Contract Year Effect in the NBA

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June 3, 2020



Introduction

- Contract Effects
 - Work Ethic
 - Overall Goal
- Contract Year Phenomenon
 - Players underperforming
 - Forced effort
- Performance in that year
 - Sign a long term contract



Literature Review

- Holmstrom (1982) and Gibbons & Murphy (1992) discuss career concerns
 - Applicable to superstars, not applicable to worse players who may mostly care about money
- Contract year phenomenon is a principal-agent problem
 - Incentive incompatible contracts create shirking behavior and moral hazard
 Alchian and Demsetz (1972), Holmstrom (1979), Ress (1994)
- Sports-specific research yields conflicting results of opportunistic behavior
 - Lehn (182), Scogins (1993), Stiroh (2007), Paulsen (2018) find evidence of opportunistic behavior
 - Krautmann (1990), Maxcy et al. (2002, Berri & Krautmann (2006) do not
- Conflicting results come from different tests, per Krautmann & Donley (2009)

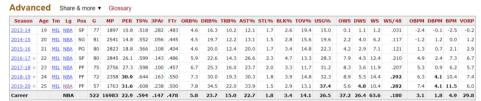
Summary Statistics





Data Collection - Salary and Advanced Stats

- Scraped Salary Data and advanced stats from basketballreference.com for all current NBA players
 - Scraper visits the basketballreference page for every current NBA player and scrapes relevant statistics
- Focus on the 2016-2017 to 2019-2020 regular seasons



Data Collection - Speed and Box-Out Data

Scraped Box out and Hustle Data from stats.nba.com for all current NBA players

	TEAM			MIN	BOX OUTS	OFF BOX OUTS	DEF BOX OUTS	TEAM REB ON BOX OUTS	PLAYER REB ON BOX OUTS	% BOX OUTS OFF	% BOX OUTS DEF	% TEAM REB WHEN BOX OUT	% PLAYER REB WHEN BOX OUT
Aaron Gordon	ORL	23	78	33.8	2.4	0.2	2.2	1.1	0.4	9.1	90.9	85.6	28.8
Aaron Holiday	IND	22	50	12.9	0.5	0.0	0.5	0.3	0.0	0.0	100	92.9	0.0
Abdel Nader	ОКС	25	61	11.4	0.8	0.0	0.8	0.4	0.2	0.0	100	79.4	29.4
Al Horford	BOS	33	68	29.0	6.5	0.5	6.0	3.3	1.1	7.4	92.6	86.0	30.0
Al-Farouq Aminu	POR	28	81	28.3	3.6	0.3	3.3	1.6	0.7	8.0	92.0	87.5	37.5
Alan Williams	BKN	26	5	5.1	0.8	0.2	0.6	0.0	0.0	25.0	75.0	0.0	0.0
Alec Burks	SAC	27	64	21.5	0.5	0.0	0.5	0.3	0.1	0.0	100	95.0	20.0
Alex Abrines	ОКС	25	31	19.0	1.4	0.0	1.4	0.7	0.1	0.0	100	74.2	9.7
Alex Caruso	LAL	25	25	21.2	1.2	0.0	1.2	0.8	0.2	0.0	100	86.4	18.2
Alex Len	ATL	26	77	20.1	5.7	0.8	5.0	2.9	0.9	13.4	86.6	89.3	26.5
Alex Poythress	ATL	25	21	14.5	2.5	0.3	2.2	1.5	0.7	11.3	88.7	88.6	40.0

Data Collection - Speed and Box-Out Data



			Salary							
Rk	Player	Tm	2019-20	2020-21	2021-22	2022-23	2023-24	2024-25	Signed Using	Guaranteed
1	Stephen Curry	GSW	\$40,231,758	\$43,006,362	\$45,780,966				Bird Rights	\$129,019,086
2	Chris Paul	OKC	\$38,506,482	\$41,358,814	\$44,211,146				Bird Rights	\$79,865,296
3	Russell Westbrook	HOU	\$38,178,000	\$41,006,000	\$43,848,000	\$46,662,000			Bird Rights	\$123,032,000
4	John Wall	WAS	\$37,800,000	\$40,824,000	\$43,848,000	\$46,872,000			Bird Rights	\$122,472,000
5	James Harden	HOU	\$37,800,000	\$40,824,000	\$43,848,000	\$46,872,000			Bird Rights	\$122,472,000
6	LeBron James	LAL	\$37,436,858	\$39,219,565	\$41,002,273				Cap Space	\$76,656,423
7	Kevin Durant	BRK	\$37,199,000	\$39,058,950	\$40,918,900	\$42,778,850			Sign and Trade	\$117,176,850
8	Blake Griffin	DET	\$34,234,964	\$36,595,996	\$38,957,028				Bird Rights	\$70,830,960
9	Kyle Lowry	TOR	\$33,296,296	\$30,000,000					Bird Rights	\$63,296,296
10	Paul George	LAC	\$33,005,556	\$35,450,412	\$37,895,268				Maximum Salary	\$68,455,968
11	Klay Thompson	GSW	\$32,742,000	\$35,361,360	\$37,980,720	\$40,600,080	\$43,219,440		Bird Rights	\$189,903,600
12	Jimmy Butler	MIA	\$32,742,000	\$34,379,100	\$36,016,200	\$37,653,300			Sign and Trade	\$103,137,300
13	Kemba Walker	BOS	\$32,742,000	\$34,379,100	\$36,016,200	\$37,653,300			Sign and Trade	\$103,137,300
14	Kawhi Leonard	LAC	\$32,742,000	\$34,379,100	\$36,016,200				Cap Space	\$67,121,100
15	Gordon Hayward	BOS	\$32,700,690	\$34,187,085					Cap space	\$32,700,690
16	Mike Conley	UTA	\$32,511,623	\$34,504,132					Cap Space	\$54,938,006
17	Kyrie Irving	BRK	\$31,742,000	\$33,329,100	\$34,916,200	\$36,503,300			Cap space	\$136,490,600
18	Tobias Harris	PHI	\$31,034,483	\$33,517,241	\$36,000,000	\$38,482,759	\$40,965,517		Bird Rights	\$180,000,000
19	Khris Middleton	MIL	\$30,603,448	\$33,051,724	\$35,500,000	\$37,948,276	\$40,396,552		Bird Rights	\$137,103,448
20	Paul Millsap	DEN	\$30,500,000						Cap space	\$30,500,000

Model and Analysis

Challenges in estimating the contract year effect fall under three categories.

- Player effort cannot be observed, and existing metrics such as distance covered on the field per minute may only be loosely correlated with player effort.
- The effort put in by a particular player may also correlate with other players' performance. Since basketball is a team game, effort put in by one player may synergize with effort put in by other players.
- Heterogeneity in different individuals: unobserved variables such as skill.

References

Controlling for individual fixed effects

We use the regression model

$$y_{it} = \alpha_0 + \sum_{j=1}^{N} \alpha_j \mathbb{1} \{i = j\} + \mathbb{1} \{i_t \in \text{Contract}\} \beta + c'_{it} \gamma + u_{it}$$

Identifying assumption: unobservable effects soaked up by the individual indicator variable that simultaneously affect the outcome player statistics and the explanatory variable and covariates are time-invariant.

R.eferences

Controlling for team fixed effects

We use the same regression model

$$y_{it} = \alpha_0 + \sum_{j=1}^{N} \alpha_j \mathbb{1} \{i = j\} + x_{it}\beta + c'_{it}\gamma + u_{it}$$

This time x_{it} is the weighted number of players on a contract year.

The dataset is grouped by team and the average weighted values of each variable is computed.

Double LASSO: individual & team fixed effects

When combining datasets from three different sources, the amount of observations decrease drastically and creates a curse of dimensionality problem. To circumvent this issue we employ double LASSO.

Double LASSO: individual & team fixed effects

1. We first fit a standard Lasso regression:

$$y_{it} = \alpha_0 + \sum_{j=1}^{N} \alpha_j \mathbb{1} \{i = j\} + \mathbb{1} \{i_t \in \text{Contract}\} \beta + c'_{it} \gamma + u_{it}$$

2. Drop the zero coefficient variables, then do another Lasso regression:

$$\mathbb{1}\left\{i_t \in \text{Contract}\right\} = \alpha_0^L + \sum_{j=1}^N \alpha_j^L \mathbb{1}\left\{i = j\right\} + c'_{it} \gamma^L + u_{it}$$

3. Do a regular OLS:

$$y_{it} = \alpha_0^O + \sum_{j=1}^N + \mathbb{1} \left\{ i_t \in \text{Contract} \right\} \beta^O + z'_{it} \gamma^O + u_{it}$$

where z_{it} consists of covariates that are selected in step 1 and 2.

Double LASSO: individual & team fixed effects

The strategy is similar for team fixed effects.

Individual Fixed Effect OLS

Table: Using Average Seconds per Dribble as the Dependent Variable

	Dependent variable:				
	Average Seconds per Dribble				
Contract Year	-0.0247				
	(0.0368)				
Average Minutes Played	0.011**				
	(0.00369)				
Current Salary	0.000*				
	(0.000)				
Constant	5.117***				
	(0.664)				
Player Fixed Effects	Yes				
Year Fixed Effects	Yes				
Observations	1,057				
\mathbb{R}^2	0.974				
Adjusted R ²	0.952				
Residual Std. Error	1.609 (df = 569)				
F Statistic	44.244*** (df = 487; 569)				
Note:	*p<0.1: **p<0.05: ***p<0.01				

Individual Fixed Effect OLS

Table: Using Win Shares as the Dependent Variable

	Dependent variable:			
	Defensive Win Shares	Offensive Win Shares	Win Shares	Win Shares per 48 minutes
	(1)	(2)	(3)	(4)
Contract Year	0.09213	0.08593	0.196	-0.0002153
	(0.06077)	(0.1135)	(0.146)	(0.0035)
Average Minutes Played	0.06228***	0.1335***	0.196***	-0.002308***
	(0.006165)	(0.01152)	(0.01485)	(0.0003551)
Current Salary	-0.000	-0.000***	-0.000***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.008 (0.871)	-0.450 (1.627)	-0.494 (2.098)	0.033 (0.050)
Player Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Position	Yes	Yes	Yes	Yes
Observations	1,133	1,133	1,133	1,133
R ²	0.791	0.827	0.840	0.798
Adjusted R ² Residual Std. Error (df = 676) F Statistic (df = 456; 676)	0.650	0.710	0.731	0.661
	2.990	5.586	7.204	0.172
	5.605***	7.072***	7.756***	5.840***

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

Team Fixed Effect OLS

Table: Using Win Shares as the Dependent Variable

	Dependent variable:					
	Defensive Win Shares	Offensive Win Shares	Win Shares	Win Shares per 48 minutes		
	(1)	(2)	(3)	(4)		
Contract Year	0.476	1.017*	1.513*	0.020		
	(0.361)	(0.574)	(0.782)	(0.018)		
Average Minutes Played	-0.043	0.054	0.012	-0.002		
	(0.032)	(0.050)	(0.069)	(0.002)		
Position	0.00000***	0.00000***	0.00000***	0.000***		
	(0.00000)	(0.00000)	(0.00000)	(0.000)		
Current Salary	1.591**	-1.044	0.519	0.069**		
,	(0.688)	(1.094)	(1.490)	(0.034)		
Team Fixed Effects	Yes	Yes	Yes	Yes		
Year Fixed Effects	Yes	Yes	Yes	Yes		
Observations	120	120	120	120		
\mathbb{R}^2	0.619	0.652	0.653	0.516		
Adjusted R ²	0.461	0.507	0.508	0.314		
Residual Std. Error (df = 84)	2.405	3.822	5.206	0.119		
F Statistic (df = 35; 84)	3.906***	4.493***	4.512***	2.555***		

Note:

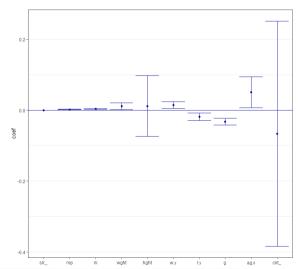
*p<0.1; **p<0.05; ***p<0.01

Double Lasso on Individual

Table: Double Lasso: Using Offensive Win Share as the Dependent Variable

	$Dependent\ variable:$				
	Offensive Win Share				
Contract Year	-0.06917				
	(0.13893)				
	p-value: 0.619				
Player Fixed Effects	Yes				
Year Fixed Effects	Yes				
Observations	621				
Note:	*p<0.1; **p<0.05; ***p<0.01				

Double Lasso on Individual: multiple inference variables



Discussion of Results

Can we reject the hypothesis?

- Consistent with literature estimating a small contract year effect
- Statistically non-significant.



Policy Implications

- It may not be fruitful to try to optimize team performance by "staggering" or shortening contracts.
- Media fixation on one or two examples of the contract year effect might simply be anomalous un-representative samples.



References

