Scoring Benefits to Eastward Travel in the NBA

James Hasbany,[1] Ryland Burke,[2] Lawrence Watson,[3] and Jacqueline Doremus[4]

June 29, 2021

[1] Orfalea College of Business, California Polytechnic State University, San Luis Obispo
[2] Orfalea College of Business, California Polytechnic State University, San Luis Obispo
[3] Ernst & Young
[4] Corresponding author: 1 Grand Avenue, Orfalea College of Business, California Polytechnic State University, San Luis Obispo CA 93407. jdoremus@calpoly.edu

Scoring Benefits to Eastward Travel in the NBA

June 29, 2021

Travel across time zones may affect player scoring through their circadian rhythm. We test how team travel affects team scoring for the US National Basketball Association from 2014-2018, a period that coincides with the start of a new game scheduler. Next, we test whether a collective bargaining agreement with schedule restrictions protecting player rest changed the relationship between travel and scoring statistics. We find eastward travel increases scoring via three-pointers and field goals. The 2017 collective bargaining agreement mitigates the eastward travel benefit on scoring and increases scoring overall, suggesting improved fairness and potential benefits for players and fans.

Scoring Benefits to Eastward Travel in the NBA

1. Introduction

The average National Basketball Association (NBA) team was valued at $2.12 billion in the beginning of 2020 (Forbes 2020), representing a 14% increase from 2019. With such a large industry revolving around a sports league and the competition it creates, perceptions of NBA fairness are important to uphold as it can affect league viewership, advertising, and sponsors. Yet Zimmer and Kuethe (2009) find suggestive evidence of bias in the NBA's playoff tournaments consistent with financial incentives to ensure teams from larger markets make it to playoffs.

The schedule of play may affect bias and fairness in less strategic ways. Like all professional athletes, NBA players face a rigorous schedule during the regular season of competition. Players frequently travel across time zones, often with little time for adjustment of their body's circadian rhythm, the internal process responsible for regulating an individual's alertness and sleep-wake cycle. Travel has been found to impact player performance in a wide variety of professional and semi-professional sports leagues, including basketball (Nutting 2009; Nutting and Price 2017), wheelchair basketball (Thornton et al. 2018), soccer (Roberts et al. 2019), and baseball (Recht et al. 1995). Player performance likely has consequences for team wins. Analyzing win percentages of the NBA, National Football League, and the National Hockey League teams over a five-year period, Roy and Forest (2018) cite circadian rhythm as a key factor for higher win percentages for teams traveling eastward. However, the effect of travel on player scoring remains poorly understood.

Using team-level NBA data from 2014-2018, this paper tests whether travel east or west affects scoring. We consider an important period unassessed in the literature, one that includes a new NBA scheduler and policy changes from a powerful new collective bargaining agreement. Like Nutting (2009) and Nutting and Price (2015) found under the previous scheduler, we find that NBA teams traveling east are more likely to win. The estimated effect of eastward travel on win percentage is very similar in magnitude and precision to Nutting and Price (2015)'s estimate for the Fall 2002-Spring 2013 and consistent with results from Roy and Forest (2018). Though the effect on win percentage from eastward travel is not statistically significant, effects on scoring are: eastward travel increases field goals and three-pointers. We find some evidence that new policies from the collective bargaining agreement in 2017 may help address the eastward travel scoring benefit and increase scoring for all games.

2 Institutional Context: Travel, Jetlag and Basketball

2.1 NBA Game Scheduling

In 2014, Matt Winick, stepped down as Senior Vice President of Scheduling and Game Operations, the position responsible for scheduling NBA games for the entire season. For over 30 NBA seasons, he determined the season schedule for every team as well as playoff schedules (NBA 2015). The quintessential problem surrounding scheduling NBA games is the availability of the arenas. NBA stadiums are often utilized for other events, such as concerts and NCAA basketball games. To remedy the multitude of possible scheduling conflicts, Winick's model utilizes an incentive point-based system that assigns points to teams making consecutive days available for games at their stadium, with each team having to reach at least 50 total points (NBAStuffer n.d.). Under his reign, Bowman (2013) uses point spreads to indicate that the NBA has gotten fairer over the previous 20-year period (1990-2009), indicating that Winick has

improved over time at scheduling games that ensure fair competition. Along similar lines, Kelly (2010) shows that scheduling bias, contrary to popular belief among NBA coaches, did not exist over the 5-year period they examined, further supporting the strength of Winick's scheduling model towards his final years.

His vacancy was filled by Evan Wasch, who changed certain aspects of the model used to schedule NBA games. This is our period of inquiry, from 2014-2018, starting when scheduling responsibility was delegated to a new individual. Our analysis seeks to determine how NBA scheduling under this new director is affecting players. It has been suggested that Wasch and colleagues have taken a deeper dive over the past few seasons into scheduling analytics to further minimize the number of nights a tired team faces a fresh opponent (NBAStuffer n.d.).

Starting from the 2017-2018 season, Wasch expanded the NBA season by a week, doing away with 4 consecutive days of play for any one team that players dreaded via a collective bargaining agreement (CBA). This CBA changed scheduling significantly: it lengthened the season, limited exhibition games before season, and increased mandatory number of days off. Some of these changes were done explicitly to address concerns over sleep deprivation from constant travel.

2.2 Jetlag and Sports Performance

Travel east has been found to affect scoring statistics in the NBA. Nutting (2009) tested this within the NBA from 1990-2007 and found no effect for the first half of the season. However, in the second half of the season teams produced significantly more wins when east of their local time zones and significantly less when traveling west. During this period the majority of NBA games started at 7:00PM-7:30PM local time, meaning when teams travel from California to New York the visiting team's circadian rhythm feels as if it is 3:00PM. Likewise, a

team going from New York to California would effectively begin their games at 10:00PM. If game start times affect player sleep, this could affect performance. Increased sleep duration among collegiate basketball players improved sprint times, shooting accuracy, and mean reaction time (Mah et al. 2011). Other benefits included improved overall feelings of physical and mental well-being during practices and games from increased sleep. However, these benefits vary across individuals; among Australian basketball players sleep duration and sleep efficiency were significant predictors of performance for some individuals, however team-level sleep metrics failed to predict performance (Staunton et al. 2017).

The time of the game, when traveling, may be important for mediating how travel affects performance. Using data from the 1991-2013 seasons and game start times, Nutting and Price (2017) find benefits to eastward travel for day games. When reassessing data used in Nutting (2009) for the period 1991-2002, Nutting and Price (2017) found that benefits from eastward travel came from games at or before 4:00PM local time. They found no significant relationship between time zone and win probability for night games across the whole period and for day games after the 2002 season. The elimination of the eastward travel benefit during day games may be due, in part, to improvements in scheduling fairness by Winick over his career as an NBA scheduler (Bowman 2013).

The interaction of human circadian rhythms and player training may explain why eastward travel is beneficial. Alertness begins to decline dramatically after twelve hours awake (Wright et al. 2002). Players likely train and peak their performance for around 7:00PM, when most games occur in their local time zone. Given this, we hypothesize that athletes traveling westward may be more tired and playing at a time with lower alertness. Athletes traveling east may benefit from greater alertness given they are playing earlier in the day, relative to their home

time zone. Benefits might come in the form of scoring statistics, like more shots made from all ranges. If this were the case, changes in scheduling that lessen the strain of travel could reduce benefits from eastward travel.

3 Data

We connect two sources of data for our analysis, data on game statistics and data on team time zone. To our knowledge, we are the first to assess the effect of travel on these outcomes.

Game Statistics: Data for each year of the 2014-2018 NBA seasons come from Basketball-Reference, an organization that collects and publicizes team and player statistics regularly for public use. The unit of observation is a single game; data are only available at the team level. While this prohibits estimation of time zone effects on individual players, it provides a straightforward unit to estimate net performance changes for the team as a whole. The dataset contained all 4,920 games played in that time period. Data include performance statistics for both visiting and home teams, such as each team's points, their field goal percentage, and assists, as well as general match information. We focus on the scoring statistics of a team's win-loss percentage, total score, total field goals scored, total three-point shots scored, free throws, field goal percentage, three-point percentage, and free throw percentage. Table 1 contains a statistical summary of each variable used in the analysis.

Time Zones: To analyze possible advantages or disadvantages visiting teams have due to traveling, we matched teams to their home location time zone. We created indicator variables to reflect the difference in time zone for away games, one for eastward travel and one for westward travel. Figure 1 showcases the home locations of various NBA teams and relates them to time zones across the contiguous United States. Our models do not account for

the fact that some states do not utilize day light savings time. Omitting this will likely add

measurement error, which will bias our estimates toward zero.

4 Empirical Strategy

We begin by characterizing the relationship between travel and scoring performance.

Next, we test whether this relationship changed after the implementation of the CBA in 2017.

For both empirical analyses, we use ordinary least squares regressions with fixed effects. Our

identifying assumption in our regression involves that the time zone difference is assigned by the

NBA scheduler in a way that minimizes bias. Our regression expressions are

$$Performance_{ijt} = \beta_1 West_{ijt} + \beta_2 East_{ijt} + \gamma_i + \delta_j + \theta_m + \sigma_{it} + \varphi_{jt} + \tau_t + \epsilon_{ijt} \quad (1)$$

$$Performance_{ijt} = \beta_1 West_{ijt} + \beta_2 East_{ijt} + \beta_3 CBA_t * West_{ijt} + \beta_4 CBA_t * East_{ijt} +$$
$$\beta_5 CBA_t + \gamma_i + \delta_j + \theta_m + \sigma_{it} + \varphi_{jt} + \tau_t + \epsilon_{ijt} \qquad (2)$$

where i is home team, j is visiting team, and t is month and year. Key variables in expression 1

are *West* and *East,* indicator variables for the game relative to the visitor's time zone at home.

The omitted category is a time zone difference of 0. Expression 2 is a richer model that

controls for whether the CBA agreement has been implemented or not and interacts the CBA

indicator variable with the east and west travel variables.

We include a suite of fixed effects. These include fixed effects for home team γ_i,

visiting team δ_j, month θ_m, year τ, home team-year σ_{it}, and visiting team-year φ_{jt}. Our fixed

effects control for average differences between successful and struggling teams from year to

year during the team building cycle. They also eliminate critical unobserved variables that

affect team performance, such as seasonal performance patterns (injuries, fatigue). In the appendix, we assess how sensitive our results are to inclusion of fixed effects.

For the Win outcome, an indicator variable, estimates are based on linear probability models to provide easily interpreted coefficients. As data are recorded on each team individually, we cluster our standard errors by team. Error distribution for the regressions followed normal patterns. Data cleaning and analysis was done using R.

4.1   Assumptions and Limitations

Our models assume that games are fairly assigned regarding time zone difference to minimize bias. Time of the game and date it is played is not randomly assigned but is supposedly done by the league to balance both the alleviation of player exhaustion and the reduction of costs. The league's commitment to maintain fairness should mitigate bias, but scheduling to reduce costs might introduce bias under some circumstances.

Our paper has limitations. First, though we observe every NBA game over the 4-year period and have data on every combination of team pairs, we cannot separate out team-team match ups from time zones. This means there might be unaccounted for effects driven by specific playstyle interaction between teams (perimeter focused teams vs traditional post teams). However, this would be true in both directions as each team will have a home game and away game against each other.

Another limitation is that we do not account for accumulated fatigue. Our model estimates the average across all games within the travel category, after adjusting for month fixed effects. If adjusted to their new time zone after playing several games, we might expect benefits or costs to travel to attenuate over the course of several games. This would bias our estimates toward zero. Two other game factors that we do not include, game frequency and time of game,

may also affect outcomes. If these factors are unassociated with the direction of travel, omitting these factors should increase measurement error, again biasing our estimates toward zero.

5 Results

We begin by presenting results for how eastward and westward travel from a home stadium affects scoring statistics, both raw outcome and, where appropriate, the percentage of winning shots. Next, we test how these relationships change after policies are put in place for the 2017 collective bargaining agreement.

5.1 Examining the 2014-2018 Seasons Together

For our period of inquiry, which is the debut of the new NBA scheduler, we find significant effects from travel on scoring performance but not for our estimate for the win indicator. In Panel A of Table 3, eastward travel of at least one time zone is associated with an increase in the likelihood of winning of 1.6%, however the estimate is not statistically significant. However, for scoring outcomes there is stronger evidence of an eastward travel benefit. Eastward travel is associated with an increase of 1.3 total points scored, which is about 1.3% of the average points scored per game from Table 1. Teams make an additional 0.75 field goals a game and 0.3 more three-point shots. Interestingly, teams make 0.5 fewer free throws per game on average. If we calculate the change in points caused by the change in number of shots made, we arrive almost precisely at 1.3 as our other model predicts, meaning no matter what metric we examine, either total points or shots made, teams traveling east are scoring more points and thus are performing better on average. In general, all estimates are robust to different sets of fixed effects (see Appendix tables).

Moving to panel B, we find a more nuanced story for the percentage of shots made. Eastward travel is associated with an increase of 0.7% for field goals, and this estimate is statistically significant at the ten percent level. The coefficients for the percentage of three-point shots and free throws are closer to zero and not statistically significant.

5.2 Collective Bargaining Agreement

Before the CBA was implemented, we see statistically significant positive effects for teams traveling east. In Table 4, we find that eastward travel before the CBA is still associated with greater team points, field goals, and three-point shots. Total points increase by 1.98, most likely as a result of increased three-point shots and overall field goals, which have coefficients of 0.57 and 0.89 respectively. The association with free throws is still negative but no longer statistically significant.

The CBA decreased the number of times teams must play consecutive games, among other changes, and we might expect some changes in scoring regardless of travel. Indeed, we find a dramatic impact on total number of three-point shots made for all teams. The CBA is associated with an increase of 3.55 three-point shots per game and the estimate is statistically significant.

Better rest from policies to satisfy the CBA may also impact scoring when on the road. For all scoring statistics, the CBA interactions appear to offset the benefits from travel pre-CBA. With the exception of free throws, the coefficients for the post-CBA period and eastward travel have an opposite sign from before the CBA. However, none of the estimates are precisely estimated. The coefficient on the interaction between CBA and eastern travel for three-point shots is -0.69 and is significant at a 10% level, effectively negating the pre-CBA

benefit from eastward travel on three-point shots. The westward travel CBA interactions are close to zero and insignificant.

6 Discussion and Conclusion

Using data collected from 2014-2018 on NBA statistics for each team, we found evidence that under the new NBA scheduler teams score better when traveling eastward. Improved scoring performance included overall team points, field goals, field goal percentage, and three-point shots. To our knowledge, our paper is the first to look at how travel affects team scoring metrics, an important outcome for sports betting markets.

For win percentage, we find eastward travel increases the likelihood of winning by 1.6%, however the estimate is not statistically significant. Our coefficient for win percentage is nearly identical in magnitude and precision to the estimate from Nutting and Price (2015) for all games between Fall 2002-Spring 2013, 1.2%, under the previous NBA scheduler's regime. We conclude that under the new NBA scheduler there has likely been no change in the eastward travel benefit, as compared to the previous NBA scheduler.

We also assessed whether a new, powerful collective bargaining agreement changed benefits from eastward travel. We find that for most outcomes, the CBA reduced the benefits to scoring from eastward travel, though our coefficients are imprecisely estimated. The CBA seems to have had the greatest impact on three-point shooting, nearly eliminating the eastward travel benefit.

Though we are unable to directly test the mechanism driving our results, our results support the hypothesis that travel and circadian rhythm, which affects player alertness and rest, may be what drives increases in scoring and winning when traveling eastward. Our results are

consistent with Roy and Forest (2018), who find benefits to eastward travel for basketball, football, and hockey teams which they link to circadian rhythm. Circadian rhythm and alertness peaks earlier in the day, with alertness deteriorating particularly fast after twelve hours awake. Given most NBA games are in the evening, travel east lets players compete with an earlier internal clock, which seems to give them an edge in scoring. The collective bargaining agreement of 2017 added protections to players sleep and greater recovery within their travel schedule, which seems to have increased scoring overall and reduced the benefits from eastward travel.

Eliminating bias within schedules is vital for fair play. Fair play affects not only the league's reputation, and thus fan and investor support, but also betting markets. Currently, betting markets fail to properly adjust for player fatigue (Ashman et al. 2010). As sports betting becomes legal in a growing number of states, the importance of fair scheduling and mitigating bias NBA is magnified. We discovered a new benefit from eastward travel, increased scoring, which can affect betting markets. We also find the new scheduling policies for the 2017 collective bargaining agreement seem to have helped with player fatigue and resulted in higher scoring. Given scoring by away teams increases fan interest and game attendance (Copenhaver 2008), we conclude that the policies from the collective bargaining agreement may have benefited both players and the league alike.

7. References

Ashman, Thomas, R. Alan Bowman, and James Lambrinos. "The role of fatigue in NBA wagering markets: The surprising ''Home Disadvantage Situation''." *Journal of Sports Economics* 11, no. 6 (2010): 602-613.

Bowman, R. Alan, James Lambrinos, and Thomas Ashman. "Competitive balance in the eyes of the sports fan: Prospective measures using point spreads in the NFL and NBA." *Journal of Sports Economics* 14, no. 5 (2013): 498-520.

Copenhaver, Todd. "Does NBA attendance respond to an increased emphasis on offense?" (2008). Minneapolis Fed Working Paper. Accessed on April 1, 2021: https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.508.1261&rep=rep1&type=pdf

How the NBA Schedule is Made (n.d.) NBAStuffer https://www.nbastuffer.com/analytics101/how-the-nba-schedule-is-made/

Kelly, Yvan J. "The myth of scheduling bias with back-to-back games in the NBA*." Journal of Sports Economics* 11, no. 1 (2010): 100-105.

Mah, Cheri D, Mah, Kenneth E, Kezirian, Eric J, and Dement, William C. "The Effects of Sleep Extension on the Athletic Performance of Collegiate Basketball Players." *Sleep* 34, no. 7 (2011): 943-950.

NBA (2015) Accessed on September 3, 2020. URL: https://careers.nba.com/2015/08/18/matt-winick/

Nutting, Andrew. "Travel Costs in the NBA Production Function." *Journal of Sports Economics* 11, no. 5 (2009): 533–548.

Nutting, Andrew, and Joseph Price. "Time Zones, Game Start Times, and Team Performance: Evidence From the NBA." *Journal of Sports Economics* 18, no. 5 (2017): 471–478.

Releases, Forbes Press. "The Business of Basketball: Forbes Releases 22nd Annual NBA Team Valuations." *Forbes*, Forbes Magazine, 11 Feb. 2020, www.forbes.com/sites/forbespr/2020/02/11/the-business-of-basketball-forbes-releases-22nd-annual-nba-team-valuations

Recht, Lawrence D, Robert A. Lew, and William J. Schwartz. "Baseball Teams Beaten by Jet Lag." *Nature* 377, no. 6550 (1995): 583-583.

Roberts SSH, Teo W, Warmington SA. "Effects of training and competition on the sleep of elite athletes: a systematic review and meta-analysis." *British Journal of Sports Medicine* 53, no. 8 (2019): 513-522.

Roy, Jonathan, and Geneviève Forest. "Greater circadian disadvantage during evening games for the National Basketball Association (NBA), National Hockey League (NHL) and National Football League (NFL) teams travelling westward." *Journal of Sleep Research* 27, no. 1 (2018): 86-89.

Staunton, Craig, Brett Gordon, Edhem Custovic, Jonathan Stanger, and Michael Kingsley. "Sleep Patterns and Match Performance in Elite Australian Basketball Athletes." *Journal of Science and Medicine in Sport* 20, no. 8 (2017): 786-89.

Taylor, Beck A., and Justin G. Trogdon. "Losing to win: Tournament incentives in the National Basketball Association." Journal of Labor Economics 20, no. 1 (2002): 23-41.

Thornton, Heidi R., Joanna Miller, Lee Taylor, Charli Sargent, Michele Lastella, and Peter M. Fowler. "Impact of Short- Compared to Long-haul International Travel on the Sleep and Wellbeing of National Wheelchair Basketball Athletes." *Journal of Sports Sciences* 36, no. 13 (2018): 1476-484.

Walters, Christopher, and Tyler Williams. "To tank or not to tank? Evidence from the NBA." In MIT Sloan Sports Conference March. Boston, MA. 2012.

Wright Jr, Kenneth P., Joseph T. Hull, and Charles A. Czeisler. "Relationship between alertness, performance, and body temperature in humans." *American Journal of Physiology-Regulatory, Integrative and Comparative Physiology* (2002).

Zimmer, Timothy, and Todd H. Kuethe. "Testing for bias and manipulation in the National Basketball Association playoffs." *Journal of Quantitative Analysis in Sports* 5, no. 3 (2009).

8. Tables

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Win Loss	4,920	0.42	0.49	0	0	1	1
Team Points	4,920	102.36	12.21	66	94	110	148
Field Goals	4,920	38.18	4.98	22	35	41	58
3 Point Shots	4,920	9.01	3.60	0	6	11	25
Free Throws	4,920	16.98	5.97	1	13	21	42
Free Throws Pct	4,920	0.76	0.11	0.18	0.69	0.83	1.00
3 Point Shots Pct	4,920	0.35	0.10	0.00	0.29	0.42	0.75
Field Goals Pct	4,920	0.45	0.05	0.27	0.41	0.49	0.67
East	4,920	0.32	0.47	0	0	1	1
West	4,920	0.32	0.47	0	0	1	1

Notes: Data are from Basketball-Reference over the 2014-2018 period, Win Loss was the only variable altered, as it was converted to be binary.

Table 2: Distribution of Time Zone Difference

	Location	HomeTZ	N	West3	West2	West1	Same	East1	East2	East3
ATL	Atlanta, GA	3	164	20	12	42	90	0	0	0
BOS	Boston, MA	3	164	20	12	43	89	0	0	0
BRK	New York, NY	3	164	20	12	42	90	0	0	0
CHI	Chicago, IL	2	164	0	20	12	36	96	0	0
CHO	Charlotte, NC	3	164	20	12	43	89	0	0	0
CLE	Cleveland, OH	3	164	20	12	44	88	0	0	0
DAL	Dallas, TX	2	164	0	35	22	55	52	0	0
DEN	Denver, CO	1	164	0	0	36	16	60	52	0
DET	Detroit, MI	3	164	20	12	44	88	0	0	0
GSW	San Francisco, CA	0	164	0	0	0	30	23	59	52
HOU	Houston, TX	2	164	0	36	22	54	52	0	0
IND	Indianapolis, IN	3	164	20	12	44	88	0	0	0
LAC	Los Angeles, CA	0	164	0	0	0	32	23	57	52
LAL	Los Angeles, CA	0	164	0	0	0	31	22	59	52
MEM	Memphis, TN	2	164	0	37	21	54	52	0	0
MIA	Miami, FL	3	164	20	12	42	90	0	0	0
MIL	Milwaukee, WI	2	164	0	20	12	36	96	0	0
MIN	Minneapolis, MN	2	164	0	37	23	52	52	0	0
NOP	New Orleans, LA	2	164	0	36	21	55	52	0	0
NYK	New York, NY	3	164	20	12	42	90	0	0	0
OKC	Oklahoma City, OK	2	164	0	37	23	52	52	0	0
ORL	Orlando, FL	3	164	20	12	44	88	0	0	0
PHI	Philadelphia, PA	3	164	20	12	42	90	0	0	0
PHO	Pheonix, AZ	1	164	0	0	40	13	59	52	0
POR	Portland, OR	0	164	0	0	0	29	23	60	52
SAC	Sacramento, CA	0	164	0	0	0	31	23	58	52
SAS	San Antonio, TX	2	164	0	36	22	54	52	0	0
TOR	Toronto, ON	3	164	20	12	43	89	0	0	0
UTA	Salt Lake City, UT	1	164	0	0	37	15	60	52	0
WAS	Washington, DC	3	164	20	12	41	91	0	0	0

Notes: Data are from Basketball-Reference over the 2014-2018 period. A HomeTZ value of 0 indicates Pacific Time Zone, 1 indicates Mountain Time Zone, 2 indicates Central Time Zone, 3 indicates Eastern Time Zone. West 3 indicates how many games that team has played three time zones to the west, with similar interpretations for the other columns.

Table 3: Scoring Metrics

| | Panel 1: Raw Values | | | | |
| | Win Loss | Team Points | Field Goals | 3 Point Shots | Free Throws |
	(1)	(2)	(3)	(4)	(5)
Westward Travel	0.003	0.215	-0.083	0.109	0.272
	(0.021)	(0.723)	(0.294)	(0.118)	(0.337)
Eastward Travel	0.016	1.316**	0.767***	0.300***	-0.518*
	(0.022)	(0.562)	(0.227)	(0.111)	(0.306)
Constant	0.406***	100.729***	37.497***	9.493***	16.242***
	(0.098)	(2.678)	(1.180)	(0.872)	(1.591)
R^2	0.220	0.259	0.218	0.337	0.180

| | Panel 2: Percentages | | |
		(6)	(7)	(8)
Westward Travel		-0.002	0.001	-0.001
		(0.004)	(0.004)	(0.006)
Eastward Travel		0.007*	0.005	-0.0004
		(0.003)	(0.005)	(0.006)
Constant		0.455***	0.363***	0.778***
		(0.016)	(0.031)	(0.036)
R^2		0.145	0.084	0.125

Notes: N=4,920. *p<0.1; **p<0.05; ***p<0.01. Data are from Basketball-Reference over the 2014-2018 period, each observation is an NBA game. N=4,920. Coefficient estimates from an OLS regression, standard errors are in parentheses. Regression includes fixed effects for home team, opponent, month, year, home team x year, opponent x year. Standard errors are clustered by home team.

Table 4: Scoring Metrics w/ CBA Agreement

	Win Loss	Team Points	Field Goals	3 Point Shots	Free Throws
	(1)	(2)	(3)	(4)	(5)
Westward Travel	0.034	0.220	-0.092	0.020	0.383
	(0.027)	(0.935)	(0.365)	(0.160)	(0.440)
Eastward Travel	0.017	1.987***	0.889***	0.569***	-0.360
	(0.026)	(0.754)	(0.310)	(0.187)	(0.456)
CBA	0.046	4.506	0.823	3.547***	-0.686
	(0.163)	(4.681)	(1.799)	(1.139)	(1.721)
Westward Travel:CBA	-0.076	-0.022	0.019	0.218	-0.278
	(0.044)	(1.335)	(0.481)	(0.337)	(0.713)
Eastward Travel:CBA	-0.004	-1.720	-0.313	-0.685*	-0.409
	(0.048)	(1.548)	(0.602)	(0.410)	(0.849)
Constant	0.406***	100.653***	37.483***	9.462***	16.224***
	(0.099)	(2.713)	(1.187)	(0.877)	(1.603)
R^2	0.220	0.260	0.218	0.338	0.180

Notes: N=4,920. *p<0.1; **p<0.05; ***p<0.01. Data are from Basketball-Reference over the 2014-2018 period, each observation is an NBA game. N=4,920. Coefficient estimates from an OLS regression, standard errors are in parentheses. Regression includes fixed effects for home team, opponent, month, year, home team x year, opponent x year. Standard errors are clustered by home team.

9. Figures

Figure 1: NBA team locations
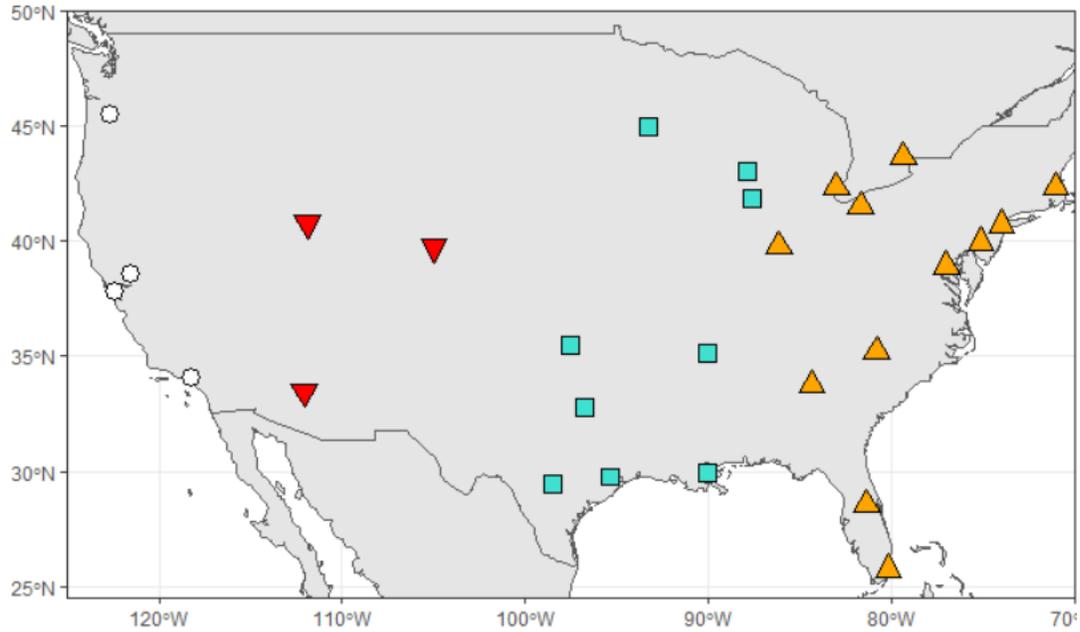
Notes: Each icon represents a city where an NBA team is located, similar color and icon indicates that those cities are in the same time zone. Circular icons represent cities with teams in the Pacific Time Zone. Upside down triangles indicate Mountain Time Zone. Squares represent Central Time Zone. Traditional triangles indicate Eastern Time Zone. Note, Arizona does not observe daylight savings time, potentially impacting Phoenix Sun game data.

10. Appendix

Table A: Win-Loss Fixed Effects Testing

	Win Loss		
	(1)	(2)	(3)
Westward Travel	0.027	0.001	0.003
	(0.036)	(0.021)	(0.021)
Eastward Travel	-0.010	0.014	0.016
	(0.020)	(0.023)	(0.022)
Constant	0.413***	0.461***	0.406***
	(0.027)	(0.047)	(0.098)
R^2	0.001	0.130	0.220

Notes: N=4,920. *p<0.1; **p<0.05; ***p<0.01. Data are from Basketball-Reference over the 2014-2018 period, each observation is an NBA game. N=4,920. Coefficient estimates from an OLS regression, standard errors are in parentheses. Table demonstrates robustness of the Win-Loss variable to different sets of fixed effects. Regression (1) is the simple regression, (2) contains covariates Team, Opponent, Month, and Year. (3) contains (2) with interaction terms. (3) is the model utilized in main results. Standard errors are clustered by home team.

Table B: Team Points Fixed Effects Testing

	Team Points		
	(1)	(2)	(3)
Westward Travel	1.723**	0.170	0.215
	(0.768)	(0.683)	(0.723)
Eastward Travel	0.626	1.397**	1.316**
	(0.499)	(0.551)	(0.562)
Constant	101.617***	97.197***	100.729***
	(0.581)	(1.534)	(2.678)
R^2	0.003	0.172	0.259

Notes: N=4,920. *$p<0.1$; **$p<0.05$; ***$p<0.01$. Data are from Basketball-Reference over the 2014-2018 period, each observation is an NBA game. N=4,920. Coefficient estimates from an OLS regression, standard errors are in parentheses. Table demonstrates robustness of the Team Points variable to different sets of fixed effects. Regression (1) is the simple regression, (2) contains covariates Team, Opponent, Month, and Year. (3) contains (2) with interaction terms. (3) is the model utilized in main results. Standard errors are clustered by home team.

Table C: Field Goals Fixed Effects Testing

	Field Goals		
	(1)	(2)	(3)
Westward Travel	0.586**	-0.082	-0.083
	(0.292)	(0.269)	(0.294)
Eastward Travel	0.235	0.773***	0.767***
	(0.165)	(0.220)	(0.227)
Constant	37.924***	36.340***	37.497***
	(0.172)	(0.506)	(1.180)
R^2	0.002	0.128	0.218

Notes: N=4,920. *p<0.1; **p<0.05; ***p<0.01. Data are from Basketball-Reference over the 2014-2018 period, each observation is an NBA game. N=4,920. Coefficient estimates from an OLS regression, standard errors are in parentheses. Table demonstrates robustness of the Field Goals variable to different sets of fixed effects. Regression (1) is the simple regression, (2) contains covariates Team, Opponent, Month, and Year. (3) contains (2) with interaction terms. (3) is the model utilized in main results. Standard errors are clustered by home team.

Table D: 3 Point Shots Fixed Effects Testing

	3 Point Shots		
	(1)	(2)	(3)
Westward Travel	0.149	0.060	0.109
	(0.283)	(0.120)	(0.118)
Eastward Travel	0.010	0.254**	0.300***
	(0.102)	(0.115)	(0.111)
Constant	8.963***	8.592***	9.493***
	(0.255)	(0.362)	(0.872)
R^2	0.0003	0.249	0.337

Notes: N=4,920. *p<0.1; **p<0.05; ***p<0.01. Data are from Basketball-Reference over the 2014-2018 period, each observation is an NBA game. N=4,920. Coefficient estimates from an OLS regression, standard errors are in parentheses. Table demonstrates robustness of the 3 Point Shots variable to different sets of fixed effects. Regression (1) is the simple regression, (2) contains covariates Team, Opponent, Month, and Year. (3) contains (2) with interaction terms. (3) is the model utilized in main results. Standard errors are clustered by home team.

Table E: Free Throw Fixed Effects Testing

	Free Throws		
	(1)	(2)	(3)
Westward Travel	0.402	0.275	0.272
	(0.285)	(0.327)	(0.337)
Eastward Travel	0.146	-0.402	-0.518*
	(0.203)	(0.302)	(0.306)
Constant	16.805***	15.925***	16.242***
	(0.272)	(0.818)	(1.591)
R^2	0.001	0.100	0.180

Notes: N=4,920. *$p<0.1$; **$p<0.05$; ***$p<0.01$. Data are from Basketball-Reference over the 2014-2018 period, each observation is an NBA game. N=4,920. Coefficient estimates from an OLS regression, standard errors are in parentheses. Table demonstrates robustness of the Free Throws variable to different sets of fixed effects. Regression (1) is the simple regression, (2) contains covariates Team, Opponent, Month, and Year. (3) contains (2) with interaction terms. (3) is the model utilized in main results. Standard errors are clustered by home team.

Table F: Field Goal Percentage Fixed Effects Testing

	Field Goal Pct		
	(1)	(2)	(3)
Westward Travel	0.006*	-0.003	-0.002
	(0.003)	(0.003)	(0.004)
Eastward Travel	0.002	0.007**	0.007*
	(0.002)	(0.003)	(0.003)
Constant	0.448***	0.445***	0.455***
	(0.002)	(0.006)	(0.016)
R^2	0.002	0.073	0.145

Notes: N=4,920. *p<0.1; **p<0.05; ***p<0.01. Data are from Basketball-Reference over the 2014-2018 period, each observation is an NBA game. N=4,920. Coefficient estimates from an OLS regression, standard errors are in parentheses. Table demonstrates robustness of the Field Goal Percentage variable to different sets of fixed effects. Regression (1) is the simple regression, (2) contains covariates Team, Opponent, Month, and Year. (3) contains (2) with interaction terms. (3) is the model utilized in main results. Standard errors are clustered by home team.

Table G: 3 Point Shot Percentage Fixed Effects Testing

	3 Point Shot Pct		
	(1)	(2)	(3)
Westward Travel	0.009***	-0.0003	0.001
	(0.003)	(0.004)	(0.004)
Eastward Travel	0.001	0.006	0.005
	(0.003)	(0.005)	(0.005)
Constant	0.347***	0.352***	0.363***
	(0.002)	(0.011)	(0.031)
R^2	0.002	0.030	0.084

Notes: N=4,920. *p<0.1; **p<0.05; ***p<0.01. Data are from Basketball-Reference over the 2014-2018 period, each observation is an NBA game. N=4,920. Coefficient estimates from an OLS regression, standard errors are in parentheses. Table demonstrates robustness of the 3 Point Shot Percentage variable to different sets of fixed effects. Regression (1) is the simple regression, (2) contains covariates Team, Opponent, Month, and Year. (3) contains (2) with interaction terms. (3) is the model utilized in main results. Standard errors are clustered by home team.

Table H: Free Throw Percentage Fixed Effects Testing

	Free Throws Pct		
	(1)	(2)	(3)
Westward Travel	-0.001	-0.001	-0.001
	(0.007)	(0.006)	(0.006)
Eastward Travel	-0.002	0.001	-0.0004
	(0.004)	(0.006)	(0.006)
Constant	0.762***	0.752***	0.778***
	(0.006)	(0.013)	(0.036)
R^2	0.00004	0.062	0.125

Notes: N=4,920. *p<0.1; **p<0.05; ***p<0.01. Data are from Basketball-Reference over the 2014-2018 period, each observation is an NBA game. N=4,920. Coefficient estimates from an OLS regression, standard errors are in parentheses. Table demonstrates robustness of the Free Throws Percentage variable to different sets of fixed effects. Regression (1) is the simple regression, (2) contains covariates Team, Opponent, Month, and Year. (3) contains (2) with interaction terms. (3) is the model utilized in main results. Standard errors are clustered by home team.