Deciphering the drivers and trends of an NBA player's salary in the past 20 years

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Abstract—**The study tests the relative importance of different player metrics in determining an NBA player's salary. Points Scored per game and Age seem to be most dominant factors in the polynomial regression model with an adjusted R2 of 0.72. The game has become more offensive and higher scoring, especially in the last 10 years, due to sharp rise in 3-Point shots leading to greater value in the team for forward players than in the past. A player's golden age for earnings is between the age of 30-34 when he earns the maximum value per point scored. Average salary growth has also beaten inflation by a wide margin in the study period.**

I. Introduction

NBA (National Basketball Association) league in US is one of the biggest sports leagues in the world which started in 1946 and continues to grow in scale and popularity. Being an avid basketball player, I have been actively following NBA for last 5 years and analysing the game closely. I always found it perplexing to see the wide variances and trends in player earnings and their contracts/transfers across teams. This curiosity inspired me to unravel the rationale and the math behind their price tag. In this research paper, I have attempted to decode the key drivers of salary for a player and trends in the same over the past 20 years. Given the multiple statistics tracked at a player and team level, idea of the research is to identify the most relevant indicators to be used which seem to determine a player's salary over his tenure. I also developed a best-fit polynomial regression model to determine a player's salary using those critical variables. The study highlights key insights from time-series and cross-sectional analysis of historical data to assess how the game has evolved over the years. The research also tracks the lifecycle of a player in the league in terms of linkages between annual salary and its key drivers.

II. Methodology

I downloaded the entire 20-year (2006-2025) data player wise and team wise from NBA website (https://NBA.com/Stats) in MS Excel. I used statistics per game for this study. ***Details of statistics tracked and abbreviations used for study are provided in the Appendix***. Further, this data was organized by years and cleaned to remove inconsistencies. To make dataset more reliable, I removed all players who played just 1 or 2 games in a season as they could skew the statistics for a year. The resultant final data set used for study was large (8798 rows) which was consistent with ~400-500 players in the league each year. A sample dataset is shown below *(Fig 1)*.

Figure 1 Sample excel dataset

Player	Pos	Team	G	GS	FG	FGA	FG%	3PA	3P%	2PA	2P%	eFG%	FTA	FT%	PF	TOV	TRB	2P	3P	FT	STL	BLK	ORB	MP	AST	DRB	Age	PTS	Salary	Year
Al Harrington	PF	ATL	76	76	7.3	16.1	0.5	2.5	0.4	13.5	0.5	0.5	4.6	0.7	4.0	2.6	6.9	6.4	0.9	3.2	1.1	0.2	1.7	36.6	3.1	5.1	25	18.6	7.0	2006
Donta Smith	SG	ATL	23	-	0.7	1.2	0.6	0.2	0.5	1.0	0.6	0.6	0.5	0.5	0.9	0.2	0.6	0.6	0.1	0.3	0.3	-	0.1	5.5	0.4	0.5	22	1.7	0.6	2006
Esteban Batista	PF	ATL	57	3	0.6	1.4	0.4	-	-	1.4	0.4	0.4	0.9	0.6	1.9	0.7	2.5	0.6	-	0.6	0.3	0.2	1.1	8.7	0.1	1.5	22	1.8	0.6	2006
Joe Johnson	SG	ATL	82	82	7.7	17.0	0.5	4.4	0.4	12.6	0.5	0.5	4.0	0.8	2.3	3.3	4.1	6.1	1.6	3.2	1.3	0.4	1.2	40.7	6.5	2.9	24	20.2	12.0	2006
John Edwards	C	ATL	40	4	0.8	1.6	0.5	-		1.6	0.5	0.5	0.3	0.7	1.9	0.3	1.2	0.8	-	0.2	0.1	0.4	0.5	7.4	0.1	0.8	24	1.8	1.0	2006
Josh Childress	SF	ATL	74	10	3.8	6.8	0.6	0.9	0.5	5.9	0.6	0.6	2.7	0.8	2.5	1.4	5.2	3.3	0.4	2.1	1.2	0.5	1.8	30.4	1.8	3.4	22	10.0	2.7	2006
Josh Smith	SF	ATL	80	73	4.1	9.7	0.4	1.4	0.3	8.3	0.4	0.5	3.7	0.7	3.3	2.0	6.6	3.7	0.4	2.6	0.8	2.6	2.2	32.0	2.4	4.4	20	11.3	1.6	2006
Marvin Williams	PF	ATL	79	7	3.0	6.7	0.4	0.7	0.3	6.1	0.5	0.5	3.2	0.8	2.9	1.1	4.8	2.8	0.2	2.4	0.6	0.3	1.5	24.7	0.8	3.3	19	8.5	3.9	2006
Royal Ivey	PG	ATL	73	66	1.6	3.6	0.4	0.1	0.4	3.5	0.4	0.5	0.5	0.7	2.0	0.3	1.3	1.5	0.1	0.3	0.3	0.1	0.4	13.4	1.0	0.9	24	3.6	0.6	2006
Salim Stoudamire	SG	ATL	61	1	3.3	8.1	0.4	3.5	0.4	4.5	0.4	0.5	1.8	0.9	1.9	1.3	1.9	2.0	1.3	1.6	0.4	-	0.2	20.3	1.2	1.7	23	9.7	0.7	2006
Tyronn Lue	PG	ATL	51	10	3.8	8.2	0.5	2.5	0.5	5.7	0.5	0.5	2.7	0.9	2.2	1.5	1.6	2.6	1.1	2.3	0.5	0.1	0.3	24.2	3.1	1.4	28	11.0	3.5	2006
Zaza Pachulia	C	ATL	78	78	3.9	8.7	0.5	-	-	8.7	0.5	0.5	5.2	0.7	3.7	2.3	7.9	3.9	-	3.8	1.1	0.5	3.4	31.4	1.7	4.5	21	11.7	4.0	2006
Al Jefferson	PF	BOS	59	7	3.2	6.4	0.5	0.1	-	6.4	0.5	0.5	2.3	0.6	2.8	1.1	5.1	3.2	-	1.5	0.5	0.8	1.6	18.0	0.5	3.4	21	7.9	1.5	2006
Brian Scalabrine	PF	BOS	71	1	1.0	2.7	0.4	1.2	0.4	1.5	0.4	0.5	0.5	0.7	1.8	0.7	1.6	0.6	0.4	0.4	0.3	0.3	0.4	13.2	0.7	1.2	27	2.9	2.6	2006
Dan Dickau	PG	BOS	19	-	0.9	2.4	0.4	1.1	0.5	1.4	0.3	0.5	0.9	1.0	2.1	0.9	0.8	0.4	0.5	0.9	0.6	0.1	0.3	12.3	2.1	0.6	27	3.3	2.3	2006
Delonte West	PG	BOS	71	71	4.7	9.6	0.5	3.1	0.4	6.6	0.5	0.6	1.4	0.9	2.8	1.9	4.1	3.5	1.2	1.2	1.2	0.6	0.8	34.1	4.6	3.3	22	11.8	1.0	2006
Gerald Green	SG	BOS	32	3	2.1	4.3	0.5	0.6	0.3	3.7	0.5	0.5	1.2	0.8	1.3	0.7	1.3	1.9	0.2	0.9	0.4	0.1	0.3	11.7	0.6	1.0	20	5.2	1.3	2006

Ochai Agbaji	SG	TOR	64	45	4.2	8.3	0.5	4.0	0.4	4.4	0.6	0.6	0.8	0.7	2.0	0.8	3.8	2.6	1.6	0.5	0.9	0.5	1.0	27.2	1.5	2.8	10.4	24	4.3	2025
Orlando Robinson	C	TOR	44	8	2.6	5.9	0.4	1.2	0.3	4.8	0.5	0.5	1.6	0.8	2.3	1.1	5.0	2.3	0.4	1.2	0.4	0.4	2.0	17.5	1.8	3.0	6.9	24	1.7	2025
RJ Barrett	SF	TOR	58	58	7.9	16.9	0.5	5.3	0.4	11.7	0.5	0.5	5.4	0.6	2.4	2.8	6.3	6.1	1.8	3.4	0.8	0.3	1.1	32.2	5.4	5.3	21.1	24	25.8	2025
Scottie Barnes	PF	TOR	65	65	7.3	16.4	0.4	4.3	0.3	12.0	0.5	0.5	4.6	0.8	1.7	2.8	7.7	6.1	1.2	3.5	1.4	1.0	1.7	32.8	5.8	6.0	19.3	23	10.1	2025
Brice Sensabaugh	SF	UTA	71	15	3.9	8.4	0.5	5.2	0.4	3.2	0.5	0.6	1.0	0.9	1.6	1.5	3.0	1.7	2.2	0.9	0.6	0.1	0.6	20.2	1.5	2.4	10.9	21	2.6	2025
Cody Williams	SG	UTA	50	21	1.7	5.1	0.3	2.7	0.3	2.4	0.4	0.4	0.8	0.7	1.9	0.9	2.3	1.0	0.7	0.6	0.5	0.3	0.5	21.2	1.2	1.7	4.6	20	5.5	2025
Collin Sexton	SG	UTA	63	61	6.6	13.8	0.5	4.3	0.4	9.5	0.5	0.5	4.0	0.9	2.3	2.5	2.7	4.9	1.7	3.4	0.7	0.1	1.0	27.9	4.2	1.8	18.4	26	18.4	2025
Isaiah Collier	PG	UTA	71	46	3.3	7.8	0.4	2.4	0.2	5.4	0.5	0.5	2.2	0.7	2.1	2.9	3.3	2.7	0.6	1.5	0.9	0.2	0.5	25.9	6.3	2.9	8.7	20	2.5	2025
Jaden Springer	SG	UTA	43	2	0.8	2.1	0.4	1.1	0.3	1.0	0.5	0.5	0.9	0.7	1.0	0.4	1.3	0.5	0.3	0.6	0.6	0.1	0.4	8.5	0.8	1.0	2.5	22	4.8	2025
John Collins	PF	UTA	40	31	7.0	13.3	0.5	3.7	0.4	9.6	0.6	0.6	4.1	0.8	2.9	2.6	8.2	5.5	1.5	3.5	1.0	1.0	2.2	30.5	2.0	6.0	19.0	27	26.6	2025
Johnny Juzang	SG	UTA	64	18	3.2	7.4	0.4	4.9	0.4	2.5	0.5	0.6	0.8	0.8	2.0	0.6	2.9	1.3	1.8	0.7	0.6	0.1	0.7	19.8	1.1	2.2	8.9	23	3.1	2025
Jordan Clarkson	SG	UTA	37	9	5.4	13.3	0.4	6.3	0.4	7.1	0.4	0.5	3.9	0.8	1.4	2.3	3.2	3.2	2.3	3.1	0.8	0.2	0.7	26.0	3.7	2.5	16.2	32	14.1	2025
KJ Martin	PF	UTA	43	16	2.6	4.7	0.6	1.3	0.3	3.3	0.7	0.6	1.1	0.8	2.3	0.6	2.9	2.2	0.3	0.9	0.4	0.5	0.7	21.2	1.1	2.2	6.4	24	8.0	2025
Keyonte George	PG	UTA	67	35	5.4	13.7	0.4	7.6	0.3	6.1	0.4	0.5	4.3	0.8	1.7	2.7	3.8	2.8	2.6	3.5	0.7	0.1	0.4	31.5	5.6	3.4	16.8	21	4.1	2025
Kyle Filipowski	C	UTA	72	27	3.6	7.2	0.5	3.1	0.4	4.1	0.6	0.6	2.0	0.7	2.4	1.4	6.1	2.5	1.1	1.3	0.7	0.3	1.6	21.1	1.9	4.6	9.6	21	3.0	2025
Lauri Markkanen	PF	UTA	47	47	6.3	14.9	0.4	8.5	0.3	6.4	0.5	0.5	3.9	0.9	1.7	1.4	5.9	3.4	2.9	3.4	0.7	0.4	1.5	31.4	1.5	4.4	19.0	27	42.2	2025
Svi Mykhailiuk	SF	UTA	38	13	3.1	7.9	0.4	5.3	0.3	2.6	0.5	0.5	0.9	0.8	1.1	1.4	2.4	1.3	1.8	0.7	0.5	0.2	0.6	20.0	2.0	1.8	8.8	27	3.5	2025
Taylor Hendricks	PF	UTA	3	3	1.3	6.0	0.2	4.0	0.3	2.0	0.2	0.3	1.3	0.8	2.7	0.7	5.0	0.3	1.0	1.0	1.7	1.3	1.7	25.0	0.7	3.3	4.7	21	5.8	2025

III. Analysis and Results

A. <u>Salary Predictors- Regression model</u>

I did the analysis on annual basis and over 2–3-year period buckets (to smoothen out annual anomalies, if any) as salaries have kept steadily going up over the years due to inflation effect. Thus, a player earning $ 1mn in 2006 has vastly different game statistics than a player earning the same today. Hence, either salary must be inflation-adjusted (in real terms) or compared in same period to keep data statistically comparable over the longer period. To understand the relative importance of different variables for determining salary, I initially developed a correlation output for various years. The tables below (Fig 2 and 3) show the same.

Figure 2: Correlation results of a player's salary with key statistics

Year	G	GS	FG	FGA	FG%	3PA	3P%	2PA	2P%	eFG%	FTA	FT%	PF	TOV
2006	0.27	0.54	0.64	0.63	0.15	0.31	0.07	0.63	0.15	0.16	0.61	0.14	0.43	0.60
2007	0.27	0.55	0.63	0.62	0.15	0.32	0.02	0.61	0.18	0.12	0.62	0.08	0.41	0.59
2008	0.34	0.59	0.65	0.64	0.16	0.32	0.02	0.63	0.15	0.17	0.60	0.15	0.43	0.60
2009	0.25	0.53	0.61	0.60	0.13	0.28	0.05	0.59	0.12	0.14	0.55	0.15	0.36	0.55
2010	0.26	0.52	0.61	0.59	0.15	0.26	0.03	0.58	0.14	0.16	0.58	0.14	0.41	0.53
2011	0.29	0.53	0.63	0.60	0.18	0.23	0.03	0.60	0.19	0.16	0.56	0.19	0.40	0.53
2012	0.31	0.57	0.67	0.65	0.23	0.20	-0.01	0.67	0.19	0.21	0.59	0.12	0.36	0.54
2013	0.30	0.51	0.66	0.64	0.17	0.22	0.05	0.64	0.14	0.14	0.64	0.18	0.35	0.57
2014	0.22	0.53	0.64	0.60	0.23	0.15	-0.04	0.64	0.18	0.15	0.58	0.12	0.34	0.60
2015	0.29	0.54	0.66	0.64	0.16	0.24	0.12	0.64	0.11	0.13	0.60	0.13	0.33	0.60
2016	0.33	0.61	0.70	0.68	0.15	0.33	0.04	0.67	0.11	0.13	0.64	0.14	0.44	0.59
2017	0.38	0.58	0.65	0.65	0.14	0.38	0.10	0.63	0.08	0.14	0.62	0.17	0.37	0.56
2018	0.22	0.56	0.58	0.56	0.11	0.38	0.08	0.51	0.10	0.13	0.57	0.15	0.33	0.48
2019	0.30	0.53	0.61	0.61	0.16	0.40	0.09	0.57	0.12	0.16	0.58	0.17	0.33	0.58
2020	0.19	0.50	0.62	0.62	0.06	0.43	0.11	0.58	0.00	0.05	0.60	0.15	0.34	0.59
2021	0.32	0.62	0.73	0.72	0.15	0.51	0.14	0.68	0.06	0.16	0.66	0.21	0.42	0.69
2022	0.37	0.59	0.73	0.72	0.12	0.51	0.12	0.69	0.04	0.13	0.69	0.19	0.41	0.66
2023	0.33	0.60	0.72	0.71	0.09	0.49	0.09	0.68	0.05	0.08	0.67	0.22	0.42	0.67
2024	0.41	0.67	0.75	0.73	0.17	0.52	0.17	0.70	0.06	0.18	0.70	0.25	0.45	0.68
2025	0.27	0.61	0.73	0.72	0.12	0.49	0.12	0.68	0.04	0.10	0.69	0.23	0.38	0.64

Figure 3: Correlation results of a player's salary with key statistics

Year	TRB	2P	3P	FT	STL	BLK	ORB	MP	AST	DRB	PTS	AGE
2006	0.55	0.62	0.30	0.59	0.44	0.32	0.35	0.61	0.42	0.59	0.63	0.36
2007	0.54	0.61	0.30	0.59	0.40	0.35	0.36	0.60	0.42	0.59	0.65	0.28
2008	0.55	0.62	0.31	0.60	0.47	0.34	0.37	0.63	0.44	0.57	0.61	0.37
2009	0.51	0.59	0.28	0.54	0.43	0.31	0.30	0.59	0.41	0.55	0.61	0.31
2010	0.49	0.59	0.24	0.57	0.39	0.33	0.29	0.56	0.39	0.56	0.62	0.32
2011	0.50	0.62	0.21	0.56	0.42	0.34	0.31	0.60	0.41	0.63	0.66	0.28
2012	0.56	0.67	0.19	0.59	0.39	0.34	0.33	0.64	0.40	0.57	0.66	0.25
2013	0.51	0.65	0.20	0.63	0.41	0.35	0.32	0.61	0.43	0.56	0.62	0.31
2014	0.50	0.65	0.14	0.57	0.37	0.30	0.31	0.57	0.41	0.54	0.66	0.25
2015	0.48	0.64	0.25	0.60	0.39	0.27	0.28	0.59	0.49	0.59	0.70	0.20
2016	0.54	0.68	0.32	0.65	0.49	0.31	0.34	0.65	0.51	0.58	0.66	0.27
2017	0.53	0.62	0.38	0.61	0.46	0.27	0.31	0.62	0.48	0.49	0.59	0.32
2018	0.47	0.52	0.37	0.57	0.37	0.31	0.30	0.54	0.41	0.53	0.63	0.29
2019	0.48	0.56	0.40	0.59	0.50	0.27	0.28	0.58	0.52	0.54	0.63	0.37
2020	0.49	0.56	0.40	0.61	0.43	0.28	0.28	0.56	0.55	0.61	0.73	0.40
2021	0.54	0.66	0.51	0.67	0.56	0.27	0.24	0.65	0.67	0.61	0.74	0.36
2022	0.53	0.67	0.50	0.70	0.48	0.31	0.21	0.65	0.63	0.58	0.73	0.42
2023	0.51	0.67	0.48	0.67	0.47	0.31	0.22	0.65	0.61	0.59	0.76	0.42
2024	0.51	0.70	0.53	0.71	0.53	0.31	0.23	0.69	0.65	0.54	0.74	0.33
2025	0.47	0.67	0.49	0.70	0.47	0.23	0.21	0.65	0.62	0.54	0.74	0.33

The variables with highest correlation to Salary are PTS, FT, FTA, MP, GS, FG, FGA, 2P, 2PA ***(abbreviations explained below)*****.** There are multiple dependent variables in the above statistics. Also given the multi-collinearity among certain variables, the dependent variables were removed from the study using the correlation matrix results given below (Fig 4).

Figure 4: Correlation matrix results of all input variables with each other

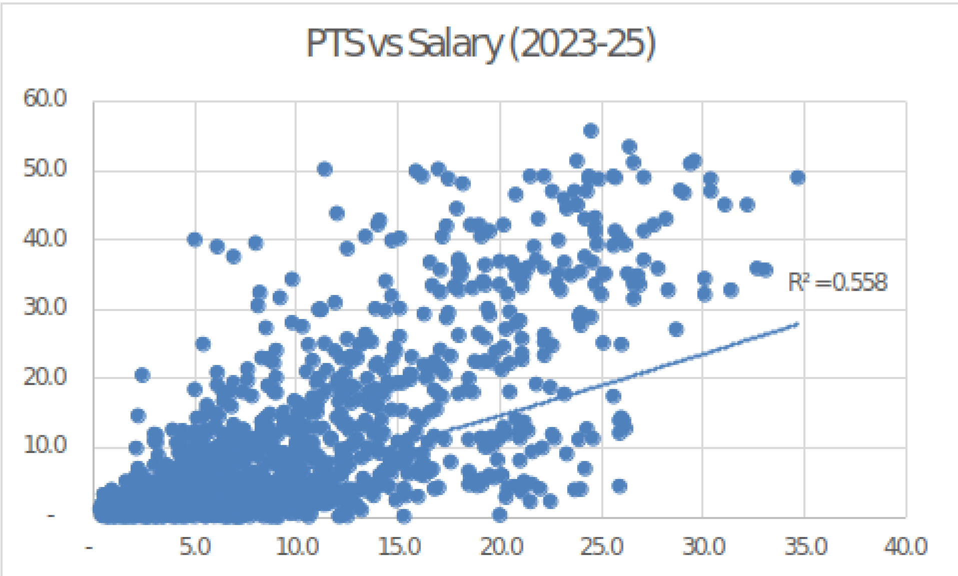
Correlation	G	GS	FG	FGA	FG%	3PA	3P%	2PA	2P%	eFG%	FTA	FT%	PF	TOV	TRB	2P	3P	FT	STL	BLK	ORB	MP	AST	DRB	PTS	AGE
G	1.00	0.60	0.50	0.49	0.22	0.29	0.12	0.45	0.16	0.26	0.38	0.23	0.51	0.41	0.42	0.46	0.31	0.38	0.44	0.25	0.29	0.63	0.35	0.44	0.49	0.04
GS	0.60	1.00	0.74	0.73	0.20	0.38	0.09	0.71	0.13	0.20	0.63	0.18	0.59	0.66	0.61	0.71	0.39	0.62	0.61	0.38	0.41	0.82	0.55	0.65	0.73	0.06
FG	0.50	0.74	1.00	0.98	0.25	0.55	0.17	0.93	0.19	0.26	0.84	0.30	0.58	0.83	0.64	0.94	0.55	0.85	0.65	0.35	0.37	0.88	0.66	0.71	0.99	0.02
FGA	0.49	0.73	0.98	1.00	0.10	0.65	0.20	0.90	0.07	0.15	0.82	0.34	0.54	0.84	0.55	0.88	0.63	0.84	0.68	0.25	0.26	0.89	0.70	0.64	0.98	0.02
FG%	0.22	0.20	0.25	0.10	1.00	-0.21	-0.05	0.24	0.81	0.87	0.22	-0.11	0.31	0.13	0.42	0.36	-0.15	0.17	0.06	0.40	0.48	0.17	-0.00	0.36	0.20	-0.01
3PA	0.29	0.38	0.55	0.65	-0.21	1.00	0.46	0.26	-0.02	0.14	0.33	0.40	0.18	0.45	0.05	0.24	0.98	0.40	0.46	-0.14	-0.26	0.56	0.52	0.18	0.62	0.07
3P%	0.12	0.09	0.17	0.20	-0.05	0.46	1.00	0.01	-0.07	0.28	0.03	0.26	-0.04	0.10	-0.14	-0.01	0.50	0.08	0.15	-0.19	-0.30	0.18	0.20	-0.05	0.20	0.06
2PA	0.45	0.71	0.93	0.90	0.24	0.26	0.01	1.00	0.11	0.11	0.86	0.21	0.59	0.82	0.68	0.98	0.25	0.84	0.60	0.40	0.48	0.82	0.60	0.71	0.90	-0.01
2P%	0.16	0.13	0.19	0.07	0.81	-0.02	-0.07	0.11	1.00	0.78	0.12	-0.04	0.19	0.06	0.29	0.23	-0.01	0.10	0.05	0.27	0.30	0.12	-0.00	0.26	0.16	-0.03
eFG%	0.26	0.20	0.26	0.15	0.87	0.14	0.28	0.11	0.78	1.00	0.13	0.05	0.23	0.10	0.28	0.22	0.21	0.12	0.11	0.25	0.26	0.22	0.06	0.27	0.25	0.04
FTA	0.38	0.63	0.84	0.82	0.22	0.33	0.03	0.86	0.12	0.13	1.00	0.20	0.53	0.80	0.61	0.85	0.31	0.98	0.56	0.36	0.40	0.73	0.58	0.65	0.88	-0.01
FT%	0.23	0.18	0.30	0.34	-0.11	0.40	0.26	0.21	-0.04	0.05	0.20	1.00	0.09	0.24	-0.01	0.18	0.40	0.30	0.22	-0.12	-0.16	0.31	0.28	0.06	0.34	0.08
PF	0.51	0.59	0.58	0.54	0.31	0.18	-0.04	0.59	0.19	0.23	0.53	0.09	1.00	0.57	0.68	0.60	0.18	0.49	0.50	0.51	0.58	0.70	0.33	0.67	0.55	0.03
TOV	0.41	0.66	0.83	0.84	0.13	0.45	0.10	0.82	0.06	0.10	0.80	0.24	0.57	1.00	0.53	0.79	0.43	0.80	0.68	0.26	0.27	0.80	0.81	0.60	0.84	0.02
TRB	0.42	0.61	0.64	0.55	0.42	0.05	-0.14	0.68	0.29	0.28	0.61	-0.01	0.68	0.53	1.00	0.72	0.05	0.55	0.40	0.69	0.87	0.65	0.25	0.98	0.60	0.04
2P	0.46	0.71	0.94	0.88	0.36	0.24	-0.01	0.98	0.23	0.22	0.85	0.18	0.60	0.79	0.72	1.00	0.23	0.83	0.58	0.45	0.54	0.80	0.57	0.75	0.90	-0.01
3P	0.31	0.39	0.55	0.63	-0.15	0.98	0.50	0.25	-0.01	0.21	0.31	0.40	0.18	0.43	0.05	0.23	1.00	0.38	0.44	-0.13	-0.25	0.55	0.49	0.18	0.61	0.09
FT	0.38	0.62	0.85	0.84	0.17	0.40	0.08	0.84	0.10	0.12	0.98	0.30	0.49	0.80	0.55	0.83	0.38	1.00	0.57	0.29	0.32	0.74	0.61	0.60	0.89	0.01
STL	0.44	0.61	0.65	0.68	0.06	0.46	0.15	0.60	0.05	0.11	0.56	0.22	0.50	0.68	0.40	0.58	0.44	0.57	1.00	0.18	0.19	0.75	0.68	0.46	0.66	0.03
BLK	0.25	0.38	0.35	0.25	0.40	-0.14	-0.19	0.40	0.27	0.25	0.36	-0.12	0.51	0.26	0.69	0.45	-0.13	0.29	0.18	1.00	0.68	0.36	0.00	0.64	0.30	-0.02
ORB	0.29	0.41	0.37	0.26	0.48	-0.26	-0.30	0.48	0.30	0.26	0.40	-0.16	0.58	0.27	0.87	0.54	-0.25	0.32	0.19	0.68	1.00	0.39	-0.01	0.74	0.31	-0.03
MP	0.63	0.82	0.88	0.89	0.17	0.56	0.18	0.82	0.12	0.22	0.73	0.31	0.70	0.80	0.65	0.80	0.55	0.74	0.75	0.36	0.39	1.00	0.68	0.72	0.88	0.08
AST	0.35	0.55	0.66	0.70	-0.00	0.52	0.20	0.60	-0.00	0.06	0.58	0.28	0.33	0.81	0.25	0.57	0.49	0.61	0.68	0.00	-0.01	0.68	1.00	0.35	0.68	0.09
DRB	0.44	0.65	0.71	0.64	0.36	0.18	-0.05	0.71	0.26	0.27	0.65	0.06	0.67	0.60	0.98	0.75	0.18	0.60	0.46	0.64	0.74	0.72	0.35	1.00	0.67	0.07
PTS	0.49	0.73	0.99	0.98	0.20	0.62	0.20	0.90	0.16	0.25	0.88	0.34	0.55	0.84	0.60	0.90	0.61	0.89	0.66	0.30	0.31	0.88	0.68	0.67	1.00	0.03
AGE	0.04	0.06	0.02	0.02	-0.01	0.07	0.06	-0.01	-0.03	0.04	-0.01	0.08	0.03	0.02	0.04	-0.01	0.09	0.01	0.03	-0.02	-0.03	0.08	0.09	0.07	0.03	1.00

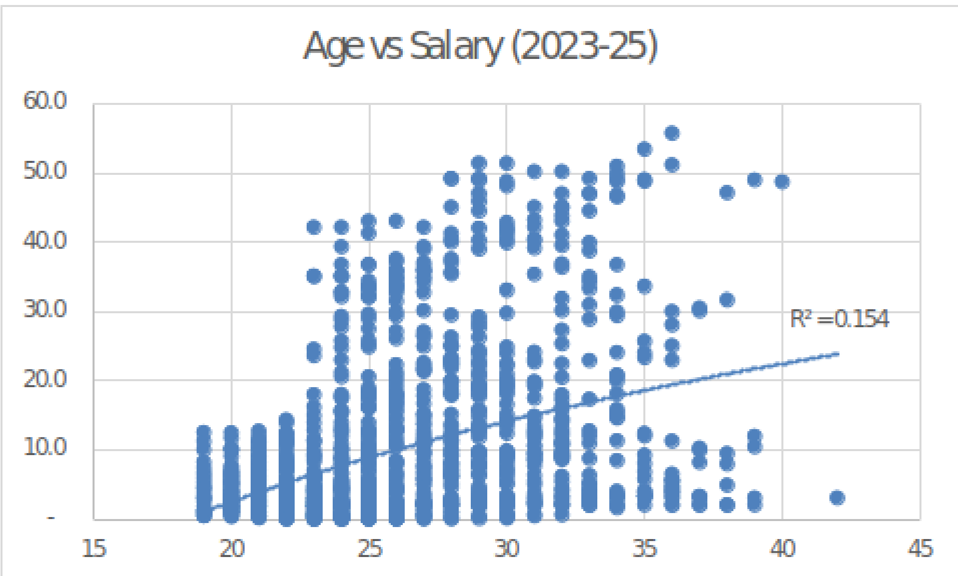
E.g. FG (Field goals is a summation of 2P (2 Pointers) and 3P (3 Pointers). TRB (Total Rebound) equates to ORB (Offensive Rebounds) +DRB (Defensive Rebounds). TOV (Turnover) and PF (Personal Fouls) are negative contributors to an individual's value but seem to be falsely positively correlated due to their high correlation with MP (Minutes Played). PTS (Points per game) captures 2P, 3P and FT (Free Throws) of the player into one combined metric which is the best measure of his scoring ability**. PTS has the highest correlation with Salary and has very high correlation with most other independent variables as well, such as STL (Steal), BLK (Block), DRB and AST (Assist)**. PTS also has high correlation (>0.7) with GS (Games Started) and MP, which in turn has high correlation to Salary. Thus, PTS seems to be the most important metric to include in the regression analysis. On the other hand, **AGE seems to be the most un-correlated and independent statistic which has low correlation with every other game statistic and even output variable, Salary.**

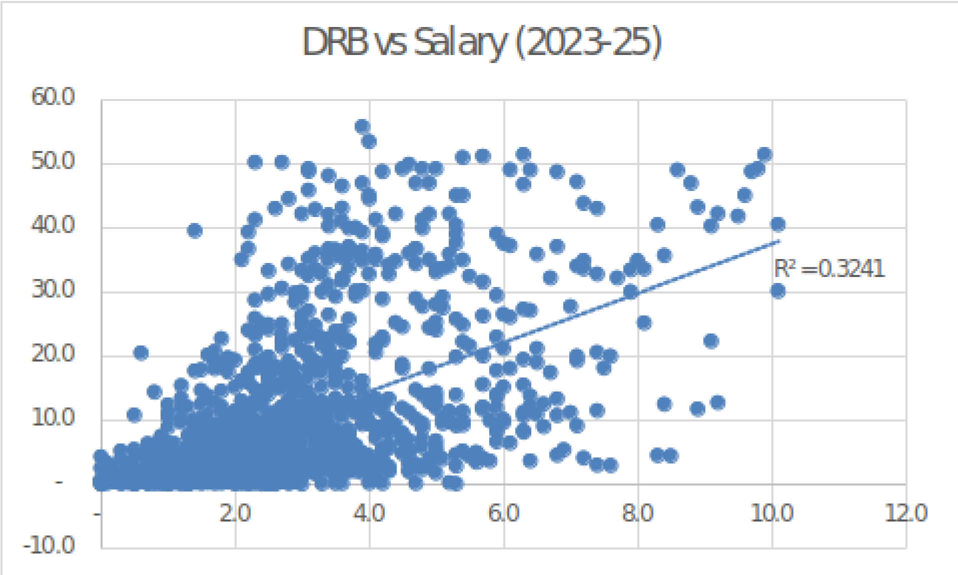
Surprisingly, conversion efficiency of a player (2P%, 3P%, FT%, eFG%) which measures conversion ratio of a 2P, 3P, FT or FG (Field Goals) basis attempts made (e.g., 2P%= (2P/2PA) *100) **do not have significant correlation (<0.3) to a player's salary**. Even combining PTS and MP into a single **scoring efficiency metric (Points scored/minutes played) did not yield better coefficient of determination (R^2) than PTS alone** (0.3 for scoring efficiency vs 0.55 for PTS) which implies that **PTS remains the key predictor of a player salary among all these statistics** and thus it is the best metric to include in the regression model while other highly correlated statistics can be removed.

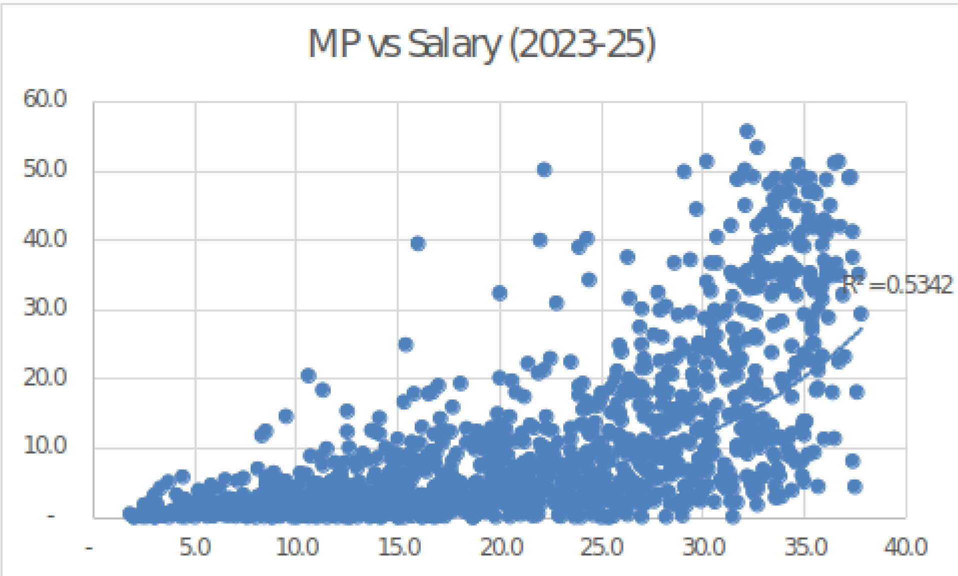
The scatter plots and R^2 analysis for the key variables and Salary over the recent past (2023-25) highlights their relationship and predictive power in the charts (Fig 5-12) below. **PTS (0.55) and MP (0.53) have highest R^2 followed by AST (0.39), DRB (0.32) and AST (0.27)**. Age (0.15), BLK (0.09), eFG% (0.01) have very low R^2 on their own.

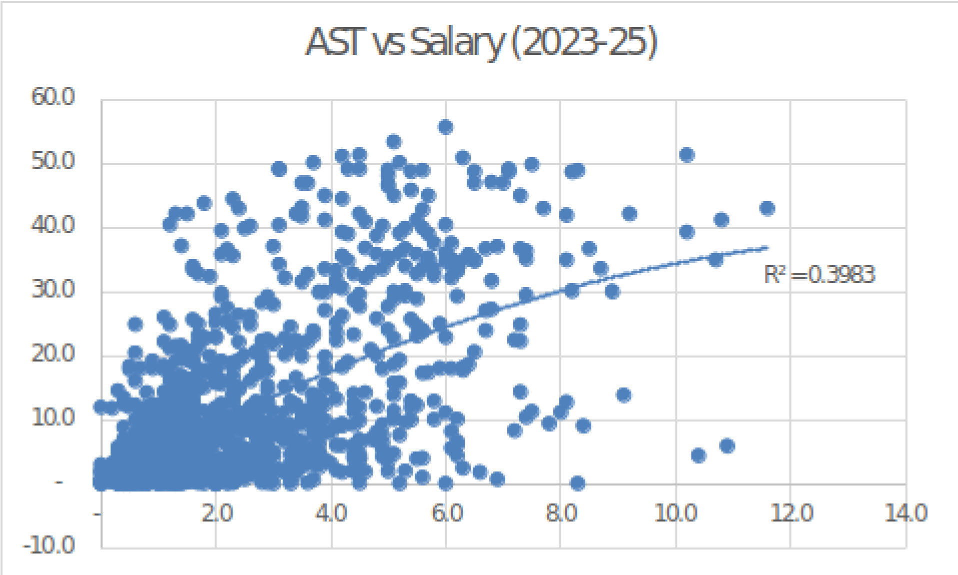
Figure 5-12: Individual Scatter Plots of key variables vs PTS along with respective R^2

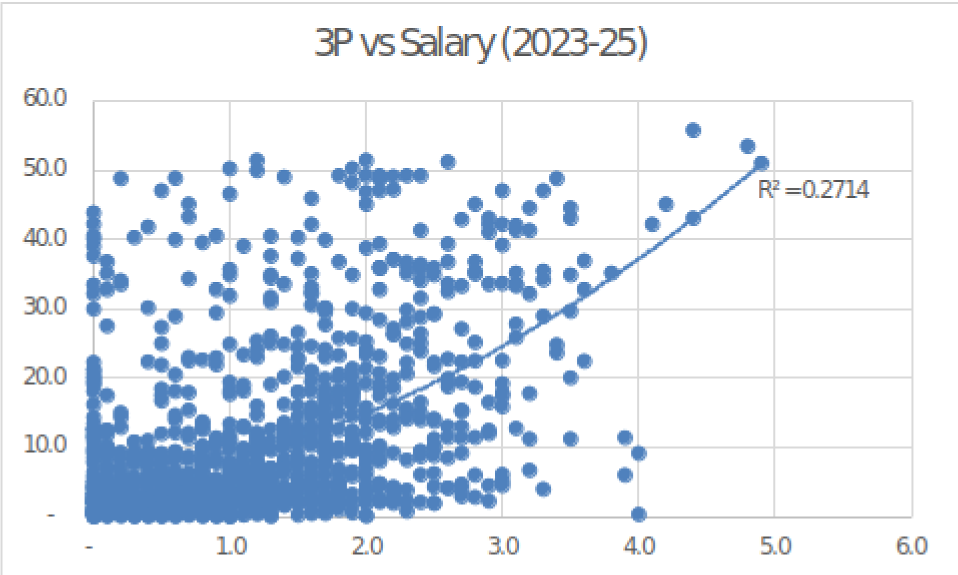


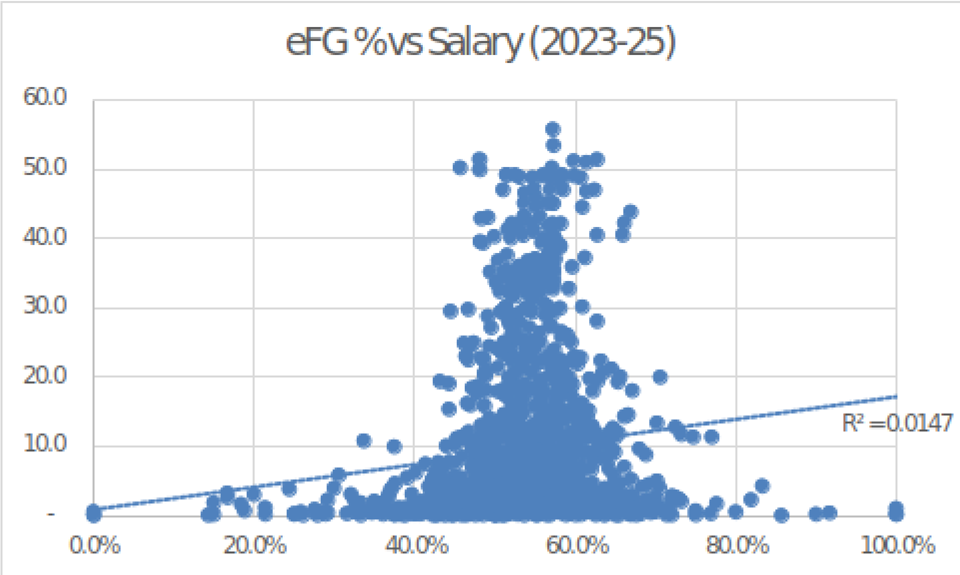


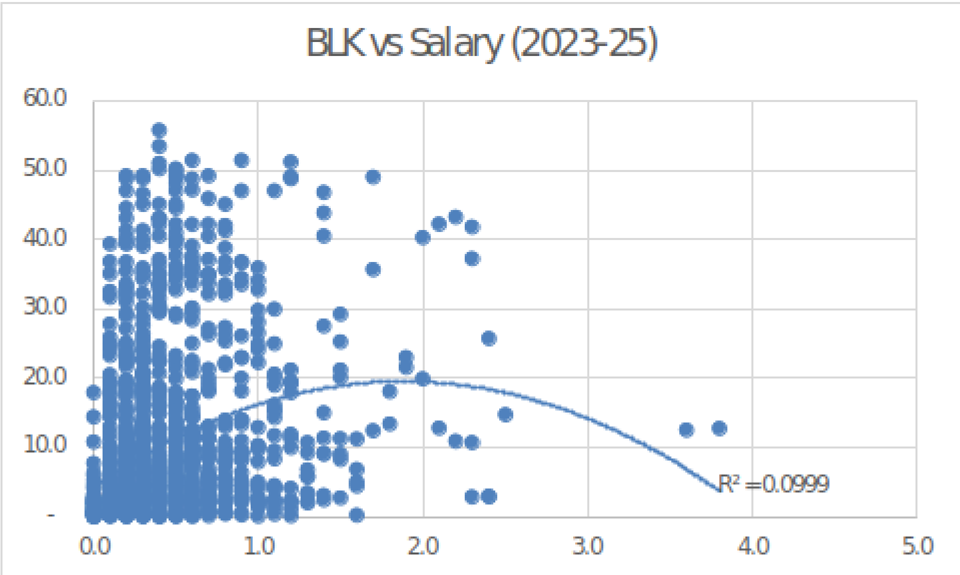

DRB vs Salary (2023-25)
60.0
50.0
40.0
30.0
20.0
10.0
-
-10.0
-
2.0
4.0
6.0
8.0
10.0
12.0
R² = 0.3241


MP vs Salary (2023-25)
60.0
50.0
40.0
30.0
20.0
10.0
-
-
5.0
10.0
15.0
20.0
25.0
30.0
35.0
40.0
R² = 0.5342


AST vs Salary (2023-25)
60.0
50.0
40.0
30.0
20.0
10.0
-
-10.0
-
2.0
4.0
6.0
8.0
10.0
12.0
14.0
R² = 0.3983


3P vs Salary (2023-25)
60.0
50.0
40.0
30.0
20.0
10.0
-
-
1.0
2.0
3.0
4.0
5.0
6.0
R² = 0.2714





Based on the correlation matrix and R^2 analysis of the key independent variables, **the most important match statistics for determining a player's salary are PTS, AST and DRB.** While PTS captures individual offensive ability in terms of scoring, DRB is a measure of defensive capabilities of a player and AST measures additional team contribution through assisting other team players in scoring.

Using the above three statistics to prepare a linear-regression model (Fig 13), **model Adjusted R^2 comes to 0.56** with p-values for all 3 input variables below 0.05 and t-values above 2.5 making them statistically relevant for the model. However, adjusted R^2 is not much better than single variable, PTS, which has R^2 of 0.55. **I tried using an exponential and polynomial model instead of linear model for the above input variables, but adjusted R^2 dropped to 0.46 implying that linear model is a better predictor.**

Figure 13: Linear regression Three-Factor model output

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.752118
R Square	0.565682
Adjusted R Square	0.564759
Standard Error	7.809098
Observations	1416

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	112150.2	37383.41	613.0236	4.4283E-255
Residual	1412	86106.59	60.982		
Total	1415	198256.8			

	Coefficients	*Standard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-3.39591	0.394994	-8.59737	2.13E-17	-4.170750952	-2.62107	-4.17075095	-2.62107303
AST	0.985647	0.169587	5.812043	7.62E-09	0.652977262	1.318316	0.65297726	1.31831623
DRB	0.729182	0.166538	4.378469	1.28E-05	0.402493365	1.055871	0.40249336	1.05587117
PTS	0.955068	0.058123	16.43197	1.18E-55	0.841051882	1.069083	0.84105188	1.06908343

In attempts to improve model adjusted R^2, through adding relevant variables and dropping least relevant variables to reduce model complexity, **the best output was achieved by adding AGE as an input variable even though its correlation (~0.35) and R^2 (0.15) were low**. Intuitively, it made sense for AGE to be a part of model given the nature of contracts at NBA where a rookie who starts at age of 18/19 gets a lower salary in first few years (initial contract) compared to a 25/26-year-old player even if he performs at the same level. While PTS capture on-field performance, AGE captures contract lifecycle and leverage of the player as PTS cannot see a player's future potential or their physical decline that AGE can. This scenario is known as **conditional significance or cooperative prediction where an input variable relationship with the output is hidden**, and it improves adjusted R^2 only when combined with others. **AGE is a suppressor variable in this analysis and acts as a baseline stabilizer helping the main predictor variable, PTS, forecast more accurately.** When added to a multi-variable model, it sucks out and cancels the background noise.

The table below (Fig 14) shows linear regression output of a **simple two-factor model using PTS and AGE which gave the highest adjusted R^2 of 0.645.**

Figure 14: Linear regression Two-factor model output

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.80441							
R Square	0.647075							
Adjusted R Square	0.646576							
Standard Error	7.036943							
Observations	1416							
ANOVA								
	df	*SS*	*MS*	*F*	*ignificance F*			
Regression	2	128287.1	64143.54	1295.343	0			
Residual	1413	69969.74	49.51857					
Total	1415	198256.8						
	Coefficients	*andard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Intercept	-24.1175	1.147638	-21.0149	1.55E-85	-26.36873	-21.8662	-26.3687	-21.8662
PTS	1.2409	0.027813	44.61504	5.2E-272	1.18634	1.29546	1.18634	1.29546
AGE	0.856597	0.043607	19.64375	3.77E-76	0.771056	0.942137	0.771056	0.942137

Given AGE is a suppressor variable with dampening impact in extreme age groups (low salary in initial years and end years), **a polynomial regression model provides a better output** as shown in Fig 15 below. **Adjusted R^2 improves to ~0.72 and standard error also reduces from ~7.03 for a linear model to ~6.26 for the polynomial model.** Thus, this model has better predictive power compared to a linear model using the same variables.

Basis polynomial regression output values (Fig 15), the equation can be written as:

ANNUAL SALARY (in \$ mn) = -12.3 - (1.78 * PTS PER GAME) + (0.95 * AGE) + (0.009 * PTS^2) - (0.018 * AGE^2) + (0.1 * PTS * AGE)

Figure 15: Polynomial regression Two-factor model output

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.848795
R Square	0.720454
Adjusted R Square	0.719462
Standard Error	6.269478
Observations	1416

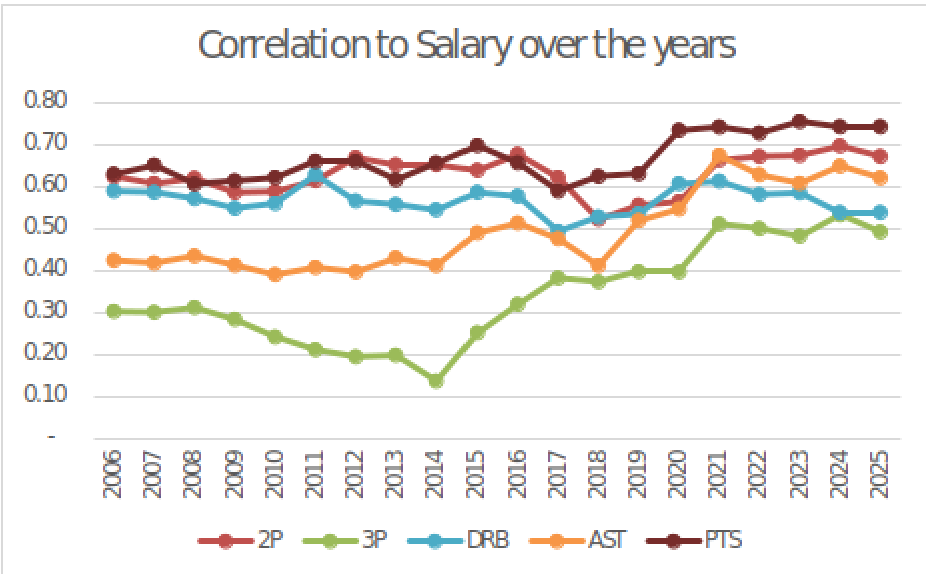
ANOVA

	df	*SS*	*MS*	*F*	*gnificance F*
Regression	5	142834.9	28566.97	726.7774	0
Residual	1410	55421.96	39.30636		
Total	1415	198256.8			

	Coefficients	*andard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Intercept	-12.3066	5.55941	-2.21365	0.027012	-23.2122	-1.40099	-23.2122	-1.40099
PTS	-1.78201	0.16172	-11.0191	3.82E-27	-2.09925	-1.46477	-2.09925	-1.46477
AGE	0.950907	0.406181	2.341093	0.019366	0.154123	1.74769	0.154123	1.74769
PTS ^2	0.009145	0.003164	2.89044	0.003906	0.002939	0.015352	0.002939	0.015352
AGE ^2	-0.01863	0.007324	-2.54441	0.011052	-0.033	-0.00427	-0.033	-0.00427
PTS * AGE	0.104507	0.005814	17.97386	3.36E-65	0.093101	0.115913	0.093101	0.115913

I believe the balance ~28% unexplained part of the model is essential intangible or difficult to model factors such as "Star value" premium, relative importance within the team and nature of contracts (multi-year contracts leading to lead/lag salary impact vs game performance in a year). It means that it is difficult to have a very high adjusted R^2 for an output like player's salary.

Figure 16: Correlation of key variables to salary over the years



As discussed earlier, these predictive models are time-period dependent. Going back to history, correlation chart above (Fig 16) shows that relative importance of the key statistics has changed over the period. As it can be observed in the chart above, **3P has been growing in importance in the last 10 years compared to 2P**. Additionally, **PTS and AST have become more critical than DRB now,** which is visible from the fact that the NBA game has become more offensive and has a higher average score now than in the past**. The above 2-factor model's adjusted R^2 drops to 0.58 during 2006-08 period. However, adding DRB to that model, improves it back to 0.65 as PTS was not as dominant as a predictor than of a player salary as it is today. Also, DRB and AGE had a more critical role in determining a player's salary**.

B. Cross-sectional and time-series analysis

Historical data of player distribution by age (Fig 17) throws up some interesting shifts visible in the game**. The league has become younger as size of teams gradually increased over the period**. While number of teams remained constant at 30 throughout the period, league had a total of ~450 players in initial study years of 2006-08 (average of 14-15 players per team) vs total players reaching ~550 in last few years (average of ~18-19 players per team). **This has resulted in average age of players in the league reducing from 26.58 years to 25.91 years**. The table and graph below indicate how proportion of players up to 24 years increased to 44% in total in 2023-25 compared to only 36% during 2006-08. Also, the proportion of players above age of 30 decreased from 20% to 16% during the same period.

Figure 17: Distribution statistics of players by age

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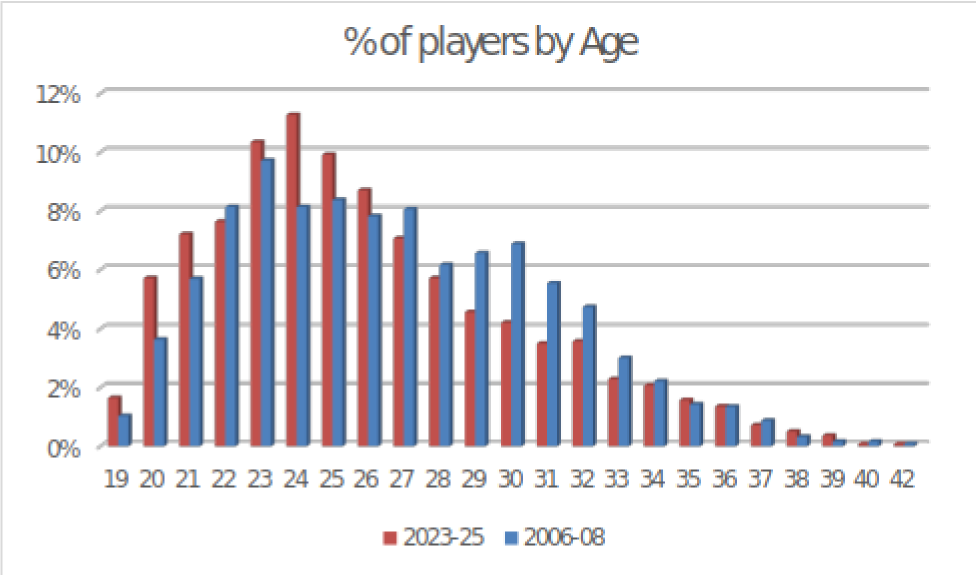


% of players	2023-25	2006-08
Upto 24 years	44%	36%
25-30 years	40%	44%
Above 30 years	16%	20%
Average Age	25.91	26.58

Figure 18: Player split during 2023-25 from data set

Position	Count	Salary	PTS	DRB	ASTS	ORB	MP	BLK	STL	3P
Centre	252	9.2	8.3	3.8	1.4	1.8	18.6	0.8	0.5	0.4
PF	269	10.5	9.3	3.2	1.7	1.1	20.2	0.5	0.6	1.0
PG	249	12.8	10.8	2.3	3.9	0.5	22.1	0.3	0.8	1.4
SF	271	8.5	8.8	2.5	1.7	0.8	20.0	0.3	0.6	1.1
SG	361	7.8	9.2	2.1	2.2	0.6	20.0	0.3	0.7	1.3
Total/Avg	1417.00	9.60	9.29	2.72	2.17	0.92	20.17	0.41	0.65	1.04

Figure 19: Player split during 2006-08 from data set

Position	Count	Salary	PTS	DRB	ASTS	ORB	MP	BLK	STL	3P
Centre	272	4.4	6.7	3.4	0.8	1.6	18.7	0.8	0.4	0.0
PF	260	4.4	8.1	3.4	1.1	1.4	20.5	0.5	0.5	0.3
PG	235	3.6	8.9	1.8	3.8	0.4	22.2	0.1	0.8	0.7
SF	209	4.2	10.0	2.8	1.7	0.9	23.8	0.4	0.8	0.8
SG	247	3.9	9.8	2.1	2.1	0.6	22.8	0.2	0.7	0.9
Total/Avg	1253.00	4.10	8.57	2.69	1.84	1.01	21.50	0.42	0.64	0.51

A deeper cross-sectional per player per game analysis of statistics across the two time periods (Fig 18 and 19) reveals the following interesting insights:

- **Average player salary has more than doubled from $4.1mn to $9.6mn implying a CAGR of ~5.1% which is higher than US inflation rate of ~2.5% over the period**.
- Average PTS score per player in a game has increased by 8.1% from 8.6 to 9.3.
- **Average 3P per player has more than doubled** from 0.51 to 1.04 in a game and now every position player is expected to contribute via this.
- **Average AST per player has increased from 1.8 to 2.2**, a 22.1% increase.
- **DRB, BLK and STL have remained constant** over the period.
- MP and ORB have marginally come down over the period.
- **The highest proportion of players were playing in Centre position (for DRB and BLK) and PF (Power Forward) for rebounds earlier compared to a greater proportion of SG (Shooting Guard) which are 3P specialists and SF (Small Forward)** which are good at scoring and assists. This clearly shows the **shift in game from focus on defence to offence now.**
- **The highest paid players used to be Centre and PF earlier in a team while now PG (Point Guard) and PF are the highest paid.**
- **PG is also the highest scoring player within the teams now vs SF and SG earlier.**
- **Centre player now is doing from DRB, AST and even scoring 3P than in the past.**

The league was static from 2006-15 (the first 10-year period of analysis). The transition in the game happened post 2015 (Fig 20 and 21) as per the tables below. I ran a t-test for comparing means of two samples (since n=10, t-test is feasible compared to z-test) in two distinct time periods, 2006-15 and 2016-25. As visible in results in tables below, **t-stats value for most statistics (except STL and BLK) imply significant mean differences (t-stat >2) in the two time periods. Positive sign indicates that the mean of first sample (2006-15) is higher while negative sign indicates that the mean of second sample (2016-25) is higher. Most significant increase in mean in 2016-25 were in 3P attempted, 3P%, 3P, eFG% and Salary while most significant decrease in mean in 2016-25 were in 2PA, 2P, AGE and FTA.** In summary post 2015, the game picked up in pace, offense and efficiency. The transformation included more players per team, each player playing for fewer minutes, more 3P per game and lesser number of 2P, shooting efficiency going up for 3P and FT, more assists, lesser turnovers and personal fouls.

Figure 20: Average year wise statistics per player

YEAR	G	GS	FG	FGA	FG%	3PA	3P%	2PA	2P%	eFG%	FTA	FT%	PF	TOV
2006	57.8	29.1	3.2	7.0	44%	1.4	27%	5.6	46%	47%	2.3	72%	2.1	1.2
2007	57.5	29.2	3.2	7.0	45%	1.4	27%	5.6	47%	48%	2.3	72%	2.0	1.3
2008	57.1	29.2	3.2	7.1	44%	1.5	27%	5.5	46%	48%	2.2	72%	1.9	1.2
2009	56.0	28.2	3.2	7.1	45%	1.5	30%	5.5	47%	49%	2.1	73%	1.9	1.2
2010	57.5	28.8	3.3	7.2	45%	1.6	27%	5.6	48%	49%	2.2	72%	1.9	1.2
2011	57.1	28.3	3.2	7.0	45%	1.5	28%	5.4	47%	48%	2.1	72%	1.9	1.2
2012	45.0	21.9	3.1	7.0	43%	1.6	28%	5.4	46%	47%	1.9	72%	1.8	1.2
2013	56.1	27.2	3.1	6.9	44%	1.7	28%	5.2	47%	48%	1.8	72%	1.7	1.2
2014	58.1	28.7	3.3	7.3	45%	1.9	29%	5.4	48%	49%	2.0	74%	1.9	1.3
2015	54.2	25.6	3.1	7.0	44%	1.9	29%	5.1	47%	48%	1.9	73%	1.8	1.2
2016	56.6	26.8	3.2	7.1	45%	2.0	30%	5.1	48%	49%	2.0	74%	1.8	1.2
2017	55.4	26.2	3.2	7.1	45%	2.2	30%	4.8	49%	50%	1.9	74%	1.7	1.1
2018	55.2	28.4	3.4	7.6	46%	2.5	32%	5.1	50%	51%	1.9	74%	1.8	1.2
2019	55.8	26.8	3.5	7.7	45%	2.8	32%	5.0	50%	51%	2.0	74%	1.9	1.2
2020	48.2	23.4	3.6	7.8	46%	3.0	32%	4.8	52%	52%	2.0	75%	1.9	1.2
2021	43.4	20.6	3.3	7.2	45%	2.8	32%	4.4	52%	52%	1.8	75%	1.6	1.1
2022	45.3	21.9	3.2	7.1	45%	2.8	31%	4.3	52%	52%	1.8	75%	1.7	1.1
2023	49.2	23.1	3.4	7.2	47%	2.8	32%	4.4	54%	54%	1.9	72%	1.7	1.1
2024	47.6	22.2	3.2	6.9	46%	2.7	31%	4.1	53%	53%	1.7	72%	1.5	1.0
2025	52.1	25.4	3.6	7.9	46%	3.3	33%	4.6	54%	54%	1.9	75%	1.7	1.2
t Stat	3.05	3.65	-3.31	-2.48	-3.54	-12.54	-10.07	8.94	-8.56	-8.98	4.17	-3.43	3.99	2.17
t Critical one-tail	1.83	1.83	1.83	1.83	1.83	1.83	1.83	1.83	1.83	1.83	1.83	1.83	1.83	1.83
t Critical two-tail	2.26	2.26	2.26	2.26	2.26	2.26	2.26	2.26	2.26	2.26	2.26	2.26	2.26	2.26

Figure 21: Average year wise statistics per player

YEAR	TRB	2P	3P	FT	STL	BLK	ORB	MP	AST	DRB	PTS	AGE	Salary	No of players
2006	3.7	2.7	0.5	1.7	0.6	0.4	1.0	21.7	1.8	2.7	8.5	26.5	4.0	416
2007	3.7	2.7	0.5	1.7	0.6	0.4	1.0	21.6	1.9	2.7	8.6	26.5	4.1	413
2008	3.7	2.7	0.5	1.6	0.6	0.4	1.0	21.3	1.9	2.7	8.6	26.8	4.3	415
2009	3.7	2.7	0.6	1.6	0.6	0.4	1.0	21.3	1.8	2.7	8.6	26.6	4.6	419
2010	3.7	2.7	0.6	1.6	0.6	0.4	1.0	21.5	1.9	2.7	8.8	26.7	4.6	416
2011	3.6	2.6	0.5	1.6	0.6	0.4	1.0	21.1	1.8	2.7	8.5	26.7	4.4	424
2012	3.7	2.5	0.5	1.4	0.7	0.4	1.0	21.1	1.8	2.7	8.2	26.7	4.1	438
2013	3.6	2.5	0.6	1.4	0.7	0.4	1.0	20.6	1.9	2.6	8.1	26.6	4.3	427
2014	3.8	2.6	0.7	1.6	0.7	0.4	1.0	21.4	2.0	2.8	8.8	26.4	4.4	403
2015	3.6	2.5	0.7	1.4	0.7	0.4	0.9	20.5	1.9	2.7	8.3	26.6	4.1	453
2016	3.7	2.5	0.7	1.5	0.7	0.4	0.9	20.6	1.9	2.8	8.6	26.6	4.7	439
2017	3.7	2.4	0.8	1.5	0.6	0.4	0.9	20.3	1.9	2.8	8.6	26.4	5.9	451
2018	3.8	2.6	0.9	1.5	0.7	0.4	0.9	21.3	2.0	2.9	9.3	26.1	7.4	413
2019	4.0	2.6	1.0	1.5	0.7	0.4	0.9	21.1	2.1	3.1	9.5	26.2	7.2	436
2020	4.0	2.5	1.1	1.6	0.7	0.4	0.9	21.5	2.1	3.1	9.8	25.9	7.8	429
2021	3.7	2.3	1.0	1.4	0.6	0.4	0.8	19.8	2.0	2.8	9.1	25.6	8.9	474
2022	3.6	2.3	1.0	1.4	0.6	0.4	0.9	19.7	2.0	2.8	8.8	25.9	8.0	508
2023	3.5	2.4	1.0	1.5	0.6	0.4	0.9	20.0	2.1	2.7	9.2	25.8	9.1	462
2024	3.4	2.2	1.0	1.3	0.6	0.4	0.9	19.2	2.1	2.6	8.7	25.8	9.1	479
2025	3.9	2.5	1.2	1.5	0.7	0.4	1.0	21.4	2.3	2.9	10.0	26.2	10.7	476
t Stat	-0.95	4.77	-11.94	3.09	-0.38	0.90	3.92	2.55	-5.44	-2.80	-3.65	4.88	-6.76	-4.18
t Critical one-tail	1.83	1.83	1.83	1.83	1.83	1.83	1.83	1.83	1.83	1.83	1.83	1.83	1.83	1.83
t Critical two-tail	2.26	2.26	2.26	2.26	2.26	2.26	2.26	2.26	2.26	2.26	2.26	2.26	2.26	2.26

C. A Player Lifecycle analysis- Salary linkage with PTS and AGE

While the importance of PTS and AGE as key predictor variables has been established in our regression model study earlier, I attempted to witness how a player's salary and PTS moved with AGE on our dataset. The charts below (Fig 22) depict the same.

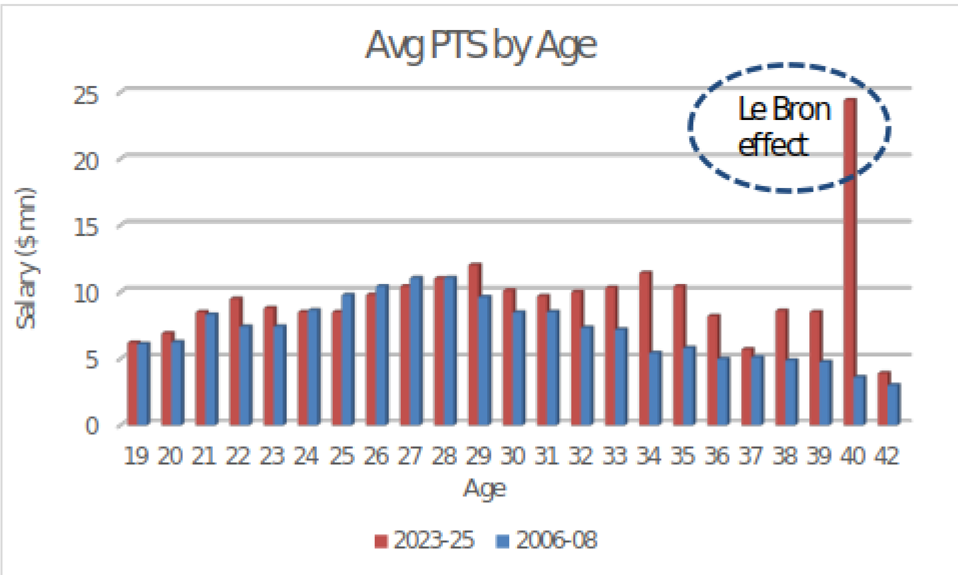
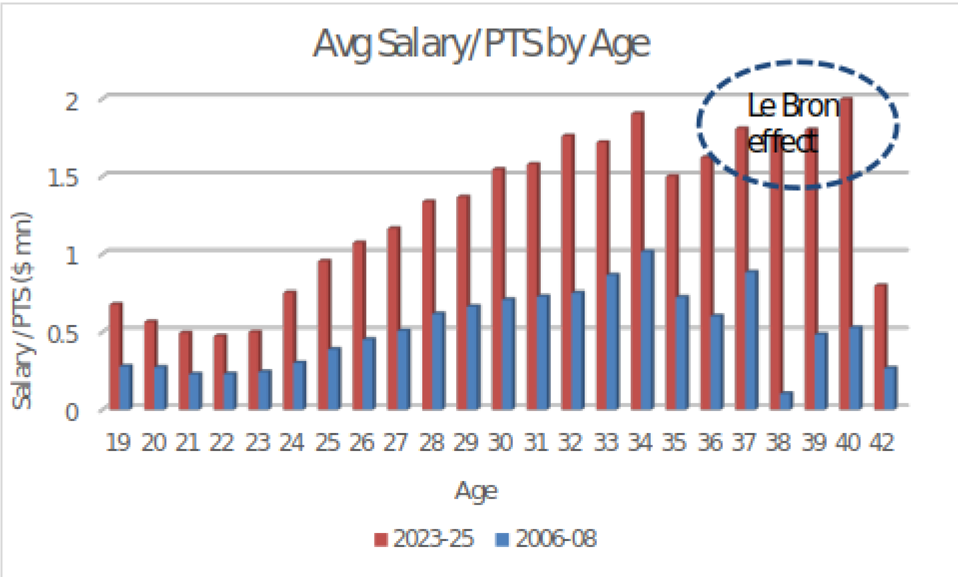


Figure 22: Average PTS trend per player by AGE

It is quite apparent from the above chart that **PTS keeps improving with AGE (starts at ~5 PTS per game at age of 19-20 and peaks up to ~10 PTS per game and peaks at age of 28-29. There is not much difference in this growth trajectory of a player in the two distinct time periods.** However, **in the earlier era (2006-08), the fall in PTS was sharp and came back to 5 PTS average by the time a player hit age of 34-35. However, in the last few years (2023-25), the older players in the league (age >30 years), have done exceptionally well and are able to maintain their scoring ability till age of 34-35.** Perhaps, the reason behind the same might be improved fitness and training routines and 3P skills. In this study, age 38-40 bucket average numbers were positively impacted by performance of the legendary player, Le Bron James, who has continued to score 20 PTS+ even at age of 40.

Next, I use PTS, the single biggest determining factor of a player's salary, in this analysis of Salary changes with Age. The chart below (Fig 23) shows Average Salary per PTS scored for different age groups in the two distinct time periods. As visible in the chart, **Average Salary/PTS drops from age of 19 to 23 due to initial rookie contracts of 3-4 years which caps their salary even though they keep scoring more PTS. Post that period, Salary/PTS really shoots up from Age of 24 till 34, with 30-34 age bucket being perhaps the Golden period, for a player to earn as he makes maximum buck for every PTS scored. It's interesting to note that while PTS peak at age of 30, a player's salary/PTS keeps rising till age of 34, a lag of ~4 years. As seen in PTS, in the recent period, players have been able to keep their Salary/PTS equation steady even post age of 34 (also partly helped by Le Bron effect), compared to earlier period (2006-08) when salaries used to drop sharply.**

Figure 23: Average Salary per PTS per player by AGE



From the charts above during 2023-25 period, a "Rookie player" gets ~\$0.5mn salary per PTS scored for first 4 years. So, 5 PTS scored on average by a rookie implies salary of ~\$2-2.5 mn. As he graduates to be a 7-8 PTS per game player by age of 25-26, his annual salary could be in range of ~\$7-8 mn (~1mn/PTS). As he steadily keeps improving and goes up to 10-11 PTS per game at age of 30/31, his salary would reach ~\$16-20 mn (~1.6mn/PTS). I observed in the dataset that for "Star player" in the team, average Salary/PTS can even go upto ~2-2.5x, and thus a Star player scoring ~20-25 PTS per game in a season, ends up earning close to ~\$40-50mn annual salary. **So, the journey from ~\$2 mn *Rookie* to ~\$40-50mn *Star* takes 12-13 years. The same journey 20 years back was from \$1 mn (\$0.2mn/PTS) *Rookie* to \$15-17 mn *Star* (\$ 0.7-0.8mn/PTS) in those 12-13 years**.

IV. Conclusion

PTS and AGE are the most important factors which determine a player's salary. PTS seem to be an all-encompassing statistic which has high correlation with most other game statistics. While AGE has low individual correlation with Salary but acts as suppressor variable of conditional significance and helps provide the best Adjusted R^2 of 0.72 for a predictive polynomial regression model (without AGE model R^2 was ~0.56). The game has changed significantly post 2015 with addition of more players in the league and pace of the game has stepped-up leading to more offensive play. PTS, AST, 3P, 3P%, 2P% per game statistics have all gone up significantly while AGE, MP, 2P, ORB, PF have all reduced as shows in paired sample mean t-test outputs. Centre position defense specialist which used to be most important player in the team has passed on this status to attacking Point guard position while Power Forwards remain the second most critical player. Average player salary has more than doubled from $4.1mn to $9.6mn implying a CAGR of ~5.1% over last 20 years which is higher than US inflation rate of ~2.5% over the period. However, all this increase has come in last 10 years when average salaries have grown at 10% CAGR. During the lifecycle of a player, a rookie player starting at age of 19, earns an average of ~$0.5mn/PTS for the first 3-4 years post which the 10- year golden period for earnings when his annual salary steadily goes upto ~$1.6mn/PTS, roughly 3x return compared to his initial rookie year for the same PTS scored. Annual earnings per PTS achieve their peak ~30-34 age bucket. While PTS usually peaks out by age of 30, Salaries/PTS keep rising till age of 34 due to brand and star value created. While lifecycle of a player hasn’t changed much over the period of study in terms of years of ramp-up and peaking in PTS, and Salary/PTS trend, it is clearly evident that in the recent years older players (>30 years old) have been able to maintain their PTS and Salary/PTS metric much better compared to 20 years back when it used to drop down sharply with age.

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V. Appendix

The statistics used at player level are shown below.

TEAMS	POSITIONS	STATISTICS USED	
Atlanta Hawks (ATL)	Center (C)	G	Games Played
Boston Celtics (BOS)	Point Guard (PG)	GS	Games Started
Brooklyn Nets (BRK)	Power Forward (PF)	MP	Minutes Played
Charlotte Hornets (CHO)	Shooting Guard (SG)	FG	Field Goals
Chicago Bulls (CHI)	Small Forward (SF)	FGA	Field Goals Attempted
Cleveland Cavaliers (CLE)		FG%	Field Goal percentage
Dallas Mavericks (DAL)		3P	3P shots made
Denver Nuggets (DEN)		3PA	3P shots attempted
Detroit Pistons (DET)		3P%	3 Point percentage
Golden State Warriors (GSW)		2P	2P shots made
Houston Rockets (HOU)		2PA	2P shots attempted
Indiana Pacers (IND)		2P%	2 Point percentage
Los Angeles Clippers (LAC)		eFG%	Effective Field Goal percentage
Los Angeles Lakers (LAL)		FT	Free Throws made
Memphis Grizzlies (MEM)		FTA	Free Throws Attempted
Miami Heat (MIA)		FT%	Free Throw percentage
Milwaukee Bucks (MIL)		ORB	Offensive Rebound
Minnesota Timberwolves (MIN)		DRB	Defensive Rebound
New Orleans Pelicans (NOP)		TRB	Total Rebound
New York Knicks (NYK)		AST	Assists
Oklahoma City Thunder (OKC)		STL	Steals
Orlando Magic (ORL)		BLK	Blocks
Philadelphia 76ers (PHI)		TOV	Turnovers
Phoenix Suns (PHX)		PF	Personal Fouls
Portland Trail Blazers (POR)		PTS	Points Scored
Sacramento Kings (SAC)		* Averages have been used	
San Antonio Spurs (SAS)			
Toronto Raptors (TOR)			
Utah Jazz (UTA)			
Washington Wizards (WAS)			