Research Article

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To Fair Catch, or not to Fair Catch?

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Abstract: Kickoffs in American football are widely regarded as the most injurious play type. Numerous rule changes across the three major levels of football (high school, collegiate, and professional) have attempted to curb injuries during kickoffs with varying success. A new proposal from Dartmouth College to the Ivy League conference suggests allowing teams to announce their intention to fair catch a kickoff before the play begins, avoiding injuries on plays where the outcome is predetermined. This analysis considers the strategic merit of teams electing a fair catch prior to the play, proposing a novel expected points model.

Keywords: Football Analytics, EPA, multinomial logistic regression

1 Introduction

In American football, a kickoff occurs at the start of each half and after all scores, except for a safety. A kicker from the one team will line up at a set point on the field (the "kickoff line") and boot the ball toward the returner from the other team. The returner can then choose to catch and run with the ball (return), let the ball go out-of-bounds or catch it and kneel in the end zone (both touchbacks), or call for a fair catch. Both a fair catch and touchback allow the returner's team to advance the ball to a specified point on the field (the "touchback line"). Meanwhile, the kicker's teammates (the coverage unit) attempt to tackle the returner before he can gain yardage, while the returner's teammates (the blocking unit) attempt to block the coverage unit from tackling the returner. There are many collisions between the blocking and coverage units, even on plays where there is a touchback or the returner calls for a fair catch.

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1.1 Kickoffs and Injuries

A general consensus exists among experts that kickoffs are as the most dangerous play in football, both in terms of frequency and severity of injury. Most football plays start with both teams lined up within ten yards of the line of scrimmage, but kickoffs start with opponents lined up between ten and fifty yards apart, after which the collide with each other running at full speed. As Kevin Seifert of ESPN suggests: "one day...the NFL will outlaw the kickoff. It's one of the most dangerous plays in football, a sub-concussive factory" (Seifert 2016). Previous work has addressed the injury rate on kickoffs in high school, collegiate, and professional levels of football.

In 2018, attempting to reduce the frequency of highly injurious return plays, the football bowl subdivision (FBS) of the NCAA implemented a rule change, moving the touchback line from the 20-yard line to the 25-yard line.

1.2 Expected Points

To complement the literature on the injury impact of kickoffs, this study attempts to evaluate the strategic implications of the fair catch versus return decision, specifically after the 2018 rule change. While there are many dimensions on which one can evaluate the success of football plays, I will use the expected points added (EPA) metric, comparing the EPA of kick returns to the counterfactual expected points (EP) if the returner had instead called for a fair catch.

1.3 Motivation

In 2020, Dartmouth football proposed a kickoff rule change in the Ivy League. The suggested rule change would allow a returning team that intends to fair catch *before* the kickoff play begins to announce this intention to its opponents. If the returning team makes the announcement, it will receive possession at the 25-yard line, the same result as the fair catch. An alternative mechanism will replace the onside kick to prevent the return team from precluding onside kick attempts with the new rule.

The goal of this rule change is to prevent potential injury during a play that is strategically meaningless, since the outcome is predetermined, but could still result in injuries from non-contact injuries or collisions between the blocking and coverage units before the players realize the fair catch occurs.

Prior rule change proposals have attempt to curtail injuries by altering game dynamics, either by increasing the number of touchbacks or increasing the value of a touchback or fair catch (Tyszkiewicz 2020). This proposal, however, only aims to prevent needless injuries without affecting game strategy. The theory behind the proposal is that the value of a typical return under the current rules is similar to the value of a fair catch. In other words, implementing such a rule change would have a minor impact on optimal game strategy and expected game outcomes. Specifically, if the value of a return is similar to the value of a fair catch (or equivalent result from a pre-play announcement), rational teams may often choose to take advantage of the rule to avoid injuries to players without incurring a significant strategic penalty.

2 Previous Work

2.1 Kickoffs and Injuries

Kickoffs have recently come under increasing public scrutiny as a result of their increased injury rate compared to other play types. Research has examined the count and rate of injuries across high school, college, and professional football.

Injury research is especially common in the professional football. This is likely a result of greater general interest in professional football and more accessible data. American interest in professional football is generally greater than interest in other levels of football (Saul 2022). Additionally, National Football League (NFL) teams release weekly injury reports and game telecasts are easier to access than telecasts for high school and collegiate games, making data collection easier.

Research on injuries in the NFL consistently suggests that kickoffs are the most injurious play type. Pellman et al. (2003) studied NFL injuries from 1996 to 2001, concluding that "kickoffs and punts were associated with significantly higher injury rates than were rushing or passing plays," especially in terms of concussions and injuries that lasted more than seven days. A follow-up study with data from 2002 to 2007 found similar results, including that "special-team players have a statistically increased risk" of concussions, which they attribute to the prevalence of high-speed collisions during special-team plays (Casson et al. 2011). Other authors found that injuries other than concussions are more common on kickoffs. Elliott et al. (2011) found that kickoffs had an injury rate of 4.90 injuries per 1000 plays compared to rate of 0.79, 1.55, and 3.27 injuries per 1000 plays, respectively.

The high rate of NFL kickoff injuries has caused outcry in popular media. The *New York Times* called kickoffs in the NFL a "train wreck of a play," quoting a former NFL special-teams player (Battista 2012). In 2016, Seifert of ESPN speculated that the kickoff would soon be abolished (Seifert 2016). A Youtube video titled "Kickoffs are stupid and bad" garnered almost two million views and highlights many of the potential dangers, including the fact that injuries can still occur during touchbacks (Bois 2017).

In high school football, Yard and Comstock (2009) demonstrate that injuries are more common and more likely to be severe on kickoffs compared to general plays.

Kickoff injuries are also a concern in college football. Consistent with findings from high school and the NFL, Houck et al. (2016) find that the rate of concussions during kicks are significantly higher than both non–special teams offensive plays and non–special teams defensive plays. In 2012, two conferences, the Ivy League and Big Ten, started collaborating to study head injuries across the sport (Campbell-McGovern 2018).

Previous rule changes have generally been successful in reducing the rate of kickoff injuries. There have been two approaches taken to reducing kickoff injuries. One option is to attempt to make the kickoffs themselves safer by devaluing returns. The other is simply to reduce the number of possible returns by increasing touchbacks.

In the NFL, a rule change prior to the 2011 season moved the kickoff line from the 30 to 35. The change brought the rate of touchbacks from 16.4 percent to 43.5 percent and decreased the rate of kickoff concussions by 40 percent, according to the NFL (Battista 2012). The incidence of injuries did not change on plays where the kick was returned, and punt return injuries remained similar, suggesting the rule change succeeded in reducing injuries (Ruestow et al. 2015). A rule change in 2016 moved the touchback line to the 25-yard line. This change ended up backfiring, since it penalized kicking teams for touchbacks and encouraged them to kick shorter to force returns. Consequently, injuries did not decrease significantly as a result of the 2016 change (Agarwal 2020). Even after the 2016 changes, the NFL reported that kickoffs were still five times as likely as other plays to result in concussions (Seifert 2018). Fittingly, another change in the 2018 season implemented five rule tweaks aimed at increasing kickoff safety, which were more effective at improving safety (Maske 2019).

As part of an NFL-run competition to use data to inform injury-reducing rule change proposals, Pelechrinis et al. (2019) suggested rule changes to punts rather than kickoffs, but they analyze both the estimated injury impact **and** estimated strategic impact of their proposed proposals, a model for this study.

In college football, rule changes both across the NCAA and within individual conferences have attempted to address player safety on kickoffs. In 2016, the Ivy League in college football altered the kickoff line and touchback line in an attempt to curtail injuries. Wiebe et al. (2018) find that these changes reduced concussions during kickoffs in the 2016-2017 seasons by encouraging fewer returns and more touchbacks and fair catches. The Ivy League went from touchbacks on 12.4% of kickoffs in 2015 to touchbacks on 44% of kickoffs in 2016 (Ivy League 2017). The experimental rule in the Ivy League was instituted across the NCAA for the 2018 season.

A counterpoint to the common narrative on some of the rule changes is the argument that rule changes that make touchbacks more valuable for the return team actually promote kicking teams to alter their strategy to force returns more often. For both the 2016 and 2018 rules change in the NFL, some speculated that the rule changes would actually lead to *more* returns (Seifert 2018; Schatz 2016; Agarwal 2020). This theory demonstrates how football strategy can interact with attempts to reduce injury to provide unexpected results.

Players themselves, including special teams players who take part in the high-risk kickoffs, have also spoken out in opposition to rule change proposals (Battista 2012). This opposition, however, may be a consequence of fear that the abolition of kickoffs may lead some players to lose their jobs.

2.2 Valuing General Plays

To measure the value of a kickoff return, we first must identify a mechanism to value plays generally. While traditional box score measures like yards gained are helpful, they are not sufficient for measuring the total quality of a team's play. The notion of expected points added provides a more detailed alternative. Expected Points (EP) is the expected value for the *next* score in the game, where we define scores for one team (the home team) as positive and scores for its opponent as negative. Expected points added (EPA) for a play measures the ΔEP during that play.

Carter (an NFL quarterback himself at the time) and Machol (1971) first introduced the notion of expected points. They only consider expected points for a first down and 10 and bin the field into "strips" (a nearest neighbors approach). Carroll et al. (1988) introduced an even simpler model in their popular *Hidden Game of Football* book, modeling expected points linearly as $EP = -2 + 0.1x$, where x indicates the yards from a team's own end zone. This model ignores down and distance altogether. Romer (2005) uses the approach of dynamic programming to model expected points, specifically to answer the question of decisions to kick or "go for it" on fourth downs. Romer restricts his study to the first quarter of games to rationalize an assumption that teams are risk-neutral over points scored and only considers first down and 10 situations.

In 2008, Brian Burke spurred wide interest in expected points with his work for ESPN and his personal blog, Advanced Football Analytics. Burke's early work accounts for down and distance scenarios other than first and 10, but only considers the first and third quarters and did not include plays where teams were separated by more than 10 points.

Since Burke published his 2008 blog post, a flurry of academic and non-academic research has discussed expected points. Causey (2015) averages next scores from each exact scenario, bootstrapping confidence intervals. Goldner (2012; 2017) uses an absorbing Markov chain, deriving expected points from the absorption probabilities for each drive-ending event (score, turnover, punt, etc.). ESPN's PlayStation Player Impact Rating depends on a Bayesian EPA model (Sabin and Walder 2019).

Yurko et al. (2019) calculate EPA with a multinomial logit model. Variables include the down, time remaining, yards to end zone, and indicators for whether it is a "goal-to-go" situation and whether the play occurs in the final two minutes of the half. One benefit of this model is the ability to model the probability for each scoring event directly rather than averaging the "next score" outcome of similar plays.

An alternative method of measuring play value is win probability added (WPA). If we assume that we can assign a team a a probability $\mathrm{WP}_i = P_a(win)$ of eventually winning the game before play i starts, $\mathrm{WPA}_i = \Delta\mathrm{WP} = \mathrm{WP}_{i+1} - \mathrm{WP}_i$.

Stern (1986) estimates win probability using point spreads, which Burke revisits along with expected points in 2008. Golder (2017) uses a Markov model similar to the one for expected points. Machine learning approaches are also common for win probability estimates (Lock and Nettleton 2014; Causey 2013).

Yurko et al. (2019) model win probability with a GAM. The model considers down and distance, time remaining, half of game, and time outs for each team. The authors also derive some extra variables, such as a ratio of time to score differential and an indicator for whether the play occurs in the final two minutes of the half.

2.3 Evaluating Kickoffs

While a general model for evaluating plays is an important component of evaluating kickoffs, the ultimate aim of this study is to compare kickoff returns to fair catches.

In the NFL, Burke (2009) argues that a touchback is a positive-EPA play given 2009 rules. Burke and Katz (2016) analyze expected points in kickoff outcomes after the 2016 NFL rule change, specifically comparing a return to a touchback. They find that "moving the touchback on kickoffs to the 25-yard line puts the decision to return right at the point of indifference."

Schnell (2019) investigates college football kickoffs after the 2018 rule change, finding that the mean starting field position is $\mu = 25.67$, just past the 25-yard line where the ball would go after a fair catch. Schnell fails to reject the null hypothesis $\mu = 25$, however, which he considers evidence that "there is not a clear advantage in returning a kick" (Schnell 2019). He also notes that 55 percent of returns *do not* pass the 25-yard line and speculates that touchdown outliers are skewing μ. One of the issues with drawing conclusion based on the mean field position after returns is that the field is not symmetrical with respect to the fair catch line. That is, a return for a touchdown can go to the opponent's end zone, but a return cannot go behind the return team's end zone. This asymmetry renders the mean a biased statistic to measure kick return effectiveness.

3 Data and Methods

3.1 Data: Ivy League

Using R, I attempted scraped data for every Ivy League kickoff from 2010-2021 from ESPN play-by-play records. However, the Ivy League data was plagued by issues that ultimately made it not suitable as input for the model.

1. **Impossible Values** Some of ESPN's reported values were impossible given the rules of football. For example, from a Dartmouth vs. Yale game: "Blake Horn kickoff for 88 yds for a touchback."
2. **Penalties** The way kickoffs with penalties are reported is inconsistent and unpredictable.

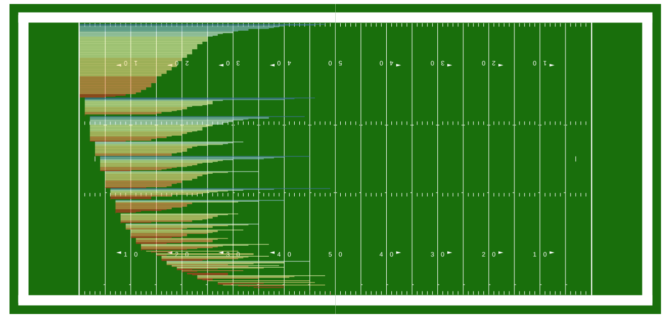

Fig. 1: Ivy League returns 2017-2021

3. **Lack of variables** Compared to the FBS, for which publicly available data sets offer information on spread and other non-game information that can be useful in EPA and WPA models.

Despite not using Ivy League data as input to the model, there is still a lot of value that can be salvaged from the work scraping the data.

1. **Unique Data Set** All the current APIs and data sets available online for college football use FBS-only data. We now have a unique collection of kickoff data from the FCS Ivy League, even if it is partially flawed.
2. **Descriptive Statistics** Although we did not use the Ivy data in the model, there remains opportunities to summarize and visualize the data. For example, Figure 1 depicts Ivy returns from 2017-2021 sorted by start line. Blue lines represent longer returns and red lines represent shorter returns.

3.2 Data: FBS

Because of the issues with the Ivy League data, I decided to instead gather use play-by-play data from the more popular FBS division, for which data are more prevalent and reliable. The Ivy League is part of the FCS, which receives less media coverage. The cfbfastR package provides data back to 2003 natively, with options to retrieve data back to 2001 through collegefootballdata.com. This study uses data from the 2018 and 2019 seasons found online. A link to download the data appears at the end of the manuscript.

The following table summarizes some of the general statistics for the FBS data from 2018 (when the NCAA implemented the new fair catch rule) to the the most recent 2021 season:

Similar to Schnell (2019), we notice a modest advantage for kick returns from the summary statistics. Returns tend to have a much better mean and median field posi-

Kickoff Type	n	Median field pos.	Mean field pos.
Fair Catch	196	25	27.2
Return	14679	25	28.3
Touchback	13786	25	25
Total	28661	25	27.2

Tab. 1: Summary Statistics for FBS Kickoffs, 2018-2021

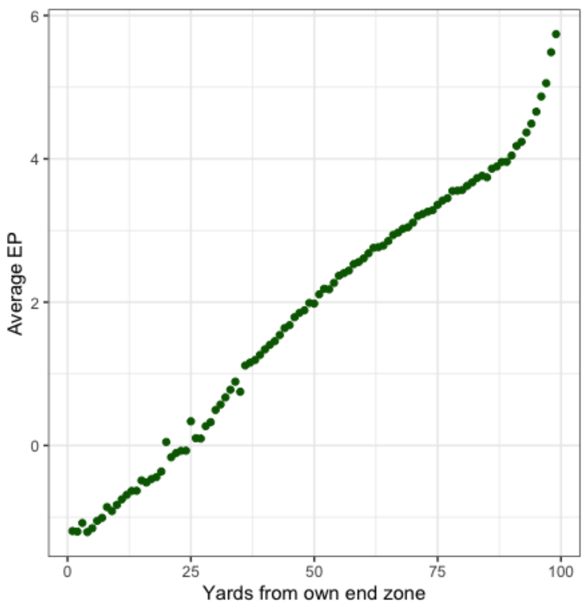

Fig. 2: Average EP vs. Yards from own end zone, 2018-2019

tion than touchbacks, but only slightly better than fair catches.

3.3 Expected Points Model

In general, letting X be the current game context and S be the set of all possible *next* scores for a play (-7, -3, 0, 3, or 7 points), Equation 1 gives the definition of expected points.

$$EP = \sum_{s \in S} s * P(s \mid X) \tag{1}$$

Figure 2 depicts how EP (for the offensive team) changes as they move closer to the opponent's end zone.

We follow the approach of Yurko et al. on NFL data to generate an EPA model for college football, with some modifications. We fit a multinomial logit model, using predictors of down, distance, time remaining, yards from end zone, and end-of-half indicators. Our model also includes interaction terms between some of the main variables to reflect the importance of a difference between, for instance, a fourth down in the opponent's territory (where a field goal can be kicked) and a fourth down in one's own territory (where a field goal is less reasonable).

The fitted coefficients can be used to give probabilities for each scoring outcome being the *next* score type from a certain play given X, the values of the predictor variables for that play. We then use Equation 1 to calculate the expected points for that play.

3.4 Evaluating Plays Versus Counterfactual

After building the EP model, we can look at each *returned* kickoff and assess the counterfactual, imagining instead the returner had selected to call for a fair catch. Then, we look at the change in EPA that results from the returner's choice to return instead of calling for a fair catch.

We can take advantage of the fact that the result of a fair catch is known. The ball is simply placed at the 25-yard line. There is no chance of a touchdown or other unique outcome. Given this fact, we evaluate returns against a fair catch that the returner could have made by comparing the EPA of the return to the EPA that would result from the ball going to the 25-yard line (as it would from a fair catch). We also add seven seconds back to account for the fact that returns tend to take time off the clock, while fair catches do not cause the game clock to run.

It would be possible to evaluate fair catches against counterfactual returns **only** by building a reliable, realistic simulator of returns. In real data, it is impossible to know the result of a return that is forgone when the returner instead calls for a fair catch. The return could have gone for negative yards or a touchdown! Video game manufacturers attempt to build realistic football simulations, but that task is outside the scope of this study.

3.5 Win Probability

We also used the cfbfastr package to assess WPA for returns and fair catches. Since this study focuses on EPA, a proprietary win probability was beyond the scope of the study, but cfbfastr provides win probability estimates for each play. Since this model is pre-calculated and cannot recieve custom inputs, it is not possible to perform the counterfactual fair catch analysis described in section 3.4. Instead, we will investigate general statistics about the WPA of returns and fair catches.

4 Results

4.1 EPA

Table 2 summarizes the sign and significance of the predictor variables from the fitted model. The table indicates the sign of the predictor coefficient. Significance is depicted by color, with significant values in black and insignificant values in red.

Score Type	-3	-2	2	3	7
Off. is Home Team?	-	+	+	+	+
Half	-	+	-	-	-
Down	+	+	-	+	-
Distance	+	+	+	+	-
Is final 2 mins.	+	-	-	+	+
Sec. Left	+	+	-	+	+
Down:Distance	-	-	-	-	+
Down:Yards to Go	-	+	+	-	+

Tab. 2: Signs and significance of predictor variables

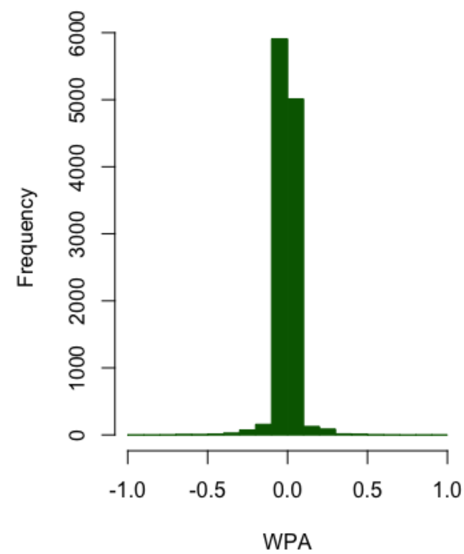

Fig. 3: Histogram of return WPA, 2018-2021

Based on the proprietary EPA model and the 2018-2019 data, returners **lose 0.008 EPA per return** by choosing to return instead of call for a fair catch.

4.2 WPA

Figures 3 and 4 show histograms of the return and fair catch WPA, respectively.

Based on the summary statistics of the WPA model from cfbfastr, kick returners **gain** 0.12% win probability on average by returning kicks instead of fair cacthing.

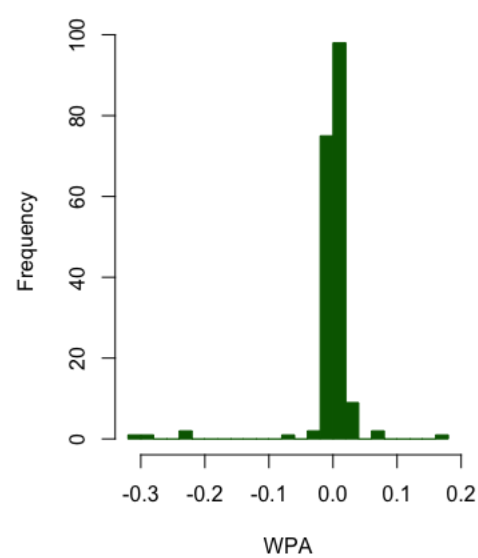

Fig. 4: Histogram of fair catch WPA, 2018-2021

4.3 Takeaway

The fact that the sign of our results for WPA contradict the results based on EPA provides further evidence that the value of one strategy over the other is marginal, if it exists at all. At the very least, the strategic benefit of either option is not so great to preclude consideration of a rule change for injury prevention.

5 Discussion

5.1 Value of Injuries

In addition to the strategic implications of pure play outcomes, there is also another dimension to consider when evaluating the value of plays to the teams involved–injuries. Although team roster decision are not necessarily perfectly value-maximizing (Massey and Thaler 2013), we can assume injuries to players will usually result in a decrease in in-game probability for the team whose player gets injured. Therefore, even a team that marginally benefits from a return needs to consider the potential for one of their players on the play. Also possible is an injury to a player from a team's opponent, potentially *increasing* the team's in-game win probability. For injuries that last multiple games, however, it is in the best interest of both teams to avoid injuries during the game, assuming, naively, that injuries to the kicking and return team are equally likely. Therefore, preventing injuries is a positive-EP decision for both teams across the course of the entire season, another reason that teams can benefit strategically from this rule change.

As an extension of the EPA model, Yurko et al. propose a WAR metric that measures a single player's contribution to the EPA of the play. Measuring the WAR lost by replacing players injured on kickoffs with their backups is an area for future research.

Figuring out how the rule change may impact injuries themselves is far from trivial. Pelechrinis et al. (2019) attempt to estimate the effect of their punt rule change proposals by modeling injuries as a function of how close to the sideline the returner catches the punt. While this model does not seem to fit intuitively for kickoffs and we do not have access to injuries that occur on "meaningless" fair catch plays, there is evidence that injuries do occur on these plays.

Obvious moral costs accompany injuries and an ethical dilemma to attempting to assign them "value" at all. Even if an injury to a player is only worth 1% WP over the course of the games he misses, it may be worth much more to his parents or teammates. As discussed previously, players themselves do not appear to be the main proponents of kickoff rule changes. However, it is likely that most players view their injuries negatively in retrospect as they experience pain and potential loss of playing time.

5.2 Beyond Injuries and Strategy

Results of injury research suggests that kickoffs are disproportionately a cause of injuries across all levels of football (Pellman et al. 2011; Elliott et al. 2011; Houck et al. 2016; Campbell-McGovern 2018). Football is an inherently dangerous game, and kickoffs are not the only culprit. Player safety and strategy are not the only dimension on which decision makers want to optimize. Safety decision must be balanced with entertainment and player employment concerns.

5.3 Other Strategic Implications

Some detractors of the pre-play announcement rule change point to the effect such a rule would have on onside kicks. Especially concerning are "surprise" onside kicks, where the returning team does not expect the kicking team to opt for an onside kick. One solution to this issue would be to allow the kicking team to announce their intention to perform an onside kick before the beginning of the play, preventing the returning team from electing to enforce the automatic fair catch. This would unfortunately prevent surprise onside kicks, violating the goal of the rule change proposal to leave strategy intact.

Another option would be an alternative onside kick, where teams could elect to try to convert a fourth down with a similar expected conversion probability as an onside kick.

5.4 Future Research

Another area for future work is a more robust set of data for FCS conferences such as the Ivy League. Whether the conferences themselves step in, ESPN improves data validation, or computer vision techniques automate data collection, more reliable data is needed to enable serious research on Ivy League football.

The increased availability of tracking data in football will provide opportunities for future research. Tracking data can augment EPA models, improve studies on injury, and reduce error in data collection.

Finally, there is potential for new, more specialized ways to model the value of kickoffs. We use an approach of a universal EPA, but a different EPA model for different play types (punts, kickoffs, field goals, etc.) may improve results. Future research could, for example, incorporate the yards above expected on a return, since a 25-yard return is better if the returner starts at the 15 than if he starts at the 0. This is partially accounted for by the final field position after the return in the current model, but there are opportunities for more nuanced approaches.

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Replication Files: The code, path model (DAG), data dictionary, DDSDreplication files, and other supplemental material for this study can be found at the study website.

References

[1] Agarwal, Satyam. 2020. "Unintended Consequences of NFL Rule Changes–Evolution of Kickoff Strategies." PhD diss., Stern School of Business New York.
bibitem Battista, Judy. "'Train Wreck of a Play' Collides With Consciences." *New York Times*. Last modified December 15, 2012. https://www.nytimes.com/2012/12/16/sports/football/tradition-vs-player-safety-in-nfl-kickoff-debate.html.

[2] Bois, Jon. 2017. "Kickoffs are stupid and bad." November 13, 2017. https://www.youtube.com/watch?v=t_SsIKgwvz4.

[3] Burke, Brian. 2008. "Expected Points." Advanced NFL Stats. Last modified August 3, 2008. http://www.advancednflstats.com/2008/08/expected-points.html.

[4] Campbell-McGovern, Carolyn, Bernadette A. D'Alonzo, Martha Cooper, Margot Putukian, and Douglas J. Wiebe. 2018. "Ivy League–Big Ten epidemiology of concussion study." (2018): 319-320.

[5] Carroll, Bob Newhardt, Pete Palmer, and John Thorn. 1988. *The hidden game of football*. Warner books.

[6] Carter, Virgil, and Robert E. Machol. 1971. "Operations research on football." *Operations Research* 19, no. 2 (1971): 541-544.

[7] Casson, Ira R., David C. Viano, John W. Powell, and Elliot J. Pellman. 2011. "Repeat concussions in the national football league." *Sports Health* 3, no. 1 (2011): 11-24.

[8] Causey, Trey. 2015. "Expected Points Part 1: Building a Model and Estimating Uncertainty." The Spread. Last modified September 23, 2015. http://thespread.us:80/expected-points.html.

[9] Causey, Trey. 2013. "Building a win probability model part 1." The Spread. Last modified December 8, 2013. http://thespread.us/building-a-win-probability-model-part-1.html.

[10] Elliott, Marcus CCW, Bertram Zarins, John W. Powell, and Charles D. Kenyon. 2011. "Hamstring muscle strains in professional football players: a 10-year review." *The American journal of sports medicine* 39, no. 4 (2011): 843-850.

[11] Goldner, Keith. 2012. "A Markov model of football: Using stochastic processes to model a football drive." *Journal of Quantitative Analysis* in Sports 8, no. 1 (2012).

[12] Goldner, Keith. 2017. "Situational success: Evaluating decision-making in football." In *Handbook of Statistical Methods and Analyses in Sports*, pp. 199-214. Chapman and Hall/CRC.

[13] Houck, Zachary, Breton Asken, Russell Bauer, Jason Pothast, Charlie Michaudet, and James Clugston. 2016. "Epidemiology of sport-related concussion in an NCAA Division I Football Bowl Subdivision sample." *The American Journal of Sports Medicine* 44, no. 9 (2016): 2269-2275.
bibitem Ivy League. 2017. "Ivy League Experimental Kickoff Rule Leads to Significant Decrease in Concussions." https://ivyleague.com/news/2017/10/18/football-ivy-league-experimental-kickoff-rule-leads-to-significant-decrease-in-concussions.aspx.

[14] Lock, Dennis, and Dan Nettleton. 2014. "Using random forests to estimate win probability before each play of an NFL game." Journal of Quantitative Analysis in Sports 10, no. 2 (2014): 197-205.

[15] Maske, Mark. 2018. "Will the NFL's new rules save the kickoff from extinction? The league sure hopes so." *Washington Post*. August 16, 2018. https://www.washingtonpost.com/news/sports/wp/2018/08/16/will-the-nfls-new-rules-save-the-kickoff-from-extinction-the-league-sure-hopes-so/?noredirect=on.

[16] Massey, Cade, and Richard H. Thaler. 2013. "The loser's curse: Decision making and market efficiency in the National Football League draft." Management Science 59, no. 7 (2013): 1479-1495.

[17] Pelechrinis, Konstantinos, Ronald Yurko, and Sam Ventura. 2019. "Reducing Concussions in the NFL: A Data-Driven Approach." *CHANCE* 32, no. 4 (2019): 46-56.

[18] Pellman, Elliot J., David C. Viano, Andrew M. Tucker, Ira R. Casson, and Joe F. Waeckerle. 2003. "Concussion in professional football: reconstruction of game impacts and injuries." *Neurosurgery* 53, no. 4 (2003): 799-814.

[19] Romer, David. 2006. "Do firms maximize? Evidence from professional football." *Journal of Political Economy* 114, no. 2 (2006): 340-365.

[20] Ruestow, Peter S., Tina J. Duke, Brent L. Finley, and Jennifer S. Pierce. 2015. "Effects of the NFL's Amendments to the Free Kick Rule on Injuries during the 2010 and 2011 Seasons." *Journal of occupational and environmental hygiene* 12, no. 12 (2015): 875-882.

[21] Sabin, Paul and Seth Walder. 2019. "Introducing a new way to rate college football players." *ESPN*. August 19, 2019. https://www.espn.com/college-football/story/_/page/PSimpactrating0819/introducing-new-way-rate-college-football-players.

[22] Saul, Derek. 2022. "Viewership For College Football Playoff Championship Up From Record Low 2021 — But Still Below NFL's Ratings." *Forbes*. https://www.forbes.com/sites/dereksaul/2022/01/11/viewership-for-college-football-playoff-championship-up-from-record-low-2021—but-still-below-nfls-ratings/?sh=30dd9f1b3622.

[23] Schatz, Aaron. 2016. "NFL Moves Touchbacks to the 25." Football Outsiders. Last modified March 23, 2016.

https://www.footballoutsiders.com/extra-points/2016/nfl-moves-touchbacks-25.
[24] Schnell, Matthew. 2019. "With College Football's New Kickoff Changes, is Returning the Kick Really Worth the Risk?" Dartmouth Sports Analytics. Last modified March 22, 2019. https://sites.dartmouth.edu/sportsanalytics/2019/03/22/with-college-footballs-new-kickoff-changes-is-returning-the-kick-really-worth-the-risk/.
[25] Seifert, Kevin. 2016. "NFL one step closer to eliminating kickoff returns." *ESPN*. March 22, 2016. https://www.espn.com/blog/nflnation/post/_/id/200481/nfl-one-step-closer-to-eliminating-kickoff-returns.
[26] Seifert, Kevin. 2018. "NFL approves rule changes regarding kickoffs, ejections in effort to bolster player safety." *ESPN*. May 22, 2018. https://www.espn.com/nfl/story/_/id/23575001/nfl-approves-rule-changes-kickoffs-allows-replay-review-ejections.
[27] Stern, Hal. 1986. "The probability of winning a football game as a function of the pointspread." In *Technical Report No. 59*. Stanford, CA: Department of Statistics, Stanford University, 1986.
[28] Tyszkiewicz, Zack. 2020. "College Football: The statistical impact of the 2018 kickoff rule." Fansided. Last modified April 29, 2020. https://saturdayblitz.com/2020/04/29/college-football-statistical-impact-2018-kickoff-rule/.
[29] Wiebe, Douglas J., Bernadette A. D'Alonzo, Robin Harris, Margot Putukian, and Carolyn Campbell-McGovern. 2018. "Association between the experimental kickoff rule and concussion rates in Ivy League football." *JAMA* 320, no. 19 (2018): 2035-2036.
[30] Yard, Ellen E., and R. Dawn Comstock. 2009. "Effects of field location, time in competition, and phase of play on injury severity in high school football." *Research in sports medicine* 17, no. 1 (2009): 35-49.
[31] Yurko, Ronald, Samuel Ventura, and Maksim Horowitz. 2019. "nflwar: A reproducible method for offensive player evaluation in football." *Journal of Quantitative Analysis in Sports* 15, no. 3 (2019): 163-183.