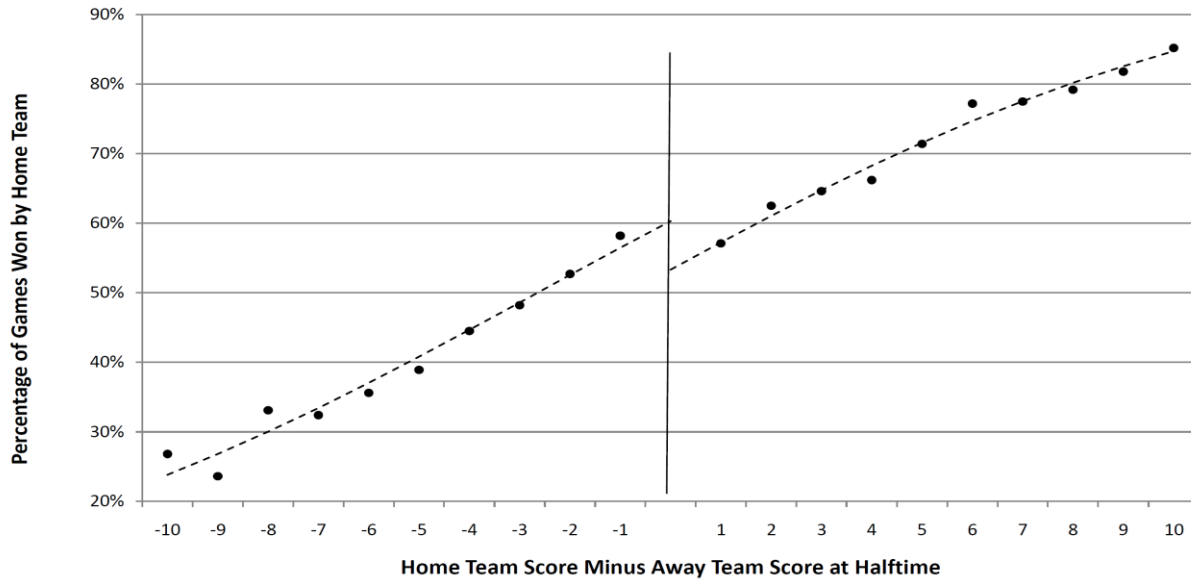
1b. NCAA DATA
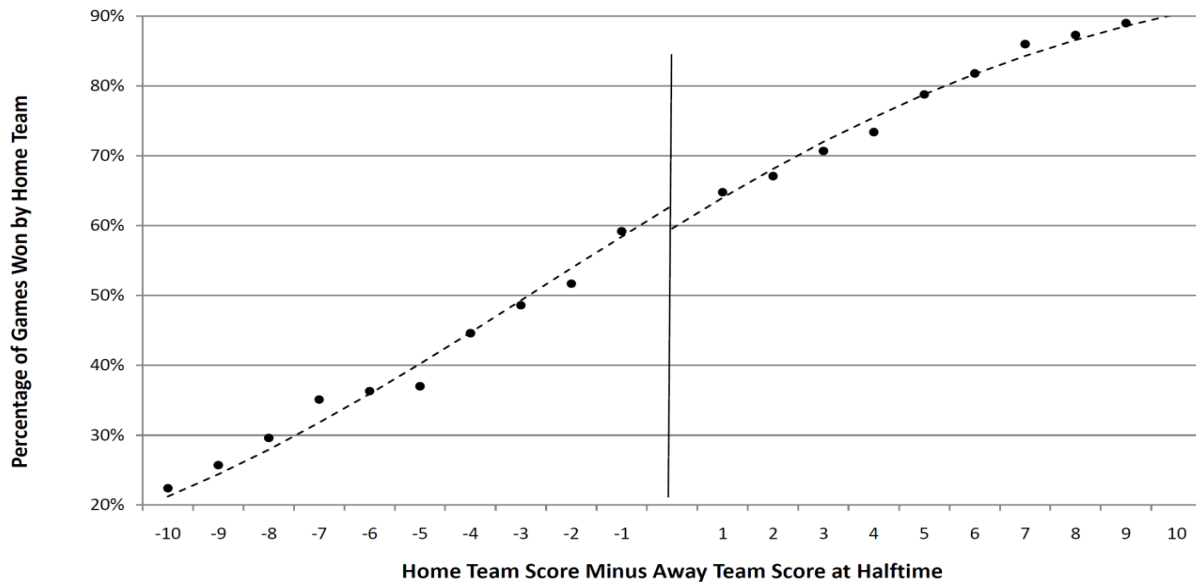
Figure 2. This figure plots the season winning percentage of the home team by the score difference (home team minus away team) at halftime for NBA (1a) and NCAA (2a) basketball games. The raw data are presented with dots. The dotted line represented a logistic linear fit of score difference on season 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.
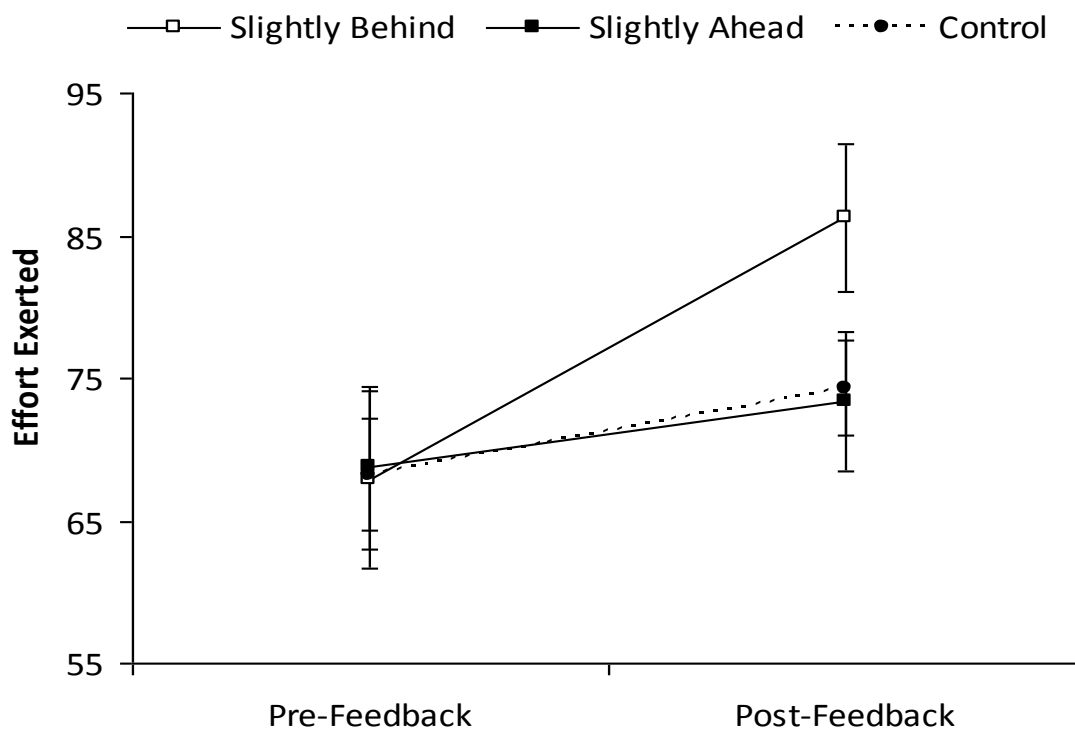
3a. NBA DATA
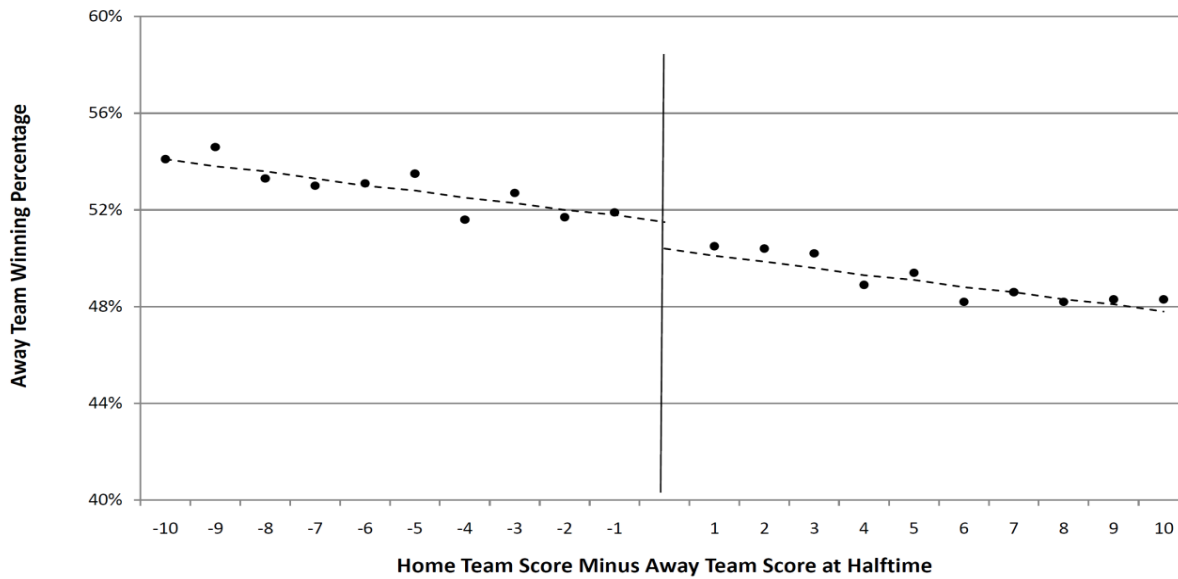
3b. NCAA DATA
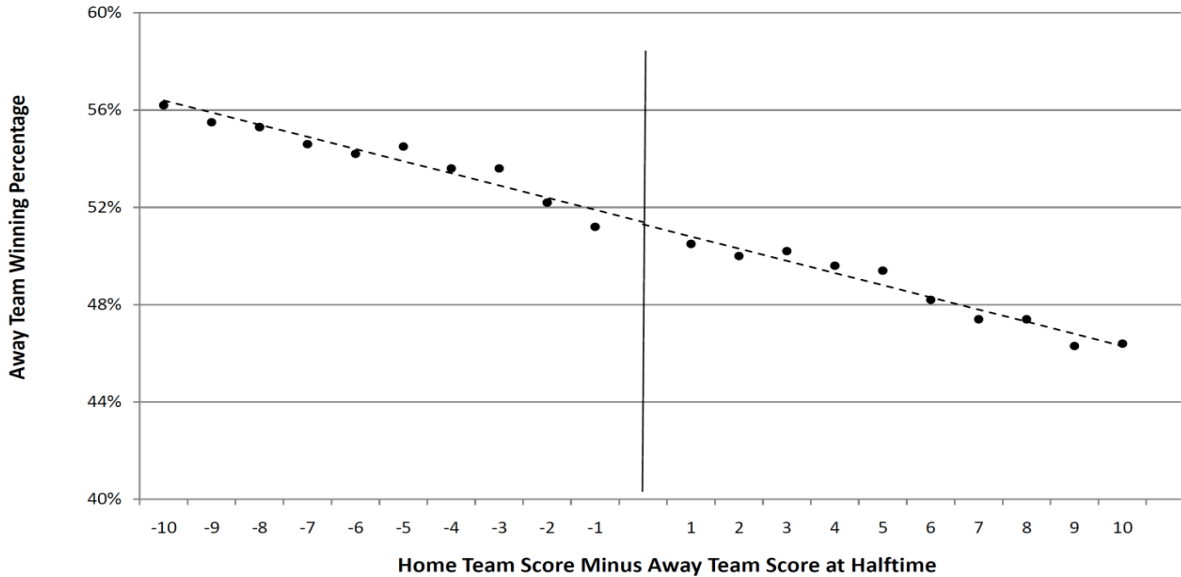
Figure 3. This figure plots effort (the number of button preses) in the first and second period of the experiment described in the paper. The results are presented separately for the three conditions (slightly behind, slightly ahead, and control (no feedback)). Error bars are standard errors of the mean.

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***	.074***	.062***	.080***
	(.015)	(.021)	(.015)	(.020)
Home Team Win. Pct.			.0068***	.0068***
			(.0002)	(.0002)
Away Team Win. Pct.			-.0065***	-.0065***
			(.0002)	(.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***	.023*	.025***	0.021
	(.010)	(.014)	(.009)	(.013)
Home Team Win. Pct.			.0057***	.0057***
			(.0001)	(.0001)
Away Team Win. Pct.			-.0055***	-.0055***
			(.0001)	(.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	-0.021	0.008	-0.019
	(.016)	(.024)	(.016)	(.023)
Home Team Win. Pct.			.0048**	.0048**
			(.0003)	(.0003)
Away Team Win. Pct.			-.0051**	-.0051**
			(.0003)	(.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	0.020	0.013	0.009
	(.015)	(.022)	(.014)	(.020)
Home Team Win. Pct.			.0078**	.0078**
			(.0002)	(.0002)
Away Team Win. Pct.			-.0073**	-.0073**
			(.0002)	(.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%