Studying Managerial Foresight in Sports Analytics

Major Qualifying Project

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Abstract

The study of managerial performance is increasingly important in people analytics, especially the topic of managerial foresight. We developed insights into this topic using data from the National Basketball Association (NBA), collecting detailed managerial and player performance data for all teams in the NBA between 1976 and 2015. By leveraging the semi-random allocation of drafting positions in the NBA draft, we developed causal insights into the factors that best inform a manager's ability to make effective long-term decisions.

Our analysis suggests that while managers with greater experience in drafts is statistically strongly correlated with drafting of higher performing players, managers with prior playing experience are statistically no or weakly better than managers without playing experience. These results are robust to the inclusion of a battery of fixed and random effects to address potential heterogeneities. We discuss these results in the broader context of people analytics and human resource management.

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1. Introduction

1.1 Tale of Two Managers

Consider this: looking at two general managers in the National Basketball Association (NBA). The first manager, Elgin Baylor, had a tenure of almost 23 years, and at the time of the NBA draft in 2000, he had already been manager for 14 previous drafts. Additionally, he is regarded as one of the top 25 players in NBA history (Staff, 2022). The second manager, Rod Thorn, had a tenure of seven years, and at the time of the NBA draft in 1984, he had been a manager for six previous drafts. Thorn also played basketball professionally but didn't have a standout career like Baylor did. In both of their respective drafts, they each had the third overall pick. Baylor's draft pick, Darius Miles, ended up playing seven total seasons and suffered a career-ending injury (Ferrari-King, 2017). In those seven seasons, only three seasons did he obtain an above-average player efficiency rating (PER). Conversely, Thorn's pick, Michael Jordan, is the PER leader in NBA history, having 15 seasons with an above-average PER ("NBA & ABA Career Leaders," 2022).

One may look at this scenario and find it surprising. Baylor, with more years of experience and a longer tenure as a general manager, chose a player that did not have a very successful career. Meanwhile, Thorn, with less than half the experience, managed to draft a player that is considered by many to be the greatest player in the history of professional basketball. While we should not over-extrapolate off these anecdotal examples, they do serve as illustrations for an increasingly important topic in human resource management. What makes a good manager? What characteristics in managers are associated with good foresight in decision making?

In this project, we aimed to perform a causal analysis between managerial characteristics and experiences and the impact they have on long term decision making. We leverage the unique empirical setup that the NBA draft affords us, to develop causal insights into the question.

1.2 Motivation

Managerial foresight and strategy have been a popular area of study for over a century now; however, as further discussed later on, this partly due to the difficult in disentangling the sorting effect from the treatment effect, reducing the ability to gauge a manager's full ability in choosing effective long-term employees (Amsteus, 2011). It is also a topic of curiosity in many fields, from human resource management to people analytics.

We intend to analyze data collected from two sources, Data.world and basketball-refrance.com. The project will entail the creation of an analytical dataset that will aggregate historical data on:

1) NBA managers

2) Drafting decisions

3) Individual NBA player (and team) performance

The analysis will then be conducted on the dataset to derive actionable insights on the role of managers, both in and beyond professional sports, in identifying successful long-term employee performance.

2. Background

2.1 Professional Sports in North America

Millions of people across the world love watching their favorite sports teams. In 2021 the Sports Market in the United States generated over $71 Billion. The NBA made the third most out of the major sports, about $7.4 Billion, making it one of the top watched sports in the country. A good portion of the money that each franchise makes goes back into the team through whatever spot the executives think it would benefit the team. A growing part of sports is the analytics department. Today nearly all NBA teams have data analysts working in the front office. Capitalizing on data analytics is a trend that is seeping into every facet of the sport such as rookie scouting, spotting undervalued players, and calculating efficient shots. As of now, teams tend to focus on the player statistics and rookie scouting.

All of the top Major Sports Leagues such as the National Football League (NFL), Major League Baseball (MLB), Etc. record statistics on every aspect of the game. We Specifically chose the NBA because it has more individual player statistics, and data on the General Managers available compared to the NFL and other Major Sports. The NBA utilizes a randomized drafting system for new players that allows us to more clearly identify the role of managers in identifying future employee performance.

2.2 Managerial Foresight

Managerial Foresight is one of the most pressing and "hot" topics in the people analytics field. Yet there is very little evidence to support any decision (Amsteus, 2011). Foresight is defined as the ability to predict or the action of predicting what will happen or be needed in the future. Managerial Foresight is the ability to predict how a manager's actions can give the organization a competitive advantage. This regards how accurate are the general managers of the NBA teams at picking long-term high performing players in the draft, as well as overall team performance throughout the season. The NBA records data on almost every aspect of the game, however there is little to no data that can help determine just how big of a role managers play in drafting these high performing players.

Foresight has also been increasing as a tool regarding strategy and decision making to provoke competition and innovation (Alsan & Oner, 2003). This looks at foresight also having an impact on future management. Regarding the NBA and sports analytics, this could lead to teams hiring and choosing future managers based partly on characteristics that could result in them drafting better long-term players.

There exists a presumed influence that managers have on organizational performance, showing that having a long-term productive manager can be as equally important as having long-term productive players (Andersen, 2006). It's also determined that organizational effectiveness comes less from managers having special personality traits, and it is more about actions and decision-making. While this project was limited in the essence that no personality traits or psychological factors were used or taken into account of neither the players nor managers, it is still relevant that certain characteristics and experiences can lead to better long-term actions from managers.

Effective and successful can be created through an ability to sense and determine potential for an organization (Uotila et al., 2005). This foresight does, however, come with some limitations and difficulties. Some argue with the fact that there will always exist randomness and probabilities regarding chance and that there are simply too many factors to account for (Hadfield, 2005). While many studies contain inconclusive results regarding managerial foresight, there is still the increasing interest in looking past these factors and uncovering characteristics and experiences that can make managers excel in their role and provide long-term benefits to their organizations.

2.3 Player Efficiency Rating

The Player Efficiency Rating (PER) is a rating system developed by John Hollinger, a former ESPN NBA analyst and former Vice President of Basketball Operations for the Memphis Grizzlies. It creates a cumulative rating of each player in the NBA. It takes into account the positive statistical contributions of a player as well as the negative statistical contributions of a player to create an all-in-one evaluation on player performance. This data is important because it is what is used to determine end of season awards such as Most Valuable Player, Defensive Player of the Year, Rookie of the year, and any other individual awards. This data can also help the franchises determine which players they want to keep or potentially trade.

Along with the PER metric, the NBA was partly chosen because each player plays both offense and defense, with the main difference coming from positions and the respective roles for those positions. When looking at players of different positions, there are certain accomplishments and features that have a greater influence on their PER (Zhang et al., 2011). If given an optimized PER value that incorporates weights based on position, then the demands and roles of these positions are quantitatively apparent. This difference in player positions helps illustrate the benefit and need of controlling for respective positions in our analysis.

Further differences in play styles and roles are shown between teams, with some having a much different pace, resulting in more or fewer average possessions than other teams. While teams also have different paces, the paces also vary within each game based on score differentials, with players adjusting their play styles based on how close the games are (Xin, 2012). This team and game pace alteration is also why the PER accounts for team and league pace when the value is standardized.

2.4 Panel Data

Panel data follows individuals of a given sample over time. For this project, our panel data consists of both player and general manager statistics and characteristics over the course of their respective careers from 1976-2015. Panel Data has more variability, efficiency, and overall information than pure time-series data or cross-sectional data. This allows us to do a deeper analysis than other types of data sets (Chamberlain, 1984).

This kind of data deals with latent variables, or variables that cannot be observed. Panel data does contain benefits in analysis, with one relevant example being it provides a vast capacity in capturing human behavior and its complexity (Hsiao, 2007). Furthermore, it simplifies both computation and statistical inference.

Panel data are an extension of longitudinal data, as longitudinal data are repetitive measurements over time, while panel data deals with these measurements where the observed entities remain the same (Diggle et al., 2002). NBA data consists of objective panel data allowing for the development of unbiased estimates.

2.5 Sorting Effect & Treatment Effect

A sorting effect describes systems able to attract certain individuals with distinct characteristics. It is found in many industries, including schooling, people analytics, and business competition (Alderighi, 2009). Within companies, good employees have the ability to choose and join a good manager to work for, instead of being found and selected. In professional sports leagues like the NBA, there is a pseudo randomized draft that occurs each year. This draft essentially eliminates the need to observe a sorting effect as the players are not able to choose the team that drafts them.

Sorting effects occur in many industries, ranging from business, to sports, to education. A look into charter school policies examined the sorting effect from charter schools to traditional public schools (Ni, 2012). This showed the complexity in studying a sorting effect, while also showing the ability to observe without having an entangled treatment effect.

A treatment effect can refer to the benefits stemming from an entity's characteristics, where it can be an individual, a group, or an entire company (Guzman, 2021). Within companies, the treatment effect relates to a manager's ability to find and hire an employee that ends up being very beneficial in the long term. In the NBA, we are able to observe a general manager's ability in drafting players that are believed to be the best and most productive options for their team in hopes of winning more games.

This treatment effect can be seen as the manager's foresight in possibly simulating the future to see what the best long-term decision is (Dawkins & Davis, 2017).

2.6 Random-Effect Model

When using panel data, the two most common methods for data analysis are a fixed-effect model and random-effect model. Because of the time invariance of our managerial characteristics, with respect to the players, the random-effect model was the most appropriate and primary model we used (Geisser, 1974). This modeling is also ideal when wanting to make causality assumptions on a population based on the sample. It can sometimes be difficult and contradictory on what the optimal model is when deciding between fixed-effect and random-effect models, but the random variation of managerial characteristics further reinforces the benefits of using a random-effect model with our dataset (Clark & Linzer, 2015).

There are theories and considerations suggesting that treatment effects are not fixed and instead vary across different treatment implementations (Hedges, 1983). Additionally, random-effect models have the potential to provide insights that cannot be determined by looking at quantifiable values like means and standard deviations of effect-size estimates. Since we are not looking to classify a good manager versus a bad manager, and this project focuses more on creating a foundation with insights regarding the causality within managerial foresight, using a random-effect model provides us with the ability to quantify those insights and develop an understanding into certain characteristics and experiences that could give NBA general managers a competitive advantage over other organizations.

2.7 NBA Draft and Its Significance

The NBA Draft determines the order in which the teams will select players with their respective draft picks. Both the number of teams and the number of total picks have changed over time, along with the concept of the draft lottery, which determines the first few picks in the draft. While the finalization of each draft pick has altered several times throughout NBA history, the general overview is that teams are selected in reverse order of their win-loss record from the previous season. This typically allows for the worst team in a previous season to draft the seemingly best player and improve their team, while the teams that performed better have a much lower probability of drafting the best long-term players.

While the number of teams, number of players, and process for the lottery have all changed over time, what has remained consistent is the pseudo randomized nature as it contains elements that appear to be entirely random but are in fact generated from a repeatable process. What this means is the NBA draft is essentially a unique mini data market where the sorting effect (the player’s ability to choose a good team/manager) is disentangled from the treatment effect (ability to choose a good player) of the managers. Many past studies are inconclusive partly because of the problem where the sorting effect and treatment effect cannot be clearly disentangled

(Amsteus, 2011). With this objective and longitudinal data of the NBA, we are able to disentangle these effects and focus on analyzing the causality between managers and the long-term results of the players they draft.

3. Data Collection

To establish a dataset containing all the information we needed, we had to combine three separate datasets through a series of left joins once the individual datasets were collected and cleaned.

The first dataset was collected with data.world – a free, public collaborative data community. This contained information of NBA drafts from 1976 to 2015, which became the range of our data. The information included important data identifying both players and general managers that identified valuable characteristics of the general managers. We also added characteristics to the dataset, being both if a general manager was a prior player or not and their ethnicity.

The second dataset was collected from basketball-reference.com, an online encyclopedia for NBA statistics and history, with it containing seasonal statistics on NBA players from 1950 to 2017. Due to our limitation from the first dataset, we filtered the data, so it contained the players from 1976 to 2015. This was then combined through the draft dataset through a left join, allowing us to see the drafted player and manager combination while also seeing the player's seasonal stats for each season they played.

The third dataset was primarily created with data from basketball-reference.com as well. The dataset contains the year (season); a team's wins, losses, and win percentage; and also, an identifier if a team made the playoffs and championship. This dataset was combined with the joint first and second dataset through another left join, allowing us to see the drafted player and manager combination, the player's seasonal stats, and the respective team's seasonal stats and accomplishments.

To conduct our analysis, we had to gather additional information about the managers. One characteristic was ethnicity. We included a categorical variable that identified a manager as African American, Asian, or White, as those were the only ethnicities of the managers in our dataset. We also needed to determine prior playing experience, so we used a Boolean notation to solely identify if the manager previously played in the NBA, as the length and extent of the playing career was not important.

Our finalized dataset used for analysis contained information of 161 NBA general managers and over 2,000 NBA players. This resulted in over 16,000 total rows of data since a row was created for each season a player had stats recorded in the NBA.

3.1 Data Cleaning

Before joining the separate datasets, some values had to be changed so that the joins would be doable and accurate. One such instance dealt with team abbreviations for both the player dataset and the team dataset. Teams that had previous names and/or locations sometimes contained different abbreviations than others of the same organization. To correct this, each team was assigned the same abbreviation to their respective organization regardless of the time period. For example, if a data point contained information about the Seattle Supersonics, it was ensured that it would use the same abbreviation as data points containing information regarding the Oklahoma City Thunder, as those teams are part of the same organization/franchise.

There also had to be changes made to player names regarding both the draft dataset and the player dataset. Since some players have hyphenated names, several used names, and suffixes, all player names were adjusted so that all characters were lowercase, combined into one string, and had punctuation (hyphens and periods) removed, resulting in a single string containing only lowercase letters. The same process was done for managers in the draft dataset to ensure that all people's names followed the same pattern suitable for analysis.

After joining the three datasets into one, we then searched through our data for any omitted values or values that were extreme and unusable.

When looking at player efficiency rating (PER) values for the players, some appeared to be outside of the normal bounds of values, as PER typically ranges from 0.0 to about 35.0. Some values were below the bounds (negative), while others were significantly above (some reaching around 70) contributing to the dataset as noise and inappropriate data to analyze.

It was also important to ensure that the players to analyze did not have null or missing values. The first step in this was choosing players that did have career games to make initial analysis easier. If a player was drafted but did not have any career games, they were omitted from analysis. Additionally, if a player was missing PER values for a season, which typically resulted in many stats also missing for the same season, then the row was omitted from analysis.

4. Variables and Measures

4.1 Players

In professional basketball, one of the primary key performance indicators (KPIs) of a player is their player efficiency rating (PER), which is our dependent variable in our analysis. The PER of a player was created by NBA columnist John Hollinger to try and establish a single number to a player's overall contributions. This calculation takes into account a player's positive accomplishments, such as points scored and assists, while also subtracting their negative accomplishments, including missed shots and turnovers. The PER calculation also entails team and league statistics to evaluate a player's production and contribution based on their individual statistics. Figure 1 displays the unadjusted calculation of a player's PER.

```
uPER = (1 / MP) *
     [ 3P
     + (2/3) * AST
     + (2 - factor * (team_AST / team_FG)) * FG
     + (FT *0.5 * (1 + (1 - (team_AST / team_FG)) + (2/3) * (team_AST / team_FG)))
     - VOP * TOV
     - VOP * DRB% * (FGA - FG)
     - VOP * 0.44 * (0.44 + (0.56 * DRB%)) * (FTA - FT)
     + VOP * (1 - DRB%) * (TRB - ORB)
     + VOP * DRB% * ORB
     + VOP * STL
     + VOP * DRB% * BLK
     - PF * ((lg_FT / lg_PF) - 0.44 * (lg_FTA / lg_PF) * VOP) ]
```

Figure 1: Hollinger's Unadjusted PER Formula

This unadjusted formula created by Hollinger has an average of about 0.28 using 12 different stats that can pertain to any player in the NBA. These stats, however, are weighted differently, with some categories being weighted more based on Hollinger's belief that some stats are more important than those he viewed as having less of a factor. Once the unadjusted PER is calculated, it is then adjusted for team pace and normalized to a league average of 15.00. Figure 2 shows this relationship to normalize the league average PER.

$$PER = \left(uPER \times \frac{lgPace}{tmPace}\right) \times \frac{15}{lguPER}$$

Figure 2: Adjusted PER Formula

Since some teams have more of a fastbreak style, where the team attempts to get into scoring position as soon as possible leading to the possibility of more possessions, Hollinger's adjusted formula takes into account a team's pace versus the league pace. It is then multiplied by 15 divided by the league unadjusted PER to normalize it at 15.00 as the league average. This also helps in comparing production between players that have varying minutes but can still be similarly effective on their respective teams.

4.2 Managers

The primary explanatory variables in this study are characteristics of general managers. This includes *prior_player*, indicating if a manager was previously a player in the NBA or American Basketball Association (ABA; was separate from NBA before their merger in 1976). The next variable is *tenure_years*, which is the time, in years, that a person spent in their role as general manager. The third primary variable we used is *Exec_draft_exp*, representing how many drafts the manager has been in their role. For example, if a manager's *Exec_draft_exp* value is 6, then it is their sixth time being a general manager when the draft takes place. We also use *Pk*, representing the spot in a draft in which a player was chosen, in initial regression models to attempt to predict player PERs. Figure 3 below shows a part of our dataset with respective explanatory variables for managers.

Executive	Prior_Playe	tenure_yea	Exec_draft_
AlAttles	1	9.98	1
BernieBick	0	3.62	9
RodThorn	1	6.88	7
ElginBaylor	1	22.5	19

= Prior Playing Experience

= Manager Tenure (in years)

= Manager Draft Experience (in years)

Figure 3: Dataset Sample Showing Managers with Respective Explanatory Variables

5. Descriptive Statistics

Typically, the earlier in the draft a player is selected by a team and general manager, the higher potential and greater production they are believed to bring to the organization. For example, the first overall pick in an NBA draft is expected to be a better overall player than someone selected with the thirtieth pick in the draft. With this in mind, we looked at the average PER of players regarding the spot they were picked at when drafted. Figure 4 compares the average PER of players that were drafted with the first 30 picks in the NBA draft.

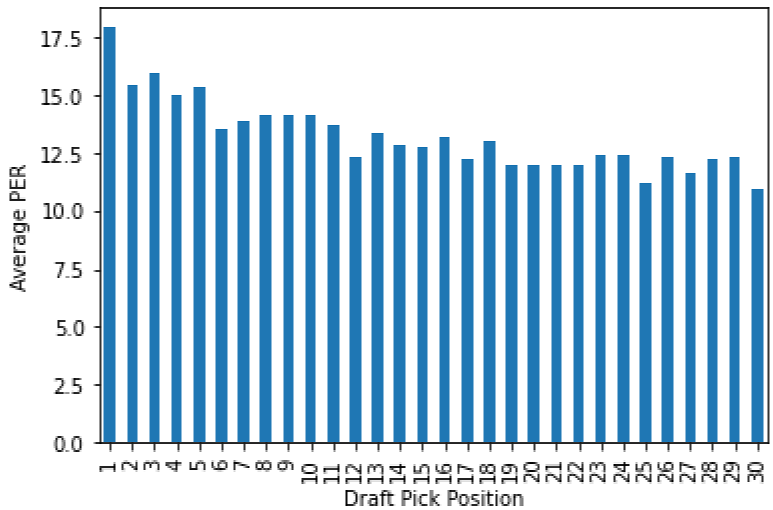

Figure 4: Average PER vs. Draft Pick Position

Figure 4 primarily follows the trend that more effective players are drafted earlier on, with some slight discrepancies around positions including the sixth and twelfth draft spots. The difference in the first overall picks having an average PER over 17.5, while the next highest by position is around 16.0, shows how first overall picks tend to follow the belief that they will be the most productive players.

Regarding the tenure of general managers, we also looked at the draft experience of general managers compared to the average PER of the players they drafted. Figure 5 shows this comparison, with managers being grouped by every two years of experience for easier viewing and comparisons.

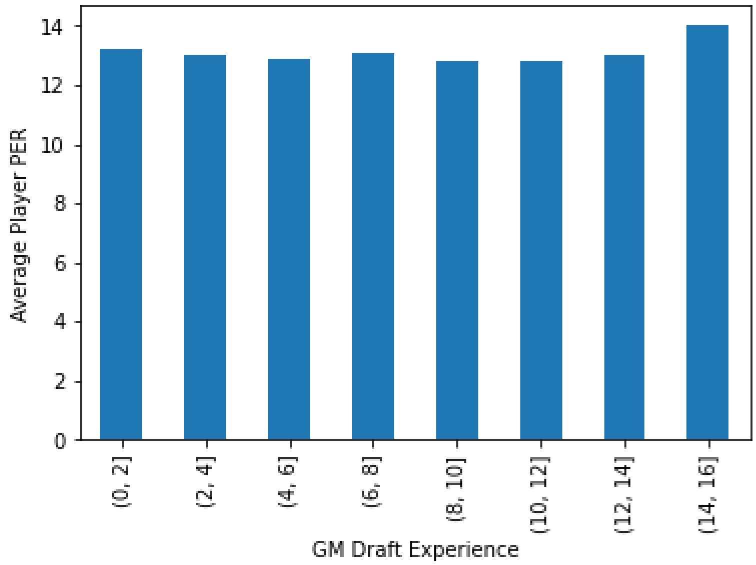

Figure 5: General Manager Draft Experience vs. Average Player PER

Figure 5 shows fairly similar player PER values for the first 14 or so years of draft experience, with a slight peak at around 15 years. Managerial draft experience reaches upwards of 24 years, but the number of data points is significantly less than the first 16 years. While this figure implies a rather insignificant change in PER based on a manager's draft experience, our analysis determined the impact this experience does have.

6. Data Analysis

In this analysis, a "better" player is a player with a higher PER rating as that is a popular metric used in analyzing player performance and is therefore used as our measurement of player production and effectiveness. There are some disputed flaws and drawbacks of Hollinger's creation of the PER statistic. This entails that it favors more offensive accomplishments while some players are defensive specialists and that the weights should take into account comparisons by position as opposed to the rest of the league as a whole (Zein, 2016). There is no single metric to adequately measure and take into account every aspect of a player's accomplishments and career; however, the PER provides a wrap to gather 12 of a player's accomplishments, both negative and positive, with a weighted adjustment to represent their production both in a season and throughout their entire career.

6.1 Linear Regression

The initial statistical model we used for analyzing our data was multiple linear regression (MLR). This was used to see the relationship between explanatory variables – *prior_player, tenure_years, Exec_draft_exp,* and *Pk* – and the quantitative PERs of individual players. Once the respective coefficients and intercept were calculated, we ran a classification model and a multiple linear regression model. The classification model was conducted to see if the explanatory variables could accurately predict the PERs of the players. This entailed splitting the data into testing and training sets, with the training set being all data points up to the 2012-2013 season, and the rest of the data points being the testing set. The multiple linear regression model was used to determine the significance of the explanatory variables in determining a player's PER value.

Our regression model followed a standard MLR equation in Equation 1. The player PERs were the outcome variable (y), while the managerial variables (x) are multiplied by their respective coefficients (b) and the intercept for the equation.

$$y = b_0 + b_1x_1 + b_2x_2 + \ldots + b_nx_n$$

Equation 1: Multiple Linear Regression

6.2 Fixed-Effect Model

The next method in analyzing the data was our fixed-effect model. Fixed-effect models are fairly popular in the social sciences when working with panel data, or data that follows individuals of a given sample over time (Hsiao, 2014). With our dataset, we were able to analyze observations and statistics on both players and general managers over either part of or their entire careers. We chose a fixed-effect model because our dependent variable, a player's PER, changes over as it can be calculated as a seasonal average. This analysis also consisted of variables that are intrinsic and cannot be measured, including a general manager's experience, or lack thereof, as a player (Date, 2022).

Our analysis was conducted using the statistics and characteristics of both individual players and general managers from a large sample of NBA data. With our fixed-effect model, we hoped to provide insights to our original hypotheses:

1. Does having experience as an NBA player have significance on the effectiveness of a general manager?
2. Do general managers with a longer tenure select more productive and efficient players during the NBA draft?
3. Do general managers with more draft experience have a significantly greater history at selecting better players than managers with less draft experience?

The model we used followed a standard fixed-effect equation in Equation 2. In this, our dependent player PER (*Y*) is observed for the i^{th} individual at time *t*. This also takes into account the unobserved individual variables that are time-invariant (α) and the error term (u).

$$Y_{it} = \alpha + \beta X_{it} + u_{it}$$

Equation 2: Fixed-Effect model

6.3 Random Effect Model

Because our managerial characteristics are modeled as time-invariant with respect to the players, the random-effect model is the most appropriate method. Along with this, random-effect models give an estimate of an effect's magnitude regarding the population. While both fixed-effect and random-effect models are the primary methods of analyzing panel data, both the time-invariance and desire to determine an effect's impact on the entire population of managers make the random-effect model the best method for our data (Bollen & Brand, 2008). With our sample data, we aimed to discover how significant a manager's playing experience, draft experience, and tenure length are when it comes to drafting the best possible player.

Our model followed a standard random-effect equation in Equation 3. In this, there is the PER (*Y*) of the i^{th} team of the j^{th} player. This comes from the population average PER (μ), the team-specific random effect (*U*), and the individual-specific random effect (*W*).

$$Y_{ij} = \mu + U_i + W_{ij}$$

Equation 3: Random-Effect Model

7. Results

7.1 Linear Regression

We conducted the multiple linear regression (MLR) with our three explanatory managerial variables along with the player's pick position (the spot in which they were chosen in the draft) to see if the regression followed our descriptive statistics that the lower the number, the better the player. Table 1 shows the results of our MLR model, showing that both being a prior player and having a large tenure result in a slightly lower PER, while more draft experience can result in a slightly better player.

Explanatory Variable	Intercept	Coefficient	P-value
Prior Player	14.1654	-0.1068	0.243
Tenure	14.1654	-0.0142	0.060
Draft Experience	14.1654	0.0054	0.593
Pick Position (in draft)	14.1654	-0.0490	0.000

Table 1: Multiple Linear Regression Results

7.2 Fixed-Effect Model & Random-Effect Model

Our linear regression model suggests that there are managerial characteristics that are statistically correlated with the performance of players; however, this could be the result of the underlying ability of players as opposed to the managers' characteristics. To control for this, we consider a fixed-effect model, but since the managerial characteristics are modeled as time-invariant, we use a random-effect model as it is most appropriate (Wooldridge, 2015).

With our random-effect model, we were able to get the best results of the causality of a manager's draft experience, tenure, and prior playing experience in drafting effective players for their teams. Because of our data, we modeled the log values of tenure, draft experience, and PER. We also controlled for the team, year, and players' positions in the model. Table 2 shows the results of the random-effect model on our dataset.

Explanatory Variable	Coefficient	Impact on ln(PER)	P-value
Prior Player	0.007	3.38%	$p<0.05$
ln(Tenure)	-0.011	-3.43%	$p<0.001$
ln(Draft Experience)	0.008	5.05%	$p<0.001$

Table 2: Random-Effect Model Results

The coefficients of the respective managerial variables show how prior playing experience and draft experience have a positive relationship on a player's PER, while tenure has a negative effect. However, compared to the other two variables, prior playing experience is not as statistically significant, meaning it has the least effect in determining a manager's ability to draft good long-term players. Surprisingly, tenure turns out to have a negative impact on a manager's ability, showing that a 100% increase in a manager's tenure corresponds to a 3.43% decrease in a player's PER. While a 100% increase in a manager's draft experience results in a 5.05% increase in a player's PER.

8. Conclusion

Once we obtained the results of the random-effects model, it was surprising to see the lack of statistical significance a manager's playing experience has, as it is common discussion and belief that if a person was a good player, then they would probably be a good fit in a managerial position.

Another surprise to us was the negative impact that tenure has on a player's production. Typically, the more experience someone has, the better they perform, but that is not necessarily the case of our NBA data. Between this and the positive impact draft experience has, it shows that it can be beneficial for a manager to have some experience in their role, but it does not mean you want someone that has as much experience as possible. This reflects back on the tale of two managers. Would a less experienced manager have picked Darius Miles with the third pick in the 2000 NBA draft? Or would they have picked someone that would have a longer, more productive career. Conversely, would a more experienced manager have also picked Michael Jordan in 1984? Or would they have believed that a different player possessed more potential?

This analysis wasn't conducted to determine if a manager is skilled or inept at selecting players in a draft. It was conducted to determine any causality between a manager's experiences and characteristics, and if they have a causal impact on drafting good long-term players. We were able to conclude that having the most experience possible doesn't necessarily mean the manager will choose the best player. We also uncovered that having a manager who previously played in the NBA doesn't provide a statistically significant advantage in choosing better players than a manager that has no NBA playing experience.

8.1 Beyond Basketball

Managerial foresight is an increasingly popular topic, but it is a difficult topic to study (Amsteus, 2011). Having to account for the sorting effect of employees in industries beyond professional sports is not easy, and that is partly why we chose the NBA data. NBA data's objective and longitudinal nature enabled us to conjure unbiased estimates for the antecedents of a manager's foresight and ability. While our methods involved sports analytics, this project led to a development of insights that have far reaching implications in human resource management, labor economics, and people analytics.

8.2 Future Works

The data collected for this project was obtained through a collaborative data community (data.world) and online encyclopedia of NBA history (basketball-reference.com). Looking at sports, basketball-reference.com stems from a larger website called sports-reference.com. This contains free online encyclopedias to some of the other professional sports leagues in North America, including the National Football League, Major League Baseball, and National Hockey League, along with collegiate sports and professional soccer. Using the foundation that this project provides in conducting an analysis on managerial foresight through the use of sports analytics, it is possible to mirror this project’s work and accomplishments through other professional sports.

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