An Analytical View of Football's Placekicker

Completed for the Certificate in Applied Statistical Modeling
Spring 2024

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Abstract

Field goal kicking is simultaneously the most productive and most overlooked aspect of scoring in American Football. Despite the significant gravity of each kick, only two stats are officially kept for field goals: distance and outcome. Oftentimes kickers are unfairly criticized or praised for their field goal percentage. While a high field goal percentage is good, the stat strips any and all nuance from the art that is kicking field goals. For this project, I gathered contextual and in-game data that helps to quantify the difficulty and quality of kicks in the 2022 National Football League (NFL) season. Using coach input, weather data, spatial data, and more, I built models that predict the quality of a field goal attempt based on the circumstances that surround it. Testing how kickers performed against these models enabled me to grade their performance over a season and quantify their value to a team. These scores may lend an explanation to patterns around NFL kicker development and inform new ways to examine kicking as a whole. Performing these calculations now is a stepping stone to more advanced analytics later, especially in the form of biometric analysis based on motion capture.

Introduction

American Football's placekicker is perhaps the most specialized position in all of sports. In a game characterized by speed, strength, and toughness, kickers often look like toothpicks amongst a team of two-by-fours. Their singular role of kicking the ball between the uprights of the goalpost is bewilderingly unrelated to any other play in football. They regularly play less than 10 snaps per game, outside of which they hold no value. Yet, it is kickers that make up 49 of the top 50 scorers of all time (Sports Reference). It is kickers that contribute on virtually every scoring drive. It is kickers that hold the weight of entire fan bases on their backs at the end of close games. Surely, in decades of football stat keeping, there is more than a single, bias-ridden percentage that effectively quantifies the skill level of a kicker.

Alas, kicking prowess is most widely judged on a single, binary percentage: the aptly named 'field goal percentage' measures the ratio of a kicker's successful kicks to their total attempts, ignoring a multitude of other factors that go into field goal kicking. Field goal percentage does not take into account the difficulty of various kicks and the situations that surround them, thus favoring kickers who took easier kicks. It also treats every made field goal equally; a kick that barely sneaks inside the upright is less impressive than one perfectly down the middle. In order to more thoughtfully grade kickers, a data set capable of delivering higher-resolution metrics for place kicking must be compiled.

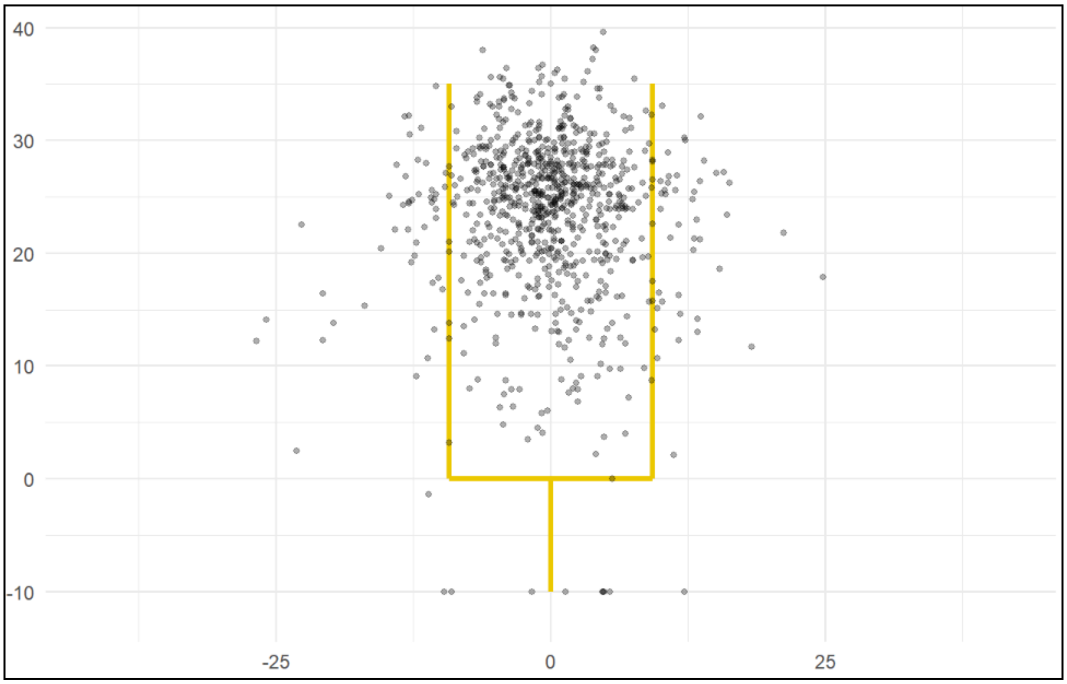
Materials and Method

The first step of this research project was the arduous data collection. I started by acquiring 15 weeks of play-by-play data from the 2021-2022 season (limitations in NFLsavant prevented further data collection). The data contained game dates, yard lines, teams, play types, play descriptions, time remaining, and more. The most important data (kicker, kick distance, outcome) came from parsing the play description. After filtering this down to just field goals, I watched and charted each of the 864 attempts, recording the hashmark orientation, dominant leg of the kicker (every kicker in the data is right footed, so this becomes irrelevant), and the x-y coordinates at which the ball crossed the uprights with the origin where the crossbar meets the base (@FrankieG, 2023; @thatonefootballcardguy, 2023). Using a one-to-one graphical representation of the uprights (Desmos), I could record the estimated coordinates within a tenth of a foot. The results (see Figure 1) reflect that kickers generally aim high and in the middle, as would be expected.

Once each kick had been charted, I sought out contextual information to determine the difficulty level of each kick. To learn more about the kickers themselves, I recorded their extra point attempt percentage from 2022 (Sports Reference). Though extra points also fluctuate in difficulty, they remain much more constant than normal field goals (and thus extra point percentage possibly provides a measure of how consistent a player is). Age and salary were also added to the data to indicate the perceived value and stage of career each player was (Spotrac). The most involved contextual information that I added to the data set was weather data. Using each game location (with longitude and latitude) and start time, I wrote a Python script that accessed the elevation, wind speed, wind gusts, precipitation, and temperature (of course, only for outdoor games) using OpenMeteo's API. I also added field material (i.e. grass, turf, hybrid) to the data to test if it has an impact. All modeling from this point forward was done in RStudio.

Figure 1

Charted NFL Kicks (2022-2023 Season)



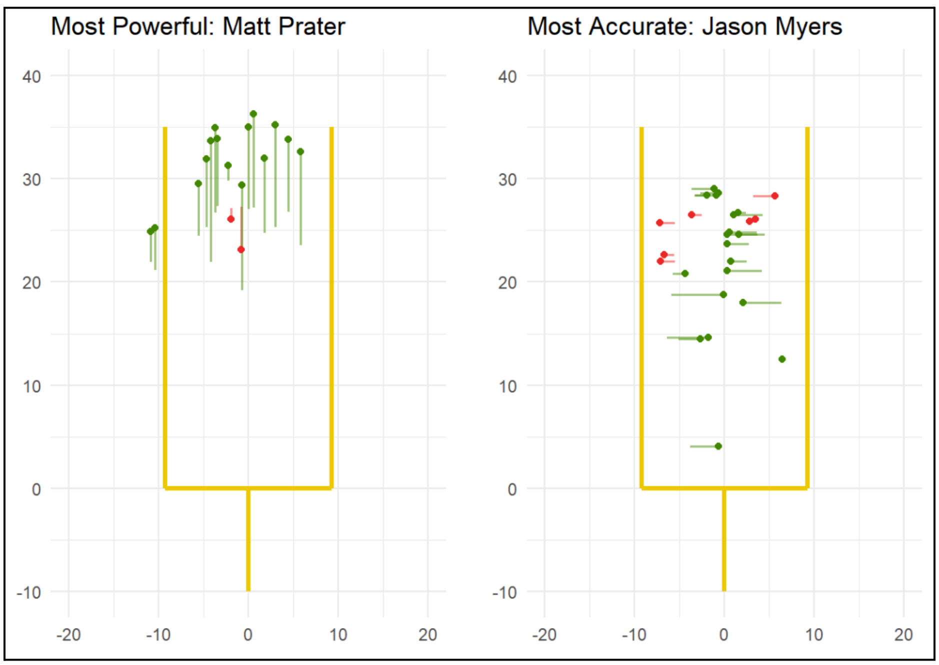
Note. Each point represents a single field goal attempt.

In order to model a player's 'success rate' on field goals, I must establish a proper definition of success. A unique aspect of football that makes it difficult to model is that there is no singular definition of success for every player. The roles that each position takes on are so unique that it is difficult for a viewer to determine whether or not the play was successful. For example, a perfectly thrown pass that seems inaccurate on TV could be the fault of the receiver. To ensure this misinterpretation would not happen in my models, I reached out to Jeff Crosby, Special Teams Analyst for Texas Football. He confirmed a few things: (1) kickers are "always trying to split the uprights perfectly," never aiming off-center for any reason, (2) kickers are taught to kick every attempt with the same power, (3) kickers should not prefer a certain hash mark over another, and (4) accuracy is more important than power when coaches evaluate kickers. Based on his input, I decided to make separate models for power and accuracy. A kicker's power would be defined as their ability to kick higher than a predicted y-value, and a kicker's accuracy would be defined as their ability to kick closer to the center than a predicted x-value. Based on the information provided by Coach Crosby, both of these claims should follow closely with how coaches evaluate kickers on the field.

To build the accuracy model, I first filtered out the blocked field goals (they provide little insight into the quality of a kick and will skew the results if included) and grouped by the individual kickers. I used a linear regression to predict the absolute value of the x coordinate, the distance from the center of the uprights. The inputs for this model included distance of the field goal, elevation, and wind speed. With a root mean squared error of about 3.1 feet (when tested on a 80/20 training and testing split), this model does a good job of explaining variation in the kicks while providing insight into which kickers are better and worse at out-performing expectation. I constructed an accuracy score for each kick calculated by the actual distance from the center divided by the predicted distance from the center ($\hat{X}/X$, where a score close to zero is ideal). The model built for power follows the same process for the y coordinate. The root mean squared error for this model is worse at about 5.5 feet, but this can be mostly explained by consistent outliers in the data (see Matt Prater in Figure 2). After getting a predicted value for y, the power over expectation metric is created simply by subtracting the expected y-value from the actual y-value ($Y - \hat{Y}$, where a higher score is better). By taking the median power score and accuracy score for each kicker, I constructed a percentile ranking for each metric. The most accurate and most powerful kickers consistently outperformed expectations (see Figure 2). To combine these scores into a composite, I added the two percentile scores together for each kicker. Since Coach Crosby stressed the relative importance of accuracy over power, the power percentile is reduced by 30% before this addition.

Figure 2

Matt Prater and Jason Myers Kick Log 2022



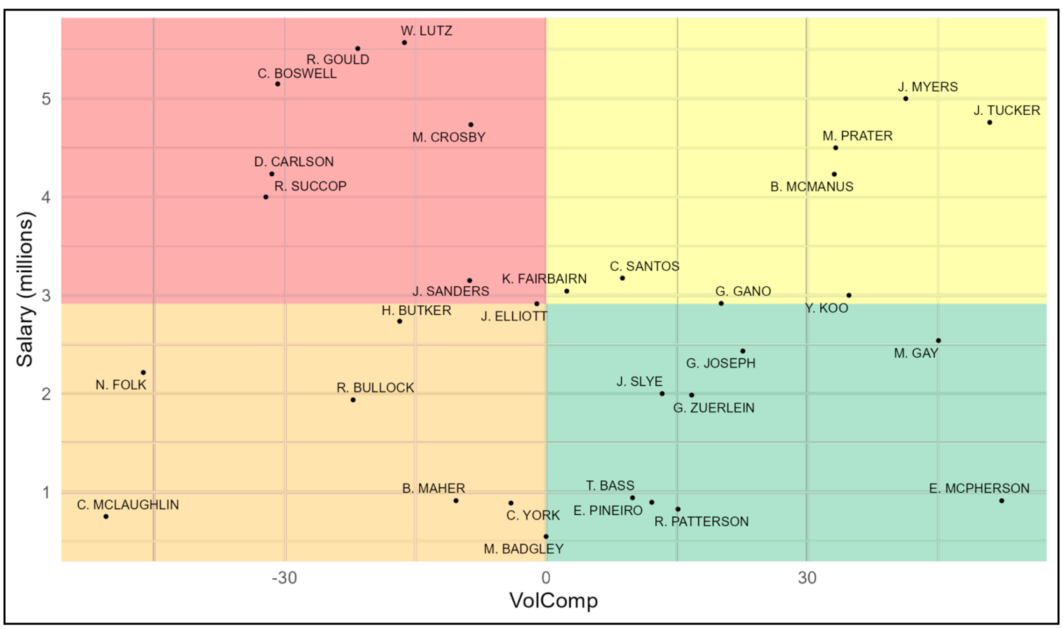
Note. The above figure shows each of Prater's and Myers' kicks with a line that connects them to the x- or y-value where the kicks were expected to be. Green indicates that they performed better than expected while red indicates the opposite.

Now that there is a composite rating for each kicker, I can produce a ranking of which kickers had the best season in 2022. However, this does not necessarily indicate who is the most talented kicker. A telling sign of a kicker's aptitude is the coach's trust in them. Coaches who trust their kicking unit will attempt more field goals from a farther distance. To reflect this, I created two more percentiles: a volume score to reflect total number of kicks and a 'long' volume score to reflect the number of attempts 50 yards or longer. I combined both in a formula that weighed them $((.3 * Long\ Volume) + (.2 * Volume) + .5)$ to create a comprehensive volume score that reflects the coach's trust in a player from .5 to 1. By subtracting the median composite score from each kicker's current composite score, this volume value could be multiplied by the new composite score to create a score I will call VolComp. By multiplying the adjusted volume in this way, kickers without high volume will regress to the median. After applying this computation, I produced a graph with VolComp charted with salary (Figure 3). Observe that Justin Tucker and Evan McPherson top the list, both kickers with great reputations, especially in 2022 (Breech, 2022). This is a good check that our model accurately grades kickers' play.

There are issues with this model that I have neglected to address. For power, close kicks may be misrepresented. From my experience charting the kicks, attempts within 30 yards often do not reach their apex until after passing through the uprights. For accuracy, predicting the absolute value of the x coordinate skews the model and produces a suboptimal result. Additionally, the composite and volume calculations were too arbitrary and disproportionately benefited kickers with longer attempts. Attempting to model 'trust' is problematic because it is too difficult to distinguish with reliance. Some teams will use their kicker more often because they trust him, while others will do so because they have no other option. Furthermore, I did not perform cross-validation or variable selection on this model. Rather, I let VolComp be a thought experiment that yielded enlightening enough results to include in the research's documentation. Nonetheless, the next model must correct these errors.

Figure 3

VolComp and Salary (2022)



Note. Each point indicates a kicker plotted by their salary and VolComp score. The quadrants are broken up by the medians of both salary and VolComp.

To remedy the issues, I changed my approach. Rather than splitting up power and accuracy into separate outputs, each kick was assigned a grade based on its coordinates. The grade would range from zero to one based on the location of the kick between the uprights. This solves the issues of training on the absolute value and biasing against short kicks. A kick receives a high grade for being high and inside and a low grade for being low or off-target.

Assigning the score to each kick is not an arbitrary process. Once again referencing Coach Crosby, a kicker should be aiming high and down the middle every single time. To model this, I used two sigmoid functions (after filtering out the blocked attempts). The x-axis sigmoid inputs the absolute value of a given x coordinate, a midpoint of 6, and a steepness coefficient of 0.6. The y-axis sigmoid inputs a given y coordinate, a midpoint of 7.5, and a steepness coefficient of 0.25. This logistic approach is optimal because it reflects the way we grade these

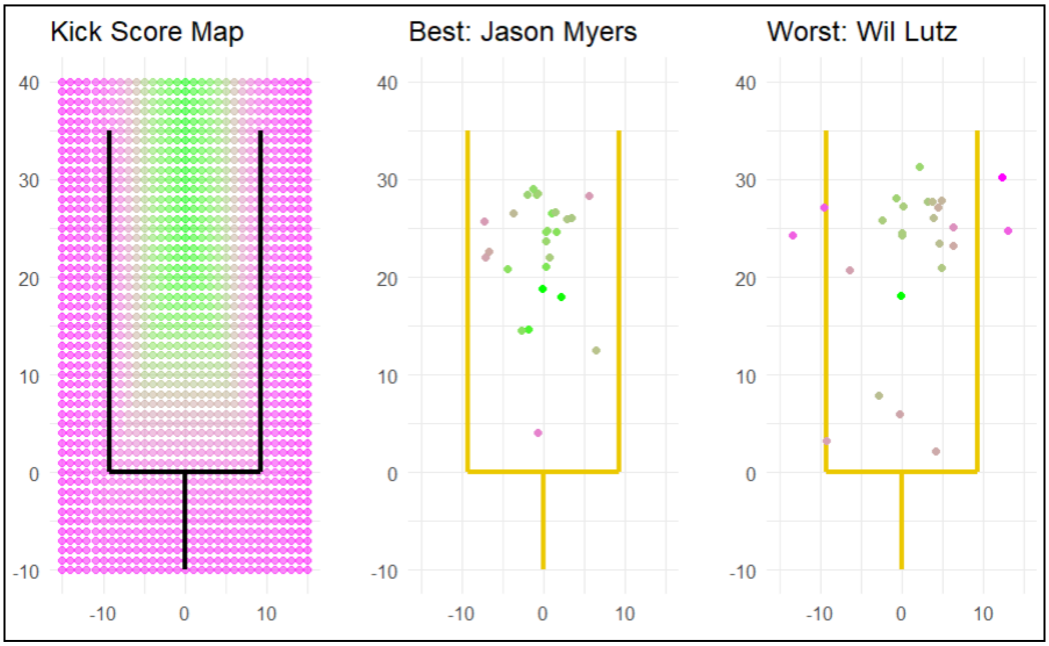
$$\textbf{X-score} = 1 - \frac{1}{1 + e^{-.6\cdot(|x|-6)}}, \ \textbf{Y-score} = \frac{1}{1 + e^{-.25\cdot(y-7.5)}}$$

kicks in real life. Any point close to the center in the x direction will output a value of nearly one. This drops off as the point moves laterally away from the center, steeply dropping almost to 0 as it passes the goalpost. In the same way, the y-score function will output about one for any point at least 20 feet above the crossbar and about zero for anything beneath the crossbar. A kick is only as good as its worst attribute (i.e. powerful yet inaccurate kicks and accurate yet weak kicks are both suboptimal). Thus, the final score for each kick is the minimum of its x and y scores. A visual representation of the result may be seen on the left map in Figure 4.

Now that each kick has a score, I trained a linear model to predict the expected score of a given kick based on the same inputs as before: the distance of the kick with a second degree polynomial expansion, the elevation, and the wind speed. I used a polynomial expansion on the distance because it does a better job of reflecting the increased difficulty of a longer attempt. It is worth noting that the wind speed input performed marginally better than the wind gust input, and thus it alone was included. Adding both would introduce unwanted collinearity. These three variables were the baseline inputs that I deemed necessary for the model. Additional inputs, such as precipitation, grass type, stadium type, temperature, and hash mark orientation, were also considered. When conducting an analysis of variance (ANOVA) test, these inputs were shown not to provide a significant enough improvement to the model to justify their inclusion. Adding the extra variables would reduce explainability and risk overfitting. I also considered modeling with a random forest or a neural network. On a 10-fold cross validation (using the caret library), the random forest had a root mean squared error of about .02 higher than the linear model. The neural network performed about as well as the linear model (marginally better than the random forest), but the increase was too inconsequential to justify its added complexity. Thus, I chose the linear model and assigned a predicted score to each kick.

Figure 4

Kick Score Map and Leader (2022)

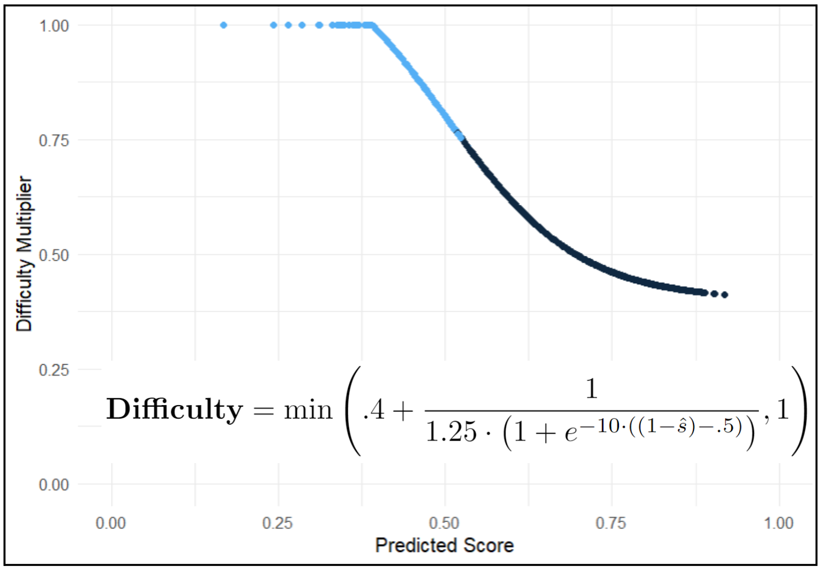


Note. The left graph displays the kick score at a grid of possible locations. The scores range from zero to one, zero being the worst possible score (magenta) and one being the best (green). The middle and right graphs indicate each of Jason Myers' and Wil Lutz' kicks respectively. A green point represents a score above expectation while a magenta point represents a score below expectation.

Rather than assigning 'points above expectation' as I did in the VolComp calculation, I chose to adjust for kick difficulty within the score of each kick (using the predicted score). This allowed me to use an empirical Bayes estimation later. The difficulty score would be implemented as a multiplier between .4 and one. A high difficulty kick (i.e. a kick with a low expected score) would receive a multiplier near one, while an easier kick would receive a score of about .5 (Figure 5). By multiplying the difficulty score by the actual score, each kick earned a difficulty-adjusted score based on the model prediction. From this, each kicker received a 'score per kick' ratio. The purpose of using a ratio is to allow for a less arbitrary volume adjustment. Using empirical Bayes, I fit a Beta distribution to the ratios with $\alpha_0 \approx 77.94$ and $\beta_0 \approx 133.97$ (Robinson, 2015) using the fitdistr function in the MASS library. After adjusting each of the ratios with these parameters and creating a pseudo-percentile with another sigmoid function, I produced a list of the kickers with grades out of 100 to indicate their effectiveness (Figure 6). I decided against incorporating coaches' 'trust' into this score because there was no objective way to measure it without resorting to my personal judgment or introducing bias.

Figure 5

Difficulty Multipliers Based on Predicted Score



Note. This is the plot of the difficulty multiplier for each field goal attempt in the dataset as a function of the predicted score. Highlighted in light blue are the attempts of 50 or more yards. The corresponding equation is defined underneath. Observe that the multiplier ranges from about .4 to 1.

Results

The main objective of this paper was to introduce new methods capable of generating higher-resolution characterizations of individual kicking performances in the NFL and using them to identify the players that out-performed their peers. Jason Myers, Graham Gano, Justin Tucker, Evan McPherson, and Younghoe Koo perform the best (Figure 6), and each provide a unique perspective on the career paths of kickers as a whole.

Jason Myers and Younghoe Koo, both in their late twenties at the time of data collection, ranked first and fifth respectively. The way their careers progressed was similar: a few good years followed by a breakout year in the second half of their twenties and a regression to the mean afterwards. They highlight the fluky nature of kicking field goals in the NFL. Every single kicker that earns a starting job in the NFL is undoubtedly extremely talented. Since the gap in talent can be so small at the top, favorable circumstances and luck can play a large role in a kicker's in-game performance. Ideally, the modeling done in this paper could be used to effectively weed out those who over-perform, but, at the end of the day, place kicking is too difficult a position to continuously perform at an elite level (unless your name is Justin Tucker). Predicting an increase in production is not as simple as finding the best players. Rather, a kicker's success is dependent on their team, confidence, opportunities, and circumstances. Myers and Koo are undeniably remarkable players, but this model reflects the unpredictability of kicker performance. After playing at a replaceable level in their early twenties, they blossomed into stars at an older age.

Figure 6

Top Kickers of 2022

	Kicker	Team	Salary ($)	Total Kicks	Raw Score	Final Score
1	Jason Myers	Seattle Seahawks	$5,000,000	27	0.433	97.95
2	Graham Gano	New York Giants	$2,917,962	24	0.429	96.5
3	Justin Tucker	Baltimore Ravens	$4,758,333	32	0.408	94.34
4	Evan McPherson	Cincinnati Bengals	$910,928	25	0.415	93.61
5	Younghoe Koo	Atlanta Falcons	$3,000,000	27	0.412	93.59
	…	…	...	...	…	...
32	Harrison Butker	Kansas City Chiefs	$2,736,525	21	0.308	7.53
33	Wil Lutz	New Orleans Saints	$5,570,000	25	0.315	7.04

Note. The above table displays the top five and bottom two kickers in my model and their teams. Salary is the amount the players were paid in 2022. Total Kicks refers to the number of field goals they attempted. Raw Score corresponds to the ability of that kicker to outperform expectations. Final Score is the adjusted Raw Score on a logistic scale from zero to one hundred.

Graham Gano is the oldest player in the top five. As a 35 year old at the time of data collection, Gano represents the longevity potential of kickers. After entering the league as a 22 year old, Gano converted about 75 percent of his field goals over his first four years. Since then, Gano has shot over 86 percent. Again, this shows the learning curve for NFL kicking; kickers that are given a chance to develop will perform better once they are comfortable. Likely a result of his age, Gano's performance dropped to under 65 percent the year after this study. While older players seem like more trustworthy kickers, predicting when their production drops is an issue. The success at their position is so volatile: kickers can switch from dominant to detrimental in a single season. Gano, then, is a cautionary tale. A reliable kicker is only reliable for so long.

Unsurprisingly to any NFL fan, Justin Tucker ends up near the top. The 34-year-old (32-33 at the time of data collection) is the consensus greatest kicker of all time (Hylton, 2022). What sets him apart is his consistency. Tucker has earned awards for his kicking each of the past eight seasons. To appreciate how phenomenal this effort is, observe Josh Lambo, former kicker for the Jacksonville Jaguars, as a case study. Lambo was great in 2017 and 2018, posting a field goal percentage over five percent better than league average both years. His breakout in 2019, then, was not entirely unexpected. The established veteran missed only one field goal in the 2019-2020 season, good for a field goal percentage of 97.1 percent (over 15 percent better than the league average). While I have established the flaws of using field goal percentage to gauge a player's performance, Lambo's dominance in 2019 was impressive enough to earn him second team all-pro honors (outdone only by Justin Tucker, predictably). After that stunning season, Lambo attempted a mere eight more field goals in his career, converting on five of them (Sports Reference). Lambo's story puts into perspective how impressive Tucker's dominance has been, especially as his career approaches its end. Lambo's room for error was nearly nonexistent. When the sample size is so small, the gap between the greatest of all time and the average player shrinks exponentially. The key with Tucker will be watching out for his drop off. As seen with Gano, it is difficult to predict when an old kicker will lose their touch.

Evan McPherson, fourth in my model, is the youngest of the top players. Unlike Gano, Tucker, Myers, and Koo, McPherson was selected in the NFL draft.[1] While there are higher expectations of a kicker that is drafted as opposed to signed as an undrafted free agent, there is also more faith. When a team invests draft capital in a player, they are more likely to keep that player on the roster regardless of their performance (an interesting case of the sunk-cost fallacy). This has not been the case for McPherson. Despite having slightly below average field goal percentage through the first 3 years of his career, McPherson has built a strong reputation. He was a big part of the Bengals super bowl appearance his rookie year, making all 14 of his playoff attempts and immediately validating the Cincinnati Bengals' decision to draft a kicker (Sports Reference). Though he seems like a budding superstar, there are concerns with a young kicker. Recall that McPherson led the league in VolComp (seen in Figure 3). I created a late-game version of the same calculation, taking into account only kicks that occurred in the last 4 minutes of the fourth quarter or overtime. In this plot (Figure 7), McPherson falls to dead last by a remarkable margin. This could be a result of his team putting him in disproportionately challenging situations, but it is more likely that he just struggled late in games. While just taking the last 4 minutes shrinks sample size significantly and lacks nuance, it captures many of the high leverage attempts that kickers are forced to make. Kicking under pressure is the most important part of a kicker's job; if McPherson struggles, it will cost his team wins in the future. The dropoff in pressure scenarios from his seemingly successful playoff campaign the year before is startling, but probably just indicates growing pains. If McPherson can stay consistent and healthy, Tucker, Myers, Gano, and Koo have proven that aging is a good thing for kickers.

Discussion

The point of this paper is not to retroactively praise kicker's for their accomplishments in the past. It would be easy to just congratulate the kickers on top, but I want to dig deeper. Can we predict future success based on the data I've gathered? All of the kickers mentioned above have enjoyed good seasons since this data was collected (with the exception of Gano), each from a different stage in their career. A common theme in all of their careers is a cushion of a few years at the beginning to allow them to acclimate. Many kickers who struggle initially do not get the chance to develop their game in the NFL. With a limit of how many players can be kept on a team, teams are quick to cut kickers, who they deem as more replaceable than other positions on the roster. Many kickers do not get the chance to develop as a result. However, as seen with the older guys, having faith in your kicker might be the key to success. Tucker and Gano were given a few years to acclimate to the NFL, after which they thrived. Once Myers and Koo were given real chances, they found their footing and succeeded. McPherson, as a drafted player, was great immediately because his team trusted him. Their stories inform my hypothesis: the difference in talent amongst NFL kickers is so miniscule and the room for error so small, that the ability to perform under mental stress is the most important attribute for a professional kicker.

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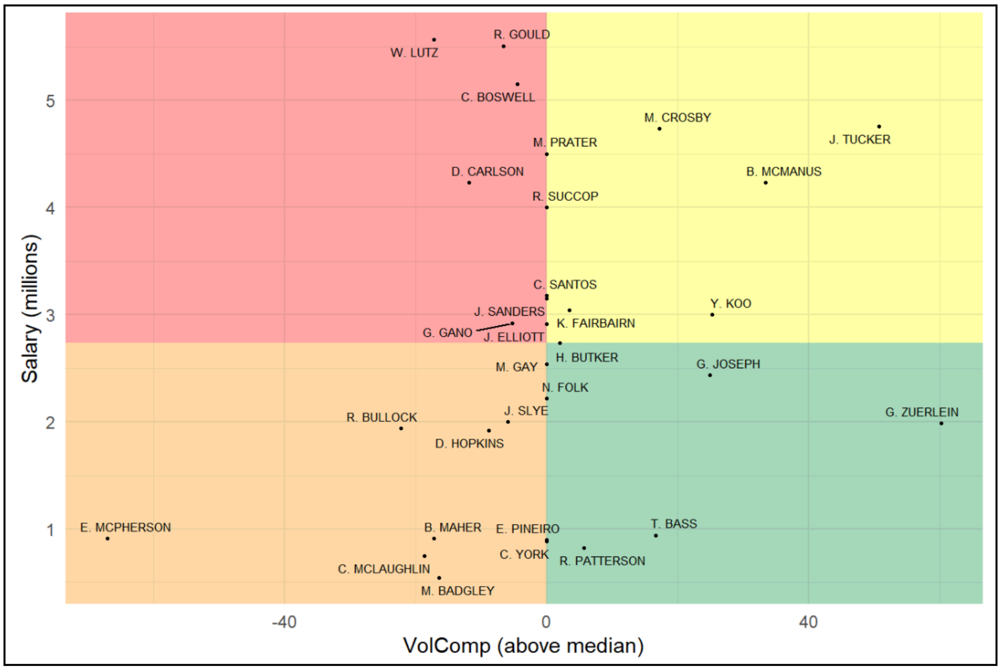
[1] Interestingly, Jason Myers was working valet in San Diego after college and did not find success until after bouncing around the NFL a bit (Condotta, 2023). Younghoe Koo was cut as a rookie, forcing him to take a year away from the NFL before eventually signing and sticking with the Atlanta Falcons (Sports Reference). Their late blooming most likely has something to do with having such tumultuous beginnings to their careers.

Figure 7

Late-game VolComp and Salary (2022)



Note. The above plot is the same as Figure 3, just recalculated on only late-game attempts. Each point indicates a kicker plotted by their salary and VolComp score. The quadrants are broken up by the median salary and median VolComp. Note that a smaller sample size makes this a more volatile calculation. Note that kickers with fewer attempts will tend towards the median.

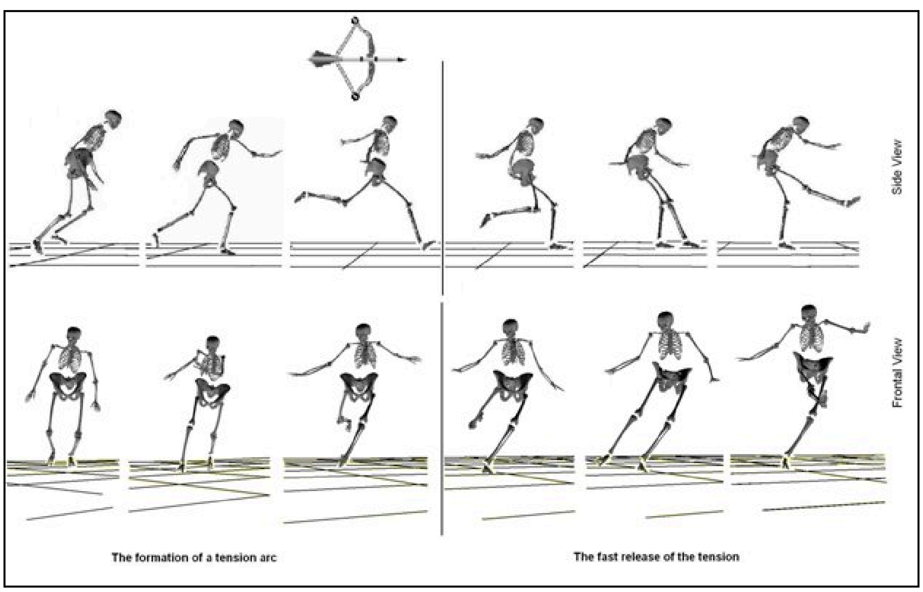
In September of 2021, Justin Tucker made the longest field goal in NFL history. Stunningly, the 66-yard attempt occurred with 3 seconds left with the game on the line. The combination of difficulty and pressure makes this one of greatest kicks of all time. How did he do it? Especially towards the beginning of his career, Tucker was not afraid to tweak his form. He watched film on other talented kickers, adopting the qualities that helped them perform. This was not remarkable on its own; all players watch film and change. What set Tucker apart from the rest was his coordination. His ability to keep the exact rhythm he wanted, even when he changed his method of striking the ball, is unmatched. Stephen Gostkowski, legendary kicker for the New England Patriots, called him “the most in-rhythm kicker that [he has] ever seen” (Hylton, 2022). Therein lies the key to professional success: consistency. Recall Figure 2 and Figure 4, and observe the consistency of Jason Myers. He hit the ball the same way every time. My data simply records the results of his consistency. Ideally, one could identify the root cause. If it was possible to know what was special about his ability, maybe it could be taught. Maybe, a team armed with the secret to kicking could *manufacture* the next Justin Tucker, Graham Gano, or Jason Myers. This secret is biometric data.

The next step in football analytics is modeling kickers’ movement. In the same way that baseball has used motion capture for pitching, golf for swinging, and basketball for shooting, placekickers will turn to biometric data collection to hone in on the optimal kicking strategy. Since it is one of the few activities in its sport that changes very little from practice to game, field goals are the obvious entry point for biometrics in football. By measuring the benchmarks of talented kickers, it is possible to identify commonalities between the best players and use that information to train others. Much of this biometric tracking has already been researched for soccer applications (Figure 8). By measuring knee and ankle flexion angles, quantifying the loads on limbs, and determining the way a player is balanced at the different stages of a kick, it is possible to identify an optimal form for both power and control (Bousfield, 2015). The point of my project is to demonstrate that an increase in data collection can create a more complete picture of what is actually happening on the field. By modeling this picture, we may better represent players and their abilities. However, my coordinate collection is just the beginning. The race for data in the NFL will accelerate soon, reshaping the viewing experience both in front offices and living rooms across the country..

Will fans notice any changes? Not at the moment. While it's possible that the NFL or individual teams keep coordinate-based field goal data and have started biometric tracking, it is not available to the public. Even if (or when) a third party like Amazon Web Services starts tracking it, the data will likely be used in-house for broadcasts and social media. The data itself may be provided to the public behind a paywall. As computer vision continues to improve, in-game ball and player tracking will become commonplace in all sports, but especially the NFL. The NFL is significantly behind schedule in the analytics department. Because of the number of positions, diversity in technique, and complexity of the game, creating football models is incredibly difficult. When combined with the old school reliance on the 'eye test' for player evaluation, this makes football data analysts' jobs an uphill battle. Eventually, it will happen. Eventually, analytics will take over like it has in baseball and basketball. Until then, fans should be wary of being too reliant on box score statistics.

Figure 8

Preliminary Biometric Tracking for Soccer



Note. The above depicts the six major phases of kicking a soccer ball from the front and side views. (Lees & Nolan, 1998)

Acknowledgements

Special thanks to Kirk Goldsberry, Lorenzo Dube, and Jeff Crosby. This project would not have been possible without the compiling efforts of @thatonefootballcardguy and @FrankieG on YouTube.

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