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Determining Factors of Risk Tolerance: Evidence from Fantasy Football Snake Drafts

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Abstract

This paper utilizes fantasy football snake drafts to analyze risk tolerance of individuals who are trying to maximize their present and future utility, but are faced with unknown factors and only have limited resources. Fantasy football provides a unique perspective on risk tolerance, different than the commonly researched fields of auctions, financial portfolios, and lotteries. I examine mock draft data from Fantasy Football Calculator as well as rankings data from Fantasy Pros to gauge the amount of risk associated with each draft pick. I find that the more perceived uncertainty that is connected to an individual selection, the more likely the selection will exhibit risk averse characteristics.

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1. Introduction

Despite the various questionnaires and scientific approaches that exist today, risk tolerance is a difficult concept to quantify. There are numerous factors that contribute to an individual's risk tolerance, which ultimately culminate in decisions that align with the amount of risk each person deems acceptable. Most of the research regarding risk tolerance focuses on financial investing (see for example, Treich 1997 and Wong 2016), auctions (see for example, Beggs 1997 and Mezzetti 2011), and lotteries (see for example, Garrett 1999).

The financial risk tolerance analysis is centered around the elements that determine the appropriate amount of risk investors are willing to take in their own portfolio (Treich 1997 and Wong 2016) whereas the risk tolerance concerning auctions and lotteries are more focused on payoff uncertainty and the availability of resources (Beggs 1997). Moreover, the analysis of what factors contribute to financial portfolio risk and lotteries typically uses volatility or uncertainty of returns as a proxy for risk (see for example, Wong 2016, Grable 2000, and Garrett 1999). On the other hand, studies on auctions often focus on the price a good is acquired (see for example, Mezzetti 2011 and Beggs 1997), where the bidding process typically involves all owners.

However, there are other aspects of risk tolerance that receive less attention but are important to understand when examining consumer preferences. For instance, the only existing literature regarding risk tolerance with similar goods is focused on auctions (McAfee 1993). But there are other contexts where risk tolerance can be examined besides the heavily structured auction setting. There is a significant aspect of consumer decision making that occurs repeatedly when individuals are presented with choosing between purchasing a good in the present or waiting for the price of the good to decrease. Although waiting comes with the risk of the good being purchased by another party. If this were to take place the individual would be forced to purchase a less preferred good. These circumstances are common with hotel rooms and airplane flights, but can occur with any finite good that has a number of inferior replacements. Obtaining more knowledge regarding consumer risk tolerance of these goods can have a substantial impact on the way they are priced and marketed.

The main aspect of risk tolerance that has the most impact is loss aversion (Guillemette 2014). Typically risk tolerance is measured through the imperfect mechanism of surveys and studies like the FinaMetrica questionnaire and various others designed by financial services firms. While collecting and judging risk tolerance through direct observation is preferred, there are inherent challenges with that methodology as well. For instance, there is no perfect measure for risk tolerance and so often times it is interpreted from a proxy metric. There are studies examining if a study participant prefers a more certain payoff with a lower expected value versus a payoff with a higher expected value, but the potential to receive zero benefit (see Bhattacharya 2008). However, there is little research done regarding how an individual's risk tolerance is affected when there are unknown factors, numerous options, and the individual has limited resources.

The purpose of this paper is to add to the existing literature by analyzing risk tolerance for individuals who are trying to maximize their present and future utility, but have limited resources and are presented with unknown factors that reduce future choice.

Specifically, this paper focuses on fantasy football snake drafts[1], which offer a unique lens through which one can observe risk tolerance.[2]

First, this is the case because in snake drafts, the maximum players the owner of a fantasy team can select is equal to the number of available roster spots. Also, the frequency at which an owner can make selections is also predetermined and known by all parties. In conjunction with limited resources, there is the additional element of uncertainty that manifests itself through the other owners systematically reducing the number of remaining players in the process of forming their own teams. Contrary to the traditional methods of analysis for financial portfolio or lottery risk tolerance, I am not looking at the risk of the asset, but the divergence from consensus industry rankings. In addition, snake drafts are different than auctions, as snake drafts consist of each owner selecting players one at a time, with no explicit bidding involved.

Using data from Fantasy Football Calculator and Fantasy Pros I create a binary proxy measure for risk based on the methodology proposed in Ozbeklik and Smith (2014). Using the idea laid out in their research, I leverage the difference between expected outcomes and observed outcomes to quantify risk. I find that selections exhibit lower risk tolerance when there is a large degree of uncertainty resulting from either a large distance between selections by the same owner or a small number of humans present in the draft. In addition, when owners choose to select a player who plays the same position as multiple prior selected players, he or she tends to display more risk

[1] A snake draft is when each participant takes turns selecting a good in the first round and in all subsequent rounds, the order reverses. So the individual with the first selection in odd rounds has the last selection in even rounds and so on. See Section II: Background of Fantasy Football for a more in depth explanation.

[2] While there are some studies investigating fantasy football auction drafts (see for example, Anagnostopoulos 2016 and Cockcroft 2017), they mostly deal with optimal auction strategies, not risk. Further, to the best of my knowledge there is no literature specifically looking at the risk connected with snake drafts.

averse behavior. This could potentially be due to owners fear of missing out on a specific player. When owners perceive the chance of the particular player as high, he or she may select that player before another owner has the opportunity to do so.

I begin in the next section by providing background on fantasy football and the elements of snake drafts and mock drafts. Then I discuss the existing literature regarding risk tolerance in Section III. Section IV describes the data used and provides relevant summary statistics. Section V expands on my empirical strategy and examines the results from different economic models. Finally, Section VI presents concluding thoughts and provides potential avenues for future research.

2. Background of Fantasy Football

Fantasy football drafts create a unique and informative set of conditions that are ideal for investigating risk tolerance and preference strength. Fantasy football is a competitive game played between individuals that utilize real life performance of the National Football League (NFL) players to award fantasy points to those same players. Typically fantasy football is played by a number of owners who together make up a "league". The most common size of a league is 10-12 owners, however a league can be any size.

The objective of fantasy football is to assemble a team comprised of NFL players that scores the most points in a given week. The specifics of scoring depend on each leagues' settings, but the majority of leagues award points to offensive positions (quarterback, running back, wide receiver, and tight end) for yards, touchdowns, and receptions, to defenses/special teams for fewer points conceded, interceptions, fumbles recovered, and touchdowns scored, and to kickers for made field goals and extra points.

Often times prior to an owner's draft, he or she will participate in a mock draft. Mock drafts serve as a practice setting for fantasy football owners to test their various draft strategies in a low risk environment before participating in their official draft where money or pride may be on the line. The purpose of a mock draft is to acquire information for official drafts through the experimentation of various strategies as well as understand how other owners value certain players. Owners are attempting to identify the previously unknown market value for players in order to infer the expected team structure associated with a particular set of draft picks, of which they might be completely unfamiliar. So, the incentive structure of mock drafts must also be considered when analyzing the underlying causes of an owner's tolerance for risk. As a result, mock drafts provide valuable information on how owners view risk and potential uncertainty in numerous particular strategies.

Due to a variety of reasons, the more volatile positions in fantasy football tend to be kicker and defense, followed by running back, then wide receiver and tight end, with quarterbacks typically retaining their value for most of the year. The reason kickers tend to be the most volatile is that NFL teams in the majority of cases only carry one kicker on the roster. In addition, if the kicker underperforms for even a short amount of time, often times he will be cut from the NFL team. Players who are not recording statistics for their NFL team cannot score fantasy points and thus, fantasy football owners tend to drop kickers from their roster if they are cut from their NFL team. Likewise, defense and special teams units also tend to be volatile, but for different reasons. Since defenses and special teams units consist of over 11 different players, often times in between seasons players leave certain teams and join others. This results in a change in effectiveness of the defensive and special teams' unit that may be challenging to predict before the season starts. Injuries also play a large role, as there exists the potential for multiple key defensive players to get hurt, reshaping the defensive unit as a whole. Even though running back and wide receiver are not as inherently risky as kicker and defensive units, both positions come with a level of unpredictability. A reason for this is the increased injury risk associated with running backs and wide receivers in contrast with the much lower injury risk linked with quarterbacks.

One factor contributing to positional value in fantasy football is roster construction, both in fantasy football and real world football. The standard fantasy roster only requires owners start one quarterback and one tight end, but two wide receivers and two running backs, along with a flex that is typically either a third running back or wide receiver. Compounding this built in risk is the fact that most NFL teams carry more wide receivers on their roster than running backs and teams prefer to primarily rely on one running back, but multiple receivers.

As previously stated, all of these factors allow for investigating risk through an atypical, yet informative lens. Certain information is known to all parties involved, such as the exact set of picks each owner possesses well as the number of roster spots on each team. Conversely, owners do not know the private valuations of other owners in the draft. So as owners continue to select players, they are reducing the available resources for other individuals in the draft. Also, snake drafts allow risk tolerance to be measured through disparity of expected outcome and observed outcome. Whereas the other three avenues of analysis, financial risk tolerance, auctions, and lotteries traditionally measure risk in different ways.

3. Literature Review

As mentioned briefly earlier, the existing literature concerning fantasy football is mostly focused on optimal auction draft strategies and roster construction. Cockcroft (2017) investigates the state of the NFL each year and the best approach to take when approaching an auction draft. However, his annual work does not examine determinants of risk tolerance with regards to snake drafts.

Chakravarthy (2012) specifically examines risk, but in an attempt to discover an optimal auction draft strategy. He finds risk neutral betting during the auction is the strategy that maximizes the owner's utility and that risk averse behavior is only an optimal strategy under certain conditions. That condition being when there are a large number of owners in the draft who exhibit risk neutral or risk loving behavior, it is more optimal to adopt a risk neutral bidding strategy. Anagnostopoulos et al. (2016) look at how to create a strategy in an auction draft that mitigates any potential downside. Similar to Cockcroft's analysis, Chakravarthy and Anagnostopoulos et al. (2016) focus solely on auctions and do not dive into the underlying elements that determine an owners risk profile.

To augment the limited literature regarding fantasy football, three other fields of economic analysis and their findings regarding risk tolerance are discussed. Specifically the existing literature centered around financial investing, auctions, and lotteries that looks at risk tolerance, its root causes, and its effect on the price of goods. I discuss each in turn.

Looking at the literature discussing financial investing, there are a number of studies investigating the value of information with respect to risk tolerance. Based on casual observation and intuition, individuals with a lower risk tolerance would place a high premium on information. This way they can ensure their risk is minimized. But Treich (1997) and Eeckhoudt (2000) show there exists the potential for risk averse individuals to in fact place a lower value on information than their more risk neutral counterparts since risk averse individuals prefer less risky assets in any case. As such, the amount of information may or may not have a material impact on the decision making process, depending on the inherent risk tolerance of the individual.

Wong (2016) looks at the relationship between financial risk tolerance and ambiguity tolerance, which is defined as the ability to accept uncertainty despite the discomfort of not knowing the answer. He finds, despite traditional reasoning, there is no relationship between the two. Even considering that both factors have something to do with unpredictability, there is the possibility that risk uncertainty is viewed differently than ambiguity uncertainty. Relating this to risk in fantasy football, there are certain positions that are intrinsically riskier than others, but this risk is known. Whereas, the risk associated with uncertainty could manifest itself through the distance between selections by the same owner. The greater the distance between picks, the larger the uncertainty.

Moving onto auctions, one can see some similarities between a snake draft and a first-price, or Dutch auction. A first price auction is where the person with the highest bid wins the item and pays his or her bid. In practice, first price auctions often involve the auctioneer starting with a high price and reducing it until one person chooses to pay the most recently stated price for the item. Snake drafts share certain characteristics with a Dutch auction, namely with regards to when a player is selected, the owner is technically paying the highest price any of the other owners is willing to pay.

Schotter (1988) shows that the perfect equilibrium bids in an auction are a good predictor of prices, which would indicate that all draft selections follow the rankings relatively well with little deviation. But this assumes rankings can be ordinal, whereas fantasy football rankings, or equilibrium values, are cardinal. Thus private valuations are forced to be dependent on other available assets. An additional element is that only when the perfect equilibrium bids are below each players' valuation does the perfect equilibrium serve as a good estimate for prices. This is not inherently the case in all scenarios, as an owner could have a private value of a player could be higher than the perfect equilibrium bid.

McAfee (1993) confirms the idea of the winner of the item not having the highest valuation for that specific item in sequential auctions because the auction consists of both the items to be sold as well as an additional risk element. This is what is known as a declining price anomaly in auctions. van den Berg et al. (2001) further explores this effect, specifically with regards to Dutch auctions. They conclude the phenomenon not only exists, but also increases in magnitude as the number of remaining units decreases.

Auctions that are ordered by descending estimated values, tend to see the price relative to the pre-auction estimate decreases (Beggs 1997). This requires the assumption that snake drafts are ordered by descending value. Since by construction, players are selected in declining order of valuation, the assumption seems reasonable. Given this, as the draft continues, the draft position relative to the pre-draft ranking will begin to vary.

Mezzetti (2011) shows when approximate market values are known for the items in the auction, thus decreasing value interdependencies, the prices are expected to decrease as the rounds progress. This supports the idea that, while information may have differing value depending on the risk tolerance of the owner, it still has positive value. Rodriguez (2009) identifies an equilibrium when dealing with sequential auctions with any number of periods and bidders, but the equilibrium relies on the assumption of complete information.

Another economic area of analysis which relates to fantasy football snake drafts is lotteries, as the players selected are not accompanied by guaranteed performance, but inherent risk. Risk arising from injuries, under performance, or over performance by the given player or other members on the same team, which deprives said player of chances to succeed. Certain players are viewed as "safer" and are considered to have a smaller band of likely outcomes, whereas some players are viewed as "riskier" and have a wider band of likely outcomes.

Casual observation suggests that as the draft progresses, owners are more likely to diverge from draft rankings because the expected performance of the player selected generally declines as the draft occurs. As the draft progresses, the increased variance in performance makes the draft go from appearing like an auction with similarly priced items to a lottery. As such, at the late stages in the draft, owners are attempting to select players whose performance has a high variance and could result in a much higher level of performance than expected. Bhattacharya (2008) confirms the idea that gamblers are willing to trade expected value for an increase in variance, even when the expected value is originally negative. Garrett (1999) shows that this phenomenon is not simply lottery participants who are risk loving, but in fact it applies also to the risk averse players. Thus, as the expected value of the player decreases, the more likely an owner will be willing to select that player if his performance is viewed as having a higher variance.

Smith and Ozbeklik (2016) examine risk taking in a tournament setting by analyzing rounds of golf. They create a metric based off deviation from the norm to evaluate the amount of risk taken. The further away from the norm, the more risk a golfer took. In order to identify what is the norm, they use the par score for each hole. If an individual golfer does better or worse than the par score, that is a sign he took a risk when playing the hole. If the golfer scored well, the risk paid off and if he scored poorly, the risk did not pay off. However, this study is not perfect. While the tournaments are between a large number of contestants, only two golfers competed against each other at one time. So this analysis does not provide the opportunity to examine if the number of contestants participating had an effect on the level of risk taken.

This paper builds upon the current knowledge base by testing the findings that previous studies demonstrate under a different set of circumstances. For instance, Schotter's (1988) findings of perfect equilibrium bids accurately predicting prices is restricted to auctions where the rankings are cardinal. As fantasy football rankings are ordinal, it is impossible for every selection to be classified as below the valuation. This inevitably leads to owners selecting players prior to when the market believes they should be picked.

McAfee (1993) and other auction studies use similar items in order to examine the legitimacy of the declining price effect. In snake drafts, it is certainly possible for the owner with the highest valuation of a player to not select that player. This indicates there is some potential for owners to select players earlier than their internal valuation would suggest in order to ensure another owner could not select the given player. This paper quantifies some of the reasoning behind why some owners are more risk averse and choose to select players well before their ranking.

Previous analyses of risk tolerance focus on similar goods in order to isolate the reduction of supply. Whereas this paper is concerned with different types of goods, typically drafted in descending order of value, and examining other contributing factors to risk tolerance besides a limited supply.

4. Data

The data used in this paper were acquired from two separate fantasy football websites: fantasyfootballcalculator.com (FFC) and fantasypros.com (FP). FFC is a website that allows users to participate in mock drafts for a variety of different league sizes and scoring systems. In order to ensure the mock drafts are consistently taking place without exorbitant wait times, FFC employs a system where mock drafts are held at regular intervals regardless of how many participants are signed up to take part in a draft. Since the draft beginning even if it is not completely filled with users, FFC has a computer algorithm to control the unoccupied draft slots. As long as there is one human participating in the mock draft, the draft will continue. But if all the humans drafting exit the draft page, the draft immediately concludes. FFC is one of the only websites that publishes their fantasy football draft data, as most of the popular fantasy football platforms, such as ESPN, Yahoo, and CBS, choose to keep their individual draft data proprietary and only release aggregated data. I focus solely on drafts that consist of eight teams and 15 rounds, for a total of 120 selections per fully completed draft with standard scoring rules. In order to extract the data from each of the 975 available drafts, or 117,000 draft picks, a web scraper was written and designed in Python. Data extracted from FFC mock drafts includes the player selected with each pick, the round number, the number of humans in the draft, the number of rounds completed, the position of the player selected, and the overall pick number in the draft.

Player rankings were acquired from FP in order to calculate a proxy for risk associated with each selection. FP averages the rankings for standard scoring leagues of 100 fantasy football writers in order to determine an industry consensus ranking. The only information utilized from FP consists of the ranking for each player.

I restrict the sample of draft picks to only those that occurred in complete drafts. That is, I exclude all picks from drafts where at some during the draft, there are no more humans participating. This could be due to a number of reasons. Potentially humans participating in the draft were not paying attention throughout the entire process, lost interest midway through the draft, or an owner's internet connection malfunctioned. As a result, the 116 incomplete drafts and all 13,920 associated draft picks are excluded from the analysis. I also restrict the sample to players on an NFL team which excludes an additional 16 draft picks.[3] Furthermore, I restrict the sample to human selections since

[3] Most of the excluded selections were quarterback Colin Kaepernick.

the purpose of this paper is to ascertain human risk tolerance. As such, the 58,950 non-human draft picks are excluded from the analysis.[4]

In order to measure the risk tolerance of individual selections, a method similar to that of the one used by Smith and Ozbeklik (2016) is employed. They measure risk in two different ways, percentage of holes conceded and standard deviation of player scores relative to par. Since owners cannot concede picks in fantasy football drafts, my risk metric focuses on the second component of their risk measure. Instead of par values for a benchmark for risk, I use the aggregated set of rankings from FP. So the rankings serve as the expected outcome and the owners selection serves as the measure for observed outcome. By comparing the two and analyzing the sign and magnitude of the difference I am able to examine the amount of risk tolerance associated with each pick. Specifically, my main measure of risk is the comparison of a player's' rank with the overall draft pick that was used to select him.

A positive figure indicates the player selected should have been selected earlier in the draft. This is a sign the owner made a good selection and was able to capitalize on other owners selecting players before their rank. On the other hand, a large negative figure would signify an owner selected a player before his ranking showed he should be drafted. In other words, a large negative figure would indicate the person does not want to take the risk of that player being selected before his or her next selection. The larger the difference between the two numbers in the negative direction, the lower risk tolerance a person has. Due to the construction of the measurement, the highest possible sum of

[4] I discuss one exception to this sample restriction in detail below.

pick versus rank across an entire draft is zero, which would indicate all selections in the given draft consisted of the top 120 players in the ranking in some order.

When the pick versus rank difference is positive, this indicates the owner was able to select a player later than the consensus rankings believes he should be selected. All that indicates is the selection captured value due to the selections of the other participants in the draft. This does not allow for any type of interpretation regarding the amount of risk an owner is willing to tolerate. Therefore, all 20,664 individual draft picks where the pick versus rank figure is positive are omitted from any analysis. There are also two draft pick observations that have overall pick numbers greater than 120 that are treated as outliers and dropped from the dataset. The final sample size is 23,448 individual draft picks from numerous different owners and drafts.

The problem with solely using the gross difference is the unequal value of selections across various rounds in the draft. For example, a value of negative five would be treated the same way if it was applied to the first overall pick versus the last overall pick. The distribution of negative pick versus rank values is heavily skewed towards zero.[6] However, the median value of the pick versus rank difference is drastically larger in the later rounds of the draft as compared to the early rounds.[7] There is a clear increase in the magnitude of the pick versus rank values as the round increases. This indicates owners are more likely to diverge from the ranking as the draft continues.

In order to account for this variation across rounds, I create a binary variable to identify the lowest quartile of pick versus rank values for each round. The binary variable

[6] See Figure 1 in the appendix.
[7] Figure 2 shows the 25th, 50th, and 75th percentile of pick versus rank for each of the 15 rounds.

takes the value of one when the selection is within the highest 75th percentile of pick versus rank and zero otherwise. This indicator variable, henceforth referred to as risk25, serves as a way to account for the different distributions of pick versus rank throughout the 15 rounds. To help identify further effects of drafting a player in a late round, I create an indicator variable for a late round which is defined by whether or not the pick occurred in the final five rounds of the draft.

A major factor in determining how an owner chooses to construct his or her team is by looking at the different positions and how the average team is constructed.[8] The average team drafts almost three times as many running backs and wide receivers as quarterbacks and five times as many as defense/special teams and kickers. As a result of owners inherently valuing each of the positions differently, I create indicator variables for each of the six positions that could be drafted: quarterback, running back, wide receiver, tight end, defense/special teams, and place kicker.

A crucial element of fantasy football snake drafts is the potential for "runs". A run occurs when multiple sequential picks are used on players who play the same position. Three indicator variables are created to capture the possible effect a run can have on the risk of a selection. The first variable takes the value of one when the three previous selections are players of the same position. In order to examine the effect of longer runs, two additional variables are created that take the value of one when the four and five previous selections are players who play the same position. This set of three variables will henceforth be referred to as non-participating run variables.

[8] See Appendix Table 3 for a breakdown of the average team by position for human teams.

The second set of three variables are designed to examine the effect of an owner participating in the run. So they are defined the same way as the non-participating run variables except they only take the value of one if the owner who is making the current selection also selects a player who plays the same position. In other words, these three variables only take the value of one if the owner participates in the run on a specific position. These three variables will be referred to in future discussion as participating run variables.

So despite computer observations being dropped for most of the analysis, they are included in the calculation for all of the variables which consider previous picks. All six of these indicator variables consider computer selections as well when identifying the existence of a run. In order to ensure the variables are mutually exclusive, each selection can only be included in one of the variables.

Another measure of uncertainty is the number of selections by other teams between the same team's selections. This variable, henceforth referred to as picks until the next pick, is defined as the number of picks until the next pick by the same team. Since there are eight teams in each draft, the value for picks until the next picks repeats the same sequence, going from 14 to one, decreasing by two each time until the value is two, and then going to one before repeating the same cycle.

Looking at the summary statistics for participating and non-participating run variables, it appears there are fewer runs of three than four or five.[9] This may indicate a potential snow ball effect, where if owners see a position taken the previous few picks, he

[9] Complete descriptive statistics are presented in Table 4 in the appendix.

or she might feel the need to take the same position as well to avoid being stuck with an inferior player.

At first glance it appears strange that there are an unequal number of selections in the early, middle, and late round dummy variables. But, this is due to the increased number of selections with a negative pick versus rank value in the later rounds. This is a sign owners take more risks as the round increases. If the distribution of selections with negative pick versus rank values was uniform across all 15 rounds, the average would be eight. However, the fact the average round number is 8.43 is also an indication there are more selections with a negative pick versus rank value in the later rounds.

5. Empirical Strategy and Results

In order to examine the determinants of risk tolerance, I estimate a probit model of the following form:

$$Y_i^* = \beta X_i + \varepsilon_i \tag{1}$$

where Y is an indicator variable, risk25, such that:

$$Y_i = \begin{Bmatrix} 1 \; if \; Y_i^* > 0 \\ 0 \; if \; Y_i^* \leq 0 \end{Bmatrix} \tag{2}$$

and i represents each individual draft pick. X is a vector of observable characteristics (number of humans in the draft, picks until the next pick by the same team, whether or not the most recent picks are of the same position, and position indicator variables), and ε is an error term with the usual properties. The marginal probit effects and standard errors are presented for ease of interpretation with standard errors estimated using the delta method.

Table 1

Determinants of Risk Tolerance

Variable	Dprobit
Number of Humans	0.001
	(0.002)
Picks Until Next Pick	-0.001
	(0.001)*
Same Position Selected Three Prior Picks	-0.008
	(0.012)
Same Position Selected Four Prior Picks	-0.012
	(0.021)
Same Position Selected Five Prior Picks	-0.038
	(0.035)
Quarterback Dummy	-0.068
	(0.014)**
Running Back Dummy	-0.114
	(0.012)**
Wide Receiver Dummy	0.037
	(0.012)**
Defense Dummy	-0.163
	(0.015)**
Place Kicker Dummy	-0.329
	(0.015)**

Notes: Probit and dprobit coefficient estimates with standard errors in parenthesis. Position dummies are one if the player selected is listed as playing that position in FFC's database. Significance at the 5% level is noted with a single asterisk and significance at the 1% level is noted with two asterisks.

The results are presented in Table 1. It can be seen that the greater the difference between picks from the same team, the lower the risk tolerance. Picks until the next user pick is significant at the 5% level, which indicates that as the distance between picks increases, owners exhibit more risk averse behavior. This could be due to the increased uncertainty with each additional selection before the same owner picks again. An owner is less willing to take the chance a player he or she wants will be selected when there is a large distance between his or her selections. For example, if an owner has the last selection in the one round, they are presumably aware after they select first in the following round, there are 14 selections before they pick again. When deciding which player to select, the owner thinks about which players will still be available when they select next. As a result, the owner must consider how the other seven owners will behave. If they fear one of the other seven owners in the league has the same value for a player, it is in their best interest to select the given player. Even if the player is ranked much lower than where he was drafted. This is contrary to the findings of Treich (1997) and Eeckhoudt (2000) that show risk averse owners place a lower value on information than risk neutral owners. So perhaps the majority of owners are not risk averse to begin with and thus still place a high value on more information.

The same position selected variables appear to not be significant in this model. This could be due to a self-selection element where the choice to participate in the run is an indication of a low risk tolerance, not the run itself. So another probit model will be examined that has the exact same characteristics except for the non-participating run variables have been replaced with participating run variables.

In the updated model all of the original coefficients show similar effects on risk tolerance, but the participating run variables become significant with a larger marginal effect the greater number of previous selections were the same position.[10] This appears to

[10] See Table 5 in the Appendix for complete model output

indicate the run itself does not suggest an owner will take part in a low risk strategy, but rather the choice to participate in the run does. Partaking in the run is a sign that an owner has a lower risk tolerance, not just the fact that a run occurred before hand. The maximum impact on risk tolerance is observed when the five previous selections are of the same position as the current pick and that occurrence decreases the probability of inclusion in the top 75% of pick versus rank by 18.2 percentage points. This aligns with intuition, since only those with low risk tolerances would worry that the position was running out of players and choose to select a player who plays the same position. The more risk neutral owners would recognize that if a run occurred before their pick there might be value to be had with other positions.

Position also impacts if a selection falls within the lowest 25th percentile of pick versus rank values. Both models suggest the riskiest positions, kicker and defense, appear to indicate a low risk tolerance when selected relative to the left out category, tight end. This could be due to the overwhelming number of defenses and kickers selected in the later rounds.[11] It is difficult to interpret the coefficient in this context without considering the effect of the skewed distribution on the model.

These models serve as a solid foundation to build upon, but there are some issues. First, the models do not account for the heavily skewed distribution of defenses and kickers in the final rounds of the draft. Another potential issue is this model shows the number of humans is not a significant predictor of risk tolerance.

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[11] See appendix for breakdown of positions by round (Table 6)

However, there is some significant difference between one human in a draft and three and four humans when analyzing the number of humans in the draft as individual binary variables.[12] In order to examine if there are any additional unobserved effects by treating picks until the next pick as a linear variable, each category is separated and analyzed. The high picks until the next pick values, 12 and 14, are statistically different than one.[13] The owner who

As a result of these two findings, the next model replaces the linear number of humans variable with a dummy variable that takes the value of one when there are only one or two humans in the draft. The linear picks until the next pick variable is also replaced with a binary variable that takes the value of one only when there are 12 or 14 selections before the same owner selects again.

The next model also considers the potential interactions between different positions and the final five rounds in an attempt to control for the vast increase in kickers and defenses/special teams selected in these final rounds. With all of the interaction terms only taking the value of one when the selection is of the specified position and the round number is 11 or greater. Indicator variables are still included for quarterback, running back, and wide receiver to analyze the effect of position on risk in the first ten rounds in comparison to tight end. Defense/special teams and kickers are not included as level terms due to the limited number of them drafted through the first ten rounds. Since the dependent variable is still risk25, a binary variable, it would be more appropriate to use a probit model. However, due to the complex interaction terms, a standard linear regression

[12] See appendix for complete model with coefficients (Table 7)
[13] See appendix for complete model with coefficients (Table 8)

is used to make interpreting the coefficients easier.[14] The updated model has the structure of a typical OLS model:

$$Y_i = \alpha + \beta X_i + \gamma(X_{pos} * Late\ Round) + \varepsilon_i \qquad (3)$$

The alterations to this new model include certain changes in the number of observable characteristics included in the vector X_i. Namely a binary variable which takes the value of one when only one or two humans are present to begin a draft and a binary variable that takes the value of one when the round is 11 through 15. Beta is the vector of coefficients with the non-interacted terms.

The added interaction term in the model is comprised of X_{pos} and the dummy variable late round, which takes the value of one when the round is 11 or later and zero otherwise. X_{pos} is a vector that contains every binary position variable except for the left out group, tight end. With gamma being a vector of coefficients corresponding to the interacted terms in the model.

[14] Results are similar for a Dprobit model. Available upon request.

Table 2

The Effect of the Interacting Positional Terms with Late Round Selections

Variable	Coefficients
Rounds 11 through 15	0.219
	(0.025)**
Quarterback Selected in a Late Round Dummy	0.047
	(0.032)
Running Back Selected in a Late Round Dummy	0.045
	(0.029)
Wide Receiver Selected in a Late Round Dummy	-0.062
	(0.029)*
Defense Selected in a Late Round Dummy	-0.235
	(0.025)**
Kicker Selected in a Late Round Dummy	-0.424
	(0.025)**
Quarterback Dummy	-0.011
	(0.013)
Running Back Dummy	-0.041
	(0.011)**
Wide Receiver Dummy	0.087
	(0.012)**
Same Position Selected Three Prior Picks Plus Current Pick	-0.057
	(0.020)**
Same Position Selected Four Prior Picks Plus Current Pick	-0.135
	(0.038)**
Same Position Selected Five Prior Picks Plus Current Pick	-0.174
	(0.058)**
One or Two Humans in the Draft	-0.018
	(0.008)*
12 or 14 Picks Until the Next Pick by the Same Team	-0.016
	(0.006)*

Notes: OLS coefficient estimates with standard errors in parenthesis. Position dummies are one if the player selected is listed as playing that position in FFC's database. Significance at the 5% level is noted with a single asterisk and significance at the 1% level is noted with two asterisks.

Table 2 presents the OLS results. Even though most of the coefficients are in line with intuition, there are a few initial observations. First, a selection is more risk averse when an owner selects a defense/special teams or a kicker in the later rounds as compared to the middle and early rounds. Also, the participating run variables are all the same sign, and become more negative as the run increases in size. Furthermore, the high picks until next pick variable, or the instance when there are 12 or 14 selections before an owner appears to be significant as well. If there are a sizable number of selections by either other human owners or computer owners, before an owner selects again, that owner is 1.5 percentage points less likely to make a risky selection. This supports the existence of a snow ball effect where owners are nervous all of the high quality players at a given position will be taken before they have another opportunity to pick.

One coefficient that is perhaps a bit counterintuitive is the coefficient corresponding to one or two humans in the draft. Compared to when there are more than two humans in a draft, an owner's selection has a 1.8 percentage point lower chance to make a selection indicative of a high risk tolerance. At first glance it would seem that the more humans present in a draft, the more uncertainty since humans might have unpredictable valuations. But perhaps the owners consider the inverse to be true. Owners could potentially view computer drafters as more variable and difficult to anticipate. In order to counter that suspicion, owners in drafts with only one or two humans might diverge from their private valuations and select players before they normally would.

Moving onto analyzing the non-interacted positional terms, there are two indicator variables that are significant, running back and wide receiver. Both coefficients identify the effect of drafting a position as compared to tight end in the early or middle rounds. The coefficient associated with selecting a running back over a tight end is -0.041, which means by selecting a running back an owner has decreased the chance of that selection being classified as a risk neutral pick versus a risk averse by 4.1 percentage points. When an owner selects a running back over a tight end in the early and middle rounds, this reduces the chance of a pick being classified as risk averse, since running backs are less predictable and oft injured. Tight ends are the more stable and known asset, so selecting one later in the draft does not have the same associated risk as selecting a running back early in the draft. On the other hand, selecting a wide receiver over a tight end reduces the probability of a selection having low risk tolerance by 8.7 percentage points. This is due to the relative scarcity at the tight end position. The most common formation in today's NFL involves three wide receivers with only one running back and one tight end on the field. As teams are running more and more plays with three wide receivers, the viable player pool for wide receiver increases and decreases for tight end. This shift appears to be more powerful than the roster construction requirements of two starting wide receivers versus one starting tight end as it indicates a wide receiver is a riskier selection in the early and middle rounds of a draft.

Focusing now on the positional interaction terms, the three interaction terms that are significant at the 5% level or greater are the wide receiver, defense/special teams, and kicker interactions. Since position interaction terms are all compared to a tight end selected in the late round, it can be understood that the interaction terms describe the difference between the given position in the early and middle rounds versus the same position in the late rounds.

The coefficients for the defense and kicker interactions terms are -.235 and -.424 respectively which indicate that as compared to defenses and kickers selected in the early and middle rounds, either selected in the late rounds is 23.5 percentage points and 42.4

percentage points more likely to have a risk25 value of zero, which indicates low risk tolerance. So the defense/special teams and kicker interaction terms indicate there is a distinct shift in how the round in the draft affects the risk of the selections. It is distinctively less risky to select a kicker or a defense/special teams in the later rounds as compared to the early and middle rounds, as they are much more variable and less valuable. An owner who selects one before the final five rounds is diverging from the typical strategy and displaying risk neutral behaviors.

The wide receiver interaction term also indicates that owners who select wide receivers in the late rounds are exhibiting a risk averse behavior. This is a little strange as running backs and wide receivers are typically the positions that are more commonly selected in the early and middle rounds, thus selecting either position in the earlier rounds would be in line with the prototypical strategy and thus indicate a lower risk tolerance. But, if one considers the distribution of positions selected by round, it does not appear as if owners are taking the same number of running backs and wide receivers, especially in the early part of the draft. It appears as if the normal strategy is to then select running backs early in the draft and wide receivers later. So the divergence from that strategy is indicative of low risk tolerance and so when wide receivers are selected in the early and middle rounds it is a greater indication of a low risk tolerance because they are selecting more running backs in the earlier rounds.

6. Conclusion

Fantasy football drafts exist in a unique realm, displaying characteristics differing from auctions, lotteries, and financial investing. This paper examines how individuals deal with risk given the set of circumstances where there are unknown elements, limited resources, and dissimilar goods. These set of conditions can arise when individuals are deciding whether to allocate more valuable resources to a good or service in the present or wait in an attempt to allocate fewer resources to the same good or service at the risk of another party acquiring it in the meantime.

This paper analyzes the elements of fantasy football drafts in order to identify which factors contribute to the risk tolerance of a selection. Using mock draft data acquired from Fantasy Football Calculator and ranking data from Fantasy Pros, the risk tolerance associated with each individual selection was examined. It is shown that as uncertainty, or ambiguity risk, increases, he or she is more likely to select a player before his rank. The conclusion that risk averse individuals place additional value on information as compared to risk neutral people, contradicts the findings of Treich (1997) and Eeckhoudt (2000), that say risk averse individuals place less value on information. Also, in accordance with McAfee and the declining price anomaly early on in the draft, owners are more risk averse and stick to the rankings, but as the draft progresses there is more variability.

Owners also tended to make more conservative selections when they decided to participate in a run where they selected a player of the same position as the previous three, four, or five picks. The risk aversion grew stronger as the number of previous selections that were the same position increased. The position of the player selected tended to influence the probability of inclusion in the lowest 25th percentile of selections as well. The more valuable a position was to the market, the lower risk it had associated with it. Running back was deemed as the least risky selection, with defense/special teams and kicker increasing the chance of a riskier selection by a substantial margin.

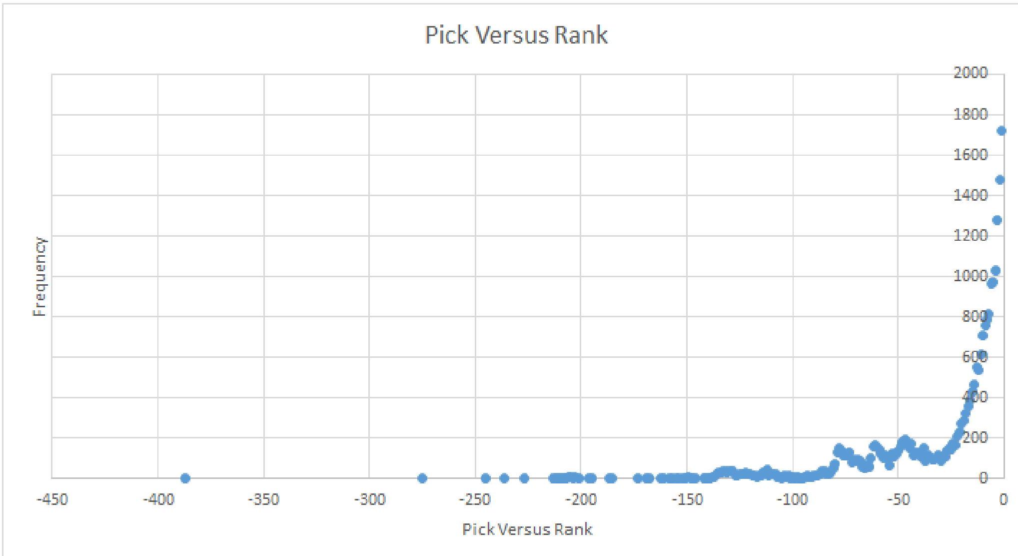
However, there are some limitations with the analysis of this paper. First of which is the ranking set from Fantasy Pros that was used to determine which picks were included in the lowest 25th percentile was designed for league sizes that are larger than eight teams, so some of the kickers and defenses/special teams are ranked lower than they should be given only 120 selections in the draft. Second, there is the issue of approximating owners' sets of personal valuations with a set of rankings. As opposed to previous papers that look at risk tolerance in auctions which typically consider their actual valuations to compare against where the player was drafted. Also, since the data is acquired from mock drafts as opposed to actual drafts, owners may not have revealed their true risk tolerance with each selection since there is nothing on the line.

One potential area for future research regarding risk tolerance in fantasy football drafts is looking at drafts involving more than eight teams. By looking at ten or twelve team leagues, more relationships might be found between the distance between selections by the same owner and the number of humans in the draft. Also, as the league size increases, certain positions may be valued differently, as more teams are attempting to acquire starting caliber players.

APPENDIX

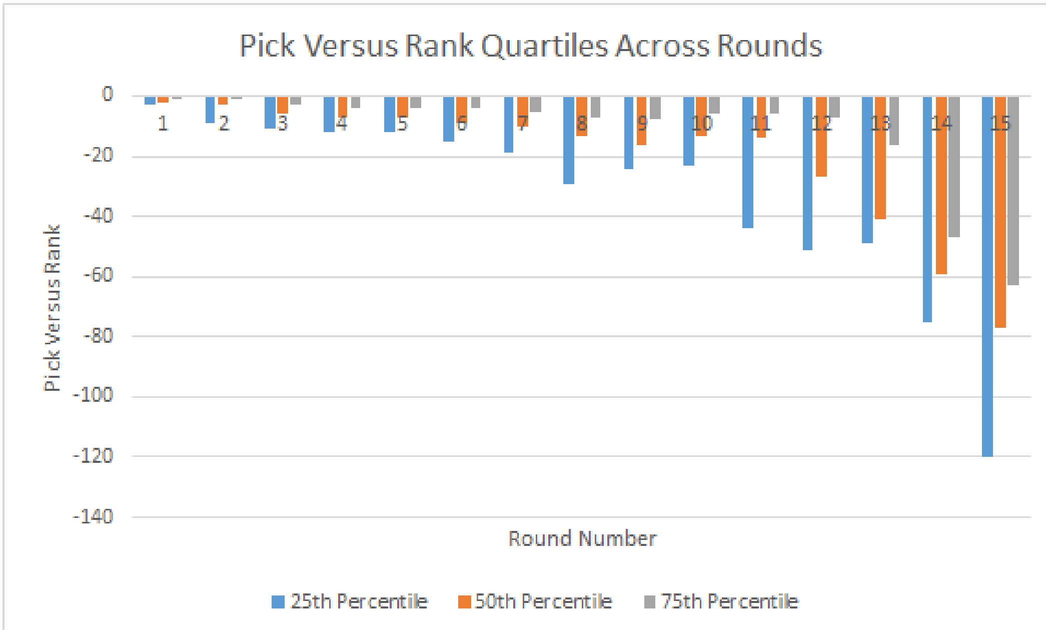
Figure 1

Scatterplot of Pick Versus Rank Values



Frequency of Pick Versus Rank Values

Figure 2



Pick Versus Rank Quartiles for Rounds One through Fifteen. The more negative the value, the larger the selection deviated from the ranking.

Table 3

Breakdown of all Selections by Round by Humans

Round Number	QB	RB	WR	TE	DEF	PK
1	22	1719	1200	1	1	0
2	40	1528	1293	80	1	0
3	385	1146	1098	310	1	1
4	316	1422	1154	49	0	0
5	222	1041	1426	251	2	0
6	240	909	1425	363	3	1
7	299	1092	970	578	2	1
8	589	969	968	404	9	2
9	432	1049	1121	284	43	13
10	386	933	1309	205	81	26
11	666	812	983	238	210	33
12	598	760	776	238	480	89
13	469	615	747	232	663	214
14	146	207	201	115	1194	1076
15	281	384	563	182	256	1271
Sum	5091	14586	15234	3530	2946	2727
Avg. Per Team	1.729867	4.956167	5.176351	1.199456	1.001019	0.926606

Distributions of positions selected by round from the 44,112 observations that are human selected players. With the average obtained by dividing each total by 2943, the number of complete teams drafted by humans.

Table 4

Selected Descriptive Statistics for Relevant Variables

Variable			
Round Number	8.430 (4.370)	Late Round Number	0.365 (0.481)
Number of Humans	4.317 (1.691)	Low Picks Until Next Pick	0.375 (0.484)
Pick Number	63.894 (34.997)	Middle Picks Until Next Pick	0.367 (0.482)
Rank	90.526 (60.443)	High Picks Until Next Pick	0.259 (0.438)
Pick Versus Rank	26.6317 (31.606)	Wide Receiver Dummy	0.200 (0.400)
Picks Until Next Pick	7.160 (4.442)	Running Back Dummy	0.332 (0.471)
Three of the Same Position	0.002 (0.048)	Quarterback Dummy	0.130 (0.336)
Four of the Same Position	0.006 (0.075)	Tight End Dummy	0.096 (0.295)
Five of the Same Position	0.019 (0.135)	Defense Dummy	0.126 (0.331)
Three or of Four the Same Position	0.058 (0.233)	Place Kicker Dummy	0.116 (0.320)
Lowest 25th Percentile Pick Versus Rank	0.731 (0.443)	Quarterback Dummy * Late Round Number	0.023 (0.150)
Low Number of Humans in Draft	0.140 (0.347)	Running Back Dummy * Late Round Number	0.044 (0.204)
Middle Number of Humans in Draft	0.740 (0.438)	Tight End Dummy * Late Round Number	0.014 (0.118)
High Number of Humans in Draft	0.119 (0.324)	Wide Receiver Dummy * Late Round Number	0.050 (0.217)
Early Round Number	0.300 (0.458)	Defense Dummy * Late Round Number	0.120 (0.324)
Middle Round Number	0.335 (0.472)	Place Kicker Dummy * Late Round Number	0.114 (0.318)

Summary Statistics for all relevant variables. Mean with standard errors in parenthesis underneath.

Table 5

Regression Coefficient Significance for Risk25 with Participating Run Variables

Variable	Dprobit
Number of Humans	0.001
	(0.002)
Picks Until Next Pick	-0.001
	(0.001)*
Same Position Selected Three Prior Picks Plus Current Pick	-0.074
	(0.023)**
Same Position Selected Four Prior Picks Plus Current Pick	-0.159
	(0.044)**
Same Position Selected Five Prior Picks Plus Current Pick	-0.183
	(0.071)**
Quarterback Dummy	-0.068
	(0.014)**
Running Back Dummy	-0.110
	(0.012)**
Wide Receiver Dummy	0.043
	(0.012)**
Defense Dummy	-0.161
	(0.015)**
Place Kicker Dummy	-0.325
	(0.015)**

Table 6

Positional Distribution by Round of Human Selections with a Negative Pick Versus Rank

Round Number	QB	RB	WR	TE	DEF	PK
1	22	692	410	1	1	0
2	40	827	369	80	1	0
3	385	722	151	287	1	1
4	316	859	359	40	0	0
5	215	641	542	71	2	0
6	173	613	635	239	3	1
7	287	735	389	424	2	1
8	431	490	332	358	9	2
9	371	615	225	251	43	13
10	274	562	105	176	81	26
11	169	287	285	144	210	33
12	191	215	316	79	480	89
13	133	240	273	53	663	214
14	25	116	110	24	1194	1076
15	20	167	182	34	256	1269
Sum	3052	7781	4683	2261	2946	2725

Distribution and total number drafted of positions selected by round from the 23,448 observations that are human selected players with a pick before their ranking.

Table 7

Probit Regression Coefficient Significance for Risk25 Against Number of Human Dummies

Variable	Probit
2 Humans in the Draft	0.059
	(0.052)
3 Humans in the Draft	0.084
	(0.049)
4 Humans in the Draft	0.103
	(0.048)*
5 Humans in the Draft	0.060
	(0.049)
6 Humans in the Draft	0.030
	(0.052)
7 Humans in the Draft	0.073
	(0.055)
8 Humans in the Draft	0.052
	(0.062)

Probit model with risk25 as the dependent variable and individual number of humans as independent variables. Coefficient estimates with standard errors in parenthesis. One human in the draft is the left out group. Statistical significance is denoted by one asterisk ($p < 0.05$).

Table 8

Probit Regression Coefficient Significance for Risk25 Against Picks Until Next Selection by the Same Owner

Variable	Probit
2 Selections before Same Owner Picks	-0.058
	(0.035)
4 Selections before Same Owner Picks	-0.018
	(0.035)
6 Selections before Same Owner Picks	0.020
	(0.035)
8 Selections before Same Owner Picks	0.020
	(0.035)
10 Selections before Same Owner Picks	-0.062
	(0.035)
12 Selections before Same Owner Picks	-0.084
	(0.035)**
14 Selections before Same Owner Picks	-0.052
	(0.025)

Probit model with risk25 as the dependent variable Picks Until Next Selection by the Same Owner, pup, as independent variables. Coefficient estimates with standard errors in parenthesis. One pick before the same owner selects, in other words the same owner has multiple picks in a row, is the left out group. Statistical significance is denoted by one asterisk ($p < 0.05$).

Table 9

Breakdown of all Selections by Round

Round Number	RB	WR	QB	TE	DEF	PK
1	3860	2989	23	1	1	1
2	3644	3047	54	126	1	0
3	2756	2626	771	716	1	1
4	3290	2735	772	74	0	0
5	3285	2499	573	513	2	0
6	2039	3339	935	554	3	1
7	2292	1959	871	1747	2	1
8	1901	1508	2055	1396	9	2
9	3025	2347	820	624	43	13
10	3921	2109	477	255	82	26
11	1718	2975	1561	243	342	33
12	1963	2065	1423	264	1065	91
13	1531	2118	1196	351	1457	217
14	213	201	148	118	3463	2726
15	744	1211	689	277	404	3540

Distribution of all human and computer selections by round.

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