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HETEROGENEOUS CONSUMER PREFERENCES FOR PRODUCT QUALITY AND UNCERTAINTY

Urban
Transport
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Heterogeneous consumer preferences for product quality and uncertainty*

Abstract: We provide evidence for heterogeneous consumer preferences for product quality and game outcome uncertainty (GOU) in Major League Baseball. Using attendance data from 2013 to 2019, we explore functional data clustering techniques to detect common patterns in predictive margins of team-specific winning probability. As a central result, we identify five groups of teams with similar GOU effects. However, only a few teams' fans show GOU preferences that resemble the typical hump-shape that is postulated by the uncertainty of outcome hypothesis; the largest cluster is comprised of teams with fans whose attendance behavior is relatively insensitive to differences in GOU.

Key words: Consumer demand; Heterogeneous preferences; Product quality; Uncertainty of outcome hypothesis; Clustering; Functional data analysis
JEL: D12; L15; L2; L83; Z2

1 Introduction

As perhaps the most prominent example of economic peculiarities associated with product quality and professional sports markets, the uncertainty of outcome hypothesis (UOH) postulates that spectators prefer games with uncertain outcomes (Rottenberg, 1956). However, the vast majority of studies on sport demand and UOH does not account for the potential existence of differences in fan base-specific preferences for product quality (see, e.g., Schreyer & Ansari (2021), Downward et al. (2009), and Borland & Macdonald (2003) for corresponding literature surveys). Yet, it is unclear to which extent fan preferences apply uniformly across local market areas. Cities vary with their population's demographics, socio-economic environment and history, sport culture, and further characteristics that are likely to shape fan preferences differently across teams (Madura, 1980; Mueller, 2020). Contributing to previous findings on heterogeneous consumer behavior in the modern sports industry (Benz et al., 2009; Bradbury, 2019; Buraimo & Simmons, 2009; Humphreys & Miceli, 2020; Mills & Fort, 2018; Schreyer et al., 2016), this paper identifies substantial heterogeneity in fans' game outcome uncertainty (GOU) preferences across teams in Major League Baseball (MLB).

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To this end, we estimate pooled and team-specific censored regression models on the basis of individual game data from the 2013 to 2019 regular seasons. GOU is measured using a quadratic home team winning probability specification; outcome probabilities are derived from betting odds (money lines). As a key result, using functional data clustering techniques, we identify five groups of teams with similar GOU effects that significantly differ across clusters, e.g., while some fans are insensitive to differences in GOU, some teams experience attendance to consistently increase in their winning probability, and some teams have fans with GOU preferences that are roughly in line with the UOH.

The remainder of the paper is organized as follows: Section 2 reviews relevant literature and Section 3 describes the data that are employed in this study. Section 4 describes our empirical strategy, shows our main findings, and summarizes the results of various robustness checks. Section 5 presents the conclusions of the paper.

2 Sport demand and uncertain game outcomes

The UOH implies an inverse U-shaped functional relationship of game preference and GOU (Rottenberg, 1956). While this study focuses on GOU at the individual game level, the sport demand literature typically distinguishes between three different temporal dimensions of the UOH: short- (e.g., game level), medium- (e.g., League championship), and long-term (e.g., seasonal level) (Downward et al., 2009). However, as with other sports, such as basketball (Humphreys & Miceli, 2020), hockey (Mills & Fort, 2014), and European league football (Forrest & Simmons, 2002; Pawlowclubski & Anders, 2012), there is no consistent empirical support for the UOH in baseball. To give some examples for studies that analyze short-run GOU in MLB using a quadratic home team winning probability specification: Using game level data from 1988 and 1996, Knowles et al. (1992) and Rascher (1999) find that attendance is maximized when home team winning probability is at 60% and 66%, respectively; in contrast, Tainsky & Winfree (2010) analyze data from 1996 to 2009 and do not find significant preferences for uncertain game outcomes. (see, e.g., Borland & Macdonald (2003), Paul Downward et al. (2009) and Coates et al. (2014) for summaries of previous UOH research covering various sports).

Further inherent aspects of GOU that have recently been addressed include ex-post and ex-ante GOU (Chung et al., 2016), subjective and objective measures of GOU (Pawlowski et al., 2018) and within-game GOU (Buraimo et al., 2019), thereby distinguishing between moments of suspense and

surprise. However, to the best of our knowledge, only Mills & Fort (2018) account for UOH differences across teams. Concisely, they employ a time-series break-point analysis using seasonal aggregated data from MLB, the National Basketball Association (NBA), and the National Hockey League (NHL) to analyze long-term GOU; while they find both relevant differences in GOU effects across Leagues and across teams within Leagues, their findings are not consistent with the UOH. In contrast to Mills & Fort (2018), we extend previous UOH and sport demand research by analyzing heterogeneity in fans' GOU preferences in MLB at the game-level, thereby exploring functional data clustering techniques to identify groups of teams with fans that show similar preferences for uncertain game outcomes.

3 Data and empirical strategy

Our data sample covers all 17,008 MLB games that were played over the course of the 2013 to 2019 regular seasons. We choose 2013 as the first year of our sample because it is the first season after the last MLB division realignment[1]; 2019 is chosen as the last season in our sample because of the attendance restrictions due to the Covid pandemic. Since we aim to discover potential differences in fan base-specific preferences for GOU, we drop 32 games that were not played at teams' home stadiums.[2] Hence, our sample exclusively features stable team-city combinations. Then, we discard each team's first home game per season, because we include information on a team's last preceding game. In addition, we drop all 439 double headers and rescheduled games, since it is not always possible to distinguish between fans who purchased tickets for both or only for one game of a double header, and, because we cannot distinguish between fans who bought tickets for rescheduled games before they were announced to get rescheduled. Likewise, we discard 18 games that were extended to another date. The final data sample includes observations on 16,309 games.

[1] In general, the more teams are competing in a division, the harder it is to win the division, vice versa. Between 1998 and 2012, both the National League (NL) and the American League (AL) comprised three divisions each, but the NL Central division consisted of six teams, whereas the AL West division comprised only four teams. After the 2012 season, the Houston Astros moved from NL Central to AL West, which has been resulting in balanced Leagues with five teams per division from 2013 onwards.

[2] A few games per season are typically not played at the corresponding home teams' home stadiums because of bad weather conditions, international promotions, or other extreme events.

We regress game attendance (ticket sales) on several team-performance and GOU measures while controlling for home team fixed effects, year fixed effects, and a battery of variables that have frequently been identified as major attendance factors (for an overview, see, e.g., Borland & Macdonald (2003)). Table 1 provides a summary and description of the explanatory variables that are employed in this study. For a detailed overview of variable specifications and summary statistics, see Appendix, Section 2.

Table 1. Description of explanatory variables

Variable	Description
GAttend	Outcome: Game attendance censored at stadium capacity
HT Wprob (%)	Home team (HT) winning probability (%) (calculated from money lines)
HT Wprob²	HT winning probability squared
HT GB	Games behind between HT and its division-leading team
VT GB	Games behind between VT and its division-leading team
HT Wper	HT's winning percentage (within season)
VT Wper	VT's winning percentage of
HT WSW*	HT is last year's World Series winner
VT WSW	VT is last year's World Series winner
HT LCW*	HT is last year's League Championship Series winner
VT LCW	VT is last year's League Championship Series winner
HT PS*	HT reached last year's postseason
VT PS	VT reached last year's postseason
Control variables	
Lag GAttend	Lagged HT-specific game attendance
HT id*	Home-team identification: ARI, ATL, BAL, BOS, CHC, … , WSN
Year	Season year: 2013, 2014, …, 2019
Month	Month: Apr., May, Jun., Jul., Aug, Sep.
WDay	Weekday: Mon, Tue, Wed, Thu, Fri, Sat, Sun
Night	Night game: No, Yes
PHoliday	Public holiday: No, Yes (Labor Day, 4th of July, or Memorial Day)
Rain	Precipitation: No, Yes
IL Game	Interleague game: No, Yes
Rivalry	Rivalry game: No, Yes
BHeads	Bobblehead promotion: No, Yes
New Stadium*	HT opened a new stadium during a given season
Distance	Distance between HT's and VT's stadiums (in miles)

Notes: * Included in the pooled regression; not included in the individual team-specific regressions because of perfect multicollinearity with year fixed effects. We combine data from various sources: retrosheet.org (game-log data), seamheads.com (information on stadiums), stadiumgiveawayexchange.com (bobble head promotions), darksky.net (weather data API), sportsbookreviewsonline.com (betting odds), and Mueller (2020) (team rivalries).

Concerning our main variables of interest for measuring product quality, we use home team winning probability derived from betting odds (via the method of Shin (1993)) and its square to measure

fans' GOU preferences: First, in contrast to simple GOU measures, such as the absolute difference between home and visiting team winning probability, specifying a quadratic polynomial relationship allows to investigate non-linear GOU effects that can directly be compared to their postulated inverse U-shape.[3] Second, across various sports, previous research has widely established that outcome predictions derived from betting odds typically provide more accurate predictions on future game outcomes than alternative sources of sport outcome forecasts, including (non-linear) regression approaches (Forrest et al., 2005), expert tipsters (Spann & Skiera, 2009), and lay predictions (Scheibehenne & Bröder, 2007). As a result, outcome probabilities derived from betting-odds are considered to provide more accurate information on GOU than alternative sources, such as, e.g., league positions or points (Dawson & Downward, 2005). Our variables of secondary interest comprise of team performance measures and include both home and visiting team's games behind and winning percentage (measured before game day). Likewise, in addition to controlling for various other relevant attendance factors, we include binary variables to capture whether a team made it to the last season's play offs and whether a team is last season's world and/or league championship series winner.

4 Implementation and results

We use Tobit regression to account for game sell outs; attendance is censored at stadium capacity (see Appendix, Section 2 for attendance summary statistics by team). Table 2 shows the corresponding regression results on the basis of pooling all teams' observations using clustered standard errors at the team-level (1) in addition to the results of five selected individual team-specific regressions using robust (Huber/White) standard errors (2-6). The complete results for all 30 team-specific regressions are provided in the Appendix, Section 4.1.

[3] As a note, unlike in sports such as European Football or cricket, in MLB, there is (practically) no possibility of a draw.

Table 2. Tobit regression models of home game attendance

	(1) Pooled	(2) Team: SDP	(3) Team: WAS	(4) Team: DET	(5) Team: COL	(6) Team: SFG
HT Wprob (%)	-98.80* [c]	-747.22*** [c]	-415.03* [a]	-121.56 [b]	14.79 [a]	-73.04
	(58.15)	(238.88)	(225.88)	(84.16)	(264.74)	(68.46)
HT Wprob²	1.29** [c]	7.08*** [c]	3.15* [a]	1.55* [b]	-0.85 [a]	0.73
	(0.54)	(2.43)	(1.88)	(0.82)	(2.62)	(0.66)
HT GB	-90.28***	-135.27**	-242.94***	-60.45***	-47.85	-22.79*
	(13.20)	(61.10)	(77.06)	(21.42)	(53.79)	(12.70)
VT GB	-24.05***	32.98	-129.03***	32.86	39.04	-15.75
	(8.57)	(39.02)	(27.83)	(20.76)	(44.33)	(14.69)
HT Wper	60.54***	160.20***	-37.56	-49.22**	119.70***	44.96***
	(9.26)	(33.90)	(29.99)	(22.64)	(43.18)	(11.98)
VT Wper	50.73***	102.76***	11.66	61.84***	98.63***	-7.65
	(9.06)	(29.97)	(24.17)	(15.46)	(33.31)	(9.55)
HT WSW	-22.61					
	(752.28)					
VT WSW	747.82**	4074.22***	-229.26	989.48	462.62	213.88
	(343.28)	(1385.29)	(1585.27)	(842.94)	(1026.67)	(617.32)
HT LCW	1776.14***					
	(577.64)					
VT LCW	672.77***	544.71	642.91	-633.24	1317.45	867.41**
	(227.08)	(1016.54)	(887.94)	(669.51)	(821.39)	(440.97)
HT PS	1688.72***					
	(361.23)					
VT PS	601.31***	2070.34***	1799.55***	550.82	1406.61**	-157.27
	(109.78)	(492.27)	(484.50)	(373.42)	(578.18)	(207.38)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Team FE	Yes	-	-	-	-	-
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R2 Cox-Snell	0.778	0.677	0.655	0.893	0.625	0.815
N	16309	554	513	534	536	557

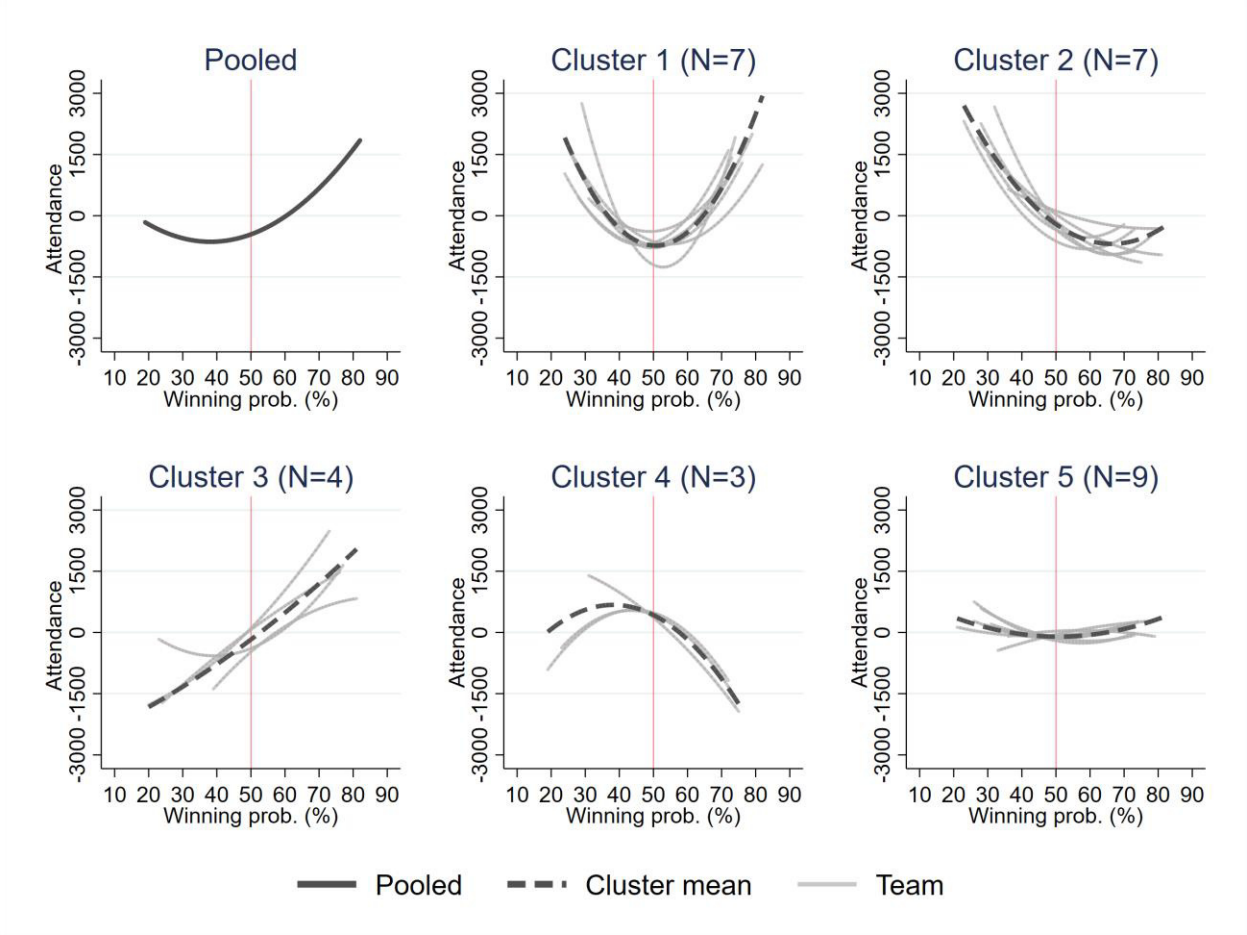
Notes: Data cover individual MLB games from 2013 to 2019. Dependent variable is team-specific regular season game attendance censored at stadium capacity. Model (1) pools the observation of all teams and reports clustered standard errors at the home team level. Models (2)-(6) show individual team-specific regression results for the San Diego Padres (SDP) (2), Washington Nationals (WAS) (3), Detroit Tigers (DET) (4), Colorado Rockies (COL) (5), and San Francisco Giants (SFG) (6) using robust standard errors (for detailed results covering all teams, see Appendix, Section 4.1). All model specifications include a constant term (omitted for brevity). The reported coefficient estimates correspond to partial and marginal effects on the unobservable latent outcome (sport demand). Individual coefficient's t-test significance is indicated as: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Using chi-square tests, the joint significance of HT Wprob and HT Wprob^2 is indicated as: ^{a} $p < 0.1$, ^{b} $p < 0.05$, ^{c} $p < 0.01$.

First, Table 2 confirms previous studies' findings regarding the impact of team performance on sport demand as our results suggest significant positive [negative] effects for home and visiting teams' winning percentage [games behind]. When considering the distribution of effect estimates across all 30 individual team regressions, only one team shows a contrasting significant negative home team winning percentage effect. Moreover, the effect for the home team games behind coefficient

is, on average, of smaller magnitude than the corresponding visiting team coefficient – fans appear to favor the home team over the visiting team (see Appendix, Figure A4). However, we also find several coefficient estimates to significantly vary at the team-level: While some home team games behind estimates are not significantly different from zero, other teams show large positive significant effects that significantly differ across teams. Hence, our results show significant variation in team-specific fan preferences in MLB. Furthermore, as with the within-season measures, the last season performance measures' estimates are consistent with previous research.

Regarding our main variables of interest, Table 2 shows that the joint significance tests of simple and squared home team winning probability indicate significant estimates for the pooled model as well as for four out of the five selected team-specific models. However, the estimates of the home team winning probability and squares in Table 2 make it difficult to compare non-linear GOU effects across 30 teams. As a consequence, to assess the impact of GOU on sport demand, we compute predictive margins of home team winning probability derived from the pooled and individual team-specific Tobit regressions. The corresponding predictions are mean-centered to make them better comparable across models and teams, respectively.

Figure 1. Mean-centered predictive margins of home team winning probability



Notes: Panel 1 shows mean-centered predictive margins (adjusted predictions at representative values) of home team winning probability derived from the pooled game attendance Tobit regressions presented in Table 1. The remaining panels show the corresponding predictions derived from individual team-specific Tobit regressions (see Appendix, Section 4). The predictions correspond to the impact of winning probability on the unobservable latent outcome (sport demand). We identify five groups of teams with similar winning probability effects by functional high dimensional data clustering (funHDDC). N is the number of teams per cluster. Predictive margin intervals are team- and cluster-specific and correspond to minimum and maximum winning probabilities.

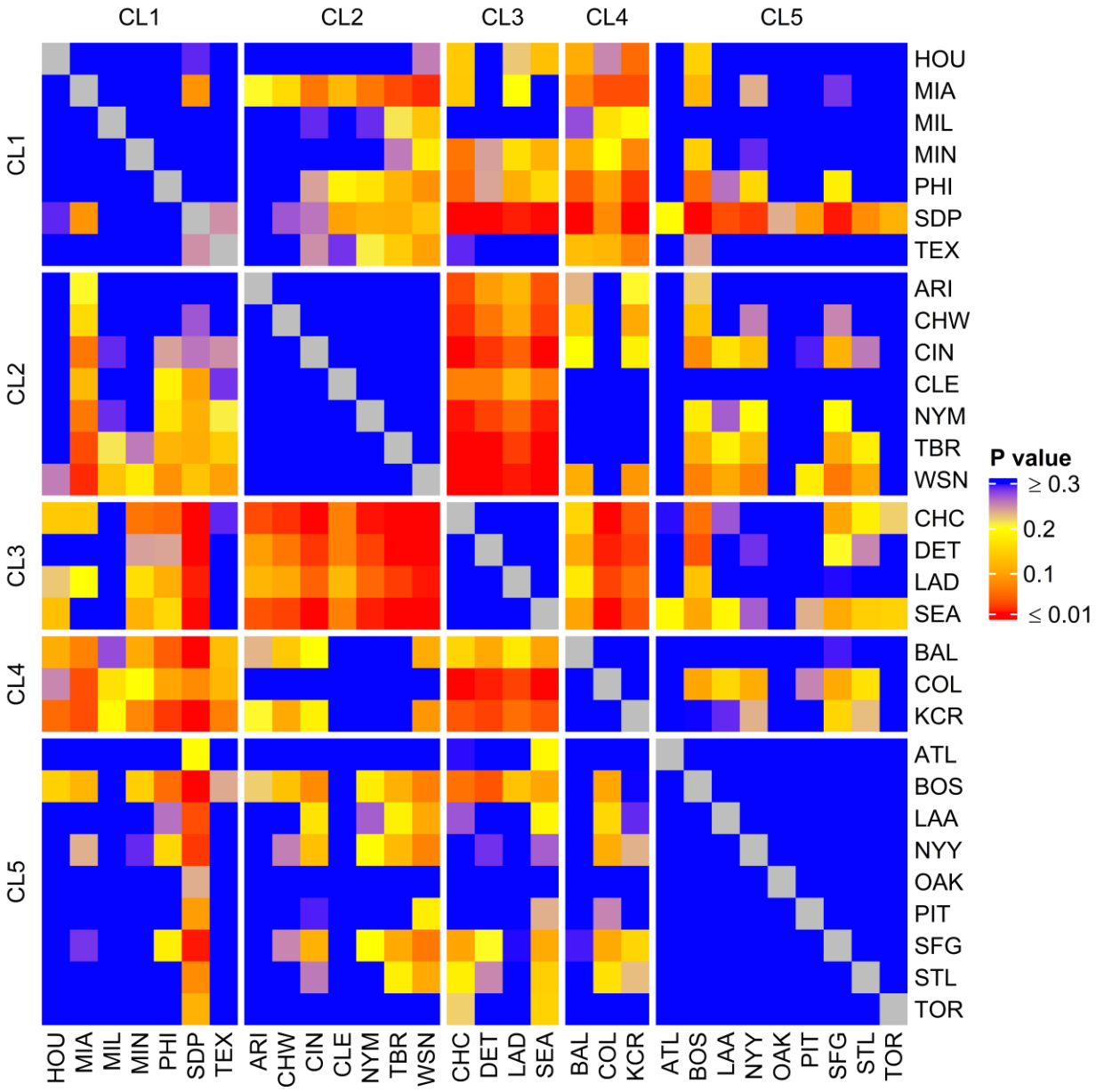
Figure 1, panel 1 shows the mean-centered predictive margins (adjusted predictions at representative values) of home team winning probability derived from the pooled game attendance Tobit regression. In contrast to the inverse U-shaped relationship that is suggested by the UOH, the pooled model results indicate rather U-shaped GOU preferences: On average, fans appear to prefer higher home team winning probabilities over uncertain game outcomes; though, while ticket sales is lowest at around 40%, we can observe that stadium attendance starts to increase again for games with lower home team winning probabilities.

The remaining panels of Figure 1 show the corresponding predictions derived from the individual team-specific Tobit regressions. Using functional high dimensional data clustering (funHDDC)

(Bouveyron & Jacques, 2011), we can identify five groups of teams with similar GOU effects: The fans from teams within cluster one (N=7) show U-shaped GOU preferences, attendance is minimized at approximately 50% winning probability. Conversely, the teams belonging to the fourth cluster (N=3) show GOU preferences that are roughly in line with the UOH; however, one team shows rather linear decreasing GOU effects, and while the other two teams in cluster four show inverse U-shaped GOU effects, their attendance is approximately maximized at 40%, rather than at 50%. For the teams in the second cluster (N=7), the impact of home team winning probability on attendance decreases strongly between 20% to 50% and then quickly flattens out until it begins to slightly increase again from 70% onwards**.** In stark contrast to cluster two, the fans from teams belonging to the third cluster (N=4) appear to consistently prefer games with higher home team winning chances – attendance increases linearly in home team winning probability. Last, when considering the fifth cluster (N=9), our results indicate that a fairly large number of teams have fans whose attendance behavior is relatively insensitive to differences in GOU; substantiating these findings, all joint significance tests of simple and squared winning probability for teams belonging to the fifth cluster are non-significant (see Appendix, Table A6). The 30 individual team-specific predictive margins (with confidence intervals) are included in the Appendix, Section 4.

To further investigate differences in GOU effects across (and within) clusters, Figure 2 shows the *p* values from pairwise joint significance tests of home-team-specific winning probability estimates derived from the individual team-specific Tobit regressions.

Figure 2. Pairwise joint significance tests between team-specific winning probability effects



Notes: This Figure reports *p* values from pairwise chi-square joint significance tests of home team winning probability estimates derived from individual team-specific Tobit regressions using robust standard errors (the corresponding 30 team-specific regressions results are presented in the Appendix, Section 4.1, Table A4, A5, and A6). The dependent variable is team-specific regular season game attendance from 2013 to 2019. The tested coefficient estimates correspond to the impact of simple and squared home team winning probability on the unobservable latent outcome (sport demand). We identify five groups of teams with similar winning probability effects (CL=1, 2, ..., 5) by functional high dimensional data clustering (funHDDC). The team-specific test results are sorted by cluster group; within clusters, the results are sorted in alphabetical order by team name.

Figure 2 highlights the existing heterogeneity in team-specific marginal home team winning probability effect and demonstrates the effectiveness of the functional data clustering approach – while we find some minor differences between teams within the first cluster, all other within-cluster team comparisons do not indicate any significant differences in fans' GOU preferences. In addition

to the second and third cluster's GOU effects that run diametrically to each other (cf. Figure 1), the most significant differences can be observed when comparing teams from the third and fourth cluster, followed by differences between teams from the first cluster and fourth cluster.

Last, to complement our analysis, we conduct several robustness checks to examine whether our findings are sensitive to alternative outcome variables, estimation procedures, and model specifications. For brevity, the analyses are relegated to the Appendix, Section 3 and Section 4; the main findings are summarized as follows: First, our results are robust to using attendance rate (attendance divided by stadium capacity) instead of using total game attendance. Second, while linear regression does not account for the censoring problem that is posed by game sell outs, using least square dummy variable (LSDV) regression instead of Tobit regression slightly deflates the impact of GOU on team-specific game attendance. Third, using Tobit regression, we can consider between different types of effects, such as the effect on the unobservable latent outcome (sport demand) and the effect on the unconditional expected value of the censored outcome (attendance). Similar to using LSDV, the partial and marginal team performance and GOU estimates regarding the unconditional expected value of attendance only differ marginally to the estimates associated with the latent outcome. Fourth, in addition to quadratic specification of home team winning probability, we further evaluate higher order polynomials to allow for a more flexible functional relationship of GOU preferences. For both the pooled model as well as the vast majority of team-specific models, the higher order polynomial results are very similar to the quadratic estimates; in general, there are only minor differences in the tail-behavior of the predictive margins of winning probability.

5 Conclusion

This study provides new insight into heterogeneous consumer behavior in the modern sports industry by documenting the existence of differences in team-specific fan preferences for uncertain game outcomes in MLB. Using regular season data from 2013 to 2019, we find that only a few teams show GOU effects that resemble the typical hump-shape that is postulated by the UOH. Specifically, using functional data clustering techniques to detect systematic differences in team-specific predictive margins of home team winning probability, we identify five clusters of teams with fans who show similar GOU preferences. In addition to rather hump-shaped GOU preferences, we find teams

with U-shaped, decreasing, and approximately linearly increasing GOU effects; yet, the teams belonging to largest cluster with similar GOU effects have fans whose attendance behavior is relatively insensitive to differences in home team winning probability.

While our study demonstrates that we can identify several groups of teams with similar GOU effects, it is unclear why teams belonging to the same cluster appear to have fans with homogeneous preferences for uncertain game outcomes, hence, raising the question: Where do such differences and similarities in fan preferences originate from? Likewise, future research is necessary to investigate the potential existence of team-level differences in GOU effects in other sports than MLB and, more generally, in which other aspects than product quality there exists heterogeneous consumer preferences in professional sports markets.

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Heterogeneous consumer preferences for product quality and uncertainty

Appendix

1 Introduction

This online Appendix provides additional information on the empirical specifications of the data that are used in this study, descriptive statistics, the complete results of the pooled and individual team-specific Tobit regressions, and complements the main text by providing the results of various robustness tests as well as other secondary analyses that are omitted from the main text for brevity.

2 Descriptive summary statistics

This section shows attendance summary statistics by team in Table A1. A complete list of the variables used in our study, their precise encodings, and summary statistics are presented in Table A2.

Table A1. Attendance summary statistics by team

Team	Team name	N	Mean Att	SD Att	Mean Att rate	SD Att rate	Sold outs	Mean Wprob	SD Wprob
ARI	Arizona Diamond Backs	557	25877.94	7148.35	53.23%	14.70%	0.18%	52.85%	7.94%
ATL	Atlanta Braves	546	29259.98	8453.88	64.56%	20.64%	4.21%	52.61%	9.26%
BAL	Baltimore Orioles	520	25089.81	9980.36	54.58%	21.71%	1.35%	50.26%	8.99%
BOS	Boston Red Sox	533	35842.62	1799.54	95.00%	4.75%	10.32%	58.60%	7.72%
CHC	Chicago Cubs	539	36835.51	4267.77	89.45%	10.27%	15.40%	57.24%	8.97%
CHW	Chicago White Sox	524	21010.74	6428.69	51.73%	15.83%	0.00%	47.79%	9.30%
CIN	Cincinnati Reds	539	25522.35	8703.88	60.31%	20.57%	0.74%	50.59%	8.19%
CLE	Cleveland Indians	535	20867.13	7171.51	53.48%	19.46%	0.00%	59.08%	8.41%
COL	Colorado Rockies	536	34625.42	7462.25	68.69%	14.81%	0.00%	52.35%	8.05%
DET	Detroit Tigers	534	29875.9	7830.82	71.97%	18.88%	7.30%	52.30%	10.50%
HOU	Houston Astros	555	28305.81	8166.17	67.65%	19.68%	3.96%	56.27%	11.38%
KCR	Kansas City Royals	537	25206.98	7631.72	66.50%	20.13%	6.70%	50.61%	8.58%
LAA	Los Angeles Angels	555	37393.36	4048.90	82.17%	8.90%	0.00%	53.90%	8.25%
LAD	Los Angeles Dodgers	561	46734.13	4686.97	85.10%	8.62%	0.00%	62.05%	7.50%
MIA	Miami Marlins	556	17534.44	6418.97	45.83%	17.16%	0.00%	47.37%	8.57%
MIL	Milwaukee Brewers	560	32365.29	6401.64	77.24%	15.28 %	9.46%	52.25%	7.69%
MIN	Minnesota Twins	525	26975.62	5833.59	69.27%	15.00%	2.48%	50.61%	8.62%
NYM	New York Mets	540	29731.61	6385.81	70.92%	15.23%	3.89%	53.55%	8.66%
NYY	New York Yankees	531	40593.53	4910.14	82.21%	10.12%	0.19%	58.04%	8.42%
OAK	Oakland Athletics	553	20658.54	8045.12	52.97%	22.66%	6.87%	54.36%	8.64%
PHI	Philadelphia Phillies	538	28370.11	7452.65	64.99%	17.07%	2.42%	49.62%	8.67%
PIT	Pittsburgh Pirates	544	25356.73	8539.49	66.10%	22.26 %	3.86%	53.91%	7.66%
SDP	San Diego Padres	554	27673.61	7276.80	67.04%	17.63%	7.40%	49.06%	7.83%
SEA	Seattle Mariners	560	25347.51	9187.33	53.24%	19.31%	0.00%	52.95%	8.34%
SFG	San Francisco Giants	557	39874.70	3249.61	95.13%	7.75%	14.00%	52.97%	8.24%
STL	St. Louis Cardinals	541	42348.13	2605.35	94.47%	5.60%	22.74%	57.82%	6.93%
TBR	Tampa Bay Rays	553	15877.73	5462.71	51.99%	17.81%	1.27%	55.18%	8.21%
TEX	Texas Rangers	555	31234.43	7746.82	64.77%	16.16%	0.00%	51.20%	9.37%
TOR	Toronto Blue Jays	558	32300.69	10636.64	65.05%	22.06%	0.00%	53.25%	8.97%
WSN	Washington Nationals	513	31092.56	5727.54	75.14%	13.93%	3.31%	60.04%	7.94%
	Mean across teams	544	29659.43	6655.37	68.69%	15.80%	4.27%	53.62%	8.53%

Notes: The data sample covers 16309 games from the 2013 to 2019 MLB regular seasons from all 30 teams. We only consider games that were played at the home teams' corresponding home stadiums. First home-team- (HT-) specific season games, rescheduled games, double-headers, and extended games are not included (see Main text for data cleaning details). Attendance (Att) is censored to fit to stadium capacity. Attendance rate is computed as attendance divided by stadium capacity multiplied by 100. Sold outs indicate games with attendance at capacity. Home team winning probability (Wprob) is derived from betting odds (money lines) using Shin's conversion method (Shin, 1992, 1993).

Table A2. Variable specifications, descriptions, and summary statistics

Variable	Levels	Description	Mean	SD	Min	Max
Dependent						
GAttend	-	Game attendance (GA)	29671.89	10052.68	5265.00	54307.00
GAttend rate	-	Game attendance rate (GAR) (%)	68.68	21.51	12.71	100.00
Explanatory						
Lag GAttend	-	Lagged GA	29786.19	10104.07	0.00	54307.00
Lag Gattend rate	-	Lagged GAR	68.95	21.63	12.71	100.00
HT Wprob	-	Home team (HT) winning probability (%)	53.62	9.28	18.33	82.78
HT Wprob^2	-	HT winning probability squared	2961.13	989.49	336.11	6853.17
HT GB	-	Games behind between HT and division leader	7.85	8.51	0.00	61.00
VT GB	-	Games behind between VT and division leader	7.80	8.49	0.00	60.50
HT Wper	-	HT's winning percentage (within season) (%)	50.03	9.98	0.00	100.00
VT Wper	-	VT's winning percentage (within season) (%)	49.97	10.04	0.00	100.00
HT WSW*	1	HT won last year's World Series	0.03	0.18	0.00	1.00
VT WSW	1	VT won last year's World Series	0.03	0.18	0.00	1.00
HT LCW*	1	HT won last year's League Championship	0.07	0.25	0.00	1.00
VT LCW	1	VT won last year's League Championship	0.07	0.25	0.00	1.00
HT PS*	1	HT reached last year's postseason	0.29	0.45	0.00	1.00
VT PS	1	VT reached last year's postseason	0.29	0.45	0.00	1.00
IL Game	1	Interleague game	0.12	0.33	0.00	1.00
Rivalry	1	Rivalry game	0.12	0.33	0.00	1.00
BHeads	1	Bobblehead promotion	0.07	0.26	0.00	1.00
Night	1	Night game	0.68	0.47	0.00	1.00
PHoliday	1	Labor Day / 4th of July / Memorial Day	0.02	0.12	0.00	1.00
Rain	1	Precipitation	0.09	0.29	0.00	1.00
New Stadium*	1	HT opened a new stadium during a season	0.00	0.07	0.00	1.00
Distance	-	Distance between HT's and VT's stadiums	998.18	699.45	6.55	2731.99
Wday	1	Monday	0.10	0.30	0.00	1.00
	2	Tuesday	0.15	0.36	0.00	1.00
	3	Wednesday	0.15	0.36	0.00	1.00
	4	Thursday	0.10	0.31	0.00	1.00
	5	Friday	0.16	0.37	0.00	1.00
	6	Saturday	0.16	0.37	0.00	1.00
	7	Sunday	0.17	0.37	0.00	1.00
Month	1	April	0.15	0.36	0.00	1.00
	2	May	0.17	0.38	0.00	1.00
	3	June	0.17	0.38	0.00	1.00
	4	July	0.16	0.36	0.00	1.00
	5	August	0.17	0.38	0.00	1.00
	6	September	0.17	0.38	0.00	1.00
Year	1	2013	0.14	0.35	0.00	1.00
	2	2014	0.14	0.35	0.00	1.00
	3	2015	0.14	0.35	0.00	1.00
	4	2016	0.14	0.35	0.00	1.00
	5	2017	0.14	0.35	0.00	1.00
	6	2018	0.14	0.35	0.00	1.00
	7	2019	0.14	0.35	0.00	1.00

Notes: The data sample covers 16309 games from the 2013 to 2019 MLB regular seasons from all 30 teams. First home-team- (HT-) specific season games, rescheduled games, double-headers, and extended games are not included (see Main text for data cleaning details). Attendance is censored to fit to stadium capacity. Game attendance rate (GAR) is computed as attendance divided by stadium capacity multiplied by 100. Home team winning probability (Wprob) is derived from betting odds (money lines) using Shin's conversion method (Shin, 1992, 1993). * Not included in the team-specific regressions because of perfect multicollinearity with year fixed effects.

3 Pooled model results

In the following sections, we provide the detailed results for the pooled model specification that we omit from the main text for brevity.

3.1 Tobit and linear regression results: Attendance and attendance rate

First, in Table A3, we show the linear and Tobit regression results for our pooled model specification for two alternative outcome variables: game attendance and game attendance rate (game attendance divided by stadium capacity (in %)).

Table A3. Pooled Tobit and linear regression results of game attendance and attendance rate

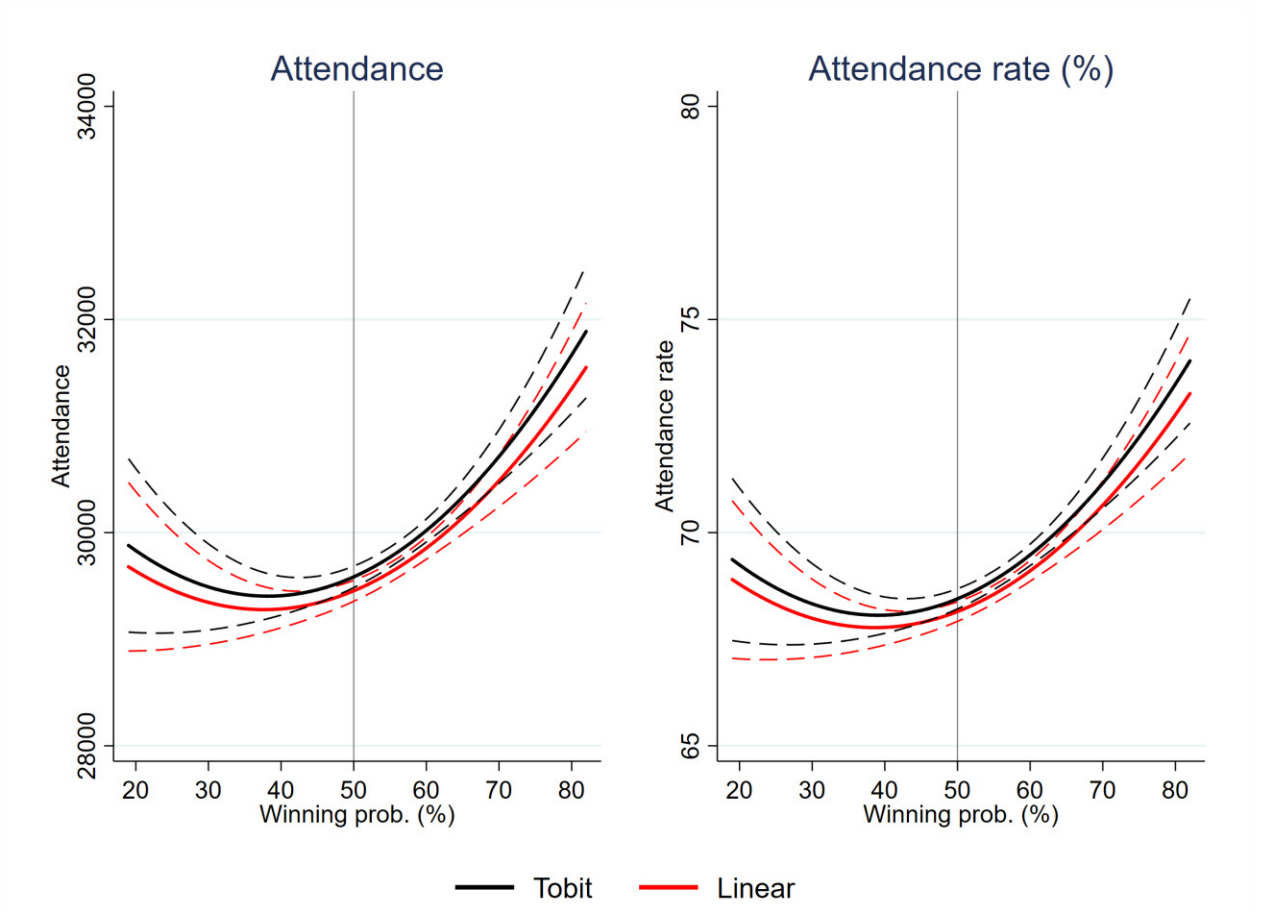
	(1) GA Tobit	(2) GA Linear	(3) GAR Tobit	(4) GAR Linear
HT Wprob (%)	-98.802* [c]	-87.058 [c]	-0.253* [c]	-0.226 [c]
	(58.145)	(56.062)	(0.143)	(0.138)
HT Wprob²	1.294** [c]	1.156** [c]	0.003** [c]	0.003** [c]
	(0.540)	(0.515)	(0.001)	(0.001)
HT GB	-90.281***	-83.892***	-0.203***	-0.189***
	(13.200)	(12.782)	(0.032)	(0.031)
VT GB	-24.049***	-21.629**	-0.059***	-0.053***
	(8.567)	(7.997)	(0.020)	(0.019)
HT Wper	60.540***	59.067***	0.144***	0.141***
	(9.261)	(9.151)	(0.022)	(0.022)
VT Wper	50.726***	49.419***	0.117***	0.115***
	(9.065)	(8.821)	(0.021)	(0.020)
HT WSW	-22.607	-260.731	-0.173	-0.727
	(752.281)	(696.047)	(1.838)	(1.682)
VT WSW	747.825**	693.877**	2.046**	1.928**
	(343.283)	(311.906)	(0.850)	(0.771)
HT LCW	1776.136***	1533.894***	4.323***	3.777***
	(577.643)	(397.497)	(1.501)	(1.083)
VT LCW	672.768***	660.808***	1.395***	1.373***
	(227.084)	(205.769)	(0.477)	(0.427)
HT PS	1688.719***	1717.889***	3.951***	4.027***
	(361.228)	(328.241)	(0.860)	(0.775)
VT PS	601.309***	577.858***	1.343***	1.288***
	(109.778)	(103.824)	(0.254)	(0.240)
Lag GAttend	0.412***	0.408***		
	(0.024)	(0.025)		
Lag GAttend rate			0.441***	0.437***
			(0.022)	(0.022)
IL Game	1043.654***	943.598***	2.323***	2.099***
	(217.969)	(214.423)	(0.515)	(0.505)
Rivalry	854.818***	718.565**	1.763**	1.456**
	(318.489)	(303.331)	(0.696)	(0.661)
BHeads	2000.603***	1996.647***	4.545***	4.540***
	(291.439)	(284.217)	(0.641)	(0.625)
Night	-296.668	-308.466	-0.728	-0.750
	(408.439)	(415.060)	(0.860)	(0.875)

PHoliday	3497.852***	3260.453***	7.909***	7.377***
	(751.791)	(742.048)	(1.557)	(1.536)
Rain	-1004.151***	-944.381***	-2.343***	-2.205***
	(155.345)	(153.045)	(0.358)	(0.351)
New Stadium	3149.140***	3008.003***	11.784***	11.488***
	(302.603)	(292.348)	(0.847)	(0.818)
Distance	-0.286***	-0.275***	-0.001***	-0.001***
	(0.076)	(0.073)	(0.000)	(0.000)
Tuesday	2088.420***	2071.769***	4.972***	4.922***
	(227.173)	(230.798)	(0.531)	(0.538)
Wednesday	3013.675***	2998.949***	7.254***	7.206***
	(258.221)	(258.482)	(0.594)	(0.591)
Thursday	3548.473***	3518.897***	8.388***	8.307***
	(290.370)	(290.163)	(0.705)	(0.700)
Friday	7074.279***	6932.854***	16.579***	16.249***
	(626.372)	(636.161)	(1.461)	(1.481)
Saturday	8778.225***	8397.024***	20.327***	19.464***
	(662.249)	(677.055)	(1.520)	(1.546)
Sunday	4916.067***	4778.395***	11.094***	10.797***
	(464.230)	(473.091)	(1.012)	(1.029)
May	1611.010***	1589.182***	3.804***	3.760***
	(258.348)	(251.272)	(0.610)	(0.593)
June	2950.491***	2861.897***	6.808***	6.619***
	(330.345)	(320.705)	(0.783)	(0.759)
July	3773.502***	3568.019***	8.620***	8.167***
	(356.032)	(360.977)	(0.826)	(0.834)
August	3106.881***	2995.731***	7.122***	6.888***
	(428.061)	(420.156)	(0.967)	(0.947)
September	2524.782***	2427.690***	5.914***	5.703***
	(343.123)	(324.516)	(0.784)	(0.736)
Constant	6024.680***	6799.572***	8.647**	14.087***
	(1499.349)	(1583.393)	(3.551)	(3.742)
Sigma	4793.505***		11.216***	
	(1344.455)		(3.092)	
Outcome	Attendance	Attendance	Att. rate	Att. rate
Team FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R2	-	0.784	-	0.742
Adjusted R2	-	0.783	-	0.741
Cox-Snell R2	0.778	-	0.739	-
N	16309	16309	16309	16309

Notes: Dependent variable is regular season game attendance (GA) ((1) and (2)) and game attendance rate (GAR) (in%) ((3) and (4)) from 2013 to 2019. GAR is computed as attendance divided by stadium capacity multiplied by 100. For the Tobit regressions, GA [GAR] is censored at stadium capacity [100%]. The Tobit coefficient estimates correspond to the impact of winning probability on the unobservable latent outcome (sport demand). Standard errors clustered at the home team level. Individual coefficient's t-test significance is indicated as: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Using chi-square tests, the joint significance of HT Wprob and HT Wprob^2 is indicated as: * $a < 0.1$, ** $b < 0.05$, *** $c < 0.01$.

Second, in Figure A1, we present the predictive margins (adjusted predictions at representative values) of home team winning probability derived from the pooled linear and Tobit regression for both using game attendance (left panel) and game attendance rate (right panel) as outcome variable.

Figure A1. Predictive margins of home team winning probability: Tobit vs. linear



Notes: The left [right] panel shows predictive margins (adjusted predictions at representative values) of home team winning probability derived from the pooled game attendance [attendance rate] Tobit and linear regressions presented in Table A1. The Tobit and linear regression estimates correspond to the impact on the unobservable latent outcome (sport demand). Predictive margin intervals covers the minimum and maximum home team winning probabilities. Dashed lines indicate 95% confidence intervals.

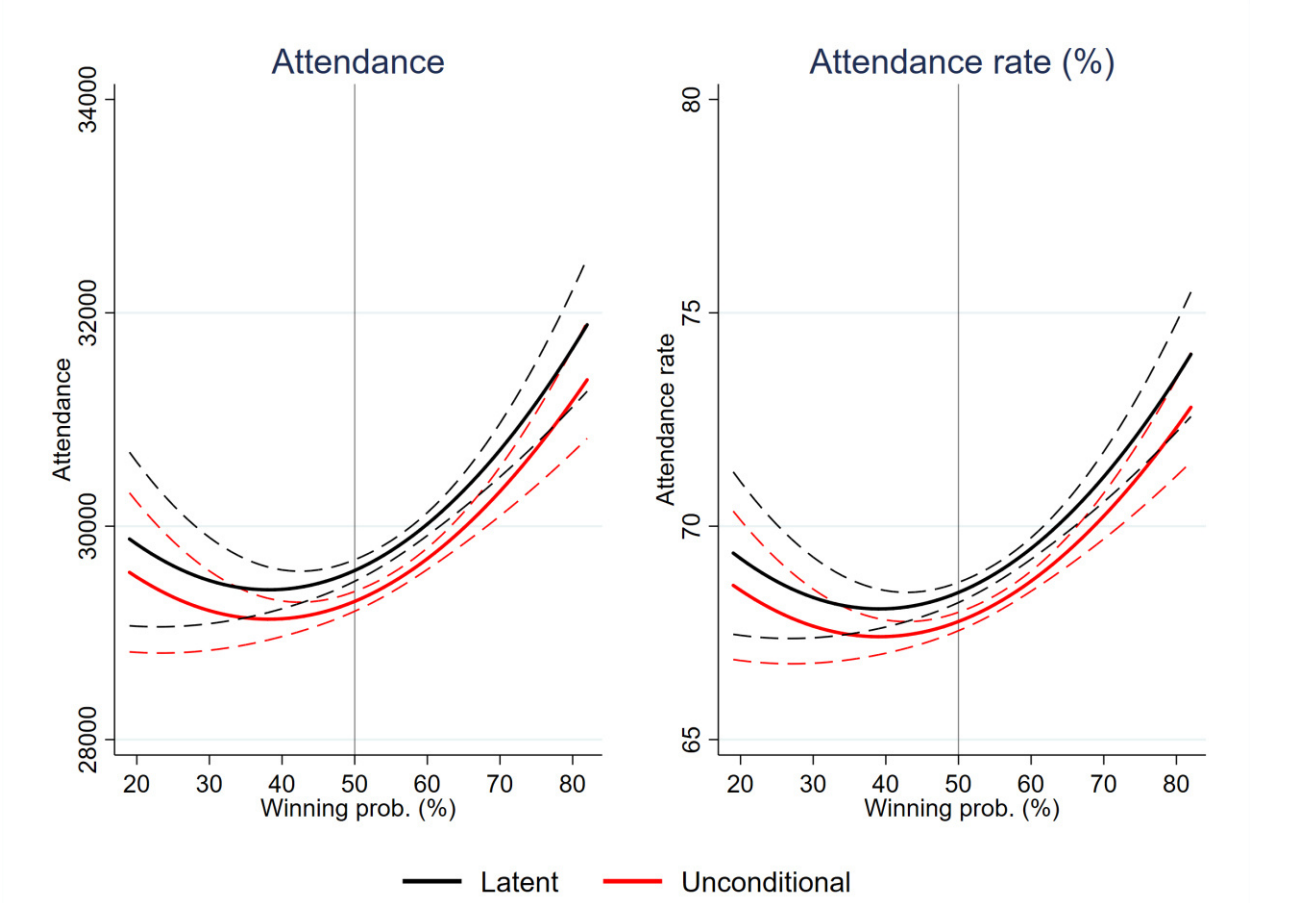
There exist only small differences across the different model specifications and their corresponding coefficient estimates (cf. Table A4, A5, and A6); though, with respect to the differences in the predictive margins of home team winning probability, Figure A1 shows that the linear models deflate the estimated impact on sport demand.

3.2 Tobit regression results: Unconditional expected attendance

In this section, we analyze potential differences in Tobit estimates of home team winning probability on the unobservable latent outcome (sport demand) and the effect on the unconditional expected value of the censored outcome (attendance). Specifically, in Figure A2 we show the corresponding predictive margins (adjusted predictions at representative values) of home team winning

probability on attendance and sport demand, respectively. Similar to our comparison of the predictive margins derived from the linear and Tobit regressions (Section 3.2), the estimated impact on the unconditional expected value of attendance is deflated when compared to the estimates associated with the latent outcome (sport demand).

Figure A2. Predictive margins of home team winning probability: Latent vs. unconditional

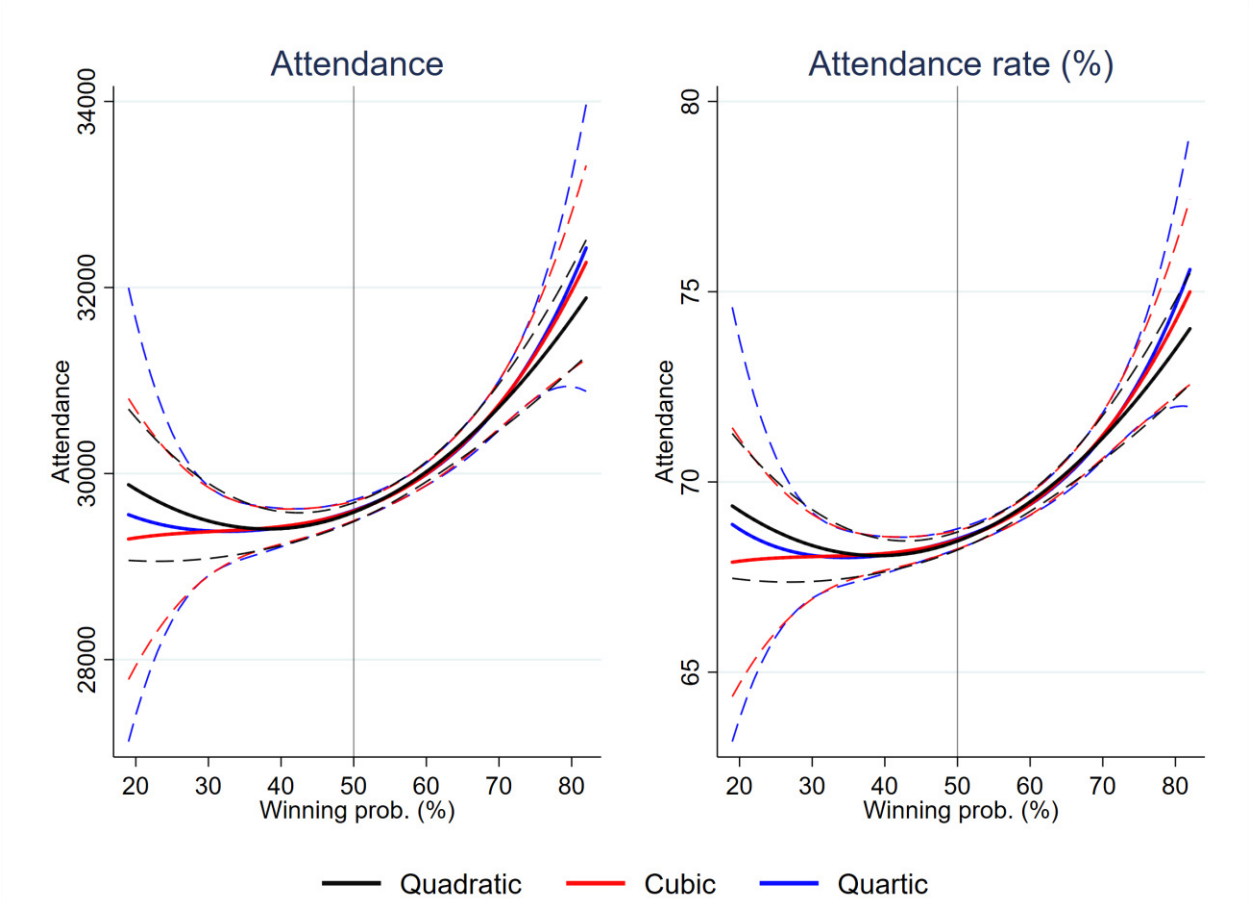


Notes: The left [right] panel shows predictive margins (adjusted predictions at representative values) of home team winning probability derived from the pooled game attendance [attendance rate] Tobit regressions presented in Table A1. The black curves show the predictive margins on the unobservable latent outcome (sport demand), whereas the red curves show the unconditional predictive margins on the expected value of the censored outcome (ticket sales). Predictive margin intervals covers the minimum and maximum home team winning probabilities. Dashed lines indicate 95% confidence intervals.

3.3 Tobit regression results: Cubic and quartic winning probability specifications

To allow for a more flexible functional relationship between home team winning probability and attendance, in this section we compare the predictive margins using a different polynomial specification of home team winning probability to measure GOU.

Figure A3. Predictive margins of home team winning probability: Different polynomials



Notes: The left [right] panel shows predictive margins (adjusted predictions at representative values) of home team winning probability derived from the pooled game attendance [attendance rate] Tobit regressions using quadratic, cubic, and quartic winning probability effects. The predictions correspond to the impact of winning probability on the unobservable latent outcome (sport demand). All models include the same set of explanatory variables. The precise regression results for the quadratic winning probability specification is presented in Table A1. Predictive margin intervals covers the minimum and maximum home team winning probabilities. Dashed lines indicate 95% confidence intervals.

In Figure A3, we present the corresponding predictive margins for using a quadratic, cubic, and quartic polynomial specification for both game attendance and game attendance rate. In general, all three model specifications yield similar results; only the cubic specification does not suggest sport demand to increase again for home team winning probability smaller 30%.

4 Team racial composition effects

Throughout the following sections, we provide all team-specific regression results that are omitted from the main text for brevity.

4.1 Team-specific Tobit regression results

First, we show the results of the individual team-specific Tobit regressions in Table A4, A5, and A6.

Table A4. Team-specific Tobit regression results of game attendance I

	(1) HOU	(2) MIA	(3) MIL	(4) MIN	(5) PHI	(6) SDP	(7) TEX	(8) ARI	(9) CHW	(10) CIN
HT Wprob (%)	-291.95*	-324.18*	-245.85	-348.88*	-409.72** [a]	-747.22*** [c]	-277.06	-290.52	-286.23*	-282.75 [a]
	(167.98)	(172.47)	(281.83)	(185.96)	(169.64)	(238.88)	(201.97)	(221.18)	(162.59)	(216.00)
HT Wprob²	2.66*	3.50*	2.51	3.38*	4.11** [a]	7.08*** [c]	2.88	2.48	2.43	2.11 [a]
	(1.43)	(1.78)	(2.69)	(1.91)	(1.72)	(2.43)	(1.90)	(2.15)	(1.55)	(2.11)
HT GB	25.79	78.70**	-235.60***	-167.65***	-198.64***	-135.27**	-43.97	-39.78	-0.42	-94.42*
	(50.77)	(40.04)	(54.87)	(60.34)	(55.01)	(61.10)	(48.99)	(63.49)	(55.27)	(53.75)
VT GB	-25.31	-44.61*	-17.32	10.75	-32.71	32.98	-62.79	19.70	0.27	-13.61
	(36.99)	(26.43)	(39.64)	(35.07)	(35.81)	(39.02)	(45.00)	(42.36)	(35.81)	(33.59)
HT Wper	38.44	57.47	21.85	2.84	63.77	160.20***	72.22*	-71.15	67.71**	40.60
	(31.67)	(35.58)	(27.58)	(37.68)	(39.35)	(33.90)	(41.04)	(58.76)	(33.96)	(27.33)
VT Wper	77.85***	11.11	25.53	41.78	11.76	102.76***	20.09	110.57***	78.09***	12.73
	(27.09)	(20.82)	(25.48)	(28.32)	(24.78)	(29.97)	(31.90)	(40.02)	(25.83)	(24.46)
VT WSW	-789.73	-282.64	6230.16***	1131.49	-764.14	4074.22***	1748.65	308.68	2331.89	3536.53**
	(1626.44)	(1198.23)	(1335.34)	(1128.35)	(1832.23)	(1385.29)	(1883.30)	(1316.92)	(1523.80)	(1390.63)
VT LCW	387.97	2016.52***	-305.06	-285.93	984.86	544.71	-490.44	1336.57	137.66	708.47
	(1095.06)	(723.05)	(827.58)	(860.62)	(1244.76)	(1016.54)	(1503.09)	(996.75)	(859.87)	(1029.84)
VT PS	-391.84	-63.45	-289.77	14.35	1031.30**	2070.34***	1050.94**	1359.91***	-54.87	951.52*
	(444.66)	(384.34)	(479.20)	(425.44)	(513.63)	(492.27)	(525.50)	(473.73)	(450.63)	(490.47)
Lag GAttend	0.27***	0.18***	0.13***	0.30***	0.25***	0.27***	0.21***	0.14***	0.22***	0.25***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.03)
IL Game	1684.97***	955.19*	-126.39	2151.62***	1852.43***	1201.33*	-1.29	667.30	2563.26***	1380.27**
	(602.94)	(559.28)	(582.99)	(542.16)	(697.56)	(676.89)	(618.76)	(648.53)	(706.07)	(641.74)
Rivalry	1137.39	-99.49	2750.76***	113.95	2428.77***	0.00	3248.18***	-1116.10*	259.35	2351.96**
	(808.82)	(526.48)	(634.20)	(466.59)	(589.80)	(.)	(942.44)	(638.84)	(506.95)	(1087.46)
BHeads	941.86	552.17	772.95	1050.39*	1150.89	0.00	2024.78**	911.81	1264.58*	2403.16***
	(615.28)	(636.31)	(552.76)	(633.15)	(825.47)	(.)	(855.49)	(1006.80)	(761.19)	(675.38)
Night	-616.85	-1736.49***	-2607.98***	-664.63	-978.79*	1224.13*	2744.43***	1304.36**	276.39	-923.07*
	(483.96)	(645.02)	(606.42)	(473.81)	(564.34)	(741.80)	(721.16)	(619.00)	(578.35)	(546.81)
PHoliday	3200.07*	-1470.06	6867.04**	2265.33*	1233.67*	7979.57**	10827.31***	12295.89***	2830.42	1229.77
	(1854.30)	(1574.71)	(2678.56)	(1332.57)	(699.62)	(3282.10)	(1869.34)	(2628.60)	(2071.71)	(1356.06)
Rain	-194.39	-993.00***	-830.55	-1179.41**	-1084.45*	-2533.02**	-871.68	-2166.05	-551.53	-1904.64***
	(497.54)	(340.74)	(555.18)	(476.08)	(564.42)	(1060.92)	(797.24)	(1413.07)	(442.43)	(487.54)

Distance	-0.18	-0.40	-1.03***	-1.27***	-0.18	-0.22	1.36*	0.09	-0.99***	-0.81**
	(0.59)	(0.27)	(0.35)	(0.43)	(0.28)	(0.26)	(0.69)	(0.30)	(0.38)	(0.32)
Tuesday	2269.53***	751.58	1676.66**	1895.33***	2170.07***	3341.70***	2330.31***	1797.57**	96.03	1389.70*
	(830.08)	(561.51)	(723.01)	(676.04)	(782.80)	(683.93)	(800.22)	(783.44)	(752.73)	(752.80)
Wednesday	2537.67***	697.20	940.20	2925.71***	2263.68***	2762.05***	4172.99***	2022.12**	1407.13*	1771.07**
	(831.36)	(572.67)	(769.31)	(747.54)	(751.24)	(813.28)	(806.49)	(866.92)	(787.01)	(773.23)
Thursday	2136.09**	1583.90**	1829.60**	2638.17***	3776.89***	3824.65***	3293.30***	1456.18*	2413.19***	753.67
	(894.42)	(630.55)	(909.01)	(683.30)	(866.63)	(781.70)	(959.13)	(857.99)	(800.28)	(876.67)
Friday	7547.21***	1785.14***	6202.01***	4677.47***	3702.45***	8975.37***	7965.24***	9013.40***	4871.76***	9100.27***
	(846.98)	(464.64)	(714.23)	(694.84)	(803.36)	(710.96)	(802.45)	(849.99)	(785.73)	(773.31)
Saturday	9251.80***	4739.02***	9512.47***	7147.38***	7958.83***	14497.95***	10431.92***	13525.98***	8629.17***	11144.82***
	(828.84)	(625.22)	(720.44)	(741.41)	(769.00)	(796.72)	(847.65)	(794.03)	(861.73)	(895.12)
Sunday	5897.14***	1796.60**	6176.81***	3952.50***	6054.79***	8047.64***	8390.32***	9119.45***	7228.18***	5367.26***
	(925.39)	(770.51)	(982.16)	(873.66)	(879.21)	(1092.05)	(1083.42)	(891.51)	(915.61)	(929.78)
May	-473.77	-778.58	2949.07***	4908.02***	844.78	-1160.41	3098.13***	-312.08	3668.48***	3211.99***
	(605.14)	(604.53)	(609.50)	(692.81)	(603.53)	(718.05)	(722.11)	(730.90)	(683.61)	(693.47)
June	2272.95***	-68.29	3350.52***	6627.87***	3102.31***	380.07	1750.37**	2410.61***	4653.15***	6725.64***
	(700.90)	(676.27)	(615.59)	(768.48)	(727.09)	(852.32)	(724.98)	(719.92)	(747.23)	(804.22)
July	3368.54***	770.33	5464.56***	7966.66***	3306.13***	3251.71***	2930.37***	1346.62	5688.54***	5378.21***
	(800.82)	(752.67)	(709.42)	(973.13)	(853.19)	(979.68)	(935.82)	(877.22)	(894.00)	(861.07)
August	955.41	150.84	6096.42***	7487.44***	2383.87**	1568.10	-845.48	370.78	4415.41***	3691.67***
	(833.81)	(842.00)	(776.74)	(1037.91)	(925.35)	(1185.90)	(843.76)	(991.73)	(1002.10)	(916.92)
September	2078.40**	-444.34	5091.96***	5610.80***	1288.06	962.86	1854.55*	2711.88***	1623.12	3175.59***
	(849.76)	(991.94)	(888.52)	(1147.62)	(1158.44)	(1356.85)	(1015.11)	(995.64)	(1237.77)	(1037.33)
Constant	10904.85*	19438.99***	27979.16***	21829.83***	31553.06***	19146.77***	20786.91***	20816.07***	11147.95**	22468.85***
	(5884.43)	(4685.55)	(8239.27)	(5177.60)	(5627.49)	(7049.76)	(6770.40)	(7527.24)	(4854.79)	(5700.97)
Sigma	3986.38***	3280.24***	4052.57***	3478.17***	4096.19***	4348.20***	4405.87***	4302.80***	3932.42***	4131.36***
	(989.72)	(803.33)	(1022.38)	(872.20)	(1020.17)	(1094.06)	(1079.48)	(1054.09)	(977.43)	(1022.11)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	555	556	560	525	538	554	555	557	524	539
Cluster group	1	1	1	1	1	1	1	2	2	2
R2 Cox-Snell	0.769	0.738	0.649	0.654	0.705	0.677	0.676	0.638	0.625	0.776

Notes: Data cover individual MLB games from 2013 to 2019. Dependent variable is team-specific regular season home game attendance censored at stadium capacity. Models (1-10) show individual team-specific regression results using robust (Huber/White) standard errors (see Table A1 for an overview of team name abbreviations). All model specifications include a constant term (omitted for brevity). The reported coefficient estimates correspond to partial and marginal effects on the unobservable latent outcome (sport demand). Individual coefficient's t-test significance is indicated as: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Using chi-square tests, the joint significance of HT Wprob and HT Wprob^2 is indicated as: ^{a} $p < 0.1$, ^{b} $p < 0.05$, ^{c} $p < 0.01$.

Table A5. Team-specific Tobit regression results of game attendance II

	(1) CLE	(2) NYM	(3) TBR	(4) WSN	(5) CHC	(6) DET	(7) LAD	(8) SEA	(9) BAL	(10) COL
HT Wprob (%)	-84.12	-146.26	-167.75 [a]	-415.03* [a]	90.10 b	-121.56 [b]	168.68	8.09 [a]	201.85	14.79 [a]
	(222.57)	(188.26)	(204.21)	(225.88)	(131.65)	(84.16)	(216.27)	(246.82)	(185.00)	(264.74)
HT Wprob²	0.54	0.87	1.02 [a]	3.15* [a]	-0.29 b	1.55* [b]	-0.97	0.78 [a]	-2.27	-0.85 [a]
	(1.90)	(1.78)	(1.87)	(1.88)	(1.14)	(0.82)	(1.75)	(2.36)	(1.86)	(2.62)
HT GB	-166.19**	-210.29***	-9.38	-242.94***	10.47	-60.45***	-75.30	-91.25	-66.30*	-47.85
	(70.49)	(74.96)	(57.83)	(77.06)	(43.59)	(21.42)	(106.00)	(72.00)	(34.60)	(53.79)
VT GB	45.66*	-40.29	9.81	-129.03***	-71.10***	32.86	-16.00	-66.53	42.45	39.04
	(26.61)	(39.77)	(27.39)	(27.83)	(24.20)	(20.76)	(30.58)	(43.16)	(45.38)	(44.33)
HT Wper	125.57**	23.44	100.05***	-37.56	-6.17	-49.22**	81.65*	32.61	42.44	119.70***
	(54.51)	(34.62)	(28.58)	(29.99)	(23.83)	(22.64)	(46.24)	(47.83)	(39.95)	(43.18)
VT Wper	86.58***	8.36	76.44***	11.66	-24.90	61.84***	2.85	83.23**	89.37***	98.63***
	(21.75)	(30.99)	(24.93)	(24.17)	(20.61)	(15.46)	(26.94)	(38.32)	(33.11)	(33.31)
VT WSW	-1570.84	-751.17	2265.47**	-229.26	1319.25	989.48	1369.64	2262.44	-3347.69	462.62
	(1131.91)	(1386.30)	(1069.99)	(1585.27)	(1224.92)	(842.94)	(1246.96)	(1569.09)	(2064.77)	(1026.67)
VT LCW	1655.39*	598.37	-633.46	642.91	546.43	-633.24	-610.83	191.76	2714.31	1317.45
	(887.03)	(937.86)	(817.49)	(887.94)	(820.52)	(669.51)	(1008.11)	(1144.37)	(1922.41)	(821.39)
VT PS	149.43	1375.70**	274.76	1799.55***	375.81	550.82	1438.14***	969.69	-622.90	1406.61**
	(410.41)	(586.49)	(409.26)	(484.50)	(257.53)	(373.42)	(379.08)	(595.46)	(642.37)	(578.18)
Lag GAttend	0.26***	0.24***	0.32***	0.12***	0.38***	0.28***	0.07*	0.24***	0.11***	0.24***
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
IL Game	1056.53**	2220.63***	2036.06***	974.99	771.94***	81.93	1876.21***	1021.92	2822.35***	970.97
	(427.99)	(761.60)	(666.67)	(684.90)	(292.18)	(410.63)	(455.40)	(753.53)	(811.57)	(694.98)
Rivalry	1232.61**	849.12*	-4835.00***	3803.20***	548.17*	-831.96*	2375.53***	0.00	3810.77***	-1206.59
	(482.91)	(465.16)	(937.30)	(1248.75)	(290.00)	(457.45)	(508.48)	(.)	(694.02)	(733.39)
BHeads	1651.93**	1361.19*	33.37	3015.54***	829.47*	497.03	2207.12***	1742.76*	2325.15*	3288.68***
	(742.49)	(824.30)	(846.42)	(575.38)	(443.52)	(470.21)	(412.24)	(939.49)	(1207.42)	(979.80)
Night	-291.16	-1286.67**	-1098.79**	-2617.25***	95.27	-2751.42***	2025.73***	-3547.31***	-3783.36***	385.96
	(452.99)	(598.78)	(496.12)	(461.59)	(347.29)	(357.67)	(560.01)	(797.23)	(1115.56)	(631.27)
PHoliday	6133.94***	2586.83	1680.29	2903.61**	586.88	-55.44	3692.02***	2204.58	9368.61***	6321.73***
	(1714.23)	(1896.42)	(1312.60)	(1123.56)	(1260.26)	(1450.60)	(964.27)	(1418.48)	(2733.38)	(1142.06)
Rain	-521.74	-1257.00**	473.67	-1766.57**	-1326.71***	70.76	11.36	-2023.71***	-1960.60***	-893.87
	(568.77)	(493.30)	(461.22)	(773.49)	(280.68)	(589.55)	(855.67)	(710.97)	(631.85)	(1273.00)
Distance	-0.54**	-0.06	-0.82**	-0.77***	0.25	-0.47**	0.14	1.02**	-0.29	0.77
	(0.26)	(0.27)	(0.32)	(0.22)	(0.22)	(0.22)	(0.21)	(0.42)	(0.37)	(0.73)
Tuesday	2193.32***	580.65	1254.17**	2128.58***	372.33	1583.64***	2165.17***	1165.45	2298.94**	1804.59**
	(568.95)	(723.74)	(624.40)	(756.94)	(436.75)	(491.47)	(627.96)	(856.14)	(906.59)	(799.72)

Wednesday	3290.65***	1990.09**	2343.62***	2400.48***	80.26	2097.72***	1463.12**	4045.37***	2994.44***	2658.12***
	(616.04)	(777.77)	(655.78)	(698.83)	(429.09)	(508.50)	(692.10)	(982.00)	(932.34)	(847.59)
Thursday	3850.05***	2598.10***	1766.67***	2213.76***	1165.01**	2619.26***	3092.99***	2992.30***	3258.88***	3670.11***
	(683.98)	(885.01)	(675.99)	(725.16)	(490.73)	(569.18)	(769.03)	(1044.15)	(1003.08)	(951.81)
Friday	11678.70***	5571.27***	4861.83***	7039.94***	1945.78***	5274.17***	5289.52***	12051.40***	12491.94***	7365.23***
	(610.40)	(758.09)	(633.94)	(690.95)	(529.37)	(492.38)	(607.47)	(1005.21)	(932.27)	(846.80)
Saturday	10083.45***	7757.78***	8202.02***	8557.99***	4464.35***	7407.69***	6896.05***	13399.42***	14167.10***	9997.61***
	(647.78)	(791.41)	(723.68)	(708.75)	(522.82)	(507.42)	(643.96)	(983.50)	(1047.84)	(798.52)
Sunday	5215.55***	3754.81***	4300.18***	3860.39***	1383.59***	2212.59***	5423.15***	7333.51***	9295.20***	6724.40***
	(712.06)	(879.03)	(754.93)	(810.23)	(476.92)	(585.89)	(849.38)	(1218.29)	(1440.68)	(1111.25)
May	3486.56***	2482.43***	-179.42	3573.11***	2067.47***	3256.46***	-639.48	1581.39*	3945.19***	3025.96***
	(532.98)	(770.25)	(588.44)	(572.17)	(451.74)	(443.34)	(630.01)	(867.33)	(869.93)	(800.65)
June	6672.97***	3319.56***	91.36	5953.84***	2760.30***	4674.42***	-10.27	2981.56***	3803.15***	5941.59***
	(654.37)	(927.11)	(667.57)	(593.40)	(446.74)	(539.33)	(595.28)	(1026.78)	(866.80)	(824.96)
July	7444.39***	3918.84***	1668.39**	5606.52***	3865.97***	5836.08***	1425.22**	5334.21***	4801.62***	8003.76***
	(823.05)	(1058.34)	(740.60)	(624.49)	(506.37)	(647.80)	(636.52)	(1188.02)	(1009.01)	(1027.05)
August	7246.65***	4567.00***	424.97	4947.62***	3289.95***	5291.13***	1227.58*	6698.17***	3700.87***	4758.84***
	(838.56)	(1125.35)	(921.53)	(633.99)	(483.86)	(581.48)	(630.20)	(1281.38)	(967.31)	(1026.96)
September	4231.11***	3912.30***	-334.85	3378.04***	2463.49***	2653.96***	1662.40**	560.33	1700.14	3289.36***
	(840.44)	(1253.62)	(988.38)	(643.81)	(480.60)	(604.69)	(721.79)	(1515.34)	(1204.94)	(1174.69)
Constant	-4239.40	20514.83***	7428.09	40754.78***	14141.12***	24124.17***	25399.00***	1282.23	6520.64	5940.65
	(7586.09)	(6266.32)	(6521.40)	(7449.88)	(4315.70)	(2972.37)	(7447.24)	(7967.67)	(6357.95)	(7685.55)
Sigma	3337.97***	4326.26***	3572.69***	3438.15***	2348.16***	2589.84***	3495.47***	5311.98***	5227.17***	4562.39***
	(825.37)	(1082.38)	(880.60)	(868.73)	(607.47)	(654.85)	(854.13)	(1298.57)	(1307.70)	(1127.61)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	535	540	553	513	539	534	561	560	520	536
Cluster group	2	2	2	2	3	3	3	3	4	4
R2 Cox-Snell	0.783	0.566	0.579	0.655	0.739	0.893	0.443	0.665	0.730	0.625

Notes: Data cover individual MLB games from 2013 to 2019. Dependent variable is team-specific regular season home game attendance censored at stadium capacity. Models (1-10) show individual team-specific regression results using robust (Huber/White) standard errors (see Table A1 for an overview of team name abbreviations). All model specifications include a constant term (omitted for brevity). The reported coefficient estimates correspond to partial and marginal effects on the unobservable latent outcome (sport demand). Individual coefficient's t-test significance is indicated as: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Using chi-square tests, the joint significance of HT Wprob and HT Wprob^2 is indicated as: ^{a} $p < 0.1$, ^{b} $p < 0.05$, ^{c} $p < 0.01$.

Table A6. Team-specific Tobit regression results of game attendance III

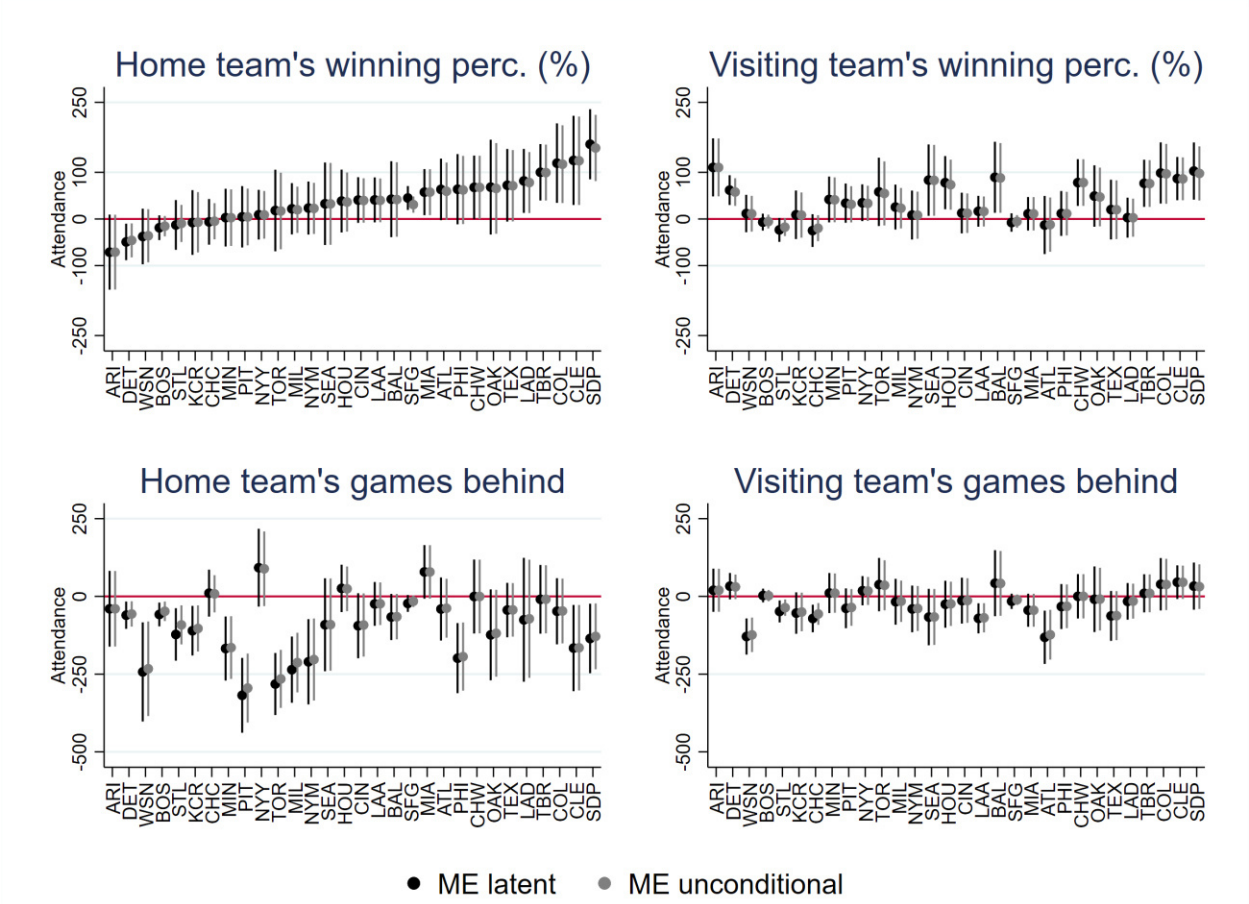
	(1) KCR	(2) ATL	(3) BOS	(4) LAA	(5) NYY	(6) OAK	(7) PIT	(8) SFG	(9) STL	(10) TOR
HT Wprob (%)	194.13	-117.21	36.41	-36.04	42.86	-78.35	-71.95	-73.04	-69.90	-94.32
	(159.75)	(254.50)	(73.08)	(156.80)	(168.59)	(315.49)	(215.32)	(68.46)	(185.67)	(203.32)
HT Wprob²	-2.25	1.02	-0.32	0.41	-0.24	0.76	0.72	0.73	0.69	0.79
	(1.57)	(2.35)	(0.63)	(1.48)	(1.46)	(2.99)	(2.06)	(0.66)	(1.65)	(1.91)
HT GB	-110.34***	-40.60	-58.14***	-24.24	92.36	-123.74	-318.15***	-22.79*	-122.37***	-281.85***
	(39.04)	(48.56)	(18.31)	(36.26)	(69.85)	(76.51)	(60.94)	(12.70)	(40.46)	(54.06)
VT GB	-53.61*	-131.58***	2.89	-70.63***	18.20	-9.23	-38.34	-15.75	-48.35***	37.92
	(31.74)	(39.30)	(10.99)	(24.76)	(23.06)	(69.46)	(30.83)	(14.69)	(18.30)	(41.30)
HT Wper	-7.58	63.36**	-18.76	40.84	9.19	68.26	4.63	44.96***	-12.82	18.17
	(39.79)	(30.84)	(15.79)	(27.52)	(25.47)	(50.26)	(42.37)	(11.98)	(27.52)	(42.27)
VT Wper	8.98	-12.97	-6.80	16.45	34.75*	49.17	33.93	-7.65	-23.36*	58.15
	(27.05)	(30.52)	(12.82)	(19.51)	(17.81)	(39.31)	(23.73)	(9.55)	(12.30)	(36.64)
VT WSW	59.17	5010.61**	545.01	-2665.29**	1068.82	-107.01	52.68	213.88	552.86	2192.01
	(1844.54)	(2511.32)	(578.63)	(1141.47)	(1512.22)	(1901.23)	(1211.87)	(617.32)	(663.69)	(1632.92)
VT LCW	-1577.01	2094.29	-170.12	1725.60*	-91.91	3124.28*	274.50	867.41**	-216.96	2068.18
	(1286.70)	(1397.86)	(350.68)	(929.10)	(1257.84)	(1599.15)	(799.54)	(440.97)	(581.20)	(1398.50)
VT PS	230.61	545.91	236.97	-172.69	-44.72	810.60	574.15	-157.27	371.92	545.82
	(519.92)	(562.32)	(149.63)	(315.34)	(357.76)	(716.65)	(441.13)	(207.38)	(228.73)	(528.79)
Lag GAttend	0.11***	0.19***	0.35***	0.21***	0.26***	0.08*	0.29***	0.37***	0.32***	0.27***
	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.09)	(0.05)	(0.04)
IL Game	3036.60***	2377.67***	659.16***	879.93**	1038.60**	5284.38***	946.15*	153.66	411.03	797.63
	(678.99)	(752.39)	(174.27)	(422.28)	(456.70)	(1005.17)	(545.39)	(176.39)	(284.57)	(743.54)
Rivalry	3068.49**	-810.31	734.24***	1782.23***	4487.02***	5408.06***	0.00	633.99**	1895.27***	3736.11***
	(1525.50)	(570.63)	(228.95)	(506.09)	(483.66)	(1000.16)	(.)	(251.98)	(314.22)	(735.94)
BHeads	567.84	3273.60***	475.41*	3585.29***	1274.62**	3944.53***	910.96	-42.75	-60.48	1724.43*
	(810.67)	(779.39)	(248.71)	(447.87)	(610.35)	(1199.35)	(779.22)	(193.81)	(256.77)	(984.81)
Night	988.31	884.76	-504.05***	1989.04***	-1920.28***	1331.67	-1065.31*	-27.61	428.86*	-9288.86***
	(746.88)	(827.60)	(188.24)	(588.43)	(474.62)	(873.14)	(551.44)	(164.44)	(257.21)	(1295.44)
PHoliday	3798.88**	8302.11***	-310.88	5347.27***	738.44	5673.58**	3050.94*	1987.97**	2231.81**	-1851.96
	(1606.79)	(2124.76)	(500.72)	(716.90)	(1812.39)	(2368.71)	(1671.53)	(994.13)	(1063.17)	(1429.63)
Rain	-558.23	-1183.42*	-173.08	3252.60***	-261.17	-936.71	-1395.44***	-528.20	-656.86**	116.30
	(944.67)	(706.69)	(160.98)	(1016.41)	(432.69)	(978.38)	(489.15)	(354.77)	(319.96)	(958.39)
Distance	-0.17	-0.27	-0.09	0.27	0.13	0.60	-0.29	0.03	-0.29	-0.25
	(0.57)	(0.40)	(0.08)	(0.26)	(0.20)	(0.52)	(0.26)	(0.11)	(0.22)	(0.36)
Tuesday	-32.90	2588.89***	-129.86	1078.90**	830.56	1361.93	2230.49***	473.25	452.67	2939.14***
	(784.53)	(774.36)	(289.49)	(518.61)	(650.25)	(1290.88)	(722.92)	(297.99)	(406.49)	(939.96)

Wednesday	182.52	2773.04***	-123.50	1987.30***	1658.86**	2744.24*	4560.94***	728.82***	1381.15***	3462.86***
	(772.57)	(769.74)	(290.02)	(552.97)	(663.81)	(1444.63)	(789.52)	(278.33)	(404.28)	(985.68)
Thursday	1555.28*	5439.54***	596.44**	1857.08***	2903.72***	2136.11	5556.90***	936.63***	1706.50***	5400.18***
	(866.92)	(883.46)	(292.32)	(604.33)	(702.53)	(1427.78)	(836.54)	(298.26)	(426.64)	(954.43)
Friday	5971.72***	12465.77***	856.23***	5283.52***	4340.16***	6651.34***	11567.99***	1274.88***	3726.70***	7412.41***
	(850.63)	(756.89)	(273.68)	(520.29)	(624.82)	(1297.78)	(770.91)	(277.63)	(394.33)	(935.38)
Saturday	6278.92***	15332.69***	934.06***	5712.75***	3966.03***	12336.67***	12731.73***	1254.94***	4763.00***	4963.08***
	(869.37)	(774.62)	(293.32)	(516.09)	(782.86)	(1572.74)	(761.46)	(311.72)	(419.17)	(1355.79)
Sunday	4467.06***	9014.50***	22.90	4374.53***	2821.30***	9088.82***	7384.38***	1479.02***	3878.73***	2132.69
	(1106.86)	(1267.15)	(315.63)	(752.68)	(778.80)	(1666.28)	(866.24)	(330.23)	(463.46)	(1352.54)
May	3804.47***	1141.45	742.95***	-178.32	2126.17***	741.22	4171.25***	-303.35	770.25**	2326.55***
	(819.25)	(721.99)	(281.57)	(540.54)	(497.83)	(982.81)	(697.43)	(221.67)	(338.48)	(827.23)
June	6161.89***	3767.03***	1701.25***	895.64	3496.66***	2017.64*	7372.71***	-207.02	1815.08***	5968.47***
	(860.04)	(736.09)	(301.87)	(580.29)	(497.54)	(1087.87)	(788.16)	(248.31)	(356.88)	(939.93)
July	5953.16***	4790.23***	1995.63***	1768.02***	3190.53***	3654.25***	8654.21***	525.12*	1614.23***	7592.60***
	(922.67)	(901.05)	(322.36)	(611.67)	(537.51)	(1253.64)	(839.65)	(285.45)	(350.32)	(1085.59)
August	5206.50***	1837.18**	1820.21***	1682.51***	3215.10***	2739.18**	8778.96***	179.66	728.91**	9696.90***
	(965.17)	(829.07)	(338.25)	(636.76)	(569.08)	(1089.92)	(837.15)	(323.05)	(367.09)	(1198.86)
September	5530.78***	4146.92***	1210.25***	382.28	-18.15	2801.45*	7610.85***	-215.39	1599.42***	7194.63***
	(1100.50)	(918.12)	(357.95)	(740.66)	(615.70)	(1593.41)	(983.05)	(297.23)	(390.47)	(1359.30)
Constant	7525.62	15624.80**	22071.00***	21853.50***	20914.89***	5522.49	8432.85	25655.16***	28740.18***	20413.34***
	(5661.67)	(7896.05)	(3042.65)	(4950.91)	(5242.49)	(10091.60)	(6318.76)	(4413.95)	(6008.73)	(6839.72)
Sigma	4310.34***	4821.00***	1316.94***	2848.85***	2993.01***	5961.38***	3783.76***	1403.19***	1892.19***	4885.43***
	(1089.34)	(1201.58)	(337.33)	(698.00)	(741.90)	(1499.56)	(941.78)	(357.96)	(504.54)	(1195.37)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	537	546	533	555	531	553	544	557	541	558
Cluster group	4	5	5	5	5	5	5	5	5	5
R2 Cox-Snell	0.705	0.691	0.524	0.504	0.629	0.510	0.811	0.815	0.593	0.789

Notes: Data cover individual MLB games from 2013 to 2019. Dependent variable is team-specific regular season home game attendance censored at stadium capacity. Models (1-10) show individual team-specific regression results using robust (Huber/White) standard errors (see Table A1 for an overview of team name abbreviations). All model specifications include a constant term (omitted for brevity). The reported coefficient estimates correspond to partial and marginal effects on the unobservable latent outcome (sport demand). Individual coefficient's t-test significance is indicated as: * p < 0.1, ** p < 0.05, *** p < 0.01. Using chi-square tests, the joint significance of HT Wprob and HT Wprob^2 is indicated as: ^{a} $p < 0.1$, ^{b} $p < 0.05$, ^{c} $p < 0.01$.

Second, in Figure A4 we show the distribution of team-specific estimates for the home and visiting team's (within-season) winning percentage and games behind coefficients with respect to both the effect on the unobservable latent outcome (sport demand) and the effect on the unconditional expected value of the censored outcome (attendance).

Figure A4. Team-specific regression coefficient estimates



Notes: This figure shows coefficient estimates derived from team-specific home game attendance Tobit regressions. For each of the team-specific coefficients' estimates, we report the average marginal effects (MEs) on the unobservable latent outcome (sport demand) together with the average MEs on the unconditional expected value of the censored outcome (ticket sales). The detailed individual team-specific Tobit regression result are reported in Table A4, A5, and A6. The order of ME estimates is sorted by the magnitude of the team-specific MEs of home team winning percentage on the unobservable latent outcome (sport demand). Error bars indicate 95% confidence intervals based on robust (Huber/White) standard errors.

In line with previous sport demand research, Figure A4 shows that, on average, attendance increases in both home and visiting team's winning percentage; only DET shows a significant negative coefficient estimate, though, it is of relatively small magnitude. Likewise, all team-specific home and visiting team games behind coefficient estimates that are significantly different from zero are negative. Moreover, the estimated effect for the home team games behind coefficient is, on average, of smaller magnitude than the corresponding visiting team coefficient – intuitively,

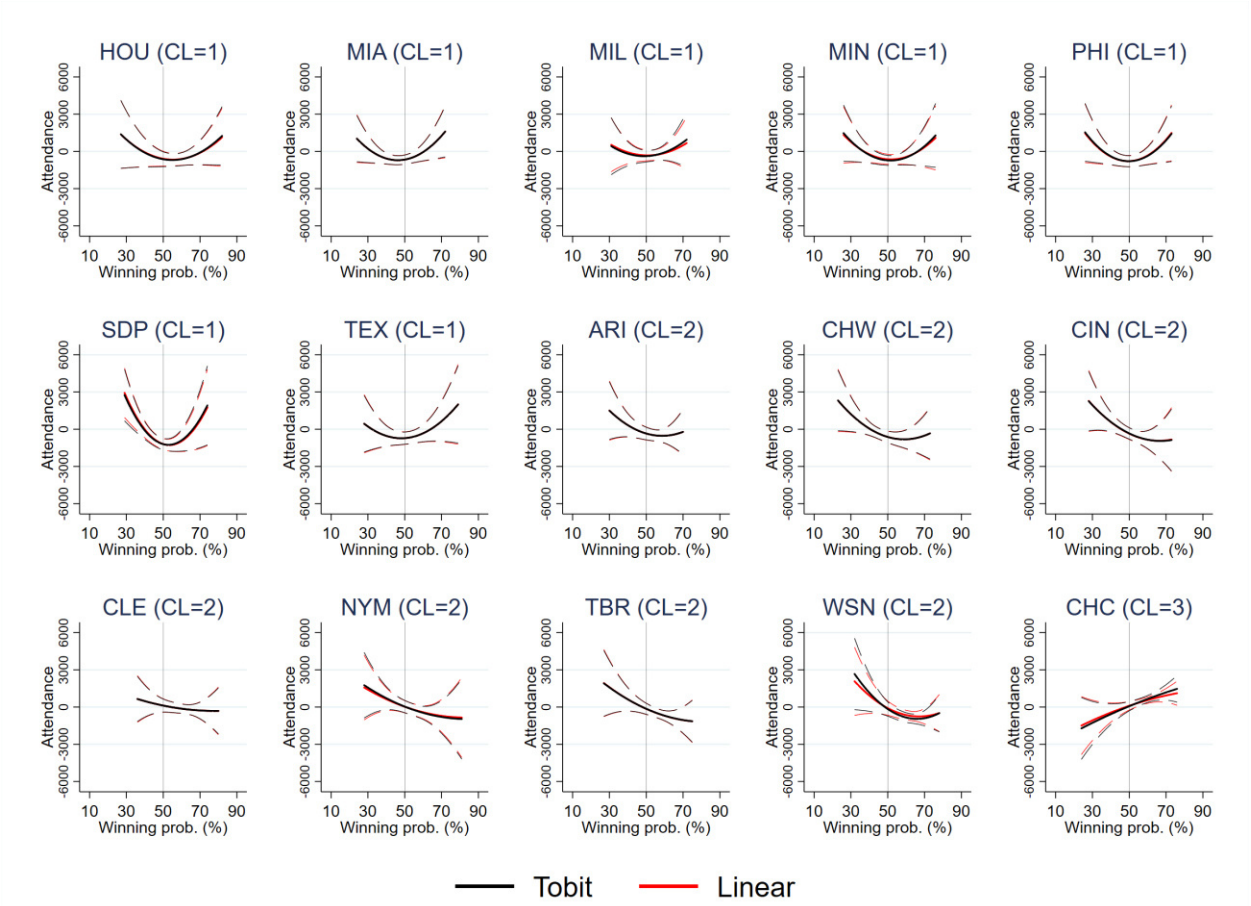
fans appear to favor the home team over the visiting team. Furthermore, we do not find substantial differences in the team-specific Tobit estimates with respect to the impact on the unobservable latent outcome (sport demand) and the unconditional expected outcome (attendance).

However, Figure A4 also shows that there exist significant differences between individual team-specific coefficient estimates. As an example, while the home team games behind coefficient for CHC and NYY is not significantly different from zero, PIT and TOR show large positive estimates that significantly differ from the estimates of CHC and NYY. Furthermore, SFG shows by far the smallest confidence intervals with respect to all four coefficient estimates; a potential explanation for these findings, which is in line with SFG's fans to be relatively insensitive to differences in GOU, is the low variation in SFG's game attendance in combination with their high mean game attendance rate.

4.2 Team-specific regression results: Tobit vs. linear

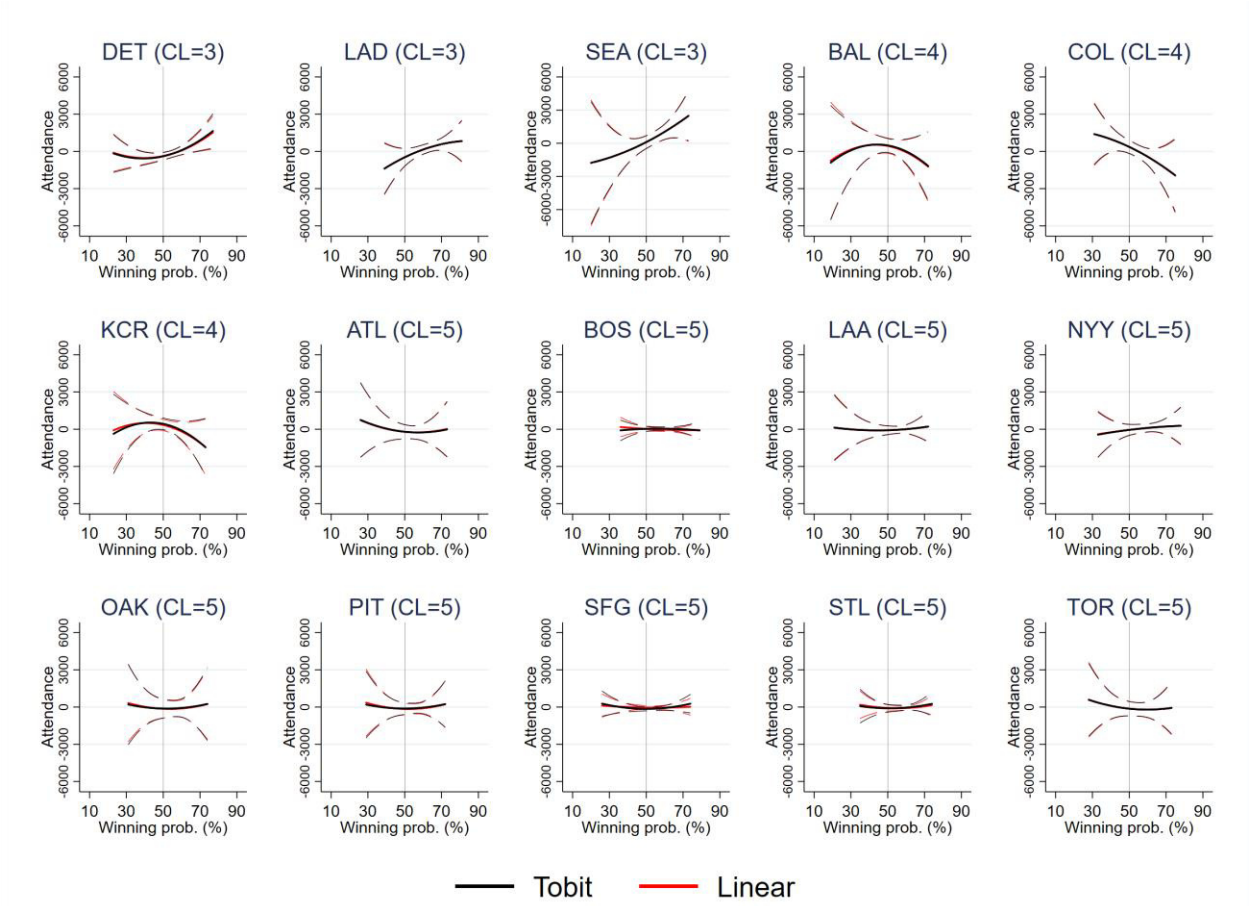
In this section, we compare the team-specific mean-centered predictive margins of home team winning probability derived from linear and Tobit regression models. The corresponding results are presented in Figure A6 and A7.

Figure A6. Mean-centered predictive margins of home team winning probability by team: Tobit vs. linear I



Notes: This figure shows mean-centered predictive margins (adjusted predictions at representative values) of home team winning probability derived from individual team-specific game attendance Tobit regressions (presented in Section 4.1) and linear regressions (results omitted for brevity). The Tobit and linear regression predictions correspond to the impact of winning probability on the unobservable latent outcome (sport demand). We identify five groups of teams (CL=1, 2, ..., 5) with similar winning probability effects by functional high dimensional data clustering (funHDDC). Predictive margin intervals correspond to team-specific minimum and maximum winning probabilities. Dashed lines indicate 95% confidence intervals.

Figure A7. Mean-centered predictive margins of home team winning probability by team: Tobit vs. linear I



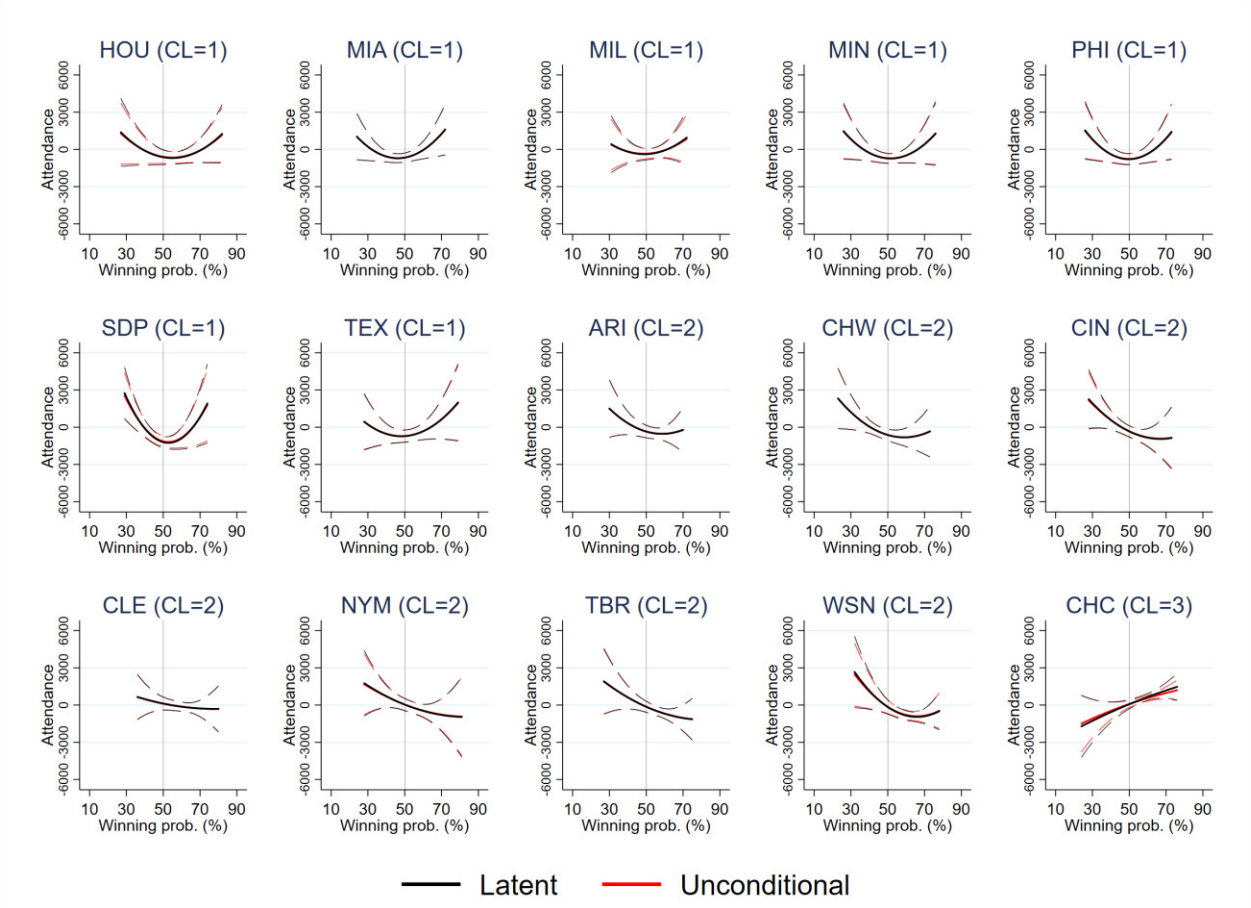
Notes: This figure shows mean-centered predictive margins (adjusted predictions at representative values) of home team winning probability derived from individual team-specific game attendance Tobit regressions (presented in Section 4.1) and linear regressions (results omitted for brevity). The Tobit and linear regression predictions correspond to the impact of winning probability on the unobservable latent outcome (sport demand). We identify five groups of teams (CL=1, 2, ..., 5) with similar winning probability effects by functional high dimensional data clustering (funHDDC). Predictive margin intervals correspond to team-specific minimum and maximum winning probabilities. Dashed lines indicate 95% confidence intervals.

Figure A6 and A7 show that for most teams the estimated impact of GOU on sport demand derived from the linear regressions is only slightly deflated when compared to the corresponding Tobit regression estimates.

4.3 Team-specific Tobit regression results: Unconditional expected attendance

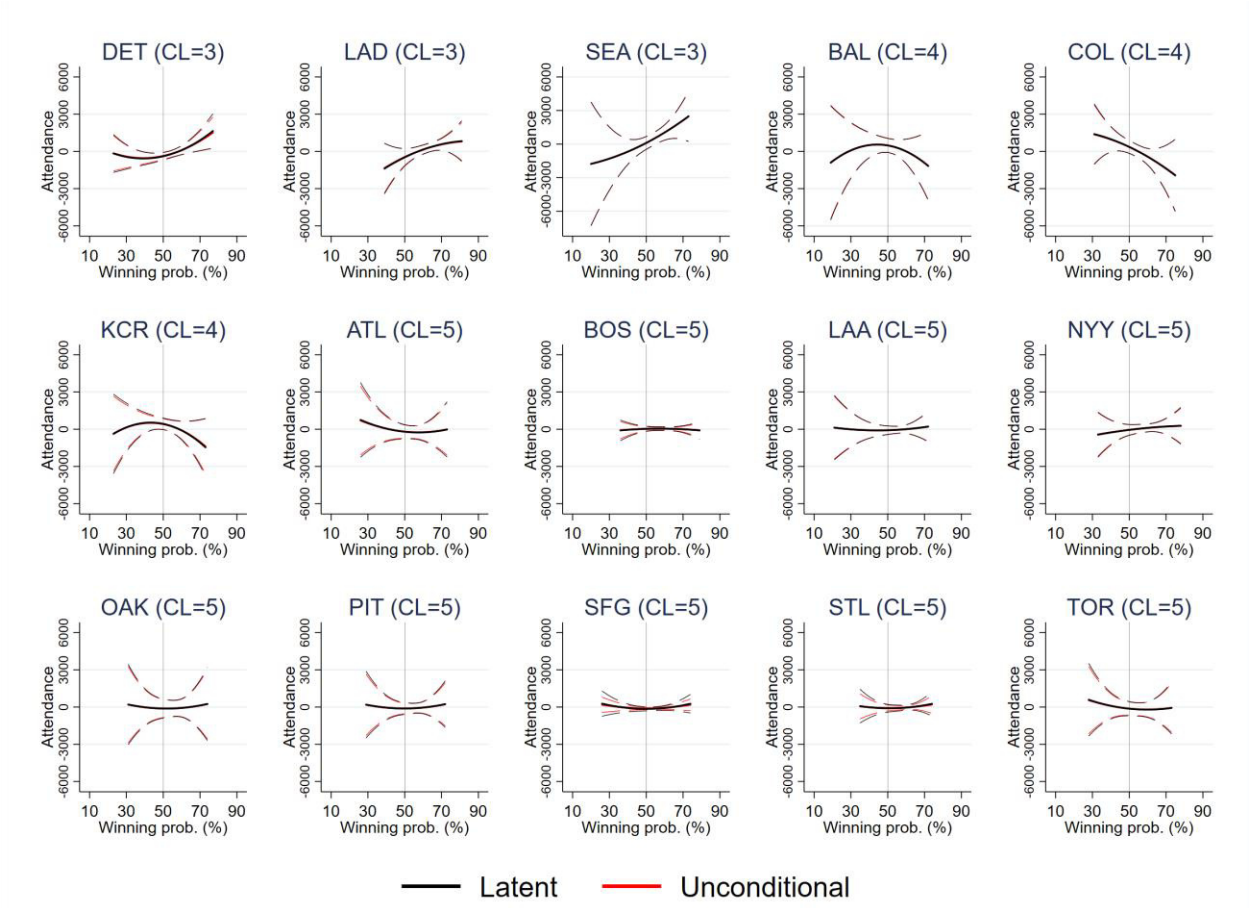
Throughout this section, we compare the team-specific Tobit estimates of home team winning probability on the unobservable latent outcome (sport demand) and the effect on the unconditional expected value of the censored outcome (attendance). To this end, we show the predictive margins of home team winning probability on attendance and sport demand in Figure A8 and A9.

Figure A8. Mean-centered predictive margins of home team winning probability by team: Latent vs. unconditional I



Notes: This figure shows mean-centered predictive margins (adjusted predictions at representative values) of home team winning probability derived from the individual team-specific game attendance Tobit regressions (presented in Section 4.1) and linear regressions (omitted for brevity). The black curves show the predictive margins on the unobservable latent outcome (sport demand), whereas the red curves show the unconditional predictive margins on the expected value of the censored outcome (ticket sales). We identify five groups of teams (CL=1, 2, ..., 5) with similar winning probability effects by functional high dimensional data clustering (funHDDC). Predictive margin intervals correspond to team-specific minimum and maximum winning probabilities. Dashed lines indicate 95% confidence intervals.

Figure A9. Mean-centered predictive margins of home team winning probability by team: Latent vs. unconditional II



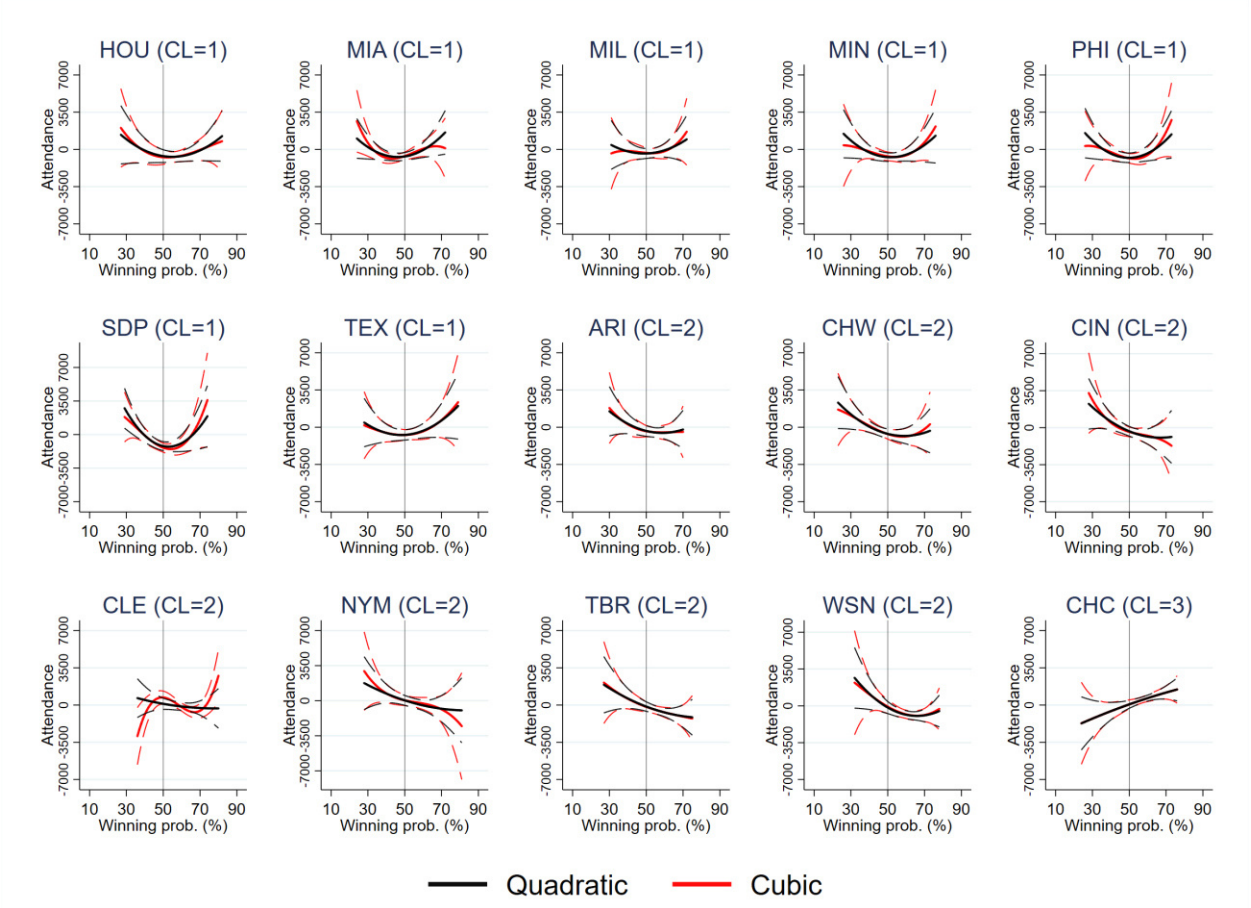
Notes: This figure shows mean-centered predictive margins (adjusted predictions at representative values) of home team winning probability derived from the individual team-specific game attendance Tobit regressions (presented in Section 4.1) and linear regressions (omitted for brevity). The black curves show the predictive margins on the unobservable latent outcome (sport demand), whereas the red curves show the unconditional predictive margins on the expected value of the censored outcome (ticket sales). We identify five groups of teams (CL=1, 2, ..., 5) with similar winning probability effects by functional high dimensional data clustering (funHDDC). Predictive margin intervals correspond to team-specific minimum and maximum winning probabilities. Dashed lines indicate 95% confidence intervals.

Figure A8 and A9 show that there exist only marginal differences in the team-specific mean-centered predictive margins with respect to the Tobit estimates on the unobservable latent outcome and the unconditional expected outcome.

4.4 Team-specific Tobit regression results: Quadratic vs. cubic winning probability

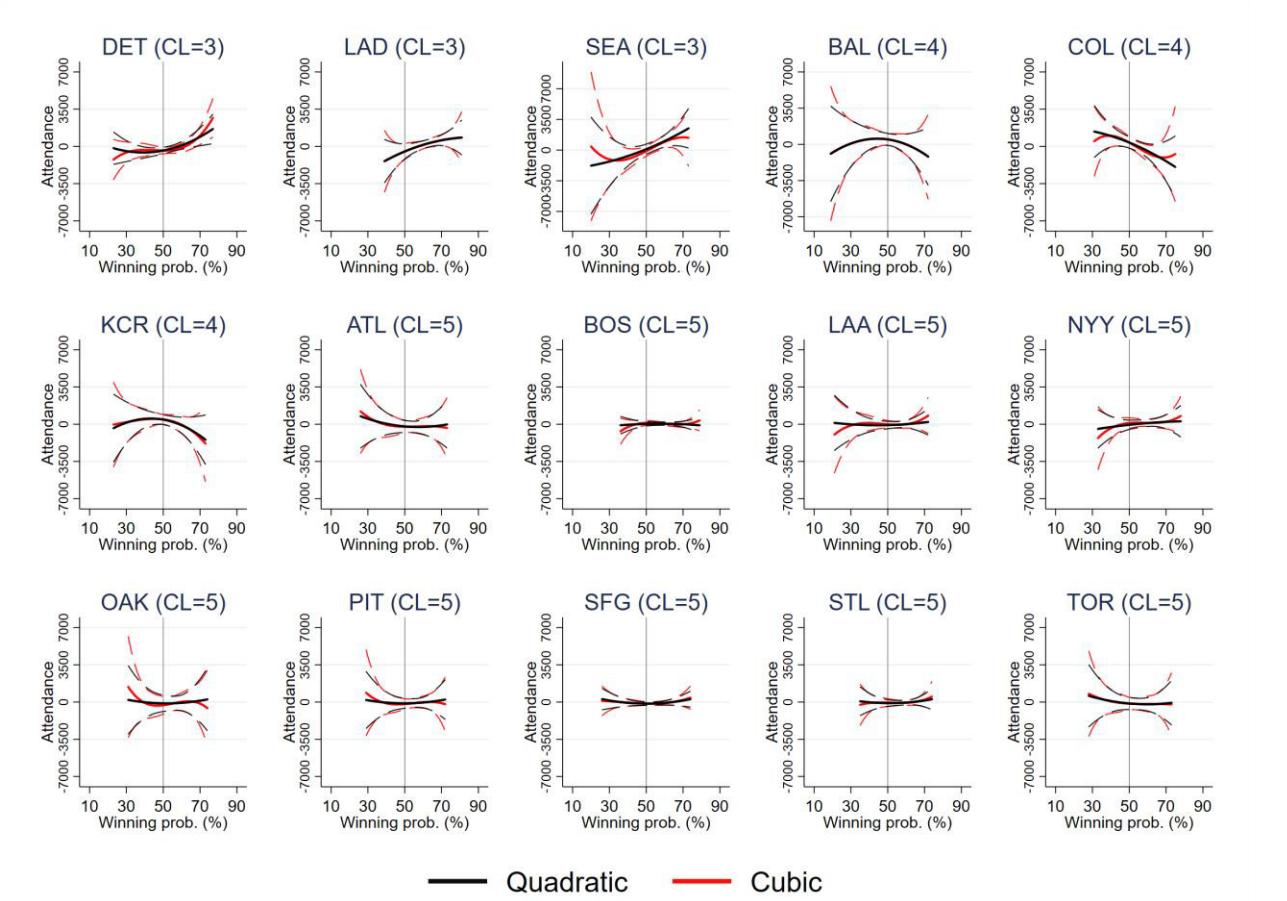
As with our pooled model comparison in Section 3.3, in this section we allow for a more flexible functional relationship between home team winning probability and sport demand by comparing the mean-centered predictive margins derived from quadratic and cubic polynomial specifications of home team winning probability; the corresponding results are presented in Figure A10 and A11.

Figure A10. Mean-centered predictive margins of home team winning probability by team: Quadratic vs. cubic I



Notes: This figure shows mean-centered predictive margins (adjusted predictions at representative values) of home team winning probability derived from individual team-specific game attendance Tobit regressions using quadratic and cubic winning probability effects. The predictions correspond to the impact of winning probability on the unobservable latent outcome (sport demand). We identify five groups of teams (CL=1, 2, ..., 5) with similar winning probability effects by functional high dimensional data clustering (funHDDC). All models include the same set of controls. The detailed regression results for the quadratic winning probability specification are presented in Section 4.1 (cubic specification results omitted for brevity). Predictive margin intervals covers the minimum and maximum team-specific winning probabilities. Dashed lines indicate 95% confidence intervals.

Figure A11. Mean-centered predictive margins of home team winning probability by team: Quadratic vs. cubic II



Notes: This figure shows mean-centered predictive margins (adjusted predictions at representative values) of home team winning probability derived from individual team-specific game attendance Tobit regressions using quadratic and cubic winning probability effects. The predictions correspond to the impact of winning probability on the unobservable latent outcome (sport demand). We identify five groups of teams (CL=1, 2, ..., 5) with similar winning probability effects by functional high dimensional data clustering (funHDDC). All models include the same set of explanatory variables. The detailed regression results for the quadratic winning probability specification are presented in Section 4.1 (cubic specification results omitted for brevity). Predictive margin intervals covers the minimum and maximum team-specific winning probabilities. Dashed lines indicate 95% confidence intervals.

Figure A10 and A11 shows that, except for CLE, there exist only small differences in the tails of the team-specific predictive margins derived from the quadratic and cubic model specifications.

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