IMPROVING MANAGERIAL DECISION-MAKING QUALITY IN THE NBA DRAFT -

A CLOSER LOOK AT THE POLICY, BEHAVIORAL ECONOMIC DYNAMICS, AND COGNITIVE BIASES

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To trusting the process, in basketball and life

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Since this sentiment is not easily translatable, I will end this section with a few German words:

Ich weiß mein Glück zu schätzen.

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LIST OF PUBLICATIONS

This cumulative dissertation is based on the following four peer-reviewed articles:

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Berger, T. & Daumann, F. (accepted). Investigating the quality of the managerial NBA Draft decision-making – Does the 'human factor' prevent the mechanism from ever reaching its intended results? *Essays in Sports Research (former: European Journal of Science Studies).*

STUDY II

Berger, T., & Daumann, F. (2021). Anchoring bias in the evaluation of basketball players: A closer look at NBA draft decision-making. Managerial and Decision Economics, 42(5), 1248–1262. https://doi.org/10.1002/mde.3305

STUDY III

Berger, T., & Daumann, F. (2021). Jumping to conclusions – an analysis of the NBA Draft Combine athleticism data and its influence on managerial decision-making. *Sport, Business and Management: An International Journal*, *11*(5), 515–534. https://doi.org/10.1108/SBM-11-2020-0117

STUDY IV

Berger, T., & Daumann, F. (submitted). Increasing the shot at a quality draft-decision – A Bayesian approach to explain historical three-point-accuracy translation in the NBA Draft.

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CHAPTER 1

INTRODUCTION

1. INTRODUCTION

To an economist, life is nothing but a constant string of decisions and transactions. Our entire existence constantly seems to evolve around getting presented with problems, threats, opportunities, or other crucial circumstances which prompt a conscious or unconscious choice between alternatives (Saaty, 2008). These issues can be rather mundane, simple and of little consequence such as picking out a hot beverage to start the day with. However, they can also be incredibly complex challenges and pose stakes on a planetary scale, e.g., deciding how to steer the global population through the very imminent climate crisis which will not only have effects on every living being today but will impact generations to come.

Interestingly, no matter what problem we face, the processes behind the choices we make stay strikingly similar: To be able to determine and pick a favorable option, we are first forced to frame the issue at hand, possibly guided by a parameter-setting policy, to make it conceivable. Second, we commonly gather intelligence to, third, employ judgement in combination with a decision-making system. At the end of the process, we usually strive for quality choices (Schoemaker & Russo, 2006).

In theory this recipe for supreme decisions sounds straight-forward. Therefore, following those steps should easily lead to the preferred outcomes. Additionally, for a long time classic economic theory claimed human actions could easily be modeled along the lines of the image of the homo economicus, especially in a business context - a fully rational and omniscient agent taking on this task (Simon, 1979). They would perform their transactional choices mostly free from internal and external influences such as emotions, ending up with practically perfect utility-maximizing decision-making without surprises or mistakes.

And yet, low-quality choices can be found everywhere - even in extremely competitive, high stakes environments with mostly very intelligent and well-educated people performing the task such as politics, economics, medicine, law, or sports. According to Kahneman and Tversky, many of these low-quality decision-making outcomes can be attributed to cognitive dissonances within the judgement and choice processes. As they showed in their body of work at the intersection of psychology and economics (e.g., Tversky & Kahneman 1971, 1973, 1974; 1981; Kahneman & Tversky 1986) which ultimately culminated in their well-known Nobel prize awarded concept of prospect theory (Kahneman & Tversky 1979), most decision-makers are prone to many fallacies and cognitive biases which can harm the intended results. Interestingly, these biases are usually not caused by a lack of information but often stem from an unwarranted overreliance on unquestioned data, information, and knowledge during the decision-making process. Or to put it in a more colorful manner with a quote which is often attributed to Mark Twain (Massey & Thaler, 2013):

“It ain’t what you don’t know that gets you into trouble. It’s what you know for sure that just ain’t so.”

Consequently, identifying and reducing these cognitive dissonances could improve decision-making quality within a given setting such as the successful implementation of a policy.

To study these behavioral economic principles at the intersection of psychology, management and economics, the field of sports presents an extremely interesting domain which provides many advantages. Rules within the sector are usually well-defined and transparent. Studied subjects are comparably observable, have supreme incentives to perform to the best of their abilities and operate as highly skilled and experienced individuals or groups in actual work environments. Such conditions can never be met in a laboratory (Balafoutas, Chowdhury & Plessner, 2019). Therefore, even decision-making luminary Daniel Kahneman advocates for more research in the sports sector since this fruitful environment with its clearly defined conditions promises enlightening results (Raab, Bar-Eli, Plessner & Araújo, 2011).

This thesis follows this practical advice. It investigates the NBA Draft, a regulating policy of a professional sports league. This mechanism is supposed to balance out the competition within the market it is implemented in. But in its outcomes the policy is highly dependent on high-quality decision-making of every single party involved. The goal of this research is to study the underlying managerial decision-making processes of the regulation to identify potential areas of improvement within the mechanism to optimize decision-making quality and the intended results of the regulation on a league-wide basis.

This cumulative dissertation is divided into three overarching sections. Chapter 2 and 3 provide a theoretical framework and communicate the objectives of the thesis. The chapters 4 to 7 constitute the main research body, presenting four published, accepted, and/or submitted peer-reviewed academic papers. Chapters 8 concludes the dissertation with a discussion of the afore presented materials. Theoretical and methodological considerations and limitations as well as an outlook and opportunities for future research are voiced.

CHAPTER 2

THEORETICAL FRAMEWORK

2. THEORETICAL FRAMEWORK

2.1 GENERAL INTRODUCTION

Decision-making is an extremely complex and interdisciplinary subject matter. To enable precise theoretical work and understanding in this dissertation, a few critical, overarching concepts and terminologies concerning decision-making need to be defined first, which will apply for the entirety of this cumulative dissertation. The following segments will provide a description of the underlying theory which constitutes the basis of every single one of the peer-reviewed papers presented in the chapters 4 to 7. All these articles share the same understanding of key terms and concepts, behavioral economic approach to decision-making, idealized decision-making process as well as understanding of decision-making quality. Therefore, an explanation of the chosen foundational principles is provided in the next sections.

Within the papers projections of these concepts were developed based on the explored environment of professional basketball, organizational management within this specific context and the NBA Draft as a regulatory policy. To ensure a coherent reading experience all NBA Draft related theory fragments will be introduced within this second chapter even though they are mainly borrowed from the theory sections of the following papers. This will lead to some repetitions. Yet, this form of presentation is necessary to provide the full theoretical frame of the dissertation within one chapter while including the peer-reviewed papers in their state of publication, acceptance, or submission. If there is one, a reference to the corresponding article fragments will be given for every section here.

2.2 DECISION-MAKING

2.2.1 KEY TERMS AND CONCEPTS

Koehler and Harvey (2004) define *judgment* "as the set of evaluative and inferential processes that people have at their disposal and can draw on in the process of making decisions" (p. xv); this constitutes the definition used for this thesis. In this realm, *Decision-making* can be introduced as the mechanism of committing to a course of action which is intended to yield satisfying results. (Yates & Tschihart 2006). Bar-Eli, Plessner & Raab (2011) specify that this course of action involves selecting an option from a presented collection of alternatives, which can be considered the *choice* mechanism. For the outcome of the process, they add the effects of this choice need to be pivotal for the future of the decision-maker to count as a meaningful decision-making entity.

Decisions can be simple. Whether or not to have a morning coffee before leaving the house, poses an interesting question. But in the end this decision does not involve great stakes or threatens crucial consequences for the future. Most decision problems though, can be considered as difficult and convoluted (Skinner, 2001). Apart from yielding more consequential outcomes, these decision-making characteristics usually stem from *risk* and *uncertainty* as framing parameters. As real-world decision-makers tend to work in environments of enormous complexity most decisions are made under one of these two states (Mishra, Barclay & Sparks, 2017). Thus, it has been indispensable to clearly distinguish between these concepts for a long time (Edwards, 1954).

Decision-making under risk involves a choice with an unknown outcome but from options with clearly known variances. In contrast, *decisions under uncertainty* present the decision-maker options with unknown decision outcomes and consequences (Mishra, Barclay & Sparks, 2017). Probabilities of the alternatives and their potential payoff are not only inaccessible but mostly unknowable, which makes it incredibly hard and sometimes even impossible to anticipate or predict future results under these circumstances (Volz & Gigerenzer, 2012).

Decision-difficulty is mostly tied to the range of outcomes a potential choice can trigger and not necessarily to the state of either certainty, risk, or uncertainty. To illustrate this point, the 'trolley problem' can be taken as an example (e.g., Thomson, 1976). In this well-known moral dilemma, a person can pull a lever to decide if an out-of-control train runs over either five people or one person. Being in full control over the outcome, letting a coin flip with known variance decide or even letting a total stranger make that choice as a stand-in without control over the consequences does not make the decision any simpler for the original decision-maker. All alternatives result in the death of at least one human being. One might even argue less agency and certainty in this process might make it easier to decide in this particular case.

Therefore, it cannot be stated that the reduction of risk, or the elimination of uncertainty makes decisions easier. However, narrowing the range of consequences helps with the perceived simplicity of the choices. When buying mushrooms at the supermarket to prepare a meal one can be confident the sold options are not deadly. Several policies would prevent grocery stores from selling toxic plants. Yet, collecting unknown species of fungi in the forest for dinner might be dangerous. Eating them poses more uncertainty and a greater range of outcomes.

Finally, the differentiation between normative and descriptive decision-making approaches is relevant for this thesis. *Normative theory* strives to identify the most rational choice a person can make depending on the problem and the circumstances. They formulate what a decider ought to do, why a choice is made and what the ideal results would look like in a state of total rationality and perfect computation. Such rather rational conceptions of behavior under risk and uncertainty like 'expected utility' were popular for a long time (Friedman & Savage, 1948; 1952).

Descriptive or positive theory, on the other hand, is concerned with underlying dynamics in decision-making which cause observable behavior. Its goal is to investigate the essence of actual human decision-making and how decisions are made (MacCrimmon, 1968; Mishra, 2014). Therefore, models within this realm added psychological components focusing on risk-sensitivity and heuristics amongst others (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981; Gigerenzer & Gaissmaier, 2011).

Both theoretical approaches to choices are helpful and thus worthy to mention and keep in mind. The former with its idea of the idealized decision-making helps with general evaluation, since it is necessary to know the hypothetical best case to analyze the decision-making process, based on how far away it deviates from its perfect theoretical blueprint. For this dissertation however, the descriptive approach also seems useful as the goal of the thesis is to observe, analyze and evaluate real world problems as well as behavior. This requires trading a classical economic perspective for a behavioral economic view. The next segment explains this decision in more detail.

2.2.2 THE CASE FOR A BEHAVIORAL ECONOMIC APPROACH TO DECISION-MAKING

The long history of decision-making theory dates back over 250 years (Lipshitz, Klein, Orasanu & Salas, 2001). Back in 1738 the mathematician Bernoulli delivered first research on what can be called Classical Decision-Making today. The Swiss scientists proposed a paper which solved the co-called 'St. Petersburg paradox':

Within a card game gambling setting people were not always trying to maximize their monetary gain. Even though from a purely economic perspective they had all the incentives to do so. Bernoulli was able to explain the reasons for this odd, deviating behavior introducing the concept of utility. He defined this term as a measure of individual benefits and satisfaction which can include money. But the key discovery was to also account for other dimensions such as freedom and for the relative value of money for every individual (Bernoulli, 1738). With this discovery he introduced interesting concepts like risk aversion. Additionally, he defined a flexible currency which decision-making entities are trying to maximize as the preferred outcome of their decision-making process.

Later these key mechanisms were combined with the idea of the homo economicus/economic human, a term which was used in the late 19th century within the realm of political economy for the first time (Persky, 1995). Under the assumption of human beings as homines economici being completely informed, infinitely sensitive and rational at all times (Edwards, 1954), the how of the decision-making process was defined in a clear and simple way.

Consequently, perspectives and models, such as 'subjective expected utility' or 'subjective probability', which were built on these two approaches, found many proponents (Morgenstern & von Neumann, 1953; Savage, 1972). They perform well investigating decision-making under risk, due to the flexible component of utility. Constituting an individual, subjective factor, which needs to be redefined for every investigated environment, utility leaves room to interpret even deviating outcomes in a satisfactory manner, while giving the impression total objectivity within the process could be possible.

Yet, all approaches which were solely based on total rationalism of the acting parties were questioned in the following decades. From the mid-20th century on, the idea of an omniscient, completely rational, infallible decision-maker was deemed unrealistic - especially for decision-making environments of uncertainty (Edwards, 1954). As Gigerenzer and Selten (2001) put it, all decision-makers are human after all and not "heavenly beings equipped with practically unlimited time, knowledge, memory, and other infinite resources" (p.28).

Consequently, the idea of the homo economicus regarding complex real-world decision problems was challenged strongly (Keren & Teigen, 2004). Many researchers with an academic background in psychology provided important work for decision-making theory under the umbrella of "bounded rationality" (Simon, 1979). This new concept introduced the consideration that the process of judgement under uncertainty always leaves the door open for human fallibility (Lewis, 2017) considering people are regularly limited in their objectivity and logic (Golub, 1997).

Even though decision-makers are usually striving for rational choices, they also tend to take shortcuts and make mistakes in their decision-making as Kahneman and Tversky famously showed with their extensive work on heuristics and biases (e.g., Tversky & Kahneman, 1974). They proved humans to be bad intuitive statisticians, which makes it tough to trust their calculations of subjective probabilities or weighing of individual utilities in a Bernoulli sense correctly (Kahneman & Tversky, 1972). In addition, they demonstrated that under uncertainty people do not necessarily follow rational principles, . A condition, leading to serious systematic errors in judgement and unexpected low-quality decision-making outcomes in certain cases (Kahneman & Tversky, 1973).

Hence, deviating from a homo economicusian perspective seems necessary to be able to depict reality within decision-making environments better. Yet, totally discounting this entire approach is not useful either. Early models and ideas can bring satisfying results since more often than not humans do approach decisions of consequences at least with the premise of trying to find the utility maximizing choice by using a rational mode of judgement (Gigerenzer & Selten, 2001).

An interesting line of research manages to merge these opposing school of thoughts. According to Howard (1980) decision-making can either be intuitive and holistic, or rather analytic and rational. For Dhami and Thomson (2012) there seems to be a plausible middle ground in this debate. They call this concept *quasirationality* which is based on Hammond's (1996) cognitive continuum theory. Depending on the situation a decision-maker varies in the degrees in which intuitive or analytical thought patterns are applied. Properties of the problem dictate a resulting mode of cognition.

Usually, a combination of both mechanisms is used and the distribution between the two modes can change during the problem-solving process. Thus, Dhami and Thomson (2012) argue intuition needs to be part of decision-making even though it is usually not sufficient on its own. According to Blattberg and Hoch (1990) quasirational models outperformed process ideas which solely focused on pure intuition or analysis.

As Raab, Bar-Eli, Plessner and Araújo (2018) showed in their review of the history of decision-making research in the field of sports, bounded rationality, heuristics and quasirationality are crucial concepts. In their carefully crafted citation network of the sector, most sports decision-making papers can be traced back to either Simon, Kahneman, Tversky, Gigerenzer or Brunswik, no matter if the publications approached the issue with an economic, ecologic, social, or cognitive perspective.

Thus, a behavioral economic lens, which combines analytical and intuitive cognition patterns by applying quasirationality appears to be very useful when investigating the discipline of sports economics. Therefore, it seems appropriate to ultimately apply this approach for decision-making in this dissertation as an overarching framework.

2.2.3 Decision-making process

Statistician George Box allegedly once said: "All models are wrong, but some are useful" (Reiter, 2018, p. 235). There is a lot of truth to this statement. Finding a framework which perfectly covers every little detail reality offers is impossible. Yet, it is helpful to look for an overarching design of the important dynamics at play to break down the decision-making process down into its essential components to find a common understanding of the mechanism for this thesis.

First and foremost, every decision requires a definition of the problem, the need, and the purpose it addresses. Additionally, the decision-maker needs to know the surrounding criteria of the decision, all stakeholders involved and the details of the options of choice to be able to prioritize alternatives within the therewith defined framework (Saaty, 2008). These are the basic components needed at the beginning of a decision-making process.

To add more detail, the subsequent decision-making process can be broken down even further. An idealized model divides the ensuing course of actions into four phases: framing, intelligence-gathering, choosing, and learning from feedback (Schoemaker & Russo, 2006). Spelling out these different stages does not only help to get a better understanding of the dynamics, it also allows to anticipate at what point quality-lowering mechanisms can enter the process, e.g., in the form of fallacies and biases.

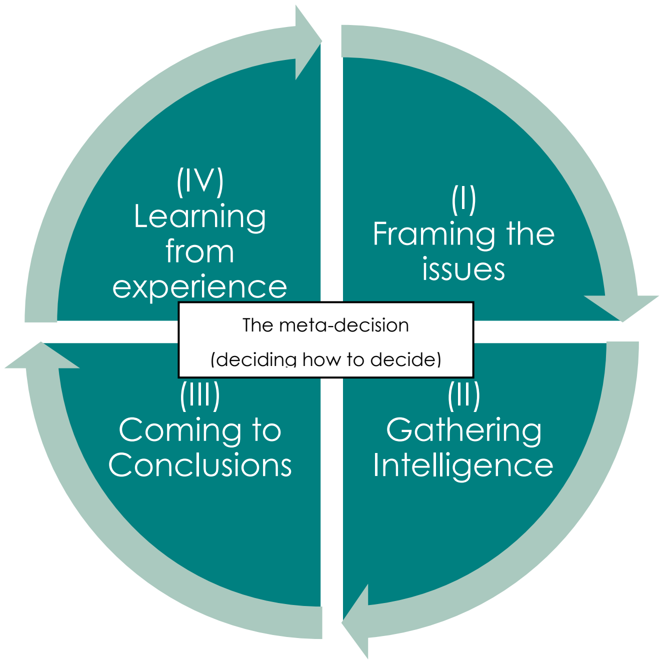

FIGURE 2-1. IDEALIZED DECISION-MAKING PROCESS ACCORDING TO SCHOEMAKER & RUSSO (2006).

These four components shown in the figure are usually executed successively and are iterative:

(I) A decision frame needs to be established. This concludes an analysis of the decision problem which defines the acts, contingencies, and possible outcomes around it as the decision-maker views them at the time (Kahneman & Tversky, 1986). Furthermore, the framing of the decision sets boundaries around the subject in question, determines and marks the reference point the decision-maker starts the process from and in some cases introduces a metric as currency which makes the quality of the decision measurable later on. This step is usually considered as the most crucial and fundamental one, since it is impossible to find the right answer to a problem if the asked question is wrong (Howard, 1988).

(II) Decision-problem-relevant data needs to be collected and converted into information and knowledge to help inform the subsequent choices. Schoemaker and Russo (2006) argue early bias issues for decision-makers can arise in this phase already due to overconfidence, flawed estimation heuristics and selective, subjective information-gathering based on confirmation tendencies.

(III) The assembled data, information, and knowledge regarding the decision task gets translated into a deciding action (or sometimes inaction). This stage includes the calculation of risks as well as the evaluation of uncertainty or ambiguity. Naturally, depending on the judgement strategy and the quality of the information these computations are based on, systematic errors can occur. Yet, those choice mechanisms need to be judged for the specific environment they occur in and therewith depend on. It is assumed human judgement tends to be rather domain-specific than following general mental logic (Gigerenzer, 1991).

(IV) In the idealized version of the process potential decision outcomes are analyzed after their careful implementation and educate future decisions. To optimize learning an environment encouraging retrospective evaluations of behavior, permitting creativity, diversity and most importantly mistakes must be provided to the decision-making entities (Kahneman & Klein, 2009).

While these series of actions take place, according to the model, the decision-makers constantly debate overarching meta-questions regarding the self-defined decision-making environment (Schoemaker & Russo, 2006). These internal disputes concern the general topic of deciding on how to decide. These could incorporate the reevaluation of the problem framing at later stages of the process, the conclusion on who to involve in the process for an optimal outcome or the investigation whether the particular decision problem demands a specific focus on one of the phases to get to preferred results in an optimized way. This fifth segment of the process is somewhat independent from the other phases and adds an interesting wrinkle to the mechanism. It basically functions as a constant controlling mechanism to ensure high-quality decisions by enhancing the integral components of a decision by ensuring the best possible process surrounding all the available information.

This described model of the process seems to cover the essential steps of decision-making. Other approaches in the realm of quasirationality mostly differ in the number of phases they propose. Models can be broader by assigning only three segments (e.g., decision-preliminaries, the decision core, and the decision aftermath for Yates and Tschibart (2006)). Other systems are more detailed and divide the intelligence gathering segment further. They not only add a significant number of steps, but also provide neat acronyms such as GOFER (Mann, Harmoni, Power & Ormond, 1988) or DECIDE (Guo, 2008) for their sequence of actions.

Considering these options, the model of Schoemaker and Russo seems to be the most useful for the sake of this thesis, to follow the one criterion George Box deemed most important for models trying to replicate reality. Compared to the three-step concept it is more granular in a very important section of the described process. Simultaneously, it summarizes segments of more detailed models surrounding the phases of options generation and fact-findings very well. A more in-depth approach to these segments does not provide much value, when trying to find a description of the mechanism which follows the golden rule Einstein allegedly put out: "Everything should be made as simple as possible, but no simpler" (Robinson, 2018). Therefore, the idealized decision-making process of Schoemaker and Russo will be the basis for decision-making theory in this dissertation.

2.2.4 Decision-making quality

Defining quality outcomes in the decision-making context clearly is a complicated endeavor. Barely understanding the cognitive processing dynamic humans perform before making a decision; it has been hard for researchers to find measures which evaluate the nature of a decision-making process and the resulting choices. Yet, to fulfill one of the objectives of this thesis – assessing and improving managerial decision-making quality within the parameters of a policy – an evaluation scheme with a sound theoretical background is needed.

General definitions of (high) decision-making quality can be found. Yates, Veinott and Patalano (2003) describe a good decision as an action which "yields a more satisfying state of affairs for the implied beneficiary" (p.15). Yet, the authors add decision-making quality consists of various imperfectly linked dimensions which do not necessarily have the same makeup for every person involved. Depending on the framing of a problem and the introduced currency as a measure of excellence for process and outcome, various factors could be perceived as satisfactory. Consequently, decision-making quality is usually a matter of perspective and requirements the evaluator applies. This mirrors the idea surrounding utility, alluded to in chapter 2.2.2, which was discussed as a measure of individual benefit and satisfaction.

Howard (1988) uses numerous elements to grade decision-making quality as part of his decision-analysis process. He proposes to take the accuracy of the decision framing, the excellence of the gathered intelligence and creativity in the pursuit of significant, possible alternative into consideration. Additionally, he deems the clear upholding of values, logic, and balance in the judgement process as well as a high level of commitment to a resulting action as potential measures of decision-making quality. Once again, these categories are vague and can be up to interpretation depending on the needs and goals of the people involved in the process. However, the important step taken with this approach is to connect decision-making quality criteria not only to the outcome of the choices, but also to the process which led to them.

Yates, Veinott and Patalano (2003) present similar ideas by introducing seven categories (outcome, options, process, possibilities, clarity, value, advisor) in which decision-makers could be aided in. They argue reducing opaqueness in these facets helps every decision-maker with judgement and choice. Thus, it should improve decision-making quality. Again, it usually is up for debate what contributes most in the quest for opaqueness reduction in the different dimensions.

Although, one point stands out when reviewing literature regarding decision quality: It is the concept of "relative decision adequacy" (Yates, Veinott & Patalano, 2003). This term suggests a high-quality decision should be partially detached from simple outcome satisfaction measures. Depending on the arrangement of the problem, the position of the decision-makers and the set of given options, absolute fulfillment of the anticipated satisfaction might have never been possible in the first place. In such an environment a good decision could simply be choosing the lesser of two evils. Therefore, a high-quality decision can additionally be defined as choosing the best option which is accessible in the moment the decision needs to be made. This adds an important facet to the to the definition outlined in the first paragraph.

Furthermore, Skinner suggests the need for decision-making quality increases with the projected time and impact horizon of a decision (Skinner, 2001). Even though decision-makers should always strive for high-quality decisions, the pursuit of optimal results should become even more crucial the greater the consequences these choices endure. If they set new long-term directions for groups of people, companies, let alone nations or build the basis for future decisions or policies, the urge for maximized decision-making quality should become even more paramount.

In addition to this argument, Howard (1988) highlights the conceptual consideration that the clear distinction between process and outcome in the decision-making realm cannot be overstated enough. He defines a good decision as "an action we take that is logically consistent with the alternatives we perceive, the information we have, and the preferences we feel" (p. 682).

On the one hand, this rationale defines clear avenues towards decision-making quality improvement. Decision-makers could creatively broaden the set of options, gather additional or more insightful intelligence on the given problem or could question their own possibly faulty, unjustified preferences when making choices. In some circumstances it could also help to reduce or even avoid further information on the choice subject, as more information does not necessarily need to lead to a higher decision-making quality at all times (Saaty, 2008). However, by improving the individual decision-making process in these ways, decision-making quality automatically rises, no matter the outcome.

On the other hand, Howard's (1988) description clearly supports the view of decision-making process over outcome – a view which has many proponents (e.g., Simon, 1979; Vlek, 1984; Golub, 1997; Skinner, 2001). Especially under risk and uncertainty good decisions can occasionally produce bad results, and vice versa. Naturally, in decision-making environments with imperfect and limited information, occasional surprises cannot be avoided (Fischhoff, 1975).

And yet, peculiarly, many people think decisions with a poor outcome can never have been of high quality. Like many of the decision-making research community, the author of this dissertation would advocate for a contrarian view on this matter. As outcomes of decisions in uncertain and risky environments often depend on some portion of luck (Vlek, 1984), the only path to sustainable high-quality decisions is to additionally focus on process quality. If the result of a decision cannot be explained by its process it is impossible for a decision-maker to avoid made mistakes or repeat favorable outcomes on a constant basis in the future.

Consequently, it would be hard to keep up continuous high decision-making quality and with this success over the long-term. Inversely, it can be assumed though, the longer a series of decision becomes the less likely only sheer luck and other variances will inform the results. Outcomes over time will tend to regress to the mean decision-making process quality of the decision-makers.

Lastly, another point needs to be made on the evaluation of a single choice. Decisions should be investigated considering the circumstances around them and the context in which they were made. Oftentimes the aggregate of decisions looks different than the individual evaluation of the single choices made within a string of selections would. Gigerenzer (1991) illustrates this point with the story of the 'Welsh village idiot':

When this person was asked to pick between a pound and a shilling, they opted for the lower-value alternative of the shilling. This 'stupidity' led to people from all over the world also wanting to witness this spectacle, repeatedly offering them the same two options to choose from. The 'idiot' always decided to take the shilling. Evaluating the individual decisions, these choices would need to be seen as irrational. Looking at the individual outcomes they would have to be evaluated as low-quality. However, including the social context behind it, with them simply setting up more opportunities to make the same choice again and again, their decision-making quality all the sudden does present itself in a different light.

To summarize all these approaches for decision-making quality: Striving for excellence in this measure means to pursue beneficial results on the outcome level. Yet, to be able to set up such high-quality choices, it is important to enable superior performance in all phases of the decision-making process which were described in chapter 2.3. To improve decision-making quality could be based on a more accurate framing of the issue at hand, gathering more insightful intelligence and reducing judgement errors such as biases in the choice mechanism as much as possible.

Improving the process in these areas does not guarantee instant positive results, but long-term decision-making quality-gains will be hard to avoid. Ideally, every decision is put in perspective before its evaluation. Considering choices as independent from each other or perceiving them as connected steps within an overarching strategy behind them can make all the difference when evaluating their decision-making quality.

2.2.5 DECISION-MAKING BIASES

Decision-making biases can be defined as cognitive dissonances which are clouding the judgement process. They produce systematic deviations from the norm or a preference for one form of judgement than another, without basing this divergent behavior on a valid, rational explanation. Such biases can be caused by faulty processing strategies, perceptual organizing principles, cognitive limitations, specific motivations and preferences, individual perspectives, and circumstances as well as cognitive limitations (Keren & Teigen, 2004). Especially for decisions under uncertainty they can lead to systematic errors with severe, quality-harming consequences (Kahneman & Tversky, 1973).

This definition shows again why a quasirational view was attributed to decision-making entities for this thesis. Such described irrational, divergent behavior would technically not be possible for omniscient, objective and perfectly rational decision-makers in the homo economicusian sense (Edwards, 1954). Investigating the issue through a behavioral economic lens which somewhat fades out the homo economicus allows a more realistic depiction of reality. Among other rather irrational behavior, human decision-makers do take mental short-cuts i.e., utilize heuristics (Kahneman & Tversky, 1973) and can be inconsequential in their choices (Raab, MacMahon, Avugos & Bar-Eli, 2019). These two dynamics can be major sources of decision-making biases.

However, the utilization of heuristics can also be useful decision-making mechanisms. They allow for faster choices with less computational work and do not necessarily lead to errors. Depending on the context, they can even be the foundation of superior decision-making processes (Gigerenzer, 1991). Therefore, the clear distinction between useful heuristics and problem-causing fallacies is crucial, by examining potential decision-making quality-lowering dynamics. Much scientific research focuses on the positive effects of heuristics and tries to debunk the myth of the solely negative attributes for this approach to choices (e.g., Cohen, 1979; Gigerenzer, 1991, 2011; Gonzales, Mishra & Camp, 2017).

Yet, identified as error-producing biases, these cognitive dissonances can influence the process of judgement and therewith occur at every single step of the proposed decision-making model (Schoemaker & Russo, 2006): The framing of a problem can be based on false premises. The gathering of intelligence could fail to be neutral, holistic, or complete. Conclusion from this information can be tainted if data is not weighted correctly or irrelevant factors influence a decision. Even the learning phase after the actual choice can be affected if outcomes are legitimized by faulty reasons or interpreted inaccurately.

Looking at a small, incomplete selection of proven phenomena, research has shown there are identified fallacies for every segment of the chosen model:

(I) faulty decision framing (Tversky & Kahneman, 1981; Kahneman & Tversky 1986), status-quo bias (Samuelson & Zeckhauser, 1988)

(II) confirmation bias (Klayman & Ha, 1987), sampling bias (Tversky & Kahneman, 1971)

(III) availability bias (Tversky & Kahneman, 1974), anchoring bias (Tversky & Kahneman, 1974), overconfidence bias (Kahneman & Tversky, 1973)

(IV) hindsight bias (Fischhoff, 1975), gambler's fallacy (Tversky & Kahneman, 1971)

All these dynamics have been confirmed to cause problems for proper judgement processes under certain circumstances and consequently to affect decision-making quality in a negative way.

Such biases can be compared to optical illusions (Cohen, 1979). Humans are prone to certain perceptual deceptions. A person can untangle and maybe even unsee them. This helps them to obtain a more objective view afterwards. Yet, for this to happen, one must learn about these phenomena, recognize them in their particular environment, and then account for them by consciously implementing this knowledge in individual thinking and action. This process needs a fair amount of cognitive work, mental energy, and self-reflection (Tversky & Kahneman, 1974).

Applied and accounted for successfully, bias recognition can result in increased decision-making quality. However, completely tuning them out seems to be impossible depending on the environment. Some cognitive dissonances can never be unlearned but only minimized in their impact on the individual actions and choices (Tversky & Kahneman, 1971).

Nonetheless, the described process to improve the decision-making mechanism requires the identification of these fallacies within their particular choice environments and contexts in the first place. Consequently, after describing the concrete research realm of the NBA and its draft policy, a careful investigation of the specific mechanism and its underlying decision-making process will follow.

2.3 THE SPORTS ECONOMICAL CONTEXT

2.3.1 THE NBA AS A FIELD FOR ECONOMIC RESEARCH

Over the past decades commercial sports leagues and their teams developed into extremely successful business entities gaining relevance by the day on a global scale. The economic value of sports leagues and teams is increasing rapidly in various sports disciplines (Totty & Owens, 2011).

The National Basketball Association (NBA), a North American professional sports league, is no exception to this trend. Since its foundation in 1946 it developed into one of the most successful sports enterprises in the world. The league expects revenues of over ten billion dollars for the 2021/2022 season (Young, 2021). Its individual team organizations, which are called franchises due to the underlying organizational structure, had an average value of 2.5 billion dollars in 2021. A number that increased 13% from the season before, despite the league suffering from severe difficulties in the practical operation of the games due to COVID-19 (Ozanian, 2021).

Structurally the NBA can be considered a self-created closed market. The qualification as monopoly might be appropriate, since no rival league with equal earning potential for basketball employees is likely to emerge in the future, even though there had been competition in the past (Soebbing & Mason, 2009). This gives the organization enormous power over its market participants. The league administration alone determines which cities get supplied with teams in its franchise system and are therewith allowed to participate in its business environment. Furthermore, it is defining rules and framework conditions under which each participant of the market must operate.

On the one hand, these regulations concern the sports micro level, such as the parameters of the court, the duration of a match or the size of the ball, which regulate the course of each game between two league participants. Compliance with these rules is ensured by the league administration through the provision of trained referees for each match (NBA & NBPA, 2017).

On the other hand, and more importantly the league determines basic processes at the macro level by defining further framework conditions and thereby influencing the management processes of the individual franchises. In a contract negotiated with the players'/workers' union, called the Collective Bargaining Agreement (CBA), the league determines, how many players a team can employ at the same time, how these employees are permitted to enter the market, how much salary an athlete may receive or under which conditions workers are allowed change their employer, amongst other regulations (NBA & NBPA, 2017).

Additionally, the marketing of the game operation is the second major task on the league's agenda. It conducts global advertising and distribution of its product to increase its popularity.

For instance, it distributes worldwide broadcasting rights for the individual games and provides its own broadcasting network on the Internet and TV (Murray, 2019).

The NBA itself issued the following mission statement: "Our Mission: Inspire and connect people everywhere through the power of basketball." (NBA Careers, 2021). This shows the league is an organization with global ambitions and (economic) desires. The NBA wants to manufacture its basketball product, which can be considered as an entertainment service (Soebbing & Mason, 2009), in the most attractive way possible so it can be marketed with maximum profit. It can be assumed every regulation installed by the league is supposed to contribute to this overarching goal of the organization.

To increase and then maintain the attractiveness of its product, theory suggests the NBA needs to ensure two important factors regarding their entertainment service.

First, quality of play has been proven essential to attract consumers to in-person games or remote viewing opportunities via different forms of media (Hausmann & Leonard, 1997; Berri, Schmidt & Brook, 2004). On a team level people want to watch championship contenders compete against each other, rather than a game of two teams from the bottom of the standings assuming no emotional attachment to either of the franchises. On an individual level, observers of the sport like to see individual excellence and are typically drawn to performances of best athletes of the sports, often referred to as 'superstars'.

The league knows about these dynamics and uses its powers and regulations to profit off them e.g., by scheduling high-quality matchups on national holidays to market them even more effectively or installing a playoff system to make sure the best teams of the league have to compete against each other in high stakes situations every season (NBA & NBPA, 2017). Additionally, the league controls the number of teams and roster spots. So, it indirectly regulates the size of the league's player pool. Providing top salaries for players, which no other league in the world can match (Askounis, 2019), ensures the top talent of the sport mostly being drawn to play in the NBA due to earning potential and sportive prestige.

Second, uncertainty of outcome is an important concept every sports league needs to strive for, at least to some extent, to provide an attractive product (Rottenberg, 1956). According to Szymanski (2003) these dynamics work on several temporal levels. He describes match uncertainty (short-term), seasonal uncertainty (medium-term) and championship uncertainty (long-term) as desirable objectives of a sports league. Not knowing what to expect before a given game or a season respectively creates consumer excitement and suspense towards the league's product. The creation of a situation where one competitor without challengers dominates a market is not an optimal situation as the famous Louis-Schmeling-paradox in the past showed (Neale, 1964).

To maximize the attractiveness of a sports entertainment product ideally both components - star-power and uncertainty of outcome – work closely intertwined. The league has set up policies to ensure such a connection of the concepts.

2.3.2 The NBA Draft

The theoretical groundwork for the NBA Draft is covered extensively in the four papers which follow in the chapters 4 to 7. Nevertheless, these sections will also be presented here, to guarantee the coherent reading experience of this dissertation. This leads to repeating segments within this work. These reproductions will be noted here at the beginning of every duplicated item.

2.3.2.1 THE NBA DRAFT MECHANISM

(*Uses paragraphs of chapters 4.2.1 and 5.2.1*)

To ensure uncertainty of outcome and spread superstar talent equitably throughout the entire league, the NBA has installed policies which are supposed to establish competitive balance between the teams by equally distributing athletic talent. One of these policies is a salary cap every franchise must operate under, setting a maximum amount of money that can be spent to employ players. This amount is the same for every team in the league. Hence, the strategy of simply outspending the competition to collect the greatest amount of player talent is not as viable as e.g., in European soccer leagues (NBA & NBPA, 2017).

The NBA Draft policy is a tool the league administration installed to improve competitive balance. It is a yearly event which brings young, talented basketball players from North American colleges and international basketball clubs into the association. The NBA needs this talent-infusion-and-resource-delivery-apparatus since franchises do not run youth teams to develop future players. This regulation dates to 1947, even though its character has changed dramatically since then, when the entire policy had a more territorial, hence regional approach (Soebbing & Mason, 2009).

Nowadays, in theory, every player in the world can sign up to be part of a given annual draft pool if they meet certain age criteria and send a letter of intent (NBA & NBPA, 2017). NBA teams can then draft two players of this selected group of individuals every year on a set date between seasons. To 'draft' a player gives a franchise the exclusive right to offer the draftee their first NBA contract. If the claimed athlete wants to enter the league, they can only sign with the organization which holds their rights (NBA & NBPA, 2017).

The order in which the teams select the draft eligible players is determined by the success every franchise had in the most recent season. The winningest team gets the 30th pick of every draft round, the second-best organization holds the 29th selection and so forth. Only the first four draft selections are determined through a weighted lottery system. All teams which missed the playoffs are part of this lottery process and get assigned certain probabilities to receive such a top-selection based on their win-loss record. The weaker the team, the higher the chances for such a premier selection opportunity (NBA, 2020a). The lottery system is supposed to prevent losing on purpose to improve one's draft position, also known as 'tanking', which has become a valid strategy but unintended consequence as reaction to this policy over the years (e.g., Walters & Williams, 2012; Choi, 2019; Taylor & Trogdon, 2002).

The intention of the draft regulation is clear and noble. It acts as a gateway for young basketball players to enter the league and is supposed to achieve a fairness-and-balance-driven talent distribution. The league wants to aid its weaker franchises with better opportunities to acquire talent on an annual basis (Soebbing & Mason 2009). The goal is to provide those organizations with the ability to catch up with the stronger franchises in the medium-term and even provide them with a chance to contend for titles long-term while the most recent winners of championships slowly decline in their performance due to factors like age or contract issues with their best players.

In a perfect world, the application of this policy distributes talent so well, every team in the league is equally strong. This would raise the attractiveness of the league's product and the earning potential tied to it immensely. Competitive balance and uncertainty of outcome would be maximized. However, this league-wide performance equilibrium is illusory in the infinitely complex world of sports.

In a still idealized but more realistic scenario the NBA administration presumably envisions a draft-supported life cycle, as depicted in the figure below, every franchise constantly runs through (Tingling, Masri & Martell, 2011). The factor time is key here. Talent and success distribution are not equal at all times of the process. However, over the long-run sportive accomplishments of all the league participants should roughly be the same.

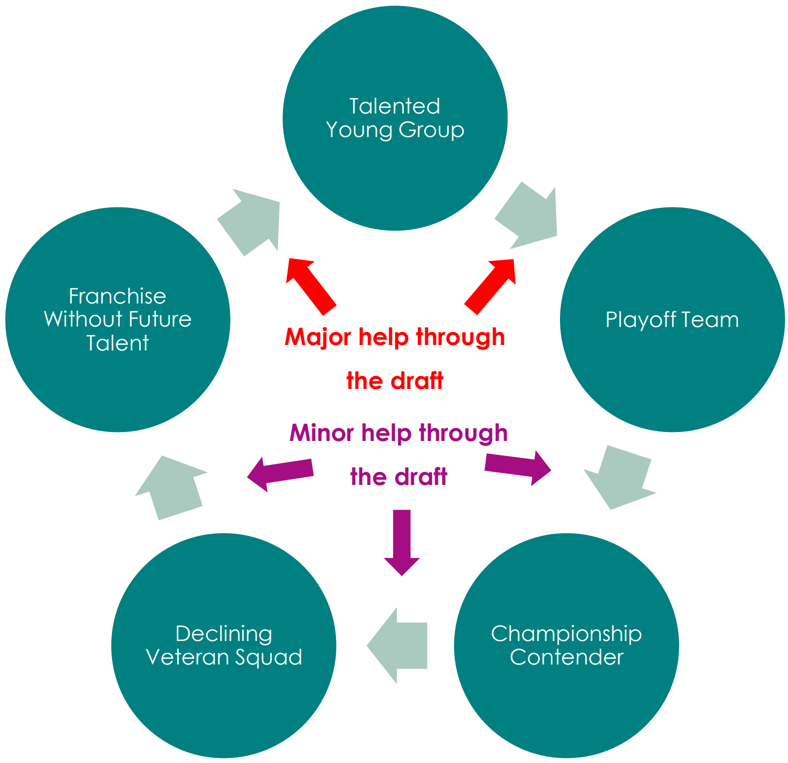

FIGURE 2-2. IDEALIZED LIFE-CYCLE OF AN NBA TEAM.

The idea is simple. Through the draft every league member gets the chance to employ a superstar at some point who opens a window to contend for a title in the medium-term until team performance eventually declines due to age. Through this mechanism the league can sell hope and excitement even to the fanbases of the least successful teams every year because one great draft pick can potentially change the fortunes of a franchise forever (Motomura, 2016).

But as Tingling, Masri and Martell (2011) proclaim, this entire regulation is based on the assumptions that a) the right to an earlier draft selection provides more potential on-court value than later ones and b) all the decision-makers in the NBA have the ability and process installed to exploit this inherent value. Without these requisites in place the entire draft regulation as a useful league policy is bound to fail. These premises need further investigation.

2.3.2.2 THE NBA DRAFT AS A POLICY

(As in chapter 4.2.2 with minor changes)

On the most basic level, Salamon (2001) describes policies as "collections of programs [...] aimed at some general objective" (p. 1643). These regulations installed by a governing body are supposed to guide the decision-making of executive powers, managers or the behavior of objects which are controlled by such to reach a greater goal (Wies, 1996).

Knill and Tolsun (2012) also identify an acting organization which has control over stakeholders, a regulating mechanism able to influence stakeholder actions and a clear overarching intent of the program as key definitory requirements for a policy. The term is most common in the political domain, describing laws, programs or agendas introduced by governments. But policies can be found in nearly every organizational form and environment.

To analyze and evaluate policies, according to Salamon (2001) there are many criteria. Efficiency, equity, manageability, legitimacy, and feasibility all can play a role in the investigation of their quality. But the simplest measure of the quality and goodness of such a mechanism is its plain effectiveness. To broadly evaluate a policy the only question which matters is: Does the introduced dynamic produce the intended outcomes? After this point is answered it can be discussed if tweaks to the policy could lead to even better results or if the introduction of an alternative is necessary because the current approach is not reaching its intended goal.

In this paper the NBA Draft regulation will be treated as a policy since it fulfils all the definitory requirements. The league as a governing body has the power to introduce the draft dynamic as a regulation, guiding the behavior of its governed objects i.e., the franchises, towards an overarching goal which in some dimensions is even different from their individual pursuits.

2.3.2.3 THE IDEALIZED DECISION-MAKING PROCESS WITHIN THE NBA DRAFT CONTEXT

(As in chapter 4.2.3 with minor changes)

This dissertation investigates how draft decisions are made as well as if process improvements could result in better policy results for the franchises and in extension the entire league. To be able to find such hidden potentials within the decision-making structure the examined environment needs to be defined first. To achieve this, the decision-making process model of Schoemaker and Russo (2006) need to be applied to the NBA Draft:

This model describes decision-making as a mechanism with four consecutive parts and one overarching dynamic. In the following, the individual entities are applied within the NBA Draft context:

PHASE I: FRAMING THE ISSUE

According to the model, the first step is a careful framing of the problem. This task is not easy since multiple parties are involved in the process. The league can be identified as one important body entangled in this decision-problem. It installed the draft policy as a mechanism to distribute talent equally and strengthen its entertainment product due to better competitive balance in the league resulting in increased uncertainty of outcome (Soebbing & Mason, 2009). This dynamic should contribute to profit maximization. As has been addressed, as controlling authority the league sets the rules for the decision-making environment and is indirectly influenced by the decisions its members make as a whole in the draft process.

On the administrative level below, the actual decision-makers in this defined problem can be identified - the franchises. Parallel to the league they follow simple (sports) economic principles They always strive for utility maximization (Friedman & Savage, 1948). On a team-level this goal can be reached by being part of a growing, successful league as part of the revenues of the entire overarching organization are shared among all its members (NBA & NBPA, 2017). Additionally, the individual franchise owners want to maximize the income generated by their business entities at hand. These profits are mostly closely intertwined with the on-court success of the team. Employing superstar players as well as winning games and championships can be marketed more successfully than losses and uninspiring rosters. Sportive achievements can help to build long-lasting brands which generate income (e.g., Berri, Schmidt & Brook, 2004; Yang, Shi & Goldfarb, 2009; van Liedekerke, 2017).

Due to this reasoning, and under the assumption of general profit maximization, it should be the ultimate goal of every basketball organization to collect as much sustainable on-court talent as possible at any point in the business process under the given rules of the NBA. This approach maximizes the chance of lasting greatness in the sports and business department. Hence, utility optimization is reached.

In the realm of the draft decisions, the general organizational aim under the given assumption of talent maximization as a form of draft utility is straight-forward: Every franchise should strive to optimize the opportunity its current draft position provides by selecting the best talent available. Though, to define the best talent available can be immensely difficult even if off-court and soft factor dimensions like injury-risk or marketability of a player are excluded.

The problem space itself needs to be defined as dynamic, extremely complex and of great uncertainty when following the model of Howard (1968). Franchises need to monitor a large, increasingly global talent pool (Motomura, 2016). Even though in the end the options of choice for a given draft are finite at some point since a player becomes draft eligible only by declaration for the event. Yet, complexity still reigns as teams do not know with certainty who will declare for a given draft year at the end of every season.

Furthermore, many variables need to be considered to determine who the most talented player is. The problem with these traits is their isolation for single athletes can be hard because some performance indicators of players might be dependent on team context (Moxley & Towne, 2015). Meanwhile, it is not known to a satisfying degree which factor contributes how much to future performance. Development curves of players can follow certain predictable patterns but in the end are usually highly individual (Berri, Brook & Fenn, 2011). Thus, there is always at least some uncertainty with every possible alternative in this decision-problem.

Time also plays a crucial role within the framing of the issue. Basketball as a sport is constantly evolving. Even if teams could perfectly determine how talented a player is and what their exact development in the future will be, the decision-makers might still have problems projecting the exact value of their pick. Player traits which were extremely precious only a decade ago, might not be as valuable and impactful anymore because of a change of playing style due to new tactics or rules (e.g., Chatterjee & Lemann, 1997; Narsu, 2017). These dynamics increase the difficulty of a decision immensely since decision-makers not only need to foresee how a potential draft option and their own team will develop into in the future. The evolution of the sport itself as the market everybody acts in needs to be predicted accurately as well to create lasting value with the decisions which are made.

The crux with this dynamic is the fact that the league administration has little to no influence on the outcomes in the entire matter. It must hope the single franchises make good decisions for their entire premise of fair and equal talent distribution to work. Hence, for draft setups the team organizations can be identified as acting decision-makers. Their individual judgements and the quality of their choices make up the most integral part of the process. The success of the draft policy hinges on their decision-making abilities and the quality of their choices (Tingling, Masri & Martell, 2011).

PHASE II: GATHERING INTELLIGENCE

Second, the decision-process model describes the stage of intelligence gathering. In terms of the draft process this phase describes the effort of the teams to collect data to aid their decisions with creating a larger set of alternatives by identifying possibly suitable players as well reduce the uncertainty within these options by prudently evaluating them.

In order to do so, franchises employ draft scouts and data analytics experts to assess potential talents by identifying their basketball relevant skills, studying their biomechanical prerequisites, and analyzing their performance statistics. They might even monitor their off-court background and perform psychological test by interviewing them to be able to measure a player's mental composure. This can help predicting how hard a given athletes might work to improve themselves in the future, how well they will get along with future teammates or a certain tactical philosophy regarding the sport (Sailofsky, 2018; Beene, 2019).

PHASE III: COMING TO CONCLUSIONS

This collected data needs to be analyzed carefully to reach conclusions. This is a complex endeavor - talent evaluation in basketball is often described as an 'inexact science'. There are general ideas about attributes which translate into future performance value. Yet, effects tend to be small and oftentimes not generalizable (e.g., Berri, Brook & Fenn, 2011; Harris & Berri, 2015; Moxley & Towne, 2015). Furthermore, this view only considers looking at hard performance data. Projecting individual marketing opportunities, potential team fit, bad luck with injuries or adaptability problems due to a certain coach, team situation or cultural differences are even more complex to model. However, such soft factors quite certainly play a significant role for post-draft outcomes (Beene, 2019).

Even though the futures of some young talents seem to be more certain than others, draft decisions will always be made under some degree of uncertainty. Decision-makers can only ensure they have the complete set of options, know as much relevant information about these alternatives as possible and attempt to ensure their own preferences to be in order.

However, the last point needs to be highlighted as key dynamic of the process. Since judgements of draft prospects are always made under some form of uncertainty, choices are hugely prone to systematic errors based on faulty, decision quality-lowering mistakes such as wrongly applied heuristics or potential biases as the creators of prospect theory Kahneman and Tversky (1979) have demonstrated in various settings (e.g., Tversky & Kahneman, 1971; 1973; 1974; Kahneman & Tversky, 1972). Such errors emerge in nearly every decision-making dynamic and are very common in the world of sports as well (Raab, Bar-Eli, Plessner & Araújo, 2018). To decrease the severity of these effects or avoid them all together presents enormous potential for the improvement of decision-quality within any choice process design.

PHASE IV: LEARNING FROM EXPERIENCE

In the fourth phase, managers ideally look at the historical track record of draft picks and evaluate all the decisions made - especially their own. To assess the past should help to improve decision-making quality in the future. The essence of this process is to carefully reiterate on what basis past picks were evaluated and how decisions were made. To truly learn from prior decisions and be able to find patterns in own behavior a certain sample size is needed because, even with maximized preparation, chance (or bad luck for that matter) can play a key role in this mechanism.

Unfortunately, the complicated part in this regard might be the highly competitive environment the NBA managers are in. It rarely provides the opportunity to make many unsuccessful draft choices and still be in the position to learn from them the subsequent years. Organizations tend to fire executives who do not provide at least a glimpse of a successful future with their managerial performance (Wong & Deubert, 2011). To give such an impression a manager presumably needs to draft well early in the job's tenure. Skill development by trial and error is usually not supported within this particular domain.

THE META-DECISION

Looking at the NBA Draft process, the problem definition should not be the crucial hurdle for the organizations. The incentives and avenues to success are well-defined and straight-forward. But to see who needs to be involved and what to focus on in the decision-process leading into the draft are hugely complicated questions franchises have to deal with. Team owners, management, coaching, the scouting unit, and the data analytics department are all groups within the organization which provide information in the process or need to be involved in some way (Sailofsky, 2018; Beene, 2019).

This can produce largely complicated dynamics. Perhaps a manager wants to pick a certain player who as they know is not liked by the team owners. With a potential firing in sight, this player might not be picked in order not to weaken the fading bond with the employer further. Mechanisms like this within social decision-setups can lead to dilemma situations for decision-makers which further complicate the resolving of the described decision-problem (Raab, 2012).

2.3.2.4 THE NBA DRAFT POLICY AND ITS SHORTCOMINGS

(Combines paragraphs from the chapters 4.2.4 and 6.2.1)

The draft as a regulating sports mechanism has drawn an increasing amount of research attention. The dynamic is an integral dynamic of North American major leagues with enormous influence on their entertainment products offered and revenues generated due to the close relationship with quality of play and uncertainty of outcome (e.g., Rottenberg, 1956; Soebbing & Mason, 2009). Hence, it has been investigated in many environments. Researchers mostly analyze the structure as well as the decision-making within the process or look for inefficiencies from an economic standpoint. Papers on the draft can be found for the National Hockey League (e.g., Tingling, Masri & Martell, 2011; Deaner, Lowen & Cobley, 2013), the Major League Baseball (e.g., Caporale & Collier, 2013; Sims & Addona, 2016), the National Football League (e.g., Hendricks, DeBrock & Koenker, 2003; Massey & Thaler, 2013) and the Women's National Basketball Association (e.g., Harris & Berri, 2015; Hendrick, 2016).

The decision-problem the draft represents is clear. Making a choice within this setup is about selecting the best available talent to provide utility maximization for the drafting sports organization in the classical economic sense (Friedman & Savage, 1948; Kahneman & Tversky, 1979). Talent in this realm can be defined as a mix of on-court but also off-court benefits the prospects will generate for their new employers. Such provided benefits allow the drafting franchise to maximize utility in the form of financial and sportive success. However, solving this problem is immensely complex. The process in this environment can be defined as decision-making under uncertainty, since probabilities of decision-outcomes within this particular framework can only roughly be estimated and are mostly unknowable (Volz & Gigerenzer, 2012).

On the one hand, managers must evaluate the talent-level of the potential draftees at the moment of the draft, while factoring in probable future development. On the other hand, the decision-makers need to assess the future of the entire sports of basketball correctly, since its structure poses as the underlying framework the athletes need to perform in. This leads to a complicated dynamic. While it is possible to gage the value of an athlete at the draft fairly accurately if the correct data gets assessed in an optimized way, the development of the league and the progression of players skills will always have uncertainty attached to them. Therefore, a draft decision can be perfectly reasonable and even be backed up by data at the actual selection event and still pose bad results in the future. For quality choices a team needs to evaluate all three factors well. However, the second and third factor represent moving targets due to their high level of uncertainty. Hence, variance should be expected when teams are trying to hit them with their player and league assessments.

The recent emergence of sports analytics, a huge part of ongoing further professionalization of basketball helps to reduce some uncertainties and better understand the sport as whole (Alamar, 2013; Lewis, 2017). Player evaluation as a craft, along the triangulation of eyes (e.g., scouting, personal workouts), ears (e.g., personal interviews, medical records exploration, further background research) and numbers (e.g., anthropometric measurements, high school, and college performance metrics) has become much more sophisticated (Beene, 2019). Leaguewide playing trends are recognized and reacted to earlier than ever before (Shields, 2017).

Yet, judging and evaluating basketball players is still not a task anybody can be perfect in - even today, with more information and data available than ever before. After all, it is almost impossible to accurately predict the future development of a young player or to isolate and judge individual greatness differences in a team sport, especially if the margins between players are slim (e.g., Martínez, 2012; Taylor, 2016, 2017).

Due to this perceived field of tension the NBA Draft policy has been a subject of research for over half a century. Early on, scientists investigated the mechanism from a legal perspective (e.g., Burger, 1972; Carlson, 1972; Allison, 1973). Subsequently, its competitive balance-strengthening effects (or the lack thereof) became the focus of scholars.

First structural criticism of the NBA draft mechanism parallel to the proclaimed need to improve the underlying decision processes occurred in the 1980s (Burkow & Slaughter, 1981). Since then, research agrees upon the fact that the policy itself is valid and provides a framework to produce beneficial outcomes for the league and all its members. Yet, the mechanism fails to generate its intended results due to poor managerial decision-making. Research declared the NBA the most competitively imbalanced American sports league (Soebbing & Mason, 2009). Managers are simply not able to constantly seize the opportunities the draft presents them with. Most of the drafting organizations seem to lack proper talent evaluation abilities (Berri, Brook & Fenn, 2011) and are prone to several judgement biases within this concrete setup (Sailofsky, 2018).

Papers concerning the draft mostly discuss decision-making errors caused by cognitive dissonance in the managerial player evaluation process, addressing disconnects within the second and third phase of the above presented process (e.g., Berri & Schmidt, 2010; Berri, Brook & Fenn, 2011; Moxley & Towne, 2015; Motomura, 2016). This is the point at which player evaluations, particularly within a draft setting, come down to taste, preferences, and the decision-maker's philosophy on how the sports of basketball should be played (Raab, MacMahon, Avugos & Bar-Eli, 2019). These clear aspects of individual judgment, open the entire process to classical decision-making-quality-lowering heuristics and biases. Within the realm of the NBA Draft many of those have been investigated with the aim to avoid hidden systematic errors and reduce uncertainties.

To correct this dissonance within the policy and reach its intended goals the baseline-competency of the decision-makers needs to be raised on a league-wide basis (Motomura, Roberts, Leeds & Leeds, 2016). To ideally improve systemic errors holistically, fallacies and biases in the general process must be identified. Such gained insights would give the chance to correct disadvantageous behavior and increase the decision-making quality, which holds much value for all parties involved.

Following this conclusion, researchers have been exploring the draft policy outcomes from a judgement and behavioral economics perspective for a long time. Many biases have been observed within the NBA Draft environment: Among the cognitive dissonances explored and identified were biases caused by nationality (Motomura, 2016), recency and availability (Berri, Brook & Fenn, 2011; Ichniowski & Preston, 2012), college background (Burdekin & Van, 2018), height regarding the position played as well as age as a marker for unfulfilled potential (Groothius, Hill & Perri, 2007; Berri & Schmidt, 2010; Ashley, 2017;). Most of these decision-making fallacies are classic behavioral economic mechanisms within complex and uncertain judgement environments as they have been found on various fields based on fundamental psychological principles (Tversky & Kahneman, 1974).

The papers presented in the chapters 4 to 7 build on this research and explore the draft mechanism through a similar lens to find additional biases or intelligence to improve decision-making quality within the mechanism.

CHAPTER 3

OBJECTIVES & FURTHER STRUCTURE OF THE THESIS

3. OBJECTIVES & FURTHER STRUCTURE OF THE THESIS

"(Drafting) is an inexact science."- Bill Parcells

This is a famous American sports quote which usually gets attributed to NFL Executive Bill Parcells, who oversaw drafting players as a front office decision-maker for many years (Little, 2008). Over the past decades the statement has become a catchphrase in the American sports realm to describe the state of the draft policy in every league it is applied in - no matter if it is basketball, baseball, hockey, or football athletes being drafted.

Especially management groups and mass media outlets seem to utilize the implied notion of unpredictability cited above to explain the surprising outcomes of "sure-fire" players failing or "underdog" athletes overcoming the odds. And to some extent they are right – in a highly uncertain decision-making environment unforeseen outcomes are to be expected.

Only about five percent of future NBA performance in basketball players were explained by draft position when looking at research from only a decade ago (Berri & Schmidt, 2010). This can feel like total randomness and lead to the slight implication many people seem to take from the quote, of not having any control over one's draft fortunes and seeing the entire system as a spin of the roulette wheel.

The NBA Draft definitely is a "highly imperfect exercise in prediction" (Motomura, Roberts, Leeds & Leeds, 2016, p. 503) right now. However, as has been shown, it is a policy with great intentions and potential benefits for most of its stakeholders. The entire league and its franchises would immensely profit from a perfectly functioning draft regulation, as explained in the segments 2.3.1 and 2.3.2.1. Nonetheless, historically it has failed to produce these positive outcomes regarding creating more competitive balance for the entire market (Soebbing & Mason, 2009).

The NBA Draft policy hinges on human decision-making. Making choices in such a complex environment is hard. It can be brutally unforgiving due uncontrollable factors and most likely will never be perfect. And yet, especially with such unsatisfying results in the first place, managerial decision-making quality within the mechanism can almost certainly be improved. As many researchers have shown with their work over the past decades, a fruitful approach of doing so is to treat drafting as an exact science (e.g., Soebbing & Mason, 2009; Berri, Brook & Fenn, 2011; Ichniowski & Preston, 2012; Motomura, Roberts & Leeds 2016; Cui, Lui, Bao, Liu, Zhang & Gómez, 2019)!

This dissertation follows these academic trailblazers and tries to find new paths to contribute to the still fairly new field of NBA Draft research. The primary objective of this thesis is to investigate the entire mechanism from a behavioral economic perspective. Using this approach, the overarching goal is to identify segments within the underlying managerial decision-making processes which propose room for decision-making quality improvement. These improvements in judgements and choices which could ultimately lead to a superior policy performance on a league-wide level, could be achieved by avoiding error-producing biases or enhancing the information subsequent draft decisions are based on.

To reach this main objective, four academic papers were written to tackle important sub-issues of decision-making in the uncertain domain of the NBA draft. The first article in chapter 4 lays the theoretical foundation for all following papers by taking a step back and investigating the often-foregone conclusions of drafting being a managerial skill and the mechanism providing the opportunity to apply such a capability in a meaningful way. Additionally, the collective performance of all teams in drafting was evaluated to see if the league as a whole still performs badly. Without investigating these pre-conditions, examining the NBA Draft decision-making process for decision-making quality-increasing components would not be viable. This setup was belabored, analyzing historical draft data.

After establishing this important information as an essential foundation for further research, the subsequent three papers dove into concrete judgement issues which each occur at certain segments of the NBA Draft decision-making process. In terms of the chosen model of the decision-making process (Schoemaker & Russo, 2006), all the work concerns the second and third phases, to further inform the gathered intelligence and the actual managerial decision-making mechanisms.

In the theoretical framework, drafting is described as a triangulation of gathering an accurate pre-draft picture of the athletes (Moxley & Towne, 2015) while also being able to project their post-draft development as precise as possible (Berri, Brook & Fenn, 2011). At the same time, the development of the entire sport of basketball also needs to be anticipated correctly, to know in which future environment the selected players will have to perform in (Chatterjee & Lemann, 1997; Narsu, 2017). In this regard, the following papers only briefly touch the league-development issues and focus mainly on the player evaluation and progression dimensions.

Paper II examines a potential anchoring bias produced by the high school reputation of draftees. Paper III investigates a pre-draft bias caused by certain perceptions of athleticism. Both analyze historical data to test their hypotheses. These works show particular cognitive dissonances and therewith illuminate systemic errors within the common player evaluation process.

Paper IV challenges the common assumptions of the translation of the skill three-point-shooting. It proposes a novel approach on how to distil true shooting capabilities of an athlete. The article additionally suggests an option to project pre-to-post-draft translation of the skill more accurately. In the future, this new information could inform better judgement by delivering superior intelligence as the foundation for choices.

All three papers - either by highlighting biases which could be avoided or offering smarter data for the judgement processes - provide sources for decision-making quality improvements within the NBA Draft setup. These are not only supposed to increase the performance of the individual managers and franchises, but also to enhance the results of the overarching league-wide policy with benefits for many stakeholders.

CHAPTER 4

INVESTIGATING THE QUALITY OF THE MANAGERIAL NBA DRAFT DECISION-MAKING – DOES THE ‘HUMAN FACTOR’ PREVENT THE MECHANISM FROM EVER REACHING ITS INTENDED RESULTS?

STUDY I

Tobias Berger & Frank Daumann

ACCEPTED AS

Berger, T. & Daumann, F. (accepted). Investigating the quality of the managerial NBA Draft decision-making – Does the ‘human factor’ prevent the mechanism from ever reaching its intended results? *Essays in Sports Research (former: European Journal of Science Studies)*.

4. STUDY I: INVERSTIGATING THE QUALITY OF THE MANAGERIAL NBA DRAFT DECISION-MAKING

ABSTRACT

The NBA Draft is a mechanism to regulate the competitive balance of a sports league. Its ambition - to give the worst franchises a chance to acquire young prospects to improve long-term and close the on-court talent gap to the better teams - is clear and noble. In theory this seems to be a valid policy. This paper investigates the assumptions under which this regulation was created and the underlying managerial decision-making. Multiple analytic approaches are used to examine the policy from various angles. We test three basic assumptions of the league's administration and research the outcomes of the procedure of the past few decades. Our analysis discusses if the mechanism in its current setup could ever produce the results it is intended to facilitate and how far away the league is from improving the effects of the draft policy. We found that the mechanism was created under somewhat faulty assumptions. In theory, it would have the chance of working, fulfilling its intended aim of fair talent distribution. In practice, 'the human factor' prevents the dynamic from constantly producing the outcomes for which it was designed. Further investigations of the managerial pre-draft decision-making dynamics as potential adjustment tools are suggested. To identify possibly outdated managerial thought patterns as well as classical decision-making biases on a process level and to eliminate them on a league-wide scale could be relevant sources for the future progress of this policy.

4.1 INTRODUCTION

Organizations define themselves largely through their decisions. Many of these choices are incredibly complicated because they are made under risk or uncertainty (Mishra, 2014). Yet, people are usually striving for optimal decisions with the best possible results. To maximize judgement and decision-making capabilities it is necessary to study decision-making dynamics deeply. With better understanding for the process, mistakes can be minimized, and influences of cognitive biases reduced to achieve improvement with the aggregate of choices. Depending on the field this can lead to considerable optimization of existing mechanisms and policies (Golup, 1997).

Thus, choice, judgement and decision-making are crucial processes of human behavior that play a role in every imaginable field of study. That is why research regarding these terms and ideas has a long history and is touching more and more disciplines. Starting out as a solely psychological topic, judgement and decision-making recently draw interest from e.g., medical professionals, lawyers, politicians, and economists. Since Tversky and Kahneman's work on heuristics and biases (e.g., 1971; 1973; 1974) led to the formulation of prospect theory (1979) as one of the foundations for behavioral economics the ideas have been applied in many different contexts.

To study decision-making and behavioral economic principles at the intersection of psychology, management and economics, the field of sports presents an extremely interesting domain which provides many advantages. Rules within the sector are usually well-defined and transparent. Studied subjects are comparably observable, have high incentives to perform to the best of their abilities and operate as extraordinarily skilled and experienced individuals or groups in actual work environments. Such conditions can never be met in a laboratory (Balafoutas, Chowdhury & Plessner, 2019). Thus, the sports sector is an extremely fruitful environment for testing behavioral economic theory that promises great conditions and enlightening results (Raab, Bar-Eli, Plessner & Araújo, 2018).

This paper aspires to follow this advice as it sets to investigate the underlying managerial decision-making quality of a regulating policy in the professional sports league NBA that is supposed to balance out the competition within the market. By mapping out and analyzing the decision-making structure of the process, the goal of this research is to identify potential areas of improvement in the mechanism to optimize decision-making quality and the intended results.

4.2 KEY TERMS AND CONCEPTS

4.2.1 THE NBA DRAFT MECHANISM

The National Basketball Association (NBA), as a professional sports league, developed into one of the most successful sports enterprises in the world. The organization reported revenues of over eight billion dollars for 2019 (Forbes, 2019). To increase and maintain the attractiveness of its product, theory suggests the NBA needs to ensure two important factors regarding their entertainment service. First, quality of play has been proven essential to attract consumers to games (Hausmann & Leonard, 1997; Berri, Schmidt & Brook, 2004). Second, uncertainty of outcome closely linked to competitive balance is an important concept every sports league needs to strive for (Rottenberg, 1956).

The NBA Draft policy is a tool the league administration installed to improve competitive balance. It is a yearly event which brings young, talented basketball players from North American colleges and international basketball clubs into the association. The NBA needs this talent-infusion-and-resource-delivery-apparatus since franchises do not run youth teams to develop future players like e.g., European football clubs do.

In theory, every player in the world can sign up to be part of a given annual draft pool if they meet certain age criteria and send a letter of intent (NBA & NBPA 2017). NBA teams then can draft two players of this select group of individuals every year on a set date between seasons. To 'draft' a player gives a franchise the exclusive right to offer the draftee their first NBA contract. If the claimed athlete wants to enter the league, he can only sign with the organization that holds their rights (NBA & NBPA 2017).

The order in which the teams select the draft eligible players is determined by the success every franchise had in the most recent season. The winningest team gets the 30th pick of every draft round, the second-best organization holds the 29th selection and so forth. Only the first four draft selections are determined through a weighted lottery system. All teams that missed the playoffs are part of this lottery process and get assigned certain probabilities to receive such a top-selection based on their win-loss record. The weaker the team, the higher the chances for such a premier selection opportunity (NBA, 2020a). The lottery system is supposed to prevent losing on purpose to improve one's draft position ('tanking') which became a valid strategy as an unintended consequence as reaction to this policy over the years (e.g., Taylor & Trogdon, 2002; Walters & Williams, 2012; Choi, 2019).

4.2.2 THE NBA DRAFT AS A POLICY

Salamon (2001) describes policies as "collections of programs […] aimed at some general objective" (p. 1643). These regulations installed by a governing body are supposed to guide the decision-making of managers or the behavior of objects that are controlled by such to reach a greater goal (Wies, 1996). Knill and Tolsun (2012) also identify an acting organization that has control over stakeholders, a regulating mechanism able to influence stakeholder actions and a clear overarching intent of the program as key definitory requirements for a policy. The term is most common in the political domain, describing laws or agendas introduced by governments. But policies can be found in nearly every other organizational form and environment as well.

To analyze and evaluate policies, according to Salamon (2001) there are many criteria. Efficiency, equity, manageability, legitimacy, and feasibility all can play a role in the investigation of their quality. But the simplest measure of the goodness of such a mechanism is its plain effectiveness. To broadly evaluate a policy the only question that matters first and foremost is: Does the introduced dynamic produce the intended outcomes? After this point is answered it can be discussed if tweaks to the policy could lead to even better results or if the introduction of an alternative is necessary because the current approach is not reaching its goal.

In this paper we will treat the NBA Draft regulation as a policy since it fulfils all the definitory requirements. The league as a governing body has the power to introduce the draft dynamic as a regulation, guiding the behavior of its governed objects - the franchises - towards an overarching goal that in some dimensions is even different from their individual pursuits.

4.2.3 THE DECISION-MAKING PROCESS WITHIN THE NBA DRAFT CONTEXT

In this paper we want to investigate how draft decisions are made and if process improvements could result in better policy results for the franchises and in extension the entire league. To be able to find such hidden potentials within the decision-making structure we need to define the environment we are investigating first. For this we will apply the decision-process-model of Schoemaker and Russo (2006) to the NBA Draft:

This model describes choice entities as a mechanism with four consecutive parts and one overarching dynamic. In the following, we will present the individual entities applied within the NBA Draft context.

4.2.3.1 FRAMING THE ISSUE

According to the model, first, the framing of the problem needs to be done carefully. This task is not easy since we have multiple parties involved in the process. On the one hand, we can identify the league as one important body entangled in this decision-problem. It installed the draft policy as a mechanism to distribute talent equally to strengthen its entertainment product due to better competitive balance in the league resulting in increased uncertainty of outcome (Soebbing & Mason, 2009). This should contribute to profit maximization. As we already addressed the league as controlling authority sets the rules for the decision-environment and additionally is indirectly influenced by the decisions its members make as a whole in the draft process.

On the other hand, on the administrative level below we can identify the actual decision-makers in this defined problem - the franchises. Parallel to the league they follow simple (sports) economic principles, always striving for utility maximization (Friedman & Savage, 1948). On a team-level this goal can be reached by being part of a growing, successful league since part of the revenues of the entire overarching organization get shared among all its members (NBA & NBPA, 2017). Besides this, the individual franchise owners want to maximize the income generated by their business entities at hand. These profits are for the most part closely intertwined with the on-court success of the team. Superstar players as well as winning games and championships can be marketed more successfully than losses and uninspiring rosters. Sportive achievements can help to build long-lasting brands that generate income (e.g., Berri, Schmidt & Brook, 2004; Yang, Shi & Goldfarb, 2009; van Liedekerke, 2017). Due to this reasoning, under the assumption of general profit maximization, it should be the ultimate goal of every basketball organization to collect as much sustainable on-court talent as possible under the given rules of the NBA at any point in the business process to maximize the chance of lasting greatness in the sports and business department.

In the realm of the draft decisions, the general organizational aim under the given assumption of talent maximization as a form of draft utility is straight forward: Every franchise should strive to optimize the opportunity its current draft position provides by selecting the best talent available. Though, to define the best talent available can be difficult even if off-court and soft factor dimensions like injury-risk or marketability of a player are excluded.

The problem space needs to be defined as dynamic and extremely complex while being situated within an environment of great uncertainty when following the model of Howard (1968). Franchises need to monitor an extremely large and increasingly global talent pool (Motomura, 2016) even though in the end the options of choice for a given draft are finite at some point since only by declaration for the event a player becomes draftable. But complexity still reigns as teams do not know for sure who will declare for a given draft year at the end of every season. Furthermore, many variables need to be considered to determine who the most talented player is. The problem with these traits is that their isolation for single athletes can be hard as some performance indicators of players might be dependent on team context (Moxley & Towne, 2015). Meanwhile, it is not known to a satisfying degree which factor contributes how much to future performance as development curves of players can follow certain predictable patterns but in the end are usually highly individual (Berri, Brook & Fenn, 2011). Thus, there is always at least some uncertainty with every possible alternative in this decision-problem.

Additionally, time also plays a huge role within the framing of the issue. Basketball as a sport is constantly evolving. Even if teams could perfectly determine how talented a player is and what their exact development in the future will be, the decision-makers might still have problems projecting the exact value of their pick. Player traits that were extremely precious only a decade ago, might not be valued as much anymore because of a change of playing style due to new tactics or rules (e.g., Chatterjee & Lemann, 1997; Narsu, 2017). These dynamics increase the difficulty of a decision immensely since a decision-maker not only needs to foresee how a potential draft option and the own team will develop into in the future. The evolution of the sport itself as the market everybody acts in needs to be predicted accurately as well to create lasting value with the decisions that are made.

The crux with this dynamic is that the league administration has little to no influence on the outcomes in the entire matter. It must hope that the single franchises make good decisions for their entire premise of fair and equal talent distribution to work. Hence, for draft setups we can identify the team organizations as acting decision-makers. Their individual judgements and the quality of their choices make up the most integral part of the process (Tingling, Masri & Martell, 2011).

4.2.3.2 GATHERING INTELLIGENCE

Second, the decision-process model describes the stage intelligence gathering. In terms of the draft process this phase describes the effort of the teams to collect data to aid their decisions with creating a larger set of alternatives by identifying possibly suitable players as well reduce the uncertainty within these options by prudently evaluating them. In order to do so, franchises employ draft scouts and data analytics experts to assess potential talents by identifying their basketball relevant skills, studying their biomechanical prerequisites, analyzing their statistics. They might even monitor their off-court background and perform psychological test by interviewing them to be able to measure a player's mentality. This can help predicting how hard given athletes might work to improve themselves in the future, how well they will get along with future teammates or a certain tactical philosophy regarding the sport (e.g., Sailofsky, 2018; Beene, 2019).

4.2.3.3 COMING TO CONCLUSIONS

This collected data needs to be analyzed carefully to reach conclusions. This is a complex endeavor as talent evaluation in basketball gets described as 'inexact science' quiet often. There are general ideas about attributes that translate into future performance value, but effects tend to be small and often are not greatly generalizable (e.g., Berri, Brook & Fenn, 2011; Harris & Berri, 2015; Moxley & Towne, 2015). And this view only considers looking at hard performance data. Measuring individual marketing opportunities, potential team fit, bad luck with injuries or adaptability problems due to a certain coach, team situation or cultural differences are even more complex to model, while possibly playing a significant role for post-draft outcomes (Beene, 2019).

Even though some futures of young talents seem to be more certain than others, draft decisions will always be made under some degree of uncertainty. Decision-makers can only ensure that they have the complete set of options, know as much relevant information about these alternatives as possible and that their own preferences are in order.

However, the last point needs to be highlighted as key dynamic of the process. Since judgements of draft prospects are always made under some form of uncertainty, choices are hugely prone to systematic errors based on faulty, decision-quality-lowering mistakes such as wrongly applied heuristics or potential biases as the creators of prospect theory Kahneman and Tversky (1979) in various settings (e.g., Tversky & Kahneman, 1971; 1973; 1974; Kahneman & Tversky, 1972). Such errors emerge in nearly every decision-making dynamic and are very common in the world of sports as well (Raab, Bar-Eli, Plessner & Araújo, 2018). To decrease the severity of these effects or eliminate them all together presents huge potential for the improvement of decision-quality within any choice process design.

4.2.3.4 LEARNING FROM EXPERIENCE

In the fourth phase, ideally managers look at the track record of draft picks and evaluate all the decisions that were made constantly - especially their own. To assess the past should help to improve decision-quality in the future. The essence of this process is to carefully reiterate on what basis past picks were evaluated and how decisions were made. To truly learn from prior decisions and being able to find patterns in the own behavior a certain sample size is needed as chance (or bad luck for that matter) can play an important role in this mechanism. Unfortunately, the complicated part in this regard might be the highly competitive environment the NBA managers are in. It rarely provides the opportunity to make many unsuccessful draft choices and still being in the position to learn from them for very long. Organizations tend to fire executives that do not at least provide the glimpse of a successful future with their managerial performance (Wong & Deubert, 2011). To give such an impression a manager presumably needs to draft well early in the job's tenure.

4.2.3.5 THE META-DECISION

While this series of actions takes place the decision-makers constantly debate overarching meta-questions regarding the self-defined choice environment. According to Schoemaker and Russo (2006), these include internal debates such as: Did we define our problem correctly? Are we involving the right people in the decision? Which phase of the process should we focus on specifically regarding the individual features of the problem at hand?

Looking at the NBA Draft process, the problem definition should not be the crucial hurdle for the organizations. The incentives and avenues to success are well defined and straight forward. But to see who needs to be involved and what to focus on in the decision-process leading into the draft must be hugely complicated questions franchises have to deal with. Team owners, management, coaching, the scouting unit, and the data analytics department are all groups within the organization that provide information in the process or need to be involved in some way (Sailofsky, 2018; Beene, 2019). This can produce largely complicated dynamics. Maybe a manager wants to pick a certain player that they know the team owners do not like. With a potential firing in sight, this player might not be picked to not further weaken a bond with the employer. Mechanisms like this within social decision-setups can lead to dilemma situations for decision-makers that further complicate the resolving of the described decision-problem (Raab, 2012).

4.2.4 The NBA Draft policy and its decision-making-based shortcomings

To present the research gap this paper aims to investigate, we are combining the policy approach on the NBA Draft mechanism with the underlying decision-making process. We are summing up the presented theory here to derive hypotheses for our further analysis:

Through the draft the NBA intends to give every league member a fair chance to employ basketball star talent and have a window for title contention. With such results, the leagues overarching goal of maximized competitive balance and uncertainty of outcome would theoretically be strengthened. But as Tingling, Masri and Martell (2011) proclaim, this entire regulation is based on the administration's assumptions that the right of an earlier draft selection provides more potential on-court value than later ones and that all the franchise organizations in the NBA have the decision-making capabilities as well as process installed to exploit this inherent value. Without these requisites in place the entire draft regulation as a useful league policy is bound to fail. These premises need further investigation to see whether the underlying managerial decision-making quality is sufficient to make this policy effective. As of now it results should be questioned. Research declared the NBA the most competitively imbalanced American sports league (Soebbing & Mason, 2009). Papers concerning the draft mostly discusses decision-making errors caused by cognitive dissonance in the managerial player evaluation process, addressing disconnects within the second and third phase of the above presented process (e.g., Berri and Schmidt, 2010; Berri, Brook & Fenn, 2011; Moxley & Towne, 2015; Motomura, 2016).

These investigations assume that the draft mechanism from a decision-making standpoint already works like the process Schoemaker and Russo (2006). They have clearly identified the intelligence gathering and conclusion phases as stand-ins for judgement as the main area for improvement. Increasing decision-quality by optimizing these steps of the process should lead to general advances towards the desired outcomes for the policy.

With our investigation, we want to take a step back and take a closer look the underlying assumptions these papers work under. All of them operate under the premises that the NBA Draft is a mechanism which provides value and opportunity to the league's teams if they use player evaluation skills correctly. Advancements within the league-wide decision-making quality by improving the process should lead to improving results from an overarching perspective.

While this train of thought is highly logical, it is still usually treated as a foregone conclusion. Hence, we want to test and verify the underlying assumptions of these approaches in the form of derived hypotheses from the presented theory. To our knowledge no research on the NBA Draft mechanism has taken this approach to justify decision-making-quality-improving analysis on potential biases and systematic judgement errors within the described setup as policy results improving entities. Thus, we will investigate the following hypotheses:

H1: The pool of draftable players contains talents who provide an NBA franchise with more on-court value than others.

H2: Drafting is a managerial skill.

H3: All NBA organizations are equally able to exploit the opportunities the draft policy provides them with.

4.3 METHODOLOGY

4.3.1 DATA

We collected draft-class-data from the well-known basketball statistics website 'Basketball Reference' (Basketball Reference, 2020a). We used an R-script to scrape the data of all draft prospects from 1989 to 2015 (N=1562) and the win-loss-data of all franchises over that span. This starting year was chosen, because the NBA switched to the still ongoing two-round draft system back then (NBA, 2020a). 2015 was declared the end of the investigated time frame for sample-size reasons. Draftees from this class have had the chance to play four full seasons and establish themselves in the league. More recent classes were not considered. These players are too far away from their expected performance peak (Vaci, Cocic, Gula & Bilalic, 2019).

The collected cases include descriptive information (name, drafting team [1], draft position etc.), basic performance data (years of experience, games, points etc.) and advanced metrics regarding player value (VORP (Value Above Replacement Player), WAR (Wins Above Replacement etc.)).

One important limitation to the dataset is its ongoing nature. While active players still have the chance to improve their total numbers, retired athletes cannot change their body of work anymore. We scraped the data in the beginning of December 2019 and will mostly use numbers on a season-average basis to account for this limitation of the dataset. For tasks involving undrafted players we used the NBA's official statistics site, where filtering for draft status is possible (NBA, 2020b).

4.3.2 MEASURING DRAFT OUTCOME ON A PLAYER LEVEL

An important task to be able to evaluate the draft policy is to find a decision-making currency that helps to measure outcomes. In this case the performance of the picked basketball players is supposed to be assessed to evaluate the managerial choices. Occasionally, just looking at simple performance indicators such as points is enough to distinguish good from bad players. They show who performs well in certain individual facets of the sport. But these simple effectiveness metrics do not account for e.g., efficiency, tactical restraints, or players positions. Additionally, isolating the value of an individual in a dynamic team situation is an extraordinary complex assignment. Martínez (2012) has compared this quest with the search for the holy grail. An ultimately satisfying answer has not been found yet. Technological and analytical advances as well as extensive research still evolve and deepen the understanding of the sport. Still, deciding on a metric to evaluate players inevitably leads to a specific view of the discipline and poses some limitations. We are aware of that.

Nevertheless, we need to make choices for this paper. If we can, we will keep it simple and use basic basketball production figures such as points or assists to evaluate players. As far as available advanced statistics go, we have identified the metric 'Wins Above Replacement (WAR)' as the most useful for the task at hand (Basketball-Reference, 2020c).

All calculations for WAR are based on the Box Plus/Minus (BPM) model by Daniel Myers (2020) [2]. In simple terms, offensive (points, assists, ball losses etc.) and defensive actions (rebounds, ball wins etc.) are combined with the individual efficiency of a player in this formula. Afterwards team variables are added and an estimate for how much a given player contributes on a per-100-possession-basis to the efforts of the team are calculated. This approach produces a rate statistic.

To add more context playing time and the theoretical construct 'replacement player' are incorporated into the model, forming a metric named 'Value Over Replacement Player (VORP)'. The construct 'replacement player' represents an athlete whose performance neither helps nor harms their team. On the scale of the statistic such a player receives a fixed value.

The distance to this point estimates how much better or worse the athlete in question is in comparison. Not only quality but also quantity of play is captured by this metric.

Multiplying the value by 2,7 converts the metric VORP to WAR. This gives an estimate of how many wins a player provided or cost their franchise and puts individual performance in a team context. This number is rated for one season and gives a useful estimate for player impact in a given year.

WAR does not include many factors that allow to assess the defensive value of players accurately. The core of its estimations is the boxscore which sometimes gets labelled as outdated as newer more accurate metrics got developed recently based on tracking data or video indexing (e.g., Synergy Sports Technology, 2020). Still, it also has the advantage that it can be calculated for players ranging back to the 1970s and thus, gives us the chance to compare a huge number of athletes from different eras. We chose this imperfect, but useful metric to rate the quality and impact of a basketball player mainly for these comparability reasons. [3]

4.4 ANALYSIS AND RESULTS

4.4.1 H1: EXAMINING DRAFT POOL QUALITY

It is assumed that the pool of draftable players contains talents that provide NBA franchises with more on-court value than others. Hence, to have a choice between them through holding the right to an earlier selection opportunity provides teams with a benefit. This premise should not be up for debate. In nearly every trait of life some people are more talented or skilled than others and therefore perform better at given tasks. It is the same in basketball. Due to a blend of mental, physical, and game-specific skills (Trniniél, Perica & Dizdar, 1999) some athletes perform better than their competition. Of course, their performance value can vary or be not fully pronounced yet, partly depending on factors like team context, style of play, health or opportunity given by the coaching staff (Deshpande & Jensen, 2016). Still, the history of sports has proven, that some athletes are better than their colleagues. The manager’s mission is to find them.

Keeping it simple, we can look at basic performance indicators first. Played minutes and years in the league provide us with an overview how much time a league employee worked in game situations:

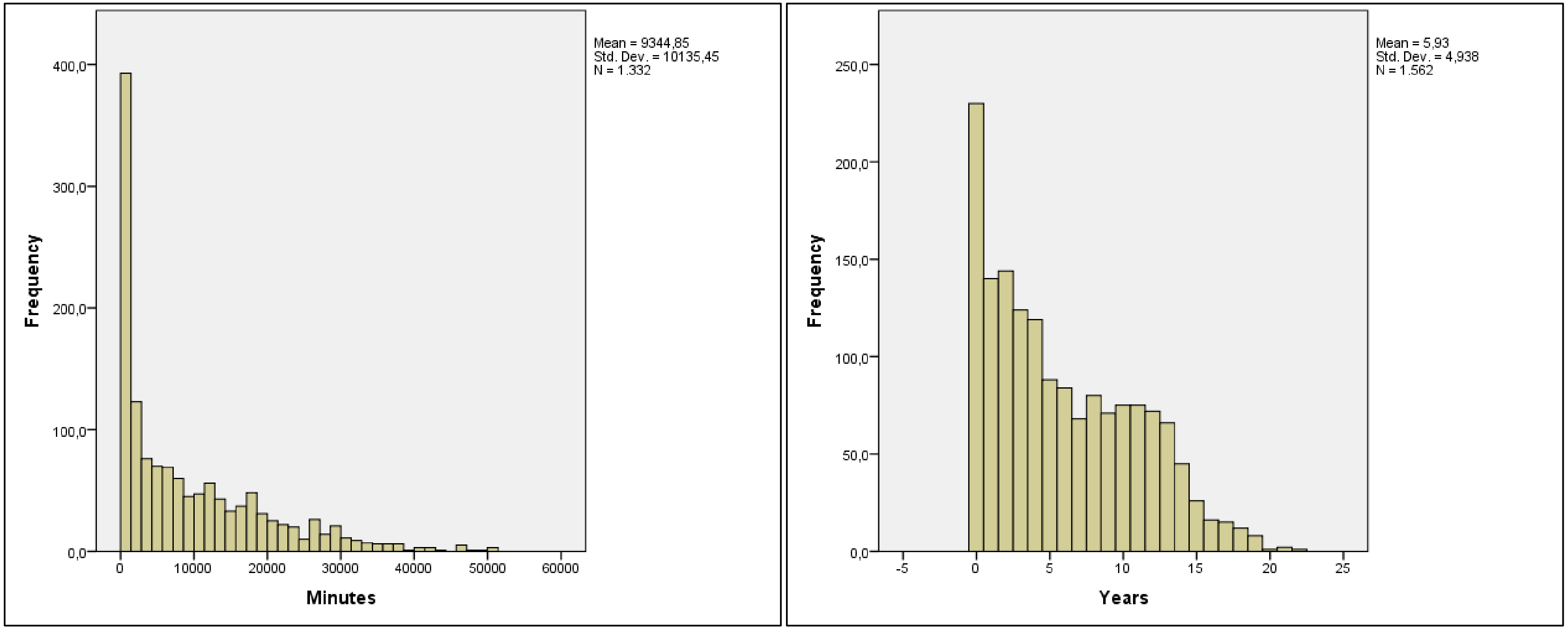

FIGURE 4-1. MINUTES AND EXPERIENCE AS PERFORMANCE INDICATORS.

While 230 drafted players in the data set did not play any minutes in the NBA and therefore did not produce any value for the team that picked them, there are 1332 athletes that performed in games over at least one season. The number of players that manage to surpass increasing time thresholds is steadily shrinking as expected. Playing a huge amount of NBA minutes over many seasons is an accomplishment that gets harder and harder to achieve. To stay on the court for a long time an athlete needs to convince franchises, managers, and coaches of their sportive value for many years and stay healthy and in shape. They simply need to perform better than the competition for the same job. As we can see, there are basketball players that manage this situation better than others.

The same goes for simple performance metrics like points or assists. The goal of the sport of basketball is to outscore the opponent team over the time of a game. Hence, the ability to find ways to manufacture those points by himself or for others is a valuable skill for an employee in this field of work. Again, we can see, that some players are better at it than their competition:

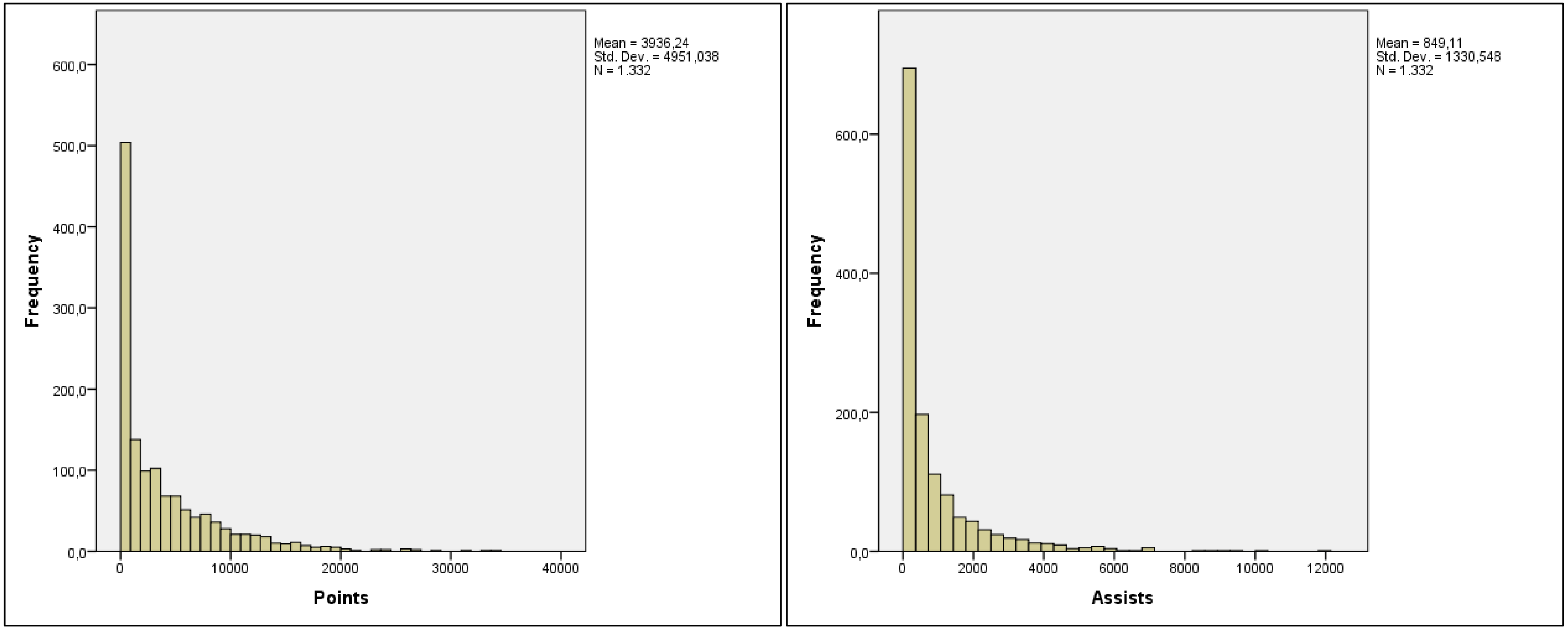

FIGURE 4-2. POINTS AND ASSISTS AS PERFORMANCE INDICATORS.

While the average player drafted between 1989 and 2015 has scored about 4000 points and 850 assists during their career, there have been exceptional basketball players who managed to reach over 30000 points and 10000 assists. It seems undeniable that certain players are better than their colleagues at given basketball activities.

To constantly identify and pick these better talents is the key task of drafting decision-makers to make the policy work. The problem with this value extraction is the distribution of talent within the game of basketball, which roughly follows a bell curve form: The majority of players generates only marginal to even negative value, while only very few players have the ability to alter the course of a franchise with their elite skills by producing extraordinary on-court performance. Within these extremes the number of players reaching certain performance thresholds is decreasing exponentially. Durable star players are an extremely scarce resource:

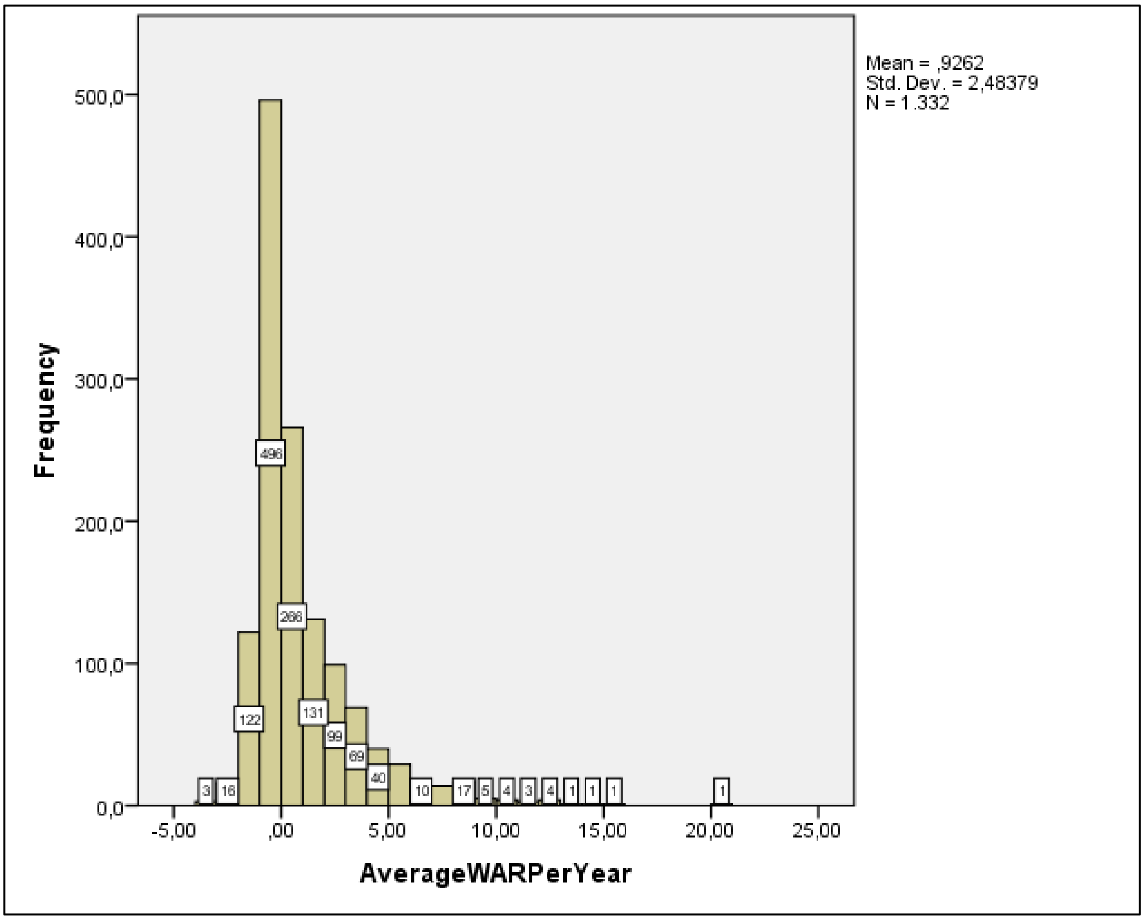

FIGURE 4-3. AVERAGE WAR PER YEAR AS PERFORMANCE INDICATORS.

This leaves us with policy problems that boil down to availability. Within a given year every player pool provides certain natural cut-offs. There is e.g., only a fixed number of above-replacement-level athletes that are draft eligible in each season. If this group of players is exhausted, identifying the next best player creates only theoretical value for a franchise. These cut-offs between different players levels exist at a few stages throughout the draft. Our data helps to illustrate this thought. We looked at the draftees of the player pools between 1989 and 2015. Average season WAR can determine overarching player categories that provide an overview about player quality. Talents with negative or neutral values did not produce any benefits for their employers. For players with positive numbers, we formed categories using terminologies and player quality ideas based on a tier system many draft and general basketball experts agree on (e.g., Paine & Bradshaw, 2015; The Stepien, 2020a; Go-to-Guys, 2020; Myers, 2020). We added the average minutes for each level. As expected, we see an increase in playing time if we go up in player tiers. This seems very logic. Teams want to maximize their wins. To reach this goal, they should optimize the playing time of their employees according to provided value. Legitimized by the playing time decisions franchises made, these categories seem valid.

TABLE 4-1. PLAYER TIER CUT-OFFS.

Category	WAR Range	Total Players in Database	Average Occurrence per Draft	Minutes per Game	Average Draft Position	Draft Position Min	Draft Position Max	General Value
Superstar*	>= 10	15	0,6	34,6	6,3	1	41	
All Star*	6.0 - 9.99	46	1,7	33,2	12,2	1	57	
Starter/Value Role-player*	2.0 - 5.99	237	8,8	27,9	17,4	1	60	↑ Positive
Role-player* (Experience >= 2)	0 - 1.99	352	13,0	19,9	25,7	1	60	
'One-Hit-Wonder' Roleplayer (Experience < 2)	0 - 1.99	45	1,7	5,6	43,3	14	58	
Bust	< 0	637	23,6	13,1	30,3	1	60	↓ Negative
Never played in the league	-	230	8,5	-	48	11	60	

*Every player of these categories played more than one season in the league.

The most intuitive cut-off represented in this table is the one between regular role-players and the one-hit-wonder role-guys, we count as bust due to limited asset value. The numbers in the average draft column show that the regular year only holds about 24 viable options to draft, which is an astounding number, given the fact, that 60 players get picked every year.

The lost margins get greater as we move up in the player performance categories. As the table illustrates, athletes from better player categories become scarcer with the superstars being rarest commodity in the entire sport. Every drafting team hopes to find such a franchise cornerstone. The numbers show though, that this player type is simply not available every year as no draft pool is created equal. Even with perfect evaluation, judgement and decision-making, a franchise is dependent on the group of players it is drafting from and might never have a chance to profit from the policies aim, to provide superstars for the weakest team, due to availability issues.

A phenomenon experts call the 'treadmill of mediocrity' can occur: Bad teams drafting perfectly get better to a certain degree, preventing them from receiving high draft selections in the medium term, but never actually getting the superstar talent boost, big enough to give them a realistic chance to compete for a title. Consequently, the status quo of the league's power structure at the top is never threatened (Motomura, Roberts, Leeds & Leeds, 2016). On the other hand, the policy leaves the door open for great teams to get a lot better after missing the playoffs due to injuries and some lottery luck. Such outcomes do not fall in the realm of intended consequences of this policy.

4.4.2 H2: Drafting as a skill

For the draft policy to work, it needs to be assumed that drafting is a managerial skill. Without the premise that NBA teams are generally able to identify and select the best option from a given pool of players the draft policy would be worthless since its intended consequences could never be reached constantly. This premise can be questioned easily as errors in evaluating players seem to occur constantly. Therefore, the fundamental belief that drafting is a skill needs to be tested.

A logical first step is to analyze the collective of undrafted players. Due to the rules of the league those players were eligible for a draft at some point (NBA & NBPA, 2017) but were not selected. No team considered them their best option when it was their turn to pick a player. Still, if such a basketball player turns out to be an asset NBA franchises will sign him to a contract anyway despite the undrafted status because one of their goals is to maximize on-court success. According to Hendricks, DeBrock and Koenker (2003) every undrafted player producing value by definition is a collective draft mistake. The better they perform the worse the error all the teams that had the chance to pick them made.

To generally evaluate draft skills of managers we can look at the general NBA landscape first. If franchises drafted perfectly no players of value would go undrafted. Comparing the two populations of drafted and undrafted players in the league historically in a peer/control group manner gives us an idea if managers generally tend to pick most of the valuable players in the drafts and therefore are at least somewhat skilled in evaluating and selecting basketball talent.

We collected data from the NBA.com stats-portal (NBA, 2020b). For the available 23 years between the seasons 1997 to 2019 we investigated which proportion of certain player types entered the league with the status 'undrafted'. Unfortunately, the NBA.com stats-portal does not offer VORP as a metric. So, we could not use the already established player tiers from the previous chapter. To represent different player levels, we filtered for thresholds in the variables 'games played' (out of 82 possible regular season games) and 'minutes played per game' (out of possible 48 minutes per contest). We defined player categories that represent how meaningful a given player contribution to a team was by on-court body of work. As we could see in the previous section, playing time is related to player quality. Hence, the formed groups loosely represent quality of play, as better players tend to receive more playing opportunities by their coaches. Though, we cannot trace their exact player value for certain. Therefore, we named the different player levels according to their workload. But we based the applied minutes per game thresholds on the player value levels we established earlier. Those categories were logged for all available 23 seasons and the averages of total players of a certain player class each year depending on draft status were calculated:

TABLE 4-2. OVERVIEW UNDRAFTED PLAYERS.

Category	Total Players in the Category in Average Season	Undrafted Players in the Category in Average Season	Percentage Undrafted in the Category in Average Season
General NBA Player (>= 1 minute played per season)	461,86	79,08	16,98
Useful Player* (>= 20 GP and >= 5 MpG)	391,21	52,43	13,35
Rotation Player* (>= 20 GP and >= 15 MpG)	289,91	30,47	10,43
Key Player* (>= 20 GP and >= 25 MpG)	158,69	8,73	5,52
Heavy Usage Player* (>= 20 GP and >= 35 MpG)	42,21	1,04	1,89

NBA managers seem to miss many players in the draft they later employ to fill minutes for their respective organizations. Over the investigated time period about 17 percent of the players that played on an NBA court had the undrafted status. This number seems high but can easily be explained because franchises sometimes just want to test players or are forced to sign undrafted athletes as a reaction to injuries of their drafted employees. As we increase the number of minutes thresholds for the players to qualify, we can see that less of these categories are made of undrafted players. Therefore, we can assume that managers miss on useful players or even rotation players a lot in the draft. Still, only few truly impactful athletes with high on-court value went undrafted. During the investigated time period only 5,5 percent of all the players with key player-value did not get drafted. Just 1,9 percent of heavy usage players were undrafted athletes. Only two undrafted players reached the NBA-All-Star-status during that span. Only one player received All-NBA-Team-honors, which loosely translates into being one of the top 15 players of any given season (NBA, 2020b).

Hence, NBA teams tend to be able to identify the useful from the less useful players in each draft pool. To evaluate the quality of their decision-making, we need to look at yearly samples and see if talent within the group of drafted players gets judged correctly. To provide thoughts on this matter the quality of the players of every draft class needs to be assessed and compared to the competition in the given year as every draft has an ideal ranking based on the player outcomes. The closer the leagues ranking is to the optimal order the better it drafted as a whole. For the pursued talent distribution via the draft policy to work high quality draft decisions are needed.

Analyzing the data, we can confirm the already determined trend that NBA front offices tend to know who to draft. We plotted general career WAR as a measure of accumulative performance, average WAR per season played as a measure of player level and years played as a measure of career longevity:

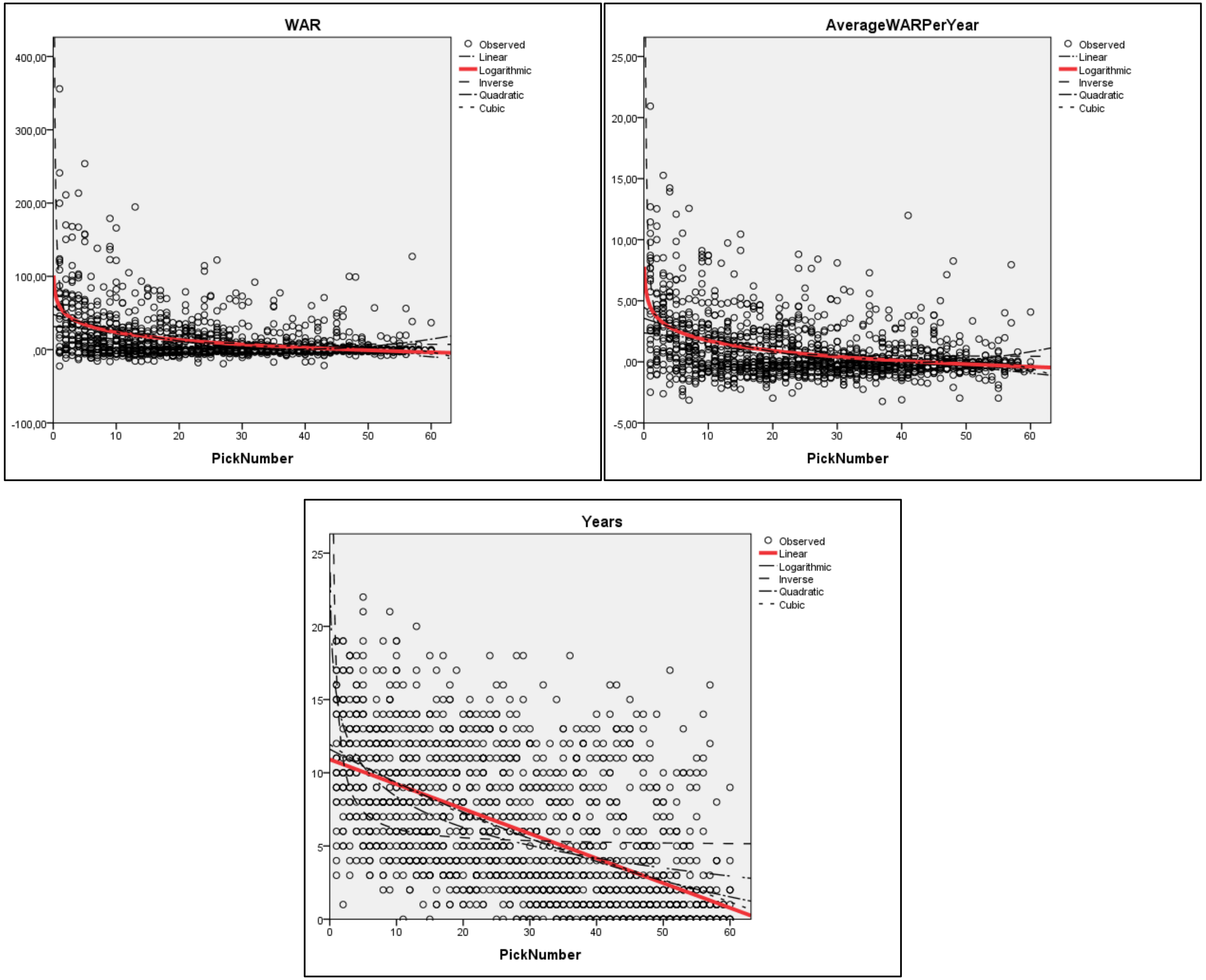

FIGURE 4-4. RELATIONSHIP PICK NUMBER VERSUS SEVERAL PERFORMANCE INDICATORS.

All three indicators behave as expected. The performance metrics and measures for longevity decrease with the number of the draft slot increasing. This shows that over the past three decades decision-makers managed to convert draft picks into beneficial outcomes by selecting better players earlier than less productive alternatives. But we can also see numerous outliers. There are many top 10 picks that did not live up to expectations, barely performing better than a replacement player, while on the other hand stars have been falling to later draft spots regularly. Those two types of draft mistakes are called 'bust' and 'steal' (Boulier, Stekler, Coburn & Rankins, 2010). Both occur regularly as the r^2-values for the plotted relationships between the variables show.

We ran a curve estimation for the three examined connection. For all instances we several tested relationship types (linear, logarithmic, inverse, quadratic, cubic). For WAR and Average WAR per year a logarithmic relationship fitted best as the most variance was explained in a highly significant construct, while offering a high F-value. For simple years, a linear equation fitted best, in a highly significant and variance explaining manner. But draft position always only explained between 17 and 34 percent of the basketball performance goodness metrics.

To examine whether the quality in draft decision-making followed any trend over the past three decades we sliced up our data set into bundles of three seasons. We then checked for each of these bundles how well draft position correlated the already introduced metrics 'Average WAR per Season played' and 'Years in the league':

TABLE 4-3. DRAFT PERFORMANCE OF THE FRANCHISES OVER TIME.

Timespan	N	Pearson's R - PickNumber – WAR per Year	N	Pearson's R - PickNumber - Years
1989-1991	144	-0.390**	162	-0,502**
1992-1994	136	-0,425**	162	-0,671**
1995-1997	144	-0,464**	173	-0,643**
1998-2000	152	-0,357**	174	-0,594**
2001-2003	144	-0,311**	172	-0,499**
2004-2006	153	-0,281**	179	-0,549**
2007-2009	150	-0,324**	180	-0,639**
2010-2012	161	-0,374**	180	-0,689**
2013-2015	148	-0,261**	180	-0,695**
1998-2015	1332	-0,349**	156	-0,575**

** Correlation is significant at the 0.01 level (2-tailed).

The results show that franchises have a general idea who will perform post-draft since both impact and staying power in the league are significantly negatively correlated with draft position. The smaller the pick number, the higher the output the prospects produced on average. Curiously, the values of the correlation coefficients show that franchises are better at judging who will stay in the league the longest than evaluating the best talents in the draft. Besides this dynamic, no real trend seems to have manifested over the past decades, which must disappoint the policy makers. The NBA draft in its current form has been in place for over two decades now. Therefore, it should be expected that decision-making quality within this system should be improving by better understanding the underlying dynamics, using more information due to new technologies and learning from historical data as well as past experiences. It is astonishing that there is no tangible evidence for advances in the draft decision-quality over the years. Experts even argue that the NBA is not only not improving in their draft decision-making but that the franchise collective is getting worse at evaluating and selecting players (Haberstroh, 2019). Looking at the data we investigated, leaning in this direction could be a viable interpretation of the analysis.

4.4.3 H3: Exploiting draft opportunities constantly on a franchise level

To find out whether certain teams draft better than their competition we first used the established expected value for each draft position and subtracted this draft slot specific number from the actual value a player selected in this spot produced on an annual basis. The calculated difference gives an estimate whether a single franchise made a good decision by finding a player outperforming their expected value or not. Added up year by year and then filtered by the franchise name a trend regarding their aggregate of draft choices in relation to general historic performance is observable:

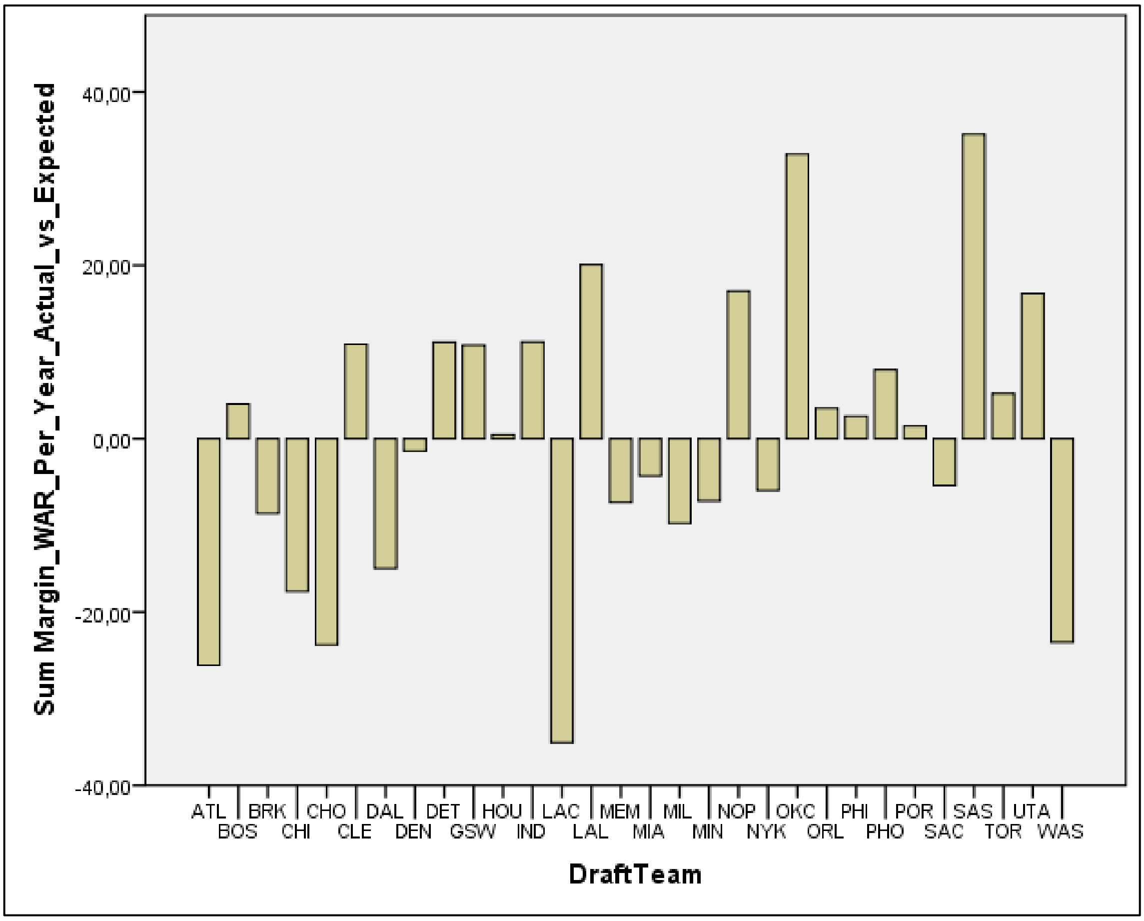

FIGURE 4-5. TEAM DRAFT PERFORMANCE USING HISTORICAL EXPECTATION.

This measure is not perfect. On the micro level this calculation cannot show whether an organization picked a solid player in their spot but still missed on a super star or if it picked someone below average but maybe made a good decision anyway because no other player would have outperformed the expected value. On a macro level this created metric looks at franchise draft performance as a whole. We do not account for managerial changes within the two decades. On the same note we do not account for player movement after the night of the draft. If a player switches teams later in their career, we still credit the drafting franchise with the value they produced, since they identified the players talent in the first place. Consequently, this statistic is not about checking who gained the most value through the draft, but who evaluated talent best at the point of the draft.

Knowing these limitations, we can still conclude that only a few teams managed to maintain high quality decision-making over the past two and a half decades. Only one sixth of the league constantly found players that outperformed their draft spot expectations. Three additional teams came in with results around zero, meaning that their decision-making can be considered balanced and therefore knowledgeable. The rest, more than two thirds of the league's members, performed poorly in this approach by mostly finding below average players accounting for draft slot. These results look devastating regarding the underlying tested hypothesis.

For further investigations we refined our method. In the first approach we used all the draft classes as a collective to extract an expected value for every draft slot. For a general discussion, this perspective is reasonable. Nevertheless, looking at single player pools in an isolated way is a method we want to explore in the light of the availability argument we made in 5.1 as well. As no draft class is created equal managers should be judged by the choices they made in relation to the accessible alternatives in these particular years.

We adapted the approach of Goldenberg (2017). Draft decisions are now measured within the year they occurred in. Every actual selection at every position is judged versus the player who should have been available at this spot if every team would have drafted perfectly. For example, in 1996 Kobe Bryant was taken at the 13th spot. His produced career value in this metric now gets compared to Žydrūnas Ilgauskas, who in hindsight turned out to be the actual 13th most valuable player of this class. Bryant outperformed the on-court value of Ilgauskas significantly. Hence, the statistic marks him down as a huge steal at the position they were taken at by calculating the exact difference between their performance values.

As a quality metric for the athlete's value simple VORP [4] is used. This accumulative version of this statistic encapsulated produced basketball value over time and therefore mirrors a player's quality as well as their career longevity. We can use this simple form of the metric because all players measured against each other have the same starting point for their path in the league. The results produced compared to the former method differ slightly due to a different decision-approach. Generally, managers are punished more for missing on great players early as well as rewarded more for finding good players late in this metric we simply call 'Steal/Bust-Rating'.

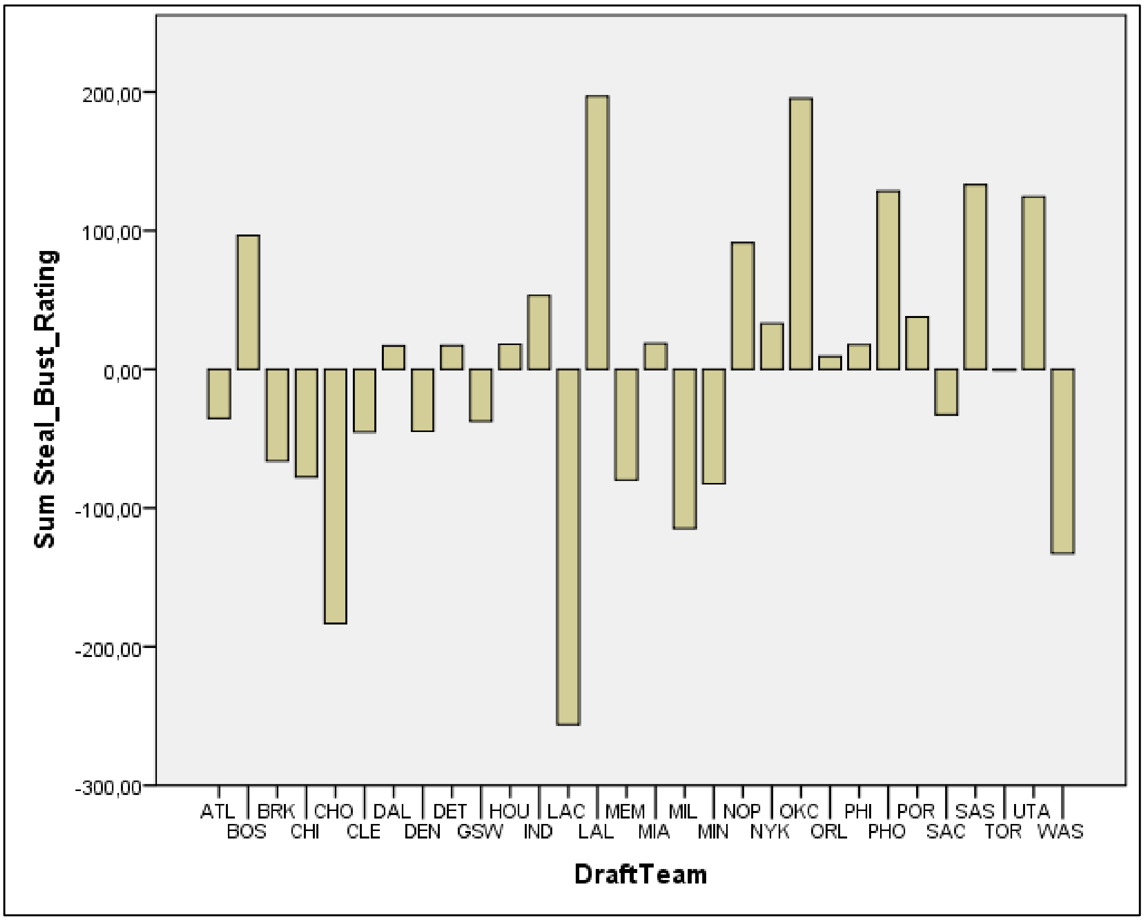

FIGURE 4-6. TEAM DRAFT PERFORMANCE USING STEAL/BUST-RATING.

Accounting for availability in each year, the results show that more NBA teams drafted around or better than average when accumulating all their choices between 1989 and 2015. Still, thirteen franchises have been performing below average, mostly failing to convert premier selection opportunities into the good to great player in a given draft. These results are nonetheless concerning. About half of the league does not seem to have the ability to constantly use the opportunities the NBA Draft policy is providing them with, while the other franchises seem to profit from their competitions lack of quality decision-making. Eying the third hypothesis these numbers are problematic.

Lastly, we constructed the 'BPA -Rating' [5], updating the Goldenberg (2017) approach. Our new metric not only accounts for the perfect hindsight ranking of a class and compares the picks with it but also accounts for who the best player available was at any given position of the draft as the specific drafts unfolded in real time. With the Steal/Bust-Metric in 1996 only one team gets punished for not taking Kobe Bryant as the most valuable player in his year. In our minds though, every franchise which had the chance to pick him, made a mistake by passing on him. Therefore, all the twelve teams that decided against him should be awarded a negative score deriving from the difference of the player the team actually selected compared to Kobe Bryant's quality. His draft team gets a rating of zero because it found the optimal selection. The team that had the 14th selection then gets judged versus the best player after Kobe Bryant, after eliminating all the made selections till this point from the perfect draft list. With this approach we can rate how close teams were to an optimal decision accounting for player pool availability in two ways – the class strength in general and the availability in the moment of selection.

Filtering for all the cases of players with a rating of zero in this metric, we can point out all the draft selections of teams which can be considered optimal. Out of the 1562 picks made between 1989 and 2015 only about 14,6 percent (228 cases) fall into this category. During this time period there has been no year in which more than 16 perfect picks occurred. For some draft classes (1999, 2011) we measured as little as only three optimal selections regarding best player available. On average all franchises together produced 8 perfect selections per draft. An astonishingly low number given the fact that at least 54 choices were made in every class. No learning-effect-trend over the years is observable:

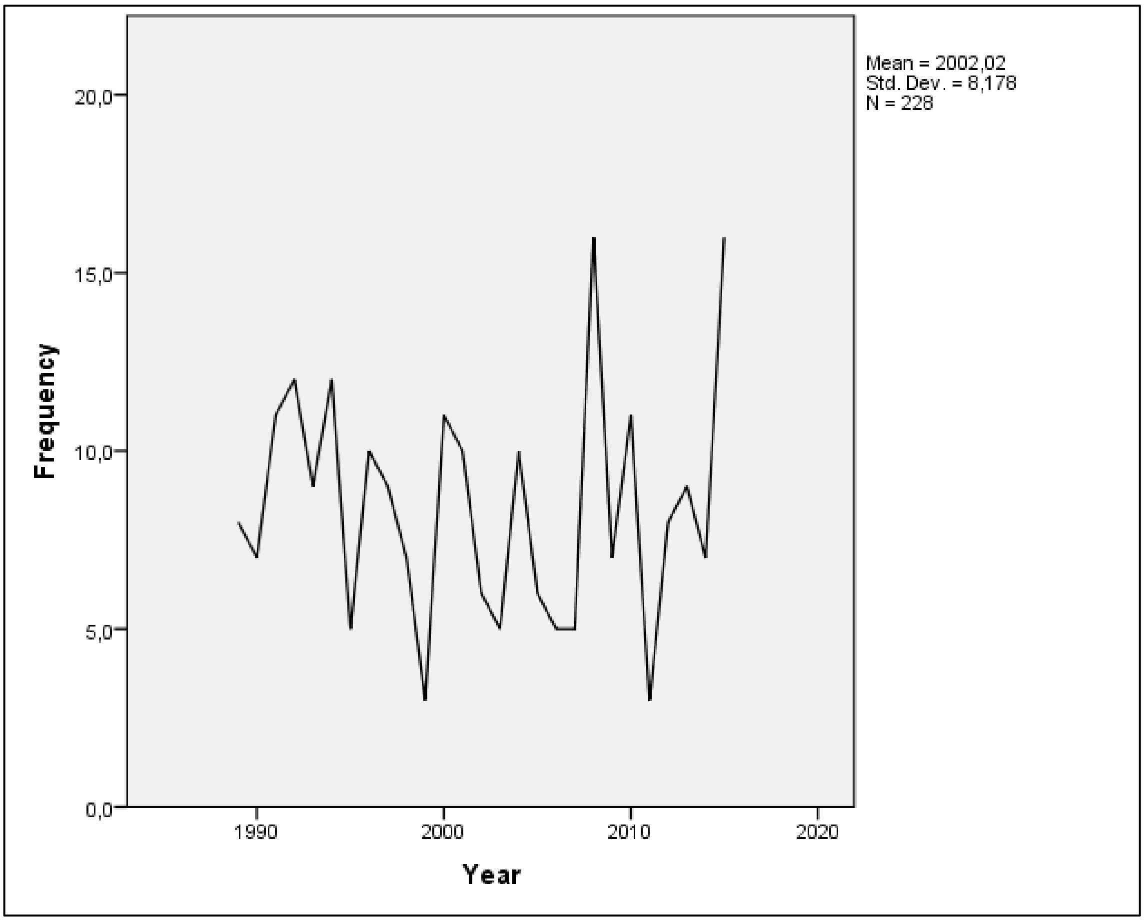

FIGURE 4-7. PERFECT PICKS OVER TIME.

Comparing all franchises, we can find vast differences draft decision-quality:

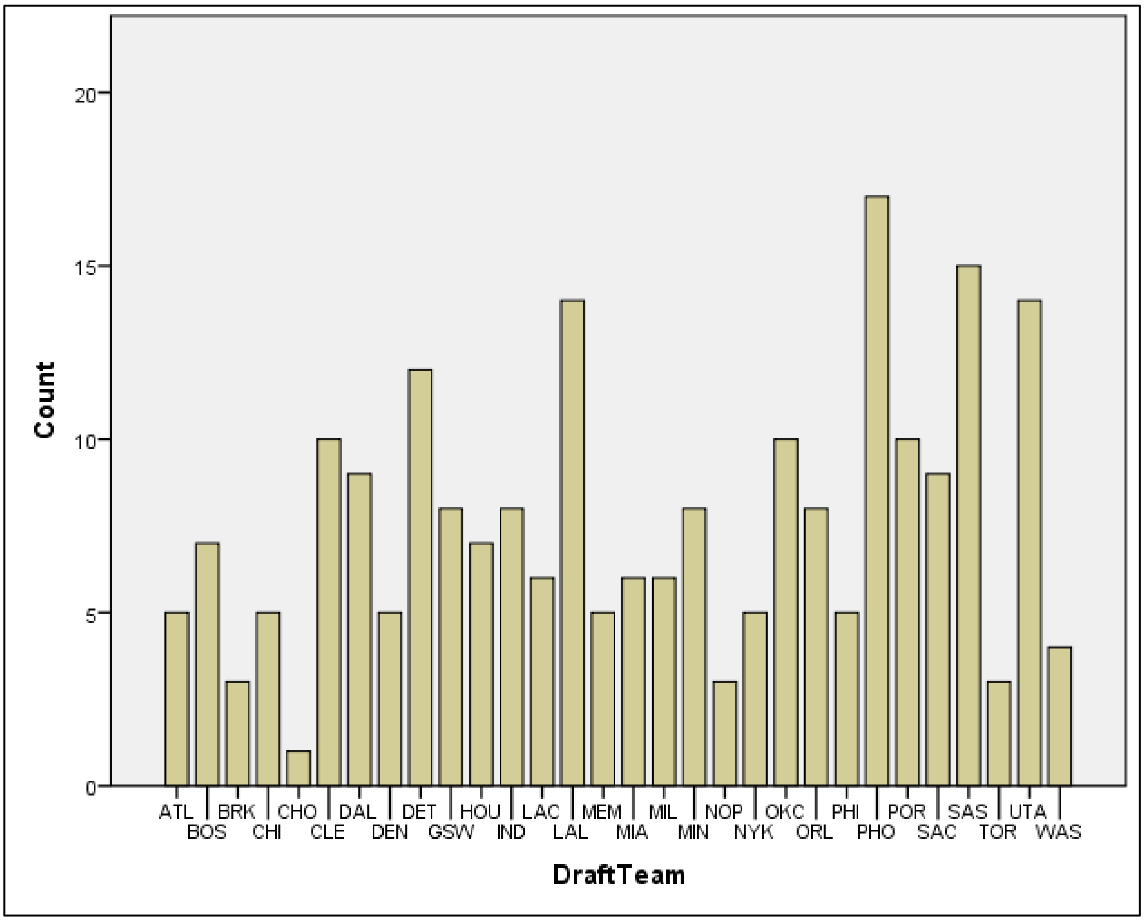

FIGURE 4-8. PERFECT PICKS BY FRANCHISE.

While some teams find the perfect selection with over 25 percent of their picks (N = 4), most other franchises only make optimal decisions with 15 or less percent of their selections (N = 19). This points to a huge imbalance in organizational draft decision-quality. Factoring in all the non-optimal draft decisions we can investigate the team divides regarding drafting abilities a little further:

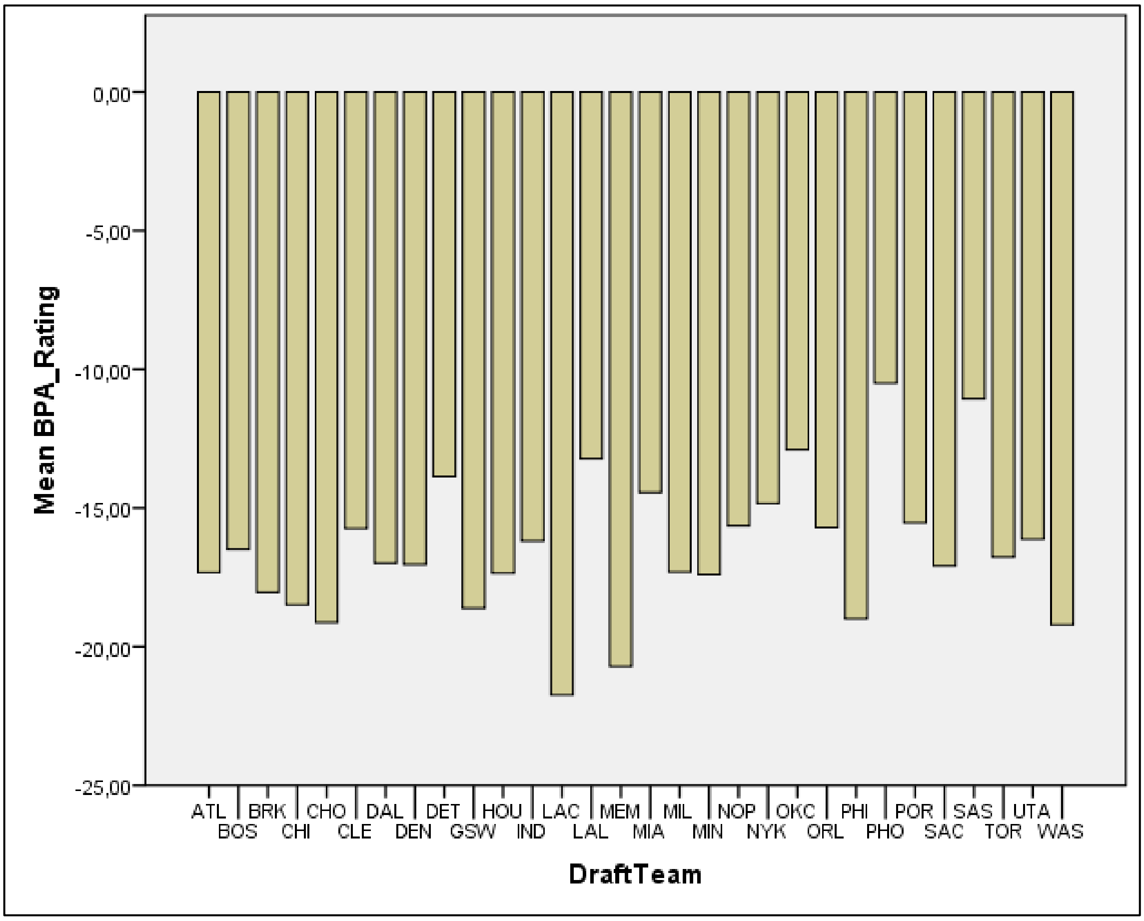

FIGURE 4-9. BPA-RATING BY FRANCHISE.

Accounting for all picks made and looking at the average value lost on them, we can see that differences between teams are not as glaring anymore. Every team in the league misses better players with most picks that they make. The average franchise missed about 19,4 VORP with every non-optimal selection they made, which is about the equivalent of a good ten-year-starter-career.

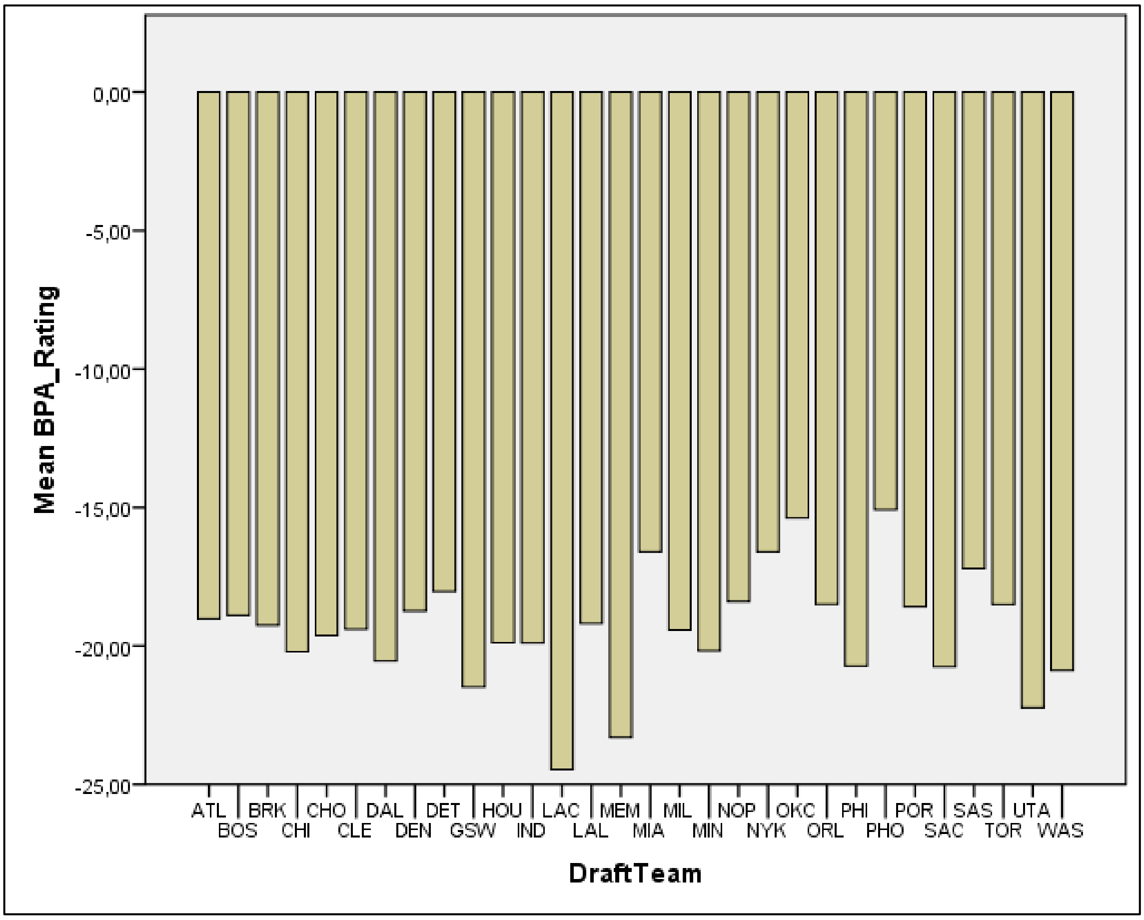

FIGURE **4-10. BPA-R**ATING BY FRANCHISE WITHOUT PERFECT PICKS.

Interestingly, the teams that made more optimal decisions are not necessarily missing less value with the decisions the get wrong. The teams who had the fewest perfect selections, though, also tend to lose more value with their non-optimal picks. This underlines the notion that some teams are better at drafting than others. On the flipside we also see that every franchise makes mistakes with their selections. Therefore, we can conclude that no organization evaluates and selects prospects perfectly.

This illuminates the key problem: Only few teams possess the decision-making quality to profit from the draft in a sustainable way. Hence, the entire policy has no chance to reach its intended goal of fair league-wide talent distribution and contributing to competitive balance constantly.

4.5 DISCUSSION

4.5.1 THE BEST ABILITY IS AVAILABILITY

The analysis shows that there is no general problem with this underlying premise. It cannot be falsified. Certain players possess more basketball-specific ability than others and therefore produce additional benefits on the court compared to their peers. Hence, if a team correctly identifies the best player from a given player pool it can gain competitive advantages. Providing weaker teams with better opportunities to select such talents, while better teams receive lesser chances to do the same should strengthen the competitive balance of the league long-term – the leagues intended result. We have no problem with this premise regarding the draft policy.

Still, a few remarks must be made. Policy outcome issues arise due to how scarce superstar players are and how much value they provide. Research has shown that those players create huge surplus benefits even though being the most highly paid entity in the sport (Robbins-Kelley, 2018). Compared to other disciplines the impact one transcendent player can have on the leagues landscape is enormous. For the timeframe from 1989 to 2019 there have been only three teams [6] which won the championship without a player meeting the 10,0 WAR threshold we set for superstar players in this paper. The average season WAR of the best player of the respective champions over the past three decades was 16.96 (Basketball-Reference, 2020d). Thus, the typical championship team is usually led by an absolute superstar. From a franchise perspective we learn that a superstar level player is needed to compete for a title, the ultimate goal in the NBA. From the league's perspective, competitive balance is a main objective. To reach it on the highest possible level, every team would have to have the same chances to win a championship. Hence, every franchise would need to be provided with a star player at some point.

The problem is their availability in relation to their impact. In the past three decades by our measures only eleven superstars entered the league. Even with a favorable distribution this gave only about a third of the leagues teams a chance to employ such an impactful player. On a lower-level basis this argument can be made for e.g., all-star players as well. Even if the draft distributes talent perfectly in any given year, availability and chance to some point affect the results for the actual teams drafting. Winning the draft lottery as a bad NBA franchise can mean hitting the jackpot and improving the team's title chances dramatically for the next decade by picking such a described superstar-level player. Or it leads only to receiving a less valuable reward by being able to select a lower-level all-star who improves the team just enough to not have the chance again of drafting a star for the foreseeable future, since top picks are out of reach.

Chances of acquiring such a superstar in a different way other than the draft are slim. As an unintended consequence, losing on purpose (so called 'tanking') to improve one's draft chances has become a viable strategy for teams now, which reduces quality of play as well as competitive balance in the league. These dynamics caused by the scarcity, impact and availability of superstar players are problematic for the overall policy outcome.

The distribution of superstar talent among draft classes is more or less random. There is simply no way for the league to guarantee that every player generation offers such an impactful talent as described above. Therefore, the mentioned availability problem is impossible to fix from a league's perspective. The NBA already acts in the only department it can have influence in concerning this issue. It popularizes the sport on a global level and therefore plants the seeds to unlock other continents than North America as a talent base for the annual draft pools. Players with a European background find their way into the association more often than a few decades ago (Motomura, 2016). Players from South America, Asia and especially Africa project to catch up in the immediate future with the NBA pushing several basketball endeavors on the respective continents. The NBA recently installed development academies in global key locations (NBA Academy, 2020) and even helped to install a continental sister league in Africa (NBA - BAL, 2020). In the long run a larger global player base should increase the chances of having more star talent in every draft class. Yet, the distribution of these especially impactful athletes will always come down to luck. With chance being such a big factor, no policy adjustment is needed. The draft framework should take note of this issue, but still should continue in its idealistic way with treating every draft class the same.

4.5.2 VALUE IS IN THE EYE OF THE BEHOLDER

This second investigated hypothesis also holds in most regards. NBA managers proved themselves knowledgeable in the task of picking between players who are capable of playing in the league or those who are not. But to correctly evaluate useful players and determine who provides the most value from this group is still challenging to the league's teams. Franchises are far away from judging and selecting talent perfectly. This hurts the general premises of the policy.

Possible explanations for this circumstance seem endless. First and foremost, the concept of value is a complex topic to discuss in the realm of team sports. Even with the use of statistics to reduce the subjectivity in player evaluations complete objectivity can never be reached. Depending on the metric used different athletes can prove to be the most valuable player in a discipline. Since there is no overall agreed upon understanding of what actions truly contribute the most to winning basketball games in any given context and how to correctly measure them, faultless and complete objectivity is unattainable.

Furthermore, players can never be evaluated in a vacuum. The impact they provide is usually dependent on the environment they are in. Due to this point to judge a talents raw ability becomes an even more complex task. What skills does a player provide in a specific team context? Do their abilities scale within the organizational setup or are there diminishing returns with other colleagues? Will some factors hinder the development of the acquired player? Team specific variables like this tend to play a role and make accurate evaluations harder.

Additionally, the problem of correct foresight exists as well. Managers must evaluate players not only based on their current of idea of basketball but also on their view of the future of the sport. The discipline with ever evolving strategies, tactics and possible rules changes continuously changes over time. To have a perfect knowledge about the entire history of the discipline and the current state of the game provides some value in player evaluation. But without a reasonable anticipation of where the sport is going in the future, betting on talents can become dangerous as new league dynamics might incentivize playstyles that diminish the value of certain player types and vice versa.

Besides these very sport specific reasons, the lack in player evaluation ability sometimes is caused by psychological reasons that are well known from other fields. Wherever there are decisions, there tend to be biases, fallacies, and misconceptions at work, often worsening those calls of judgement and choices. In the NBA Draft world such issues have been of interest for many academics:

Research in the field usually investigates what pre-draft factors influence post-draft on-court performance. Moxley and Towne (2015) suggest age, college production and college quality as useful predictors for NBA success, while they consider physical attributes as overrated by managers or them being biased towards those player characteristics. Berri, Brook, and Fenn (2011) showed that age and basketball indicators like rebounds, steals and shooting efficiency marginally predict future NBA production of a player, while other variables like college team success and relative height do not influence the same target metric. By proving some of these factors to have no influence in predicting future performance of a player but on the draft position Berri, Brook, and Fenn (2011) point out potential managerial biases. Motomura (2016) presents evidence that a bias towards draft prospects with a non-American background existed. International players tended to outperform their draft position until managers (arguably even over-) adjusted selection behavior in this regard.

To sum up: Drafting is a skill. Based on the data the second hypothesis cannot be falsified. Though, there are two important points that are damaging to the results of this mechanism. First, teams are rather bad at drafting players. Second, over the past years the league's organizations have not shown signs of learning effects and improvement in the general ability to evaluate and select players within these dynamics. Hence, the results of the policy have not been getting closer to the goals it pursues.

The franchises need to improve their draft decision-making skills to raise overall outcome quality. To go back to the presented decision-making process model of Schoemaker and Russo (2006), huge potentials seem to be located within the third and fourth step of their approach. Managers do not tend to judge the available information correctly due to cognitive dissonances. Identifying more managerial biases as a root for these constant judgement errors on the league-level could potentially provide much needed improvement. Additionally, the two researchers have identified ‘learning from experience‘ as an important part of a recurring decision-making problem such as the NBA Draft. Our analysis showed that such learning effects are not impactful enough to change league-wide outcomes right now. It should be assumed that teams learn from their mistakes. But at the moment teams seem to still just play catchup as draft accuracy in terms of correlation between pick number and post-draft performance have not gotten significantly better over the past few decades. The everchanging environment of a developing sports discipline simply seems to present to many opportunities to make more decision-making mistakes after eradicating one error source from the past. More research on the topic could provide opportunity to close this gap in the future and gradually increase draft decision-making quality in the long run to improve the policy outcomes in the intended direction.

4.5.3 UNFORTUNATELY, NOT EVERYBODY IS EQUALLY BAD AT DRAFTING

The third hypothesis does not hold. Not all team organizations are able to convert the opportunities this regulation sets up for them. The caused problems for the overarching draft policy that emerge due to this dynamic are twofold. If weak teams constantly make bad decisions by drafting underachieving players in premier selection positions, they not only fail to give themselves the chance to improve in the long-term and close the gap towards the competition due to a much-needed talent infusion. They consequently also provide better teams with later draft selections with a chance of selecting stronger talents, which then might even increase the margin between the competing organizations, if these franchises select the misjudged high-quality players. This issue can even be magnified by other rules the league provides. Draft picks can be traded. Meaning a team contending for the title could even hold the first draft selection chance in the same year if they somehow acquired this draft pick in a trade with a recklessly run weak franchise. These mechanisms can cause outcomes totally contrary to the intended goals of the policy.

Creating the draft mechanism, the league did not account enough for 'the human factor' in general and especially the differences in managerial ability in the front offices. The draft aids weaker franchises with opportunities to turn their fortunes around by drafting great players. The logical error with this dynamic is that unsuccessful organizations tend to be poorly run from a management standpoint. For teams to lose many games in a season (disregarding less controllable factors like player injuries, strength of schedule etc.) front offices must have made bad talent evaluation decisions beforehand by e.g., hiring incompetent coaches or misjudging the quality of their added players for a longer period of time.

Interestingly, the draft policy expects those franchises in this new situation to suddenly possess positive talent evaluation capabilities and a functioning decision-making environment – abilities that these dysfunctional franchises often clearly lacked in the first place. Other research agrees with this identified core problem of the policy. Motomura, Roberts, Leeds, and Leeds (2016) found that the draft is not helping weaker franchises as much as it often appears due to the described dynamic.

We checked if we could find a link between bad draft decision-quality and the simplest measure for overall management performance in the NBA – constantly winning games. For this idea we looked over the overall win-loss-records of the drafting franchises over this timespan and brought this statistic into a format that makes it comparable to our variables that measured the quality of team's draft decisions. For wins we looked at how many victories a franchise produced per season and put it into relation with the expected average of 41 won games out of 82 regular season matches.

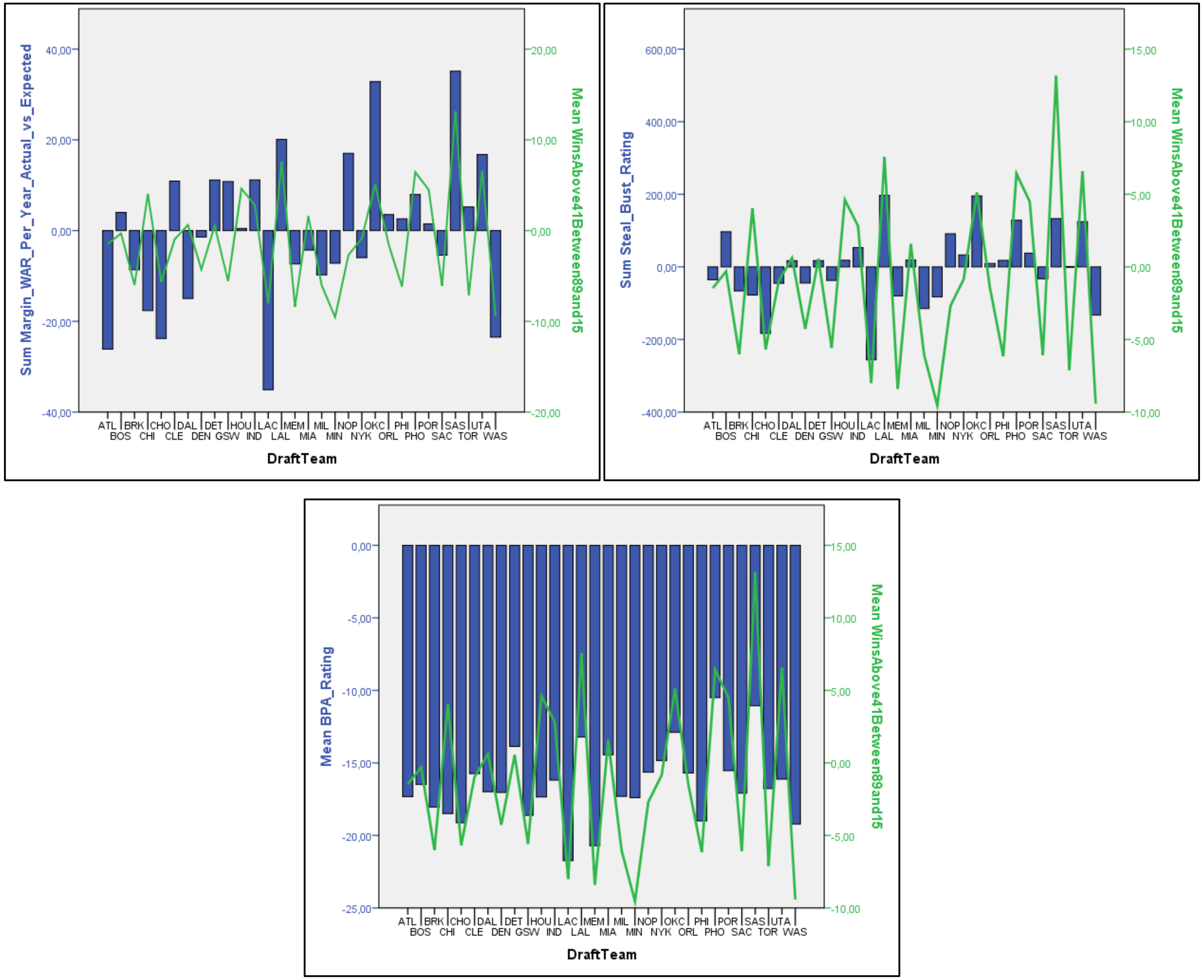

FIGURE 4-11. DRAFT DECISION QUALITY VERSUS HISTORICAL WINNING PERCENTAGE.

Plotted in one figure we can observe, with a few exceptions, that teams that drafted badly also performed below average in the simple win-loss-metric over the same time span. Testing for correlation, we found highly significant yet rather weak relationships between the win-loss-metric and the Expectation-Approach (r=0,104, sig.=0,000, N=1331), the Steal/Bust-Rating (r=0,137, sig.=0,000, N=1562) as well as the BPA-Rating (r=0,127, sig.=0,000, N=1516), respectively. Hence, the argument about poorly run organizations making bad draft decisions because of their overall lack of great managerial capabilities does not seem to be farfetched. But we are aware that these weak connections should not be overstated as logic also dictates that many more factors than drafting influence a team win total.

Still, revisiting the third hypothesis we conclude: The opportunities the league provides for weaker teams due to the policy are helpful. The crux is that each team must find its own unaided way to take advantage of them. But as we saw, most teams are drafting poorly, while a few good franchises seem to profit from the players the competition misses. For the league-wide policy to work better the decision-making quality regarding talent evaluation needs to increase dramatically. If every franchise would reach a certain threshold in this dimension the regulation would create outcomes closer to the intended results even acknowledging the fact that perfect draft decisions by all teams can never be expected. As we alluded to in the previous section, increasing draft-decision-quality is the key concerning this issue, though. Referring to the Schoemaker and Russo model (2006) such improvements could be reached by a more accurate problem definition, better intelligence gathering, more precise judgements and conclusions as well as more carefully extracted learnings from decisions of the past. In all these departments, further research could act as an aiding entity.

4.5.4 Conclusion - The NBA Draft is a valid policy suffering from inexact execution

NFL-coach Bill Parcell once called the draft 'an inexact science'. This figure of speech is often used in basketball circles as well (e.g., Kuo, 2019). As a reference to this famous quote, we want to call the NBA Draft a valid policy suffering from inexact execution. In this paper we evaluated the league installed mechanism on its general effectiveness by investigating the underlying assumptions of the association as hypotheses while comparing intended goals with actual results on a team-level. We found that the mechanism was found under somewhat faulty assumptions. In a theoretical world it would have the chance of working, fulfilling its intended aim of fair talent distribution. In practice 'the human factor' prevents the dynamic from producing the competitive balance-strengthening outcomes for which it was designed. Decision-making quality needs to be improved to allow more satisfying policy results under the current rules it operates under.

4.6 OUTLOOK

The NBA Draft mechanism needs improvement to increase its intended performance. All its failures are based on the faulty assumption, that the decision-making skills of the individual teams are sufficient, to constantly convert the opportunities the mechanism provides for the teams. We concluded that the decision-making quality of the managers needs to be enhanced to produce better policy outcomes. Further research must show which areas of improvement present the most promise. We want to suggest some interesting areas for potential advancements.

4.6.1 POTENTIALS FROM WITHIN

4.6.1.1 OUTCOME VS. PROCESS

According to Howard (1988) a good decision is "an action we take that is logically consistent with the alternatives we perceive, the information we have, and the preferences we feel" (p. 682) and therefore more than just its outcome. Thus, to truly enhance draft decision-making quality the process of the organizations making the draft choices needs to be analyzed more carefully to provide additional decision-context.

Especially if the goal is continuous decision-making success over the long-term improving process quality is key. By evaluating the typical NBA teams draft decision-making process using decision-making process models (Schoemaker & Russo 2006), future research could test league-wide franchise habits in the phases framing, intelligence-gathering, choice and learning from feedback in detail. Identifying problems or biases within those stages and then eliminating them could further leaguewide advancements and strengthen the policy in its current state.

4.6.1.2 NATURE VS. NURTURE

Research on the NBA Draft typically investigates environments players are coming from and what their performances in them can predict about their future development (e.g., Moxley & Towne 2015; Sailofsky 2018; Teramoto, Cross, Rieger, Maak & Willick, 2018). Hence, player development is usually only approached as a simple and constant process from a pre-draft perspective.

But it is most likely more complex than this. Positive developmental situations can possibly unlock abilities of a player other teams thought they would never have, while poorly run organizations might not be able to maximize all the abilities their draftee might possess. Nevertheless, proper research on this topic, which can be summarized under the umbrella of ‘nature versus nurture’, is lacking in the realm of basketball. We have found no articles that analyzes what environment players should get drafted into to optimize their development, even though we suspect draftee/team-fit to play a huge role in many cases. Advances in this direction could help franchises to have a clearer picture of player-performance-curves and how to better predict and possibly enhance them. Hence, talent evaluation und draft decision-making should improve and consequently strengthen the policy itself.

4.6.2 Potentials through making structural changes

All the discussed measures to improve decision-making quality are directly reliant on the NBA franchises and their managers improving their draft process. The league could just hope for them to further their own talent evaluation abilities. But the NBA could also find adjustments within the policy or the framework around it to refine the mechanism to achieve results closer to the intended goals. This does not necessarily mean to discuss a totally new system to navigate the talent influx of the league, as it has been done in many places now (e.g., Lowe, 2013; Jonke, 2014; Sharpe, 2018).

We only want to put up two points surrounding the existing dynamic for debate. If the goal of the policy is competitive balance, the league could think about excluding playoff teams from the draft and the player pool it is drawing from completely. This modification of the current system would make the draft a sole catching-up opportunity. Second, the administration could emphasize the importance of the policy by requiring its franchises to invest more resources towards the process by rule. Forcing teams to e.g., employ a certain number of draft experts while providing them with a determined budget could be such a requirement. We are aware that just committing resources to a task does not necessarily lead to quality improvement. But raising the franchises awareness for the importance of the draft, could guide the teams to better decision-making, like an effective policy should.

NOTES

1. We edited this information in two ways. First, we accorded for franchise movements and name changes. Draft history was assigned with this logic to the current setup of teams in the league. Second, we accounted for draft day trades and edited the data base based on the RealGM transaction page according to the season (RealGM, 2019).
2. WAR = [[BPM - (-2.0)] * (% of possessions played) * (team games/82) * 2.7].
3. At this point one can argue that measures of league-wide uncertainty of outcome as another immensely important measure of draft outcome should be discussed as well. Especially regarding the analysis of the general effectiveness of the entire policy, investigating uncertainty of outcome on the match or even season level would be a very interesting. We chose against these measures on a more global, league-wide level and opted to focus on team-individual choices. Decision-making effects on this level do not need to be isolated from other policies like the salary cap, which is also supposed to increase the uncertainty of outcome measures within the league setup. Such work would go beyond the scope of this article, which has the draft decision-making process at its center of interest but would lend a very intriguing starting point for additional research.
4. As explained in 4.1, VORP is based on the rate statistic BPM for player quality informed by playing time. It can be simply converted to WAR, a metric that shows how many wins a player provided for their team.
5. Best Player Available.
6. These teams' best players had a regular season WAR of 9.72, 9.99 and 9.99.

CHAPTER 5

ANCHORING BIAS IN THE EVALUATION OF BASKETBALL PLAYERS – A CLOSER LOOK AT NBA DRAFT DECISION-MAKING

STUDY II

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5. STUDY II: ANCHORING BIAS IN THE EVALUATION OF BASKETBALL PLAYERS

ABSTRACT

The NBA installed the draft-mechanism to fairly distribute young amateur players among its franchises. As this policy hinges on appropriate talent evaluation skills of the respective organizations, it can be considered a proxy for decision-making under uncertainty. Such judgements are prone to fallacies and systemic mistakes. The article found the RSCI-rank as a problematic metric which is the source for systematic draft errors. It can be shown, in many cases managers do not deviate enough from the pre-draft rankings of players, leading to systematically over- and undervaluing certain groups of talents. This can be described as a decision-quality-lowering anchoring bias.

5.1 INTRODUCTION

The NBA Draft is a mechanism to regulate competitive balance of a sports league. Its goal - to give the weak franchises an opportunity to acquire young players and close the on-field talent gap to their stronger competitors as those prospects develop over time - is clear and noble. In theory the policy creates value for NBA's product by distributing league-entering player capital equally in two important ways. First, such a mechanism is potentially beneficial for the general quality of play within the league by steadily improving the talent level among all participating teams. This increases interest in the product as star players and elite performances seem to drive revenues (Hausman & Leonard, 1997; Berri, Schmidt & Brook, 2004). More importantly the competitive balance among all competitors is theoretically strengthened as well, resulting in a higher uncertainty of outcome on a game and season-level. These two outcomes have been deemed important managerial goals for sports league administrations for decades (Rottenberg, 1956).

Elite quality of play and high uncertainty of outcome increase the attractiveness of the entertainment service the NBA offers and hence should help to maximize profits for the league and its franchises. While other dynamics like the salary cap-rules also contribute to the achievement of these favorable outcomes, ensuring that the draft mechanism performs optimally should be a major priority for the league and its team organizations. It promises huge benefits for all parties involved.

Such positive results are hardly reached on a constant basis. The crux of the draft is the nature of the mechanism itself and the people making the decisions. To reach the intended results, all

NBA managers need to constantly seize the opportunity the NBA Draft provides them with. Unfortunately, this is an incredibly complex expectation to have within the realm of sports. The acting decision-makers in the draft environment are mostly forced to make choices without known variance, but among alternatives with widely unknown outcomes. Therefore, the draft mechanism can be treated as a proxy for decisions under uncertainty (Mishra, Barclay & Sparks, 2017).

Draft decision-makers go through a very complex process to find the best option for their teams. Ultimately such managers must carry out multiple immensely difficult judgements correctly to maximize the potential value of their decision. They do not only have to judge who the best prospect at the moment of the draft is, but also have to anticipate who might possess the most room to grow as a basketball player. Furthermore, managers need to evaluate if their particular organization has the capabilities to enable ideal development for the picked talent (Beene, 2019). Additionally (among considering other external factors) forecasting the direction in which the sport itself is moving in the long-term is key, since the parameters their draftees need to perform can change over time and therefore have influence on the value of an athlete. This opens the door for individual failures due to personal misconceptions or misjudgments by the managers and provides room for systematic errors on a leaguewide level caused by collective decision-making biases (Sailofsky, 2018).

Over the past few decades many efforts have been made to improve draft decision-making quality and produce the favorable outcomes the draft mechanism intends to achieve. Still, the mechanism fails to reach those goals constantly, even though they prove to be beneficial for all league organizations. Research has shown that solely building up a franchise through the draft does not work yet, because the decision-making of most of the franchise executives is questionable (Berri, 2013; Motomura, 2016). Furthermore, the NBA has been proven to be the most imbalanced of all the North American sports leagues historically (Soebbing & Mason, 2009). This state of the association to a large extent can be based on the rather poor draft decision-making quality besides e.g., salary cap-induced factors (Totty & Owens, 2011).

In this paper we will investigate the NBA Draft policy as a proxy for decision-making under uncertainty. The main goal of this paper is to analyze the underlying judgement process and provide an opportunity to increase decision-making quality. Improvements within this dimension should help the draft mechanism to produce its intended outcomes. This result benefits the league as well as all its franchises. Since theory suggests that errors in human judgement pose huge problems to this complex dynamic, investigating a particular decision-making bias or fallacy seems to be necessary, considering the aim of the paper. Considering the research already performed within the draft environment, we decided to investigate possible anchoring bias-effects in the decision-making of franchises.

5.2 BACKGROUND, RELATED LITERATURE, AND MODELS

5.2.1 THE NBA DRAFT MECHANISM

The draft is an annual event which brings amateur basketball players from North American colleges and international clubs into the association. Since franchises do not run youth teams to develop future players like e.g., European soccer clubs do, this talent-infusion-and-resource-delivery-apparatus is much needed. To be part of a given yearly draft pool, interested players only need to meet certain age criteria and send a letter of intend to the league's office (NBA & NBPA, 2017). In between seasons NBA teams then can draft two players of this select group of individuals every year on a set date. To 'draft' a player gives a franchise the exclusive right to offer the draftee their first NBA contract. If a drafted player, then has the intention to join the league, they can only sign with the organization which acquired their rights (NBA & NBPA, 2017).

Franchise success in the most recent season determines the order in which the teams select from the draft eligible players. The winningest team gets the 30th pick of every draft round, the second-best organization holds the 29th selection and so forth. Only the order of first four draft selections is resolved through a weighted lottery system. All non-playoff teams of a given year are part of this lottery process and assigned fixed probabilities to receive such a premier selection opportunity based on their win-loss record. The stronger the team, the lower the chances for such a premier selection opportunity (NBA, 2020a).

5.2.2 THE NBA DRAFT POLICY AND ITS SHORTCOMINGS

The draft as a regulating sports mechanism has drawn an increasing amount of research attention. The dynamic is an integral dynamic of North American major leagues with great influence on their entertainment products offered and revenues generated due to the close relationship with quality of play and uncertainty of outcome (e.g., Rottenberg, 1956; Soebbing & Mason, 2009). Hence, it has been investigated in many environments. Researchers mostly analyze the structure as well as the decision-making within the process or look for inefficiencies from an economic standpoint. Papers on the draft can be found for the NHL (e.g., Tingling, Masri & Martell, 2011; Deaner, Lowen & Cobley, 2013), the MLB (e.g., Caporale & Collier, 2013; Sims & Addona, 2016), the NFL (e.g., Hendricks, DeBrock & Koenker, 2003; Massey & Thaler, 2013) and the WNBA (e.g., Harris & Berri, 2015; Hendrick, 2016).

First structural criticism of the NBA draft mechanism and the need to improve the underlying decision occurred in the 1980s (Burkow & Slaughter, 1981). Since then, research agrees upon the fact that the policy itself is valid and provides a framework to produce beneficial outcomes for the league and all its members. Yet, the mechanism fails to generate its intended results due to poor managerial decision-making. Managers are simply not able to constantly seize the opportunities the draft presents them with. Most of the drafting organizations seem to lack proper talent evaluation abilities (Berri, Brook & Fenn, 2011) and are prone to several judgement biases within this concrete setup (Sailofsky, 2018).

To correct this dissonance within the policy and reach its intended goals the baseline-competency of the decision-makers needs to be raised on a league-wide basis (Motomura, Roberts, Leeds, & Leeds, 2016). To improve holistically ideally systemic errors, fallacies and biases in the general process must be identified. The insights gained give the chance to correct disadvantageous behavior and increase the decision-making quality, which holds much value for all parties involved.

Following this conclusion, researchers have been exploring the draft policy outcomes from a judgement and behavioral economics perspective for a long time now. Many biases have been observed within the NBA Draft environment: Among the cognitive dissonances explored and identified were biases caused by nationality (Motomura, 2016), recency and availability (Berri, Brook & Fenn, 2011; Ichniowski & Preston, 2012), college background (Burdekin & Van, 2018), height regarding the position played as well as age as a marker for unfulfilled potential (Groothius, Hill & Perri, 2007; Berri & Schmidt, 2010; Ashley, 2017). Most of these decision-making fallacies are classic behavioral economic mechanisms within complex and uncertain judgement environments as they have been found on various fields based on fundamental psychological principles (Tversky & Kahneman, 1974).

5.2.3 Anchoring and the NBA Draft

The investigation of anchoring as a psychological effect in decision-making dates back at least until the midpoint of the last century (Sherif, Taub & Hovland, 1958), though the notion of it appeared in psychophysics well before that (Cohen, 1937). This cognitive bias occurs when a subject is presented a certain piece of information and then tends to value this portion of data too heavily in the judgement process of a decision-making problem which takes place afterwards (Kahneman, 2012). Interestingly, research has shown, the initially presented value does not necessarily have to be strongly connected to the choice entity to have an influence (Tversky & Kahneman, 1974).

Tversky and Kahneman (1971) proclaim every information - unless promptly considered as total nonsense or a lie - to have some impact on a deciding person. Even if this subject is aware of the power of anchoring it is impossible to disregard the information received. The state of mind without the set anchor is unattainable all the sudden. Even experts and professionals, who should be immune to such effects, can be clouded in their judgement because of anchoring dynamics as studies e.g., in the field of real estate revealed (Northcraft & Neale, 1987).

How exactly this dynamic influences decision-makers in their choice-process is debated extensively among scientists. Some experts believe anchoring to cause an adjustment mechanism. The initial information sets a marker, and the decision-maker then slowly moves away from it until a certain deviation feels satisfactory. Depending on the rationality in adjusting and the quality of the anchor, this can even lead to a useful decision dynamic (Lieder, Griffiths, Huys & Goodman, 2018). However, insufficient adjustments within the mechanism consequently constitute a bias.

A different view considers anchoring foremost a priming effect. After being exposed to the anchor decision-makers tend to look for information which relates to or confirms the data with which they were initially presented. Such priming can be numeric as well as semantic in nature (Strack, Bahník & Mussweiler, 2016). Systematic errors in this approach are caused by selective intelligence gathering and judgement. Research on the topic has proven both perspectives to be valid depending on the environment (Adjustment-based view: e.g., Epley & Gilovich, 2004; LeBoeuf & Shafir, 2006; Priming-based view: e.g., Mussweiler & Strack, 1999a, 1999b).

Research has shown that such ordering and ranking of choice options can produce anchoring-effects that influence the decision-makers in their judgement. Evidence for anchoring ranking-effects can be found in the music sector (Salganik, Dodds & Watts, 2006) the field of university reputation (Bowman & Bastedo, 2011) and sports in general (Keefer, 2016). Therefore, this dynamic should be applicable to the NBA environment.

To our knowledge, anchoring as a bias-causing mechanism has not been explored yet in the NBA Draft policy context. This is surprising to us, since the draft environment yields all the elements that can cause this phenomenon. It is a complex decision-problem within an uncertain environment. Rankings and categorizations of the basketball players as the alternatives of this difficult choice problem are omnipresent (e.g., RSCIHoops, 2021; ESPN, 2021; ToTheMean, 2021). Especially the high school-ranking is a widely used data point for draft prospects, which measures their basketball reputation and performances compared to their peers during the last year of primary education. Recruiting Services Consensus Index (RSCI)-rank [1] fits perfectly right into the common understanding of reputation, which is defined as "the history of […] previously observed actions" (Wilson, 1985, p.28).

For the NFL research has shown, that such RSCI-reputation heavily influences managerial decision-making in the draft process (Lourim, 2019). Therefore, a similar connection in the comparable policy environment of the NBA Draft should be tested, as such an effect could prove harmful for the overall draft policy and its intended outcomes.

5.2.4 RESEARCH DESIGN & HYPOTHESES

Based on the evidence and discussion presented above, we suspect a potentially policy-outcome-harming effect of high school-rankings within the setup of the NBA Draft regulation. Consequently, in this paper we want to investigate such a possible connection. This general arrangement that derives from the literature does not only follow the principles that cause ranking-effects in the literature (e.g., Salganik, Dodds & Watts, 2006; Bowman & Bastedo, 2011; Keefer, 2016). It additionally has been observed in this particular fashion in the very comparable NFL Draft-environment (Lourim, 2019).

RSCI-rank, as a measure of the reputation of players during their high school years among several player evaluation portals, is a piece of information that could clearly act as an anchor in the evaluation process of general managers. As NBA managers constantly collect information on draftable talents, they can hardly avoid such priming details on the prospects. As laid out earlier, no matter if the RSCI details are actively used in the decision-process or not, once exposed to the information it influences the judgments nevertheless as managers cannot erase it from their minds. Such dynamic can be possibly harmful if there is a disconnect between the pre-draft reputation of players and the actual post-draft value they propose for their teams. With reputation being defined as the sum of previous actions (Wilson, 1985) the effect of unwarranted reputations should wear off over time, as new information due to new actions overwrite and correct earlier evaluations continuously.

To analyze the impact on the intended results of the overarching NBA Draft policy, the utility derived from picks needs to be examined. As a measure of draft decision-making quality -the metric that needs to be maximized to guarantee ideal policy outcomes - we examine the difference between the managerial choices and the perfect decision in retrospect. We will add individual college-performance in the form of “Win Shares”[2] as a controlling variable for all further presented avenues of thought. Research has shown pre-draft performance to be an important factor in the draft dynamic (e.g., Coates & Oguntimein, 2010; Berri, Brook & Fenn, 2011). Hence, it should be logical that such an impact-metric should affect managerial decision-making in all our examined instances as well. Controlling for it in all our calculations allows us to measure what additional impact on the dependent variables might be caused by the RSCI-ranking and insufficient adjustment to it. Following the foundational theory and literature, found effects would point towards anchoring dynamics.

Therefore, we arrive at the following main hypothesis for this paper:

H: *Insufficient adjustments to RSCI-rank-induced reputation influence the quality of draft decision-making.*

Such a potential effect would be apparent, if managers fail to adjust properly in response to a misrepresenting RSCI-rank and the managerial draft-decision-quality was influenced. Hence, we arrived at this estimated equation with pre-draft experience as a measure of time between the reputation giving RSCI-high school ranking and the moment of the draft of the players. College performance is added as a controlling term.

$$DraftDecisionQuality = \beta_0 + \beta_1\, RSCIRankAdjustment + \beta_2\, PreDraftExperience + \beta_3\, CollegePerformance$$

Yet, to test this main hypothesis several sub-hypotheses need to be investigated. The theory-derived major inference that RSCI-induced anchoring effects influence the managerial draft decision-making is based on three minor assumptions. The anchoring in the NBA Draft policy setup can only occur if the RSCI rank has influence (A) on the general draft-status and (B) the draft-rank, but (C) is not necessarily linked to post-draft NBA performance and therefore creating a problematic cognitive dissonance.

Building on these three assumptions, we created sub-hypotheses with estimated equations we will investigate before testing the main theory. Again, college performance is controlled for in all equations to better be able to isolate possibly RSCI-based effects.

H1A: The higher basketball players were ranked in the RSCI, the higher are their chances of getting drafted.

$$DraftStatus = \beta_0 + \beta_1\, RSCIRank + \beta_2\, CollegePerformance$$

H1B: The higher basketball players were ranked in the RSCI, the earlier they are selected in the draft.

$$DraftRank = \beta_0 + \beta_1\, RSCIRank + \beta_2\, CollegePerformance$$

H1C: The higher basketball players were ranked in the RSCI, the better they perform in the NBA.

$$PostDraftPerformance = \beta_0 + \beta_1\, RSCIRank + \beta_2\, CollegePerformance$$

To conclude, by testing the main hypothesis with the three sub-hypotheses we can potentially uncover a bias within the process of the NBA Draft policy caused by insufficient adjustment to the possibly priming high school-rankings. Identifying and decreasing harming anchoring effects could lead to improvement in the draft decision-making quality and strengthen the overall policy.

5.3 METHODOLOGY & DATA

5.3.1 THE DATA SET

The website 'Basketball-Reference' was used as a source for all the high school-ranking and draft-data (Basketball-Reference, 2020b). We scraped the data of all recruiting classes from 1998 to 2015 (N = 1800). 2015 was used as the end point of the investigated time frame because we only wanted to look at prospects who already had the chance to establish themselves in the league. Usually players hit their peak-performances after about four to five years depending on their age of league entry (Vaci, Cocić, Gula & Bilalić, 2019). We wanted to provide our observed draft prospects with this time.

The collected cases include pre-draft information (name, Recruiting-Services-Consensus-Index-Rank (RSCI-Rank), CBB-WS (Win Shares in college) etc.), draft-day data (draft-spot, draft-team, year of league-entry etc.) and post-draft metrics (last season played in league, NBA-WS). The ongoing nature of the dataset is an important limitation we want to point out. While retired players cannot change their body of work, active players still have the chance to improve their total numbers. The data was scraped in August 2019 and will mostly use season-average numbers rather than cumulative information to account for this constraint.

5.3.1.1 PRE-DRAFT-REPUTATION-METRIC

'RSCI' collects the ranking-data of many well-known and accepted high school-ranking-services and builds its own list by averaging out the player evaluations of all outlets. The results provide a yearly consensus overview for the allegedly best 100 basketball players in the US (Basketball-Reference, 2020b). This metric gives a general idea about the perceived basketball-ability relevant players presented during their final high school-season compared to their peers on a national level. To be rated on such a list and by that gain the reputation of being a promising talent helps a player to receive scholarship offers by colleges and draft interest by NBA teams. There is evidence for higher ranks to lead to proposals by more successful institutions and to predict college basketball-performance well (Moore, 2014).

5.3.1.2 PLAYER-PERFORMANCE-METRICS

'Win Shares' (WS) shows how much influence a player's sporting-performance had on the success of their team. WS are an appealing metric because it calculates the share individual players contributed to their team's wins based on very comparable box-score-statistics. Added up, the WS-values of all active players of a team over an 82-game season [3] give the actual number of wins achieved by the franchise (with a deviation of ~2.74 games). This makes it possible to extrapolate exactly which athlete contributed what share to the achieved sporting-performance. For example, if a player has a WS-value of 5.0, their on-court-performance was worth about five wins for their team over this season.

This statistic has problems evaluating certain facets of the sport and therefore does not paint the most nuanced picture regarding player-value since it only uses basic boxscore-data. But this fact also makes it appealing to work within a historical context. Due to the lack of complex components, it can be calculated for players of many decades and allows to easily compare athletes no matter the era or on-court role they played in (Basketball-Reference, 2020c). Broad player-quality-levels are comparable if we take the average WS-outputs and control for college or NBA environment and their respective playing time in terms of games or years played, respectively.

To look deeper into the matter for the NBA, we converted this performance metric into a new variable for player-level which captures the impact an athlete has on the basketball-court based on the WS-measures combined with a well-accepted tier-grouping-system (Paine & Bradshaw, 2015). We put every drafted player with recorded playing time into one of six categories, rating their performance following certain thresholds in the WS/Year-metric. [4]

5.3.1.3 DRAFT DECISION-MAKING QUALITY METRIC

To measure draft decision-making quality, we needed to establish a new variable (Over-Under—Drafted-Rating (OUDR)) which represents whether a prospect selected too early (overdrafted) or too late (underdrafted) in relation to their post-draft-performances. We looked at all the drafts from 1998 to 2015 and sorted the classes retroperspectively into their perfect order according to WS/Year as our performance measure. We averaged out all the years with this optimal-order-approach to determine a historically derived expected-performance-mean for every draft-position. Combining this value with our 'Player-Level'-categorization, we see how many players of each tier were in the average draft over the investigated timeframe and in what range they would have been picked if teams selected perfectly.

TABLE 5-1. AVERAGE PLAYER-LEVEL THRESHOLDS ASSUMING PERFECT DRAFT ORDER.

Player-Level	Average Group-Size in Draft	Corresponding Draft Region
Superstar (> 7 WS/Y)	1	1
Star (6,99 - 5 WS/Y)	3	2-4
Starter (4,99 - 3 WS/Y)	8	5-12
Roleplayer (2,99 - 1 WS/Y)	17	13-29
Replacement Level (0,99 - 0 WS/Y)	15	30-44
Negative Players (< 0 WS/Y)	16	45-60

We then used these values to determine whether a player in our dataset was over-, under-, or correctly drafted given their actual post-draft-performance and the range in which they were picked. Prospects were rated on a centralized scale. We coded 0 as neutral and then went in both directions depending how many tiers a player was off from the expected player-level according to their draft-spot. If a roleplayer-level athlete offering 1.5 WS/Y got drafted in a spot where a star would be expected (e.g., #4), a '-2' gets assigned because of the two-tier difference between expectation and actual performance. A deviation in this direction marks a talent as overdrafted. On the flipside, we would give a superstar player producing 7,5 WS/Y having been drafted in the replacement-level region (e.g., #41) a '3' for the exact same reason. This identifies him as vastly underdrafted.

5.3.2 Research method

The goal of our research design is to test causal effects. Therefore, we implement regression methods to verify if and to what degree our target-variables are connected. Given our ambition to control for college performance in each of our estimated equations we opted for a hierarchical multiple regression-approach. This method allows to measure the impact of single variables or new variable terms by adding them in a stepwise fashion to another model. Such a setup proves to be beneficial for the testing of all proposed hypotheses.

5.4 EMPIRICAL ANALYSIS

5.4.1 RSCI-Rank and Draft-Status

To see if the RSCI identifies relevant players for the draft process of NBA teams, an investigation of the draft-status of all listed players is necessary. Between 1998 and 2015 513 RSCI-ranked high school players (N = 1800) were drafted. If we consider that only 60 draft-spots are available every year and that on average 13,6 non-American players (who cannot appear in the US-based RSCI) got drafted annually over the observed time period, players from the consensus high school listing filled about 62% of all available draft-spots. Consequently, the RSCI can be considered helpful in terms of the draft process. The rankings identify many players who are on the radar of NBA decision-makers.

To dive deeper into the data, we can explore how the ratio of players getting drafted changes as we go up in the RSCI-rankings. In theory, players with a higher listing should get drafted more often as such placements suggest that these players possess superior basketball skills. Therefore, these talents should provide more long-term value for NBA teams and should be picked earlier in a draft scenario. For our analysis we divided the top 100 of every RSCI class into six levels and checked the draft-status of these subcategories.

TABLE 5-2. RSCI-RANK VERSUS DRAFT-STATUS.

RSCI-Rank	Players with Draft-Status "Drafted"	Percentage with Draft-Status "Drafted"
100-80	45	11.9
79-60	50	13.9
59-40	62	17.2
39-20	120	33.3
19-10	102	56.7
9-1	134	82.7

Table 1 shows, the RSCI identifies basketball talent in high school players well assuming NBA managers have some skill in selecting the players. The higher the RSCI-rank of a player the higher the general chance of being selected by a franchise decision-maker. This conclusion aligns well with our expectations. Though, the link between RSCI-rank and draft-status does not seem to follow a linear correlation but rather appears to be exponential. The difference between the ranks regarding getting drafted increases only slowly at first but seems to grow more steeply moving up the list.

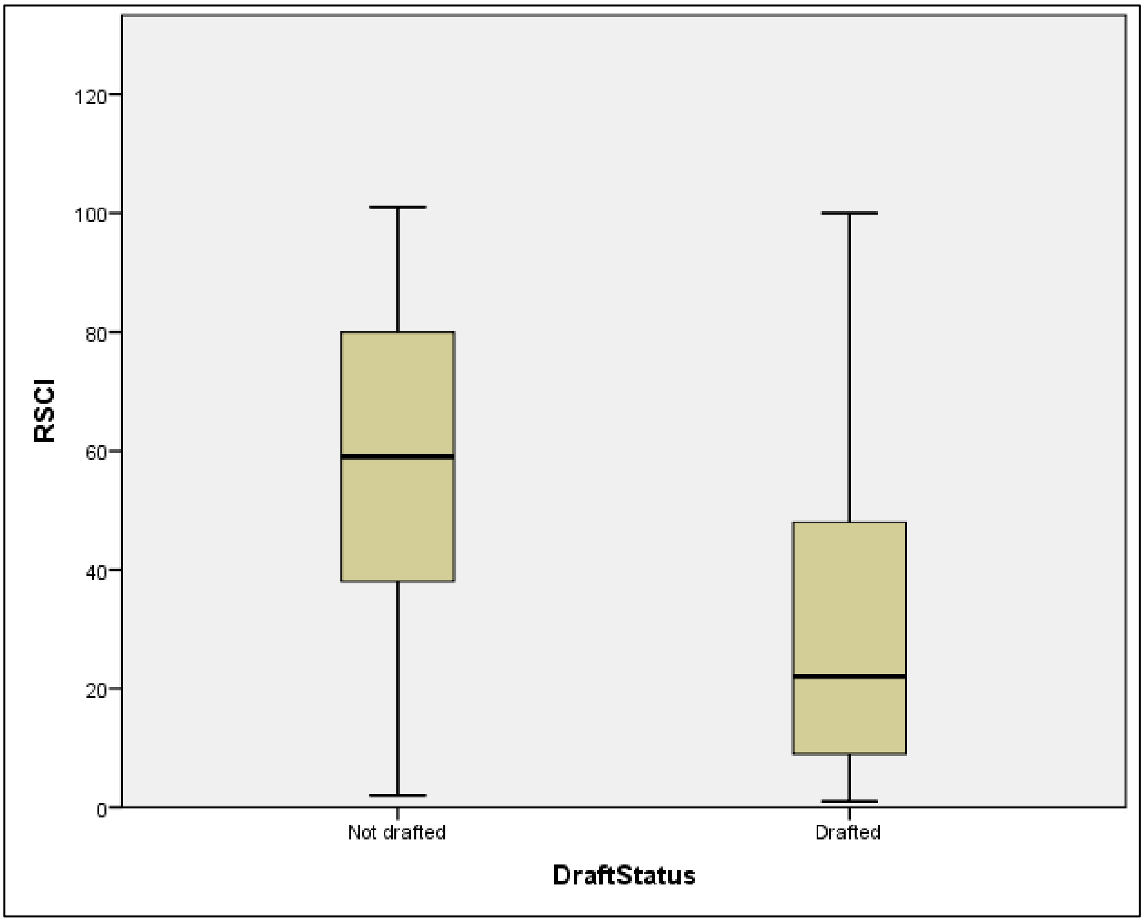

FIGURE 5-1. BOXPLOTS OF RSCI RANK VERSUS DRAFT STATUS.

The boxplots show, basically no particular ranking in the RSCI guarantees being drafted. Over the investigated time only the #1 ranked talent was selected in the draft every time. On the other hand, figure 1 also indicates that drafted prospects tend to have received a higher RSCI-rank.

We can test for a simple connection between the ordinal-scaled RSCI and the binary variable for draft-status using the point-biserial correlation. A highly significant Pearson's r of -0.417 suggests a medium-sized connection between the RSCI and the draft-status variable in the direction we estimated. As the values of the RSCI get lower (or therefore the ranking of the athletes in the lists gets higher), the more likely the membership in the group with the 'drafted'-status becomes.

Afterwards, we applied a multiple linear regression model for 'general draft status' as the dependent variable. To be able to isolate potential effects better, we controlled for the possibly draft selection behavior-influencing 'pre-draft college-performance' by using a hierarchical approach in the construct. RSCI-rank was also used as an independent variable.

TABLE 5-3. HIERARCHICAL MULTIPLE LINEAR REGRESSION MODEL FOR RSCI-RANK AND DRAFT-STATUS.

		Unstandardized Coefficients		Standardized Coefficients		
Model	Component	B	Std. Error	Beta	t	Sig.
1[a]	(Constant)	-0.229	0.020		-11.444	0.000
	CBB WS per Game	5.959	0.207	0.571	28.727	0.000
2[b]	(Constant)	0.038	0.030		1.248	0.212
	CBB WS per Game	5.039	0.215	0.483	23.401	0.000
	RSCI-Rank	-0.004	0.000	-0.237	-11.505	0.000

a. Variable entered on step 1: CBB WS per game.
b. Variable entered on step 2: RSCI-Rank.

We were able to use 1709 complete cases for our analyses. Both models proved to be significant on a 0.000-level. The addition of the RSCI-rank leads to an improvement of the Adjusted R^2 from 0.325 to 0.374, which is a meaningful increase in explained variance within the chosen setup. Looking at the single component loadings, we can examine that as expected, pre-draft performance significantly influences if a prospect gets drafted at all in the positive direction. Interestingly, RSCI-ranking likewise contributes in a highly significant way to the model, proposing that while controlling for pre-draft performance, the players with better high school reputation are preferably drafted. The loading of the coefficient shows that with an increasing ranking number the likelihood of getting drafted at all is decreasing. This lets us falsify the H1A0. RSCI-rank has a positive effect on draft-status. We conclude, players ranked higher in the RSCI are more likely to get drafted.

5.4.2 RSCI-RANK AND DRAFT-RANK

We next examine whether high school praise through ranking services not only helps talents to get drafted but leads to being selected earlier in a draft scenario:

TABLE 5-4. RSCI-RANK VERSUS DRAFT-SPOT.

RSCI-Rank	N	Average RSCI-Rank	Average Draft-Spot	Minimum Draft-Spot	Maximum Draft-Spot
100-80	45	91.4	32.5	2	60
79-60	50	69.6	29.3	2	58
59-40	62	49.4	28.2	2	58
39-20	120	28.0	29.3	3	58
19-10	102	14.5	27.8	1	58
9-1	134	4.7	15.2	1	49

On the surface-level the RSCI-rank affects future draft position only marginally. All the observed categories present an average draft-spot of about 30 which marks the halfway-point of the two-round-draft mechanism which has been taking place over the observed timespan. Only for the RSCI top 9 we found a meaningful difference in average draft-spot. The minimum and maximum draft-spot values for the RSCI levels reinforce this idea. Over the investigated period there have been future NBA top 3 picks from every region of the RSCI. In the same vein, a top high school-ranking does not prevent athletes from falling deep into the second draft round if they are selected at all.

We can conclude, the general RSCI-ranking outside of the top 9 does not appear to influence future draft position in a significant way. But there might be circumstances where a ranking effect have a stronger influence on the draft-spot. Being marked as a basketball prodigy coming out of high school generates attention by the media. We can call this hype as a form of reputation and assume, the more years there are between coming out of high school, going to college, and then entering the draft, the less the RSCI reputation should help a prospect. We can test for this reputation-using behavior in the data.

TABLE 5-5. RSCI-RANK AND DRAFT-SPOT BY COLLEGE EXPERIENCE.

Pre-Draft Experience in Years	N	Average RSCI-Rank	Average Draft-Spot	Minimum Draft-Spot	Maximum Draft-Spot
5 years	17	55.7	40.9	20	60
4 years	124	46.8	35.9	5	60
3 years	110	39.6	26.0	2	60
2 years	115	27.9	22.2	1	56
1 year	114	13.6	16.1	1	51
0 years*	33	8.1	20.1	1	56

Note:
* Getting drafted right out of high school was only an option until 2006. The NBA later installed a rule which forbids this possibility until today.

Table 4 shows, drafted players with a higher RSCI-rank tend to have left college earlier. They additionally are more likely to get selected in higher draft-spots. On the flipside lower-ranked RSCI high schoolers attend college longer and get drafted lower than their peers. Reputation effects among other factors could explain such findings. While top-ranked prospects are on the NBA draft radar right away due to hype-generated name recognition and being more likely to play for an elite basketball college with many televised games and other media exposure (Moore, 2014), lower-ranked talents need to stay in the NCAA environment longer to play themselves into consideration for a draft selection.

To further tested this notion, we coded pre-draft experience into the six categories used in table 4 and added the 'not drafted'-status.

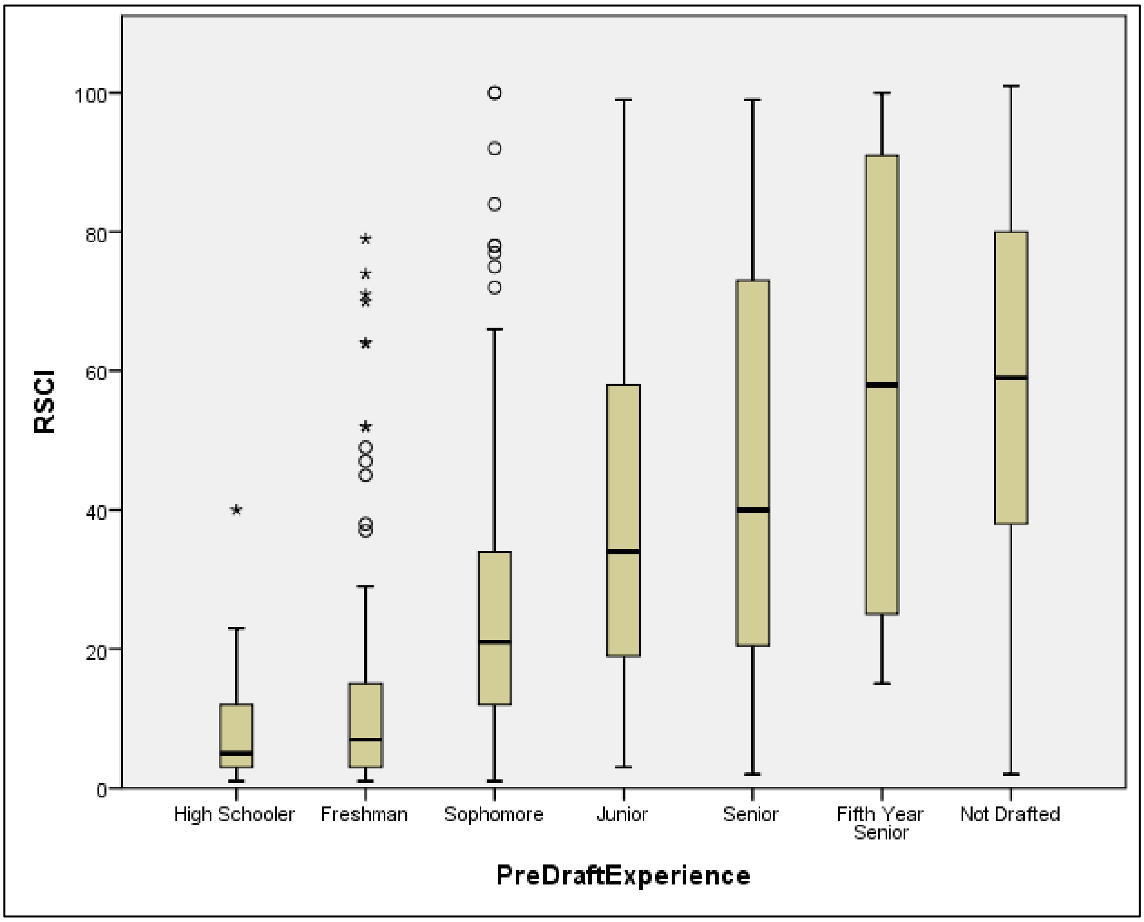

FIGURE 5-2. BOXPLOTS OF RSCI RANK VERSUS PRE-DRAFT EXPERIENCE.

The boxplots for the pre-draft experience categories indicate, a higher ranking in the RSCI makes it more likely to leave college early for the NBA draft (or never attend it at all for that matter), borrowing a few outliers. In contrast, the lower the RSCI-rank, the more likely an athlete is to not get drafted at all. To verify these sentiments, we performed an ordinal regression by running the RSCI-rank as covariate against the established pre-draft experience variable, to see if it could predict when a drafted prospect had entered the draft. We found a significant model (N = 513, Chi-Square = 150.19, p = 0.000):

TABLE 5-6. PARAMETERS RSCI-RANK VERSUS PRE-DRAFT EXPERIENCE.

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Threshold	High Schooler	-1.862	.195	91.050	1	.000	-2.245	-1.480
	Freshman	.099	.129	.587	1	.444	-.154	.351
	Sophomore	1.283	.139	85.654	1	.000	1.011	1.555
	Junior	2.430	.170	204.659	1	.000	2.097	2.763
	Senior	5.160	.315	269.075	1	.000	4.543	5.776
Location	RSCI-rank	.038	.003	130.399	1	.000	.032	.045

Note:
Link function: Logit.

The test shows, the higher the RSCI-rank of a talent the more likely they are to get drafted after fewer years. Being listed lower in the RSCI makes it more likely to attend college for more than one year before getting drafted. This underlines the idea that RSCI has some valid predictable power for when a prospect leaves to get drafted. The Nagelkerke R2 for the observed circumstance of 0,264 indicates a respectable connection.

This general dynamic of higher-ranked players leaving earlier to enter the draft might be totally justified if both RSCI-rankings and draft selections were performed perfectly. Naturally, the best players would be ranked and drafted highly. To see if any reputation-caused effects lead to systematic errors, we need to check for post-draft performance. We will do this in the following section.

Beforehand we need to examine if RSCI-rank also influences the spot at which prospects get selected in the draft. To investigate this link, we look at the Spearman rank correlation coefficient for this relationship of variables. The highly significant rho of 0,349 translates into a small-sized correlation between the two variables. This relationship shows, within the group of drafted players a higher RSCI-rank does correlate with a higher spot in the NBA draft.

To even do further testing we coded the regions of the NBA draft into five categories and looked at the corresponding RSCI-ranks:

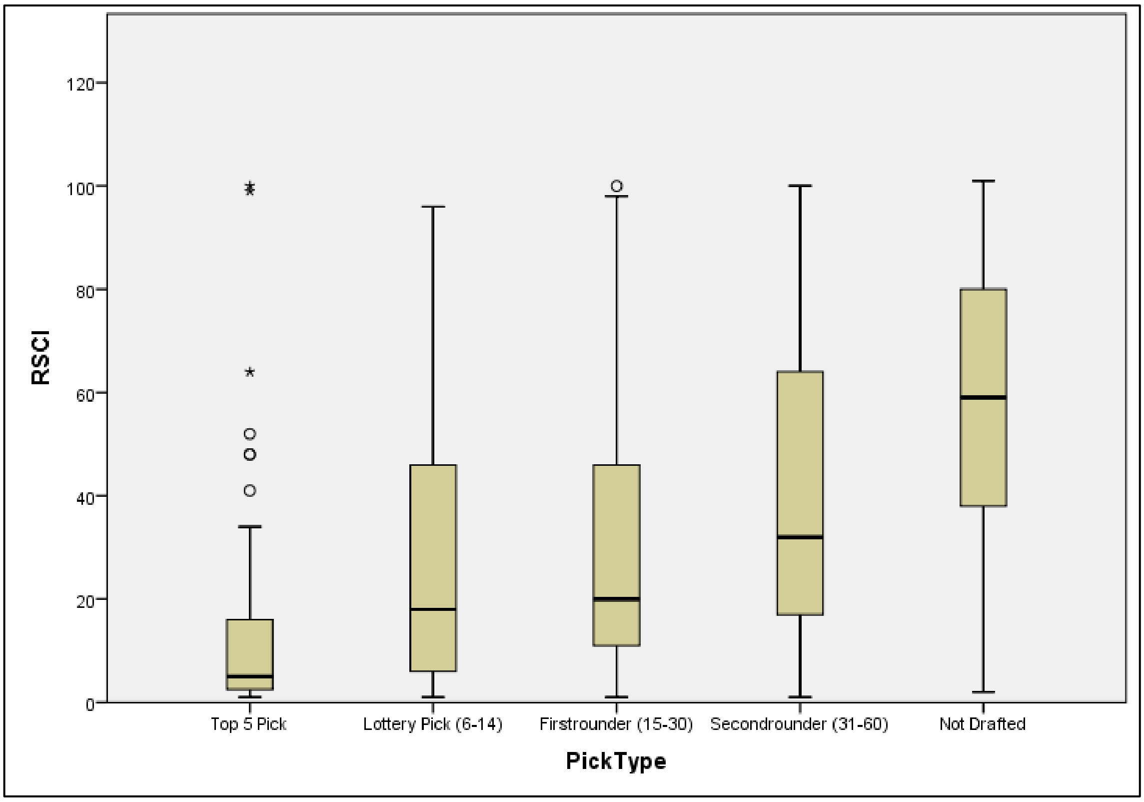

FIGURE 5-3. BOXPLOTS OF RSC RANK VERSUS DRAFT-SPOT REGION.

Figure 3 shows, a better RSCI-ranking might make it more likely to be drafted higher. As we go up in pick region the corresponding RSCI listings decrease for the found investigated populations.

We verified this graphically presented notion with a hierarchical multiple regression analysis of the two variables. We tested the H20 that RSCI has no influence on draft-rank, controlling for pre-draft performance.

TABLE 5-7. HIERARCHICAL MULTIPLE LINEAR REGRESSION MODEL FOR RSCI-RANK AND DRAFT-RANK.

		Unstandardized Coefficients		Standardized Coefficients		
Model	Component	B	Std. Error	Beta	t	Sig.
1a	(Constant)	39.688	1.541		25.760	0.000
	CBB WS per Game	-164.927	15.969	-0.432	-10.328	0.000
2b	(Constant)	34.304	2.390		14.356	0.000
	CBB WS per Game	-146.342	17.062	-0.383	-8.577	0.000
	RSCI-Rank	0.075	0.026	0.131	2.931	0.004

a. Variable entered on step 1: CBB WS per game.
b. Variable entered on step 2: RSCI-Rank.

For this analysis, 513 cases were included. Both investigated models were highly significant with p-values of 0.000 and 0.004. An Adjusted R^2 improvement from 0.185 to 0.198 was observable. This indicates that adding the RSCI-rank component increases the explained variance. In this setup 'pre-draft performance' is highly significant and has a loading in the expected direction. More college production leads to a lower draft-rank. Hence, performing better before the draft corresponds with getting selected earlier. The added RSCI-rank variable also proved to be a significant factor within the model. The coefficient reveals that within the examined sample that a good HS-reputation contributes positively to getting selected earlier, since a lower RSCI-rank number corresponds with a lower draft-selection number for the prospects.

This leaves us with two main observations. First, this test shows, RSCI-rank and draft-rank are linked in a positive way, even controlling for college contributions. Second, the influence of the RSCI-listing on draft position seems to decrease with every added rank.

Finally, we can reject the H1B0 since we found RSCI-rank as a significant influential variable for draft-rank. Therefore, our H1B cannot be falsified. We conclude, a higher RSCI-ranking contributes positively to an earlier selection of a draft prospect.

5.4.3 RSCI-Rank and Post-Draft Performance

Furthermore, we need to examine whether these high school-rankings are additionally a good predictor for post-draft performance:

Table 5-8. RSCI-Rank versus WS/Year.

RSCI-Rank	N	Average WS/Year	Minimum WS/Year	Maximum WS/Year	Average Years in the League
100-80	43	1.67	-0.25	6.19	4.95
79-60	47	1.67	-0.45	6.78	5.49
59-40	60	1.90	-0.18	8.23	6.38
39-20	117	1.31	-0.37	6.67	5.68
19-10	100	1.94	-0.55	12.19	6.26
9-1	134	3.02	-0.35	14.16	8.10

The data echoes the results from the previous chapter. In general, the differences in average yearly performance are only marginal when looking at the RSCI-ranks from 100 to 10. All values hover around 1,75 WS/Year without meaningful deviations. Only the top 9 and the RSCI region between 20 and 39 are exceptions to these observations. The highest-ranked high schoolers seem to perform significantly better than their peers and back up their pre-draft reputations with post-draft on-court impact for their teams. On the contrary, the second half of the RSCI top 39 seems to have the tendency to not do so.

The observed inclinations can be backed up by a highly significant correlation measure. Pearson's r for RSCI-rank and WS/Year is -0,145 (N=501). Hence, we can observe a small negative correlation between the two variables. The lower a prospect's RSCI-rank the smaller their post-draft performance indicator tends to be.

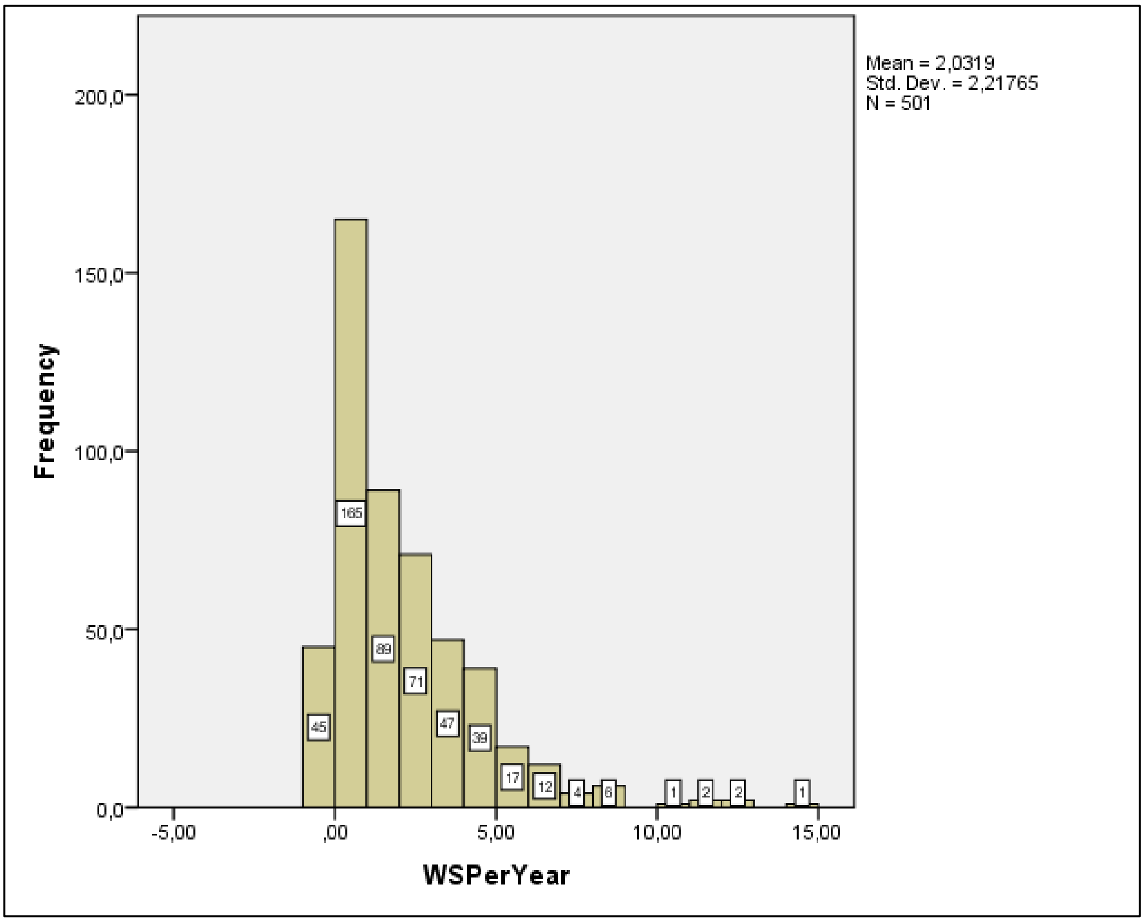

FIGURE 5-4. HISTOGRAM OF WS/YEAR.

Looking at the frequencies for WS/Year, this variable follows a one-sided normal distribution but only into the positive direction. [5] Hence, with increasing impact criteria there are fewer and fewer players who can meet them. To look deeper into the matter, we converted this performance metric into a new variable for player-level which captures the impact an athlete has on the basketball-court based on the Win Share measures combined with a well-accepted tier grouping system (e.g., Paine & Bradshaw, 2015; The Stepien, 2020a; Go-to-Guys, 2020). We put every drafted player with recorded playing time into one of six categories, rating their performance following certain thresholds in the WS/Year-metric.

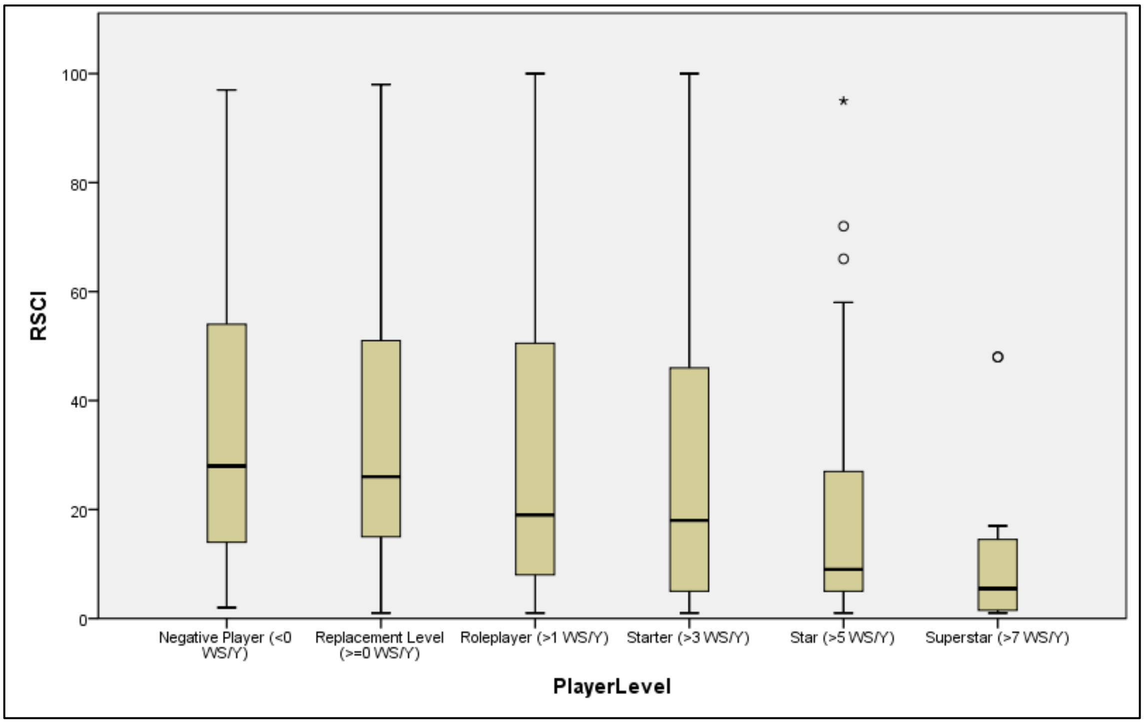

FIGURE 5-5. BOXPLOT OF PLAYER LEVEL VERSUS RSCI RANK.

This plot suggests, RSCI is not an influential predictor for what player-level a prospect reaches later in their career except for the superstar category. Players who fall into this tier tend to have been ranked highly in the RSCI. For all other player types, its average group members fall into the top 30 of the RSCI. But better rankings do not seem to guarantee a better performance level later.

Using the hierarchical multiple regression approach again to test whether RSCI has influence on post-draft performance (N = 644), only one highly significant model can be found for the dependent variable 'WS per Year'. The first setup, only looking at post-draft performance and pre-draft contributions offers a p-value of 0.000 and an Adjusted R^2 of 0.212. Adding RSCI as an independent variable in the second level of modeling increases the p-value to 0.598 and even decreasing the Adjusted R^2 to 0.211.

TABLE 5-9. HIERARCHICAL MULTIPLE LINEAR REGRESSION MODEL FOR RSCI-RANK AND POST-DRAFT PERFORMANCE.

		Unstandardized Coefficients		Standardized Coefficients		
Model	Component	B	Std. Error	Beta	t	Sig.
1[a]	(Constant)	0.621	0.093		6.712	0.000
	CBB WS per Game	12.170	0.959	0.462	12.694	0.000
2[b]	(Constant)	0.680	0.145		4.696	0.000
	CBB WS per Game	11.968	1.033	0.454	11.581	0.000
	RSCI-Rank	-0.001	0.002	-0.021	-0.528	0.598

a. Variable entered on step 1: CBB WS per game.
b. Variable entered on step 2: RSCI-Rank.

Looking at the coefficients-table, pre-draft and post-draft performance interact in the expected direction. While not translating perfectly to the next level, meaningful college contribution makes it more likely for players to also have on-court impact in the NBA.

However, RSCI-rank itself does not prove to be a significant variable. High school reputation does not seem to have a meaningful and significant effect on post-draft performance. Hence, we cannot reject the H30. We conclude, RSCI-ranking does not predict a draft prospect’s post-draft impact measures in any sufficient way.

5.4.4 ABSOLUTE RSCI-RANK ADJUSTMENT AND DRAFT-OUTCOME

In this chapter we investigate the possible bias by checking whether certain RSCI-ranks and a lack of adjustment to them cause league-wide over- or underdrafting behavior of certain player types.

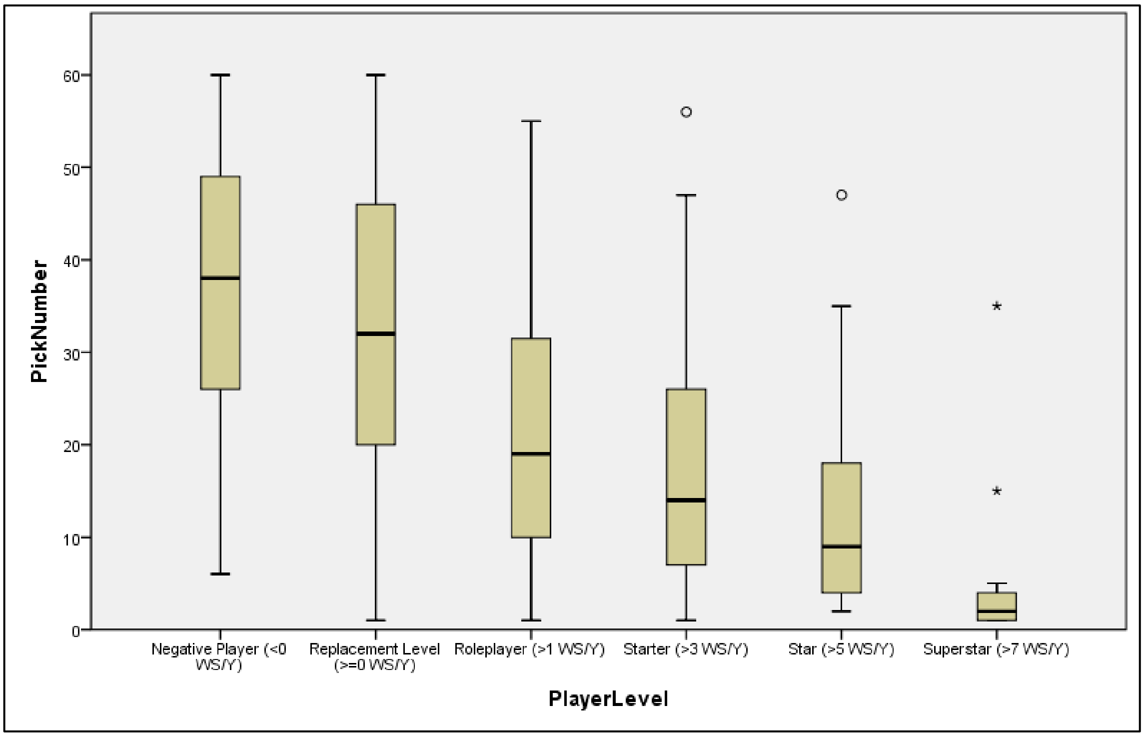

FIGURE 5-6. BOXPLOTS FOR PICK NUMBER BY PLAYER LEVEL.

Examining the overall picking practice of all the NBA teams by where impact players were found, we see, the general talent evaluation skills of managers seem to be solid. With an increase in player-level the median pick number of the corresponding prospects decreases. This shows, better players tend to be found earlier in the draft. But as the boxplots also displays there are weak players being drafted very early and great players falling far in their respective drafts.

The newly established Over-Under-Drafted-Rating (OUDR) (see 5.3.1.3) has a distribution is close to normal. [6] NBA managers pick most players near their expected region as 408 of the 501 qualifying players reached a value between 1 and -1. Hence, only 18.5 percent of players went hugely over- or underdrafted.

But if we add pre-draft experience as a factor, first trends become visible:

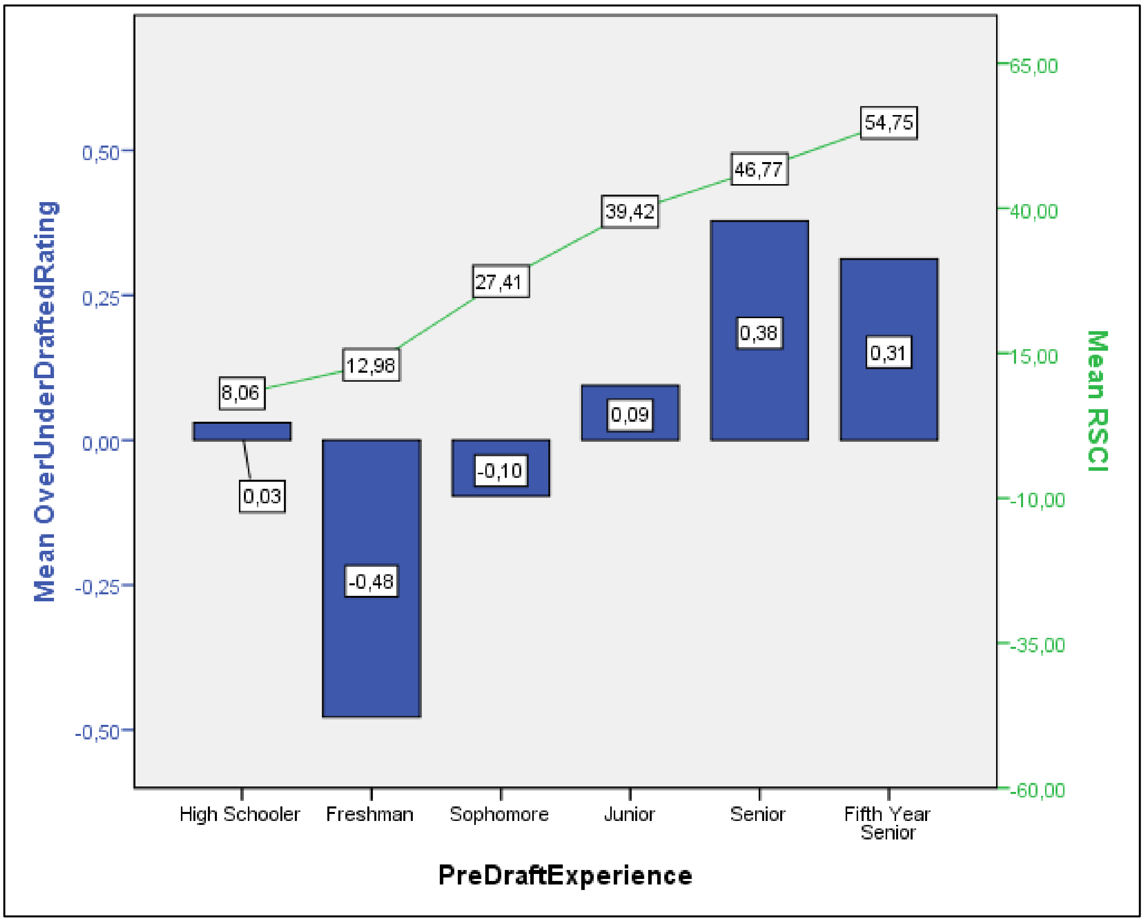

FIGURE 5-7. DUAL-AXIS PLOT OF PRE-DRAFT EXPERIENCE, OUDR, AND RSCI RANK.

Freshmen tend to get overdrafted while both senior groups lean towards getting underdrafted more often. Additionally, we can see again, less pre-draft experience corresponds with a higher mean ranking in the RSCI. With these meaningful results on both sides of the OUDR, outcomes might be linked through pre-draft experience.

Interestingly time as a component offered does not produce the results one would expect:

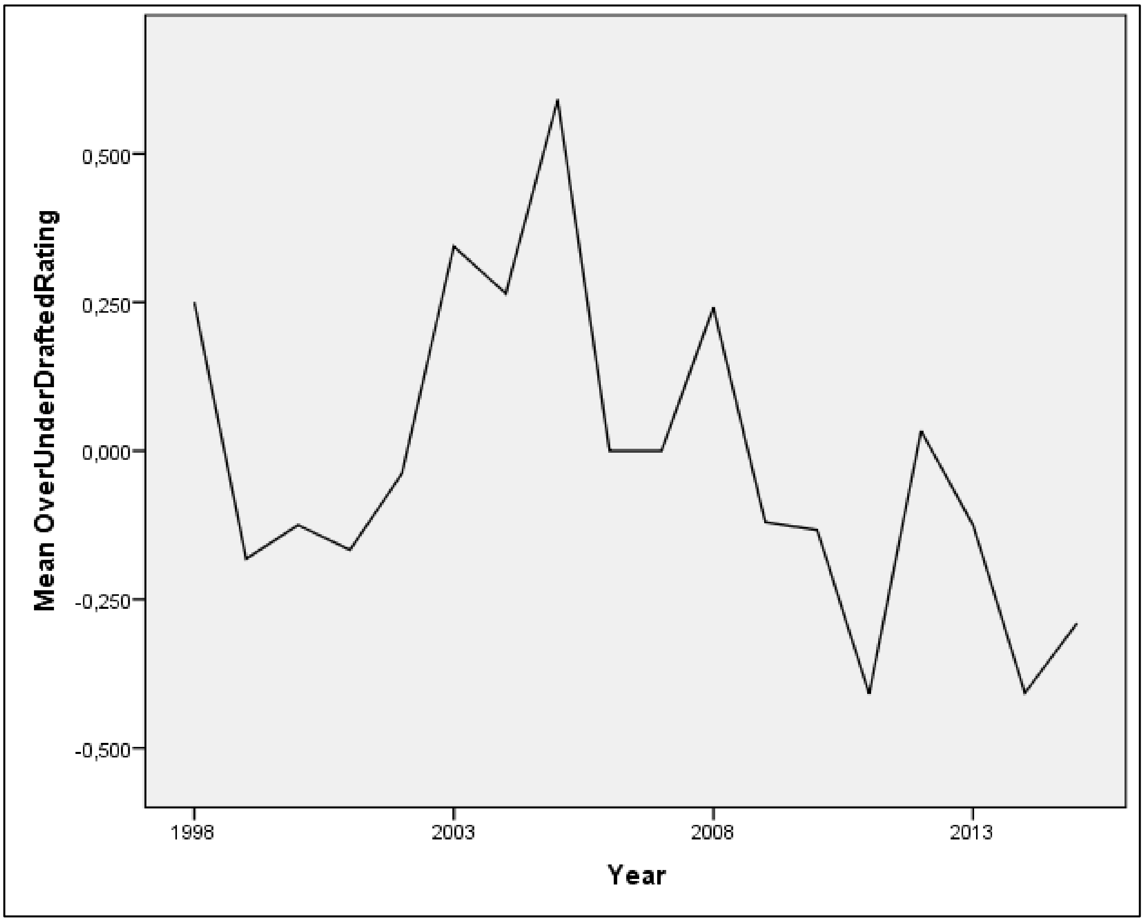

FIGURE 5-8. OUDR AND RSCI YEAR.

Theory would suggest NBA managers as a group should have improved in their draft decision-making quality over time due to learning effects and a more data-driven and allegedly objective evaluation approach based on the upcoming sports analytics. The data does not support such a trend. If anything, our metric suggests that decision-makers have overdrafted RSCI-ranked players more in recent years as they have in the early to mid-2000s, implicating that non-RSCI-ranked players have been underrated as little as five years ago. These results seem to mirror the findings Motomura (2016) presented on a potential nationality bias with non-American (or non-RSCI-ranked for that matter) players. He described that international athletes were underrated between 1999 and 2001, while becoming overrated soon thereafter between 2002 and 2005. Our results line up with these findings with presenting the flipside of this argument, showing that RSCI-ranked players went underdrafted over the same time span.

Investigating a possible anchoring effect of the RSCI-rank on draft-rank causing draft mistakes of either vastly overrating or underrating a player in a draft setting, we derived a new variable from the data we already had. We first transposed the RSCI-rankings from 100-spot-scale into a 60-spot-scale matching the regular draft range by multiplying every RSCI-rank by 0.6. This translation puts the high school-rankings into a draft-expectation-perspective stating that a talent ranked 50th in the RSCI should get drafted 30th and the 100th prospect was supposed to be a candidate for the 60th pick. The difference between the translated RSCI and the actual draft position of a draftee now gives us the size of the adjustments managers have made with their picking-behavior relative to the initial RSCI-rank-induced reputation of a player.

With these differences we can examine how far managers went away from possibly priming RSCI-ranks when drafting a prospect and if insufficient adjustment might have caused draft mistakes. Negative values in the derived metric show, ranked high schoolers got drafted lower than the initial expectation suggested. On the flipside a positive value indicates, a prospect ended up being selected earlier than the RSCI initially led to expect. The absolute value states the margin of differences.

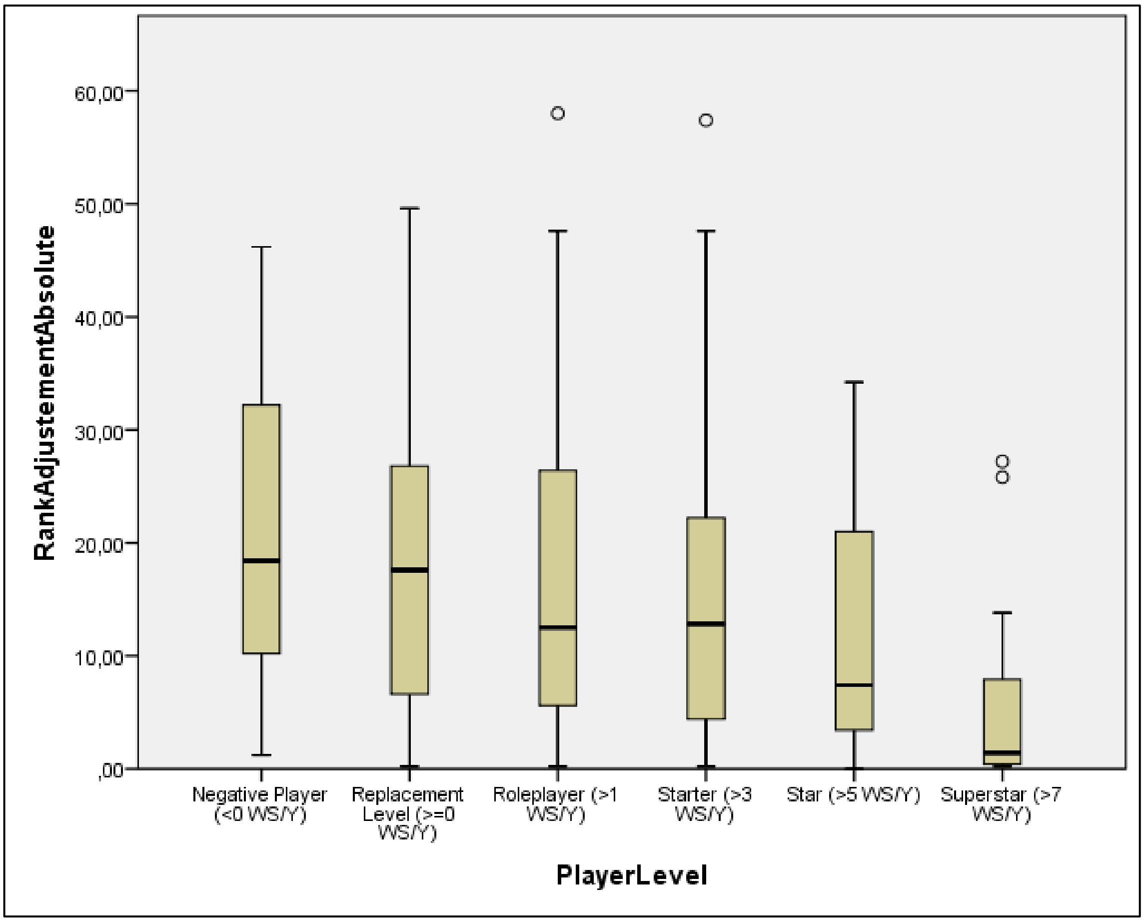

FIGURE 5-9. BOXPLOT OF PLAYER LEVEL VERSUS RANK-DIFFERENCE ABSOLUTE.

When looking at player-level we can see, only superstars get identified correctly by both the RSCI and drafting managers constantly. These obvious great players justifiably usually get ranked and picked highly. Hence, not much adjustment from the RSCI-rank is needed. Going down in player-level on average more and more overall adjustment from the RSCI-rank was applied to identify such players, while the range from not adjusting at all to heavily deviating from the RSCI with the draft selection increased. The initial RSCI-rank-evaluation was less and less reliable.

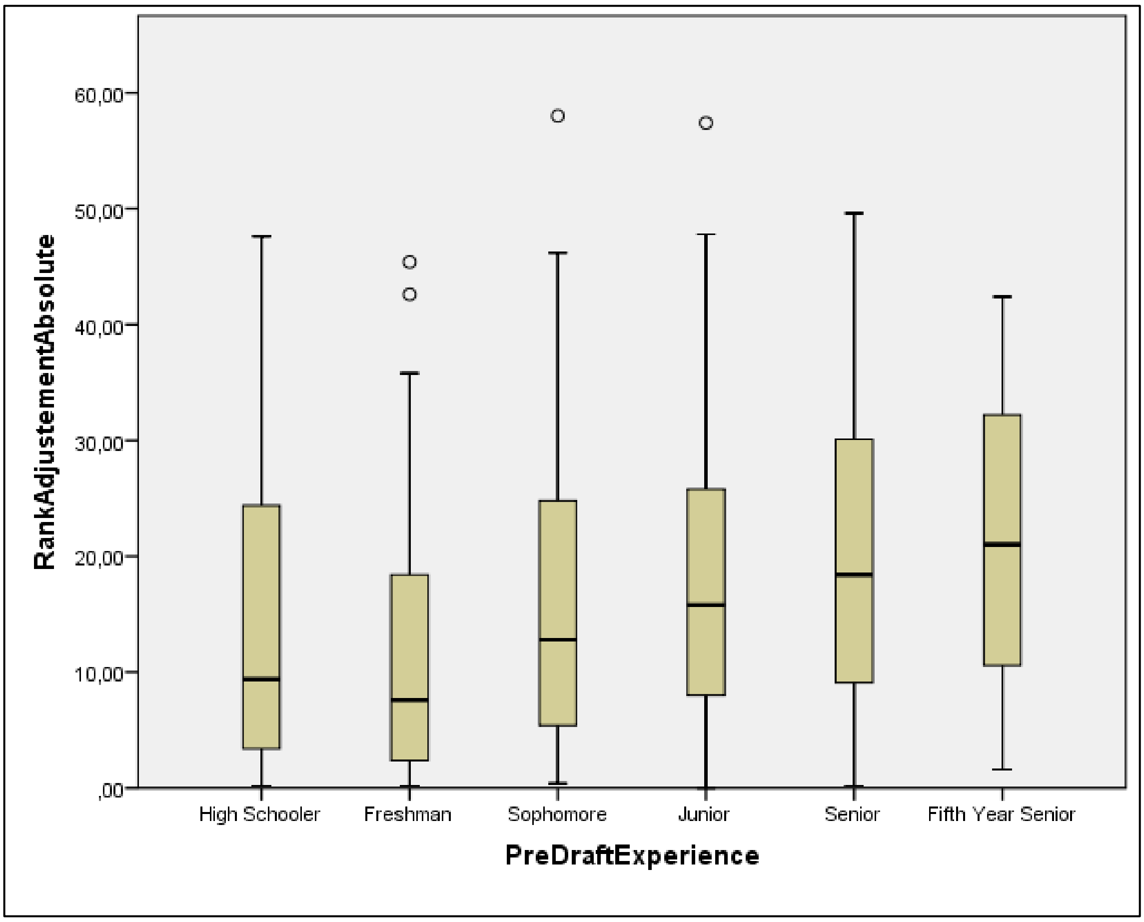

FIGURE 5-10. BOXPLOT OF PRE-DRAFT EXPERIENCE VERSUS RANK-DIFFERENCE ABSOLUTE.

Looking at pre-draft experience as the time component here and the absolute rank differences behave as expected. The less time prospects spend in college the less their draft-rank deviate from their initial RSCI-rank-indication. This observation can be explained logically. The RSCI seems to make a strong impression at first and it takes time to lose a reputation for better or worse in this case. Lower-ranked high schoolers need to stay longer in school to convince NBA decision-makers of their value, while highly-ranked talents will get the benefit of the doubt for a season or two even if their performance is not living up to their surrounding hype. A highly significant Spearman's rho of 0.239 can be reported (N = 513, p = 0.000), stating that the greater a prospect's pre-draft experience becomes the more adjustment between their RSCI- and draft-rank tends to happen.

We need to check now, if a lack of adjusting to possibly anchoring RSCI-rankings correlates with our found OUDR.

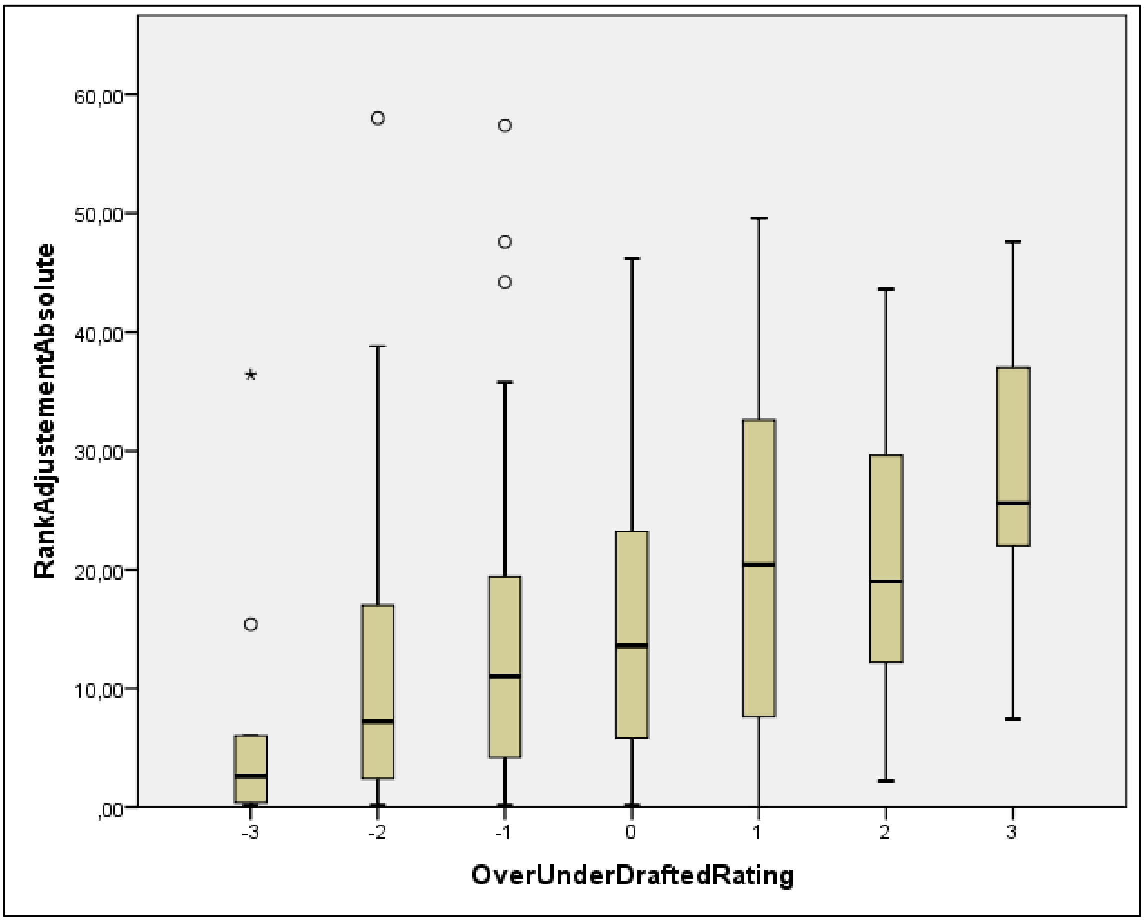

FIGURE 5-11. BOXPLOT OF RANK-DIFFERENCE ABSOLUTE AND OUDR:

We already established earlier, vastly overdrafted players tended to be freshmen. This figure additionally shows, especially the worst draft mistakes were made because only insufficient adjustment from RSCI to the draft ranking took place. Furthermore, we can see that for overdrafted players on average less adjustment in relation to the high school-rankings occurred.

This effect can be explored and verified through another hierarchical multiple regression model, taking the OUDR as the dependent component and adding absolute RSCI-rank adjustments and pre-draft experience as independent variables.

TABLE 5-10. HIERARCHICAL MULTIPLE LINEAR REGRESSION MODEL FOR ABSOLUTE RSCI-RANK ADJUSTMENT, PRE-DRAFT EXPERIENCE AND DRAFT-OUTCOME.

		Unstandardized Coefficients		Standardized Coefficients		
Model	Component	B	Std. Error	Beta	t	Sig.
1[a]	(Constant)	0.161	0.126		1.281	0.201
	CBB WS per Game	-1.964	1.307	-0.070	-1.503	0.133
2[b]	(Constant)	-0.798	0.184		-4.346	0.000
	CBB WS per Game	0.415	1.283	0.015	0.323	0.747
	Absolute RSCI-Rank Adjustment	0.024	0.004	0.261	5.620	0.000
	Pre-Draft Experience	0.143	0.042	0.157	3.433	0.001

a. Variable entered on step 1: CBB WS per game.
b. Variables entered on step 2: Absolute RSCI-Rank Adjustment & Pre-Draft Experience.

The first model, only introducing pre-draft performance as a predictor, did not provide any value (N = 501, $p = 0.133$, Adjusted $R^2 = 0.003$). As expected, college impact alone does not help to determine whether players are more likely to get over- or underdrafted. Interestingly, adding the independent variables 'pre-draft experience' and 'absolute RSCI-adjustment' to this arrangement improves the setup to a highly significant p-value of 0.000 and raises the Adjusted R^2 to 0.102.

The parameters behave as expected. 'Absolute rank adjustments' are highly significant and have a positive coefficient, suggesting greater management adjustments from the RSCI making it less likely to overdraft a player. Additionally, pre-draft experience is a significant measure for the explored model. Its positive coefficient indicates that the longer players performed within a college setting the less likely it gets to overdraft them. On the other hand, less college-proven talents are more likely to get overdrafted in general. These coefficients also behave as theory on reputation and anchoring would suggest. The analysis therefore points towards insufficient adjustment to the RSCI to influence the draft decision-making quality in a negative way, especially for highly rated players with little pre-draft experience.

This lets us reject the null hypothesis of our overarching H. We can conclude, there is evidence for a possible RSCI-enforced anchoring bias which produces systematical drafting errors by teams through insufficient adjustments. Our regression models show, over the investigated timeframe selecting younger players without proper questioning of their initial RSCI-ranking made it more likely to land overdraft a player.

5.5 CONCLUDING REMARKS

Although the predictability of the RSCI for post-draft performance is basically non-existent, managers seem to be affected by the RSCI-rank as a talent-measurement proxy. Especially freshmen with a high RSCI-rank have a higher likelihood of getting overdrafted. However, upperclassmen with a lower initial RSCI-listing tend to get undervalued because most managers seem to possess a preference for younger options possibly disregarding lower variance players with a larger college sample-size as finished products.

These findings provide evidence for a possible anchoring-bias-effect within the NBA Draft policy. We identified the RSCI-rank as a problematic metric which can be source for systematic draft errors. This effect seems to wear off over time for prospects the farther they are removed from the moment they received their HS ranking as larger pre-draft-performance sample-sizes of players paint a clearer picture of what player-impact-level they might reach in the future.

By picking young players with a great high school-reputation without questioning this past-judgement sufficiently, managers often emphasize misleading factors like potential, youth, and hype too much and possibly overestimate the future development skills of their organization and the ultimate post-draft-impact of these players. Wishful thinking caused by over-confidence and optimism might be at work (Heger & Papageorge, 2018). Decision-makers often-insufficient adjustments from the RSCI-rank cause systematic draft errors throughout the league which hurt the NBA draft-policy as dynamic that is supposed to strengthen the association's product by benefiting quality of play and uncertainty of outcome.

More research on this topic is of importance, especially facing a possible termination of the one-and-done-rule in the near future (Maese, 2019), which has prevented high schoolers from entering the NBA draft directly, forcing them to attend college or join an international club team before entering the NBA draft. In the face of this development, RSCI-data might become even more important for decision-makers again. NBA teams currently lack the infrastructure to scout on the high school-level heavily and accurately by themselves. This possibly forces them to further rely on external scouting opinions such as the RSCI at least for the short-term.

NOTES

1. Further explanation of the metric in 3.1.1.
2. Further explanation of the metric in 3.1.2.
3. This game-win-number is adjusted if WS are calculated for the college environment.
4. Negative-player (< 0 WS/Y), Replacement-level (0 - 0.99 WS/Y), Roleplayer (1 - 2.99 WS/Y), Starter (3 - 4.99 WS/Y), Star (5.00-6.99 WS/Y) and Superstar (>=7 WS/Y).
5. It is illogical for teams to play prospects who contribute negatively on the court.
6. There were two players with a deviation of 4 and three other athletes with a deviation of -4. We incorporated them into the third categories to each side, respectively.

CHAPTER 6

Jumping to conclusions – An analysis of the NBA Draft Combine athleticism data and its influence on managerial decision-making

STUDY III

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6. STUDY III: JUMPING TO CONCLUSIONS

ABSTRACT

Purpose – The NBA Draft policy pursues the goal to provide the weakest teams with the most talented young players to close the gap to the superior competition. But it hinges on appropriate talent evaluation skills of the respective organizations. Research suggests the policy might be valid but to date unable to produce its intended results due to the 'human judgement-factor'. This paper investigates specific managerial selection-behavior-influencing information to examine why decision-makers seem to fail to constantly seize the opportunities the draft presents them with.

Design/methodology/approach – Athleticism data produced within the NBA Draft Combine setting is strongly considered in the player evaluations and consequently informs the draft decisions of NBA managers. Curiously, research has failed to find much predictive power within the players pre-draft combine results for their post-draft performance. This paper investigates this clear disconnect, by examining the pre- and post-draft data from 2000 to 2019 using principal component and regression analysis.

Findings – Evidence for an athletic-induced decision-quality-lowering bias within the NBA Draft process was found. The analysis proves that players with better NBA Draft Combine results tend to get drafted earlier. Controlling for position, age, and pre-draft performance there seems to be no proper justification based on post-draft performance for this managerial behavior. This produces systematic errors within the structure of the NBA Draft process and leads to problematic outcomes for the entire league-policy.

Originality/value – The paper delivers first evidence for an athleticism-induced decision-making bias regarding the NBA Draft process. Informing future selection-behavior of managers this research could improve NBA Draft decision-making quality.

6.1. INTRODUCTION

The NBA Draft is a policy the league installed to fairly distribute young amateur players among its franchises. The mechanism pursues the noble goal to provide the weakest teams with the most talented young players to close the gap to the superior competition. But this policy hinges on appropriate talent evaluation skills of the respective organizations. Their managers must examine the annual player pool and select the most promising option. If correctly predicted, such a draft pick can change the financial and sportive fortunes of a team forever. But these choices are extremely difficult because they are made in an uncertain environment, based on many complex factors and therefore prone to many judgment-clouding biases and fallacies.

Among classical video-scouting or in-person evaluations, statistical analysis or background interviews of the potential draftees, the NBA Draft Combine presents another very popular option to gather information and reduce uncertainties regarding the available talents in a given draft year. The Combine is a multi-day, annual event that typically takes place a few weeks before the draft date. The attendees participate in several measurements, drills, and scrimmages, which allow to collect data on their anthropometrics, athletic abilities and shooting skills. Additionally, this environment provides a space for the franchises to perform medical testing as well as personal interviews. This generated information is strongly considered in the player evaluations and consequently informs the draft decisions of NBA decision-makers (Moxley & Towne, 2015; Sailofsky, 2018; Beene, 2019).

Such combine setups are popular practice in many sports disciplines and therefore have drawn much scientific attention. Researchers have investigated these showcases and their results for the National Hockey League (NHL) (e.g., Vescovi, Murray, Fiala & VanHeest, 2006; Chiarlitti, Delisle-Houde, Reid & Kennedy, 2018), the National Football League (NFL) (e.g., Kuzmits & Adams, 2008; Robbins, 2010; Hartman, 2011) and the Australian Football League (AFL) (e.g., Burgess, Naughton & Hopkins, 2012; Gogos, Larkin, Haycraft & Collier, 2020). Curiously, for the NBA, previous research failed to find much predictive power within the players pre-draft combine results for their post-draft performance (e.g., Teramoto, Cross, Rieger, Maak & Willick, 2018; Ranisavljev, Mandic, Cosic, Blagojevic & Dopsaj, 2021). This dynamic could pose an enormous problem for the overall NBA Draft policy, as Moxley and Towne (2015) explained in their previous research on perceived potential in draft prospects. If certain results of the combine drills and measurements – considered as a proxy for athleticism – influence managers heavily in their selection behavior, although they cannot be trusted as a viable predictor for future value, the NBA combine information presents a potential source for managerial biases. Such decision-making quality-lowering factors could even result in systematic errors that harm the overall outcomes of the entire draft policy. The dynamic hinges on high quality decision-making of every franchise. Only if all participating organizations seize the opportunities the draft presents them with, the overarching league goals of maximized competitive balance and high uncertainty of outcome can be strengthened. Every individual, questionable draft-decision works to the detriment of these intended results.

This paper sets out to investigate such possible NBA draft combine-induced decision-making biases in detail for the first time. We hypothesize that the structure of the event allows physically more gifted players to showcase certain talents that could influence managers to favor them over less athletic competition. However, if these identified traits do not prove to lead to more post-draft performance, they are faulty draft-decision-making criteria. Therefore, the main goal of this paper is – if existing – to identify possible bias effects in the decision-making of franchises in the NBA Draft process.

6.2 Background and related literature

6.2.1 THE NBA DRAFT POLICY AND ITS SHORTCOMINGS

The NBA draft is an annual event that integrates amateur basketball players from North American colleges and international clubs into the association. Franchises do not run youth teams to develop future players like, e.g., European soccer clubs do. Therefore, this talent-infusion-and-resource-delivery-apparatus that complements regular free-agency and player trade activities is much needed. To be part of a given yearly draft pool, interested players only need to meet certain age criteria and send a letter of intent to the league's office (NBA & NBPA, 2017). In between seasons, NBA teams can draft two players of this select group of individuals every year on a set date. To "draft" a player gives a franchise the exclusive right to offer the draftee their first NBA contract. If a drafted player, then has the intention to join the league, they can only sign with the organization that previously acquired their rights (NBA & NBPA, 2017). Franchise success in the most recent season determines the order in which the teams select from the pool of draft eligible players. The winningest team gets the 30th pick of every draft round, the second-best organization holds the 29th selection and so forth. The first 14 spots are determined through a lottery system incorporating all organizations that missed the playoffs. Again, the system favors weaker teams over franchises with more wins in the past season via a weighted odds mechanism (NBA, 2020a).

The NBA Draft policy has been a subject of research for over half a century now. Early on, scientists investigated the mechanism from a legal perspective (e.g., Burger, 1972; Carlson, 1972; Allison, 1973). Subsequently, its competitive balance-strengthening effects (or the lack thereof) became the focus of scholars. Academic evidence suggests the policy might be valid but to date unable to produce its intended results due to the "human judgement-factor". Due to poor pre-draft talent evaluation skills managers are simply not able to constantly seize the opportunities the draft presents them with (e.g., Berri, Brook & Fenn, 2011; Berri, 2013; Motomura, Roberts, Leeds & Leeds, 2016).

The decision-problem the draft represents is clear. Making a choice within this setup is about selecting the best available talent to provide utility maximization for the drafting sports organization in the classical economic sense (Friedman & Savage, 1948; Kahneman & Tversky, 1979). Talent in this realm can be defined as a mix of mostly on-court but also off-court benefits the prospects will generate for their new employers. Such provided benefits allow the drafting franchise to maximize utility in the form of financial and sportive success. However, solving this problem is immensely complex. The process in this environment can be defined as decision-making under uncertainty, since probabilities of decision-outcomes within this particular framework can only be roughly estimated and are mostly unknowable (Volz & Gigerenzer, 2012).

On the one hand, managers must evaluate the talent-level of the potential draftees at the moment of the draft, while factoring in probable future development. On the other hand, the decision-makers also need to assess the future of the entire sports of basketball correctly, since its structure poses as the underlying framework the athletes need to perform in. The recent emergence of sports analytics, a huge part of ongoing further professionalization of basketball helps to reduce some uncertainties and better understand the sport as whole (Alamar, 2013; Lewis, 2017). Player evaluation as a craft, along with the triangulation of eyes (e.g., scouting, personal workouts), ears (e.g., personal interviews, medical records exploration, further background research) and numbers (e.g., anthropometric measurements, high school, and college performance metrics) has become much more sophisticated (Beene, 2019). Leaguewide playing trends are recognized and reacted to earlier than ever before (Shields, 2017). Yet, judging and evaluating basketball players is still not a task anybody can be perfect in. Even today, with more information and data available than ever before, drafting still is an "inexact science" as former NFL-coach and executive Bill Parcells famously once claimed (Little, 2008), due to all the complex factors defining the sport. After all, it is almost impossible to accurately predict the future development of a young player or to isolate and judge individual greatness differences in a team sport, especially if the margins between players are slim (e.g., Martínez, 2012; Taylor, 2016, 2017; Basketball-Reference, 2020c).

This is the point at which player evaluations, particularly within a draft setting, come down to taste, preferences, and the decision-maker's philosophy on how the sports of basketball should be played (Raab, MacMahon, Avugos & Bar-Eli, 2019). These clear aspects of judgment, which are defined as "the set of evaluative and inferential processes that people have at their disposal and can draw on in the process of making decisions" (Koehler & Harvey, 2004, p. XV) open up the entire process to classical decision-making-quality-lowering heuristics and biases. Within the realm of the NBA Draft many of those have been investigated with the aim to eliminate hidden systematic errors and reduce uncertainties.

Basketball draft research has covered nationality bias (Motomura, 2016) as well as recency and availability bias (Berri, Brook & Fenn, 2011; Ichniowski & Preston, 2012; Burdekin & Van, 2018). Additionally, age and favorable positional length as proxies for potential get misjudged constantly (Groothius, Hill & Perri, 2007; Berri & Schmidt, 2010; Ashley, 2017). Additionally, certain boxscore-statistics do not translate as smoothly from the amateur to the professional level as one would expect (e.g., Coates & Oguntimein, 2010; Salador, 2011; Harris & Berri, 2015).

With this paper we want to continue this research direction investigating "athleticism." We will examine athletic abilities as a reliable predictor for post-draft performance and therefore will have a close look at historic NBA Draft Combine data – an event that focuses on measuring the athleticism of potential draft prospects.

6.2.2 THE NBA DRAFT COMBINE AS A PROXY FOR ATHLETICISM IN BASKETBALL

Before getting selected, many of the draft-eligible players participate in the NBA Draft Combine. This event can be considered a talent showcase-opportunity for the attending players. The most intriguing draft suiters from American colleges and international club-play get invited to perform within this setup. The invitation list is based on player suggestions of the league's franchises. This consequently shows that all performing players are at least considered as a draft option by one or more NBA teams (Austin, 2014). Besides offering personal interview, medical information and official anthropometrics, prospects have a chance to prove their athletic abilities in the dimensions like explosiveness, speed, agility, and strength in addition to their general shooting skill by taking part in standardized testing drills. Furthermore, players have the chance to prove their basketball abilities against direct draft pool competition by competing in NBA Combine scrimmage games (Lockie, Beljic, Ducheny, Kammerer & Dawes, 2020). Since 2000 about 1,350 athletes went through the standardized NBA Draft Combine procedures and workouts, producing a respectable, publicly available database that allows general player classification and historical comparisons (NBA, 2020c; NBAthletes, 2020) [1].

The event was founded to help decision-makers to gather more information about draft prospects, to reduce uncertainty and allow more accurate player evaluations. Yet, several studies have shown, that the pre-draft NBA Combine data lacks predictive power regarding post-draft performance (e.g., Teramoto, Cross, Rieger, Maak & Willick, 2018; Ranisavljev, Mandic, Cosic, Blagojevic & Dopsaj, 2021). Hence, one must wonder, why managers still incorporate this information into their decision-making process, as it seems to cloud their judgment, harming the overall outcome of the draft policy (Moxley & Towne, 2015). We suspect the term "athleticism", which is closely linked to the NBA Draft Combine-measurements, and corresponding heuristics as well as biases to be the root of problematic judgment-processes.

6.2.3 POTENTIAL ATHLETICISM BIASES IN BASKETBALL

"Athleticism" is a broad term that often gets discussed in the basketball realm, especially in connection with the NBA Draft Combine (e.g., Cui, Lui, Bao, Liu, Zhang & Gómez, 2019; Milan, La Soares, Quinaud, Kós, Palheta, Mendes, Nascimento & Carvalho, 2019; Perrin & Jensen, 2019; Ranisavljev, Mandic, Cosic, Blagojevic & Dopsaj, 2021). Generally viewed as a critical component for basketball performance, "athleticism" is a factor supposedly investigated closely by general managers via scouting and statistical work, when evaluating players in their pre-draft process (e.g., Moxley & Towne, 2015; Beene, 2019). Without an agreed upon scientific definition, we will simplify the concept of "athleticism" within the examined sport, as Dawes Marshall and Spiteri (2016) suggested, as a combination of anthropometric attributes and physical capabilities, which can be divided into power, strength, aerobic, an-aerobic, speed and agility for this discipline. The NBA Draft Combine's drills and measurements arguably capture all these dimensions fairly well (Teramoto, Cross, Rieger, Maak & Willick, 2018).

Investigating the NBA Draft, Moxley and Towne (2015) found evidence that physical abilities seem to get overvalued when it comes to the managerial selection-behavior, possibly due to a false pretense of future potential. In their study, NBA Draft Combine data did not prove to be a reliable predictor for post-draft performance. These results mirrored the conclusion of several other papers on the topic (e.g., Teramoto, Cross, Rieger, Maak & Willick, 2018; Ranisavljev, Mandic, Cosic, Blagojevic & Dopsaj, 2021). Though, Moxley and Towne (2015) additionally showed that certain athleticism measurements influence the draft-rank of prospects. This observed disconnect led them to assume a decision-making bias around the concept of "athleticism" and "potential" in basketball players.

According to them, their results can be explained by the well-known *selection bias* (Heckman, 1979). Certain physical capabilities are needed to be able to provide on-court value in the NBA. It is hard to disregard such basic requirements. However, the process of getting into a position to be considered for a selection within a draft setting automatically weeds out all options that are too far away from these minimum qualifications. Within the group that survives – the potential draft pool for the franchises, including all the NBA Draft Combine attendees – athleticism-based advantages among talents are diminished, since relative to the average person only great athletes with superior physical dimensions and skills can become viable draft options. Following this thought, selection bias explains why athleticism is a weak predictor for future performance. Yet, it fails to illustrate why athleticism still seems to influence managers in their drafting-behavior wrongly. We assume two error producing cognitive biases within the athleticism-draft-dynamic that also affect managerial decision-making:

First, we see the possibility for *availability bias*. As Tversky and Kahneman (1973) famously showed, people tend to overestimate frequencies or probabilities of events they can recall with ease. On the flipside, occurrences that are harder to remember are undervalued (also: Tversky & Kahneman, 1974; Kahneman & Tversky, 1972). In a basketball player evaluation this dynamic could be at play and drive managers towards more physically gifted players. In the sport at question, the most spectacular actions, such as dunks, layups, blocks and steals usually have a direct link to superior speed, power, jumping ability, length, or agility. Hence, within these basketball plays athletic traits are directly connected with a concrete action and they are mostly tracked as an event (Lee, Moon, Nam & Yoo, 2018). Additionally, these are usually the plays that find their way into the post-game statistics and video summaries because they trigger excitement (Lee, Kim & Kim, 2009; Bettadapura, Pantofaru & Essa, 2016). In the current media landscape entire TV shows are built around these highlights (Farred, 2000). Furthermore, in the age of social media and its echoing effects, such short video clippings of sport highlights have become a deeply personal and emotional entity (e.g., Babaguchi, Kawai, Ogura & Kitahashi, 2004; Tang & Boring, 2012). It would only be logical for such athletic highlight plays to manifest themselves in the memory of the decision-makers quickly and make the corresponding athlete easier to recall.

Interestingly, there are basketball on-court events that do not show up in the post-game statistics-sheet, because they are not counted as an action and do not allow to show classical athletic skills in a memorable way: Not having to block someone in the first place because of correct initial positioning, not losing the ball, or creating space for own actions with good deceleration rather than with an explosive first step are valuable basketball plays (Cohen, 2017) that are usually not recognized as a positive on-court event that easily. The ease of remembering the athletic actions could lead to managers overestimating the number of positive actions a more athletic player seems to deliver and could probably generate in the future, while underestimating players with lesser athletic capabilities or a less spectacular playing style.

Second, as proven in other NBA circumstances (e.g., Sailofsky, 2018; Beene, 2019), *overconfidence bias* (Kahneman & Tversky, 1973; Gigerenzer, 1991) could influence the investigated dynamic surrounding athleticism as well. Decision-makers often seem to “bet on athletic tools” as they are perceived as “promising, untapped potential” by many managers (Vashro, 2014; Moxley & Towne, 2015). The idea is that out of two prospects with an equal pre-draft performance-level the one with superior athletic traits has more room to develop as a basketball player. These decision-makers are confident that lacking basketball skills can be taught, while on the opposite the old basketball axiom “You can’t teach height” is basically projected on to all physical capabilities like speed, strength, or explosiveness. However, the opposite could prove to be true as well. If a college player only dominated by being a superior athlete, they might struggle as their relative physical advantages will diminish on the professional playing level with survivor mechanics raising the average athleticism of the competition in the NBA compared to the NCAA or international play. Less athletic players on the other hand might maintain their basketball related skills that helped them to produce all their value. They might also improve their physical capabilities rapidly, moving to professional training conditions in team training and with personal coaching (Simenz, Dugan & Ebben, 2005). Interestingly, managerial overconfidence in the development capabilities of the own staff and franchise could be at work in both ways, believing that either physical or basketball skill improvement is easier to reach with far-reaching decision-making consequences (Vashro, 2014).

We will investigate this matter by examining if athletic traits possibly lead to wrongly

influenced managerial draft-decision-making. Isolating single biases is hard, as we can only assume the reasons for draft decisions without interviewing the managers. Yet, many heuristics and biases can logically be applied to the dynamic that would explain systematic overvaluing of NBA Draft Combine-induced athletic markers in a basketball draft setting from a behavioral economic standpoint. In our analysis we try to replicate and further develop the results of Moxley and Towne (2015) by examining whether such mechanisms can be found in the most recent historic data.

6.3 METHODOLOGY

6.3.1 GENERAL DATA

The website "NBAthlete" was used as a primary data resource (NBAthlete, 2020). Their data base allowed us to capture the results of every NBA Combine participant from 2000 to 2019 (N = 1,354). We combined this data set with the actual draft results from the corresponding years (N = 1,189) (Basketball-Reference, 2020b). Even though a lot of overlap occurred, we ended up with a slightly bigger data pool (N = 1702), since some Combine participants went undrafted and while some non-participants (especially international players) were selected.

Consequently, the constructed data set includes pre-draft information (e.g., name, team, position, age, years of pre-draft-experience, college basketball performance data), detailed combine drill results (e.g., height, wingspan, jumping and running measurements) and (post-) draft data (e.g., pick number, years in the league, NBA basketball performance data). 2000 became the starting point for our records by default since it was the first year the NBA Combine took place.

The ongoing nature of the dataset is an important limitation we want to point out. While the players pre-draft statistics cannot change anymore, their post-draft numbers are still developing as many of the players are currently active in the league. The data was scraped in September 2020 and does not include the continuation of the 2019/20 NBA season after a COVID-19-induced intermission or any 2020/2021 data.

6.3.2 NBA DRAFT COMBINE VARIABLES

The NBA Draft Combine is a multi-day event which measures anthropometrics as well as the speed, strength, and agility of basketball talents in several ways. We will ignore data from the scrimmages and shooting practices described in 2.2 for two reasons. On the one hand, these events were introduced late in the combine history and hence are not available for all investigated cases. On the other hand, we want to focus our research completely on the athleticism measures as derived from theory in 2.3 and hence do not need to investigate these other player activities at the NBA Draft Combine.

To give a detailed overview over the measurements and drills of the event regarding the term "athleticism," we will use the scheme Teramoto, Cross, Rieger, Maak and Willick (2018) prepared:

TABLE 6-1. DESCRIPTION OF THE NATIONAL BASKETBALL ASSOCIATION DRAFT COMBINE MEASUREMENTS AND DRILLS.

Combine measure	Testing protocol
Anthropometrics	
Body fat percentage	Body fat percentage is assessed by measuring the skinfold thickness of pectoral, abdomen, and quadriceps using a skinfold caliper.
Hand length	The bottom of the palm to the tip of the middle finger is measured in inches using a measuring tape.
Hand width	The tip of the thumb to the tip of the small finger is measured in inches using a measuring tape.
Height without shoes	Height is measured in feet and inches using a physician scale, while the player is not wearing shoes.
Height with shoes	Height is measured in feet and inches using a physician scale, while the player is wearing shoes.
Standing reach	Reach is measured in feet and inches using a measuring tape, while the player is standing and reaching straight up.
Weight	Body weight is measured in pounds using a physician scale.
Wingspan	The tip of the left hand to the tip of the right hand is measured in feet and inches using a measuring tape, while the player is stretching the arms horizontally.
Speed, strength, and agility	
Lane agility	A cone is placed at each 4 corners of the lane. Starting from the left corner of the free-throw line, the player runs forward to the baseline, side-shuffle to the right corner of the lane, backpedal to the right corner of the free-throw line, and side-shuffle to the left to go back to the starting point. Then, the player changes the direction, side-shuffle to the right corner of the free-throw line, runs forward to the baseline, side-shuffle to the left corner of the lane, and backpedal to go back to the starting point. The score is the time to cover the distance measured in seconds.
Shuttle run	Starting from the middle line of the lane, the player runs either to the right or left as indicated by the timing gate. When the foot crosses the sideline of the lane, the player runs back to the opposite line, and then runs back to the starting point. The score is the time to cover the distance measured in seconds.

Three-quarter court sprint	Two cones are placed at the corners of the lane along the baseline, and other 2 cones are placed at the corners of the opposite free-throw line. The player sprints from the baseline to the three-quarter length of the court as fast as possible. The score is the time to cover the distance measured in seconds.
Standing vertical jump	After the standing reach is measured, the player jumps vertically as high as possible and taps the Vertec device without a running start (both feet flat on the floor). The score is the difference between the standing reach and the jump reach measured in inches.
Maximum vertical jump	After the standing reach is measured, the player jumps vertically as high as possible and taps the Vertec device with a running start. The player can take any number of steps as long as the approach distance is between the free-throw line and a 15-foot (4.6 m) arc and can choose either a 1-foot or 2-foot takeoff. The score is the difference between the standing reach and the jump reach measured in inches.
Bench press	The player performs 185-lb (83.9 kg) bench press as many repetitions as possible with a standard, proper technique. The score is the total number of completed repetitions.
Based on Teramoto, Cross, Rieger, Maak & Willick, 2018, p. 398	

In addition to these measures in Table 1, we calculated one more metric based on these standardized numbers to add more context. Wingspan by itself is not a very useful statistic, since it is highly correlated with height. In our sample (N = 1,324) we can report a Pearson's r = 0.837, p < 0.001, which shows that these two dimensions are closely related. Hence, to examine the wingspan of a player in relation to their height adds valuable context. To possess a 7'0'' wingspan is a lot more impressive for a 6'4'' playmaker than for a 7'2'' bigman.

Managers are looking for positive outliers in this variable as extraordinarily long arms relative to their height potentially allow a prospect to have more impact on a basketball game than their comparable peers due to a greater reaching ability. Therefore, we introduced the difference wingspan and height as a newly computed, individual anthropometric. A positive value speaks for additional positional length, while a negative value historically has been raising concerns for decision-makers in the evaluation of players (Zetterberg & Hallmark, 2011).

6.3.3 PLAYER-PERFORMANCE-METRIC

The very commonly used basketball impact measure "Win Shares" (WS) shows how much influence the sporting-performance of a player had on the success of their teams. WS is an appealing metric because it calculates the contribution of individual players to their team's wins based on comparable box-score-statistics. Its computations attempt to gather the offensive and defensive impact of a player. Within the formular statistics are incorporated on a per-possession-basis to control for differences in playing speed due to team or era context. Added up, the WS-values of all active players of a team over an 82-game season [2] give the actual number of wins achieved by the franchise (with a deviation of ~2.74 games). This allows an assessment of the share an athlete contributed to the achieved sporting-performance. For example, if a player had a WS-value of 5.0, their on-court-performance was worth about five wins for their team over this season.

This statistic has problems evaluating certain facets of the sport and therefore does not paint the most nuanced picture regarding player-value since it only uses basic boxscore-data. But this fact also makes it appealing to work with in a historical context. Due to the lack of complex components, it can be calculated for players of many decades and allows to compare athletes no matter the era or on-court role they played in. Additionally, the statistic also works as a reliable performance estimate for college basketball players. Controlling for either NBA or NCAA environment makes broad player-quality-levels comparable considering the average WS-outputs achieved on a per-year or per-game basis (Basketball-Reference, 2020b).

6.3.4 Research structure and hypotheses

This paper aims to investigate the relationship between athleticism and managerial decision-making regarding player evaluation and choice behavior in a concrete selection process. We are analyzing this dynamic because theoretical frameworks and previous research have proven this connection to be problematic in various environment, as presented in 2.3. Therefore, it should be tested for such an effect within the realm for the NBA Draft, since it could pose serious difficulties for the entire league-policy.

Previous research in basketball suggests treating the broad term "athleticism" in this discipline as the combination of anthropometrics and specific physical capabilities. Performance dimensions that have been deemed important for the sport historically are, e.g., speed, quickness, strength and jumping ability. Isolating these factors within the NBA Draft Combine data is the first goal of our analysis. Second, we will investigate if these then clearly defined pre-draft dimensions as a proxy for athleticism encourage certain concrete managerial draft behavior. And if so, we additionally test whether post-draft outcomes justify such behavior of the decision-makers. The variables position, age and pre-draft performance will be controlled for, to better isolate potential athleticism-induced effects.

We will examine these hypotheses, to fulfill our initial research aim:

H1A. The better the anthropometrics of a player measured at the NBA Draft Combine, the higher are their chances of getting drafted.

H1B. The better the sport-specific physical capabilities of a player measured at the NBA Draft Combine, the higher are their chances of getting drafted.

H2A. The better the anthropometrics of a player measured at the NBA Draft Combine, the earlier they are selected in the draft.

H2B. The better the sport-specific physical capabilities of a player measured at the NBA Draft Combine, the earlier they are selected in the draft.

H3A. The better the anthropometrics of a player measured at the NBA Draft Combine, the better they perform in the NBA.

H3B. The better the sport-specific physical capabilities of a player measured at the NBA Draft Combine, the better they perform in the NBA.

6.4 ANALYSIS

6.4.1 SIMPLIFYING PRE-DRAFT NBA COMBINE PERFORMANCE TO ATHLETICISM FACTORS

In the first analysis phase, we performed a principal component analysis within the available NBA Draft Combine variables. As shown in previous research on the topic (Teramoto, Cross, Rieger, Maak & Willick, 2018), this method is a useful tool to reduce the dimensions of the data and translate the individual drills into clear athleticism factors.

6.4.1.1 MODEL PCA

We used all the NBA Draft Combine variables in 3.2 for the model except for these three components: "Shuttle run" was excluded since this drill was only introduced into the Combine schedule in 2013 and therefore presented many missing values (79.8% of cases were missing). "Height with shoes" was left out since it is highly correlated with height without shoes anyway ($r = 0.995$; $p < 0.001$), a metric that measures the same physical dimensions, only without individual shoe model-induced variance. Lastly, we removed "lane agility" from the model because it showed up as a complex, but indecisive variable in the resulting factors, producing coefficients of 0.5 for more than one component in the matrix. This arrangement left us with 373 complete observations for our analysis.

The KMO value (0.755) and Bartlett's test results ($p < 0.001$) show that our data is a valid input for the principal component analysis (Bartlett, 1954; Kaiser, 1974). Using the scree plot output, we were able to identify four valid components with an eigenvalue of 1 or greater, which can be extracted as potentially useful components for the NBA Draft Combine data (Cattell, 1966). These factors explain a total variance of 78.8%, while individually contributing 43.9, 16.7, 9.7 and

8.4% variance, respectively. A direct oblimin rotation was applied to the extracted factors to simplify their interpretation.

TABLE 6-2. FACTOR MATRIX OF THE NBA DRAFT COMBINE DATA DERIVED FROM PCA WITH DIRECT OBLIMIN ROTATION.

	Component			
	1	2	3	4
Height	**.892**	-.460	.203	.100
Standing Reach	**.884**	-.520	.120	.272
Wingspan	**.869**	-.369	.179	.566
Hand Length	**.802**	-.204	.186	.456
Weight	**.726**	-.526	.576	.312
Hand Width	**.676**	-.012	.087	-.011
Maximum Vertical	-.354	**.887**	.047	-.041
Standing Vertical	-.186	**.840**	.179	.073
Three Quarter Sprint	.349	**-.738**	.114	.126
Body Fat Percentage	.014	**-.688**	.482	.275
Bench Press	.168	.116	**.863**	-.030
Wingspan/Height Difference	.193	.024	.002	**.941**
Factor Interpretation	Anthropometrics	Explosiveness & Speed	Strength	Positional Length

N = 373

6.4.1.2 RESULTS

The resulting factors, shown in Table 2, allow useful interpretations. First, measures of the athletes' bodies clearly add up to basic anthropometrics, representing length and size of the prospects. The second factor brings together jumping and sprinting drills, measuring the explosiveness, power, and speed of the talents. 'Body fat percentage' as a component within this factor makes sense as well. In our cohort of highly trained athletes a low body fat percentage usually means more relative muscle mass, which mostly contributes positively to explosiveness and speed. The third identified factor represents arm and torso strength since a clear upper body drill has the highest coefficient loading, while weight and body fat percentage contribute largely in the expected direction. Lastly, our own introduced measure of wingspan/height difference builds its own factor with hand length and regular wingspan contributing meaningfully within this setup. We interpret this as a measure of positional length. The found components were then saved to enable them to be used as variables in the further analysis. The isolated dimensions "Anthropometrics," "Explosiveness and Speed," "Strength" and "Positional Length" fit well with the approach to basketball athleticism we extracted from theory in 2.3. This justifies using them in the following steps of our analysis.

6.4.2 PRE-DRAFT COMBINE PERFORMANCE AND MANAGERIAL SELECTION BEHAVIOR

Due to the invitation system described earlier in 2.2, it can be assumed that all Combine attendees are on the draft radar of at least one NBA franchise. Without presenting any draft appeal the athletes would not be asked to participate. Hence, the NBA Draft Combine already produces a pre-selected list of NBA prospects. Left with this specific sample of closely considered prospects [3], we want to examine whether superior athletic attributes presented within the NBA Draft Combine environment – as we contextualized it with the four extracted athleticism factors – influence the managerial selection behavior in the NBA draft significantly and substantially. In a first step, we will look at general draft status and investigate if better athletic traits lead to a higher likelihood of getting drafted. Our second analysis goes one step further by researching if better NBA Combine performance also results in better draft positions.

6.4.2.1 MODEL GENERAL DRAFT STATUS

Considering the type of dependent variable, we applied a binary logistic regression model for "general draft status". To be able to isolate potential effects better, we controlled for the possibly draft selection behavior-influencing measures "Age", "Position" and "Pre-Draft Performance" [4] (e.g., Berri, Brook & Fenn, 2011; Moxley & Towne, 2015; Sailofsky, 2018), by using a hierarchical approach for the construct. We were able to use 363 complete cases for our analyses.

TABLE 6-3. HIERARCHICAL BINARY REGRESSION MODEL FOR ATHLETIC TRAITS AND GENERAL DRAFT STATUS.

Model	Component	B	S.E.	Wald	df	Sig.	Exp(B)
1[a]	Position	.005	.087	.003	1	.958	1.005
	Pre-Draft Performance	15.125	3.630	17.359	1	.000	3703508.915
	Age	-.168	.085	3.890	1	.049	.846
	Constant	2.896	1.840	2.476	1	.116	18.096
2[b]	Position	.045	.167	.073	1	.787	1.046
	Pre-Draft Performance	16.483	3.852	18.309	1	.000	14405110.490
	Age	-.174	.087	4.004	1	.045	.840
	Anthropometrics	.152	.219	.479	1	.489	1.164
	Explosiveness & Speed	.388	.137	8.064	1	.005	1.474
	Strength	.031	.141	.047	1	.828	1.031
	Positional Length	-.116	.128	.823	1	.364	.890

a. Variable(s) entered on step 1: Position. Pre-Draft Performance. Age.
b. Variable(s) entered on step 2: Anthropometrics. Explosiveness & Speed. Strength. Positional Length.

6.4.2.2 RESULTS FOR H1A AND H1B

Table 3 shows, that both models within the hierarchical construct proved to be highly significant. The addition of the four athleticism factors leads to an improvement of the Nagelkerke R2 from 0.085 ($p < 0.001$) to 0.124 ($p < 0.001$), which is a meaningful increase in explained variance within the chosen setup.

Looking at the single component loadings for the second model that incorporated all variables, we can examine that as expected, "Age" ($B = -0.174$, $p < 0.05$) and "Pre-Draft Performance" ($B = 16.48$, $p < 0.001$) significantly influence if a prospect gets drafted at all out of the pre-selected NBA Draft Combine pool. Their respective loadings point in the expected direction. While increasing performance in college makes it more like to get drafted, being younger is favorable for a selection in this process. "Position" ($B = 0.045$, $p = 0.787$) does not matter in a noteworthy way.

Interestingly, our extracted athleticism factor "Explosiveness and Speed" ($B = 0.388$, $p = 0.005$) contributes in a significant way to the model, proposing that while controlling for position, age and pre-draft performance, the quickest and highest leaping talents are preferably drafted. The other NBA Draft Combine components "Anthropometrics" ($B = 0.152$, $p = 0.489$), "Strength" ($B = 0.031$, $p = 0.828$) and "Positional Length" ($B = -0.116$, $p = 0.364$) are not significant.

These findings allow us to reject the H1B. In the component "Explosiveness and Speed" we found sport-specific physical capabilities to influence the managerial selection behavior in the draft process regarding the general draft status. Faster, more explosive NBA Draft Combine participants are more likely to drafted out of the sample that was examined, even controlling for the factors age, position, and pre-draft performance.

However, H1A cannot be falsified after our analysis. The model did not present any evidence that better anthropometrics make it more likely to get drafted out of the group of NBA Combine participants.

6.4.2.3 MODEL DRAFT RANK

In this analysis we investigated the resulting draft ranking as the dependent variable using a multiple hierarchical regression model including the same independent factors and controlling for the same components as above. This time we were able to include 265 complete cases into our analysis:

TABLE 6-4. HIERARCHICAL MULTIPLE LINEAR REGRESSION MODEL FOR ATHLETIC TRAITS AND DRAFT RANK.

		Unstandardized Coefficients		Standardized Coefficients		
Model	Component	B	Std. Error	Beta	t	Sig.
1[a]	(Constant)	-48.521	12.673		-3.829	.000
	Age	4.714	.578	.431	8.157	.000
	Position	-1.103	.596	-.098	-1.852	.065
	Pre-Draft Performance	-146.277	23.866	-.326	-6.129	.000
2[b]	(Constant)	-52.470	12.834		-4.088	.000
	Age	4.585	.572	.419	8.016	.000
	Position	1.580	1.127	.141	1.402	.162
	Pre-Draft Performance	-162.496	23.709	-.362	-6.854	.000
	Anthropometrics	-5.588	1.493	-.345	-3.742	.000
	Explosiveness & Speed	-2.153	.927	-.132	-2.322	.021
	Strength	-.773	.877	-.050	-.882	.379
	Positional Length	.058	.815	.004	.072	.943

a. Variable(s) entered on step 1: Position. Pre-Draft Performance. Age.
b. Variable(s) entered on step 2: Anthropometrics. Explosiveness & Speed. Strength. Positional Length.

6.4.2.4 RESULTS FOR H2A AND H2B

Table 4 displays both models were highly significant. An improvement of the Adjusted R2 from 0.267 ($p < 0.001$) to 0.314 ($p < 0.001$) was reached. This shows that adding the NBA Draft Combine components increases the explained variance. In the combined setup "Age" (B = 4.585, $p < 0.001$) and "Pre-Draft Performance" (B = -162.496, $p < 0.001$) are highly significant and have loadings in the expected direction. With increasing age, the draft rank increases as well, meaning that older players within the examined sample tend to get drafted later. Pre-draft performance works in the other direction.

As expected, more college production leads to a lower draft rank. Hence, a more impactful player is more likely to get selected earlier. "Position" (B = 0.045, p = 0.787) does not contribute to the model in a relevant way.

Out of the added athleticism factors "Anthropometrics" (B = -5.588, $p < 0.001$) and "Explosiveness and Speed" (B = -2.153, $p < 0.05$) are significant variables in the model, while "Strength" (B = -0.773, p = 0.379) and "Positional Length" (B = 0.058, p = 0.943) do not prove to be significant. The coefficients reveal that within the NBA Draft Combine player pool controlling for position, age and pre-draft performance, more explosive and faster talents with longer physical measurements tend to get drafted earlier than their slower and smaller peers. This allows us to reject both, the H2A and the H2B. The analysis displayed that there are anthropometrics as well as sport-specific physical capabilities that influence the managerial selection behavior in the draft process in terms of the ranks at which talents gets selected at within the sample we examined.

6.4.3 PRE-DRAFT COMBINE PERFORMANCE AND POST-DRAFT ON-COURT PERFORMANCE

In the third phase of the analysis, we checked whether our extracted athleticism components have predictive value for post-draft performance of the prospects. The approach to test this hypothesis was similar to the one taken in the previous chapter.

6.4.3.1 MODEL POST-DRAFT PERFORMANCE

Again, we used multiple hierarchical linear regression as our statistical method. NBA-Win Shares were used as a measure for post-draft performance and introduced as the dependent variable of the construct. The statistic was employed on a per-game-basis to be able to compare players with different experience levels. Additionally, we applied 100 games played as a filter to guarantee a meaningful sample size for all investigated subjects of a little more than an entire season played (N = 151). Again, we controlled for "age," "position" and "pre-draft performance" as possibly influencing factors:

TABLE 6-5. HIERARCHICAL MULTIPLE LINEAR REGRESSION MODEL FOR ATHLETIC TRAITS AND POST-DRAFT PERFORMANCE.

		Unstandardized Coefficients		Standardized Coefficients		
Model	Component	B	Std. Error	Beta	t	Sig.
1[a]	(Constant)	.053	.034		1.543	.125
	Age	-.003	.002	-.131	-1.723	.087
	Position	.006	.002	.312	4.076	.000
	Pre-Draft Performance	.194	.063	.236	3.081	.002
2[b]	(Constant)	.049	.036		1.384	.168
	Age	-.002	.002	-.091	-1.174	.242
	Position	.001	.003	.026	.168	.867
	Pre-Draft Performance	.235	.065	.285	3.588	.000
	Anthropometrics	.010	.004	.333	2.339	.021
	Explosiveness & Speed	.000	.003	.012	.140	.889
	Strength	.000	.002	.016	.185	.854
	Positional Length	.003	.002	.098	1.275	.204

a. Variable(s) entered on step 1: Position. Pre-Draft Performance. Age.
b. Variable(s) entered on step 2: Anthropometrics. Explosiveness & Speed. Strength. Positional Length.

6.4.3.2 RESULTS FOR H3A AND H3B

Table 5 exhibits, two tested models are both highly significant. Adding the athleticism factors in the second step increased the Adjusted R^2 from 0.133 ($p < 0.001$) to 0.156 ($p < 0.001$). While "Pre-Draft Performance" ($B = 0.235$, $p < 0.001$) seems to be a decent, highly significant predictor for post-draft performance in both constructs, “Age” (B = -0.002, p = 0.242) and “Position” (B = 0.001, p = 0.867) do not behave in the same way. This shows, out of the sample we have examined, that more impactful college players tend to produce the most post-draft value for teams. However, there seems to be no specific advantage for players of a certain position group. Neither do the numbers give reason to form any generalization concerning age, which is an important finding. Relative youth in basketball talents usually corresponds with more uncertainty due to a smaller pre-draft performance sample size. Often these talents have only played one college season before entering the draft process. Such uncertainty can be interpreted as potential future development opportunities for a prospect that do not seem realistic anymore for older players. Yet, the downside to them is the risk of misjudgment of their skill-level based on lucky small sample-size performances or even still lasting, but unwarranted high school reputation (Berger & Daumann, 2021). This is less likely to happen with players who have played multiple years in college. Curiously, our model indicates that these potential effects seem to cancel each other out within the examined sample of Combine participants.

Out of the athleticism factors only “Anthropometrics” (B = 0.010, $p < 0.05$) proves to be of significance regarding post-draft performance. Controlling for “Age,” “Position” and “Pre-Draft Performance” only this dimension influences NBA on-court value. The factor with its positive loading behaves as expected. As theory suggests, possessing more general length and size seems to help players to perform in the NBA if the other dimensions are controlled for. However, neither “Explosiveness and Speed” (B = 0.000, p = 0.889), “Strength” (B = 0.000, p = 854) nor “Positional length” (B = 0.003, p = 0.204) add meaningful information in this setup. This suggests that within the NBA Draft Combine sample that was analyzed, faster, stronger player with more jumping ability do not necessarily outperform their competition (post-draft, age, position, and college impact being controlled for).

While we can reject the hypothesis H3A since anthropometrics seem to influence NBA performance, we cannot falsify H3B based on the results of our model. The sport-specific physical capabilities, as measured at the NBA Draft Combine, do not seem to influence post-draft performance in a significant way.

6.5 CONCLUSION

The NBA Draft Combine athleticism factors we extracted out of the available data through a principal component analysis influence the draft-decision-making of NBA managers selecting athletes from the NBA Draft Combine player pool in various ways. Analyzing hypotheses which we derived from theory, several important dynamics can be observed dynamic.

6.5.1 ANTHROPOMETRICS

"Anthropometrics" proved to be useful in the prediction of future player value, even when controlling for age, position, and pre-draft performance. Hence, this information should be considered in the player evaluation process. This might seem counterintuitive for keen observers of the sport, as the average height of NBA players has peaked in the 1980 and 2000s. The league generally has been downsizing regarding average player height ever since (Curcic, 2020). Still, positional height and length are key. The almost significant contribution of our wingspan induced factor toward post-draft performance additionally points in this direction. Today's game often mistakenly gets called the "small ball-era" of the NBA. It should better be called the "skill ball-era" as many experts argue (e.g., Favale, 2015; Narsu, 2017). Due to the recent analytics-induced emergence of the three point-shot (e.g., Alamar, 2013; Lewis, 2017; Goldsberry, 2019), most players are required to be able to shoot from distance. Players without this skill have a hard time earning playing time. In the past, taller players have not been trained with the requirement of this skill in mind, therefore usually lacking it. With current generations of taller players catching up in the skill dimension due to better youth development, the league might even get taller at the top-end again. Out of two equally skilled players, managers, and coaches usually would and should prefer the taller, longer, and stronger one. As the global basketball population is getting more skilled due to the growing popularity of the sport, such a dynamic can be shown when looking at the lower end of the height and weight spectrum: (see Figure 1).

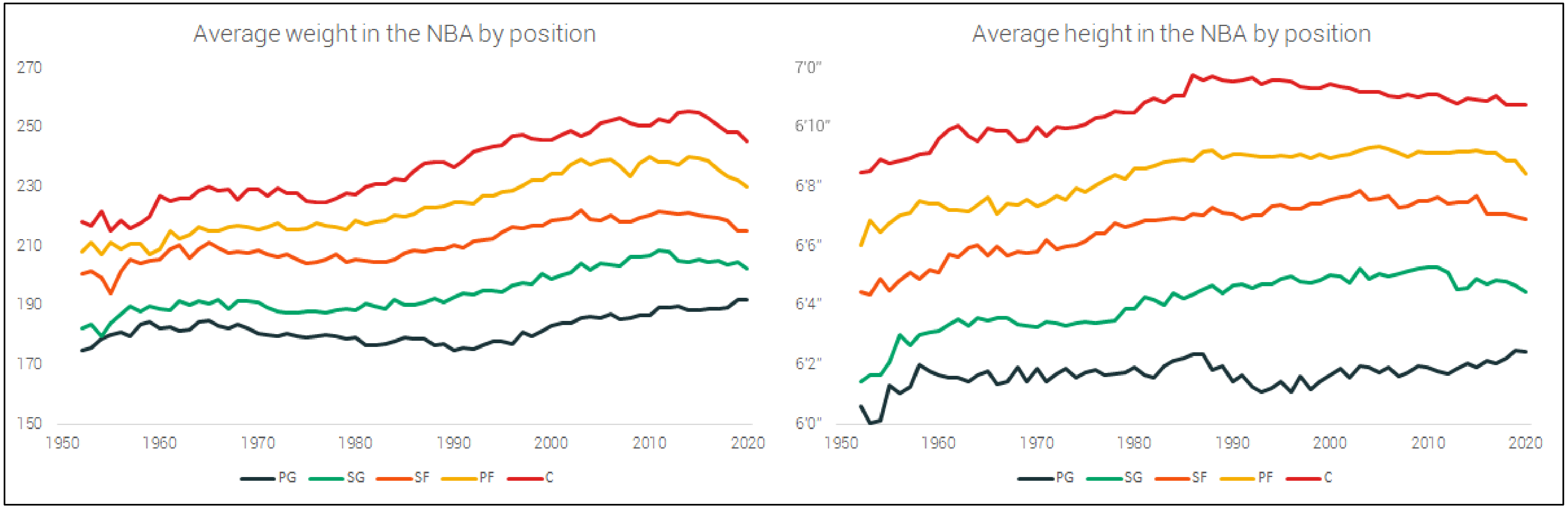

FIGURE 6-1. OVERVIEW PLAYER HEIGHTS AND WEIGHTS IN NBA OVER TIME.

The smallest and lightest players of the league getting taller and heavier in the times of "small ball" shows why our result of anthropometrics being a significant driver for post-draft performance is an important one. Decision-makers seem to know about this relationship of the two variables and act accordingly. After controlling for position, age and pre-draft performance, managers rightfully select talents with better anthropometrics earlier than their peers in the observed sample.

Nonetheless, the data also suggests that superior anthropometrics do not make it more likely to get drafted at all, proposing that the threshold a prospect needs to exceed in the first place is not athletically but concerning the basketball skills. This is logical, looking at the sample that we have analyzed and the survivorship bias that goes into it. Even compared to other great basketball players, NBA Draft Combine participants are usually required to be good athletes relative to this competition. Hence, the differentiating factor between them for making the league is a certain college basketball production level and not certain anthropometrics advantages.

6.5.2 SPORT-SPECIFIC PHYSICAL CAPABILITIES

However, most importantly, we have found a problematic disconnect caused by the NBA Draft combine factor "Explosiveness and Speed", as a dimension of sport-specific physical capabilities. Within our model this factor significantly influences the managerial drafting-behavior while not being a trustworthy predictor for future NBA success. This gives us evidence to assume managers are somewhat clouded in their judgment of athletes by it, even controlling for age, position, and pre-draft performance.

To understand why "Explosiveness and Speed" can be deceiving in a basketball context, even though these are almost always positively connotated traits, one needs to examine the nuances of this dimension. Basketball evaluators often discuss the terms "Functional Athleticism" and 'Run and Jump – Athleticism" (e.g., The Stepien, 2020b; Go-to-Guys, 2020) at this point. The key differentiation this distinction is trying to communicate is that a basketball talent needs to be able to apply athletic traits on the court to leverage their physical gifts completely into sportive production. This can be difficult observing "Explosiveness and Speed"-components if certain basic basketball skills are underdeveloped or lacking. In a simplified example, a basketball player could be the fastest runner in the world. Without matching ballhandling skills they would never fully be able to use their speed to their advantage in an onball-scenario because they either lose control of the ball or produce a travel, when going at maximum speed. Our findings could be evidence for such missing functionality within the measured elite physical tools in prospects at the event.

Even worse than the lack of predictability of the "Explosiveness and Speed"-factor for future performance is its influence on the drafting behavior. Controlled for age, pre-draft production and position, within the examined group of NBA Draft Combine participants elite jumpers with superb speed wrongfully tend to get drafted higher. An explanation for this observed phenomenon could be the two cognitive dissonance we mentioned in 2.3 – availability and overconfidence bias. Due to potentially more spectacular actions on the court in their pre-draft sample, better athletes are more memorable as players and therefore easier to recall in a choice environment, while their current and future production gets overvalued. On the other hand, overconfidence bias might additionally influence the envisioned development curve of a talent. Many managers might overestimate the abilities of their organization in teaching and enhancing the correct skills to "unlock" all athletic traits to their fullest extent in a basketball setting. This misjudgment promises false potential, as many experts have discussed (e.g., Vashro, 2014; Moxley & Towne, 2015). On the other hand, actions of faster and more explosive athletes are possibly more memorable, potentially making them to come to mind earlier in a draft-selection scenario, caused by availability bias dynamics (e.g., Tversky & Kahneman, 1973). This reduced quality of the draft decision-making quality-lowering mechanism is highly problematic for the entire NBA Draft policy and the results it intends to reach.

The factor "Strength" did not prove to be significant within the examined process. Therefore, it does not provide much value for our discussion. Yet, this factor should be revisited in the future, as the factors "positional strength" and "core strength" gained importance in basketball talent evaluation over the past few years, with some research behind it providing a promising foundation (e.g., Tsukagoshi, Shima, Nakase, Goshima, Takahashi, Aiba, Yoneda, Moriyama & Kitaoka, 2011; Sannicandro & Cofano, 2017).

6.5.3 IMPLICATIONS AND FUTURE RESEARCH

NBA franchises and managers should use our results to question their use of NBA Draft Combine data and their historical focus on athletic traits. While "Anthropometrics" seem to be very important data to be considered in the player evaluation process, the factor "Explosiveness and Speed" should not be relied on as heavily when making these choices. The league could rethink the measurements and drills they implement in future NBA Draft Combine settings. The data has shown that the athleticism information collected there does not provide much value for decision-makers as the current data fails to project future post-draft impact in a reliable way. The NBA should think about adding more exercises to the event that allow to capture functional athleticism better if their goal is to inform the overall draft process in its entirety.

By the league and NBA franchises installing measures to avoid this athleticism-induced bias, we would expect draft decision-making quality to improve, enhancing the league-wide outcome of the NBA draft policy. Future research could test additional athleticism qualities as sources for systematic errors and try to isolate the biases that we suggested as explanatory underlying dynamics for the investigated decision-making process.

NOTES

1. This paper will focus on the standardized anthropometrics and athletic testing data. A detailed overview over the measured and later investigated dimensions will follow in the methodology Section 3.2.
2. This game-win-number is adjusted if WS are calculated for the college environment, where a maximum of 40 games can be played in one season.
3. We leave out some game theory thoughts, which would make it an interesting strategic option for franchises to only propose to invite prospects, that they do not closely consider distracting competing teams from the options they secretly favor.
4. Win shares on a per game basis were used to measure pre-draft performance to be able to compare prospects with different experience levels and even account for injuries of one-year-players.

CHAPTER 7

Increasing the shot at a quality draft-decision – A Bayesian approach to explain historical three-point-accuracy translation in the NBA Draft

STUDY IV

Tobias Berger & Frank Daumann

SUBMITTED AS

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7. STUDY IV: INCREASING THE SHOT AT A QUALITY DRAFT-DECISION

ABSTRACT

This paper presents explanatory models for post-draft three-point-shooting-accuracy and volume based on pre-draft statistics. To improve former ideas, we added college two-point-jumper-percentage and an estimate of informed pre-draft three-point-percentage as novel components to our approaches. The former was derived from NCAA play-by-play-data, while the latter was generated from updating historical pre-draft data, using an empirical Bayesian shrinkage technique including beta-binomial regression.

Both newly introduced variables add valuable information to our explanatory models for post-draft shooting-accuracy and post-draft shooting-volume. The resulting systems, using beta and multiple linear regression, performed better than other publicly available designs. Thus, their potential application as a decision-aiding tool should reduce error and with this a little bit of uncertainty in the projection of pre- to post-draft shooting-translation. These outcomes could improve the draft decision-making quality of NBA executives and ultimately enhance the league-wide results of the draft policy.

7.1 INTRODUCTION

The NBA Draft is a mechanism to regulate competitive balance of a sports league. Its ambition - to give the worst franchises a chance to acquire young prospects, improve long-term and close the on-field talent gap to better teams - is clear and noble. In theory the policy strengthens the NBA's product in many ways. It is supposed to distribute league-entering player capital equally, and by this dynamic improve the quality of play (Hausmann & Leonard 1997, Berri, Schmidt & Brook, 2004) while increasing the competitive balance among all competitors by raising the uncertainty of outcome on a game and season-level. This has been deemed an important goal for sports leagues for a long time (Rottenberg, 1956). The potential benefits of the mechanism should lead to increasing attractiveness of the entertainment product the NBA offers.

The crux of these theoretical outcomes is the nature of the mechanism itself. For the described dynamics to work, all NBA managers need to constantly seize the opportunity the NBA Draft provides them with. Unfortunately, this is an incredibly complex expectation to have for the acting decision-makers. In the draft environment, choices are not made within a known variance, but among widely unknown outcomes. The policy can therefore be treated as a proxy for decisions under uncertainty (Mishra, Barclay & Sparks, 2017). Within this complex process decision-makers ultimately do not only have to judge who the best prospect is at the moment of the draft, but also who will develop into the most valuable player in the future, while additionally (among considering other external factors) forecasting the direction in which the sport itself is moving in the long-term. This provides much room for individual failures due to personal misjudgments or misconceptions by the managers, and leaves the door open for systematic errors on a leaguewide level caused by collective decision-making biases (Sailofsky, 2018).

Over the past few decades many efforts have been made to improve draft decision-making quality and reach the goals the draft mechanism intends to fulfill. Still, the mechanism does not produce such positive outcomes constantly, even though it would be beneficial for the entire league. Research has shown that it does not pay off to solely build up a franchise through the draft (Berri, 2013; Motomura, 2016). The mechanism of the policy did not seem to level the playing field as much as it was supposed to, since most of the deciding organizations seem to lack proper talent evaluation abilities (Berri, Brook & Fenn, 2011). Stronger teams tend to profit more from the policy than bad ones, which is completely contrary to its intentions (Berri, 2013). Consequently, research even advices against the draft policy as league-wide tool to strengthen competitive balance. Historical results show, there are not enough competent decision-makers to implement the mechanism well enough to produce those favorable outcomes for the entire association constantly (Motomura, Roberts, Leeds & Leeds, 2016). Meanwhile, the NBA historically has performed as the most imbalanced of all the North American sports leagues (Soebbing & Mason, 2009). At least to some extent this state of the association can be based on the rather poor draft decision-making quality next to salary cap-induced factors (Totty & Owens, 2011).

We identified the increase of managerial decision-making quality within the dynamics as a crucial component to fulfill the aims of the fundamental policy proposal. Initial judgements in talent evaluation and future predictions of performance for the potential draftees and the environment they will play in need to be improved in their accuracy and reliability to reduce uncertainty inside the complex choice mechanism and thus, provoke better overall results.

This paper aspires to reach this goal by examining one of the key components of the sport more closely – shooting the basketball from distance. We will explore league-wide three-point scoring tendencies and investigate in which direction the sport has developed and will progress. Afterwards we strive for better explaining historical shooting-translation from the college to the professional level by implementing an empirical Bayesian approach to pre-draft metrics and including a play-by-play-based metric into modeling. Being able to explain the translation of an important basketball skill more accurately should improve the individual managers player evaluations and, in the end, increase the draft decision-making quality on a leaguewide level. The results will provide a new baseline for the judgement of draft prospects within one of the most important performance facets of the sport.

7.2 BACKGROUND AND RELATED LITERATURE

7.2.1 THE NBA DRAFT DYNAMIC AS A PROXY FOR DECISIONS UNDER UNCERTAINTY

The reasons for the policy shortcomings of the NBA Draft are manifold but can mostly be attributed to the 'human judgement-factor' in many parts of this particular decision-making equation. The decision problem of the entire mechanism is clear. Every franchise strives to optimize the opportunity its current draft position provides them with by selecting the best talent available. Talent in this environment can be seen as a mixture of mostly on-court but also off-court benefits the prospect will generate for their new employer. This value allows the drafting organization to maximize financial and sportive utility following classical economic theory (Friedman & Savage, 1948; Kahneman & Tversky, 1979). The process towards solving this problem is immensely complex due to the hurdles the decision-makers must master. Within this straight-forward setup a draft choice requires NBA front offices to give their judgement in two main areas which both present huge levels of uncertainty, as probabilities of decision outcomes in this framework can only be roughly estimated and are mostly unknowable (Volz & Gigerenzer, 2012).

One the one hand, a manager needs to evaluate the talent level and concrete basketball traits of all the players at the moment of the draft, while factoring their potential development in the future. On the other hand, the direction of the entire sports, as an underlying environment the athlete needs to perform in, must be correctly anticipated as well. The NBA has come a long way over the past two decades by installing more sophisticated processes around these interwoven dynamics. Especially with the recent emergence of sports analytics huge steps have been taken towards a more scientific approach of the sport to better understand the entire discipline and reduce uncertainties (Alamar, 2013; Lewis, 2017) while league-wide playing trends can be discovered and followed more closely than ever before (Shields, 2017).

The evaluation of player talent has become much more sophisticated striving for more objectivity (Beene, 2019). Yet, at some point the analysis of athletes and their basketball traits simply comes down to taste, preferences, and the decision-maker's philosophy on how the sports of basketball should be played. These clear aspects of judgement, which are defined as 'the set of evaluative and inferential processes that people have at their disposal and can draw on in the process of making decisions' (Koehler & Harvey, 2004, p. XV) open up the entire process to the realm of classical decision-making-quality-lowering fallacies and biases.

Many of those have been investigated in the NBA Draft environment to either reduce uncertainty or uncover hidden systematic errors. Basketball draft research has covered nationality bias (Motomura, 2016) as well as recency and availability bias (Berri, Brook & Fenn, 2011; Ichniowski & Preston, 2012; Burdekin & Van, 2018). Additionally, it was shown that age and favorable positional length as proxies for potential (Groothius, Hill & Perri, 2007; Berri & Schmidt, 2010; Ashley, 2017) get misjudged constantly, while certain boxscore statistics do not translate as smoothly from the amateur to the professional level as one would expect (e.g., Coates & Oguntimein, 2010; Salador, 2011; Harris & Berri, 2015).

7.2.2 THE NBA THREE-POINT REVOLUTION

Arguably the most influential rule change in the history of basketball was the implementation of the three point-line. After much experimentation in other basketball environments the three-point line was introduced to the NBA in 1979. This rule change was a clear reaction to the dominance of the bigmen in early decades of the sport. It was intentionally designed to give smaller players better opportunities to score, while making the game more enjoyable to watch for the fans (Harper, 2013).

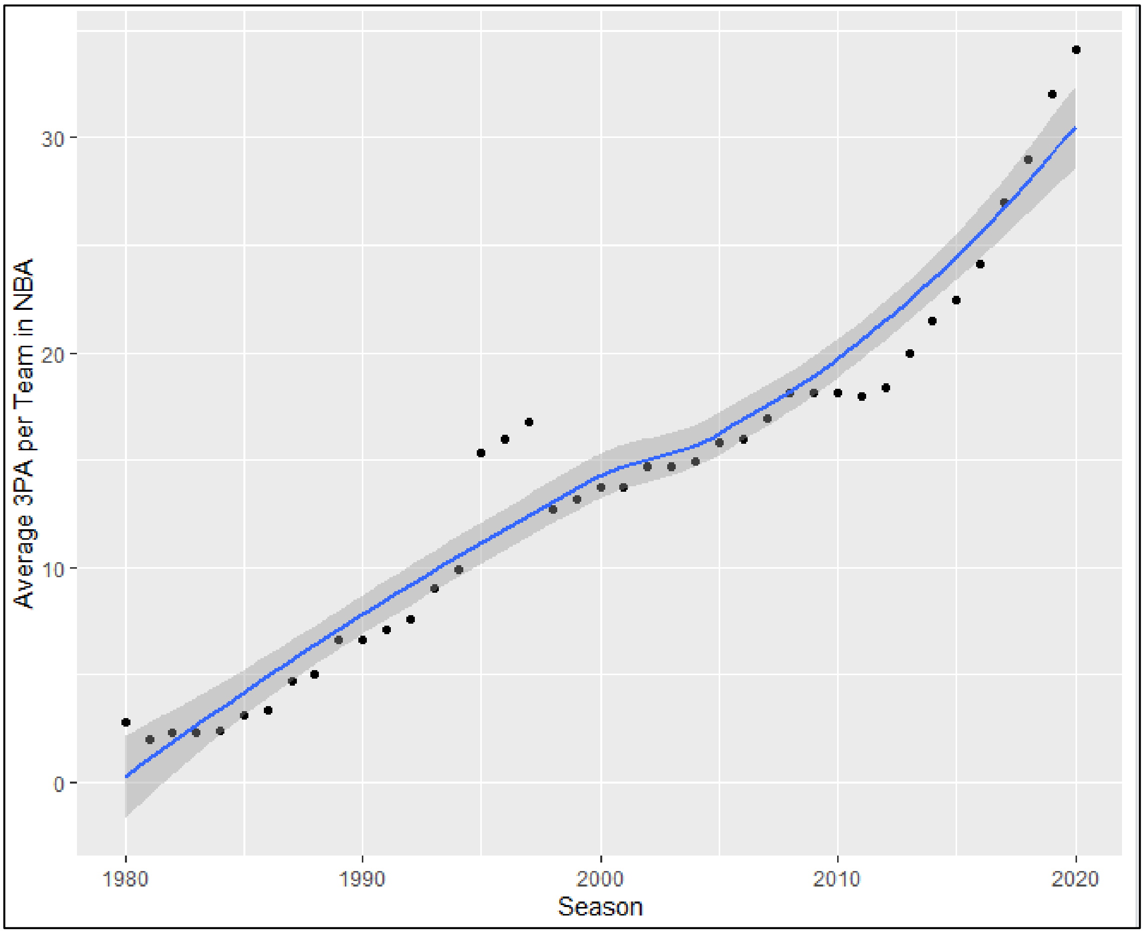

FIGURE 7-1. LEAGUEWIDE AVERAGE OF THREE-POINT ATTEMPTS PER GAME (3PAPG) OVER TIME IN NBA.

At first the league was slow to react to this change, as Figure 1 shows. Only a few players possessed the shooting skills to use this new offensive weapon constantly, while managers and coaches had not fully grasped the advantages the additional way of scoring does provide. But as more athletes were raised with the three-point line being present for their entire basketball upbringing shooting-competence and the acceptance of the three-pointer rose in the NBA (Goldsberry, 2019). The smoothed trendline with its grey confidence corridors in Figure 1 clearly underline this trend. In a trickle-down fashion this change affected college basketball as well, which introduced its own shortened three-point line in 1986 and underwent some rule-changes moving it further back in 2007 2020 on the men's side (NCAA, 2019).

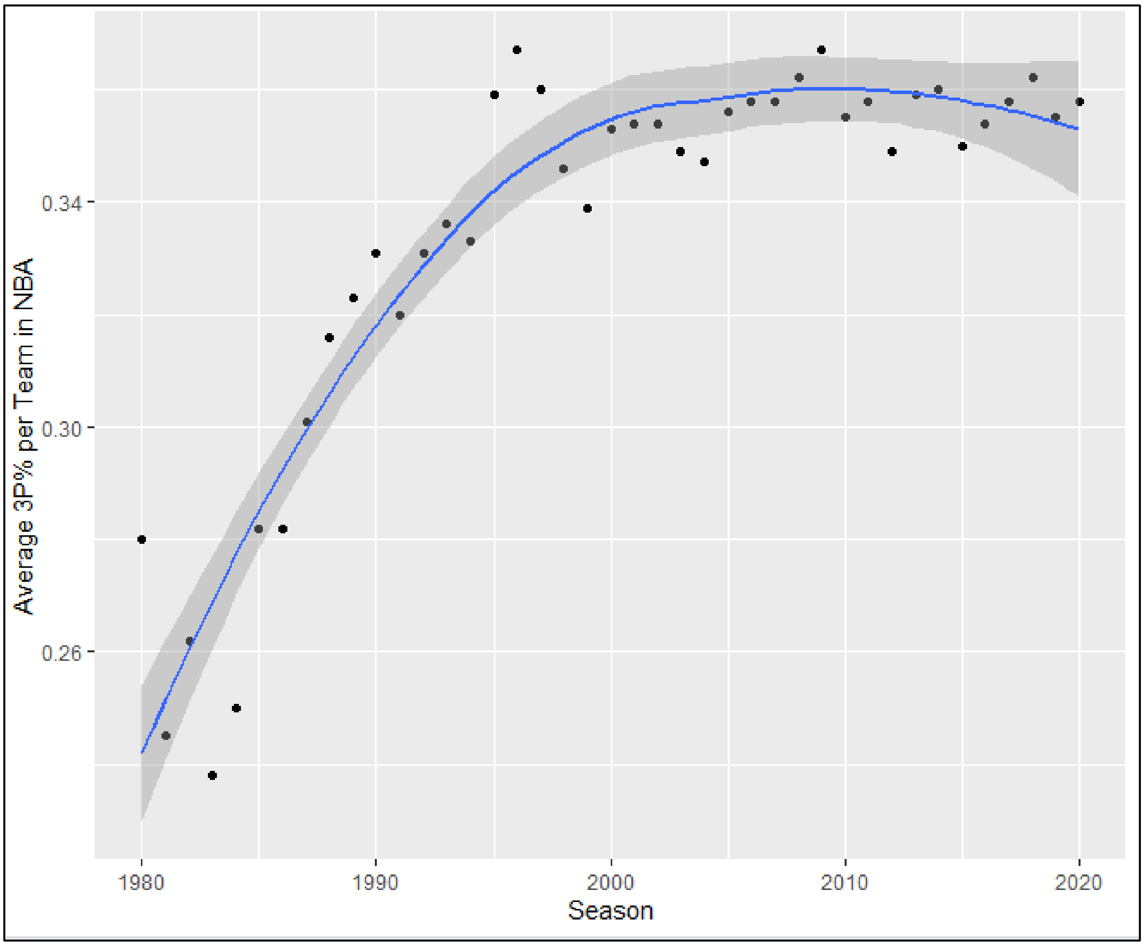

FIGURE 7-2. LEAGUEWIDE AVERAGE THREE-POINT PERCENTAGE OVER TIME IN NBA.

Figure 2 indicates, with the general skill level of the players catching up, the era of sports analytics led to shooting from distance becoming even more fashionable. The accuracy level of the players seems to be plateauing in terms of three-point percentage for a few years now, as the trendline indicates. However, this indicates a still rising skill level, since stable percentages are reached even though the number of overall three-point attempts has been rising every year, as Figure 1 presented.

Building on the 'moneyball'-ideas early introduced by the Oakland As in baseball (Lewis, 2004), which center around the use of data to find exploitable inefficiencies within the sport (e.g., Alamar, 2015; Lewis, 2017), the three-pointer as a strategic option was finally recognized as an excellent driver for efficient basketball offenses (Oliver, 2004). Backed up by numbers, managers and players not only started to realize the huge benefit the potential extra-point the shot grants. They also recognized the positive effect the threat of such attempts alone produced, forcing opposing defenses to space out, opening room for other basketball actions as well. The entire geometry of the sport changed (e.g., Shea, 2014; Goldsberry, 2019).

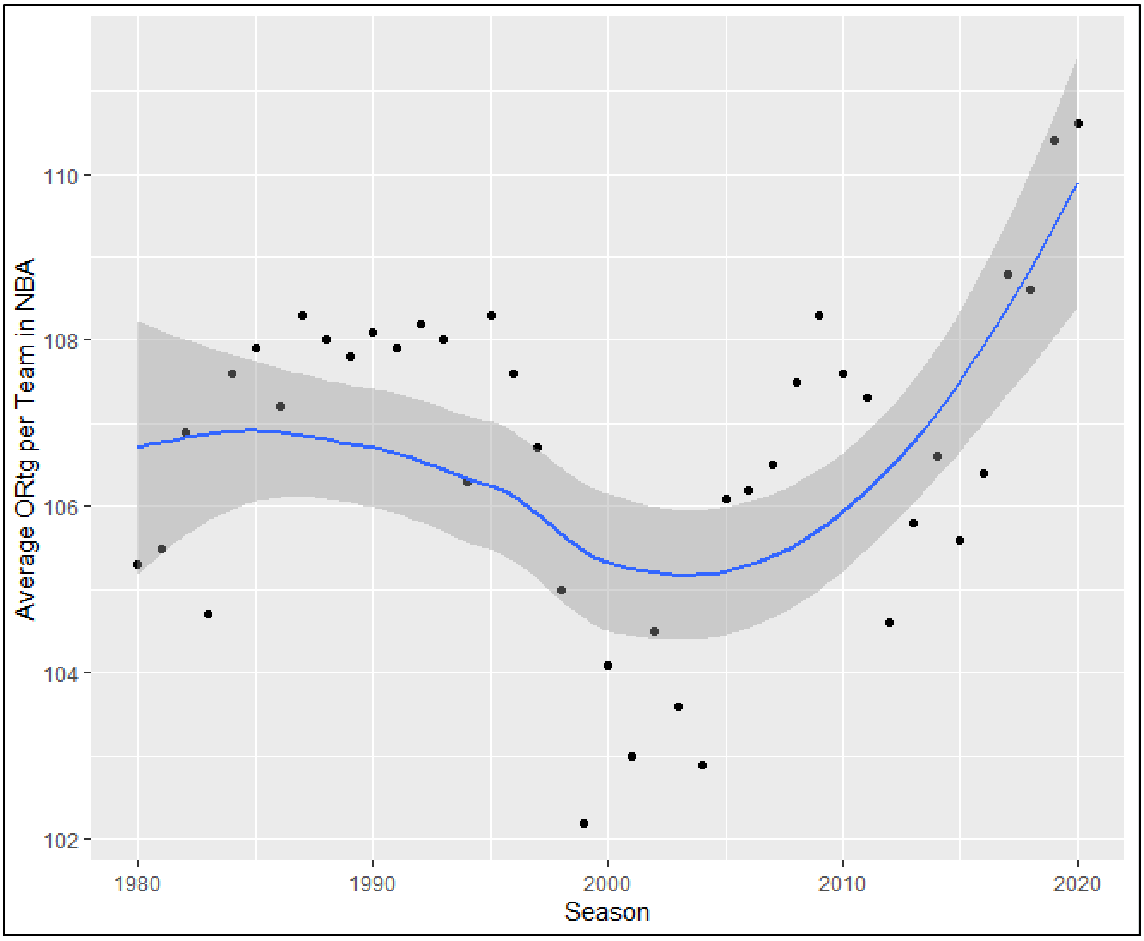

FIGURE 7-3. LEAGUEWIDE AVERAGE OFFENSIVE RATING OVER TIME IN NBA.

The strategic and stylistic innovation the extensive use of the three-pointer has caused within sport is enormous, as shown by Figure 3. The increased application of sports analytics only fuels this development to this day. Currently, some of the arguably most influential players of the sport make more three-pointers over a season than entire teams did over a year just three decades ago (Basketball-Reference, 2020a). This trend should last since it has led to a vast increase in the NBAs average team offensive rating. This metric does not only indicate the productivity and efficiency of a franchise offensive efforts on the court, but also has been proven to be one of the key factors in winning basketball games (Oliver, 2004). Thus, the league-wide demand for competent three-point shooters is increasing.

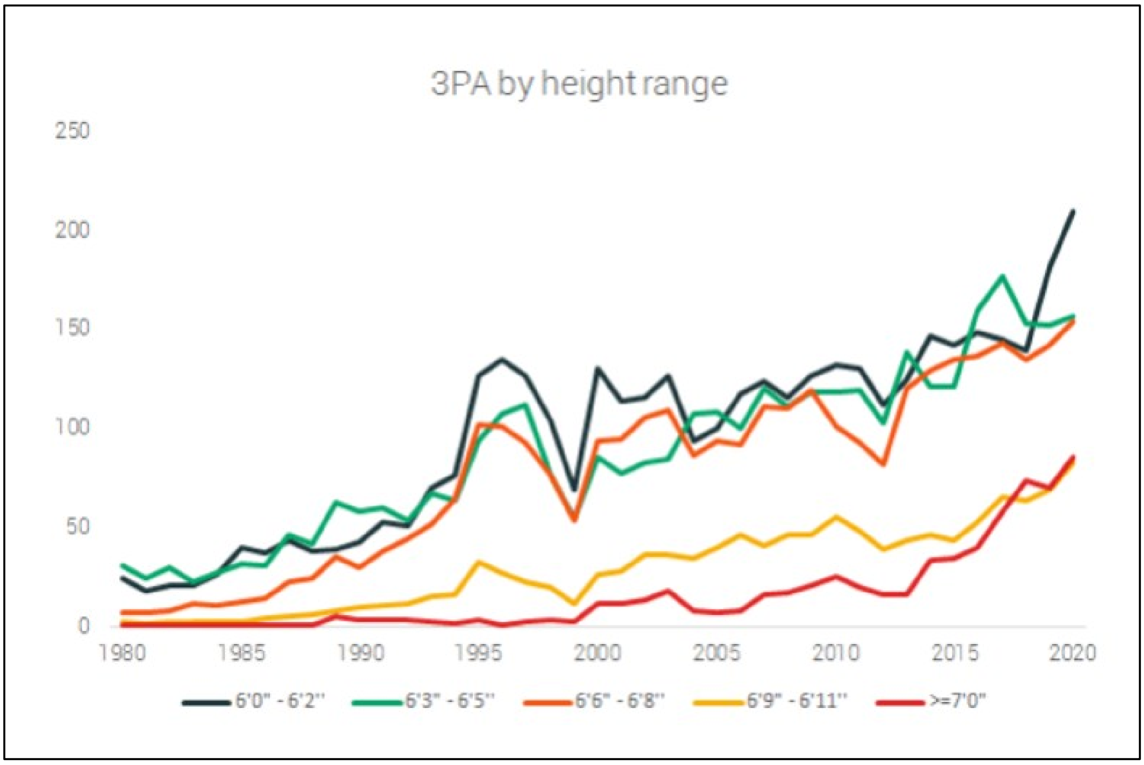

FIGURE 7-4. LEAGUEWIDE AVERAGE THREE-POINT-ATTEMPTS PER YEAR BY PLAYER HEIGHT IN NBA (CURCIC, 2020).

Observing Figure 4, this development becomes especially obvious by looking at functional demands for different positions. The tallest of players of the NBA used to have the simple job of converting scoring opportunities close to the basket. Since the start of the analytics era, most teams want all their players to be able to shoot the three, making the ability to hit open triples one of the most valuable individual basketball traits no matter the height or position (Curcic, 2020). As we can see in Figure 4 everybody is supposed to shoot more. Players of all heights are increasing their average three-point attempts per year. Yet, the biggest jump over the past decade can be observed among the athletes 6’9’’ and taller. Curiously, NBA front offices seem to be slow to react to this trend. They arguably still draft more non-shooting bigmen in higher spots than they should (Paine & Herring, 2018), which potentially illustrates rigid underlying management structures and a potential status-quo-bias.

7.2.3 THREE-POINT SHOOTING AS AN NBA DRAFT TRAIT

Due to the current league environment and general playstyle, we have identified three-point shooting as a valuable skillset-element for every NBA player. Experts forecast this association-wide shooting-trend to last since an increasing number of athletes and teams is adapting (e.g., Brahme, 2017; Narsu, 2017, Goldsberry, 2019). Consequently, this trait becomes an increasingly interesting pre-draft ability to evaluate. Identified and correctly projected, the accurate judgement of a prospects three-point shooting skills can result in better draft decision-making.

However, explaining or even projecting the translation of pre-draft three-point shooting towards NBA performance in this category is rather complex and difficult because many factors need to be considered. From an internal perspective, managers need to judge the shooting technique (e.g., Hudson, 1985; Knudson, 1993) while considering the prospect's mental and physical capabilities (e.g., Pates, Cummings & Maynard, 2002; Ardigò, Kuvacic, Iacono, Dasciano & Padulto, 2018). External variables like adaption to the greater NBA shooting distance [1], differing level of play around the player, varying role within the team system, change of player position as well as potentially shifting degrees of difficulty of the types of three-point attempts a prospect is taking, complicate a clean projection. Due to differing circumstances and the uncertainty such external factors produce, even smart forecasts for NBA performance based on pre-draft indictors can never be fully accurate (Moxley & Towne, 2015).

Additionally, within these pre-draft components several biases can cloud judgement. Recency, availability, or small sample size-biases can negatively influence evaluators, if a prospect has a hot shooting streak in the march madness tournament (Berri, Brook & Fenn, 2011). Overconfidence might also lead to inaccurate projections on three-point ability, as managers falsely believe that they will teach a non-shooting player how to hit more threes, or on the contrary, irrationally disregard a solid shooter because of their unorthodox, non-textbook throwing motion (Sailofsky, 2018). To avoid some of these biases, analytics would suggest blocking out as much subjective noise as possible by projecting shooting and its potential development using a model based on tangible, historic data.

7.3 METHODOLOGY

7.3.1 DATA

The website 'Hoop-Math' was used as a primary data resource (Hoop-Math, 2020). Their data base allowed us to capture the shooting statistics of every NCAA athlete and their respective schools from 2012 to 2020. We isolated the drafted players from this sample and were able to match further, missing shooting data from the stats-portal 'Barttorvik' as well as scraping and adding the NBA performance data of all draftees from 'Basketball-Reference' (Barttorvik, 2020; Basketball-Reference, 2020a).

Consequently, the constructed data set includes pre-draft information (e.g., name, college, position, age, years of pre-draft-experience), detailed pre-draft shooting data (e.g., shot attempts and makes from several distances) based on play-by-play information and detailed post-draft performance data (e.g., shot attempts and makes from several distances) of all college players who were drafted between 2012 and 2020 (N = 386). 2012 became the natural starting point for our records since college basketball play-by-play data and resulting deeper statistics for full draft classes were only available to us from this point on.

The ongoing nature of the dataset is an important limitation we want to point out. While the players pre-draft statistics cannot change anymore, their post-draft numbers are still developing as most of the players are currently active in the league. The data was scraped in June 2020 and does not include the most recent continuation of the NBA season after an intermission of the 2019/20 season, induced by the COVID-19 pandemic.

We used the 'R'-software to prepare and analyze the data. For empirical Bayes binominal estimations, we relied on the 'Empirical Bayes on the Binomial in R' (ebbr)-package within this program. This software provides the tools to take datasets that are based on an observation logic of success by total counts and easily perform empirical Bayes shrinkage and estimations on the data. (Robinson, 2020).

7.3.2 Modeling three-point accuracy translation by using different shooting measures

Explaining, let alone predicting the translation of three-point accuracy from the college to the NBA level is difficult. There are many context variables (e.g., pre-draft team tactical system, teammates, competition) that would need to be included into a more holistic approach. We chose to disregard these factors completely to simplify our approach as much as possible and reduce the amount of potential statistical noise around the two introduced metrics. Consequently, we approached shooting-ability simply as a measure of how many of the three-pointers a player attempted (3PA) they converted (3PM).

Introducing shooting as this basic measure of volume and efficiency already poses some difficulties. Research has shown that three-point percentage (3P%) as a metric stabilizes at around 750 attempts (Blackport, 2014). Using the Kuder-Richardson Formula 21 (KR21) the author showed that NBA three-point shooting crosses the standard reliability threshold of 0.7 roughly after this number of attempts. From that point on skill can be assumed as the main driver of this accuracy measure and not noisy measures like individual shooting luck. This methodology has been proven helpful and widely accepted in a baseball context (e.g., Carleton, 2012; Healey, 2017). Hence, it needs a certain kind of volume until this statistic becomes a reliable measure for a player's shooting competence. This creates a draft projection dilemma, because almost no potential draftee plays enough official games to be able to offer such a dependable pre-draft sample-size. Especially since drafted players have been getting a lot younger over the past few decades (Philipps, 2017).

Current publicly available models try to account for this complication by factoring in other potentially useful dimensions that contribute to measuring shooting ability. Regular three-point metrics in these models are usually considered with raw percentages and a shooting volume estimate based on three-point makes or attempts on a 'per-40-minutes-basis' to be able to compare talents with different playing times. Pre-draft free-throw-percentage (FT%) is a popular addition in such designs as well. It has been shown that including free-throw percentage in models significantly improves explanation of NBA three-point accuracy, even though the shots seem to differ a lot in terms of distance or game circumstance (e.g., Goldblatt, 2008; Johnson, 2014; 2015; Sun, Yu & Centeno, 2017). Despite the differences, it seems logical, that free-throw percentage contributes to the evaluation of three-point skills. In its core it is only capturing another throwing-activity on the court and is therefore just an additional, interesting measure of 'shooting touch', while increasing the data basis the system can gather meaningful information from.

In our later modeling we will add two-point-jumper accuracy (2PJ%) as another shooting metric to our explanation attempt with the same logic. We assume two-point jumpers require a draftee to apply many of the same biomechanical capabilities that are needed to hit a three-pointer or a free-throw. Even though the game context differs a lot in the given situations, all scoring attempts are usually executed with a similar shooting technique or style and require a level of 'shooting touch' to successfully put the ball into the basket (Oudejans, van de Langenberg & Hutter, 2002). Hence, two-point-jump shooting could also be a reliable measure of overall shooting-ability and should therefore contribute to the analysis of three-point competence in the NBA. This hypothesis will be tested.

7.3.3 Using empirical Bayes to identify pre-draft shooting competence more accurately

To 'apply a Bayesian approach' usually means to use statistical techniques relying on 'Bayes theorem', which assigns a rather subjective treatment to probabilities and handles unknown information probabilistically (Bernardo & Smith, 2009). Taking a Bayesian perspective when dealing with statistical problems has become popular in many fields because it provides several advantages. For the discipline of sports science and analytics particularly - facing a data influx rapidly growing in volume and complexity - it proves to be beneficial especially because it allows to: "

- incorporate expert information or prior believes, […]

- use Bayesian learning where the current posterior distribution becomes the prior for future data, […]
- model complex problems, […]
- deal more effectively with small dataset using prior information to improve the parameter estimates, […]
- make predictions taking into consideration uncertainty"

(Santos-Fernandez, Wu & Mengersen, 2019, p.2) among other listed benefits. Various applications of Bayesian methods for basketball shooting problems and modeling can be found (e.g., Richey & Zorn, 2005; Goldsberry 2012; Wetzels, Tutschkow, Dolan, van der Sluis, Dutilh & Wagenmakers, 2016; Berg, 2020).

In our opinion, such an approach should be favorable for pre-draft three-point shooting as well because it allows to add more context and potentially assign more meaning to this measure by using an empirical Bayesian shrinkage towards a beta prior based on historical data. This technique has been applied successfully to produce a more well-informed assessment of baseball's batting average, an estimate of a player's hitting ability (Robinson, 2017). Statistically speaking, the logic of batting average is very similar to three-point-shooting in many ways. This approach has therefore already been applied to pre-draft three-point percentage and provided interesting results in the basketball realm as well (Miller, 2018). With our analysis, we will build on this first modeling attempt and hope for even more accurate results by adding more informed data, factoring in two-point-jumper accuracy.

7.4 ANALYSIS

7.4.1 EMPIRICAL BAYES ESTIMATION AND BETA-BINOMIAL REGRESSION OF PRE-DRAFT THREE-POINT PERCENTAGE

Three-point-percentage is a straight-forward statistic. It is calculated by dividing the number of three-point-makes (3PM) by the number of three-point-attempts (3PA):

$$3P\% = \frac{3PM}{3PA}$$

As the term shows, three-point-percentage measures shooting accuracy and will always be a value somewhere between 0 and 1. Carelessly just going by 3P% a manager looking for a good shooting prospect would have to draft a talent that went 1/2 over a player who converted 40/100 of their triples. But when evaluating and projecting shooting ability and not only accuracy this approach seems silly. We intuitively know that the number of attempts a player needed for their results should be factored in since even though they present the same accuracy on the surface.

Thus, to produce a more useful, informed estimate of shooting abilities, more context needs to be added to the simple percentage. Often basic filtering is sufficient. As described earlier, after crossing a certain threshold in sample-size plain percentages become reliable statistics. For three-point shooting this point has been suggested to be around 750 attempts (Blackport, 2014), meaning we can use simple 3P% as a tool to compare shooting capabilities of talents somewhat confidently if all the evaluated players have hit this mark.

However, this excludes most of draft prospects. As we want to be able to analyze all potential NBA players in their shooting translation, we chose empirical Bayes estimation in combination with beta binomial regression as our method to work with pre-draft three-point-percentage. With this technique, context is added by fitting an individual beta distribution for every athlete as a prior. These distinctive priors are based on the number of threes a player has taken in their pre-draft sample (Robinson, 2017).

To produce individualized priors based on pre-draft shooting volume accounts for a very important dynamic within the sport of basketball: Weak shooters generally tend to shoot less than better long-range threats due to e.g., a lack of self-confidence or coaching staffs restricting prospects from taking triples. On the flipside strong shooters usually get the green light in their team's offense, even if they hit a cold streak, because they showed their talents in practices or earlier games. Using a one-fit-all-prior by solely using empirical Bayes without any adjustments, would tend to overrate the shooting ability of small sample size players dramatically.

Consequently, we want our priors to be influenced by the number of threes a prospect has taken/was allowed to take. Robinson (2017) suggests using beta-binomial regression in combination with an empirical Bayes approach in the model in a generative process, with pi being defined as the informed shooting percentage of player i and letting $3PA_i$ be known and fixed per player:

$$p_i \sim Beta\ (\alpha_{0,i}, \beta_{0,i})$$

$$3PM_i \sim Binom\ (3PA_i, p_i)$$

The "ebbr"-package in R lets us calculate individual priors for our shooting estimation, based on the number of attempts. An exemplary selection of graphs based on maximum-likelihood fitting of univariate distributions looks like this:

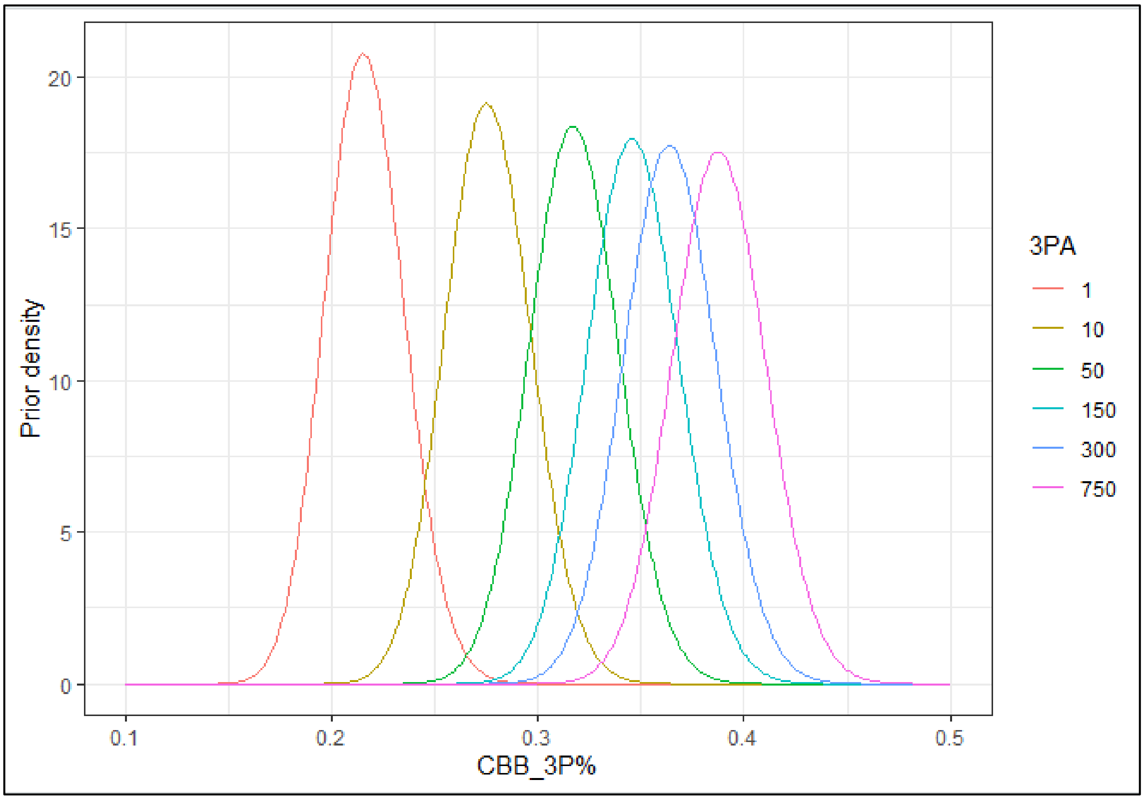

Figure 7-5. Overview over individualized priors based on beta-binomial regression.

Our newfound priors still state a fairly great amount of uncertainty, as can be examined in Figure 5. Attempting 750 threes in college still leaves open a broad corridor of an informed pre-draft shooting-percentage of .31 to .46 for a prospect as the range of probable results. But with the range depending on 3PA, it can be assumed that a talent that only attempted 10 threes is almost certainly a worse shooter than a player taking 750 triples, assumed they had equal playing opportunities.

With the new priors most of the percentage estimates for players with small sample sizes from three adjust profoundly.

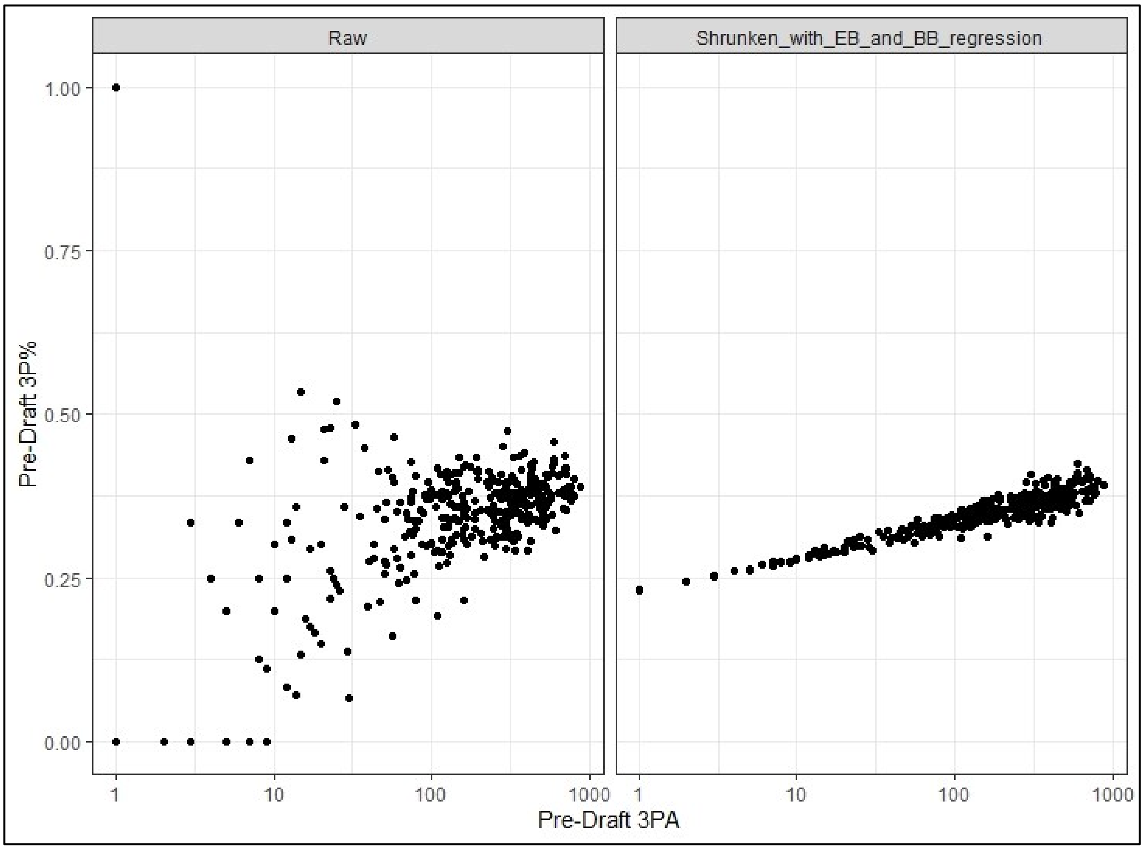

FIGURE 7-6. OVERVIEW OF RAW 3P% AND PRE-DRAFT 3P% ESTIMATE WITH REGRESSION BY PRE-DRAFT THREE-POINT ATTEMPTS.

Investigating the effects of our transformation, we reached our intended results. Figures 6 shows a plot of the raw three-point percentages we started with and additionally presents the adjustment of the distribution after the new values we calculated, using Empirical Bayes shrinkage and beta-binomial regression, respectively. Our new basic shooting-estimate is more context-driven and therefore more informative than the raw percentages. We eliminated unreasonably high or low percentages produced by (bad) shooting luck in small sample-size circumstances, using individual priors for every player based on their number of three-point attempts as basketball logic suggests that this factor should play a role in the estimation of shooting ability.

The newfound statistic is still problematic as various external factors (e.g., tactical system, injury, suspensions, competition) can influence the number of three-point attempts a player is taking despite their assumed shooting ability as our simple approach puts to the forefront here. However, our values now better line up with the median average a certain attempt threshold dictates, which is promising. Additionally, the found pre-draft estimates are only one piece of the three-point-translation-model presented later.

7.4.2 MODELING THREE-POINT-PERCENTAGE TRANSLATION ADDING TWO-POINT-JUMPER ACCURACY

Finally, we can put together the prepared component and combine them into a modeling approach. Based on our theoretical work we assume the pre-draft factors free-throw percentage, two-point-jumper percentage, and our estimation of three-point-percentage (after an empirical Bayes estimation while accounting for three-point-attempts in our priors) to be a fruitful foundation for the analysis of NBA three-point-shooting translation based on pre-draft-data.

Neither the empirical Bayes shrinkage nor the beta-binomial approach were used to update the pre-draft free-throw or two-point-jumper percentage. While this might seem inconsequential, there are simple basketball reasons for not adjusting those variables in the same way we did it with pre-draft three-point percentage.

The first step shrinkage is about eliminating small sample-size shooting luck. Yet, these shot types are way more common for the average basketball player and do not suffer from these extreme low volume cases we displayed in Figure 6. Every player in the sample (except two athletes who got injured early in their college season) took at least 20 free-throws and 20 two-point jumper. However, 63 athletes attempted less than 20 threes. This made the shrinkage essential for this variable but not as urgent for the other two dimensions. Second and more importantly, the beta-binomial regression approach to assume shooting ability information from the number of attempts as we explained for long-range shooting in 3.3 does not work in the same way for two-point shots and especially free-throws. One can reasonably argue that taking many two-point jumpers signals more, that a player does not quite have three-point range on their jump shot or has problems getting to the basket to create more efficient rim attempts. Therefore, a high attempt rate in this area might be more indicative for lack of ability in other facets of the game as an interesting indicator for two-point jumper capabilities. Potentially very strong two-point shooters are highly incentivized to either take a three instead of a long two, due to the additionally point it provides or to shoot closer to the basket if they can, as closer-range shots are generally more efficient. With free-throws the logic of 'more attempts mean more ability' is even more flawed. A player is reliant on calls of the referees to get to the line in the first place. To generate these can be a skill that indicates aggressive, forcing plays. Yet, it is hard for a player to control their own destiny in this facet. In reverse, a defense can sometimes control who they send to the line by fouling on purpose. In these situations, they are incentivized to opt for the weakest free-throw shooter of the opponent. This can drive up attempts for weak foul shooters. Dynamics like this make it illogical to apply the beta-binomial approach to the variables as attempts do not necessarily mean more ability but makes do indicate touch.

Hence, the formula of our regression model (M1) with post-shooting-accuracy as our dependent variable shall be:

$$M1: PostDraft3P\% = \beta_0 + \beta_1\, PreDraftFT\% + \beta_2\, PreDraft2PJ\% + \beta_3\, PreDraft3P\%Estimate$$

We will compare the results of this approach with two other popular methods we found (Johnson, 2014; 2015), using pre-draft three-point-accuracy-data without a shrinkage concept. While the second model (M2) adds simple pre-draft three-point-percentage and three-point attempt-rate per 40 minutes, the third model (M3) factors in a combination of the two variables by calling on three-pointers made per 40 minutes:

$$M2: PostDraft3P\% = \beta_0 + \beta_1\, PreDraftFT\% + \beta_2\, PreDraft3P\% + \beta_3\, PreDraft3PAp40$$

$$M3: PostDraft3P\% = \beta_0 + \beta_1\, PreDraftFT\% + \beta_2\, PreDraft3PMp40$$

To test these approaches, we chose beta regression as our analytical structure for all models with post-draft three-point percentage as the dependent variable. This method was developed to handle continuous proportion and rate data within the interval (0,1) (Ferrari & Cribari-Neto, 2004). We used the R-package 'betareg' that is backed by careful research (Cribari-Neto & Zeileis, 2010; Grün, Kosmidis & Zeileis, 2012) and applied a mean model with logit link based on maximum likelihood estimation as our structure for all three options.

We tested the modeling ideas on our data set for all athletes who attempted at least one three in college (to be able to calculate a pre-draft three-point-percentage estimate) and played at least 50 games in the NBA already (N = 251). We chose this threshold to be able to include as many players as possible, while working with a reasonable sample-size of games. Even rookies from the 2019/20 season had the chance to qualify if they played enough until the COVID-19 intermission.

M1 proved to be a highly significant general model ($p < 0.000$) with an overall explanatory power of an adjusted R^2 of 0.225. We can reject the H0 of these factors not having an influence on the dependent variable. All individual components were highly significant as well and having a small effect in the expected direction. Good pre-draft performance translates into better post-draft skills, as Table 1 shows:

TABLE 7-1. COEFFICIENT OVERVIEW MODEL 1.

Model 1		Estimate	Std. Error	z	Sig.
1	(Constant)	-2.779	.233	-11.889	.000
	Pre-Draft-3P%-Estimate	3.003	.648	4.631	.000
	Pre-Draft-FT%	.770	.276	2.786	.005
	Pre-Draft-2PJ%	1.089	.348	3.130	.001

M2 also presents a highly significant model ($p < 0.000$) with and an adjusted R^2 of 0.207. Contrary to M1, it does not only consist of highly significant parts. Curiously, Pre-Draft-3P% does not improve the explained variance of the design, as presented in Table 2.

TABLE 7-2. COEFFICIENT OVERVIEW MODEL 2.

Model 2		Estimate	Std. Error	z	Sig.
1	(Constant)	-1.648	.183	-9.026	.000
	Pre-Draft-FT%	1.057	.264	4.005	.000
	Pre-Draft-3PAp40	0.037	.008	4.358	.000
	Pre-Draft-3P%	-0.125	.192	-0.655	.513

M3 is similar to M2 in its results. Presenting a highly significant modeling concept again ($p < 0.000$), M3 has an adjusted R^2 of 0.208. Table 3 indicates, its individual variables are all highly significant and have an effect in the expected direction:

TABLE 7-3. COEFFICIENT OVERVIEW MODEL 3.

Model 3		Estimate	Std. Error	z	Sig.
1	(Constant)	-1.632	.181	-8.988	.000
	Pre-Draft-FT%	.989	.265	3.741	.000
	Pre-Draft-3PMp40	.096	.021	4.496	.000

Comparing the explained variance of all the designs, M1 fares the best. Its explanation of Post-Draft-3P% based on pre-draft-statistics is superior to the explored publicly available methods. Examining the coefficient estimated, the Pre-Draft-3P%-Estimate has the most influence on the variance explanation of the dependent variable. But taking two-point-jump shoot-accuracy into account also contributes to the overall model performance. Without posing a huge increase in explained variance, our design still delivers a slight improvement over the known technique.

To further evaluate the models, we calculated the root mean square error (RMSE) and mean absolute deviation (MAE) for all designs.

TABLE 7-4. OVERVIEW RMSE AND MAE.

	RMSE	MAE
Model 1	.0559	.0407
Model 2	.0568	.0422
Model 3	.0566	.0419

Once more, the differences Table 4 presents seem marginal, but are still relevant.

7.4.3 ANALYZING POST-DRAFT THREE-POINT-ATTEMPT RATE

Shooting ability in the NBA is surely about how accurate players are at hitting the basket when taking shots from distance. Therefore, we investigated Post-Draft-3P% as a metric, managers should be eager to project accurately in a draftee. However, prospects also need to be willing to take these kinds of shots at a reasonable rate to make enough use of their own competence and keep defenses honest. Only a combination of accuracy and volume represents shooting-ability correctly. That is why we incorporated three-point-attempts into our estimations of pre-draft-three-point-percentage.

Consequently, in our quest of analyzing and explaining historical shooting-translation from the NCAA to the NBA, we also need to look at the three-point-attempt-rate at the professional level and suggest a model that allows to potentially project this metric as accurate as possible to aid draft decision-making even further.

Thus, we chose a rather exploratory approach since we could not derive a regression design solely from theory. We selected NBA three-point-attempt rate per 40 minutes as our dependent variable. For the independent components of the model, we took all six available factors from the three already explored ideas for three-point-percentage as all of these can be argued as measures for shooting ability (all pre-draft measures: 3P%, 3PAp40, 3PMp40, FT%, 2PJ%, 3P%-estimate). Afterwards, we applied a stepwise linear multiple regression method. The forward selection process was used to check if a significant approach was there, and which combination of the individual parts would offer the most explanatory power. Again, we used the entire data set, filtering for one college three attempt and 50 played NBA games.

TABLE 7-5. MODEL SUMMARIES OF VIABLE DESIGNS WITH STEPWISE ADDITION OF VARIABLES.

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.750[a]	.562	.560	1.531	.562	324.692	1	253	.000
2	.759[b]	.575	.572	1.511	.013	7.962	1	252	.005
3	.767[c]	.588	.583	1.491	.012	7.547	1	251	.006

a. Predictors: (Constant), Pre-Draft-3PMp40
b. Predictors: (Constant), Pre-Draft-3PMp40, Pre-Draft-2PJ%
c. Predictors: (Constant), Pre-Draft-3PMp40, Pre-Draft-2PJ%, Pre-Draft-3P%-Estimate
d. Dependent Variable: Post-Draft-3PAp40

TABLE 7-6. COEFFICIENT OVERVIEW STEPWISE MODEL.

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	1.696	.181		9.396	.000		
	Pre-Draft-3PMp40	.685	.038	.750	18.019	.000	1.000	1.000
2	(Constant)	-.203	.696		-.292	.770		
	Pre-Draft-3PMp40	.687	.038	.752	18.320	.000	1.000	1.000
	Pre-Draft-2PJ%	4.977	1.764	.116	2.822	.005	1.000	1.000
3	(Constant)	-3.830	1.488		-2.573	.011		
	Pre-Draft-3PMp40	.563	.058	.616	9.642	.000	.402	2.488
	Pre-Draft-2PJ%	4.990	1.741	.116	2.865	.005	1.000	1.000
	Pre-Draft-3P%-Estimate	11.955	4.352	.176	2.747	.006	.402	2.488

a. Dependent Variable: Post-Draft-3PAp40

Evaluating Table 6, the best model appears to include Pre-Draft-3PMp40, Pre-Draft-2PJ%, and our newly introduced Pre-Draft-3P%-Estimate. The model itself is highly significant as well as all its individual components. Table 5 shows, the adjusted R^2 of 0.588 is fairly strong, while all component coefficients have an effect in the anticipated direction.

This gives us reason to believe, that the found model (M4)

$$M4: PostDraft3PAp40 = \beta_0 + \beta_1\ PreDraft3PMp40 + \beta_2\ PreDraft2PJ\% + \beta_3\ PreDraft3P\%Estimate$$

should be useful in the analysis of historical shooting competence translation, while our newly introduced components contribute to this explanation.

Again, we evaluated the model by investigating its error terms. The RMSE is 1.483 and the MAE of the design is 1.211. Both terms seem reasonable results, when analyzing Post-Draft 3PAp40.

7.5 CONCLUSION AND OUTLOOK

In this paper we investigated whether an Empirical Bayesian derived informed Pre-Draft-3P%-Estimate and Pre-Draft-2PJ% could contribute positively to the quest of analyzing and explaining the historical shooting translation of NBA draft prospects. Our analysis showed that in addition to Pre-Draft-FT% both statistics provide value as a basis for explanatory modeling. The newfound three-point-percentage estimate based on data-introduced Bayesian priors, factoring in the number of attempts as an indicator for basic shooting-quality lends more context to the former simple percentages. The two-point jumper-percentage also behaves as expected. Our notion of this metric being another indicator of general 'shooting touch', just like free-throw percentage, turned out to be right and should be considered for shooting translation ideas from now on.

Interestingly, this statistic also contributes positively to the modeling of post-draft three-point-attempt-rate, which should draw some attention. The showed connection indicates that the popular basketball narrative, implying that hitting midrange-shots effectively could be an indicator for a player having shooting-range which might be expandable to behind the three-point line, could be true.

The general model we found, including the components in question, presents an improvement to other publicly available designs of shooting-translation. We were able to show that compared to systems based on simpler metrics, our model was able to explain post-draft three-point accuracy with less errors than former approaches. Additionally, we were pleased to see that our introduced variables offer an even more promising basis for the explanation of post-draft three-point shooting-volume, adding even more information to the evaluation of a prospects shooting-competence. Such contributions could ultimately improve draft decision-making league-wide and therefore move the results of the policy towards the intended outcomes.

However, the simple modeling presented here, cannot be used reliably on its own. As we can see with the shares of variance that both models for shooting translation fail to explain, many important dynamics are not captured by the simple metrics including the Bayesian informed three-point percentage and two-point jump-shooting. The design has difficulties picking up on e.g., conservative college schemes suppressing shooting aspirations of talented bigmen or possible non-linear future development of players due to improved coaching or shooting mechanic change. Hence, it should rather be used as a valuable decision-informing tool during the draft process, triggering conversation and possibly closer investigations of prospects, rather than being the main argument for a choice.

To produce more accurate and powerful model, more research, time, and data is needed. Our approach regarding two-point-jumpers was based on pre-draft play-by-play data that has been available for NCAA prospects for a decade only. Such a sample-size is not satisfying, but will automatically expand in the coming years, maybe even with the addition of information on international prospects, to allow more accurate results.

Besides this natural progression, more sophisticated future approaches should consider capturing more of the external factors that potentially go into the projection of shooting progression. Having data on system-based shooting suppression/enhancement of a former team or a more detailed overview of the types of threes a player took, would further inform estimations of pre-draft three-point percentage. Analysis of biomechanical or psychological attributes could educate estimates of development curves as well, by e.g., showing an obvious, but easy to fix flaw in the shooting motion, a lack of throwing consistency due to weak conditioning or a lack of confidence in the own abilities and then indicating a high likelihood of improvement in these areas by showing a good work-ethic and high coachability with psychological profiling. Picking up on such signals, which should inform shooting translation even further, would allow to improve draft decision-making quality even more.

NOTES

1. The NBA line (7.24m) is farther back than the one in college and FIBA basketball (both 6.75m) (Wilco, 2019).

CHAPTER 8

DISCUSSION

8. DISCUSSION

The research of this dissertation produced valuable results for the field of sports economics. Applying a behavioral economic approach to investigate the mechanisms of the NBA Draft policy added important new findings to the field of general draft research. Examining the underlying processes through the lens of quasirationality this thesis produced several important findings.

It confirmed the NBA draft policy to be a valid regulation to achieve the league-wide goal of developing more competitive balance within the market. It was shown that it takes managerial decision-making skills to produce those intended results. Yet, the research also revealed the league-wide decision-making qualities do not seem to be adequate to produce these envisioned outcomes on a consistent basis. Examining NBA Draft decision-making more closely showed these lacking capabilities are not distributed equally (chapter 4). Since the policy is generally aiming for balance, in theory, identical inability to draft the right athletes and basically every team drafting at random would not necessarily lead to more competitive balance but would not worsen it either. However, as shown in chapter 4 some teams are better at identifying talents within the draft setting than other franchises. This leads to several problems, which will be discussed later.

The central aspect of these findings concerns the level of league-wide managerial decision-making within the draft environment which needs to be raised significantly to give the regulation the chance to strengthen competitive balance among all franchises. Investigating the underlying decision-making process suggested, aiding better judgement and therewith increasing decision-making quality on a scale which affects all stakeholders in the market should be the ultimate goal for the league and all its franchises involved. Derived from general decision-making quality practices, the identification of systemic-error producing biases as well as the search for superior decision-aiding intelligence as valid tools for the objectives at hand were chosen.

The subsequent research allowed to provide the NBA and its franchises with three now proven phenomena which fit these criteria exactly. In the second and third paper NBA Draft-specific decision-making biases were identified. The analyses confirmed anchoring biases in relation to high school reputation of certain draftees (chapter 5) and a mélange of overconfidence and availability bias regarding particular athleticism traits of eligible talents (chapter 6) are producing systematic errors within the NBA Draft setup on a league-wide scale.

Consequently, the correct application of this newfound knowledge should help boosting managerial decision-making quality in the draft and therewith aid the overall performance of the entire policy. In the case of the biases, decision-makers should try to avoid their effects by being mindful of them. Regarding the novel approach the pre-to-post-draft shooting capabilities evaluation and translation (chapter 7), a skill which is becoming more and more important in the basketball realm, managers should try to incorporate this in their intelligence gathering and choice mechanisms to inform their decisions better. If all market members adapt equally well to these concrete decision-aiding principles the overall drafting capabilities would rise in a balanced way. This is the only way the overarching draft regulation as well as its intended outcome of distributing incoming player talent in a fair and even way can be strengthened.

8.1 THEORETICAL CONSIDERATIONS & LIMITATIONS

In the quest of improving the results of the NBA Draft policy as a competitive balance strengthening league-wide regulation, this dissertation identified a valid way to fulfill this goal. The focus on investigating the underlying choice process in the hope of identifying potential novel avenues to raise the league-wide decision-making quality is reasonable because it tries to fix the biggest flaw research has diagnosed. The mechanism hinges on the choice competencies of the acting managers (Motomura, Roberts, Leeds & Leeds, 2016). The presented papers found several useful levers to pull to improve the overall draft decision-making quality in a sustainable fashion. Two identified biases and one new metric to evaluate talents more accurately in the pre-draft phase as well as project the translation of one of their key skills provide valuable information in this domain.

However, there are still some theoretical topics regarding the NBA Draft policy which need to be discussed. Even if the general decision-making quality among franchises in the NBA is improved, there are still some build-in dynamics in the regulations which could lead to results which do not reach the highest of standards. These points will be explored in these theoretical considerations.

8.1.1 IMPROVED DECISION-MAKING QUALITY DOES NOT MEAN DECISION-MAKING CAPABILITY BALANCE

All research on the NBA draft helps to raise the general decision-making quality of the league. Every identified, highlighted and then mindfully avoided bias prevents repeating harmful mistakes across teams. Every novel metric to predict skill translation more precisely shows each franchise the same new player evaluation technique. Improving the capabilities of each team in the same way is great and should generally produce better results for the policy. Every team gets better at seizing the opportunities the draft presents them with.

However, simply raising the draft decision-making quality level for every team by the same magnitude does not solve another crucial, underlying problem of the draft regulation. Unless all the teams become perfect at draft decision-making it is unlikely that every team is equally as good at seizing the opportunities the draft policy presents them with. This is a huge problem, especially because of the most likely distribution of these drafting capabilities.

The way the policy is set up, the worst teams of a given season get to pick the earliest. Losing a lot of games, (leaving long-term injuries of key players aside) is usually rooted in lacking the on-court talent to compete with other franchises. And in a league with a salary cap i.e., every team has more or less equal spending opportunities (assuming the ability to pay luxury tax within this concept is excluded), lacking on-court talent means bad managerial decisions must have been made somewhere along the way. Free agency signings did not work out, trades were disadvantageous, draft picks from the past are performing subpar or a detrimental coaching staff is holding back players who could have some potential. Either way, these management groups have shown they might lack some skills in evaluating basketball talent relative to their competitors in one aspect or another. Now the league dares them to solve yet another basketball talent evaluation problem to close the sportive gap. If they fail their more skilled competitors will directly profit from their mistakes by selecting talents, they missed on.

With additional knowledge created through draft research the level of decision-making quality now raised equally among all organizations. This might help weaker teams to avoid more mistakes than in the past, which is generally speaking a preferred outcome. Yet, they are still more likely to perform worse than their more competent competitors. The draft decision-making quality playing field is only elevated, it does not get leveled by this influx of more information for everybody, still potentially leading to lopsided performances in seizing draft opportunities. However, in an ideal world every team would need equal skills at converting draft chances for the policy to perform perfectly. Therefore, providing information for every franchise is insufficient in reaching this goal. Additional knowledge and capabilities would need to be provided to the weaker franchises.

It could also be considered that learning about e.g., a draft-relevant bias might have more relative value to these weaker teams, if the stronger franchises have better draft decision-making quality because they already knew about the newly found cognitive dissonance beforehand. This dynamic would contribute positively to the needed balance in decision-making quality on a league-wide level.

8.1.2 DRAFTING IS ABOUT TAKING CALCULATED RISKS

From a scientific perspective it might be wise to view draft eligible talents as a distribution of probabilities in terms of their player level outcome. These potential outcomes could be analog to the performance tier system presented in chapter 4, which was based on extensive work of trusted draft entities (e.g., Paine & Bradshaw, 2015; The Stepien, 2020a; Go-to-Guys, 2020; Myers, 2020). This approach of probabilistic thinking does the uncertain decision-making environment justice. Every draft prospect, no matter their initial quality, has a chance to fail. Most of them can become solid players, while a few of these talents could move on to be a star player if everything worked out for them. All these potential outcomes are dependent on several factors e.g., development, opportunity, or health. A probabilities distribution approach would put percentage estimates to every single of these probable futures for a player. Models like this are based on historical data (The Stepien, 2020a).

Interestingly, as shown in chapter 4, the value of these performance tiers is not linear. Going up in tiers the number of players decreases exponentially. Superstars are the rarest commodities in the league. Yet, this makes them also the most valuable proposition a franchise can have on their team - in a sportive (Massey & Thaler, 2013) and in an economic sense (Berri, Schmidt & Brook, 2004). They are the most marketable athletes and vital to have any reasonable hope of winning a championship. As was shown in chapter 4, only three teams have won a title without a clear-cut superstar since 1989 (Basketball-Reference, 2020d).

Consequently, teams should value players with potential superstar outcomes more than anything else in the draft setting. Yet, this approach can mean teams will have to make riskier picks, selecting higher variance athletes. By definition these players pose more inherent risk but also present a greater range of outcomes. They offer the very slim but existing chance they could become a star if they developed perfectly, but at the same time have a higher possibility of complete failure by not being able to stay in the league as a relevant player. Their future performance distribution curve is fairly broad. Conversely there are players who are deemed safe picks. They have a narrower outcome curve, failing to present any chance to reach star status but appear to be fail-prove. Drafting them is less risky. This phenomenon is mostly tied to age as was discussed in chapter 5.

Building on this, risk seeking- and risk aversion-influencing dynamics need to be discussed. Borrowing from biology one can say risk sensitivity is usually tied to survival (Mishra, 2014). No individual has only one mode. Even the smallest creature can become risk seeking if their life is on the line – as the relative state model suggests (Mishra, Barclay & Sparks, 2017). Yet, nature also shows the starting point within the state model does play a role. A large carnivore can take more risks than a weak herbivore. Their risk sensitivity is dependent on their relative safety. A lion is much less likely to die from a fight for food with another animal than a gazelle.

These mechanisms might come into play when looking at the draft. More successful teams, maybe positioned in one of the big market cities with long-term stability in the front office due to generous and trusting ownership backing are more in the position of taking swings at high risk-high reward players. Such organizational safety allows to gamble more because the team can afford to miss.

At the same time, less successful teams with a management group on the verge of being fired might opt against taking such risks even though they have identified and evaluated players in the same way. Their state of relative safety prevents them from playing the odds. While their strategy grants them a higher probability of getting a player contributing to the team's success, their approach also makes it less likely for them to pick a superstar. This is contrary to general risk sensitivity theory, which states decision-makers in high-need situations should prefer high-risk options if low-risk options are unlikely to satisfy their needs (Mishra & Fiddick, 2012).

Therefore, such teams can get stuck in the 'treadmill of mediocrity' as NBA experts call it (Quinn, 2021). The competent players they draft constantly make these franchises good enough to prevent them from getting top picks for years. However, not taking risks also makes them lack a superstar, hindering to have a chance to compete for championships. This is to the detriment of the league which wants to ensure every team has the chance to realistically contend for a title with its general competitive balance ambitions (Motomura, Roberts, Leeds & Leeds, 2016).

Again, the result of the policy is not necessarily dependent on the correct judgement of the player talent. It is rather another external factor hindering the regulation to reach its intended results. In a sense, this phenomenon can be claimed to be an issue of the framing of the decision-problem as well. If the ultimate goal of a franchise is to win a title (and the league with its draft policy assumes that it is), always putting a premium on potential superstar outcomes of draftees would be the rational, utility-maximizing strategy. Yet, risk aversion and opting for safer players can be a sensible and logical behavior (next to simple job survival issues concerning the managers) if the objective of an organization is to plainly be competent without the pressing need to necessarily compete for titles. This approach is especially popular among smaller market teams which cannot afford to have a losing record as an organization because they are dependent on their gate revenues produced by success hungry fans to be profitable (Quinn, 2021).

Without being able to align these approaches towards the draft in their overarching process problem framing and definition, decision-making quality improvement can influence the outcomes of the entire draft policy only to a smaller extent. Or to put it differently, even more valid intelligence concerning judgement problems of the mechanism will not matter from a results perspective if this added knowledge is used differently among the teams because some managers are trying to solve slightly different problems than their peers. Theory would suggest more risk seeking behavior should be incorporated by every team to maximize the chances draft opportunities present them with.

8.1.3 BIASES IN THE EVALUATION OF POST-DRAFT PERFORMANCE HINDER OVERALL DECISION-MAKING QUALITY

This dissertation applied the decision-making of Schoemaker and Russo (2006) to the NBA Draft process. To improve general decision-making quality within this mechanism this thesis focused on informing the phases of intelligence gathering and conclusion creating. Adjusting the process in these areas of judgement based on analyzed past results is vital to generate quality in any given year. However, adjustment based on outcomes can also hinder overall decision-making quality.

Considering perfect performance within the second and third phase of the decision-making process model still might not lead to sustainable success. This is possible if the fourth phase of evaluating and learning from outcomes is not executed well. It is conceivable teams could achieve an ideal process, constitute only quality choices and not even recognize they did so, because their perspective on their results could be tainted and flawed. Such a dynamic would lead to fundamental problems. Yet, such a scenario seems somewhat plausible exploring the way the evaluation of managerial decisions can be biased. To make progress in the decision-making dynamics of the NBA Draft policy, judgement needs to be improved and then managers also must recognize their choice making mechanisms have improved to steadily build up further skills. But this exact procedure might be hard, due to underlying biases again.

As alluded to in the last section, talents and their potential trajectory as players can be viewed as a distribution of likely outcomes. Such a probabilistic approach is reasonable because the sports of basketball represents a highly uncertain environment. Such distributions can be very widespread or rather narrow and are somewhat dependent on the amount of information available for the particular player at a given time. This amount of information is most closely tied to age.

Predicting the professional future of a child just entering kindergarten is impossible. Nearly infinite possibilities are still on the table. However, 20 years later, after the young adult has completed their first few years in med-school becoming a physician becomes more likely than this person turning into lawyer.

Within the probable domain there will be high and low percentile outcomes which are tied to the point in time of examination. Hitting the 100th percentile in medicine at the beginning of studying might mean winning the Nobel Prize for curing cancer once and for all, while the 1st percentile might mean failing to become a certified doctor at all. After receiving a degree and a few years of successful practice a Nobel Prize might still be possible, while failing by virtue of being an active practitioner of the craft is not anymore.

This mode of probabilistic thinking is applied to the evaluation of basketball talent regularly (e.g., The Stepien, 2020a; Fisher, 2021), which is great from a scientific standpoint. The approach incorporates the important facts that player development trajectories are mostly not linear and highly circumstantial. Factors like playing time, leadership, team chemistry, team fit, or injuries can influence a talent's career for better or for worse. Especially in a highly regulated labor market where employees cannot choose their working environment right away and have a hard time switching employers on their own terms due to the draft and salary cap rules (NBA & NBPA, 2017), such effects on career developments can be massive and even be out of the control of any individual. At the end of a player's career, there is always the 'what if' question - hypothetically in a different universe or on an alternate timeline, other paths would have been possible, as the probabilistic distribution approach suggests.

However, acknowledging this concept and practicing this mode of thinking is hard because one existing reality can only show one path. This is the point where several biases concerning the evaluation of outcomes can enter the picture. After all, quoting notes of Amos Tversky, "Man is a deterministic device thrown into a probabilistic Universe. In this match, surprises are expected" (Lewis, 2017, p. 197). Applying a probabilistic approach for choices under uncertainty is reasonable but tough to do for humans, because they have been proven to be bad intuitive statisticians (Kahneman & Tversky, 1972).

In theory, managers can get the pre-draft evaluation of a player and the projection of their future potential completely right and still doubt the high-quality choice they made. Due to hindsight bias, it is easy to overinterpret particularly lower or higher percentile outcomes of prospects, as perceived foresight-probabilities often and easily get altered after the occurrence of the outcome (Fischhoff, 1975). This is a dangerous game since hindsight-biased interpretations of results have proven to be able to anchor future decision-making in an error-prone way (Tversky & Kahneman, 1974; Fischhoff, 1975).

Such dynamic is exactly the reason decision-making process and outcome need to be somewhat separated in an uncertain environment, as discussed in chapter 2.2.4. Under uncertainty some results are simply caused by (bad) luck greatly swinging an outcome towards one of the more unlikely sides of the realistic trajectories of player development (Vlek, 1984). Yet, such outlier dynamics need to be identified and treated as such to ensure sustainable high-quality decision-making. Not doing so and wrongly adjusting the entire process of choice to unlikely outcomes will decrease decision-making quality long-term. Here it is important to not become outcome biased like the gambler who after a long unlikely series of heads attributes more probabilities to tails, because they expect a 'fair' coin, ignoring chances always stay 50-50.

8.2 METHODOLOGICAL CONSIDERATIONS & LIMITATIONS

There are some methodological topics regarding this thesis and the NBA Draft policy which need to be reviewed. Due to the complexity of the draft decision-making some research choices had to be made to frame the issue in a way which made a structured, scientific analysis possible. Yet, every choice has its consequences. These points will be explored in this following discussion.

8.2.1 ADDING MORE DEPTH TO THE EVALUATION OF DRAFT DECISION-MAKING QUALITY

In this dissertation the main objective was to evaluate and potentially improve managerial draft decision-making quality. To accomplish this mission, a framing of quality choices in the draft realm was necessary to show what good or bad decisions within the mechanism even look like.

This thesis mainly built on existing research in choosing boxscore-based all-in-one metrics as the basis for any post-draft performance calculation (e.g., Berri, Brook & Fenn, 2011; Moxley & Towne, 2015; Teramoto, Cross, Rieger, Maak & Willick, 2018). The used metrics Win Shares and Value Above Replacement Player are not perfect statistics. Especially measuring defensive impact of basketball players accurately are weaknesses of the metrics chosen (Basketball-Reference, 2020c). However, as the holy grail for basketball performance evaluation has not been found yet (Martínez, 2012), using general performance metrics which allow to compare as many players as possible over time seemed to have been the right choice to maximize sample size.

To then evaluate individual team accomplishments in selecting players, the post-draft performance of the picked talents needs to be examined. However, in this thesis it was deemed important to put two critical components to this simple measure to add context to these numbers.

First, to examine whether a team is able to seize the opportunities the draft presents them with, draft position and the historical value attached to it, had to be considered. Looking at the historical data, finding a useful player with pick 41 is much more impressive than drafting decent talent with the premier choice.

Second, sportive opportunity cost of the choice was also priced in. To represent this important dynamic the best player available approach was created. This system considers finding a player who outperforms their draft spot does not have to be the correct choice right away if even more impactful options were available. In terms of decision-making quality such differentiation in decision-making quality is valuable as another layer of detail is added.

The considerations of this dissertation regarding draft decision-making value stopped here for simplicity and data availability reasons. However, examinations could have gone deeper and therefore need to be discussed here. Opportunity costs do not only emerge looking at straight-forward on-court performance. They can be based on team situation and roster construction as well.

For franchises competing for a title, an older player who contributes crucially within the championship window, which is open right now, might pose more relative value than a younger player who ultimately has a higher ceiling but would need years of development to get there. Again, the concept of opportunity costs would apply on the sportive level, if the slightly more ready player A was the missing puzzle piece for winning a title, even if talent B ends up having a better career.

Another manifestation of the dynamic can emerge due to positional considerations and team fit. In general, the draft is about maximizing the talent a franchise can get at their given draft position. Thus, teams should always choose the best player available.

Nevertheless, this can get complicated if a team has certain roster constructions. For particular roles on the court, there is a limit on how many athletes can see meaningful playing time in this function. However, young players need minutes in game settings to develop their craft. This problematic dynamic is best illustrated using soccer as an analogy: If a team already had a great young goalkeeper, it would not make sense to add another goalie who is not significantly better than the current option available, even though they might be the best player available in a draft situation. The reasons are twofold, and both are based on opportunity costs again.

First, playing time is an issue. Only being able to start one youngster and not playing the other will leave one of the talents underdeveloped and hinder them from reaching their full potential. Splitting the time in half though, might not guarantee optimized development for either of them. Both players would not maximize their potential. Hence, picking the second goalie into such a problematic situation would not only damage the value of the already acquired asset but also diminish the returns of the newest acquisition.

Second, in such a scenario opportunity costs do arise on the team level due to the franchise not having invested this pick in a talented midfielder. In general terms they might be a worse player than the picked goalie. However, for the particular team with they hold much more relative value due to positional considerations.

Basketball is trending towards positionless tactical approaches (Narsu, 2017) right now, which makes this described dynamic a minor issue. Yet, this problem can still emerge and therefore is a viable issue of constant debate (e.g., Beene, 2019; Duale, 2021).

Moreover, athletes additionally possess value as trade assets and are marketable entities (e.g., Berri, Schmidt & Brook, 2004). These factors usually are closely connected to on-court performance. Nevertheless, they could be considered separately for a more detailed look at player value and therewith at managerial decision-making quality in picking them.

Again, all these dynamics need to be acknowledged as relevant. Yet, they were consciously left out because no standardized information is available on all relevant players. To calculate relative value and opportunity costs for the draft picks of the past decades in a form which makes them useful for quantitative scientific work was not possible. Therefore, the complexity of the subject was reduced to simple performance statistics only, like most of the research of the field tends to do.

However, the incorporation of relative team value with positional considerations, marketability, and trade value would be a valuable proposition to incorporate in future research, if reliable data on all players, fans preferences and franchise situations as well as intentions ever becomes available for these dimensions.

8.2.2 FRANCHISE-SPECIFIC DECISION-MAKING AS A BLACK BOX

To model the decision-making of NBA franchises from the outside might be the most important limitation of this dissertation. In the theoretical framework it was laid out in detail why it is unwise to only judge decisions only by their outcome. Particularly in an uncertain environment it might be even more important to evaluate the judgement processes which took place before the actual choice. An investigation of the path to a decision can teach more about the decision-making quality than simply looking at results which are to an extent are based on variance (Skinner, 2001). Reiter (2018) quoted baseball manager Sig Mejdal within the context of baseball. However, his statement also applies to basketball or any other complex decision-making environment and sums up this issue perfectly: "[…] all we can control is the process [...] The rest [...] is hope" (p. 58).

In this thesis these processes were explored thoroughly. The research structure was created to explore biases to be avoided and to find better intelligence to be used to support particular choice problems at a pre-decision stage. Therewith the general approach of the work is correct coming from a perspective that tries to value the decision-making process and not only results. However, the fact that the draft regulation takes place in a highly competitive, non-public, and therefore fairly secretive field poses problems in terms of data availability, especially concerning detailed information about internal processes leading up to decisions.

In the various papers theory and limited league intel was used to create a general picture of what the draft decision-making process of an average team could look like (e.g., Berri, Brook & Fenn, 2011; Moxley & Towne, 2015; Sailofsky, 2018, Beene, 2019). The research projects of the chapters 5 and 6 showed how concrete information (in the form of RSCI ranking and NBA Combine data) is incorporated into the process of draft decision-making and influences the selections on a league-wide basis.

Yet, on a broader level, such influences, while proven on a scientific level for the entirety of the league, are hard to apply to individual contexts. Without insides of every single management group on their concrete decision-making process for every draft choice, there is a level of detail research in this area can never reach. Due to the highly competitive environment, it is highly unlikely franchises will share their methods and processes in the future. This dynamic needs to be considered when exploring results which every scientific examination presents.

Isolating single draft decisions and evaluating them correctly is virtually impossible, given this information and data environment. It is already hard enough to decide if a franchise should get credit for drafting a player with their later picks if they had the chance to draft them earlier with their early selections rights but opted against it and drafted an alternative.

At the same time, it is possible to stumble into a good decision and, without knowing context of the single choice, researchers would have difficulties to identify this correctly. In a scenario, where a team picked a great player with the third overall pick but actually had two worse players on top of their list, who happened to be selected right before them, it would look like they made a quality-decision. Whereas in reality it was only luck and the lack of competence of two other teams that rescued them from making a bad decision themselves.

Inversely, knowing the context of a decision and putting it in perspective with other surrounding choices can shed a different light on their quality. This important dynamic was discussed in section 2.2.4, borrowing Gigerenzer's (1991) image of the Welsh village idiot. A team could select a bad player with one of their later picks who would look like a subpar draft selection by themselves. However, if this athlete is the best friend of one of the earlier draft picks and enables optimized development of the other player just by virtue of creating a better environment for the more talented prospect, this selection all of the sudden could provide more value than the isolated quality of the later selected player might suggest.

Within this team-specific process there are many dynamics at play, which influence draft decision-making processes and, in the end, overall draft decision-making quality immensely. Additional phenomena could arise from group-dynamics, as they might incorporate different processes motivations and stresses (Gonzales, Mishra & Camp, 2017). Job security for different members of the organization was already mentioned, triggering different risk sensitivities due to survival mechanisms (Mishra & Fiddick, 2012; Mishra, 2014). Groupthink as an interesting bias (Janis, 1972) allegedly plays a huge role within franchises with group-members being anchored in their thinking by shared internal rankings of prospects, hindering to think outside of the box and discouraging dissent at the end of the decision-making process (Selig, 2018).

However, without detailed information of the processes of the acting decision-makers such interesting effects can never be isolated. Until more context becomes available these franchise-individual processes will stay 'black boxes' to some extent. Consequently, this dissertation did not go into these details, judging single processes and choices of organizations. It focused more on general mechanisms which were clearly graspable with reliable data.

This leads to two clear limitations of the thesis. First, the entire ocean of clearly valuable individual decision-making dynamics which could impact the overall performance of the draft policy immensely basically stays untapped. But to perform this research this project simply lacked the access to intel and data. Maybe future projects can expand this work to this particular field, performing qualitative research by interviewing management groups and tracking their entire processes leading up to their draft decisions. Until such research is possible, applying a quantitative approach analyzing secondary data will stay the most relevant and promising way to explore the topic.

Second, it needs to be acknowledged, that focusing on general results of the draft regulation without the chance of investigating every single process of every team, this work might suffer from outcome bias (Baron & Hershey, 1988) and adjacent phenomena such as underestimating performance randomness (Gauriot & Page, 2019), even though preventing them was a priority in setting up every single research articles.

8.2.3 Drafting as a small sample-size event

Depending on the availability of the data for the particular topics, the papers presented in this dissertation have examined to 26 years of draft information. In most fields this lengthy timespan would mean vast amounts of information. Regarding the draft policy, the number of data points is limited though, as a phenomenon with a maximum of 60 annual decisions i.e., picks got explored.

In the cases of the first and second paper in the chapters 4 and 5, the availability of standardized statistics for players which were active outside of the American college system at their pre-draft stage slimmed down data sets even further. In the chapters 6 and 7 data availability contributed to smaller sample sizes since the NBA Combine was only established in

2000 (NBAthlete, 2020) and play-by-play-data became only available in 2012 for the entire college basketball world in a standardized way (Hoop-Math, 2020; Barttorvik, 2020).

In every individual research project of this thesis the sample size of the used data set was maximized by incorporating all publicly available data to the best of the authors knowledge and abilities. Yet, the data sets never reached an N greater than 2000 and sometimes even being below 400, which means that effects and effect sizes need to be treated accordingly.

The more important point regarding sample sizes connects well to the discussion of individual draft decision investigation of the former section. As alluded to earlier, decades worth of decisions have been investigated. In a sports environment this usually mean, various management groups have been in charge of every franchise at different points in time. In a highly competitive field, high turnover in these positions is the norm. It is rare to manage a franchise for longer than ten years. Simply looking at some management group draft statistics, it can be stated that at the point of the 2020 draft the average involved NBA manager had performed 6.4 drafts on their own. Removing the five most experienced decision-makers who combined for an average of 20.2 drafts per person the remaining franchises only averaged 3.6 drafts per active management group (Partnow, 2021).

Given a timeframe of over 20 years this means on average at least three regimes with different circumstances, preferences, incentives, and strategies have been selecting players for every team. To differentiate between those on a franchise-level would add more context to selections made and therewith would hold some value from a decision-making process analysis standpoint.

However, looking at such two-to-six-year chunks of draft decisions of franchises effectively means to see only around 15 to 20 data points at maximum for particular management groups. This is working under the assumption their team kept all their picks and additionally traded for some additional selection. (This inversely means some other teams traded away their picks and reduced their number of data points.) Even in this idealized scenario of maximized sample size it would be difficult to expect meaningful insight from any quantitative research approach.

Considering the possibility of managers working for different teams and expanding the number of draft picks in this way is also problematic. It would be unclear if they possessed the exact same decision-making power for selecting players between the different franchises. The terrain would be interesting to enter; yet the associated hurdles are not easy to overcome. Therefore, such an approach was not included in any of the papers presented here. As sample sizes of draft datasets were bound by timeframe and the nature of the policy already, no further limitation of the available information was incorporated.

8.3 FUTURE RESEARCH & OUTLOOK

By identifying new biases and a novel approach towards a key component of player evaluation, the findings of this dissertation have opened several new avenues within the field of NBA Draft research. To conclude this thesis, some of these paths which could lead to sector-specific research in the future are explored, building either on the presented results or going beyond them.

8.3.1 THE NBA DRAFT AS AN EXACT SCIENCE

All the results of the presented research were based on the analysis of data. In science collecting evidence and testing hypotheses building on sound theoretical background work is the only way to generate progress within a field. In the sport of basketball and especially in the draft realm such advancements through the application of data analytics by the franchises themselves are still rather new. The past two decades, following baseball and its huge 'moneyball' hype (Lewis, 2004), have seen major advances in these directions on a league-wide scale, with e.g., more teams installing analytics departments and actively incorporating their generated information into their various decision-making processes (Alamar, 2013; Partnow, 2021). Early adopters seemed to have an inherent advantage for a short period of time. More data-driven teams were outperforming less analytics-savvy franchises in terms of draft and free agency decision-making quality for a few years (Berger, Daumann & Kuchinke, 2019).

However, today every NBA franchise has adapted to this new reality and employs a group of data analysists to keep up with the latest trends of the field (Berger, Daumann & Kuchinke, 2019). As a result of this, more data than ever gets produced, evaluated, and implemented in decisions (Shields, 2017). Looking at these vast amounts of data which are now available, not the task of creating even more but the action of separating the relevant from the irrelevant information has become the largest driver of value. All teams are now actively using these concepts and cherishing a more scientific approach to the sport itself. This development enhances more nuanced, objective and therewith smarter managerial decisions in the sportive and business department (Alamar, 2013).

In general, this is great news. Especially from a league-perspective, raising the level of competency among all franchises should be beneficial for the execution of the draft policy and the sustained success of the entire basketball association. From a team perspective though, this also means, single franchises cannot generate competitive advantages in this field as easily. Only two decades ago simply employing analytics people and incorporating their generated intelligence in decision-making processes could create benefits. Nowadays this dynamic seems to shift. Data analytics have become the regular homework every franchise has to do simply to keep up with the rest of the class. While no huge advantage is to be gained just from fulfilling these basic duties, major disadvantages could arise if a single team was the only one not following the latest data-driven trends of the sector (Berger, Daumann & Kuchinke, 2019).

Following this logic, only the further spread of data analytics experts by itself cannot be expected to raise managerial decision-making quality regarding the draft, like they did in baseball with the 'moneyball approach' of the Oakland A's (Lewis, 2004). Concrete analytics goals, revolutionary new data sources or novel modelling approaches and ongoing sophistication of methods will need to lead the way the make the draft an exact science (Partnow, 2021), as alluded to in chapter 3.

To cluster these steps towards the improvement of the NBA Draft policy and its process to reach better results on a league-wide basis, the logic of chapter 4.6.1 will be used.

8.3.2 PATHS FOR FUTURE RESEARCH - POTENTIALS FROM WITHIN

8.3.2.1 BROADENING THE NBA DRAFT TALENT POOL

Chapter 4 has shown that the draft policy, despite all its problems within the decision-making process, has issues that are caused by the natural fluctuation of draft eligible talent from year to year - especially regarding top-level talent. In a league, where team success and other surplus benefits are clearly driven by superstar players (Robbins-Kelley, 2018), it is an issue that on average less than one of these players is in any given draft class. Even in a world where every team picked correctly, this would mean a weak team in need could miss out on a superstar player, simply by the virtue getting their high pick opportunity in the 'wrong' i.e., a weaker year. This dynamic realistically can never be avoided completely as the talent within individual draft classes and player generations is mostly distributed randomly.

Yet, this undeniable circumstance can be balanced out to some extent by continuously increasing the pool of draftable players. This number is closely tied to the amount of people attributing a vast majority of their time towards the craft of playing basketball, especially at a young age. This issue is of course closely related to socio-economic factors (e.g., Kamphius, van Lenthe, Giskes, Huisman, Brug & Mackenbach, 2008). Sports is a trait people can only focus on when do not have to worry about their fundamental needs like food and shelter being met on a regular basis. While the NBA cannot influence how social justice and societal as well as economic growth are reached on a global level, the association has understood it needs to reach out to local communities and grow its product on a global scale to reach best possible outcomes in this dimension.

Popularizing the sport on continents and in countries all around the world does not only increase earning potentials due to expanding viewership. Combined with contributing to the local basketball playing scenes, e.g., by setting up a continental sister-league with active teams in 12 different African countries (NBA - BAL, 2020) or installing development academies in global key locations (NBA Academy, 2020), such advances help the draft policy indirectly by growing the available player base and therewith increasing the pool of viable options to choose from in the future.

Attracting, training, and enabling more people from upcoming generations to start a journey as athletes within the realm of professional basketball does not guarantee superstar talent in every class. However, increasing the number of players who enter the sport in a serious fashion, does heighten the odds – potentially reducing the severeness of the availability issue of top-level talent. Research could examine what strategies could be employed for a further popularization of the sport on the global scale and what talent canalization approach within this plan would be most effective to make use of the ever-broadening talent pool in a critical manner.

Yet, completely solving this matter does seem like an impossible task. Even if more superstar athletes became available due to more people being interested in actively participating in the sport, this still might not fix the availability issue at hand here. The value of basketball players does follow simple inflation principles. Having more superstar talent available to select from in a draft setting would probably only mean the generational mega star player is the new, scarce commodity, which is not available in every class, as value of talents needs to be measured in relative terms compared to peers at the time. With this in mind, the availability issue at the top of each draft is hard to solve.

However, increasing the quality of the overall talent pool irons out issues for the later stages of the policy. In chapter 4, it was shown the average draft has produced only about 24 competent players, less than one viable option for the 30 franchises. Given this historical data, 36 of the 60 picks must be marked as bad decisions annually.

Reducing this number would lead to a better performance of the policy, setting aside the concrete distribution of the players because more teams would receive at least some kind of value through the draft mechanism. Overall draft performance on a league-wide level would increase and therefore, future research in how to bolster the NBA draft talent pool in an optimal way would do as well. Side-effects could be a shortening of the average NBA career and therefore a higher turnover of players within the league. Such increased player turnover could be problematic from a marketing perspective as basketball seems to revolve around personal brands of individual players more than other disciplines. Future research could explore these dynamics to investigate and evaluate potential trade-offs.

8.3.2.2 PLAYER DEVELOPMENT & NATURE VERSUS NURTURE

In the former segment the number of valid draft options and how to increase them has been discussed. A different approach to enhance the performance of the draft policy could be to support optimal development for drafted players in a more sophisticated way. Ensuring maximized progression of every drafted talent would additionally lead to more draft successes. This topic leads to an interesting issue which stems from the field of biology but plays a role in many sectors – nature versus nurture.

Every craft is reliant on certain qualities, traits, skills, and capabilities a person brings to the table. Basketball is not an exception. Individual excellence within the sector is based on how the person combines these relevant attributes while performing. The interesting questions concerning these qualities are if and to what extent excellence within these dimensions is obtainable for every individual who tries to train and learn - and what might help or hinder such developments. Opinions vary from everything can be learned if enough time is put in (e.g., Chase & Simon, 1973; Gladwell, 2008) to the idea that actual greatness within a field can only being achieved if a person has a special talent for it (Epstein, 2014).

Closer scientific examination of certain basketball traits through this lens would be fascinating since it can be assumed that the answer for many of the skills relevant for the sport lays between these describes extremes. Capabilities - apart from genetically bound anthropometric measures – like shooting, dribbling, or passing surely can all be trained (Gandolfi, 2009). Again, the questions are how well, how fast and to what extent. For draft purposes it would be great to know what the general likelihood of improvement within all of these areas is, depending on the skill-specific individual base level an athlete is starting from.

This would allow for a better understanding of the basketball skills evolution landscape and could produce data-driven expectations for fairly assumable, realistic future developments. Such advancements would help the overall decision-making because more judgement relevant data would inform the draft choices. Therefore, the chance for improved results of the overarching policy would increase.

As was shown in chapter 6, there seem to be many biases towards this issue which could be rooted in general development overconfidence by the acting managers. The data implied organizations might underestimate the difficulties of teaching a bad shooter how to hit more three-pointers. This leads to faulty evaluations. A better understanding of skill development would protect managers from such dangerous assumptions.

However, taking this issue one step further, generating such intel on a player individual basis could be even more valuable in many ways and therefore present huge opportunity for future research. To be able to boost general draft decision-making quality it would be helpful to know how much room a basketball player had left to grow in terms of their basketball skills and how certain this development was.

On a more granular level it would aid league-wide draft decision-making in the best possible way if every team could accurately evaluate what particular circumstances an athlete would need to maximize their potential. This would include the ability to self-reflect and see if their particular franchise could possibly provide the player with those prerequisites or if another talent presents a better fit with their current situation and resources. Determining the general value of a player but also optimizing their developmental fits maximizes intended draft policy outcomes.

In terms of resources, this field might actually hold some hidden potentials which are just waiting to be unlocked. Investments in trainers, facilities, technology, and data might enable player development and do not count against the salary cap (NBA & NBPA, 2017). Outspending the competition in these sectors therefore could therefore provide the opportunity for competitive advantages and might propose a viable strategic route, especially for teams located in smaller markets.

Superior player development could not only help create more superstar players by developing good to great talents in the post-draft process. It also helps teams to reduce the number of complete misses within their selections since even mediocre choices could flourish into decent players providing at least some value if they are trained the right way. For baseball such a shift already seems to happen. While the early 2000s were about finding better talents than the competition (Lewis, 2004) the current period is about building up players by developing them better than the other teams in the league (Lindbergh & Sawchik, 2019). NBA franchises could start the strategic transition to a similar style of thinking soon.

Such valuable insights could be triggered by research advances in the fields of nutrition, trainings science and psychology. Further optimization of players in terms of dieting, practicing, learning, resting and especially sleeping would deem beneficial (e.g., Singh, Bird, Charest, Huyghe & Calleja-Gonzales, 2021; Stephen, Yep & Fain, 2021). More specific data generated through motion-tracking, particularly in the field of biomechanics, would help to find personalized areas of improvements, allow to create individualized exercises to tackle these problems, and could also help in targeted injury prevention (e.g., Casals & Finch, 2017; Mack, Meisel, Herzog, Callahan, Oakkar, Walden, Sharpe, Dreyer & DiFiori, 2019).

Additionally psychological aspects need to be mentioned here. Mental makeup of a player does not only determine how likely they are to work hard to improve, how well they might fit in with teammates of certain characteristics or how likely they are to take on a leadership role. Psychological well-being in parallel to physical health is paramount to optimize the performance of every drafted player. For draft decision-making quality to profit on a league-wide basis it would be extremely beneficial if future research could provide better instructions on how to ensure all the mentioned factors to upgrade the learning and playing environment for every single draftee.

8.3.2.3 INVESTIGATION OF MORE DRAFT-SPECIFIC DECISION-MAKING BIASES

Future research could build on the vast academic work this dissertation contributed to by exploring potential pre-draft biases (e.g., Groothius, Hill & Perri, 2007; Berri & Schmidt, 2010; Berri, Brook & Fenn, 2011; Ichniowski & Preston, 2012; Motomura, 2016; Ashley, 2017; Burdekin & Van, 2018). Considering the decision-making process within the NBA environment, the overarching work of behavioral economics and psychology, as well as rather draft specific work, two additional ideas shall shortly be discussed here.

First, the potentially systematic error-producing nature of player comparisons for draft eligible players could be investigated. It is a well-known human practice to compare new people, items, or experiences to known entities. Such practice - as a form of utilizing heuristics - allows to categorize and make sense of the unfamiliar encounters, situations, and environments a lot faster. Voluntarily leaving out some information or generalizing some details speeds up decision-making (Raab, MacMahon, Avugos & Bar-Eli, 2019). As has already been discussed, such heuristics can be immensely helpful in many instances, if the left-out information is not essential to solve the decision-problem (Tversky & Kahneman, 1974).

Yet, it is easy to fall victim to cognitive traps through carelessly comparing draftees to former athletes. Research has described a nationality bias in drafting which can be an example for the dynamics at play here. Motomura (2016) showed there had been resentments against drafting non-American players for a long time, systematically underrating them. There were assumptions they would have issues adjusting to the American way of life and style of basketball after the first players, who were drafted from outside the US seemed to fail in the league more often than their peers. In the subsequent years international talents were lazily compared to them, and it was hard for managers to envision them ever succeeding.

Then, after a few international players had long-lasting success, the pendulum swung the other way. Non-American players became all the sudden even overrated. This was presumably because incoming international players entering the draft were instantly compared to the most recent success stories of the time of amongst others., the German 2007 regular-season-MVP Dirk Nowitzki, the French 2003 finals-MVP Tony Parker, the Spanish rookie-of-the-year 2002 Pau Gasol, or the Argentinian 2008 sixth-man-of-the-year Manu Ginobili (Basketball-Reference, 2020e).

Managerial evaluations either systematically over- or undervaluing internationals were tainted by the recent past and faulty comparisons in both cases. Front offices were putting a worthless dimension to the forefront of their judgements, forgetting that skills, not a passport, determines a basketball player.

While international players are probably valued correctly nowadays, still pre-draft comparisons and nicknames are very common in the draft environment and can lead to many mistakes, as anecdotal evidence suggests (Lewis, 2017). The tendency to look for NBA players a draft eligible talent might resemble - if done in an inaccurate fashion - can be dangerous for several reasons.

An attached name to a talent, which most likely belongs to a currently active player (because of recency bias dynamics (Kahneman, 2012)) can act like an anchor (Tversky & Kahneman, 1974). For better or worse, similar player level and development are expected from the incoming talent once a comparison is accepted and widely adopted. Experts in the league call it the 'development fallacy' (Partnow, 2021). If this comparison or reputation is unwarranted such anchoring can cause problems like in the case of RSCI shown in chapter 5.

Most of the time such connections with other athletes are overly enthusiastic and lead to the systemic overvaluation of talents. As they are usually compared to NBA players, survivorship bias is occurring. Since only names of successful athletes get attached to talents, it is hard to see them fail, even though this might be a very real possibility (Partnow, 2021). And even worse, being associated with an all-time-great player might suggest an unrealistic development arch for a talent which would warrant a high draft position even though the actual pre-draft performances do not. To actively correct for this dynamic within their judgement process can be hard for managers, since they tend to suffer from overconfidence bias in their own capabilities (Kahneman & Tversky, 1973). If they see potential in a player, they will heavily rely on their judgement and trust in their abilities to develop an athlete to the fullest.

At the same time, player comparisons for draftees can additionally serve the purpose of confirmation bias, which is closely linked to overconfidence fallacies (Koriat, Lichtenstein & Fischhoff, 1980). If a manager already likes a player and notice other decision-makers, scouts or media outlets comparing this athlete favorably to great talents from the past, this could hinder them to come to an informed judgement as they might stop the intelligence gathering process early. The same mechanism could be in place if a draftee resembles a player who they did not like or who performed poorly in their opinion. Again, the result would be an irrational misjudging of draft options.

Research could investigate these dynamics and test these hypotheses around recency, anchoring, overconfidence, and confirmation biases as cognitive dissonances. It should be investigated if evaluations of prospects are more accurate if comparisons are avoided. Instead, managers could experiment by plainly using player archetypes and potential performance levels (e.g., Paine & Bradshaw, 2015; The Stepien, 2020a; Go-to-Guys, 2020; Myers,

2020) as established in chapter 4 and used all in the papers of this dissertation. This could be a useful categorization mechanism which might allow more neutral assessments.

Additional future research should cover the other extreme as well which could be indirectly linked to the comparison mechanism. Yet, this phenomenon could be a manifestation of other biases. In the draft realm it seems to be equally problematic for a talent if no historical comparison can be found due to e.g., unorthodox and unique playing style, background, or body type.

If a draftee and their way of playing the game of basketball appears to be a novelty, decision-makers tend to have a hard time imagining it translating to the NBA and working in the future. And such an approach might play the probabilities in the uncertain draft environment correctly most of the times. In the 75 years of history of NBA basketball alone (Young, 2021), certain ways of playing the game have been weeded out, while other approaches have been proven to be successful and therefore get perfected further and further.

However, it was established that game of basketball is not a stagnant proposition. Rules, tactics, and the athletes playing the sport are ever-changing. Therefore, too much status-quo bias (Samuelson & Zeckhauser, 1988) and therewith a lack of imagination and potentially also faulty risk aversion tendencies to unique skillsets might lead some managers to miss on truly disruptive athletes who could revolutionize the game in their time.

Research can investigate how to avoid these dynamics that are bound in past comparison on a league-wide basis to help front offices take more risks on the right kind of hidden talents. This outcome would strengthen the overall policy. However, there are many more judgement and decision-making biases which would warrant more scientific work in the future in the quest of increasing decision-making quality.

8.3.2.4 BETTER PRE-DRAFT EVALUATION BASED ON NOVEL DATA AND METRICS

Chapter 7 set out to find a metric to measure the players more accurately in one particular skill dimension in the pre-draft phase. This novel approach was possible due to a newly available form of data and a unique way of calculating shooting performance.

This overall mechanism can be implemented for many other facets of the game as well. Looking at future research opportunities today can lead to finding potential for innovation in the fields of biomechanics, psychology, and general player on-court tracking. These sectors are relevant for the entire NBA but could be a game changer for draft decision-making quality as well.

Standardized biomechanical research on draftees directly connects with the papers presented in chapter 5 and 6. Detailed lab research accurately measuring athletes' biomechanical apparatus and athletic capabilities could generate a better projection of functional athleticism of players. This could add valuable information to the data the NBA combine provides. In a world where conventional wisdom points towards speed and explosiveness, talking about athleticism, such labs e.g., recently established the ability to decelerate quickly as a valuable athletic capability and were able to put statistical evidence to it (Cohen, 2017). Many more nuanced athleticism dimensions like hand-eye-coordination, in-the-air-balance, or contortion ability, are out there, waiting to be researched properly in regard to their predictability for post-draft performance.

A detailed analysis of the shooting motion of a player would deliver a novel dimension to the shooting profile of a talent which might allow to predict how this skill could translate to the professional level more accurately. It could also give a clearer picture of the likelihood of a player improving this skill because not only simple outcome statistics but also the complex process of how a player throws a ball towards the basket is judged. This paints a more granular picture of shooting skills. With the right expertise to analyze the newfound data, this could improve draft-decision-making quality. First publicly available resources for shooting motion tracking have been emerging at the end of 2021 and should be interesting resources to build future research on (Sajdak, 2021).

Furthermore, such detailed biomechanical profiles of athletes would also serve as a potential-verification and risk-minimization mechanism. On the one hand, a clear biomechanical picture would allow closer estimations of how much physical improvement can realistically be expected of a talent. On the other hand, athletic load identification during games for fatigue management (Partnow, 2021) or mid- to long-term injury threats due to structural problems of a player's body could be identified early, treated with care to prolong their careers, and give more context to draft decisions in this way as well.

Injury risk, especially in a chronic form, needs to be part of the judgement of draft options as well. Applied sport science companies which could enhance athletic performance and provide injury prevention intelligence do already exist (e.g., Peak Performance Project, 2021). Future research needs to investigate how their incorporation in the process could be standardized and scaled to a league-wide level.

Moving from the physical to the mental part of the game of basketball, psychology presents huge opportunities for the draft process. Future research could investigate how to measure work ethic, leadership, performance under pressure or evaluate team fit from a character standpoint in a scientific way. More information on these relevant 'people analytics' factors (Partnow, 2021) would reduce the uncertainty of draft decision-making and could help player development immensely.

Interestingly, a combination of the two worlds might be the biggest frontier to conquer for the evaluation of basketball players and therewith draftees' assessments as well. To measure how players think and process the game is a regularly analyzed aspect. It is the foundation, the connective tissue for all skills an athlete is able to perform. Yet, to measure this skill often referred to as 'feel', 'on-court decision-making' or 'basketball IQ' is hard due to its inherent complexity (Zaucha, 2021). The combination of special player tracking, psychological work, and the tracking of athletes' vision, gestures, verbal clues, and maybe even neuronal activity might make it possible to establish a more tangible construct of this concept in the future.

Lastly, the concept of introducing new basketball performance statistics for the pre-draft process holds a lot of value, as shown in chapter 7. In this paper the upgrade from simple boxscore to more granular play-by-play-numbers allowed to introduce statistics which made evaluation and projection of draftees more accurate. More innovation can be expected in this field due to technological advances.

Soon, an introduction of reliable player-tracking for college and potentially international talents as well, could be introduced on a broad level (Patton, Scott, Walker, Ottenwess, Power, Cherukumundi & Lucey, 2021). This innovation would ensure further improvement, since it would provide an even more detailed level of data allowing further refinement of existing basketball performance measures and eventually offers the possibility to introduce completely new metrics.

The greatest potentials probably lie in a more sophisticated way of measuring defense, which currently might be the hardest skill dimension to evaluate reliably in a scientific way. Future research can help with this development and would need to test such new metrics in terms of added value for pre-draft evaluation and post-draft projection. Capturing audio on the court to measure defensive communication skills of players could introduce an entirely new concept to basketball statistics keeping and could represent one key to unlock more knowledge to better understand the defensive side of basketball (Partnow, 2021). Theoretically this could be implemented for every level of the sport and would make this dimension more quantifiable not only for professional NBA athletes but also draft talents at their international clubs or at colleges in North America.

Again, more quality metrics to evaluate draft talents and predict their development more accurately would improve overall draft decision-making quality and aid the preferred outcomes of the entire NBA Draft policy.

8.3.3 PATHS FOR FUTURE RESEARCH - IMPLEMENTING STRUCTURAL CHANGES TO THE EXISTING REGULATION

In this entire thesis it was discussed how to improve the draft policy in its exiting form by sharpening the judgement of the underlying managerial decision-making process. Naturally, it is also possible to adapt or change the entire mechanism to reach the intended league result of distributing incoming talents in a fair way to foster competitive balance.

8.3.3.1 RESTRUCTURING THE NBA DRAFT COMBINE

Based on the research of this dissertation, one clear advice can be given in this department. Chapter 6 has shown the necessity to restructure the NBA Draft combine. The original idea behind the event is useful. It gives all draftees a chance to showcase their talents and the franchises the opportunity to gather intelligence regarding the draftable talents in a structured form. The appeal of an annual event where players participate in standardized drills which have not been changed for decades is also clear. Performances are easily comparable among peers from one class and even over time among different draft generations (Teramoto, Cross, Rieger, Maak & Willick, 2018). Such historical comparisons are extremely helpful in classifying players generally and do provide some value.

Suggesting to completely change certain drills of this event now would eliminate the opportunity to compare future performances to historical data. This would not be wise. Nevertheless, the research has shown some of the generated information is not as valuable as management consensus seems to make it out to be. The measurements of anthropometrics have been proven to be extremely useful. All recorded statistics on sport-specific physical capabilities, however, have failed to be a significant predictor for post-draft performance historically. There is a difference in the measured 'run & jump athleticism' and what was called '(basketball) functional athleticism' (e.g., The Stepien, 2020b; Go-to-Guys, 2020). NBA managers need to be educated about the historical bias concerning these issues.

With the goal of informing managerial decision-making quality the NBA should consider replacing the exercises which have not proven to be significant predictors for future performance or at least add such drills to the NBA Draft combine schedule. This would produce better information for decision-makers. The NFL has the same problem and is discussing such proposed changes at the moment. It wants to add more game-like drills to its version of the Combine event, to mimic actual game situations a little more closely. This should produce more reliable athleticism data for managers to use in their draft decision-making process (Maaddi, 2022).

Future research could examine which type of drills could fulfill the requirement of simulating real basketball situations and problems more closely to have more predictive value than the other exercises. The factors 'positional strength' and 'core strength' seem to be promising here (e.g., Tsukagoshi, Shima, Nakase, Goshima, Takahashi, Aiba, Yoneda, Moriyama & Kitaoka, 2011; Sannicandro & Cofano, 2017).

Furthermore, wearables (Aroganam, Manivannan & Harrison, 2019) or other player tracking technology such as SportsVU (Shea, 2014) combined with real basketball scrimmages of the event could provide benefits. Measures on jumping, acceleration or general speed (and maybe even other skills like feel for space on the court) would not be as standardized as in the clean, interference-free former drills but would be recorded while playing basketball interacting with other players. This would simulate the environment they will have to perform their athletic actions in after the draft more precisely and therefore ultimately might hold more predictive value.

8.3.3.2 INSTALLING ORGANIZATIONAL DRAFT-RELEVANT INVESTMENT REQUIREMENTS

Another indirect, softer change of the current state of the regulation, which could help to generate more decision-making quality-fueling intelligence, could be the league enforcing draft-relevant investment and resource allocation requirements on the franchise level. The NBA could install a regulation which makes it mandatory for a team to employ a certain number of people working on draft topics or sets a minimum budget a franchise must spend on the subject. Future projects could be built around examining such additional draft-related incentives or regulations and evaluate their consequences, opportunities and trade-offs for decision-making quality.

8.3.3.3 DEVELOPING LEARNING ENVIRONMENTS WITHIN FRONT OFFICES

Chapter 4 has established that the NBA as a whole was fairly reluctant to learn from past draft mistakes. Overall market-wide draft performance has not increased since 1989. If anything, the league in its entirety has actually gotten worse at selecting the impactful players at the right spots and seizing the opportunities the draft presents them with (chapter 4.4.2).

This observed trend can be explained in a trifold fashion. NBA managers can be reluctant to learn from their past mistakes. This might be due to overconfidence biases which they have in regard to their own skills which ultimately lead them to attributing subpar picks to bad luck (Kahneman & Tversky, 1973; Gigerenzer, 1991). However, research also shows, managers are overly attached to their own draft picks, which could be another reason why it is hard for them to acknowledge, they made a mistake due to sunk costs dynamics. This dynamic makes it more difficult to learn and improve (Leeds, Leeds & Motomura, 2015; Partnow, 2021). Lastly, it could also be another example for the phenomenon that even when people are aware of their biases or systematic error-producing preferences, they might not be able to prevent them from influencing their judgement (Tversky & Kahneman, 1974).

Furthermore, there is the possibility, the average NBA franchise environment simply does not provide the opportunity to learn from past mistakes in a reasonable fashion. To improve a skill it usually takes training, feedback, and experience. These essential requirements can be hard to come by, if a franchise fires a management group right away if first draft decisions turn out to be sub-par. As already mentioned in chapter 8.2, in the 2020 season the average NBA manager had performed 6.4 drafts on their own. Subtracting the five most experienced decision-makers who combined for an average of 20.2 drafts per person the other 25 franchises only averaged 3.6 drafts per active front office including the year 2020 (Partnow, 2021). Such level of experience is not sufficient to evaluate one's choices in a meaningful manner as experts are saying it takes at least four years for players entering the league to fully develop in the new professional environment (The Stepien, 2020a; Go-to-Guys, 2020; Partnow, 2021). Even after this timespan player development can happen. Therefore, evaluating draft picks after one or two seasons is foolish as there is still some uncertainty regarding the careers of the picked players is left.

Future research could investigate the described dynamics more closely and examine what the greatest obstacle seems to be for organizational learning within the draft context. If identified, measures to provide teams and management groups with a better learning environment regarding the draft decision-making process could raise general choice quality in the future.

8.3.3.4 INCORPORATING A FAIL-SAFE STRUCTURE IN THE CURRENT NBA DRAFT REGULATION

Until then, it could be wise for the association to react to the described dynamic of organizations failing to improve in the draft decision-making department by installing a dynamic which could be called a 'fail-safe system'. The entire league historically not improving in their average draft performance would not be a problem if every team was equally bad at seizing their draft opportunities. Yet, chapter 4 also showed some franchises tend to be more successful in finding impactful players within the setup than others. This imbalance is detrimental to the intention of the policy.

The NBA envisions the draft as a mechanism for weaker teams to catch up to their more successful competitor by providing them with more player talent. Drafting superior players is supposed to close the gap in terms of ability to win games in the future. However, if weaker teams fail to select the most impactful players due to the design of the mechanism, these impactful athletes can fall to already very talent-rich teams. The weaker teams do not only fail to close the gap to their competitors by missing out on these draft prospects. They indirectly get punished a second time, because disparity is increasing if stronger teams now also pick up those quality athletes, who are remaining in the pool of draftable players.

This is surely not the outcome the league wishes for a mechanism supposed to increase competitive balance. To bring sustainable growth within this dimension better decision-making quality on a league-wide level is key. However, until this state of sufficient average competency is reached the NBA could consider avoiding potentially gap-widening draft mechanisms which are caused by deficient drafting skills of weaker teams. Research would need to be done first to find a favorable policy adaption to reach intended outcomes.

One idea worth investigating could be to only make non-lottery teams eligible for drafting. This way strong but missed-on players could only land among them. Hence, the draft policy would solely be responsible for decreasing the gap between the weak and the strong.

8.3.3.5 Remodeling the entire NBA Draft policy

Lastly, it would be surely possible to abolish the current NBA Draft policy completely and search for a different mechanism which distributes talent entering the league among the franchises. There have been many ideas out there for years. Determining the draft order via a predetermined 30-year plan, a tournament, or other mechanisms have been discussed publicly in the media sphere (e.g., Lowe, 2013; Jonke, 2014; Sharpe, 2018), but not in an academic setting.

Getting rid of the entire concept of drafting could also be an option. The system could be changed into a dynamic which closely mirrors free agency with every team bidding on every player entering the league. The amount of money they could offer would be tied to their recent team success. This way the new regulation would still have competitive balance-supporting elements to it (Davis, 2017).

Such radical changes need to be investigated by future research beforehand, exploring if better competitive balance-increasing results could be expected after implementing them. It would be important though to additionally test for any unintended consequences such adjustments could cause. In the current system lottery odds for pick determination of non-playoff teams needed to be added in order to lessen the partially incentivized losing on purpose also known as 'tanking' as a viable strategy to receive a higher draft pick (e.g., Taylor & Trogdon, 2002; Walters & Williams, 2012; Choi, 2019).

Reverting to the beginning of this dissertation: Life is nothing but a constant string of decisions and transactions. Within this realm, uncertainty can be the worst enemy. While it is impossible to defeat this nemesis in this infinitely complex world, it is still worth to fight and weaken this eternal opponent in the quest of optimal decisions. The weapon of choice, reducing biases, creating new intelligence and maximizing the noble intents of a policy, should be science. In this spirit: May future research provide us with even more knowledge.

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