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Can Losing Lead to Winning?

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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.

Key words: competition; motivation; performance; prospect theory
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1. Introduction

Intuition suggests that being ahead in everything from bonus competitions to sales contests should increase the likelihood of winning. In sports, for example, teams that are ahead early in the game win over two-thirds of the time (Cooper et al. 1992), and teams that are further ahead tend to win more (Stern 1994). But could being slightly behind actually increase success? Could losing lead to winning?

Competitions are pervasive and have an important influence on motivation and performance (Bloom 1999, DeVaro 2006, Erev et al. 1993, Lazear and Rosen 1981, Zajonc 1965). One concern with tournament incentives, however, is that people who are losing may get discouraged and reduce their effort (e.g., Barankay 2010, Fershtman and Gneezy 2011). Telling employees how they are doing in a monthly sales competition, for example, might lead some workers to give up. But whereas one could imagine that being far behind might lead people to quit, the impact of losing by only a small amount is less clear. How do people respond when they are only slightly behind? Could losing by a little actually *increase* motivation and performance?

We suggest this possibility based on research on goals and motivation. Goals drive people to achieve (Lewin 1946). Although finishing part of a project or scoring a touchdown requires the same amount of effort whether a person or team is ahead or behind, goals can act as reference points (Heath et al. 1999). Consequently, position relative to a goal can influence motivation in a manner consistent with prospect theory's (Kahneman and Tversky 1979, Tversky and Kahneman 1992) key tenets: (1) reference points, whereby people categorize outcomes as gains (success) or losses (failure) depending on where they fall relative to a particular standard; (2) loss aversion, whereby losses are more painful than gains are pleasurable; and (3) diminishing sensitivity, whereby outcomes have a smaller marginal impact as they move further from the reference point. Loss aversion suggests that compared to people who are above their goal by a similar amount, people who are below or behind their goal will work harder because they see their performance as a loss. Furthermore, because of diminishing sensitivity, people who are slightly below their goals should work harder than those for whom the goal is further away (Heath et al. 1999, Kivetz et al. 2006).

These ideas have important implications for competition. Because winning involves doing better than one's adversaries, an opponent's performance should serve as a salient benchmark, and individuals and teams are likely to evaluate their own performance relative to that reference point. Though the actual level of this point may move around throughout the competition, whether people code their current performance as a gain or loss should depend on whether they are ahead or behind at that particular moment. As a result, as long as people are aware of how they are doing relative to their competition, being slightly behind may actually increase motivation and make them more likely to win.

We test how losing by a little affects motivation and performance in both the laboratory and the field. First, we analyze more than 18,000 National Basketball Association (NBA) basketball games (Study 1) and 45,000 collegiate basketball games (Study 2) to examine how being slightly behind at halftime affects whether teams win or lose. Building on these findings, we then use controlled experiments to directly test the causal impact of being slightly behind on individual effort (Study 3) and the role of self-efficacy in these effects (Study 4).

2. Study 1: Being Slightly Behind in Professional Basketball

First, we examined how NBA basketball teams' likelihood of winning varies based on the halftime point differential. Our analysis focuses on halftime for a number of reasons. First, feedback helps people adjust their effort to meet their goals (Locke and Latham 2002), and the break provides a chance for all players to be aware of the score. Second, time to consider one's relative position should invite reflection and increase the salience of the reference point. Third, especially in situations where performance depends on members working together, increased performance is more likely if everyone understands where they stand relative to the goal. Overall, because of the sustained break, halftime provides an ideal opportunity for all team members to know their position relative to their opponent, reflect on it, discuss it, and become motivated.[1]

Importantly, rather than just looking at overall winning percentages based on halftime score, we use a regression discontinuity (RD) design to estimate the *causal* impact of being slightly behind. Unlike a randomized experiment, basketball teams are not randomly assigned to be winning or losing. A regression discontinuity design allows us to overcome this lack of randomization and make causal inferences. Teams that are on either side of the discontinuity (barely winning versus barely losing) should be similar on other factors (something we explicitly test below), allowing us to examine the causal impact of losing by a small amount. Intuitively, our design allows us to construct an underlying model for how well teams "should" do given their halftime score relative to their opponent. We can then identify whether a discontinuity occurs in actual success relative to predicted success between teams that are just barely losing and teams that are just barely winning at halftime. The discontinuity in actual versus predicted success that we estimate can be interpreted as the causal effect of a team that is losing relative to winning at halftime while holding all else constant.

Overall, we expect that being slightly behind should increase a team's chance of winning. If this boost is large enough, teams behind by a point at halftime may actually be more likely than their opponents to win.

2.1. Method

Our data consist of all games played between the 1993/1994 season and March 1, 2009. This represents 18,060 unique games. These data include information about the date of each game, team identifiers, and an indicator for the home team. NBA games last 48 minutes with a 15-minute break for halftime and an overtime period if the game ends in a tie. Importantly, the data not only indicate the winner of each game, but also contain the score for both teams at halftime. Using the dates and team identifiers, we also calculate the season winning percentage for each team.[2]

Our analyses compare home and away teams. To not double count all of the data, only one team can be chosen from each game to use in the analysis. Rather than choosing a team at random (which can result in different figures, depending on the random selection of teams), we chose 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.

To identify the causal effect of losing on subsequent performance, we use an 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 Lemieux 2008, 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 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.

[1] Regular time-outs may also provide time for reflection, but it is difficult to infer causation because they may be endogenous (i.e., team performance may shape whether coaches call a time-out) and they require much more detailed data.

[2] 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.

In its most simple form, our 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, $losing\ at\ halftime_i$ is an indicator equal to 1 if the home team was losing by 1 or more points at the halftime break,[3] and $(score\ difference\ at\ halftime)_i$ is the forcing variable that indicates the difference between the home team score and the away team score at halftime. Although the equation above specifies that the forcing variable enter linearly, we relax this assumption and include a more flexible form in robustness specifications. Denoted by X_i is a matrix of control variables for game i such as the winning percentages of the home and away teams.

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 ancillary analyses below, 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 around the threshold are not causing systematic bias.

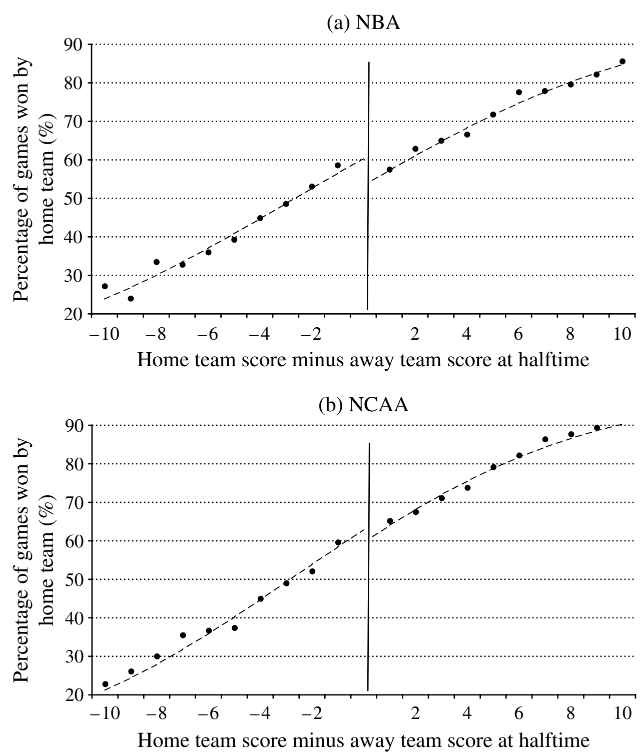
Importantly, our identification strategy allows us to make causal inferences about how being behind at halftime affects performance, but such claims can only be made about points near the discontinuity. As one moves further from the discontinuity, potential nonlinearity in the halftime score difference variable makes 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 affects subsequent performance. In RD settings, this treatment effect is oftentimes referred to as a "local average treatment effect." In other words, we are able to identify the impact of losing on motivation "locally" around the discontinuity, whereas the impact of losing on motivation for teams that are not close to the discontinuity at halftime is not tightly identified.

2.2. Results

We first examine the relationship between score differential and winning percentage by graphing the raw data. Figure 1(a) illustrates the percentage of games won by the home team with respect to the halftime score difference. The dotted line represents a linear fit (linear in a logistic model) of the data while allowing for a discontinuity at zero. This line enables a graphical illustration of the size of the discontinuity in the data.

Not surprisingly, the further teams are ahead, the more likely they generally are to win. Teams score 97.3 points each on average each game, and teams ahead 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 a six to eight percentage point increase in the probability of winning.

Figure 1 **The Percentage of Games Won by the Home Team by the Score Difference (Home Team Minus Away Team) at Halftime for NBA (a) and NCAA (b) Basketball Games**



Notes. The raw data are presented with dots. The dotted lines represent the logistic linear fit of the score difference on winning, allowing for a discontinuity when a team is behind.

[3] A question arises in our analysis regarding what to do with teams tied at halftime. It is unclear whether being tied is like losing and thus should be classified as "losing at halftime" or 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. Figure A.1 in the appendix allows a visual view of tied teams.

There is a strong discontinuity, however, around zero. Rather than having a winning percentage that is six to eight 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% of games); see Figure A.1 in the appendix for a close-up with error bars. (Alternatively, focusing on away teams also shows that away teams behind by a point are more likely than their opponents to win: 42.9% versus 41.8%.) This is particularly noteworthy given the many reasons why teams losing by one should be less likely to win. They are not as good as their opponents,[4] for example, and, mechanically, have to score two more points than their opponents to emerge victorious.

To formally test whether the difference in winning percentage is statistically different than expected, we conduct the regression specified earlier. Table 1, panel A displays the results. Columns (1) and (3) control for the halftime score difference linearly, and columns (2) and (4) include a cubic function of the halftime score difference.[5] Columns (1) and (2) include no additional controls, and columns (3) and (4) include the home and away teams' season winning percentages as controls. Across specifications, results indicate that being slightly behind significantly increases a team's chance of winning. Overall, teams that are losing at halftime win 5.8 to 8.0 percentage points more often than expected. These numbers are economically large and highly significant.

2.2.1. Ancillary Analyses. Further analyses show that various factors affecting winning percentage do not change discontinuously around zero, supporting our interpretation that these results are causal. First, the number of games in which the home team was behind versus ahead by a point at halftime does not change discontinuously around zero (Figure 2). Second, teams with higher season winning percentages were not more likely to end the first half at a slight deficit (home team: $p = 0.90$; Figure 3(a)). The same test for away teams (Figure 4(a)) actually shows a small but insignificant discontinuity in the opposite direction (away teams are directionally better when the home team is down by one; $p = 0.18$), which explains why the results in Table 1 increase slightly in panel A when controlling for home and away team winning percentages.

Table 1 The Impact of Losing at Halftime on Winning

	Dependent variable: Indicator = 1 if the home team won			
	(1)	(2)	(3)	(4)
Panel A: NBA data				
Losing at halftime	0.058***	0.074***	0.062***	0.080***
	(0.015)	(0.021)	(0.015)	(0.020)
Home team winning percentage			0.0068***	0.0068***
			(0.0002)	(0.0002)
Away team winning percentage			−0.0065***	−0.0065***
			(0.0002)	(0.0002)
Halftime score difference (linear)	X	X	X	X
Halftime score difference (cubic)		X		X
Pseudo-R^2	0.097	0.097	0.172	0.172
Observations	11,968	11,968	11,968	11,968
Panel B: NCAA data				
Losing at halftime	0.025***	0.023*	0.025***	0.021
	(0.010)	(0.014)	(0.009)	(0.013)
Home team winning percentage			0.0057***	0.0057***
			(0.0001)	(0.0001)
Away team winning percentage			−0.0055***	−0.0055***
			(0.0001)	(0.0001)
Halftime score difference (linear)	X	X	X	X
Halftime score difference (cubic)		X		X
Pseudo-R^2	0.143	0.144	0.207	0.208
Observations	29,159	29,159	28,808	28,808

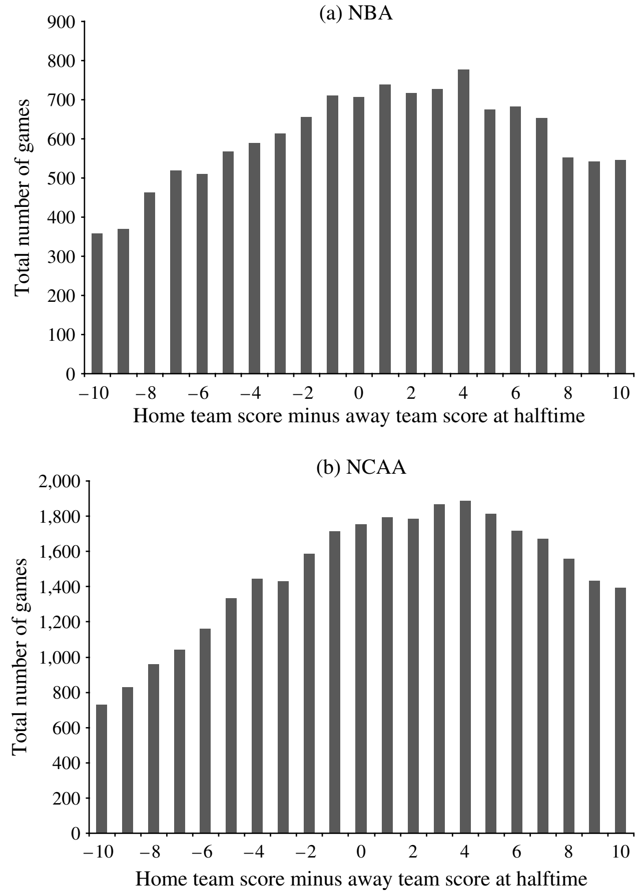
Notes. This table reports marginal-effects coefficients and robust standard errors using a logit model. The dependent variable is an indicator that equals one if the home team won. *Losing at halftime* is an indicator of whether the home team was losing by one or more points. The *halftime score difference* 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%.

Differences in coaching also have trouble explaining the results. Though it seems unlikely for teams down by only a point, one could argue that being slightly behind led to winning not because it motivated the players but because it led coaches to give a different type of speech or change their strategy. To test these possibilities, we collected data on the career winning percentage for all of the coaches in our data. Coaches with a higher career winning percentage should give stronger halftime speeches or change strategy more effectively, so we examined whether teams down by one at halftime were even more likely to win if they were led by a more experienced coach. They were not. Teams that were slightly behind were no more likely to win if their coach had a higher career winning percentage (losing by one x coach career winning percentage interaction;

[4] Ancillary analyses show that, on average, teams that are down by a point are worse teams than teams ahead by a point: they have a lower season winning percentage (49.81% versus 50.90%).

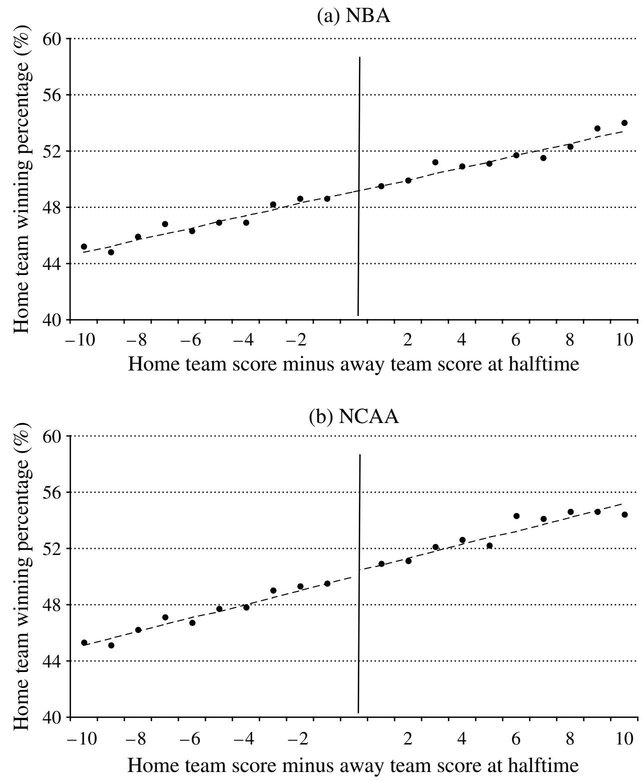
[5] In our analysis, there is a strong reason to assume that the slope of the forcing variable (score difference at halftime) is similar above and below the discontinuity. However, it is not necessary to make this assumption. We have also performed regressions separately above and below the discontinuity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

Figure 2 **The Density of the Forcing Variable**



Notes. Specifically, for every possible point difference at halftime between the home team and away team, the total number of games with that point difference is shown (for both the NBA (a) and NCAA (b)).

Figure 3 **The Season Winning Percentage of the Home Team by the Score Difference (Home Team Minus Away Team) at Halftime for NBA (a) and NCAA (b) Basketball Games**



Notes. The raw data are presented with dots. The dotted lines represent the logistic linear fit of score difference on season winning percentage, allowing for a discontinuity when a team is behind.

$p = 0.17$), casting doubt on the possibility that the effect is driven by strength of the coach's speech or halftime strategy adjustment.

Finally, if being slightly behind is motivating, as we suggest, then the greatest impact of being behind at halftime should be strongest immediately following that break. Using the quarter-by-quarter score data for the NBA, we tested this possibility by looking at whether losing at halftime had a larger impact on winning in the third quarter or the fourth quarter. Table 2 provides the results of losing at halftime on an indicator for whether the home team scored more points than the away team in the third quarter (panel A) and the fourth quarter (panel B). The signs of the coefficients suggest that losing at halftime increased the probability of the home team winning in both the third and fourth quarters. However, the coefficients are larger and statistically significant only for the third quarter.

2.3. Discussion

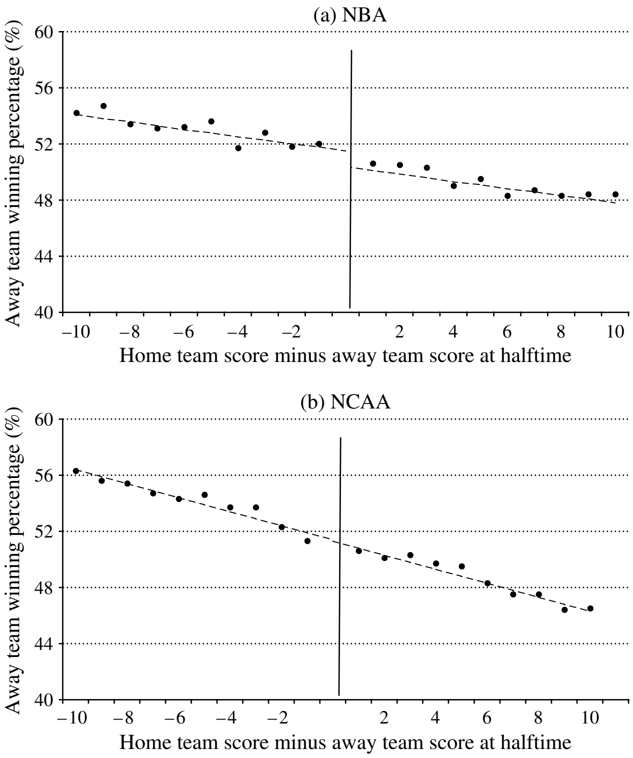
Can losing lead to winning? Analysis of more than 18,000 NBA basketball games suggests it can. Not only did being behind at halftime increase a team's chance of winning (between 5.8% and 8.0%), but compared to their opponents, teams that were behind by one were actually *more* likely to win. The boost is comparable to the increase in winning percentage from being ahead by two points at the half, or about half the size of the proverbial home-team advantage (Cooper et al. 1992).

We can also cast doubt on some alternative explanations. Though one could argue that being behind might induce a strategy change, such changes are unlikely if a team is only down by a point. Furthermore, any change in strategy should not necessarily lead teams to be more likely to win. Similarly, though one could argue that being behind might encourage people to take risks (Larrick et al. 2009), it is unclear that this should increase success. If anything, riskier play could lead teams to lose.

3. Study 2: Being Slightly Behind in the NCAA

In Study 2, we examined whether similar effects would also be observed in another domain (i.e., college basketball). Though the players are not as

Figure 4 The Season Winning Percentage of the Away Team by the Score Difference (Home Team Minus Away Team) at Halftime for NBA (a) and NCAA (b) Basketball Games



Notes. The raw data are presented with dots. The dotted lines represent the logistic linear fit of score difference on season winning percentage, allowing for a discontinuity when a team is behind.

experienced, and the stakes arguably are not as large, it provides another setting to examine how being slightly behind affects performance.

3.1. Method

Our data consist of all the National Collegiate Athletic Association (NCAA) basketball games played between the 1999/2000 season and March 22, 2009, which represents 45,579 unique games. NCAA games are slightly shorter (40 minutes) but still have a 15-minute break for halftime. We use the same type of data (e.g., halftime scores, final scores, etc.) and analysis structure as used in our NBA analysis.

3.2. Results

Results were consistent with those observed in the NBA. First, graphing the relationship between score differential and winning percentage again shows a significant discontinuity around zero (Figure 1(b)). Next, to formally test whether the difference in winning percentage is statistically different than expected, we conducted the regression specified earlier. Results indicate that being slightly behind significantly increases a team's chance of winning (Table 1, panel B). Though smaller than the NBA results, these effects continue to be statistically significant for most specifications. Furthermore, Figures 2(b), 3(b), and 4(b) also show the same pattern as observed in the NBA data, whereby factors that affect winning percentage do not change discontinuously around zero.

Table 2 The Impact of Losing at Halftime on Winning the Third and Fourth Quarters

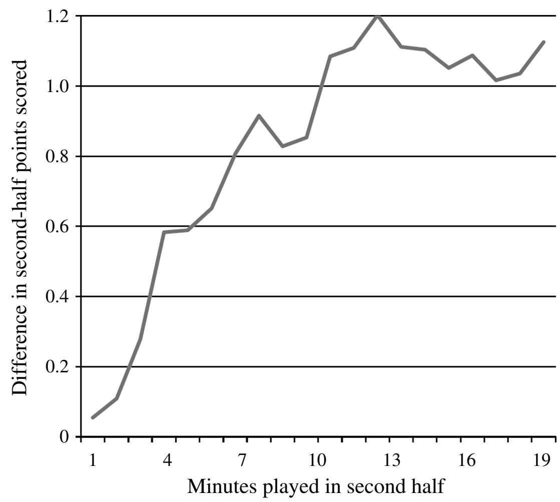
Panel A: Third quarter				
	Dependent variable: Indicator = 1 if the home team won the third quarter			
	(1)	(2)	(3)	(4)
Losing at halftime	0.032* (0.019)	0.037* (0.027)	0.037** (0.018)	0.042 (0.026)
Home team winning percentage			0.0054*** (0.0003)	0.0054*** (0.0003)
Away team winning percentage			−0.0045*** (0.0003)	−0.0045*** (0.0003)
Halftime score difference (linear)	X	X	X	X
Halftime score difference (cubic)		X		X
Pseudo-R^2	0.003	0.003	0.039	0.039
Observations	11,968	11,968	11,968	11,968
Panel B: Fourth quarter				
	Dependent variable: Indicator = 1 if the home team won the fourth quarter			
	(1)	(2)	(3)	(4)
Losing at halftime	0.020 (0.019)	0.026 (0.027)	0.024 (0.018)	0.029 (0.026)
Home team winning percentage			0.0037*** (0.0003)	0.0037*** (0.0003)
Away team winning percentage			−0.0033*** (0.0003)	−0.0033*** (0.0003)
Halftime score difference (linear)	X	X	X	X
Halftime score difference (cubic)		X		X
Pseudo-R^2	0.002	0.002	0.019	0.019
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 scored more points than the away team in the third quarter (panel A) or fourth quarter (panel B). *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%.

3.2.1. Ancillary Analyses. We also conducted a more fine-grained analysis of whether being slightly behind at halftime had the greatest impact immediately following that break. We looked at the minute-by-minute scoring differential for a subset of NCAA games for teams down by one at the half

Figure 5 Point Difference Narrowing over the Second Half



over the rest of the game.[6] These teams scored almost 1.2 points more than their opponents during the second half. More importantly, and consistent with our hypotheses, nearly half this difference occurred in the first four minutes (see Figure 5). This further suggests that the increased probability of winning is driven largely by the losing team exerting more effort immediately after they are slightly behind.

3.3. Discussion

Analysis of NCAA basketball games provides further evidence that losing can lead to winning. Replicating the pattern from the NBA data, being down at halftime significantly increased a team's likelihood of winning. Ancillary results further indicate that the increased winning percentage is driven by the losing team exerting additional effort directly following being behind. Teams that were slightly behind at halftime scored more in the second half, but did so most strongly right after the break. Finally, teams that are slightly behind are no more likely to win if their coach has a higher winning percentage, casting doubt on the possibility that the effect is driven by strength of the coach's speech or halftime strategy adjustment.

Results of the field analyses (Studies 1 and 2) support our hypothesis, but as with most field data, it is difficult to rule out all possible alternatives. Though unlikely, one could argue that teams that are slightly behind win more because referees treat them differently. Alternatively, one might suggest that the second-half scoring differential is driven by winning teams becoming complacent. Because one team's effort directly affects the other's output, however, it is difficult to tease apart these mechanisms in the field data. There is no evidence of reduced scoring by the winning team, for example, but even if there were, it would be difficult to tease apart complacency from better defense by the team down by one. Consequently, we conducted two laboratory experiments to look at how competitive feedback influences motivation. By directly manipulating competitive feedback, we provide evidence for its causal impact on effort.

4. Study 3: Competitive Feedback and Effort

The next two studies examine how competitive feedback influences effort.

Participants engaged in a short competition task divided into two periods. Between periods, participants were either told nothing or given competitive feedback: they were either told they were far behind, slightly behind, tied, or slightly ahead of another participant with whom they were competing. These conditions allow us to test whether being slightly behind increases effort relative to being tied, being slightly ahead, or even not receiving any feedback at all. Furthermore, they allow us to test whether the motivating effects of being behind hold even for being far behind and whether being slightly ahead induces complacency.

We predicted that competitive feedback would influence effort. Whereas loss aversion suggests that competitors who are behind should work harder than those who are ahead, diminishing sensitivity suggests that the motivating effects of being behind should be particularly likely when close to the goal. Consequently, participants given competitive feedback that they are behind their opponent should exert more effort, but only when they are relatively close behind. Individuals who are far behind should show no such effort boost.

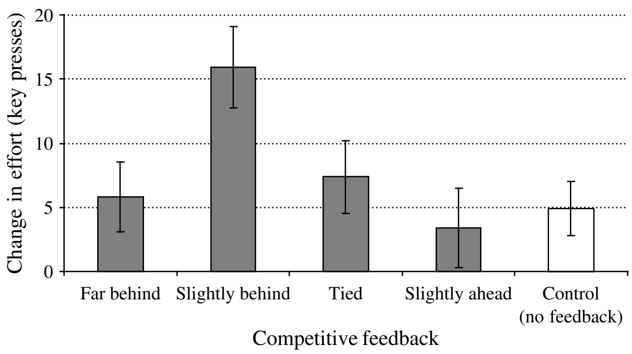
4.1. Method

Participants ($N = 171$) completed a short game as part of a larger series of experiments for which they were paid \$10. They were told the experimenters were interested in how personality influenced competition and completed some innocuous items to complete the cover story. Participants were then instructed about the game. They were told they would engage in a competition with another participant, and whoever had the most points would win an additional \$3. The game involved pressing the "a" and "b" keys in succession as quickly as possible. Pressing the combination in order scored a point. The game had two 30-second periods divided by a short break.

The only difference between conditions was the information participants received between the two periods. In the competitive feedback conditions, they were told they were far behind (−50 points), slightly

[6] We extracted play-by-play data for all of the regular-season NCAA games posted on ESPN.com—3,286 games.

Figure 6 Extra Effort as a Result of Competitive Feedback



behind (−1 points), tied, or slightly ahead (+1 points) of their opponent.[7] In the control condition, they were given no information about their relative performance and were just told that the second period was about to begin.

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

4.2. Results and Discussion

Does being slightly behind an opponent lead people to exert more effort? Results of a one-way analysis of variance suggest that it does (Figure 6). Overall, competitive feedback influenced effort ($F(4, 166) = 2.49$, $p < 0.05$). Furthermore, planned contrasts revealed that being behind opponents led people to exert more effort, but only when they were slightly behind. Participants informed that they were slightly behind exerted more effort than participants in any of the other conditions (all t values > 1.96, all p values < 0.05). All other conditions were equivalent (all t values < 1.0, all p values > 0.35), indicating that being far behind did not increase effort, and being slightly ahead did not decrease effort.

These results both underscore and clarify the results of the field data. First, merely telling people they were slightly behind an opponent led them to exert more effort. Competitive feedback that they were slightly behind not only increased effort in general, but did so more than being tied, slightly ahead, or receiving no competitive feedback at all. Second, although being behind boosted effort, it did so only when participants were slightly (versus far) behind. This is consistent with diminishing sensitivity, whereby individuals should work harder when they are closer to, compared to farther from, their goal (Heath et al. 1999). Though being too far behind should eventually become demotivating and reduce performance, our "far behind" manipulation may not have been so drastic that participants gave up. Third, the results cast doubt on the notion that the field results were driven by winning team complacency. Though people may get complacent when they are far ahead, these data show no evidence that being slightly ahead decreased effort.

More broadly, although competitive feedback could lead to strategy change in some instances (e.g., when individual are far behind), results of Study 3 provide further evidence consistent with the notion that our effects are driven by changes in effort. The experimental results show that being slightly behind can lead to increased performance even in a situation where strategies do not exist (there are not really different strategies to press keys faster). Combined with the fact that our effect is not stronger for better coaches in the NBA (who should be better at changing strategy), these results suggest that our effects are driven by teams and individuals exerting more effort when they are slightly behind.

5. Study 4: Moderating Role of Self-Efficacy

The final study looked to provide additional insight into the underlying mechanism behind the observed effects. We have suggested that being behind motivates individuals and teams to work harder, but this should only occur if people believe they can actually achieve their goal. Although some people may believe they can come back from being behind, for example, others may not think they can do it and, and a result, should be unlikely to work as hard.

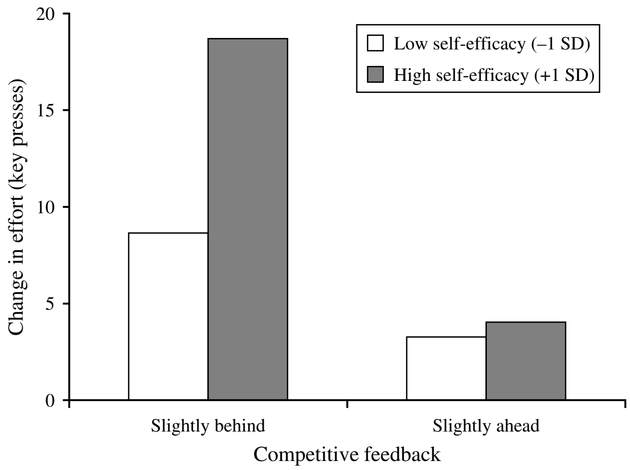
Along these lines, Study 4 examined the moderating role of self-efficacy. Self-efficacy (Bandura 1997) describes the belief that one can achieve desired outcomes and has been shown to play an important role in goal setting, motivation, and performance (see Stajkovic and Luthans 1998 for a review). In particular, individuals with high self-efficacy are more likely to sustain or even heighten effort in the face of setbacks (Bandura 1997). Consequently, we argue that the motivating effects of being slightly behind should be more likely to occur among individuals with higher self-efficacy.

5.1. Method

Participants ($N = 114$) were paid \$10 to complete a set of experiments. First, they filled out an eight-item general self-efficacy scale (e.g., "In general, I think that I can obtain outcomes that are important to me": 1 = strongly disagree, 5 = strongly agree; Chen et al. 2001). Then, after completing some filler tasks, they completed the competition task from Study 3. To simplify the design, participants were told that they were either slightly behind (−1 point) or slightly ahead (+1 point) of their opponent.

[7] The far-behind amount was selected because average scores in a period were around 140 points.

Figure 7 **Extra Effort as a Result of Competitive Feedback and Self-Efficacy**



5.2. Results and Discussion

We again examined how competitive feedback influenced effort by taking the difference in participants' output across the periods and comparing it across conditions. Responses to the self-efficacy scale were averaged across items, and we followed Aiken and West's (1991) recommended procedure for multiple regression, mean centering self-efficacy and examining change in effort as a function of competitive feedback, self-efficacy, and their interaction.

Results indicated that main effects of competitive feedback ($\beta = 0.24$, $t = 2.32$, $p < 0.03$) and self-efficacy ($\beta = 0.24$, $t = 2.37$, $p < 0.02$) were qualified by the predicted competitive feedback x self-efficacy interaction ($\beta = 0.21$, $t = 2.04$, $p < 0.04$; Figure 7). Specifically, among participants who thought they were slightly behind their opponent, there was a significant effect of self-efficacy on effort ($\beta = 0.45$, $t = 3.43$, $p < 0.001$), such that participants with higher self-efficacy exerted more effort. There was no corresponding effect of self-efficacy among participants informed that they were slightly ahead ($\beta = 0.03$, $t < 0.3$, $p > 0.80$). We also looked at the data another way by decomposing the interaction at one standard deviation above and below the mean for self-efficacy. This revealed that compared to being told they were slightly ahead, being told they were slightly behind their opponent increased effort among high-self-efficacy participants ($\beta = 0.45$, $t = 2.90$, $p < 0.005$). There was no corresponding effect of competitive feedback among low-self-efficacy participants ($\beta = 0.03$, $t < 0.2$, $p > 0.80$).

The results of Study 4 provide further insight into when and why being slightly behind an opponent will increase effort. Compared to being slightly ahead, being behind an opponent again led participants to exert more effort, but this was moderated by individual differences in self-efficacy. Individuals who had high self-efficacy, or greater belief in their ability to achieve their goals, were more likely to respond to feedback that they were behind by working harder and exerting more effort.

6. Discussion

Competitions and tournaments are pervasive. Individuals compete for promotions, teams compete for performance bonuses, and companies compete for government contracts. But whereas research has begun to look at the overall effects of tournaments and competitions, less is known about how they might affect the motivation and performance of individuals based on where they stand relative to their competitors. This issue is particularly important given that people who are losing may give up or reduce their effort (see Fershtman and Gneezy 2011).

Our findings, however, demonstrate that losing can sometimes lead to winning. Using a credible identification strategy and analyzing more than 60,000 NBA and NCAA basketball games, we show large and significant effects of being slightly behind an opponent on increased success (Studies 1 and 2). NBA teams that are down by a point at halftime, for example, win 5.8 to 8.0 percentage points more often than expected. This psychological effect is roughly half the size of the proverbial home-team advantage. Furthermore, the increased winning percentage is driven by the losing team exerting additional effort directly following the decrement. Teams that were slightly behind at halftime scored more in the second half, but did so most strongly right after the break.

Experimental results (Studies 3 and 4) underscore these findings and bolster their generalizability. Being slightly behind an opponent can boost effort among individuals (rather than just teams), even in situations in which coaches and referees are not present. The results further illustrate the important role of self-efficacy in moderating these effects: people who believe they can achieve their goals even in the face of setbacks are more likely to increase effort after being slightly behind.

6.1. Implications and Directions for Future Research

The level at which an individual or team feels slightly behind should be context dependent. Whereas one point is barely behind in basketball, for example, one unit is actually a much bigger deficit in something like soccer, where goal scoring is much less frequent. Similarly, whereas being one behind in a sales competition may be motivating if sales are relatively easy, if most people complete only three sales a month, such a deficit may seem much larger and thus have little boost on motivation.

Being further behind is less likely to have positive effects. Regression discontinuity analysis does not allow for broader causal inferences about potential benefits (or costs) of being behind by several or more points, but rough examination suggests that teams that were down by more than a point did not win more often than their opponents. This is likely due to a number of factors. Diminishing sensitivity suggests that teams that are further behind their opponents should exert less effort than those that are only slightly behind. Teams that are further behind also tend to be worse, and the magnitude of the deficit makes it unlikely that even motivated teams that are further behind can catch up. Teams that were two points behind scored more than expected relative to their opponents, for example, but not enough to boost their winning percentage. More generally, as shown in Study 4, being behind should only be motivating when the deficit seems surmountable.

We focused on situations where individuals evaluated their performance relative to competitors, but fixed numbers can also sometimes serve as the comparative standard (e.g., surpassing a round number like 1,200 or 1,300 on the SAT; Pope and Simonsohn 2011). Whether relative performance (to a competitor) or fixed standards serve as reference points may depend in part on the salience of the different types of information, the norms associated with different domains, or the incentives involved. In head-to-head competitions, a competitor's score may be the most salient reference point, whereas in more individual tasks (e.g., SAT taking) a fixed standard may be more salient.

Our findings also speak to the ongoing debate about whether psychological 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). Our findings suggest, however, that even experienced professionals (NBA basketball players) competing for large stakes are prone to exhibit nonstandard behavior. In fact, our results are even stronger in the NBA (where the players are more experienced) than in the NCAA. One potential explanation for this finding may be due to selection. NBA basketball players may be particularly susceptible to a psychological motivation driven by losing, given that these are individuals who selected into a job that rewards competitiveness.

These findings have important implications for incentive design and motivating employees and others. Rather than giving people the full distribution (i.e., how they did relative to everyone else), telling them about their performance relative to the person directly in front of them should encourage everyone to work harder. Similarly, creating smaller tournament groups where people are organized by ability should put everyone closer to the reference point and improve performance. Golfers are flighted into groups with similar skill levels, and students can be grouped into classes by ability.

In conclusion, encouraging people to see themselves as behind others, albeit slightly, should increase effort. Managers trying to encourage employees to work harder, for example, might provide feedback about how a person is doing relative to a slightly better performer. Strategically scheduling breaks when someone is slightly behind should also help focus people on the deficit and subsequently increase effort. This should lead to stronger performance, and ultimately, success.

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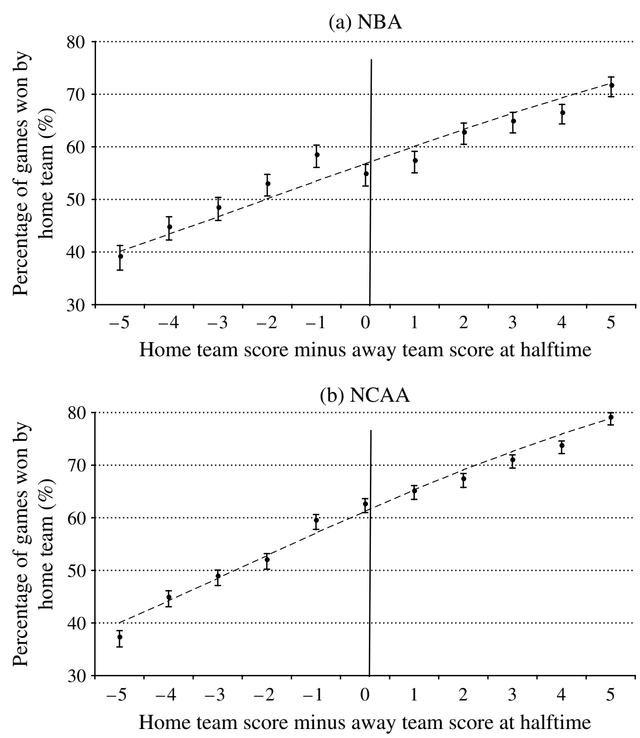
Appendix

Figure A.1 The Percentage of Games Won by the Home Team by the Score Difference (Home Team Minus Away Team) at Halftime for NBA (a) and NCAA (b) Basketball Games



Notes. The raw data are presented with dots and include standard error bars. The dotted lines represent the logistic linear fit of score difference on winning that does not include a discontinuity when a team is behind.

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