On "Trusting the Process": Dominant Strategy Truthfulness in Draft Systems

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The problem of "tanking" to improve draft position has been ever-present in North American professional sports leagues over the past decade. In this paper, we present a game-theoretic model of draft systems, and rephrase the question of "tanking" as that of ensuring dominant-strategy truthfulness in a mechanism design setting. We apply our model to analyze existing draft mechanisms from the NFL and NBA, and propose two of our own mechanisms with varying trade-offs.

Contents

1 Introduction

In any sports league, all teams share the same goal: winning as many championships as possible. In any ideal sports league, all teams are competing for a championship each season. This means all teams are ideally trying to consolidate the best possible roster of players, along with a coaching staff, that will maximize their chances of winning it all. However, without any restrictions in place, the richest teams in the biggest cities can simply sign all of the best players and hire all of the best coaches, essentially ensuring a championship – or at least a very good chance at one – each year.

As a result, sports leagues across the world have implemented draft systems, along with other restrictions, that can ensure that building a championship-caliber roster isn't that simple. In most cases, these yearly drafts are an opportunity for teams to "pick" (and subsequently sign) players who have just become eligible to play in a certain league (these eligibility requirements vary across leagues). By giving each team the same amount of draft picks, the league is able to prevent the richest teams from using their excessive wealth to sign all of the best young players.

Drafts are not only used to limit the amount of players that each team can sign, though. There is also an intentional order to these picks, giving the worst teams the earliest picks – and therefore, the best chance at drafting a franchise-altering player – and the best teams the latest picks. By doing this, the worst teams are ideally able to gain the most from the draft, increasing the level of competition throughout future years.

We once again claim that in an ideal league, each team is competing for a championship every year. A draft in which the worst teams from the previous year possess the earliest picks has this goal in mind. However, the very real possibility of selecting a franchise-altering player with one of the first picks in a draft is enough of an incentive for some teams to "tank," or intentionally not compete for a championship one year with hopes of increasing their odds of winning a championship in future years.

As an example, we look at the Oklahoma City Thunder, an NBA team that is openly tanking this season. There is clear evidence of this - they have traded away their older good players for more draft picks and young players, and they have forced 5-time All-Star Al Horford to sit out the remainder of the season. They are doing this with future seasons and championships in mind, but it has resulted in extremely unwatchable basketball: they lost 14 games in a row last month, and they lost by 57 on May 1 – the largest home loss in NBA history. While a Thunder fan would (probably correctly) argue that tanking is the best thing for the team to do in the long run (they have acquired at least 20 draft picks over the next 5 seasons – much more than the average of 2 per team - along with many talented young players), an overall NBA fan would rather watch teams that actually try to win a championship.

We can see the same thing happening in other sports – for instance, the Jacksonville Jaguars did a similar thing this past year, trading away some of their older talented players for younger players and increasing their chances at the first pick in the NFL draft, with which they could draft a top prospect in Trevor Lawrence (widely regarded as one of the best quarterback prospects in the past decade). While these teams, once again, have incentives to intentionally play badly for a season, an average sports fan would rather see all teams trying to win each year.

This is our goal – we are aware that the current draft system gives an incentive for teams to lose temporarily, and we want to see if there are more advanced options for a draft mechanism in which the dominant strategy is to actually try to win each year.

2 A Mathematical Model for Drafts

Now that we understand the history of draft systems and their goals, we can begin to think more abstractly about how to design draft systems. To do this, we propose the following model of a draft system, which captures the main goals of a draft system while simplifying some of the complexities of modeling the behavior of an entire sports league:

Definition 2.1 (A Draft Mechanism)**.** A *draft* taking place before season t is comprised of the following elements:

- A *universe* of M players $\mathcal{U}^t$ available to play during season t. Each player $i \in \mathcal{U}^t$ has a collection of facets that makes them desirable to teams, *in a notion that we will make more precise shortly.*
- A collection of n teams $\mathcal{T}$. Every team $j \in \mathcal{T}$ has a *roster* of players $R_j^t \subseteq \mathcal{U}^t$ that is comprised of the players R_j^{t-1} (barring retirees) plus any players allocated during the draft, where for two teams $a \neq b$, $R_a^t \cap R_b^t = \emptyset$.

The goal of a draft mechanism is to distribute players in $\mathcal{U}^t \setminus \mathcal{U}^{t-1}$ in order to maximize some objective function.

Some sports leagues, particularly those following the European model, do not hold traditional drafts in the way North American sports fans are used to. In this case, one could still apply the above model, because there is still some mechanism for distributing players in $\mathcal{U}^t \setminus \mathcal{U}^{t-1}$, it just does not resemble those we mentioned above. Because players are signed on the open market (and particularly because most European sports leagues also lack a salary cap), a traditional multi-good auction system with social welfare maximization might be an appropriate choice to model their behavior.

For this analysis, however, we will only focus on draft systems that resemble those used by North American sports leagues, which we will call "Competitive Drafts":

Definition 2.2 (Competitive Drafts)**.** In a *competitive draft*, we have the following additional information:

- Each of the n teams j has a value $m_j^t \in [0,1]$, which can be thought of as capturing the effectiveness of the management and coaching of the team. The importance of this will be evident later.
- There is a *match-up function* $\mathcal{C}^t : ([0,1] \times 2^{U^t}) \times ([0,1] \times 2^{U^t}) \to [0,1]$ that represents the probability that the team with the first roster and management beats the team with the second roster and management.

The goal in a competitive draft is to maximize the "competitiveness" of the league, which corresponds to guaranteeing that for all pairs of teams i and j, $\mathcal{C}^t((m_i^t, R_i^t), (m_j^t, R_j^t)) \approx 0.50$.

2.1 Simplifying Assumptions

For the purposes of this paper, we will make a couple additional simplifying assumptions:

Assumption 1. *Each player $i \in \mathcal{U}^t$ has a* performance value *p_i^t summarizing all of their facets that they contribute to whichever team they are on.*

In reality, players often mesh well with each other or do not get along with certain coaches, so p_i^t might be roster-dependent and team-dependent, but for the purposes of our analysis we will assume that p_i^t is a constant.

Assumption 2. *The match-up function $\mathcal{C}^t$ has the following form:*

$$\mathcal{C}^t((m_i^t, R_i^t), (m_j^t, R_j^t)) = \frac{m_i^t \cdot \sum_{k \in R_i^t} p_k^t}{m_i^t \cdot \sum_{k \in R_i^t} p_k^t + m_j^t \cdot \sum_{k \in R_j^t} p_k^t}$$

We chose this match-up function because it has several nice properties that align well with how competition behaves in real life:

- The probability that either team i or team j wins is 1, since

  $$\begin{aligned}
  &\mathcal{C}^t((m_i^t, R_i^t), (m_j^t, R_j^t)) + \mathcal{C}^t((m_j^t, R_j^t), (m_i^t, R_i^t)) \\
  &\quad = \frac{m_i^t \cdot \sum_{k \in R_i^t} p_k^t}{m_i^t \cdot \sum_{k \in R_i^t} p_k^t + m_j^t \cdot \sum_{k \in R_j^t} p_k^t} + \frac{m_j^t \cdot \sum_{k \in R_j^t} p_k^t}{m_i^t \cdot \sum_{k \in R_i^t} p_k^t + m_j^t \cdot \sum_{k \in R_j^t} p_k^t} \\
  &\quad = \frac{m_i^t \cdot \sum_{k \in R_i^t} p_k^t + m_j^t \cdot \sum_{k \in R_j^t} p_k^t}{m_i^t \cdot \sum_{k \in R_i^t} p_k^t + m_j^t \cdot \sum_{k \in R_j^t} p_k^t} \\
  &\quad = 1
  \end{aligned}$$

  For simplicity, we'll ignore the possibility (usually small in most sports) of a tie.

- $\mathcal{C}$ is strictly increasing in both m_i and $\sum_{k \in R_i} p_i$ (when $m_j \neq 0$ and $\sum_{k \in R_j} p_j \neq 0$), which tracks with our expectations that teams that are coached well and/or have good players will generally outperform teams that are coached poorly and/or have bad players.

- $\mathcal{C}$ assigns a 0% chance of winning to a team when $m_i = 0$. We can use this fact to say that teams are "tanking" when $m_i \ll 1$.

Assumption 3. *In most cases, teams will have management scores* $m_i \approx 1$.

This allows us to represent the fact that some teams are managed better than others but also gives a lot of wiggle room to model situations when teams' coaches have given up (i.e. when $m_i \ll 1$).

2.2 Tanking in the Competitive Draft Model

One problem endemic to most sports leagues is the problem of determining an athlete's ability to contribute to a team before signing or drafting them. In our model above, this would correspond to the following assumption:

Assumption 4. *Although players have performance values* p_i *for every* $i \in \mathcal{U}^t$*, these performance values are unknown.*

There may be ways to gain a partial understanding of some players' values of p_i (i.e. through scouting, projecting past performance, etc.), but a player's performance in past seasons can never perfectly predict their future contributions to the team. One clear example of this is injury; we can model a player i being injured as having $p_i \approx 0$, because they are no longer able to contribute to the performance of their team. But there is no way to predict that in a given year a player will be injured, so there is always some degree of uncertainty in the value of a particular team's roster at any given time.

Because of this, sports leagues that employ "competitive" drafts usually rely on past performance to determine who gets which draft picks. Different mechanisms may use different metrics of previous performance, but in most "competitive draft" mechanisms they will allocate better new players to the teams with worse previous performance.

When viewing a past-performance competitive draft mechanism through the lens of a mechanism design problem, then, the following takes place:

- Teams play out season $t-1$ with rosters R^{t-1} and management scores m^{t-1}, and at the end of the season each team's performance is recorded in the metrics deemed important by the mechanism.

- Using these recorded performance metrics, the mechanism decides how to allocate players to teams in an effort to ensure roughly equal competition.

In this context, we can begin to understand what tanking means.

One of the main concerns in mechanism design is that of "dominant-strategy truthfulness." Because the draft problem has slightly different reward and payoff structure to a typical mechanism design problem, we will need to adapt the notion of "dominant-strategy truthfulness" slightly. In this context, what we really want to see is that teams are truthful with respect to their ability to perform in a given season, or formally:

Definition 2.3. We say that a competitive draft mechanism is *dominant-strategy truthful* if it is a dominant strategy for teams to "report" the management value m_j^t and roster R_j^t that give them the best chance of a successful season, i.e. they report their management values and roster so as to maximize $\mathcal{C}^t((m_j^t, R_j^t), -)$.

Using this definition, we can formally define what "tanking" is in the context of a past-performance competitive draft mechanism as follows:

Definition 2.4. We say that a team j is *tanking* at time t if they are reporting false performance data in order to increase their allocation by the draft mechanism at time $t + 1$.

Within the context of a competitive draft, this corresponds to one of two possibilities:

- Reporting a management value ${m'_j}^t < m_j^t$. In the context of a real sport, this means making intentionally poor coaching decisions with the intention of decreasing their probability of winning games.
- Reporting a worse roster ${R'_j}^t < R_j^t$. In the context of a real sport, this might mean trading away superstar players in return for some future benefit like better draft picks.

In other words, sacrificing a chance at winning this year to guarantee better draft picks for success in future years.

Therefore, if we view tanking in this context, the problem of tanking boils down to a regular mechanism design problem; that is, we can avoid tanking by finding a mechanism that maximizes our objective function to maximize competition that is dominant-strategy truthful with respect to m^t and R^t.

3 Analysis of Current Draft Implementations

Now that we have a framework for evaluating draft systems, we can begin to evaluate the systems current sports leagues use to allocate players to teams, to determine how successful they are at fulfilling the goals of mechanism design.

3.1 The (Naive) NFL Draft System

The NFL draft takes place annually to allocate newly eligible players (the majority being recent college graduates) to teams. The set of teams $\mathcal{T}$, $|\mathcal{T}| = 32$ is assigned a strict total order $\prec$, and teams make picks over the course of 7 rounds $i \in [1, 7]$ with 1 pick per team per round. The teams pick in order, where being earlier in the order gives an advantage in expectation (the best players are usually drafted first), or

$$\begin{aligned} &\mathbb{E}[\mathcal{C}^t((m_i^t, R_i^t), (m_j^t, R_j^t)) - \mathcal{C}^{t-1}((m_i^{t-1}, R_i^{t-1}), (m_j^{t-1}, R_j^{t-1}))] \geq 0 \\ &\iff \text{team i picks before team j} \\ &\iff i \prec j \end{aligned}$$

The key aspect of the mechanism is determining $\prec$ (the NFL also allows trading picks, and gives additional "compensatory picks" to teams who lose free agents in the off season, but we will omit the first for simplicity and omit the second because the NFL does not release the algorithm which determines these picks).

To help define $\prec$, we will define the following:

Definition 3.1. Let the *realized match-up function* $\Gamma^t : \mathcal{T} \times [1..g] \to \{0, 1\}$ be defined such that:

$$\Gamma^t(i, j) = 1 \iff \text{team } i \text{ wins the } j'th \text{ game of season t.}$$

where there are g games in a season (and where we again ignore the possibility of a tie).

$\prec$ is then determined by the below algorithm using the following "record" function $\rho : \mathcal{T} \to \mathbb{N}$ which counts the number of wins:

$$\rho(i) = \sum_{j=1}^{g} \Gamma^{t-1}(i, j)$$

If we focus just on teams that did not make the playoffs (teams who do make the playoffs have a large incentive to not tank because their draft ordering is determined by playoff performance, not regular-season performance), $\prec$ is determined as follows:[1]

For two non-playoff teams i and j,

- If $\rho(i) < \rho(j)$, set $i \prec j$.
- If $\rho(i) > \rho(j)$, set $j \prec i$.
- Otherwise, rank teams i and j according to a series of tiebreakers, the first of which is the "strength of schedule" measure obtained by summing over

[1] NFL Football Operations, *The Rules of the Draft*.

the records of each opponent of i and j and awarding the earlier pick to the team with the larger strength of schedule.

Thus, teams who are eliminated from playoff contention after playing their k^{th} game has an incentive to minimize the expected number of games they will win over the course of the rest of the season

$$\sum_{j=k}^{16} \mathcal{C}^{t-1}((m_i^{t-1}, R_i^{t-1}), (m_j^{t-1}, R_j^{t-1}))$$

which can be achieved by minimizing m_i since $\mathcal{C}$ is strictly increasing in m_i; this creates an incentive for tanking.

3.2 Randomization: The NBA's Take on Tanking

The NBA draft has made multiple changes to its drafting pattern over the years to reduce tanking while also rewarding the worst teams. Most notably, a lottery system has been implemented to randomize the order of the first few picks in each draft, which have the best probability of completely changing a franchise. There is once again an ordering of the teams $\prec$ that is determined after a season is completed, with the worst teams at the beginning of the ordering and the best teams closer to the end. However, $i \prec j$ does not automatically imply that team i picks before team j in the draft.

Prior to 2019, the lottery method worked as follows: the worst team had a 25% chance of receiving the first pick in the draft, the second-worst team had a 19.9% chance of receiving the first pick, the third-worst team had a 13.8% chance of receiving the first pick, and so on through the 14 worst teams the previous season (the 14 teams that did not make the playoffs).[2] Very similar probabilities were provided for the second and third picks in the draft, with the worst teams most likely to secure these picks (though a team could not receive multiple picks in a draft unless they received another team's pick through a trade). After the teams receiving the first 3 picks were determined, the remaining 27 draft picks are ordered in reverse order of the teams' records the previous year - this guarantees that each team will select at most 3 spots after they would select if the picks were ordered in the same manner as the NFL.

Unfortunately, this draft system still provides an incentive to tank, albeit less of an incentive than the NFL. This is evident because teams have historically tanked despite the lottery system that was put in place – for example, the Philadelphia 76ers tanked for the better part of the last decade, but they got 4 top-3 picks out of it in the span of 4 years. Mathematically, we can see that this is the case for essentially the same reason as in the NFL, which is that the *expected* draft pick placement for a team will be the highest if they lose the most games. Therefore, in an 82-game NBA season, a team i who has been eliminated from the playoffs after playing opponent k, once again, has an

[2] Givony and Schmitz, *NBA draft lottery: Likely picks, odds and stakes for every team.*

incentive to minimize

$$\sum_{j=k}^{82} \mathcal{C}^t((m_i^t, R_i^t), (m_j^t, R_j^t))$$

which can once again be achieved by minimizing $\mathcal{C}$; this creates an incentive for tanking.

4 The New NBA Approach

Fortunately, it appears that some sports leagues recognize the flaws in current draft models, and are making strides to improve their mechanisms. Using our language for talking about draft models, we can evaluate some of the changes that the NBA in particular has adopted which seem to be decreasing the rate of tanking, and analyze whether or not they are likely to do this in practice.

Over the past 2 years, the NBA has made multiple changes that have resulted in less of an incentive to tank, largely caused by the Philadelphia 76ers throughout the past decade. First, the league significantly reduced the odds of the worst teams receiving the best draft picks. Second, the league gave the same odds to the 3 worst teams: all 3 teams have just a 14% chance of getting the first overall pick - note that this is a significantly smaller probability than their odds before 2019. Also, the odds of receiving the first pick among other non-playoff teams decrease at a much slower rate: the fourth-worst team now has a 12.5% chance of receiving this pick, and the fifth-worst team has a 10.5% chance. Once again, similar probabilities are given for the second, third, and fourth picks in the draft, with the probabilities becoming slightly more uniform for the later picks.[3]

Another large change was the implementation of a play-in tournament to get into the playoffs. The play-in tournament, which was created in 2020, gives the 9th and 10th best teams in each conference a chance at making the playoffs (in past years, only the 8 best teams in each conference would make it).

Unlike other mechanisms that we will propose below, we can see the results of these changes in real time. At this exact moment, most teams have 6 or 7 games left this season, yet only 6 teams have been eliminated from the playoffs - and therefore, there are still 24 teams who have an incentive to win as many games as possible for the rest of the season. This, by itself, is enough to make fans happy, as there are very few games where a team is willing to not compete. Along with this, the more "evened-out" odds for the best draft picks are giving teams less of an incentive to lose intentionally, as it won't necessarily give them a better pick in the draft. This essentially allows the teams on the cusp of the playoffs to benefit if they win or lose, as they can either make the playoffs or have good chances of receiving a great draft pick.

This plan is clearly not perfect at preventing tanking - as mentioned earlier, the Oklahoma City Thunder are still openly tanking this season. But it has made teams find a new way to do this. The Thunder are not just losing games

[3] ESPN.com, *2021 NBA draft lottery projections and traded pick odds*.

in the same manner as the 76ers in 2012-2016, they are instead compiling huge amounts of draft picks over the next few seasons by trading away their best players to teams who want to win right now. They are definitely not a "good" team (and they definitely still have an incentive to lose – an increased chance at a better draft pick), but they are not simply throwing away their season in the same manner as other teams in the past with the guarantee that they'll be able to select a superstar in the making during the draft.

5 A First Mechanism Design Attempt

We propose first a modified version of the NFL draft algorithm which calculates $\prec$ in a different manner:

Instead of ordering teams opposite their final standings, $\prec$ is determined by a new function $\phi : \mathcal{T} \to \mathbb{Z}$:

$$\phi(i) = \sum_{j=1}^{k} \Gamma(i,j) - \sum_{j=k+1}^{16} \Gamma(i,j)$$

such that $i \prec j \iff \phi(i) > \phi(j)$ where ties are broken via the same strength of schedule metric as the regular NFL draft documented above. We note this ordering is equivalent to the current system when $k = 16$ (which maximizes the objective function in expectation, assuming truthfulness) but not with other values of k.

Considering dominant strategy truthfulness, letting $k = 0$ is dominant strategy truthful as teams can only gain an advantage by maximizing $E[\Gamma] = \mathcal{C}$ for each matchup. However, this obviously fails to maximize the objective function, because in maximum likelihood it is assigning i a better pick than j exactly when $\mathcal{C}^t((m_i^t, R_i^t), (m_j^t, R_j^t)) > 0.5$

Thus, increasing k will increase the objective function, while decreasing k approaches dominant strategy truthfulness, and thus a mechanism designer can choose some $8 < k < 16$ to optimize for their desired mix of these objectives (setting $k \leq 8$ is very unlikely to be optimal as it is nearly impossible for a team to be eliminated from championship contention in the first half of the season under current NFL rules, and we consider the utility of a championship to be much higher than incremental draft advantages).

6 A More Advanced Mechanism: Leveraging Quadratic Payments

None of these mechanisms, however, consider the preference weights that exist between players and teams. For example, suppose some team A values player γ 10 times more than player β. This is treated the same as if Team A valued player γ only 1.1 times more than player β when team A makes a binary selection between the two.

Additionally, there has been a consistent track record of certain teams remaining at the bottom of leagues while others remain at the top. Since 1978 in the NFL, for example, the historical average win percentage for the Jaguars, $\bar{X}_{\mathcal{C}} = 0.425$ while for the Steelers $\bar{X}_{\mathcal{C}} = 0.605$[4]. This loss in the objective function, or deviation from the ideal $\mathcal{C} = 0.5$ is even more undesirable when it extends stochastically over such a large sample size of seasons.

Thus, in searching for a mechanism, we desire to introduce more noise (more random deviation in outcome than a traditional draft), while also better expressing preference weight, and remaining dominant strategy truthful. We thus settled on a quadratic voting based lottery system.

> **Definition 6.1.** Quadratic Voting or Quadratic Payments is a mechanism in which purchasing a k^{th} unit of influence in a vote or lottery costs k units (so purchasing n units costs $\approx n^2/2$).

Quadratic voting has been shown to be highly effective in democratic binary decision making, with proven Nash equilibria that approach optimal social welfare.[5] We chose to apply it to this more complex domain, however, for the property that in probabilistic outcomes, quadratic voting aligns valuations with amount of influence or probability purchased.[6]

If some agent A values outcome s with $v_A(s) = \alpha$ and another agent B values it $v_B(s) = 2\alpha$, and they are asked to pay for a probability of receiving s, then A will pay until one percent probability equals $\alpha/100$ while B will pay until one percent probability equals $2\alpha/100$. Thus, B will purchase twice as many units, truthfully expressing their preference weight.

With this in mind, we define the mechanism as follows:

Borrowing from the new NBA mechanism, let P be the set of teams that made the playoffs in year $t-1$. We assign each team $i \in P$ a budget $B_i = j$ voting tokens, while every team $i \in \mathcal{T} \setminus P$ receives $B_i = k > j$ purchasing tokens, where k and j can be tuned to promote competition while not incentivizing tanking too much.

We put all the players in U^t/U^{t-1} up for individual auctions. Say $|U^t/U^{t-1}| = \mu$. We then allow μ concurrent sealed bid auctions to occur, where each team i can only spend B_i tokens across all auctions. Assume integer bids for simplicity. The payment rule includes every team paying their bid (in voting tokens) for this player regardless of outcome. We then run μ auctions, one for each player p, with the following allocation rule for each player p:

> Define $\hat{y} \in \mathbb{Z}^{|\mathcal{T}|}$ to be the vector of all bids on p, where $\hat{y}_t$ is the bid by team $t \in \mathcal{T}$.

[4] Barbieri, *Here's where Bears' win percentage ranks during 16-game era*.
[5] Lalley and Weyl, "Nash Equilibria for a Quadratic Voting Game".
[6] Buterin, *Quadratic Payments: A Primer*.

We will allocate player p to team t with probability:

$$\Pr[X_p(\hat{y}) = t] = \frac{\sqrt{\hat{y}_t}}{\sum_{t' \in \mathcal{T}} \sqrt{\hat{y}_{t'}}}$$

The order of the auctions is determined by the total amount bid on each player i.e.

$$\text{auction p is run before auction } p' \iff |\hat{y}_p|^1 > |\hat{y}_{p'}|^1$$
$$\text{with ties broken arbitrarily } (||^1 \text{ is the 1-norm})$$

We remove a team $t \in \mathcal{T}$ from all further auctions after they reach some predetermined player limit, and continue running auctions until all limits are reached.

This mechanism is dominant strategy truthful because there is no advantage between ranking of teams which do not make the playoffs, and we can tune k and j such that being in the playoffs is more desirable than having $k - j$ extra voting tokens. It also allows for teams to express directly their strength of preference for various players, with purchased probability directly proportional to preference strength due to quadratic payment.

This draft mechanism also has several improvements over other, more traditional draft formats. First of all, it introduces more random noise than a traditional multi round draft, to improve the stochastic variance of $\mathcal{C}$ and hopefully cause more churn in the top and bottom franchises over time. It will also guarantee more excitement on draft night. One facet of most drafts is, because there is a set picking order which is known ahead of time, the first couple of draft choices can reasonably be inferred ahead of time, so other teams do not even have a chance at these players. In the case of the 2021 NFL draft, fans were sure that the Jaguars were going to draft Trevor Lawrence for months leading up to the draft, so all of the focus in the pre-draft coverage was on which other quarterbacks would go early. In our probabilistic model, however, top choices are never guaranteed. Additionally, because of the quadratic payments model teams do not gain much advantage by attempting to out-spend every other team on a particular player; they only get a marginal increase in influence which corresponds to a small increase in probability.

7 Conclusion

Using our new draft model, we have been able to evaluate current competitive draft models and propose our own alternatives which attempt to guarantee good competition while striving for dominant-strategy truthfulness. The NFL and pre-2019 NBA drafts were heavily focused on guaranteeing good competition, but because those mechanisms are especially prone to tanking, they are not very good mechanisms in practice. Using our tools, we could then see why the new additions to the NBA's draft are likely significant improvements towards dominant-strategy truthfulness. Finally, we put our own heads to developing our own models, one adapted from the NFL's and the other leveraging the new theory of quadratic payments, to attempt to strike a good balance between maximizing fairness and minimizing incentives for tanking. The quadratic payments method, in particular, gives a good balance between the two goals even while discarding some of the assumptions we made at the beginning of the paper.

One question which is still open, however, is whether or not we can design a mechanism that guarantees *both* an optimal distribution of new players *and* dominant-strategy truthfulness. To answer such a question, further research is necessary in mapping the precise utility functions that sports teams respond to; in particular, understanding the impact of playoff births on utility, and the relative magnitude of the utility gained by tanking relative to that gained by making the playoffs. If a team faces an incentive to tank that far surpasses the amount of utility they could otherwise gain in a single season by playing truthfully, some method of external payments might be required to elicit dominant-strategy truthful play, or such play might not be feasible for any mechanism maximizing fairness. The above is also likely to narrowly depend on the circumstances of a particular league, so research might for example find that a mechanism that works well in the NBA to prevent tanking (likely similar to the post-2019 draft system) would not work well in the NFL.

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