Journal of Quantitative Analysis in Sports

Volume 3, *Issue* 2 2007 *Article* 5

A Player Selection Heuristic for a Sports League Draft

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Abstract

Sports leagues conduct new player entry drafts in which franchises select, in a pre-determined order, players to complement their existing rosters. We model the decision-making process of a single sports franchise during a player selection draft. The basic premise of our model is that a team selects a particular player based on a combination of the player's estimated value, the value of the other players currently available, and the team's need at each position. We first conceptualize a sports league draft using a stochastic dynamic program. However, this formulation is not directly solvable for practical-sized problems due to the overwhelming computational complexity. Therefore, we introduce additional assumptions and restrictions that result in a tractable deterministic dynamic program. We implement the model within a spreadsheet-based decision support system that allows the user to compute solutions under a variety of conditions. To benchmark our approach, we perform computational comparisons against several competing draft strategies in a series of simulated fantasy football drafts for the 2005 season. With perfect information regarding opposing teams' selections, our drafting strategy dominates these competing strategies. With imperfect information, there are draft instances in which our method is not guaranteed to dominate an alternate strategy; however, our drafting strategy outperforms the competing strategies on average and is more robust on the instances tested. Furthermore, we demonstrate that the decision-maker can incorporate information regarding the drafting behavior of opposing teams to improve the performance of our method.

KEYWORDS: dynamic programming, sports draft

1 Introduction

In most professional sports leagues, new players enter into the league via a draft in which franchises select players from a candidate pool in a pre-determined order. These annual league drafts are critical instruments for the construction of a competitive team (Rapaport, 1993). In particular, the annual league draft for the National Football League (NFL) is one of the most highly anticipated and most-widely covered events in sports today. Television coverage of the NFL draft now includes almost non-stop live footage and commentary on ESPN. It is estimated that more than 4.7 million households tuned in to the first day of the NFL draft in 2005 (Williams, 2006a).

The decision making process in a sports draft can be broken down into two basic phases: player evaluation and selection strategy. In the player evaluation phase, each team observes, measures and compares hundreds of draft-eligible players. Additionally, professional scouting services and draft "gurus" provide their own ratings and evaluations of draft prospects. As one can imagine, player evaluations exhibit some degree of variability. In particular, teams may value players' abilities differently due to their system or style of play (Williams, 2006b).

Once teams have evaluated and ranked the draft-eligible players, this information is shaped into a draft-day strategy for selecting players. Two prominent (and often diametric) draft strategies commonly referenced by sports analysts are (1) the *best player available* (BPA) strategy and (2) the *needs-based* strategy. Proponents of the BPA strategy feel that if a team bases its selection strictly on its needs, it risks the chance of passing over more talented players and therefore not maximizing the value acquired. Advocates of drafting based on team-needs point out that strictly drafting the best player available may result in a roster that has severe shortcomings in certain positions or skill areas.

The draft strategy employed by most general managers (GMs) and coaches is generally described as a combination of choosing the best player available and choosing players based on the team needs. Chris Polian, general manager of the NFL's Indianapolis Colts and an admitted advocate of the BPA strategy states, "You're cognizant of how you're trying to build the roster and what your needs are, yet our philosophy is not to overtly reach" (Oehser, 2006). The degree to which the ideal draft strategy is simply choosing the best player available versus consideration of a team's needs is widely debated. Our model aims to quantify this balance to develop a more robust draft strategy.

In addition, the relative depth of the different player positions in the draft should affect a team's draft strategy. For example, consider the scenario in

which the BPA at a certain point in a draft is player X of position A, but there are many players of the same position who are valued only slightly less than player X. The second best player available at this point in the draft is player Y, of position B, but there is a large drop-off in talent at this position after player Y. Drafting player X at this point would incur the cost of missing the opportunity to draft a high-value player at another position. Therefore, it may not make sense to draft player X at this point if a player of the same position with similar ability would be available in future rounds.

We quantify the player selection process by modeling the sequential decision-making of a single sports franchise during a draft. The basic premise of our model is that a team should select a particular player based on consideration of a player's estimated value, the availability and value of other players, and the team's need at each position. We explicitly consider the relative depth of the players available at different positions as well as the personnel needs of the drafting team to develop a draft strategy that seeks to acquire players of maximum collective value to the team.

The rest of this paper is outlined as follows. In §2, we survey academic literature related to the topic of this paper. We discuss the development of a model and solution methodology for draft-day decision-making in §3. In §4, we analyze the effectiveness of our proposed solution in comparison to several competing draft strategies. We conclude the paper with a summary in §5.

2 Literature Review

Sports drafts are a relatively unexplored application of sequential decision-making. We are not aware of any previous work that utilizes similar methodology as this paper to model a sports draft. We provide a brief survey of research involving aspects of a sports draft.

Brams and Straffin (1979) consider the selection strategies of teams from a game theoretic perspective and reveal paradoxes regarding player selection in small examples (two- and three-team leagues). In their model, each team exhibits ordinal preferences for players, which are known to the entire league. Brams and Straffin (1979) prove that if each team strictly adheres to its own player ranking to determine its selections, then the resulting selections across the league are Pareto-optimal. Conversely, they show that if teams do not adhere to their player rankings and instead select players in an attempt to exploit the differences in player rankings across teams, then the resulting draft outcome may not be Pareto-optimal.

In comparison to Brams and Straffin (1979), our model considers a metric

DOI: 10.2202/1559-0410.1050

of player *value* rather than relying solely on ordinal rank and it further differentiates players by their position played. Furthermore, while the results of Brams and Straffin (1979) are intriguing, we conjecture that for sufficiently large sports leagues, a team's opportunity to exploit the differences in other teams' preferences by altering their selection strategy is mitigated. That is, we argue that teams in sufficiently large leagues have no incentive to deviate from their ordinal preferences. While our model is general enough to consider such "gaming" actions, we are more concerned with the situation in which a team may possibly deviate from picking the best player available due to the relative consideration of team need and the draft's depth at that player's position.

Summers et al. (2005) determine the optimal strategy for drafting a fantasy team in a NHL playoff-pool. In this contest, the contestants draft the players they think will score the most points (goals, assists, etc.) in the NHL Stanley Cup playoffs. A contest of this nature brings up interesting issues, as a draftee has to consider the relative success of a player's team as well as the skill of the player (note that a player on a team that goes deeper into the playoffs will have more opportunities to score points). Summers et al. (2005) attempt to maximize the probability that a certain lineup will outscore all other lineups, and uses simulation to test the optimal strategy. While the problem and methodology of Summers et al. (2005) is fundamentally different than our treatment of a sports draft, we observe some general similarities. In both Summers et al. (2005) and our work, the proposed strategies are compared to competing strategies, which are designed to simulate the decision-making logic used by opponents. Also, in both works, computer power and processing time become an issue, and methods for increasing the efficiency of the algorithms are explored.

Price and Rao (1976) consider league policies regarding the ordering of teams' selections in the draft. In this analysis, they conclude that having the worst teams pick first in a draft may not be the best way to format a draft if the objective is to facilitate the development of parity between the teams. Their model quantifies total player quality on a team, which the authors assert is increased by the addition of new talent from the draft (the probability that a player becomes a star is dependent on draft position), and lessened by the decline in quality of players due to age and injuries. Their conclusion is that it takes too long for weaker teams to get better, and they propose a number of alternative draft schemes which would decrease the time it takes to increase the overall parity in a league. In our analysis, we do not concern ourselves with such league policy. Rather, we determine a player selection strategy for a known draft ordering of teams; the mechanism used to determine this ordering is inconsequential to our results.

3 Development of Model

We utilize dynamic programming (DP) to develop our sports draft model. Dynamic programming is a mathematical technique for modeling sequential decision-making problems and is, therefore, well-suited to model a sports draft. While conceptualizing a sports draft with a DP formulation is relatively straight-forward, such models become intractable as the problem size grows due to the "curse of dimensionality" (Bellman, 1957). Therefore, we introduce additional assumptions and restrictions that facilitate the solution of the model within a spreadsheet implementation. To solve the model, we translate the DP formulation into a linear program (LP) in order to take advantage of commonly available solution engines (e.g., Microsoft Excel's Solver).

3.1 Dynamic Programming Formulation

In this section, we present a formulation of a sports draft from the perspective of a single decision maker's team as a dynamic program. We assume that each player available in a draft is classified into a position at which he will play, and that these positions are common to each team in the league. For instance, in football, a team drafts players to play positions such as quarterback (QB), running back (RB), wide receiver (WR), etc.

To model the impact of a team's current roster, and therefore its team needs, on its draft strategy, we assume that each team possesses a "needs vector" that defines the maximum number of players at each position that a team would consider drafting. Let $\vec{i}^k$ denote the n-vector whose j^{th} element reflects the number of players at position j that team k would consider drafting, where n is the total number of positions. That is, $\vec{i}^k$ reflects the "positional needs" of team k. Note that the total number of specified needs could be larger than the number of draft picks, D, i.e., $||\vec{i}^k||_1 \geq D$.

We denote the decision maker's team as team 0. We view the draft as a series of decision epochs at which the decision maker (DM) must make a selection each time it is team 0's turn to select a player. For notational and expository convenience, we assume that team 0 drafts exactly once in each round. We make this assumption to clarify our explanation of the model; when we refer to a point in time as "at round t," it is clear that we are referring to the single point in round t at which it is team 0's turn to select a player. We note that this assumption implies no loss of generality; if this assumption does not hold, the model still accurately describes a sports draft, but now the accompanying explanation must more carefully describe the decision epoch to ensure clear identification.

DOI: 10.2202/1559-0410.1050

Before we state our model formulation, we must define some additional notation. Let I_t denote the set consisting of the needs vectors for each team in the league at round t, for $t = 1, \ldots, T$. Let A_t be the set that contains all players available in round t, for $t = 1, \ldots, T$. Let $r_t(a, \vec{i^0})$ be the value added when team 0 selects player a (from A_t) in round t when its needs vector is given by $\vec{i^0}$. The value of a player to team 0 depends on team 0's current roster (including draft selections in previous rounds) as expressed through its current needs vector. That is, the value of choosing a player a in round t depends on the needs vector in round t. This is because the value a player adds to a team can depend on what role he will play on the team. A simple way of determining a player's "valued added" to a team would be to distinguish between whether the potential draftee is anticipated to be a starter or to provide depth as a reserve player. We model this by discounting the value of a back-up player at position i by β_i, where $0 < \beta_i \leq 1$, for $i = 1, \ldots, n$.

The process of evaluating players and defining an appropriate functional measure for $r_t(a, \vec{i^0})$ that estimates a drafted player's contribution to the team is itself a difficult problem. NFL teams such as the Atlanta Falcons have developed systematic methods to grade potential draftees and implicitly evaluate their impact on current and future rosters (Williams, 2006b). Such systems could provide the necessary input into our dynamic programming model. We leave the determination of an appropriate metric to team management and note that our dynamic programming formulation remains valid for any additive measure for evaluating a potential draftee's contribution to a team.

The fundamental idea behind a dynamic programming formulation is that one can determine the optimal sequence of decisions by considering their impact on the future. In a sports draft, uncertainty about the future stems from the actions of opposing teams. To model uncertainty, let $\pi_t(I_{t+1}, A_{t+1}|I_t, A_t, a)$ denote the probability of transitioning from state (I_t, A_t) to (I_{t+1}, A_{t+1}) given that team 0 selects player a in round t. Let $v_t(I_t, A_t)$ be defined as the maximum value a team can draft from round t through the end of the draft (round T) if in state (I_t, A_t) in round t. Thus,

$$v_t(I_t, A_t) = \max_{a \in A_t} \left\{ r_t(a, \vec{i^0}) + \sum_{I_{t+1}, A_{t+1}} \pi_t(I_{t+1}, A_{t+1}|I_t, A_t, a) v_{t+1}(I_{t+1}, A_{t+1}) \right\} \quad (1)$$

where $v_{T+1}(\cdot) = 0$.

Equation (1) represents a stochastic dynamic program that conceptually models the draft from the perspective of team 0. Unfortunately, this model can

only be solved for a trivially-small problem in terms of the number of teams, player positions, and available players; otherwise, the number of states, (I_t, A_t), creates an intractable model. Furthermore, the transition probabilities, π_t, are generally very difficult to express as they are functions of the opposing teams' selection strategies. To obtain a computationally tractable model, we introduce Assumptions 1, 2, and 3 which reduce the stochastic dynamic program in Equation (1) to a deterministic dynamic program.

Assumption 1. *The decision maker knows the player valuation of every opposing team.*

Assumption 2. *The decision maker knows every opposing team's initial needs vector.*

Assumption 3. *The decision maker knows every opposing team's selection strategy.*

Although Assumption 1 may seem like a strong assumption, we believe that it is realistic, especially for potential early-round draft choices of teams, in an era of computerized player rating services and scouting combines. For instance, in the NFL there are a pair of scouting organizations, BLESTO and National Football Scouting, to which all but five NFL teams subscribe (Williams, 2006b). While individual teams tailor player rankings based on the input of their own coaches, scouts, and team management, teams have a general sense of each others' rankings through scouting intelligence (Williams, 2006b). As mentioned previously, there are many so-called draft "gurus" that specialize in projecting draft picks. Curtis (2001) and Rutter (2006) discuss the performance of some of the better known draft gurus in projecting recent NFL drafts. The best gurus are able to correctly predict approximately 80% of the players that are ultimately chosen in the first round of the NFL draft[1]. Similarly, we justify Assumption 2 by noting that teams are aware of their opponents' rosters and have an accurate notion of the position needs for each team. Indeed, the sports media commonly reports each team's needs prior to the actual draft.

Assumption 3 states that the DM is aware of the decision rule that each opposing team implements to select players throughout the draft. This assumption is supported by the observation that many teams often assign scouts to research other teams in order to anticipate their actions both on game day and on draft day. Furthermore, we mitigate the restriction of this assumption

[1]The website http://www.thehuddlereport.com tracks the performance of many popular NFL draft gurus.

DOI: 10.2202/1559-0410.1050

by testing a variety of common draft selection strategies to govern other teams' actions in our computational examples.

Assumptions 1, 2, and 3 eliminate the uncertainty in the dynamic programming formulation described in Equation (1) since we know with certainty how each opposing team will draft when faced with a specified pool of available players. However, the pool of available players at each team's draft slot is directly affected by the other teams' previous selections, including the DM's prior selections – which are decision variables. Therefore, to determine the pool of players available to the DM in round t, it suffices to know the DM's draft selections in all previous rounds as opposing teams' selections can then be deterministically determined. Thus, the state space at round t must include the DM's previous draft selections, so that the DM can accurately anticipate the draft selection of every opposing team.

For $t = 2, \ldots, T$, let $\vec{h}_t$ be the vector containing the history of the DM's draft choices in rounds $1, \ldots, t-1$, and let $\vec{h}_1 = \{\}$. Equation (1) can be reduced to the deterministic dynamic program as follows:

$$v_t(\vec{h}_t) = \max_{a \in A_t(\vec{h}_t)} \left\{ r_t(a, \vec{h}_t) + v_{t+1}(\vec{h}_t; a) \right\} \tag{2}$$

where $v_{T+1}(\cdot) = 0$. Equation (2) is valid for each possible $\vec{h}_t$ because at each point in the draft from the first overall draft slot to team 0's slot in round t we can determine which players are available and how we assume each team (including team 0) drafts given these pools of available players.

The ability to solve Equation (2) for practical-sized problems is still dictated by the "curse of dimensionality." For example, without any action elimination, a league of K teams in a repeating ordinal (non-serpentine) draft results in $\Pi_{i=0}^{T-1}(m - iK)$ possible states (histories) over the course of a T-round draft, where m is the total number of players available at team 0's first draft slot.

Note that many of these states will not lie on an optimal path in the corresponding network, i.e., there are many histories that correspond to sub-optimal draft strategies. However, in general it is difficult to significantly prune these states without losing the guarantee of optimality. Nevertheless, we develop a series of restrictions to prune the state space and obtain a tractable model.

3.2 Restricted Model Formulation

To obtain a model that we can quickly solve in a spreadsheet-based implementation, we implement a series of restrictions to the deterministic DP formula-

tion in Equation (2) to prune the state space.

Restriction 1. *For each round t, we consider a single available-player pool, A_t, that is independent of $\vec{h}_t$, the decision maker's previous selections in rounds $1, \ldots, t-1$.*

Strictly speaking, for Equation (2), the pool of players available to team 0 in round t relies on the DM's selections in previous rounds, i.e., A_t is a function of $\vec{h}_t$. However, we observe that for sufficiently large sports leagues, $A_t(\vec{h}_t)$ is nearly identical (and often times exactly identical) for the various values of $\vec{h}_t$. This observation reflects the fact that although the DM's deterministic projections of the actions of opposing teams may not precisely predict the selections, they are accurate in identifying which players will be taken before the DM's next selection. Via Restriction 1, we take advantage of this observation and simplify the way in which we determine the pool of available players at each decision epoch. Instead of generating an available-player pool for every possible selection history at round t, we instead create a single available-player pool at round t by assuming that the DM's team (in addition to all other opposing teams) select players according to some known selection rule. Notationally, this creates a set of T available-player pools, $A_1 \supset A_2 \supset \ldots \supset A_T$, rather than the combinatorially large number of action sets, $A_t(\vec{h}_t)$, for $t = 1, \ldots, T$.

While we possibly introduce error in the forecast of available-player pools in future rounds by adopting Restriction 1, we observe that any such difference in the DM's forecasted A_t and any single $A_t(\vec{h}_t)$ typically consists of only a few players and occurs multiple rounds in the future (where the error is less likely to impact the current decision). We mitigate the effect of any error in the available-player pools by using a rolling horizon (Alden and Smith, 1992). That is, after making the selection in the current round (round t), we update the model based on the opposing teams' selections up to the DM's draft slot in round $t+1$ at which point we resolve the model to determine the player selection. Thus, as the draft evolves, we update the available-player pool to reflect the actual players chosen and then resolve the problem in each round. This limits the effect of the draft's unpredictability on determining the available-player pools.

If we maintain the strict definition of A_t as the set of players available to the DM in round t, $|A_t|$ can be overwhelmingly large for practically-sized problems. By only considering the selection of players that will not be available in a future round, Restriction 2 reduces the number of possible actions in round t.

Restriction 2. *In round t, the decision maker only considers drafting players in the set $\Omega_t = (A_t - A_{t+1}) \subset A_t$.*

DOI: 10.2202/1559-0410.1050

Counter-example

There exist situations where utilizing Restriction 2 will result in drafting less than maximum value. Consider a simple example from a football draft where the initial needs vector, $\vec{i}^0$, consists of three players: one quarterback and two running backs. The quarterbacks that are projected to be available in rounds 1, 2, and 3 are Q_A, Q_B, and Q_C, respectively. Their values are 100, 99, and 98 points, respectively. The best running back available is R_A, valued at 80 points and projected to be available in both rounds 1 and 2. The next best RB available is R_B, valued at 79 points and projected to be available in both rounds 1 and 2. The best RB projected to be available in round 3 is R_C, worth 70 points.

According to Restriction 2, we will not draft R_A or R_B in the 1st round, since we know they will both be available in the 2nd round. Therefore we would draft Q_A in the 1st round, followed by R_A in the second round, and R_C in the 3rd round. This yields a total value drafted of $100 + 80 + 70 = 250$ points. However, we can generate greater value by first selecting R_A, followed by R_B and then Q_C. This yields a total value drafted of $80 + 79 + 98 = 257$ points.

This counter-example occurs when Restriction 2 forces us to delay the selection of a player until a later round s and this delay prevents the acquisition of other highly DM-valued players who are available in round s (and therefore all previous rounds), but not in any later round. We remark that this counter-example is contrived, but may occur in situations in which the decision-maker values players significantly different than the opposing teams, i.e., the "Billy Bean" counter-example (Lewis, 2004). In such cases, if this counter-example did arise, we note that it could be remedied by suitably modifying the opposing teams' player rankings. To illustrate, in this specific counter-example, we would elevate R_A's ranking by the opposing teams so that we project this player to only be available in round 1. Then, our algorithm would consider R_A as a potential round 1 selection.

Restrictions 1 and 2 allow us to reformulate the deterministic DP described by Equation (2). Specifically, Restriction 1 allows us to modify the state definition of our DP formulation, since we no longer include the history of the DM's selections in the state space. It suffices to define the state space as $\vec{i}_t^0$, the needs vector of the DM's team in round t. The modified formulation,

which we henceforth call the "restricted model," is

$$v_t(\vec{i}_t^{\,0}) = \max_{a \in \Omega_t} \left\{ r(a, \vec{i}_t^{\,0}) + v_{t+1}(g(\vec{i}_t^{\,0}, a)) \right\}, \tag{3}$$

where $g(\vec{i}_t^{\,0}, a)$ is a function that returns the needs vector resulting when the DM selects player a while in state $\vec{i}_t^{\,0}$.

The price of the reduced complexity obtained from Restrictions 1 and 2 is the possibility that an optimal solution to Equation (3) may not coincide with an optimal solution to the complete deterministic formulation described by Equation (2). However, these restrictions do hold in the optimal solution to Equation (2) in many cases and our computational experiments suggest that it does not significantly alter the recommended policy. In §4, we present a small computational example that suggests that these restrictions have little to no effect on the solution.

3.3 Solution Approach

To solve our draft model within a spreadsheet-based decision support system, we convert the restricted DP formulation described by Equation (3) into a linear program to take advantage of the large number of readily available software tools for solving linear programs such as Microsoft Excel's Solver (see Puterman, 1994, pages 223-231, for a discussion of transforming dynamic programming models into equivalent linear programs). The objective of the corresponding linear program (displayed below) is to maximize the total value drafted when beginning with a needs vector of $\vec{i}_1^{\,0}$. There is a constraint for every round-needs vector-action combination. Upon solving, there will be at least one binding constraint for each needs vector. The action that corresponds to the binding constraint specifies the player to be selected in order to maximize the draft value.

$$\begin{aligned} \min \quad & v_1(\vec{i}_1^{\,0}) \\ \text{s.t.} \quad & v_t(\vec{i}_t^{\,0}) \geq r(a, \vec{i}_t^{\,0}) + v_{t+1}(g(\vec{i}_t^{\,0}, a)) \quad \forall t, \vec{i}_t^{\,0}, \text{ and } a \in \Omega_t. \end{aligned}$$

We solve the linear program using Microsoft Excel Solver within a decision support system based on macros written with Visual Basic for Applications that allows for easy and robust implementation of our model. In our computational testing, we observe that some instances result in linear programs with more constraints than the maximum allowed by Microsoft Excel Solver. For these instances, we reduce the number of constraints in the linear program by

DOI: 10.2202/1559-0410.1050

assuming a forecast horizon of k rounds where $k \leq T - t$. A forecast horizon is a finite problem horizon with the property that the corresponding immediate-round optimal decision remains optimal regardless of projections beyond this horizon (Federgruen and Tzur, 1996). Thus, a forecast horizon allows us to reduce the amount of future data we need to forecast to solve for an optimal player selection in the immediate round. While theoretically determining a lower bound on the length of a forecast horizon is in general difficult, our computational testing suggests assuming a forecast horizon of five or six rounds does not impact the DM's immediate player selection decision.

Computation times for reasonably-sized problems (e.g., a ten-team, 16-round draft using a forecast horizon of five rounds) are less than 30 seconds using Microsoft Excel 2003 on a 2.66 GHz desktop PC with 512 MB RAM. These fast solution times allow our model to be run multiple times under various assumptions regarding the selection behavior of opposing teams. In addition, fast solution time facilitates the execution of the rolling horizon approach described in §3.2.

4 Analysis

In this section, we evaluate the effectiveness of our proposed solution approach with respect to a series of benchmarks. First, we compare the restricted dynamic programming formulation of Equation (3) to the complete deterministic dynamic program represented by Equation (2) to gauge the effect of Restrictions 1 and 2. Then, we compare the restricted model solutions to several competing draft strategies by performing a series of simulated drafts. We conclude the analysis by using our model to evaluate the relative value of different spots in a draft (i.e., the value of drafting first versus drafting last in a round, etc.).

For the purposes of this analysis, all simulated drafts are based on the 2005 fantasy football season. Fantasy football is a game where participants construct teams of actual NFL football players. The participants then score points based on the actual players' statistical performances during games. It is estimated that more than 15 million people participated in fantasy sports in the United States in 2005 and that the market impact surpasses $1 billion annually (Boyle, 2005). We choose to focus on fantasy drafts due to the transparent metric to value players. Projected player values and draft rankings are widely available in fantasy sports; we obtain player data from http://www.fantasyguru.com and determine two metrics for our draft analysis: *player value* and *player rank*. Player value is based on predicted player

performance in 2005; a player's value is the estimated number of fantasy points a player will earn in a fantasy football season under assumed scoring rules. Player value is the basis of the DM's valuation system in our testing. We define a player's *rank* as the average draft position of the player as determined from looking at a sample of historical fantasy football drafts for the 2005 season as given by http://www.fantasyguru.com.[2] In our testing, we use player rank (and in some cases, player value) to anticipate the selections of opposing teams and project the available-player pools for future rounds.

To simulate the opposing teams' behavior, we assume that they adhere to a known draft strategy. Each of the draft strategies is defined in terms of drafting a player feasible with respect to its needs vector; each draft choice must be feasible with respect to the current needs vector of the drafting team. For example, a team cannot draft a third QB if the original needs vector contains less than three QBs. We consider the following four competing draft strategies based on the implicit assumption that teams draft to improve the value of their own rosters rather than impair the value of their opponents' rosters.

Draft Strategy I Team picks the highest ranked feasible player.

Draft Strategy II Team picks the highest ranked feasible starter. If no starting position remains to be filled, team picks the highest ranked feasible player.

Draft Strategy III Team picks the highest ranked feasible starter, unless that player is ranked $x \in [1, 2, 3, \ldots)$ slots lower than the highest ranked feasible player available (this strategy is also referred to as the "hybrid" strategy). If no starting position remains to be filled, team picks the highest ranked feasible player.

Draft Strategy IV Team picks the highest valued feasible player.

Draft strategies I, II, and III imply that a team's selections are based on player rank (estimated average draft positions of players). Strategy I strictly adheres to the player rankings regardless of position, while a team following strategy II will not draft any backup player until all starting positions have been filled. Strategy III acknowledges that it may be beneficial to select a highly-ranked player who will be a backup at a position instead of a lower-ranked starter at another position. Thus, strategy III is a hybrid of strategies

[2] A partial list of player values and ranks used for the analysis contained in this paper is contained in Appendix B; complete lists are available from the authors.

DOI: 10.2202/1559-0410.1050

I and II that mandates the selection of starters unless a highly-ranked backup player is available.

For strategy IV, we assume a team's draft strategy is based on player value (estimated number of fantasy points). Strategy IV simply chooses the highest valued player. For the purposes of our testing with strategy IV, we assume that each opposing teams' player valuation is identical to the DM's player valuation. While our model is capable of incorporating team-specific player valuations, we present test results for strategy IV using common player valuations to maintain a league-wide consensus of player value and equitably illustrate our model's ability to maximize value drafted.

We execute serpentine-style drafts (the common format of fantasy sports drafts) throughout our analysis. In this style of draft, the order in which teams select players is reversed in alternating rounds. That is, the team that picks first in round n picks last in round $n+1$. We assume that each team begins with the same needs vector; each team in a fantasy league typically starts the year with a blank roster.

We emphasize that our dynamic programming model has no inherent reliance on the structure of fantasy football. We select fantasy football as our computational testing arena due to the readily available data. Our model could be implemented in a real sports league draft by determining player valuations and defining an appropriate function to measure a drafted player's contribution to a team's current roster. To forecast the actions of opposing teams, player rankings could be determined from mock drafts and scout feedback. In present-day draft operations, many NFL teams already collect and utilize this information in a less formalized manner (Williams, 2006b). Furthermore, our model allows the specification of a different initial needs vector for each team in the league (based on their current roster).

4.1 Comparing Restricted Model to Complete Deterministic Model

To evaluate the effect of Restrictions 1 and 2, we compare solutions obtained from the restricted model corresponding to Equation (3) to the solutions generated by solving the exact deterministic model described by Equation (2). Due to the computational complexity required to solve Equation (2), we limit our consideration to a small computational example. Consider a ten-team, four-round draft where the needs vector for each team is (1 QB, 2 RB, 1 WR) and one of the RBs is considered a backup. We assume that we pick fifth in the odd rounds and sixth in the even rounds. For the purpose of projecting the

	Restricted Formulation		
Round	**Pick**	**Position**	**Value**
1	D. Culpepper	QB	343
2	C. Dillon	RB	224
3	B. Westbrook	RB	128
4	N. Burleson	WR	190
	Total Value Drafted:		**885**
	Complete Formulation		
Round	**Pick**	**Position**	**Value**
1	D. Culpepper	QB	343
2	C. Dillon	RB	224
3	B. Westbrook	RB	128
4	R. Wayne	WR	191
	Total Value Drafted:		**886**

Table 1: Comparison of Projected Drafts (At Round One) Resulting from Restricted and Complete Deterministic Models

draft and determining the available-player pools (Restriction 1), we assume that all teams follow draft strategy III.

The recommended draft choices for rounds one through four (as projected at round one) using both the complete formulation and the restricted formulation are shown in Table 1. At round one, the use of the restricted formulation results in a projected total loss of one point of value (885 versus 886) due to the anticipated choice of R. Wayne in the fourth round instead of N. Burleson. This is caused by our use of Restriction 1 which generates the available-player pool for each round independent of our draft history. In this particular case, A_4 does not contain R. Wayne as he is projected to be selected prior to the DM's draft slot in round four. However, recall that our algorithm is intended to be run in real-time during the draft and thus only the first draft choice of D. Culpepper will be implemented. Our model would then be rerun in each subsequent round after updating the available-player pool to reflect those players that are actually taken. Updating the available-player pool and resolving the restricted model in each round results in the exact same players chosen as in the complete model shown in Table 1, and thus, there is no loss of value from using the restricted formulation in this example.

Further testing of different scenarios suggests that this small example is representative of the performance of the restricted model. Therefore, we anticipate that the restricted model will result in very little value loss except

DOI: 10.2202/1559-0410.1050

in the most pathological of examples. While the value loss from using the restricted formulation is typically negligible, the time savings is substantial. For a 16-round draft with needs vector (2 QB, 4 RB, 4 WR, 2 TE, 2 D, 2 K)[3], the complete formulation would require approximately 2.2 billion available-player pools to be generated as a function of possible draft choice histories. Given our computational results (where we can generate about five different available-player pools per second for a problem of this size), the complete formulation of this problem would require approximately 4.4×10^8 seconds (or about 14 years) of continuous processing time to set up the problem. On the other hand, our restricted formulation requires less than 30 seconds to set up the same-sized problem. For the computational experiments in the remainder of the paper, we implement the restricted version of our model represented by Equation (3).

4.2 Restricted Model Versus Competing Draft Strategies

To evaluate the benefit of using the restricted model versus commonly-employed draft strategies based on rules-of-thumb, we perform a series of computational experiments involving simulated drafts. In all computational experiments, we assume that there is a consensus among our opponents on the value of each player. While this is not required (Assumption 1 can be satisfied by knowing the possibly unique player valuation of each team), this provides experimental control and allows us to investigate our model's ability to maximize value in instances where the notion of player value is consistent across the league. By assuming that teams share the same player valuations, the benefit of the draft strategy based on our model comes from considering the impact of the DM's current selection on consequent selections. In contrast, instances of drafts in which teams have varied valuations of players will allow our model to improve the draft process both by considering the impact of a current selection on consequent selections and by possibly taking advantage of discrepancies in our opponents' valuation schemes.

In the first set of experiments, we consider drafts in which the DM has perfect knowledge of each opposing team's draft strategy. That is, Assumption 3 holds perfectly in the testing of §4.2.1. In §4.2.2, we consider instances in which Assumption 3 does not hold perfectly.

[3]This represents a common team roster in fantasy football leagues where QB=quarterback, RB=running back, WR=wide receiver, TE=tight end, D=team defense, and K=kicker.

Team	Instance #1	Instance #2	Instance #3	Instance #4	Instance #5
1	III	II	I	III	I
2	II	III	IV	I	III
3	III	III	II	II	II
4	II	III	IV	IV	III
5	**Decision Maker's Team**				
6	I	II	IV	II	IV
7	II	IV	II	I	IV
8	II	I	II	IV	II
9	III	I	III	II	I
10	IV	IV	II	I	II

Table 2: Assignment of Opposing Teams' Strategies in Five Considered Draft Instances

4.2.1 Drafts with Perfect Knowledge of Opponents' Draft Strategies

To evaluate drafts in which the DM has perfect knowledge of each opposing team's draft strategy, we first generate five draft instances by randomly assigning each opposing team's draft strategy[4]. Table 2 displays the strategies being employed by the opposing teams in each of these five randomly generated draft instances[5].

For each of the five draft instances, we consider a ten-team, 16-round draft. We assume that all teams begin with a needs vector of (2 QB, 4 RB, 4 WR, 2 TE, 2 D, 2 K). Half of the players to be drafted at each position will be considered backups and we will assume that backups are discounted by a value of $\beta = 0.6$.[6] When solving our model, we use a forecast horizon length of $k = 5$ rounds and project the available-player pools using the knowledge of the opposing teams' draft strategies. For the purposes of projecting available-player pools for future rounds, we use draft strategy III to forecast the DM's

[4]A draft strategy $P \in \{I, II, III, IV\}$ is assigned randomly to each team subject to the conditions that in each draft instance: 1) each draft strategy is used by at least one opposing team; 2) no more than four opponents use the same draft strategy.

[5]The small sample here is due to the time-consuming nature of completing each draft. We believe that the impact of assigning various draft strategies by opposing teams is apparent from this sample.

[6]While we assume a single discount value, β, for all player positions, one could also assign different values, β_i, for each player position i to reflect the relative worth of backups at different positions.

DOI: 10.2202/1559-0410.1050

selections.

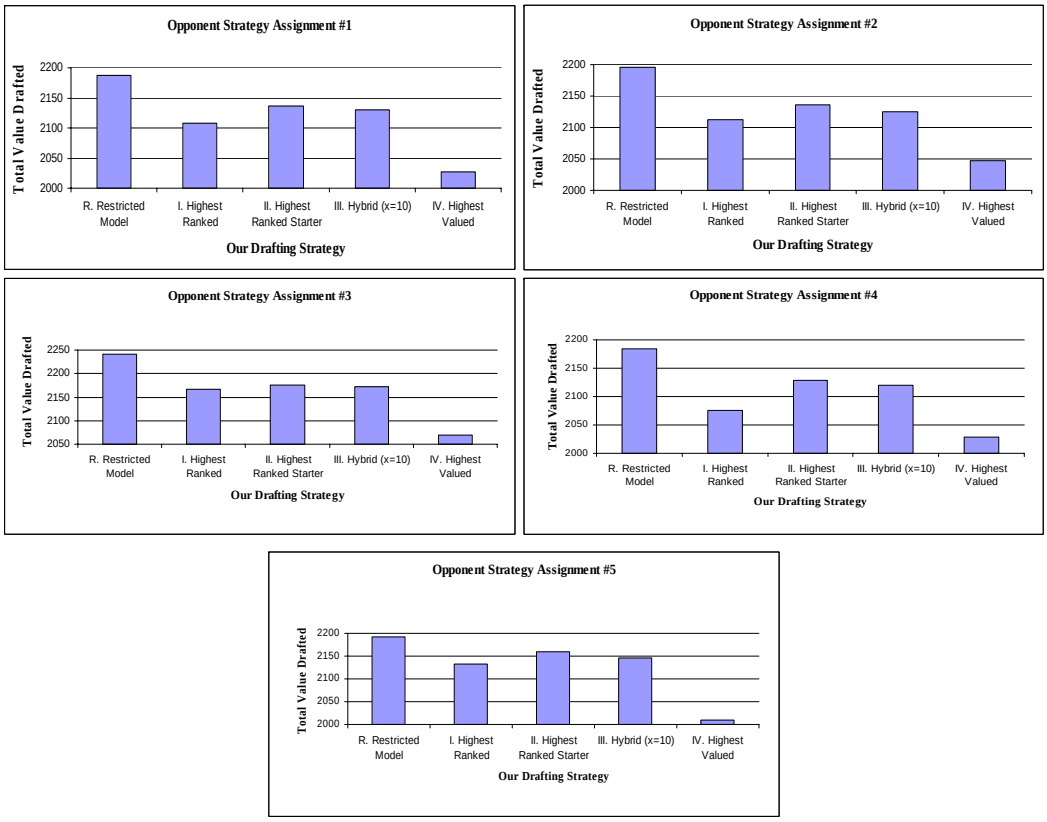

Figure 1: Perfect Information: Restricted Model versus Competing Strategies

As Figure 1 illustrates, our model generates solutions resulting in more total value drafted than the competing draft strategies in each of the five draft instances. Our model is able to achieve greater value since it explicitly considers the relative depth of players at each position. The solutions to our model will tend to draft players at a particular position so that they are selected just before significant declines in player value occur at that position. Figure 2 demonstrates this observation by plotting the value for the top 40 players at the running back position. Our model will typically recommend selecting two starting running backs (such as Rudi Johnson and Curtis Martin) before the sharp decline in RB value, occurring just two running backs after Curtis Martin. Thus, our model seeks to ensure filling our starting running back needs before the sharp decline by considering the impact of the current draft pick on the evolution of the draft. In contrast, standard draft rules-of-thumb

are myopic; they simply suggest taking the best player currently available (according to some defined metric) without explicitly considering the impact of this action on future draft selections.

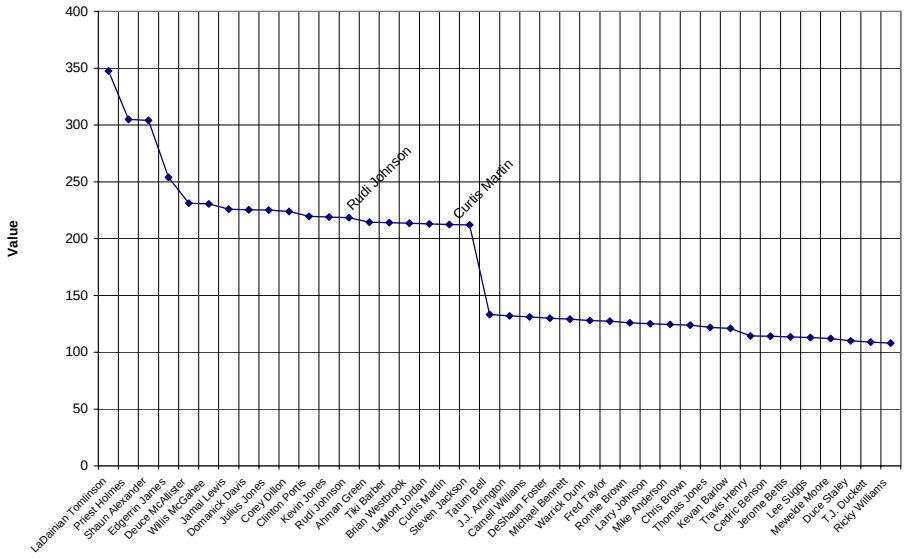

Figure 2: RB Values Ordered by Expected Selection

4.2.2 Drafts with Imperfect Knowledge of Opponents' Draft Strategies

In this section, we relax Assumption 3 by considering drafts in which the collection of opponents' draft strategies that the DM utilizes to project available-player pools for future rounds does not perfectly match the actual draft strategies implemented by the opposing teams. Our computational experiments examine the robustness of our model to the discrepancies in the projected versus realized available-player pools created by this imperfect information. As Figure 2 illustrates, one concern in using our model is that, if the DM's draft projections are not accurate, we may be exposing ourselves to potentially severe losses in player value by waiting to take a certain player immediately before a sharp decline in value at that player position. That is, by miscalculating the evolution of the draft, we may wait too long and end up drafting a player *after* a sharp decline in value at a position. Clearly, no DM will ever know precisely the strategies and player rankings used by all opponents. To

DOI: 10.2202/1559-0410.1050

test the effect of imperfect knowledge of opponents' draft strategies, we devise a pair of computational experiments.

We consider a pair of computational "imperfect information" experiments with varying degrees of the DM's awareness of opposing teams' draft strategies. In the first experiment, we consider a "worst-case" scenario in which the DM is totally naïve with respect to the opposing teams' draft strategies. Lacking any a priori knowledge of opposing teams' draft strategies, we assume that the DM implements our model and "guesses" that opposing teams will draft according to strategy III (Hybrid). Table 2 again displays the actual strategies being employed by each of the opposing teams in each of these instances.

Figure 3 compares the performance of our model (using the naïve projection) to the performance of competing draft strategies in each of the five draft instances of Table 2. Our model no longer outperforms the competing strategies in every instance (see strategies II and III in Instance #3 and strategy II in Instance #5), although on average it still outperforms the competing strategies (see Table 4). In each case where our model is outperformed, the difference in total value drafted is less than 4 value points (0.2%).

Any deterministic assumption of the opposing team's drafting strategies will inevitably generate incorrect projected available-player pools when there is uncertainty as to how the opposing teams will actually choose players. In the testing corresponding to Figure 3, we assume that the DM has no information regarding the opposing teams' draft strategies and simply projects the available-player pools at future draft epochs by assuming each team drafts according to strategy III. Rather than simply project available-player pools by assuming each team in the league drafts according to the same strategy, it is intuitive that a better approach is to incorporate any knowledge that might be available, even if it is incomplete, regarding opposing teams' draft strategies. While the DM may not have exact information regarding the draft strategy of each team, the DM may be able to develop a heterogeneous assignment of draft strategies that will, at the aggregate level, better estimate the evolution of the draft. It is less important to project exactly where each player will be drafted (i.e., by which team), than it is to have an accurate projection of which players will be available to the DM in each round of the draft.

In the second computational experiment, we consider a situation where the DM possesses some aggregate information about the draft strategies across the league and uses this aggregate information (perhaps from past drafts) to develop an assignment of opposing teams' draft strategies. Specifically, we assign a heterogeneous mix of draft strategies to the opposing teams in order to project the available-player pools. For the purposes of our computational experiment, we develop this assignment (given in Table 3) by randomly as-

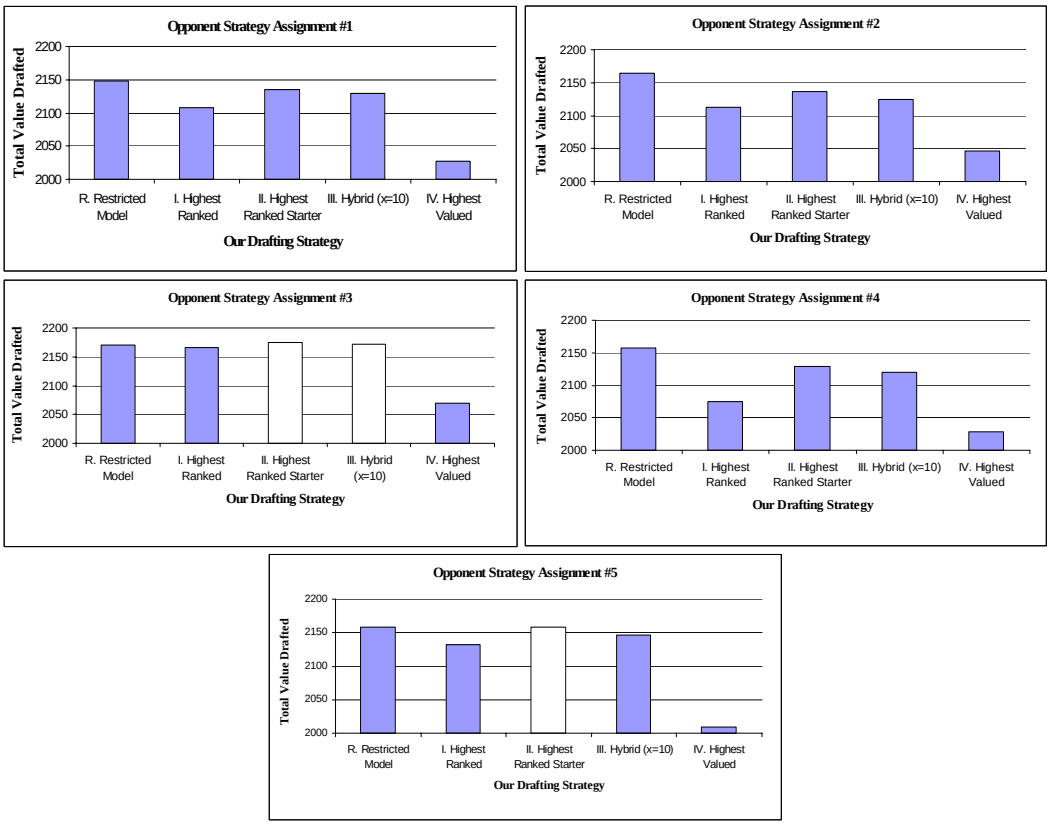

Figure 3: Imperfect Information: Restricted Model with Naïve Projection versus Competing Strategies

signing strategies to the opposing teams subject to the following restrictions: (1) each strategy is used by at least two and at most three of the opposing teams; (2) at least one of the teams using each strategy must draft before and after the DM. We continue to assume that the DM will choose according to Draft Strategy III for the purpose of satisfying Restriction 1.

Figure 4 illustrates the results when implementing our model, using the assignment in Table 3 to project the available-player pools, on each of the five "actual" draft instances of Table 2. Utilizing the aggregate, although imperfect, information regarding draft strategies, our model generates solutions resulting in more total value drafted than the competing draft strategies in each of the five draft instances.

Comparing the actual projected player pools and players drafted[7] in this

[7]The complete projected player pools and lists of players drafted for each scenario are

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Team	Draft Strategy
1	I
2	II
3	IV
4	III
5	III
6	III
7	IV
8	II
9	I
10	IV

Table 3: DM's (Imperfect) Belief of Opponents' Strategies Used To Project Available-Player Pools

case to that illustrated in Figure 3, we note several findings that help explain our improvement. We notice that the projected player pools appear to be more accurate when we allow for a heterogeneous assignment of draft strategies. In particular, we appear to do better at projecting when less valuable player positions will be drafted (e.g., kickers and defenses). To generate the results in Figure 3, we assumed that all opponents were using strategy III in order to project the available-player pool. However, if an opponent was actually using strategy II (selecting the highest ranked starter), we would overestimate how long some players would be available, particularly those players at lower-valued positions. As a consequence, we often waited too long to draft players at the kicker and defense positions, thereby missing out on many of the highly valued players at these positions.

As Figure 4 attests, our heterogeneous mix of strategy assumptions for opponents now captures that at least some opponents may be selecting according to strategy II. Although the DM's assumed belief of the opposing teams' draft strategies (Table 3) is largely inaccurate at the individual team level in each instance of Table 2, incorporating this knowledge at the aggregate level results in an improved draft strategy by more accurately anticipating the selection of players by opposing teams. In these examples, this knowledge was conveyed via the improved projection of players at the kicker and defense positions.

Table 4 summarizes the value of information in our testing across all five instances. On average, our model outperforms the competing strategies even

not presented here, but they are available from the authors.

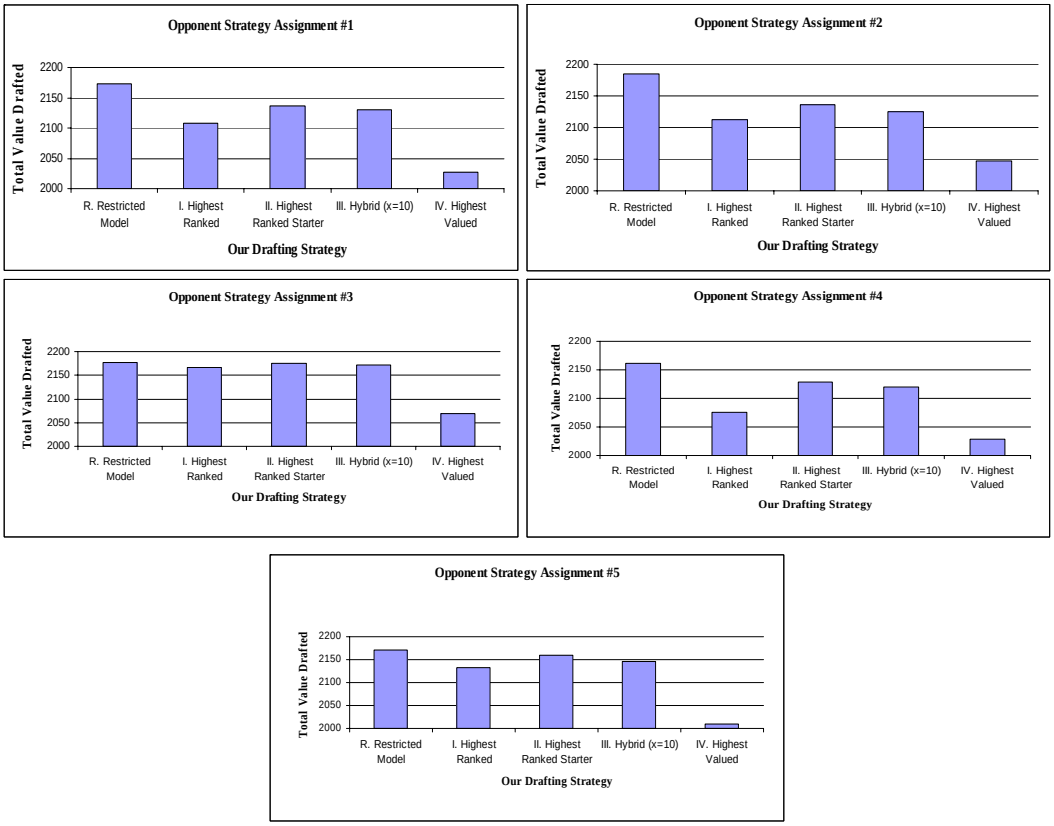

Figure 4: Imperfect Information: Restricted Model using Table 3 For Projection versus Competing Strategies

DM's Draft Strategy	**Value Drafted**		**% Value Loss Compared To:**		
	Avg.	**Std.Dev.**	$\mathbf{R}_N$	$\mathbf{R}_H$	$\mathbf{R}_P$
R_N. Restricted, Naïve	2159.7	8.3	-	0.6%	1.8%
R_H. Restricted, Heterogeneous	2173.7	8.3	-	-	1.2%
R_P. Restricted, Perfect	2200.1	23.0	-	-	-
I. Highest Ranked	2119.0	33.3	1.9%	2.5%	3.7%
II. Highest Ranked Starter	2147.0	19.3	0.6%	1.2%	2.4%
III. Hybrid (x=10)	2138.5	21.5	1.0%	1.6%	2.8%
IV. Highest Valued	2036.0	22.6	5.7%	6.3%	7.5%

Table 4: Performance Across All Five Draft Instances of Table 2

DOI: 10.2202/1559-0410.1050

with the naïve method of projecting available-player pools. Furthermore, our analysis confirms the intuition that more information, even if it is at the aggregate league level, improves the effectiveness of our model. Figure 5 compares the performance of our model under varying degrees of information known by the DM to the best competing strategy for each of the five draft instances. As illustrated, the restricted model provides significantly better results across these instances. For additional computational testing, we refer the reader to Appendix A.

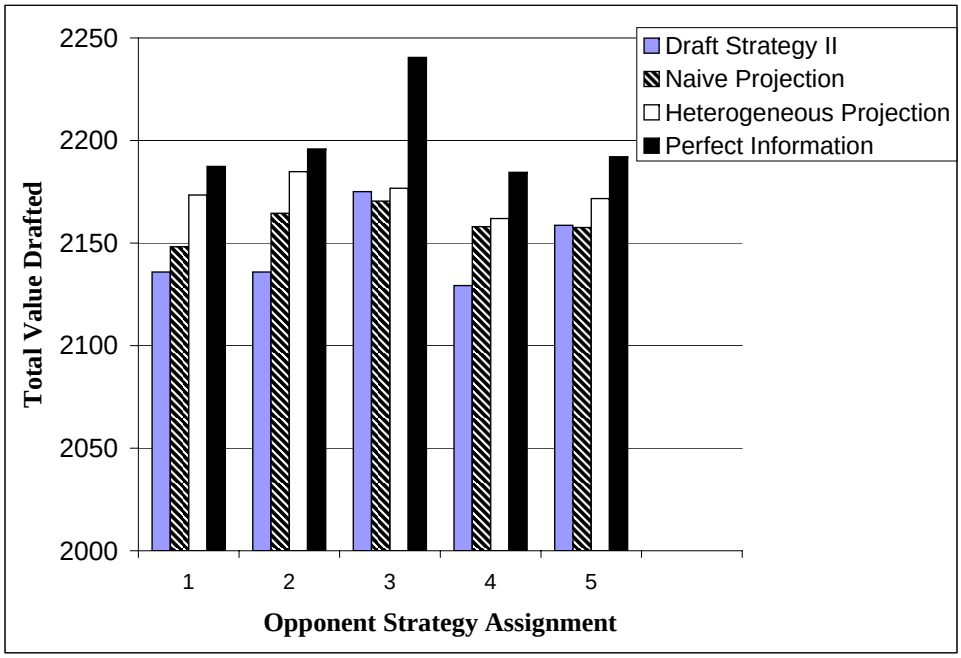

Figure 5: Comparison of Draft Strategy II and the Restricted Model with Varying Degrees of Information on Each Draft Instance from Table 2

4.3 Evaluating the Worth of a Draft Position

Another potential use of our model is in determining the worth of a given drafting position. Serpentine-style drafts are thought to promote parity in drafting positions; however, we show below that there are still differences in the relative worth of different draft positions. Table 5 evaluates the relative worth of each possible drafting position for a ten-team league in the 2005 fantasy football draft. To generate the results shown here, each team is assumed to determine draft selections according to our restricted model (where the available-player pools are projected using draft strategy III). In other words,

our restricted model has been solved 160 consecutive times to generate all 16 draft picks for each of the 10 teams. This represents a case where all teams in the league are particularly shrewd drafters since all teams choose according to our model.

Team	Value Drafted	% of Total Points Drafted
1	2219.7	10.46%
2	2208.1	10.40%
3	2136.8	10.07%
4	2114.5	9.96%
5	2106.1	9.92%
6	2089.8	9.84%
7	2074.6	9.77%
8	2105.8	9.92%
9	2106.4	9.92%
10	2066.1	9.73%

Table 5: Value of Draft Positions When All Teams Draft According to Restricted Model

Note in Table 5 that while Team 1 (who drafts first in odd-numbered rounds and last in even-numbered rounds) receives the maximum total value drafted, the valuations are not monotonically decreasing. For example, the total value drafted by Team 8 exceeds the total value drafted by Teams 6 and 7. This indicates a possible trading opportunity. Team 7 could offer to swap draft positions with Team 8. Because teams are often eager to move up in draft position in the first round, a less-than-shrewd Team 8 manager may agree to this and even may agree to give additional compensation for the earlier first-round draft pick, even though our analysis shows that Team 8 is in the better draft position. A similar analysis could be done to evaluate the worth of trading draft picks in a single (or multiple) rounds. As our model can be solved quickly, various drafting scenarios can be analyzed to determine the value gained (or lost) in trading individual draft picks.

Table 6 shows a similar listing of total drafted value by draft position, but here only Team i ($i \in [1, 2, \ldots, 10]$) chooses players according to our model; all other teams are assumed to choose players based on draft strategy II. Table 6 gives an indication of the draft positions in which our algorithm can be best used to exploit "average" opponents (i.e., opponents who are choosing players similarly to how historical evidence of past drafts indicate players will be chosen). Here we see that Team 3 now receives the highest total value drafted, ahead of even Team 1. We also notice that Teams 8 and 9 continue to do quite

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Team, i	**Value Drafted**
1	2223.3
2	2172.9
3	2228.3
4	2173.9
5	2179.3
6	2180.1
7	2186.9
8	2188.0
9	2191.6
10	2164.1

Table 6: Value of Draft Positions When Only Team i Drafts According to Restricted Model and Opposing Teams use Draft Strategy II

well. Again, the total values drafted are both unequal and non-monotonic. Thus, there again appears to be potential inequities in draft positions. We leave it to further consideration of how to determine a more equitable draft position assignment strategy – an issue first examined by Price and Rao (1976) for non-serpentine style sports drafts.

Clearly, results such as those in Tables 5 and 6 are dependent on the particular player valuations of the players available to be drafted. Thus, the relative value of draft positions would be expected to vary from year-to-year. However, our model can determine the relative worth of different draft positions for any particular draft player pool and valuation system.

5 Conclusion

Developing a tractable model to determine player selections in a sports draft is a very challenging task. A team's decision is a function of many variables including the decisions of all opposing teams, the pool of players available at each of the DM's decision epochs, and the positional needs of each team. A stochastic model that captures the uncertainty in a sports draft would be ideal. However, a direct formulation of a stochastic dynamic program to model a sports draft is intractable by classical solution methods and relies upon transition probabilities that are functions of the opposing teams' selection strategies. By introducing several model assumptions and restrictions, we obtain a more manageable deterministic dynamic program that considers both the positional needs of the team as well as the relative depth of players at each

position in the draft to develop a draft strategy. This restricted model can be solved quickly within a spreadsheet-based implementation allowing for real-time, up-to-date decision support during a draft.

We compare our model's suggested draft strategy to several competing draft heuristics. We find that our model results in a higher total player value drafted than any of the competing heuristics in instances where the DM has perfect information regarding the opponents' draft strategies. When uncertainty is introduced regarding the opposing draft strategies, we find that our model still performs very well in comparison to competing draft strategies. While imperfect information may create instances in which our method does not dominate competing strategies, we demonstrate that it is possible for the decision maker to incorporate information regarding league trends to improve the effectiveness of our approach. This suggest that any error that our model's assumptions and restrictions introduce can be compensated for with aggregate-level draft information. Thus, we believe that our model and solution methods are applicable to real-world scenarios where uncertainty clearly exists regarding opponents' actions. We also demonstrate several potential uses of our model including the determination of the relative worth of different draft slots. We further show that a serpentine-style draft can still result in unequal allocation of player talent and that the value of draft slots is non-monotonic.

Our work represents one of the first attempts at modeling realistic-sized drafts for team sports. Previous work has either considered leagues containing only a few teams (as in Brams and Straffin, 1979) or special draft situations (e.g., Summers et al., 2005) that reduce the decision-making complexity. Possible extensions of our work include the development of alternative approximation models and associated solution methods. We choose to solve our model via linear programming because this makes it quite easy to utilize existing solvers and to incorporate our model into a useful user-interface (namely spreadsheet software such as Microsoft Excel). However, the LP formulation results in a large number of constraints and, in general, LP algorithms are not the most efficient methods for solving dynamic programming recursions. Alternative solution methods that intelligently search the state space could be effective; an example of such a solution method is the A^* algorithm (Pearl, 1984). Regarding the stochastic version of our model, to determine the transition probabilities necessary to specify Equation (1), one could examine multiple historical drafts (in the case of fantasy sports) or multiple mock drafts (for real sports leagues). However, this model still has very large state spaces; thus, effective approximate dynamic programming solution methods are even more important for solving practical problem instances.

DOI: 10.2202/1559-0410.1050

Appendix A Additional Computational Results

A.1 Further Testing of Robustness of Competing Strategies

In the results presented in the §4.2, draft strategy II was the best competing strategy in each of instances. However, we demonstrate in this section that this may not always be the case. Suppose the DM has perfect information regarding each opposing team's draft strategy, and each opposing team is using the same strategy. This results in the four groups of five draft instances given in Table 7. We distinguish each group of drafts by the assumption used for the opponents' draft strategy ($P \in \{I, II, III, IV\}$). The DM's drafting strategy is given by Q, where $Q \in \{R, I, II, III, IV\}$, where $Q = R$ refers to the drafting strategy as defined by the restricted dynamic programming model. Thus, Draft $\{P, Q\}$ defines the specific draft in which the opponents' drafting strategy is given by P and the DM's drafting strategy is given by Q.

For each Draft $\{P, Q\}$, we consider a ten-team, 16-round draft. We assume that all teams begin with a needs vector of (2 QB, 4 RB, 4 WR, 2 TE, 2 D, 2 K). Half of the players to be drafted at each position will be considered backups and we will assume that backups are discounted by a value of $\beta = 0.6$. When solving our model, we use a forecast horizon length of $k = 5$ rounds. Figure 6 displays the results for these drafts. In each chart we fix the opponents draft strategy, P, and compare the total value drafted by our restricted model to each of the competing draft strategies.

Figure 6 shows that the solutions to our model generate greater total value drafted than the competing draft strategies, regardless of the opponents' draft strategy. While our model leads to the highest value drafted in each case, the performances of the competing strategies are much less robust. Although strategy II is again the best competing strategy on average, as illustrated by Table 8, it only out-performs the other competing strategies in one of the four draft instances.

A.2 Further Testing on Value of Information Regarding Opposing Teams' Draft Strategies

In the results presented in §4.2, there was a monotonic increase in the value drafted as the DM incorporated more information into the mechanism to generate available-player pools (see Figure 5). The computations of Figure 5 suggest that perfect information is better than no information, and some information is better than no information. In this section, we demonstrate that

Opponents' Strategy, P	**DM's Strategy,** Q
I - Highest Ranked Player	R - Restricted Model I - Highest Ranked Player II - Highest Ranked Starter III - Hybrid, x=10 IV - Highest Valued Player
II - Hightest Ranked Starter	R - Restricted Model I - Highest Ranked Player II - Highest Ranked Starter III - Hybrid, x=10 IV - Highest Valued Player
III - Hybrid, x=10	R - Restricted Model I - Highest Ranked Player II - Highest Ranked Starter III - Hybrid, x=10 IV - Highest Valued Player
IV - Highest Valued Player	R - Restricted Model I - Highest Ranked Player II - Highest Ranked Starter III - Hybrid, x=10 IV - Highest Valued Player

Table 7: Computational Tests on Four Draft Instances In Which Opponents Each Employ the Same Strategy

	Value Drafted		
DM's Draft Strategy, Q	**Avg.**	**Std.Dev.**	**% Loss**
R. Restricted Model	2226.0	60.2	-
I. Highest Ranked	2118.8	81.7	4.8%
II. Highest Ranked Starter	2170.3	84.3	2.5%
III. Hybrid (x=10)	2152.5	70.6	3.3%
IV. Highest Valued	2116.3	22.3	4.9%

Table 8: Performance of Draft Strategies Across the Four Homogenous Draft Instances

the effect of varying degrees of information between the two extremes of perfect information and no information is not necessarily predictable.

Specifically, we consider the imperfect information case in which the DM projects the available-player pools at future rounds according to the assign-

DOI: 10.2202/1559-0410.1050

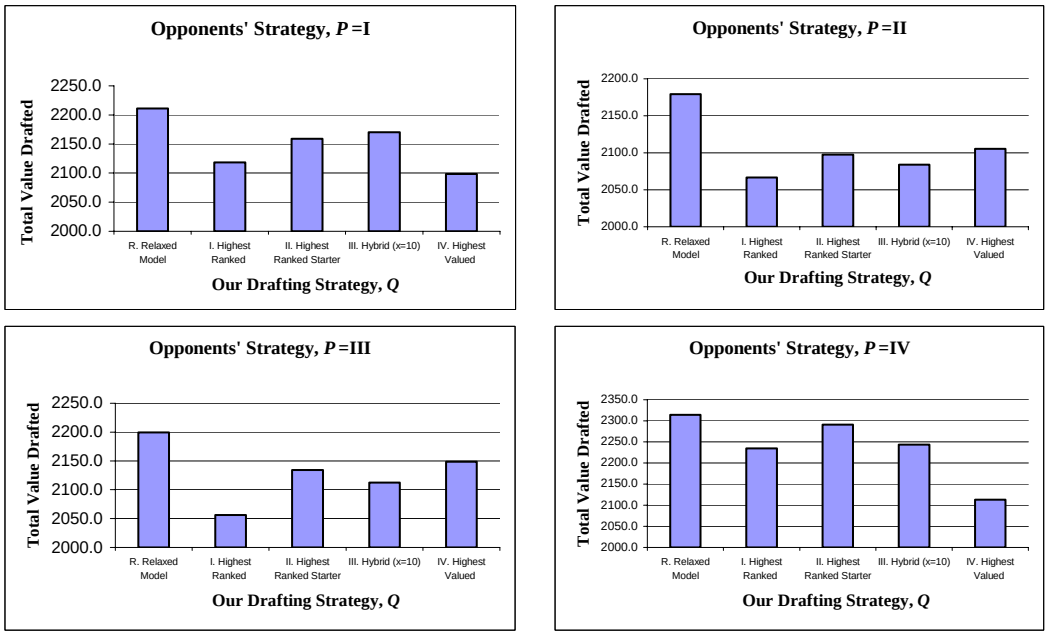

Figure 6: Draft Results Comparing Restricted Model Solutions to Competing Strategies

Team	Draft Strategy
1	I
2	I
3	IV
4	I
5	I
6	I
7	IV
8	I
9	I
10	IV

Table 9: DM's (Imperfect) Belief of Opponents' Strategies Used To Project Available-Player Pools

ment given in Table 9. With respect to the five draft instances of Table 2, the DM's beliefs in Table 9 are less informed (or at least not more informed) than the DM beliefs in Table 3 according to any obvious metric, e.g., number

of teams' strategies correctly identified, total number of each type of strategy, etc. However, Figure 7 illustrates that there are instances in which the DM would draft better if using the "less informed" beliefs, suggesting that the manner in which the DM should incorporate information about opposing teams' behavior has potential as an area of future research.

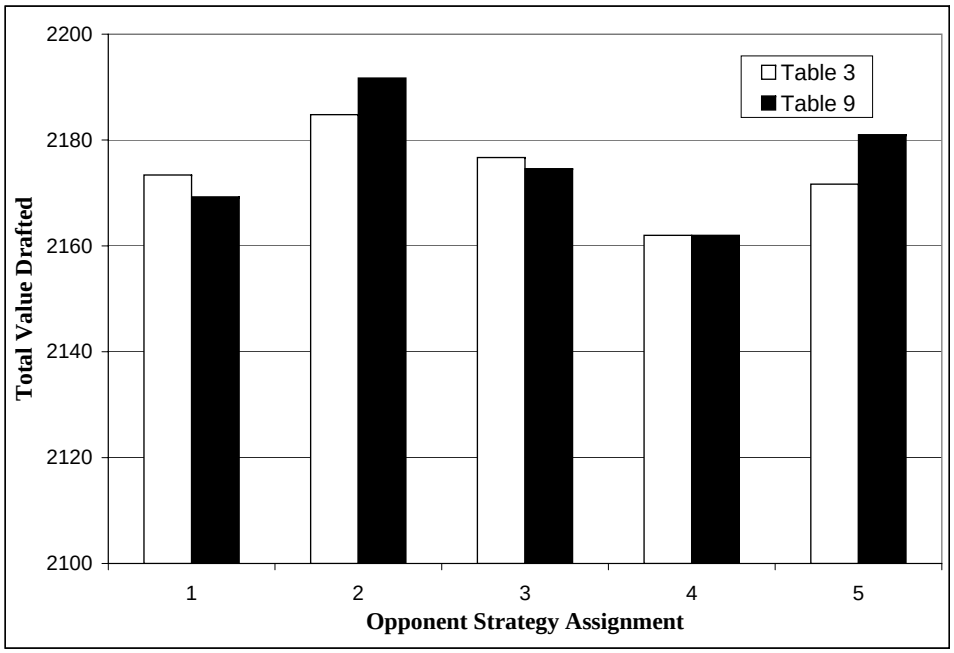

Figure 7: Imperfect Information: Restricted Model Using Table 9 Versus Using Table 3

DOI: 10.2202/1559-0410.1050

Appendix B Partial List of Player Values and Rankings

Rank	Player	Position	Value
1	L. Tomlinson	RB	347.5
2	P. Holmes	RB	305
3	S. Alexander	RB	304
4	P. Manning	QB	351.5
5	E. James	RB	254
6	D. McAllister	RB	231
7	W. McGahee	RB	230.5
8	J. Lewis	RB	226
9	D. Davis	RB	225.5
10	R. Moss	WR	219
11	D. Culpepper	QB	343
12	J. Jones	RB	225
13	C. Dillon	RB	224
14	C. Portis	RB	219.5
15	K. Jones	RB	219
16	R. Johnson	RB	218.5
17	A. Green	RB	214.5
18	T. Holt	WR	216.5
19	T. Owens	WR	216
20	T. Barber	RB	214
21	C. Johnson	WR	215.5
22	B. Westbrook	RB	213.5
23	M. Harrison	WR	211.5
24	L. Jordan	RB	213
25	C. Martin	RB	212.5
26	J. Walker	WR	211
27	S. Jackson	RB	212
28	T. Gonzalez	TE	171.5
29	J. Horn	WR	194
30	A. Johnson	WR	191.5
⋮	⋮	⋮	⋮

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