Putting a Price on Popularity: Evidence from Superstars in the National Basketball Association*

Scott M. Kaplan

Assistant Professor
Department of Economics, United States Naval Academy

Abstract

This paper estimates spectator willingness-to-pay (WTP) for superstars in the National Basketball Association. Using microdata from an online secondary ticket marketplace and player absence announcements, I find 4-22% ($4-$41) reductions in prices when superstars are announced to miss games. Additionally, LeBron James and Stephen Curry exhibit larger impacts in away games: 21% ($73/ticket) for James and 18% ($50/ticket) for Curry. The findings suggest popularity is a better predictor of WTP than productivity, and in line with existing superstar literature, popularity predicts price impacts convexly. This paper provides a novel methodology to estimate superstar value, generating implications for the entertainment industry.

Keywords: superstar, willingness-to-pay, dynamic pricing, secondary ticket marketplace, difference-in-differences, event study

JEL Classifications: D12, Z20, J44, L83, C55, C33

*Contact information: email: skaplan@usna.edu. Phone: +1 (410) 293-6971. Mailing Address: Economics Department, United States Naval Academy, 106 & 107 Maryland Avenue, Annapolis, MD 21402.

I Introduction

Understanding the interest in and impact of superstars began with Rosen (1981), which developed a model to explain how certain talented individuals in a specific occupation are able to differentiate themselves from the rest of a pool of individuals, and obtain differentially higher salaries as a result. Superstars are prevalent across all types of activities and industries – for instance, the impact Steve Jobs made on the technology sector, Henry Ford in automobile manufacturing, or Rosen himself on the field of economics. Rosen (1981) emphasized two common elements describing superstars: "a close connection between personal reward and the size of one's own market," and "a strong tendency of market size and reward to be skewed towards the most talented people in the activity."

A natural place to examine superstars is in sports, where the word "superstar" is actually used to describe individuals that fit Rosen's description. Superstars are not necessarily the "best" players from a statistical standpoint – they are defined as much by their popularity as they are by their productivity (Adler 1985). While different leagues have varying degrees of superstar influence, the National Basketball Association (NBA) is widely regarded as "superstar-driven" (Knox 2012; Heindl 2018). More than other sports, the NBA's surge in popularity can be largely attributed to the fame and marketability of its top players (Morris 2018; Adgate 2018). In addition, the observable nature of a player's productivity, popularity, and resulting compensation makes it an appealing empirical laboratory to measure and evaluate the economic impacts of these individuals.

While several studies have examined the impact of player performance on compensation (as laid out in Rosen and Sanderson 2001), there is limited understanding of how different individual characteristics, including both player productivity (i.e. the actual contribution to the performance of their team) and popularity, translate into a compensation distribution, and whether or not these relationships support the economic theory of superstars. Furthermore, there has been limited empirical research comprehensively examining the returns to a superstar's marketability, and how the pure popularity of an individual drives demand for their services.

This paper attempts to understand the separate impacts of superstar productivity and popularity on consumer demand. In particular, what is the overall premium, as measured by television viewership and ticket prices, associated with watching superstar players, and to what extent is this premium driven by player productivity versus popularity? More specifically, what is the loss in value, as measured by listed price changes on a secondary ticket marketplace, associated with the announcement of a specific superstar's absence for a game? This analysis provides a novel framework to causally assess the value of superstars, particularly in sports, which can be applied to other select industries. The findings have significant ramifications for leagues in general, including policies on announcement timing of player absences and player compensation schemes based on popularity. They also inform team decision-making with respect to player personnel and potential implications of introducing dynamic pricing in primary ticket marketplaces. Finally, the analysis provides important insights on superstar marketability outside of on-court competition, including their relative value in sponsorships and other advertising arrangements.

The empirical approach taken is two-fold and relies on data from the 2017-18 and 2018-19 NBA seasons. First, I use game-level data in a fixed effects panel estimation to examine the impact of player popularity and productivity on ticket prices and television viewership. I find that a 1% increase in the popularity of a game, as measured by the cumulative number of All-Star votes of all players playing, leads to an approximately 0.13-0.14% increase in ticket prices and TV viewership, while a 1% increase in the productivity of a game, as measured by cumulative value over replacement player (VORP) of all players playing, has no statistically significant impact. These results suggest that the superstar allure for fans is primarily associated with a player's popularity.

The next component of the analysis relies on within-game, temporal changes in ticket prices. I take advantage of exogenous variation in a superstar's availability for specific games, where players may miss games for unforeseen reasons. Superstar player absences have been an especially relevant point of discussion with respect to the NBA, since absences are trending upwards as a result of teams choosing to "load manage" (purposefully rest) players earlier in the season and more often (Whitehead 2017). Using difference-in-differences (DID) and event study methodologies, I examine ticket price impacts when superstar players are announced out of specific games. The findings suggest statistically significant price declines for the most popular stars, including LeBron James, Stephen Curry, and Dwyane Wade, among others, ranging from 4-22% ($4-$41) per ticket. In addition, I analyze absences in home versus away games, finding that the away effects for LeBron James and Stephen Curry are even larger, at 20% ($73) per ticket for James and 17% ($50) per ticket for Curry. The findings from the two sets of analyses are largely consistent both qualitatively and quantitatively – the most popular stars lead to the largest impacts on prices and television viewership, the relationship between popularity and impact on prices is convex, and these impacts are on the order of 4-22%.

The paper proceeds as follows. First, I review the literature this paper contributes to. The third section discusses the data collection strategy and presents relevant summary statistics. The fourth section presents the empirical strategy and results from the panel estimation. The fifth section describes the DID and event study strategies, provides important assumptions for identification, and showcases the results of these estimations. I discuss and synthesize all of the findings in section six. Finally, the paper concludes.

II Literature Review

This work falls into several important bodies of literature. First, there has been substantial research in hedonic pricing, which attempts to value specific, non-market attributes of goods. It also contributes to the literature on dynamic pricing and strategic interactions among buyers and sellers in secondary ticket marketplaces. Finally, several papers have examined the impact of superstars in different labor contexts, including sports, suggesting that productivity and popularity of players are important factors for spectators. This line of literature examines superstar athlete impacts on a variety of metrics, including attendance, player salaries, and broadcast audiences, as well as on contest design and competitive behavior in leagues. I extend all of this research by (1) using a novel and well-identified methodology to esimate consumer willingness-to-pay to watch superstars by looking at ticket price movements in a secondary ticket marketplace, (2) testing heterogeneous, game-specific characteristics that may impact the value associated with a superstar, and (3) leveraging unique, high temporal frequency microdata on ticket prices for all NBA games for the 2017-18 and 2018-19 seasons.

A Hedonic Pricing and Player Value

The literature on hedonic pricing aims to understand and estimate the relative value of each attribute of a good. The theory of hedonic pricing was developed in Rosen (1974), which was the first paper to describe the total value of a good as a combination of the values of its attributes. There have been numerous empirical papers attempting to price attributes in different settings, from vehicles (Busse et al. 2013; Sallee et al. 2016) to air quality (Currie and Walker 2011; Chay and Greenstone 2005) to real estate (Luttik 2000). These papers use data on similar products with varying attributes of interest in an attempt to estimate the marginal value of these attributes. One of the most fundamentally important characteristics of entertainment, and sporting events in particular, is outcome uncertainty, which was first observed in Rottenberg (1956) and later expanded on in Neale (1964). Coates et al. (2014) develops a model of consumer demand for such uncertainty using a theory of reference-dependent preferences (Card and Dahl 2009), finding that individuals receive two types of utility from attending a live sporting event: consumption utility, which is the standard utility gained from consuming a good, and gain-loss utility, which is utility dependent on different states of and the outcome of a game (Kőszegi and Rabin 2006).

While outcome uncertainty is clearly an attribute of entertainment events demanded by consumers, individual performers attract substantial interest as well. Scully (1974) was the first paper to examine the marginal revenue product of athletes, comparing how much they are paid with how much they contribute to their team's success, finding that player salary relative to their contribution to winning was still lower than 50%. Kahn (2000) provides a seminal overview examining the key relationship between athlete productivity and pay, how players are allocated across a league, and how league market structures affect player salaries. Specifically, Johnson and Minuci (2020) describes the primary features of the NBA labor market while examining whether a player's race leads to a wage gap, finding that Black players are paid significantly less than other players. The research presented here contributes to this literature by being the first to utilize rich microdata with substantial variation in confounding factors (e.g. competitiveness of opponents, market size, etc.) to perform a well-identified, plausibly exogenous estimation of the economic value of superstars.

B Dynamic Pricing in Secondary Ticket Marketplaces

The second relevant body of literature includes work on dynamic pricing in primary and secondary marketplaces, including event tickets, hotels and home-sharing (e.g. AirBnB), and airline tickets (Jiaqi Xu et al. 2019; Williams et al. 2017; Sweeting 2012; Blake et al. 2018; Levin et al. 2009; Oskam et al. 2018; Mills et al. 2016; Courty and Davey 2020). Early research on dynamic pricing examined how in airline ticket markets, consumers often learn new information about their demands over time, which may be an important reason for the existence of both primary and secondary ticket marketplaces (Courty 2003a). Additionally, the dynamic pricing nature of secondary ticket marketplaces allows for real-time updating of preferences of both consumers and producers, which may lead to real-time price changes in response to realized information about an event (Courty 2003b). The research presented here differs substantially from much of the previous theoretical work on pricing in these marketplaces, in particular ticket marketplaces, in that it relies on changes in the quality of attributes of an event to determine individuals' value for those attributes.

While this research builds on many of the theoretical aspects of ticket pricing, it takes a primarily empirical approach. The seminal empirical paper in this field explaining dynamic pricing patterns using secondary ticket marketplace microdata is Sweeting (2012), which examines Major League Baseball games and develops a game-theoretic framework to discuss the dynamics of buyer-seller interactions on secondary marketplaces as a game approaches. Sweeting (2012) finds that much of the buying and selling activity in marketplaces, including price adjustments, occurs in the few days before an event, which is the same pattern I observe in the data used in this analysis. Clarke (2016) uses microdata from a secondary ticket marketplace to assess seller dynamics on ticket resale markets, finding that there is a great deal of heterogeneity in seller pricing strategies. Most notably, Clarke finds that 40% of sellers have a negative scrap value (i.e. if their ticket does not sell, they have a zero or negative value associated with attending the game) and 20% of sellers value their tickets above the franchise's face value. Thus, negative price effects associated with the announcement of a superstar absence may reflect a lower bound (in absolute value terms) because sellers who do not adjust still have a weakly negative value associated with this announcement, but may face transaction costs that are too high or fall victim to the sunk cost fallacy.

C Economics of Superstars

Rosen was the first to understand the economic concept of superstars in Rosen (1981), which was later expanded upon in Rosen and Sanderson (2001). Their work developed a model to explain how certain talented individuals in an occupation are able to differentiate themselves from the rest of a pool of individuals, and obtain differentially higher salaries as a result. MacDonald (1988) uses a stochastic dynamic version of the model of superstars presented in Rosen (1981) to understand an observed equilibrium where performers enter the market when they are young, and those receiving positive reviews tend to advance and become more popular over the course of their careers, while others receiving less positive reviews exit the industry. An expansion of this work attempts to differentiate between the popularity and productivity of a star performer; namely there may be a premium for watching a player with average talent, but who is quite popular for other reasons (Adler 1985). In particular, Adler (1985) posits that superstardom in an individual can manifest despite identical productivity to other, non-superstar individuals. He suggests the notion of a superstar requires common knowledge among consumers, which means that consumers must discuss such knowledge with one another. Thus, superstars exist in equilibrium because search costs associated with discussion are reduced with fewer popular individuals. Krueger (2005) examines "rockstars" in the music industry, creatively using the number of millimeters of print columns in *The Rolling Stone Encyclopedia of Rock and Roll* to measure musician prominence, showing that a 200 millimeter increase in print leads to a 5-15% increases in prices. Interestingly, he also finds the superstar effect (measured by concert ticket prices) nearly tripled between 1981-2003. The research I present in this paper synthesizes nicely with these results, finding that (i) there is a convex relationship between a superstar's presence and willingness-to-pay, and (ii) superstar popularity is a more meaningful factor in ticket price and TV viewership adjustments than superstar productivity.

Other papers have examined superstar effects specifically in the context of sports. One important effect is the impact superstars have on the competitive behavior of other contestants. Brown (2011) assesses the impact of Tiger Woods' presence on the performance of competing golfers, finding an adverse effect on their performance when competing in the same tournaments as Woods. On the other hand, Babington et al. (2020) tests this effect in other settings, including women's golf and men's and women's professional alpine skiing, finding little evidence to support the adverse superstar effect found in Brown (2011). Brady and Insler (2019) leverages randomized pairings and similar shot location in professional golf, finding that positive peer effects associated with playing second (as opposed to first) dominate any potential adverse superstar effects. Lackner (2016) examines decision-making behavior of and effort exerted by Olympic basketball teams when they face an opposing superstar team. While this work examines team-wide superstar effects, the findings translate to individual superstar players, showing that in the case of the Olympics, facing a superstar team reduces the amount of effort exerted by the non-superstar team.

Several other studies have examined brand alliances between companies and superstars, determining the extent to which these partnerships drive value (Yang et al. 2009; Chung et al. 2013). In professional soccer, there have been several empirical studies that attempt to identify demand for superstar talent through television viewership, attendance, and ticket sales (Buraimo and Simmons 2015, Brandes et al. 2008, Lawson et al. 2008), and quantify the characteristics that affect superstar wages, including both on-field performance and popularity (Scarfe et al. 2021; Bryson et al. 2014; Bryson et al. 2013). In German professional soccer, Lehmann and Schulze (2008) regresses salary proxies of 359 players on indicators of talent and performance, finding neither explains salaries for the upper 95^{th} percentile of players. Franck and Nüesch (2012) find opposite evidence, namely that both player talent and popularity increase the market value of star players. In addition, they find that marginal returns to productivity in terms of player salaries are much larger among stars than average players.

Hausman and Leonard (1997) was the first empirical paper to analyze the economics of superstar players in the NBA, examining their effect on attendance and television viewership. They find substantial impacts for these players, especially in the case of away games, where fans in those markets were enthusiastic to watch these superstars when they came to town. Berri et al. (2004) and Humphreys and Johnson (2020) extend this work by more comprehensively examining consumer demand for NBA superstars through individual game attendance. In particular, Berri et al. (2004) studies the relationship between team performance and a team's individual stars, finding that individual stars can supplement consumer demand when competitive imbalance exists in a league. Similarly and more recently, Grimshaw and Larson (2021) study television viewership for NBA All-Star games over 16 years and attempt to differentiate consumer interest in productivity versus popularity, finding that both play important roles in generating viewership. Other analyses have estimated the impact of All-Star votes on fan attendance, finding that top vote-getters can lead to thousands of additional tickets sold (Berri and Schmidt 2006; Jane 2016). This paper expands on previous analyses by measuring the relative impacts of popularity and productivity on willingness-to-pay using ticket price data, and examining plausibly exogenous price changes to causally identify superstar value under heterogeneous conditions.

III Overview of Data Collection and Characteristics

This paper leverages unique, high temporal frequency microdata from a large online secondary ticket marketplace, as well as data on exact timing of absence announcements for different players. The analysis is supplemented with television viewership data from The Nielsen Company©.[1] This section briefly describes each source of data and presents high-level summary statistics. A more detailed overview of the data, including the collection procedure, and additional summary statistics are presented in Appendix A.

A Secondary Ticket Marketplace

An integral component of this analysis was collecting ticket-listing data from a large, online secondary ticket marketplace that offers tickets for events ranging from concerts to sporting events. The analysis relies on the use of such a marketplace since sellers and buyers can react instantaneously to announcements about player absences. The data was collected every 30

[1]Data granted from The Nielsen Company (US), LLC. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

minutes (or a total of 48 collections per day) for every remaining NBA game in the season. Each observation is a specific ticket listing for a game collected at a specific time. In particular, I collect the listing price, quantity of tickets available for that listing,[2] time of data collection, and metadata on the corresponding NBA game, which includes home and away teams as well as the date and time of the game. The analysis presented in this paper relies on a sample of ticket prices within three days of a game,[3] primarily because this is when the majority of single-game superstar absence announcements occur, and also because most of the buyer/seller activity on the secondary market occurs during this timeframe.[4] A summary of relevant variables collected from the secondary ticket marketplace microdata is presented in Table 5 in Appendix A.

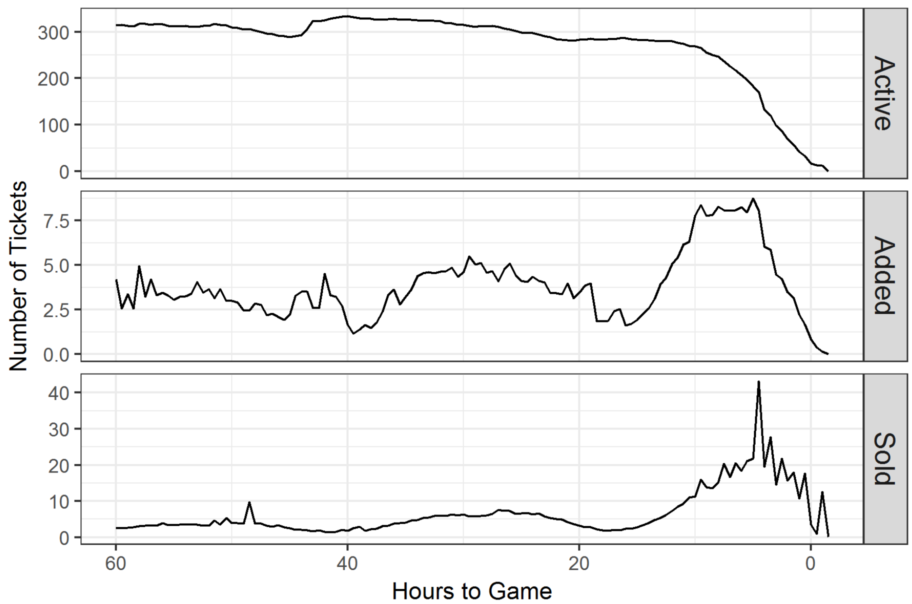
Because of the temporal frequency of this microdata, I observe time trends in both prices and quantities of tickets posted to a secondary marketplace for each game. Figure 1 presents three different quantity time trends in terms of hours to game: the top pane presents the average total quantity of tickets available on the secondary marketplace for each game, the second pane presents the average number of tickets *added* (i.e. posted by sellers) to the marketplace per game, and the third pane the average number of tickets *sold* on the marketplace per game. I assume the disappearance of a listing implies that this listing was sold, either to a buyer or to the "seller" of the listing who decided to go themselves.[5]

One can see that the quantity of tickets available for a given game declines as the game approaches. This is intuitive, as these tickets represent a perishable good and have no value once a game is completed. Interestingly, the average number of tickets posted (added) to the marketplace is somewhat uniform in terms of hours to game (with the exception of dips during night-time hours when most sellers and buyers are asleep), but the average number of tickets sold spikes in the five or so hours before a game.

Figure 2 plots the average listing price across all games by hours to game. There is generally a downward trend in prices as a game approaches, decreasing from around \$145/ticket two days

[2] Each ticket within a listing must have the same price.
[3] Within three days of a game refers to the day of a game and two full days prior.
[4] An interesting and important avenue of future research is to examine ticket price movements in response to longer-term absence announcements.
[5] In other words, a seller may have their tickets purchased by another buyer, or decide to "purchase" their own tickets (i.e. remove the listing and go to the game themselves).
[6] Please note the different y-axis scale for each pane.

Figure 1: Per-Game Average Number of Active, Added, and Sold Listings by Hours to Game[6]



before a game to around $100/ticket just before game-time. It is also clear that the volatility in prices substantially increases closer to the game. This may be attributed to an increase in activity on the marketplace; there are games where sellers are trying to offload tickets and continue to lower prices, and other games where buyers are trying to obtain tickets, causing remaining sellers to increase their prices. This heightened activity appears to occur beginning about 10 hours before a game starts.

B Absence Announcements

Absence announcements were collected from `Rotoworld`, a popular fantasy basketball website, which provides detailed, timestamped injury information and other reports for all players.[7] Since all announcements are documented and accessible going back several years, I examined announcements pertaining to each qualifying player for the 2017-18 and 2018-19 NBA seasons.[8]

[7]On February 9, 2021, Rotoworld rebranded to NBC Sports Edge. All of the announcement content is the same, and can be found here: https://www.nbcsportsedge.com/edge/basketball/nba/player-news. To confirm accurate timing of announcements collected from Rotoworld, I cross-validate a random sample of 10% of announcements collected with a different source, Rotowire (www.rotowire.com). Within this random subsample, I find an average time deviation of 15.6 minutes across the two sources, which is shorter than the 30-minute frequency with which I collect ticket prices.

[8]The criteria for selecting qualifying players analyzed in this paper can be found in the description of Table 1.

Figure 2: Average Listing Price by Hours to Game

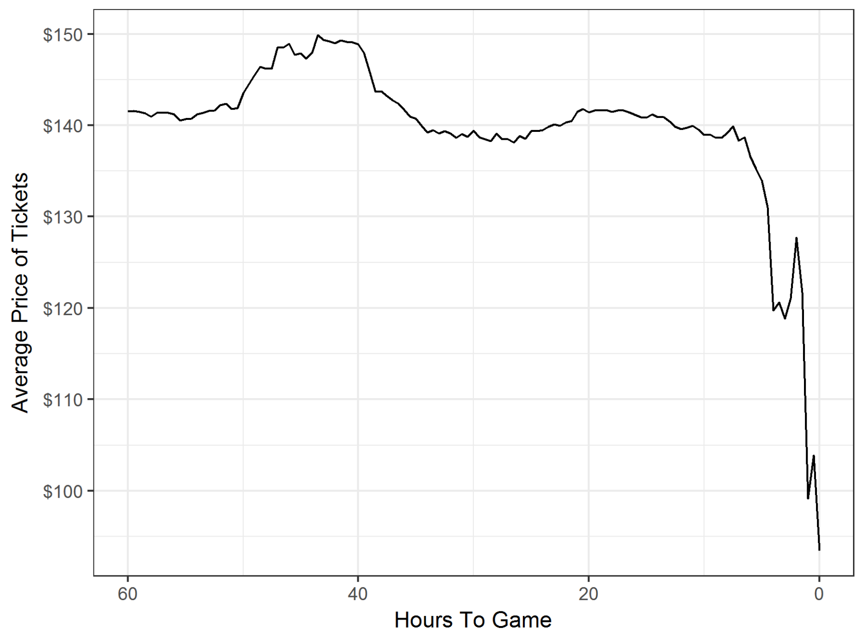


Figure 3 presents the distribution of announcements for all qualifying players across the 2017-18 and 2018-19 NBA seasons in terms of hours to game. In the case of announcements referring to multiple games, I only include observations corresponding to announcements within three days of a game to maintain consistency with the chosen time window.[9] In Figure 3, there are 254 announcement-game pairs falling within three days of a game. One can see that most of these announcements occur within 12 hours of a game, some coming as close as a few minutes beforehand. This inherently limits the sample size of games that can be analyzed, since there needs to be an adequate timeframe pre- and post-announcement to witness ticket price changes. Many announcements also occur approximately 24 hours prior to a game, which may be the result of a player experiencing an injury during the first game of a back-to-back (when two games are played on consecutive days), or an injury that does not require a "game-time decision." There are also noticeable dips in announcement counts 12-20 hours prior to a game because these times often fall during the middle of the night. Rarely do announcements for a player absence for a specific game occur more than 36 hours prior to a game; Figure 11 in

[9] Table 1 provides both the "total number of games missed" (not just the most immediate game corresponding to a given announcement) for each All-Star player corresponding to all documented announcements, as well as the "total number of games analyzed" in the analysis.

Appendix A plots the entire distribution of absence announcements prior to a game.[10]

Figure 3: Distribution of Player Absence Announcements by Hours to Game

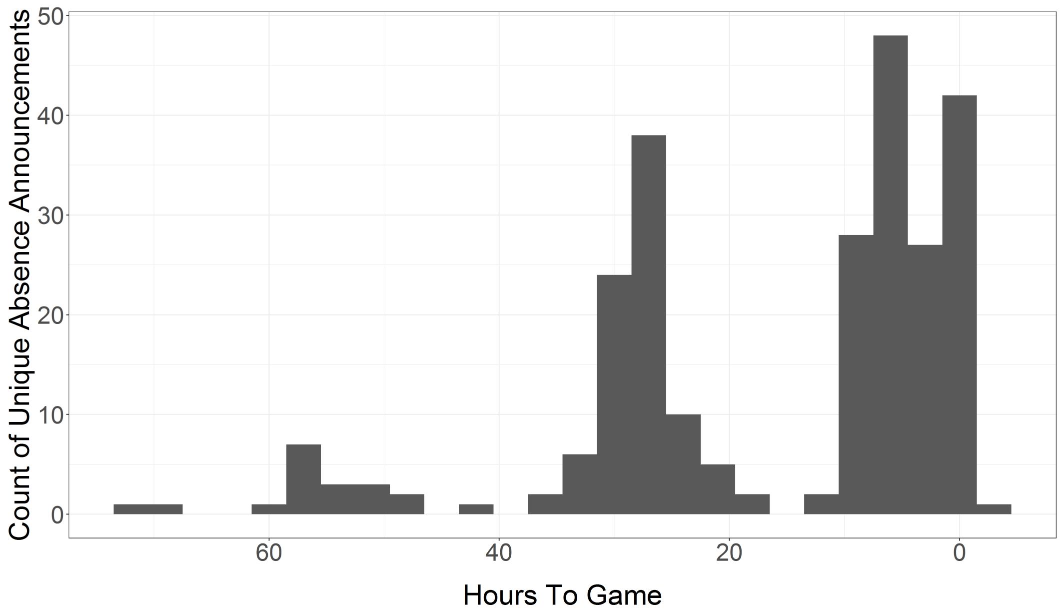


Table 1 presents the list of specific players analyzed in this paper. In order for a player to be chosen for analysis, they must have met either one of the following criteria: (i) they were selected as an All-Star starter in at least one of the 2017-18 and 2018-19 seasons, or (ii) they would have been selected as an All-Star starter in at least one of these two seasons had the fan vote counted 100%. In particular, the starters for the All-Star rosters are based on a weighted average of votes between fans (50%), players (25%), and select media members (25%). Thus, there are cases when a player is not selected as an All-Star starter, but would have been selected had the fan vote been given 100% of the weight.[11] The only player in Table 1 to not meet this criteria is Dirk Nowitzki, who was selected as a special All-Star by NBA Commissioner Adam Silver because of his career achievements (and 2018-19 was likely to be his last season). Dwyane Wade was also a special selection by the commissioner, but he meets criteria (ii).

Previous work has used various selection criteria to identify superstars. Humphreys and Johnson (2020) identifies and analyzes NBA superstars using three categories: value over re-

[10] As mentioned previously, this analysis does not consider the effect of a long-term injury announcement on games more than 3 days into the future.

[11] In fact, the fan vote was given 100% of the weight for All-Star starter selections until the 2017 All-Star game, when the NBA moved to a three-tiered voting system for starters.

Table 1: Count (by Reason) of Qualifying Missed Games for each Qualifying Player

Player	Injury	Rest	Other	Total	Total Analyzed
Anthony Davis	26	3	1	30	20
DeMar DeRozan	4	3	0	7	4
DeMarcus Cousins	35	6	0	41	7
Giannis Antetokounmpo	17	0	0	17	14
James Harden	10	2	0	12	6
Joel Embiid	12	6	0	18	14
Kemba Walker	2	0	0	2	2
Kevin Durant	17	1	0	18	12
Kyrie Irving	35	1	1	37	23
Paul George	8	0	0	8	5
Stephen Curry	42	1	0	43	15
Luka Dončić	10	0	0	10	7
Dwyane Wade	3	0	7	10	7
Dirk Nowitzki	2	2	0	4	3
LeBron James	22	3	0	25	14
Kawhi Leonard	6	14	1	21	19
Derrick Rose	32	0	0	32	17
Draymond Green	24	2	1	27	22
Manu Ginóbili	7	9	0	16	11

placement player (VORP), 1st team All-NBA selections, and All-Star votes. Other notable studies in the context of the NBA have also relied on All-Star votes (Berri and Schmidt 2006; Yang and Shi 2011; Jane 2016). The use of All-star votes as a selection criteria is advantageous because it provides a continuous measure of both productivity and popularity. Additionally, fan All-Star votes provides a direct signal of interest from spectators themselves, and this paper estimates spectator WTP for superstars.[12]

For each player selected under this criteria, Table 1 includes how many qualifying games they missed (i.e. an explicit announcement for a game indicating the exogenous nature of a player's absence) as a result of injury, rest, or "other" reasons, the total number of games, and the number of games for each player that was included in the analysis on ticket price changes. For each listed player, I am able to analyze most, if not all, of the qualifying games they were absent for. Reasons for not being able to analyze certain qualifying games include if the announcement occurred "too close" to a game, "too far" from a game, or if another superstar

[12] While fan All-star votes is the desired selection criteria, I do assess the impacts of VORP and All-NBA selections on spectator demand in Section IV, following Humphreys and Johnson (2020).

was announced as out for that qualifying game as well.

C Game Characteristics and Television Viewership

To perform the panel estimation analyzing ticket prices and TV viewership at the game-level, I rely on a rich dataset of game-specific characteristics collected from several different sources, including `NBA.com`, `FiveThirtyEight`, and `Basketball Reference`, and television viewership data for all nationally televised games during the 2017-18 and 2018-19 seasons from The Nielsen Company©. Game characteristics include state variables corresponding to each game (i.e. number of All-Star votes of each player playing, date and time information, absolute point spread, aggregate value over replacement player (VORP) of each player playing, average winning percentage of the two teams, etc.). For television viewership, I have data on the projected number of total individuals watching across the United States at the start of each game.

A summary of relevant game characteristics data is presented in Table 6 in Appendix A. The average number of cumulative All-Star votes in a game is just over 3.8 million. For context, LeBron James received 4.6 million votes and Stephen Curry 3.8 million for the 2018-19 season, suggesting that each of these players *alone* generates as much popularity as the average NBA game. Table 7 in Appendix A summarizes the total projected number of viewers from the television viewership data as well as the corresponding game characteristics. Note that this data only includes *nationally televised* games during the 2017-18 and 2018-19 seasons, of which there were 477 in total (329 non-playoff games and 148 playoff games). Table 7 shows a couple of interesting characteristics of this data. First, when distinguishing between playoff and non-playoff games, average viewership increases from 1.5 million for non-playoff games to nearly 3.5 million for playoff games. Additionally, the range of cumulative All-Star votes found in a nationally televised game is quite large. There are nearly 6.7 million total All-Star votes in a game on average, but a game can have as few as 372,000 votes and as many as 18.4 million. A game featuring LeBron James or Stephen Curry alone would include more than an order of magnitude more All-Star votes than the lowest total All-Star votes game from this sample!

Figure 12 in Appendix A visually depicts the cumulative distribution of average All-Star fan votes across all 659 eligible players over the 2017-18 and 2018-19 seasons. It shows that a sizable majority of players receive a negligible number of votes, and that 75% of all votes are concentrated within the top 5% of players (approximately 33 players). This is a product of the concentration of popularity towards the top several players in the league.

IV Panel Estimation and Results

The first set of analyses uses a rich panel regression approach to estimate the impact of player popularity and productivity, among other factors, on ticket prices and TV viewership. Additionally, I implement a quasi-LASSO framework (using motivation from Athey and Levin 2001) to determine the relationship between residualized popularity, productivity, and team quality on residualized ticket prices and TV viewership over the entire support of the data using a rich set of controls with flexibility in the functional form. This entire analysis examines ticket prices and TV viewership at the game level, and does not rely on within-game, time varying prices and quantities.

A *Estimation Approach*

Equation (1) presents the general specification of the panel regression. I estimate the impact of player popularity, as measured by the cumulative number of All-Star votes of all players in a specific game, and player productivity, as measured by the cumulative Value over Replacement Player (VORP) of all players in a specific game.[13] One feature of the NBA regular season schedule that provides rich variation in the data used here is that all teams play each other no less than two times and no more than four times. The estimating equation is written below:

$$y_i = \eta AllStarVotes_i + \theta VORP_i + \mathbf{X_i}\boldsymbol{\beta} + \epsilon_i \tag{1}$$

where y_i represents the outcome variable for game i. I examine two separate analyses with two different outcome variables: (i) weighted average ticket price on the secondary marketplace for game i, and (ii) start time TV viewership for game i. $\mathbf{X_i}$ represents a rich set of game-

[13] There are several measures of productivity that one might consider using. I follow Humphreys and Johnson (2020) in using VORP as the measure of productivity used in this analysis.

specific controls, including the current average win percentage of the two teams in the game, whether or not the home team is favored, and the pre-game win probability differential between the two teams (i.e. how close the game is projected to be).[14]

To more flexibly understand the impacts of popularity and productivity on ticket prices and TV viewership, I conduct a "quasi-LASSO" reduced form analysis that performs separate kernel-density (LOESS) regressions for each of the residualized independent variables – popularity and productivity – on each of the residualized outcome variables – ticket prices and TV viewership (following Athey and Levin 2001). This procedure allows for the estimation of a smooth relationship between each independent variable and each outcome variable, while accounting for an extremely rich set of controls with flexible functional forms. It is particularly useful when the independent variables are highly correlated with one another, which is the case with player popularity and productivity.[15]

There are two sets of estimating equations needed to conduct this analysis. First, equation (2) regresses independent variable $x_i \in \{AllStarVotes_i, VORP_i\}$ on a rich set of controls, which includes a flexible 5^{th} order polynomial for the control $\neq x_i$, which is represented by $g(V_i)$, and a rich set of individual and interaction terms of all other controls represented by $\boldsymbol{\Gamma_i}$.

$$x_i = g(V_i) + \boldsymbol{\Gamma_i}\boldsymbol{\eta} + \epsilon_i \tag{2}$$

Equation (2) is estimated for each $x_i \in \{AllStarVotes_i, VORP_i\}$. So, in the estimating equation for $x_i = AllStarVotes_i$, $g(V_i)$ represents $g(VORP_i)$. Next, equation (3) regresses the weighted average ticket price (or start-time TV viewership) for game i on the same right-hand side as equation (2), namely:

$$y_i = g(V_i) + \boldsymbol{\Gamma_i}\boldsymbol{\beta} + \nu_i \tag{3}$$

where equation (3) is estimated when y_i denotes the weighted average ticket price for game i in one specification, and the start-time TV viewership for game i in a separate specification.

[14]Results Tables 2 and 3 denote the control variables used in each of the two analyses.
[15]The raw correlation between player popularity and productivity is 0.49.

This is done for each $x_i \in \{AllStarVotes_i, VORP_i\}$, and so there are four total estimations conducted. I then take the residuals from equations (2) and (3) and estimate a LOESS (kernel-density) regression of the vector of residualized y_i, denoted $\tilde{y}_i$, on the vector of residualized x_i, denoted $\tilde{x}_i$. The estimating equation for this analysis is as follows:

$$\tilde{y}_i = f(\tilde{x}_i) + \lambda_i \tag{4}$$

where $f(\cdot)$ is the kernel estimated for a LOESS regression (Cleveland 1979).

B Results

This subsection presents findings from the panel and quasi-LASSO analyses. Tables 2 and 3 present the results of two separate estimations of equation (1): Table 2 using weighted average listed ticket prices (of all tickets that eventually sold) at the game-level as the dependent variable, and Table 3 using start-time TV viewership (thousands of projected individuals watching) at the game-level as the dependent variable. Win probability differential (WPD) denotes the difference in win probability (in percentage points) of the favored team and underdog team prior to a game.[16] Meanings of the other included variables can be found in the table footnotes.

In Table 2, there are four different specifications presented. The first specification does not account for a differential effect on ticket prices associated with a large win probability differential and the home team being favored. One might think this would be important since the majority of fans attending a game are likely to be supportive of the home team, and thus may exhibit differentially higher WTP in cases when the win probability differential is high but the home team is favored. Specification (2) is identical to specification (1) except in that it accounts for a differential impact of the win probability differential on ticket prices, depending on whether or not the home team is favored. In this specification, a 1% increase in cumulative All-Star votes of all players playing in a game leads to an approximately 0.23% increase in ticket prices. This effect is almost identical in magnitude to the impact of a 1% increase in the

[16] Win probability differential is calculated by converting point spreads to money lines, and then converting money lines to win probabilities. More information on this conversion can be found on The Action Network (https://www.actionnetwork.com/betting-calculators/). The use of direct win probabilities is preferred to the absolute point spread due to behavioral biases of individual consumers and bettors (Moskowitz 2015).

Table 2: Impact of Player Popularity and Productivity on Ticket Prices

	Dependent Variable: log(Avg. Listed Price) (Game-Level)			
log(Aggregate All-Star Votes)	0.2209***	0.2253***	0.1364***	0.1364***
	(0.0200)	(0.0196)	(0.0223)	(0.0168)
log(Aggregate VORP)	−0.0398	−0.0328	0.0819	0.0819*
	(0.0455)	(0.0461)	(0.0422)	(0.0338)
log(Avg. Current Win PCT)	0.2337**	0.2586**	0.3488***	0.3488***
	(0.0777)	(0.0851)	(0.0852)	(0.0698)
Home Team Favored (HTF)	−0.0008	−0.0652*	−0.0215	−0.0215
	(0.0451)	(0.0248)	(0.0197)	(0.0214)
Win Probability Differential (WPD)	0.0008	−0.0017	−0.0038*	−0.0038**
	(0.0007)	(0.0018)	(0.0016)	(0.0013)
HTF*WPD		0.0034	0.0051*	0.0051**
		(0.0024)	(0.0021)	(0.0016)
Month FE	Yes	Yes	Yes	Yes
Time-of-Day FE	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes
Streak FE	Yes	Yes	Yes	Yes
Home Team FE	Yes	Yes	Yes	Yes
Away Team FE	No	No	Yes	Yes
TV Network FE	Yes	Yes	Yes	Yes
Holiday Indicator	Yes	Yes	Yes	Yes
Clustered Robust SEs (Home Team)	Yes	Yes	Yes	No
Clustered Robust SEs (Home Team-by-Season)	No	No	No	Yes
Observations	2,318	2,318	2,318	2,318
R^2	0.6267	0.6294	0.7120	0.7120

Note: The dependent variable is the log Average Listed Price at the game-level. The mean of the dependent variable is $139.58. Aggregate All-Star Votes refers to the cumulative number of All-Star votes received by all players playing in a game. Aggregate VORP, which refers to "Value over Replacement Rating," is the cumulative VORP of all players playing in a game. VORP is a player-specific productivity metric indicating their on-court value compared to a typical player at their position. Avg. Current Win PCT is the average win percentage at time of game of the two teams playing. Home Team Favored (HTF) is an indicator variable =1 if the home team is favored (as given by the point spread). Win Probability Differential (WPD) is the absolute difference in win probabilities between the two teams playing prior to the start of the game, and is in percentage point terms. Fixed effects for month-of-year, time-of-day (in local time, grouped into before 5pm, 5-7pm, 7-9pm, and after 9pm), day-of-week, two different sets of fixed effects for length of winning streak of home team and away team coming into a game, home team, away team, which TV network the game is being broadcasted on (TNT, ESPN, ABC, NBA TV, and local), and a Holiday indicator =1 if the game is played on a holiday. Specifications (1) - (3) cluster standard errors at the home team level, while specification (4) clusters standard errors at the home team-by-season level. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

average current winning percentage of the two teams playing in the game.

Specification (3) is identical to specification (2), with the exception that it includes "Away Team" fixed effects in addition to "Home Team" fixed effects, and is the preferred specification. One can see that there are substantial adjustments to several of the estimates, in particular the magnitude of the coefficient on Avg. Current Win PCT increases by approximately 35%, Win Probability Differential now has a statistically significant negative impact on listed prices, and when the home team is favored, win probability differential does not have a significant impact on ticket prices (i.e. home fans want to see their team win, regardless of expected competitiveness). Under this specification, a 1% increase in cumulative All-Star votes in a game leads to a 0.14% increase in ticket prices. Because the popularity metric used is the cumulative All-Star votes of all players *actually playing* in a given game, including Home Team + Away Team fixed effects suggests that the coefficient on the popularity variable relies on *changes* in the lineups of teams across a season to drive residual variation in the popularity metric. This variation is similar to the identifying variation used in the DID and event study estimations presented in section V, and allows for useful comparisons across the two different estimation approaches. Specifications (1) - (3) cluster standard errors at the "Home Team" level, while specification (4) clusters standard errors at the "Home Team-by-Season" level.

Table 3 presents the impact of each of these characteristics (omitting the "Home Team Favored" binary variable) on TV viewership for nationally televised games. There are three different specifications: specification (1) includes all nationally-televised games from the 2017-18 and 2018-19 seasons, while specification (2) includes only regular season games and specification (3) only playoff games. Each of these specifications uses an "Aggregate Team Value" continuous control variable to account for the number of people that may be expected to watch independent of other important factors.[17] These team values are calculated each year by Forbes, and are a good indicator of the total size of each team's fan base (Badenhausen and Ozanian 2019). One can see in specification (1) that aggregate popularity and average current team win percentage

[17] Since these are national audiences, a home team fixed effect does not make as much sense in these specifications as it does in the context of the ticket price analysis (since there are geographic preferences). Including a dummy for each team present in a game leads to insignificant point estimates for all variables, likely because of the insufficient power associated due to the relatively low number of nationally-televised games.

Table 3: Impact of Player Popularity and Productivity on Start-Time TV Viewership

	Dependent Variable: log(Total Proj. Viewers) (Game-Level)		
	All Games	Regular Season Only	Playoffs Only
log(Aggregate All-Star Votes)	0.1300**	0.1653***	−0.0250
	(0.0403)	(0.0324)	(0.0833)
log(Aggregate VORP)	−0.0788	−0.0464	−0.1172
	(0.1108)	(0.0839)	(0.2305)
log(Avg. Current Win PCT)	0.3059*	0.1176	0.7477***
	(0.1430)	(0.1560)	(0.1922)
Win Probability Differential	−0.0001	−0.0002	0.0008
	(0.0009)	(0.0016)	(0.0016)
log(Aggregate Team Value)	0.1484	0.0943	0.3416
	(0.0933)	(0.0941)	(0.1974)
Month FE	Yes	Yes	Yes
Time-of-Day FE	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes
Streak FE	Yes	Yes	Yes
TV Network FE	Yes	Yes	Yes
Double Header FE	Yes	Yes	Yes
Holiday Indicator	Yes	Yes	Yes
Playoff Indicator	Yes	No	No
Clustered Robust SEs (Home + Away)	Yes	Yes	Yes
Dependent Variable Mean (thousands)	2123.2	1513.22	3479.16
Observations	477	329	148
R^2	0.7449	0.6496	0.7094

Note: The dependent variable is the log Total Projected Viewers at the game-level (in 1000s). Aggregate All-Star Votes refers to the cumulative number of All-Star votes received by all players playing in a game. Aggregate VORP, which refers to "Value over Replacement Rating," is the cumulative VORP of all players playing in a game. VORP is a player-specific productivity metric indicating their on-court value compared to a typical player at their position. Avg. Current Win PCT is the average win percentage at time of game of the two teams playing. Win Probability Differential (WPD) is the absolute difference in win probabilities between the two teams playing prior to the start of the game, and is in percentage point terms. Aggregate Team Value is the sum of the monetary value (in millions of $) of the two teams playing. Fixed effects for month-of-year, time-of-day (in local time, grouped into before 5pm, 5-7pm, 7-9pm, and after 9pm), day-of-week, two different sets of fixed effects for length of winning streak of home team and away team coming into a game, which TV network the game is being broadcasted on (TNT, ESPN, ABC, NBA TV, and local), Double Header (first game of a double header, second game of a double header, or not applicable), a Holiday indicator =1 if the game is played on a holiday, and a Playoff indicator =1 for playoff games. All specifications cluster standard errors at the home team + away team level. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

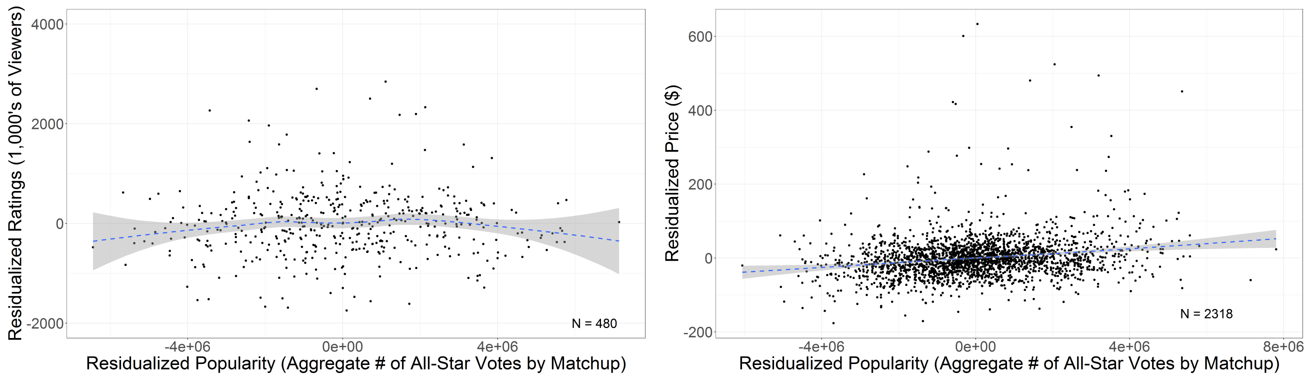
are the only statistically significant estimates. The findings suggest that for a 1% increase in the cumulative number of All-Star votes in a game, start-time viewership increases by approximately 0.13%, and similarly for a 1% increase in the average current win percentage of the two competing teams, viewership increases by nearly 0.31%. Additionally, in specification (2), which limits the sample to only regular season games, this estimate increases to approximately 0.16%, while specification (3), which limits the sample to only playoff games, shows no impact. This suggests that player popularity may be a more important factor in the regular season than the playoffs. One potential explanation for this is that playoff games have an elimination component, and so encompass a different viewership utility function that down-weights player popularity. Note that I reset each team's record for the playoffs, and so the "Avg. Current Win PCT" variable simply reflects that better teams move to future rounds by construction, where each subsequent playoff round experiences higher viewership. All specifications are clustered at the "Home Team + Away Team" level.[18]

Next, I present results from the quasi-LASSO estimation described in equations (2) – (4). This procedure is conducted for the two correlated independent variables of interest: (i) cumulative All-Star votes of all players who played in a game (popularity), and (ii) the cumulative value over replacement player (VORP) of all players who played in a game (productivity), and the two dependent variables: (i) weighted average ticket price at the game-level, and (ii) start-time TV viewership. Figures 4a and 4b present the results for residualized popularity and productivity, respectively, with the left pane in each figure corresponding to the impact on residualized TV viewership and the right pane the impact on residualized ticket prices.

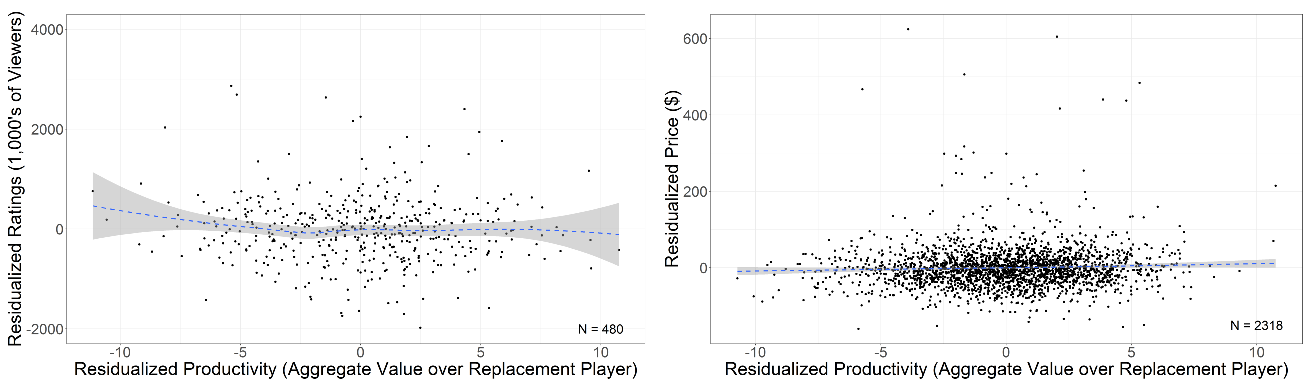
One can see that within the primary support of the residualized independent variables, player popularity significantly affects ticket prices, as seen in Figure 4a. In the case of TV viewership, there does not appear to be enough data to trace out a meaningful relationship between either productivity or popularity, while in the ticket prices case there is a clear convex relationship throughout the entire support of the data.

[18] In addition to Aggregate All-Star Votes and VORP, Tables 8 and 9 in Appendix B examine total All-NBA 1st and 2nd team selections of all players playing in a game, finding no statistically significant or economically meaningful impact on ticket prices or TV viewership.

Figure 4: Quasi-LASSO Results



a. Impact of Residualized Cumulative # of All-Star Votes on Residualized TV Viewership (left pane) and Residualized Ticket Prices (right pane)



b. Impact of Residualized Aggregate Value over Replacement Player (VORP) on Residualized TV Viewership (left pane) and Residualized Ticket Prices (right pane)

V Difference-in-Differences and Event Study Estimation and Results

The second set of analyses uses difference-in-differences (DID) and event study frameworks to identify the causal impact of a specific superstar's absence on ticket prices for a certain game. Under important assumptions regarding identification, these estimates represent the per-ticket value of each superstar's presence to fans in attendance. This framework relies on a plausibly exogenous announcement of a player's absence for an upcoming game, at which point ticket prices for that game should respond according to the missing player's value. I then conduct heterogeneity analyses to determine how these values differ for home vs. away absences.

A Estimation Approach

To obtain a plausibly causal effect of ticket price responses to a player's absence, I construct a counterfactual group that models ticket price movements without a player's absence, and compare those movements to the "treated" games, where a specific superstar player is announced to be absent. This is important because there are underlying trends in ticket prices for NBA games that may bias the estimate of a player's absence if not controlled for with an appropriate counterfactual. There are several different ways of doing this – for example, I could use ticket listings from all other games on the same day and compare their price movements to ticket listings for the treated game(s) on that day, which I denote the *same day counterfactual*. The primary weakness behind this approach is that there are a different number of games each day (including days with only one or two games), which inherently limits the size of the counterfactual group.

A second way of constructing a counterfactual is through the *same team counterfactual*. This counterfactual compares games for the team of a specific superstar where that superstar was absent, to other games of that same team not confounded by *any* superstar absences. For example, Golden State Warriors guard Stephen Curry missed the game on December 6, 2017 against the Charlotte Hornets in Charlotte. The same team counterfactual would consist of a subset of other Golden State Warriors games where Stephen Curry played *and no other superstar players were announced to be absent*.[19] So, the game where Warriors forward Kevin Durant was announced out due to injury against the Brooklyn Nets in Brooklyn on November 19, 2017 would not be included in this subset of potential counterfactual games. This counterfactual is attractive since it accounts for team-specific trends of ticket prices that may be common across many of their games.

One may consider a *restricted* same team counterfactual that relies on a forward- and backward-looking subset of games (i.e. a 5 or 10 game window in either direction). Similar to the same day counterfactual, this inherently limits the sample of games that can be used in the

[19] This only includes qualifying games for other superstars, as defined in section III subsection B. Namely, I _do_ include games that another superstar may have missed, but that weren't explicitly announced (for example, if another superstar was known to be out for the rest of the season prior to the treated game being analyzed).

counterfactual group. With appropriate controls for game-specific, time-invariant confounding effects, which I describe in equation (6), an *unrestricted* same team counterfactual provides the largest set of games that are reasonable to include in the counterfactual group.

A.1 Primary Estimating Equations

Using the unrestricted same-team counterfactual, the DID estimating equation is written as follows:

$$\ln(Price_{ish}) = \beta_1(Absence * PostAnn)_{ih} + \alpha_i + \alpha_s + \alpha_h + \epsilon_{ish} \quad (5)$$

where $Price_{ish}$ represents the average listed price for tickets in arena section s for game i at hours-to-game h. So, an observation for the left-hand side variable would be the average listed price of tickets in section 201 of Oracle Arena for the Golden State Warriors vs. Houston Rockets game on October 17, 2017 four hours before the game. $Absence_i$ is a binary variable $= 1$ if there was a superstar absence for game i, and $PostAnn_h$ is a binary variable $= 1$ if the announcement had already been made at hours-to-game h. Hours-to-game is used as the measure of time since games occur at different times during the day (e.g. 7:30pm EST or 10:30pm EST) and across days (e.g. October 16th vs. October 17th). Additionally, average ticket price trajectories are heavily dependent on the number of hours before the start time of a game, as quantity of tickets available and prices on the secondary marketplace are very time-dependent (see Figures 1 and 2). Thus, for the Golden State Warriors @ Brooklyn Nets game on November 19, 2017, Kevin Durant was announced out of the game at 8:49am EST, which would correspond to 6 hours and 11 minutes to the game (which was at 3:00pm EST). The DID treatment coefficient is represented by β_1, which approximately represents the proportional change in ticket prices associated with a superstar absence, and is the primary coefficient of interest. Finally, α_i represents individual game fixed-effects, α_s are arena-specific section fixed effects, and α_h are hours-to-game fixed effects. A log-level specification is preferred since the distribution of prices is censored at zero.

Because I am attempting to determine the causal impact of a superstar absence on ticket prices, I estimate an event study to i) confirm parallel pre-trends in ticket prices for the treatment and counterfactual games, and ii) to determine the effect of a superstar absence on ticket prices in each 30-minute time period following the announcement (instead of just the post-announcement versus pre-announcement average effect that is obtained by the DID estimation). This strategy provides compelling identification, since I am able to examine within-game changes in prices in response to plausibly exogenous announcements.

Employing the same-team counterfactual, the primary empirical specification can be written as follows:

$$\ln(Price_{lisht}) = \sum_{t=-14}^{14\backslash\{-1\}} \mathbf{D}_t \mathbf{Absence}_{t,ih} + \alpha_i + \alpha_s + \alpha_h + \epsilon_{lisht} \quad (6)$$

Prices used in this analysis are at the listing-level l. $\mathbf{Absence}_{t,ih}$ is a vector of binary variables indexed by event-time t. Event-time t is in the half-hours-to-game unit, since that is the observed temporal frequency of the ticket price data, and is normalized to $t = 0$ based on the half-hours-to-game value when the announcement of a superstar's absence takes place. As is standard in event study estimations, each variable takes a value $= 1$ if the observation in the data refers to a game i where a superstar was absent and the observation of data corresponds to event-time t. $\mathbf{D}_t$ is a vector of estimated coefficients distinguishing the price differential between the treated game and counterfactual games at event-time t compared to an omitted period (which for this analysis will correspond to $t = -1$). As can also be seen in the estimating equation, I restrict the event-time horizon to $t = [-14, 14]$, where the left (right) binned endpoint coefficient represents the average treatment effects for all pre- (post-) periods not included in $t = (-14, 14)$. The dependent variable and fixed effects remain identical to the DID estimating equation.

In addition to estimating an effect for each individual game that experienced a superstar absence, I also estimate an aggregate absence effect for each superstar, which requires a slightly more complex method of constructing the same-team counterfactual. Because each treated game for a specific player has a different announcement time in terms of hours-to-game, one cannot simply assign the same announcement time to all games in the counterfactual as was done in the individual game case. Rather, announcement times are randomly assigned for all games in the counterfactual by sampling from the pool of announcement times observed for the treated games. For example, James Harden was absent from six qualifying games that were analyzed (1/3/18, 3/11/18, 3/26/18, 4/11/18, 10/25/18, and 2/23/18), and was announced absent for these games at 47.5, 22, 26.5, 1.5, 33.5, and 2 hours-to-game, respectively. For each of these 6 treated games, I randomly pair a proportional number of counterfactual games based on the total set of eligible counterfactual games for the Houston Rockets, and assign the announcement time (in hours-to-game) of the treated game to each counterfactual game with which it was paired. In the case of Harden, there are 148 eligible, untreated games in the counterfactual group, so 4 treated games receive 25 counterfactual games each and the remaining two games receives 24 counterfactual games. Once the pairings are assigned, the same announcement time is assigned to each group and the announcement time of each grouping is normalized to 0. The estimation is then performed for each player. To ensure robustness of the random counterfactual game-pairing algorithm, the aggregate-game analysis for each player is performed three times, each with a different random counterfactual pairing.[20]

Finally, it is important to note that listed prices are used in this analysis. While a listed price does not necessarily indicate a seller's true willingness-to-sell (i.e. the reservation price of attending the game) since the choice of the listing price is a function of the prices of other listings of comparable seats, *changes* in listed prices due to superstar absences should reflect the combined effect of sellers' and buyers' lower value of attending the corresponding game. Therefore, the effect I estimate is the value loss associated with the absence of a specific superstar for the average NBA game attendee. In addition, I restrict the sample to ticket listings that eventually sold, since these are listings that at some point reflect a market-clearing equilibrium price between sellers and buyers.

[20]The estimating equations remain the same as in the case of the individual game analysis with one key difference – for games in the counterfactual, $PostAnn_h$ is determined based on the assigned announcement time within each grouping.

A.2 Identification Concerns

With any empirical estimation, there are concerns over identification of a causal estimate. In this estimation, I am assuming that there are no omitted variables correlated with announcements that also affect ticket prices, namely:

$$\mathbb{E}[\epsilon_{lisht} | \boldsymbol{Absence}_{t,ih}, \boldsymbol{X}_{isht}] = 0 \tag{7}$$

where $\boldsymbol{X}_{isht}$ represents the vector of covariates controlled for. However, because injury announcements are plausibly random (the occurrence of an injury is not predictable), and I only look at price movements the day of a game and two full days prior, there is only concern if a confounding event occurs that adjusts the price trajectory of a treated game differently than counterfactual games during this time horizon. In particular, to the extent characteristics of a game are known prior to this three-day window leading up to a game, and are not changing within the window, they are controlled for in the individual game fixed effects. For instance, this includes the up-to-date average win percentage of the two teams playing, seasonality effects, and the time-of-day the game is being played.

One potential threat to identification is if an absence announcement of a player is correlated with having already made the playoffs and their team's seeding set. This may occur if the likelihood of a superstar missing a game due to injury is higher once a team's playoff seeding is already known. In this case, it would be difficult to disentangle the price effect associated with a team having already made the playoffs and determined their seeding, and the price effect due to the injury of a superstar player.

While it is difficult to imagine important identification issues with respect to injury announcements, announcements about superstars being "intentionally rested" may face a different set of concerns. First, decisions to rest superstar players may be dependent on several factors, for example the second of two games played on consecutive days or the third game in four days may exhibit a higher likelihood of superstars resting (e.g. Joel Embiid all of the 2017-18 season), competitiveness of the opponent, home vs. away games, etc. However, to the extent these characteristics are known prior to the three-day window I analyze before a game, they would be accounted for in the individual game fixed-effects.

B Results

B.1 Difference-in-Differences

Figure 5 presents the results of the DID estimation. Each estimate reflects the average treatment effect (per ticket) on listed prices from the entire sample of analyzed absences for each qualifying superstar. The confidence intervals presented are at the 95% level. Importantly, all players included exhibit parallel pre-trends in ticket prices between the counterfactual and treated games prior to a superstar's absence announcement, satisfying the identifying assumption that the DID estimate is causal.

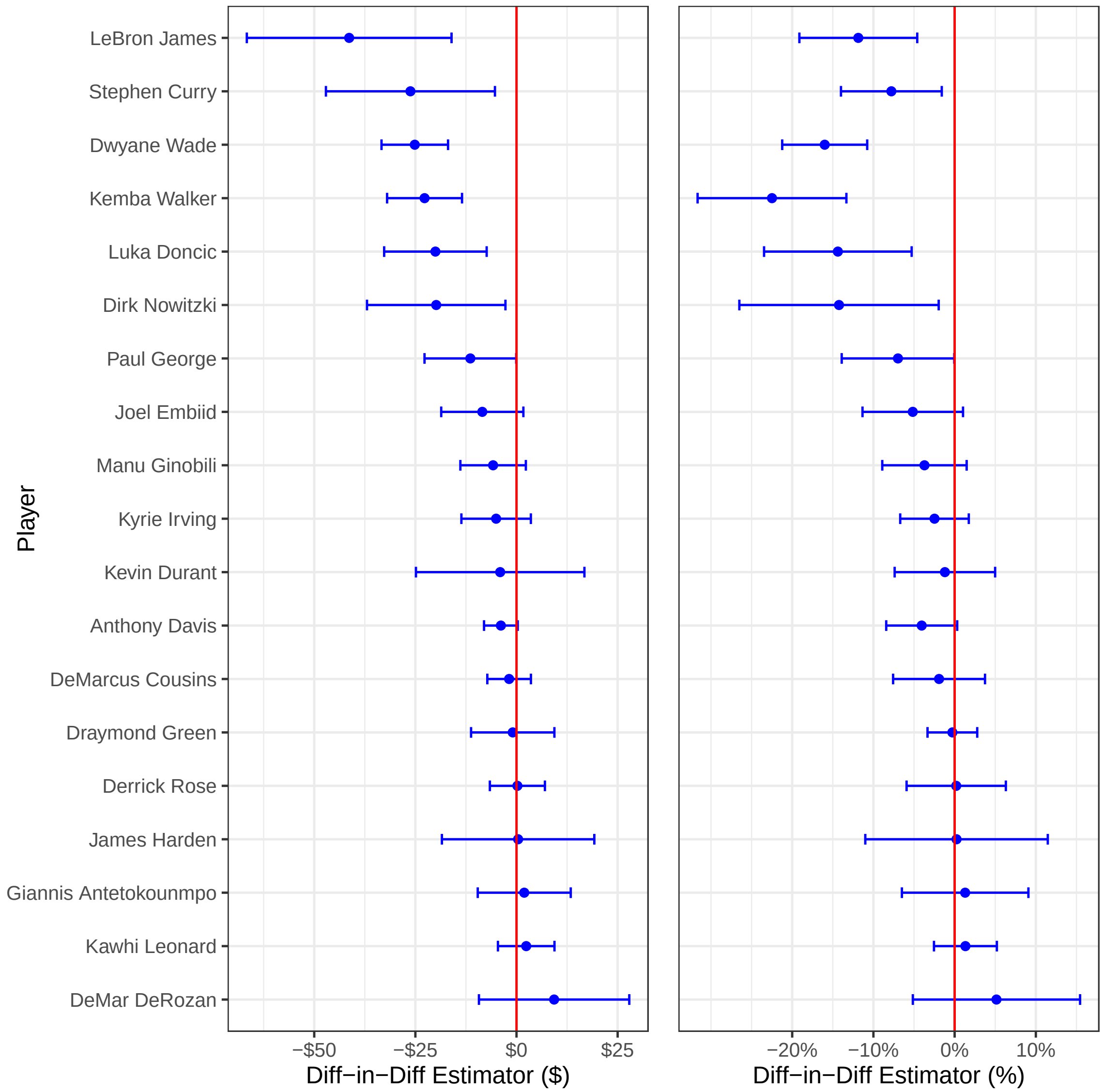
In examining the results, the reduction in prices due to absence announcements in dollars (left pane) is largest for LeBron James and Stephen Curry, with ticket prices falling an average of $41 and $26 per ticket, respectively. There are a number of other players whose absences lead to economically meaningful and statistically significant price reductions, including Dwyane Wade, Dirk Nowitzki, and Luka Dončić, ranging between $4-25. The percentage reduction in prices (right pane) is largest for Dwyane Wade, Kemba Walker, Dirk Nowitzki, and Luka Dončić, whose absences lead to price reductions of 14-16%.[21]

I do find null impacts for some superstars, including Giannis Antetokounmpo and Kawhi Leonard.[22] There are several potential reasons for this, but one important mechanism may be economic or behavioral differences among fan bases of different teams. In particular, fans may be loyal to their teams independent of individual superstars. Kurlantzick (1982), and later Mason (1999), suggest that higher fan loyalty means there are likely to be fewer competitive substitutes to attract their attention and engagement. Thus, these fans may be less responsive to changes in characteristics of the game experience for their team. Another potential mechanism tied to differences in fan bases is the impact of the size of the local entertainment market and the availability of related activities. Rascher et al. (2009) uses the 2004-05 National Hockey League

[21] The difference in ordering of magnitudes between dollar and percent reductions is due to differences in average ticket prices of each player's team.

[22] Other relatively non-intuitive null effects exist for Kevin Durant and James Harden. The case of Harden is discussed in conjunction with Figure 9 and Durant with Figure 10.

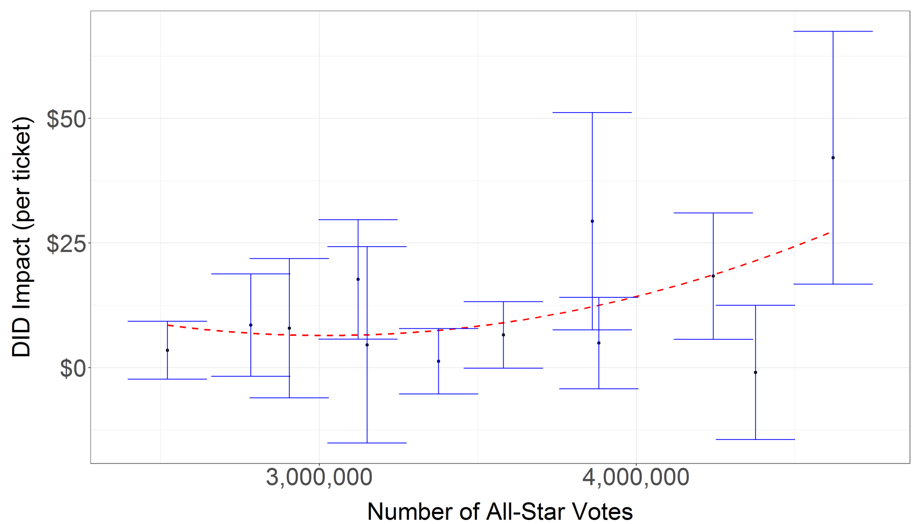
Figure 5: Difference-in-Differences Results for Superstar Absences



(NHL) lockout to assess changes in demand for minor league hockey and the NBA in cities with NHL teams, finding that on average these five competitor leagues saw demand increases of 2%. In an entertainment center like Los Angeles there are many other appealing substitutes to a Los Angeles Lakers game, and so if LeBron James is announced out, individuals may be more willing to substitute towards a related activity. In a smaller market like Milwaukee these substitutes may be less available, and thus willingness-to-pay may be less responsive to superstar absences.

To gain a better understanding of how player popularity factors into the magnitudes of these estimates, Figure 6 visualizes the relationship between player absence impact (in dollars per ticket) and their maximum single-season All-Star vote total from the 2017-18 and 2018-19 seasons, and fits a quadratic approximation to showcase the general shape. One can see that there is a convex relationship between each player's impact and the number of fan votes they receive, again supporting the economic theory of superstars.[23]

Figure 6: Difference-in-Differences Results by All-Star Votes

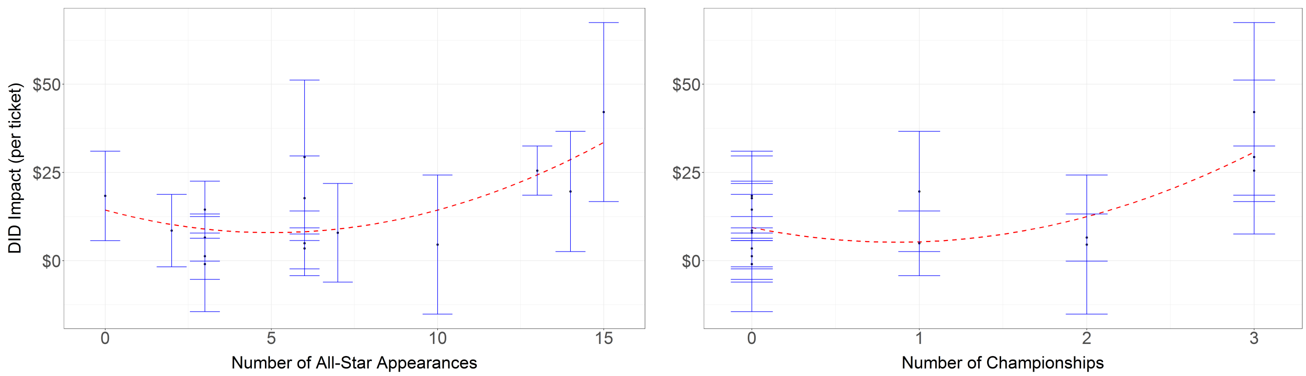


To capture different measures of popularity, and in particular "career-long" popularity, which weights legacy players relatively more than recently popular stars, Figure 7 plots the player-specific ticket price impacts on total number of career All-Star appearances (left) and championships won (right). Both exhibit relatively convex relationships, although there is a bit of a U-shape in both panes as a result of the discrete nature of the career-long popularity variables. In particular, the slight U-shape in the left pane of Figure 7 is largely due to the significant global popularity of Luka Dončić, who played internationally for several seasons as a highly-renowned teenager before coming to the NBA but had not had a chance to accumulate any All-Star appearances. In the right-pane, the slight U-shape is due to the fact that only one

[23] This figure omits Dwyane Wade, Dirk Nowitzki, and Kemba Walker. Wade and Nowitzki were "legacy picks" by the NBA commissioner to take part in the All-Star game because of their career achievements, and thus had lower fan vote totals but large impacts on prices when they missed games. Despite Walker's significant impact on prices, his maximum single-season vote total was half the size of the next lowest vote-getter, and only missed two games over the course of these two seasons (both of which were at home), which was the lowest missed game total among all players analyzed here. His somewhat large effect is likely due to a small sample size of missed games and the fact that those games were missed in one of the NBA's smallest markets (Charlotte). The graph including these players is found in the Appendix in Figure 13.

team can win the championship each season, and so even some of the most popular stars do not end up achieving this feat.

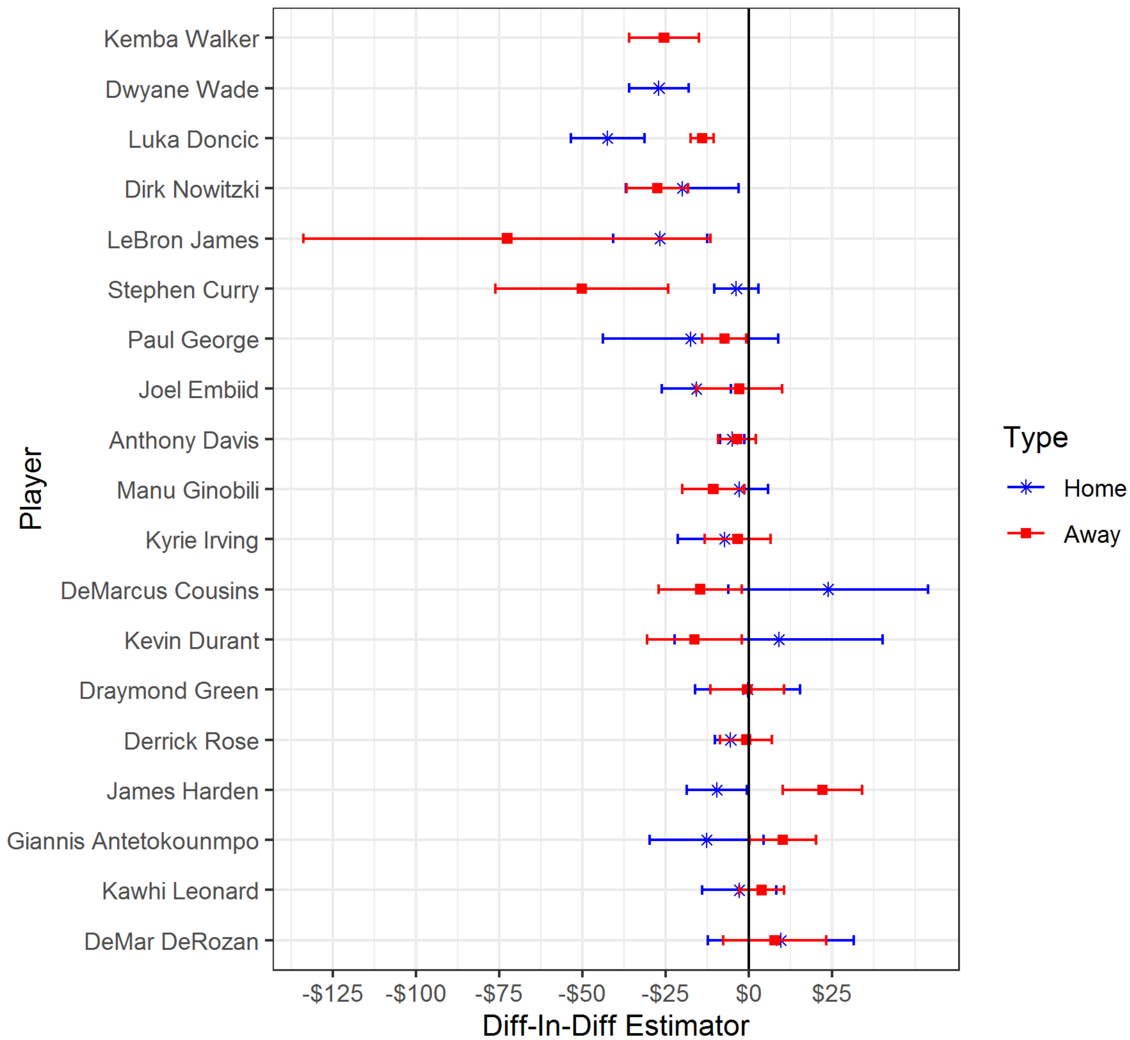
Figure 7: Difference-in-Differences Results by All-Star Appearances (left) and Championships (right)



Finally, I estimate treatment effects separately for home and away games for each player. Figure 8 presents two distinct DID estimators (exhibiting level price changes) for each player: one for home games missed and another for away games missed.[24] One can see there are some striking differences in effects for certain players. For example, Stephen Curry and LeBron James' absence effects are sizably larger in magnitude for away absences than for home absences. James' average away-game effect is $73/ticket, while Stephen Curry's is $50/ticket. This suggests that the spectator value of these players in away arenas is higher than in their home arena, likely because they only play in opposing arenas at most two times per year. On the other hand, Luka Dončić, and to a lesser extent James Harden and Joel Embiid, all exhibit the opposite effect, where their absences are more meaningful for home games than for away games. This is also quite intuitive – each of these players is not just entertaining to watch, but without them their teams become much less competitive and thus more likely to lose a game. The same argument could be made for LeBron James' impact on the Los Angeles Lakers, who also exhibits a large negative effect for home game absences (despite an even larger away game absence effect). Home fans value the competitiveness of their team, and thus the absence of these stars substantially reduces their team's chances of winning. Figure 14 in the Appendix exhibits these changes in percentage point terms.

[24]Note that Kemba Walker was not absent for any qualifying home games, and Dwyane Wade was not absent for any qualifying away games.

Figure 8: Difference-in-Differences Results by Home vs. Away Game Absence (in $)



I also conduct heterogeneity tests analyzing the differential effect of absence announcements depending on the competitiveness of the game (as measured by the win probability differential), the total number of other starting-caliber superstars present, and the market size of the home team. This analysis relies on a triple differences estimation, where the DID treatment variable is interacted with the relevant metrics for competitiveness, total superstar power, and market size, respectively, in separate estimations. The results of these analyses suggest there are no meaningful or statistically significant relationships between ticket prices and these additional characteristics. One potential explanation for this finding is that there are not enough events of different types to estimate a robust statistical relationship. Future work should aim to incorporate additional absences to add to the power of such an estimation.

B.2 Event Study

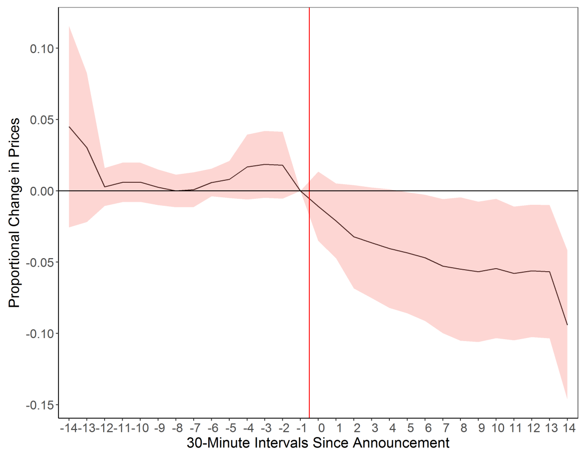
The event study results present coefficients for each of the 30-minute intervals before and after an absence announcement takes place. Figure 9 shows the results for the top three impact players with respect to ticket price declines as a result of their absences, again using the aggregate estimation, and James Harden, who was the 2017-18 MVP.[25] Each point on the graph can be interpreted as the differential effect on listed ticket prices of a superstar absence announcement on the treated group vs. the counterfactual group. Coefficients statistically insignificantly different from zero prior to an absence announcement, which is indicated by the vertical line, suggest that parallel pre-trends in ticket prices hold in each of these cases. The event study estimates exactly when prices change as a result of an announcement. One can see that there is a slight delay in the full responsiveness of listed ticket prices to the announcement of a superstar's absence – typically the effects are smaller closer to the announcement time and larger further away. This is intuitive, as many sellers and buyers do not have immediate access to announcement information or the ability to immediately change their listing on the secondary marketplace. The endpoints are binned at -7 and $+7$ hours in event-time with respect to when the announcement occurs (at $t = 0$).

In Figure 5, one can see that Kevin Durant's absence announcements on average lead to no statistically significant ticket price adjustments. This is particularly interesting given that there is a meaningful reduction for his teammate Stephen Curry's absences. Figure 10 presents the event study results for Kevin Durant and Stephen Curry. From a productivity standpoint, Kevin Durant and Stephen Curry were nearly identical during the 2017-18 and 2018-19 seasons. However, Curry's popularity with NBA fans as "the best shooter of all-time" and his unique style of play may make him a more desirable player to watch from an entertainment standpoint.

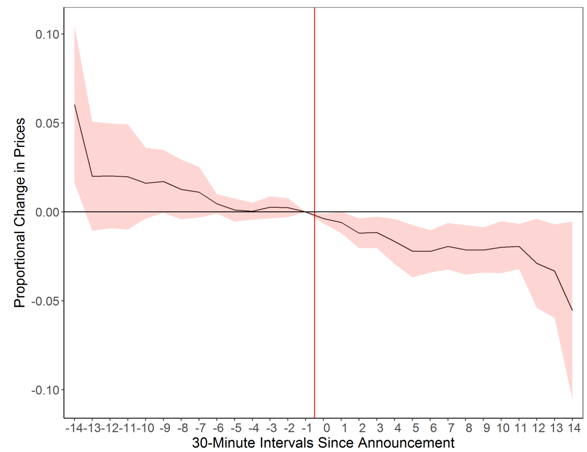
[25]The event study results for the remaining eligible players are presented in the Appendix.

Figure 9: Event Study Results for Top Impact Superstars

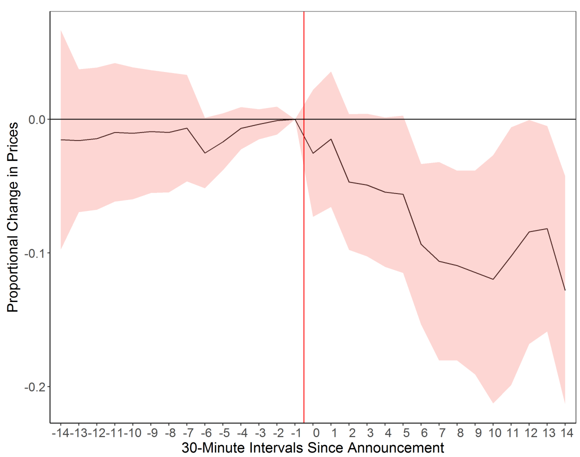
(a) LeBron James



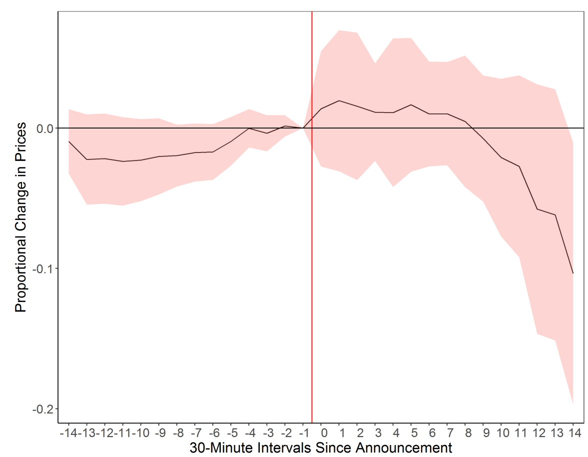
(b) Stephen Curry



(c) Dwyane Wade



(d) James Harden



VI Discussion

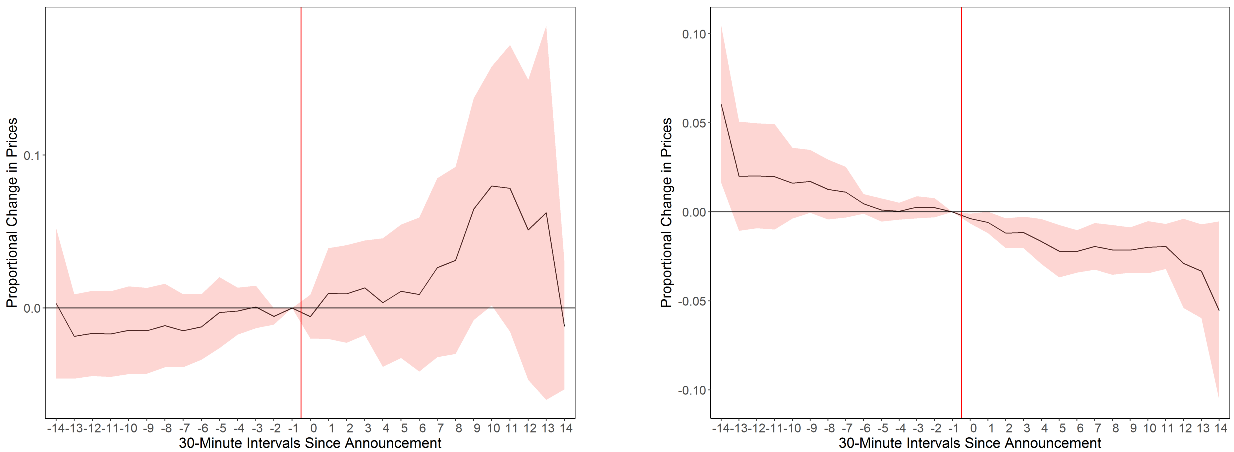
The results from the panel and difference-in-differences/event study methodologies yield largely consistent findings at an aggregate level, despite differences in estimation approach. The panel analysis found that in the presence of a player holding 100% of the average cumulative number of All-Star votes for all players in a game, ticket prices were on average 13.6% higher. This is comparable to the range found in the DID and event study approaches, where ticket price reductions due to superstar player absences were on the order of 4-22% on average.

For additional context, LeBron James averaged just over 3.6 million fan votes over the 2017-18 and 2018-19 seasons, which corresponds to approximately 95% of the average cumulative

Figure 10: Kevin Durant vs. Stephen Curry Absence Impacts

(a) Kevin Durant

(b) Stephen Curry



number of All-Star fan votes of all players in a game (3.8 million). In other words, James' average fan All-Star vote total is just below the total number of All-Star votes of all players in an average game. Using the results from the panel analysis, the presence of James alone results in an approximately 13.0% increase in ticket prices and TV viewership. The DID analysis yields a very similar result – the absence of James leads to an 11.9% average reduction in ticket prices.

For the remaining superstar players analyzed, Table 4 presents the average game-level impact under the DID method (column 3) and ticket prices panel estimation method (column 4). The impacts in column 3 are based on the results in Figure 5, while the impacts in column 4 are using the results from Table 2. Interestingly, there are a couple of notable players significantly underestimated by the panel analysis compared to their DID impacts. During the 2017-18 and 2018-19 seasons, Dwyane Wade and Dirk Nowitzki were not playing at an All-Star level, but since the 2018-19 season was known (or in the case of Nowitzki, almost certainly known) to be their last, they were "hand-picked" by the NBA commissioner to be All-Stars that year. It appears that the DID impact may represent a legacy effect that considers the total popularity of these players over the course of their entire careers, and the desire to see them play before they officially retired.

Table 4: Game-Level Difference-in-Differences and Panel Estimation Impacts

Player	All-Star Votes	DID Impact in $ (%)	Panel Impact in $ (%)
Luka Dončić	4,242,980[x]	20.0 (14.4)*	21.2 (15.2)
LeBron James	3,629,552	41.4 (11.9)*	45.4 (13.0)
Giannis Antetokounmpo	3,452,979	-1.9 (-1.3)	18.3 (12.4)
Stephen Curry	3,120,266	26.2 (7.8)*	37.7 (11.2)
Kyrie Irving	3,026,300	5 (2.5)	22.1 (10.9)
Kevin Durant	2,694,527	4 (1.2)	32.6 (9.7)
James Harden	2,196,159	-0.4 (-0.2)	13.2 (7.9)
Kawhi Leonard	2,161,185	-2.4 (-1.3)	14.0 (7.8)
Joel Embiid	2,034,710	8.5 (5.1)	12.0 (7.3)
Paul George	2,001,817	11.4 (7.0)*	11.8 (7.2)
Manu Ginóbili	1,808,860[y]	5.8 (3.7)	10.1 (6.5)
Anthony Davis	1,804,479	3.9 (4.1)*	6.2 (6.5)
Derrick Rose	1,761,379	-0.2 (-0.2)	7.0 (6.3)
Dwyane Wade	1,412,935	25.1 (16.0)*	8.0 (5.1)
Draymond Green	1,047,120	0.9 (0.3)	12.7 (3.8)
DeMar DeRozan	1,019,329	-9.3 (-5.2)	6.6 (3.7)
DeMarcus Cousins	806,996	1.8 (1.9)	2.8 (2.9)
Kemba Walker	747,981	22.7 (22.5)*	2.7 (2.7)
Dirk Nowitzki	246,708	19.8 (14.2)*	1.2 (0.9)

Note: These estimates represent the average estimated game-level ticket price impacts of each player based on the difference-in-differences (DID) and panel estimations. For the DID estimates, this is a representation of the results in the Figure 5. A * indicates a statistically significant result at the 5% level, and a negative number indicates the player's absence has a positive impact on ticket prices (although there are no such statistically significant impacts). The panel estimates are taken from Table 2, which generates estimates using log-log specifications, so the game-level impacts are determined using the player-specific % total of the average cumulative number of All-Star votes present for all players in games featuring the given player's team and the average listing price for games featuring the given player's team. All-Star Votes is the average number of fan votes received from the 2017-18 and 2018-19 seasons. 95% confidence intervals are reported in Figure 5 for the DID estimates and Table 2 for the panel estimates.

[x] Only represents the 2018-19 fan vote total. Luka Dončić was a rookie during the 2018-19 season.

[y] Only represents the 2017-18 fan vote total. Manu Ginóbili retired after the 2017-18 season.

VII Concluding Remarks

This paper measures the economic value of superstars to spectators. I estimate flexible panel as well as DID and event study models using ticket price and TV viewership data, as well as plausibly exogenous player absence announcements, to examine spectator WTP to watch superstar players perform. In particular, I examine two primary characteristics of a superstar athlete: popularity with fans and on-court productivity. The results suggest that a 1% increase in the aggregate popularity of a game increases ticket prices and TV viewership by approximately 0.13-0.14%, while increases in player productivity have no significant impact. In the DID and event study analyses, I find that absences of several superstars do have statistically significant and economically meaningful impacts, ranging from a 4-22% ($4-$41) reduction in average ticket prices. Additionally, I examine the differential in superstar absence effects for home vs. away games, finding that the most popular players, like LeBron James and Stephen Curry, exhibit much larger away game absence effects; prices fall an average of $73/ticket for James' absences and $50/ticket for Curry's absences.

This paper provides a novel methodology and framework to causally estimate the economic value of superstars, particularly in the context of sports and entertainment. The findings explicitly connect the theory of superstars to player value. In particular, the analysis delivers important insights on superstar marketability outside of competition, including their relative value in sponsorships and other advertising arrangements. It is the first study to provide quantifiable, plausibly causal evidence that there are significant reductions in WTP for events when superstars are absent. It also emphasizes heterogeneity in the financial importance of superstar allure for different types of franchises, especially those experiencing low ticket sell-out rates. Furthermore, it suggests franchises may experience significant financial returns to investing in popular players that do not necessarily have substantial impacts on team performance.

Future work should aim to expand on the scope of superstar impacts, including examining other leagues, entertainment and arts sectors, and other economically important sectors by using dynamic pricing and other mechanisms that allow the use of high-quality exogenous variation to estimate well-identified impacts. Within sports specifically, there are interesting opportunities to examine different behavioral responses in secondary ticket marketplaces based on the timing of superstar absence announcements and the estimated duration of a player's absence. One potential expansion is to study the impact of long-term injuries on ticket prices. In particular, do ticket prices for near-term games associated with a long-term absence announcement adjust differently than games further in the future? This may provide insight into the time horizon with which sellers and buyers process information and adjust selling or purchasing behavior.

In a similar vein, what is the impact of uncertainty associated with some players' timelines in returning from injury or rest on ticket prices for future, potentially impacted games? Each of these scenarios may impact how consumers respond, and provide insight into consumer time preferences and behavior under uncertainty.

VIII Acknowledgments

I would like to thank Vaibhav Ramamoorthy, Cheenar Gupte, and Amit Sagar for excellent research assistance, and to the Undergraduate Research Apprenticeship Program (URAP) at UC Berkeley for providing a mechanism to support undergraduate research. Thanks to Deepak Premkumar, Jim Sallee, Sofia Villas-Boas, Joshua Wilbur, Hal Gordon, and David Zilberman for thoughtful comments. Special thanks to participants at the *2019 MIT Sloan Sports Analytics Conference* for useful comments and conversations. Finally, I would like to thank editor Rob Simmons and two anonymous referees for useful comments and suggestions. All remaining errors are my own.

References

Adgate, B. (2018). Why the 2017-18 season was great for the NBA. *Forbes*. link here, (last accessed 2018-11-21).

Adler, M. (1985). Stardom and talent. *The American economic review 75*(1), 208–212.

Athey, S. and J. Levin (2001). Information and competition in us forest service timber auctions. *Journal of Political economy 109*(2), 375–417.

Babington, M., S. J. Goerg, and C. Kitchens (2020). Do tournaments with superstars encourage or discourage competition? *Journal of Sports Economics 21*(1), 44–63.

Badenhausen, K. and M. Ozanian (2019). NBA valuations. *Forbes*. link here, (last accessed 2020-01-30).

Berri, D. J. and M. B. Schmidt (2006). On the road with the National Basketball Association's superstar externality. *Journal of Sports Economics 7*(4), 347–358.

Berri, D. J., M. B. Schmidt, and S. L. Brook (2004). Stars at the gate: The impact of star power on nba gate revenues. *Journal of Sports Economics 5*(1), 33–50.

Blake, T., S. Moshary, K. Sweeney, and S. Tadelis (2018). Price salience and product choice. *NBER Working Paper* (w25186).

Brady, R. R. and M. A. Insler (2019). Order of play advantage in sequential tournaments: Evidence from randomized settings in professional golf. *Journal of Behavioral and Experimental Economics 79*, 79–92.

Brandes, L., E. Franck, and S. Nüesch (2008). Local heroes and superstars: An empirical analysis of star attraction in german soccer. *Journal of Sports Economics 9*(3), 266–286.

Brown, J. (2011). Quitters never win: The (adverse) incentive effects of competing with superstars. *Journal of Political Economy 119*(5), 982–1013.

Bryson, A., B. Frick, and R. Simmons (2013). The returns to scarce talent: Footedness and player remuneration in european soccer. *Journal of Sports Economics 14*(6), 606–628.

Bryson, A., G. Rossi, and R. Simmons (2014). The migrant wage premium in professional football: a superstar effect? *Kyklos 67*(1), 12–28.

Buraimo, B. and R. Simmons (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.

Busse, M. R., C. R. Knittel, and F. Zettelmeyer (2013). Are consumers myopic? Evidence from new and used car purchases. *American Economic Review 103*(1), 220–56.

Card, D. and G. Dahl (2009). Family violence and football: The effect of unexpected emotional cues on violent behavior. Technical report, National Bureau of Economic Research.

Chay, K. Y. and M. Greenstone (2005). Does air quality matter? Evidence from the housing market. *Journal of political Economy 113*(2), 376–424.

Chung, K. Y., T. P. Derdenger, and K. Srinivasan (2013). Economic value of celebrity endorsements: Tiger woods' impact on sales of nike golf balls. *Marketing Science 32*(2), 271–293.

Clarke, K. (2016). The gains from dynamic pricing for ticket resellers. *PhD Dissertation, University of Minnesota Department of Applied Economics*.

Cleveland, W. S. (1979). Robust locally weighted regression and smoothing scatterplots. *Journal of the American statistical association 74*(368), 829–836.

Coates, D., B. R. Humphreys, and L. Zhou (2014). Reference-dependent preferences, loss aversion, and live game attendance. *Economic Inquiry 52*(3), 959–973.

Courty, P. (2003a). Some economics of ticket resale. *Journal of Economic Perspectives 17*(2), 85–97.

Courty, P. (2003b). Ticket pricing under demand uncertainty. *The Journal of Law and Economics 46*(2), 627–652.

Courty, P. and L. Davey (2020). The impact of variable pricing, dynamic pricing, and sponsored secondary markets in major league baseball. *Journal of Sports Economics 21*(2), 115–138.

Currie, J. and R. Walker (2011). Traffic congestion and infant health: Evidence from e-zpass. *American Economic Journal: Applied Economics 3*(1), 65–90.

Franck, E. and S. Nüesch (2012). Talent and/or popularity: what does it take to be a superstar? *Economic Inquiry 50*(1), 202–216.

Grimshaw, S. D. and J. S. Larson (2021). Effect of star power on nba all-star game tv audience. *Journal of Sports Economics 22*(2), 139–163.

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

Heindl, K. (2018). Free agency in the new player narrative driven NBA. *RealGM*. link here, (last accessed 2018-11-21).

Humphreys, B. R. and C. Johnson (2020). The effect of superstars on game attendance: Evidence from the nba. *Journal of Sports Economics 21*(2), 152–175.

Jane, W.-J. (2016). The effect of star quality on attendance demand: The case of the National Basketball Association. *Journal of Sports Economics 17*(4), 396–417.

Jiaqi Xu, J., P. S. Fader, and S. Veeraraghavan (2019). Designing and evaluating dynamic pricing policies for major league baseball tickets. *Manufacturing & Service Operations Management 21*(1), 121–138.

Johnson, C. and E. Minuci (2020). Wage discrimination in the nba: Evidence using free agent signings. *Southern Economic Journal 87*(2), 517–539.

Kahn, L. M. (2000). The sports business as a labor market laboratory. *Journal of Economic Perspectives 14*(3), 75–94.

Knox, B. (2012). Breaking down why the NBA will always be a star-driven league. *Bleacher Report*. link here, (last accessed 2018-11-21).

Kőszegi, B. and M. Rabin (2006). A model of reference-dependent preferences. *The Quarterly Journal of Economics 121*(4), 1133–1165.

Krueger, A. B. (2005). The economics of real superstars: The market for rock concerts in the material world. *Journal of Labor Economics 23*(1), 1–30.

Kurlantzick, L. S. (1982). Thoughts on professional sports and the antitrust laws: Los angeles memorial coliseum commission v. national football league. *Conn. L. Rev. 15*, 183.

Lackner, M. (2016). Teams as superstars: Effort and risk taking in rank-order tournaments for women and men. Technical report, Working Paper.

Lawson, R. A., K. Sheehan, and E. F. Stephenson (2008). Vend it like beckham: David beckham's effect on mls ticket sales. *International Journal of Sport Finance 3*(4).

Lehmann, E. E. and G. G. Schulze (2008). What does it take to be a star?-the role of performance and the media for german soccer players. *Applied Economics Quarterly 54*(1), 59.

Levin, Y., J. McGill, and M. Nediak (2009). Dynamic pricing in the presence of strategic consumers and oligopolistic competition. *Management science 55*(1), 32–46.

Luttik, J. (2000). The value of trees, water and open space as reflected by house prices in the Netherlands. *Landscape and urban planning 48*(3-4), 161–167.

MacDonald, G. M. (1988). The economics of rising stars. *The American Economic Review*, 155–166.

Mason, D. S. (1999). What is the sports product and who buys it? the marketing of professional sports leagues. *European Journal of Marketing*.

Mills, B. M., S. Salaga, and S. Tainsky (2016). Nba primary market ticket consumers: Ex ante expectations and consumer market origination. *Journal of Sport Management 30*(5), 538–552.

Morris, D. (2018). NFL vs. NBA: Which will be America's biggest sport 10 years from now? *Fortune*. link here, (last accessed 2018-11-21).

Moskowitz, T. J. (2015). Asset pricing and sports betting. *Chicago Booth Research Paper* (15-26).

Neale, W. C. (1964). The peculiar economics of professional sports. *The quarterly journal of economics 78*(1), 1–14.

Oskam, J., J.-P. van der Rest, and B. Telkamp (2018). What's mine is yours—but at what price? dynamic pricing behavior as an indicator of airbnb host professionalization. *Journal of Revenue and Pricing Management 17*(5), 311–328.

Rascher, D. A., M. T. Brown, M. S. Nagel, and C. D. McEvoy (2009). Where did national hockey league fans go during the 2004-2005 lockout? an analysis of economic competition between leagues. *International Journal of Sport Management and Marketing 5*(1-2), 183–195.

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of political economy 82*(1), 34–55.

Rosen, S. (1981). The economics of superstars. *The American economic review 71*(5), 845–858.

Rosen, S. and A. Sanderson (2001). Labour markets in professional sports. *The economic journal 111*(469), F47–F68.

Rottenberg, S. (1956). The baseball players' labor market. *Journal of political economy 64*(3), 242–258.

Sallee, J. M., S. E. West, and W. Fan (2016). Do consumers recognize the value of fuel economy? Evidence from used car prices and gasoline price fluctuations. *Journal of Public Economics 135*, 61–73.

Scarfe, R., C. Singleton, and P. Telemo (2021). Extreme wages, performance, and superstars in a market for footballers. *Industrial Relations: A Journal of Economy and Society 60*(1), 84–118.

Scully, G. W. (1974). Pay and performance in major league baseball. *The American Economic Review 64*(6), 915–930.

Sweeting, A. (2012). Dynamic pricing behavior in perishable goods markets: Evidence from secondary markets for major league baseball tickets. *Journal of Political Economy 120*(6), 1133–1172.

Whitehead, T. (2017). NBA teams are resting players earlier and earlier. *FiveThirtyEight*. link here, (last accessed 2018-11-21).

Williams, K. R. et al. (2017). Dynamic airline pricing and seat availability. Technical report, Cowles Foundation for Research in Economics, Yale University.

Yang, Y. and M. Shi (2011). Rise and fall of stars: Investigating the evolution of star status in professional team sports. *International Journal of Research in Marketing 28*(4), 352–366.

Yang, Y., M. Shi, and A. Goldfarb (2009). Estimating the value of brand alliances in professional team sports. *Marketing Science 28*(6), 1095–1111.

Appendix

A Overview of Data

This section provides additional details on the different sources of data used in the analysis.

A.1 Secondary Ticket Marketplace

This data was accessed by routinely querying a REST (Representational State Transfer, a protocol built on-top of the standard web protocols) service provided by the secondary ticket marketplace every 30 minutes (or a total of 48 collections per day) for every remaining NBA game in the season. A REST service is an HTTP-backed protocol that defines a set of rules for querying, updating, adding, and deleting data on a website. The REST protocol is how a website can securely expose its database without giving everyone unlimited control over the data. Each observation is a specific ticket listing for a game collected at a specific time. In particular, I collect the listing price, quantity of tickets available for that listing,[26] time of data collection, and metadata on the corresponding NBA game, which includes home and away teams as well as the date and time of the game.

A summary of relevant variables collected from the secondary ticket marketplace microdata is presented in Table 5. It should be noted that these are the primary summary statistics of the per-game *averages* for the continuous variables (listing price and quantity per listing), and the per-game *counts* for the count variables (number of observations, listing IDs, section IDs, and collection IDs). The data spans 2,330 NBA games, corresponding to 95% of the total number of regular games played over two NBA seasons (2,460).[27] The "Listing Price" refers to the price posted by a seller for a specific listing. The "Quantity per Listing" denotes the number of seats available in a specific listing posted by a seller. The "Listing ID" is a unique listing-specific identifier, the "Collection ID" is a unique identifier corresponding to when the data was collected (i.e. each 30 minute collection gets a unique identifier), and "Section ID" corresponds to the section of the arena the listing is located in. Finally, "Number of Observations" corresponds to

[26] Each ticket within a listing must have the same price.

[27] Reasons for missing data for certain games include server restarts and changes of event-names mid-season on the secondary ticket marketplace that were not automatically identified by the data collection program.

the number of unique listing-by-collection ID data points for each game.

Table 5: Across-Game Ticket Data Summary Statistics (2,330 Total Games)

Data Characteristic	Mean	SD	Min.	Max.
Num. Obs.	37,660.88	26,648.85	70	215,346
Listing Price	$157.12	$107.06	$12.75	$995.01
Quantity per Listing	3.39	0.73	1.92	5.69
Listing IDs	826.80	682.10	28	5,357
Collection IDs	114.31	29.43	4	139
Section IDs	113.30	35.66	18	228

Table 5 shows that there is an average of 114.31 collection times for each game, which corresponds to approximately 57.16 hours prior to each game. There is an average of 826.80 unique listings per game across an average of 113.30 different arena sections. The average per-game listing price is $157.12 with a quantity per listing of 3.39.

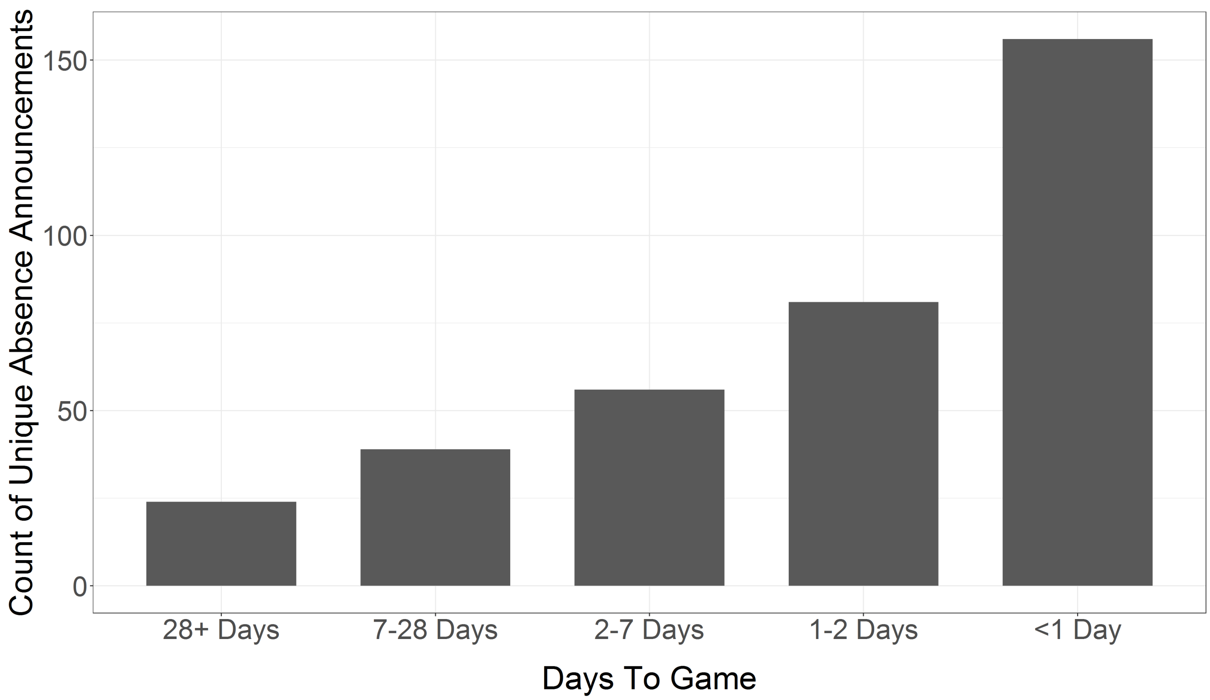
A.2 Absence Announcements

Absence announcements were collected from Rotoworld, a popular fantasy basketball website, which provides detailed injury information and other reports for all players.[28] This website provides regular updates on announcements from teams regarding player absences. Since all announcements are documented and accessible going back several years, I examined announcements pertaining to each qualifying player for the 2017-18 and 2018-19 NBA seasons. Because of the complex nature of many of the announcements and their timing, I manually examine every announcement pertaining to each of these players to determine which corresponded to missed games, and the exact time an announcement was made. When announcements were vague about the expected duration of missed time for a player (for example, if a player was announced to be out for "several weeks"), a very conservative lower bound horizon of the expected number of missed games was used. Once all relevant announcements were classified, I matched the time of announcement applicable to a specific game and player to ticket prices at that time for the relevant game.

[28] On February 9, 2021, Rotoworld rebranded to NBC Sports Edge. All of the announcement content is the same, and can be found here: https://www.nbcsportsedge.com/edge/basketball/nba/player-news.

While Figure 3 presents absence announcements for all qualifying players within the three day window before a game, Figure 11 presents the distribution for the entire time horizon prior to a game in units of days to game. One can see most of the announcements take place quite close to when games are played, but there is a long left-tail of announcements occurring further out. This is due to longer-term and season-ending injuries.

Figure 11: Distribution of All Unique Absence Announcement-by-Game Pairs (for Qualifying Players) by Days to Game



A.3 Game Characteristics and Television Viewership

To perform the panel analysis analyzing ticket prices and TV viewership at the game-level, I rely on a rich dataset of game-specific characteristics collected from several different sources, including `NBA.com`, `fivethirtyeight.com`, and `Basketball Reference`. These characteristics include state variables corresponding to each game (i.e. date and time information, absolute point spread, aggregate number of All-Star votes of all players playing, aggregate value over replacement player of all players playing, average final winning percentage of the two teams, etc.).

A summary of relevant game characteristics data for all NBA games (regular season and playoffs) during the 2017-18 and 2018-19 seasons is presented in Table 6.

Table 6: Game Characteristics Summary Statistics (2,624 Total Games)

Data Characteristic	Mean	SD	Min.	Max.
Aggregate # of All-Star Votes (1,000's)	3,875.82	3,280.69	31.10	18,347.76
Absolute Point Spread	5.88	4.30	0	26
Aggregate Value Over Replacement Player (VORP)	18.72	7.32	−5.00	37.00
Avg. Final Win %	0.50	0.10	0.22	0.76
Aggregate Market Size (1,000's of people)	3,536.48	1,055.93	2,025	7,700
Attendance	18,059.40	1,961.90	10,079.00	22,983.00

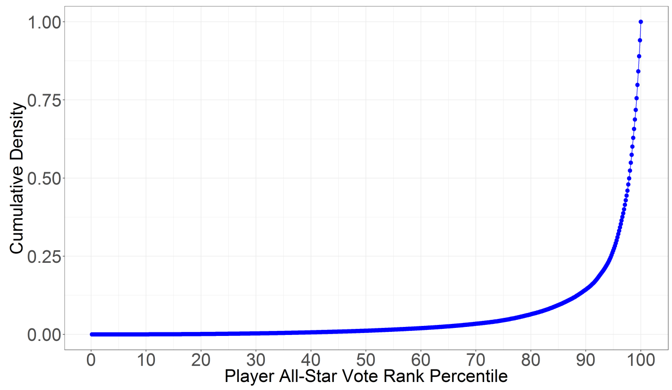
I use television viewership data for all nationally televised games during the 2017-18 and 2018-19 seasons from the Nielsen Company©. The data includes the projected number of total individuals watching across the United States at the start of each game. Table 7 summarizes these same game characteristics as well as the total projected number of viewers from the television viewership data.

Table 7: TV Viewership and Game Characteristics Summary Statistics (477 Total Games)

Data Characteristic	Mean	SD	Min.	Max.
Projected # of Viewers (1,000's)	2,123.20	1,627.52	265	11,151
Aggregate # of All-Star Votes (1,000's)	6,654.05	3,869.99	372	17,035.61
Absolute Point Spread	4.92	3.56	0	18
Aggregate Value Over Replacement Player (VORP)	24.62	5.80	4.80	37.00
Avg. Final Win %	0.60	0.08	0.27	0.75
Aggregate Market Size (1,000's of people)	3,898.67	1,095.59	2,125	7,199

Finally, Figure 12 visually depicts the cumulative distribution of average All-Star fan votes across all 659 eligible players over the 2017-18 and 2018-19 seasons.

Figure 12: Cumulative Distribution of All-Star Votes by Player Rank



B Additional Results

Table 8: Impact of Player Popularity and Productivity on Ticket Prices

	Dependent Variable: log(Avg. Listed Price) (Game-Level)			
log(Aggregate All-Star Votes)	0.2157***	0.2184***	0.1385***	0.1385***
	(0.0221)	(0.0215)	(0.0236)	(0.0178)
log(Aggregate VORP)	−0.0444	−0.0388	0.0858*	0.0858**
	(0.0429)	(0.0427)	(0.0396)	(0.0325)
log(Avg. Current Win PCT)	0.2282**	0.2524**	0.3487***	0.3487***
	(0.0767)	(0.0828)	(0.0856)	(0.0700)
Home Team Favored (HTF)	0.0034	−0.0633*	−0.0212	−0.0212
	(0.0471)	(0.0248)	(0.0197)	(0.0213)
Win Probability Differential (WPD)	0.0008	−0.0018	−0.0038*	−0.0038**
	(0.0007)	(0.0018)	(0.0016)	(0.0013)
HTF*WPD	0.0241	0.0338	−0.0160	−0.0160
	(0.0285)	(0.0317)	(0.0354)	(0.0287)
Num. All-NBA 1st or 2nd Team Players		0.0036	0.0051*	0.0051**
		(0.0025)	(0.0021)	(0.0017)
Month FE	Yes	Yes	Yes	Yes
Time-of-Day FE	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes
Streak FE	Yes	Yes	Yes	Yes
Home Team FE	Yes	Yes	Yes	Yes
Away Team FE	No	No	No	Yes
TV Network FE	Yes	Yes	Yes	Yes
Holiday Indicator	Yes	Yes	Yes	Yes
Clustered Robust SEs (Home Team)	No	Yes	Yes	Yes
Clustered Robust SEs (Home Team-by-Season)	No	No	No	Yes
Observations	2,318	2,318	2,318	2,318
R^2	0.6270	0.6300	0.7121	0.7121

Note: Num. All-NBA 1st or 2nd Team Players refers to the cumulative number of 1st and 2nd team All-NBA selections of players playing in a game. For all other table information, see Table 2. *p<0.05; **p<0.01; ***p<0.001

Table 9: Impact of Player Popularity and Productivity on Start-Time TV Viewership

	Dependent Variable: log(Total Proj. Viewers) (Game-Level)		
	All Games	Regular Season Only	Playoffs Only
log(Aggregate All-Star Votes)	0.1296**	0.1740***	−0.0658
	(0.0427)	(0.0414)	(0.0878)
log(Aggregate VORP)	−0.0792	−0.0331	−0.1328
	(0.1189)	(0.1010)	(0.2299)
log(Avg. Current Win PCT)	0.3057*	0.1247	0.7144***
	(0.1463)	(0.1591)	(0.1942)
Win Probability Differential	−0.0001	−0.0002	0.0010
	(0.0010)	(0.0029)	(0.0016)
log(Aggregate Team Value)	0.1486	0.0873	0.3497
	(0.0925)	(0.0959)	(0.1941)
Num. All-NBA 1st or 2nd Team Players	0.0006	−0.0165	0.0615
	(0.0327)	(0.0447)	(0.0523)
Month FE	Yes	Yes	Yes
Time-of-Day FE	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes
Streak FE	Yes	Yes	Yes
TV Network FE	Yes	Yes	Yes
Double Header FE	Yes	Yes	Yes
Holiday Indicator	Yes	Yes	Yes
Playoff Indicator	Yes	No	No
Clustered Robust SEs (Home + Away)	Yes	Yes	Yes
Dependent Variable Mean (thousands)	2123.2	1513.22	3479.16
Observations	477	329	148
R^2	0.7449	0.6499	0.7105

Note: Num. All-NBA 1st or 2nd Team Players refers to the cumulative number of 1st and 2nd team All-NBA selections of players playing in a game. For all other table information, see Table 3. *p<0.05; **p<0.01; ***p<0.001

Figure 13: Difference-in-Differences Results by All-Star Votes

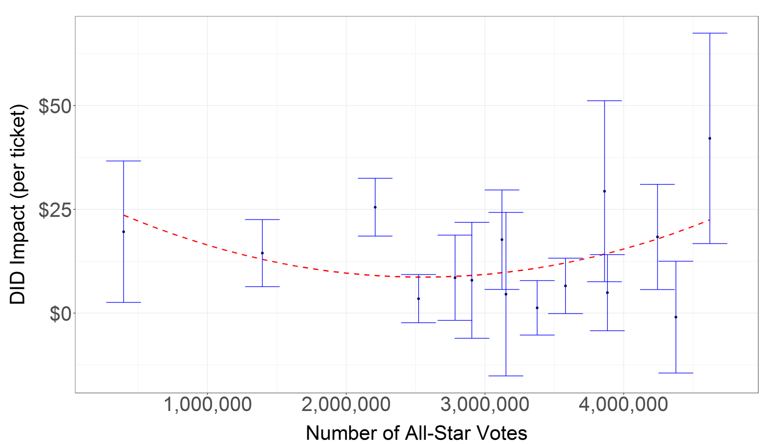


Figure 14: Difference-in-Differences Results by Home vs. Away Game Absences (in %)

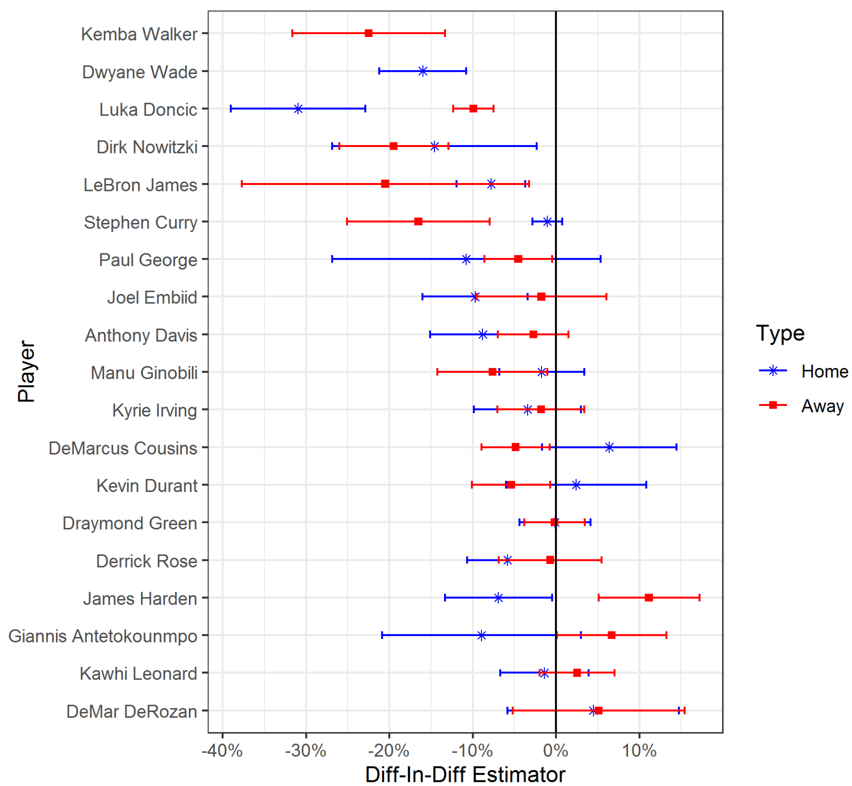
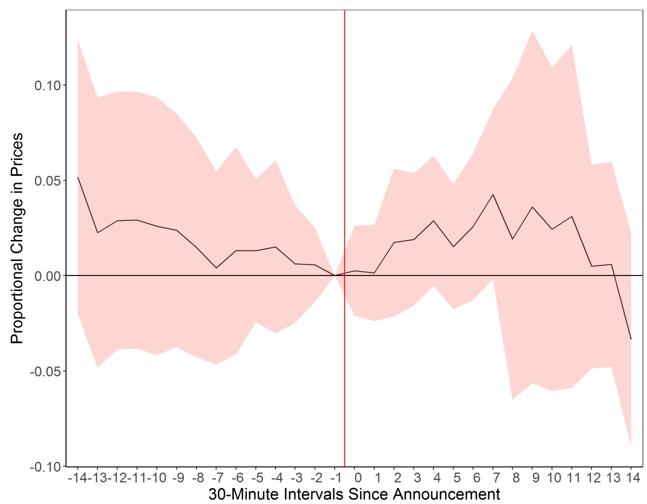
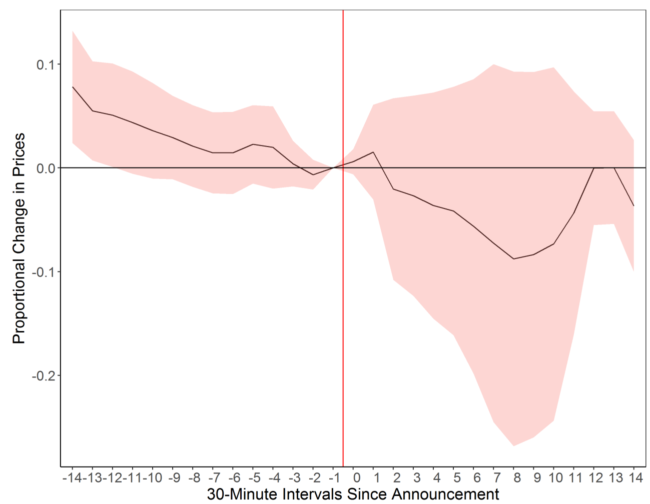


Figure 15: Event Study Results for Other Superstars

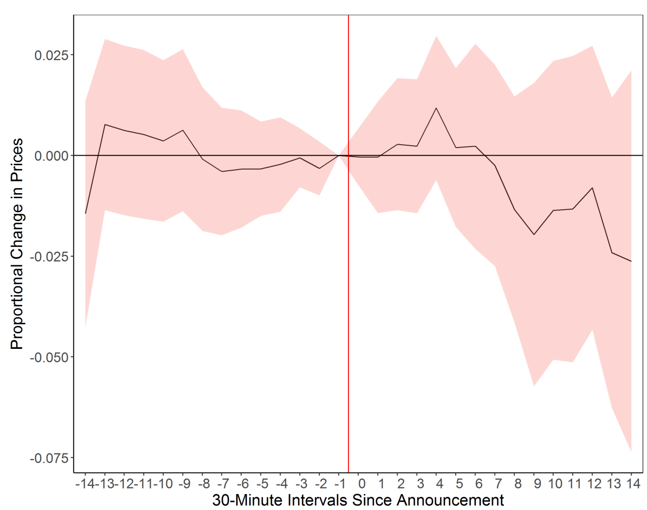
(a) Event Study for Paul George



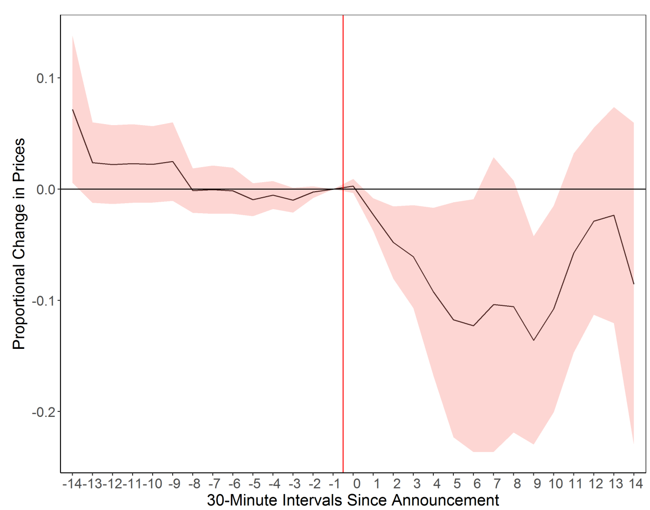
(b) Event Study for Luka Dončić



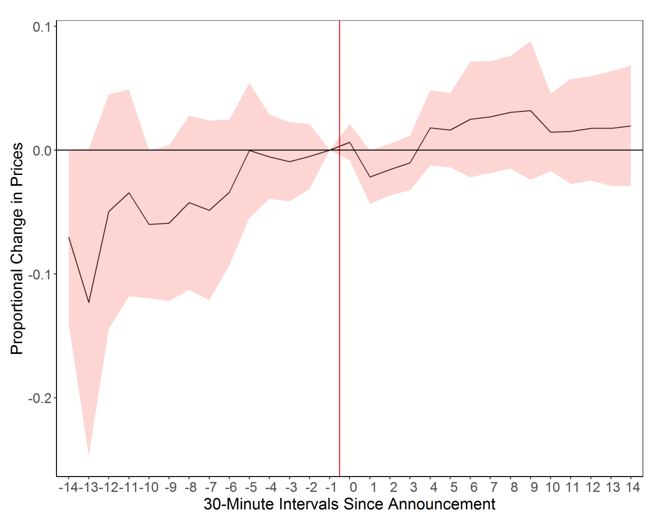
(c) Event Study for Kyrie Irving



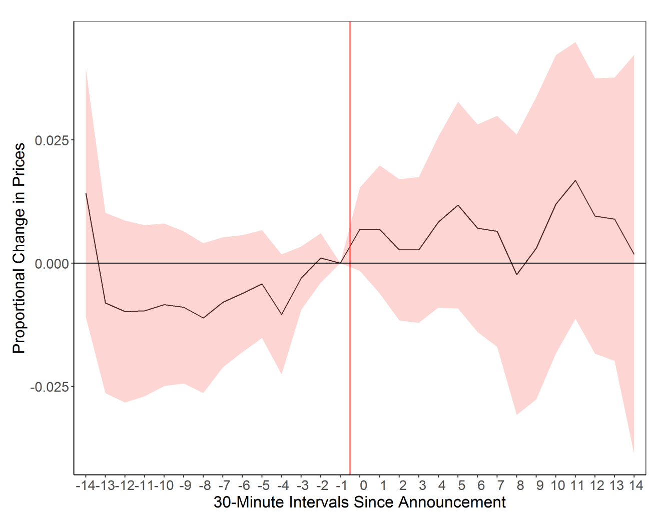
(d) Event Study for Kemba Walker



(e) Event Study for DeMar DeRozan

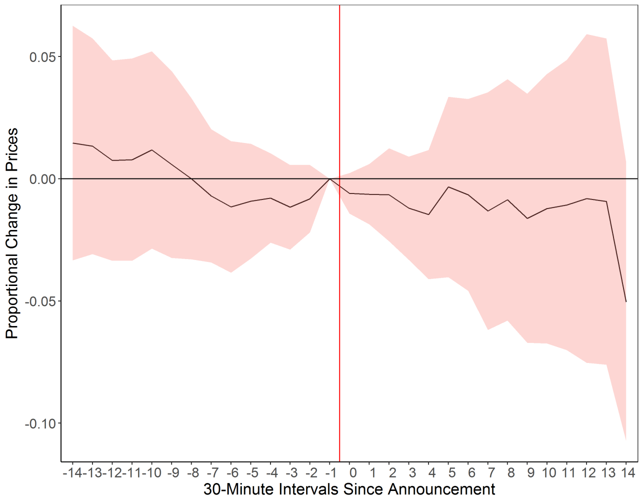


(f) Event Study for Draymond Green

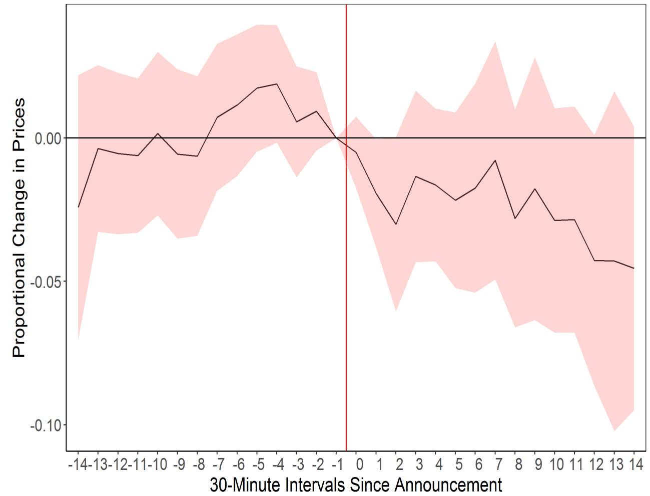


Event Study Results for Other Superstars (Cont'd.)

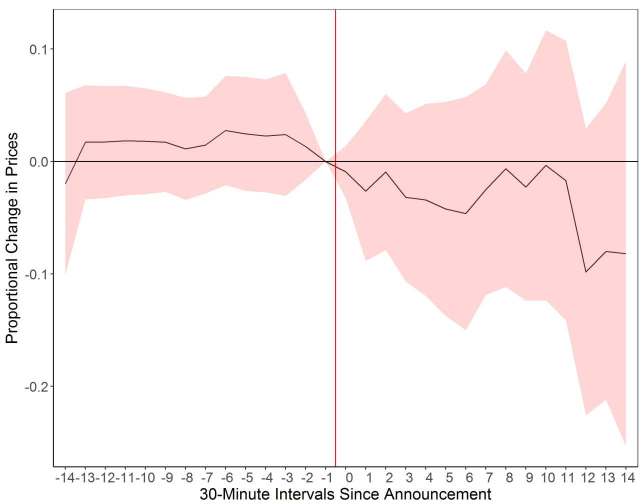
(g) Event Study for Joel Embiid



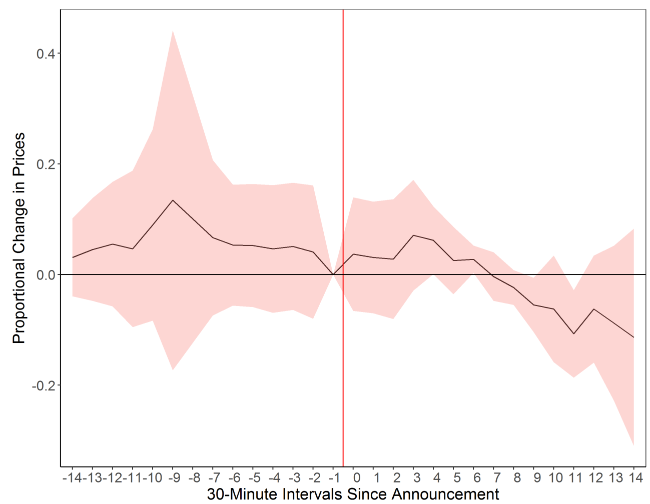
(h) Event Study for Kawhi Leonard



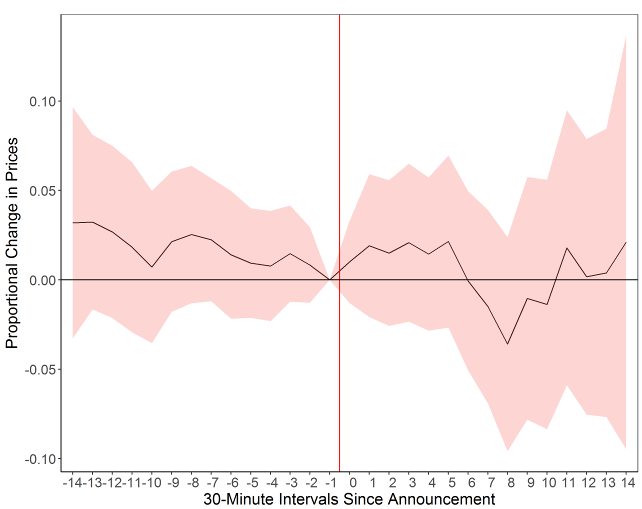
(i) Event Study for Giannis Antetokounmpo



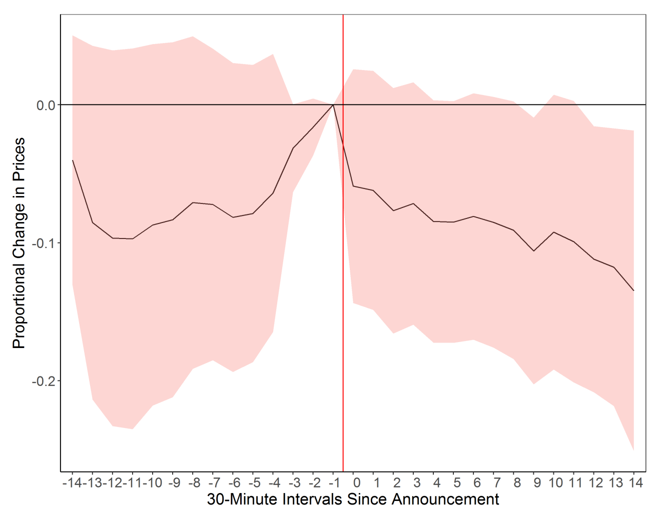
(j) Event Study for Dirk Nowitzki



(k) Event Study for Derrick Rose

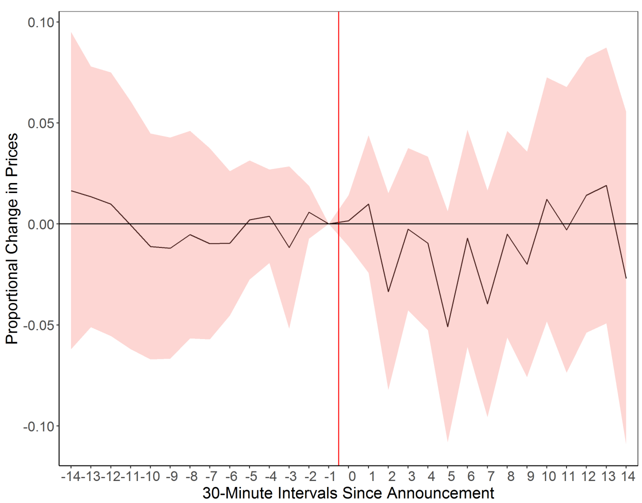


(l) Event Study for Anthony Davis



Event Study Results for Other Superstars (Cont'd.)

(m) Event Study for Manu Ginóbili



(n) Event Study for DeMarcus Cousins