Does a Better Running Back Mean More Rushing? Game Theory and the NFL

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Does a Better Running Back Mean More Rushing?

Game Theory and the NFL

Eric Lofquist
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Table of Contents

Abstract........................................................................................................................................3
Introduction.................................................................4
Related Literature........................................................5
Data Description..........................................................7
Estimation Strategy........................................................8
Main Results......................................................................10
Case Studies....................................................................12
Caveats...........................................................................16
Discussion.......................................................................18
Bibliography....................................................................21

Appendices

Appendix A: Simple Run/Pass Game..............................35
Appendix B: Regression Set 1 Results............................38
Appendix C: Regression Set 2 Results............................39
Abstract

In this paper I attempt to answer the question of whether or not teams in the National Football League (NFL) rush less with a better running back. This seems counterintuitive, but game theory supposes that this is true. Defenses facing a better running back will generally expect the offense to rush more and therefore defend the run more often. The offense, foreseeing the defense’s actions, will choose to pass more to counteract the run defense. This is the basis of the difference between the strategic effect and the direct effect in mixed strategies. The direct effect is when a player takes an improved strategy more often. The strategic effect is when a player takes an improved strategy less often. I attempt to verify the game theory assumption that the strategic effect dominates the direct effect by analyzing data from all 32 NFL teams over 14 seasons. The data measures offenses’ play selection, rushing efficiency, passing efficiency, and ratings for running backs, quarterbacks, and offensive lines. After running regressions and analyzing specific cases, the results show that game theory is incorrect and the direct effect dominates the strategic effect. Teams rush more often with a higher rated running back than with a lower rated running back.
Introduction

In a simplified game within game theory, two players each have two strategies, the combinations of which yield different payoffs for each player. Sometimes a player in such a game does not have a dominant strategy. A lack of a dominant strategy means that the player does not have one strategy that always outperforms all other strategies. In the game of football the offense generally has two strategies: run and pass. The defense also generally has two strategies: defend the run and defend the pass. No team’s offense in the National Football League has a dominant strategy in this simplified game. If one did, that team would pass on 100% of plays or run on 100% of plays. When a player does not have a dominant strategy, that player resorts to mixed strategies, where a probability is assigned to each strategy. This is what we see in football games. Offensive play callers choose a certain percentage of passing and rushing plays. The only way the offense can maximize its payoffs is by making the defense indifferent between choosing to defend the run and defend the pass. The defense is made indifferent by assigning probabilities to the pass and rush so that the expected payoff from each is the same. If one strategy is improved, there are two effects: the direct effect and the strategic effect. The direct effect is when the player benefitted plays the improved strategy more often. The strategic effect is when the player benefitted plays the improved strategy less often. The strategic effect is the result of making the defense indifferent. When one strategy is benefitted, the defense will choose to defend it more often, so the offense should play it less often. Imagine in the NFL, a team suddenly acquires a superstar running back. Do they rush more or less? This is the question I seek to answer. I attempt to do this by regressing all of the variables and analyzing whether or not a benefit to rushing results in an increase in passing plays. The method

1 This theory is explained via an annotated, simplified example in Appendix A
by which I attempt to answer the question answers a slightly different question: Do teams with better running backs, all else equal, rush less than teams with worse running backs? With sufficient controls, I can accurately answer the primary question by looking at the data for all teams as opposed to a single team. In addition to the regressions I also analyze six specific instances for individual teams where there was a change to the primary running back in order to help answer the question of whether or not an improved strategy is played more or less.

**Related Literature**

Game theory has been used to analyze sports, including football, before. Such research has various implications on my research. In “Do Firms Maximize?” economist David Romer analyzes the choice of NFL teams on fourth down to either kick or try for a first down. Romer looks at average payoffs for kicking and trying for a first down to determine if teams really attempt to maximize their payoffs. Romer explains that NFL games are an ideal setting for game theory analysis because “there are copious, detailed data describing the circumstances teams face when they make… decisions” and profit-maximization is simplified to maximizing the probability of winning.² Romer’s research shows that teams’ choices on fourth down significantly depart from the profit-maximizing choices. Game theory does not always apply to real world situations. Romer’s work is complementary to my analysis because it confirms the viability of the study of game theory in NFL football.

In “Minimax Play at Wimbledon,” economists Mark Walker and John Wooders analyze professional tennis championship matches in an attempt to validate the Minimax Theorem of game theory, which concerns Nash equilibria in mixed strategies. Walker and Wooders analyze

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servers’ decisions to serve to the left or right of the receiver and who won the point. They state, “Many experiments designed to test the theory of mixed-strategy play using human subjects have been carried out” and “The theory has not fared well.”

This has implications for my research because at its core lies the decision of humans of how often to run and pass the ball given the quality of the running back. If game theory is typically not valid in real-world, mixed-strategy scenarios, then I may find the same in my research. Walker and Wooders find that the results of their research “are consistent with the minimax hypothesis.” It is therefore possible that the decisions of play callers conform to game theory and the strategic effect dominates the direct effect.

Economist Ignacio Palacios-Huerta also attempts to validate the minimax theorem using natural data in “Professionals Play Minimax.” Palacios-Huerta analyzes penalty kicks in professional soccer games. In a penalty kick, the kicker has the choice to kick left or right, and the goalkeeper has the choice to jump left or right. Palacios-Huerta finds his results “consistent with the implications of the Minimax theorem.” Again, this bodes well for the study of game theory in real-world scenarios. Palacios-Huerta’s research, like Walker and Wooder’s, provides the possibility of the validity of game theory in sports.

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Data Description

Dependent Variable

Passing Play Percentage (%): This variable measures the percentage of all offensive plays that are passing plays.

Independent Variables

Best Running Back Rating (Defense-adjusted Yards Above Replacement [DYAR]) (minimum 100 rush attempts): “This [variable] gives the value of the performance on plays where this RB carried/caught the ball compared to replacement level, adjusted for situation and opponent and then translated into yardage.” DYAR represents the total value of a running back.

Yards per Rush Attempt (yards/attempt): This variable measures the average number of yards gained by an offense per rushing attempt. This variable serves as a measure of the total effectiveness of an NFL team’s running back group. This variable is useful for situations when a team switched running backs or did not have a single starting running back.

Control Variables

Best Quarterback Rating (DYAR) (minimum 100 pass attempts): “This [variable] gives the value of the quarterback’s performance compared to replacement level, adjusted for situation

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6 Data for this variable obtained from Team Rankings  
7 Data for this variable obtained from Football Outsiders  
9 Data for this variable obtained from Team Rankings  
10 Data for this variable obtained from Football Outsiders
and opponent and then translated into yardage.” DYAR represents the total value of a quarterback.\textsuperscript{11}

Average Team Passer Rating (scale of 0-158.3)\textsuperscript{12}: Average passer rating of all passers on a team. This variable serves as a measure of the total effectiveness of an NFL team’s quarterbacks. This variable is useful for situations when a team switched starting quarterbacks for any reason.

Offensive Line Rating (Adjusted Line Yards [ALY])\textsuperscript{13}: ALY measures the running back yards for which the offensive line is partially responsible. ALY is adjusted for “down, distance, situation, opponent, and the difference in rushing average between shotgun compared to standard formations.”\textsuperscript{14} This variable measures the effectiveness of a team’s offensive line at run blocking.

**Estimation Strategy**

In order to estimate the effect of improved rushing on passing play percentage, I performed multiple linear regressions. I use two different sets of regressions. Both regression sets use passing play percentage as the dependent variable. The first set uses the individual statistic variables for the independent and first control variable. The second set uses the team statistic variables for the independent and first control variable. Both sets use the offensive line rating as the final control variable. Each regression set begins with no controls then controls are added one by one. The final estimating equations are as follows:

\begin{itemize}
  \item \textsuperscript{12} Data for this variable obtained from *Team Rankings*
  \item \textsuperscript{13} Data for this variable obtained from *Football Outsiders*
\end{itemize}
(Passing play percentage) = \alpha + \beta_1*(best \ running \ back \ rating) + \beta_2*(best \ quarterback \ rating) + \beta_3*(offensive \ line \ rating) + \epsilon \\
(Passing \ play \ percentage) = \alpha + \beta_1*(yards \ per \ rush \ attempt) + \beta_2*(average \ team \ passer \ rating) + \beta_3*(offensive \ line \ rating) + \epsilon \\

where:
\alpha = \text{constant}, \\
\beta_X = \text{coefficient for each explanatory variable}, \\
\epsilon = \text{error term}.

The reason I use both individual and team statistic variables is because of certain situations in the NFL. Occasionally, teams will not feature a single starting running back. They will sometimes utilize what is called a running back by committee. A running back by committee is a group of two or more running backs who share carries fairly equally. In this sense, a team’s statistically best running back may not actually rush any more than other running backs on the team, especially if the difference is small. Another situation is when injuries result in teams switching players at different times throughout the season. This could interfere with my analysis of the best running backs effect on passing play percentage, so I also collected data on team statistics. While the individual statistics measure the effectiveness of individuals, the team statistics measure the effectiveness of groups such as all of a team’s rushers and passers. These team statistics can account for the aforementioned situations that affect analysis of running back ratings on passing play percentage.
Main Results

The first set of regressions uses variables that measure individual statistics.

Regression Set 1

\[1.1\] (Passing play percentage) = \alpha + \beta_1*(best\ running\ back\ rating) + \varepsilon

\[1.2\] (Passing play percentage) = \alpha + \beta_1*(best\ running\ back\ rating) + \beta_2*(best\ quarterback\ rating) + \varepsilon

\[1.3\] (Passing play percentage) = \alpha + \beta_1*(best\ running\ back\ rating) + \beta_2*(best\ quarterback\ rating) + \beta_3*(offensive\ line\ rating) + \varepsilon

Regression 1.1 yields an \(\alpha\) value of 58.61 and a \(\beta_1\) value of -0.0180, both statistically significant at the \(p<0.01\) level. The \(R\)-squared value for this regression is 0.170. The results of this regression imply that an increase in running back rating decreases passing play percentage. If the strategic effect dominates the direct effect then we should see a positive correlation between the two. One problem is the fairly low \(R\)-squared. Only a small percentage of the variation in passing play percentage is explained by changes in running back rating. I can increase \(R\)-squared by including more variables in the regression as I do next.

Regression 1.2 yields an \(\alpha\) value of 58.07, a \(\beta_1\) value of -0.0207, and a \(\beta_2\) value of 0.00165, all of which are statistically significant at the \(p<0.01\) level. The \(R\)-squared value for this regression is 0.207. The increase in \(R\)-squared is good because it means I have included an additional explanatory variable: quarterback rating. The sign of the \(\beta_2\) coefficient means that an increase in the team’s best quarterback rating results in an increase in passing play percentage, which my intuition tells me is correct. The better a team’s best quarterback, the more effective he is at throwing the ball, so the offense will pass more. The negative \(\beta_2\) coefficient again means
that increasing a team’s best running back rating will result in less passing, or conversely, more running.

Regression 1.3 yields an $\alpha$ value of 74.50, a $\beta_1$ value of -0.0137, a $\beta_2$ value of 0.00221, and a $\beta_3$ value of -4.335, all of which are statistically significant at the $p<0.01$ level. The $R^2$ value for this regression is .256. The further increase in $R^2$ is good, although it remains somewhat low. The coefficient for best quarterback rating remains positive as expected. Once again, the coefficient for best running back rating is negative, which suggests that game theory is wrong. The coefficient for offensive line rating is exceptionally low. While I expect it to negatively correlate with passing play percentage because it measures an offensive line’s run blocking ability, it has the greatest effect of all the variables. This is likely due to the very high constant.

The second set of regressions uses the variables that measure team statistics.

**Regression Set 2**

[2.1] (Passing play percentage) = $\alpha + \beta_1*(\text{yards per rush attempt}) + \varepsilon$

[2.2] (Passing play percentage) = $\alpha + \beta_1*(\text{yards per rush attempt}) + \beta_2*(\text{average team passer rating}) + \varepsilon$

[2.3] (Passing play percentage) = $\alpha + \beta_1*(\text{yards per rush attempt}) + \beta_2*(\text{average team passer rating}) + \beta_3*(\text{offensive line rating}) + \varepsilon$

Regression 2.1 yields an $\alpha$ value of 57.97 significant at the $p<0.01$ level and a $\beta_1$ value of -0.265 statistically significant at the $p<0.1$ level. The $R^2$ value for this regression is 0.008. The most obvious problem with this regression is the extremely low $R^2$ value. Team rushing yards per attempt can only explain eight-tenths of one percent of the variation in passing play percentage. Additionally, the coefficient for team rushing yards per attempt is
statistically significant at the lowest level. The results of this regression do not suffice for answering the question of whether or not the strategic effect dominates the direct effect.

Regression 2.2 yields an \( \alpha \) value of 55.68 significant at the \( p<0.01 \) level, a \( \beta_1 \) value of -0.263 significant at the \( p<0.1 \) level, and a \( \beta_2 \) value of 0.0272, which is not significant. The R-squared value for this regression is .012. The R-squared value remains low, which is troubling. The lack of greater statistical significance of \( \beta_1 \) and any significance of \( \beta_2 \) in combination with the low R-squared value means the results of this regression are also not useful in evaluating the accuracy of game theory.

Regression 2.3 yields an \( \alpha \) value of 76.19, a \( \beta_1 \) value of -0.136, a \( \beta_2 \) value of 0.0823, and a \( \beta_3 \) value of -6.389. \( \alpha, \beta_2, \) and \( \beta_3 \) are all statistically significant at the \( p<0.01 \) level. \( \beta_1 \) is not statistically significant. The R-squared value for this regression is .179. The lack of significance of the \( \beta_1 \) value means that it cannot be accurately used to describe the effect of team rushing yards per attempt on passing play percentage. The coefficients of the other variables can, however. The signs of the \( \beta_2 \) and \( \beta_3 \) coefficients are as expected. Passing play percentage increases with average team passer rating and decreases with offensive line rating. While the R-squared value increases significantly from regression 2.1, it is still fairly low. The statistically significant variable coefficients only explain 17.9% of the variation in passing play percentage.

**Case Studies\(^{15}\)**

Oakland Raiders (2011-2012)

In the 2011-2012 NFL season, Oakland Raiders’ starting running back Darren McFadden was injured during the team’s seventh game. He started the six games prior. Running back

\(^{15}\) All information on injuries, pass attempts, and rush attempts from *Pro Football Reference*
Michael Bush replaced the injured McFadden, starting the remaining games of the season.

Darren McFadden was injured after only two rushes. Michael Bush totaled 17 rushes, earning the title of starter for that game. During the first six games of the season, with Darren McFadden (DYAR = 87) at starting running back, the Oakland Raiders passed on an average 48.701% of offensive plays. When Michael Bush (DYAR = 65) started, the Oakland Raiders passed on an average 55.539% of offensive plays. This contradicts game theory’s assumption that the strategic effect dominates the direct effect. The Oakland Raiders’ rushing strategy in a simplified game was devalued. Their passing strategy therefore became relatively better. Had the strategic effect dominated, the Oakland Raiders would have rushed more with Michael Bush than Darren McFadden, but they did not.

Houston Texans (2013-2014)

During the 2013-2014 NFL season, the Houston Texans’ starting running back Arian Foster suffered a season-ending injury. He started six full games for the Texans before being injured in the team’s seventh game. He played in one other game, but did not participate enough to be considered the starter. His replacement was Ben Tate, who started games seven through sixteen for the Houston Texans. With Arian Foster (DYAR = 99) starting, the Houston Texans passed on an average 59.418% of offensive plays. With Ben Tate (DYAR = 50) starting, the Houston Texans passed on an average 60.489% of offensive plays. The Houston Texans passed more when they were forced to start a lower rated running back, contrary to what game theory predicts.
Kansas City Chiefs (2015-2016)

The Kansas City Chiefs’ starting running back Jamaal Charles tore his ACL in the Chiefs’ fifth game of the 2015-2016 NFL season. The injury ended his season. Charcandrick West replaced Jamaal Charles, starting the remainder of the Kansas City Chiefs’ games. Jamaal Charles had the most carries of any running back during the team’s fifth game. I therefore count Jamaal Charles as the starter for the fifth game and each of the previous games. During the games in which Jamaal Charles (DYAR = 96) started, the Kansas City Chiefs passed on an average 57.525% of offensive plays. When Charcandrick West (DYAR = 77) started for the Kansas City Chiefs the team passed on an average 49.266% of offensive plays. Interestingly, after the Kansas City Chiefs suffered a loss at the starting running back position, they rushed significantly more. In this situation, game theory is validated. The Kansas City Chiefs rushed more with a worse running back.

San Francisco 49ers (2015-2016)

Running back Carlos Hyde started the first seven games of the 2015-2016 NFL season for the San Francisco 49ers before suffering a season-ending injury. Running back Mike Davis started the eighth and sixteenth games of the season, spending the intermediate games on the sidelines due to injury. Running back Shaun Draughn started games nine through fifteen. With Carlos Hyde (DYAR = 60) starting at running back, the San Francisco 49ers passed on an average 52.294% of offensive plays. With Mike Davis (DYAR = -13) or Shaun Draughn (DYAR = -24) starting, the San Francisco 49ers passed on an average 61.531% of offensive plays. Contradictory to game theory, the San Francisco 49ers rushed less often after worse running backs replaced their starter.
Pittsburgh Steelers (2015-2016)

Le’Veon Bell, the Pittsburgh Steelers starting running back, suffered a season ending injury in the team’s eighth game of the 2015-2016 NFL season. Running back DeAngelo Williams started the first two games of the season while Le’Veon served a 2-game suspension for a violation of the NFL’s substance abuse policy. DeAngelo Williams also started the last eight games of the season after Le’Veon Bell’s injury. With Le’Veon Bell (DYAR = 162) starting, the Pittsburgh Steelers passed on an average 52.385% of offensive plays. With DeAngelo Williams (DYAR = 184) starting, the Pittsburgh Steelers passed on an average of 63.730% of offensive plays. DeAngelo Williams at starting running back benefitted the Pittsburgh Steelers rushing strategy in a simplified game. Game theory dictates that a player will play the improved strategy less often. This is the case in this example. The Steelers passed more with a better starting running back. In this example, game theory is valid.

Denver Broncos (2016-2017)

Running back C.J. Anderson started the first six games of the 2016-2017 NFL season for the Denver Broncos. In the team’s seventh game, he was injured. He missed a few plays before returning to the game. Running back Devontae Booker narrowly out-carried C.J. Anderson in this game and is therefore the starter. The Denver Broncos placed C.J. Anderson on the injured reserve list due to his injury before the team’s next game, ending his season. Devontae Booker started games seven through 12. Running back Justin Forsett started the thirteenth, fourteenth, and sixteenth games for the Denver Broncos. In the team’s fifteenth game, Justin Forsett and Devontae Booker split carries equally. In the first six games of the season, with C.J. Anderson
(DYAR = -24) starting, the Denver Broncos pass on an average 57.244% of offensive plays. In the team’s last ten games, with Devontae Booker (DYAR = -98) or Justin Forsett (DYAR = -91), the Denver Broncos passed on an average 59.398% of offensive plays. In this case, game theory is not valid. The Broncos’ rushing strategy was worsened. Their passing strategy became relatively better. However, the Broncos passed more with the worse starting running backs, meaning the direct effect dominated the strategic effect.

Caveats

There are a few conditions that limit the validity of the research and the ability to make a definitive conclusion. At the core of this research are the variables that are used to estimate the effect of rushing ability on passing play percentage. These variables are not perfect. While the individual statistic variables and the offensive line ratings are adjusted for the level of defense faced during the season, some of the variables are codependent. The metric for offensive line rating is partly based on running back performance, which is used to measure the effectiveness of the offensive line at run blocking. In addition to the limited quality of the variables, there is limited quantity of control variables. There are certain things that happen in an NFL game that are hard to quantify. There exists a vast array of variables on NFL teams’ statistics but only so many of them are relevant. It is difficult to include a large number of these variables without their descriptive ability overlapping.

Passing play percentage is not an entirely accurate variable. Not every passing play is recorded as such. A passing play can quickly turn into a rush play if the quarterback has no open receivers and runs for a gain. Also, some rushing plays may be recorded as passing plays. If the quarterback is sacked on a designed quarterback rush play, it may be recorded as a passing play,
and a failed one at that. If a quarterback’s handoff to a running back is botched, the quarterback may recover the ball on the ground and be touched down. This fumble may be recorded as a passing play because it is technically a sack. Play calling also varies based on the game situation, which passing play percentage does not account for. If a team is winning by a significant amount of points, they are going to run the ball more, regardless of their starting running back’s ability. Similarly, if a team is trailing by a significant amount of points, they are going to pass the ball more in an attempt to drive down the field and catch up, regardless of the starting quarterback’s ability. Play calling therefore depends somewhat on the success of the team’s defense at stopping the other team from scoring.

The case studies provide some semblance of hope for the validity of game theory. These case studies however are not all-inclusive. Each one only measures the passing play percentage by game for an entire season, and divides the games among different starting running backs based on injury. The studies do not account for the different opponents faced, which could affect play calling. Some games were attributed to a running back as his start despite the running back only getting one more carry than the next running back. By analyzing a single team over a single season, I limit differences that could be attributed to changes in passing play percentage without needing control variables. However, changes may have occurred to the team during the season in question that could affect passing play percentage. For instance, if a team’s starting quarterback were injured during the season it could affect passing play percentage, but it would not be attributed to the quarterback’s injury. It could be attributed to a starting running back’s injury. Ideally, a team in the case studies will have experienced no other changes to its roster, so any change in passing play percentage could be accurately attributed to the running back, and
nothing else. In the case studies, all changes in passing play percentage are attributed to the team’s starting running back.

**Discussion**

In mixed strategies of game theory, there are two results of an improved strategy. The direct effect is that the benefitted player chooses the improved strategy more often. The strategic effect is that the benefitted player chooses the improved strategy less often in an attempt to keep his opponent indifferent. Applied to football, if a team’s running back suddenly improves, would the team rush more or less? This is the question I have attempted to answer. According to the regression results, teams with better running backs tend to rush more. There is a negative correlation between running back ratings and passing play percentage. If a team’s running back improves, the team is likely to rush more. The collection of data and performance of regressions enable me to analyze a large sample size: 32 NFL teams over 14 seasons. This data provides the best tool for predicting what happens over most of the league. The regressions teach us that individual statistics are more predictive than team statistics. Focusing solely on the team’s starting running back yields a higher R-squared value than focusing on the team’s general rushing ability. Team statistics can include rushing plays not executed by running backs and passing plays not executed by quarterbacks, the two of which are the center of the offense. Team statistics also include plays run by backups that affect the statistics, especially averages, even though they do not constitute the majority of play. The regressions also teach us that offensive lines greatly affect the choice between running and passing, perhaps more than any other position group. A running back’s ability to run and a quarterback’s ability to pass greatly depend
on the offensive line’s ability to run and pass block, creating holes for the running back and time for the quarterback.

In addition to the regressions, I analyzed six instances in which a team lost its starting running back due to injury. Since teams usually start their best-rated running back, the starters were replaced by lower rated running backs in five of the six instances. Only in one instance was the starting running back replaced by a higher rated backup. After worse running backs replaced the starters, the team should have passed less according to game theory. When the better running back replaced the starter, game theory predicts the team would pass more. These scenarios happened only twice out of the six instances: to the 2015 Pittsburgh Steelers and the 2015 Kansas City Chiefs. The Chiefs replaced their starting running back with a worse one, but passed less, choosing to rush more often. The Steelers replaced their starting running back with a better one, but passed more, choosing to rush less often. These two instances provide some slim hope for the validity of game theory. There are a few reasons for game theory’s lack of ability to predict effects on mixed strategies. One reason could be that the assumption of rationality of players is false. Most, if not all, play callers in the NFL are not trained econometricians or game theorists. They may make the obvious choice of choosing to play the improved strategy more often without thinking of what the defense is expecting.

The research I have conducted is not conclusive enough to explicitly state that game theory’s prediction that the strategic effect dominates the direct effect is false. Regressions yielded R-squared values too low to deny the plausibility that game theory is valid. The regressions would have been improved with greater observations and the inclusion of more variables but there is an unfortunate unavailability of data. While the case studies provide at least two instances where game theory’s prediction is valid, the sample size of case studies is too
small to conclude anything. Based on the results at hand, the direct effect dominates the strategic
effect and game theory’s prediction is invalid. Teams with better running backs rush the ball
more so a team whose starting running back suddenly improves is likely to rush the ball more as
a result, contrary to game theory’s prediction.
Bibliography


Appendices

Appendix A: Simple Run/Pass Game

The offense chooses to either run or pass the ball. The defense chooses to either defend the run or defend the pass. Payoffs are given in terms of yardage.

<table>
<thead>
<tr>
<th></th>
<th>Defense</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Defend Run (x)</td>
<td>Defend Pass (1-x)</td>
</tr>
<tr>
<td>Run (q)</td>
<td>0, 0</td>
<td>5, -5</td>
</tr>
<tr>
<td>Pass (1-q)</td>
<td>9, -9</td>
<td>0, 0</td>
</tr>
</tbody>
</table>

These payoffs are randomly assigned. Yards per pass attempt typically exceed yards per rush attempt, so payoffs for passing exceed payoffs for running. We assume that if the defense predicts the play type correctly and defends accordingly, the play will result in no gain or loss. We assume that if the defense predicts the play type incorrectly and defends accordingly, the offense successfully gains yardage.

In the game above, neither player has a dominant strategy. As a result, each player resorts to mixed strategies, where a probability is assigned to each pure strategy (run, pass, defend run, defend pass). These probabilities are represented by the variables q and x. Each player maximizes his own expected payoffs by equating his opponent’s payoffs for each pure strategy. This is done mathematically.

\[ q = \text{percentage of plays offense runs} \]

\[ 1 - q = \text{percentage of plays offense passes} \]

Defense can choose to either defend the run or defend the pass. Following are the expected payoffs for each of the defense’s pure strategies based on the offense’s choice of q.
Defend run: $0q + (1-q)(-9) = 9q – 9$

Defend pass: $-5q + (1-q)(0) = -5q$

These payoffs are then equated.

$$9q – 9 = -5q$$

$$14q = 9$$

$$q = 9/14 = .64$$

Based on mixed strategies the offense will run on 64% of plays and pass on 36% of plays.

$x =$ percentage of plays defense defends run

$1 – x =$ percentage of plays defense defends pass

Offense will either run or pass. Following are the expected payoffs for each of the offense’s pure strategies based on the defense’s choice of $x$.

Run: $0x + (1-x)(5) = 5 – 5x$

Pass: $9x + (1-x)(0) = 9x$

The payoffs are then equated.

$$5 – 5x = 9x$$

$$5 = 14x$$

$$x = 5/14 = .36$$

Based on mixed strategies, the defense will defend the run on 36% of plays and defend the pass on 64% of plays.

Now, suppose that the offense’s running game improves. The pass payoffs remain the same while the run payoffs improve.
<table>
<thead>
<tr>
<th></th>
<th>Defend Run (x)</th>
<th>Defend Pass (1-x)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Run (q)</td>
<td>1, -1</td>
<td>8, -8</td>
</tr>
<tr>
<td>Pass (1-q)</td>
<td>9, -9</td>
<td>0, 0</td>
</tr>
</tbody>
</table>

Still, neither player has a dominant strategy. We then recalculate the players’ mixed strategies based on the new payoffs.

The offense equates the defense’s expected payoffs by choice of $q$.

Defend run: $-1q + (1-q)(-9) = 8q - 9$

Defend pass: $-8q + (1-q)(0) = -8q$

$$8q - 9 = -8q$$

$$16q = 9$$

$$q = 9/16 = .56$$

Based on mixed strategies, the offense will run on 56% of plays and pass on 44% of plays.

The defense equates the offense’s expected payoffs by choice of $x$.

Run: $1x + (1-x)(8) = 8 - 7x$

Pass: $9x + (1-x)(0) = 9x$

$$8 - 7x = 9x$$

$$8 = 16x$$

$$x = 8/16 = .5$$

Based on mixed strategies, the defense will defend the run on 50% of plays and defend the pass on 50% of plays.
According to mixed strategies in game theory, an offense will run less after a benefit to its run strategy. This is the strategic effect of an improved strategy. If we ignore mixed strategies and pay attention to the real world, where players are not always rational, the offense would likely run the ball more, because that is people’s general intuition. This is the direct effect of an improved strategy.

Game theory makes assumptions of rationality and common knowledge that steer the game in a certain direction. Game theory assumes that each player is rational and will take the appropriate actions to maximize his payoffs. Game theory therefore supposes that the strategic effect would be the true outcome. Hence the strategic effect dominates the direct effect.

Appendix B: Regression Set 1 Results

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable: Passing Play Percentage</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Best Running Back DYAR</td>
<td>-0.0180***</td>
<td>-0.0207***</td>
<td>-0.0137***</td>
</tr>
<tr>
<td></td>
<td>(0.00189)</td>
<td>(0.00194)</td>
<td>(0.00229)</td>
</tr>
<tr>
<td>Best Quarterback DYAR</td>
<td>0.00165***</td>
<td>0.00221***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000365)</td>
<td>(0.000369)</td>
<td></td>
</tr>
<tr>
<td>Offensive Line Adjusted Line Yards</td>
<td>-4.335***</td>
<td></td>
<td>(0.811)</td>
</tr>
<tr>
<td>Constant</td>
<td>58.61***</td>
<td>58.07***</td>
<td>74.50***</td>
</tr>
<tr>
<td></td>
<td>(0.288)</td>
<td>(0.307)</td>
<td>(3.087)</td>
</tr>
<tr>
<td>Observations</td>
<td>443</td>
<td>443</td>
<td>443</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.170</td>
<td>0.207</td>
<td>0.256</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Appendix C: Regression Set 2 Results

<table>
<thead>
<tr>
<th>VARIABLES</th>
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<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable: Passing Play Percentage</td>
<td>0.265*</td>
<td>0.263*</td>
<td>-0.136</td>
</tr>
<tr>
<td>Rushing Yards per Attempt</td>
<td>(0.142)</td>
<td>(0.142)</td>
<td>(0.130)</td>
</tr>
<tr>
<td>Average Team Passer Rating</td>
<td>0.0272</td>
<td>0.0823***</td>
<td>(0.0194)</td>
</tr>
<tr>
<td>Offensive Line Adjusted Line Yards</td>
<td>-6.389***</td>
<td>(0.672)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>57.97***</td>
<td>55.68***</td>
<td>76.19***</td>
</tr>
<tr>
<td>(0.644)</td>
<td>(1.823)</td>
<td>(2.725)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>448</td>
<td>448</td>
<td>448</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.008</td>
<td>0.012</td>
<td>0.179</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1