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Individual Performance after Success and Failure - A Natural Experiment

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Individual Performance after Success and Failure - A Natural Experiment

Christoph Bühren, Stefan Krabel♠*

Abstract

The main goal of our study is to analyze how success and failure in crucial situations affect subsequent individual performance. Our study is based on evidence from a natural experiment of NBA (National Basketball Association) players: Based on play-by-play statistics of NBA games in 10 seasons (1818 observations of 345 sportsmen), we identify players who are responsible for the overtime by taking the last shot of the game. Players who miss the shot when the game is tied perform better in overtime than in the last quarter (within-subject comparison) but not significantly different to their game and season averages. Players who score the equalizer in the last shot of the regular game perform substantially worse in overtime compared to their 4th quarter performance as well as compared to their game and season averages. Yet the average performances in overtime of both groups do not differ significantly (between-subject comparison). We conclude that success in crucial situations leads to lower subsequent individual performance. Psychological explanations for this phenomenon, e.g. the role of overconfidence, are discussed. We argue that our findings can be transferred to behavior after success or failure in business settings since we have distinct identifications of performance and responsibility: the observed overtimes are clear and immediate outcomes of the last shots of our analyzed players; without their success or failure, the game would have been over after regular time.

Keywords: success, failure, performance, psychological pressure, overconfidence, hot hand fallacy, natural experiment, basketball, NBA

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Research Highlights:

- We analyze performance after success and failure by studying NBA overtime matches.
- We identify players responsible for overtime by taking the last shot of the game.
- Players who miss the last shot of the regular game perform slightly better in overtime.
- Players who score the equalizer in the last shot perform substantially worse in overtime.
- We argue that employees' productivity drops after very successful events.

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1. Introduction

How do individuals react to successes and failures in their daily work? Do they perform better or worse afterwards? This question is of interest to behavioral economics, management, and psychology. Imagine a young scientist having published a great paper or imagine a programmer having solved an important algorithm: Should you encourage them to instantly work on the next paper or the next software problem? Or should you give them a week off?

The central question how individuals react to failure and success has inspired previous streams of literature in behavioral economics and psychology. Previous (mostly psychological) literature has addressed this question by providing theoretical considerations and experiments designed to analyze the impact of priming and feedback on performance. While this literature has provided important insights, an unresolved issue is the “generalizability” of the results and the external validity of laboratory settings (Apesteguia and Palacios-Huerta, 2010). The best way to study individuals’ performance after (un-)successful events would be to study work behavior in business. Yet, in business it is very difficult to study the impact of success on subsequent performance because individuals’ tasks have become manifold. Workers are responsible for many projects and perform in multiple roles at the same time. This makes it extremely difficult to identify cases of success or failure and their impact on subsequent performance as it would require an assessment of each task fulfilled. Moreover, relating performance to cases of success would also require a control of the previous productivity of workers.

In this paper, we take advantage of a natural experiment, which provides the opportunity to analyze the impact of relevant cases of success and failure on subsequent performance in an unusually clean setting. Drawing upon play-by-play statistics of NBA basketball games, we are able to pool overtime games and to identify players who are responsible for the overtime – either by scoring the equalizer on the last seconds of the shot-clock or by missing the last shot (when the game was tied). In this example of a natural experiment, the subjects are professionals who are highly incentivized to win the game as their salary, titles, careers, and audience support greatly depends on how well they and their team perform. Furthermore, the players automatically receive feedback. When they miss the last shot of a tied game, they know that the game would have been won if they had scored the last shot. Likewise, players know that the game would have been lost if they had not scored the equalizer on the last move. Thus, players are aware that they are responsible for the overtime and that the game would have already been decided in their favor (in the favor of the opponent team) if they had not missed (scored) the last shot.

In order to assess the relative performance of players in overtime, we apply several measures used by NBA scouts, specifically the hit-to-miss-ratio of shots as well as assists, rebounds, steals, and blocks normalized to minutes played. These performance indicators are available for each quarter. The data allows an assessment of how well players perform in overtime compared to their own performance in the last quarter of the game, the regular playing time, and the corresponding season. Moreover, we use information on the distance of the last shot in order to assess whether the shot was attempted from a reasonable distance given the players playing position. We take into account further proxies of psychological pressure like the final score after overtime and also distinguish between home and away matches.

Our results suggest that players who force overtime by scoring the equalizing shot in the last scene of the 4th period perform substantially worse in overtime. Their average scoring percentage drops by approximately 13 percentage points. Other performance indicators seem to confirm this result. Players who force overtime by missing the last shot perform approximately 9 percentage points better in overtime compared to the rest of the game. Again, other performance indicators verify this result. We try to control for the selection bias in our treatment groups, which ceteris paribus differ in their 4th quarter scoring percentage because of missing or scoring the last goal, by dropping this last shot and by comparing performance to game and season averages. Further, we add a control group to our dataset with players who are not directly responsible for the overtime. We also analyze the endurance of the effect induced by success vs. failure by looking at games with more than one overtime. Finally, we conduct multivariate analyses in order to control for player and game specific variables.

Our results suggest that players' precision drops substantially after having experienced the success of forcing the overtime. Yet, the drop of performance is mainly based on superior performance during the 4th quarter rather than on inferior performance in overtime. Comparing the group of players who force overtime by scoring the equalizer in regular playing time with the group of players who miss the last shot when the game is tied as well as with the control group (of players not taking the last shot) we find that performance of these three groups in overtime is not significantly different. We discuss different reasons for these findings: first, experiencing success may lead to subsequent mental lapses or overconfidence, such that these players cannot transfer their superior performance in the regular playing period to overtime. Second, experiencing failure may lead to taking less risks as compared to before and trying to compensate for the failure. Lastly, professional players' performance may be largely independent of prior performance such that neither making nor missing the last shot – and similarly overall performance – in the regular playing period affects subsequent performance.

Our findings have important implications for the business world and other real life settings. Our analysis suggests that individuals' productivity decreases after successes. Managers should not deliberately assign important tasks to employees who have experienced a recent success. Rather the opposite might proof useful: they should assign important tasks to employees who recently experienced failure and subsequently compensate for their previous failure by improving their productivity.

The remainder of the paper is structured as follows. Section 2 introduces literature related to our central research question. Section 3 describes the data source, the measurement of variables and provides descriptive statistics. In section 4.1., our results are derived by nonparametric statistics and in section 4.2. we conduct multivariate analyses. Section 5 concludes.

2. Related Literature

By investigating how individuals' performance is affected by previous successes or failure events in crucial situations, this paper relates to several existing literature streams in economics, management and psychology. Behavioral economics and psychology have addressed this question by investigating how individuals react to feedback. A number of studies use experimental settings or hypothetical scenarios in order to analyze how individuals react to positive or negative feedback.

In a lab experiment on feedback and goal-setting by Matsui et al. (1987), subjects get a half-time feedback on their performance in a 15 minute perceptual speed task for which they earn prizes based on their performance. If individuals or groups performed badly according to self-set goals after half of the time, i.e. after negative feedback, their performance increased significantly. McFarlin and Blascovich (1981) show that the responsiveness to feedback is influenced by self-esteem: In their study, self-esteem (measured by the Texas Social Behavior Inventory) had a larger impact on subjects' perceived ability in future performance than feedback on their actual performance. Derr and Laing (1987) find that after negative feedback (without goal-setting), students with low self-esteem perform worse in subsequent exams than students with high self-esteem whereas they perform equally well after positive feedback. Similarly, in a two-stage basketball dribbling task studied by Martin-Krumm et al. (2003) optimistic participants performed better than pessimistic ones in the second stage after negative feedback regarding the first stage. However, Martin-Krumm et al. (2003) gave false feedback: They told every subject that he or she performed worse compared to other participants.

The self-confidence of individuals rises with positive feedback and falls with negative feedback: McCarty (1986) finds that women are especially responsive to negative feedback -

While men are more confident than women per se, this difference gets smaller in his positive feedback treatment and much larger in his negative feedback treatment. Eil and Rao (2010) find that participants on average respond less to negative than positive feedback when estimating their own IQ- and attractiveness.

Some studies find that individuals may become overconfident after positive feedback and tend to overestimate their skills. For instance, previous superior performance on financial markets leads to overconfidence of investors (Menkhoff, Schmeling, and Schmidt, 2013). Similarly, in experimental settings individuals overestimate their own performance when given unbiased but noisy feedback on their scores (Grossman and Owens, 2012). The latter study indicates that belief-updating compared to the Bayesian benchmark is biased due to false interpretation of the noisy feedback.

The difficulty to identify success and failure and subsequent changes in performance in business favors the examination of our research question in an experimental setting. In recent years, several studies have utilized natural experiments in sports in order to analyze research questions which otherwise could not have been analyzed in a natural business environment. For example, with the help of NBA performance measures Berri and Krautman (2007) find that long-term contracts can increase shirking. Complementing this result, Stiroh (2007) finds that performance of NBA players increases in the year before they sign a long-term contract and decreases afterwards. Analyzing risk taking behavior of NBA teams, Grund et al. (2013) are able to show that trailing teams' risk taking is inefficiently high. While providing very clean measures of performance and quasi-experimental designs with transparent rules, these sport economics findings can also have large impact on the design of work contracts (Charness and Kuhn, 2011) and tournaments incentives (Shen and Zhang, 2012).

A related discussion in sports and psychology that refers to our research question is if phenomena like "momentum" or "hot hand" exist or not (see Bar-Eli et al., 2006, for a good overview and Avugos et al., 2013, for a meta-analysis). E.g. Klaassen and Magnus (2014) and Dumangane et al. (2009) show that winning a point in tennis as well as scoring a goal in handball is not an i.i.d. (independent and identical distributed) process. However, Dumangane et al. (2009) do not find a direct effect of previous handball performance on the probability of scoring (only an effect of goal difference). And although Klaassen and Magnus (2014: 193ff) observe in tennis data that the previous point won on service increases the probability of winning the current point on service, they find this effect to be small when controlling for quality of players and insignificant when adding further control variables. Gilovich et al. (1985) analyze basketball shooting records of home matches of the Philadelphia 76ers in the season 1980/1981. They cannot confirm the belief of surveyed basketball fans that players are more likely to miss (hit) after a previous miss (hit). Likewise, Vergin (2000) is not able to find unexpected winning or losing streaks of NBA teams in the seasons 1996/1997 and 1997/1998 and Koehler and Conley (2003) deny that basketball players are "on fire" in the annual NBA long distance shootout contests of 1994-1997. However, Miller and Sanjurjo (2014) do find the "hot hand" in a controlled field experiment in which 8 basketball players take two times 300 shots from the same position (with a rebounder and without defense).

Our approach is new as it is not trying to find or deny streaks of any failure or successful events; it rather analyzes behavior after very important events of success and failure. Our subject is either responsible that his team might lose a game which he could have won for the team or responsible that his team has still the chance to win a game which would have been lost without him. In our view, this special responsibility is crucial if you want to apply your findings to behavior after success or failure in business, e.g. to managerial responsibility.

3. Data Source, Variables, and Descriptive Statistics

We analyzed 1516 overtimes of the NBA (men's National Basketball Association of North America) in ten seasons from 2003/2004 until 2013/2014. We obtained the data from the espn.com and nba.com websites.[1] ESPN provides play-by-play statistics in which every event of NBA games is described in detail (approximately every 10 seconds): e.g., Dirk Nowitzki scored a buzzer beater for the tie in the 4th quarter from the 3-point line. The ESPN and NBA websites provide individual performance measures such as field goal or free throw attempts and scores, blocks, rebounds, assists, steals, and turnover by season, game, quarter or overtime. Additionally, they record the time played in the corresponding period and provide further individual data of the players (e.g. position). Our dataset includes 1818 observations of 345 NBA-players (80 point guards, 102 shooting guards, 68 small forwards, 56 power forwards, and 39 centers). In 838 cases, these players were responsible for the overtime because they scored the last shot (success); in 678 cases, they were responsible for the overtime because they missed the last shot (failure). The remaining 302 cases serve as a control group, which contains players who played in the 4th quarter and in the overtime but who were not directly responsible for the overtime. Our dataset allows for between-subject as well as within-subject comparison of the different performance measures.

Table 1 summarizes means and standard deviations of NBA performance measures in our sample for different time periods.

[1] We provide our dataset upon request.

Table 1: Descriptive Statistics for NBA performance measures from 2003/2004 until 2013/2014 of our 345 (male) players

period		field goal attempts (fga)	field goals made	field goal % if fga>0	3 point attempts (3pa)	3 point % if 3pa>0	free throw attempts (fta)	free throw % if fta>0	blocks	rebounds	turn-over	assists	steals	minutes played
4^{th} quarter (n=1818)	mean	**4.38**	**1.94**	**42.24**	**1.14**	**42.75**	**1.67**	**79.23**	**0.14**	**1.52**	**0.56**	**0.88**	**0.25**	**9.48**
	std. dev.	2.39	1.81	27.35	1.26	31.76	2.01	28.12	0.41	1.46	0.77	1.12	0.52	9.72
overtime (n=1818)	mean	**2.22**	**0.91**	**41.61**	**0.57**	**31.86**	**0.94**	**80.14**	**0.10**	**0.90**	**0.27**	**0.46**	**0.13**	**4.43**
	std. dev.	1.84	1.03	35.47	0.90	41.18	1.51	28.50	0.33	1.13	0.53	0.75	0.38	1.44
game (n=1818)	mean	**17.73**	**7.98**	**44.69**	**4.05**	**36.01**	**5.88**	**79.09**	**0.64**	**6.70**	**2.50**	**4.53**	**1.20**	**41.22**
	std. dev.	7.44	4.35	13.34	3.32	25.83	4.60	21.83	1.02	4.28	1.81	3.59	1.24	10.57
season (n=141450)	mean	**13.27**	**6.02**	**45.22**	**3.01**	**32.84**	**4.39**	**78.65**	**0.53**	**5.15**	**2.16**	**3.86**	**1.08**	**33.16**
	std. dev.	4.46	2.14	4.19	2.01	10.41	2.44	9.00	0.54	2.53	0.82	2.39	0.47	6.25

Notes: 4^{th} quarter = 12 minutes; overtime = 5 minutes; game: games with overtime from 2003/2004 until 2013/2014, season: game average of 82 games per season in which player is observed in dataset; n season: 82 games per season times 345 players times number of seasons of the respective player in our dataset (on average 5 seasons), standard deviation of season is calculated with n=1818; field goals include 2 point and 3 point shots; minutes played in game is high, because every game lasted longer than 48 minutes as every game in our dataset includes at least one overtime and most of our subjects (in the treatment groups) are "go to guys" from the starting 5 that play longer than average players; especially in the 4^{th} quarter and in overtime, some averages are low and standard deviations high, because some players' records are 0 in the respective categories; therefore, the high number of observations (1818 of 345 players) is needed for profound comparisons (see section 4); goal percentages are calculated for players with at least one attempt.

Table 2: Wilcoxon signed rank tests and Kruskal-Wallis tests of field goal percentage in overtime, 4th quarter, game, and season (if fga>0)

	(1) overtime			**(2) 4th quarter**			**(3) 4th quarter adjusted**			**(4) game**		**(5) season**	
group	n	mean	std. err.	n	mean	std. err.	n	mean	std. err.	mean	std. err.	mean	std. err.
last shot made	585	**40.66%**	1.42%	573	**53.34%*** **	1.02%	524	**40.33%**	1.23%	**46.50%*** **	0.49%	**45.19%** **	0.18%
last shot missed	688	**42.11%**	1.36%	685	**32.91%*** **	0.88%	649	**44.02%***	1.17%	**42.80%**	0.45%	**45.30%**	0.14%
control	189	**42.82%**	2.75%	183	**44.68%**	2.26%	167	**43.57%**	2.15%	**45.14%**	0.92%	**45.05%**	0.28%
Kruskal-Wallis test	p=0.802			p<0.001			p=0.138			p<0.001		p=0.446	

Notes: Wilcoxon signed rank tests of different time periods compared to overtime: *****: p<0.1, ******: p<0.01, *******: p<0.001; n overtime: players with goal attempts in overtime; n 4th quarter: players with goal attempts in overtime and in the 4th quarter; n 4th quarter adjusted: players with goal attempts in overtime and in the 4th quarter excluding the last shot in the 4th quarter, n of game and season equals n of overtime.

Figure 1: Comparison of field goal percentages by group in the 4th quarter and in overtime

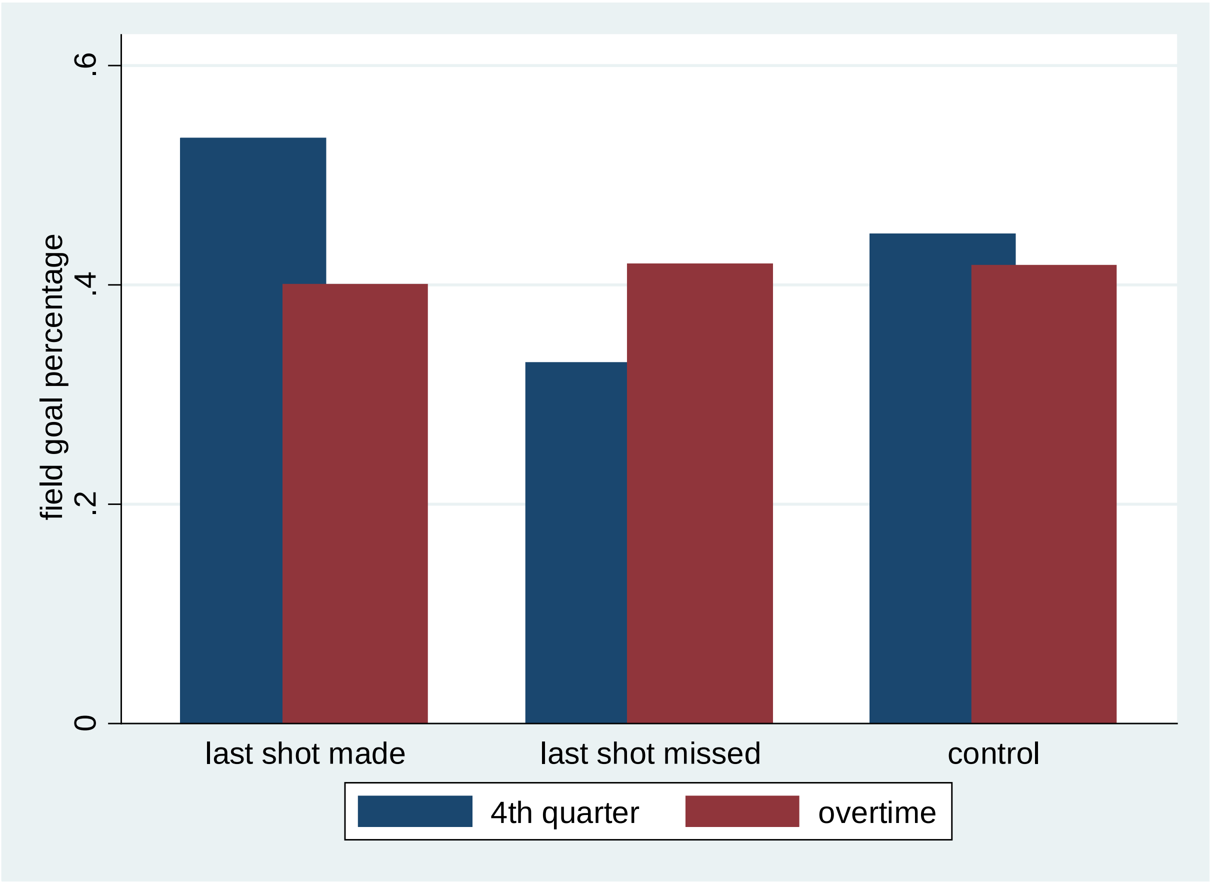

Figure 2: Comparison of further performance indices by group in the 4th quarter and in overtime

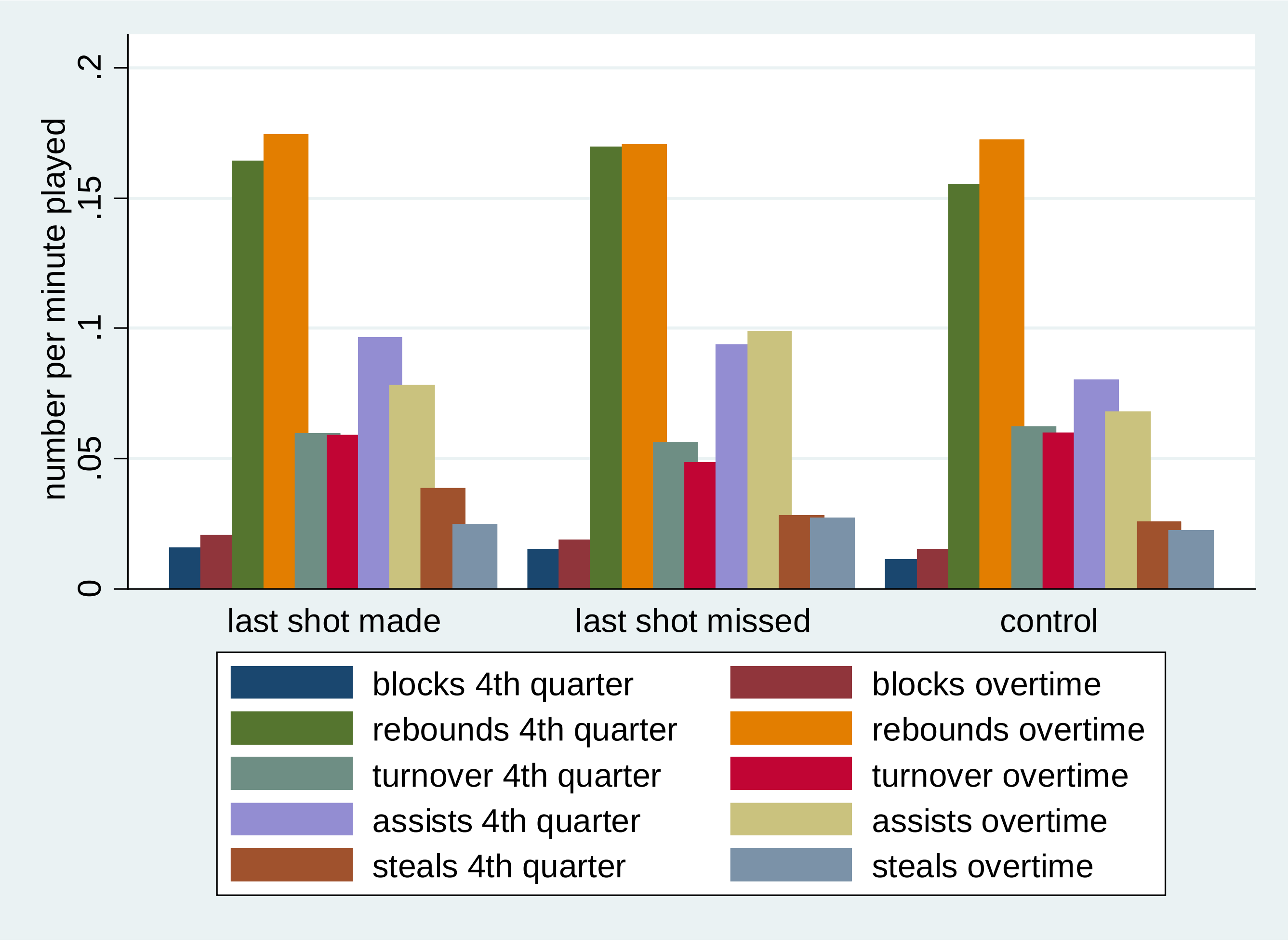

Table 3: Two limit Tobit and OLS regressions of overtime field goal percentage and its difference to 4th quarter, game, and season

	(1) overtime two limit Tobit		**(2) overtime - 4th quarter** two limit Tobit		**(3) overtime - 4th quarter adj.** two limit Tobit		**(4) overtime – game** OLS			**(5) overtime – season** OLS		
	coef.	robust std. err.	coef.	robust std. err.	coef.	robust std. err.	coef.	robust std. err.	tolerance value	coef.	robust std. err.	tolerance value
last shot	-0.0333	0.0573	**-0.2361******	0.0397	0.0229	0.0425	**-0.0546***	0.0278	0.4216	-0.0212	0.0301	0.4213
shooting guard	0.0538	0.0524	0.0464	0.0340	0.0376	0.0405	0.0264	0.0237	0.6921	0.0303	0.0282	0.6919
small forward	**0.1024***	0.0532	**0.0632***	0.0357	0.0468	0.0414	0.0271	0.0277	0.7153	0.0479	0.0292	0.7151
power forward	0.0354	0.0649	-0.0279	0.0382	-0.0654	0.0482	-0.0164	0.0285	0.7509	-0.0111	0.0337	0.7508
center	0.1319	0.1104	0.0545	0.0806	0.0826	0.0777	0.0219	0.0549	0.8365	-0.0045	0.0544	0.8360
minutes 4th q.	-0.0035	0.0022	-0.0004	0.0007	-0.0006	0.0007	**-0.0010*****	0.0004	0.9843	**-0.0012****	0.0005	0.9843
minutes overtime	0.0012	0.0015	0.0022	0.0015	0.0009	0.0033	0.0000	0.0016	0.9439	0.0005	0.0017	0.9439
fga 4th quarter	0.0053	0.0090	**-0.0162****	0.0068	-0.0104	0.0084	-0.0027	0.0044	0.9034	0.0008	0.0049	0.9037
fga overtime	0.0035	0.0099	-0.0005	0.0075	-0.0016	0.0089	-0.0006	0.0049	0.8953	-0.0086	0.0054	0.8954
home	-0.0132	0.0414	-0.0195	0.0291	-0.0408	0.0337	0.0041	0.0204	0.9741	-0.0031	0.0218	0.9744
last shot*distance	0.0000	0.0027	-0.0005	0.0018	-0.0005	0.0018	0.0000	0.0013	0.4239	0.0004	0.0014	0.4240
|score difference|	0.0069	0.0072	0.0054	0.0049	0.0036	0.0057	0.0044	0.0035	0.9842	0.0046	0.0038	0.9843
cons	0.2786**	0.0820	0.1346**	0.0565	0.0260	0.0684	-0.0166	0.0391		-0.0415	0.0443	
N	1242		1235		1150		1241			1242		
left censored	375		23		31							
right censored	208		36		32							
Pseudo R^2	0.0037		0.0646		0.0093							
R^2							0.0118			0.0086		
Adjusted R^2							0.002			-0.001		
F, Prob>F	0.88, 0.565		7.66, <0.001		0.99, 0.455		1.99, 0.025			1.33, 0.200		

Notes: Reference position: point guard; standard errors clustered at individual level, *: p<0.1, **: p<0.05, ***: p<0.01, ****p<0.001; calculating the treatment effects of “last shot” with the nearest neighbor matching estimation (Abadie et al. 2004) yields very similar results; when replacing the dummy “last shot” with the field goal percentage of the 4th quarter in (1), the coefficient is not significantly different from 0 either.

4. Results

4.1. Nonparametric Tests

We start by comparing the difference in field goal percentages in overtime to other time periods. The field goal percentage of players is the most important performance measure as it directly determines game outcome. Furthermore, it is a good indicator of personal performance in Basketball: Of course, the own team's offence and the opposing team's defense quality influence one's field goal percentage, but on average the main determinant for a good or bad field goal percentage is personal skill. This is especially true for the NBA because the variance of team skills is not high and the teams play man-to-man defense.[2] Furthermore, in the "contactless sport" basketball the defender does not have many opportunities to prevent a good offensive player from scoring.

Table 2 displays field goal percentages by time period (overtime, 4th quarter, game, season) and by group: the "last shot made" group consists of players who scored the equalizer in the last seconds of the regular game, the "last shot missed" group consists of players who failed to score the winning shot in the last seconds of the regular game, and the control group consists of players who are not directly responsible for the overtime. The first two groups can be regarded as our experimental groups. As can be seen from the large standard deviations in Table 1, the data is not normally distributed – Shapiro-Wilk tests show that the data violates the assumption of normality with a p-value of <0.001. Parametric tests could have been used, nevertheless, because we have up to 1818 observations (of 345 players). However, for comparisons between the three groups further requirements for ANOVA are violated: Levene tests significantly reject the null hypothesis of variance homogeneity between groups and the number of observations varies notably by group. Therefore, we decided to use nonparametric tests in this section: Kruskal-Wallis tests to compare our three groups in one period, Mann-Whitney U tests to compare two groups in one period, and Wilcoxon signed rank tests to compare the field goal percentages in different periods within groups. Yet we report the means (and standard errors) rather than the mean ranks of the field goal percentages in order to convey better insight into the data.

First, we compare the overtime to the 4th quarter because these periods are very similar with regard to psychological pressure and exhaustion. As we can see from Table 1, the field goal percentages in the 4th quarter and in overtime are very similar on average (slightly

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[2] Since the season 2001/2002, an offensive friendly zone defense is allowed in which it is forbidden for a defender to stay longer than 3 seconds in the zone. Yet teams usually rely an man-to-man defense.

smaller in overtime, Wilcoxon signed rank test, p=0.059) but both are much smaller than in the entire game (p<0.001)[3]. Columns (1) and (2) of Table 2 and Figure 1 indicate a large discrepancy between players who find themselves in the overtime because of personal success vs. personal failure: After having made the last shot in the 4th quarter, players' field goal percentage drops 12.68 percentage points on average, whereas the field goal percentage of players who missed the last shot rises 9.20 percentage points on average. Our control group performs slightly worse in overtime but not significantly different from the 4th quarter.

Having experienced a success before may lead players to take relatively more shots in overtime since the subsequent playing situations resemble the situation in which they scored the equalizing shot. This might be induced by the recognition bias of remembering successful events (strengths) better than memorizing failure (weaknesses) (Dodgson and Wood, 1998). If we look at the field goal attempts per minute during overtime, we see that the reason for the opposing development of performance in our two treatment groups seems to be due to overconfidence of the "last shot made" group and a safer play of the "last shot missed" group. Players who made the last shot increase their attempts per minute from 0.44 in the whole game to 0.46 in overtime (however, this is not significantly different, p=0.309). Players who missed the last shot reduce their attempts per minute from 0.43 to 0.42 (p=0.003). Compared to players in our treatment groups, players in the control group stay at a constantly low level of 0.39 attempts per minute on average.

However, we should not overstress the magnitude of the large differences in field goal percentages in columns (1) and (2) as there might be a selection bias: All else equal, players in the group "last shot made" have a higher field goal percentage in the 4th quarter than players of the group "last shot missed". Although the overtime percentage is lower in the former group compared to the latter and to the control group, two sided Mann-Whitney U tests by group do not indicate significant differences. The insignificant Kruskal-Wallis test displayed in the last row of column (1) confirms this result. Significantly different field goal percentages by group can only be observed at game level and in the 4th quarter. The differences in field goal percentages in the 4th quarter converge in overtime (see Figure 1) – in overtime, players in the "last shot made" group cannot keep up their good field goal percentage of the 4th quarter and players in the "last shot missed" group are able to compensate for their relatively bad percentage of the 4th quarter. Both results could not be

[3] If not explicitly mentioned, we use Wilcoxon signed rank tests in this section.

expected beforehand. On the contrary, if there is something like "momentum" or "hot hand", it should be the other way round.

We adjusted the 4th quarter field goal percentage by omitting the last shot in column (3). With this drastic adjustment the discussed differences disappear and even seem to be reversed. However, compared to column (2), the adjustment of the field goal percentage in the 4th quarter in column (3) is a bias of the percentage by group in the opposite direction. Thus, we compare the overtime percentage with the percentage in the whole game and season in columns 4 and 5 (without adjusting the 4th quarter percentage).

Column (4) shows that, compared to column (2), only the effect in the "last shot made" group persists: Overtime performance drops compared to game performance after a success in the last scene of the regular game. After failure in the last scene of the regular game, there is no difference between overtime and game performance. The selection bias of the field goal percentage of our groups "last shot made" and "last shot missed" is much smaller if we have a look at game data rather than 4th quarter data: Table 1 shows that on average there are 17.73 field goal attempts per game in our dataset from which 7.98 are successful. If we exclude our control group, attempts rise to 18.58 (min. 1 and max. 45) and successes to 8.31 (min. 0 and max. 23): Most of the players who take the last important shot of the (regular) game are the teams' "go to guys".

In order to completely diminish the selection bias, we compare overtime performance to the corresponding season average in column (5). According to Table 1, an average player in our dataset attempts to score 82*13.27≈1088 times per season and is successful 82*6.02≈494 times. The outcome of the shot which distinguishes our two treatment group plays no role here. Column (5) confirms the impression that on average players perform worse in overtime compared to their usual performance during the season (see also Table 1). This applies not only to the "last shot made" but also to the "last shot missed" group. However, according to Wilcoxon signed rank tests only the drop in performance of the former group is significant, indicating that relative performance indeed goes down directly after personal success.

We conducted the same comparisons of Table 2 for 3-point and free-throw percentages. The 3-point percentage of players who scored the last shot significantly drops in overtime (from 55.41% in the 4th quarter to 35.97%, $p<0.001$). Those who missed the last shot have a constant 3 point percentage of about 30% in the 4th quarter and in overtime; in the control group, the percentage drops from 41% to 27% ($p=0.019$). If we exclude the observations for which the last shot is a three point goal, the "last shot made" group performs equally well in the 4th period and in overtime, whereas the "last shot missed" group performs slightly, but not significantly better in the 4th period than in overtime (39.87% vs. 31.29%, p=0.129). Compared to game averages, the "last shot made" group performs substantially worse and the "last shot missed" group slightly (but also significantly) worse in overtime. In relation to season averages, however, only the decrease of the 3-point percentage of those who missed the last shot is significant. In contrast to field goals, in which 2- and 3-point shots are included, the 3-point percentage on average is highest in the 4th quarter of overtime games[4] and lowest in the overtime itself; the season average of all games is just slightly better than overtime performance (see Table 1). The free-throw percentage does not change by period or by group but stays constant at a high level of approximately 80% (see Table 1).

To have a broader look at different performance indicators, we also compared rebounds, assists, steals, blocks, and turnover per minute played in the 4th quarter and in overtime (see Figure 2).

The blocks per minute do not change significantly by group or by period if we look at the pooled data with all player positions. However, especially for this indicator, performance varies noticeably by position: It seems solely to be important to centers. By just analyzing this position, a two-sided Mann-Whitney U test confirms that centers who missed the last shot of the 4th quarter, and are thus negatively responsible for overtime, block more shots per minute played in overtime than centers in our control group (on average 0.07 vs. 0.02, p=0.072). Rebounds, however, do not differ significantly by experimental groups even if we control for position.

The finding that performance increases after personal failure is also supported by turnovers: On average, players who missed the last shot in the 4th quarter lose the ball 0.55 times (0.06 times per minute played) in this last quarter, whereas they only lose the ball 0.25 times (0.05 times per minute played) in the overtime ($p<0.001$). Average turnovers per minute in the control group and in the "last shot made" group stay constant. In the latter group, however, turnovers significantly decrease within subjects from the 4th quarter to overtime (0.0595 vs. 0.0593, p=0.023), indicating that the drop in precision of the "last shot made" group might not be explained by less effort and concentration.

[4] A relatively high percentage of successful last shots are from the 3-point line: in our dataset 36.83 %. The last shot is attempted in 43.84% of our observations as a 3 pointer.

Support for the finding that precision and team play drops after personal success comes from the variable that measures assists per minute. Players who made the last shot of the 4th quarter had 0.97 assists on average in the 4th quarter (0.10 per minute played) and 0.42 in overtime (0.08 per minute played ($p<0.001$). In the “last shot missed” group, assists per minute are constant over periods, and in our control group assists per minute slightly drop from 0.08 to 0.07 ($p=0.058$). If we analyze assists per minute played in overtime by group, two-sided Mann Whitney U tests show that this indicator is significantly higher in the “last shot missed” than in the “last shot made” and control group ($p<0.001$ and $p=0.003$ respectively); the ”last shot made” and the control group do not differ significantly.

Furthermore, players of the “last shot made” group steal the ball significantly fewer times per minute in overtime compared to the 4th quarter (on average 0.038 vs. 0.025, $p=0.001$). In the control group and in the “last shot missed” group, the average steals per minute stay constant. Yet the Wilcoxon signed rank test also detects a small drop in steals per minute after the last shot is missed (0.028 vs. 0.027, $p=0.004$).

In order to control how long the “last shot effect” lasts, we analyze games in which there is more than one overtime and compare the development of field goal percentages of players in our three groups. We exclude observations in which a player from our groups is responsible for the second or third overtime. If we compare the field goal percentage of the 4th quarter to that of the second overtime, Wilcoxon signed rank tests find a significant drop in performance of the “last shot made” group (53.15%[5] vs. 41.78%, $p=0.037$) but no significant increase in the “last shot missed” group (35.66% vs. 44.40%, $p=0.117$). This means, that the deteriorating effect of success on performance can still be observed in the second overtime. After the second overtime, we do not find significant changes anymore because the number of observations declines sharply.

4.2. Multivariate analysis

In order to quantify the effect of failure vs. success on subsequent performance more precisely, we conducted two limit Tobit and OLS regressions and included our treatment variable as a dummy. In column (1) of Table 3, the specification aims to explain overtime performance; in columns (2) to (4), the differences of overtime performance vs. performance in the 4th quarter, game, or season serve as the dependent variables. We decided to use Tobit regressions because field goal percentages are naturally censored between 0 and 1 and the

[5] The field goal percentage of the 4th quarter slightly differs from Table 2 as the number of observations decreases in this analysis.

difference of percentages is censored between -1 and 1 but our aim is to measure the latent variable (relatively) bad performance (low percentage or negative difference) vs. (relatively) good performance (high percentage or positive difference). For regressions in which the values of the dependent variable never reach the above mentioned limits, we use OLS regressions because its coefficients are easier to interpret (columns (4) and (5)).

The dummy variable "last shot" is 0 if the player missed the last shot (failure) and 1 if the player scored the last shot of the 4^{th} quarter (success). The control group that we use in section 4.1. is excluded from the multivariate analysis because we want to take into account further information on the last shot. The regression controls for the position of a player as well as minutes played and field goal attempts in the 4^{th} period and in overtime. Furthermore, we wanted to control for psychological pressure indicators. First, we consider the dummy variable "home" (1 if a player plays at home, 0 if he plays away): Baumeister and Steinhilber (1984) were the first to identify a home disadvantage due to psychological pressure. Marcelino et al. (2009) identify a non-linear (U-shaped) home advantage over time played in volleyball matches. For NBA matches, Jones (2007) observes a frontloaded home advantage (in the first period) of matches in the two seasons 2002/2003 and 2003/2004. Next, the interaction of "last shot" and the distance of the last shot[6] serves as another control for psychological influence: Given a player's position (control variable), misses from very close and goals from far away should have a greater impact on perceived failure and success. Finally, the modulus of the difference of the final score can be regarded as a further indicator of psychological pressure: Matches with overtime are close by nature, yet pressure should be even higher if the final score is also close, i.e. a low difference in final goals represents high pressure in overtime.

In order to check for multicollinearity, we estimated OLS regressions for all our specifications in Table 3 and calculated tolerance values = inverses of the variance inflation factors (1/vif). The tolerance values of our controls are all far above 0.1. Tolerance values reported in columns (4) and (5) are nearly identical; the same applies to the other regressions if OLS is used instead of Tobit. This means that there is no problem of multicollinearity (Hair et al. 2010). The R^2 of the OLS regressions in (4) and (5) are very low (and the Pseudo R^2 of (1) to (3) are also low) indicating that there are important other factors that explain the difference between overtime and game or season performance (as well as overtime performance and its difference to the 4^{th} quarter). We estimated robust standard errors

[6] In our data, the average distance amounts to 16.82 ft.

clustered at individual player level because the dataset includes more than one observation per player (see section 3).

In column (1), we seek to explain the field goal percentage in overtime with a two-limit Tobit regression (upper limit 1, lower limit 0). The coefficient of the dummy variable “last shot” is not significantly different from 0. This confirms the result from Figure 1 (and Table 2) that the overtime field goal percentage of players who scored or missed the last shot in the 4th quarter converges.

The same applies to our control variables – except for the dummy variable “small forward”: An OLS regression with the same specification suggests that a small forwards’ field goal percentage is on average 6.11 percentage points higher than that of point guards, ceteris paribus. We did not include further individual data like height or weight as it strongly correlates to the position of a player. Age is also not included in our dataset because there is only little variance of age within the analyzed players.

The effect of better field goal percentages of small forwards vs. point guards in overtime persists if we consider the difference of overtime vs. 4th quarter performance (2). Further, the dependent variable in (2) is smaller (i.e. more negative) if a player takes more shots in the 4th quarter. On average, the field goal percentage is higher in the 4th quarter than in overtime (thus the difference is negative) and average field goal percentages are less than 50%; i.e., all else equal more attempts in the 4th quarter reduce the field goal percentage in the 4th quarter. This effect is not significant in overtime. The dummy variable “last shot” is highly significantly negative in (2) with a regression coefficient on the latent variable of -0.2361. If we use the same specification in an OLS-regression, this coefficient becomes -0.2257, which means that ceteris paribus the difference in performance of players who are positively responsible for the overtime is on average 22.57 percentage points worse than that of players who are negatively responsible for the overtime. If we want to compare this effect with the results from Table 2, we have to calculate the distance of the differences of field goal percentages: (53.34% - 40.66%) – (32.91% - 42.11%) = 12.68 + 9.20 percentage points = 21.88 percentage points. This means: if we control for the above described variables, the effect of the last shot is slightly higher and very robust.

Nevertheless, we need to keep in mind that part of this discrepancy is favored by the construction of the variable “last shot” which indicates failure vs. success (see also analyses in Table 2). The drastic adjustment to exclude the last shot of the 4th quarter from our multivariate analysis yields results similar to those in Table 2 and seems to reverse the "last shot effect" (but not significantly). Also the other variables in (3) are not significant.

Since the adjustment in (3) biases the 4th quarter field goal percentage in the opposite direction to that found in (2), we compare overtime performance to wider time spans (game and season averages) in (4) and (5) in which the last shot of the 4th quarter plays a minor or close to no role (see section 4.1) and do not adjust the field goal percentage. Yet we know (from Table 1) that performance in overtime is better comparable to that in the 4th quarter and not to that in the whole game or season. In the last two regressions in Table 3, we can use OLS because the limits of the Tobit regressions in (2) and (3) (-1 and 1) are never reached: In (4) and (5), the lowest value is -58.82 percentage points and the highest +62.96 percentage points.

Column (4) confirms the univariate result from column (4) in Table 2: the strong decrease in overtime performance after a success in the last scene of the 4th quarter diminishes if we compare overtime to game performance. Nevertheless, it is still significantly negative. The control variable "minutes played in the 4th quarter" has a very small negative impact on the difference between overtime and season performance because the overtime field goal percentage of exhausted players, who played for a long time in the 4th quarter, slightly decreases.

The effect of responsibility for overtime due to failure vs. success is no longer significant if we compare overtime performance to season averages (5). The small negative impact of playing for a long time in the 4th quarter is still visible.

5. Conclusion

After especially good performance (success), it is likely that performance will decrease afterwards. This seems to be an intuitive assumption although it is in the opposite direction of the "hot hand" belief. Our natural experiment confirms the assumption. Our results suggest that the drop in performance is that large that individuals perform even worse than their usual performance level (in our case: season averages) after events of success. Our data analysis implies overconfidence as a possible explanation for this phenomenon. On the other hand, especially bad performance in a certain event (failure) brings along an increase in performance afterwards. Possible explanations that cannot be ruled out by our data are more cautious behavior when missing the last shot and a "break even" effect in which people try to compensate for previous failure.

The increase in performance after failure is not as strong as the decrease in performance after success. Thus, the increase in performance after failure could simply occur because it might be likely to observe it after especially bad performance. Further, the large drop of our successful players' performance is mainly driven by superior performance in the 4^{th} quarter rather than inferior overtime performance. The performance in overtime is not significantly different comparing the three groups of (i) players who force overtime by scoring the equalizer in regular playing time, (ii) the group of players who miss the last shot when the game is tied and (iii) the control group (of players not taking the last shot). Overtime performance of the first group is just slightly lower than that of the last two groups.

Our results are comparable to the "hot hand fallacy" first mentioned by Gilovich et al. (1985). The belief of sport fans that successful outcome predicts further success is widespread, yet most empirical research in sports cannot confirm this belief (Avugos et al. 2013). Our data even supports the opposite: After an outstanding success in which a player is crucially responsible for the teams' probability of success, individual performance goes down. Correspondingly, after a serious failure in which a player is directly responsible that his team is not winning (yet), individual performance slightly increases.

We argue that our findings can be transferred to other competitive settings, e.g. business negotiations. The outcome of games in professional sports is the most important evaluation criterion of success of the organization/team. Furthermore, players receive instant and clear feedback about the success or failure of an especially important shot which is similar to the outcome of an important business meeting. Using data from professional sports allows us to investigate the impact of previous responsibility for success or failure on individual performance while good data from important negotiations and employees involved is unlikely to be available.

We conclude that the young scientist who has published a great paper and the programmer who solved an important algorithm could indeed be given a week off. In the same vein, young scientists with a terrible paper submission and programmers that are responsible for bugs should be given a second chance. Similarly, football players who scored a penalty kick in regular time and NBA players who made a buzzer beater should not be given the ball too often. On the other hand, it might be worthwhile not to substitute football players who missed a penalty kick or NBA players who missed an important shot.

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