The Economic Value of Superstars: Evidence from Secondary Marketplace and Television Ratings Data from the National Basketball Association*

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January 23, 2020

Abstract

The National Basketball Association (NBA) is widely regarded as a "superstar-driven league." However, superstars may be forced to miss games due to injury or "load managed" (purposefully rested) by teams. A superstar's absence has detrimental effects on the quality of games, especially with respect to the fan experience. Our paper aims to empirically estimate the willingness-to-pay for NBA superstars, and, in particular, distinguish between a players competitive value (skill) versus their popularity in driving this willingness-to-pay. Our empirical approach is two-fold, and relies on data from the 2017-18 and 2018-19 NBA seasons. First, we combine ticket price data for every regular season game and initial TV ratings for all nationally televised games with a rich set of game characteristics to estimate the impact of superstar popularity and skill on consumer willingness-to-pay and watch. We find that a 1% increase in the aggregate "popularity" of a matchup (as measured by the cumulative number of All-Star votes of all players playing in a matchup) leads to a statistically significant 0.10-0.21% increase in ticket prices and TV ratings, while the aggregate "skill" in a matchup (as measured by cumulative player-efficiency rating of all players playing in a matchup) has no impact on prices or ratings. Next, using high temporal frequency microdata collected from an online secondary ticket marketplace and the exact timing of player absence announcements, we determine the within-matchup reduction in willingness-to-pay associated with a superstar absence for an NBA game attendee. We find the absences of several superstars, including some of the most popular like LeBron James and Stephen Curry, lead to a statistically significant and economically meaningful reduction in prices, ranging from 4-16% ($7-$42). We also find much larger impacts for James and Curry for away game absences–21% ($75) per ticket for LeBron and 18% ($55) per ticket for Curry. These findings have significant ramifications for the NBA, individual franchises, and ticket companies, including policies on resting players, franchise decision-making about dynamic pricing schemes, and compensation schemes for fans when superstars are "load managed."

Keywords: superstar, National Basketball Association, ticket prices, TV ratings, difference-in-differences, event study

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*I would like to thank Vaibhav Ramamoorthy, Cheenar Gupte, and Amit Sagar for excellent research assistance. Thanks to Deepak Premkumar, Jim Sallee, Sofia Villas-Boas, Joshua Wilbur, Hal Gordon, and David Zilberman for insightful conversations and thoughtful comments. Special thanks to participants at the *2019 MIT Sloan Sports Analytics Conference* for useful comments and conversations. All remaining errors are my own.

I Introduction

The National Basketball Association (NBA) has exploded in popularity over the last several years (Morris 2018; Adgate 2018). More than other sports, the NBA's surge in popularity can be largely attributed to the fame and skill of its top players, including LeBron James and Stephen Curry, and has often been labeled a "superstar-driven league" (Knox 2012; Heindl 2018). Because of this, fan viewership and the entertainment value associated with the NBA product is strongly tied to fans' desire to watch superstars play. Therefore, when it is announced that a star player will miss a game (either through an injury sustained, purposeful rest, suspension, etc.), there may be significant reductions in welfare associated with attending that game. This has been an especially relevant point of discussion with respect to the NBA, since player 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). This paper leverages recent advances in data availability as well as rigorous econometric methods in an attempt to provide a quantitative measure of fan willingness-to-pay to watch NBA superstars play.

What is a "superstar" player? Superstars are not necessarily the "best" players from a statistical standpoint – they are defined as much by their skill as they are by their popularity (Adler 1985). To encapsulate both of these factors in our analysis, and attempt to distinguish between them, we analyze all players who made the NBA All-Star Team at least once across the 2017-18 and 2018-19 seasons (primarily focusing on All-Star starters), which is a similar approach taken by other notable studies (Berri and Schmidt 2006; Jane 2016). The list of players making the All-Star Team provides a great comparison of popularity and skill – 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%), while the bench players are selected through a vote by coaches from each respective conference (NBA-AllStar.com 2018). Of course, there are other metrics that may be useful to rank player popularity and skill; jersey sales for each player may indicate their relative popularity, and a players "efficiency rating" (PER) may indicate their skill. We use the All-Star criteria as a cutoff to determine which players to analyze, as it has been used in previous studies and incorporates notions of both popularity and skill.[1] One of the primary goals of this paper is to isolate independent variation in popularity and skill across superstars, so that we can compare their relative impacts on a player's economic value.

This paper attempts to answer a set of research questions focusing on the value of superstars to leagues as a whole. First, what is the overall premium in terms of TV viewership and ticket prices associated with watching superstar players? 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 has significant ramifications for NBA policies on resting players (as well as compensation schemes for fans in such cases) and announcement timing of player absences, team decision-making with respect to signing free agents, drafting players, trading players, and scheduling promotional events, as well as implications for whether or not teams choose to engage in dynamic pricing on their primary ticket marketplaces. Additionally, it may inform NBA national TV scheduling prior to the season, and the impact of "flexing" a national TV game between one where a superstar may be absent to a different game with superstars present.

We take a two-fold approach to estimate the economic value of superstars, using data from the 2017-18 and 2018-19 NBA seasons. First, we estimate panel fixed-effect regressions at the matchup-level, finding that a 1% increase in the popularity effect of a matchup (as measured by

[1] Along with all players selected to the 2017-18 and 2018-19 All-Star teams, we also include players that would have made the All-Star team had the fan vote counted 100%. This includes Manu Ginobili, Luka Doncic, and Derrick Rose. We also include Dwyane Wade and Dirk Nowitzki, who were additions to the 2018-19 All-Star team made by Commissioner Adam Silver.

the cumulative number of All-Star votes of all players playing) leads to a 0.10-0.21% increase in ticket prices and TV ratings, while parity (as measured by the absolute point spread) and cumulative player skill (as measured by cumulative PER) have no statistically significant impact on TV ratings and ticket prices. These results provide evidence that the superstar allure for fans is primarily associated with a "popularity" effect, not a skill or competitiveness effect (i.e. a superstars presence changes the expected win probability of each team in the matchup).

The next component of our analysis focuses on plausibly exogenous variation, relying on within-matchup, temporal variation in ticket prices. Using difference-in-differences (DID) and event-study methodologies, we examine ticket price impacts when superstar players are announced out of specific matchups. Here, we find economically meaningful and statistically significant price declines for the most popular stars, including LeBron James, Stephen Curry, and Dwyane Wade, among others, ranging from a 4-16% ($7-$42) reduction in the average ticket price for those matchups. In addition, we analyze absences in home vs. away games, finding that the away effects for LeBron James and Stephen Curry are even larger, at 21% ($75) per ticket for LeBron and 18% ($55) 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 ratings, and these impacts are on the order of 4-25%. From ticket sales alone, there are hundreds of thousands of dollars in welfare lost for each of these matchups, and millions of dollars lost across all superstar absences over the course of a season. Aggregate losses are likely to be substantially higher when considering similar declines in TV ratings.

The paper will proceed as follows. First, we present a review of relevant fields of literature this paper contributes to. Second, we discuss our data collection strategy and present relevant summary statistics. The third section overviews our empirical strategy and assumptions for identification, and the fourth section showcases our results. Finally, the paper concludes.

II Literature Review

This work falls into several important strains of literature. First, there has been a large amount of research in hedonic pricing, which attempts to value specific, nonmarket attributes of goods. Second, it contributes to the literature on dynamic pricing and strategic interactions among buyers and sellers in secondary ticket marketplaces. Finally, several academic papers have examined the impact of superstars in different labor contexts, including sports, suggesting that quality and popularity of players are important factors for spectators. These papers examine superstar athlete impacts on a variety of metrics, including attendance, player salaries, and broadcast audiences. We extend all of this literature by (1) estimating consumer willingness-to-pay to watch superstars by looking at ticket price movements in a secondary ticket marketplace and supporting this analysis with TV ratings, (2) testing heterogeneous, matchup-specific factors that may impact the loss in value associated with a superstar absence, 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. Additionally, 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 salaries of players. Our paper contributes to this literature by being the first to look at a hedonic component of event ticket values, namely the marginal contribution of a superstar player to the value of attending an NBA game. Additionally, compared to hedonic papers written to date, this paper is able to utilize rich microdata with substantial variation in potentially confounding factors (e.g. competitiveness of opponents, market size, etc.) and perform a well-identified, plausibly exogenous estimation of the economic value of players.

B Dynamic Pricing in Secondary Ticket Marketplaces

The second relevant strand of literature includes work on pricing in secondary marketplaces, including event tickets, hotels and home-sharing (e.g. AirBnB), and airline tickets (Jiaqi Xu et al. 2019; Williams 2018; Sweeting 2012; Levin et al. 2009; Oskam et al. 2018). Early research on dynamic pricing in these marketplaces borrowed from the literature on airline ticket pricing, suggesting that 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). Our research 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 (i.e. their value for watching a specific superstar play).

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 develops a game-theoretic framework to discuss the dynamics of buyer-seller interactions on secondary marketplaces as a matchup gets closer. Similar to our research, Sweeting (2012) finds that much of the buying and selling activity in marketplaces, including price adjustments, occurs in the few days before an event. A different paper 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 (Clarke 2016). Most notably, this work 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, if we do observe negative price effects associated with the announcement of a superstar absence, it may reflect a lower bound (in absolute value terms). This is 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"

Understanding the interest in and impact of superstars began with Rosen (1981), and was later expanded upon in Rosen and Sanderson (2001), which developed a model to explain how certain talented individuals in a specific occupation are able to differentiate themselves from the rest of the pool of individuals, and obtain differentially higher salaries as a result. Interestingly, the model suggests that firm revenues have increasing marginal returns to talent, and the attraction of a superstar can have large implications for firm profits. An expansion of this work attempts to differentiate between the "popularity" and "skill" 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). Our work synthesizes nicely with these findings, finding that (i) there is an economically meaningful and statistically significant impact of the presence of superstars on demand for a sporting event, and (ii) superstar popularity is a more meaningful factor in ticket price and TV ratings adjustments than the skill level of each superstar.

Other papers have examined superstar effects in the context of sports, primarily using attendance (quantity) metrics. There have been several studies looking at soccer, finding increases in attendance when superstars are present in Italian soccer (Lucifora and Simmons 2003), the MLS (Lawson et al. 2008), and German soccer (Brandes et al. 2008). In the context of the NBA, Jane (2016) finds a much larger impact on game attendance for "popular players" (those that received All-Star votes) than for "skill players" (those that were ranked the highest in the top statistical performance categories). The first empirical paper to analyze the effect of superstar players in the NBA looked at their effects on attendance and television viewership (Hausman and Leonard 1997). 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. A different paper conducted a more comprehensive analysis by estimating the marginal effect of one additional All-Star vote on increases in away-game attendance, finding that for top All-Star vote-getters this can lead to thousands of additional tickets sold annually in away arenas (Berri and Schmidt 2006). Most recently, researchers conducted a comprehensive analysis examining the effect of superstars on attendance at both home and away games, using attendance data for every NBA game from 1981-2014, finding that there is significantly higher attendance at both home and away games when a superstar player is present (Humphreys and Johnson 2017). Again, our paper expands on previous analysis, which has largely focused on analyzing quantity metrics like attendance and viewership, by targeting plausibly exogenous price changes using rich high frequency data. With this data, we can estimate reductions in willingness-to-pay associated with superstar absences, as well as examine heterogeneous impacts depending on other characteristics of the matchup.

III Overview of Data Collection and Characteristics

This project leverages unique, high temporal frequency microdata from a secondary ticket marketplace, as well as data on exact timing of injury announcements for different players. Additionally, we supplement the analysis with television ratings data from The Nielsen Company©.[2] This section (i) describes our data collection and organization methodology for each source of data, and (ii) presents high-level summary statistics.

A Overview of Data

A.1 Secondary Ticket Marketplace

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

We accessed this data 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 matchup in the season.[3] For each ticket listing, we collected metadata on the NBA game

[2]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.

[3]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.

itself (e.g. home and away teams as well as date and time of matchup), data on the listing characteristics (listing price, quantity available, and a listing identifier), and identifiers for the time of data collection. With this data, we had adequate snapshots for observing price changes at relatively fine time granularity before and after superstar absence announcements.

The analysis presented in this paper relies on a sample of ticket prices within 3 days of a matchup, primarily due to computational purposes and because this is when the majority of superstar absence announcements occur. Additionally, ticket buyers and sellers may exhibit different types of responses (in terms of timing) depending on the amount of time between the announcement and the affected game. Announcements impacting games in this three-day window are likely to exhibit more immediate changes, and thus make for clearer analysis of price impacts.

A.2 Absence Announcements

We utilize a popular fantasy basketball website to access injury and other reports for all players. This website provides regular updates on announcements from teams regarding player absences. Since all announcements are documented and accessible going back several years, we examined announcements pertaining to each All-Star player for the 2017-18 and 2018-19 NBA seasons. Because of the complex nature of many of the announcements and their timing, we manually combed through every announcement pertaining to each of these players to determine which corresponded to missed games, and the exact time the 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”), we took a very conservative lower bound horizon of the expected number of missed games. Once all relevant announcements were classified, we were able to match time of announcement applicable to a specific game to ticket prices at that time for the relevant game.

A.3 Television Ratings

We supplement the analysis examining ticket price drops associated with superstar absence announcements with television ratings data for all nationally televised games during the 2017-18 and 2018-19 seasons from A.C. Nielsen. There are two different metrics we examine: (i) percent of all applicable households watching, and (ii) projected number of total households watching. While we have data on TV ratings in 15-minute intervals for each game, superstar absence announcements occur before a game and thus we do not observe "real-time" TV ratings drops associated with such announcements. Thus, we use this data, as well as the ticket price data (at a more aggregated level), to observe the impact of aggregate superstar influence of a game (as measured by the cumulative number of all-star votes across all players suiting up for a game) on initial TV ratings and ticket prices.

A.4 Game Characteristics

In order to perform the panel analysis analyzing ticket prices and TV ratings at the matchup-level, we collect a rich dataset of matchup-specific characteristics from several different sources, including `NBA.com`, `fivethirtyeight.com`, and `Basketball Reference`. These characteristics include state variables corresponding to each matchup (i.e. date and time information, absolute point spread, aggregate number of All-Star votes of all players playing, aggregate player-efficiency rating of all players playing, average winning percentage of the two teams, etc.). Section B.3 lays out the set of covariates included and provides relevant summary statistics.

B Summary Statistics

B.1 Secondary Ticket Marketplace Data

A summary of relevant variables collected from the secondary ticket marketplace microdata is presented in Table 1 below. 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). We have data from 2,330 NBA matchups, corresponding to 95% of the total number of regular games played over two NBA seasons (2,460).[4] 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 the number of unique listing-by-collection ID data points for each matchup.

[TABLE 1 HERE]

Table 1 shows that there is an average of 114.31 collection times for each matchup, which corresponds to approximately 57.16 hours prior to each matchup. We observe an average of 826.80 unique listings per matchup across an average of 113.30 different arena sections. The average per-matchup listing price is $157.12 with a quantity per listing of 3.39.

Because of the high temporal frequency of our microdata, we can observe the time trends of average listing price and quantity of tickets posted to a secondary marketplace for each

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

matchup. Figure 1 below 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 matchup, and how this evolves as the matchup approaches. The second pane presents the average number of tickets *added* (i.e. posted by sellers) to the marketplace per matchup as the game approaches, and the third pane the average number of tickets *sold* on the marketplace per matchup as the game approaches. It should be noted that I assume the disappearance of a listing on the marketplace 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 matchup declines as the matchup approaches. This is intuitive, as these tickets represent a "perishable good" and have no value once a matchup 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 1 HERE]

Additionally, Figure 2 plots the average listing price across all matchups by hours to game. One can see that there is generally a downward trend in prices as a matchup approaches, decreasing from around \$145/ticket two days before a matchup to around \$100/ticket just before game-time. One can also see that the volatility in prices substantially increases as game-time approaches. This can be attributed to an increase in activity on the marketplace – there are matchups where sellers may be trying to get rid of tickets and continuing to lower prices, and other matchups where buyers are trying to obtain tickets, causing remaining sellers to

[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).

increase their prices. In both situations, agents are entering and exiting the marketplace at a much higher frequency in the 7.5 or so hours before a matchup.

[FIGURE 2 HERE]

B.2 Player Absence Announcements

The second strain of the collected data is the timing of player absence announcements. Figure 3 presents the distribution of announcements for all analyzed (starting-caliber) All-Star players across the 2017-18 and 2018-19 NBA seasons in terms of hours to game. In the case of announcements corresponding to multiple games, we only include observations corresponding to announcements within three days of a game to maintain consistency with our chosen time window.[6] In the histogram in Figure 3 below, there are 192 announcement-matchup pairs falling within three days of a matchup.

[FIGURE 3 HERE]

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 we need 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, 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

[6] Table 2 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 our analysis.

fall during the middle of the night. Rarely do announcements for a player absence for a specific matchup occur more than 36 hours prior to a game.[7]

Table 2 below presents the names of each starting All-Star player (or players that would have been voted a starter had the fan vote counted for 100%), how many "qualifying" games they missed (i.e. an explicit announcement for a matchup indicating the exogenous nature of a players 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 our analysis on ticket price changes.

[TABLE 2 HERE]

For each listed player, we are 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 the matchup, "too far" from a matchup (since we only analyze announcements within three days of the corresponding matchup), missing ticket price data as a result of event-name changes on the secondary marketplace, or if another superstar was announced as out for that qualifying game as well.

B.3 Matchup Characteristics and Television Ratings

A summary of relevant variables from the game characteristics data, which was collected from `NBA.com`, `fivethirtyeight.com`, and `Basketball Reference` for all NBA games (regular season and playoffs) during the 2017-18 and 2018-19 NBA seasons, is presented in Table 3. One can see that the average number of cumulative All-Star votes in a matchup is just over 3.8 million. For context, LeBron James received 4.6 million All-Star votes and Stephen Curry 3.8 million for the 2018-19 season, suggesting that each of these players *alone* generate just as much popularity as the average NBA game.

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

[TABLE 3 HERE]

Table 4 summarizes these same game characeristics as well as the total projected number of viewing households from the television ratings data. Note that this data comes from the sample of all *nationally televised* games during the 2017-18 and 2018-19 seasons, of which there were 480 in total (332 non-playoff games and 148 playoff games).

[TABLE 4 HERE]

There are a couple of very interesting characteristics of this data that can be understood from Table 4. First, one can see that the average number of viewing households is larger than 2 million for a nationally televised game. In fact, when separating the sample between playoff and non-playoff games, the average viewership number increases from 1.5 million for non-playoff games to nearly 3.5 million for playoff games. Next, the range of aggregate number of All-Star votes found in a single nationally televised matchup is quite large. On average, there are nearly 6.7 million All-Star votes across all players playing in a matchup, but this can be as little as 372,000 and as high as 18.35 million. A game featuring LeBron or Steph alone would already include more than an order of magnitude more All-Star votes than the lowest total All-Star votes game from this sample!

IV Empirical Methodology

Our empirical methodology in this analysis is two-fold. First, we use a fixed-effects panel regression approach to estimate the impact of player popularity and skill, among other factors, on ticket prices and TV ratings. We rely on a quasi-LASSO framework (as presented in Athey and Levin 2001) to determine the relationship between residualized popularity and skill on residualized ticket prices/TV ratings over the entire support of the data using a rich set of controls with flexibility in the functional form. Next, we use difference-in-differences (DID) and event study frameworks to identify the causal effect of a specific superstars absence on ticket prices within a certain matchup. Under important assumptions regarding identification, these estimates represent the value of each superstars presence in a game. This framework relies on a plausibly exogenous "announcement" of a players absence for an upcoming game, at which point ticket prices for that game should respond according to the missing players value. We then conduct heterogeneity analyses to determine how these values differ for home vs. away absences and the market size of the home team.

A *Panel Analysis*

Our initial analysis examines ticket prices and TV ratings at the matchup-level. First, we use a simple fixed effects model to measure the impact of player popularity, as measured by the cumulative number of All-Star votes of all players in a specific matchup, player skill, as measured by the cumulative PER of all players in a specific matchup, and expected parity, as measured by the absolute point spread, on ticket prices and TV ratings. This estimating equation is written in equation (1) as follows:

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

where y_i represents the outcome variable for matchup i. In this case, we examine two separate analyses with two different outcome variables: (i) weighted average ticket price on the secondary marketplace for matchup i, and (ii) starting TV rating (as measured by projected number of household viewership) for matchup i. $\mathbf{X_i}$ represents a rich set of covariate controls that are matchup specific.[8]

Of course, there are numerous identification and functional form specification issues as-

[8] Results Tables 5 and 6 in Section 5A denote the control variables used in each of the two analyses.

sociated with this analysis. To more rigorously understand the impacts of popularity, skill, and expected parity on ticket prices and TV ratings, we conduct a "quasi-LASSO" reduced form analysis that performs separate kernel-density (LOESS) regressions for each of the residualized independent variables (popularity, skill, and point spread) on each of the residualized outcome variables (following Athey and Levin 2001). This procedure allows for the estimation of a "smooth" relationship between each independent variable and either prices or initial TV ratings, while accounting for an extremely rich set of controls with flexible functional forms.

There are three sets of estimating equations needed to conduct this analysis. First, equation (2) regresses independent variable $j \in \{AbsSpread_i, AllStarVotes_i, PER_i\}$ on a rich set of controls, which includes flexible 5^{th} order polynomials for all controls $\neq j$ as well as the average combined current win percentage of the two participating teams, $h(W_i)$. Additionally, a rich set of interactions of the controls is included in $\boldsymbol{\Gamma_i}$.

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

This equation is estimated six times for each $x_i \in \{AbsSpread_i, AllStarVotes_i, PER_i\}$ and whether the corresponding outcome variable of interest is TV ratings or ticket prices.[9] For instance, in the estimating equation for $x_i = AbsSpread_i$, $g(V_i)$ and $z(P_i)$ represent $g(AllStarVotes_i)$ and $z(PER_i)$.

Next, equation (3) regresses the weighted average ticket price (or initial TV rating) for matchup i on the same right-hand side as equation (2), namely:

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

[9] These controls are the same as those found in Table 5 for ticket price as the outcome variable, and Table 6 for TV ratings as the outcome variable.

where equation (3) is estimated when y_i denotes the weighted average ticket price for matchup i in one specification, and the initial TV rating for matchup i in a separate specification. This is, again, done for each of $x_i \in \{AbsSpread_i, AllStarVotes_i, PER_i\}$.

We 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 *Difference-in-Differences and Event-Study Analyses*

To obtain a more accurate (and plausibly causal) effect of ticket price responses to a player's absence, we must construct a counterfactual group that models ticket price movements without a player's absence, and compare those movements to our "treated" games, where a specific superstar player is announced to be out. This is important because there could be underlying trends in ticket prices for NBA games that may bias our estimate of a player's absence if not controlled for by selecting an appropriate counterfactual. There are several different ways one may consider doing this–for example, we could use ticket listings from all other games on the same day and compare their price movements to ticket listings for the treated game on that day. We call this the *same day counterfactual*. There are both pros and cons to this method. On one hand, we are comparing games that occur during the same point in the season. On the other hand, there are a different number of games each day, which could limit the size of the counterfactual group, as well as completely different teams and markets involved each day.

A second way of constructing a counterfactual is what we call 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 specific 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. Our 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.*[10] The game where 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. We prefer this counterfactual for our analysis since it allows us to control for "team-specific" trends of ticket prices and their movements that may be common across many of their games, which we believe to be more valuable than the controls allowed by the same day counterfactual.

B.1 Primary Estimating Equations

Our analysis conducts both difference-in-differences (DID) and event-study estimations for each superstar player. Using the same-team counterfactual, the DID estimating equation is written as follows:

$$\ln(Price_{ish}) = \beta_1 Absence_i + \beta_2 PostAnn_h + \beta_3 (Absence * PostAnn)_{ih} + \alpha_{is} + \alpha_h + \epsilon_{ish} \tag{5}$$

where $Price_{ish}$ represents the average listed price for tickets in section s for matchup 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 for the Golden State Warriors vs. Houston Rockets matchup on

[10] This only includes "qualifying games" for other superstars, as defined in our "Data Characteristics" section. Namely, we <u>*do*</u> 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).

October 17, 2017 listed on October 17, 2017 four hours before the game. $Absence_i$ is a binary variable = 1 if there was a superstar absence for matchup i, and $PostAnn_h$ is a binary variable = 1 if the announcement had already been made at hours-to-game h. We use hours-to-game as our measure of time since matchups 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 game-time, 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 matchup 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_3, which approximately represents the percentage change in ticket prices associated with a superstar absence, and is our primary coefficient of interest.[11] Finally, α_{is} represents section fixed-effects (which are matchup-specific as well) and α_h is an hours-to-game fixed effect. We prefer to use a log-level specification since prices cannot fall below zero, and thus the distribution of prices is censored. We also prefer to interpret the effect of a player absence on the percentage change in listed prices.

Because we are attempting to determine a causal impact on ticket prices associated with a superstar absence, we estimate an event study to i) confirm parallel pre-trends in ticket prices for the treatment and counterfactual matchups, and ii) to determine the effect of a superstar absence on ticket prices in each time-period following the announcement (instead of just a post-announcement versus pre-announcement average effect that is obtained by the DID in equation 5).

We believe this strategy provides compelling identification, since we are able to examine

[11] In any log-level regression, the coefficients represent a log-point change, but for reasonably small coefficient values, these can be approximated as percent changes.

"within-matchup" changes in prices in response to plausibly exogenous announcements.

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

$$\ln(Price_{isht}) = \sum_{t=-14}^{14\setminus\{-1\}} \mathbf{D_t Absence_{t,ih}} + \alpha_{is} + \alpha_h + \epsilon_{isht} \tag{6}$$

$\mathbf{Absence_{t,ih}}$ is a vector of binary variables indexed by event-time t. Event-time t is in the half-hours-to-game unit, but 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 matchup 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 our analysis will correspond to $t = -1$). As can also be seen in the estimating equation, we restrict our 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 simple DID estimating equation.

In addition to estimating an effect for each individual matchup that experienced a superstar absence, we also sought to estimate an aggregate absence effect for each superstar, which required a slightly more complex method of constructing the same-team counterfactual. Because each "treated" matchup for a specific player has a different announcement time in terms of hours-to-game, we cannot simply assign the same announcement time to all matchups in the counterfactual as we did in the individual matchup case. Rather, we randomly assign announcement times for all matchups in the counterfactual sampling from the pool of announcement times observed for the treated matchups. For example, James Harden was absent from six qualifying matchups that we were able to analyze (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 matchups at 47.5, 22, 26.5, 1.5, 33.5, and 2 hours-to-game, respectively. For each of these 6 treated matchups, we randomly pair a proportional number of counterfactual matchups based on the total set of eligible counterfactual matchups for the Houston Rockets, and assign the announcement time (in hours-to-game) of the treated matchup to each counterfactual matchup with which it was paired. In the case of Harden, there are 148 eligible, untreated matchups in the counterfactual group, so 4 treated matchups receive 25 counterfactual matchups each and the remaining two matchups receives 24 counterfactual matchups. Once the pairings are assigned, we assign the same announcement time to the group and then normalize the announcement time of each grouping to 0. Finally, we merge groups into a single table for the given player on which we can then perform the estimation. The estimating equations remain the same as in the case of the individual matchup analysis with one key difference for matchups in the counterfactual, $PostAnn_h$ is determined based on the assigned announcement time within each grouping. To ensure robustness of the random counterfactual matchup-pairing algorithm, we perform the aggregate-matchup analysis for each player 3 times, each with a different random counterfactual pairing.

Finally, it is important to note that we are using listed prices for this analysis, and subsample only to listings that were ever "sold" on the marketplace. 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 matchup. Therefore, the effect we estimate is the value loss associated with the absence of a specific superstar for the average NBA game attendee. In addition, we restrict our sample to tickets that "sold," since these are listings that reflect a true, market-clearing equilibrium price between sellers and buyers.

B.2 Identification Concerns

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

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

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 we only look at price movements 3 days prior to a matchup, there is only concern if something else occurs that adjusts the price trajectory of a treated game differently than counterfactual games. 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 propensity to sit a superstar due to injury is higher once a teams playoff seeding is already set. In this case, it would be difficult to untangle 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 resting may face more serious concerns. First, decisions to rest superstar players may be dependent on several factors, for example the second night of back-to-back games or fourth game in five nights 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, these characteristics are likely known prior to the three-days before a matchup, and so would be accounted for in the matchup-specific fixed-effect.

Future work will attempt to more rigorously examine rest announcements once controlling for important factors.

V Results

In this section, we present our findings for the panel and quasi-LASSO analyses, the DID estimation, event studies, and tests of heterogeneity of superstar absence impacts in home vs. away games, market size of the home team, competitiveness of the matchup, and number of other superstar players in the matchup.

A Panel Analysis

Tables 5 and 6 present the results of two separate estimations of equation (1): Table 5 using weighted average listed ticket prices (of all tickets that eventually sold) at the matchup-level as the dependent variable, and Table 6 using initial TV rating (projected total number of households watching) at the matchup-level.

[TABLE 5 HERE]

In Table 5, there are four different specifications presented. The first specification does not cluster the standard errors and does not account for a differential effect on ticket prices associated with a large absolute point spread and the home team 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 willingness-to-pay in cases when the absolute point spread is high but the home team is favored. We see here that in the preferred specification (specification 3), a 1% increase in cumulative All-Star votes in a matchup leads to a 0.2% increase in ticket prices. This effect is almost identical in magnitude to the impact of a 1% increase in the average combined winning percentage of the two teams playing in the matchup, suggesting that the popularity of players present is a significant factor driving ticket prices.

Finally, specification 4 presents results when including “Away Team” fixed effects in addition to “Home Team” fixed effects. One can see that there are substantial adjustments to some of the estimates, in particular the magnitude of the “Avg. Win PCT” variable falls by approximately half, the “Absolute Point Spread” now has a statistically significant negative impact on listed prices, and when the home team is favored, absolute point spread does not have an impact on ticket prices (i.e. home fans want to see their team win, regardless of *ex-ante* competitiveness). Because the popularity metric we use is the cumulative All-Star votes of all players in a given matchup, including both Home and Away Team fixed effects introduces a great deal of collinearity. With these fixed effects, the coefficient on our popularity variable relies on *changes* in the lineups of teams across a season to drive residual variation in the popularity metric. While this actually follows more closely to the identification we use in our DID and event study estimates, which rely on exogenous announcements of superstar player absences in specific games, it limits the variation we are able to use in this panel estimation. At the same time, the coefficient on popularity is still highly statistically significant and has an economically meaningful impact on ticket prices.

[TABLE 6 HERE]

Table 6 presents the impact of each of these factors (omitting the “Home Team Favored” binary variable) on TV ratings for nationally televised games. There are four different specifications: each of the first two specifications include all nationally-televised games from the 2017-18 and 2018-19 seasons, while specification 3 includes only regular season games and specification 4 only playoff games. Each of these specifications use a “cumulative market size” continuous control variable to account for the number of people that may be expected to watch independent of other important factors.[12] One can see that popularity and team quality are the only statistically significant estimates, with coefficients of 0.098 and .48, respectively. This suggests that for a 1% increase in the cumulative number of All-Star votes in a matchup, initial rating increases by 0.098%, and similarly for a 1% increase in the average win percentage of the two competing teams, ratings increase by nearly 0.5%. Additionally, if we limit our sample to regular season games (about 70% of our sample), this estimate increases to 0.14%, suggesting that player popularity may be a more important factor in the regular season than the playoffs. In fact, the estimates on each of our coefficients become insignficant when subsetting the set of games to include only playoff matchups. This is likely because playoff games have an "elimination" component, and so regardless of the characteristics of the teams viewers will tune in. All specifications are clustered at the "Home + Away Team" level.

Next, we present the panel analysis results using the quasi-LASSO methodology, as laid out in equations (2) – (4). We conduct this procedure for three different, yet correlated, independent variables: (i) absolute value of the point spread (a measure of parity), (ii) cumulative All-Star votes of all players who played in a matchup (a measure of popularity), and (iii) the cumulative player-efficiency rating (PER) of all players who played in a matchup (a measure of skill), and two different dependent variables: (i) weighted average ticket price at the matchup-level, and (ii) initial TV rating (as measured by the project number of households watching) at the matchup-level. Figures 4a, 4b, and 4c present the results for residualized parity, popularity, and skill, respectively, with the left pane in each figure corresponding to the impact on residualized TV ratings and the right pane the impact on residualized ticket prices.

[12]Since these are nationally televised games, 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). If we include a dummy for each team present in a matchup, we remove much of the important variation driving the popularity effect on ratings, since cumulative All-Star votes are nearly collinear with a team dummy.

[FIGURE 4 HERE]

One can see that within the primary support of the residualized independent variables, the only meaningful relationship occurs in Figure 4b, measuring the effect of residualized cumulative popularity on residualized TV ratings in each left pane, and residualized ticket prices in each right pane. One can see that the effect is slightly muted in the TV ratings case compared to the ticket prices case, where the impact of residualized cumulative popularity on residualized ticket prices is convex and has a steep upward-slope as cumulative popularity increases. The relative magnitudes and statistical significance of the relationships in each of Figures 4a-4c are quite similar to those presented in Tables 5 and 6.

[FIGURE 5 HERE]

Finally, using the estimates provided in the cross-sectional analyses, Figure 5 above traces out the precise impact each of the 659 eligible players has on ticket prices (left pane) and TV ratings (right pane) based on the maximum annual number of All-Star fan votes they received during the 2017-18 and 2018-19 seasons. One can see that these figures take on a "hockey-stick" shape – namely there is massive convexity in the returns to superstar popularity in terms of their impacts on ticket prices and TV ratings. This strongly supports the theory laid out in Rosen (1981), which suggests that in industries with large disparities in talent (or in this case, popularity), the lion's share of impact and productivity is generated by the very top individuals in the distribution.

B *Difference-in-Differences*

Figure 6 presents the results of our DID estimation as seen in equation (5). This figure measures the average percent change in ticket prices across all games a specific superstar is absent for with 95% confidence intervals. Importantly, we only include players where pre-trends in ticket prices between the counterfactual and treated matchups prior to a superstars injury announcement were parallel, satisfying the identifying assumption that the DID estimate is causal. Each of these estimates represents the results from the aggregate estimation. Therefore, each estimate reflects the average effect on listed ticket prices from all analyzed games for each qualifying superstar. In examining the results, one can see that the reduction in prices due to absence announcements in percentage terms is highest for Dwyane Wade, Kemba Walker, and Dirk Nowitzki, all resulting in 14-16% reductions in prices associated with their absence announcements.

[FIGURE 6 HERE]

Figure 7 exhibits these declines in level price reductions instead of percentage terms. One can see that because the average price of Los Angeles Lakers' and Golden State Warriors' tickets are quite high, absences for LeBron James and Stephen Curry result in the largest magnitude decrease in ticket prices at $42 and $29 per ticket, respectively. However, there are a number of other players whose absences lead to economically meaningful and statistically significant price reductions, including Dwyane Wade, Dirk Nowitzki, Luka Doncic, Paul George, Kemba Walker, and Kawhi Leonard, each of whom lead to price reductions between $7-$26 per ticket. Somewhat surprisingly, we do not observe statistically significant price reductions associated with James Harden's or Giannis Antetokounmpo's absences, who are the reigning MVPs from the previous two seasons.

[FIGURE 7 HERE]

One can put these estimates into a welfare context with some back-of-the-envelope calculations. For example, Stephen Curry's average impact on prices for games he is absent for is approximately $29. If each attendee for Golden State Warriors games loses $29 when Stephen

Curry is absent, and there are on average 20,000 fans in an NBA arena for these games, and 82 Golden State Warriors games in an NBA season, then the total value of watching Stephen Curry play in person to NBA fans is \$29 x 20,000 x 82 = \$47,560,000. Stephen Curry's current contract pays him an average of \$40,231,758 per year through the 2021-22 NBA season, which is the maximum he could have been given from the Warriors (Spotrac 2016). It should be noted we are not claiming that the sum of a player's per-game absence effect is representative of their net worth – there are several other factors that likely make Stephen Curry much more valuable to the NBA and Golden State Warriors than Steph's average maximum annual salary of \$41,000,000. However, the sum of these absence effects may indicate these players' values to the average NBA game attendee – in other words, a player's entertainment value to fans at a game.

C Event Studies

The event study results present coefficients for each of the 30-minute intervals before and after an absence announcement takes place. Figure 8 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 Kawhi Leonard, who is the reigning NBA Finals MVP.[13] 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 red line, suggest that parallel pre-trends in ticket prices hold in each of these cases. The event study allows us to observe 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

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

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. We bin our endpoints at -7 and $+7$ hours in event-time with respect to when the announcement occurs (at $t = 0$).

[FIGURE 8 HERE]

In Figures 6 and 7, we see that Kevin Durant's absence announcements on average lead to no statistically significant ticket price adjustments. This is particularly interesting given that we find a meaningful reduction for his teammate Stephen Curry's absences. Figure 9 below presents the event study results for Kevin Durant and Stephen Curry. From a skill standpoint (measured by player efficiency rating or value over replacement player), Kevin Durant and Stephen Curry were nearly identical during the 2017-18 and 2018-19 seasons. However, Curry's popularity effect with NBA fans as "the best shooter of all-time," his unique ability to make impressively difficult three-pointers, and his style of play all may make him a more desirable player to watch from an entertainment standpoint.

[FIGURE 9 HERE]

D Heterogeneity Tests

Our final set of analyses examines heterogeneity with respect to types of games superstars are absent for. We present two sets of analyses here – first, we examine the difference in the absence effect on ticket prices differentially for home games vs. away games for each qualifying player. Next, we examine the impacts of market size of the home team, matchup competitiveness, and number of other superstars present in a matchup on the absence effect of each qualifying superstar player.

Figure 10 below presents two distinct DID estimators (exhibiting level price changes) for each player: one for home games missed and another for away games missed.[14] 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 and much more negative for away absences than for home absences. LeBron's average away-game effect is $75/ticket, while Stephen Curry's is $55/ticket. This suggests that the 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, and so there is a geographic scarcity effect of not being able to substitute towards a different game. On the other hand, Luka Doncic and, to a lesser extent, James Harden both exhibit the opposite effect, where their absences are more meaningful for home games than for away games. This is also quite intuitive both of these players are not just entertaining to watch, but without them their teams become much less competitive and much more likely to lose a game. The same argument could be made for LeBron James' impact on the Lakers, who also exhibits a negative effect for home game absences, but his transcendent superstardom leads to an even larger away game absence effect. Home fans value the competitiveness of their team, and thus the absence of these players removes the star element from their team and substantially reduces their team's chances of winning. Figure 23 in the Appendix exhibits these changes in percentage point terms.

[FIGURE 10 HERE]

We also conduct heterogeneity tests analyzing the differential effect of absence announcements depending on the competitiveness of the matchup (as measured by the absolute point spread), the total number of other starting-caliber superstars present, and the market size of

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

the home team. This analysis relies on a triple differences estimation, where we interact our DID treatment variable with the relevant metrics for competitiveness, total star power, and market size, respectively, in separate estimations. We find that the results of this analysis suggest there are no meaningful or statistically significant relationships between ticket prices and these additional differentiators. One potential explanation for this finding is that we do not have 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 a triple differences estimation.

VI Conclusion

This paper presents an analysis of the entertainment value of NBA superstars to fans attending NBA games. The results from our panel analysis suggest that a 1% increase in the aggregate popularity of a matchup (as measured by the total number of All-Star fan votes of all players playing) increases ticket prices and TV ratings by 0.16-0.21%. In our difference-in-differences and event study analyses, we find that absences of several superstars, including some of the most popular like LeBron James, Stephen Curry, and Dwyane Wade do have a statistically significant and economically meaningful impact ranging from a 4-16% ($7-$42) reduction in the average ticket price. We conduct additional heterogeneity tests examining the differential in superstar absence effects for home vs. away absences, as well as the absence effect when games are played in small versus large markets. We find that certain players, like LeBron James and Stephen Curry, exhibit much larger away game absence effects–prices fall an average of $75/ticket for LeBron absences and $55/ticket for Steph absences.

The panel and difference-in-differences/event-study approaches yield largely consistent findings. For example, LeBron James averaged just over 3.6 million fan votes over the 2017-18 and 2018-19 seasons, which corresponds to approximately 98% of the average aggregate number of

All-Star fan votes of all players in a matchup (3.7 million). In other words, LeBron's average individual 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 LeBron alone results in a 15.7-20.6% increase in ticket prices and TV ratings. The difference-in-differences analysis yields a very similar resultwe find that the absence of LeBron leads to a 13% average reduction in ticket prices, and a 21% average reduction in away games. This implies millions of dollars in welfare lost for each of these matchups, and tens of millions of dollars lost across all superstar absences over the course of a season.

Our findings have significant ramifications for several important NBA stakeholders. First, this study provides quantitative evidence that there are significant reductions in welfare of NBA fans due to certain superstars missing games, and has priced those reductions in a well-identified manner. The league office may want to consider the importance of its policies surrounding timing of injury announcements (and how far in advance they need to be made), purposeful resting of players, and implications of suspensions for welfare of NBA fans. For example, there are serious welfare implications when star players are "load managed" during the only game of that season in an opposing teams arena, especially when the opposing team does not have any of their own superstars. The NBA may also want to structure certain incentive schemes for players explicitly based on their popularity.

There are also important implications for decision-making by NBA franchises. For instance, franchises may want to set up (at the very least) simple dynamic pricing schemes in the primary marketplace that adjust to absences of the most popular superstars. In addition, when franchises are signing free agents, drafting players, or making trades, and are profit-maximizing, they may not only want to consider the skill level of these players, but also the entertainment value associated with watching them play. Finally, we provide quantitative metrics for losses faced by television networks and advertisers in the absence of star players, which can be used to more strategically decide on which games to televise (and which to "flex out" to other more notable matchups).

There are several avenues of future research we would like to expand upon with this work. First, we hope to look at the effect of long-term injuries on ticket prices. For example, when a player tears their ACL and is guaranteed to be out for the remainder of the season, how does this affect the stream of ticket prices for all future games of this team? We may witness different results since sellers and buyers have more time to adjust and process this information. Additionally, do ticket prices for "near-term" games associated with a long-term absence announcement adjust differently than games further in the future? In a similar vein, we hope to explore the impact of "uncertainty" associated with some players' timelines in returning from injury or rest on ticket prices for future, potentially impacted games. For example, LeBron James experienced a lingering groin injury during the middle of the 2018-19 season, which led to a highly uncertain timetable for his return. Furthermore, we could apply this methodology to examine ticket price impacts when a superstar player joins a new team. For instance, if there is a midseason blockbuster trade that causes one team to gain a superstar player and another team to lose that player, what happens to ticket prices for future games for these teams? Finally, we plan on conducting a more comprehensive analysis examining the difference between absences due to injury and those due to purposeful rest.

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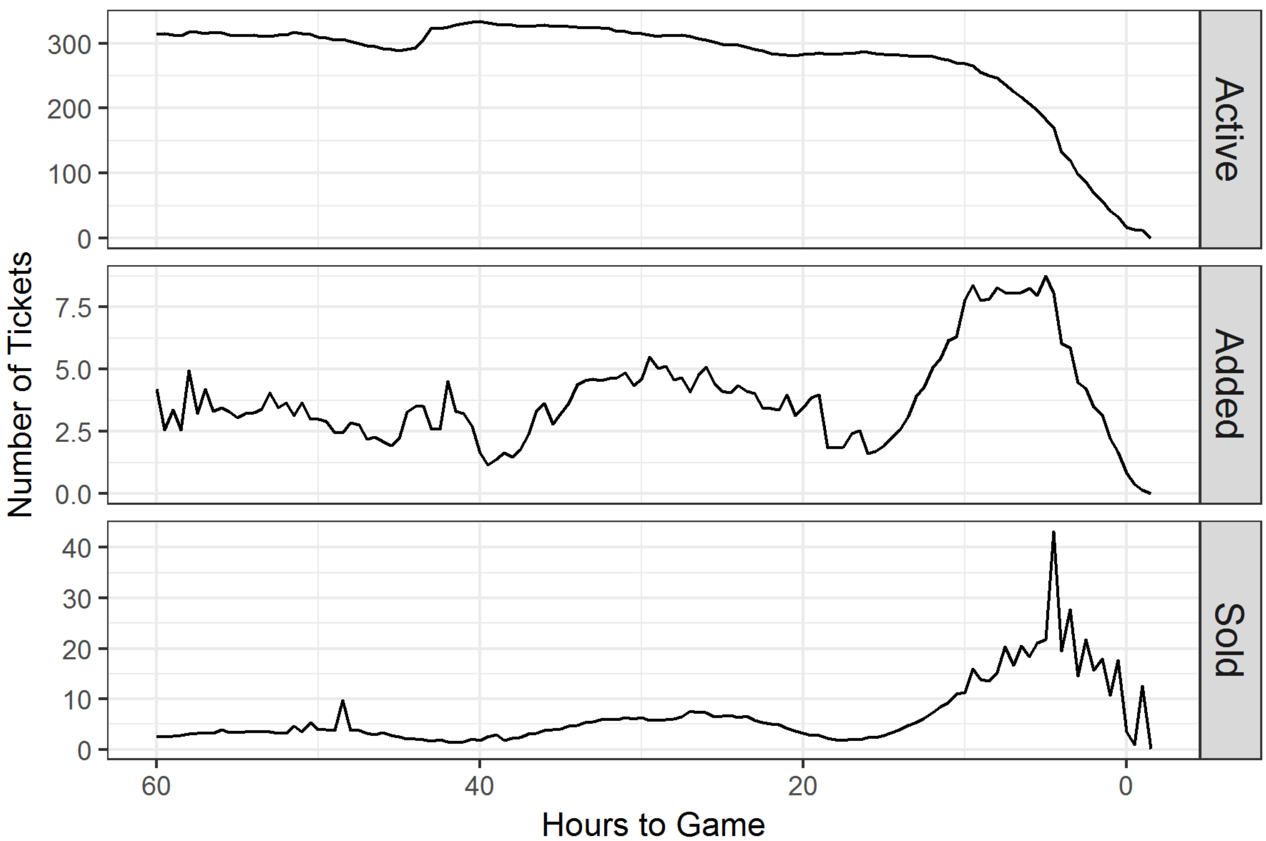
Tables and Figures

Table 1: Across-Game Ticket Data Summary Statistics (2,330 Total Matchups)

Data Characteristic	Mean	Std. Dev.	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

Figure 1: Per-Game Average Number of Active, Added, and Sold Listings by Hours to Game[15]



[15]Please note the different y-axis scale for each pane.

Figure 2: Average Listing Price by Hours to Game

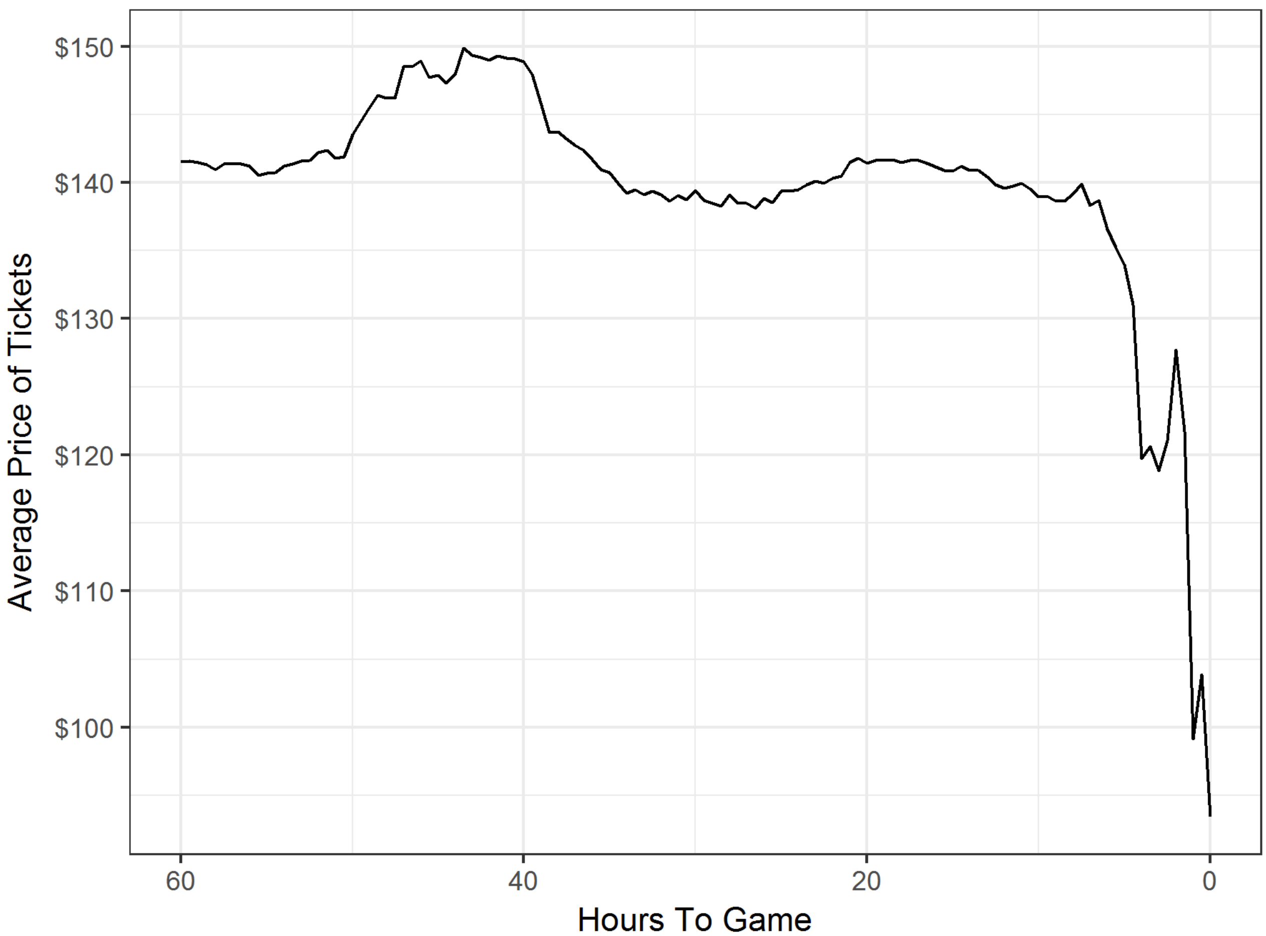


Figure 3: Distribution of Player Absence Announcements by Hours to Game

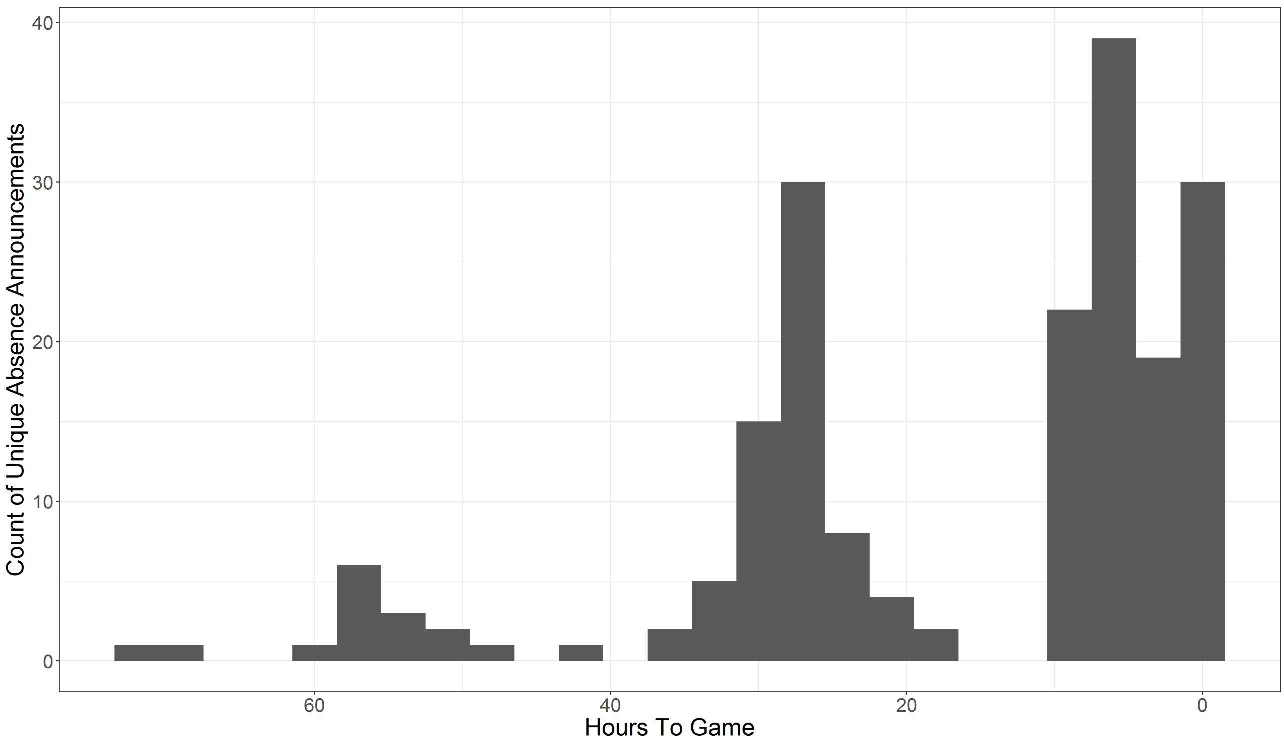


Table 2: Count (by Reason) of Qualifying Missed-Games for each Starting-Caliber All-Star Player

Player	Injury	Rest	Other	Total	Total Analyzed
Anthony Davis	26	3	1	30	21
DeMar DeRozan	4	3	0	7	0[x]
DeMarcus Cousins	35	6	0	41	0[x]
Giannis Antetokounmpo	17	0	0	17	16
James Harden	10	2	0	12	6
Joel Embiid	12	6	0	18	13
Kemba Walker	2	0	0	2	2
Kevin Durant	17	1	0	18	16
Kyrie Irving	35	1	1	37	27
Paul George	8	0	0	8	7
Stephen Curry	42	1	0	43	20
Luka Doncic	10	0	0	10	9
Dwyane Wade	3	0	7	10	8
Dirk Nowitzki	2	2	0	4	3
LeBron James	22	3	0	25	16
Kawhi Leonard	6	14	1	21	21
Derrick Rose	32	0	0	32	19

[x] We did not analyze games in which DeMarcus Cousins or DeMar DeRozan missed, as both of them did not make the All-Star Team during the 2018-19 season (despite being All-Star starters during the 2017-18 season). The criteria for a player to be analyzed was that they were an All-Star during both seasons, a starter during at least one of the two seasons, or would have been voted an All-Star starter with 100% weight on the fan vote at least one of the two seasons. Also note that Manu Ginobili is not present, as he did not miss any qualifying games during the 2017-18 season in which he would have been voted an All-Star starter with a 100% weighted fan vote.

Table 3: Game Characteristics Summary Statistics (2,624 Total Matchups)

Data Characteristic	Mean	Std. Dev.	Min.	Max.
Aggregate # of All-Star Votes (1,000's)	3,856.87	3,279.58	31.10	18,347.76
Absolute Point Spread	5.84	4.28	0	26
Aggregate Player Efficiency Rating	302.25	32.48	169.50	431.90
Avg. Final Win %	0.50	0.10	0.22	0.76
Aggregate Market Size (1,000's of people)	3,530.50	1,051.86	2,025	7,700
Attendance	18,056.58	1,964.23	10,079.00	22,983.00

Table 4: TV Ratings and Game Characteristics Summary Statistics (480 Total Matchups)

Data Characteristic	Mean	Std. Dev.	Min.	Max.
Projected # of HH's Watching (1,000's)	2,134.92	1,645.06	265	11,151
Aggregate # of All-Star Votes (1,000's)	6,669.58	3,897.47	372	18,347.76
Absolute Point Spread	4.93	3.56	0	18
Aggregate Player Efficiency Rating	313.96	34.72	226.80	430.60
Avg. Final Win %	0.60	0.08	0.27	0.75
Aggregate Market Size (1,000's of people)	3,910.41	1,105.17	2,125	7,199

Table 5: Impact of Player Popularity, Player Skill, Team Quality, and Parity on Ticket Prices

	Dependent Variable: log(Avg. Listed Price) (Matchup-Level)			
log(Ag. All-Star Votes)	0.2076***	0.2076***	0.2105***	0.1334***
	(0.0104)	(0.0185)	(0.0187)	(0.0194)
log(Ag. PER)	0.0758	0.0758	0.0760	0.1283
	(0.0797)	(0.0926)	(0.0910)	(0.0906)
log(Avg. Win PCT)	0.1770***	0.1770**	0.1946**	0.3842***
	(0.0483)	(0.0787)	(0.0855)	(0.0829)
Home Team Favored (HTF)	−0.0017	−0.0017	−0.0444	−0.0134
	(0.0213)	(0.0333)	(0.0276)	(0.0207)
Absolute Pt. Spread (APS)	0.0040*	0.0040	−0.0066	−0.0211**
	(0.0022)	(0.0042)	(0.0105)	(0.0092)
HTF*APS			0.0137	0.0240*
			(0.0129)	(0.0124)
Month FE	Yes	Yes	Yes	Yes
Time of Day	Yes	Yes	Yes	Yes
Day of Week	Yes	Yes	Yes	Yes
Holiday	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
Clustered Robust SEs (Home Team)	No	Yes	Yes	Yes
Observations	2,330	2,330	2,330	2,330
R^2	0.6354	0.6354	0.6365	0.7353
Adjusted R^2	0.6233	0.6233	0.6242	0.7229

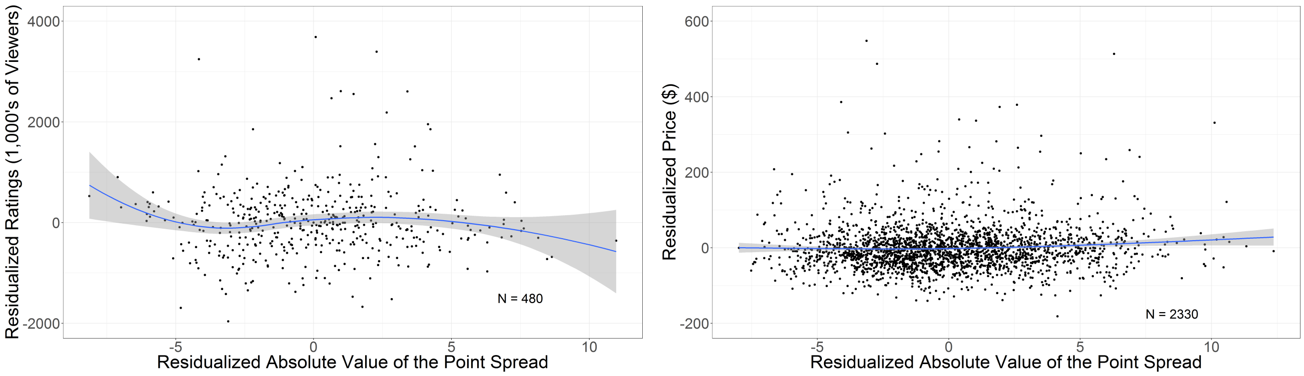
Note: *p<0.1; **p<0.05; ***p<0.01

Table 6: Impact of Player Popularity, Player Skill, Team Quality, and Parity on Initial TV Ratings

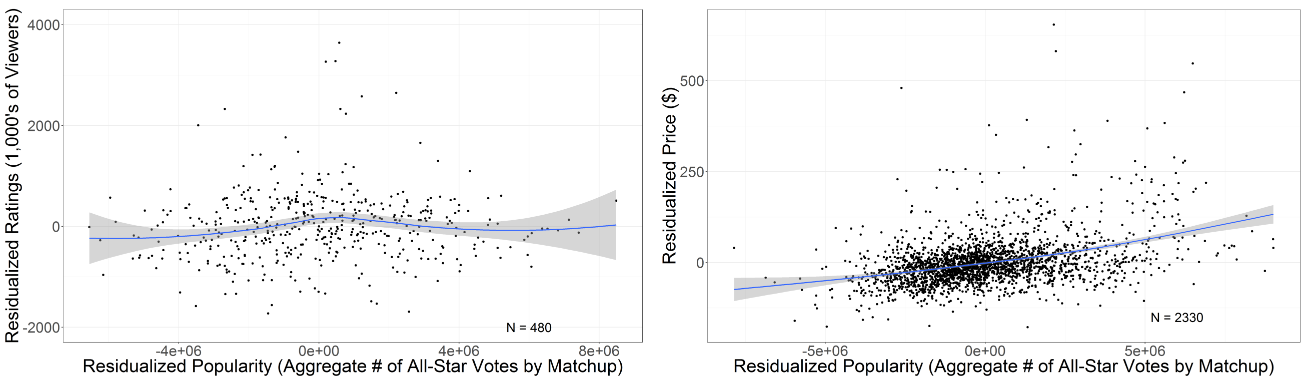
	Dependent Variable: log(Total Proj. HHs Watching) (Matchup-Level)			
	All Games	All Games	Reg. Season Only	Playoffs Only
log(Ag. All-Star Votes)	0.0979***	0.0979***	0.1373***	−0.0635
	(0.0272)	(0.0365)	(0.0311)	(0.0752)
log(Ag. PER)	−0.1024	−0.1024	−0.0355	0.0368
	(0.1487)	(0.1465)	(0.1868)	(0.2615)
log(Avg. Win PCT)	0.4797**	0.4797***	0.2894*	1.5124
	(0.2048)	(0.1608)	(0.1739)	(1.0652)
Absolute Pt. Spread (APS)	−0.0014	−0.0014	−0.0024	0.0002
	(0.0044)	(0.0051)	(0.0051)	(0.0099)
Month FE	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes
Time-of-Day FE	Yes	Yes	Yes	Yes
Streak FE	Yes	Yes	Yes	Yes
TV Network FE	Yes	Yes	Yes	Yes
Cum. Market Size	Yes	Yes	Yes	Yes
Dbl Header FE	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes
Playoff Gm FE	Yes	Yes	No	No
Clustered Robust SEs (Home + Away)	No	Yes	Yes	Yes
Observations	478	478	330	148
R^2	0.7508	0.7508	0.6694	0.7168
Adjusted R^2	0.7223	0.7223	0.6156	0.6181

Note: *p<0.1; **p<0.05; ***p<0.01

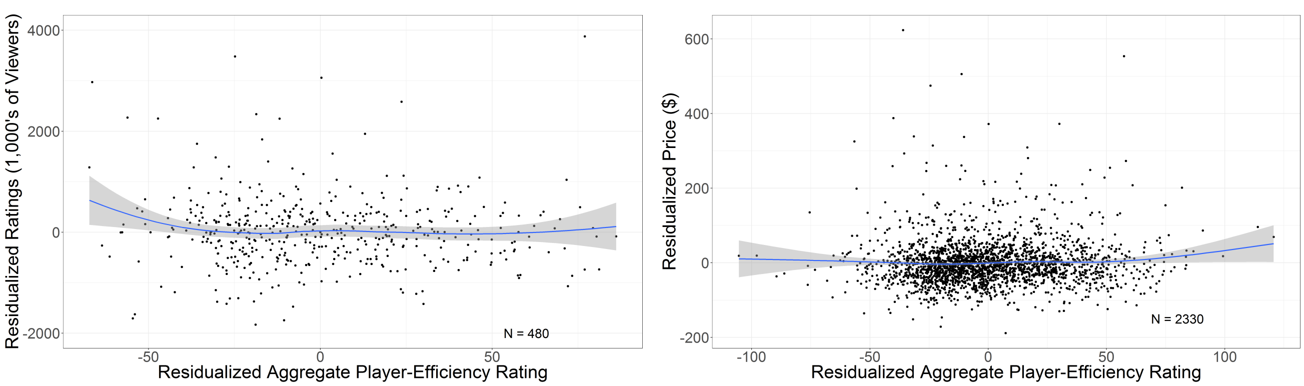
Figure 4: Quasi-LASSO Results Figures



a. Impact of Residualized Absolute Point Spread on (left pane) Residualized TV Ratings and (right pane) Residualized Ticket Prices



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



c. Impact of Residualized Aggregate Player-Efficiency Rating (PER) on (left pane) Residualized TV Ratings and (right pane) Residualized Ticket Prices

Figure 5: Percent Change in Ticket Prices (left) and TV Ratings (right) by Player All-Star Fan Vote Ranking

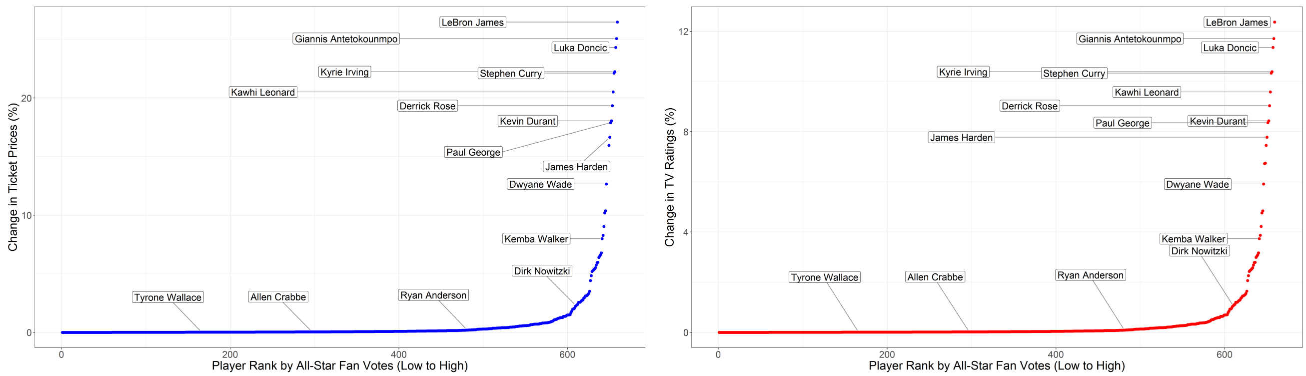


Figure 6: Difference-in-Difference Results for Superstar Absences (Percentage Change in Prices)

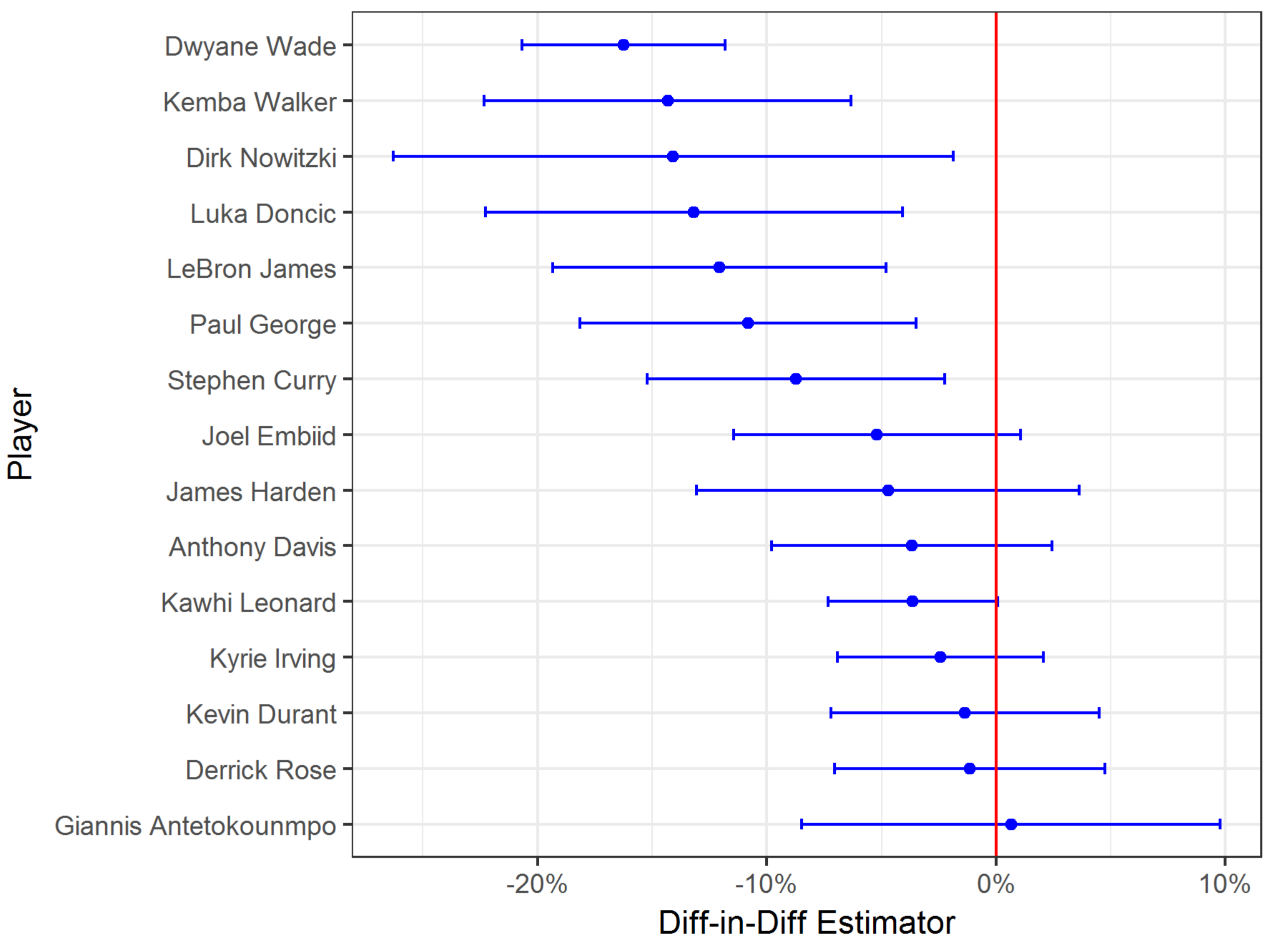


Figure 7: Difference-in-Difference Results for Superstar Absences (Level Change in Prices)

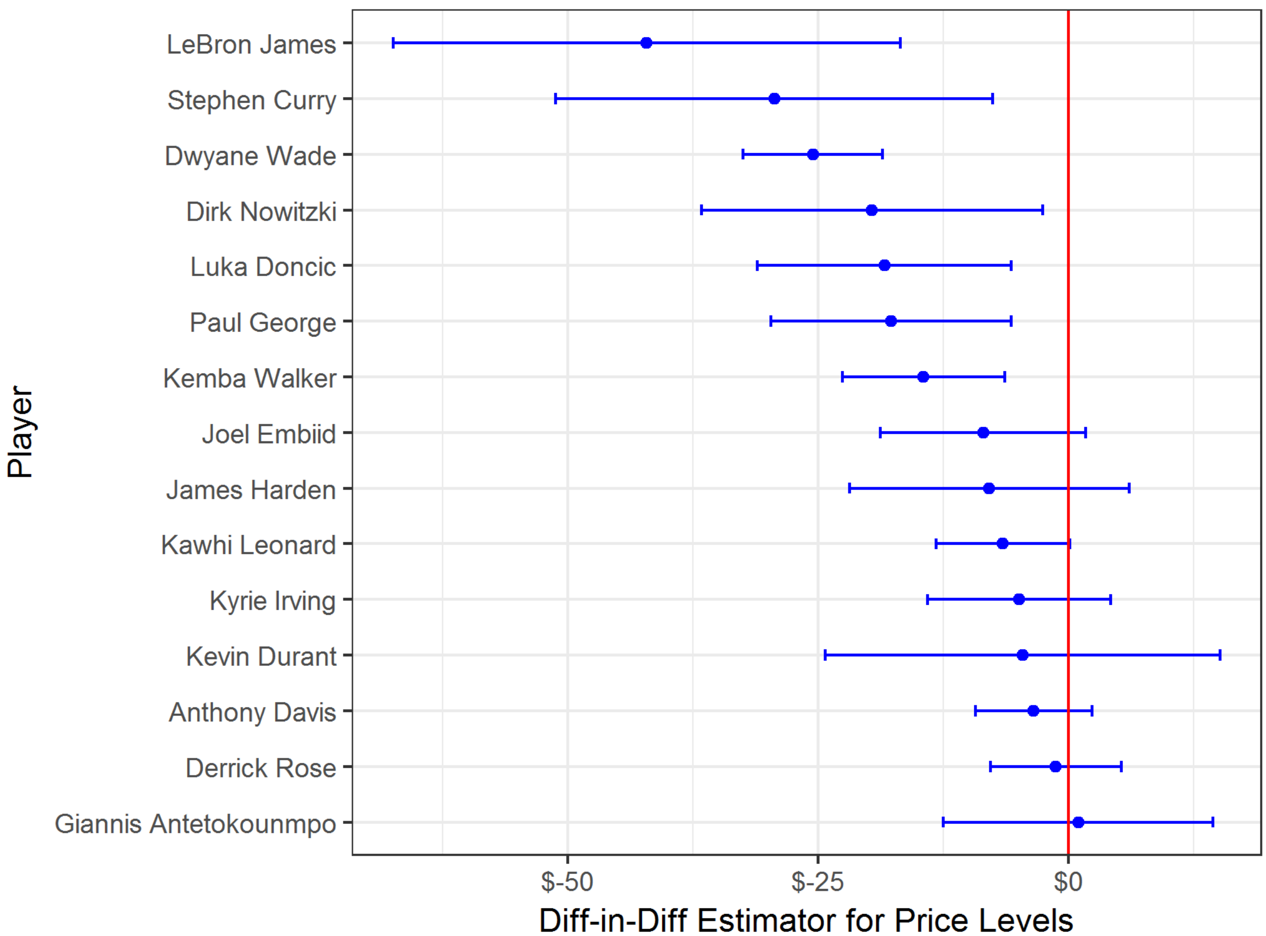
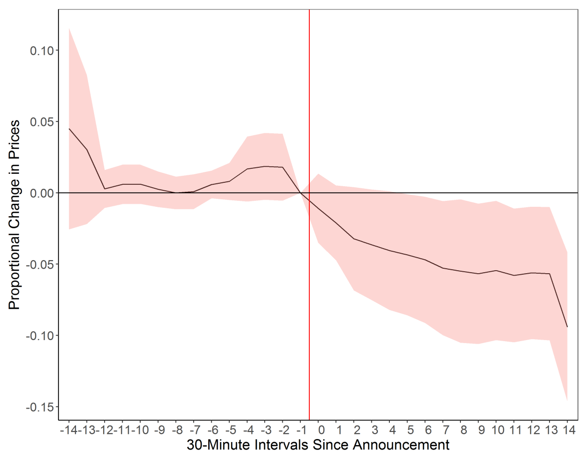
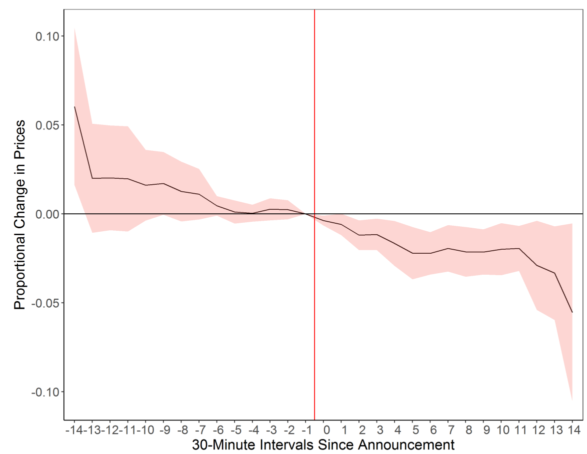


Figure 8: Event Study Results for Top Impact Superstars

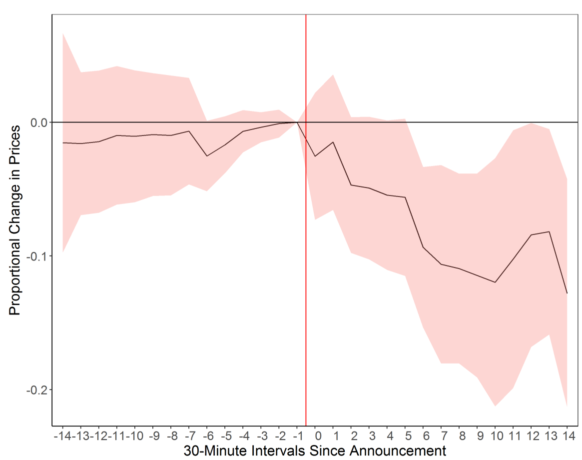
(a) LeBron James



(b) Stephen Curry



(c) Dwyane Wade



(d) Kawhi Leonard

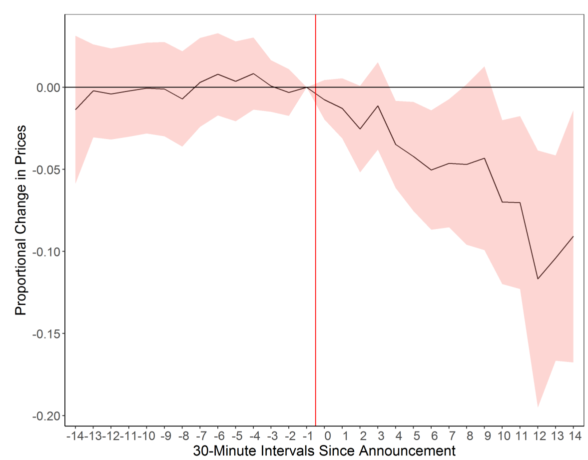
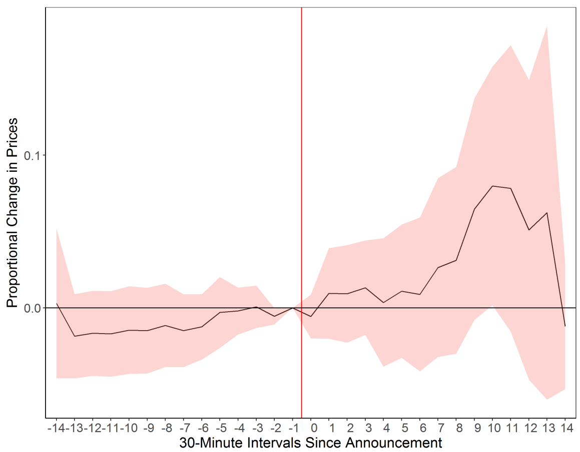


Figure 9: Kevin Durant vs. Stephen Curry Absence Impacts

(a) Kevin Durant



(b) Stephen Curry

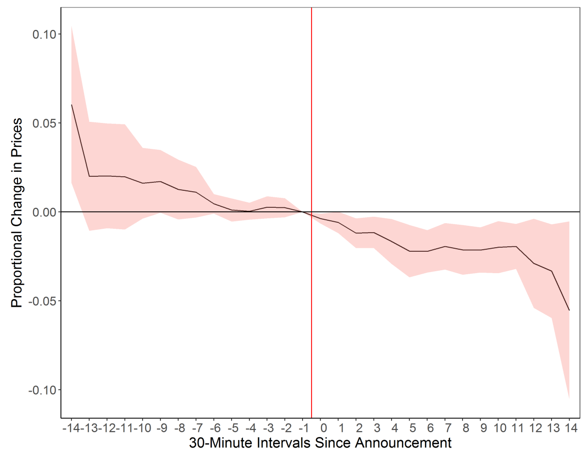
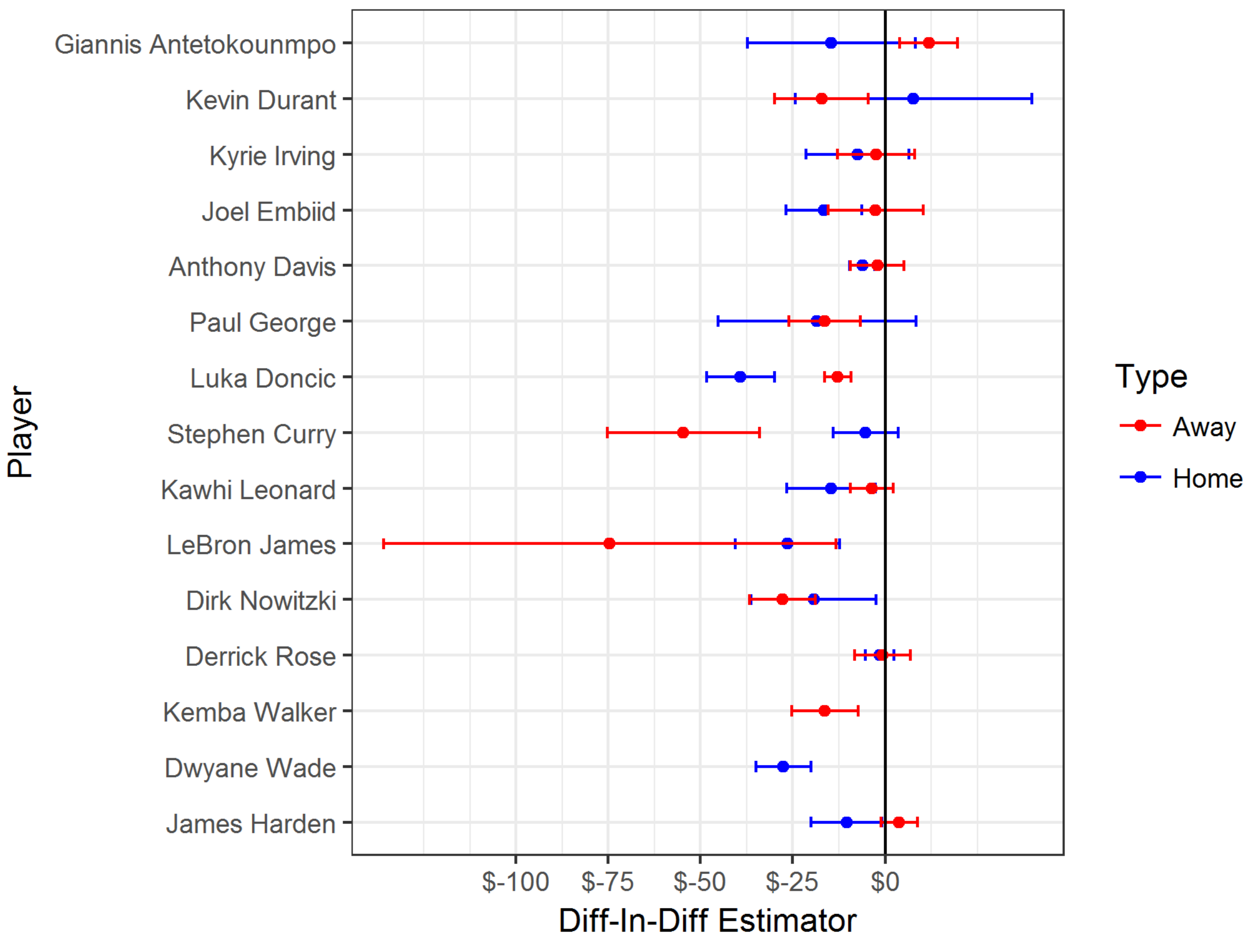


Figure 10: Difference-in-Differences Estimator by Home vs. Away Matchup Absence (Level Change in Prices)



Appendix

Figure 11: Distribution of All Unique Absence Announcement-by-Matchup Pairs (for Starting-Caliber Players) by Hours to Game

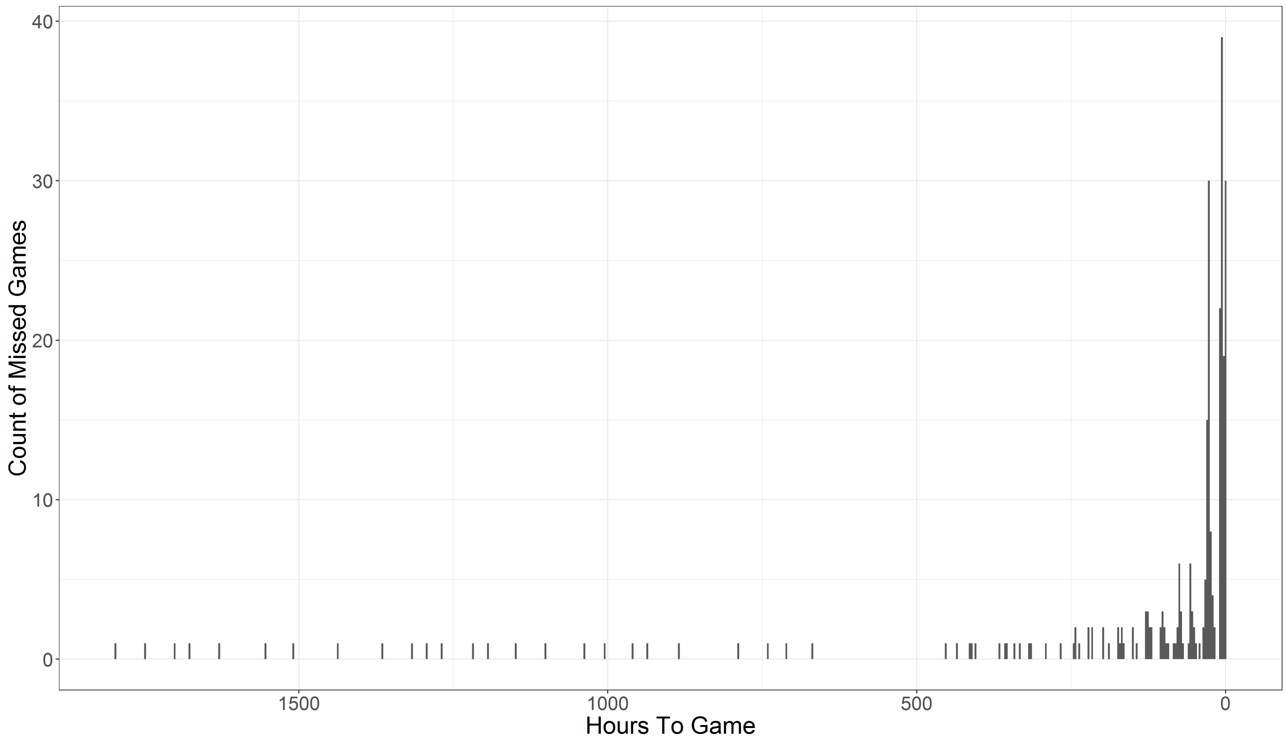


Figure 12: Percent Change in Ticket Prices (left) and TV Ratings (right) by Player All-Star Fan Vote Ranking (Average Votes over 2017-19 Seasons)

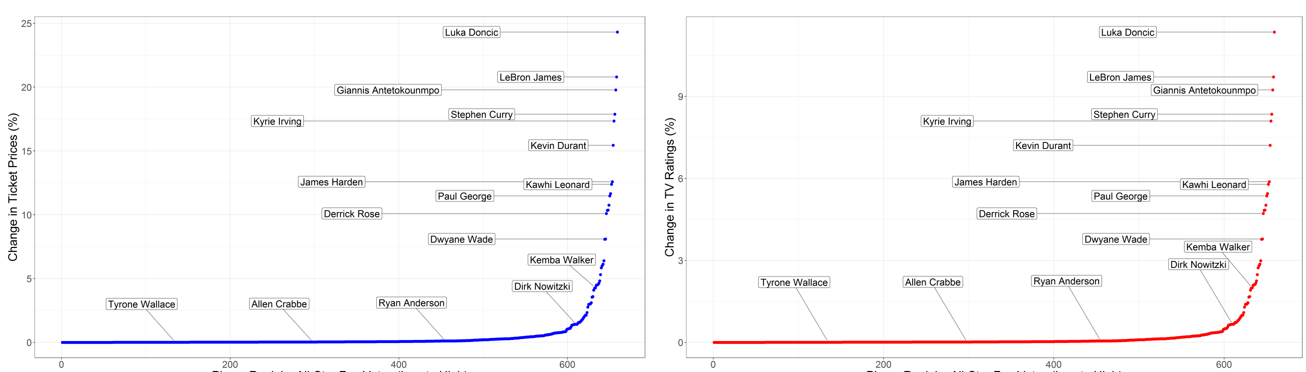


Figure 13: Event Study for Anthony Davis

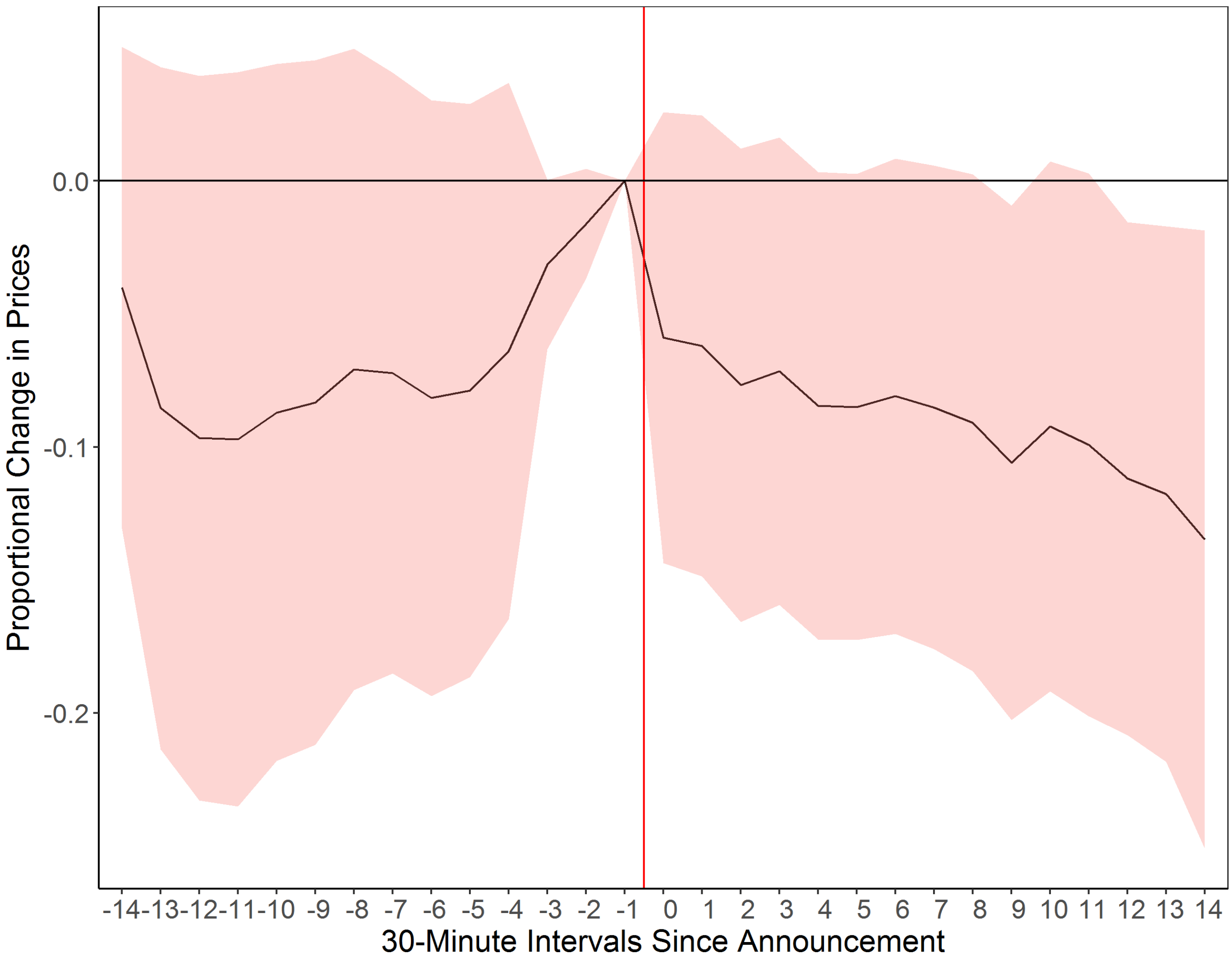


Figure 14: Event Study for Derrick Rose

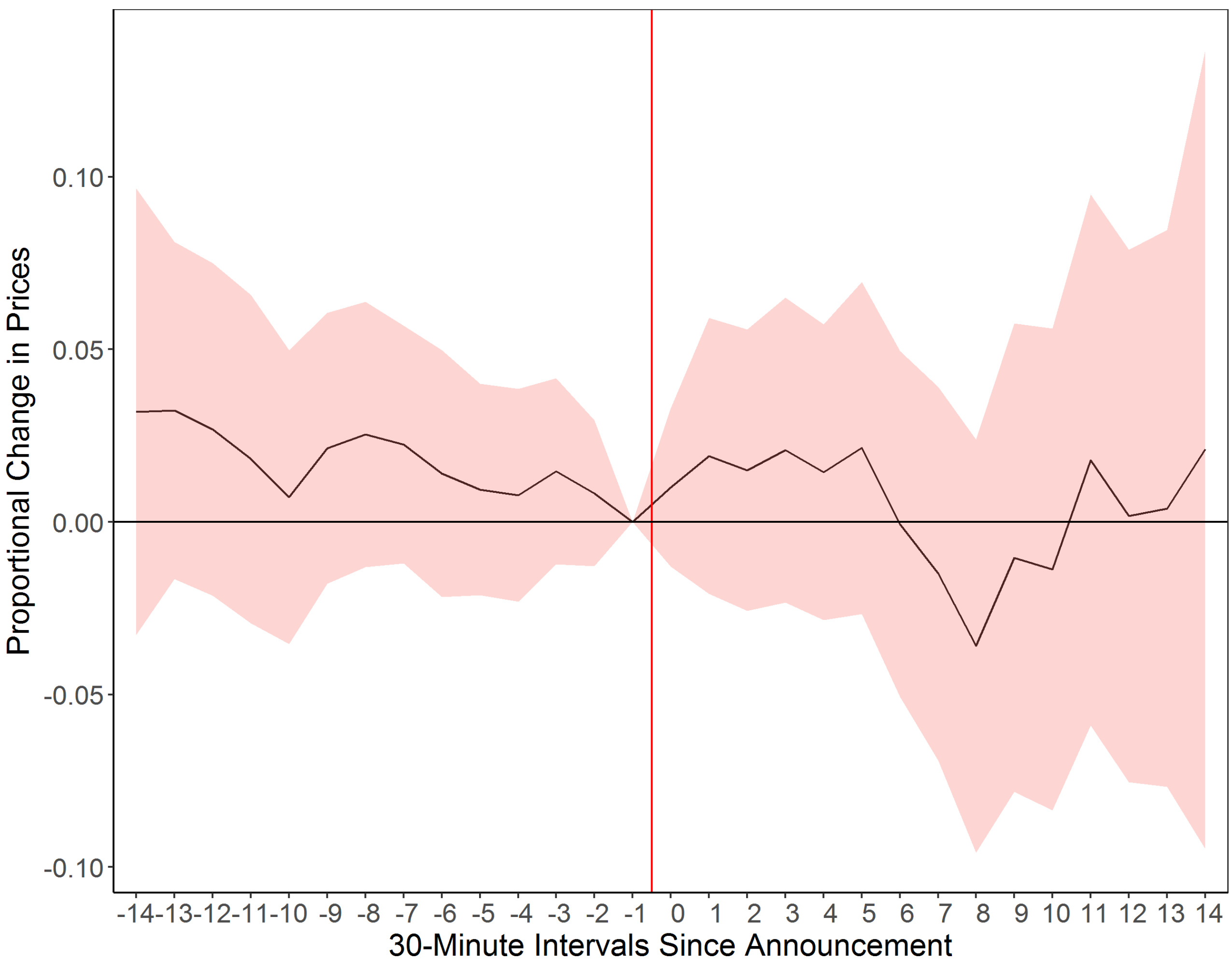


Figure 15: Event Study for Dirk Nowitzki

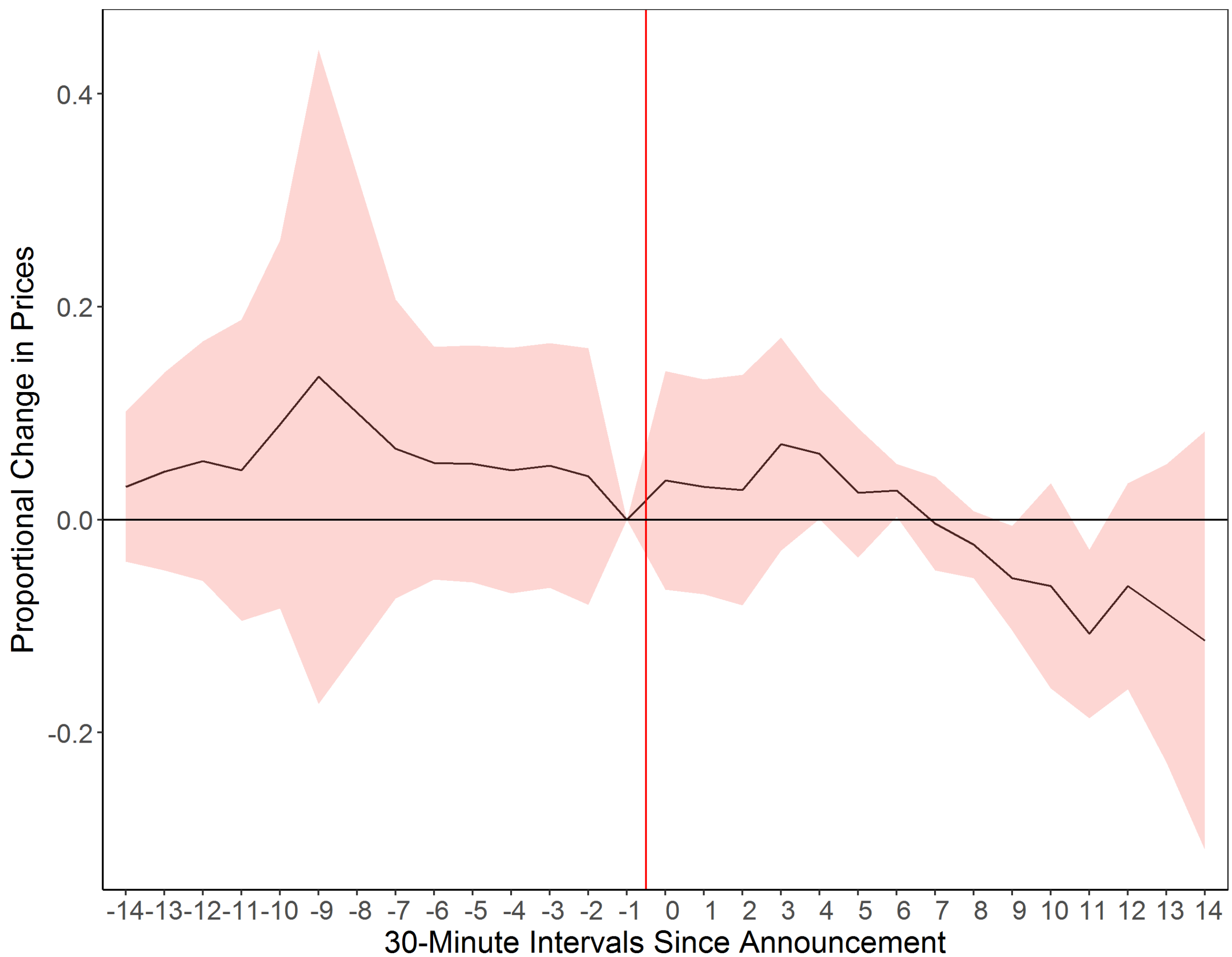


Figure 16: Event Study for Giannis Antetokounmpo

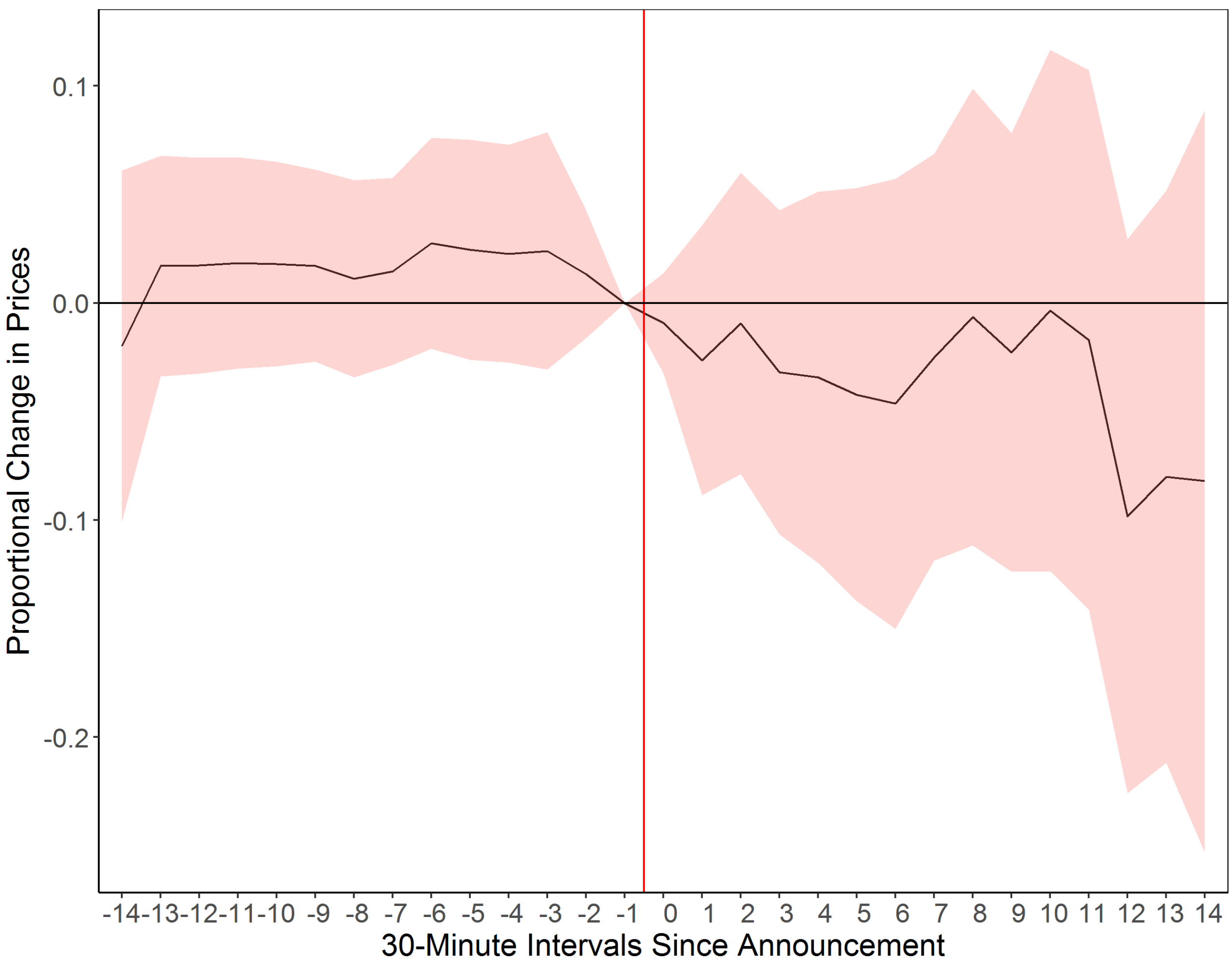


Figure 17: Event Study for James Harden

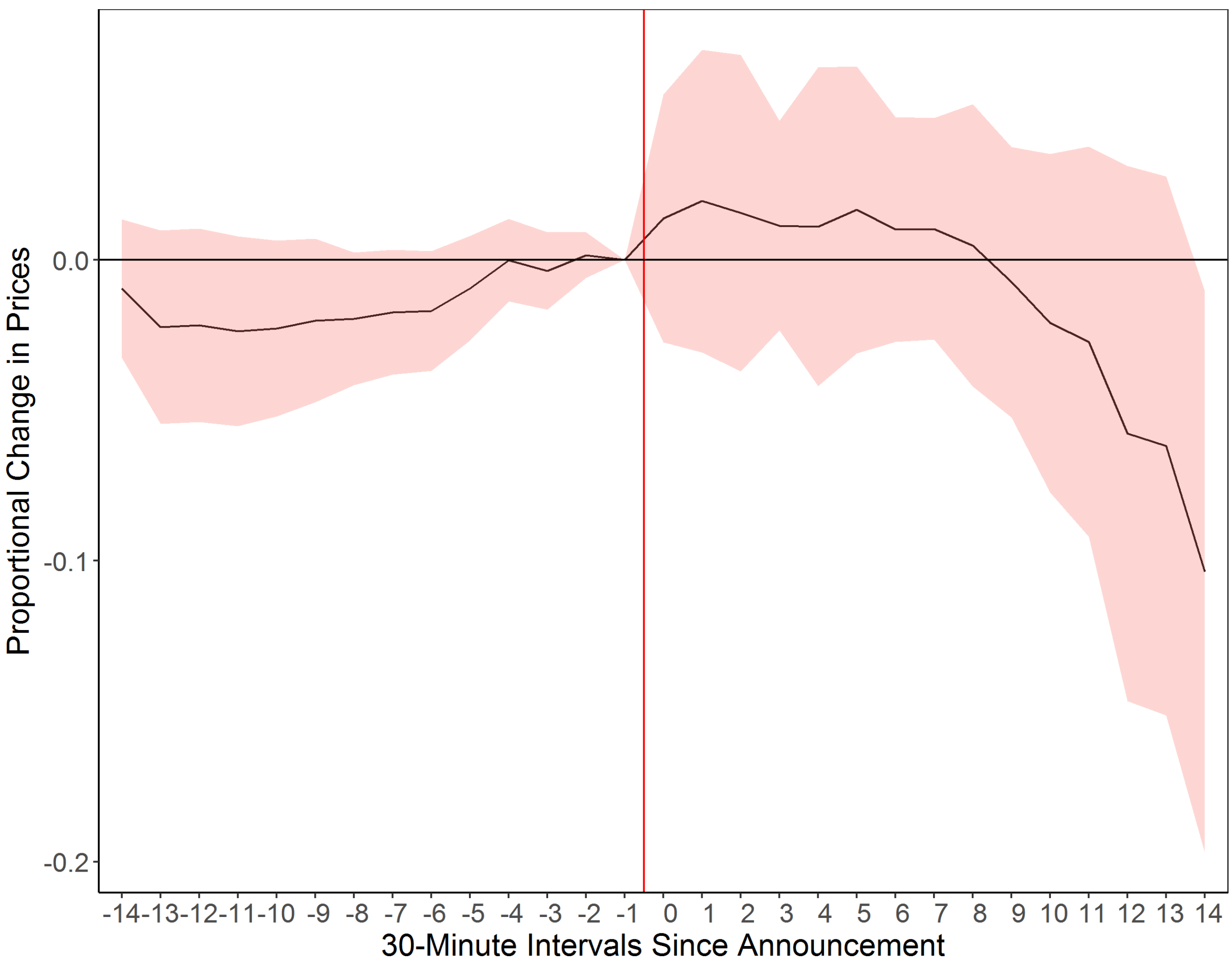


Figure 18: Event Study for Joel Embiid

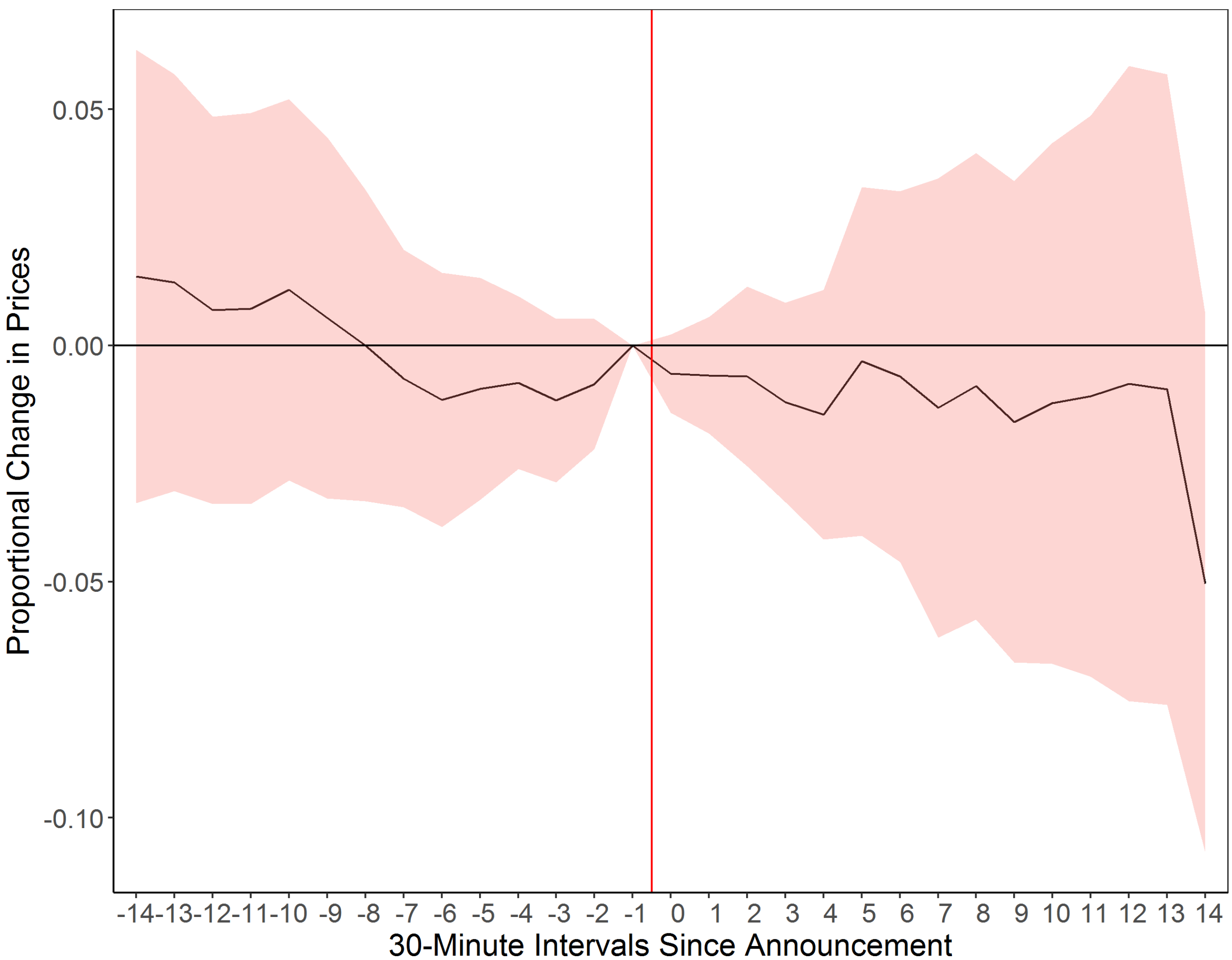


Figure 19: Event Study for Kemba Walker

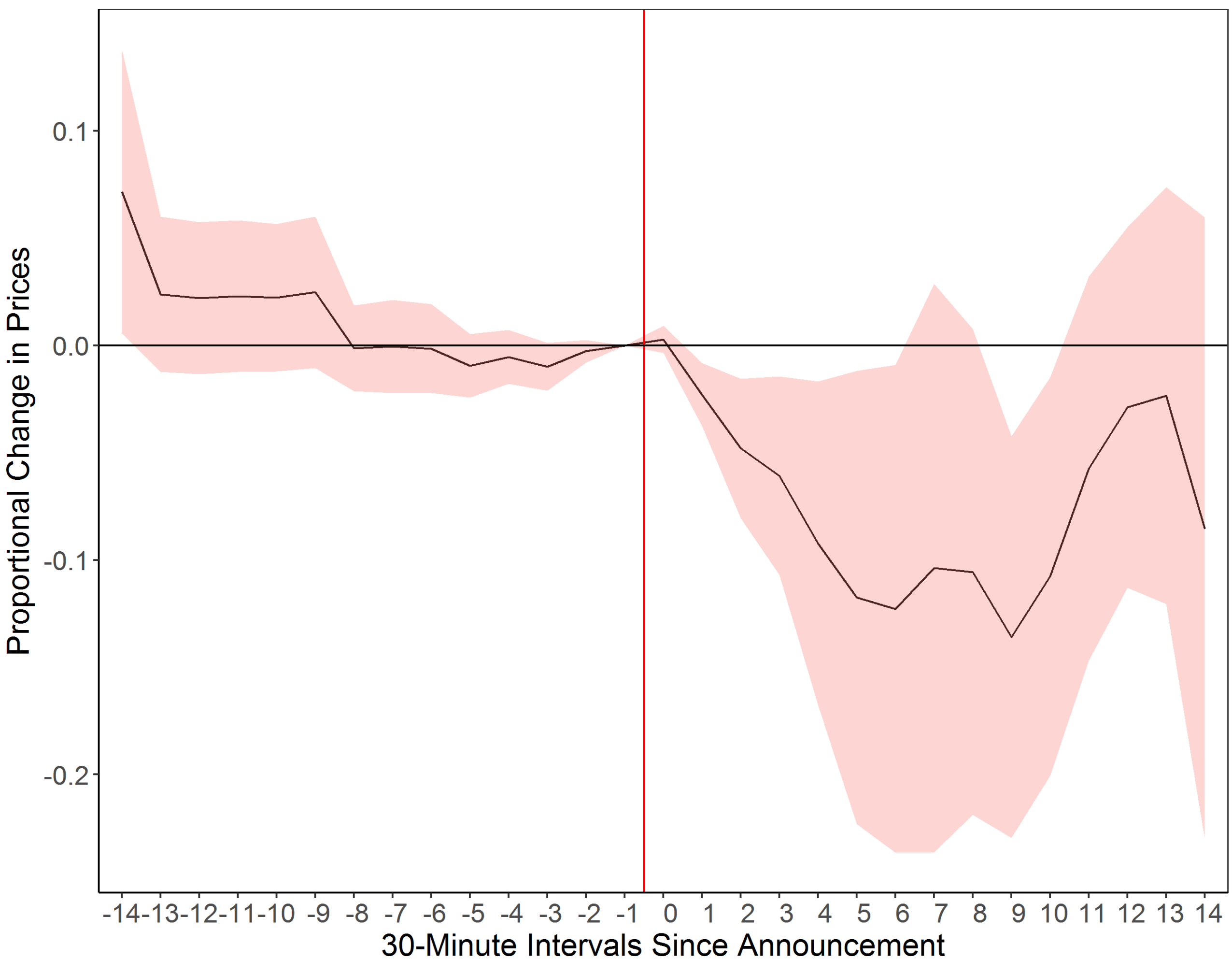


Figure 20: Event Study for Kyrie Irving

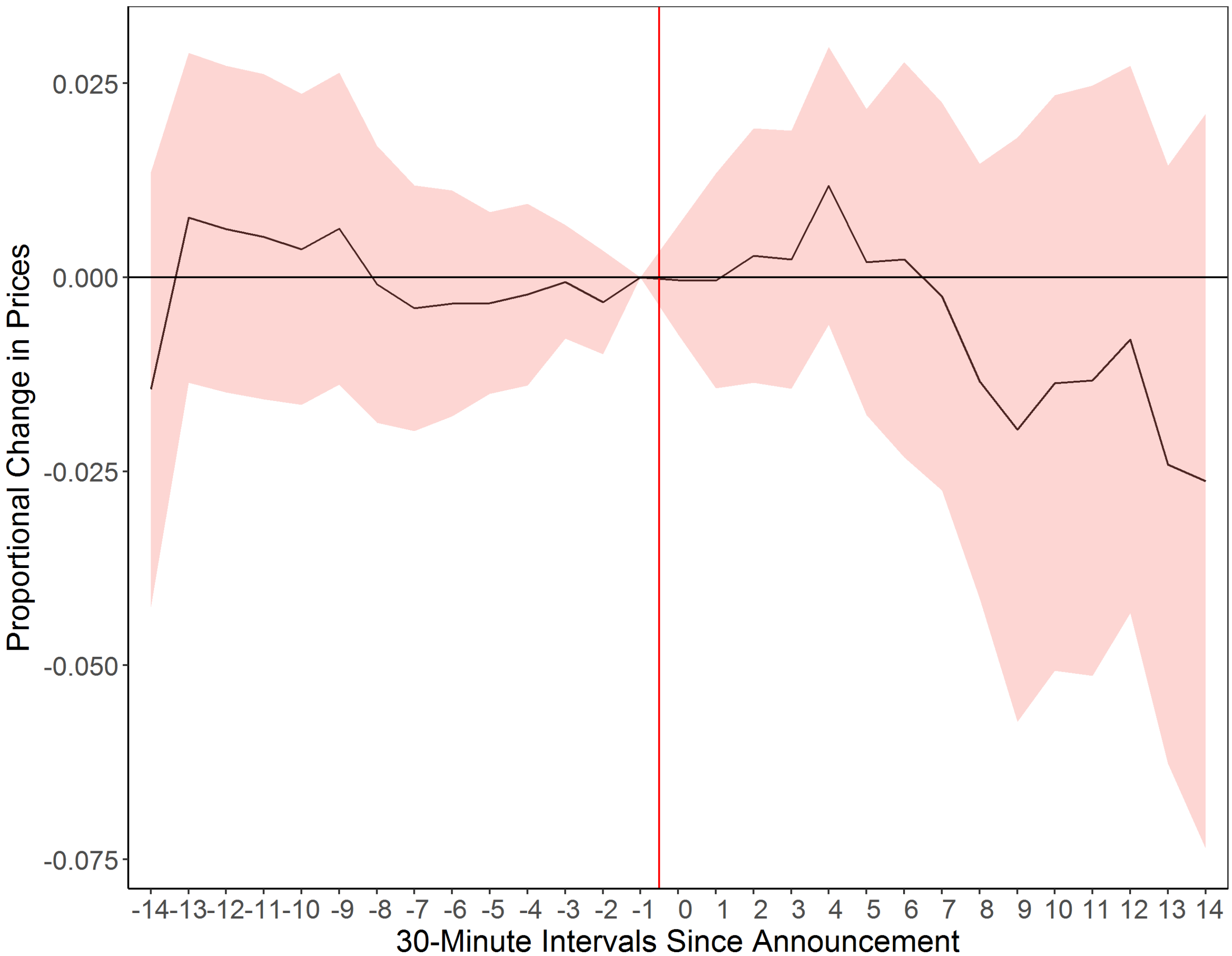


Figure 21: Event Study for Luka Doncic

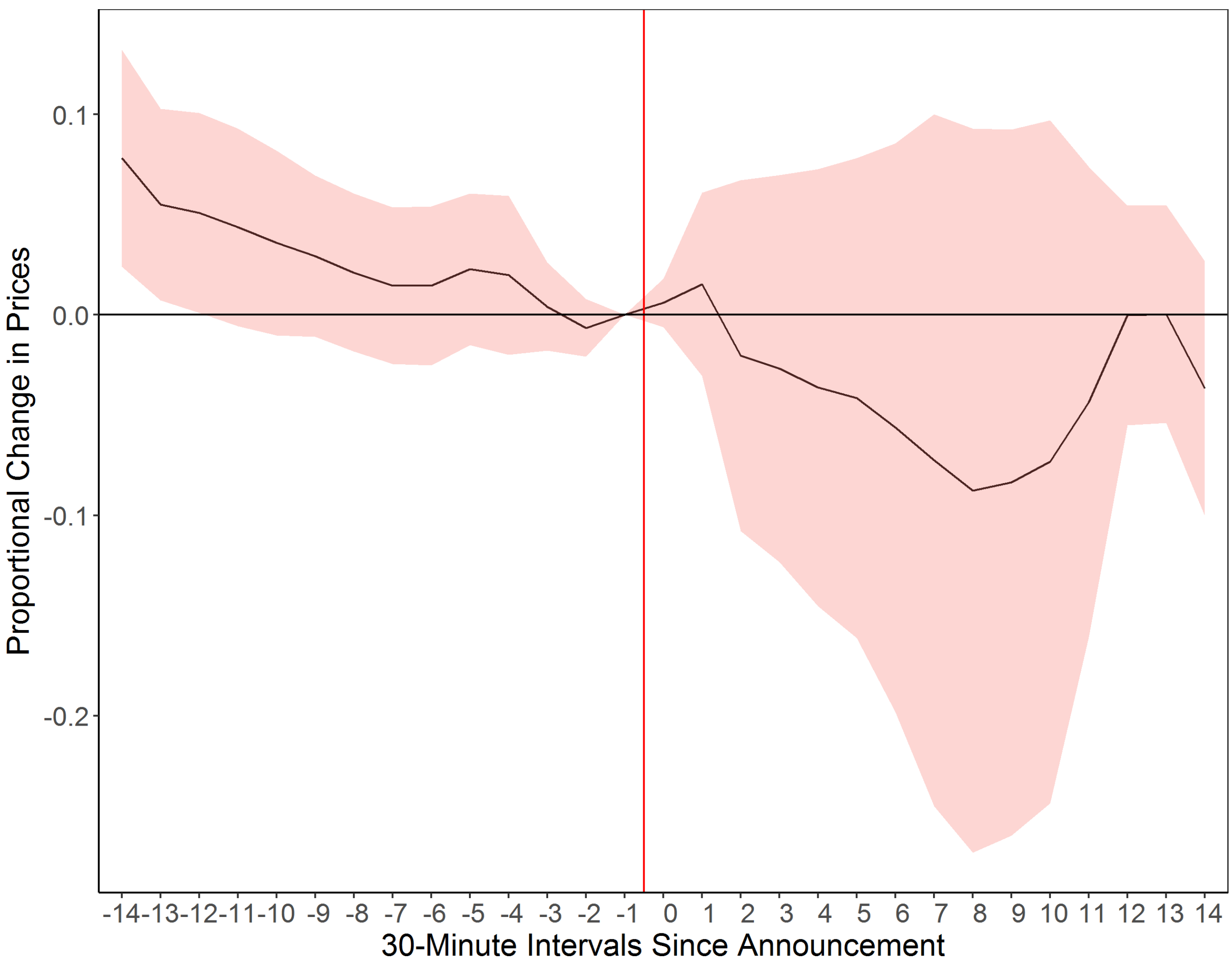


Figure 22: Event Study for Paul George

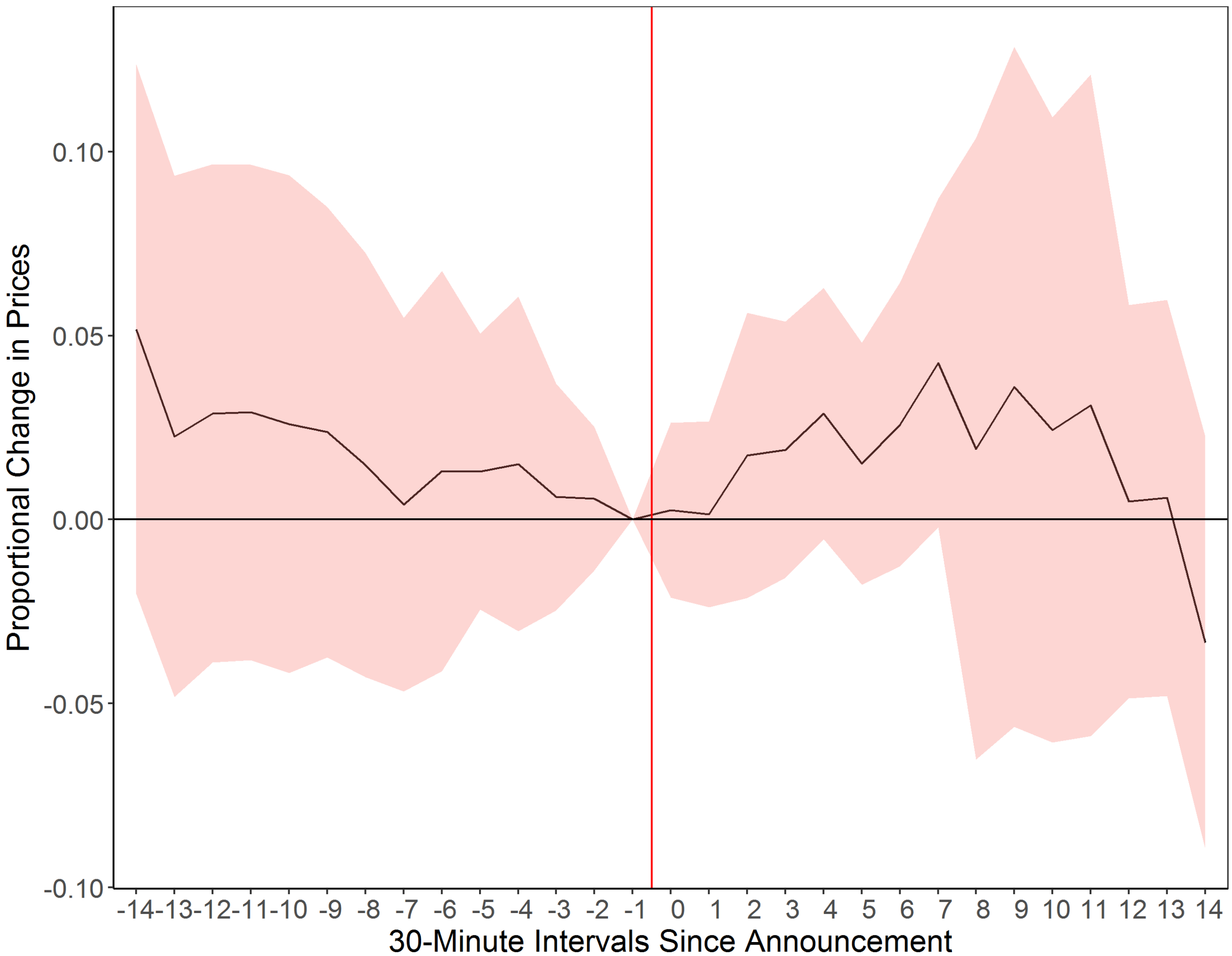


Figure 23: Difference-in-Differences Estimator by Home vs. Away Matchup Absence (Percentage Change in Prices)