國立政治大學經濟學系

碩士學位論文

球員選秀順位與未來表現之關聯性分析：以 NBA 為例

Draft Order and Players' Future Performance: Evidence from the National Basketball Association

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摘要

本研究採用美國籃球聯盟西元 2006 年至 2017 年順利通過兩輪選秀之新秀球員數據資料，以迴歸不連續法，估計球員選秀順位與其未來表現關聯性。實證結果顯示，在前三年的職業生涯中，高選秀順位球員相較於低選秀順位球員，並未擁有較佳表現。在職業生涯第二年，高選秀順位球員相較於低選秀順位球員，平均每場比賽獲得較多上場時間；然而，此結果並不穩定。去除了同一賽季中，曾有轉換過球隊的球員後，仍獲得類似結果。因此，推斷此不穩定結果現象可能為樣本數不足原因所致。

關鍵字：NBA 選秀、球員表現、運動經濟學

Abstract

The goal of this paper is to examine the correlation between draft order and players' subsequent performance using draftees' statistics between 2006 and 2017 from the National Basketball Association (NBA). A regression discontinuity design is applied to capture the effect of draft order. The results show that higher-drafted players are not more productive than lower-drafted players throughout the first three years of their career. Although higher-drafted players have more playing time per game than lower-drafted players in their second year, the results are unstable. In a subgroup analysis, I find similar results. A possible reason for the unexpected results may lie in the inadequacy of the sample size.

Keywords: NBA draft; Player performance; Sports economics

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1. Introduction

Draft number is usually seen as the prediction of player's future productivity. Team managers draft players who are expected to be beneficial to their teams. This raises the question as to whether players who are drafted earlier exactly have better subsequent performances after entering the National Basketball Association (NBA). Related studies have examined factors that play a role in determining players' subsequent performances in professional sports (Berri et al., 2010; Berri & Simmons, 2011; Rodenberg and Kim, 2011; Evans, 2018); however, the relationship between draft position and performance in the previous research has not been consistent. Thus, the present study is motivated by the intention to pinpoint the relation between draft number and future performance.

The annual NBA draft takes place in June, wherein teams select new players to join the league. The NBA draft is structured as a reverse draft: teams' playing records in the previous season determine the order of draft lottery. There are two rounds for the NBA draft, and 30 players are picked in each round. Fourteen NBA teams that did not make the playoff games in previous season are eligible to participate in the draft lottery, which aims at balancing productivity among teams by allowing worse teams to draft better players. According to the NBA draft system, four teams with the worst regular season record have a better chance to receive the first pick, and the chance of winning the lottery would decline from the fifth to the fourteenth participant. After the fifteenth pick, teams follow the reverse order to draft rookies.[1]

Regarding discrepancy between the first and second rounds, players who are drafted in the first round receive a two-year guaranteed contract with a fixed salary scale, while second-round players' contracts are decided by negotiations between agents and teams. Players' salary scales are determined before the regular season games commence. According to the NBA's Collective Bargaining Agreement (CBA), guaranteed contracts ensure that players receive the salary negotiated in advance, even if the players are later traded to other teams. Furthermore, in the first-round draft, the higher the status of the players that a team drafts, the greater the financial obligation

[1] Details of draft rules can be acquired on NBA.com.

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the team must meet; that is, teams need to offer higher salaries to draft players earlier. As long as the team picks a player in the first round, it loses the chance to select other players; therefore, draft order can be a proxy for teams' initial costs.

Economic theory tells us that a "sunk cost is sunk," meaning that an irreversible cost should have nothing to do with rational decision-makers' following behavior, and that they should instead focus on marginal benefits and costs when making decisions. If individuals take sunk cost into consideration when making subsequent decisions, then the "sunk cost fallacy" problem would occur. A growing body of research has focused on the sunk cost effect in the professional sport labor market (Staw & Hoang, 1995; Cramerer & Weber, 1999; Borland et al., 2011; Keefer, 2017; Leeds et al., 2015; Hinton & Sun, 2019), showing various conclusions. Hence, this paper attempts to reexamine whether the sunk cost fallacy exists in the NBA by using NBA drafts to determine the initial costs for NBA teams.

The major issue I am concerned with is how draft order aligns with players' utilization and future performance. Differing from previous studies, I place more emphasis on team and coach characteristics instead of players' individual properties, so I add related control variables into my estimation. Moreover, I intend to address a potential endogeneity issue in previous studies that merely use an ordinary least square regression by adopting a sharp regression discontinuity design.

This paper is divided into six sections. Section Two reviews previous literature. Section Three explains the empirical design used in this study. Section Four describes the data. Section Five reports the estimation results. Section Six draws conclusions.

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2. Literature Review

This study attempts to discuss the relationship between draft order and players' subsequent performances after entering the NBA, focusing particularly on the sunk cost effect in the NBA. In this section, I will briefly review the studies related to factors of players' future success and sunk cost fallacy in professional sport field.

2.1 Determinants of players' future success

There have been many studies related to determinants of players' performances in the NBA. Berri et al. (2011) aimed to uncover factors that dictated players' career success in the NBA. Their findings showed that players' positive accomplishments such as the points, assists, and steals made in their collegiate period are highly related to their future performance, whereas their draft numbers could merely account for less than 5 percent of their career wins-produced per 48 min (WP48).

Research conducted by Rodenberg and Kim (2011) aimed to clarify the relationship between a player's age and performance. Multiple dependent variables including average minutes played per game, PER, and number of all-star games were adopted in this estimation. It was found that age and draft number were significantly and negatively correlated with the three dependent variables, meaning that younger players and players who are drafted earlier would have better future performance after entering NBA, and that, accordingly, draft order is a good proxy by which to measure a player's subsequent ability and productivity.

More recently, Evans (2018) explored the determinants of players' performance after entering the NBA. Statistical results indicated that both precise draft number and squared draft order negatively and significantly aligned with players' playing time and win shares. This kind of test has also appeared in other professional sport leagues. Berri and Simmons (2011) studied quarterback draftees and their subsequent performance in the National Football League (NFL). Their findings demonstrated that higher-drafted quarterbacks would start in more games, yet it could not be ensured that they were more productive than lower-drafted quarterbacks. Based on previous studies, the relationship between draft order and future performance has a diverse conclusion, prompting me to further test this topic.

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2.2 Sunk cost fallacy in professional sport field

Staw and Hoang (1995) conducted three analyses for this topic. Controlling for performance on court in the previous season, they used total playing time in a single season as a measure of players' utilization to test the escalation of commitment in the NBA. Their empirical results demonstrated that draft order is a good predictor for playing time; that is to say, coaches played higher-drafted players more regardless of their performance, and escalation of commitment existed in the NBA.

Then, Camerer and Weber (1999) built on Staw and Hoang (1995) to reexamine the sunk cost fallacy in the NBA. Using playing time as dependent variable, they included the effect of backup players, pre-draft expectations, fan appeal, fixed effect of first-round pick, as well as aggregated lagged performance factors to improve the estimation. The findings supported the existence of escalation of commitment; namely, smaller draft number players would yield more playing time, and the escalation effect would last until players' third season.

Instead of concentrating on precise draft number as did previous studies, Leeds et al. (2015) paid attention to the transition from lottery pick to non-lottery pick and first-round draft to second-round draft by conducting a regression discontinuity design, which could address the endogeneity issue, to investigate the sunk cost fallacy in the NBA. Results indicated that there was no disparity between the actual number of minutes received by higher-drafted and lower-drafted players, contradicting the results derived in Staw and Hoang (1995) and Camerer and Weber (1999). Hence, the findings in Leeds et al. (2015) opposed the existence of the sunk cost fallacy in the NBA.

Studies concerning the escalation of commitment have also been conducted in relation to other professional sport associations. Using a sample of draftees from the Australia Football League (AFL), Borland et al. (2011) discovered a weak correlation between players' draft positions and future performance and tenure. In other words, only a limited escalation effect was found in the AFL. Keefer (2017) viewed players' salary cap as proxy for sunk cost and conducted a fuzzy regression discontinuity to determine whether an escalation effect occurred in the NFL. The results showed that coaches took sunk cost into consideration when making playing-time decisions.

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2.3 Extension of previous studies

Few previous studies have considered competition between players in the same position. There are five basketball positions—point guard (PG), shooting guard (SG), center (C), small forward (SF), and power forward (PF). In a basketball game, when a player is on the court, other players in the same position serve as backup players. From the coach's point of view, players in the same position are alternates. Camerer and Weber (1999) considered backup players' effect; the variables they included were performance factors of players in the same position with the most playing time. They only took account of backup players with good performance; however, for rookies, all players in the same position are competitors, as each position can only have one player on the court and coaches might not always let the best player play the whole game. Accordingly, I introduce a new variable defined as the number of existing players playing in the same position as rookies, which will be a better measurement for competition among players in the same position. Rookies generally are not priorities when coaches make player-utilization decisions, so I expect that the more potential competitors there are on a team, the less playing time rookies receive.

In addition, in this paper, I employ a better measurement for players' playing time and performance than what has been used in previous studies. Berri (2011) and Evans (2018) used WP48 and win-shares, respectively, to assess draftees' performance. Win-produced and win-shares estimate how much a player contributes to team success. Instead, I utilize PER as the proxy for players' performance as PER is a more objective measurement. PER is used to measure players' per-minute productivity, which is computed by adding up players' positive achievements and subtracting negative ones. PER is a standardized rating since it takes team pace into account and the league average is set to be 15 in all seasons. Hence, PER enables players to be compared among diverse teams and seasons, which could avoid bias caused by disparity among different teams and seasons. In regard to playing time evaluation, Cramerer and Weber (1999) and Staw and Hoang (1995) used total playing time as dependent variable. Yet, using total playing time might not be a good assessment because some players' receiving many playing minutes might result from their playing large amounts of "garbage time." Garbage time refers to the time remaining in a game after the outcome of the game has been decided. If a team has already made the playoffs or has scored enough points to inevitably win a

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game, the coach might let rookies play the remaining time. Thus, I use minutes played per game (MPPG) as the second dependent variable in order to avoid the "garbage time" problem.

In terms of empirical method, Staw and Hoang (1995) and Cramerer and Weber (1999) applied ordinary least square regressions to playing-time estimations. However, to only adopt an ordinary least square regression might raise omit-variable issues since some unobservable characteristics such as leadership, injury, or collaboration between teammates could both affect draft outcome and future performance. Undoubtedly, teams are unwilling to pick players who have the tendency to be injured or lack the ability to work well with teammates. RD design is able to circumvent the concern of potential endogeneity since players near the cutoff are expected to have similar characteristics; in other words, the last player in the first round and the first player in the second round are supposed to have a similar ability to work with teammates or exhibit leadership. Thus, these unobservable variables would be less likely to result in biased estimation. In this paper, I apply the same sharp regression discontinuity design as that of Leeds et al. (2015) to concentrate on players near the cutoff of the first and the second rounds. The major discrepancy between this paper and theirs is that I introduce additional control variables related to team and coach characteristics. Moreover, I use multiple dependent variables to verify the relationship between draft order and future performance, which has still been unclear in previous studies.

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3. Empirical Design

This paper aims to uncover the relationship between a player's draft status, subsequent performance, and utilization. I adopt a sharp regression discontinuity design with draft order as the running variable. Following Leeds et al. (2015), I focus on causality when players cross from the first to the second round. In order to consolidate the results from the regression discontinuity method, other covariates should not have discrete jump near the cutoff. In addition, a proper bandwidth plays a crucial role in the RD design. On the one hand, if the bandwidth is broadened too much, it is more likely for unobservable variables to bias the results. For instance, the differences in unobservable ability might increase along descending draft numbers. On the other hand, if the bandwidth is too narrow, a deficiency in the sample observations might occur.

3.1 Data Analysis

The samples cover players drafted into first and second rounds of the annual NBA draft between 2006 and 2017[2]. I choose 2006 as the commencement year of the sample period on account of the draft policy change. Since 2006, teams could no longer draft players from high school directly; players eligible for the NBA draft must have at least one year of experience in college basketball. As a result, players' characteristics will be more alike, which brings an advantage for estimation. Instead of focusing on all players in the NBA draft, I merely lay emphasis on rookies who entered the NBA via draft and played at least one season in NBA; hence, the observations with missing values are excluded from the estimations. I examine these draftees' performances and play times through their PER[3] and MPPG in the first three seasons of their careers after they were drafted into the NBA. If a player was drafted in 2007, then his relevant information from 2007 to 2009 is included in the dataset. I decide to test three seasons of career because of the two-year guaranteed contract for first-round players. Beyond the terms of their contracts, players are traded freely by teams. It is anticipated that the influence of a draft will degenerate alongside the rise of rookies' professional experience. Cramerer and Weber (1999) provided estimation evidence that the decline in playing time caused by an ascending draft number diminishes over time.

[2] The data are collected from Basketball-Reference.com.
[3] Details of calculating PER can be acquired on Basketball-Reference.com.

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Table 1 – Definition of all variables

Variable	Definition
Dependent variables	
PER	Player efficiency rating
MPPG	Minutes played per game = Total minutes played / Total games
Independent variables	
First round	Equals to 1 if the player is drafted in the first round
Height	Player's height measured in centimeter
Competitors	Number of players in the same position as rookies
Lagged win percentage	Team's win percentage in previous season
Lagged playoff	Equals to 1 if the team made the playoffs in previous season
Used to be player	Equals to 1 if the coach used to be a player in NBA
Coach experience	Years of experience in major coach
Coach award	Equals to 1 if the coach receives "Coach of the Year" award
Inside player	Equals to 1 if the player is a center or power forward

Table 1 tabulates the definition of all variables. As a whole, the covariates dataset is established by (1) personal characteristic, (2) team quality, and (3) coach feature. To begin with, for personal characteristic, I capture the impact of a player's height, measured in centimeters. Taller players generally have larger wingspan, which gives players an advantage by supporting their ability to catch more rebounds or block rivals' shots. Thus, it is expected that taller players may perform better on court. In addition, taller players commonly play center or power forward, so I add a position dummy variable to capture the fixed effect of position. I do not control for players' performances in the prior season because of the concern of autocorrelation.

Turning our attention to team characters, I test how the competitors in the same position would influence rookies' performance and playing time. Intuitively, too many teammates in identical positions would lead to the lack of rookies' playing time. Moreover, excellent teammates may encourage rookies to improve their ability. I compute the number of players in five positions for each team. Then, I match them to a draftee's team and position to derive the number of potential competitors. Furthermore, I introduce an additional two variables related to the preceding season, namely lagged-win percentage and lagged- playoff dummy. Win percentage is defined as the number

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of wins divided by the number of games in a regular season, and the lagged playoff dummy variable is equal to 1 if the team made the playoffs in the prior season. These two variables are used to represent the quality of a team. In this study, because of the small sample size, team fixed effect cannot be captured in the estimation.

The coach is also a possible determinant of players' performance, so coaching properties are included into estimation. Outstanding coaches may be more likely to explore and stimulate players' potential and talent. Moreover, if a coach used to play in the NBA, has received awards such as Coach of the Year, or has much prior experience as the head coach of a team, he might be more familiar with how to organize a team nicely.

In three years, 4.5, 10.9, and 16.9 percent of the draftees in the sample set changed teams within a season, respectively. This means that these players played for more than one team within a single season. Furthermore, some teams have more than one head coach within a season. In this study, players cannot be on more than one team, nor can teams have multiple head coaches, within a season. Thus, I choose teams for which rookies play more games. When the number of games played is identical for each team, these samples are dropped because there are only three observations. Similarly, I choose coaches who lead more games as the head coach of a team in that season. If number of games played is identical, the first coach in that season is chosen.[4]

Table 2 presents descriptive statistics of variables for the overall sample set. There is a notable drop in sample size in the third season, possibly because of the rule of the NBA draft. According to the NBA's Collective Bargaining Agreement, first-round draftees are granted two-year guaranteed contract; hence, after the second season, some players with worse performances might be waived by team manager. In Table 2, it can also be seen that the PER and the MPPG rise with an increase in the number of seasons played. This can be explained for two possible reasons. To begin with, as their professional experience accumulates, they could better cooperate with teammates and be trusted more by coaches. Hence, they would have more opportunities to play on

[4] I conduct analysis using the other coaches as well, and the results are similar to the analysis using the first coach.

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Table 2 – Descriptive statistics for overall sample set

Variable	First Season		Second Season		Third Season	
	Mean	SD	Mean	SD	Mean	SD
Dependent variables						
PER	11.03	5.42	12.03	5.7	13.99	7.94
MPPG	15.08	8.33	18.32	9.4	20.37	9.39
Independent variables						
First round	0.62	0.49	0.64	0.48	0.68	0.47
Height	200.32	8.54	200.68	8.65	200.93	8.67
Competitors	3.93	1.17	3.89	1.22	3.98	1.28
Lagged win percentage	0.47	0.15	0.47	0.15	0.48	0.16
Lagged playoff	0.43	0.49	0.46	0.50	0.47	0.5
Used to be player	0.60	0.49	0.58	0.49	0.51	0.5
Coach experience	7.62	6.56	7.05	6.21	6.86	5.83
Coach award	0.03	0.17	0.03	0.18	0.04	0.2
Inside player	0.40	0.49	0.40	0.49	0.43	0.5
Observations	533		530		479	

Note: SD = Standard deviation.

court. Secondly, if the players' performances did not improve or the players failed to benefit their teams, they would be unable to stay in the NBA. As some players leave the NBA, the sample size decreases in the second and third seasons.

To further understand the sample, I divide the sample set between players above and below the cutoff and compute subgroup descriptive statistics of variables. Table 3 reports the sample mean and standard deviation of variables for first- and second-round players. In Table 3, it could be noticed that first-round players have bigger PER and MPPG than second-round players throughout three seasons. Moreover, regardless of their draft round, the PER and MPPG increase alongside an increase in the number of seasons.

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Table 3 – Descriptive statistics for subgroup sample

Variable	First Season				Second Season				Third Season			
	First Round		Second Round		First Round		Second Round		First Round		Second Round	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Dependent variables												
PER	11.68	4.22	9.99	6.82	12.95	4.51	10.39	7.06	14.20	4.51	13.53	12.50
MPPG	17.65	8.26	10.94	6.6	21.12	9.11	13.35	7.73	22.65	9.09	15.41	8.07
Independent variables												
Height	200.67	8.67	199.76	8.31	200.89	8.66	200.32	8.63	201.07	8.76	200.62	8.5
Competitors	3.87	1.17	4.02	1.15	3.77	1.19	4.1	1.23	3.95	1.28	4.06	1.28
Lagged win percentage	0.45	0.15	0.49	0.15	0.46	0.15	0.49	0.15	0.47	0.16	0.5	0.16
Lagged playoff	0.38	0.49	0.5	0.5	0.42	0.49	0.52	0.5	0.44	0.5	0.55	0.5
Used to be player	0.61	0.49	0.58	0.5	0.56	0.5	0.62	0.49	0.53	0.5	0.46	0.5
Coach experience	7.39	6.74	7.99	6.24	6.71	6.17	7.64	6.25	6.66	5.65	7.3	6.2
Coach award	0.03	0.18	0.02	0.14	0.04	0.19	0.03	0.16	0.03	0.18	0.06	0.24
Inside player	0.4	0.49	0.41	0.49	0.4	0.49	0.39	0.49	0.42	0.49	0.45	0.5
Observations	329		204		339		191		328		151	

Notes: Table 3 presents the sample mean and standard deviation of variables for first-round players versus second-round players. SD = Standard deviation.

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Table 4 – Continuity of Height

Variable	First Season	Second Season	Third Season
First round	-2.084	-0.654	-1.951
	(2.460)	(2.640)	(2.598)
Running variable	-0.00165	0.191	-0.207
	(0.360)	(0.400)	(0.435)
First round x Running variable	-0.133	-0.276	0.254
	(0.484)	(0.498)	(0.543)

Notes: The results are reported in a bandwidth of 8. Robust standard errors in parentheses. * = Significant at 10% or more; ** = Significant at 5% or more; *** = Significant at 1% or more.

Table 5 – Continuity of Competitors

Variable	First Season	Second Season	Third Season
First round	-0.793**	0.684	0.213
	(0.393)	(0.508)	(0.527)
Running variable	-0.138**	0.141*	-0.0338
	(0.0628)	(0.0820)	(0.0885)
First round x Running variable	0.0913	-0.0860	0.0895
	(0.0771)	(0.0989)	(0.104)

Notes: The results are reported in a bandwidth of 8. Robust standard errors in parentheses. * = Significant at 10% or more; ** = Significant at 5% or more; *** = Significant at 1% or more.

In a regression discontinuity design, an important assumption is that observable covariates should not have noticeable discontinuity around the cutoff, or else we cannot make sure that the observed discontinuity in the outcome is attributed to the treatment effect. Hence, I conduct four continuity tests to examine the continuity of covariates. Table 4 to 7 presents continuity test results for height, competitors, lagged win percentage and coach experience, respectively. The results show that height, lagged win percentage and coach experience do not have discrete jumps at the cutoff throughout three seasons. However, the number of competitors has significant discontinuity around the cutoff in the first season, which may pose some problems to the empirical results in the first season.

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Table 6 – Continuity of Lagged win percentage

Variable	First Season	Second Season	Third Season
First round	0.0580	0.0438	0.0840
	(0.0710)	(0.0629)	(0.0601)
Running variable	-0.0158	-0.00950	0.00526
	(0.0111)	(0.0106)	(0.0103)
First round x Running variable	0.0252*	0.0238*	0.000829
	(0.0137)	(0.0125)	(0.0126)

Notes: The results are reported in a bandwidth of 8. Robust standard errors in parentheses. * = Significant at 10% or more; ** = Significant at 5% or more; *** = Significant at 1% or more.

Table 7 – Continuity of Coach experience

Variable	First Season	Second Season	Third Season
First round	-1.117	0.297	0.761
	(2.113)	(2.394)	(2.630)
Running variable	-0.329	0.332	-0.433
	(0.319)	(0.451)	(0.450)
First round x Running variable	0.298	-0.218	0.814
	(0.421)	(0.524)	(0.551)

Notes: The results are reported in a bandwidth of 8. Robust standard errors in parentheses. * = Significant at 10% or more; ** = Significant at 5% or more; *** = Significant at 1% or more.

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3.2 Method

In this study, I conduct non-parametric local linear regressions. The regression discontinuity model is indicated below:

$$Y_i = \beta_0 + \beta_1 D_i + \beta_2 \widetilde{d_\iota} + \beta_3 D_i \widetilde{d_\iota} + \beta_4 X_i + \epsilon_i, \qquad i = 1,2,3 \dots \dots N$$

Y_i refers to the outcome variable for player i. In this paper, I employ (1) PER and (2) MPPG as dependent variables. D_i is a treatment assignment for player i. D_i equals 1 if players are drafted in the treatment group; for example, D_i equals 1 if players are drafted in the first round. $\widetilde{d_\iota} = d_i - c$ is running variable, which is centered at the threshold. For instance, $\widetilde{d_\iota}$= 0.5 at the thirtieth pick and -0.5 at the thirty-first pick. X_i refers to control variables described in Section 3.1. ϵ_i is an error term. The running variable is limited within $h \leq \widetilde{d_\iota} \leq h$, where h is the bandwidth. I apply a bandwidth of 8 in this analysis. As there is a variety of missing value observations in second-round players, using a larger bandwidth may contain players with much disparity in characteristics. To consolidate this analysis, I also apply bandwidths of 5 and 10 to examine the stability of the estimation results.

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4. Results

4.1 Estimation Results

Table 8 demonstrates local liner results of PER for first- and second-round players in the bandwidth of 8. In Table 4, no evidence is found that first-round players are more productive than second-round players throughout three seasons, and this result is similar in using bandwidths of 5 and 10. The running variables show significant positive relationship with PER in the first season, demonstrating that players' playing efficiencies increase alongside higher draft statuses. This result is in line with my expectation that draft order would have the strongest effect in the first year. However, in bandwidths of 5 and 10, this significant impact disappears, meaning that this result is not stable. Thus, the relationship between draft status and performance in the first season cannot be ascertained.

In the second and third seasons, earlier-drafted players do not yield higher playing efficiencies than later-drafted ones. The contracts received by first- and second-round players vary to a large extent. First-round players are guaranteed two-year contract and fixed scale salary, whereas second-round contracts are determined by negotiation. The statistical results indicate that higher compensations would not stimulate first-round players to play more efficiently. Regarding position, inside players have the advantage of improving their playing efficiency since they are typically taller players with large wingspans, offering them a greater chance to catch rebounds and score with high efficiency. Hence, more positive accomplishments result in higher PER of inside players. As for competitors, there is no evidence that they would affect rookies' performance in all three seasons, even with bandwidths of 5 and 10.[5]

Table 9 presents local linear regression results of MPPG for first- and second-round players. The results indicate that in the second season, first-round players acquire 4.931 more minutes on average than second-round players, and this result is also statistically significant at 0.1 with bandwidths of 10; in the first and third seasons, first-round players do not gain more playing time than second-round players. A possible

[5] The estimation results in a bandwidth of 5 can be acquired in Appendix Table 10 and Table 11. And those in a bandwidth of 10 can be acquired in Appendix Table 12 and Table 13.

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explanation lies in the fact that in the first season, the team manager and coach have no idea about rookies' corporation ability, obedience, stress resistance, and leadership, so rookies are generally not prioritized by coaches for utilization, regardless of whether they are first- or second-round picks. In the second season, after receiving sufficient training, rookies adapt to their team gradually and are able to cooperate with teammates well, causing their coach's trust in them to grow. On the other hand, draft order is a proxy for team managers' and coaches' expectations for players' potential and talent. First-round players are usually believed to be more talented players. Accordingly, in the second season, coaches may grant first-round players more minutes to play on court. Shifting the emphasis to competitors in identical positions, I expect that the more identical-position players there are on a team, the less playing time rookies can get. However, the estimation result shows that competitors make no impact on rookies' playing time, which runs counter to my expectation.

Choosing a proper bandwidth plays a crucial role in a regression discontinuity design, so I conduct local linear regression using bandwidths of 5 and 10 to further check the robustness of results. In the bandwidth of 5, the treatment effect of draft round and running variable are all statistically insignificant throughout three seasons in both PER and playing-time analyses, which may be attributed to the scarcity of the sample size. In the bandwidth of 10, first-round players play on average and 6.397 more minutes per game than second-round players in the third season, and the outcome is statistically significant at 0.05. This may result from the expanding sample size from 136 to 173.

There is a matter of caution to be noted, if a player changes teams during a season, he has to adapt himself to new environment, teammates, and coaches, which might influence his performance and playing time. This, however, cannot be controlled for, and it may bias the results. To obtain a more precise result, I exclude players that have changed teams within a season from the sample set and conduct local linear regressions accordingly. The results show that first-round players do not have more productivity than second-round players in all three seasons with bandwidths of 5, 8, and 10.[6]

[6] Subgroup analysis results in a bandwidth of 8 can be acquired in Appendix Table 14 and Table 15.

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Table 8 – PER for first- and second-round picks (bandwidth of 8)

Variable	**First Season**		**Second Season**		**Third Season**	
	Without X_i	With X_i	Without X_i	With X_i	Without X_i	With X_i
First round	3.091	3.021	-2.396	-2.476	-0.326	-0.409
	(2.349)	(2.284)	(2.548)	(2.532)	(2.221)	(2.354)
Running variable	0.845**	0.688*	-0.460	-0.618	0.122	-0.179
	(0.393)	(0.405)	(0.440)	(0.448)	(0.392)	(0.410)
First round x Running variable	-1.064**	-0.890*	0.167	0.333	-0.257	0.0899
	(0.450)	(0.457)	(0.481)	(0.463)	(0.450)	(0.459)
Height		-0.175***		-0.142**		-0.0314
		(0.0599)		(0.0709)		(0.0906)
Competitors		-0.276		0.202		-0.253
		(0.415)		(0.579)		(0.326)
Lag win percentage		1.759		-1.334		0.730
		(5.075)		(4.436)		(3.941)
Lag playoff		-1.037		0.0121		-0.0496
		(1.842)		(1.543)		(1.339)
Used to be player		0.0452		-1.254		-0.131
		(0.828)		(0.944)		(0.921)
Coach experience		0.103		0.131*		-0.0239
		(0.0707)		(0.0736)		(0.0653)
Coach award		-1.445		3.604*		2.730*
		(2.477)		(2.026)		(1.489)
Inside player		4.219***		5.279***		3.759**
		(0.950)		(1.540)		(1.576)
Constant	7.415***	41.24***	13.36***	39.56***	12.91***	18.95
	(2.134)	(10.73)	(2.387)	(13.62)	(2.005)	(17.35)
Observations	157	157	156	156	136	136

Notes: Table 8 presents the estimation results for overall sample set in a bandwidth of 8. Robust standard errors in parentheses; * = Significant at 10% or more; ** = Significant at 5% or more; *** = Significant at 1% or more.

Yet first-round players yield more minutes in the second and third seasons with bandwidths of 8 and 10, which are statistically significant at 0.05 or more. These results are in line with the results derived from overall sample set. According to results presented above, I find that the sunk cost fallacy exists in the second and third seasons of players' careers.

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Table 9 – MPPG for first- and second-round picks (bandwidth of 8)

Variable	**First Season**		**Second Season**		**Third Season**	
	Without X_i	With X_i	Without X_i	With X_i	Without X_i	With X_i
First round	0.841	1.901	3.797	4.931*	3.948	4.772
	(2.445)	(2.657)	(2.737)	(2.771)	(2.913)	(3.506)
Running variable	0.333	0.142	0.594	0.699	0.429	0.413
	(0.435)	(0.460)	(0.466)	(0.506)	(0.512)	(0.575)
First round x Running variable	-0.961*	-0.605	-1.213**	-1.124*	-0.954	-0.819
	(0.501)	(0.515)	(0.576)	(0.606)	(0.628)	(0.687)
Height		-0.181***		-0.0875		-0.0259
		(0.0671)		(0.101)		(0.128)
Competitors		-0.261		-0.755		-0.779
		(0.481)		(0.480)		(0.573)
Lag win percentage		-16.08***		-11.10*		-7.175
		(5.850)		(6.529)		(6.859)
Lag playoff		0.414		0.745		2.399
		(1.985)		(2.291)		(2.214)
Used to be player		-1.260		-0.643		0.520
		(1.040)		(1.242)		(1.448)
Coach experience		-0.00747		0.00121		-0.154
		(0.0820)		(0.101)		(0.111)
Coach award		-2.820		1.861		1.149
		(2.644)		(2.846)		(3.297)
Inside player		0.562		-0.688		-0.499
		(1.347)		(1.840)		(2.107)
Constant	10.31***	55.95***	10.80***	36.52*	13.24***	24.81
	(2.185)	(13.23)	(2.356)	(20.07)	(2.436)	(26.02)
Observations	157	157	156	156	136	136

Notes: Table 9 presents the estimation results for overall sample set in a bandwidth of 8. Robust standard errors in parentheses; * = Significant at 10% or more; ** = Significant at 5% or more; *** = Significant at 1% or more.

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4.2 Graphical Results

Figure 1 illustrates the local linear regression results for first- and second-round players in their first three seasons. In Figure 1, PER in the first season has noticeable discontinuity around the threshold of draft round, as does MPPG in the first and the second seasons. However, only MPPG in the second year showed statistically significant results, which may result from standard deviation—an important determinant of statistical significance. In figure 1, I can only observe the coefficient instead of the standard deviation in the local linear regression.

In order to determine the impact of draft order on outcome variables more precisely, I centered the cutoff on nine to twenty-two and thirty-eight to fifty-one for further analysis. I run local linear regressions again, and each treatment effect coefficient in these regressions using a bandwidth of 8 is reported in Figure 2. Figure 2 illustrates that among high draft-status players, the change in PER from one move across draft position is smaller than that among lower draft-status players Precisely, the variability of performance in high draft-status players is larger than that in low draft-status players. A possible explanation for this might be that teams should have a high salary scale for high draft-status picks, so their decisions would be made with more caution. However, this result actually contradicts my expectation.

Intuitively, players with small draft number are more likely to become superstars in the future, and thus the disparity of ability between the first and second picks would be large. By contrast, the difference in ability between the fifty-ninth pick and the sixtieth pick might be small because it is common that the fifty-fifth to sixtieth picks are unable to stay in the NBA for more than one season, or that they cannot even acquire contracts.

As a further matter of caution, it should be noted that the estimation results in Figure 2 do not cover the cutoff of the first eight draft picks in first-round order and the last eight draft orders because of the regression discontinuity design with a bandwidth of 8. Hence, the treatment effect of these draft positions cannot be observed in Figure 2 and remain unclear. What can also be discovered in Figure 2 is that the coefficient of the treatment effect is not always positive or negative, meaning that moving up to a

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high draft status does not always bring higher playing efficiency or more playing time.

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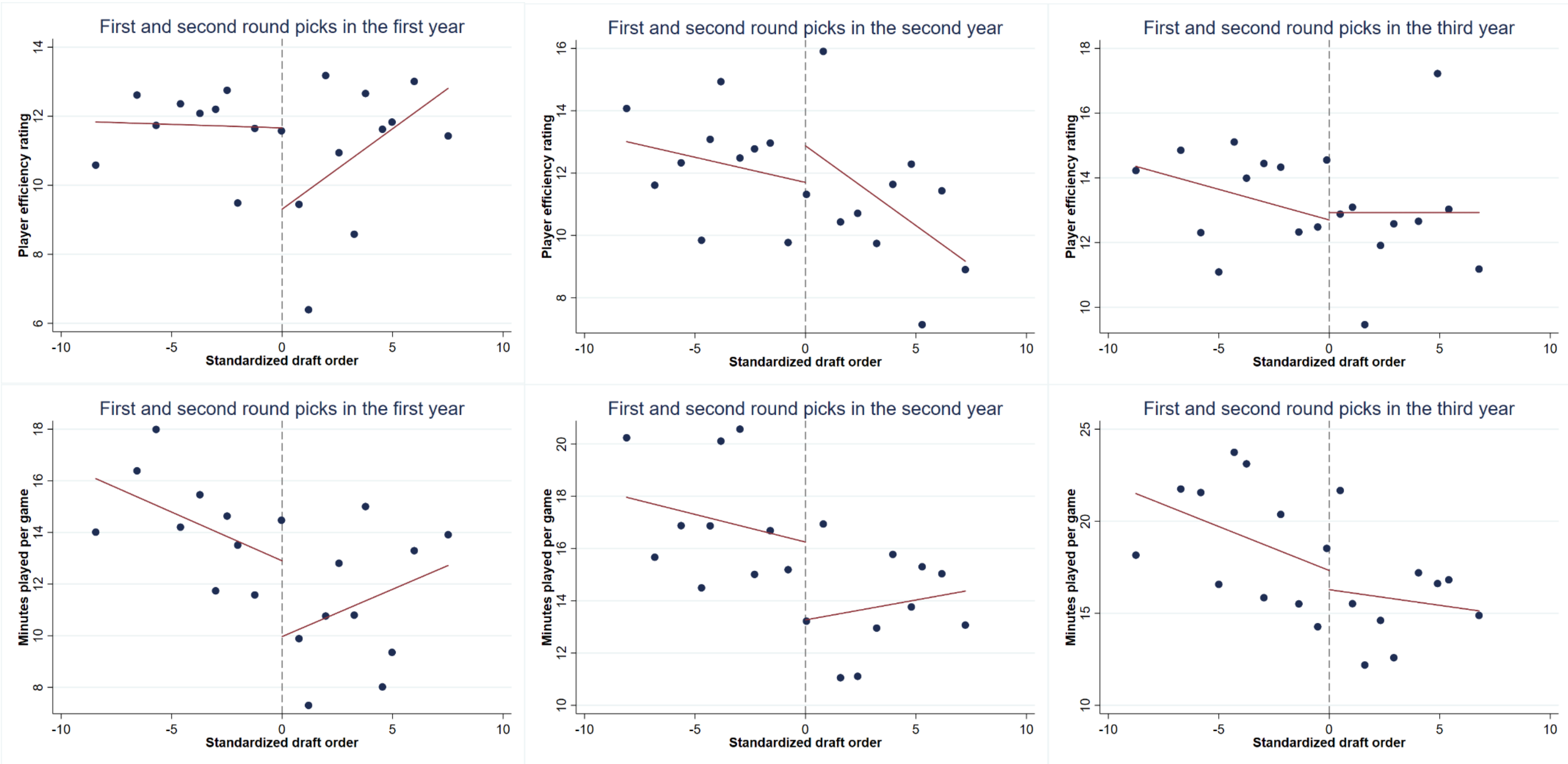

Figure 1 – Local linear regression results

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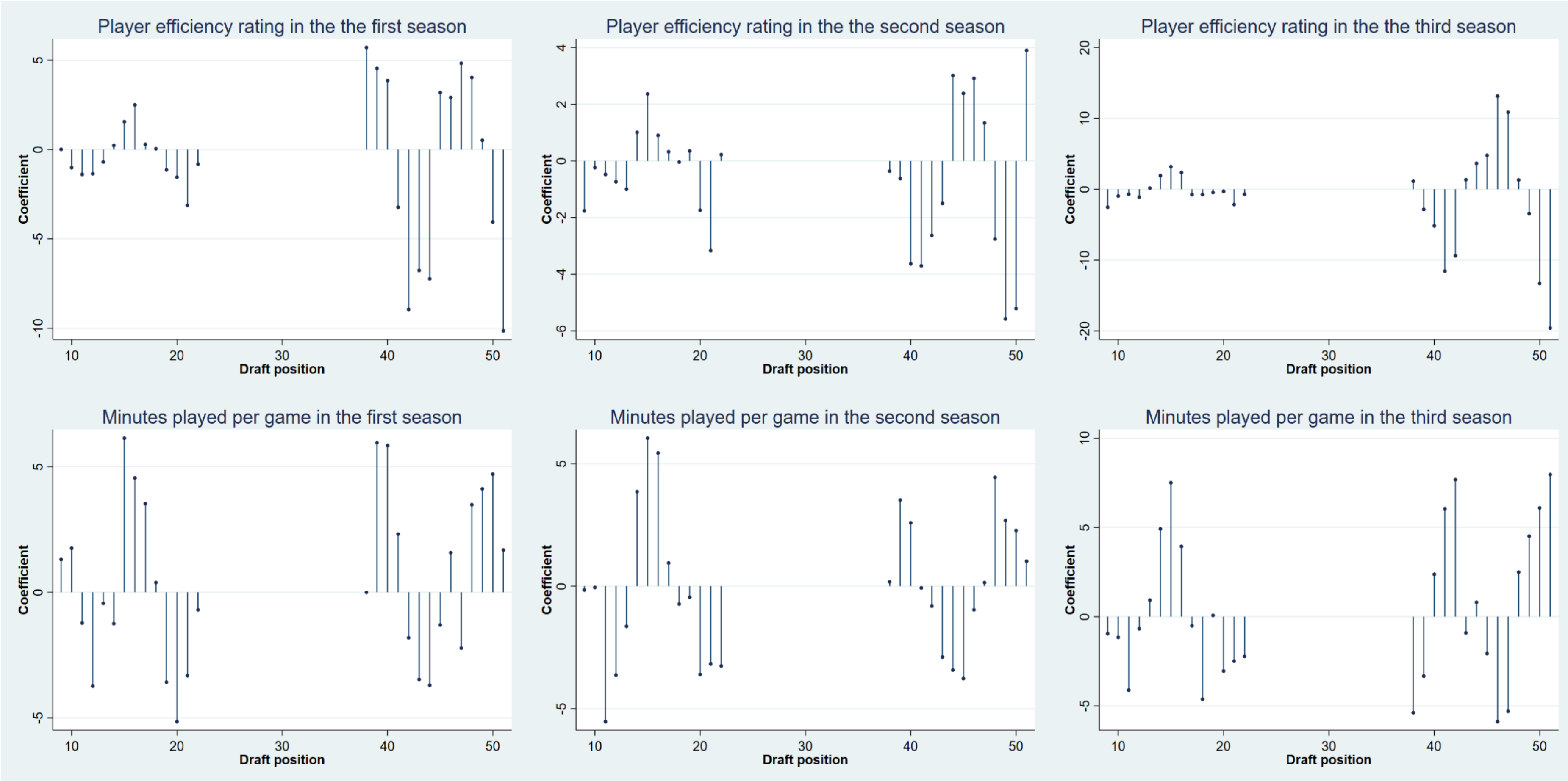

Figure 2 – Treatment effect coefficient for draft positions

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5. Conclusion and discussion

In this paper, I shed light on the relationship between draft order and players' future performances. There are two rounds in the NBA draft, and in each round 30 draftees are picked. First-round players are granted two-year guaranteed contracts and higher fixed salary scales, while contracts and salaries for second-round players are decided by negotiation. This study undertakes a regression discontinuity method with a bandwidth of 8 picks. Draft order serves as the running variable and the threshold of draft round serves as the cutoff. I investigate the impact of draft order on PER and MPPG in the first three seasons of players' careers.

The empirical results show that higher-drafted players do not have higher playing efficiency than lower-drafted players throughout three seasons. This means that a higher salary does not encourage higher-drafted players to perform well. Competitors have no impact on performance as well. Inside players are significantly more productive than players in the other three positions. In regard to player utilization, first-round players have more minutes per game to play on court than second-round players in their second season; however, this outcome is not stable when I apply other bandwidths to local linear regression. In the subgroup analysis, I filter out draftees who played for more than one team in a single season. The results of the subgroup analysis are similar to the results of the overall sample analysis. Furthermore, I center the cutoff from the ninth to twenty-second picks and the thirty-eighth to fifty-first picks, and I run local linear regression to determine the effect of other draft positions on PER and playing time. The results reveal that the difference in PER among higher-drafted players is smaller than that among lower-drafted players, and players who move up to a higher draft status do not necessarily perform better or play more.

To sum up, draft order is not a good prediction for professional performance. The estimation results in this study do not meet the expectations. The possible reasons for the unstable results may lie in the limitations of this study. First of all, second-round players are sometimes unable to obtain contracts to enter the NBA, and thus the sample size for second-round players drops markedly. Secondly, there are 60 players drafted annually in the NBA draft, which may lead to the insufficiency of overall observations.

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This research contributes to literature about the labor market in professional sports. However, this paper only considers players who entered the NBA draft and received contracts successfully. Since undrafted players still have the potential to become superstars, such as Udonis Haslem and Brad Miller, future studies can further this investigation by including undrafted players.

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Appendix: Supplemental Tables

Table 10 – PER for first- and second-round picks (bandwidth of 5)

Variable	First Season		Second Season		Third Season	
	Without X_i	With X_i	Without X_i	With X_i	Without X_i	With X_i
First round	1.788	0.510	-1.560	0.559	0.968	2.490
	(3.106)	(2.821)	(2.680)	(2.267)	(3.581)	(3.404)
Running variable	0.265	-0.410	-0.335	0.0250	0.578	1.127
	(0.785)	(0.789)	(0.762)	(0.788)	(1.274)	(1.396)
First round x Running variable	-0.298	0.512	0.234	0.0720	-0.790	-1.407
	(0.891)	(0.941)	(0.834)	(0.924)	(1.313)	(1.484)
Height		-0.246**		-0.111		0.0284
		(0.0960)		(0.0960)		(0.161)
Competitors		-0.427		0.686		-0.181
		(0.526)		(0.864)		(0.378)
Lag win percentage		1.819		-8.059		5.479
		(5.785)		(5.591)		(5.267)
Lag playoff		-1.909		3.176		-0.148
		(2.003)		(2.370)		(1.630)
Used to be player		0.575		-1.091		-0.117
		(0.994)		(1.166)		(1.222)
Coach experience		0.138		0.235**		0.0628
		(0.0953)		(0.0980)		(0.0805)
Coach award		0.517		3.618		2.269
		(4.434)		(2.793)		(1.941)
Inside player		5.205***		5.560**		3.102
		(1.175)		(2.415)		(2.287)
Constant	9.120***	58.59***	12.94***	30.01*	11.52***	0.402
	(2.852)	(18.88)	(2.483)	(18.00)	(3.421)	(34.08)
Observations	99	99	96	96	88	88

Notes: Table 10 presents the estimation results for overall sample set in a bandwidth of 5. Robust standard errors in parentheses; * = Significant at 10% or more; ** = Significant at 5% or more; *** = Significant at 1% or more.

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Table 11 – MPPG for first- and second-round picks (bandwidth of 5)

Variable	First Season		Second Season		Third Season	
	Without X_i	With X_i	Without X_i	With X_i	Without X_i	With X_i
First round	2.723	2.376	1.781	1.102	3.903	3.817
	(4.008)	(4.977)	(3.824)	(3.944)	(4.388)	(5.094)
Running variable	0.857	0.0946	-0.0555	-0.790	0.690	0.0783
	(1.151)	(1.319)	(1.024)	(1.078)	(1.274)	(1.358)
First round x Running variable	-1.250	-0.511	-0.639	0.537	-1.697	-0.983
	(1.255)	(1.396)	(1.168)	(1.187)	(1.430)	(1.504)
Height		-0.163*		-0.144		-0.0988
		(0.0853)		(0.128)		(0.165)
Competitors		-0.348		-0.939		-0.864
		(0.597)		(0.598)		(0.688)
Lag win percentage		-14.84**		-10.33		-14.38*
		(7.249)		(8.518)		(8.563)
Lag playoff		-2.103		-0.227		4.169
		(2.457)		(3.362)		(2.913)
Used to be player		-2.183		-2.484*		-1.154
		(1.373)		(1.476)		(1.868)
Coach experience		-0.0165		0.0626		-0.0921
		(0.0978)		(0.118)		(0.133)
Coach award		-1.496		0.378		-3.034
		(1.408)		(3.309)		(2.888)
Inside player		0.960		-0.862		0.209
		(1.776)		(2.393)		(2.629)
Constant	8.843**	53.86***	12.77***	53.71**	12.58***	43.33
	(3.820)	(17.67)	(3.484)	(25.95)	(3.979)	(33.83)
Observations	99	99	96	96	88	88

Notes: Table 11 presents the estimation results for overall sample set in a bandwidth of 5. Robust standard errors in parentheses; * = Significant at 10% or more; ** = Significant at 5% or more; *** = Significant at 1% or more.

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Table 12 – PER for first- and second-round picks (bandwidth of 10)

Variable	First Season		Second Season		Third Season	
	Without X_i	With X_i	Without X_i	With X_i	Without X_i	With X_i
First round	0.824	1.048	-1.284	-0.869	-1.086	-0.168
	(1.970)	(1.873)	(2.171)	(2.041)	(1.971)	(2.151)
Running variable	0.153	0.126	-0.342	-0.339	-0.155	-0.181
	(0.269)	(0.269)	(0.282)	(0.279)	(0.238)	(0.250)
First round x Running variable	-0.225	-0.251	0.306	0.314	0.0816	0.164
	(0.314)	(0.311)	(0.323)	(0.311)	(0.279)	(0.278)
Height		-0.197***		-0.134*		-0.0407
		(0.0574)		(0.0694)		(0.0736)
Competitors		-0.388		-0.111		-0.363
		(0.337)		(0.482)		(0.265)
Lag win percentage		4.143		-0.442		0.826
		(4.174)		(3.783)		(3.396)
Lag playoff		-1.928		-0.315		-0.536
		(1.528)		(1.294)		(1.181)
Used to be player		0.0446		-0.927		-0.228
		(0.743)		(0.827)		(0.796)
Coach experience		-0.0129		0.0836		-0.0447
		(0.0592)		(0.0544)		(0.0517)
Coach award		-0.827		3.344**		3.238**
		(1.803)		(1.546)		(1.249)
Inside player		4.629***		4.908***		3.712***
		(0.942)		(1.329)		(1.219)
Constant	10.04***	48.17***	12.89***	38.16***	13.83***	21.68
	(1.765)	(10.44)	(2.003)	(13.09)	(1.786)	(13.88)
Observations	199	199	197	197	173	173

Notes: Table 12 presents the estimation results for overall sample set in a bandwidth of 10. Robust standard errors in parentheses; * = Significant at 10% or more; ** = Significant at 5% or more; *** = Significant at 1% or more.

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Table 13 – MPPG for first- and second-round picks (bandwidth of 10)

Variable	First Season		Second Season		Third Season	
	Without X_i	With X_i	Without X_i	With X_i	Without X_i	With X_i
First round	2.527	3.631*	4.384*	4.986**	4.733*	6.397**
	(2.138)	(2.187)	(2.455)	(2.413)	(2.558)	(3.028)
Running variable	0.631**	0.635**	0.533	0.584	0.428	0.612
	(0.317)	(0.314)	(0.373)	(0.376)	(0.360)	(0.379)
First round x Running variable	-1.062***	-1.027***	-0.859*	-0.808*	-0.698	-0.726*
	(0.366)	(0.362)	(0.442)	(0.439)	(0.441)	(0.438)
Height		-0.182***		-0.0896		-0.0906
		(0.0692)		(0.0992)		(0.122)
Competitors		-0.298		-0.726		-0.590
		(0.419)		(0.439)		(0.463)
Lag win percentage		-12.73**		-11.81**		-11.91*
		(5.414)		(5.958)		(6.120)
Lag playoff		0.289		1.170		3.093
		(1.803)		(2.141)		(2.041)
Used to be player		-0.362		-0.656		0.997
		(0.931)		(1.112)		(1.294)
Coach experience		-0.101		-0.0495		-0.235***
		(0.0696)		(0.0864)		(0.0854)
Coach award		-3.701*		0.583		1.281
		(1.903)		(2.507)		(2.981)
Inside player		0.338		-1.211		-0.882
		(1.309)		(1.721)		(1.896)
Constant	9.142***	53.26***	10.97***	38.05*	13.15***	38.83
	(1.861)	(13.70)	(2.098)	(19.52)	(2.110)	(24.38)
Observations	199	199	197	197	173	173

Notes: Table 13 presents the estimation results for overall sample set in a bandwidth of 10. Robust standard errors in parentheses; * = Significant at 10% or more; ** = Significant at 5% or more; *** = Significant at 1% or more.

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Table 14 – PER for first- and second-round picks (subgroup analysis)

Variable	First Season		Second Season		Third Season	
	Without X_i	With X_i	Without X_i	With X_i	Without X_i	With X_i
First round	3.181	3.018	-2.282	-2.378	0.280	0.00589
	(2.452)	(2.367)	(2.853)	(2.721)	(1.820)	(1.854)
Running variable	0.850**	0.685	-0.481	-0.752	0.336	-0.0617
	(0.407)	(0.415)	(0.497)	(0.516)	(0.320)	(0.386)
First round x Running variable	-1.071**	-0.894*	0.165	0.499	-0.428	0.00565
	(0.463)	(0.465)	(0.538)	(0.538)	(0.393)	(0.446)
Height		-0.191***		-0.140*		0.00848
		(0.0588)		(0.0768)		(0.102)
Competitors		-0.313		0.249		-0.288
		(0.413)		(0.632)		(0.359)
Lag win percentage		1.972		-3.341		-1.480
		(5.142)		(4.603)		(3.995)
Lag playoff		-1.061		0.577		1.018
		(1.873)		(1.698)		(1.456)
Used to be player		0.153		-1.638		-0.632
		(0.839)		(1.024)		(0.899)
Coach experience		0.101		0.171**		-0.00442
		(0.0727)		(0.0826)		(0.0734)
Coach award		-1.406		2.811		2.325
		(2.469)		(2.098)		(1.638)
Inside player		4.469***		5.583***		4.014**
		(0.969)		(1.663)		(1.889)
Constant	7.298***	44.33***	13.54***	39.91***	12.67***	11.61
	(2.242)	(10.54)	(2.683)	(15.06)	(1.521)	(19.75)
Observations	152	152	133	133	110	110

Notes: Table 14 presents the estimation results for subgroup analysis in a bandwidth of 8. Robust standard errors in parentheses; * = Significant at 10% or more; ** = Significant at 5% or more; *** = Significant at 1% or more.

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Table 15 – MPPG for first- and second-round pick (subgroup analysis)

Variable	First Season		Second Season		Third Season	
	Without X_i	With X_i	Without X_i	With X_i	Without X_i	With X_i
First round	1.006	1.593	6.036**	7.258**	6.046**	7.631**
	(2.355)	(2.600)	(3.004)	(2.999)	(2.987)	(3.715)
Running variable	0.420	0.171	0.859*	0.966	0.985**	1.099*
	(0.428)	(0.459)	(0.517)	(0.583)	(0.488)	(0.564)
First round x Running variable	-1.084**	-0.704	-1.385**	-1.265*	-1.517**	-1.510**
	(0.493)	(0.511)	(0.632)	(0.688)	(0.634)	(0.691)
Height		-0.188***		-0.101		0.0310
		(0.0675)		(0.109)		(0.146)
Competitors		-0.395		-0.590		-1.037
		(0.482)		(0.513)		(0.646)
Lag win percentage		-13.75**		-13.78**		-9.791
		(5.825)		(6.500)		(7.673)
Lag playoff		0.298		1.258		2.932
		(2.000)		(2.392)		(2.483)
Used to be player		-0.643		-1.520		0.525
		(0.975)		(1.387)		(1.635)
Coach experience		-0.0435		-0.00815		-0.166
		(0.0736)		(0.109)		(0.132)
Coach award		-2.720		1.053		1.102
		(2.722)		(2.979)		(3.685)
Inside player		0.913		-0.693		-1.432
		(1.359)		(2.060)		(2.356)
Constant	9.787***	56.37***	9.889***	39.40*	11.74***	13.72
	(2.110)	(13.40)	(2.625)	(22.09)	(2.317)	(30.08)
Observations	152	152	133	133	110	110

Notes: Table 15 presents the estimation results for subgroup analysis in a bandwidth of 8. Robust standard errors in parentheses; * = Significant at 10% or more; ** = Significant at 5% or more; *** = Significant at 1% or more.

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