Article

Journal of Sports Economics
2020, Vol. 21(2) 152-175

DOI: 10.1177/1527002519885441
journals.sagepub.com/home/jse

The Effect of Superstars on Game Attendance: Evidence From the NBA

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Abstract

Economic models predict that "superstar" players generate externalities that increase attendance and other revenue sources beyond their individual contributions to team success. We investigate the effect of superstar players on individual game attendance at National Basketball Association games from 1981-1982 through 2013-2014. Regression models control for censoring due to sellouts, quality of teams, unobservable team/season heterogeneity, and expected game outcomes. The results show higher home and away attendance associated with some superstar players. Michael Jordan generated the largest superstar attendance externality, generating an additional 4,837/4,236 fans at home/away games.

Keywords

superstar effect, attendance demand, censored normal estimator

A substantial literature assesses the impact of superstar effects, the presence of specific individuals or organizations earning far more than others and dominating market activities. Superstar effects can exist in many markets, including corporate CEOs, graduate schools, researchers, classical and popular music performers, movie stars, textbooks, and sports. The theoretical basis for superstar effects was

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established under general conditions by Rosen (1981) and extended by Adler (1985) and MacDonald (1988).

These competing models, and their differing predictions, generated a substantial body of empirical research, much of it using outcomes from professional sports markets. Attendance represents one commonly analyzed outcome. Hausman and Leonard (1997), Berri, Schmidt, and Brook (2004), Berri and Schmidt (2006), Brandes, Franck, and Nüesch (2008), Lawson, Sheehan, and d Stephenson (2008), LeFeuvre, Stephenson, and Walcott (2013), Jane (2016), Jewell (2017), and Lewis and Yoon (2018) develop evidence supporting the presence of superstar effects on home and away attendance in a number of professional sports leagues.

We extend this literature by examining the effect of the presence of superstar players on attendance at National Basketball Association (NBA) games. Our 30-year sample of game-level attendance and game/team characteristics data is substantially longer than most used in previous research and contains many players' entire career. We augment these data with detailed information about the talent and popularity of specific NBA players. Analyzing data from one to three seasons, a common sample period in the literature, cannot rule out the possibility of short-lived superstar effects confined to one or two players. Our long sample period allows us to comprehensively test for superstar effects generated by players from different eras in the NBA and over long periods of players' careers. We find strong evidence of superstar effects associated with specific NBA players at home games and road games throughout the sample period. NBA superstar effects, including a superstar externality, appear durable over player careers and exist throughout the sample period.

Our data also permit a formal test of the Rosen (1981) model of superstars, which posits talent as the primary source of superstar effects, versus the Adler (1985) model of superstars, which posits popularity as the source. Franck and Nüesch (2012) and Jane (2016) undertook similar tests using data from German football and the NBA, respectively. Jane (2016) analyzes the effect of the total number of All-Star players, total number of All-Star votes received by players, and the total number of players earning salaries in the top 30 in the league on the rosters of the home and visiting team on attendance. This differs from an analysis of the presence of specific star players on attendance.

We find evidence of specialization of superstar effects; Larry Bird and Magic Johnson appear to be "Rosen" superstars, deriving superstar status from performance while Julius Erving, Michael Jordan, Shaquille O'Neal, and LeBron James appear to be "Adler" superstars deriving superstar status from popularity. These results indicate that the findings of Franck and Nüesch (2012) can be generalized to other settings and that findings in Jane (2016) extend to specific NBA players.

Superstars, Talent, and Popularity

Interest in the economics of superstars stems from Rosen (1981), who developed a model explaining why relatively small groups of people in a given occupation earn enormous salaries and dominate their occupations, described as the "superstar" effect. Rosen developed a model containing profit maximizing firms and utility maximizing consumers describing how the number of tickets sold by a service producing firm like a sports team or concert venue depends on both ticket prices and the talent or quality of the performers. In this model, revenues are convex in talent; high-talent performers attract audiences much larger than performers with only slightly less talent and the marginal returns to talent exceed the underlying difference in talent across performers. The model predicts that a small number of athletes with marginally more talent or ability than their peers will have far more fans who will pay to watch them play and earn much larger salaries than their peers.

Adler (1985) extended this model to show that substantial differences in the number of fans following specific performers, and the associated revenues, could arise even with no discernible difference in performer talent or ability. This model emphasizes that following a star performer requires costly acquisition of knowledge about performers and the presence of spillover benefits associated with this knowledge in the form of enhanced social interaction with others, since many people share common knowledge about star performers. Under these conditions, fans flock to performers with star power even if the underlying level of talent is identical. The implication is that popularity, not differences in skill, explains observed star effects. Adler (1985) also assumes that luck plays a large role in determining which specific performers successfully attract a sufficiently large fan base to be considered a star.

These models spawned a large, growing body of empirical research examining the effect of star players on television audiences and attendance at NBA games. The NBA represents an ideal setting for analyzing the impact of star players on consumer demand. NBA teams can only put five players on the floor at a time compared to the National Football League (NFL) (11 on the field and two full sets of different players, offense, and defense), Major League Baseball (MLB; 9 in the National League and 10 in the American League), and Major League Soccer (MLS; 11), or National Hockey League (NHL) (6), so the impact of individual players on fan interest is magnified in the NBA. Unlike football and hockey players, NBA players do not wear protective headgear and padding that distorts players' faces and body shape. Unlike the NFL and MLB, NBA games are played in smaller venues where many fans sit close to the playing surface.

Hausman and Leonard (1997) undertook the first empirical analysis of the effect of superstar players on television audiences and attendance in the NBA. Hausman and Leonard (1997) analyzed local and national television broadcast audience size data and attendance data from the 1989-1990 and 1991-1992 seasons and found that superstar players are valuable to the team that employs them and also to other teams. They found that superstars, identified by the top 25 All-Star vote recipients, increased attendance, television ratings, licensed merchandise sales, and other sources of revenues beyond their individual contributions, including increased attendance at road games. Hausman and Leonard (1997) also analyzed the impact of five specific superstar players, Magic Johnson, Larry Bird, Shaquille O'Neal, Charles

Barkley, and Michael Jordan (then in the prime of his career with the Chicago Bulls) on home and away attendance and revenues. Results showed that Michael Jordan was worth more than US$50 million to other teams in the NBA, an externality since Jordan was paid only by the Bulls.

Berri et al. (2004) and Berri and Schmidt (2006) extended the work of Hausman and Leonard (1997), analyzing gate revenue and attendance at away games played by NBA teams, respectively. The impact of star players on attendance at away games is interesting because superstars are compensated by their team, not their opponents; increased attendance and gate revenues at away games primarily benefits opposing teams, again representing a superstar player externality. Berri and Schmidt (2006) analyzed total season attendance at NBA road games over the 1992-1993 through 1995-1996 seasons and defined the presence of star players on NBA teams based on the total number of All-Star votes received by players on each team. Each additional All-Star vote was associated with an increase of 0.005 in total season attendance at road games. For top vote getters in All-Star voting in the 1995-1996 NBA season like Grant Hill (1.36 million votes) or Michael Jordan (1.34 million votes), this implies an increase in annual attendance of about 7,000 additional tickets sold or about US$220,000 in additional revenues assuming an average NBA ticket price of US$30. Berri and Schmidt (2006) also estimated the additional revenues generated by additional wins generated by star players holding the All-Star effect constant and reported estimate of the marginal revenues from an additional wins to be substantially larger than the marginal revenue from additional All-Star votes.

Jane (2016) analyzed the effect of star players on NBA game attendance rather than total season attendance using a number of measures of the presence of star players on teams. Variables reflecting star players include 30 highest paid players in the league, the top 30 players in the league in five specific performance statistics, the number of All-Star players appearing in each game for each team, and the number of All-Star votes received by players on each team. Jane (2016) found that stars, measured as All-Star vote recipients and the leagues' top performers, have a positive impact on game attendance. In differentiating between popular players that received All-Star votes and top performers, Jane (2016) found that popularity, not performance, affects attendance.

Empirical research on the effect of stars on attendance extends to other sports. Lawson et al. (2008) and Jewell (2017) analyze the impact of superstars on attendance in MLS. Brandes et al. (2008) analyze the impact of superstars on attendance in the top football league in Germany.

Lewis and Yoon (2018) analyzed both the distribution of salaries and individual game attendance at MLB games to assess the impact of star baseball players. They report evidence that the number of star players on home and visiting MLB teams increases attendance at games, controlling for other factors, and evidence that star players have a larger impact on attendance on teams playing in larger cities. Lewis and Yoon (2018) also estimated that the presence of star player Manny Ramirez on the Los Angeles Dodgers' roster in 2008 generated an additional 4,815 tickets sold and that this increase in attendance can be attributed to star power, not improvements in the Dodgers' on-field performance.

Franck and Nüesch (2012) empirically tested the determinants of superstar status. Franck and Nüesch (2012) observed that the model developed by Rosen (1981) identifies talent as the source of superstar effects, but the model developed by Adler (1985) shows that popularity could generate superstar effects among performers with identical talent. Franck and Nüesch (2012) devised a clever test of talent versus popularity using quantitative measures of media coverage of German football players as a proxy for popularity and on-pitch success in rank order tournaments as a measure of talent. They find evidence that both factors explain superstar effects in this setting.

A number of key empirical issues emerge from the existing literature on superstar effects. First, the unit of observation for attendance matters. Tests using individual game attendance provide sharper estimates of the superstar externality than aggregated data. Second, measuring superstar qualities requires some care. Superstar effects can stem from talent or popularity, so empirical models need to contain measures of both to avoid confusing superstar effects with other factors driving variation in attendance like team quality. All-Star game votes and the presence of All-Star players on team rosters represent common proxies for popularity. A wide variety of player-specific performance measures have been proposed and used as proxies for talent.

Third, identifying superstar players requires some subjective judgments, and both general measures of the presence of superstars on teams, and player-specific superstar characteristics appear to explain variation in attendance. Fourth, mixed evidence on the relative importance of talent and popularity exists in the literature. Resolving this issue requires more data and different measures of popularity and talent.

Empirical Analysis

Identifying potential superstars. Superstar status is not randomly conferred on NBA players and we lack an instrument that would permit econometric identification of superstar status relative to star players who do not fit the Rosen (1981) definition of a superstar. The models of Rosen (1981) and Adler (1985) assume superstar status applies to individual players; every NBA player cannot be considered as a potential superstar player. Given these limitations, identifying specific superstar players requires some subjective decisions about the pool of high-profile players that could be considered potential superstars. We decided to identify potential superstars based on where a player's salary falls in the overall NBA salary distribution. Both Brandes et al. (2008) and Jane (2016) take this approach. We define potential superstars as players with one of the five highest salaries in the NBA in five or more seasons in their career. Jane (2016) uses the 30 highest paid NBA players in each of two seasons, a short-run approach.

The empirical analysis proceeds as follows. First, we identify a pool of potential superstar players in each season based on the salary distribution in that season.

Second, we create indicator variables for home and away games in which each potential superstar player appeared in each season and include these variables in reduced form regression models explaining observed game attendance. We identify actual superstar players from this pool of potential superstars based on a comparison of the parameter estimate on the player indicator variables and the parameter estimate on an indicator variable for games played on weekends. Actual superstar players increase game attendance by more than the increase in attendance associated with moving a game from a weekday to a weekend (the *Weekend Test*). Finally, we identify proxy variables for talent and popularity and, for the actual superstars, replace the appearance indicator variable with these proxy variables to determine whether each actual superstar can be classified as an Adler or Rosen superstar.

Data on player salaries come from Patricia Bender's website for each season from 1982 through 2013, with the exception of the 1989-1990 season. For the 1989-1990 NBA season, we use a list of the top 64 player salaries published in the *Orlando Sentinel*. For each season, we ranked all NBA players in descending order of salary to determine the five highest salaries. Next, the frequency of each player's appearance in the top five salaries determines if that player is a superstar.

The highest frequency in the top five was Shaquille O'Neal, 14 seasons with one of the five highest salaries in the league, followed by Kevin Garnett with 13 seasons. Three players nearly qualified with four appearances. Eight players appeared in the top five of the salary distribution 3 times throughout their career.[1] Of the players appearing 3 times, Tim Duncan experienced similar career success to those that meet the potential superstar criterion. Duncan had a long career, won multiple league championships, received multiple Most Valuable Player awards, was named to multiple All-Star games, won rookie of the year, and was the first pick of the NBA draft. LeBron James has similar career accolades but does not appear among the top five salaries any in any season. In addition to the 12 players meeting the criterion, Tim Duncan and Lebron James will be included in additional models because of their career performances.

The salary-based approach to identifying potential superstars contains several drawbacks. Players on large market teams earn higher salaries than equally talented players on small market teams because of the larger marginal revenue from a win in larger markets. The presence of a salary cap in the NBA, and the many salary "exemptions" in the NBA's cap, distorts the distribution of salaries in the league, especially near the top of the distribution. The presence of a Rookie Salary Scale also distorts the league-wide salary distribution. These factors can cause problems for salary-based criterion for identifying potential superstars. Below, we use an alternative criterion for identifying potential superstars not based on salary.

Table 1 summarizes the career performance of the 12 NBA players identified as potential superstars, and the three players that nearly qualified as potential superstars, listed in the order in which each player entered the league. Players' performance, All-Star appearances, All-Star votes, draft position, and seasons played were found (using http://basketball-reference.com). In total, 12 players qualified as

Table 1. Superstar Credentials.

Player Name	Seasons Played	Draft Position	All-Star Games	All-Star Votes per Season	Champ. Won	MVP Awards	Average VORP per Season	Average Win Shares per Season	Number of Seasons in Top Five Salaries
Kareem Abdul-Jabbar	20	1	19	344,079	6	6	5.37	13.67	5
Moses Malone	21	ABA	12	318,144	1	3	2.22	8.53	6
Robert Parish	21	8	9	130,938	4	0	1.98	7	5
Larry Bird	13	6	12	500,354	3	3	6.12	11.22	5
Magic Johnson	13	1	11	576,326	5	3	5.95	11.98	9
Michael Jordan	15	3	14	1,006,967	6	5	6.97	14.26	6
Patrick Ewing	17	1	11	427,790	0	0	2.41	7.44	9
David Robinson	14	1	10	539,939	2	1	5.78	12.77	6
Shaquille O'Neal	19	1	15	1,254,453	4	1	3.89	9.56	14
Alonzo Mourning	15	2	7	495,305	1	0	1.61	5.98	5
Kevin Garnett	21	5	15	1,027,150	1	1	4.48	9.12	13
Kobe Bryant	20	13	18	1,513,047	5	1	3.62	8.63	9
Chris Webber	15	1	5	442,489	0	0	3.06	5.65	4
Juwan Howard	19	5	1	15,750	2	0	0.53	3.13	4
Jermaine O'Neal	18	17	6	398,054	0	0	0.77	3.67	4

Note. Data on All-Star voting available from the 1974-1975 season. VORP was first estimated in the 1973-1974 season. ABA = American Basketball Association; MVP = most valuable player; VORP = value over replacement player.

Table 2. Superstar Salaries.

Star Status	Mean	*SD*	Minimum	Maximum
Players in the top five 5 or more times	8,495,353	8,477,500	180,000	33,140,000
Players in the top five 3–4 times	10,002,424	7,053,405	51,976	23,180,790
Players in the top five less than 3 times	2,566,580	3,414,424	2,706	23,239,562

superstars based on this criterion. All 12 were among the first players taken in the entry draft, with the exception of Kobe Bryant (drafted 13th overall) and Moses Malone (entered the NBA from the ABA), had long careers, and played in multiple All-Star games during their careers. Each also collected large numbers of All-Star votes, indicating that these players enjoyed widespread popularity among fans. The career average value over replacement player (VORP) and Win Shares represent the career average value for these advanced performance metrics. These VORP and Win Share career averages indicate sustained performance at exceptional levels throughout each player's career.

Clear differences exist in career performance for the players below the potential superstar cutoff point. Each of the next three players in terms of top five salary frequency rank lower than the potential superstar players at the top of Table 1 in All-Star game appearances, Win Shares per season, All-Star votes when compared to players playing in the same time frame in which they played,[2] and VORP, with the exception of Chris Webber. Juwan Howard is the only player among the three to win championships. However, Howard's championships were won in the final two seasons of his career with the Miami Heat in which he averaged 6.8, and 7.3 min per game. Note that Bryant and Garnett played past the 2013-2014 season, the end of our sample, and Johnson retired relatively early due to health issues.

Table 2 summarizes the salaries of potential superstars and players close to qualifying. The average salaries of potential superstars throughout their careers were nearly US$8,500,000, approximately US$10,000,000 for those close to qualifying, and around US$2,500,000 for the rest of the sample. The higher salaries for near qualifiers can be explained by the time in which these near qualifiers played. Salaries increased substantially throughout NBA history. The highest salary in 1985, 1995, 2005, and 2015 was US$2,500,000, US$18,724,000, US$20,000,000, and US$25,000,000, respectively. Of the 11 players just below the cut-off in Table 1, only 2 did not play after 2005.[3] The pool of potential superstar players includes multiple players drafted before the 1981 and played a number of seasons before 2000.

Data Description

The data represent a comprehensive NBA game-specific attendance and outcome data set. The data set contains information on more than 34,400 NBA regular season games played over the 1981-1982 through 2013-2014 seasons, including game attendance and point spreads for nearly all games played. Most attendance research

Table 3. Summary Statistics—Continuous Variables.

Variable	Mean	*SD*	Minimum	Maximum
Attendance	15,832	4,175	1,026	62,046
Home team record before game	0.501	0.186	0	1
Away team record before game	0.502	0.187	0	1
Closing point spread	−3.856	6.275	−25	49
Metro area population	50.1	47.782	7	201
Number of All-Star vote recipients, home team (in 10,000s)	1.682	1.414	0	6
Number of All-Star vote recipients, away team (in 10,000s)	1.677	1.410	0	6
Number of All-Star votes received, home team (in 10,000s)	81	106	0	722
Number of All-Star votes received, away team (in 10,000s)	81	105	0	722
Observations	35,078			

using game-level NBA attendance data analyze outcomes from a few seasons (Jane, 2016). Attendance data are missing from 60 games in the sample period, most of which were in the 1987-1988 season.[4]

Game attendance data were collected to augment existing game outcome data. Most of the game-level NBA attendance data come from box scores (found at http://basketball-reference.com). However, these box scores are missing attendance data for some games, including a large number of games in the 1988-1989 season. We filled in these missing observations by consulting microfiche archives of past box scores from print editions of *The New York Times* and *The Washington Post*.

Table 3 contains summary statistics for key continuous variables. NBA teams sometimes play in football stadiums like the Georgia Dome in Atlanta, home to the Atlanta Hawks for several seasons, which generates games with exceptionally large attendance. In addition to the Hawks, the Detroit Pistons played home games in the Pontiac Silverdome from 1978 to 1988 (capacity more than 80,000), the Seattle SuperSonics played home games in the Kingdome in Seattle in the 1984-1985 season (basketball capacity 60,000), and the San Antonio Spurs played home games in the Alamodome between 1993 and 2002 (basketball capacity 39,500). The maximum value for game attendance in Table 3 is a March 1998 game between the Atlanta Hawks and the Chicago Bulls played in the Georgia Dome.

The team winning percentage variables reflect the fraction of past games won by each team prior to the current game. This variable reflects team quality at each point in the season. The average value of these variables is more than .500 because of missing attendance data. The missing observations tend to be for games played by home teams with winning percentages below .500.

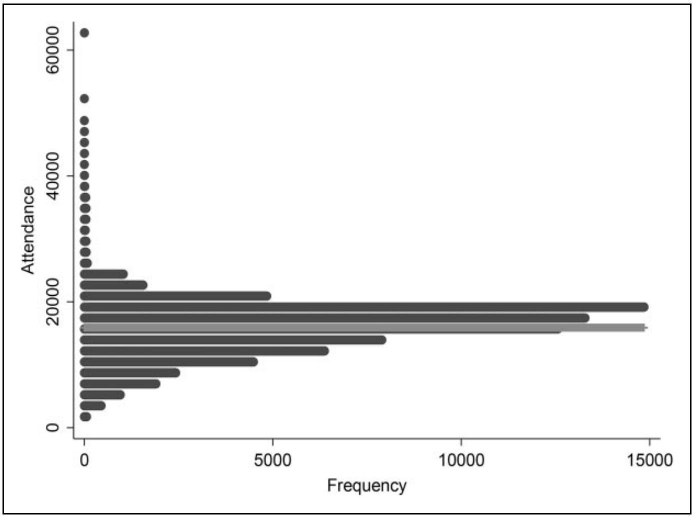

Figure 1. Game attendance distribution.

The point spread variable shows the number of points by which the home team is expected to win each game. The variable also controls for the difference in quality of teams. A negative value means the home team is favored to win. The average home team in the sample was expected to win by about 4 points, reflecting the well-known home advantage in sports.

We collected data on two team-level factors that reflect the number of "star" players on each team. Each season the NBA plays an "All-Star" game at roughly midseason. During the sample period, each conference fielded a team in this game, and the participants in the game were partially determined by fan voting, so the number of votes received by each player reflects fan's opinions about the star status of each player. We collected data on the number of players on each team that received votes from fans. On average, each team in the sample had about 1.7 players who received votes. We also collected data on the total number of votes received by players on each team, a second measure of fan opinions about the "star power" of players on each team, expressed in tens of thousands of votes. The average team in the sample contained players receiving about 810,000 All-Star votes in a season.

Game attendance represents the key outcome variable. Figure 1 shows its the distribution. The distribution has a distinct tail of games with large attendance. This tail includes high-demand games played by teams in large facilities like the Pistons, SuperSonics, and Spurs.

Table 4 summarizes the dichotomous variables. We do not report standard deviations for these variables. The first set identifies games played by the previous season's champion and games played on weekends (defined as Friday,

Table 4. Summary Statistics—Dichotomous Variables.

Variable	Mean
Home team is the defending champions	0.037
Away team is the defending champions	0.037
Weekend games	0.469
Kareem Abdul-Jabbar plays for the home team	0.009
Kareem Abdul-Jabbar plays for the away team	0.009
Moses Malone plays for the home team	0.014
Moses Malone plays for the away team	0.013
Robert Parish plays for the home team	0.018
Robert Parish plays for the away team	0.017
Larry Bird plays for the home team	0.010
Larry Bird plays for the away team	0.010
Magic Johnson plays for the home team	0.011
Magic Johnson plays for the away team	0.011
Michael Jordan plays for the home team	0.015
Michael Jordan plays for the away team	0.015
Patrick Ewing plays for the home team	0.017
Patrick Ewing plays for the away team	0.016
David Robinson plays for the home team	0.014
David Robinson plays for the away team	0.013
Shaquille O'Neal plays for the home team	0.017
Shaquille O'Neal plays for the away team	0.016
Alonzo Mourning plays for the home team	0.012
Alonzo Mourning plays for the away team	0.012
Kevin Garnett plays for the home team	0.020
Kevin Garnett plays for the away team	0.019
Kobe Bryant plays for the home team	0.018
Kobe Bryant plays for the away team	0.017
Observations	35,078

Saturday, and Sunday). A disproportionate number of NBA games are played on weekends, with nearly 47% of games being held on only three of seven possible game days.

The variables in Table 4 reflect indicator variables that identify games played by potential superstar players identified in the previous section. Variables identifying games in which potential superstars played were constructed using information from game logs during their careers through the 2013-2014 NBA season. These game logs were matched with the game attendance data. To account for missed games in which a player was a game-time decision or sat out for rest, instances where players missed a single game, such games were included in the player appearance indicator variable. These games are included because, in the case of game-time decisions, fans will likely expect the star to play in the game. When a player rests, it is commonly not announced until moments before the game begins.

Long periods of missed games due to injury are omitted from the player appearance indicator variables. Most of these cases involve extended periods where the player was injured. For example, Michael Jordan appeared in only 18 games in the 1985-1986 season, his second season in the NBA. He played in the first three games of the season, broke a bone in his hand, and did not rejoin the team until March 15. We code the period between October 29, 1985, and March 15, 1986, as Jordan not playing. A similar approach is used for other extended player injuries in the sample. Since injuries constitute random events, these periods generate plausibly exogenous variation in the presence of star players, aiding econometric identification of a superstar effect.

For the actual superstar players, data were collected to determine the extent to which they are "popular" (Adler superstars) and the extent to which they perform exceptionally (Rosen superstars). To measure popularity, the number of All-Star votes was collected for each individual player in each season. To account for performance, data on each player's VORP and Win Shares were collected. Both are advanced performance statistics.

VORP compares the impact of players to a theoretical replacement player based on their Box Score Plus/Minus (BPM) and the actual percentage of their team's minutes played. BPM estimates how well a player performs compared to the average player per 100 possessions, which is defined as 0.0. For example, in 1988-1989, Michael Jordan posted a 12.6 BPM, which means Jordan was 12.6 points better per 100 possessions than the average player in the league. For the purposes of VORP, -2 is considered the value of a replacement player. The formula for VORP is [BPM $-$ (-2.0)] $\times$ (percentage of minutes played) $\times$ (team games/82). Using the formula, Michael Jordan had a VORP of 12.0 in the 1988-1989 season.

Win Shares measure how many wins in a season can be directly attributed to the performance of a specific player and give an individual player credit for their contribution to team wins. If a team wins 65 games, 65 Win Shares will be divided between the individual players on the team.

Table 4 summarizes the dichotomous variables capturing player appearance in games, previous-season team success, and game characteristics in the sample. About 3.7% of the games in the sample included the previous season's championship team. These games may have higher attendance if fans prefer to see recent championship teams play. Almost half the games in the sample took place on Friday, Saturday, or Sunday. The NBA prefers to schedule games on weekends if possible. Relatively, few of the games in the sample had 1 of the 12 potential superstar players appear in the game. We exploit this variation to assess the impact of the presence of potential superstar players on attendance.

Empirical Methods

We follow the general approach used in the literature and estimate reduced form empirical models explaining observed variation in attendance at NBA games; Berri and Schmidt (2006), Jane (2016), and Lewis and Yoon (2018) all use this approach. The general form of this empirical model is

$$A_{ijst} = f(T_{ijst}, G_{ijst}, \mathrm{STAR}_{ijst}, e_{ijst}), \tag{1}$$

where A_{ijst} is total game attendance at a game played between home team i and visiting team j in NBA season s on date t. T_{ijst} is a vector of variables capturing the characteristics of the two teams involved in each game, including variables reflecting team quality and venue. G_{ijst} is a vector of variables reflecting the characteristics of each individual game, including factors like the day of the week the game was played on, characteristics of the arena the game is played in, and local population. STAR_{ijst} is a vector of variables reflecting the presence of superstar players on team i and team j.

e_{ijst} is a random variable reflecting all other factors that affect attendance at individual NBA games. e_{ijst} is assumed to be a mean zero random variable with possibly heteroscedastic variance that may be correlated across observations for individual teams.

Estimating the unobservable parameters of Equation 1 presents a number of econometric problems. Foremost is censoring of the dependent variable. A_{ijst} is limited by the capacity of the arena that the home team plays in. NBA games are popular, and a number of games in the sample are "sellouts" where every available ticket to the game was sold. In these cases, consumer interest in the game exceeds the capacity of the arena, potentially biasing parameter estimates from Equation 1. For example, right censoring of the dependent variable could lead to downward bias in the parameter capturing the effect of the presence of star players on team rosters on game attendance.

The standard econometric approach to correct for dependent variable censoring is to use a limited dependent variable estimator like the Tobit estimator. Jane (2016) transforms the dependent variable to the percentage of capacity based on reported arena capacity, a variable right censored at 100, and uses the Tobit estimator. Lewis and Yoon (2018) do not control for censoring; sellouts at MLB games are much less common than sellouts at NBA games. Our sample contains numerous censored observations for the dependent variable. Based on the reported capacity of NBA arenas, about 10,000 of the 36,000 games in this sample were sellouts.

We correct for censoring of the dependent variable using a censored normal estimator (Amemiya, 1973). The censored normal estimator is a maximum likelihood estimator. Amemiya (1973) proved the consistency and asymptotic efficiency of this estimator under fairly general conditions. The primary advantage of the censored normal estimator relative to the Tobit estimator is that the censored normal estimator allows for the censored value to vary across observations, while the Tobit estimator requires all observations of the dependent variable to be censored at the same value.

We also cluster correct the estimated standard errors at the home team market level. Within a season, local economic conditions, including population, may not

Table 5. Regression Results—Censored Normal Regression Estimator.

Variable	(1)	(2)	(3)
Home team record before game	4,201***	4,447***	5,253***
	6.78	7.59	8.39
Away team record before game	2874***	3065***	3701***
	9.41	10.85	11.96
Home team defending champions	2,495***	2,602***	2,524***
	4.94	5.86	4.63
Away team defending champions	1,453***	1,634***	1,204***
	6.93	7.78	6.84
Closing point spread	−59.6***	−53.6***	−74.7***
	−3.72	−3.59	−4.70
Weekend games	1,571***	1,551***	1,536***
	10.94	11.01	10.71
Metro area population	−5.91	−6.37	33.23
	−0.07	−0.08	0.40
Number of All-Star votes received by home team	9.16***		
	4.37		
Number of All-Star votes received by away team	6.09***		
	10.63		
Number of All-Star vote recipients on home team		548***	
		4.50	
Number of All-Star vote recipients on away team		316***	
		14.89	
Individual player indicators	N	N	Y
Observations	34,416	34,416	35,078
Pseudo-R^2	0.064	0.064	0.064

Note. Parameter estimates and *t* statistics. Estimates for individual players shown in Figure 2.
*Significant at 5% level. **1%. ***0.1%.

vary enough to affect attendance. Explanatory variables reflecting team composition like the number of players receiving All-Star votes on a team do not vary within season. However, the dependent variable, game attendance, varies throughout the season. This game-to-game variation reduces the estimated standard errors on variables that do not vary within season, requiring a cluster correction. We also use the standard White-Huber "sandwich" correction for heteroscedasticity.

Empirical Results

We estimate three alternative empirical models, corresponding to three different measures of star players on each team found in the literature. The results generated by estimating these models using the censored normal estimator with cluster corrected robust standard errors are shown in Table 5. Model 1 contains a variable

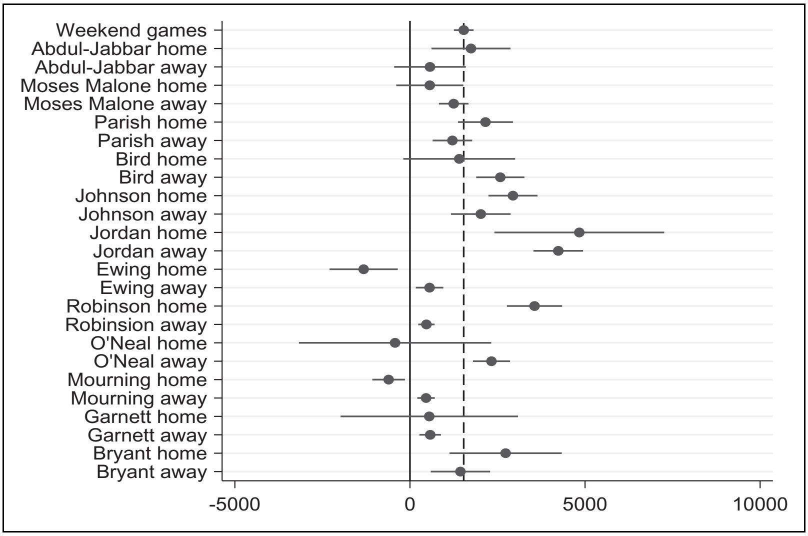

Figure 2. Potential superstar effects on game attendance—point estimates and 95% confidence intervals.

reflecting the total number of All-Star votes received by players on the home and visiting team in each game. Model 2 contains variables reflecting the total number of players on the home and visiting team in each game that received All-Star votes in that season. These models duplicate the approach in Jane (2016). Model 3 contains indicator variables for the presence of specific potential superstar players on the rosters of home and visiting teams in each game.

Models 1 and 2 reflect general popularity from the presence of star players on teams, since All-Star votes reflect fan popularity. Model 3 reflects appearances by specific high-salary players in games. The parameter estimates and estimated standard errors for the vector of individual player appearance variables appear in Figure 2. All models also contain home and visiting team-specific fixed effects and season-specific fixed effects. Using the censored normal estimator allows for an assessment of the effect of changing explanatory variables on attendance that is not limited by the capacity of the arena.

The variables capturing factors other than star player effects reported in Table 5 are generally statistically different from zero and have the expected signs. Attendance varies with both home team and visiting team quality, as measured by each team's winning percentage at that point in the season. Home team quality has a bigger impact on attendance than visiting team quality. The defending league champion draws larger crowds at home and on the road.

The results show that fans prefer to see games that the home team is expected to win. Betting market data proxies for fan expectations of game outcomes. The point spread variable is negative when the home team is favored in a game; each additional one point decrease in the point spread reflects a better expected performance by the home team relative to the visiting team. The parameter estimate on the point spread variable is negative and significant, suggesting that more fans attend games the home team is expected to perform better in. Coates and Humphreys (2010) report similar results. Weekend games draw more fans than week night games. The parameter estimate on the Metropolitan Statistical Area (MSA) population variable is not statistically different from zero, possibly due to the home team-specific fixed effects utilized. Alternatively, MSA population may not be a good proxy for the pool of potential attendees at NBA games, especially in large markets like Los Angeles, Chicago, and New York. After controlling for other factors like team quality and fan expectation, as well as season-specific unobservable heterogeneity, the size of the local market in terms of population does not explain game-to-game variation in attendance.

The parameter estimates capturing the effect of player popularity, in terms of star players, on attendance, are positive and significant in Models 1 and 2. Attendance at NBA games increases as total star player popularity for the home team and visiting team, as proxied by total team All-Star votes received, increases (Model 1), and as the number of popular star players on each team increases (Model 2). The parameter estimate on total home team All-Star votes implies that the presence of a player like Larry Bird, who received an average of 500,000 All-Star votes per season (see Table 1), would increase attendance at that game by about 450. This is consistent with results reported in Jane (2016) using a smaller sample of NBA games. Due to the 1999 All-Star game cancellation because of a lockout, Models 1 and 2 have fewer games.

Identifying Actual Superstars

We next estimate models containing indicator variables for specific potential superstar players appearing in games in order to identify the actual superstars in this pool. The empirical literature on superstar effects in the NBA contains numerous estimates of the impact of specific star players on attendance and television audiences. Hausman and Leonard (1997) estimate the impact of Larry Bird and Michael Jordan. Berri et al. (2004) estimate the impact of Michael Jordan, Shaquille O'Neal, Charles Barkley, and Grant Hill. Jane (2016) infers the impact of 80 specific players on attendance based on their All-Star vote totals. All of the potential superstars identified here who played in the 2011-2012 and 2012-2013 seasons analyzed by Jane (2016) appear in the group of specific players analyzed in that paper.

Empirical results cannot be directly compared because of differences in the dependent variables. All three of these papers use data from a relatively small number of seasons. Our larger data set permits a comprehensive assessment of the impact of specific potential superstar players on NBA game attendance and allows for an assessment of the effect of potential superstar players separately from the effect of team popularity by exploiting potential superstar player movement across teams.

Note that some players played for teams that opened new arenas while they were on the team or shortly before the players joined the teams. For example, the United Center opened in Chicago in 1994, while Michael Jordan played for the Bulls and the Verizon Center opened in Washington, DC, in 1995, a few seasons before Jordan joined the Wizards. New facilities increase attendance at sporting events, a phenomena known as the "novelty effect" (Coates & Humphreys, 2005). To control for novelty effects of these venues on attendance, we include an indicator for games played in new arenas opening during this period in the regression model. Due to the large number of new openings, the results are not reported here. A section below reports these results.

Figure 2 shows the parameter estimates and 95% confidence intervals for the 12 potential superstar players identified above using the salary frequency criteria. The careers of these 12 players span a large portion of the sample period and all clearly fall into the category of high-profile players. Jordan, O'Neal, Ewing, Mourning, Malone, and Garnett changed teams in our sample period. However, we estimate their overall effect based on their entire careers.

Figure 2 also contains the point estimate for the weekend indicator variable from Model 3 in Table 5. This parameter estimate, which represents the conditional effect of moving an NBA game from a weeknight to Friday, Saturday, or Sunday holding all other factors constant, is precisely estimated and provides an objective and intuitive test for assessing the superstar power of players. If the impact of a specific player's presence in a game is less than the impact of moving that game from Wednesday night to Saturday, then that player may not qualify as a superstar. Based on this criterion, we identify a player as an actual superstar if the point estimate and 95% confidence interval for the indicator variable for the presence of that player on either home or away games exceeds the impact of moving a game to a weekend.

Based on this criterion, the sample contains five actual superstar players: Larry Bird, Magic Johnson, Michael Jordan, David Robinson, and Shaquille O'Neal. While most other potential superstar players analyzed generate a statistically significant number of additional fans at home games, these players did not generate more additional home fans than moving their games from a weeknight to a weekend, other things equal. Of the players exhibiting large superstar effects, note that both Michael Jordan and Shaquille O'Neal have large effects on attendance despite switching teams during their careers, suggesting portability of superstar status across teams. Of these five, only three (Bird, Jordan, and O'Neal) generate superstar externalities by increasing attendance at away games.

Testing Talent Versus Popularity in Actual Superstars

Franck and Nüesch (2012) and Jane (2016) performed tests assessing the relative importance of player talent and popularity for explaining superstar effects. Given the

Table 6. Regression Results—Actual Superstar Talent Versus Popularity, Alternative Superstars Dependent Variable: Game Attendance.

	Explanatory Variable	
Player	Season VORP	All-Star Votes
Julius Erving	144.8	4.069***
	(1.48)	(4.08)
Larry Bird	398.9***	0.925
	(4.05)	(0.71)
Magic Johnson	233.9***	0.907
	(3.33)	(1.66)
Michael Jordan	59.44	3.506***
	(0.68)	(3.89)
Shaquille O'Neal	−63.16	1.129*
	(−0.28)	(2.29)
LeBron James	140.8	1.162*
	(1.27)	(2.21)
Dwight Howard	241.5	0.352
	(1.2)	(1.1)
Observations	34,416	34,416
Psuedo-R^2	0.0633	0.0633

Note. t Statistics in parentheses. VORP = value over replacement player.
*Significant at 5%. **Significant at 1%. ***Significant at 0.1%.

large panel of game attendance and player appearances, we can also empirically test for the relative effect of player-specific measures of talent and popularity on game attendance. We use the total number of All-Star votes received each season by specific players as a measure of popularity. NBA fans vote for specific players to appear in the annual All-Star game. While fan votes may depend on many factors including team effects and perceptions of player performance, the persistent appearance of some players on the All-Star team rosters suggest that All-Star votes also reflect player popularity. Jane (2016) interprets All-Star votes as a measure of player popularity. We use VORP, which depends only on player performance measures, as a proxy for talent.

The empirical approach for testing talent versus popularity as sources of superstar status estimates Equation 1, replacing the indicator variable for each actual superstar appearing in a game with that superstar player's VORP and total All-Star game votes in the current season. This provides separate measures of a player's talent (Rosen) and popularity (Adler) in each season. VORP for these actual superstars range from 0.1 for Larry Bird at the end of his career to 12 for Michael Jordan in his prime; each in the 1988-1989 NBA season. We include the five actual superstar players identified above in this regression model: Larry Bird, Magic Johnson, Michael Jordan, Shaquille O'Neal, and David Robinson.

Table 7. Regression Results—Actual Superstar Talent Versus Popularity Dependent Variable: Game Attendance.

	Explanatory Variable	
Player	Season VORP	All-Star Votes
Larry Bird	342.3***	1.256
	(3.66)	(1.14)
Magic Johnson	229.4***	0.521
	(3.31)	(0.98)
Michael Jordan	65.46	3.401***
	(0.72)	(3.66)
David Robinson	404.8	−2.242
	(1.68)	(−1.28)
Shaquille O'Neal	−107.1	1.096*
	(−0.43)	(2.27)
Observations	34,416	34,416
Psuedo-R^2	0.0617	0.0617

Note. t Statistics in parentheses. VORP = value over replacement player.
*Significant at 5%. **Significant at 1%. ***Significant at 0.1%.

Table 6 summarizes the results, reporting only the parameter estimates and t statistics for the actual superstar player-specific popularity and talent variables. All other parameter estimates are nearly identical to the results in Table 5 and are not reported.

Table 7 contains an interesting pattern. Two of these superstar players, Larry Bird and Magic Johnson, appear to generate a superstar externality based on talent. Their total season VORP, a proxy for talent, is associated with statistically significant increases in game attendance, but their All-Star vote totals are not associated with additional game attendance. Two other superstars, Michael Jordan and Shaquille O'Neal, appear to generate superstar externalities based on their popularity. Jordan and O'Neal's All-Star vote totals, a measure of popularity, are associated with statistically significant increases in game attendance, holding talent constant, but their total season VORP is not associated with additional game attendance. Bird and Johnson are "Rosen" superstars, while Jordan and O'Neal are "Adler" superstars. Franck and Nüesch (2012) and Jane (2016) find evidence that both popularity and talent generate superstar effects but neither finds evidence of specialization in superstar effects.

Note that the underlying source of David Robinson's superstar status cannot be identified using this empirical approach. Either the current theories explaining these effects omit some important source of superstar status or the talent and popularity proxy variables fail to capture Robinson's underlying characteristics. Unlike the other actual superstars, Robinson played college basketball at the U.S. Naval Academy, providing a link to the armed forces. This could be an unmeasured characteristic that NBA fans associated with Robinson.

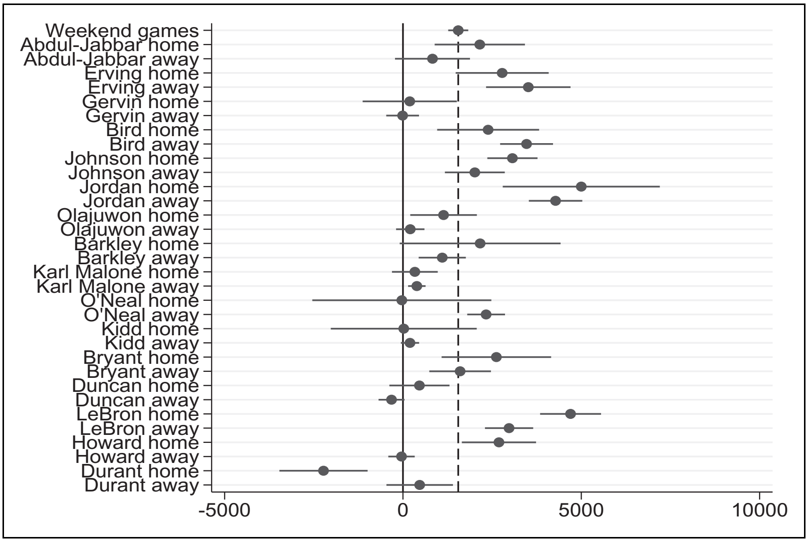

Figure 3. Superstar effects on game attendance—alternative superstar selection.

Alternative Potential Superstar Selection

We find evidence of superstar effects for a group of players identified using a salary-based criterion. There may be other players that possess superstar status that would not be identified using a salary-based criterion. For instance, a player routinely selected to the All-NBA First Team throughout his career could generate a large fan following. To assess the robustness of the salary-based criterion, we consider an alternative selection criterion for potential superstars: players with at least five All-NBA First Team selections over the sample period. This alternative criterion identifies most of the potential superstars identified by the salary-based criterion including Kareem Abdul-Jabbar, Magic Johnson, Larry Bird, Michael Jordan, Shaquille O'Neal, and Kobe Bryant. David Robinson represents the notable exception identified by the salary-based criterion but not be the All-NBA First Team criterion. In addition, the All-NBA First Team criterion identifies 10 additional potential superstars not identified by the salary-based criterion. The additional potential superstars include Julius "Dr. J" Erving, George Gervin, Hakeem Olajuwon, Charles Barkley, Karl Malone, Jason Kidd, Tim Duncan, LeBron James, Dwight Howard, and Kevin Durant. We use the same general econometric approach and control variables as above to test for superstar effects associated with players identified as potential superstars by this alternative selection criterion.

Figure 3 shows the parameter estimates and 95% confidence intervals for attendance effects generated by the presence of a player selected to five or more All-NBA First Teams throughout his career. Of course, superstar effects remain for the four superstars identified by the salary-based criterion (Jordan, Johnson, Bird, and O'Neal). Of the additional potential superstars identified by the All-NBA First Team criterion, only Julius Erving, LeBron James, and Dwight Howard pass the "weekend" test and qualify as superstars as they each have a greater impact on attendance than moving a game to the weekend.

Interestingly, Kevin Durant's presence in a lineup generates a significant negative impact on home attendance. Kevin Durant is the only potential superstar to play for a team that relocated from one city to another. He played for the Seattle SuperSonics before and after their move to Oklahoma City. The negative Durant effect could reflect fan backlash against the rumored move of the SuperSonics during Durant's tenure, along with his relatively short career fragment in this sample (from the 2007-2008 season on).

In terms of testing talent versus popularity, we again regress attendance on explanatory variables reflecting on All-Star votes and performance, measured by VORP, for each player that exhibits superstar effects. Consistent with Table 6, Michael Jordan and Shaquille O'Neal are again "Adler" superstars driven by popularity, while Magic Johnson and Larry Bird are "Rosen" superstars driven by performance. Among the additional superstars, additional attendance generated by Julis Erving and Lebron James can be attributed to their popularity, making them "Adler" superstars.

Like David Robinson, the specific source of Dwight Howard's superstar status cannot be identified by the performance and popularity proxies used here. Perhaps this relates to the fact that neither of them was identified by both the salary-based and All-NBA First Team–based criterion.

Novelty Effect Estimates

All empirical models above control for the opening of new arenas using indicator variables for the entire postopening period. Novelty effects represent a topic of interest in the literature (Coates & Humphreys, 2005; Leadley and Zygmont, 2005) and little recent evidence on the size and duration of novelty effects exists.[5] To generate estimates of the novelty effect, we follow Coates and Humphreys (2005) and include a vector of indicator variables for each of the first 10 years a new arena is open in the attendance regression model, Equation 1.

Figure 4 shows the parameter estimates and 95% confidence intervals for estimates of the annual novelty effects over the first 10 years a new facility is open. These results use the players selected by the salary-based criterion as potential superstars. The novelty effect estimates exactly match those in Coates and Humphreys (2005), with novelty effects occurring over the first 8 years a new arena is open.[6] In terms of the relative size of these novelty effects, only in the first year of operation does the new arena novelty effect exceed that of a weekend game, generating an additional 2,840 fans on average. The results for potential superstar player

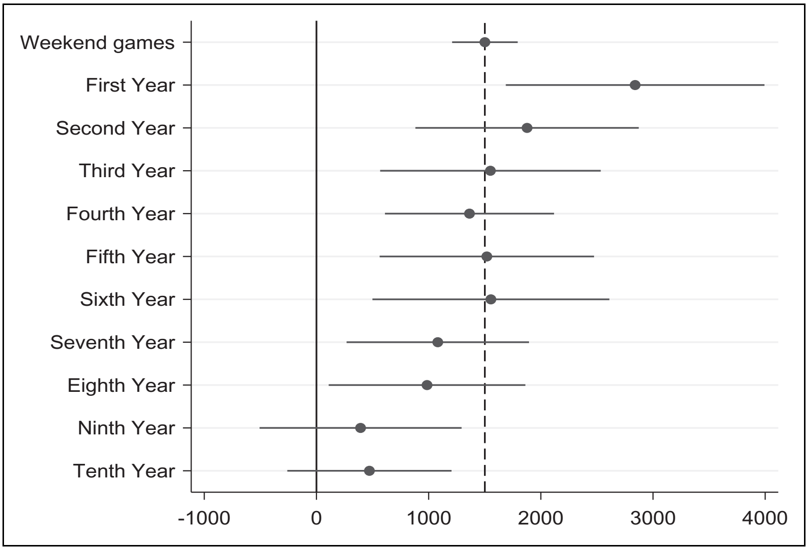

Figure 4. Novelty effects by year—parameter estimates and 95% confidence intervals.

effects on attendance resemble those reported above. Novelty effects remain important in the NBA in these more recent data.

Conclusions

Superstar models predict large differences in individual followings or earnings when differences in individual abilities are small or nonexistent. The presence of superstar effects also has important implications for policies governing player compensation and league-wide revenue distribution in professional sports leagues, a setting where the teams that pay players' salaries may not be able to capture the increased revenues generated by superstar players in road games.

This article develops new evidence documenting the presence of superstar effects in the NBA. While other papers found similar results, the data here cover a large number of NBA games played over more than 30 seasons, which permits a comprehensive empirical analysis including the entire careers of many players. We find evidence of superstar effects over the entire 30-year period, establishing that superstar effects persist throughout different eras. One or more superstar players exist in every season in this sample, showing that superstar players emerge regularly in this setting. Michael Jordan, Shaquille O'Neal, LeBron James, and Dwight Howard generate superstar effects despite moving from team to team during their careers, suggesting portability of the superstar effect. The robust nature of the superstar effect in the NBA implies that similar effects may be widespread throughout the economy in other labor markets and perhaps represent a larger explanation for observed income inequality than previously thought.

The data also permit a detailed analysis of the determinants of superstar status. We find evidence supporting both the Rosen (1981) superstar model and the Adler (1985) superstar model, although these two explanations apply to different superstar players in the sample. The results indicate that both models explain superstar effects. Again, this suggests that superstar effects may be more common in the economy than previously thought, since both talent and popularity can independently explain superstar status.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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Notes

1. These players include Tim Duncan, Jason Kidd, Joe Johnson, Allan Houston, Bill Walton, Amar'e Stoudemire, Gilbert Arenas, and Hot Rod Williams.
2. All-Star votes have trended upward over time as voting has become more accessible.
3. Bill Walton retired in 1987, and Hot Rod Williams retired in 1999.
4. Details on the construction of this data set can be found in Price, Soebbing, Berri, and Humphreys (2010) and Soebbing and Humphreys (2013). These papers use a smaller version of this data set.
5. We thank an anonymous referee for this suggestion.
6. Coates and Humphreys (2005) also find novelty effects in the first 8 years of play in a new National Basketball Association arena. Leadley and Zygmont (2005) find significant novelty effects over the first 4 years.

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