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Choking Under Pressure – Evidence of the Causal Effect of Audience Size on Performance *

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Abstract

We analyze performance under pressure and estimate the causal effect of audience size on the success of free throws in top-level professional basketball. We use data from the National Basketball Association (NBA) for the seasons 2007/08 through 2015/16. We exploit the exogenous variation in weather conditions on game day to establish a causal link between attendance size and performance. Our results confirm a sizeable and strong negative effect of the number of spectators on performance. Home teams in (non-critical) situations at the beginning of games perform worse when the audience is larger. This result is consistent with the theory of a home choke rather than a home field advantage. Our results have potentially large implications for general questions of workplace design and help to further understand how the social environment affects performance. We demonstrate that the amount of support, i.e. positive feedback, from a friendly audience does affect performance.

JEL Classification: D03, J24, M54

Keywords: Performance under pressure; choking; paradoxical performance effects on incentives; social pressure.

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1 Introduction

Theory and empirical evidence indicate that greater incentives increase effort and thus improve output (Dechenaux, Kovenock and Sheremeta, 2015; Ehrenberg and Bognanno, 1990; Lazear and Rosen, 1981). The greater the potential reward, the larger the expected improvement in performance and productivity. However, when pressure to perform increases, performance is often found to decrease (Dohmen, 2008b; Harb-Wu and Krumer, 2017). This unexpected negative consequence has been termed "choking under pressure" (Baumeister, 1984). To understand how individuals or teams respond to pressure, it is essential to analyze their performance in critical situations. This is especially important in situations where success depends on effort stimulated by increasing incentives.

Choking under pressure describes a situation in which individuals perform worse when put under pressure (Baumeister, 1984; Hill, Hanton, Matthews and Fleming, 2010). The empirical literature identifies multiple sources of pressure to perform that deteriorate performance when increased. For example, pressure is found to arise from the disadvantage of being the second mover in a particular contest (e.g., Apesteguia and Palacios-Huerta (2010) or Kocher, Lenz and Sutter (2012)). Another source of pressure is identified in intermediate standings in contests (Cohen-Zada, Krumer, Rosenboim and Shapir, 2017; Dohmen, 2008a) or the imminent importance of a certain situation (González-Díaz, Gossner and Rogers, 2012). Obviously, increased monetary incentives create pressure to perform (Hickman and Metz, 2015). In public events, pressure to perform could be affected by the presence and size of a supportive or hostile audience (Butler and Baumeister, 1998; Harb-Wu and Krumer, 2017; La, 2014; Wallace, Baumeister and Vohs, 2005).

Relatively little is known about the causal effect of audience size on performance, although an audience is generally believed to have an effect on performance, albeit in contradicting directions, depending on the assumptions made. A supportive home audience is frequently considered to raise expectations and thus increase pressure to perform well (Epting, Riggs, Knowles and Hanky, 2011). Although it seems plausible that a supportive audience provides emotional ease and reduces pressure, Taylor, Seeman, Eisenberger, Kozanian, Moore and Moons (2010) show that a supportive audience increases stress as measured by biological stress indicators. This is in contrast to the well-described "home field advantage" and the use of audience size to explain it (Boudreaux, Sanders and Walia, 2015).

In general, professional sports provide an excellent opportunity to study choking under pressure, because professional athletes exert effort to excel. The rules limit available strategies and provide a clearly defined environment, which allows us to distinguish among the effects of timing, intermediate scores, variation in prizes, or audience size on players' performance.

We estimate the causal effect of audience size on the performance of players. Our measure for performance is the success of free throws in professional basketball games in the National Basketball Association (NBA), a well-established indicator of performance (Cao, Price and Stone, 2011; La, 2014; Toma, 2015). Free throws are penalties that are awarded after rule infractions and are ideally suited to study choking under pressure. They are a particular type of scoring attempt, which is isolated from interactions with other players. Consequently, unobserved disturbances— which might originate from interactions between the teams (offense versus defense)— are eliminated. Further, a team cannot choose the player who attempts the free throw; only the player who has been fouled may attempt it.[1] This limits the potential danger of the impact of endogenous selection on performance. In addition, free throws are classical skill-based tasks, similar to penalty kicks in soccer (Dohmen, 2008a) or shooting in biathlon (Harb-Wu and Krumer, 2017), which are thought to be affected primarily by the pressure to perform (Wallace et al., 2005).

In our empirical analysis, we use play-by-play data from top-level professional basketball games (NBA) from all regular-season games in 9 seasons from 2007/08 through 2015/16. Play-by-play data identify all actions in a game: in particular, free throws and their outcomes. They allow us to control for different circumstances that could potentially influence performance, such as the score difference or time of the game. We use an instrumental variables approach to identify the causal effect of performance pressure on performance as the size of the audience is endogenous. In particular, we use weather conditions to instrument for attendance. Our instrumental variable is the four-day average of the minimal temperature at a weather station close to the arena. The underlying assumption is that the lower the temperature, the lower the attendance as travel costs increase because of bad weather. As all NBA games are staged inside domes with controlled climate conditions, there is no direct effect of the weather on the performance of the players on the court.

The empirical literature demonstrates that performance under pressure of (semi-)professional basketball players is correlated with in-game characteristics (Cao et al., 2011; Toma, 2015; Worthy, Markman and Maddox, 2009). While the size of the attendance could affect the overall performance in a game, neglecting within-game dynamics could potentially bias our results. Consequently, we extend previous work by La (2014)

[1]This is the case for personal fouls. In the comparatively rare case of a *technical foul* (i.e. a breach of the rules that does not involve physical contact or is a foul by a non-player), the team can decide who will attempt the free throw.

to play-by-play data and use attempt-level instead of game-level data. For identification of the causal effect of attendance size on performance, it is essential to also control for intermediate score differences, as well as the timing of free throws. Moreover, as the growing literature on choking under pressure illustrates, we expect the effect of the audience size to vary with the time of game and intermediate score. If the pressure to perform increases in crucial moments of a game (Cao et al., 2011; Toma, 2015), we expect to find a pronounced causal effect of the audience for attempts during such moments.

We find a negative causal effect of audience size on the probability of a successful free throw for players of the home team. The effect is driven by attempts during the first half of a game. We estimate a 7.5 percentage point (ppt) decrease in the probability of a successful free throw if attendance increases by 10 ppts. at the sample mean, this corresponds to a 10% lower success rate. Additionally, the effects are estimated for attempts when the home team is trailing, which amplifies our results.

We do not find any significant effects for the players of the away team. The results imply causal evidence for a home choke or home disadvantage (Wallace et al., 2005). In addition, our results suggest that the home choke is present in the beginning of games.

2 Psychological Theory and Related Literature

When exposed to pressure, it is plausible that individual performance is affected. However, there is no clear consensus in the psychological literature on the mechanisms that produce this result (L. Beilock and Gray, 2012). One potential channel for pressure on an individual to act is the simple act of observing his/her performance. Aiello and Douthitt (2001) provide an overview of factors that are considered to influence performance. They identify "situational factors", "task factors", and "presence factors" which affect individual factors that then interact with performance factors. In our setting, this categorization would decompose the effect of the audience on the players' free throw success into the task specific nature of a free throw, the players' characteristics, and the situational, and audience characteristics. The data allow us to proxy for all these factors.

The relationship between pressure to perform and audience presence has been studied using data from experimental setups. For example, Otten (2009) finds that some athletes perform better when their performance is videotaped. He attributes this to the athletes' reported *perceived control*, which enhances self-confidence and, consequently, performance. In another experimental study, Georganas, Tonin and Vlassopoulos (2015) show that subjects initially increase performance when being observed by a peer. Uziel (2007) conclude from a meta-analysis that the effect of pressure on performance is generally positive if the agent's social orientation is also positive; that is, if the agent is an extrovert and has high self-esteem.

In general, there exist multiple, but competing, theoretical approaches to explain choking under pressure. So-called *drive theories* postulate that performance depends on the drive or level of arousal. One set of hypotheses assumes optimal levels of arousal, for example, as in the inverted U-shape theory of Yerkes and Dodson (1908). Zajonc (1965) suggests that the dominant response will be revealed under high arousal, leading to better performance of experts and poorer performance of novices. *Failure avoidance* is another explanation for choking under pressure. Wallace et al. (2005) argue that an audience communicates expectations to the performer. This may raise the performer's will to succeed, but could also trigger choking under pressure if the fear of frustrating these expectations becomes dominant.

Attentional theories, in contrast, focus on the cognitive demand of a task, for example, as in the *self-focus theory*, which assumes that pressure increases anxiety about losing. This, in turn, increases self-consciousness and proceduralized skills are more poorly executed due to an attentional shift to task-irrelevant cues (Baumeister, 1984; Wallace, Baumeister and Vohs, 2005). Thus, a greater self-focus due to higher concentration leads to choking behavior. Analyzing biathlon competitions, Lindner (2017) finds that athletes who take more time to shoot the decisive final shot, also miss their shot more often. He states that this might be due to an athlete's possible over-thinking of the task and possible outcomes. Similarly, the *explicit monitoring* theory explains choking through cognitive processes that are detrimental to performance. The mechanisms of choking are found to operate on proceduralized task control structures (Beilock and Carr, 2001). In other words, te theory explains choking under pressure in sensorimotor skills such as putting in golf or converting a free throw in basketball.

If pressure to perform increases through an increase in attendance, we expect performance to deteriorate with more spectators. Home teams could face a different level of pressure than away teams, caused by the presence of a supportive home crowd. An increased level of pressure could have an adverse effect and — according to the self-focus theory — increased pressure might trigger explicit monitoring of the standardized task resulting in a worse performance. Audience-induced pressure could vary with the intermediate score of the game or the remaining time in a match. For example, pressure to perform could be high in close games or in the final moments of a game.

However, the empirical evidence on choking due to the type or size of the audience is mixed. Priks (2013) finds a positive effect of organized team support in soccer and uses this finding to explain the home-field advantage of soccer teams. Geir (2009) shows that high status professional football players react more strongly to pressure than players with lower status. Harb-Wu and Krumer (2017) examine biathlon competitions and find convincing evidence of athletes choking at home competitions in the presence of a supportive crowd. Similarly, Colella, Dalton and Giusti (2018) find that away teams in Argentinian professional soccer lose with a higher probability and more decisively without a supportive crowd. In contrast, Braga and Guillén (2012) use data from the Brazilian Soccer Championships 2006 and find no significant effect of pressure on performance. Epting et al. (2011) suggest that undergraduate basketball players, who do not have the same financial incentives as professional players, do not have a lower free throw conversion rate when they are exposed to supportive, discouraging or neutral audiences. In their experiment, however, the audiences consisted of ten spectators, while NBA audiences typically number up to 20,000 spectators.

Studying the performance of penalty kickers in professional soccer, Dohmen (2008a) identifies choking under pressure arising from the importance of performance due to intermediate standings. However, he finds no significant correlation between attendance size and performance. Cao et al. (2011) argue that the performance of free throws is only moderately affected by attendance size (1 ppt. decrease as attendance increases by 10,000 spectators (p.232)). La (2014) analyzes the effect of attendance size on performance in the NBA using weather and day of the week as instruments. Attendance at weekend games in the NBA is greater than during the week. However, even if the scheduling of games were random, the exclusion restriction might be violated due to systematically different types of spectators during the week and on weekends. For example, it might be the case that more passionate fans also attend games during the week, while casual fans attend only on weekends.

3 Data and Empirical Strategy

We use data on free throws from professional basketball games (NBA) to analyze how audience size impacts the performance of basketball players. We combine play-by-play data from regular season games with attendance data and detailed weather information for seasons from 2007/08 through 2015/16.[2] The NBA consists of 30 operational franchises, competing against each other in a two stage contest format. Each team plays a total of 82 regular season games, starting in October and culminating in April.[3] The data provide

[2]Play-by-play data were obtained from http://basketballvalue.com. Daily local weather information for each arena was obtained from http://wunderground.com.

[3]Due to a lock-out in the 2011/12 season, each team played only 66 games.

information on 10,760 individual games and we observe 504,657 free throws, with 51.15 percent of all free throws attempted by the home teams.

Following earlier research, we measure success by the probability of a successful attempt. Each free throw is awarded after a rule infraction (e.g., a personal foul) and is typically granted to the fouled player. He has ten seconds to throw the ball from a distance of 4.6 meters. Play-by-play data allow controlling for circumstances that could potentially influence performance. In particular, in our analyses, we control for players' characteristics, the time of the attempt, and the intermediate score.

In our data, attendance is not accurately measured, due to a divergence between reported ticket sales and actual attendance, as well as non-reported standing places. In addition, different sources report slightly varying arena capacities.[4] We use maximum capacity for each arena and account for changes in seating capacity over time. To ease comparison, we use attendance as percent of an arena's maximum capacity.

Any correlation between attendance and performance could be biased due to reverse causality. More successful teams (or teams who perform better under pressure) could attract more spectators. Better teams are more satisfying to watch and the number of spectators is larger because of better performance. We exploit random variations in weather conditions, which were measured close to the arena, to identify the causal effect of attendance on performance. As distances to an arena can be large and road conditions depend on the weather, we argue that bad weather will lead to lower attendance because of worse driving conditions. Weather conditions do not influence performance and risk taking behavior in the arena directly since all NBA games are indoors in air conditioned and heated facilities.[5] After controlling for location (home-team) fixed-effects, weather conditions can be considered perfectly random exogenous shocks.

Since weather might influence behavior more if it is consistently bad over a stretch of several days, we define our instrumental variable as the average minimum temperature on the day of the game and the three days before:

$$Z_{h,t} = \frac{1}{4} * \sum_{s=0}^{3} (\text{min temperature}_{t-s}), \tag{1}$$

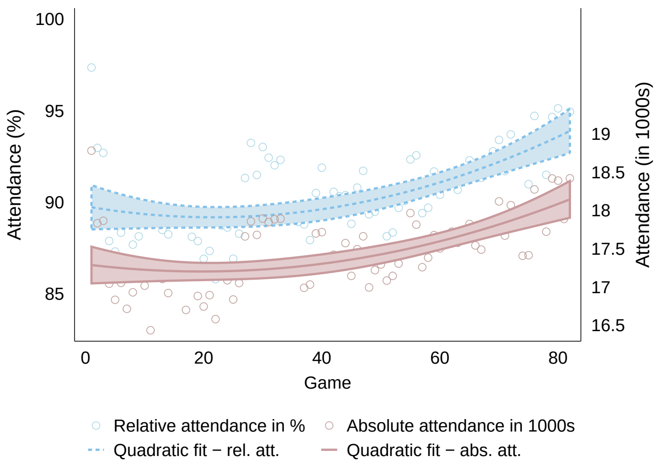
where temperatures are measured at the closest weather station to arena h on game day t. The assumption is that low temperatures induce some spectators to stay at home and not visit the arena. Figure 1 shows the relative and absolute attendances over all

[4] Recent capacities were drawn from the arenas' websites and http://espn.go.com/nba/. Historical data are available on www.wikipedia.org.

[5] This makes the existence of defiers unlikely. Defiers would be arenas which have less attendance in better weather than in bad weather. Better weather conditions make it easier to visit the arena.

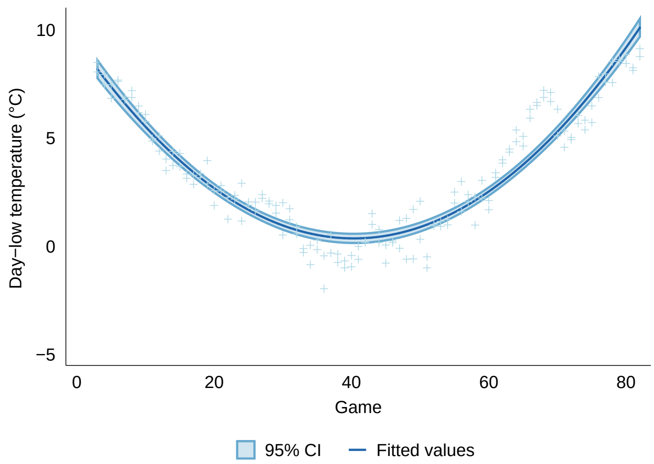
regular season games. The 4-day average minimum temperatures over time are plotted in Figure 2.

Figure 1: Attendance by NBA regular season games.



Notes: Average attendance per game in a season. Attendance is the number of spectators relative to arena capacity, capped at 100% (left axis). Absolute attendance is measured in 1,000s (right axis). Confidence intervals are at 95% level. N = 10,760 games.

Figure 2: 4-day average minimum temperature by NBA regular season games.



Notes: Averages of the lowest temperatures on game day and the three previous days, per game. N = 10,760 games.

Table 1 provides a descriptive analysis of our main variables, stratified by the location of the game. There are no systematic differences between the home and away teams. Most importantly, the players' mean conversion rate is the same for both teams.

Table 1: Summary statistics.

	Home		Away	
	mean	(sd)	mean	(sd)
Adjusted relative attendance (%)	90.4	(12.4)	90.3	(12.5)
Team score	57.1	(29.9)	55.5	(29.2)
Number of wins	19.7	(13.9)	19.9	(14.0)
Number of losses	19.7	(13.9)	19.8	(14.0)
Attempts before (player)	2.5	(2.7)	2.4	(2.7)
Player conversion rate	0.75		0.75	

Notes: N = 258,104 attempts by the home team (246,502 away team). Attendance is measured once per game. The team score is a running sum of the team's score during a game. Number of wins and number of losses are running sums of previously won and lost games by the team during a season. Player conversion rate is the number of successful free throws relative to total attempts per player, not including the current attempt.

To estimate the causal effect of attendance on success we use the following econometric specification:

$$Y_{i,p,h,t,a} = \alpha + \beta \mathbf{X}_{i,p,h,t,a} + \gamma \text{Attendance}^R_{i,t} + \delta_h + \xi_a + \epsilon_{i,p,h,t,a}, \quad (2)$$

where $Y_{i,p,h,t,a}$ is the dependent variable which equals 1 if the observed free throw i of player p in team×season h in game t with opponent×season a is a successful attempt, zero otherwise. The vector $\mathbf{X}_{i,p,h,t,a}$ includes as control variables the minute in the game the attempt was made, the score difference before the attempt, and the absolute number of wins and losses for the home team, also measured before the attempt. In some specifications, we also include the salary of player p in game t. In all specifications, we control for team-season fixed effects, δ_h, and opponent-season fixed effects, ξ_a. Intra-week variation in game attendance is captured by including day-of-the-week indicators. $\epsilon_{i,p,h,t,a} \overset{iid}{\sim} N(0, \sigma^2)$ is a well-behaved error term.[6]

We instrument attendance and the first stage is specified as

$$\text{Attendance}^R_{i,t} = \pi_0 + \pi_1 Z_{i,t} + \xi' \mathbf{X}_{i,p,h,t,a} + \delta_h + \xi_a + \nu_{i,p,h,t,a}, \quad (3)$$

where $Z_{i,t}$ is the instrumental variable as defined above.

[6] We do not include player fixed effects in our main estimation model. This would be contrary to the logic of our first stage, where game-level attendance requires controlling for team- as well as opponent-season fixed-effects as important factors. To capture the players' abilities, we use their free throw conversion rates in $t-1$. We do, however, provide estimates, including the player fixed effects, in the robustness section.

4 Results

Table 2 tabulates in columns (1) and (3) the results from estimating equation (2) for home and away teams, using OLS. We do not find a statistically significant correlation between performance and attendance for home teams. For away teams, however, we estimate a significantly negative coefficient of -0.0003. This can be interpreted as a 0.3 ppt. decrease in the probability of a successful throw if attendance increases by 10 ppts.[7]

Results from 2SLS regressions are presented in columns 2 and 4 of Table 2. In contrast to the OLS results, we do not find a significant effect of attendance size on performance for away teams. However, the effect for home teams is significantly negative and sizeable. In particular, a 10 ppt increase in game attendance decreases the probability of a successful attempt by about 5 ppts. Our instrument is sufficiently strong with Kleibergen and Paap (2006) F-statistics greater than 40. The first-stage results confirm our assumption that good weather conditions increase attendance at NBA games.

Table 2: Estimated effects of attendance on performance.

	Home teams		*Away teams*	
	OLS	IV^a	OLS	IV^a
Adjusted	-0.0002	-0.0051***	-0.0003**	-0.0011
relative attendance^b	(0.0001)	(0.0019)	(0.0001)	(0.0016)
Effect at the mean [%]	[-0.0206]	[-0.677]	[-0.0502]	[-0.146]
Number of	0.0001	0.0005***	-0.0002**	-0.0001
wins	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Number of	0.0001	0.0003*	0.0003**	0.0002
losses	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Attempts	0.0062***	0.0063***	0.0067***	0.0072***
before (player)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
1^{st} stage coefficient^c		0.1035***		0.1130***
		(0.0158)		(0.0157)
F^d		42.8		52.1
Sample mean	0.7585	0.7585	0.7564	0.7564
N	258,104	258,104	245,313	246,502

Notes: The dependent variable is a binary variable equal to 1 if the observed free throw was successful, 0 if not. All estimations include home-team-season, opponent-team-season fixed-effects, weekday, and score difference intervals. Game-level clustered standard errors in parentheses, $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. ^{a} Instrumental variable is the average of game-day and 3 days before game-day minimum temperature. ^{b} Adjusted (censured at maximum of 100) relative attendance in percent of arena capacity. ^{c} Estimated coefficients of the first stage. ^{d} Kleibergen and Paap (2006) statistics on the instrument in the first stage. Attendance is in % of arena capacity.

[7] One percentage point is a small change in attendance, so we interpret the remaining estimation results also relative to a 10 ppt increase in audience size.

The literature on choking under pressure illustrates the importance of timing within a contest. Consequently, we split the sample into attempts from the first and second halves of games. The results are tabulated in Table 3. For the first half of the game, we estimate a 10 ppt lower probability of a successful attempt for home teams, if the attendance increases by 10 ppts. We find no evidence of a causal effect for attempts during the second half for home teams. We conclude that the overall effect presented above is driven by the attempts during the first half of a game. Again, irrespective of the timing of the attempt, we do not find any negative effect of attendance on performance for away teams.

In addition to timing, the intermediate score could affect the relationship between attendance and performance. To investigate potential effect heterogeneity related to intermediate standings, we split the sample by whether the attempts were made when the score differences were small or large. Large score deficits are in the interval]-∞,-7] and small deficits are in [-6,-1]. Trailing six points is a significant threshold where pressure is high as the possibility of tying the game can be achieved in two possessions. This is known as a *two possession game*. Small leads are score differences in the interval [0,6] and large leads range in between [7,∞[.

Table 4 presents the estimated effects when we split the sample according to score differences. Again, there are no significant effects for the away team. We estimate a significant negative effect of attendance on performance for home teams when they are trailing up to 6 points in the game. We also estimate that players of away teams which trail with more than 6 points perform worse, when the audience is larger, however, the estimated coefficient is statistically insignificant (at conventional levels). Overall, the results suggest that the negative effects of audience size on performance are stronger, if the home team is trailing.

NBA players differ in their abilities to shoot free throws. A better player could be affected differently by attendance size than a worse player. Consequently, we use the conversion rate, measured before the attempt, to stratify the sample. We estimate the specifications separately for players who have a conversion rate in the lower 25^{th} percentile of the conversion rate distribution and for players who have a conversion rate in the upper 25^{th} percentile. Table 5 tabulates the estimated effects for these two subsamples. We estimate a significantly negative effect of attendance on performance for worse players on both the home and away teams. The results suggest that a 10 ppt increase in attendance decreases the probability of free throw success by 11 ppts and is slightly less, about an 8 ppt decrease for players from away teams. We do not find a significant effect of audience size on performance for players with a top conversion rate.

Table 3: Instrumental Variable — 1^{st} and 2^{nd} half.

	Home teams		*Away teams*	
	Half 1	Half 2	Half 1	Half 2
Adjusted relative attendance[a]	-0.0075***	-0.0030	-0.0021	-0.0001
	(0.0028)	(0.0025)	(0.0025)	(0.0022)
Effect at the mean [%]	[-0.996]	[-0.398]	[-0.277]	[-0.007]
1^{st} stage coefficient[b]	0.1060***	0.1012***	0.1120***	0.1134***
	(0.0165)	(0.0161)	(0.0165)	(0.0160)
N	114,855	143,249	109,420	137,082
F[c]	41.5	39.3	46.3	50.2
Sample mean	0.7571	0.7596	0.7537	0.7585

Notes: The dependent variable is a binary variable equal to 1 if the observed free throw is successful. All estimations include home-team-season, opponent-team-season fixed-effects, weekday, and score difference intervals. Game-level clustered standard errors in parentheses, $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$. Instrumental variable is the average of game-day and 3 days before game-day minimum temperature. [a] Adjusted (censured at maximum of 100) relative attendance in percent of arena capacity. [b] Estimated coefficients of the first stage regression. [c] Kleibergen and Paap (2006) statistics on the instrument in the first stage. Attendance is in percent of arena capacity.

Table 4: Instrumental Variable — Score differences.

	score difference			
Home teams	]-∞,-7]	[-6,-1]	[0,6]	[7,∞[
Adjusted relative attendance[a]	-0.0099**	-0.0082**	-0.0033	0.0007
	(0.0043)	(0.0034)	(0.0031)	(0.0042)
Effect at the mean [%]	[-1.302]	[-1.081]	[-0.427]	[0.093]
F[b]	15.8	35.5	30.7	17.0
Sample mean	0.7583	0.7586	0.7612	0.7543
N	52,166	53,909	77,046	66,114
Away teams	]-∞,-7]	[-6,-1]	[0,6]	[7,∞[
Adjusted relative attendance[a]	-0.0023	-0.0015	0.0010	0.0007
	(0.0036)	(0.0032)	(0.0026)	(0.0040)
Effect at the mean [%]	[-0.311]	[-0.197]	[0.129]	[0.091]
F[b]	23.9	37.3	40.3	13.9
Sample mean	0.7539	0.7575	0.7575	0.7575
N	78,678	57,097	64,817	39,396

Notes: The dependent variable is a binary variable equal to 1 if the observed free throw is successful. All estimations include home-team-season, opponent-team-season fixed-effects, weekday, and score difference intervals. Game-level clustered standard errors in parentheses, $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$. Instrumental variable is the average of game-day and 3 days before game-day minimum temperature. [a] Attendance in percent of arena capacity. [b] Kleibergen and Paap (2006) statistics on the instrument in the first stage.

Table 5: Instrumental Variable — Good and bad players.

	Home teams		*Away teams*	
	$\leq 25^{th}$	$\geq 75^{th}$	$\leq 25^{th}$	$\geq 75^{th}$
Adjusted relative attendance[a]	-0.0107**	-0.0013	-0.0084**	0.0021
	(0.0052)	(0.0024)	(0.0034)	(0.0027)
Effect at the mean [%]	[-1.711]	[-0.147]	[-1.359]	[0.241]
N	65,021	64,067	61,172	62,076
F[b]	18.1	45.0	48.4	32.9
Sample mean (succ. free throws)	0.6234	0.8601	0.6168	0.8558

Notes: The dependent variable is a binary variable equal to 1 if the observed free throw is successful. All estimations include home-team-season, opponent-team-season fixed-effects, weekday, and score difference intervals. The first and third column include all players with a conversion rate below the 25^{th} percentile of all players (bad), columns two and four for those who are above the 75^{th} percentile (good). Additional controls are the sum and squared sum of free throws of the shooter. Game-level clustered standard errors in parentheses, $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. Instrumental variable is the average of game-day and 3 days before game-day minimum temperature. [a]Attendance in percent of arena capacity. [b] Kleibergen and Paap (2006) statistics on the instrument in the first stage.

5 Robustness Checks

In section 3, we use the four-day average in temperature as a continuous instrumental variable. The temperature fluctuates across the United States and Canada, which could be potentially problematic for our identification if stronger teams are located in cities with relatively constant temperature. We use an alternative instrument that is a binary variable equal to 1 if the game was on a day with bad weather, and 0 otherwise. We categorize weather as bad if the average temperature on the day was below 0°C, or if it snowed, there was a thunderstorm or it rained heavily.[8] The instrument is then:

$$\text{bad weather}_{i,t} = \begin{cases} 1 & \text{if average temperature on game day} < 0°C, \\ 1 & \text{thunderstorm, snow, rain, fog, or any combination,} \\ 0 & \text{else.} \end{cases} \tag{4}$$

Figure 3 depicts the attendance averaged over all game days per season by weather condition. Attendance was significantly lower when the weather was bad, as defined by our IV. Figure 4 shows the share of days with bad weather. Figure 6 in the Appendix illustrates the standard deviations of both instruments. For some states the binary IV has less variation, however, in these cases, the continuous instrument has more variation. Table 6 reports the means of the instrument by NBA team. As a robustness check of our main results, we re-estimated all specifications using the alternative instrument. The results are shown in Tables 7, 8, 9, and 10. All results support our findings, however, there are slight differences in the magnitude of the estimates. Since both instruments produce comparable results, we are confident that our conclusions are valid.

One possible concern with our approach is the existence of defiers, which would violate a key assumption of the Local Average Treatment Effect (LATE) interpretation of the IV approach. This would be the case if some people decide to avoid attending a game on weekends, when the weather is good, perhaps expecting traffic congestion. This would violate the necessary assumption of no defiers for identifying the causal effect of attendance on choking under pressure. To check the robustness of our results, we omit all games on Saturdays and Sundays. Typically, favorable weather would mainly lead to increased traffic and although traffic in general decreases during weekends, the share of social and recreational trips is higher during clear weather days (Maze, Agarwal and

[8]The top panel of Figure 5 in the Appendix illustrates the distribution of games by bad weather, over all states with an NBA team. The bottom panel shows the mean relative adjusted attendance. The correlation between weather and attendance is evident.

Burchett, 2006). Table 11 tabulates the results restricting the sample to weekdays. The estimates confirm all earlier results.

We also considered the travel distance of the away teams as a control variable.[9] Longer distances could reduce the share of away team supporters (thereby increasing the share of home team supporters) and ultimately change the audience effect. However, we already control for this by the use of team and opponent fixed effects. In addition, splitting the sample into matches where the away team had above or below average travel time does not change our results.[10]

Another potential threat to our identification strategy is the unobserved heterogeneity of players. Our data has no direct measure of the players' abilities or the susceptibility to choking. We address this by including players' salaries[11]. We also estimate specifications that use player fixed-effects. Using player fixed-effects controls for any unobserved player characteristics and salaries should provide information on a player's ability. The results from these specifications are tabulated in Table 12 in the Appendix. Overall, the results confirm our main results presented above. We estimate that attendance has a negative effect on the performance of players from home teams, but not for players from away teams.

Another potential concern is the selection of players according to their contract status. In the NBA, players frequently change teams as free agents or get traded. A coach might select players from the roster based on their contract status (Deutscher, 2011). However, the contract status could systematically affect not only effort during free throws, but also the pressure from the fans in the audience. Unfortunately, we do not have information on the contract status for most players in this sample. Instead, we include player-team-season fixed effects in the specifications to investigate this channel, which control for potential unobserved heterogeneity coming from contract situations. In addition, we estimate an alternative specification of equation (2) where we control for the number of games that each player has played as a member of the current team. This is our best proxy for a player's tenure with a team. The estimation results for the first half of the game are presented in Table 13. Our main result of a negative effect of attendance size on free throw performance in the first half (Table 3) is confirmed and robust to unobserved player-team-season characteristics.

[9] Travel time is taken from the away team's closest airport to the airport where the game is held, using http://www.flighttime-calculator.com. A continuous variable was created measuring travel minutes and a binary variable was created being equal to 1 if travel time was above the mean travel time.
[10] Results are available on request from the authors.
[11] Salaries were obtained from http://www.ESPN.com.

Overall, our results contrast with the findings of La (2014) who finds a negative effect of the size of the audience on the performance of away teams and no effect for home teams' performance. Our use of individual attempts, rather than game-level data, allows us to control for within-game variation. We confirm the results of Goldman and Rao (2012) who report that performance is worse when the audience is larger. In addition, we extend the findings of Harb-Wu and Krumer (2017) by identifying the marginal effect of an increase in the size of home attendance on performance. We show that the negative effect of the presence of a supportive audience increases with the size of the crowd.

6 Conclusion and Discussion

We provide evidence of the effect of audience size on performance. We use play-by-play data from top-level professional basketball (NBA) to identify the causal effect of audience size on performance. Our indicator for performance is the success of the skill-based task of shooting a free throw. A free throw is a highly standardized, often-practiced sensorimotor task that is not affected by the performance or style of play of the opposing team. Psychological theory predicts a likely negative effect of audience-induced performance pressure on a player's performance. To establish the causal link between attendance and performance, we apply an instrumental variable approach using weather conditions to provide an exogenous variation in arena attendance. Weather conditions cannot have a direct effect on performance as all NBA games are held in air-conditioned and heated indoor facilities.

Counterintuitive to the home field advantage, we do not find any causal effect of attendance on the performance of away teams. This is surprising, as a non-supportive or even hostile crowd could be a major distraction for players of away teams. However, we do find a significant and sizable causal effect of crowd size on the performance of home team players. The performance of home-team players decreases as the size of the crowd increases. Overall, we estimate a sizable and significant negative effect of audience size on performance. Taking into account that the average audience size in our sample is 17,440, we estimate a total decrease of 10 ppts in the probability of a successful free throw when audience size increases by about 6,100 spectators.

In addition, we analyze if the choking under pressure that we find for the home teams' players is affected by the period of play in which the free throw is attempted. We only find a negative effect for free throws in the first half of games, and the negative effect results from attempts that are made when teams are trailing.

We construct a proxy for the players' ability to shoot free throws based on their conversion rates. We find that it is the relatively worse players, of both the home and away teams, who choke under pressure. This result confirms Wallace et al. (2005), who state that prior experience with an audience that involved a bad performance might lower future performance when the (supportive) audience is larger. All main results are confirmed by several robustness checks.

One limitation of our analysis is the omission of playoff games. The overall number of games in the NBA playoffs during our sample period is too small for our identification strategy to provide a sufficiently strong first stage. Consequently, we do not analyze how attendance does affect performance in these particular games. However, it is of potentially great interest to investigate how the attendance size effect quantifies in the relatively more important playoff games. Thus, it leaves room for future research to analyze how the general importance of a game affects the negative effect of a friendly.

Although we analyze a very specific environment, our results have potentially large implications for more general questions related to incentive design and performance evaluation in work places. For example, workers who are monitored and incentivized by supportive and encouraging feedback might actually perform worse due to increased performance pressure. Following our results, this could especially be the case for workers who are behind their target already or have recently performed below average. In any case, our results help further understand how the social environment affects performance of individuals. In essence, we demonstrate that not only a supportive audience per se (Harb-Wu and Krumer, 2017), but the amount of support plays a crucial role.

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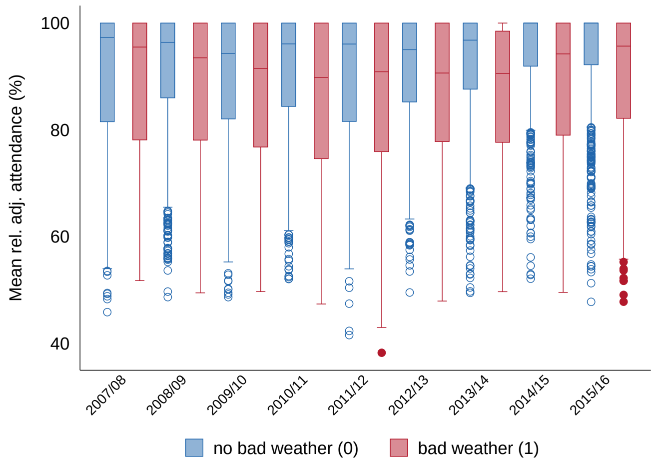
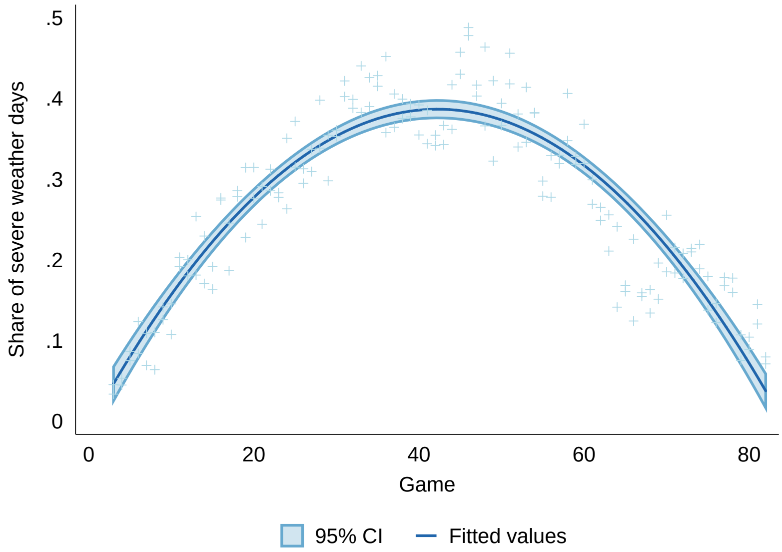
A Appendix

Figure 3: Attendance by weather condition by season.



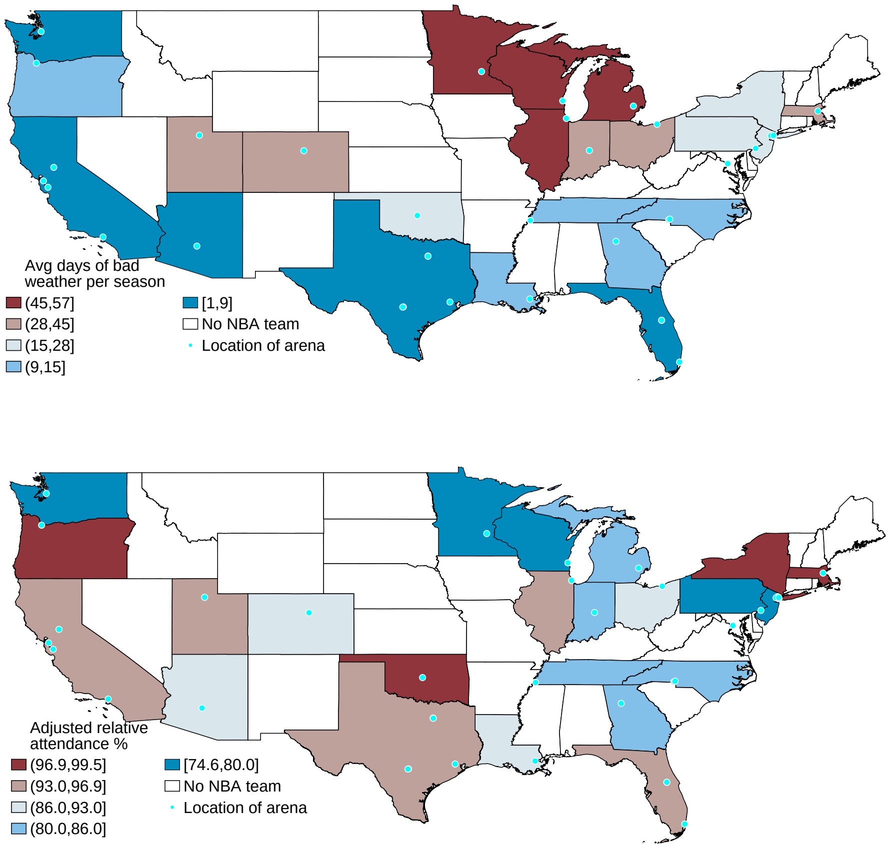
Notes: N=10,760. Bad weather (1) is defined as an average temperature below 0 °C, thunderstorm, snow, rain, fog, or any combination; 0 otherwise. Mean relative adjusted attendance is specified as the number of spectators in an arena relative to the maximum capacity, averaged over the season, capped at 100%.

Figure 4: Share of bad weather days by NBA regular season games



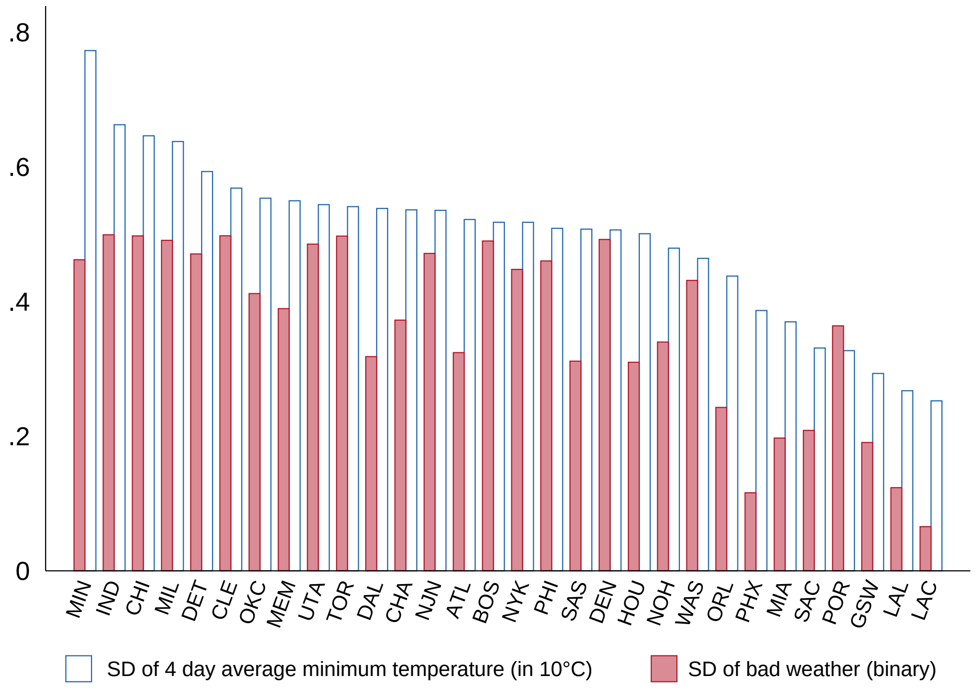
Notes: Share of bad weather days as defined in equation (4), averaged per game-day in a season (seasons 1 to 9). Number of observations = number of game-days per season = 82.

Figure 5: Geographical dispersion of NBA games with bad weather and average attendance.



Notes: Upper panel depicts the dispersion of games on days with bad weather over US states with an NBA team. (Dark) red areas indicate a higher percentage of bad weather games. Bottom panel plots average attendance by state with an NBA team. (Dark) red areas indicated a higher average attendance. Light blue markers indicate the locations of NBA arenas in our data. US states in white do not have an NBA team.

Figure 6: Standard deviations of weather conditions by team.



Notes: 4 day average minimum temperature is measured in 10 °C.

Table 6: Mean values of weather condition by team

	ATL	BOS	CHA	CHI	CLE	DAL	DEN	DET	GSW	HOU
continuous IV	0.425	-0.081	0.290	-0.244	-0.103	0.733	-0.487	-0.459	0.715	1.104
binary IV	0.119	0.400	0.166	0.551	0.549	0.114	0.412	0.669	0.038	0.108

	IND	LAC	LAL	MEM	MIA	MIL	MIN	NJN	NOH	NYK
continuous IV	-0.148	1.081	1.087	0.438	1.877	-0.409	-0.806	0.098	1.082	0.133
binary IV	0.469	0.004	0.015	0.186	0.041	0.595	0.691	0.333	0.133	0.277

	OKC	ORL	PHI	PHX	POR	SAC	SAS	TOR	UTA	WAS
continuous IV	0.246	1.368	0.099	1.060	0.350	0.531	0.870	-0.261	-0.185	0.214
binary IV	0.216	0.063	0.305	0.014	0.157	0.046	0.109	0.554	0.379	0.247

Notes: The continuous instrument is measured in 10 °C.

Table 7: Estimated effects of attendance on performance (both instruments).

	HOME		AWAY	
	IV-1[a]	IV-2[b]	IV-1[a]	IV-2[b]
Adjusted relative attendance[c]	-0.0051***	-0.0048**	-0.0011	0.0006
	(0.0019)	(0.0023)	(0.0016)	(0.0021)
Effect at the mean [%]	[-0.677]	[-0.637]	[-0.146]	[0.079]
Number of wins	0.0005***	0.0005**	-0.0001	-0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Number of losses	0.0003*	0.0003*	0.0002	0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0002)
Attempts before (by player)	0.0063***	0.0063***	0.0072***	0.0072***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
1^{st} stage coefficient[e]	0.1035***	-1.0735***	0.1130***	-1.1432***
	(0.0158)	(0.1956)	(0.0157)	(0.1963)
N	258104	258104	246502	246502
F[d]	42.8	30.1	52.1	33.9
Sample mean	0.7585	0.7585	0.7564	0.7564

Notes: The dependent variable is a binary variable equal to 1 if the observed free throw was successful, 0 if not. All estimations include home-team-season, opponent-team-season fixed-effects, weekday, and score difference intervals. Game-level clustered standard errors in parentheses, $^{*}p < 0.10$,$^{**}p < 0.05$,$^{***}p < 0.01$. [a] Instrumental variable is the average of game-day and 3 days before game-day minimum temperature. [b] Binary IV indicating minimum temperatures at game below freezing and unfavorable weather conditions. [c] Adjusted (censured at maximum of 100) relative attendance in percent of arena capacity. [d] Kleibergen and Paap (2006) statistics on the instrument in the first stage. [e] Estimated coefficients of the first stage regression with respect to the used instrument (IV-1, IV-2). Dependent variable is adjusted relative attendance.

Table 8: Binary IV - 1^{st} and 2^{nd} half.

	Home teams		*Away teams*	
	Half 1	Half 2	Half 1	Half 2
Adjusted relative attendance[a]	-0.0067**	-0.0036	0.0024	-0.0005
	(0.0032)	(0.0031)	(0.0030)	(0.0029)
Effect at the mean [%]	[-0.885]	[-0.468]	[0.322]	[-0.060]
1^{st} stage coefficient[c]	-1.1434***	-1.0108***	-1.1765***	-1.1231***
	(0.2057)	(0.1988)	(0.2039)	(0.2026)
N	114,855	143,249	109,420	137,082
F[b]	30.9	25.9	33.3	30.7
Sample mean	0.7571	0.7596	0.7537	0.7585

Notes: The dependent variable is a binary variable equal to 1 if the observed free throw is successful. All estimations include home-team-season, opponent-team-season fixed-effects, weekday, and score difference intervals. Game-level clustered standard errors in parentheses, $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. Binary IV indicating minimum temperatures at game below freezing and unfavorable weather conditions. [a] Adjusted (censured at maximum of 100) relative attendance in percent of arena capacity. [b] Kleibergen and Paap (2006) statistics on the instrument in the first stage. [c] Estimated coefficients of the first stage regression. Dependent variable is adjusted relative attendance.

Table 10: Instrumental Variable - Good and bad players.

	Home teams		*Away teams*	
	$\leq 25^{th}$	$\geq 75^{th}$	$\leq 25^{th}$	$\geq 75^{th}$
Adjusted relative attendance[a]	-0.0110*	-0.0009	-0.0022	0.0053
	(0.0058)	(0.0034)	(0.0047)	(0.0034)
Effect at the mean [%]	[-1.766]	[-0.104]	[0.371]	[0.622]
N	65,021	64,067	61,172	62,076
F[b]	15.8	23.4	23.1	24.2
Sample mean	0.6234	0.8601	0.6168	0.8558

Notes: The dependent variable is a binary variable equal to 1 if the observed free throw is successful. All estimations include home-team-season, opponent-team-season fixed-effects, weekday, and score difference intervals. Additional controls are the sum and squared sum of free throws of the shooter. Game-level clustered standard errors in parentheses, $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$ Instrumental variable is the average of game-day and 3 days before game-day minimum temperature. [a] Adjusted (censured at maximum of 100) relative attendance in percent of arena capacity. [b] Kleibergen and Paap (2006) statistics on the instrument in the first stage.

Table 9: Binary IV - Score differences

	score difference			
Home teams	]-∞,-7]	[-6,-1]	[0,6]	[7,∞[
Adjusted relative attendance[a]	-0.0056	-0.0067*	-0.0021	-0.0005
	(0.0035)	(0.0034)	(0.0045)	(0.0056)
Effect at the mean [%]	[-0.744]	[-0.883]	[-0.276]	[-0.067]
N	52,166	53,909	77,046	66,114
F^b	17.8	31.1	14.8	9.4
Sample mean	0.7583	0.7586	0.7612	0.7543
Away teams	]-∞,-7]	[-6,-1]	[0,6]	[7,∞[
Adjusted relative attendance[a]	-0.0025	0.0059	0.0043	-0.0079
	(0.0046)	(0.0047)	(0.0032)	(0.0050)
Effect at the mean [%]	[-0.337]	[0.778]	[0.565]	[-1.044]
N	78,678	57,097	64,817	39,396
F^b	14.8	18.3	29.9	11.9
Sample mean	0.7539	0.7575	0.7575	0.7575

Notes: The dependent variable is a binary variable equal to 1 if the observed free throw is successful. All estimations include home-team-season, opponent-team-season fixed-effects, weekday, and score difference intervals. Game-level clustered standard errors in parentheses, $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$. Binary IV indicating minimum temperatures at game below freezing and unfavorable weather conditions. [a] Adjusted (censured at maximum of 100) relative attendance in percent of arena capacity. [b] Kleibergen and Paap (2006) statistics on the instrument in the first stage.

Table 11: IV- 1^{st} and 2^{nd} half, Mon-Fri

	IV-1[a]		IV-2[b]	
Home teams	Half 1	Half 2	Half 1	Half 2
Adjusted relative attendance[c]	-0.0066***	-0.0004	-0.0053*	0.0006
	(0.0025)	(0.0022)	(0.0032)	(0.0032)
Effect at mean [%]	[-0.874]	[-0.053]	[-0.704]	[0.081]
1^{st} stage coefficient[e]	0.1336***	0.1280***	-1.3303***	-1.1173***
	(0.0194)	(0.0193)	(0.2446)	(0.2356)
N	83,505	104,310	83,505	104,310
Sample mean	0.7580	0.7585	0.7580	0.7585
F-stat.[d]	47.5	43.9	29.6	22.5
Away teams	Half 1	Half 2	Half 1	Half 2
Adjusted relative attendance[c]	-0.0026	0.0006	0.0000	-0.0008
	(0.0024)	(0.0021)	(0.0030)	(0.0031)
Effect at mean [%]	[-0.345]	[0.080]	[0.005]	[-0.112]
1^{st} stage coefficient[e]	0.1307***	0.1335***	-1.3311***	-1.1845***
	(0.0195)	(0.0190)	(0.2409)	(0.2408)
N	79,988	99,911	79,988	99,911
Sample mean	0.7534	0.7591	0.7534	0.7591
F-stat.[d]	45.1	49.6	30.5	24.2

Notes: The dependent variable is a binary variable equal to 1 if the observed free throw is successful. Saturday and Sunday are excluded from the sample. All estimations include home-team-season, opponent-team-season fixed-effects, weekday, and score difference intervals. Game-level clustered standard errors in parentheses, $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. [a] Instrumental variable is the average of game-day and 3 days before game-day minimum temperature. [b] Binary IV indicating minimum temperatures at game below freezing and unfavorable weather conditions. [c] Adjusted (censured at maximum of 100) relative attendance in percent of arena capacity. [d] Kleibergen and Paap (2006) statistics on the instrument in the first stage. [e] Estimated coefficients of the first stage regression with respect to the used instrument (IV-1, IV-2). Dependent variable is adjusted relative attendance.

Table 12: Instrumental Variables - Alternative specifications.

	Home teams				*Away teams*			
	IV-1[a]		IV-2[b]		IV-1[a]		IV-2[b]	
Adjusted relative attendance[c]	-0.0032*	-0.0034*	-0.0050**	-0.0036*	-0.0002	-0.0011	0.0000	0.0016
	(0.0019)	(0.0018)	(0.0025)	(0.0022)	(0.0019)	(0.0016)	(0.0023)	(0.0021)
Effect at mean [%]	[-0.422]	[-0.444]	[-0.659]	[-0.473]	[-0.022]	[-0.148]	[0.003]	[0.205]
Number of wins	0.0003*	0.0003	0.0005**	0.0003	-0.0002	-0.0002	-0.0002	-0.0004**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Number of losses	0.0003*	0.0004***	0.0003**	0.0004***	0.0003*	0.0003**	0.0003*	0.0002
	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
Attempts before (player)	0.0042***	0.0059***	0.0042***	0.0059***	0.0055***	0.0067***	0.0055***	0.0067***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0004)
log(salary)[f]	0.0156***		0.0156***		0.0153***		0.0153***	
	(0.0011)		(0.0011)		(0.0011)		(0.0011)	
player fixed-effects	*no*	*yes*	*no*	*yes*	*no*	*yes*	*no*	*yes*
1^{st} stage coefficient[e]	0.1035***	0.1033***	-1.0190***	-1.0738***	0.1035***	0.1119***	-1.0768***	-1.1236***
	(0.0156)	(0.0156)	(0.1942)	(0.1933)	(0.0158)	(0.0156)	(0.1992)	(0.1954)
F[d]	43.8	43.9	27.5	30.9	43.0	51.7	29.2	33.1
N	237,362	256,812	237,362	256,812	226,940	245,313	226,940	245,313
Sample mean	0.7592	0.7585	0.7592	0.7585	0.7563	0.7563	0.7563	0.7563

Notes: the dependent variable is a binary variable equal to 1 if the observed free throw is successful. All estimations include home-team-season, opponent-team-season fixed-effects, weekday, and score difference intervals. Game-level clustered standard errors in parentheses, $^{*}p < 0.10$,$^{**}p < 0.05$,$^{***}p < 0.01$ [a] Instrumental variable is the average of game-day and 3 days before game-day minimum temperature. [b] Binary IV indicating minimum temperatures at game below freezing and unfavorable weather conditions. [c] Adjusted (censured at maximum of 100) relative attendance in percent of arena capacity. [d] Kleibergen and Paap (2006) statistics on the instrument in the first stage. [e] Estimated coefficients of the first stage regression with respect to the used instrument (IV-1, IV-2). Dependent variable is adjusted relative attendance. [f] Team×season fixed effects are substituted by player×team×season fixed effects, all else equal. [g] Control variable for the player's yearly salary according to the contract active at the time of the game.

Table 13: Players' team affiliation — 1^{st} half

	IV-1[a]		IV-2[b]	
Home teams	FE	Affil.	FE	Affil.
Adjusted relative attendance	-0.0052** (0.0026)	-0.0071** (0.0028)	-0.0047 (0.0031)	-0.0066** (0.0032)
player-team-season FEs	*yes*	*no*	*yes*	*no*
affiliation control[f]	*no*	*yes*	*no*	*yes*
1^{st} stage coefficient[e]	0.1095*** (0.0159)	0.1058*** (0.0164)	-1.1465*** (0.1994)	-1.1360*** (0.2051)
F-stat.[d]	47.6	41.5	33.0	30.7
N	114,213	114,271	114,213	114,271
Away teams	FE	Affil.	FE	Affil.
Adjusted relative attendance	-0.0014 (0.0025)	-0.0017 (0.0025)	0.0039 (0.0031)	0.0030 (0.0030)
player-team-season FEs	*yes*	*no*	*yes*	*no*
affiliation control[f]	*no*	*yes*	*no*	*yes*
1^{st} stage coefficient[e]	0.1091*** (0.0159)	0.1109*** (0.0165)	-1.1358*** (0.1974)	-1.1684*** (0.2042)
F-stat.[d]	46.8	45.2	33.1	32.7
N	108,826	108,885	108,826	108,885

Notes: The dependent variable is a binary variable equal to 1 if the observed free throw is successful. All estimations include home-team-season, opponent-team-season fixed-effects, weekday, and score difference intervals. Columns one and three include player×team×season fixed effects. Column two and four control for the number of games consecutively played before by a player in the current team. Game-level clustered standard errors in parentheses, $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. [a] Instrumental variable is the average of game-day and 3 days before game-day minimum temperature. [b] Binary IV indicating minimum temperatures at game below freezing and unfavorable weather conditions. [c] Adjusted (censured at maximum of 100) relative attendance in percent of arena capacity. [d] Kleibergen and Paap (2006) statistics on the instrument in the first stage. [e] Estimated coefficients of the first stage regression with respect to the used instrument (IV-1, IV-2). Dependent variable is adjusted relative attendance.
[f] Specifications for columns 2 and 4 include the running sum counting the number of games an individual player attempts at least one free throw for a particular team, without interruption.