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Abstract
Differentiating and defining games of skill versus chance have major legal implications when classifying gambling, especially in relation to daily fantasy sports in the United States. This paper provides a theoretical discussion and introduces an empirical approach to analyzing game player pricing mechanisms. If game pricing mechanisms are fully efficient—player prices fully reflect the expected contributions from players—then that game is one of chance since there is no opportunity for skill to play a role in outcomes. This paper examines player prices from DraftKings' daily fantasy football product. Empirical results show that there are strategies deriving from the pricing mechanism that can be incorporated by skilled participants to increase their expected performance and improve their chances of winning. This provides evidence that daily fantasy sports are skill-based—a necessary condition for skill to be a predominant factor in game outcomes as part of the legal debate.

Keywords: daily fantasy sports, efficient market hypothesis, chance versus skill, gambling

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Introduction

Over 59.3 million people from the United States and Canada have participated or are currently participating in a fantasy sport contest, with the average fantasy player spending $653 annually.[1] Professional leagues are incentivized to help grow the fantasy sport sector, as fantasy sport participants consume 40% more content after joining, 64% watch more live events, and 61% read more about sports.[2] With team revenues driven partially by ads and sponsorship dollars, higher participant engagement equates to higher revenue totals.

Daily fantasy sports (DFS) are a subset of the fantasy sport industry, with the calendar year 2019 worldwide annual handle—the total amount of money wagered—at $3.95 billion.[3] There are over 10 million users with DFS accounts, 4.7 million of which are active. The top daily fantasy sites, DraftKings and FanDuel, hold 90% market share in DFS. Those sites are backed by major corporations, leagues, media companies, and more. This paper focuses exclusively on DraftKings' daily fantasy football product.

For an entry fee, DFS contestants create lineups from a pool of available players and compete against each other in contests to win cash prizes. In a contest, contestants are given virtual currency that they use to buy players for their lineups. Selecting a player comes at a price, which is assigned by the DFS organizer based on the player's expected point contributions. The better the player is expected to perform, the higher his salary will be. Players score points based on their real-life performances, and those points accumulate for the participants. Contestants win real prizes based on how their lineup did in comparison to the other lineups submitted to the contest.

This heightens the importance of the DFS provider's pricing mechanism—the methodology used to determine player prices. For the pricing mechanism to be efficient, the initially assigned player prices should fully reflect the players' true values. If DFS is a game of chance, a player's expected returns would be perfectly computable based on their prices, and thus there is no strategy to consistently beat the market. Alternatively, if DFS is a game of skill, there must be opportunities for skilled players to improve their probabilities of winning by taking advantage of mechanism mispricing and other lineup improving strategies.

The legal landscape for daily fantasy games varies dramatically within the United States. Twenty-two states have laws on the books specifically allowing DFS. Five states either have laws on the books banning DFS or have attorney generals who have effectively outlawed them. The remaining states are either actively considering legislation or are currently in a gray area where DFS has neither been expressly outlawed nor legalized. Despite the uncertainty, DraftKings and FanDuel currently operate in 43 states.[4] With the industry very much in flux, many of these numbers are likely to be outdated by the time this paper is published. Most of the legal debate is around the concept of chance versus skill.

Cabot and Miller (2011) opined that answering the chance versus skill question should adhere to the following methodologies:

> First, the effects-based analysis should compare the experience of average persons, without augmentation through experience or practice, with that of the most highly skilled players to determine the skill levels of the game. Second, the game should not be reviewed in isolation, but in the way it is being offered. For example, a single game of poker may be predominately chance-based, but a tournament may be skilled-based. Third, the results of a mathematical analysis of play does not need to result in the more skilled person winning virtually every time, but instead only a statistically relevant number of times in order to show that overall, in the particular game or format offered, skill is the predominate factor.[5]

Multiple legal journal articles have discussed the theory behind whether DFS is a game of chance or skill. Trippiedi (2014) differentiated between season-long contests and daily contests in that players in season-long contests can only be owned by one participant in a league, which requires significant strategy in acquiring players that does not exist in the daily game. He argued that many of the elements that make season-long contests games of skill, such as acquiring sleepers and other pickups with the long-term in mind, are not prevalent in DFS. On the other hand, Meehan (2015) argued that DFS is a game of imperfect information where utilizing game theory can lead to consistent profits over time. Ehrman (2015) identified managing one's bankroll as a skill in DFS. In particular, skillful players will have an understanding of their profit margins at various buy-in levels and league sizes. Both papers agree that DFS is a game of skill.

Deciding whether a game falls under the chance or skill umbrella comes down to two questions. First, is the game skill-based? If a game is skill-based, then over multiple contests a skilled player should win more than unskilled players and see potential profits (or at least fewer losses) in the long-run. Second, is there heterogeneity in skill level? If skill level is homogeneous, then any skill elements to the game are meaningless since all participants are applying them equally and no advantage is gained. With this, there are four types of games: chance-based games with homogeneous skill level, chance-based games with heterogeneous skill level, skill-based games with homogeneous skill level, and skill-based games with heterogeneous skill level. Following Cabot and Miller (2011), the game is only one of skill, and not chance, if it falls under that last category: skill-based game with heterogeneous skill level.

This chance versus skill classification can be applied to any game. Coin-flipping, for example, is chance-based with homogeneous skill level among participants. Assuming the coin is not rigged, the probability of calling the correct side on a coin is 50%, and although some people may be better at physically flipping and catching the coin (chance-based with heterogenous skill levels), the outcome is independent of skill input, and all participants have equivalent probabilities of winning. Therefore, coin flipping, regardless of skill level, is a game of chance.

Season-long fantasy contests, on the other hand, are very much skill-based games with heterogeneity in skill level. Participants act as general managers of their teams by drafting rosters, facilitating trades, making free agent acquisitions, and constructing lineups. The United States Congress acknowledged the skill components of season-long contests in the Unlawful Internet Gambling Enforcement Act in 2006, legalizing these sorts of contests. Compare that to sport gambling markets. When spread or odds markets are efficient, participants may be of differing skill levels with different knowledge bases, but the results are still chance based since all information is captured in the prices (if markets are efficient). The legal debate comes down to whether elements of DFS are closer to those of season-long contests or general sport gambling markets.

This paper addresses whether DFS is a skill-based game, a necessary condition for a game to be considered one of skill. I analyze DraftKings 2016–2018 football player prices to see if its pricing mechanism is efficient. In this setting, prices are efficient if they are equivalent to those set by market forces, such that players' expected point contributions match their prices. If the player pricing mechanism is efficient, DFS is a game of chance since there are no discernable strategies that can be incorporated by participants to increase their odds of winning—any randomly selected lineup that completely utilizes available resources should, on expectation, perform equivalently, and final outcomes are completely random.[6]

I show empirical evidence that certain player attributes are mispriced, providing opportunities for skilled players to increase their lineup's expected performance. While I remain agnostic about the heterogeneity condition in this paper, these results at least provide sufficient evidence for the skill-based condition for DFS to be a game of skill.

A few recent papers have applied an empirical approach to the DFS chance versus skill question. Easton and Newell (2019) used a linear programming lineup-based approach in which they randomly compiled lineups (for both football and baseball) and analyzed how they perform against lineups randomly selected based on particular criteria (in football) and against other real-life contestants (in baseball). They showed that their randomized lineups consistently do significantly worse than the strategic and real-life contestants and concluded this to be sufficient evidence that rejects the null hypothesis that DFS is a game of chance. While their results provided evidence that skill is involved, they did not definitively satisfy either of the two elements needed for DFS to be a game of skill. First, while they showed that skill is involved, they did not identify where those skillful elements originate from. Second, while they identified the existence of skill, they set a low standard for what constitutes skill (performing better than a randomly selected lineup), thus rejecting the possibility that some baseline level of skill exists where chance still becomes the deciding factor in whether a participant wins.

Getty et al. (2018) examined FanDuel data from the 2013 and 2014 seasons and produced a new metric using Monte Carlo methods that quantifies the relative role of chance versus skill for different sports. They used their metric to compare the role skill plays in a fantasy contest versus the role skill plays in the outcome of that sport at the professional level. They not only found that DFS games on FanDuel show significant elements of skill but also that the extent to which skill impacts the results of a FanDuel contest in a sport is similar to the extent to which skill impacts results in that actual sport. Their results relied on participant-level data, which works well when that participant has played in many contests but breaks down when analyzing players who, while being skilled players, only enter a small number of contests.

Other papers utilize mathematical and statistical techniques to construct optimal lineups that show profitable outcomes. Haugh and Singal (2021) designed lineup construction as an optimization problem that considers the behavior of other DFS players. Beal et al. (2020) focused on predicting player performance using machine-based methods and formed optimal fantasy lineups using mixed-integer programming.

I examine the chance versus skill question from a different perspective. By examining the pricing mechanism, I can identify specific opportunities that skilled players can take advantage of to increase their likelihood of winning. I also include well-known attributes known by participants ex-ante, such as if a player or teammate is injured, that any participant should incorporate regardless of their skill level. This allows me to identify, even while allowing for a baseline level of skill, if there are skillful strategies that can be incorporated. Ultimately, the results from this paper agree with previous papers that DFS is a skill-based game but leaves the heterogeneity in skill question to future research.

The following section discusses gambling legislation and how the chance versus skill question plays a role. The third section discusses elements of DraftKings' pricing strategy. The fourth section introduces the data and empirical approach used to determine DraftKings pricing efficiency. The fifth section identifies key results, and the final section provides summarizing and concluding remarks.

Legal Background

Gambling legislation in the United States was first introduced as part of Chapter 50 of the Federal Wire Act of 1961:

> Whoever being engaged in the business of betting or wagering knowingly uses a wire communication facility for the transmission in interstate or foreign commerce of bets or wagers or information assisting in the placing of bets or wagers on any sporting event or contest, or for the transmission of a wire communication

> which entitles the recipient to receive money or credit as a result of bets or wagers, or for information assisting in the placing of bets or wagers, shall be fined under this title or imprisoned not more than two years, or both.[7]

This law essentially banned interstate gambling and national online gambling operations. For example, a person in New York would not be allowed to receive payment from a gambling operation in New Jersey without physically travelling to that state to place the wager and collect the winnings. Thirty years later, the Professional and Amateur Sports Protection Act of 1992 (PASPA) would restrict intrastate gambling:

> It shall be unlawful for—
> (1) a government entity to sponsor, operate, advertise, promote, license, or authorize by law or compact, or
> (2) a person to sponsor, operate, advertise, or promote, pursuant to the law or compact of a government entity, a lottery, sweepstakes, or other betting, gambling, or wagering scheme based, directly or indirectly (through the use of geographical references or otherwise), on one or more competitive games in which amateur or professional athletes participate, or are intended to participate, or on one or more performances of such athletes in such games.[8]

Essentially, PASPA banned states from legalizing sports betting. Nevada was grandfathered into the law, giving Las Vegas a monopoly on legal sports betting for over 25 years. In May 2018, the United States Supreme Court ruled that PASPA violated the 10th Amendment since it forbade states from passing legislation, rather than banning the action itself.

The overturn of PASPA has opened the door for states to pass their own rules and regulations regarding sports gambling, including DFS. With that said, states still have to pass legislation, and the Federal Wire Act still prohibits interstate gambling (including interstate online gambling). In absence of state legislation, the legality of such operations is unclear and up to judicial interpretations of state and federal laws already on the books.

In 2006, Congress passed the Unlawful Internet Gambling Enforcement Act (UIGEA), creating a carve-out for fantasy sports in the Federal Wire Act. Specifically, the law specifies that the terms "bet" or "wager" do not include

> participation in any fantasy or simulation sports game or educational game or contest in which (if the game or contest involves a team or teams) no fantasy or simulation sports team is based on the current membership of an actual team that is a member of an amateur or professional sports organization.[9]

According to the UIGEA, this exception holds only if prizes and awards are made known before joining the contest and if "all winning outcomes reflect the relative knowledge and skill of the participants." The rationale behind this carve out was that fantasy sports are games of skill and not synonymous with gambling that constitutes chance.

While this exemption is well accepted for season-long fantasy contests, its interpretation is less clear for DFS. In season-long contests, players act like team managers by drafting rosters, making player transactions, and setting lineups over a full season. These leagues generally have entry fees, and the money is kept in a prize pool where the person with the best performing team wins. DFS contests also have entry fees with a predetermined prize pool. However, these contests operate under a much shorter time frame and only involve building a single (per entry) lineup. While season-long player performance is relatively predictable, a player's performance in a particular contest is much more variable. The obvious question, then, is whether there exists a strategy to beat the market or if the large variation in actual player performance is predominately due to chance. A follow-up question is whether there is an opportunity for skilled players to exist. If there are strategies for skilled players to incorporate and there is evidence skilled players exist, it can be concluded that DFS is a game of skill and should not be subject to the Federal Wire Act under the UIGEA exemption. The uncertainty in the answers to these questions has led multiple states to challenge the legality of DFS contests.

A more notable legal dispute took place in New York, one of the largest paid-entry DFS markets, where Attorney General Eric Schneiderman issued cease-and-desist orders to DraftKings and FanDuel. This set off a chain reaction of other state attorney generals looking into DFS. Following back-and-forth court proceedings that essentially maintained the status quo and heavy lobbying efforts by the industry, New York legislators legalized DFS.[10]

DraftKings Pricing Mechanism and Objective Function

Historical DraftKings data from the 2016–2018 seasons, including prices and points scored, come from RotoGuru.[11] Player prices range from 2,500 to 10,100 units of virtual currency as detailed in Table 1, with salary ranges and distributions varying by position.

When picking a lineup on DraftKings, participants select one quarterback (QB), two running backs (RB), three wide receivers (WR), a tight end (TE), a flex player (FLEX), and a defense (Def).[12] For the FLEX position, participants can choose to start an additional RB, WR, or TE. After paying the entry fee to join a contest, participants are given 50,000 units of virtual currency to create their lineup, with better players costing more to select. Prices are assigned to players in increments of 100, and many players are assigned the same price. If two players of the same position cost the same in a given week, their expected point contributions should be equal. Conversely, if one player costs more than another, that player should, on expectation, score more points. For the pricing mechanism to be efficient, player prices should fully reflect the players' expected point contributions.

Sport markets are often used to test the efficient market hypothesis (EMH). According to the EMH, a market is efficient if all available information is incorporated into the current price of an asset such that it is impossible to systematically outperform the market (Fama, 1970). When setting prices, DraftKings utilizes data that are generally accessible to the public. Most sport leagues, including the National Football League (NFL), prohibit employees from participating in any daily or other similar short duration fantasy football games that offer any prize.[13] Since price setters only incorporate publicly available data and do not have access to insider information (insiders cannot participate in contests, so operators cannot learn from these players), this paper tests for semi-strong form market efficiency in the pricing mechanism.

Once prices are published, which typically happens shortly following the completion of the previous week's games, they do not change. This means that DraftKings pricing is vulnerable to major shocks that take place between the release of the salaries and the start of the matchups. For example, if a player is ruled out for the week due to injury or suspension two days before the start of the contest, that player is worthless to select but still can be drafted at his original price. Any uncertainty about depth chart usage or questionable injury status could also change players' expected point contribution

Table 1. DraftKings Salary Summary Stats

Position	Minimums		No Minimums					
	Min Salary	# Min	# Not Min	Mean	1st Q	Median	3rd Quartile	Max
QB	4000	670*	1202	6116	5500	6000	6600	8500
2016	5000	184	445	6225	5500	6100	6800	8500
2017	4000	248*	360	6203	5700	6200	6700	8300
2018	4000	238*	397	5916	5500	5900	6300	7600
RB	3000	1932	3362	4728	3700	4200	5400	10100
2016	3000	787	991	4710	3700	4300	5500	10100
2017	3000	575	1221	4728	3800	4200	5200	9900
2018	3000	570	1150	4744	3700	4250	5400	10000
WR	3000	2731	4466	4848	3600	4400	5800	10000
2016	3000	1063	1378	5027	3700	4600	6100	10000
2017	3000	904	1458	4783	3600	4300	5800	9800
2018	3000	764	1630	4754	3600	4300	5575	9100
TE	2500	2649	1644	3636	2700	3200	4200	7400
2016	2500	889	486	3635	2800	3300	4100	7200
2017	2500	893	570	3690	2800	3200	4300	7400
2018	2500	867	588	3584	2700	3100	4100	7400

Notes: *QB minimums are calculated using 5000 as the minimum salary. Salary data comes from the 2016–2018 NFL seasons. Summary information is broken down for minimum and non-minimum salaried players.

without any adjustments being applied to their price. This is unique to sport gambling markets, as most gambling lines and spreads are impacted by new information and consumer demand.[14] While participants witness these events and can adjust their lineup selection strategies accordingly, prices are fixed.

Each position also has a designated minimum salary. The minimum QB salary was changed from 5,000 to 4,000 after 2016, but for the purposes of identifying a minimum QB level, 5,000 will be used in this paper. Even after reducing it, the minimum QB salary is significantly higher than that of any other position. This is because even the worst QB will have a relatively decent projectable floor. Meanwhile, backup RBs and WRs are much more likely to score zero or few points, making them less worthwhile pickups. In fact, the only reason a participant would select any minimum salary player is because of the 50,000-unit salary cap constraint. A substantial number of players are located at the minimum salary levels. There are almost surely distinct expected point contribution differences between players at the minimum, so knowing which minimum players are worthwhile investments could lead to higher expected payouts. This paper is only interested in examining the pricing mechanism for those players who are not priced at the minimum. Players with minimum prices are discarded in this analysis. However, it would be interesting in a future paper to see if there are players priced at the minimum that are significantly underpriced and the attribute traits that earned them that price.

Pricing inefficiencies may also result from 100-unit increment pricing. For example, two running backs priced at 4,000 would be expected to produce the same number of points on expectation based on their price. However, it may be the case that the true efficient price for one of those running backs was 4,040 while the other is 3,960. In that case, the player priced at 4,040 would score more, on expectation, than the player priced at 3,960. Although the effects here are likely very small, they are still potential marginal advantages for skilled players who can identify what the efficient prices would otherwise be.

Finally, it is possible for the actual pricing mechanism to be incorrectly specified. In that case, participants that can identify mispriced elements can gain marginal point advantages to increase their expected payoff. All subsequent mispricing explored in this paper utilizes information that is publicly available.[15] Despite being publicly available, not all participants may use this information, providing skilled players an opportunity to exploit this knowledge and gain systematic advantages over unskilled players.

To be clear, this paper is agnostic towards DraftKings' objective function as it pertains to its pricing strategy. For any single contest, the pricing mechanism implemented has zero impact on DraftKings' revenues from the contest. For each contest it hosts, DraftKings has a predetermined prize pool that it will pay out, and it does so using a portion of the entry fees. Regardless of who wins, DraftKings will always take their cut out of the pool. For example, suppose DraftKings has a contest with 176,000 entries paying $20 entry fees and a total prize pool of $3,000,000.[16] In this example, DraftKings would be collecting $3,538,000 in entry fees and earning $538,000 in profits (about 15% of the entry pool). Therefore, DraftKings does not necessarily have an incentive to provide efficient prices. In fact, given the legal landscape, it may be beneficial for DraftKings to intentionally create inefficient prices so it can pass as a skill-based game.

Empirical Approach and Data

Players score points based on their real-life offensive statistics on the field. Table 2 lists each of the categories that are counted when calculating a player's score.[17] QBs have unique passing categories, but they can also score points based on their rushing production. RBs mostly score based on their contributions to the running game, but they can also score points by catching passes from the quarterback. WRs and TEs mostly score points based on their catching production.[18]

Pricing mechanism mispricing is captured using ordinary least squares with season-week fixed effects. The outcome variable, y_{iws}, is player *i*'s score in week *w* and season *s*. The model is estimated by

$$y_{iws} = \alpha + S_{iws}\beta_{ps} + A_{iws}\gamma_{ps} + C_{iws}\eta_{ps} + I_{iws}\delta_{ps} + \lambda_{ps}H_{iws} + (S_i \times W_i)\theta_p + \varepsilon_{iws}. \quad (1)$$

Since each position has different objectives and roles, coefficient estimates are allowed to vary by position *p*. For example, an RB is less likely to be impacted by an opposing pass defense than a WR, so the adjustments made in their pricing equations should differ. S_{iws} includes both the player's salary and the square of the player's salary to capture increasing or

Table 2. DraftKings Scoring Settings

Scoring Categories			
Passing TD	+4 Pts	Rushing TD	+6 Pts
25 Passing Yards	+1 Pt	10 Rushing Yards	+1 Pt
300+ Yard Passing Game	+3 Pts	100+ Yard Rushing Game	+3 Pts
Interception	-1 Pt	Fumble Lost	-1 Pt
Receiving TD	+6 Pts	Special Teams TD	+ 6 Pts
10 Receiving Yards	+1 Pt	2 Pt Conversion	+2 Pts
100+ Receiving Yard Game	+3 Pts	Offensive Fumble TD Recovery	+6 Pts
Reception	+1 Pt		

Notes: This table contains the various DraftKings scoring categories for passing, rushing, receiving, and some of the defensive/special teams plays. DraftKings did not change their scoring settings during the sample period.

decreasing returns to salary. I test whether teammate or opponent attributes, A_{iws}, weather and player experience, C_{iws}, injury information, I_{iws}, and home field, H_{iws} are efficiently priced. Fixed effects are included for each of the individual weeks in the data. For models that aggregate the three seasons of data, the *s* subscript is dropped from Equation 1. Team fixed effects are not included since much of the team specific variation is contained in A_{iws}.

The null hypothesis is that none of the covariates, besides those in S_{iws}, impact player score since they are already priced into the salary. The alternative hypothesis is that at least one covariate impacts player score and thus is not properly accounted for in the player salary. Under the null, DFS is a chance-based game since there does not exist a strategy that allows for increased profit opportunities. Under the alternative, DFS is skill-based since a skilled participant could take advantage of market mispricing.

Summary statistics for covariates in A_{iws} and C_{iws} are contained in Table 3. The upper panel provides summary information for the full aggregate sample, while the lower panel provides covariate summary statistics for each position. Football statistics are very teammate dependent. The best wide receiver in the league will only make catches if his quarterback is able to throw the ball to him, and the quarterback might only be able to do that if the offensive line is able to provide him enough time to get rid of the football. From that, the QB and WR only complete that connection if the opposing defense fails to produce pressure in the pass rush or cover the secondary effectively. This model addresses potential teammate (own offense) and opponent (defense) related factors that may impact fantasy performance.

Player ability is measured using grades provided by Pro Football Focus.[19] These grades attempt to factor out teammate ability and only measure the performance of that player.[20] More traditional quarterback performance metrics—passing yards and passing touchdowns—and offensive line metrics—pancakes and sacks allowed—do a poor job as measures of individual player performance and ability since they are strongly dependent on the performance of players around them. All season grades are calculated by taking the individual player game grades and calculating a weighted average based on the player's snap count for that game. For example, suppose a player participated in three games during the 2017 season and had Pro Football Focus passing grades of 60, 65, and 70 on 50, 45, and 70 snaps, respectively. That player would have a weighted average passing grade of 65.6 that would be applied to that player for each game he participated in during the 2017 season.[21] This approach is applied to all Pro Football Focus grade variables.

First accounting for the effects of the quarterback's ability on WRs, RBs, and TEs, the variables *QB Overall Grade* and *QB Passing Grade* measure the performance of the quarterback. The overall grade incorporates passing ability, rushing ability, discipline, and other QB attributes. The passing grade only includes the QB's ability to pass the football. Models are estimated using each measure of QB ability separately. Given the nature of the interaction between the QB and the other positions, QB Passing Grade was used in the WR and TE models, and QB Overall Grade was used in the RB model. It is assumed that the QB starter is known well in advance such that QB ability can be properly accounted for in lineup decisions.

Table 3. Covariate Calculations and Summary Statistics

Variable	Summary Data			
	Mean	**SD**	**Min**	**Max**
Experience				
League Tenure	4.075	3.521	0	18
Quarterback				
QB Overall Grade	66.62	7.095	25.3	83.58
QB Passing Grade	66.03	7	25.6	82.87
Offensive Line				
Run Blocking	61.54	3.364	53.58	69.51
Pass Blocking	67.6	4.522	49.28	78.26
Opp Defense				
Run Defense	63.35	1.676	57.12	69.05
Pass Rush	63.13	2.473	55.77	72.08
Coverage Defense	62.53	2.053	53.19	67.86
Weather				
Wind Speed (mph)	3.354	3.263	0	18
Bad Weather	0.02	0.141	0	1

	RB		**QB**		**WR**		**TE**	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Experience								
League Tenure	3	2.682	6.066	4.864	3.224	2.841	3.818	3.272
Quarterback								
QB Overall Grade	66.64	7.221						
QB Passing Grade					65.63	7.01	65.49	6.751
Offensive Line								
Run Blocking	61.63	3.363	61.48	3.374	61.61	3.337	61.43	3.324
Pass Blocking	67.45	4.6	67.59	4.532	67.6	4.512	67.5	4.5
Opp Defense								
Run Defense	63.34	1.663	63.37	1.695	63.32	1.669	63.29	1.678
Pass Rush	63.06	2.493	63.08	2.456	63.11	2.441	63.07	2.457
Coverage Defense	62.51	2.116	62.58	2.038	62.52	2.046	62.57	2.027
Weather								
Wind Speed (mph)	3.371	3.302	3.42	3.331	3.415	3.317	3.395	3.301
Bad Weather	0.021	0.143	0.02	0.139	0.021	0.143	0.021	0.143

Notes: Data come from the 2016–2018 NFL seasons. All player grades are from Pro-Football Focus. The top panel contains summary information for the full sample of non-minimum priced DraftKings players. The bottom panel provides means and standard deviations by position.

The offensive line also impacts the QBs, WRs, RBs, and TEs. The linemen give time for the QB to throw to his WRs and TEs, and they also provide blocking for RB carries. Pro Football Focus provides two measures of offensive line performance: a run blocking grade and a pass blocking grade. Offensive lines consist of five or six players, so the overall line score is a weighted average of the starters' season grades, weighted by season snap totals.

The opposing defense also has an obvious impact on an offensive player's performance. Pro Football Focus provides overall team defense grades as well as grades for defensive skillsets, including the ability to rush the passer, defend the run, and defend the pass (pass coverage). The ability to rush the passer mostly measures defensive line performance on

Table 4. Points Score by Salary Range and Position

Salary	QB	RB	WR	TE
2,500–3,000		1.65	2.57	2.78
3,001–4,000	2.33	6.26	6.8	8.51
4,001–5,000	8.74	10.2	10.06	10.68
5,001–6,000	16.98	12.24	12.23	11.11
6,001–7,000	19.74	15.93	14.54	15.77
7,001–8,000	21.14	19.26	16.85	15.55
8,001–9,000	26.31	21.83	18.92	
9,001–10,100		25.83	20.38	

Notes: Scoring is broken down by salary range and position to examine which positions offer better returns for the flex spot given a predetermined level of investment.

Table 5. Home Field Advantage Results

Sample	QB	RB	WR	TE
All	1.612***	1.102***	0.732**	0.195
	(0.464)	(0.261)	(0.229)	(0.326)
2016	2.253**	1.572**	0.742	1.286*
	(0.702)	(0.505)	(0.431)	(0.635)
2017	1.174	0.725	0.985*	-1.081*
	(0.864)	(0.426)	(0.385)	(0.533)
2018	1.817*	1.036*	0.406	0.859
	(0.884)	(0.451)	(0.388)	(0.547)

Notes: Statistical significance is defined at the *5%, **1%, and ***0.1% levels. Each coefficient and standard error in the table come from a unique OLS model based on the season (row) and player position (column). The first row aggregates the data by season, while the bottom three rows provide season-by-season results.

passing plays, while the ability to defend the pass heavily measures the ability of corners and safeties. Season grades for the defensive starters were averaged to produce defensive grades. Variables included are *Run Defense, Pass Rush,* and *Coverage Defense.*

The model accounts for player experience with data coming from Pro-Football Reference.[22] *League Tenure* is the number of years since the player was drafted. Players that are in the league longer have more relative experience. Rookies have zero League Tenure. A squared term is included to capture any diminishing effects to experience. The experience variable is also meant to capture information about player age since the two are highly correlated. C_{iws} also includes weather conditions. It is more difficult to pass the ball when there is heavy snow and wind. Two weather variables, *Wind Speed* and *Bad Weather,* are meant to control for weather conditions. Wind Speed is measured in miles per hour. Bad Weather takes a value of one if there was snow or heavy rain at the start of kickoff. All historical NFL weather data is available on NFLweather.com.[23] For dome stadiums, Wind Speed and Bad Weather both take values of zero.

Adjusting to injuries is another potential source of strategy. If a player is injured, he may not play at full strength or may be limited in his production. If a starting teammate on the offense is out, that could provide additional opportunities for the player to be productive on offense. If the injury is sudden, especially after prices have been posted, there are potential pricing inefficiencies. If the injury is known in advance, DraftKings can adjust its prices to account for anticipated increased playing time. DraftKings does not offer prices for players they know ahead of time will not be playing, but they do include salaries for players that are either probable (*Prob*), questionable (*Ques*), or doubtful (*Doubt*) on the injury report.[24] If a player is ruled out after prices are released, but before matchups begin, that player will score zero points for the week. It is assumed that the basic DFS contestant is aware of general injury status and will choose not to select that player if he is not going to play due to injury. The variables Prob, Ques, and Doubt capture the impact of less serious, more serious, and very serious injuries, respectively. These variables should also capture the average decrease in performance because of the injury for players that do play.

Additional injury variables capture the impact of starting teammates on the offense being out. Monthly scraped archived data were used to determine who the starting and backup skill position players were for a team at any given point in time.[25] These variables exclude any injury to player *i*. I include variables for whether the starter is ruled out, whether the starter is out this week and also ruled out the previous week, and whether the player plays but is listed as questionable or doubtful. The variables include $QB_{Starter,Out}$, $QB_{Starter,Out,Not,New}$, $QB_{Starter,QuesDoutbt}$, $RB_{Starter,Out}$, $RB_{Starter,Out,NotNew}$, $RB_{Starter,QuesDoubt}$, $RB_{Backup,Out}$, $RB_{Backup,Out,NotNew}$, $RB_{Backup,QuesDoubt}$, $WR_{Starter,Out}$, $WR_{Starter,Out,Not,New,}$ and $WR_{Starter,QuesDoubt}$. The depth chart data list three WRs as starters, which is why a backup wide receiver variable is not included.

Player Pricing Results

Returns to Salary

Figure 1 breaks down return to salary estimates from each of the models. Return to salary estimates are calculated from the salary and salary squared terms and measured at various salary levels consistent with the minimums and maximums for that position. The solid lines in the figure represent the returns to salary in the aggregate models, while the other lines represent various season models for the different positions. One obvious takeaway is that each of the figures are downward sloping, illustrating that allocating additional resources towards individual players comes with diminishing benefits. That may suggest that having a more balanced lineup in terms of salary would be more optimal than having a few top players with a handful of lower-caliber players. The yearly trends, besides 2017 in the TE model, follow closely with the aggregate trends.

Starting at a 4,000 salary, returns to salary seem to be higher for RB compared to WR and TE. The return to salary for RBs at that price is about 0.365 points per 100 units of currency (95% confidence interval between 0.361 and 0.370). For WRs, the return is nearly 17% less at 0.308 points per 100 units of currency (95% confidence interval between 0.300 and 0.308) and 15% less for TEs at 0.317 points per 100 units of currency (95% confidence interval between 0.312 and 0.322). The returns to salary for RBs remain higher than that for WRs and TEs over the remainder of the salary interval, never going lower than 0.25 points per 100 units of currency.

These results have several strategic implications. First, it suggests that investing on RBs is more worthwhile than investing in either of the other two flex positions. Second, it suggests that if a participant were going to invest a large percentage of their cap space to their FLEX spot, it may be worth taking an RB over the other two positions. This FLEX strategy is supported by point totals in Table 4. As can be seen in the table, scoring is higher for RBs at the higher salary levels, suggesting that investing in high priced RBs would be more beneficial than investing in high priced WRs. However, scoring seems to be higher for TEs at the lower salary levels. The returns to salary are lower for TEs, but that may be partially due to the higher initial scoring from lower priced TEs. Therefore, for a FLEX strategy, these results suggest that an optimal investment strategy may be to invest in TEs if investing a small portion of salary cap or to invest in RBs if investing a large portion of salary cap.

The returns to salary for QBs are also sizeable—about 0.441 points per 100 units of currency for 5,500 salary players and about 0.355 points per 100 units of currency for 6,000 salary players—but diminishes quickly. The returns for investing an additional 100 units of currency for 6,500 salary players is only 0.270 points, which drops to 0.184 points for 7,000 salary players. This suggests that spending on a mid-salary-range QB (mean QB price is just over 6,100) may be the most efficient use of payroll resources. Additional dollars spent on QBs may be better spent on RBs or even WRs at a certain threshold.

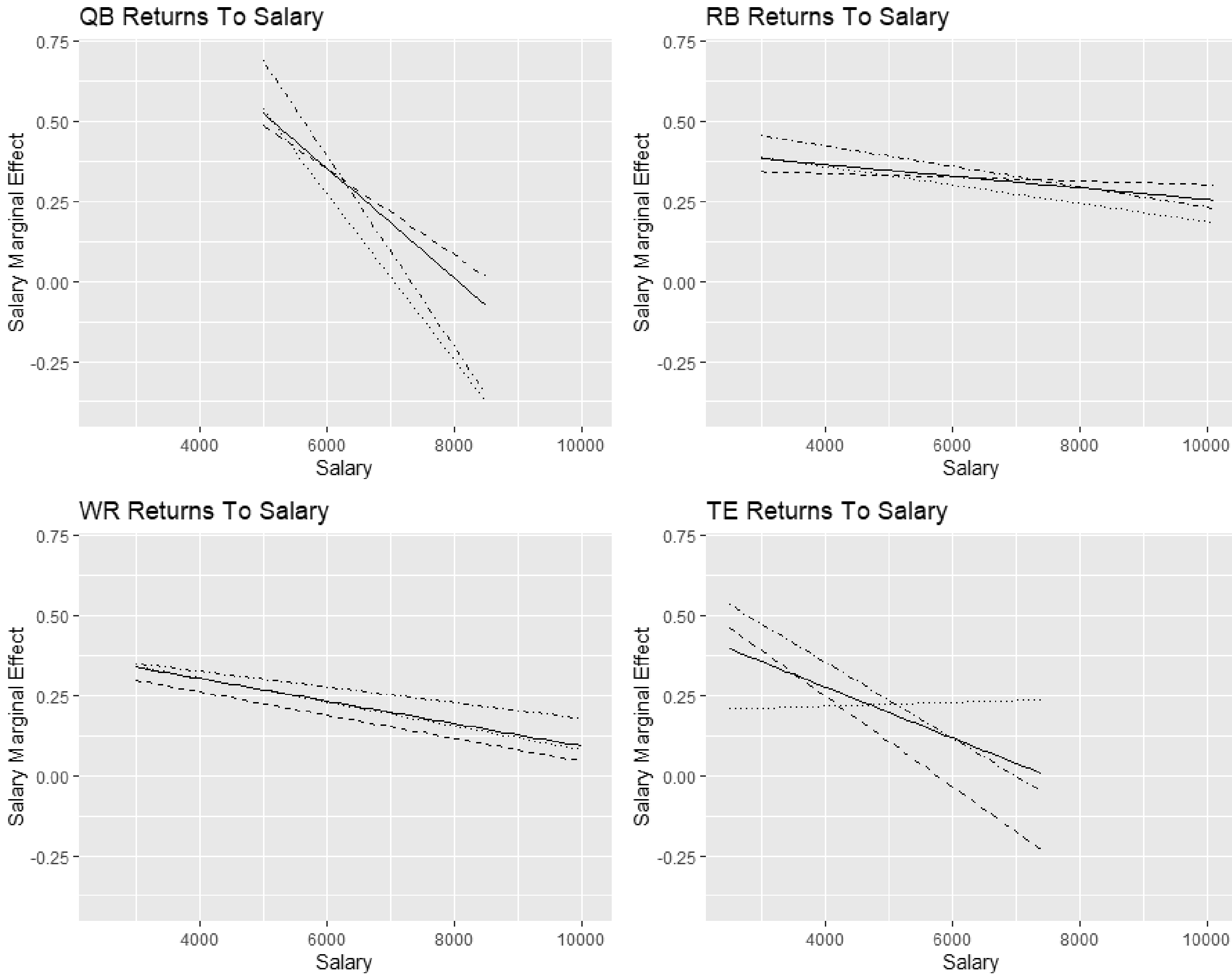

Figure 1. Returns to salary by position

Each panel takes coefficients from the various full models from Equation 1 and estimates the point returns to salary at various salary levels. These plot the coefficients from salary and salary squared showing (mostly) diminishing marginal returns. The solid line represents the trend from the aggregate data. The other lines represent 2016, 2017, and 2018. Trends are plotted over the range of actual salary values from the minimums to the maximums (see Table 1).

Home Field Advantage

The exact impact of home field advantage, if there even exists one, is up for debate. If it does exist, home field advantage should have a positive impact on a player's expected point contribution and should therefore be accounted for in player prices. A negative result would imply that home field advantage is overpriced or, potentially, that it does not exist at all. Assuming DraftKings would not purposely dock players for playing at home, a positive result would suggest that home field advantage both exists in the NFL and that it is also underpriced by DraftKings. The results in Table 5 illustrate home field effects for each of the aggregate and by-year models.

At the aggregate, picking home team players results in an additional 1.6 fantasy points for the QB, 1.1 fantasy points for RBs, and 0.7 fantasy points for WRs. This provides evidence that home field advantage exists in the NFL. However, the effects diminish slightly year over year. The strongest effects appear to be in 2016, except for WRs, with smaller, albeit some still statistically significant, coefficients at the 5% confidence level in 2017 and 2018. This suggests that DraftKings may be slowly correcting for the home field mispricing over time. The aggregate effect on TEs is not statistically significant, and the yearly coefficients jump around, suggesting that home field advantage is properly priced for TEs.

Table 6. Team Attributes, Opponent Attributes, and Other Results

	QB		RB		WR		TE	
	All	**2016**	**All**	**2016**	**All**	**2016**	**All**	**2016**
	2017	**2018**	**2017**	**2018**	**2017**	**2018**	**2017**	**2018**
Run Block	-0.250***	0.126	0.057	0.245*	-0.115***	-0.247**	0.093	-0.19
	(0.081)	(0.193)	(0.044)	(0.130)	(0.039)	(0.110)	(0.057)	(0.173)
	-0.128	-0.222	0.072	-0.043	-0.149**	-0.07	-0.103	0.022
	(0.176)	(0.190)	(0.080)	(0.098)	(0.074)	(0.085)	(0.104)	(0.117)
Pass Block	0.086	0.005	0.034	-0.059	-0.009	0.055	-0.015	0.003
	(0.059)	(0.098)	(0.032)	(0.072)	(0.028)	(0.059)	(0.040)	(0.090)
	-0.144	0.113	-0.004	0.069	-0.064	-0.044	0.029	-0.061
	(0.126)	(0.120)	(0.060)	(0.059)	(0.053)	(0.051)	(0.073)	(0.072)
Run Defense	-0.245*	-0.18	-0.037	0.002	-0.182**	-0.205	-0.157	-0.072
	(0.141)	(0.254)	(0.082)	(0.187)	(0.071)	(0.156)	(0.100)	(0.248)
	-0.209	-0.212	-0.117	0.125	-0.196	-0.096	-0.024	-0.101
	(0.290)	(0.270)	(0.141)	(0.143)	(0.121)	(0.125)	(0.168)	(0.182)
Pass Rush	0.310***	0.148	-0.160***	-0.209*	0.034	0.119	0.037	0.088
	(0.101)	(0.177)	(0.056)	(0.122)	(0.048)	(0.104)	(0.069)	(0.162)
	0.139	0.619***	-0.087	-0.132	0.099	-0.001	0.033	0.176
	(0.197)	(0.216)	(0.093)	(0.105)	(0.083)	(0.091)	(0.120)	(0.132)
Coverage	-0.051	-0.387*	-0.079	-0.320**	-0.019	-0.064	-0.165*	0.055
	(0.125)	(0.220)	(0.066)	(0.157)	(0.059)	(0.131)	(0.085)	(0.205)
	0.116	-0.025	0.014	-0.129	-0.016	0.131	-0.129	-0.298*
	(0.228)	(0.268)	(0.107)	(0.124)	(0.096)	(0.108)	(0.135)	(0.159)
Experience	-0.300*	-0.029	-0.182	0.013	-0.024	0.134	0.069	0.391
	(0.178)	(0.329)	(0.127)	(0.273)	(0.108)	(0.194)	(0.143)	(0.375)
	-0.459	0.008	-0.134	-0.407*	0.02	-0.089	0.062	-0.288
	(0.386)	(0.363)	(0.217)	(0.208)	(0.207)	(0.185)	(0.236)	(0.226)
Experience^2	0.016	0.005	0.015	-0.014	0.003	-0.004	-0.01	-0.027
	(0.011)	(0.021)	(0.013)	(0.028)	(0.010)	(0.016)	(0.010)	(0.028)
	0.025	-0.003	0.019	0.034*	-0.0005	0.002	-0.003	0.008
	(0.023)	(0.021)	(0.022)	(0.020)	(0.020)	(0.017)	(0.017)	(0.016)
Bad Weather	-0.891	2.465	-0.958	-0.366	-1.268	-1.966	0.869	3.381
	(1.646)	(2.773)	(0.930)	(1.814)	(0.834)	(1.779)	(1.163)	(2.375)
	1.655	-4.77	-0.9	-0.53	-0.53	-0.23	2.392	-3.711
	(2.995)	(3.187)	(1.483)	(1.842)	(1.285)	(1.519)	(1.765)	(2.259)
Wind	-0.065	-0.131	0.018	-0.028	-0.013	-0.029	-0.061	-0.054
	(0.074)	(0.109)	(0.041)	(0.078)	(0.036)	(0.066)	(0.053)	(0.103)
	-0.369*	0.068	-0.031	-0.006	-0.14	0.006	0.013	-0.113
	(0.197)	(0.141)	(0.100)	(0.068)	(0.089)	(0.059)	(0.126)	(0.086)

Notes: Statistical significance is defined at the *5%, **1%, and ***0.1% levels. The coefficients are from the teammate, opposing player, and additional miscellaneous variables discussed. Sample sizes are available in Table 1. Each box corresponds to the coefficients for one variable (row label) for one position (column label). The upper left coefficient in each box comes from the aggregate data, the upper right coefficient comes from 2016, the bottom left coefficient from 2017, and the bottom right coefficient from 2018.

Table 7. Player and Teammate Injury Results: QB, Starting RB, Backup RB

	QB Starter			RB Starter			RB Starter		
Sample	**Out**	**Out NN**	**Ques/ Doubt**	**Out**	**Out NN**	**Ques/ Doubt**	**Out**	**Out NN**	**Ques/ Doubt**
QB				1.216	-2.002	-0.199	2.221	-2.641	-0.486
				(1.266)	(1.922)	(0.752)	(1.636)	(2.223)	(1.117)
2016				2.593	-2.255	-0.604	-0.053	1.512	-1.078
				(1.879)	(2.814)	(1.079)	(2.439)	(3.194)	(1.446)
2017				-1.896	2.83	-0.34	6.319**	-10.703***	0.59
				(2.873)	(6.712)	(1.580)	(2.593)	(3.838)	(2.187)
2018				1.321	-4.634	0.136	-3.283	3.094	-0.229
				(2.303)	(3.150)	(1.458)	(4.781)	(6.067)	(2.964)
RB	-0.102	0.093	0.259	2.397***	-2.805**	1.091**	0.594	-1.938	0.709
	(1.048)	(1.621)	(0.689)	(0.809)	(1.164)	(0.494)	(1.028)	(0.709)	(0.657)
2016	-1.015	10.690*	-0.42	0.018	-0.979	1.242	2.896	-6.313**	0.651
	(1.970)	(6.032)	(1.346)	(1.739)	(2.463)	(0.958)	(2.014)	(2.581)	(1.032)
2017	-0.793	-0.385	-0.26	3.925	-3.634	0.308	0.628	0.244	-0.176
	(1.739)	(2.712)	(1.213)	(1.478)	(2.219)	(0.859)	(1.401)	(2.219)	(1.151)
2018	0.326	-0.358	0.727	2.232*	-3.001*	1.158	-0.793	1.398	1.223
	(1.937)	(2.545)	(1.183)	(1.238)	(1.755)	(0.829)	(2.658)	(3.565)	(1.490)
WR	-1.074	1.885	-0.811	0.843	-0.497	-0.158	0.342	0.506	-0.089
	(0.949)	(1.521)	(0.599)	(0.652)	(0.957)	(0.370)	(0.815)	(1.182)	(0.513)
2016	-2.053	2.368	-1.282	2.354*	-3.667*	-0.744	0.173	1.397	0.343
	(1.724)	(4.987)	(1.092)	(1.259)	(1.923)	(0.673)	(1.465)	(2.004)	(0.806)
2017	-1.552	0.651	-0.797	-1.251	2.366	0.174	0.562	0.592	-0.381
	(1.712)	(2.717)	(1.037)	(1.234)	(1.940)	(0.680)	(1.131)	(1.809)	(0.977)
2018	0.628	1.43	-1.002	0.48	0.245	0.008	-1.549	0.809	-0.886
	(1.644)	(2.261)	(1.086)	(1.053)	(1.453)	(0.635)	(2.302)	(3.031)	(1.021)
TE	0.564	-1.92	0.44	1.723*	0.805	0.199	0.972	-0.754	0.531
	(1.318)	(2.012)	(0.859)	(0.890)	(1.373)	(0.519)	(1.070)	(1.545)	(0.801)
2016	-1.551	-1.567	-1.416	1.113	4.657*	0.704	-0.059	-0.597	0.587
	(2.775)	(7.605)	(1.667)	(1.728)	(2.750)	(0.982)	(1.980)	(2.710)	(1.278)
2017	-2.872	2.48	0.798	-0.372	4.175	0.146	1.348	-4.245	0.215
	(2.469)	(3.750)	(1.362)	(1.829)	(2.814)	(0.927)	(1.551)	(2.642)	(1.524)
2018	3.218	-3.938	1.225	2.778**	-3.397*	-0.365	1.395	2.169	-0.267
	(2.003)	(2.798)	(1.721)	(1.362)	(2.056)	(0.877)	(2.527)	(3.313)	(1.584)

Notes: Statistical significance is defined at the *5%, **1%, and ***0.1% levels. The coefficients above are from the injury portion of the model discussed in Equation 1. Sample sizes are available in Table 1. Each row (two rows including the standard errors) corresponds to a particular model based on position and season. Each column corresponds to a different variable. NN stands for "not new," Ques stands for "questionable," and Doubt stands for "doubtful."

Table 8. Player and Teammate Injury Results: Player, WR, and TE

	Player Injuries			WR Starter			TE Starter		
Sample	**Probable**	**Ques**	**Doubt**	**Probable**	**Out NN**	**Ques/ Doubt**	**Probable**	**Out NN**	**Ques/ Doubt**
QB	0.522	-2.480*		0.421	0.117	0.408	0.467	-0.464	2.124***
	(0.677)	(1.422)		(1.184)	(1.885)	(0.576)	(1.346)	(1.853)	(0.778)
2016	0.221	-2.087		0.603	-0.003	2.447***	1.349	-1.416	2.730***
	(1.084)	(1.918)		(2.039)	(2.918)	(0.827)	(1.668)	(2.523)	(0.992)
2017	1.505	-1.614		-0.307	1.157	-1.955	1.213	-2.603	2.526
	(1.380)	(2.646)		(2.219)	(4.067)	(1.187)	(3.413)	(4.613)	(1.713)
2018	-0.474	-6.096*		-0.72	-0.918	-1.591	-1.59	2.457	0.588
	(1.299)	(3.566)		(2.157)	(3.542)	(1.130)	(3.019)	(3.726)	(1.954)
RB	-0.12	-2.460***		0.495	0.12	0.23	1.314*	-0.731	0.842*
	(0.442)	(0.620)		(0.617)	(0.914)	(0.322)	(0.794)	(1.129)	(0.438)
2016	-1.383	-2.750***		0.863	1.287	0.283	0.866	0.687	1.260*
	(0.932)	(1.054)		(1.410)	(2.019)	(0.602)	(1.253)	(2.006)	(0.748)
2017	0.053	-2.954**		0.257	-0.3	-0.267	2.583	-1.835	-0.006
	(0.700)	(1.192)		(1.015)	(1.512)	(0.578)	(1.680)	(2.521)	(0.807)
2018	0.722	-2.444**		0.396	-0.17	0.283	0.602	-0.777	0.072
	(0.750)	(1.065)		(1.006)	(1.470)	(0.554)	(1.463)	(1.875)	(0.871)
WR	-0.713**	-0.925**		0.848	-0.26	0.319	0.76	-1.178	0.456
	(0.355)	(0.422)		(0.595)	(0.866)	(0.313)	(0.691)	(0.969)	(0.386)
2016	-1.268*	-1.449**		1.912	-0.897	0.408	0.151	-1.556	0.699
	(0.724)	(0.693)		(1.310)	(1.819)	(0.571)	(1.058)	(1.603)	(0.636)
2017	-0.277	-1.019		0.627	-0.354	-0.688	1.663	-2.019	0.382
	(0.598)	(0.746)		(0.988)	(1.479)	(0.583)	(1.531)	(2.140)	(0.745)
2018	-0.692	-0.584		0.731	-0.25	0.648	0.927	-1.703	-0.769
	(0.571)	(0.786)		(0.960)	(1.385)	(0.519)	(1.296)	(1.697)	(0.738)
TE	0.124	-0.523	0.098	0.39	1.822	0.616	-0.278	0.587	0.109
	(0.527)	(0.688)	(6.601)	(0.794)	(1.158)	(0.406)	(1.314)	(1.839)	(0.758)
2016	0.801	-1.247		0.037	2.518	2.648***	-0.392	-0.315	2.056
	(1.351)	(1.037)		(1.952)	(2.747)	(0.777)	(2.696)	(3.841)	(1.314)
2017	0.354	0.08	0.546	-0.932	2.235	0.374	0.938	-1.837	-0.244
	(0.818)	(1.451)	(6.367)	(1.268)	(1.925)	(0.719)	(2.708)	(3.648)	(1.315)
2018	-0.005	-0.814		2.176*	0.613	-1.078	0.574	0.644	-0.167
	(0.828)	(1.456)		(1.240)	(1.777)	(0.678)	(1.915)	(2.694)	(1.499)

Notes: Statistical significance is defined at the *5%, **1%, and ***0.1% levels. The coefficients above are the injury portion of the model discussed in Equation 1. Sample sizes are available in Table 1. Each row (two rows including the standard errors) corresponds to a particular model based on position and season. Each column corresponds to a different variable. NN stands for "not new," Ques stands for "questionable," and Doubt stands for "doubtful." Not many players are classified as doubtful and end up playing, so the overall sample size of players who fall under that category are small, explaining why most of the models do not have results for the doubtful variable.

Teammate and Opponent Attributes

The variables in Table 6 examine various teammate specific and opponent specific attributes. On the offensive line, pass block shows no evidence of statistical significance, suggesting that it is priced properly in the pricing mechanism. Run block is negative and statistically significant in the aggregate for QB and WR. It is possible that having a better run blocking offensive line could create more opportunities in the running game and thus reduce the reliance on the passing game, which negatively impacts QBs and WRs. For QBs, none of the individual years show signs of statistical significance, although that may be a sample size issue. For WRs, the effect seems to go away from 2017, suggesting that DraftKings may have fixed the mispricing for 2018. Run blocking seems to be priced efficiently for RBs and TEs.

Variables measuring opposing defense include grades for run defense, pass rush, and coverage. Run defense is negative and statistically significant for the aggregate QB and WR models. While not definitely clear, opponents being able to stop the run could make it easier for defenses to put more resources towards pass rush and pass prevention, which could negatively impact both positions. Again, neither position shows signs of statistical significance at the year-level, although the signs are consistently negative. Pass rush is positive and statistically significant for QBs and negative and statistically significant for RBs. The aggregate effect for pass rush for QBs seems to be coming heavily from 2018, with a one unit increase in pass rush score leading to 0.619 points more for the QB. It is possible that QB prices are currently penalized too much for facing a tough opposing pass rush. For RBs, the effect is negative, although mostly in 2016. Like the previous result regarding run defense, a team with a better pass rush may be able to allocate more resources toward preventing the run and pass instead of going after the quarterback. The same thinking applies to coverage defense for RBs. However, that effect is only negative and statistically significant in 2016, after which the effect seems to go away. There is also some statistical significance for coverage and TEs, but the effect only seems to be in 2018. Overall, these mispricings seem small and do not seem to be consistent over time. Besides for a few years, most of these attributes seem to be priced efficiently by DraftKings.

None of the remaining variables seem to be inefficiently priced. Experience, wind speed, and bad weather all seem to either be efficiently priced or have a difficult-to-detect impact on point scoring.

Injury Strategy

An additional strategic decision that may not be captured in DraftKings prices is how to handle player injuries. Tables 7 and 8 break down how players perform, controlling for salary, when either they or a teammate is hurt. The starting QB getting hurt does not seem to impact player scoring, except for RBs in 2016 (although the standard error is fairly large). The RB starter getting hurt does seem to influence each of the positions besides QB. For RBs, the starter getting hurt has a strong positive effect on expected performance. However, when the starting RB is out for more than one week, that effect seems to be neutralized once DraftKings can account for it in prices. However, simply having the starting RB be questionable or doubtful seems to have at least a minor impact on player performance. If the starter is hurt, the backup often gets more carries even if the starter ends up playing. The out and extended absence trends may have been somewhat true for WRs when the starting RB is hurt, but those effects seem to disappear after 2016. For TEs, having the starting RB out seems to positively benefit them (at least in 2018), although there are mixed results regarding what happens if the starter is out for an extended absence. The backup running back being out or injured does not seem to have much of an effect.

The WR starter being out also does not seem to impact performance, at least not after 2016 for QBs and TEs. This is likely because there are multiple WRs on the field already, so one of the starters being out likely has a much smaller impact on playing time than if the starting running back got injured. The TE starter being injured also does not seem to have a consistent mispricing past 2016. However, individual player injuries do seem to impact performance. While being probable does not seem to impact perform, there does seem to be an effect with being listed as questionable. Being questionable usually means the player is dealing with a somewhat serious injury that likely has a strong negative impact on eventual playing time, and which would likely to lead to lower scoring. The results in Table 8 support that for almost every position. Staying away from players deemed questionable is likely a smart and safe strategy.

Conclusion

This paper provides evidence of past strategies skilled players could have implemented to increase their expected winnings. I show optimal strategies regarding efficient asset allocation, especially as it relates to the FLEX position. I also show that a home field bias exists in player pricing and that there are opportunities to pick up additional points by taking players coming from teams where the starting RB is injured. That said, DraftKings did seem to efficiently price most of the teammate and opposing player attributes and captured most of the injury issues. However, staying away from questionable players is still likely an effective outcome improving strategy.

These results provide some evidence that DraftKings Fantasy Football is a skill-based game. This conclusion still needs to be tested for other sport offerings, but it is likely that those sports and contests will show similar signs of mispricing. If prices were fully efficient, they would be able to address the different strategic elements discussed in the previous paragraph. These mispricings provide opportunities for skilled players to outperform the market and increase their expected winnings, leading to the skill-based game conclusion.

Proving that DFS is a skill-based game satisfies the first necessary condition needed to claim that DFS is a game of skill and not chance and therefore should be legal under Federal legislation. This paper does not address the second necessary condition, heterogeneity in skill level, and leaves that for future research.

Endnotes

[1] https://thefsga.org/industry-demographics/

[2] https://betting-sites.me.uk/unstoppable-growth-fantasy-sports-infographic/

[3] New York State Gaming Commission 2019 Interactive Fantasy Sports Report

[4] https://www.legalsportsreport.com/daily-fantasy-sports-blocked-allowed-states/

[5] This excerpt from Cabot and Miller (2011) was pulled from Meehan (2015).

[6] See Section 3 (DraftKings Pricing Mechanism and Objective Function) for more details on the rules and competition format of DraftKings contests. As an initial summary: Participants are allotted a salary cap that they use to select players and form lineups. Their lineups compete against other lineups, and the highest scoring lineups (based on the real-world production of the players selected) win.

[7] Federal Wire Act of 1961. Pub. 18 U.S. Code § 1084—Transmission of wagering information penalties. Legal Information Institute, https://www.law.cornell.edu/uscode/text/18/1084

[8] Professional and Amateur Sports Protection Act of 1992. Pub. 28 U.S. Code § 3702—Unlawful Sports Betting. Legal Information Institute.

[9] Unlawful Internet Gambling Enforcement Act of 2006. 31 U.S. Code § 5362—Definitions. Legal Information Institute.

[10] https://www.legalsportsreport.com/ny/

[11] http://rotoguru1.com/cgi-bin/fyday.pl?game=dk

[12] Due to the uniqueness of Def, the position is excluded from the analysis. In fantasy, defenses encapsulate the entire production of the defense. Participants gain points when their defense earns sacks, interceptions, forced fumbles, safeties, or defensive or special team touchdowns (special team touchdowns can come from punt returns, kick returns, and blocked kick returns for touchdowns). Defenses also earn points for allowing lower point totals (or lose points for allowing higher point totals).

[13] https://nflcommunications.com/Documents/2018%20Policies/2018%20Gambling%20Policy%20-%20FINAL.pdf

[14] If there is heavy consumer demand for one side of the spread, odds makers may adjust the line or spread to even out the money coming in on both sides.

[15] Some of the data used in this paper comes from Pro Football Focus, which charges a fee to use its player grade data. That said, the public observes the real-world performance from the various positional groups and can incorporate that information in their lineup selections. The data used here simply quantifies that production for modeling purposes. It is possible that skilled players have access and are better at incorporating this more advanced information. Also, nobody is excluded from purchasing a subscription to access the data. Finally, many media outlets use this data in periodicals and other publications. Many participants consume this content to help inform their lineup decisions, such that this less accessible information can still be considered publicly available.

[16] This is a real DraftKings contest from Week 9 of the 2019 NFL season, "NFL $3M Fantasy Football Millionaire [$1M to 1st]", contestID 79435342.

[17] https://www.draftkings.com/help/rules/nfl

[18] In Week 3 of 2016, Todd Gurley had 85 rushing yards (8.5 pts), 2 rushing TDs (12 pts), 1 reception (1 pt), and -5 receiving yards (-0.5 pts). Therefore, he scored 21 points.

[19] Website subscription is required to access these data: https://www.pff.com/

[20] Pro Football Focus grades are calculated by analysts grading every play of a game. This video and article explain the methodology they use: https://www.pff.com/grades. Their player performance measures are well accepted by sport publications.

[21] There may be issues relying on season average data to account for player ability. For example, participants selecting lineups in Week 2 have only observed performances from Week 1 and not future weeks of the season, yet these covariates capture that information. While this certainly introduces noise to the analysis, these production measures should, on expectation, be a good proxy for ex-ante expectations of production. While not true for every player, most players and positional units that are good likely were expected to be good. Again, this introduces some noise, but not in a way that should systematically bias coefficient estimates. The practice of utilizing not-yet-complete season measures is seen throughout the gambling literature, especially in papers that utilize team fixed effects.

[22] https://www.pro-football-reference.com/

[23] http://www.nflweather.com/en/

[24] Injury data come from The Football Database: https://www.footballdb.com/transactions/injuries.html?yr=2018

[25] Depth chart data were pulled from https://www.ourlads.com/nfldepthcharts/

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