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Sports Teams' Home Market Size in the Digital Age — Analyzing Social Media Drawing Power

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Abstract: The sport economic literature relies on the city size to proxy for the size of the home market of sports teams. This paper seeks to clarify whether the commonly used definition for home market size in sports economics is actually a valid measure for revenue potential in the modern digital age. Specifically, in this empirical exercise the interest is to investigate to what extent social media following is adding to our understanding of home markets. In doing so, it closely connects to the literature on outcome uncertainty, by considering the compounded season uncertainty for home games, and the literature on superstars in sport as a determinant for demand.

The econometric analysis uses NFL stadium attendance data between 2009 and 2019 to examine the question of the relationship of social media and stadium attendance. It applies censored tobit models to estimate the effects. The results suggest a significant relationship between social media following and stadium attendance, even when controlling for the metropolitan area where the stadium is located. It argues that our commonly used definition of home market size is built on the outdated concept of localized markets and should be revisited.

Keywords: home markets, national football league, social media, uncertainty of outcome, franchise reallocation, econometrics

JEL-Codes: Z20, L83, D47

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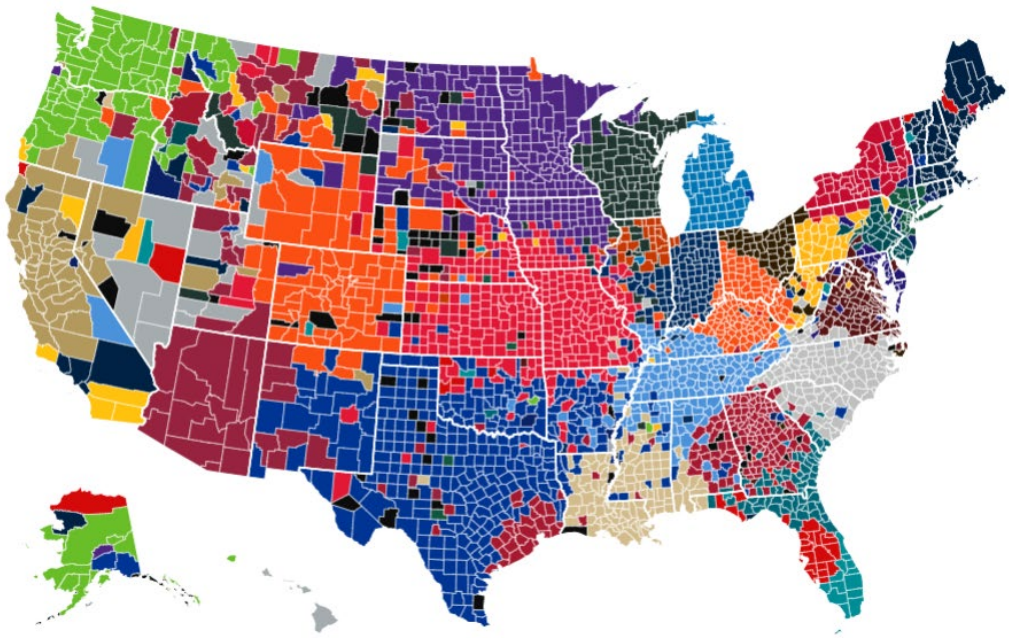
1. Introduction

The idea of sport teams home markets and their size has been used in the analysis of sport demand since its inception in the 1950s and 60s (Rottenberg, 1956; Neale, 1964; Quirk, 1973). Understanding the home market and its demand is vital to sports teams and their managers, since ticket demand is an important revenue stream, and will have impact on considerations of scheduling, pricing, and designing the stadium experience in general. The literature on home markets usually uses the population of the city as a measure of the size of their home market (see section 2). This seems reasonable, since the consumption of stadium tickets is locally bound to the stadium, and therefore mostly sold locally. Furthermore, data on the size of metropolitan areas is easily accessible, which explains the popularity of this measure in the empirical literature. However, in the digital age, a large part of the consumption of sports is through the means of online media: social media networks, streaming services etc. With the non-local nature of social media, we would expect a large number of fans to be found outside of the city's population that the team is located in. For reference, see Figure 1. Here, some clear regional fan agglomeration of NFL teams in their respective local regions are visible, (e.g., Kansas and Missouri being dominated by fans of the Kansas City Chiefs, South Florida by the Miami Dolphins etc[2]). Yet, a fair amount of irregularity in the most popular NFL team by county shows in certain areas of the United States: the Pittsburgh Steelers are popular outside of the local metropolitan area of Pittsburgh, PA; they share Alaska with the L.A. Rams and Tampa Bay Buccaneers. Dallas Cowboys fans are scattered across the entire country as well.

Figure 1, Most tickets sold on vividseats.com, by county, 2022 season only, winner take all, source: https://www.vividseats.com/blog/most-popular-nfl-teams-by-state-county



[2] For list of color coding, see Table. 5.

Drawing from this, there is evidence to support the claim that teams experience high popularity outside of their local metropolitan areas. Hence, it might be suspected that teams are participating in regional markets outside of their local city. This is usually coined as the drawing power of a team, e.g. Goddard & Sloane pointed at a similar idea in 2005 when they spoke of a team´s drawing power. Jane (2016) used the term for super star players, yet the term is rarely used in a team context. Furthermore, the non-localized, decentralized nature of streaming, and online sales of merchandise, add to the doubtfulness of the validity of city size as a home market size in the digital age.

This paper seeks to clarify whether the commonly used definition for home market size in sports economics is actually a good measure for revenue potential. Specifically, in this empirical exercise the interest is to investigate to what extent social media following is adding to our understanding of home markets. It aims to examine the question of the relationship of social media and stadium attendance. In doing so, it closely connects to the literature on outcome uncertainty by considering the compounded season uncertainty for home games as a determinant for demand. Furthermore, it connects to the literature on super star drawing power by using all-star as factors for stadium ticket demand. The results suggest that social media is a good predictor of stadium attendance. Social media following is positively related to stadium attendance—the most localized product that a sports team is offering. It therefore argues that our commonly used definition of home market size is built on the outdated concept of localized markets. It therefore may need revisiting and possible extension. This provides implications for the analysis of demand in sport, franchise reallocation, and empirical analysis of sport markets in general.

2. Literature Review

The sports economics literature on stadium attendance is plentiful, and has covered many angles. Previous authors have examined the effects of local home market size, uncertainty of outcome, superstars, simultaneous TV broadcasts, reallocations, and even weather. The following literature review gives an overview on the parts that I deem most relevant to the framing of this paper, but does not claim to be conclusive. Being conclusive seems not feasible, due to the vast body of existing literature; however, I included information on recent comprehensive overview studies. This study focuses on home market size of sports teams as the main element of the analysis of stadium attendance. Additionally, it summarizes the effects of uncertainty of outcome and the impact of superstars on demand. Importantly, it includes social media literature to draw the link to the analysis of the paper and show its significant research contribution to the already existing body of literature.

Quirk (1973) was the first to strongly advance the idea of the home market size of a sports team as a quasi-monopoly. In his seminal paper he perpetuated, that a team located in a bigger city (e.g., New York or Los Angeles) has a considerably higher revenue potential than one located in a smaller home market (Kansas City or Cincinnati). Drawing demand from a larger city would impact the potential of teams positively: people coming to see the games, buying merchandising products etc. This quasi-

monopoly view on home markets is especially applicable in American sports leagues. Their franchise driven system allows for a systematic market segmentation within the league (Quirk, 1973).

In a related paper, Bird (1982) modeled sport attendance demand as the following equation:

$$A_{it} = [P_{it}, Q_{it}, Q_{it}, M_{it}] \qquad (1)$$

where A is the average attendance for the home team in a single season. Indices *i* indicates the home team, and *t* denotes the season. Ticket price is *P*, *Q*'s are the quality of the Home and Visiting team respectively. M is the market potential of the home team to attract consumers (Bird, 1982). A larger home market size, so the argumentation, leads to ceteris paribus higher revenue. Larger home market size also leads to higher bidding on players, for the expected revenue is proportional to the home market size. This would be endangering to the competitive balance of the league. Scully (1989) wrote that "team revenues are directly related to […] the size of the market from which it draws its fans" (p.154). Assuming this is true, home market size would influence the value of the talent that is employed by a team. Testing Scully's hypothesis, Sommers & Quinton (1982) found supporting evidence with interaction effects between team wins and home market size: wins for teams in larger home markets were found to lead to revenue increases, compared to teams in smaller home markets as measured by population size, yet only marginally. Zimbalist (1992) could not confirm these findings while using baseball data from 1984-1989, yet Burger & Walters (2003) drew the conclusion from their analysis of 1995-1999 baseball data that market size as measured by city population does, in fact, matter. Examining the mentioned literature, it is evident that the sports economics literature relies heavily on population of the city, e.g., the Standard Metropolitan Statistical Area (SMSA), as a proxy for home market size. This paper aims to extend that definition. It specifically investigates the market potential of the home team in the context of social media. Since home markets are considered quasi-monopolies, the analysis adds nuance to the market delineation of sports markets. The implications extend the concept of team's drawing power to more than just the size of the city's population. Overall, the paper adds to the understanding of the home market potential as understood in the literature.

Other factors outside of home market size play a role in the analysis of sport demand, namely for the purpose of this paper: the uncertainty of outcome, superstars, and the relationship with social media. The uncertainty of outcome hypothesis has been around in sports economics for more than half a century (Rottenberg, 1956) and has been studied comprehensively[3]. It states that demand for sports will be *ceteris paribus* higher with tighter competition between the competitors. Even though the notion seems comprehensible, the evidence of decades of research shows that there are nuances to the concept of uncertainty of outcome. For TV demand, uncertainty of outcome is positively related. There is evidence for this in national and international football (Peel & Thomas, 1992; Forrest, Simmons, & Buraimo, 2005; Paul & Weinbach, 2007; Buraimo & Simmons, 2008b, 2009; Feddersen & Rott, 2011; Buraimo

[3] For a recent overview study, see inter alia Schreyer & Ansari (2022); for an evaluation of the existing studies, see Coates et al. (2014).

& Simmons, 2015; Perez et al., 2017; Humphreys & Pérez, 2019; Wills et al., 2020; Macedo et al., 2022), and american sports (Knowles et al., 1992; Coates & Humphreys, 2012) . For stadium attendance, demand preferences for uncertainty of outcome differ from this. Here, the literature shows evidence for home team win preferences and loss aversion. Peel and Thomas (1988) were the first to use an *a priori* measure of uncertainty in estimating stadium demand similar to the one in this paper—betting odds data. Rascher (1999) furthered the discussion by finding additional evidence for the uncertainty of outcome hypothesis. The more recent stadium attendance literature found high home win probabilities to increase ticket demand. This is with a fairly consistent effect across sports and measurement methods; from the Premier League (Buraimo & Simmons, 2008a), Dutch soccer (Besters et al., 2019) to the Italian Serie A (Bond & Addesa, 2020). For NHL Games, attendance increased when fans expected the home team to win and *ceteris paribus* declined when the game was projected to be close (Coates & Humphreys, 2012). Coates, Humphreys, and Zhou (2014) develop a model of reference dependent preferences which allows for asymmetric preferences over wins and losses based on prospect theory. Here, the indication is that fans want to either see their home team win, the more certain the better, or have the possibility of an upset wins, where the home team is the underdog. Later papers like Cox (2018) and Forrest (2005) confirmed this, while showing that uncertain matches affected stadium attendance and TV demand opposingly. Higher uncertainty was—while positively related to TV demand—was negatively related to stadium attendance. The understanding of the uncertainty of outcome, as proposed by Rottenberg (1956), strips the complexity of the consumer decision making under uncertainty (Coates & Humphreys, 2012). Stadium attendance does not seem to value uncertainty of outcome for games, at least not consistently.

The effects of superstars on demand for sport was first analyzed by Hausman & Leonard (1997). The paper established the positive impact of star players on demand, especially the revenue increasing impact of players like Michael Jordan on TV demand in the early 1990s. Berri & Schmidt (2006) extended their work by including away game attendance, yet found similar positive externalities of super star employment on attendance. Chamit et al. (Chmait et al., 2020) found strong positive super star effects on demand for Grand Slam Tennis. The closest research to this aspect of the analysis of this paper was done by Jane (2016). This paper solidified superstar effects in sports, by delivering evidence for increases in home and away attendance when superstar NBA players were in the match. Most recently, Humphreys & Johnson (2020) added to the related literature by looking at 30 seasons, confirming the aforementioned effects and estimating absolute number increases, as well as novelty effects.

Previous studies on social media and sports using economic underpinnings are scarce. The literature is commonly divided into content-based inquiry and audience-based inquiry (Clavio, 2011; Watanabe et al., 2015). Content-based analysis focus on thematic analysis of the content that's posted by teams and players. This study however uses an audience-based approach. In an audience approach, the underlying assumption is that individuals' activities on social media are considered as expressing consumer interest (Watanabe et al., 2015). Using this type of approach, Feddersen et al. (2017) used a single value of

Facebook likes per season to measure social media popularity. Employing a similar approach to this study, they found sentiment biases of price-insensitive bettors using data from seven professional sports leagues in Europe and North America. Clavio (2011) discovered significant differences between traditional fans and fans on social media. More specifically, the two groups of fans differed in demographic factors such as age, and income. Social media use was negatively related to age. Closely related to the design of this study, Pérez (2013) examined the relationship of sporting success and social media following. The paper found a strong significant relationship of success of soccer teams and the number of twitter followers. It proposed a framework for social media to be used as a legitimate means in measuring fan interest through the approach of an economic demand study (Watanabe et al., 2015).

Altogether, the literature offers three main insights here: TV and stadium attendance differ in their preferences on uncertainty of outcome—demand for stadium tickets is positively related to a projected home win— likely due to home win preferences and loss aversion. Superstars positively influence demand for sport. The relationship of social media and sports demand is understudied. From this, this paper derives the research question: Considering the previously studied economic demand factors—such as city population as a proxy for home market size specifically—what is the relationship of stadium demand and social media following?

3. Data & Methods

This paper uses stadium attendance data from the National Football League from 2009 to 2019. The *dependent variable,* attendance is the percentage of tickets in relation to the seats in the home team's stadium. As depicted in the summary statistics (Table 1), stadium attendance falls between 70.3 and 117.6%. This number is truncated to the right by constraints of stadium capacity, especially seats. However, the dependent variable is not limited to 100% as the NFL defines capacity as the number of regular and luxury seats. For every luxury seat, the team can elect to add a fixed number of temporary seats. Standing steads, handicapped seats and opening of tarped out areas of the stadium can increase the *de facto* capacity of the stadium above the official capacity of the stadium, enabling the percentage to exceed 100%. 36.27% of observed home team attendances exceeded the official number of the stadium's capacity (>99.9% of capacity). Similar to Buraimo & Simmons (2008a), the upper and lower bounds of the tobit regression were chosen according to the distribution of the dependent variable. Even though the exact maximum and minimum values from the data seem reasonable for censorship of the data, robustness checks were performed with different bounds, esp. setting the minimum attendance to a lower value. The data is not split in home and away fans. Attendance values for the 2020 season were eliminated due to the erratic impact of COVID-19 restrictions on stadium attendance.

Table 1, Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Attendance	430	96.643	6.877	67.7	121.4
Uncertainty	439	.45	.148	-.092	.807
Superstars	439	4.262	2.734	0	15
Reallocation	376	.005	.073	0	1
CityPopulation	410	2.158	1.508	.613	8.397
Facebook	323	2014109	1815583.8	13535.4	8749044.4
Instagram	182	712363.3	638870.1	9299	3999335
PlayoffGames	439	.346	.678	0	3

The analysis is constrained by one of the main variables of interest—social media data (*SocialMedia*). For social media data, an analysis that goes back further than 2008 is not feasible since the networks were still in their infancy phase. According to official statements, Facebook had only ~100m monthly active users in 2008, compared to 30-times that in 2022 (~3bn; Meta Platforms, 2022). The Facebook and Instagram data was collected from socialblade.com; supplemented by historical data from trackalytics.com and web.archive.com. The data contains the teams' following count on social media between 2008 and 2019[4]. Since social media networks are a dynamic market, it is not only reasonable but even useful to constrain the analysis to a few years where the social network is relatively growing in size or has a large user percentage in the market.

Uncertainty is measure out of outcome uncertainty on season level. I use historical betting odds from bet365.com and pinnaclesports.com, per game[5]. I then transformed the home team odds for every game to be "demeaned" by 0.5, which would represent perfect *ex ante* uncertainty. The variable represents deviation from a perfectly balanced game. This is for positive values of odds above 0.500, where the home team is favored (home-win), as well as negative with odds below 0.500, visiting team favored (underdog/upset-win). Both are manifestations of certainty of outcome; therefore, they both increase the variable. It then uses the squared value to create a geometric mean. The weighted geometric average of the deviation from perfectly uncertain home games is the value for a team in the season. Since in the literature we preferably use the term uncertainty of outcome, I transform it to be the reverse probability (*1-P*).

The drawing power of super star players is accounted for in the model by the number of all-stars on a team in a Season (*Superstars*). This definition of superstars follows Burdekin & Idson (1991), but adjusted from the NBA to the NFL. In the NFL, all-stars are players that won either a Pro Bowl award or at least one All-Pro award. These awards are better measures of popularity, than of skill (Kunz-Kaltenhäuser, 2021; Kunz-Kaltenhäuser et al., 2023). However, in the context of this paper that is not a shortcoming, since demand of stadium tickets is perhaps closer related to the opinions about players,

[4] Technically, Facebook refers to the number of followers of a page as likes. Factually liking a page on facebook and following it on other networks fulfills the same function: support and subscription to the feed. Therefore, I use the term follower even when refering to Facebook.
[5] Data for seasons 2014-2018 is from Pinnaclesports.com; 2018 and onwards from bet365.

than their actual production. One might argue that the title translates to increased ticket sales in the next seasons, and therefore should be lagged. However, I use it here as a proxy for player quality in the current season while the player is actually playing well, not the fame/reputational effects that may occur in the sequential seasons.

An additional variable *Reallocation* corrects for whether a team was reallocated in the season as this might affect stadium attendance. Playoff games likely systematically differ from regular season games by increasing stadium attendance. The number of playoff games is therefore taken into the model (*PlayoffGames).* City population (*CityPopulation*) is United States Census Bureau data. It refers to the core city population, not the metropolitan area, to allow for differentiation of these two factors in the model. Furthermore, the city´s population and the social media following of its team seem largely unrelated—the correlation is small and insignificant (see also variance inflation factors in the appendix). The correlation of popularity across platforms is highly significant and can be considered large at .699.

Table 2, Pairwise correlations

Variables	(1)	(2)	(3)
(1) CityPopulation	1.000		
(2) Facebook	0.010	1.000	
(3) Instagram	-0.016	0.699***	1.000

Home stadium attendance of team *i* in season *t* is modeled as a function of the uncertainty of the games in the season, the number of superstars and the following on social media plus season-fixed effects and an error term. It takes the following form:

$$ATT_{it} = \alpha + \beta_1 Uncertainty_{it} + \beta_2 Superstars_{it} + \beta_3 CityPopulation_{it} + \beta_4 SocialMedia_{it} + \beta_4 Reallocation_{it} + \beta_5 PlayoffGames_{it} + S_t + \varepsilon_{it} \quad (1)$$

The robust standard errors were clustered among teams to account for possible autocorrelation in the panel.

4. Results & Discussion

Table 3, Regression results

Tobit regression

VARIABLES	(1) Facebook (not lagged)	(2) Facebook (lagged)	(3) City population and Facebook	(4) City population only	(5) Agglomeration
Uncertainty	-7.576**	-11.39***	-8.908**	-10.65***	-7.782**
	(3.530)	(3.728)	(3.609)	(3.814)	(3.713)
Superstars	0.350**	0.187	0.324**	0.418**	0.282*
	(0.156)	(0.156)	(0.163)	(0.173)	(0.156)
Reallocation	-5.445***		-5.873**	-7.633***	-3.831**
	(1.211)		(2.545)	(2.184)	(1.498)
CityPopulation			0.138	0.0612	
			(0.527)	(0.491)	
Facebook	9.10e-07**		1.07e-06**		9.64e-07***
	(3.98e-07)		(4.62e-07)		(3.59e-07)
Facebook (lagged)		8.70e-07**			
		(4.13e-07)			
Metropolitan Area					-2.755**
					(1.317)
PlayoffGames	-0.217	-0.785	-0.0712	-0.105	-0.942
	(0.649)	(0.744)	(0.699)	(0.649)	(0.890)
Season-FE	*YES*	*YES*	YES	YES	*YES*
Constant	96.83***	101.0***	97.08***	100.4***	98.39***
	(2.529)	(2.632)	(2.662)	(2.346)	(2.708)
Observations	321	289	302	350	321

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Robust standard errors were clustered by teams. Season-level uncertainty affects stadium attendance significantly negative (-7.576**). This is in line with the home-win preferences and loss aversion expected when considering the literature. Robustness checks in the other models show evidence that points in that same direction, specifically model four using the home win probability and its squared term respectively (see model 7 in the appendix). Superstars as measured in this paper are significant in four out of the five models. The coefficient is only insignificant when using unlagged social media data, which leads to the conclusion that these two variables may be interrelated. During the time of the panel used in this study, All-star voting included public online voting by fans, so it would be expected that they are connected (Kunz-Kaltenhäuser, 2021; Kunz-Kaltenhäuser et al., 2023). Reallocation of a team negatively impacts attendance of the home stadium significantly, by -5.45% in model 1 with full specifications[6].

[6] The latent continuous variable that has not been observed over its entire range.

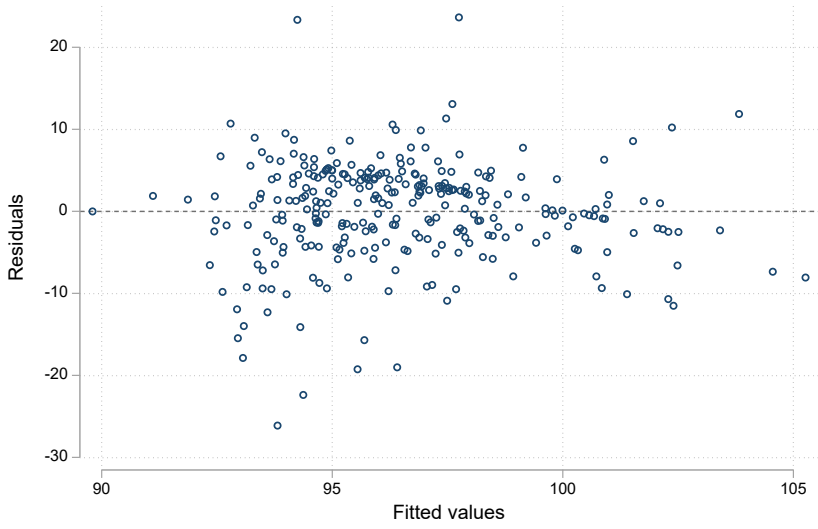
Concerning the main variable of interest—the social media following—stadium attendance increases with the number of social media followers[7]. There is evidence for positive effects of lagged as well as not lagged social media following on stadium attendance. The comparatively small coefficient estimated for Facebook followers is explained by the relatively large Facebook following that the franchises have (see Table 1). Interestingly, the effect of social media following persists, when controlling for the population of the city (model 3). This is the classic proxy of home market size, yet shows now significant effect on stadium attendance (model 4). Model 5 introduces a dummy variable, that measures if the home team is located in a metropolitan area or not. A stadium located in a highly agglomerated metropolitan area like the New York metropolitan area or the Los Angeles metropolitan area experiences significantly less stadium demand than one that is not. The marginal effect of social media following on stadium attendance does not change depending on whether the franchise is located in a metropolitan area or not (see Figure 2 in the appendix). The 95%-CI for the estimated coefficients are not significantly different from one another. All other coefficients stay consistent in their direction and significance. The number of playoff games is insignificant in the models.

I checked for multicollinearity in the models. Multicollinearity could be suspected e.g., because there is an underlying process that explains social media following and all-star selections simultaneously. However, mean variance inflation factors are below $vif = 2.0$ with a vif of $1.041 (1/vif = 0.96)$ on the main variable of interest. Same is true for the other variables of interest (see appendix). As this is well below the accepted econometric standard value, I do not support the concern of multicollinearity in the model. Residuals are evenly distributed around zero and show now systematic skewedness to one

7 When using Instagram followers as a social media variable, the effect becomes insignificant arguably due to a much smaller sample size over a shorter period, with only a fraction of the engagement (see appendix).

side. Therefore, the model matches the homoscedasticity assumption of the tobit model. The model does not appear to suffer from heteroskedasticity (see Figure 3).

Figure 2, Residuals



Choosing the lower limit of the tobit to be zero does not change the direction, size, or significance of the estimated coefficients.

5. Conclusion

This paper adds to the uncertainty of outcome literature by confirming the occurrence of loss aversion and home-win preferences for stadium attendance. It fits with the narrative of home crowds preferring more certain games. The positive superstar effects are only somewhat robust, perhaps due to the doubtful validity of the voting processes for all-stars.

This paper challenges the notion of localized home markets for sports teams. It concludes that estimating home market size by using the city's population[8] is oversimplified and should be revisited. The prediction of large metropolitan areas representing large home markets and therefore inevitably booked stadiums should be most likely scrutinized more carefully.

This analysis has implications for sport management, the econometric analysis of sports, as well as the institutional design of sports leagues. Firstly, it can inform the reallocation decisions of teams and their social media management—it confirms the importance of social media to attract fans. Since there are significant differences between sport audiences on, and not on social media (Clavio, 2011), the presence of, and engagement with, the younger demographic groups on social media make it crucially important to the mid- to long-term conservation of demand. Future research could take a content-based approach over an audience-based one. This would give us further insight on what factors make a team successful

[8] Or the metropoliation area for that matter.

on social media. Additionally, an analysis split by age groups would be insightful. However, such analysis is limited by the availability of team-specific data that relates to age.

Secondly, the analysis gives us evidence that building econometric models based on the size of the metropolitan area is likely not a good estimator in the current market dynamic. An analysis using county level social media data would provide more granular understanding of the relationship in specific markets, yet requires access to data that is currently not provided. Social media may be an option to approach the idea of a modernized sport team home market. Perhaps using the term drawing power is the more aptly named.

Thirdly, the findings have implications for the institutional design of sports leagues. The size of the home market is a critical component e.g., when regulating financial imbalances in the name of competitive balance. This analysis showed evidence, that in this context, the revenue potential from stadium ticket sales is not positively related to the size of the city. It is however, positively connected to the social media popularity. Therefore, the estimated revenue potential of teams may expand from the city/metropolitan area, to consider other factors like their social media.

6. References

Berri, D. J., & Schmidt, M. B. (2006). On the Road With the National Basketball Association's Superstar Externality. *Journal of Sports Economics*, *7*(4), 347–358.

Besters, L. M., van Ours, J. C., & van Tuijl, M. A. (2019). How outcome uncertainty, loss aversion and team quality affect stadium attendance in Dutch professional football. *Journal of Economic Psychology*, *72*, 117–127.

Bird, P. J. W. N. (1982). The demand for league football. *Applied Economics*, *14*(6), 637–649.

Bond, A. J., & Addesa, F. (2020). Competitive Intensity, Fans' Expectations, and Match-Day Tickets Sold in the Italian Football Serie A, 2012-2015. *Journal of Sports Economics*, *21*(1), 20–43.

Buraimo, B., & Simmons, R. (2008a). Do sports fans really value uncertainty of outcome? Evidence from the English Premier League. *International Journal of Sport Finance*, *3*(3), 146–155.

Buraimo, B., & Simmons, R. (2008b). Do Sports Fans Really Value Uncertainty of Outcome? Evidence from the English Premier League. *International Journal of Sport Finance*. (3), 146–155.

Buraimo, B., & Simmons, R. (2009). A tale of two audiences: Spectators, television viewers and outcome uncertainty in Spanish football. *Journal of Economics and Business*, *61*(4), 326–338.

Buraimo, B., & Simmons, R. (2015). Uncertainty of Outcome or Star Quality? Television Audience Demand for English Premier League Football. *International Journal of the Economics of Business*, *22*(3), 449–469.

Burdekin, R. C. K., & Idson, T. L. (1991). Customer preferences, attendance and the racial structure of professional basketball teams. *Applied Economics*, *23*(1), 179–186.

Burger, J. D., & Walters, S. J. K. (2003). Market Size, Pay, and Performance. *Journal of Sports Economics*, *4*(2), 108–125.

Chmait, N., Robertson, S., Westerbeek, H., Eime, R., Sellitto, C., & Reid, M. (2020). Tennis superstars: The relationship between star status and demand for tickets. *Sport Management Review*, *23*(2), 330–347.

Clavio, G. (2011). Social Media and the College Football Audience. *Journal of Issues in Intercollegiate Athletics*. (4), 309–325.

Coates, D., & Humphreys, B. R. (2012). Game Attendance and Outcome Uncertainty in the National Hockey League. *Journal of Sports Economics*, *13*(4), 364–377.

Coates, D., Humphreys, B. R., & ZHOU, L. I. (2014). REFERENCE-DEPENDENT PREFERENCES, LOSS AVERSION, AND LIVE GAME ATTENDANCE. *Economic Inquiry*, *52*(3), 959–973.

Cox, A. (2018). Spectator Demand, Uncertainty of Results, and Public Interest. *Journal of Sports Economics*, *19*(1), 3–30.

Feddersen, A., Humphreys, B. R., & Soebbing, B. P. (2017). SENTIMENT BIAS AND ASSET PRICES: EVIDENCE FROM SPORTS BETTING MARKETS AND SOCIAL MEDIA. *Economic Inquiry*, *55*(2), 1119–1129.

Feddersen, A., & Rott, A. (2011). Determinants of Demand for Televised Live Football: Features of the German National Football Team. *Journal of Sports Economics*, *12*(3), 352–369.

Forrest, D., Beaumont, J., Goddard, J., & Simmons, R. (2005). Home advantage and the debate about competitive balance in professional sports leagues. *Journal of Sports Sciences*, *23*(4), 439–445.

Forrest, D., Simmons, R., & Buraimo, B. (2005). OUTCOME UNCERTAINTY AND THE COUCH POTATO AUDIENCE. *Scottish Journal of Political Economy*, *52*(4), 641–661.

Goddard, J., & Sloane, P. J. Economics of sport. In S. W. Bowmaker (Ed.), *Economics Uncut* (Vol. 2005, Simon W. Bowmaker (ed.), Economics Uncut, chapter 12, Edward Elgar Publishing.). Edward Elgar Publishing.

Hausman, J. A., & Leonard, G. K. (1997). Superstars in the National Basketball Association: Economic Value and Policy. *Journal of Labor Economics*, *15*(4), 586–624.

Humphreys, B. R., & Johnson, C. (2020). The Effect of Superstars on Game Attendance: Evidence From the NBA. *Journal of Sports Economics*, *21*(2), 152–175.

Humphreys, B. R., & Pérez, L. (2019). Loss aversion, upset preference, and sports television viewing audience size. *Journal of Behavioral and Experimental Economics*, *78*, 61–67.

Jane, W.-J. (2016). The Effect of Star Quality on Attendance Demand. *Journal of Sports Economics*, *17*(4), 396–417.

Knowles, G., Sherony, K., & Haupert, M. (1992). The Demand for Major League Baseball: A Test of the Uncertainty of Outcome Hypothesis. *The American Economist*, *36*(2), 72–80.

Kunz-Kaltenhäuser, P. (2021). Is the NFL´s Pro Bowl Broken? Considering the Players´ Perspective. *Ilmenau Economics Discussion Papers*, *27*(149).

Kunz-Kaltenhäuser, P., Gaenssle, S., & Budzinski, O. (2023). Differences in the Voting Patterns of Experts, Peers, and Fans - Analyzing the NFL's All-Star Team Selections.

Macedo, A., Ferreira Dias, M., & Mourão, P. R. (2022). European Men's Club Football in the Eyes of Consumers: The Determinants of Television Broadcast Demand. *Journal of Sports Economics*, 152700252211439.

Meta Platforms (2022). Facebook: quarterly number of MAU (monthly active users) worldwide 2008-2022. (Statista). Retrieved from https://www.statista.com/statistics/264810/number-of-monthly-active-facebook-users-worldwide/

Neale, W. C. (1964). The Peculiar Economics of Professional Sports: A Contribution to the Theory of the Firm in Sporting Competition and in Market Competition. *The Quarterly Journal of Economics*, *78*(1), 1.

Paul, R. J., & Weinbach, A. P. (2007). The uncertainty of outcome and scoring effects on Nielsen ratings for Monday Night Football. *Journal of Economics and Business*, *59*(3), 199–211.

Peel, D., & Thomas, D. [Dennis] (1988). OUTCOME UNCERTAINTY and THE DEMAND FOR FOOTBALL: AN ANALYSIS OF MATCH ATTENDANCES IN THE ENGLISH FOOTBALL LEAGUE. *Scottish Journal of Political Economy*, *35*(3), 242–249.

Peel, D., & Thomas, D. A. (1992). The demand for football: Some evidence on outcome uncertainty. *Empirical Economics*, *17*(2), 323–331.

Perez, L., Puente, V., & Rodríguez, P. (2017). Factors determining TV soccer viewing: Does uncertainty of outcome really matter? *International Journal of Sport Finance*, *12*(2), 124–139.

Pérez, L. (2013). What drives the number of new Twitter followers? An economic note and a case study of professional soccer teams. *Economics Bulletin*, *33*(3), 1941–1947.

Quirk, J. (1973). An Economic Analysis of Team Movements in Professional Sports. *Law and Contemporary Problems*, *38*(1), 42–66.

Rascher, D. (1999). *Sports Economics: Current Research.*

Rottenberg, S. (1956). The Baseball Players' Labor Market. *Journal of Political Economy*, *64*(3), 242–258.

Schreyer, D., & Ansari, P. (2022). Stadium Attendance Demand Research: A Scoping Review. *Journal of Sports Economics*, *23*(6), 749–788.

Scully, G. W. (1989). *The Business of Major League Baseball*. Chicago: The University of Chicago Press.

Sommers, P. M., & Quinton, N. (1982). Pay and Performance in Major League Baseball: The Case of the First Family of Free Agents. *The Journal of Human Resources*, *17*(3), 426.

Watanabe, N., Yan, G., & Soebbing, B. P. (2015). Major League Baseball and Twitter Usage: The Economics of Social Media Use. *Journal of Sport Management*, *29*(6), 619–632.

Wills, G., Tacon, R., & Addesa, F. (2020). Uncertainty of outcome, team quality or star players? What drives TV audience demand for UEFA Champions League football? *European Sport Management Quarterly*, 1–19.

Zimbalist, A. S. (1992). Salaries and performance: Beyond the Scully model. In P. M. Sommers (Ed.), *Diamonds are forever* (pp. 109–133). Washington, DC: The Brookings.

Appendix

Table 4, Variance inflation factors

Variance inflation factor

	VIF	1/VIF
Uncertainty	1.337	.748
Superstars	1.207	.828
PlayoffGames	1.203	.831
Facebook	1.041	.96
Reallocation	1.012	.988
Mean VIF	1.16	.

Table 5, Instagram and home win porbability robustness checks

Tobit regression

VARIABLES	(6) Instagram (lagged)	(7) Homewin Probability
Uncertainty	-8.220*	
	(4.547)	
Superstars	0.510**	0.0914
	(0.209)	(0.133)
Reallocation	-7.263***	-4.647***
	(1.369)	(1.185)
Facebook		8.12e-07*
		(4.24e-07)
Instagram (lagged)	1.79e-06	
	(1.41e-06)	
HomewinProb		2.630
		(2.389)
HomewinProbSquared		11.99***
		(3.917)
PlayoffGames	-0.741	-0.0113
	(0.774)	(0.526)
Season-FE	*YES*	*YES*
Constant	101.1***	90.39***
	(2.292)	(2.616)
Observations	181	322

Figure 3, Marginal effect of social media

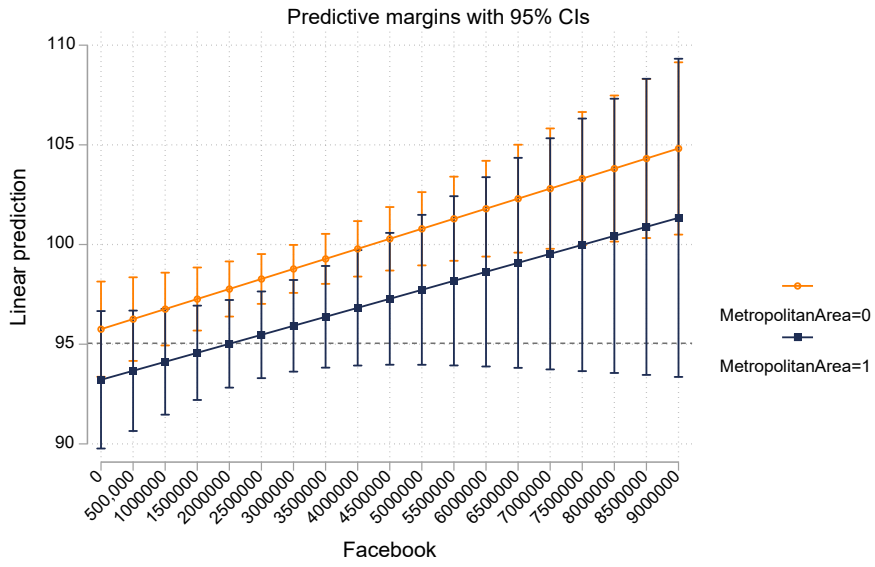


Table 6, Color coding for Fig.1

Team name	Color
Arizona Cardinals	
Atlanta Falcons	
Baltimore Ravens	
Buffalo Bills	
Carolina Panthers	
Chicago Bears	
Cincinnati Bengals	
Cleveland Browns	
Dallas Cowboys	
Denver Broncos	
Detroit Lions	
Green Bay Packers	
Houston Texans	
Indianapolis Colts	
Jacksonville Jaguars	
Kansas City Chiefs	
Las Vegas Raiders	
Los Angeles Chargers	
Los Angeles Rams	
Miami Dolphins	
Minnesota Vikings	
New England Patriots	
New Orleans Saints	
New York Giants	
New York Jets	
Philadelphia Eagles	
Pittsburgh Steelers	

San Francisco 49ers	
Seattle Seahawks	
Tampa Bay Buccaneers	
Tennessee Titans	
Washington Commanders	