NFL Football Data Analysis

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The Data Sets:

We have compiled NFL team data sets totaling 24 teams with 17 variables and 41 observations (16,728 Total Data points):

(1) NFL Team statistics (1976 - 2016)
(2) NFL Team Revenue (2001 – 2016)
(3) NFL Team Salary Capacity (2011 – 2016)
(4) Major Rule Changes (1994 - 2005)

Data	Variable
Total Losses	l
Losses at Home	l.h
Losses on the Road	l.r
Offensive Leaders (In top 15)	lead.o
Defensive Leaders (In top 15)	lead.d
Net Points (pf - pa)	netpt
Points Against (Opponents' points)	pa
Win Percentage	pct
Penalty Yards	peny
Points For (Team's points)	pf
Points Per Game	ppg
Touchdowns	td
Total Wins	w
Wins at Home	w.h
Wins on the road	w.r
Yards Per Game	ypg
Yards Per Play	ypp
Franchise Revenue	rev
Team Salary Cap	salary

Analyses Performed:

(1) Can we build a multivariate regression model to predict and model a team's winning percentage?
(2) Is there a "Home field advantage" in Football?
(3) How does pay and performance relate?
(4) How have major rule changes affected the sport?

1 Multivariate Regression Model Construction

To study the data, we wrote functions to create full team-specific data sets with all of a team's variables in one data frame. We wrote functions to create correlation tables of a teams' parameters, as well as an aggregate data correlation table, which compiled all of the observations per variable into lists and checked their correlations with each other. We also developed a regression analysis table, where the data shows the r-squared fit of the relationships in a matrix output. These data tables confirmed our suspicions of strongly related variables. Win and loss variables were often negatively correlated and because almost half of our data was derived from other variables such as with wins

$$w = w.h + w.r$$

and net points scored

$$netpt = pf - pa$$

there were predictable strong relationships. This was an issue because such correlations are redundant and can hurt the accuracy of regression models and the ability to optimize the predictor pool.

(Figure 1) We designated levels for the direction and strength of correlations in the data in the following manner:

Strong Negative	(-1 : -0.80]
Negative	(-0.81 : -0.51]
Weak Negative	(-0.50 : -0.10]
NA (Very weak)	(-0.10 : 0.10]
Weak Positive	(0.10 : 0.51]
Positive	(0.51 : 0.80]
Strong Positive	(0.81 : 1)

We constructed a correlation table for the full data set of predictors against each other, categorized them and observed the results of the group. There existed few strong relations (less than 17%) but about half were either positive or weak positive. Overall, about 60% of our data was positively correlated with other predictors and around 16% was within a very weak range [-0.1 : 0.1] which indicated that there was a significant level of independent relationships. Overall, the data shows a distribution skewed to the left (negative correlations) with mostly positive relationships. We also analyzed the individual teams' data sets and correlations but those internal-team relationships were less important to the scope of our project. However, this would be of great use in a project for predicting the winners of certain games by creating models for predicting team score a binary response of win/lose. When looking at the aggregate data (full variable) relationships in terms of linear association, we constructed a matrix of r-squared values for all possible single model regressions. We set a threshold value for r-squared at 0.5 (roughly a 50% relationship) and observed that 83 of the 272 (30.5%) values in the matrix were at or above this threshold. At a threshold of 0.7, there are 53 relationships (19.5%) at/above that threshold and at 0.9 there are 23 (8.5%). This included the obvious and derived-variable relationships.

To create the multivariate regression model, we utilized the step wise methodology as well as the all possible regression function demonstrated in class. With these two (2) methodologies, we constructed two (2) new models with each iteration. In each iteration we checked the co-linearity of the predictors to remove the most highly correlated variable. After we we dropped the variable from the data we would again construct 2 models, check their summaries for fit and significance levels and then analyze their residuals to assess normality of the data. We continued this process of check/eliminate to obtain an optimized model as thoroughly as possible.

Initially, the models had very large r-squared values and low std. error in their residuals, but the co-linearity was extremely large (Figure 1). The team data collected is highly correlated because the variables are so closely related in origin. Multiple variables have their value derived from two (2) or more of the other variables in our selected universe. This would need to be addressed thoroughly to construct the best possible model.

```
[1] "Threshold:  3.459e+15"
             Check
l.r   4.811936e+15
netpt 5.132586e+15
w     5.053356e+15
w.r   5.022202e+15
      Most Correlated with Correlation
l.r                    w.r   1.0000000
netpt                    w   0.8930777
w                    netpt   0.8930777
w.r                    l.r   1.0000000
```

Figure 1: Regression Model - High Co-linearity Exists

```
[1] "Threshold:  1.713"
       Check
pa  1.788898
ypp 1.777643
    Most Correlated with Correlation
pa                 peny   0.2047238
ypp              lead.o   0.4819462
```

Figure 2: Regression Model - Co-linearity Reduced

After 10 iterations (20 models), the co-linearity was reduced to a very reasonable level (Figure 2) where the threshold value (quartile 3 for the co-linear coefficients) was just above the average. The models now contained less but much more significant predictors. We generated a summary table in our source code showing the r-squared, std. error of the residuals and the AIC value of each model so that we could see the change. We also included a "Co-linearity monitor" column that tracked the current threshold for too much correlation and how many predictors cross that threshold. The table shows, by those statistics, that our newer models were slightly inferior in fit and accuracy (higher variance), but the older models incorporated very col-linear predictors that would have made predictions harder to accurately achieve. When we looked at the residuals, however, we noticed the histograms were becoming skewed and the boxplots() were showing large numbers of outliers as well. The qqplot() was also diverging from normality, which meant that while we had reduced correlation and optimized the model predictors as a whole, we should look to transformations to attempt to coerce the residuals closer to a normal distribution.

We then moved on to analyze the predictors by themselves and attempt to transform them with log base transforms as well as polynomial steps. After each transform the model summary statistics are logged for a "rolling analysis" as we actively made adjustments to the transforms. We chose model 20 because it was the most optimized and every predictor except for one was significant below 0.001. We tested the effects of transforming the variables on the model summary statistics and residuals, eventually finding a model that had improved over the previously chosen one. The improvement is small, however, and the residuals are still showing abnormal traits, which indicates to us that this data alone will not be a reliable model-building tool kit. For true prediction based experiments, we will need to dig deeper into the team fundamental components such as individual player data, past game performance against certain opponent types ("back-testing" for football) and a good amount of probability theory as well.

Concluding Model and Analysis

We have compiled our models and assembled our final analysis table to choose our model. We compared the full model from the beginning of our optimization procedure with the resulting model, the transformed model and a model using 3 of the 6 predictors as factors (Figure 3).

	R-sqr	sigma	AIC
Full Model	0.9933	0.01542	-5413
Optimized	0.9721	0.03159	-3998
Optimized + Transformed	0.9773	0.02880	-4163
Opt/Trans with factors	0.9773	0.02880	-4163

Figure 3: Regression Model - Final 4 models compared for selection

Using the form

$$\mu_y = b_0 + b_1x_1 + b_2x_2 + ... + b_px_p + \epsilon$$

for a multivariate regression line, our final model is

$$pct_y = 1.0085 + lead.o(0.0048) + log(pa)(-0.1432) + log(peny)(-0.0326) + w.h(0.0543) + w.r(0.0564) + log(ypp)(0.0635)$$

and it is the best fitting model we could construct given the data we used. The model summary (Figure 4) shows that all predictors are very significant and the r-squared and adjusted r-squared values show a good fit as well. When we look at the residuals (Appendix: Figure 13), however, we realize the limitations of the model as a prediction model. The residuals show many outliers, a right-skewed distribution and the QQplot() we constructed diverges from the normal distribution. In conclusion, while the model has been optimized, the variance of the residual error will severely limit the accuracy of the model.

```
Call:
lm(formula = pct ~ lead.o + log(pa) + log(peny) + w.h + w.r +
    log(ypp), data = all.data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.08177 -0.01510 -0.00167  0.01165  0.30770

Coefficients:
             Estimate Std. Error t value             Pr(>|t|)
(Intercept)  1.008456   0.037020   27.24 < 0.0000000000000002 ***
lead.o       0.004806   0.001425    3.37              0.00077 ***
log(pa)     -0.143226   0.005547  -25.82 < 0.0000000000000002 ***
log(peny)   -0.032596   0.004738   -6.88       0.000000000011 ***
w.h          0.054296   0.000645   84.13 < 0.0000000000000002 ***
w.r          0.056442   0.000679   83.09 < 0.0000000000000002 ***
log(ypp)     0.063478   0.011656    5.45       0.000000065180 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0289 on 977 degrees of freedom
Multiple R-squared:  0.977,     Adjusted R-squared:  0.976
F-statistic: 6.8e+03 on 6 and 977 DF,  p-value: <0.0000000000000002
```

Figure 4: Regression Model - Best Model selected - Summary

2 Checking the significance of "home field advantage"

In baseball, the "home field advantage" is a logical name for the home team's right to bat last and get the last chance to score and win the game. In football, however, coin tosses provided 50/50 probabilities and possession of the offensive is dictated by a team's ability to take and keep it. There is no special privilege granted to the home team over the away team in the degree that exists in baseball. We suspected that this would mean that a "home field advantage" in football would be unlikely to exist but the results of our tests are surprising. We compiled Student T-tests using a two-tailed approach of the team's data for w.h and w.r over the full 41 year time period. The Null hypothesis of this test states that the two data sets' means should not differ significantly; the confidence interval will pass through 0 and the therefore the p-value statistic will not be at or below the 95% confidence level (0.05). Looking at the data table, the confidence intervals are shown with the p-value of tests. In addition, the sample means are also shown to support the test results. At the bottom of the data set, there are two (2) rows that identify how many of the 24 teams' t-tests were significant below the respective thresholds. These results clearly state a significance to the "home field advantage" in football. The p values of 21 out of 24 teams (87.5%) are at or below 0.05 (Figure 5). To verify this data, please see (Appendix: Figure 14) where the accompanying confidence intervals are shown to not pass through 0 and the means of w.h are always greater than those in w.r. The only three (3) teams do not support this conclusion (outliers) are the Giants, Raiders and Saints. To assess the reason for these outliers, we would need to conduct an additional analysis on the teams individually, which we unfortunately were unable to conduct due to the nature of our other project experiments.

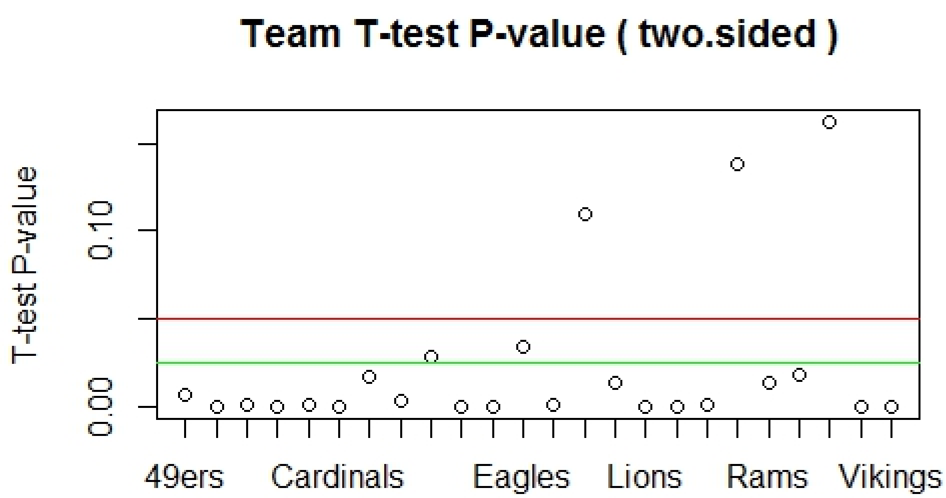

Figure 5: Two-sided Student T-test p values for NFL Teams - w.h w.r

We next checked to see how these results compared to the sport-wide data t-tests. With the string initial results, we expected the league as a whole to have similar results over larger time frames but needed to verify if this was simply a function of larger data sets or if this was significant throughout multiple time periods. The results were equally strong in favor of the "advantage" when looking at 5 year intervals from 1976 to 2016 (a 6 year interval was used from 2011 - 2016) (Figure 6).

	CI.low	CI.high	P.value	Mean (home)	Mean (rode)	Median (home)	Median (rode)	Std.dev (home)	Std.dev (rode)
Last 5 years	0.69277	1.5406	4.5185e-07	4.7167	3.6000	5	4	1.6962	1.6368
Last 10 years	0.71056	1.3561	7.1564e-10	4.6292	3.5958	5	3	1.8250	1.7736
Last 15 years	0.84120	1.3644	6.1520e-16	4.6417	3.5389	5	3	1.7873	1.7878
Last 20 years	0.97240	1.4276	7.3952e-24	4.6625	3.4625	5	3	1.7892	1.8043
Last 25 years	1.06171	1.4616	3.3048e-33	4.6900	3.4283	5	3	1.7755	1.7550
Last 30 years	1.08375	1.4468	4.2336e-40	4.6944	3.4292	5	3	1.7764	1.7350
Last 35 years	1.04252	1.3813	2.2142e-42	4.6321	3.4202	5	3	1.8056	1.7333
Last 41 years	1.07429	1.3851	2.5059e-51	4.6199	3.3902	5	3	1.7986	1.7153

Figure 6: Two-sided Student T-test result summary - Full league with varying time frames - w.h   w.r

Conclusion

We have verified two (2) major conclusions: (1) For the majority of teams in the NFL, there exists a "home field advantage" and (2) this advantage is consistent over 5 year time frames over the last 41 years. We speculate that there is some form of a physiological causation resulting from the home teams' fans support and the idea of protecting one's home turf. This is not an unfamiliar argument throughout sports globally and while we have not tested this idea, we believe it may be a valid argument and a good place to start further research and analysis.

3 How specific pay and performance variables relate and predict team performance

Athletes are some of the highest paid individuals in the world and we wanted to analyze our data and see if we could make some conclusions about pay and performance. Our data set for franchise revenue spans 16 years (2001 - 2016) and 6 years for the team's salary cap (2011 - 2016). The same analyses we will discuss were done on the 4 predictors chosen individually for their maximum data-collection time frames as well. We will comment on these results in the conclusion as complimentary information but we will not detail those tests here as the objective of the experiment is to fairly compare the variables. After manipulating the data into a usable, properly timed data set (6 years) to analyze the variables under the same assumptions, we created correlation matrices and regression tables to examine the relationships. This was done because the delimiting variable salary only hold data for 6 years. For this experiment our variables were selected and divided as the following:

Predictors	lead.o, lead.d, salary, rev
Observations	l, netpt, pct, peny, ppg, td, w, ypg, ypp

We chose lead.o and lead.d to represent "performance" because they show how many players each team had per year in the top 15 offensive and defensive ranked spots. There are 3 categories for offense and defense, each ranking players bases on specific performance metrics and we selected the top 5 as the best of the best per year. We omitted the teams: Chiefs and Rams, because we were unable to collect their franchise revenue data, so to keep out data consistent we have eliminated them from this analysis (we are only looking at 22 of the 24 teams).

We built the correlation matrix, then categorized the data in the same manner as we did for our first experiment (see section 1 for correlation threshold levels). We then counted the data and filled a summary table of our findings for the overall correlations of the data set an the variables individually. The breakdown for the entire matrix in terms of their correlation levels (Appendix: Figure 15) show that 43.6% of the relationships are in a range of -0.1 to 0.1, which indicates a very low level of correlation in both directions for almost half of the data set. Weak correlations constitute 24% of the data set and only 12% of the relationship are strong. Positive relationships overall were greater than negative relationships with 45% and 11% respectively. We can see the counts of the individual variables, paying specific attention to the 4 predictors chosen, indicate mostly uncorrelated relationships and few weak positive ones.

To make a clearer comparison, we take a look at the boxplot of this data set (Figure 7), which is constructed based on the numerical correlation matrix results. We observe that salary and rev are very poorly correlated with the rest of the data set overall, while lead.o and lead.d show, comparatively, better relationships. Of those 2, lead.o is clearly the more correlated variable, the greatest of the 4 as well.

Next, we looked specifically at the prediction strength through a simple linear regression matrix that reported the r squared values as output. The r squared statistic shows how much the x variable (independent predictor) explains the y variable (dependent response). To categorize this data, we used the following levels:

Negative	¡= 0
Weak	(0.01 : 0.2]
Semi-Weak	(0.2 : 0.4]
Average	(0.4 : 0.6]
Semi-strong	(0.6 : 0.8]
Strong	(0.8 : 0.9]
Very Strong	> 0.9

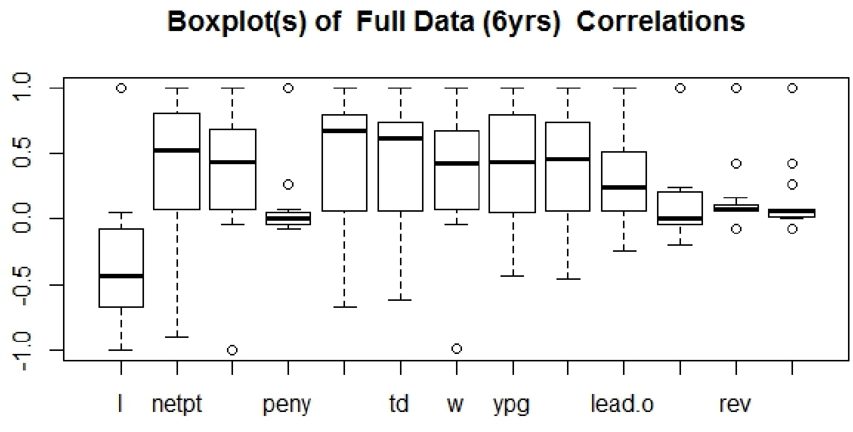

Figure 7: Pay vs. Performance - Correlation Matrix Summary Box Plot

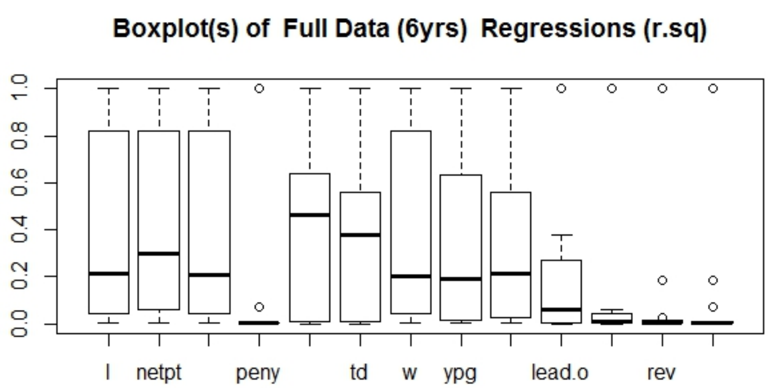

Figure 8: Pay vs. Performance - Regression Matrix Summary Box Plot

The count summary data (Appendix: Figure 16) shows that a majority (77%) of the relationships are semi-weak or weak. This tells us that as predictors, across the entire universe chosen, these variables are not strong influences individually. Lead.o is the only predictor out of four (4) to have any relationships above the weak threshold. Rev, salary and lead.d are all, consistently, weak predictors of performance. (Figure 8) When we look at this graphically in a boxplot, this weak relationship is very obvious relative to the other variables. However, lead.o is observed as the best predictor of performance, clearly standing out, relative to the other variables chosen as focus predictors for this experiment.

Conclusion

We see a very strong case against revenue and salary playing a significant role in driving performance. This can also be verified in the individual analysis where rev is only more correlated/ a better predictor than peny (Salary results are the same for the individual and combine analysis because it is the delimiting variable for time). The rev and salary variables are very poorly correlated with the data for the NFL teams and as standalone predictors show that a team that brings in more revenue or pays more money for their players will not guarantee or improve (with significant certainty) the performance of that team. While the lead.o and lead.d were not extremely correlated or strong predictors as well, they are greater in both respects when compared to the performance predictors. We can safely conclude that the skill of the players on the team is a more important and influential factor of the team's success than how much much they are paid or how great their revenue streams are. We can also safely conclude that based on our data sets, players that are leaders in their respective offense categories are the better indicators of success than defense players. A further analysis from here should be conducted, increasing the number of top players used in the data per year and looking at those players' statistics and payment data throughout the year. This would allow a test for whether offensive or defensive leaders are a better acquisition target.

PLEASE NOTE: This comparative test, while backed by the individual analyses, only uses data for rev in a 16 year period and salary in a 6 year period. This implies that our analysis conclusions are based on limited data findings and should be re-analyzed with larger, more complete revenue and salary cap data to reach a more concise conclusion.

4 Analyze significant changes of major rule changes in the NFL

We are analyzing 2 major rule changes in 1995 and 2005 and assessing the change in the statistics of the teams and league as a result to identify if a meaningful or quantifiable change had occurred. The rule changes are as follows:

Rule(s) 1995 : Encroachment (Defensive penalty, ”off-sides” for defense)
Rule(s) 2005 : Roughing the Passer, Unnecessary Roughness, Horse-Collar Tackle Ban

We created functions that would run two-tailed Student t-tests for each variable on the data before and after the rule change. This was done in varying sizes from 1 year before and after the rule change, up to n years before and after. This allowed us to analyze the changes over different time frames to assess how long they took to realize an effect. For the tests, we also compiled the % change in the mean values of the variables for each of the rules, to assess the magnitude and direction of those changes. In addition, we also conducted t-tests over 1 year ”steps” to assess the effect of the rule change on the league. This allowed us to see if the changes were effective right away and how the league reacted in the years before and after the announcements.

Analysis: Rule change in 1995

With the data tables generated we converted observations into box plots to more easily analyze the results. The time frames were [(-19:-1):(1:19) * includes the rule change year], where the numbers represent the distance in years away from the rule change year. With the 0.05 significance level marketed, we observe that for the rule change in 1995 all variables' numerical ranges crossed the significance threshold at some time period and only ypp and td were not strongly affected. This was concluded when looking at the proximity of the median bar to the threshold level. (Figure 9) P values for pa, ppg and peny were significant for almost every single time frame comparison. These 3 variables indicate that the points against a team, the number of points per game and the penalty yards the team's incurred were all significantly altered as a result of this rule change. When we observed the variables' changes in their means, every variable saw increases for almost all time frames analyzed (Figure 10) while peny, pa and ppg saw the largest increases, consistent with the t-test results.

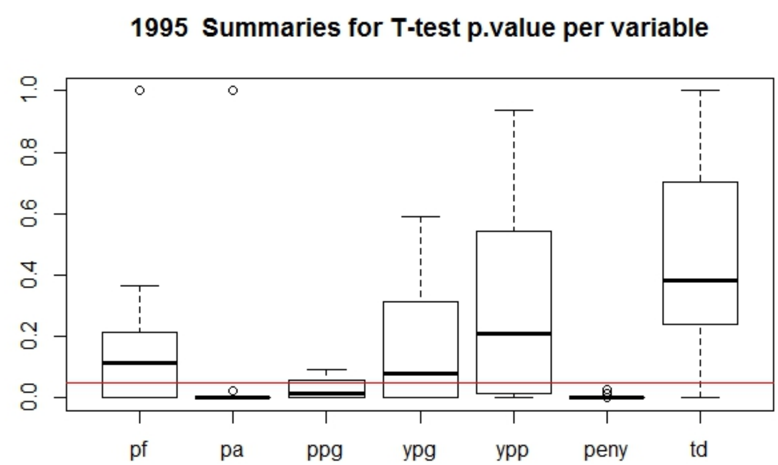

Figure 9: Rule Change Effect (1995) - T-test p value summary box plot

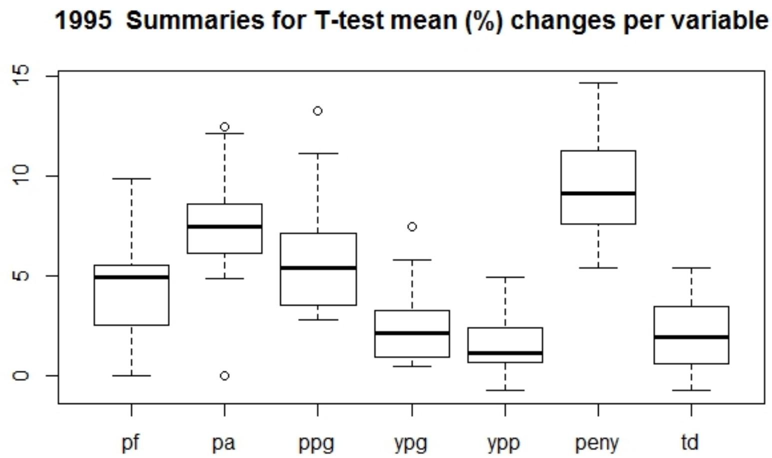

Figure 10: Rule Change Effect (1995) - % Change in means summary box plot

In addition to this, (Appendix: Figure 17) all of the variables' p values converge below the threshold as n (the number of periods on either side of the rule change) increases. This implies that the percentage of the portion of a variables p value summary that showed significant changes was directly linked to the amount of time needed to observe a significant change. (Please note, the values labeled in the legend are incorrect. The lines match the data analysis output but the colors per line are incorrect. We have included it here for reference to this observation only). This was also observed in the rule changes of 2005. When we analyzed the significance of the changes based on 1 year tests, we observed that the majority of the steps resulted in in-significant changes (Appendix: Figure 18). Even when viewing the years directly before and after the change, the one years steps tests were almost fully in-conclusive. This was found in the 2005 analysis as well.

Analysis: Rule changes in 2005

Looking at the 2005 rule changes, we noticed a different outcome. The time frame ranges were [(-11:-1):(1:11) * includes the rule change year, n = 11 because our final data point in 2016, which limited our range] Again, all numerical summaries for the p values crossed the threshold but all but ypp and peny seemed to have any serious changes overall (Figure 11). The medians were much further away from 0.05, and the range (variance) of the values was greatly increased across all variables except for peny (which was expected in this test). Looking at the mean % change boxplots (Figure 12) we observed that 2 of the 3 variables (pa, and ppg) that showed larger changes in their means in 1995 where now in line with the rest of the data, while peny and td showed an interesting outcome. The median td mean change was positive, but a considerable number of observations were negative changes, and peny, which we expected to show positive changes in the mean showed almost all changes to be negative with 1 positive outlier.

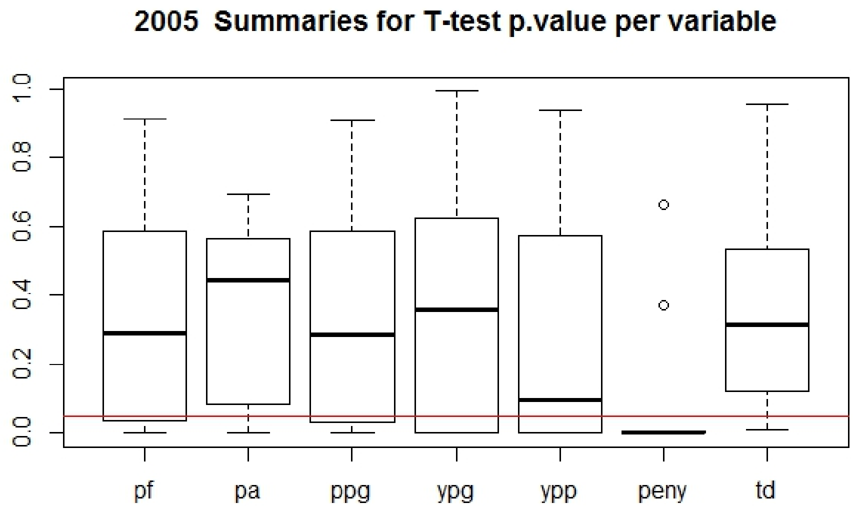

Figure 11: Rule Change Effect (2005) - T-test p value summary box plot

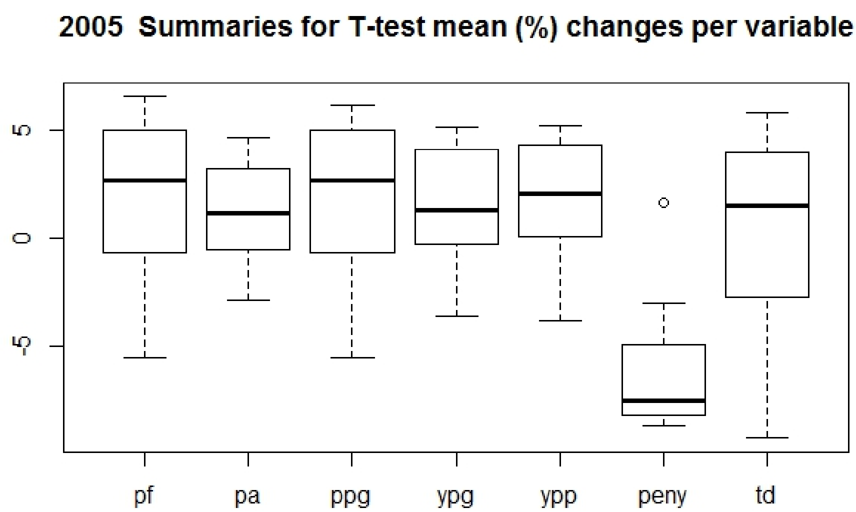

Figure 12: Rule Change Effect (2005) - % Change in means summary box plot

Conclusion

For the 1995 rule change, there was a significant impact to the NFL as a league. Adding a new penalty to game play would reasonably cause a large significant change in a team's penalty yards per year. It is also reasonable that those changes would be significant for so many time frames because all of a variable's time frames being compared to in the past exist without this rule in place. This rule, for reference, is a major rule change because it changes a popular and useful tactic for causing (provoking) offensive penalties and gaining an advantage before the play is called (momentum and placement advantage in timing an attack). The fact that the penalty is aimed at limiting the defense makes large significant changes in points against a team (pa) reasonable as well because of how the offense can now react and plan their plays.

The ppg and ypg variables showing significant changes is not odd but the fact that the changes in points as opposed to yards is more significant with a larger magnitude of change is. We would expect that the offense would see more yards per game with more successful play executions, but not necessarily scoring drives. It is also slightly odd that the median magnitude of change for ppg is so high considering td's change is much more conservative. Some theories we have developed are that passing plays, usually resulting in either a completion for a gain in yards or a no gain at all, could have increased due to better offensive line versus defensive line interactions. If the offensive line has more time to react, the "passing pocket" of the quarter back can be maintained longer for better passing attempts. The significance of pf's mean changes is also related to this explanation because more touchdowns means more points scores, and its mean change variance and median magnitude helps support the theory of field goal attempts as well.

As for ppg seeing such a large change relative to ypg and td, 3-point field goal attempts may have increased or the increase in touchdowns could be high enough to drive ppg's value higher. For example, touchdowns add 6 points and almost always 1 extra point with a field goal, so just 2 touchdowns can contribute almost 1 extra point per game, while yards per game include all offensive movements and these changes can be diluted over time. These speculations require a more in-depth analysis with more data sets that we did not have the time to retrieve.

For 2005, a significant change in penalties again would reasonably be significant while the results of the other variables seem accurate as well. The 3 rules added penalize a player for overly-aggressive contact in tackling, blocking, and when attempting to tackle the quarterback during a pass play (to protect him from hits he cannot readily prepare for) and for tackling by using the shoulder pad collar as leverage. These rules do little to aid the offense in scoring attempts because they only attempt to alter how overly-aggressive contact is made during a play. The variance of the changes was more contained across the set of data and the median magnitude was varied around 2.5%. This "tamed" result makes sense because this test had a shorter time interval that was completely contained within the time period after the 1995 rule change. The 2005 rule changes were not on integral parts of the game, so they are not as effective as the 1995 rule at changing the game in a meaningful way in terms of team's statistics and performance. The interesting observation here is the negative direction of peny. At first, it does not seem to make sense that adding 3 more penalties as opposed to 1 would result in a decrease of penalty yards per game, but the penalties levied in 2005 carry penalties of more than just losing a few yards. Roughing the passer and unnecessary roughness are more serious penalties resulting in more yards incurred and possible loss of downs (losing a play in the current drive). They can also carry fines from the league against offending players. We speculate that this has influenced player's behavior in the game successfully (as it was/is intended to do for safety purposes) and therefore has driven down the number of penalties overall.

5 Appendix: Figures referenced but used only as supporting analysis

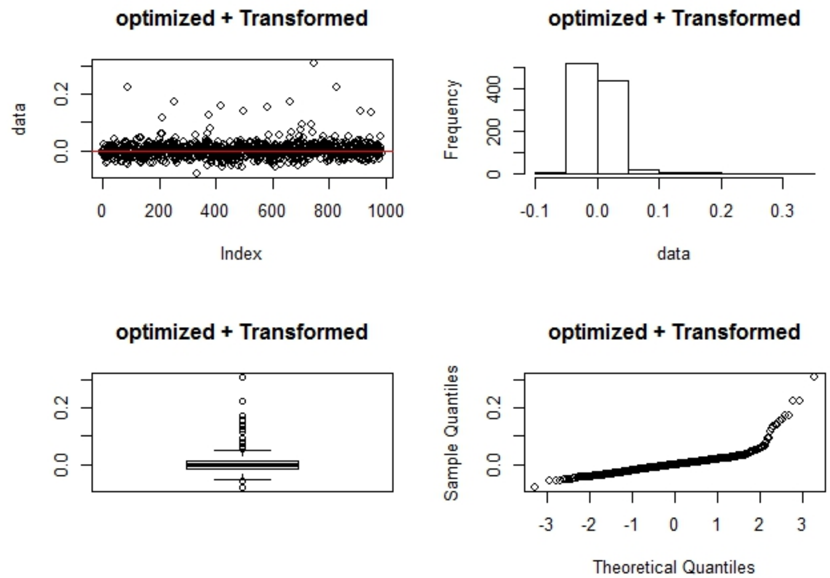

Figure 13: Part 1 : Final Model Residuals

	CI.low	CI.high	P.value	Mean (home)	Mean (rode)	Median (home)	Median (rode)	Std.dev (home)	Std.dev (rode)
49ers	0.372787981800937	2.2125778718576	0.00647078893769312	4.8780487804878	3.58536585365854	5	3	2.00243753899116	2.17916967852549
Bears	0.63744829805406	2.04547853121423	0.000289209027035865	4.34146341463415	3	5	3	1.65241877406366	1.54919333848297
Bengals	0.474491832254487	1.91575207018454	0.00144467913751509	4.14634146341463	2.95121951219512	4	3	1.58998389315358	1.68747177031492
Bills	0.719287893778247	2.15876088670956	0.000151547791249483	4.5609756097561	3.1219512195122	4	3	1.68891652380757	1.58422097497823
Broncos	0.648603780679157	2.22944499980865	0.00053191813778136	5.04878048780488	3.60975609756098	6	4	2.09703623612225	1.42965115990734
Cardinals	0.860506918215407	2.21266381349191	2.1075673462807e-05	4.02439024390244	2.48780487804878	4	2	1.45752881408994	1.61434121578296
Chargers	0.166574121310155	1.68708441527521	0.0175191165221707	4.65853658536585	3.73170731707317	5	4	1.63721953472283	1.81692584113803
Chiefs	0.433603006906314	2.05420187114247	0.00309341252731	4.46341463414634	3.21951219512195	5	3	2.08683445648678	1.55743691881808
Colts	0.102922733407178	1.84829677878794	0.0289142378675452	4.68292682926829	3.70731707317073	5	4	1.95498113021896	2.01548880471989
Cowboys	0.767905400199461	2.25648484370298	0.000122151355774455	5.48780487804878	3.97560975609756	6	4	1.55116006942405	1.82329104750241
Dolphins	0.705539295625216	2.07494850925283	0.000123140468460399	4.95121951219512	3.5609756097561	5	4	1.67259109635612	1.43263359739685
Eagles	0.0610455202757264	1.59749106509013	0.0347342774525791	4.26829268292683	3.4390243902439	4	3	1.58152442668304	1.89800922663465
Falcons	0.659329021587664	2.26750024670502	0.000513376820969576	4.65853658536585	3.19512195121951	4	3	1.91845974804739	1.73521630056777
Giants	-0.128631574627238	1.25058279413943	0.10941257862838	3.97560975609756	3.41463414634146	4	3	1.58883298175184	1.54879969260227
Jets	0.182663994103746	1.57343356687186	0.0139868593479467	4.21951219512195	3.34146341463415	4	3	1.58921671149581	1.57495644539081
Lions	1.24559129346254	2.6568477309277	5.12292456736561e-07	4.14634146341463	2.19512195121951	4	2	1.83794689272781	1.3270175619622
Packers	1.3162772563956	2.78128371921416	3.40329307908167e-07	5.46341463414634	3.41463414634146	5	4	1.73345840699467	1.596490052523
Patriots	0.479856679571092	1.91038722286793	0.00134243301074154	5.60975609756098	4.41463414634146	6	5	1.49796610075942	1.74607573942395
Raiders	-0.192813108545216	1.36354481586229	0.13832550227315	3.97560975609756	3.39024390243902	4	3	1.7100848645323	1.82863403638464
Rams	0.231134095591733	1.9152073678229	0.0131729363289898	4.34146341463415	3.26829268292683	4	3	2.0929614914943	1.71791138077467
Redskins	0.151287815149753	1.55602925802098	0.0178700576137712	4.41463414634146	3.5609756097561	5	4	1.74607573942395	1.43263359739685
Saints	-0.230873720074895	1.35282493958709	0.162435031528072	4.17073170731707	3.60975609756098	4	3	1.89608068162183	1.70114738897733
Steelers	0.792261867145289	2.08578691334252	3.00453956157503e-05	5.46341463414634	4.02439024390244	6	4	1.39816953506379	1.54090565704148
Vikings	1.06503230520325	2.49594330455284	4.05060384236156e-06	4.92682926829268	3.14634146341463	5	3	1.70865800999555	1.54209233850889
Sig. at 0.05	-	-	21 / 24	-	-	-	-	-	21 / 24
Sig. at 0.025	-	-	19 / 24	-	-	-	-	-	19 / 24

Figure 14: Part 2 : Team T-test results table

	Total.Count	Percent.of.Total	l	netpt	pct	peny	ppg	td	w	ypg	ypp	lead.o	lead.d	rev	salary
Strong Negative	6	3.846154	3	1	1	0	0	0	1	0	0	0	0	0	0
Negative	4	1.564103	2	0	0	0	1	1	0	0	0	0	0	0	0
Weak Negative	8	5.128205	3	0	0	0	0	0	0	1	1	1	1	0	0
N/A ([-0.10:0.10])	68	43.589744	3	2	3	11	4	4	3	3	3	4	8	9	10
Weak positive	30	19.230769	0	2	3	1	1	0	4	3	3	4	3	3	2
Positive	26	16.666667	0	3	2	-1	3	6	2	3	4	3	0	0	0
Strong Positive	14	8.974359	0	3	2	0	2	1	2	2	1	0	0	0	0

Figure 15: Part 3 : Correlation Matrix Summary Table

	Total.Count	Percent.of.Total	l	netpt	pct	peny	ppg	td	w	ypg	ypp	lead.o	lead.d	rev	salary
Negative	0	0.000000	0	0	0	0	0	0	0	0	0	0	0	0	0
Weak	98	61.820513	6	5	6	12	4	4	6	7	4	8	12	12	12
Semi-Weak	24	15.384615	1	2	2	0	1	4	2	2	5	4	0	0	0
Average	12	7.692308	1	0	1	0	4	2	1	0	2	0	0	0	0
Semi-strong	8	5.128205	0	1	-1	0	2	1	0	3	1	0	0	0	0
Strong	6	3.846154	1	3	1	-1	0	0	1	0	0	0	0	0	0
Very Strong	8	5.128205	2	0	2	0	0	1	2	0	0	0	0	0	0

Figure 16: Part 3 : Regression (r-squared) Matrix Summary Table

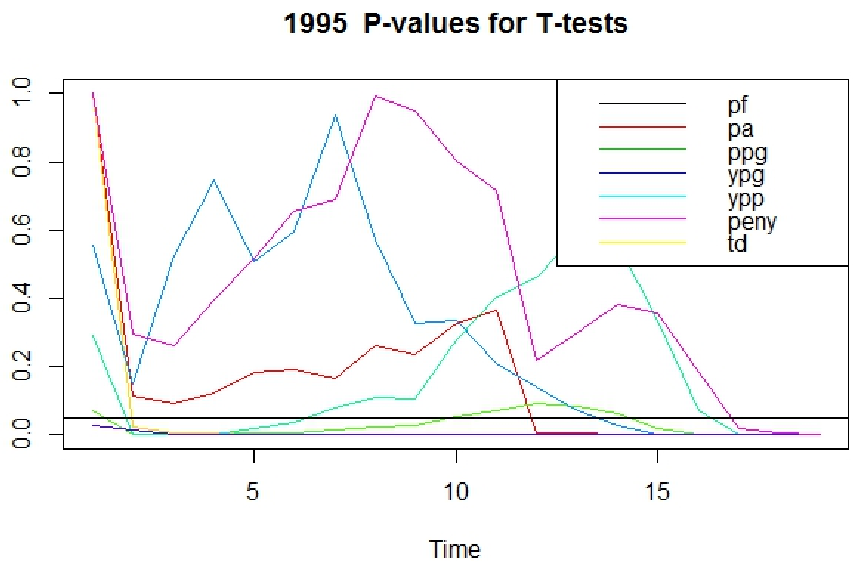

Figure 17: Part 4 : Time series plot of "waves" analysis p values over time (periods checked by test)

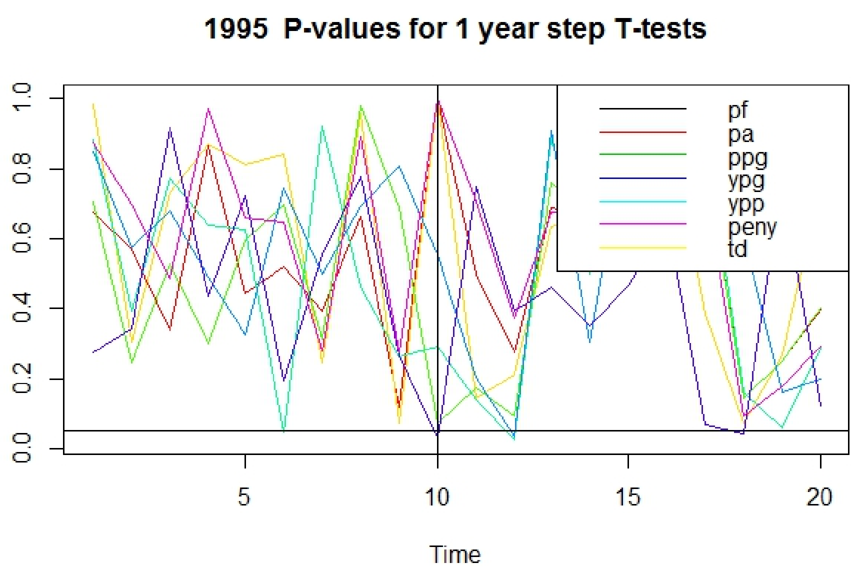

Figure 18: Part 4 : Time series plot of "steps" analysis p values over time (year by year steps)