Leveling the Playing Field: The Distributional Impact of Maximum- and Minimum-Level Contracts on Player Compensation*

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Abstract

How does the presence of maximum- and minimum-level contract restrictions impact (i) superstar compensation and (ii) the distribution of compensation across an industry? Using ticket price and observed player talent data from the NBA, I estimate expected salaries for each player as well as their value to the NBA as a whole. I find the ratio of actual to expected salary is 2.8–56.9% for the most talented players, resulting in subsidization to less talented players. The findings also suggest the most talented players generate significantly more value to the NBA than their actual and expected salaries.

Keywords: collective bargaining, salary cap, contract, superstar, National Basketball Association

JEL Classifications: J31, J40, J52, Z22

Abbreviations: National Basketball Association (NBA), Basketball-Related Income (BRI), Collective Bargaining Agreement (CBA), Most Valuable Player (MVP)

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I Introduction

Rosen (1982) identified certain industries with Pareto distributions in worker earnings and formalized important features of these settings. One primary characteristic of these industries is that they exhibit convex returns to worker talent; individuals located in the right tail of the distribution are classified as "superstars," who are considered the most skilled.

While much recent work has attempted to quantify the value of superstars to their respective industries (Humphreys and Johnson 2020; Kaplan 2022), relatively little has empirically examined the impact of the presence of superstars on both total compensation and the distribution of compensation across an industry as a whole. A natural setting to examine the effect of the presence of superstars on earnings is in professional sports, where player salaries and measures of talent are both observable to the researcher. There are several recent studies examining player salary shares and the distribution of earnings across players within a league (Scully 2004; Zimbalist 2010).

One important feature of professional sports leagues is collective bargaining agreements (CBAs) between players and team owners, which provide structure on the employer-employee relationship within a league (Dryer 2008; Lee 2010). Winfree (2017) finds that because player representation in CBA negotiations is skewed towards those who are more experienced and higher paid, policies may reflect the preferences of these players compared to those who are lower paid and less experienced. Vohra (2020) extends this finding by showing that the reduction in earning inequality across players (i.e. through maximum and minimum contracts for players) can improve aggregate player welfare and enhance bargaining power of players in CBA negotiations.

While league CBAs center on revenue sharing, they encompass a broad array of policies, particularly those that promote competitive balance like the imposition of a salary cap (Késenne 2000; Dietl et al. 2011). The imposition of a salary cap may be a condition for or result of bargaining in this setting, and could have important implications for the distribution of compensation among players as well as team productivity (Coates et al. 2016; Bykova and Coates 2020). One potential consequence of a salary cap is that superstar salaries become censored as a result of the imposition of maximum-level contracts, which may greatly impact the salaries of non-superstars.

This paper explores the following: how does the presence of maximum- and minimum-level contracts impact (i) superstar compensation and (ii) the distribution of player compensation across a league? I first present a brief conceptual framework to understand both of these questions. Then, using game-level ticket price and observed player talent data from the National Basketball Association (NBA), I estimate individual expected player salaries, which are paid at the team-level, as well as their predicted annual value to the NBA as a whole.

I find that the ratio of actual to expected salary for most talented players in the league falls between 2.8–56.9%, resulting primarily from the presence of maximum-level contracts. As a result, the most talented players in the league subsidize the salaries of lesser talented players. The results also suggest the most talented players generate significantly more value to the NBA than their actual and expected salaries. These findings have important implications for the structure of compensation in professional sports leagues as well as bargaining between players and team owners.

II Conceptual Framework

This section provides a conceptual framework to formalize the impact of league revenue sharing and the implementation of maximum-level contracts on player compensation. Most leagues institute a CBA between team owners and players, which specifies how revenue is shared across the two groups and rules about the structure of player salaries (among many other features). A key component of this agreement is the decision of whether or not to implement a salary cap for each team, and if so, what the structure of such a cap should be.

Salary caps are often implemented to create more balanced competition among teams, which in itself can be an important driver of league revenues. Generally (although specifics may differ across leagues), the team-level salary cap is set based on the total revenue players are expected to receive as determined by the league-level CBA divided by the total number of teams. A simple example is the following: suppose players and team owners bargain and agree on a 50/50 revenue sharing agreement, total expected annual revenues for a league are $8 billion, and there are 30 teams in the league. Then, the salary cap for each team would be set at \$133.33 million.[1]

One primary feature of a salary cap in many professional sports leagues is the imposition of maximum- and minimum-level contract thresholds for players, which may have important distortionary effects on player compensation. These contracts set a maximum (minimum) value on a player's salary in a given season. A key challenge to examining the impact of the presence of such contracts on player compensation is that it is difficult to construct the counterfactual earning power of each player in the absence of maximum and minimum contracts. This is one of the primary contributions of this paper.

I begin with two different distributions of total player compensation—one under the existence of contract thresholds and one without contract thresholds. I define these distributions as $g(X)$ and $f(X)$, respectively, where X is some continuous measure of talent as laid out in Rosen (1981). In particular, $f(X)$ is a function mapping talent to salary in the case of no maximum-level contracts, and $g(X)$ is a function mapping talent to salary in the case of maximum-level contracts.[2] I assume $f'(X) > 0$ and $g'(X) > 0$, but do not impose restrictions on $f''(X)$ and $g''(X)$, although Kaplan (2022) suggests convex compensation returns to talent. In the context of this paper, a "superstar" is defined as a player whose market value to an individual team is higher than the maximum amount they can be paid by their team. Finally, let $\bar{X}$ represent the maximum talent level a player can have.

Because of the way team owners and players conduct negotiations, the implementation of maximum- and minimum-level contracts should not affect *total* compensation of players, by construction. If this is the case, the following relationship holds:

$$\int_0^{\bar{X}} f(X)dX = \int_0^{\bar{X}} g(X)dX \tag{1}$$

which I call the *efficient player-owner revenue sharing condition*. It may be useful to frame this condition with intuition from a Nash bargaining setting. Under Nash bargaining, the

[1] Calculation: \$8,000,000/(2*30) = \$133.33.

[2] Talent can be thought of as either a continuous metric or as a discrete ranking with some arbitrary tiebreaker.

disagreement points of each party determine the bargaining share each obtains. In this case, if one party's disagreement point changes (i.e. their contribution to overall league revenues changes), then their bargaining share also changes.

Next, I explore the primary question of interest: how does the implementation of contract threshold restrictions affect the *distribution* of compensation among players in a league? Given the setup presented and assuming Equation (1) holds, there must be a single crossing point X^* in the talent ranking such that:

$$\int_0^{X^*} [g(X) - f(X)]\, dX = \int_{X^*}^{\bar{X}} [(f(X) - g(X)]\, dX \tag{2}$$

Equation (2) suggests it must be the case that transfers are occurring from high talent to low talent players under maximum and minimum contract restrictions, and that the amount of money being transferred is indicated by the area between $f(X)$ and $g(X)$ above and below X^*. Figure 1 provides a visual exploration of Equation (2). $f(X)$ is represented identically in both the left and right panes, while each pane provides a different sign for $g''(X)$ (the left-pane shows $g''(X) < 0$ and the right-pane $g''(X) > 0$). In both cases, transfers from high-talent to low-talent players occur under contract amount restrictions. Following Equation (2), the light grey area represents the same amount of compensation as the dark grey area.

In the following section, I empirically examine the relationship depicted in Equations (1) and (2) by generating the counterfactual earning power of players in the absence of contract amount restrictions. Specifically, I estimate the impact of player talent, as measured by total All-Star fan votes, on ticket prices, which provides a market-based measure of the value of each player to consumers. Combining these estimates with information about other, non-ticket sources of revenue, I compute expected player salaries, which are paid at the team-level, as well as each player's value to the NBA as a whole. I then compare the estimates of *expected* player salaries to their observed *actual* salaries to assess the distributional effects of compensation across players.

Figure 1: Examples of Inter-Player Compensation Transfers Under Contract Amount Restrictions

Note: Each pane presents a visual depiction of transfers from superstars (players with market rates above the maximum contract value), denoted by the light gray shaded areas, to other players (those with market rates below their contract values), denoted by the dark gray shaded areas. The left pane denotes $g''(X) < 0$ while the right pane denotes $g''(X) > 0$.

III Findings from the National Basketball Association

The National Basketball Association (NBA) implemented its modern salary cap structure prior to the 1984-85 season (Coon 2020).[3] Under this general structure, there is a CBA that acts as a legal agreement between players and owners about how to share basketball-related income (BRI), the level of the salary cap, restrictions on minimum and maximum salaries, rules on trading and drafting players, and many other important policies (for a full overview of the NBA salary cap structure, see Coon (2020), and for the current NBA CBA, see NBA (2017)).

Of primary relevance to this study, the NBA CBA introduces a maximum and minimum salary that can be paid to players on an annual basis. During the 2017-18 season, the maximum

[3] The NBA actually had a salary cap prior to it's inaugural season in 1946-47. The primary change occurring before the 1984-85 season was the introduction of revenue sharing between team owners and players.

annual salary that could be paid to a player was $34,682,550, and during the 2018-19 season it was $35,654,150, which represents 35% of a team's salary cap.[4] The minimum annual contract amount during the 2017-18 season was $816,000 and was $832,000 for the 2018-19 season.[5]

The minimum contract floor is an important feature of the salary cap structure. While $816,000 may appear significantly lower than the maximum contract value, one only has to look at salaries in the NBA's "G-League," which is the minor league affiliate of the NBA. The typical contract amount for players in the G-League during the 2017-18 and 2018-19 seasons was around $35,000 (NY Times). While there is a sharp discontinuity between the NBA league minimum contract and the typical G-League contract, it is highly unlikely there is a sharp discontinuity in player talent level—the top G-League player is likely to exhibit just as much talent as the bottom NBA player.[6] This generates important implications for understanding transfers among NBA players as a result of the maximum and minimum contract thresholds.

A *Data and Empirical Approach*

Figure 2 plots the relationship between All-Star fan votes and the actual salaries of each NBA player over the 2017-18 and 2018-19 seasons. I use All-Star fan votes as a measure of talent, following past studies (Jane 2016; Kaplan 2022). I account for players selected in the top 5 of the NBA draft still on their rookie contract (which lasts as long as four years) since some of these players exhibit superstar-level talent before they are able to sign a non-rookie maximum-level contract.[7]

One can see that there is a selection process that determines if a player receives *any* All-Star fan votes, and a separate process that determines how many votes a player receives conditional

[4] While this is the general maximum amount, a player is also required to have played more than 10 years in the NBA to qualify for this maximum. There are different maximums for players depending on the number of years they have played in the NBA. Additionally, this maximum only applies to the first year of a multi-year contract, where years after the initial year can rise at a certain percentage. Other specific cases of adjustments to a player's maximum salary can be found in Coon (2020).

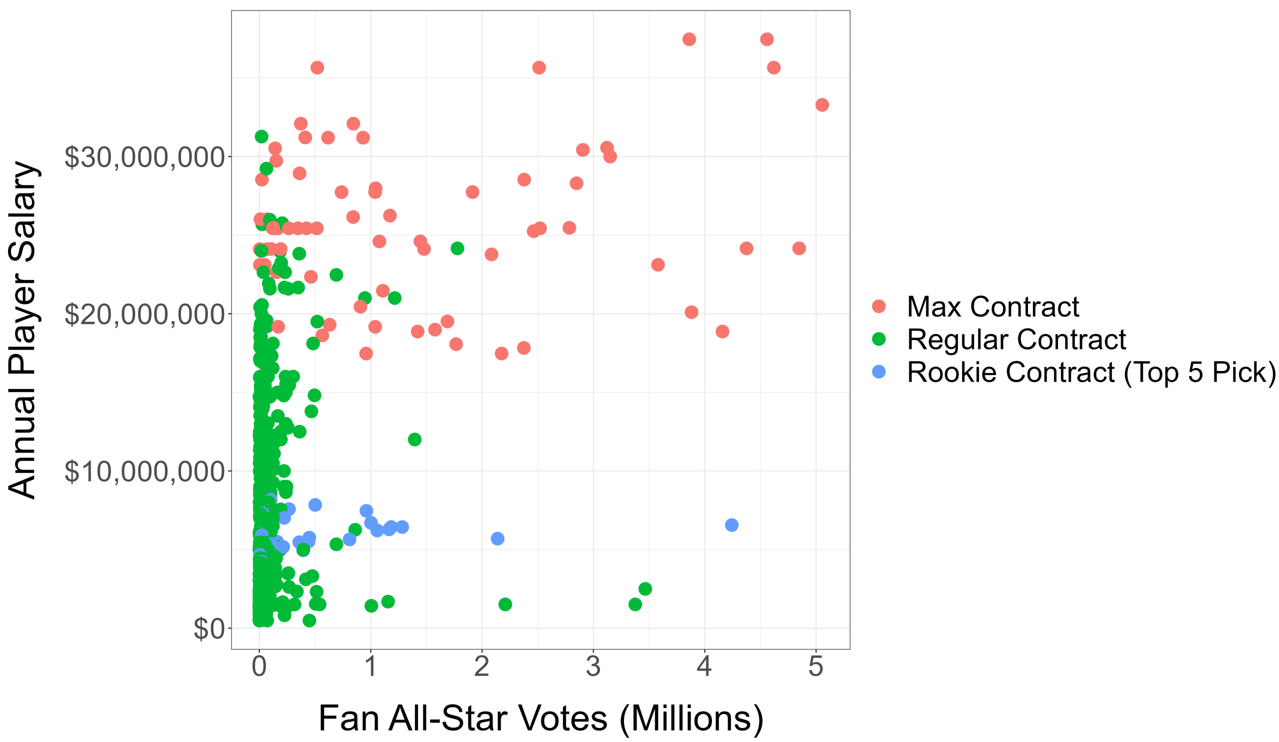
[5] These are the amounts for a player with 0 years of experience. There are incremental increases from this base minimum level for each additional year of experience. See Spotrac.com for additional details on the minimum salary scale.

[6] It should be noted that many players elect to play outside of the United States in international leagues, where salaries are higher on average than the G-League. This is important when formalizing the outside option faced by players in the NBA.

[7] Figure 2 shows the censoring of rookie contracts.

on receiving any votes at all. Additionally, the proportion of players under maximum-level contracts becomes much higher in the high popularity domain of the data.

Figure 2: Annual Player Salary by Fan All-Star Vote Total



Note: This figure plots the relationship between annual All-Star fan votes and annual salaries of each NBA player during the 2017-18 and 2018-19 seasons. There are 1,042 data points corresponding to each player-season combination (e.g. Kevin Durant in 2017-18), and each is classified as a max contract, rookie contract (top 5 pick), and regular contract.

Table 1 reinforces this finding. The data is separated into seven different total All-Star fan vote bins. The final column shows the percent of players holding maximum contracts and top 5 picks still on their rookie deals within each All-Star fan vote grouping. There is a clear positive and convex relationship between All-Star fan votes and the percent of players in a grouping signed to a maximum or top 5 rookie contract, which is 100% in the highest popularity bin. Furthermore, one can see that a vast majority of player-season observations fall in the 0-0.1 million All-Star fan votes category, supporting the selection process observed in Figure 2.

Estimating the extent to which each player actually impacts BRI is an important piece of this analysis. Because of the minimum and maximum salaries instituted by the salary cap structure,

Table 1: Salary Censoring – Number of Player-Season Combinations by Contract Status and All-Star Fan Votes

Fan Votes	# Max	# Rookie (Top 5 Picks)	# Regular	% Max or Rookie (Top 5 Picks)
3.5 Million +	9	1	0	100%
2.5-3.5 Million	7	0	2	78%
1.5-2.5 Million	9	1	2	83%
0.5-1.5 Million	20	8	12	70%
0.25-0.5 Million	7	5	20	38%
0.1-0.25 Million	9	5	59	19%
0-0.1 Million	8	14	623	3%

Note: An example of a "Player-Season" combination is Stephen Curry in the 2018-19 season. I examine the 2017-18 and 2018-19 NBA seasons. All combinations featuring a player playing less than half of the regular season (41 games) are omitted. The maximum nominal vote tally in the sample was 4,620,809 by LeBron James during the 2018-19 season. Salary information was collected from `ESPN.com`, maximum contract information was collected from `HoopsHype` and inferred manually in a few cases, and the list of top 5 picks in preceding drafts was collected from `Basketball Reference`.

actual salaries are insufficient in determining each player's true value to their individual teams and the NBA as a whole.

Several studies have examined and estimated the competing effects of player popularity and productivity on player compensation and demand (Grimshaw and Larson 2021; Scarfe et al. 2021). Using data on ticket prices and television ratings from the NBA, Kaplan (2022) shows that player popularity, measured by number of fan All-Star votes, greatly outweighs player productivity, measured by Value Over Replacement Player (VORP), in terms of its effect on prices and viewership, respectively. In particular, Kaplan (2022) shows that for a 1% increase in the number of All-Star fan votes a player receives, ticket prices increase by 0.13-0.14%, while an increase in VORP has no economically meaningful impact. Therefore, by estimating the responsiveness of ticket prices to player popularity, one can determine each player's value as a function of their talent.

Combining the empirical approach in Kaplan (2022) with information about other, non-ticket sources of revenue generated by the NBA, I compute the *expected* salary of each NBA player during the 2017-18 and 2018-19 seasons, and compare it to their actual salary. Summary statistics describing the ticket price and game characteristic data used in this estimation can be found in Table 2. One can see that the average game-level listed ticket price was \$139.58, and that the average number of All-Star fan votes present in a game is 4.76 million. Additional

Table 2: Summary Statistics for NBA Ticket Prices and Game Characteristics

Statistic	N	Mean	St. Dev.	Min	Max
Avg. Ticket Price ($)	2,330	139.58	94.23	22.40	943.96
Attendance	2,241	17,970.52	1,990.35	10,079	22,983
Aggregate Fan All-Star Votes	2,460	4,761,034.00	3,765,856.00	59,599.93	24,002,157.00
Aggregate VORP	2,460	18.12	7.14	−5.00	36.20
Avg. Current Win %	2,460	0.50	0.11	0.17	0.93
% Home Team Favored	2,460	0.71	0.45	0	1
Win Probability Differential	2,460	37.38	27.70	0.00	90.66

Note: This data comes from several sources, including `NBA.com`, `FiveThirtyEight`, `Basketball Reference`, and through manual web-scraping. Because of the web-scraping procedure, ticket price data was only available for 2,330 of the 2,460 total regular season games across the 2017-18 and 2018-19 seasons. The missing games make up a random subset of the 2,460 total regular season games. Only tickets that were eventually sold are included in the calculation of average price for each game. Attendance refers to the published number of individuals who attended a game. 219 games are missing published attendance numbers, and while reasons for the missing data are not known, the distributions of other variables for this sample of games are very similar to their distributions in the full sample. Aggregate Fan All-Star Votes refers to the cumulative number of All-Star votes received by all players playing in a game. Because the total number of fan All-Star votes may change across years (akin to inflation), and in this case increased significantly from the 2017-18 to 2018-19 season, I convert the 2017-18 raw fan All-Star votes values to 2018-19 terms using the ratio of average fan All-Star votes in 2018-19 compared to 2017-18 (average votes increased by a factor of 1.916). Aggregate VORP refers to "Value over Replacement Player" and 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 % is the average win percentage at time of game of the two teams playing. Home Team Favored is an indicator variable =1 if the home team was favored at the start of the game (as given by the point spread). Win Probability Differential is the absolute difference in win probabilities (measured in percentage points) between the two teams playing prior to the start of the game.

details about the data can be found in the accompanying note of Table 2.

B Results

Table 3 estimates the ticket price elasticity with respect to player popularity under different linear regression functional forms. In particular, I estimate linear-linear, log-log, and log-linear specifications.[8] Specification 2 suggests that for a 1% increase in Aggregate All-Star votes present in a game, there is an approximately 0.14% increase in average listed prices of tickets.

Table 7 in Appendix A estimates the *total* effect of Aggregate All-Star votes and Aggregate VORP on ticket prices by omitting the Aggregate All-Star votes variable from all specifications.

[8] Figure 4 in Appendix A provides a scatter plot depicting the positive and convex relationship between total fan All-Star votes and average ticket prices by game, justifying the use of the three linear regression functional forms in Table 3. Tables 5 and 6 in Appendix A provide two alternate specifications for each of the three linear regression functional forms.

Because VORP and All-Star votes are positively correlated (0.53), we see that for a 1% increase in Aggregate VORP present in a game, the effect on ticket prices is slightly larger (0.18%) than the direct effect of Aggregate All-Star votes observed in Table 3 (0.14%). Using the findings from Table 3 delivers a relatively conservative estimate of each player's value as a function of their talent.

Based on an average of the coefficient estimates on the "Aggregate All-Star Votes" variable in each of the three specifications in Table 3, I compute each player's per game ticket price impact using their observed season-level All-Star fan vote totals and average per-game attendance, and then aggregate these estimates to the regular season-level (82 games).[9]

However, ticket sales make up only 22% of the approximately $8 billion in annual league revenues (Badenhausen and Ozanian 2019; RunRepeat 2021). Importantly, the NBA CBA distinguishes between revenue sources that are fully allocated to the teams generating them (i.e. revenue from ticket sales and local broadcasting agreements), and sources of revenue that are shared equally across all teams (i.e. national broadcasting agreements and league merchandise) (NBA 2017). This nuance is critical for evaluating the difference in a player's value to the team they play for, which receives 1/30 of revenue generated from sources shared equally across all teams, versus their value to the NBA as a whole (which includes the value each player generates for the 29 other teams).

To account for the other streams of annual revenue generated by the NBA, I extrapolate the ticket price impact to the 78% of remaining revenue in the following manner. First, following the results in Kaplan (2022), I assume player popularity has the same marginal impact on revenues from television viewership as it does on ticket prices.[10] This manifests through local broadcast agreements, which make up approximately 15% of annual league revenues and are not subject to any revenue sharing provisions (Shea 2023), and national broadcast agreements,

[9]Each NBA team plays 82 games during the regular season. I compute the regular-season impact for each player by multiplying their per-game impact by 82, assuming they are on a team's roster for each of these 82 games. It should be noted, however, that players may not play in all 82 regular season games. I do not include additional games that may have been played during the playoffs.

[10]Kaplan (2022) provides evidence for the impact of All-Star votes on television *viewership*, but not television broadcast *revenues*. In particular, a unit-elastic relationship between viewership and broadcast revenue would suggest the impact of All-Star votes on viewership translate one-for-one with impacts on broadcast revenue. Previous studies suggest that the relationship is in fact approximately unit-elastic (Fisher et al. 1980; Anderson and Waldfogel 2015).

Table 3: Impact of Player Talent on Ticket Prices

	Dependent Variable: Avg. Listed Price (Game-Level)		
	Linear-Linear	Log-Log	Log-Linear
Aggregate All-Star Votes (100,000s)	0.8010***		0.0045***
	(0.1280)		(0.0009)
log(Aggregate All-Star Votes)		0.1373***	
		(0.0292)	
log(Aggregate VORP)	6.4140	0.0776	0.0828*
	(5.6126)	(0.0393)	(0.0375)
log(Avg. Current Win PCT)	45.5257**	0.3547***	0.3633***
	(13.7530)	(0.0792)	(0.0776)
Home Team Favored (HTF)	−0.9236	−0.0228	−0.0300
	(3.6521)	(0.0200)	(0.0199)
Win Probability Differential (WPD)	−0.2776	−0.0037*	−0.0032*
	(0.2473)	(0.0015)	(0.0014)
HTF*WPD	0.4423	0.0050*	0.0049*
	(0.2764)	(0.0021)	(0.0019)
Clustered Robust SEs (Home Team)	X	X	X
Observations	2,318	2,318	2,318
R^2	0.6288	0.7135	0.7182

Note: The dependent variable is the Average Listed Price at the game-level (logged in specifications 2 and 3). I compute a smearing estimate (following Duan 1983) for the coefficient on "Aggregate All-Star Votes (100,000s)" in specification 3, confirming that the marginal effect interpretation does not suffer from transformation bias. The mean of the dependent variable is $139.58. Descriptions of the additional covariates are included in Table 2. Fixed effects are included for home team and away team, which account for all time-invariant characteristics associated with home (away) games featuring each specific team, month-by-season (e.g. December 2017), 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 broadcast on (TNT, ESPN, ABC, NBA TV, and local), and a Holiday indicator =1 if the game is played on a holiday. All specifications cluster standard errors at the home team level. *p<0.05; **p<0.01; ***p<0.001

which make up around 30% of annual league revenues but are subject to equal revenue sharing (Vorkunov 2023).

For the remaining 33% of revenue, which consists primarily of league merchandise and sponsorships, I compute a "pass-through rate" of the estimated marginal impact of player popularity on ticket prices.[11] The pass-through rate is calculated such that the *total expected*

[11] The pass-through rate represents the extent to which the marginal impact of player popularity on ticket prices

revenue generated by all players is equal to the *sum of actual salaries* received by all players. This equality, which is depicted mathematically in Equation 1, implies that the revenue split between players and owners negotiated in the CBA is efficient, which is assumed to be the case. Further detail regarding this procedure can be found in Appendix B.

Using this approach, Figure 3 depicts the relationship between log(Salary) and All-Star vote percentile for actual and expected salaries at an individual player-season level. One can see most players have expected salaries lower than their actual salaries, as indicated by the red dots. The blue dots indicate players with expected salaries above their actual salaries. In the uppermost All-Star fan vote percentiles, all players have expected salaries larger than their actual salaries. This emphasizes the specific distributional implications of the NBA's maximum- and minimum-level contracts; players in the upper percentiles of All-Star votes are subsidizing the salaries of players in the lower percentiles. This has additional implications for bargaining *among* players.[12]

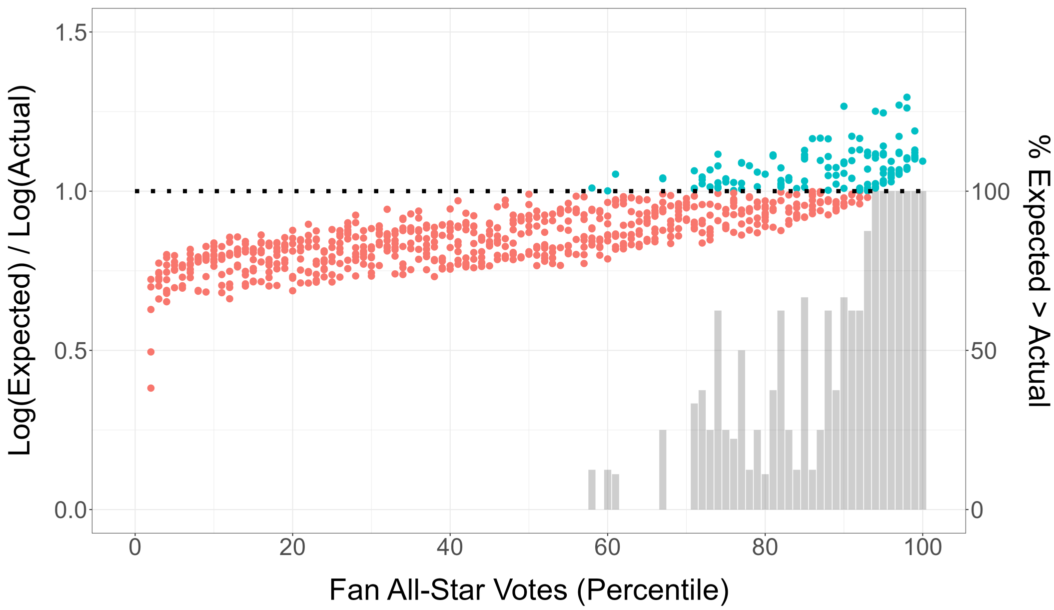
Table 4 compares the actual and expected salaries for the ten players receiving the most All-Star fan votes during the 2018-19 season. It also presents each player's annual value to the NBA as a whole. One can see that several of these players are paid two to four times less than their expected salaries, while Derrick Rose and Luka Doncic are paid more than an order of magnitude less than their expected salaries. In particular, the ratio of actual to expected salaries is between 2.8–56.9%. Table 4 also shows the value each of these players provides on an annual basis to the NBA as a whole, led by LeBron James at nearly $230 million/year, which is approximately 7.4% of sum of average annual player salaries during the 2017-19 seasons. Unsurprisingly, the most talented players provide substantial value to teams they do not play for through each of the aforementioned revenue channels.

It is important to point out possible explanations for why some of these players are not under a maximum-level contract, given each player's expected salary is higher than the maximum contract threshold as designated by the salary cap for the 2018-19 league year. Discrepancies may be due to rookie-scale contract restrictions (which is the case for Luka Doncic), player-

translates to this remaining 33% of revenues.

[12]Note that expected salary should be interpreted relative to the outside option (e.g. the NBA G-League or playing in a different professional league). This is especially true for very low All-Star vote percentile players.

Figure 3: Actual vs. Expected Player Salary by Fan All-Star Vote Percentile



Note: The red dots falling below a value of 1 (measured by the left y-axis) indicate players with an expected salary *below* their actual salary. The blue dots falling above a value of one indicate players with an expected salary *above* their actual salary. The grey bars indicate the percentage of players in each fan All-Star vote percentile with an expected salary greater than their actual salary (right y-axis).

specific maximum values that are dependent on years played in the NBA (i.e. if a player has played more than 10 years, they are eligible for 35% of the team-level salary cap, but if a player has served fewer years they will be restricted to a lower percentage), and players taking lower than the maximum value they are eligible for because of team-specific competitiveness reasons (i.e. they take a lower salary to allow the team to sign a higher quality complementary player while remaining within the bounds set by the salary cap).

A player like Derrick Rose, whose actual salary is 2.8% of his expected salary, presents an interesting case. Rose was the 2011 NBA Most Valuable Player (MVP), but his on-court productivity fell substantially following his MVP season (primarily due to injuries). However, his popularity remained extremely high with fans, and as a result, Rose generated substantial value for the Minnesota Timberwolves and the NBA during the 2018-19 season. Table 8 in Appendix C presents analogous results from sensitivity analyses over the pass-through rate to non-ticket revenue and non-broadcasting revenue BRI.

Table 4: Actual vs. Expected Salaries and Value to the NBA for Top 10 All-Star Vote Players During 2018-19 Season

Player	All-Star Votes	Actual Salary ($)	Predicted Salary ($)	Ratio (Actual/Expected)	Value to NBA ($)
LeBron James	4,620,809	35,654,150	123,350,655	28.9%	229,543,755
			(23,777,382)	(4.7)	(44,247,431)
Giannis Antetokounmpo	4,375,747	24,157,303	72,240,540	33.4%	134,432,726
			(13,351,265)	(5.2)	(24,845,426)
Luka Doncic	4,242,980	6,560,640	68,701,683	9.5%	127,847,252
			(12,669,174)	(1.5)	(23,576,120)
Kyrie Irving	3,881,766	20,099,189	82,765,803	24.3%	154,019,233
			(15,685,531)	(3.9)	(29,189,271)
Stephen Curry	3,861,038	37,457,154	120,127,051	31.2%	223,544,938
			(23,375,687)	(5.1)	(43,499,915)
Kawhi Leonard	3,580,531	23,114,067	68,591,400	33.7%	127,642,025
			(12,874,249)	(2.8)	(23,957,743)
Derrick Rose	3,376,277	1,512,601	54,194,203	2.8%	100,850,222
			(9,983,808)	(0.4)	(18,578,911)
Kevin Durant	3,150,648	30,000,000	98,024,949	30.6%	182,415,042
			(19,074,809)	(5.0)	(35,496,393)
Paul George	3,122,346	30,560,700	59,663,205	51.2%	111,027,510
			(11,195,766)	(8.1)	(20,834,247)
James Harden	2,905,488	30,421,854	53,436,134	56.9%	99,439,527
			(9,989,777)	(9.0)	(18,590,018)

Note: These estimates come from the average values of log-linear (exponential), linear-linear, and log-log regression models in Table 3. Estimates of expected salaries and value to the NBA are computed according to the formulas in Appendix B equations 3 and 4, respectively, using a pass-through rate $P = 0.12$. Differences in average prices for each player's team determine their predicted salaries from the log-linear and log-log models. Standard errors for the estimated values are found in parentheses below each estimate. Standard errors for the Actual/Expected Salary Ratio are in percentage points units.

IV Discussion and Policy Recommendations

The findings in this study suggest the extent to which maximum- and minimum-level contract restrictions distort individual player salaries away from their expected salaries. It also highlights the difference between a player's expected salary, which is paid at the team-level, versus their value to the NBA as a whole. For the most talented players, there exists a large gap in these two estimates, since these players have a meaningful impact on the revenues of teams other than the one they play for.[13]

In the NBA, we find the existence of these restrictions leads to pay compression among players; less talented players are overpaid relative to their market values, while more talented players are underpaid. It is important to note that pay compression-induced salary distortions are not isolated to professional sports leagues. In fact, any industry with a fixed pay scale that includes maximum- and minimum- salaries and workers with heterogeneous productivity may face similar issues. One prominent example of this is the US military. Glaser and Rahman (2011) show that despite a fixed salary within each officer rank in the military, there are widely varying productivity levels among officers within each rank.

Of course, there may be certain benefits to these distortions, for instance competitive balance across a league. Yet, there may be feasible policies that preserve competitive balance while at the same time narrowing the gap between a player's market value to their team and their observed salary. A primary objective of CBAs should be to recognize player salary distortions and negotiate compensation mechanisms that are independent of competitive balance considerations.

One concrete proposal is the institution of a "bonus pool," where players can earn additional compensation from a central governing body (like the league office) based on performance metrics.[14] Such a policy should be designed while keeping in mind the associated sorting incentives of players to certain teams. For instance, if bonuses are solely determined by individual performance metrics, players may be incentivized to join bad teams in order to stand out. Alternatively, if joining a team with other high productivity players increases a player's bonus, then it may compromise league parity.

An incentive compatible policy that limits re-sorting should reward players based on a combination of their individual statistics and team performance. One such metric that jointly

[13]This point was also emphasized in Hausman and Leonard (1997), which examined the impact of Michael Jordan on the value of teams other than the one he played for (the Chicago Bulls).

[14]The NBA does allow players to sign larger contracts if they receive certain league-wide accolades (e.g. MVP or making an All-NBA team), but this money comes directly from the player's team.

measures individual and team performance is "Win Shares," which is an estimate of the number of wins contributed by an individual player. Policies like this maintain competitive balance while allowing more flexibility in salaries for higher productivity players, in particular players under maximum-level contracts.

The newly ratified NBA CBA, which went into effect July 1, 2023 and will remain in place for a minimum of five seasons, suggests that the league is pursuing joint objectives of competitive balance while improving flexibility to pay higher performing players closer to their market values. Specifically, the new CBA imposes stricter penalties on higher-spending teams, which will hamper their ability to make significant roster improvements. At the same time, the new CBA increases the upper limit on the value of player contract extensions, allowing teams to extend players at 140% of the value of their current contract instead of 120% (NBA 2023).

Relatedly, the NBA is introducing policies that allow for players to further capitalize on the growth of the league. For instance, until now, owners have received 100% of team and league licensing revenues. In this new CBA, licensing revenues, which are estimated to be $160 million during the 2023-24 season, will be included in the BRI pool shared between players and owners. Additionally, an equity partnership program will be introduced, which will allow players to invest in NBA teams (Florio 2023).

V Conclusion

This research examines the effect of the presence of superstars on total compensation and distribution of earnings of other workers in the same industry. A natural setting to examine this is in professional sports, where player salaries and talent characteristics are both observable to the researcher. I examine the specific case of the NBA, where bargaining between players and team owners dictates the sharing of league revenues between the two groups and informs the structure behind many league policies. One important policy resulting from bargaining is a team-specific salary cap featuring both maximum- and minimum-level annual contracts that players can receive.

This paper provides insight on the following questions: how does the presence of maximum- and minimum-level contracts affect (i) the amount of compensation received by superstars, and

(ii) the distribution of compensation across players? Using estimates of the impact of player talent, as measured by the number of All-Star fan votes they receive each season, on ticket prices, I construct a market value for each player. I estimate both expected player salaries, which are paid at the team-level, as well as their value to the NBA as a whole.

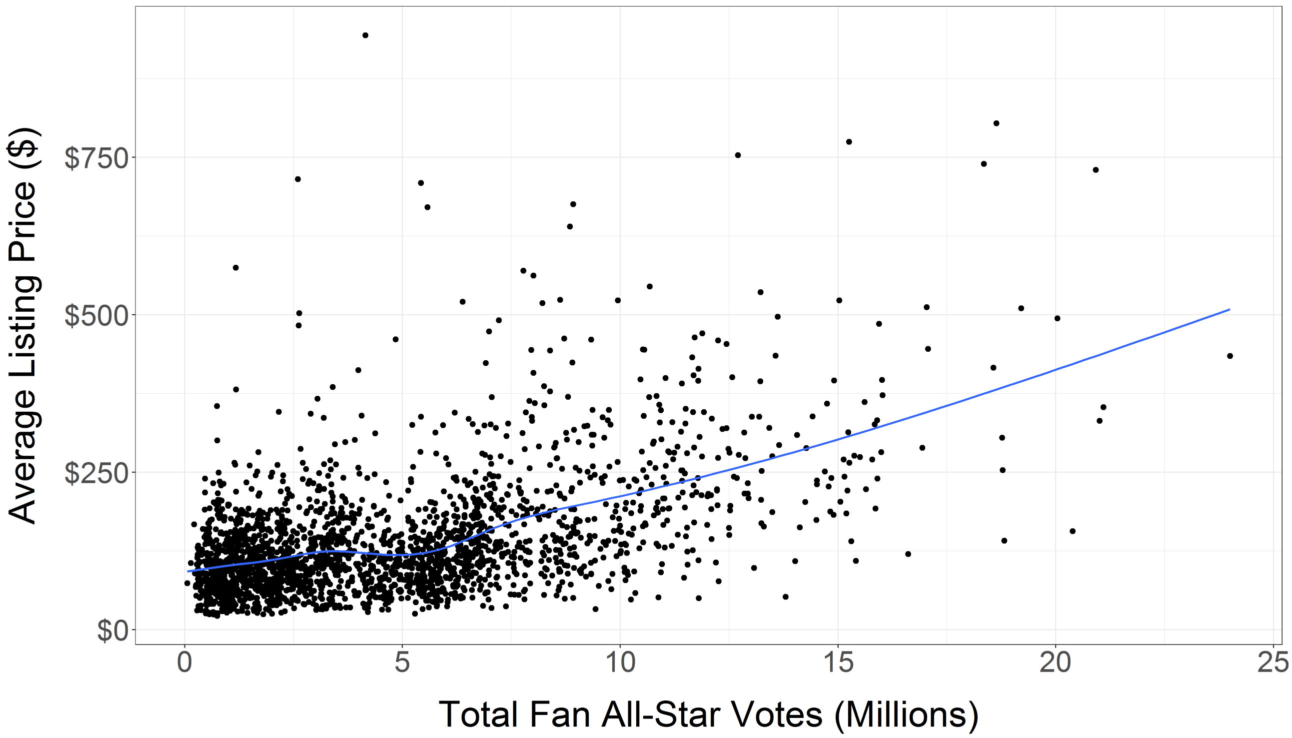
I find the ratio of actual to expected salary for the most talented players in the league falls between 2.8–56.9%, primarily as a result of a salary cap that features a maximum annual contract threshold. This leads to subsidization by the most talented players to less talented players. The results also suggest the most talented players generate substantially more value to the NBA than their actual and expected salaries.

The findings have important implications for the structure of compensation in all industries defined by a Pareto distribution in earnings, especially those that impose certain compensation restrictions. The results have specific application to professional sports leagues, which face key decisions pertaining to the design and implementation of player salary structures. Salary caps are often necessary in certain leagues because of competitive balance considerations, but the extent to which their necessity impacts bargaining should be a focus of future work. In particular, the existence of salary caps is likely to impact not only bargaining between players and team owners, but also within-player and within-owner negotiations as well.

VI Appendix

A Additional Estimations of the Impact of Player Popularity on Ticket Prices

Figure 4: Scatter Plot of Total All-Star Votes and Average Ticket Price



Note: This figure shows a scatter plot between total fan All-Star votes and average ticket prices by game. The solid blue line is a fitted locally weighted scatter plot smoothing (LOWESS) regression line. The convexity of the fitted line supports the choice of the three linear regression functional forms in Table 3.

Table 5: Impact of Player Talent on Ticket Prices (No HTF·WPD Interaction and No Away Team FE)

	Dependent Variable: Avg. Listed Price (Game-Level)		
	Linear-Linear	Log-Log	Log-Linear
Aggregate All-Star Votes (100,000s)	0.2685***		0.0076***
	(0.0216)		(0.0007)
log(Aggregate All-Star Votes)		1.2459***	
		(0.0974)	
log(Aggregate VORP)	−0.0710	−11.7651**	−0.0328
	(0.0395)	(3.8607)	(0.0356)
log(Avg. Current Win PCT)	0.2133**	29.3394*	0.2225**
	(0.0733)	(12.0379)	(0.0683)
Home Team Favored (HTF)	0.0070	2.8858	0.0186
	(0.0412)	(4.9988)	(0.0385)
Win Probability Differential (WPD)	0.0010	0.2068*	0.0013
	(0.0007)	(0.0913)	(0.0007)
Clustered Robust SEs (Home Team)	X	X	X
Observations	2,318	2,318	2,318
R^2	0.6361	0.5712	0.6598

Note: The dependent variable is the Average Listed Price at the game-level (logged in specifications 2 and 3). The mean of the dependent variable is $139.58. Fixed effects are included for home team, which account for all time-invariant characteristics associated with home games featuring each specific team, month-by-season (e.g. December 2017), 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 broadcast on (TNT, ESPN, ABC, NBA TV, and local), and a Holiday indicator =1 if the game is played on a holiday. All specifications cluster standard errors at the home team level. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 6: Impact of Player Talent on Ticket Prices (No Away Team FE)

	Dependent Variable: Avg. Listed Price (Game-Level)		
	Linear-Linear	Log-Log	Log-Linear
Aggregate All-Star Votes (100,000s)	0.2722***		0.0078***
	(0.0211)		(0.0007)
log(Aggregate All-Star Votes)		1.2648***	
		(0.1000)	
log(Aggregate VORP)	−0.0639	−10.8697**	−0.0232
	(0.0403)	(3.8907)	(0.0343)
log(Avg. Current Win PCT)	0.2370**	32.2520*	0.2536**
	(0.0784)	(12.7061)	(0.0716)
Home Team Favored (HTF)	−0.0547*	−4.9574	−0.0651*
	(0.0258)	(4.9603)	(0.0238)
Win Probability Differential (WPD)	−0.0014	−0.0998	−0.0020
	(0.0015)	(0.2235)	(0.0013)
HTF*WPD	0.0032	0.4169	0.0044*
	(0.0021)	(0.2491)	(0.0017)
Clustered Robust SEs (Home Team)	X	X	X
Observations	2,318	2,318	2,318
R^2	0.6386	0.5728	0.6644

Note: The dependent variable is the Average Listed Price at the game-level (logged in specifications 2 and 3). The mean of the dependent variable is \$139.58. Fixed effects are included for home team, which account for all time-invariant characteristics associated with home games featuring each specific team, month-by-season (e.g. December 2017), 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 broadcast on (TNT, ESPN, ABC, NBA TV, and local), and a Holiday indicator =1 if the game is played on a holiday. All specifications cluster standard errors at the home team level. *p<0.05; **p<0.01; ***p<0.001

Table 7: Impact of Player Talent on Ticket Prices (Aggregate VORP Only)

	Dependent Variable: Avg. Listed Price (Game-Level)		
	Linear-Linear	Log-Log	Log-Linear
Aggregate VORP	2.3695***		0.0175***
	(0.4598)		(0.0037)
log(Aggregate VORP)		0.1784***	
		(0.0394)	
log(Avg. Current Win PCT)	60.1515***	0.4419***	0.4456***
	(14.7609)	(0.0896)	(0.0917)
Home Team Favored (HTF)	−2.6189	−0.0263	−0.0411*
	(3.7980)	(0.0205)	(0.0193)
Win Probability Differential (WPD)	−0.3244	−0.0039*	−0.0033*
	(0.2656)	(0.0017)	(0.0016)
HTF*WPD	0.4862	0.0053*	0.0050*
	(0.3211)	(0.0024)	(0.0023)
Clustered Robust SEs (Home Team)	X	X	X
Observations	2,330	2,318	2,330
R^2	0.6098	0.7026	0.7038

Note: The dependent variable is the Average Listed Price at the game-level (logged in specifications 2 and 3). The mean of the dependent variable is $139.58. Fixed effects are included for home team and away team, which account for all time-invariant characteristics associated with home (away) games featuring each specific team, month-by-season (e.g. December 2017), 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 broadcast on (TNT, ESPN, ABC, NBA TV, and local), and a Holiday indicator =1 if the game is played on a holiday. All specifications cluster standard errors at the home team level. *p<0.05; **p<0.01; ***p<0.001

B Player Revenue Extrapolation

Basketball-related income (BRI) includes several revenue streams, including ticket sales, local and national broadcast agreements, league merchandise, league sponsorship deals, and many others (NBA 2017). The NBA CBA in place during the 2017-19 seasons stipulated that players would receive 49-51% of eligible revenues (which turned out to be 51% in each of these two seasons). During the 2017-19 seasons, the NBA generated an estimated $8 billion in total annual revenue, of which approximately 22% came from gate receipts (RunRepeat 2021; Badenhausen and Ozanian 2019). The analysis in this paper relies on the estimation performed in Kaplan (2022), which looks at the impact of number of All-Star fan votes on ticket prices.

Because player salaries are a function of all of the revenue they generate for the NBA, I extrapolate their ticket price impact into the other revenue streams in the following manner. First, I assume player popularity has the same marginal impact on revenues from television viewership as it does on ticket prices. Kaplan (2022) provides evidence that the elasticity of television viewership with respect to All-Star votes is nearly identical in magnitude to the elasticity of ticket prices with respect to All-Star votes. Specifically, they show that a 1% increase in aggregate All-Star votes present in a game leads to an approximately 13.64% increase in ticket prices and a 13.00% increase in television viewership (and a 16.53% increase in television viewership when only examining regular season games, which is the same criteria used in this study).

However, Kaplan (2022) provides evidence for the impact of All-Star votes on television *viewership*, but not television broadcast *revenues*. In particular, a unit-elastic relationship between viewership and broadcast revenue would suggest the impact of All-Star votes on viewership translate one-for-one with impacts on broadcast revenue. Previous studies suggest that the relationship is in fact approximately unit-elastic (Fisher et al. 1980; Anderson and Waldfogel 2015). This manifests through local broadcast agreements, which make up approximately 15% of annual league revenues and are not subject to any revenue sharing provisions (Shea 2023), and national broadcast agreements, which make up around 30% of annual league revenues but are subject to equal revenue sharing (Vorkunov 2023).

For the remaining 33% of revenue, which consists primarily of league merchandise and sponsorships, I compute a "pass-through rate" of the estimated marginal impact of player popularity on ticket prices.[15] There is evidence that players receiving a larger number of All-Star votes tend to drive the merchandising revenue arm of the NBA. During the 2017-18 and 2018-19 seasons, the top 15 best selling jerseys in 2017-18 (NBA 2018) and 2018-19 (NBA 2019) consisted of 47.2% of All-Star votes among all players in 2017-18 and 46.8% in 2018-19. There are approximately 450 players in the NBA each season, so the top 15 jersey-selling players (3.3% of all players) represents nearly 50% of the total number of All-Star votes accrued during each season. Second, of the 30 teams in the NBA, the top 10 in terms of merchandise sales consist of 67.5% of all All-Star Votes in 2017-18 and 62.5% of all All-Star votes in 2018-19. In other words, the top one-third of merchandising teams consist of approximately two-thirds of all All-Star votes during each of these two seasons.

The pass-through rate is calculated such that the *total expected revenue* generated by all players is equal to the *sum of actual salaries* received by all players (using an average from the two seasons spanning 2017-19).[16] This equality is represented mathematically in Equation 1, which implies that the revenue split between players and owners negotiated in the CBA is efficient. In this study, I assume this to be the case.

With this structure, I compute both the expected annual salary for each player as well as their value to the NBA as a whole. The expected annual salary for each player is calculated as follows:

[15] Teams do get to keep all revenues from merchandise sold at (and sometimes around) the arena, but I assume this is a very small share of all NBA merchandise sold and do not separately account for it in the breakdown of different sources of revenue.

[16] The sum of actual player salaries was an average of $3.12 billion during the 2017-19 seasons. It should be noted that this is less than 51% of the total estimate annual revenue of the NBA during these seasons, since the CBA revenue sharing agreement is based on revenues "net of reasonable and customary expenses," which includes "salaries and benefits directly related to the operations of the Store or New Venture, promotional and advertising costs, rent, direct overhead, general and administrative expenses of the Store or New Venture" (Jensen 2021).

$$\mathbb{E}[Salary_i] = \underbrace{(\tau_i * AvgAttendance * 82) * TRS}_{\text{Ticket Sales Impact}} + \underbrace{(\tau_i * AvgAttendance * 82) * \frac{LBRS}{TRS}}_{\text{Local Broadcast Impact}} +$$

$$\underbrace{(\tau_i * AvgAttendance * 82) * \frac{NBRS}{TRS} * \frac{1}{30}}_{\text{National Broadcast Impact}} +$$

$$\underbrace{P\left[(\tau_i * AvgAttendance * 82) * (1 - TRS - LBRS - NBRS) * \frac{1}{30}\right]}_{\text{All Other BRI Impact}} \tag{3}$$

where τ_i represents player i's impact on ticket prices as a function of their total fan All-Star votes using the estimation results in Table 3. *AvgAttendance* is the average game-level attendance in the NBA during the 2017-19 seasons, and 82 is the number of regular season games each team plays.[17] The ticket sales revenue share (TRS) is approximately 22% of total annual BRI, the local broadcasting revenue share (LBRS) is approximately 15% of total annual BRI, and the national broadcasting revenue share (NBRS) is approximately 30% of total annual BRI. Other non-ticket sales and non-broadcasting revenue streams make up the remaining 33%. Both the "National Broadcast Impact" and "All Other BRI Impact" terms are multiplied by 1/30 to indicate that these sources of revenue are subject to equal revenue sharing across all teams.

Finally, P indicates the extent to which the ticket price impact is passed-through to this remaining 33% of BRI. P is solved for according to the *efficient player-owner revenue sharing condition* (Equation 1). In words, P is the rate that equates the sum of expected salaries and the sum of actual salaries of all players. Under these parameters, $P = 0.12$. Sensitivity analyses with different values of P are shown in Table 8.

Using this same setup, I compute each player's annual value to the NBA as a whole. The only difference in the two calculations is that the value to the NBA considers each player's impact on the revenues of *both* the team they play for as well as the revenues of the other 29 teams. As a result, I no longer multiply the "National Broadcast Impact" and "All Other BRI

[17] I compute the regular-season impact for each player by multiplying their per-game impact by 82, even though players may not play in all 82 games.

Impact” terms by the equal revenue sharing factor (1/30).

$$\mathbb{E}[NBA\_Value_i] = \underbrace{(\tau_i * AvgAttendance * 82) * TRS}_{\text{Ticket Sales Impact}} + \underbrace{(\tau_i * AvgAttendance * 82) * \frac{LBRS}{TRS}}_{\text{Local Broadcast Impact}} +$$
$$\underbrace{(\tau_i * AvgAttendance * 82) * \frac{NBRS}{TRS}}_{\text{National Broadcast Impact}} +$$
$$\underbrace{P\left[(\tau_i * AvgAttendance * 82) * (1 - TRS - LBRS - NBRS)\right]}_{\text{All Other BRI Impact}} \tag{4}$$

Consider the following concrete example to explain the BRI extrapolation procedure. LeBron James’ season-level impact on ticket prices alone is \$71,166,328 (that is, extrapolating his per-game impact to an entire 82-game regular season). When accounting for the other 78% of revenue streams beyond ticket sales, we can estimate both his expected team-level salary, which includes equal sharing of revenues from national broadcast agreements and league merchandise and sponsorships, and his value to the NBA as a whole. Under the $P = 0.12$ scenario, his expected annual salary is \$123,350,655, and his annual value to the NBA is \$229,543,755 (as shown in Table 4). For reference, between his actual team-level salary and endorsement deals, James’ annual income during this time was an estimated \$94 million (NBC 2019).

C Additional Expected vs. Actual Salary Results

Table 8: Actual vs. Expected Salaries and Value to the NBA for Top 10 All-Star Vote Players During 2018-19 Season (Low and High Pass-Through Rate Scenarios)

		Low (0%) Pass-Through		High (24%) Pass-Through	
Player	Actual Salary ($)	Predicted Salary ($)	Value to NBA ($)	Predicted Salary ($)	Value to NBA ($)
LeBron James	35,654,150	122,923,657	216,733,816	123,777,653	242,353,694
		(23,695,073)	(41,778,155)	(23,859,691)	(46,716,707)
Giannis Antetokounmpo	24,157,303	71,990,468	126,930,561	72,490,612	141,934,890
		(13,305,047)	(23,458,900)	(13,397,483)	(26,231,952)
Luka Doncic	6,560,640	68,463,861	120,712,597	68,939,505	134,981,907
		(12,625,318)	(22,260,429)	(12,713,031)	(24,891,811)
Kyrie Irving	20,099,189	82,479,296	145,424,022	83,052,310	162,614,444
		(15,631,233)	(27,560,332)	(15,739,829)	(30,818,210)
Stephen Curry	37,457,154	119,711,212	211,069,769	120,542,890	236,020,106
		(23,294,769)	(41,072,355)	(23,456,606)	(45,927,476)
Kawhi Leonard	23,114,067	68,353,960	120,518,823	68,828,840	134,765,228
		(12,829,682)	(22,620,756)	(12,918,815)	(25,294,731)
Derrick Rose	1,512,601	54,006,601	95,222,165	54,381,805	106,478,278
		(9,949,248)	(17,542,095)	(10,018,369)	(19,615,727)
Kevin Durant	30,000,000	97,685,620	172,235,173	98,364,278	192,594,912
		(19,008,779)	(33,515,478)	(19,140,840)	(37,477,308)
Paul George	30,560,700	59,456,671	104,831,499	59,869,738	117,223,521
		(11,157,010)	(19,671,570)	(11,234,521)	(21,996,925)
James Harden	30,421,854	53,251,156	93,890,196	53,621,111	104,988,858
		(9,955,196)	(17,552,582)	(10,024,358)	(19,627,454)

Note: These estimates come from the average values of log-linear (exponential), linear-linear, and log-log regression models in Table 3. Estimates of expected salaries and value to the NBA are computed according to the formulas in Appendix B equations 3 and 4, respectively, using a low pass-through rate ($P = 0$) and high pass-through rate ($P = 0.24$) in the designated columns of this table. Differences in average prices for each player's team determine their predicted salaries from the log-linear and log-log models. Standard errors for the estimated values are found in parentheses below each estimate.

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